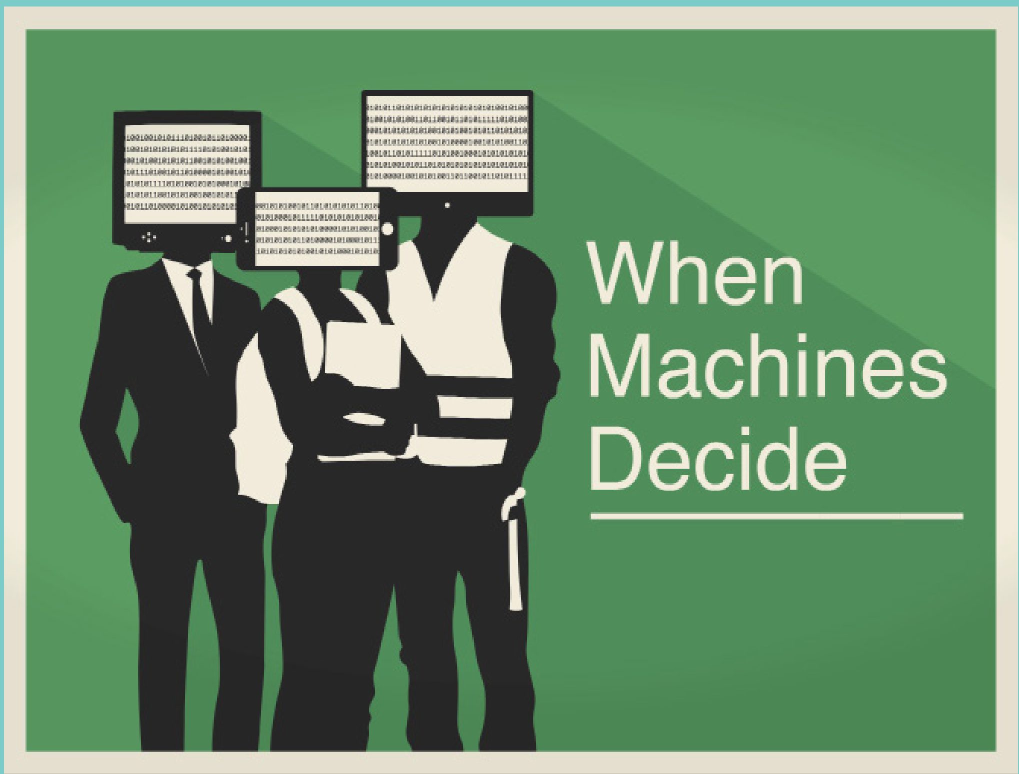
WHEN MACHINES DECIDE: CREATING JUSTICE.EXE



The Promise and Peril of Living in a Data-Driven Society
University of Utah Honors College
2016-2017 Praxis Group

When Machines Decide: The Promise and Peril of Big Data was a Praxis Lab at the University of Utah during the 2016-2017 year. The class was taught by Law Professor Randy Dryer and Computer Science Professor Suresh Venkatasubramanian. Students were Austin Anderson, Abigail Busath, Logan Cox, Morgan Cox, Logan Erickson, Zachary Grena, Joseph Hutchins, Skyler Jayson, and Andrew Yang.

Special thanks goes to librarians Valeri Craigle, Donna Ziegenfuss, Dean Sylvia Torti, and Erica Rojas.

WHEN MACHINES DECIDE: THE PROMISE AND PERIL OF BIG DATA

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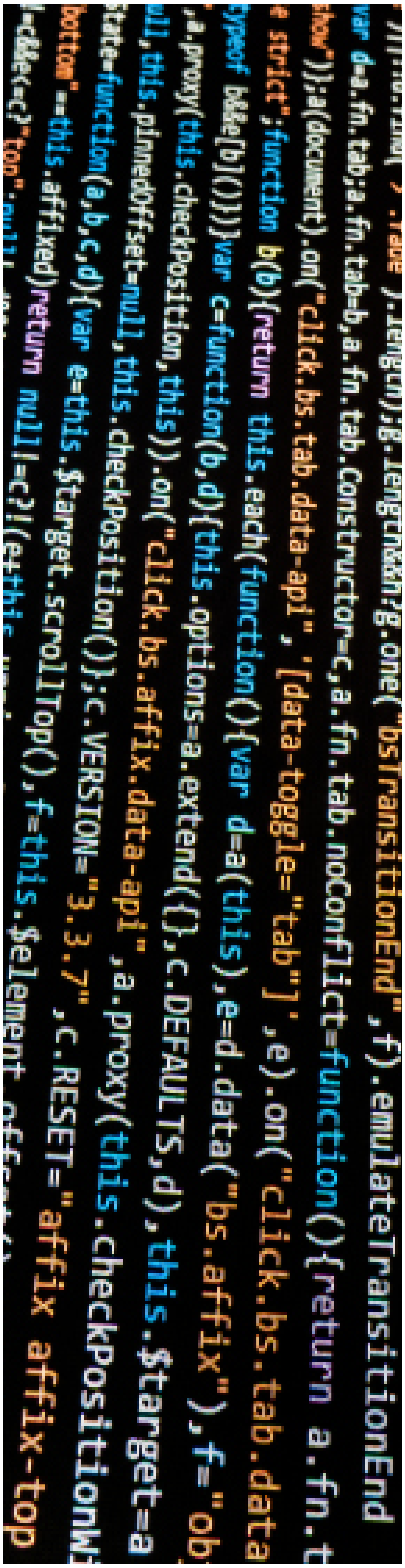
The Praxis Lab team at the Utah State Capitol after it presented to the Utah Sentencing Commission.



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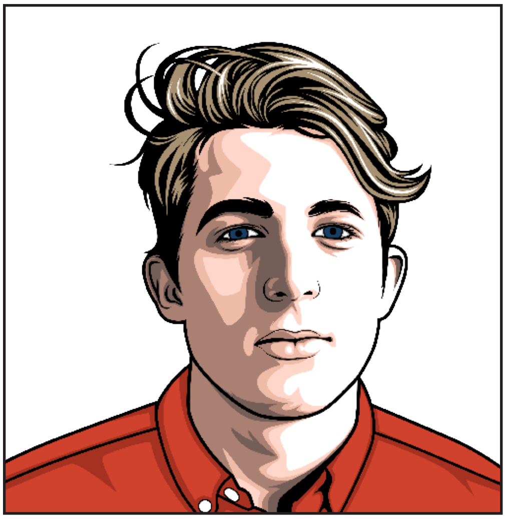
PART ONE: OUR PRAXIS LAB

THE TEAM



Zach Grena

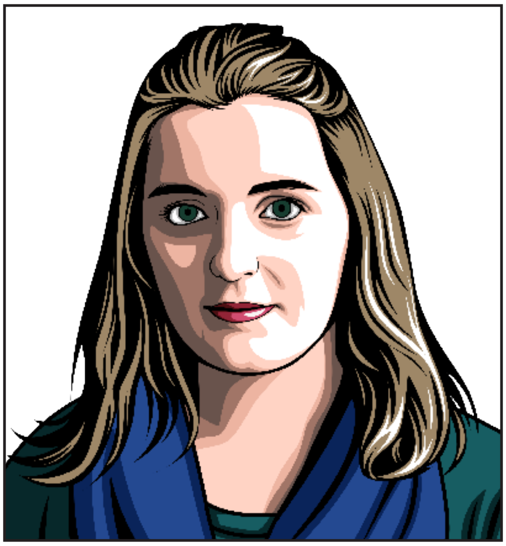
Zach is a sophomore majoring in Finance w a minor in Computer Science interested in cryptocurrencies and how societies and culture influence the technology that we build. A fan of existentialist literature, notably Camus and Dostoevsky, he enjoys drinking insane amounts of coffee and tea over a good novel in his free time away from his work in ASUU and VentureCapital.org. Zach was drawn to this Praxis lab to understand the extent to which algorithms decide our future and fate in current society. When asked about machine learning algorithms in sentencing, he feels uncomfortable about the role that these algorithms can play and how they might be unfair, but thinks that an unbiased, well developed algorithm could have a place in the justice system, provided they are fair and just. After college, Zach plans to spend a few years in management consulting before he goes back to get his Masters in data science unless he drops out in the meantime to start a yuppie tea shop that blasts depressing indie music.

Logan Erickson

Describing his life goal as “putting smiles on faces and bringing joy through gaming all while having a positive impact” Logan Erickson is a sophomore majoring in EAE - Film and Media Arts that also has a place dancing in the U’s Break Club, an undergraduate breakdancing cohort. Outside of his classwork, you can usually find him skiing and biking, and working on game development designs for fun. Logan signed up for this PRAXIS Lab to discover how he can be a part of this new future of Big Data and machine learning. While optimistic about this new future, he still is reserved about the role that algorithms should play in the judicial system. Logan believes that we have begun to adopt new technology without the proper testing and development, and that without further review, this could exacerbate injustices already present in the judicial system.

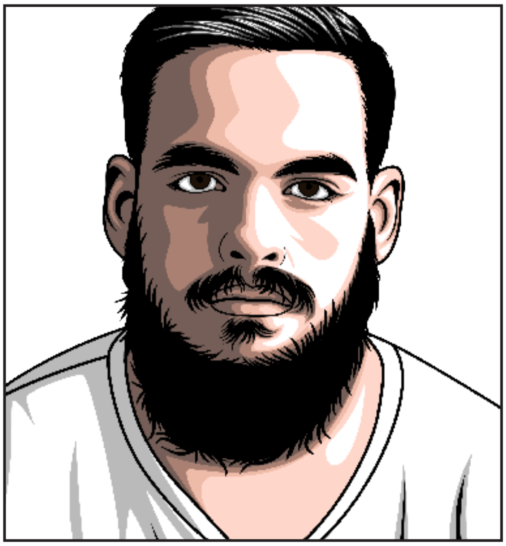
Austin Anderson

Austin is a sophomore studying computer Science with an EAE emphasis. With a mild obsession for F. Scott Fitzgerald and proud owner of four copies of the Great Gatsby, he enjoys a variety of hobbies when he isn’t coding up his next side project, including literature, film, video games, politics and graphic design. Austin signed up for this PRAXIS Lab because of his fascination with the intersection of technology and its potential effects on society. When working on this project, Austin was most moved by the fact that very few people know what when and how algorithms are being used in sentencing, and that these algorithms are even being developed. Mindful of the way that our human biases can be unintentionally picked by the algorithms, he advocates for more study on the way we can unintentionally encode our biases in algorithms before we use them to enforce justice. After college, Austin plans to kick it on the Eastern Seaboard as a software engineer.



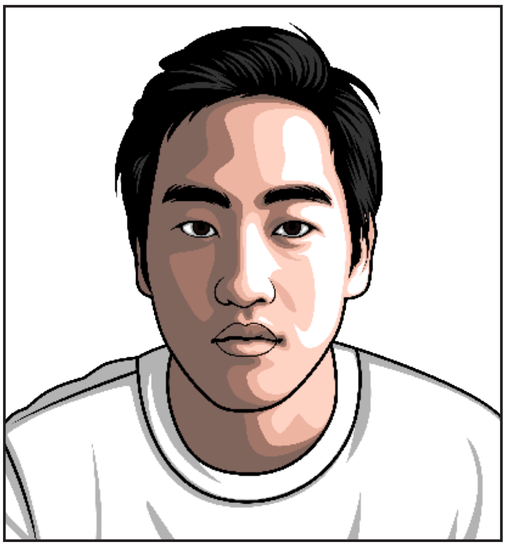
Morgan Cox

Morgan is a sophomore in the EAE program with an impressive list of extracurricular activities. A member of both kappa Kappa Gamma and Tau Beta Sigma sororities, as well as the Pride of Utah Marching Band, she also finds time to be involved with the Social Justice Scholars and the Bennion Community Service Center. When she is not being pulled every which way on campus, catch her at the Lassonde front desk helping students with a smile. She saw this class as an opportunity to understand her own relationship with Big Data and take steps to show everyone else what's being taken from them and how they can protect themselves. This attitude carries over to her views on machine learning algorithms used in sentencing - she believes that improper understanding of algorithms and their biases will leave us to trust processes that might mirror some of our prejudices. After college, she plans to continue studying the effects of media on the individuals that consume it



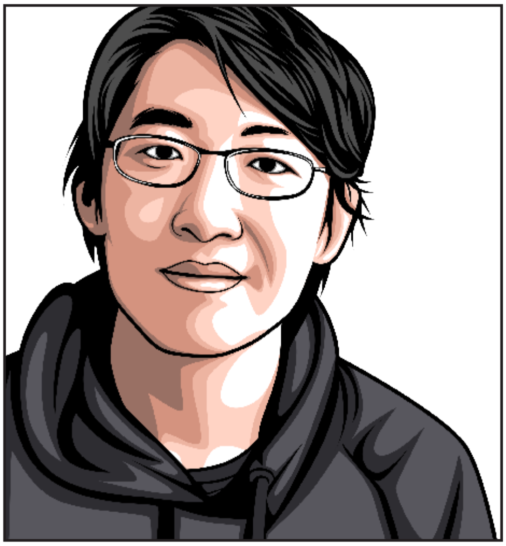
Logan Cox

While most looking at Logan's resume be impressed with his double majors in Computer Science and Finance while maintaining involvement in Legal Scholars, Business Scholars, Opportunity Scholars, and serving as an RA for Lassonde, those who personally know Logan unanimously agree that the best part of Logan is the magnificent beard. In between maintaining his stunning facial hair and impressive school schedule, Logan enjoys powerlifting, programming, business, and reading, and hopes to go to graduate school and run his own start up in Washington or northern California. While interested in the ways that algorithms have impacted our society, he sees danger in allowing them to take over sentencing in the criminal justice system. To Logan, outsourcing the task of justice to a "black box" would leave a "sizeable stain" on our society.



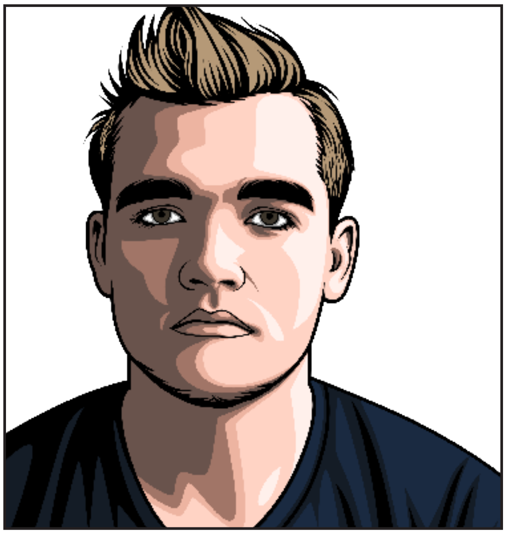
Skyler Jayson

A current Junior in the School of Engineering, Skyler is a biomedical engineering major who also has interest in coding and Big Data. He joined the Praxis Lab because he saw the influence of Big Data in his own life interesting and saw the potential of Big Data to transform the medical field, which he hopes to go into someday. When asked about the role of machine learning algorithms in sentencing, his main issue is that the advancement of technology has created a discrepancy between those who understand it and those who don't. Those who are not familiar with the way that these algorithms work can grow to fear this, and other technologies, causing many to rebel against all technology. After graduation, Skyler wants to spend a year or two in industry or research and development before applying to graduate school to study the field of prosthesis's.



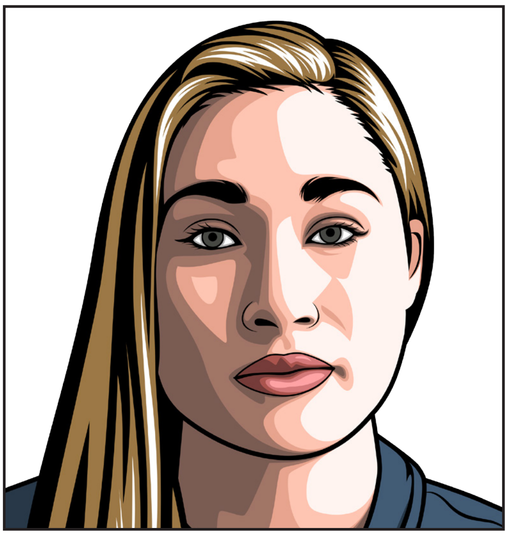
Andrew Yang

Andrew is a Math major with penchant and interest for World Religion, which he made his minor after taking a particularly interesting class his freshman year. Besides his interest in religious studies, he also is fascinated and excels in Math, and his experience in MCM (Mathematical Contest in Modeling), a five day problem solving course over Ebola in Africa, made him interested in real world problem solving which influenced his decision to sign up for this PRAXIS Lab. Andrew's concern and motivation for working on this PRAXIS problem is his observation that we know "nothing about the actual algorithms being used in sentencing" and concern that "they could be using biased data for training, or use an algorithm that is inherently biased, and we could never know". Outside of class, Andrew also enjoys coding up his own side projects, reading, and playing games. After his time in undergrad, Andrew wishes to go to graduate school for Computer Science.



Joe Hutchins

While many dream of becoming the next President of the United States, when you ask Joe about his future plans, he has none because "specific long term plans are destined for failure". Regardless, while his vision for the future might be empty, his calendar these days sure isn't. He spends time as a producer at K-UTE Radio as well as a bass in the Chamber Choir. His interests outside of his Information Systems classes include music, linguistics, mathematics, and language learning, and cites his interest in machine learning for signing up for the class. As a result of this PRAXIS Lab, Joe is concerned that algorithms in sentencing are based on biased data, which with a lack of human oversight can lead to errors in sentencing.

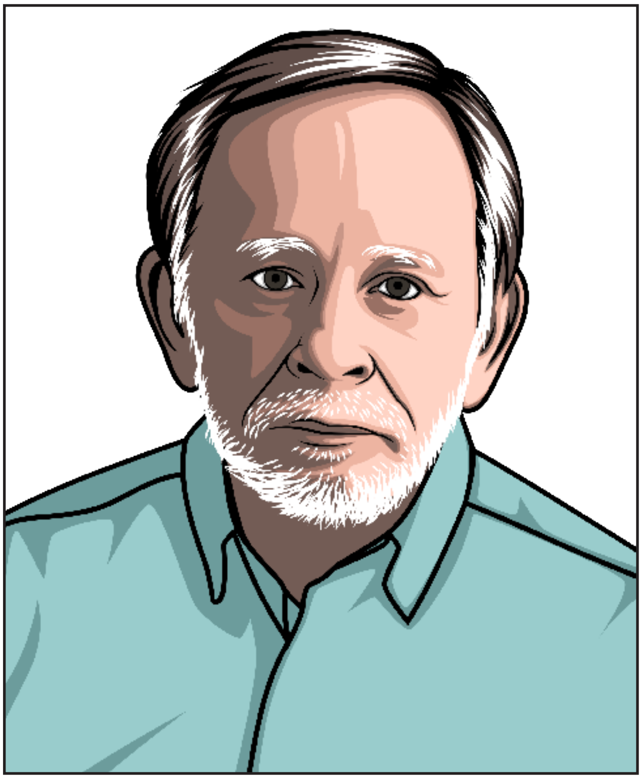


Abigail Busath

Abigal is a sophomore nursing student who is an active member of the Nursing Early Assurance Program and the National Student Nurses Association at the University of Utah. Always on top of her classes and movie schedule, Abi also finds time to work as a Patient Care Technician at Primary Children's Medical Center.

Growing up in a house with a father that made her read all of the "terms and conditions" before she proceeded onto any website or app, she developed a healthy respect and paranoia for data privacy at a young age. When she read the class in description in passing one day, she knew that she immediately had to sign up for this specific PRAXIS lab.

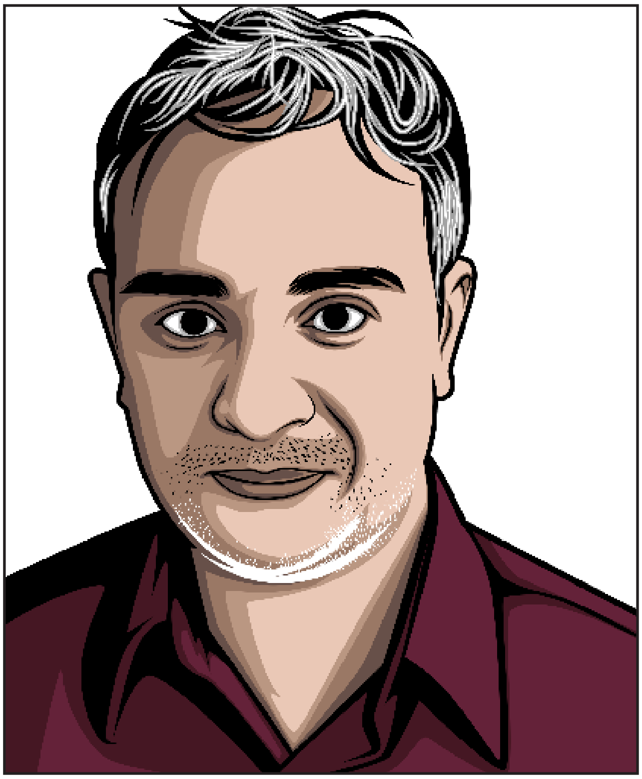
During her time working on this project, she has begun to understand that the algorithms underlying many of the decisions made for us are only as good as the programmer that made them, and feels uneasy implementing them in the justice system when we are unsure how fair and accurate they are.



Randy Dryer

I have professionally reinvented myself several times over. I started my career as a working journalist in both print and TV and then went to law school with the thought of becoming a network correspondent reporting on the Supreme Court. Along the way, I developed a love of the law and thus began my second career as a practicing lawyer at Utah's largest law firm. There, I developed a media law litigation practice where I was able to combine law and journalism by representing many local and national news organizations, including 60 minutes, CNN and the New York Times, among others. After 30 years as a practicing lawyer, I began phase three of my professional career when I was named in 2011 as the Presidential Honors Professor at the University of Utah with a joint appointment at the S.J. Quinney College of Law and the Honors College.

I became interested in algorithms as a corollary of big data and privacy law, subjects I regularly teach. We live in exciting and rapidly changing times. Big data and machine decision making are ushering in a new age of enlightenment and prosperity, but also pose challenges and threats to a degree never before experienced.



Suresh Venkatasubramnian

My background is in theoretical computer science: the study of the intrinsic complexity of computations. Over the years, I've become more interested in problems of data analysis (which I like to think of as a special case of high dimensional geometry!). I'm also a sci-fi fan, and many years spent reading cyberpunk thrillers got me thinking about our machine-enhanced future. A few years ago, I started imagining what it would be like to live in a world where all my decisions were controlled (or nudged) by algorithms that learnt things about me, and it didn't take long to realize that we're barreling into a future driven by algorithms that aren't that smart, and aren't particularly fair.

INTRODUCTION

By Professors Randy L. Dryer and Suresh Venkatasubramanian

> "'If every algorithm suddenly stopped working, it would be the end of the world as we know it.' (Pedro Domingo's The Master Algorithm). Fact: We have already turned our world over to machine learning and algorithms. The question now is, how to better understand and manage what we have done?"
> -Barry Chudakov, technologist and founder of StreamFuzion Corporation.

Algorithms are everywhere and spreading rapidly, operating invisibly behind the scenes to impact every aspect of our daily lives, often without our even knowing of their existence or use. Algorithms run the internet, complete financial transactions, give us book and travel recommendations, decide whether we get a job interview and determine what appears on our Facebook news feed. Algorithms advise judges as to who should or should not be released pending trial, approve loan applications and grant or deny visa applications. In short, algorithms are silent, automated workhorses which tirelessly analyze massive amounts of data and employ preprogrammed approaches to problem solving and everyday decision-making.

The promise of automated decision-making comes from considerations of efficiency, precision and unbiasedness. Our faith in algorithms comes from how they can process decisions involving complex data sources at superhuman speeds, identifying subtle patterns hidden inside massive data sets that humans cannot comprehend, and doing all of this using the cold logic of mathematics rather than human subjective thinking.

On the other hand, in the name of efficiency, optimization and evidence based decision-making, algorithms unavoidably delegate human function and judgment to machines. They fundamentally shift power from individuals to the corporations and governments who use them. Moreover, the recognized and accepted accountability and oversight mechanisms we have imposed on human decision-making are likely ill- suited to this technology and require new approaches.

Algorithms, because they are mathematical formulas, have an aura of neutrality or objectivity, which is a patina that may not comport with reality. Human biases, implicit or explicit, may be embedded into algorithms by programmers or through data inputs that are biased or non-representative. Consequently, automated decision-making systems can produce incorrect or unjust decisions that may not be readily apparent due to the "black box" nature of algorithmic systems. In February of 2017 the Pew Research Center surveyed more than 1300 technology experts, scholars, corporate representatives and government leaders about the potential impacts, benefits and concerns arising from the use of algorithms in the coming decade. The survey responses revealed seven major themes:

Theme 1: Algorithms will continue to spread everywhere
Theme 2: Algorithms will lead to better problem solving and greater insight into the world
Theme 3: Humanity and judgment are lost when predictive modeling by algorithms became paramount.
Theme 4: Biases exist in algorithmically-organized systems
Theme 5: Algorithmic categorization deepens existing divides (such as between the rich and poor, the creative and the not-creative)
Theme 6: Unemployment will rise
Theme 7: The need for algorithmic literacy, transparency and oversight is growing

Our Praxis Lab, to a greater or lesser degree, touched on all these themes, but this final report and the team project the students ultimately selected centered on the increasingly important need for algorithmic literacy, transparency and oversight, particularly in the context of the use of algorithms in the criminal justice system. Accordingly, we (1) designed an educational simulation to illustrate the function of algorithms in the context of criminal sentencing; (2) created several pre-packaged course modules that faculty in a variety of disciplines could integrate into their existing curriculum to educate students about algorithms and their increasing role in modern society; and (3) curated a set of best practices designed to promote the transparency and oversight of algorithmic systems.

With the exception of this Introduction, this report is authored by the students and consists of three parts. Part one chronicles the Praxis Lab organization, activities and participants. Part two describes the three "deliverables" produced by the students and Part three offers their essays and personal reflections on the experience. It was our privilege to work with such a bright, highly motivated and terrific group of students.

COURSE OVERVIEW

Our course design for When Machines Decide consisted of weekly meetings of three hours on Thursdays, from 2:00-5:00pm. In the fall, each class began with a brief lecture given by Professors Dryer and Venkatasubramanian, and then moved on to the class discussion (Question of the Week). The question of the week was a topic posed on the class website that all the class members were expected to reply to before class on Thursdays. Then, in class, everyone was asked to give a brief explanation of their answers posted on our online Libguide (the class website through which all readings and discussions were posted) and as a group we discussed the implications of each question. The Questions of the Week are posted in Appendix A and student answers to individual questions may be accessed on the course LibGuide here. After the question of the week discussions, the class group who was in charge that week led discussions on the weekly reading assignment, which always had a theme, whether that be Big Data logistics, fairness issues, regulation of Big Data, predictive policing, algorithms in healthcare, business, and education. We had a class with many varying perspectives, which allowed us to really dig deeper into the issues and look at both the positive and negative aspects of each topic.

As part of the fall semester, each student was made to conduct a research/interview paper on a topic exploring various companies' uses of Big Data and their collection, storage, and usage policies, and give 10 minute presentations on their research to the class. In addition to the individual projects, the class was divided into teams of two with one group of three who were assigned different weeks in the semester to create discussions pertaining to the readings of that week, and then work together to create a project proposal that would be presented to the class to choose for the Spring Semester.

Some weeks, as part of the discussions, Professors Dryer and Venkatasubramanian arranged for guest speakers, who were experts in their respected fields, to give brief presentations to us and allowed for questions and discussions pertaining to the presentations. These class periods gave us an opportunity to see Big Data in "action", as it were, and allowed us to ask hard questions to really gain a deeper understanding of how algorithms are implemented.

"In addition to the individual research projects, the class was divided into four teams for the purpose of researching and proposing a Team Project for the entire class to work on Spring semester. Each team made an oral presentation at the end of fall semester and the class voted on which Team project to work on. The proposed Team Projects that were not selected are described in Appendix C. The oral presentations on each

After our class decided to pursue Justice.exe in December, we worked during winter break to formulate the direction of the project and the means with which we wanted to use to create it. We split into different production groups, which we called "squads" to organize our efforts and to give everyone a responsibility in the project.

-The Algorithm Squad: Logan Cox, Skyler Jayson, and Andrew Yang worked to design the algorithm our app was built on.

-the mini-Course Squad: Morgan Cox and Joseph Hutchins developed an academic course corresponding with the game to help teachers who were teaching about algorithms and/or criminal justice.

-The Development Squad: Austin Anderson, Morgan Cox and Logan Erickson worked to create the format and style of the game.

-Marketing Squad: Joseph Hutchins, Skyler Jayson, Andrew Yang and Abi Busath formulated ideas about how we were going to get the game out into the world.

-Research and Report Squad: Zach Grena and Abi Busath collected and organized all the material we learned and transcribed the process into a physical report.

Our spring semester consisted of the same meeting schedule, but instead of lectures and discussions, each squad would give a report on what they had accomplished the previous week and set goals for the following week that the whole class could give insight and input to. Everyone played a role in the process of the game and everyone gave perspective and opinions on where we wanted to take the game.

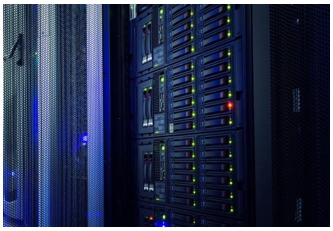
Course Objectives and Learning Outcomes

Upon successful completion of the course, you will have:

1. Gained an in-depth understanding of the substantive legal, policy and ethical dimensions of big data, predictive analytics, machine learning and automated decision-making and related technologies through exposure to a variety of sources of information and diverse perspectives.
2. Established a collaborative, self-directed, group oriented learning experience in a conducive environment.
3. Developed critical and reflective thinking skills that apply the substantive knowledge gained to the world around you and in new settings and to new issues.
4. Conceived, designed and implemented a team project that addresses a contemporary issue in our data driven society which will have educational value and/or social utility beyond the course.
5. Developed organizational, communication, decision-making and other interpersonal skills necessary to identify, set and accomplish a group objective or goal.
6. Improved your scholarly research, speaking and presentation skills.
7. Produced tangible work product that evidences intellectual rigor and practical competence that may useful in pursuing future employment or further education.

FIRST SEMESTER TIMELINE

INTRODUCTION



WHAT IS BIG DATA AND WHY IS IT IMPORTANT

THE COLLECTION, CONSOLIDATION, AND STORAGE OF DATA

THE MINING, ANALYSIS, AND USE OF DATA

AN OVERVIEW OF THE POTENTIAL BENEFITS AND DANGERS OF BIG DATA

A DEEPER DIVE INTO ALGORITHMS AND FAIRNESS ISSUES

THE REGULATION/ GOVERNANCE OF BIG DATA

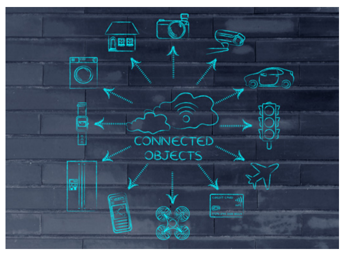
BIG DATA + LAW ENFORCEMENT

BIG DATA AND EDUCATION

BIG DATA AND BUSINESS

BIG DATA AND HEALTHCARE

INDIVIDUAL PROJECTS



TEAM PROJECT PITCH

GUEST SPEAKERS

Dr. Willard Dere

We were very fortunate to have Dr. Dere spend some time with us to discuss how Big Data helps contribute to evidence-based medicine, which is very important when it comes to the diagnosis and treatment of patients. He started out by giving the class a scenario about a woman who was thought to have cancer, and was given the option of a few medications based on how many other people had benefitted from them. Dr. Dere asked the class to choose a medication for the woman to take. Based on the number of women that had found success with one form of medication, many members of the class thought it logical to prescribe that medicine, while a few others remained skeptic. This thought exercise was intended for the class to confront the idea that just because there is a study that says 100 people had good experiences doesn't mean that everyone will have the same experience.

He went on to discuss the importance of individualized care, and by using algorithms that use family history and current patient statistics to determine logical courses of action that help patients to heal and be proactive in their own care. Many thanks to Dr. Dere and his efforts to improve the medical experience.

Trevor Dryer

Trevor Dryer, son of our very own Randy Dryer, is currently the co-founder and CEO at Mirador, a venture-backed company that "unlocks the power of machine learning for small business lenders." Mirador isn't in the business of lending money, but they are behind the scenes, providing a white label SAAS platform that allows credit-unions, banks, and non-profits to provide smarter loan decisions faster. Trevor spoke to us over Skype about the move away from a traditional FICO credit score to a more holistic approach to risk-management.

Trevor and Mirador fit nicely into our conversation over the different ways in which Big Data and algorithmic decision making is affecting our lives, and we are grateful for him to have taken time out of his schedule to speak with us.

GUEST SPEAKERS

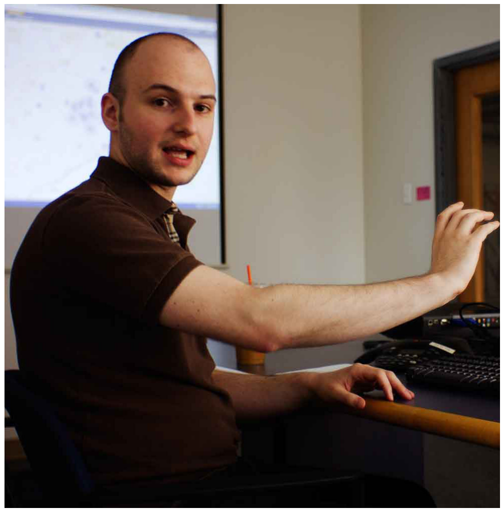
Mike Martineau

We heard from Mike Martineau, the Director of Institutional Analysis at the University of Utah. We learned that the University collects mountains of data about every student at the University. Much of this information is collected by the Registrar and Admissions offices, but also includes other information on students. This information is housed in a student "Data Warehouse." Only a limited number of persons have access to the DAta WArehouse and the University goes to great lengths to insure the data is secure and properly protected as confidential information. FERPA, HIPAA and other state and federal laws, as well as University policy, impose various requirements on how the data is used, safeguarded and processed. The University is just beginning to tap the power of its collected student data and is exploring ways to identify students who are at risk of not graduating and may be in need of early interention or special services. Mr. Martineau noted that a student's first semester's grades are an important predictor of whether a student will or will not graduate.

Loren Larsen

Mr. Larsen, the current CTO of HireVue, came to talk to us about the growing number of firms using analytics and data to make smarter hiring decisions. HireVue believes that predictive analytics can be used to make smarter hiring decisions, much like how Amazon uses algorithms to make product recommendations. As hiring managers and HR departments are forced to make better hiring decisions in shorter time, many are turning to data and analytics to make more informed decisions. Mr. Larsen came and talked about HireVue's new HireVue Insights platform, that utilizes machine learning and predictive analytics from audio and video to recommend top candidates.

GUEST SPEAKERS



David Robinson

Dave Robinson spoke to us about the rise of predictive policing, and the dangers that such prognostic tools could pose to our civil rights and minority communities. Speaking from his experience at Upturn, a thinktank that works at the intersection of technology and civil rights, he educated us on the tendency for these algorithms to send even more resources to already over-policed neighborhoods. He also cautioned against the secretive nature of these algorithms, saying that tools that are used to allocated policing resources should not stay in a black box. Mr. Robinson was one of the many who came and spoke to us about ways in which algorithms are edging their way into our lives, making decision and running behind the scenes of most of the world today.

Jeremy Heffner

Jeremy was kind enough to propose an alternate view of predictive policing technology. A data scientist at Azavea, he is a product manager over HunchLab, a new predictive policing tool. Conscious of the criticism of predictive policing tools, Jeremy and the team building HunchLab have taken care to build a tool that reflects the priorities of the police officers, and has features that stop over-policing. By keeping in mind the biases that are present in historical crime data, and the ways that algorithms can create skew patterns, they have built a fantastic tool that is able to proactively respond to risk. One of the great features of HunchLab is Advisor, an analytical plug-in in their platform. Advisor is a dashboard that gives tactics to patrolmen that might help them focus their efforts and keep the community safer.

We heard from Jeremy right after we heard from Dave, and we appreciate Jeremy's perspective on the potential benefits of the increased use of algorithms in policing.

GUEST SPEAKERS

Jennifer Valencia

We had the privilege of hosting Jennifer Valencia, the Director ofthe Utah Sentencing Commission, in our class during the second semester to propose our project to her and to learn more aboutthe current uses of algorithms in the Utah Criminal Justice System. She led us through a history of machine learning algorithms in the criminaljustice system and why they came about to help provide a more scientific approach to sentencing. She had good insights and brought visual aids that helped to explain just how the sentencing tools used functioned and made decisions. She was very insistent that these tools were not replacing human decision making, but rather they were used to help make recommendations based on a variety of factors to help ensure that each defendant was given consideration into the treatment that would benefit them more in preventing recidivism.

We were then able to present a brief description of our projectto her, and she was ableto give us advice and encouragementabout other things we could include in our material. We are grateful to her for giving us the opportunity to present to the Utah Sentencing Commission on April 5, 2017.

Rick Schwermer

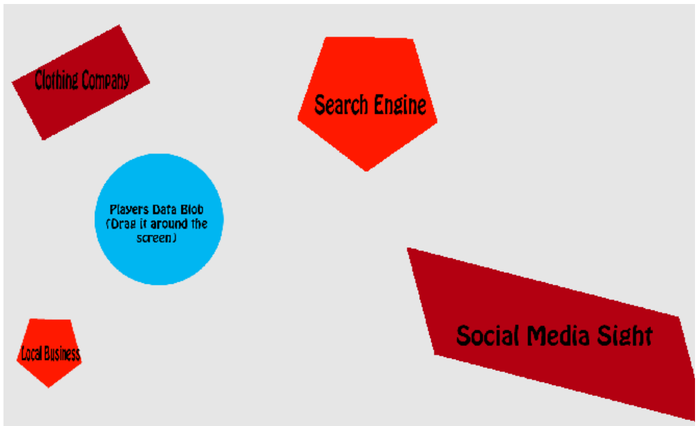
We were fortunate to have Rick Schwermer, the newly appointed state court administrator, come and talk to us about drug courts and machine learning algorithms in the criminal justice system during our second semester. With a good balance of humor and focus, Rick talked to us about the current tools used by the Utah court systems in sentencing defendants. He touched on a few points that Jennifer Valencia had previously, but also broke down the process in more detail to really help us understand. He gave us a history of his experience withand without the algorithms, and explained why these tools are beneficial to the systems now in rehabilitating instead of isolating defendants. We asked many questions to which Rick had numerous answers and jokes to tell, and he was very interested in our project and listened to our concerns. He was able to give us advice about what risk factors to take into account and what our focus should be when we talk about sentencing tools. We appreciated the insights and encouragement we received from Rick.

PROPOSED CLASS PROJECTS

Although the project our class decided to pursue was Justice.exe, there were three other proposals that our class discussed undertaking. At the beginning of the semester, the group was divided into teams of two (except for one group, which had 3) to both lead weekly discussions and research and propose Spring Project ideas. The groups dreamed big and set high goals, and we were all impressed with the level of thought that went into each proposal. While some groups explored the possibilities of awareness campaigns focusing on Big Data, others focused on best practices of data collection, and others brought the spotlight on individual data points and how they mapped the person who made them. Needless to say, there was a long period of discussion and debate to finally conclude to pursue machine learning algorithms in the criminal justice system.

DATA DISASTER

Data Disaster- The Gamification of Big Data Awareness was a project that aimed to bring Big Data to light in the eyes of the public; particularly college students. Logan Erickson, Zach Grena, and Abi Busath (the group members who proposed Data Disaster) felt strongly that there is a strong lack of knowledge of Big Data and how it affects the lives of everyone. Particularly that people generally have the attitude that, "I'm not a terrorist, so why do I care what the government knows about me?" was an unsettling sentiment that the trio wished to address.



The group proposed a simple game app that consisted of a series of mini games that followed data trails as the player acted as a data broker or a piece of data that tried to dodge hackers and malware that would attempt to steal it from the user. The game, as Logan stressed to the class, "would mimic the largely recognized game "Dumb Ways to Die" that in itself was an awareness campaign to keep people from dying on train tracks in Australia."

In the game, the player would be given a set number of lives, and as they progressed throughout the mini games, they would attempt to break their high scores. However, unknown to the player, when they initially signed on for the app, they would sign a contract that gave us the access to various parts of their phone, such as their photos, contacts, text messages, and Facebook applications. Every time they lost a life, a small piece of data collected from their phone, such as an old Facebook post would appear on their screen as a consequence. At the end of the game or the end of their lives, a final piece of data would be presented to the player with the explanation that in signing on to play the game, they allowed data to be collected from them, in short, illustrating the prevalence of how easy it is for data brokers to collect and sell user data without much consequence. The idea was to have an easy, straightforward game that would attract various kinds of people, The second aspect of Data Disaster was an awareness campaign that would both advertise the game and give students a chance to learn more about Big Data. It was proposed that 2-3 information seminars be hosted, where both students of the Praxis Lab and guest speakers from various companies would give brief, 10-15 minute presentations focusing on Big Data in specific fields, such as the Gaming Industry, Business, and Healthcare. The idea was to promote the game, but also provide a discussion platform where people could get their questions answered and learn about current policies in place regarding data.

BEST PRACTICES

Best Practices was a project that focused on the class researching University of Utah methods of data collection and storage and updating the policies associated with those methods. Students Joseph Hutchins and Andrew Yang brought forward the idea that if we could draft best practices for the University, which hadn't been updated in many years, we could encourage other universities to do so as well.

First Joseph and Andrew explained that law students are often taught the best practices associated with their field, and they asked the question, "Why not have the computer science major students learn best practices as well?" They explained that students in computer science and information systems majors need to be taught the risks and dangers of Big Data, coding and machine learning algorithms in order to improve the development of technology, such as discriminatory data and faulty coding techniques.

Next Andrew and Joseph discussed the University of Utah's currently taught ethical guidelines- of which there were none. They proposed that as a class we would research and develop a series of guidelines regarding Big Data that the University would implement. Topics that would be addressed in our recommendations included how to write good code, how to write code to address sensitive situations, how to ethically collect and store sensitive information, and how to promote transparency and a pro bono culture. They believed that if we then took these guidelines and educated the faculty about to potential risks that students ought to follow, the faculty would in turn address these risks with their students and help to contribute to a safer culture in an ever growing data-driven world.

Finally, as a conclusion to the project, Andrew and Joseph proposed that we would insist on an update on these practices every few years to ensure that they remained up to date and consistent with the current status of Big Data.

DATA ABOUT <YOU>

Data About <You> was a project that aimed to bring awareness to the individual about how their individual data had quite an insight into their subconscious mind. Proposed in the form of an app, users would be given daily prompts for small things to notice they did throughout the day, week, and month. For example, one such prompt would ask their individual how many times they had said thank you that day. The user would then be forced to confront the question and deeply reflect about themselves and their actions. With the answers to the daily prompts, the app would compile the data and display an intricate graph at the end of each day and week to show the user how their behavior changed when they became aware of their behavior.

Skyler Jayson and Morgan Cox created the by far most optimistic project (in terms of the benefits of data and algorithms) with the idea that if we showed the public the perspective of data collector by giving them the option to choose what data was collected about them, we could influence the way people behaved. By abruptly showing them subconscious facts about themselves, users would feel compelled to change the way they looked at themselves and Big Data. "In order to make Big Data accessible and to give everyone the tools they need to protect themselves in a data-driven world, we need to help them to understand how data is collected so they can be aware of their surroundings and their own personal data trail." The experience was proposed to be "all about the user", so that the average person could participate and be educated in the simplest way about Big Data and how it is used around them.

DID YOU KNOW THAT......

PREDICTIVE ALGORITHMS CAN ASSESS WHETHER YOU WILL BE:

...A RELIABLE TENANT?

...A DESIRABLE EMPLOYEE OR ONE LIKELY TO CHANGE JOBS WITHIN THE NEXT YEAR?

...LIKELY TO VOTE FOR A PARTICULARCANDIDATE?

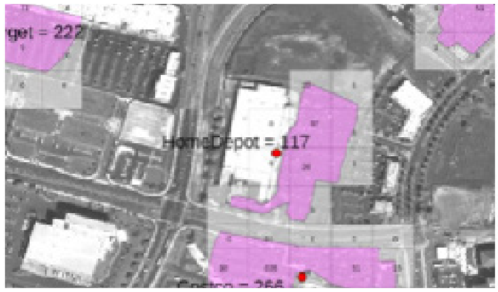
...A BAD DRIVER WHO IS INELIGIBLE FOR THE BEST INSURANCE RATE?

...A STUDENT WHO IS LIKELY TO BE AT RISK FOR NOT GRADUATING FROM COLLEGE?

INDIVIDUAL RESEARCH PROJECTS

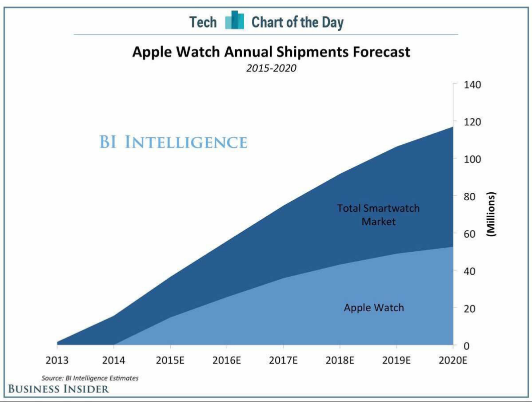
LOGAN ERICKSON - The game industry recognizes the value of Big Data and companies like Electronic Arts are on the forefront of Big Data innovation. Founded in 1982, "Electronic Arts Inc. is a leading global interactive entertainment software company." To maintain a successful brand and good standing, EA utilizes Big Data across the company. This summary covers Electronic Arts' Big Data practice with a focus on marketing and game development.

AUSTIN ANDERSON - Big data and machine learning are becoming more and more integral parts of the banking industry every day. Whether it's gathering large amounts of data in order to preserve records, providing customers with convenient access to their own data, or to making automated lending decisions to those who have no credit score and no way of obtaining one, machine learning and big data will be key factors in the progression of this industry.



ZACH GRENA - Because the methods and processes for investing with hedge funds is deregulated, a number of high tech firms have turned to machine learning to help them gain greater insight into potential investments. Through the mining of unconventional data from a variety of sources, hedge funds have been better able to use sentiment analysis, ESG data, geospatial data, fundamental, and technical analysis to provide higher return to their shareholders. Caution, however, should be taken before assuming that these methods can sustainably provide higher returns that traditionally managed hedge funds and market benchmarks.

SKYLER JAYSON- Smartwatches - a different type of accessory for the smartphone. Smartwatches are not your typical smartphone auxiliary add-on. Aside from the price being much greater than that of more common accessories like phone cases and headphones, a smartwatch is a computer connected to a paired smartphone. The question posed by this paper: Is the smartwatch just a gimmick? An over-priced toy? A spy's unfulfilled dream? Or is it much more than that? Can smartwatches have an influence on our daily



ABI BUSATH - As a leading healthcare system, Intermountain has a large data system to maintain and interpret to both contribute research and optimize patient care. Abi sat with Lee Pierce, the Chief Data Officer at the largest healthcare organization of the Intermountain West and asked questions concerning data collection, data policy, data security, and patient rights.

MORGAN COX - order to help students graduate and ensure that they do so on time, Associate Dean Zick and her colleagues have been looking for trends that indicate how successful a student might be. The research has shown that many students aren't aware of the majors that they might be interested as they go through their first few semesters. Since the students discover that their interests involve those fields of study so late, it becomes very difficult for them to transition and meet the requirements of their new majors on time. This delays graduation and can discourage students from finishing their degrees. Using these findings, the College of Social & Behavioral Sciences started an outreach program to help students find the right majors for them earlier. The results show that graduation rates have gone up significantly since implementing this program.

LOGAN COX - The use, management, collection, and decisions being made within the Information Security Office are fairly transparent and objective. The future within Cyber Security could get less transparent with the introduction of machine learning, but the implications of it could be very well worth it. If we could "let loose" some algorithms on our network that found and took care of malicious activity on our network, we would create a more secure and safe place for patients, students, researchers, and visitors.

ANDREW YANG- The University of Utah's registrar office is an office within the university that manages student information, and administrative actions regarding students. Their services range from the collection and maintenance of student records, the scheduling of classes, to evaluation of candidates for graduation. All of these services are tied to data collection and analyzation. To learn more about how the Office of the Registrar functions, Andrew interviewed the University Registrar and Data Steward, Timothy Ebner.

JOE HUTCHINS - The University's Business Intelligence Unit is the facilitator of information within the university; their role is to provide (or withhold) data to the various organizations contained within the campus. It was formed in 2011 out of a want to use the data which the university had started to collect.

DID YOU KNOW THAT...

ALGORITHMS...

...can read X-rays more accurately than highly trained doctors at a much lower cost?

...are being used in Hollywood to predict the success or failure of a proposed movie script by comparing past box office winners and losers?

...determine who is placed on the government's "no fly" list?

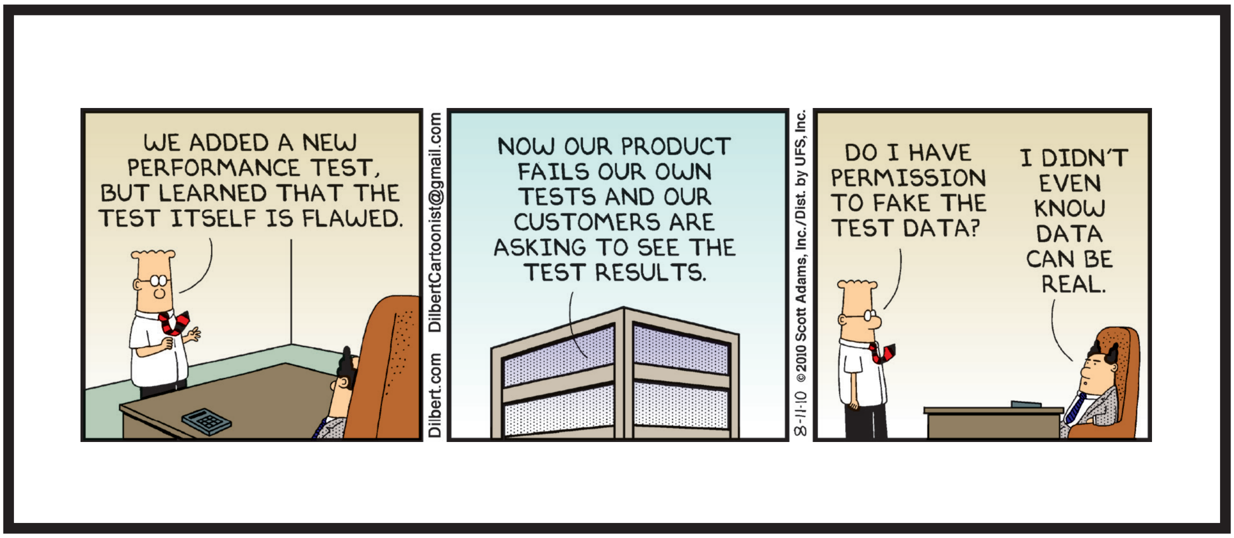
...are being used by college administrators to analyze student admission data and first semester grades to identify students who are at risk of dropping out?

...will decide whether an autonomous car will or will not swerve to avoid hitting a pedestrian if doing so puts the safety of the car's occupant at risk?

...may conclude that late night driving indicates frequent bar hopping which increases the likelihood of an automobile liability claim which justifies a higher insurance premium?

PART TWO: OUR CLASS PROJECT

The final class project we ultimately decided to pursue was a combination of the three proposed projects. Our overarching objective was to raise the public's awareness of the growing use of automated decision-making systems and help foster algorithmic literacy. We sought to accomplish this goal through the creation of four separate, but related, products: a mini-course on algorithms and machine learning; a permanent website in the form of a library subject guide; a set of best practices when dealing with automated decision-making systems; and a mobile computer game called Justice.exe which illustrates the use of an algorithm in criminal sentencing



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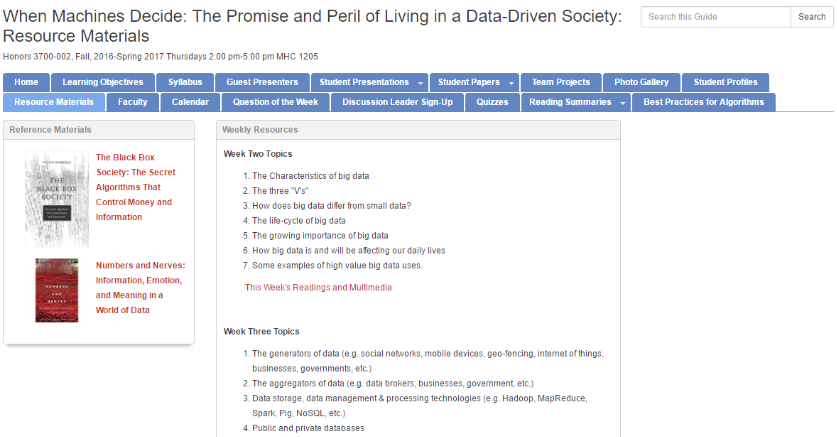
LIBRARY SUBJECT GUIDE

Want to learn more about this year's Praxis Lab over Big Data and Machine Learning? Head over to our Campus Library Guide - nicknamed LibGuide - to find links to access our course readings, individual papers, recorded videos of our presentations, and more.

The website was an incredibly useful resource for both students and those interested in the class. It centralized all of the information we both researched and discussed, and allowed for easy access during class times.



THE MINI-COURSE

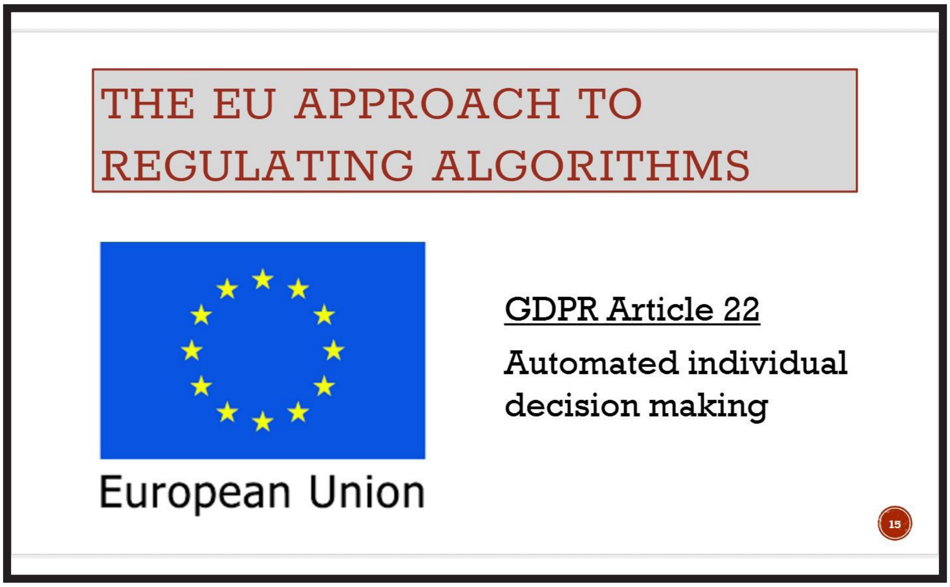
by Morgan Cox

The course module consists of five free-standing lessons. They're designed to each fit loosely into a 50 minute lecture period, though there are suggestions given on how to lengthen or shorten each one to fit the constraints of the class. Each lesson comes complete with five parts -- a teacher's guide, slides, lecture notes, student resources and activities, and the more in-depth teacher resources.

Lesson One - Part 2
Lecture Outline with commentary

1. Algorithms and Machine Learning: A Primer
    a. This lesson is intended to offer a basic understanding of algorithms and machine learning.
2. Discussion Topics
    a. Today we will discuss what algorithms are in a basic sense and how they affect our everyday lives. We'll then learn the basics of machine learning and what automated decision-making is. Finally, we will discuss both the benefits and potential dangers of automated decision-making.
3. What is an algorithm?
    a. An algorithm is simply a series of instructions designed to solve some kind of problem. It receives inputs, applies its rules, and generates outputs. For example, if we wrote an algorithm to multiply any given number by two, and decided to check what the algorithm would do given the number 5, we'd get something like this. The input is 5, the algorithm multiplies the input (which we know to be 5) by 2, and the output it gives us is 10.
4. Algorithms in everyday life
    a. We encounter algorithms constantly in our daily lives. Here are some places you might recognize them.
    b. Search results
        i. Every online search we run is remembered by the search engine and used to help future users. This is why Google is able to suggest endings for your queries -- it's aware of how other people, and how people in specifically your area, usually finish the phrase you've started to enter.
    c. Social media
        i. Social media activity is monitored by each platform's algorithm. Facebook, Twitter, Instagram, and the like keep track of user behavior to enhance user experience and for marketing purposes. Any time one of these sites suggests friends you might know, pages you might like, or articles you might read, they're using an algorithm. Similarly, any feedback you give is also fed into an algorithm to determine what content you like seeing -- pictures you like, links you click, posts you react to, etcetera. This is how Facebook determines what to show in its news feeds, and how it can determine what type of person you are, from your taste in music to your political stances, based entirely on the information you feed it.
    d. Marketing
        i. Tying into both search results and social media, algorithms use user's trends in online behavior to match them with the ads they'll most likely

These lessons are designed to be taught within another class as a short unit explaining the relationship between data science and ethics. Suggested classes include those relating to algorithms, data science, programming, general computer science, marketing, and ethics, though the material could be applied to many others. Teachers can choose to use all five lessons or pick some number of them, depending on time constraints and the background knowledge of their audience. The courses are tailored for a variety of audiences, ranging from data scientists to the lay public.



Example Slide from Lesson 4

Lesson 1 takes a very basic look at what an algorithm is and how it affects daily life in our society. It also compares the benefits and potential dangers of automated decision-making.

Lesson 2 offers further detail on what an algorithm is and explains the concept of machine learning.

Lesson 3 expands on algorithms and brings in issues of ethics. The lesson covers issues of reliability, fairness, and validation.

Lesson 4 explains algorithms as they relate to the law. Students with no computer science background can explore how algorithms affect our society and discover what regulations are currently in place to protect people from algorithms.

Lesson 5 describes the suggested Best Practices that our team developed for policy makers, data scientists, and the lay public. With some understanding of the relationship between algorithms and ethics, students can see potential applications of the other lessons and learn what they can do to protect themselves and others in a data-driven world.

Lesson Five - Part 3
Suggested Student Readings

Not only do we recommend these best practices, some companies have already put similar ideas into place. CivicScape's predictive policing software is now available online with the intention that anyone can check their code for potential bias.

-Software used to predict crime can now be scoured for bias
https://qz.com/938635/a-predictive-policing-startup-released-all-its-code-so-it-can-be-scoured-for-bias/

-CivicScape Github https://github.com/CivicScape/CivicScape/

We elected to create the course module to educate everyone around us about the reality of data in our society. Over the course of the first semester, we became increasingly aware of the fact that an individual's data determines the opportunities they can receive and the outcome of their life. Seeing as many people are unaware of how much of their data is collected and analyzed, we realized that there was a need for some form of education teaching our peers what the dangers of automated decision-making can be and how they could protect themselves. Furthermore, we saw that many data scientists are unaware of the unintended dangers of their algorithms, and elected to bring awareness to those in or entering the field. We hope that this will encourage more careful writing, training, and testing of algorithms to prevent flawed and harmful results.

BEST PRACTICES

Below are our best practices written by Randy Dryer and Suresh Venkatasubramanian and discussed and agreed upon by the whole Praxis Lab. We believe that these guidelines represent the optimal scenario as identified by our current research and thinking.

Recommended Best Practices for policy makers, data scientists, and the lay public when considering the use of algorithmic decision-making systems that impact individuals or groups in a significant and material way. *

For policy makers:

1. Expressly delineate the policy goals and objectives to be achieved through the algorithmic decision- making system.

2. Understand the inputs used in the algorithm and how each input is weighted.

3. Involve computer scientists, lawyers and social scientists in the design, evaluation, implementation and validation of the algorithm to better insure that the algorithm satisfies policy goals and objectives. Consider establishing an independent panel of experts to evaluate and test the algorithm.

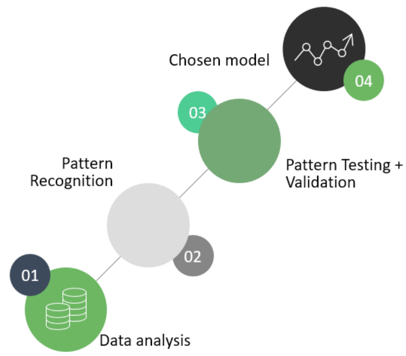
4. Promote transparency of the algorithm by requiring disclosure (either to the public, the relevant agency or the expert panel), of one or more of the following:

A.) the source code;

B.) the data sets or other "inputs", including the relative weight assigned to each input, used by the algorithm;

C.) the key decision-making procedural rules or logic used by the algorithm;

D.) the identification, logging and tracking of errors in data sources and algorithm operation in a form that is capable of being audited.



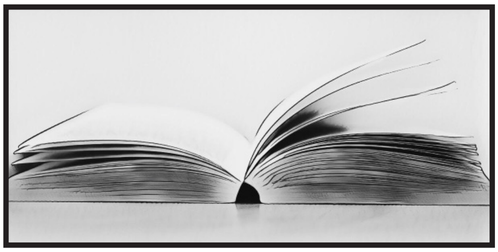
"Before using algorithmic systems in criminal sentencing, the relevant government agency should, in addition to the recommendations above, determine whether its primary objectives in sentencing are retribution, deterrence, utilitarian, rehabilitative or a combination thereof and assess the design and operation of the algorithmic system in light of the desired objectives."

BEST PRACTICES CONT.

5. Promote accountability and fairness of the algorithm by requiring, at a minimum, the following

A.) a defined avenue of redress for or a review of adverse consequences of an algorithmic decision on an individual;

B.) an opportunity to challenge the data inputs used by the algorithm in terms of accuracy, completeness or validity;



C.) an explanation in lay terms of how the algorithm works and the basis for any specific decision made;

D.) a publicly disclosed procedure for validation and evalu ation of the algorithm to ensure the algorithm does not create discriminatory or unjust impacts on protected groups or produce unintended consequences; and

E.) regular auditing of the algorithm design and operation and publication of the audit results.

6. Require a predetermined sunset provision for use of the algorithm to insure regular review, updating or reconsideration of the underlying software in light of any revised policy goals.

7. Before using algorithmic systems in criminal sentencing, the relevant government agency should, in addition to the recommendations above, determine whether its primary objectives in sentencing are retribution, deterrence, utilitarian, rehabilitative or a combination thereof and assess the design and operation of the algorithmic system in light of the desired objectives. In any event, any algorithmic system used in sentencing

A.) should not be outcome determinative, but only one of many factors to consider;

B.) should be advisory to the sentencing judge;

C.) should, wherever practicable, be tailored to the specific jurisdiction and relevant population and take into account any state statutes that identify permissible or impermissible defendant status variables such as race, national origin, religion or gender;

D.) should be used to identify appropriate risk factors and offender needs in imposing terms and conditions of probation and supervision, but not to determine the severity of a sentence or whether an offender should be incarcerated;

E.) should contain certain cautions, as appropriate, about their limitations and accuracy, including, among other things, whether the algorithm assigns scores based on group data and whether a statistically sound validation study of the system has been conducted based on the relevant sentencing population See State of Wisconsin v. Loomis, Wis. Sup. Ct. (July 13, 2016);

F.) should be the subject of a periodic validation study conducted by an independent third-party to assess whether the algorithm is working as intended and does not produce any inappropriate discriminatory, disparate or unjust impacts.

G.) should include appropriate due process mechanisms for a defendant to challenge the data inputs used by the algorithm in terms of accuracy, completeness, validity and the relative weight given to the inputs.

For students of data science:

1. Realize that models are only an imperfect snapshot of reality, and are not the same as truth.
2. Be skeptical about the "unbiasedness" of data. Interrogate sources and think about ways in which data collection might introduce or amplify biases.
3. Realize that the training process searches for some model that fits the data, not the model.
4. Question the predictions of the model on unseen data. Make efforts to audit and explain the model to understand its decision-making process.
5. Understand that the predictions of a model might be used in decisions that affect real people. Be circumspect about claims of accuracy, and be open and clear about possible sources of uncertainty.
6. Subscribe to a "Hippocratic Oath for Data Scientists" such as that formulated by IBM technologist Marie Wallance https://wiki.p2pfoundation.net/Hippocratic_Oath_for_the_Data_Scientist or British government chief scientific advisor scientist David King http://blogs.nature.com/news/2007/09/hippocratic_oath_for_scientist.html or Harvard researcher Alison Hill http://www.pbs.org/wgbh/nova/next/body/scientific-oath/
7. Insist that computer science curriculum include a component that discusses the ethical issues and challenges inherent in big data, data analytics and automated decision-making systems.

For the lay public

1. Understand that automated decision-making is a result of a training process, and is only as good as the process by which the decision-maker is trained. Ask how the model was trained before believing its conclusions.
2. Machine learning is good at finding patterns, like humans. But like the patterns humans find, ML patterns are not necessarily real.
3. Accuracy is not the same as being fair. An algorithm that makes a few mistakes (as recorded statistically) might make all its mistakes on one well defined subgroup. For this group, the mistakes are many, not few.
4. Automated decision-making works well "on average". But it is poor at making decisions on people who look like fringe cases. And we don't know what the algorithm thinks a fringe case is.
5. Above all, remember that automated decision-making exploits apparent correlations. The automated systems don't usually learn actual causal relationships. Correlation and causation are not necessarily the same, legally or scientifically.

*These recommendations are informed by the ACM "Statement on Algorithmic Transparency and Accountability" (January 12, 2017), The White House "Report on Algorithmic Systems, Opportunity and Civil Rights" (May 2016), the "Principles for Accountable Algorithms" developed by the German based non-profit organization Schloss Dagstuhl-Leibniz Center for Informatics (July 2016), the Pew Research Center Report "Code-Dependent: Pros and Cons of the Algorithmic Age" (February 2017) and the writings of various academics and commentators.


FALL 2016 - SPRING 2017
PRAXIS
THEORY + ACTION
LAB
GET IT ON
Google Play
Download on the
App Store
WHEN MACHINES DECIDE.
Justice.exe

JUSTICE.EXE: A SENTENCING GAME

by Logan Erickson

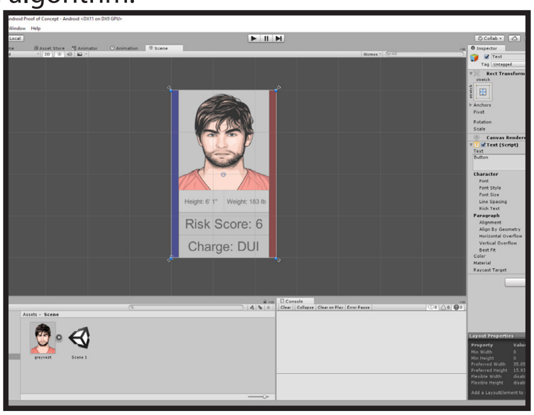
Justice.exe is a mobile game demonstrating possible biases of machine learning algorithms in the criminal justice system. You take on the role of judge swiping left and right to sentence mock criminal profiles all the while train an algorithm running in the background. Overtime the algorithm learns what information it thinks you prefer and removes what it considers to be irrelevant features. Eventually the algorithm tries to mimic your decisions and takes control.

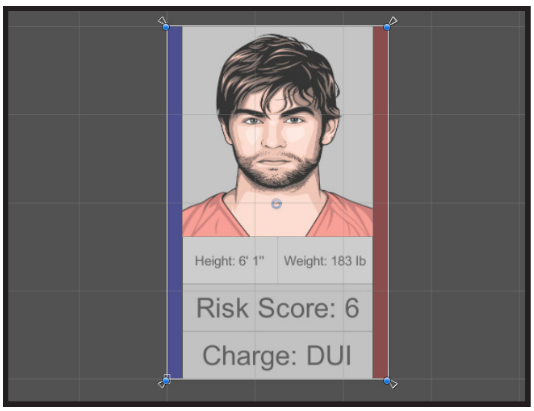
The Development of Justice.exe

The development of Justice.exe was an intense but exciting process. Once it was certain the class would be building a game, we wanted some feedback on the idea and preliminary design. We sought advice from Jose Zagal and Corrinne Lewis of the Entertainment Arts and Engineering program. They provided helpful feedback and put us in touch with much needed programing help. After multiple discussion with our class we had constructed a solid vision and were ready to begin development.

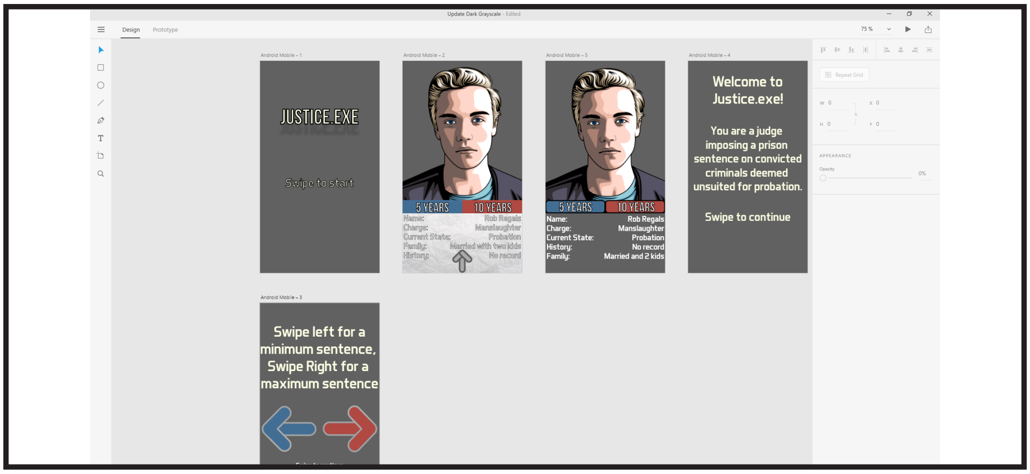
The biggest challenge we encountered while doing this project was communication. The development squad and algorithm squad had to be in constant contact to make sure milestones were completed. Meeting once per week for the praxis lab was not going to be enough time to develop the game, we needed to be efficient the other six days of the week. As mentioned earlier we utilized Slack a "cloud-based team collaboration tool" to keep in touch and updated on a daily basis. We used GitHub as our version control repository for the game. This basically means we have all the different copies of the game on the internet so if we break something we can roll it back to previous working version. Lastly, Google Drive and Dropbox served as our modes of file and documentation storage. Since all of these programs could be accessed by any team member from any location it allowed us a very agile workflow when the class was not meeting.

From the start, we knew the Unity Game Engine was the right choice for our project. Our development team already had experience in the engine and Unity streamlined the process of launching the game on multiple devices. We contacted Unity to get a license for development and begun work immediately by prototyping the game. Here are a few snapshots of an early functioning prototype in the Unity Editor without the machine learning algorithm.





In addition to using note cards to prototype mobile screens we used Adobe Experience Designer. Adobe XD is a brilliant product allowing designers to throw together rapid user interface prototypes with mild functionality for apps. Here is a screengrab from one of the many prototypes we built with this program.



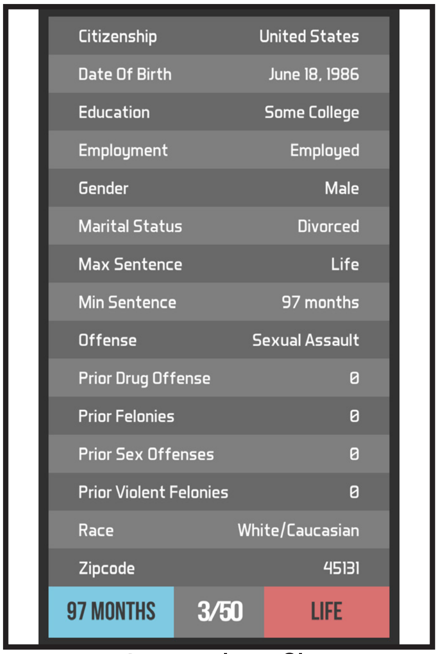
Adobe XD has two primary modes: design and prototype. In the design mode we could build our artboards or screen layouts how we would imaging them in game. In the prototype mode we were able to wire the different artboards together so when they were clicked they would move to the next artboard. Once the mock is complete we generated a link that was sharable in our slack channel for everyone on our team to see and provide feedback. This workflow allowed us to create a variety of different designs and test a lot of ideas with minimal work and overhead.

As ideas solidified we begun to build the game client. The game client is the app that operates on mobile devices and intakes and outputs data from the server running the machine learning algorithm. We used the hired programming help of Ajay Sathish and Jaden Holladay to complete this step and a big thank you is in order. However, the code was not enough. Mock criminal data is very boring to look at for a 5 minute play session and the game needed to have character. We outsourced artwork for the mugshots to Hendri an artist from Indonesia who we found using Fiverr, “the world’s largest freelance services marketplace”. A big thank you is in order to Hendri for the amazing art. In addition to the interesting technical representation of the game we wanted it to have personality and feel and through the mugshots we were able to create what we hope is an intriguing atmosphere.

We had to push an update for the android build about a week after launch. This provided a live operations opportunity. We had received a variety of feedback from user and wanted to cater to their needs as is the job of a good game developer. We created an action item list of things we had to get done and then stretch goals. Over the next week we tweaked and modified the game in preparation to push an update. By the end, we had polished the game functionality and design creating a better user experience.

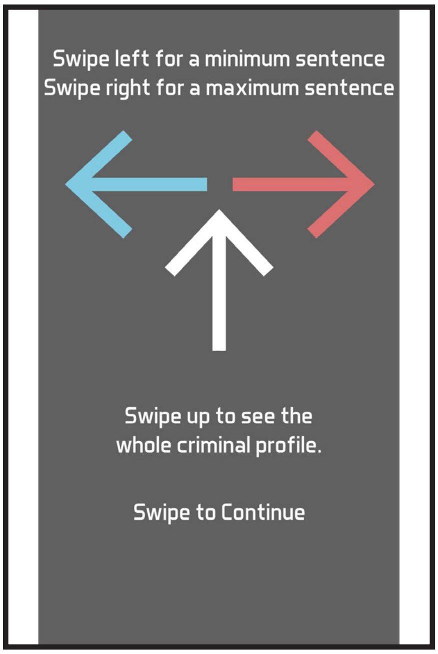
The design of Justice.exe from user interface to mechanics was a complicated and never ending process, nonetheless, interesting. A concern from the beginning was keep players engaged and helping them avoid, as we call it in the games industry, analysis paralysis. This was a big issue with the mass quantity of data on screen. Players would spend a few minutes interpreting data and debating their decisions per profile and could make play sessions last an hour. The real design challenge here was how Justice.exe could provide information clearly. We decided it was best to break it up and kept an overview on one screen with the criminal profile on the next.

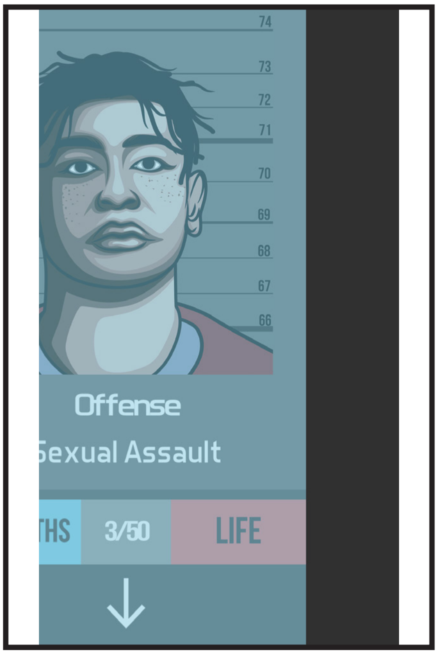
Overview Screen



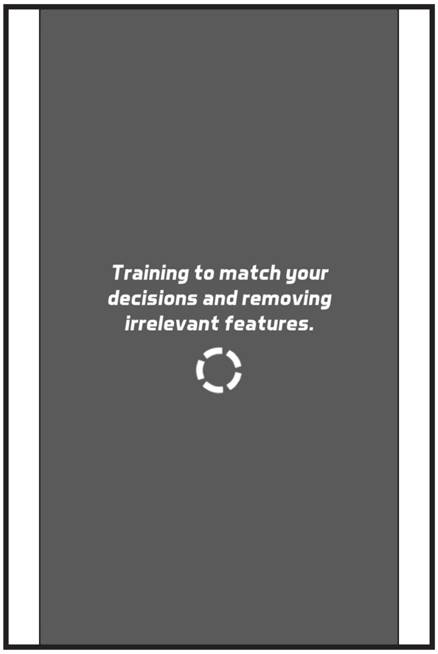
Criminal Profile

Additionally, player feedback was key to keeping the player engaged. Since we wanted gameplay to be intuitive we incorporated a tutorial alongside color coordination of swipes.

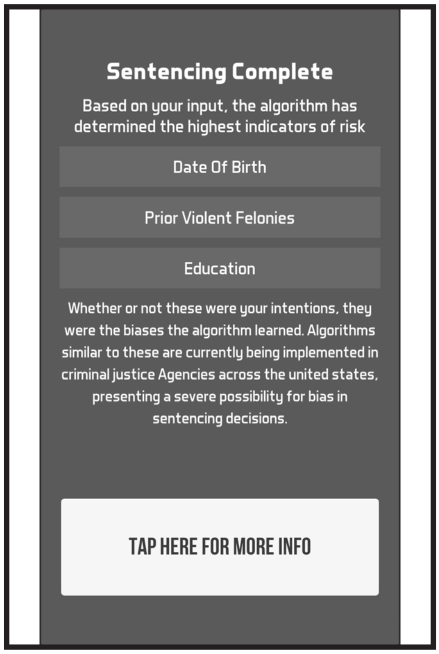




Players also needed some form of feedback for their progress and what was happening behind the scenes. Hence, we implemented little details like a loading screen after every ten profiles and created the final end game screen.



Training Screen



Final Screen

From the beginning it was decided there would be some form of conclusion to the play experience. The last hooray! It needed to provide feedback to the player on what they had just done and also explain the reason behind the game.

The end screen is supposed to surprise. It shows what the algorithm believes it has learned as the players prefered sentencing traits and it is often not what the player intended. Much of the impact of Justice.exe is relies on players being surprised or shocked. It is why data is removed at different stages of the game. To confuse player, make them question where it went and why. We hope this will get them thinking and be curious to learn more. In the end, the goal is to spread awareness and educate the general population.

THE JUSTICE.EXE ALGORITHM

by Skyler Jayson

After the events of the team proposal projects concluded and the class committed to the Justice.exe project, the students were broken up into "squads". This is about the Algorithm Squad and how it developed the back-end algorithm of the app as well as the API that facilitated the communication between the back-end algorithm and the front-end User-Interface.
The algorithm part of the project could be broken up into three separate parts: the database, the actual algorithm, and then information provided to the user as feedback. This is a report of the development process as well as the general ideas that influenced the decision-making.

In the beginning of algorithm development, it was decided that a database was the first thing to generate. With a database prior to actual algorithm development there would be familiarity with the nature of the data as well as make the process smoother. The final database was a conglomeration of three different databases taken from the National Archive of Criminal Justice Data website (http://www.icpsr.umich.edu/icpsrweb/NACJD/index.jsp). All three of the databases came from different time periods and one from Pennsylvania State while the other two from Federal. The first step is to find the different features that were used in the actual databases to see what features would be good to display in the game aspect of the app. Features that were used can be found on the next page.

The combination of all three lists manifested with a total of 25 different features. When thinking about which features to have displayed on the criminal profile cards we wanted to have features on the cards that are familiar to the user. The typical user will not need special knowledge in the process of sentencing, therefore, the features to be shown should be well-known and not contain jargon. However, if there is a feature that has a somewhat alien sounding title, simple rewording will allow quicker understanding. After debates about viability, understandability, and shear volume the final list of features was compiled to ones below. These features are common and easily understandable for the common person. That was the main goal of the features. User understanding was preferred over authenticity when it comes to actual sentencing information presented to a sentencing judge.

Citizenship
Date of Birth
Education
Employment
Gender
Marital Status
Max Sentence
Min Sentence
Offense
Prior Drug Offense
Prior Felonies
Prior Sex Offenses
Prior Violent Felonies
Race
Zip Code

Since the data obtained from the three different databanks were both limited and not very representative, we had to find a way to generate data points. There were multiple steps to do this. First, the actual sentencing data was taken in. Each category of data was organized into their sub-categories (e.g., the Age category would be organized into sub-categories of ages 20-30 and 30-40). This was done to find the distribution of that feature. That distribution would then be used to find the likeliness that a criminal profile would have which attribute of each feature.

Features extracted from Monitoring of Federal Criminal Sentences, 1987-1998 (ICPSR 9317)

(http://www.icpsr.umich.edu/icpsrweb/NACJD/studies/9317)

1. Date of Arrest
2. Previous Sentencing Time
3. Residency
4. Drug Offense
5. Warrants
6. Education
7. Age
8. Gender
9. Citizenship
10. Cost of Bail
11. Fine (damage)
12. Probation
13. Weapon

Features extracted from Monitoring of Federal Criminal Sentences, 2000 (ICPSR 3496)

(http://www.icpsr.umich.edu/icpsrweb/NACJD/studies/3496)

1. Armed Career Criminal Status Applied
2. Career Offender Status Applied
3. Defender's Country of Citizenship if not the US
4. Highest Level of Education
5. Ethnic Origin
6. Marital Status
7. Does defendant have any criminal history
8. Race
9. Date of Birth & Age
10. Gender
11. Drug usage (what type, amount, drug problem)
12. Type of offense

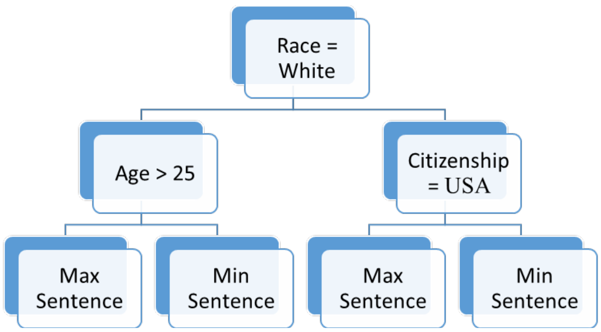
Features extracted from the Pennsylvania Sentencing Data, 1998 (ICPSR 3450)

(http://www.icpsr.umich.edu/icpsrweb/NACJD/studies/3450?q=sentencing)

1. Date of Birth (Offender's Age at Time of Offense)
2. Gender
3. Race
4. Current Status Supervision Status
    - a) Not Supervised
    - b) State Prison
    - c) County Jail
    - d) IP Program (???)
    - e) Probation (Conditions Below)
        1. Drug Treatment
        2. Alcohol Treatment
        3. 1 & 2
        4. Education/Training
        5. Community/Public Service
        6. Mental Health/Psychiatric
        7. Probation Ordered
        8. TASC
        9. House Arrest
        10. Other
        11. Unknown
    - f) Parole
    - g) Federal Incarceration
    - h) Out of State Incarceration
    - i) Other
    - j) Unknown
5. # Priors (Adjucations/Convictions)
    - a) Murder
    - b) Manslaughter
    - c) Rape
    - d) Kidnapping
    - e) Arson
    - f) Robbery
    - g) Burglary
    - h) Aggravated Assault
    - i) Felony Drug
    - j) Weapon Misdemeanor
    - k) Other Misdemeanor
    - l) DUI
6. Drug Type
7. Amount of Drug with Units (Can be Combined with 6)
8. Statutory Offense Grade
    - a) Felony 1, 2, 3
    - b) Unclassified Felony
    - c) Misdemeanor 1, 2, 3
    - d) Murder
    - e) Unknown
9. Type of Incarceration
    - a) State
    - b) County Incarceration
    - c) County Time Served
    - d) County Work Release
    - e) County Weekends
    - f) Other
    - g) Unknown
10. Minimum/Maximum Length of Incarceration
    - a) Time Served
    - b) Life Sentence
    - c) Death Sentence
    - d) Cannot Be Determined
    - e) Unknown
11. Restitution Amount
12. Height/Weight

While the drawings of the criminals were coming in, it was realized that certain features like age, gender, and race would have to be directly linked to the appearance of the drawing. There cannot be inconsistency between the criminal data and the picture of the criminal. If the picture on the criminal profile was a white female that appeared to be in her early 20's, then the corresponding data would have to be consistent with that.

There were debates on how to generate biased data. The idea was to couple a somewhat neutral feature like gender with a feature that we predict would have a very large influence in decision-making like the type of crime committed. For example, have violent crimes coupled with the Asian race, so whenever a violent crime is generated, the likelihood of Asian race being coupled with it is increased. This way the generated data would have a bias in it. The idea behind having biased generated data was to further illustrate the limitations that algorithms can have. However, due to a shortage of time, this feature did not make it into the initial launch.



There are many tools included in the scikit-learn package, but it was decided to use a decision tree as the basis for the algorithm. How decision trees work is at the there is a starting node. Based on a decision it goes one of two possible directions. Arrive at that node and then make another decision. The example decision tree below is a gross simplification of what information is in a tree but portrays the idea well. The decision made at each node here is a True or False question. The question is answered at each node until the bottom of the tree is reached at which point a conclusion can be made.

There is a separate decision created for each round of the game, where each round is ten swipes. After each round, there would be features that would be taken away from the user's access to the criminal's rap sheet. How the algorithm decides which features to remove was the debate about whether to remove what the algorithm believed the be the most influential feature or the least influential.

For the argument for removing the most influential feature is that the algorithm should remove the features that appear to have the most influence. That way it can focus on narrowing down the pattern for more indeterminate features. However, the downside is from the gameplay perspective, how would someone play if they didn't have the influential information such as crime committed? It would be quite difficult which is why we went with the second option of taking away the least influential feature(s) after each round.

THE JUSTICE.EXE ALGORITHM CONT.

By taking away the least influential features in each round, the algorithm can have more data, swipes, to help further strengthen the confidence is certain features and help weed out the ones that don't belong. As well as from the players perspective, the features that would be removed by the algorithm are most likely the ones that the player didn't give much attention initially. This way the removal of features sneaks up on the user surprisingly adding to the shock factor desired. At the end of all five rounds, there would only be a few features left which the algorithm would conclude to be the particular user's most influential features in making decisions about criminal profiles.

Even if all the coding for the algorithm goes well and the database spits out convincing profiles, it doesn't matter unless there is some sort of useful result that can be given back to the user. This wasn't a debate for only the Algorithm Squad, but for all the squads. We understood that there should be a level of shock to the user when the feedback would appear. The first idea was to take what the algorithm deemed to be the user's most influential features and have that reported back to them. And that's exactly what ended up as the feedback. These "most important" features were already calculated by the algorithm during gameplay, so it was as simple as sending them to the UI and having them displayed. The Development Squad was responsible for the look and feel of the final page that would house the features. It would be worded in a way to help explain that the features were found by the algorithm to seemingly be the most influential in making decisions. We aimed for the shock factor, but also hoped that some conflict would occur between the user and the algorithm's results. If the algorithm concluded that race played a big part but that was never the user's intention to use that but the algorithm came to that conclusion anyways, then that would hopefully cause some interest and possibly even discussion, which was the goal of this project the entire time.

THE MARKETING EFFORT

by Joe Hutchins

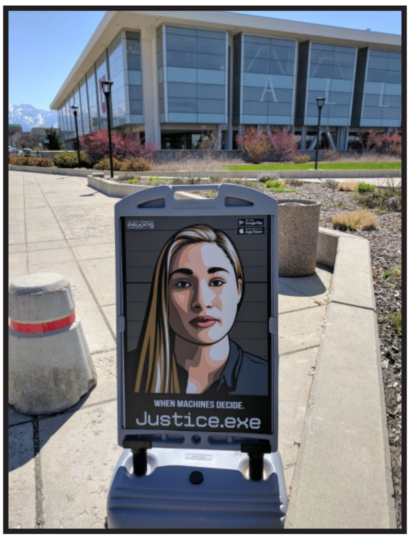
The Marketing aspect of our project was a pretty simple process. I knew basically what I wanted going into the project; I thought of the advertising that I notice the most, A-frames. A-frames are 3-foot-tall poster frames strewn across the U campus, and they get a good amount of attention. I happened to work with student media, which has a marketing department called AD Thing who are in charge of the A-frames. I got in touch with the AD Thing, and sent them our promotional material to print and distribute.

The story behind the promotional material is kind of fun; we were getting artwork done for Justice.exe and someone brought up the idea to use our faces for some of the mugshots. When we went to make the promotional material, we thought it would be a good idea to put the classes' mugshots on the posters and place the A-Frames where each student spends the most time (for example, Logan E lives at Lassonde so his mugshot went by Lassonde, and Professor Dryer's mugshot went by the law building).

Austin Anderson improved upon the initial idea for the design of the posters, and created the iconic pictures we used to bombard the campus. We also made flyers which looked like smaller versions of the posters and the class put them up in buildings across campus.

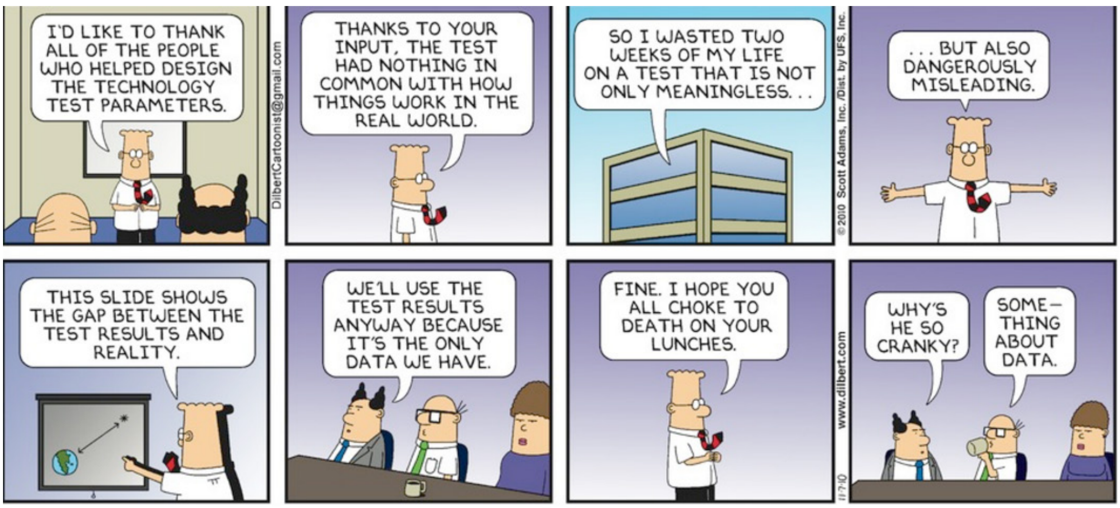
Beyond the posters and flyers, professor Dryer was able to get the media to come in and write a story on us and our project. He had a contact at the business school who used to work at in the local media network, and they sent out a press release once we released our game. Besides a little mishap where a news anchor said that our app was going to actually help judges sentence convicts, it was a great way to get our name out there. @ theU (a weekly email newsletter sent to students and faculty) also wrote a story on us, as well as the Daily Utah Chronicle.

The last part of marketing was social media; we made a Facebook page for the app and had every-one in the class share it, and also posted our story across Reddit (the largest online forum) where it gained the attention of the admin in charge of Reddit's data management, as well as people vetting pretrial sen-tencing algorithms.



An A-frame of Abi Busath; one of 14 A-frames distributed around campus to build awareness around our project.

PART THREE: POST OP



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WHEN MACHINES DECIDE: A LOOK AT WHAT WE LEARNED

We live in an age of information abundance. An age where every aspect of our daily life is monitored, tracked, recorded and stored by data aggregators and government. Video cameras, automatic license plate readers, online activity trackers are pervasively and constantly gathering data. Common, everyday inanimate objects such as TVs, fitness bands, cars and cell phones are now linked to the Internet and to each other and are "always on", collecting mountains of data about their surroundings and the people who use them. This data is being digitized and stored in massive databases for governments, businesses, scientists and others to review and analyze, using sophisticated algorithms and data analytics to make decisions that impact our lives.

We can analyze the social media activities of millions of people and deliver personalized ads and services. We can put an app on a smartphone that tracks every pothole in a road, automatically sending messages back to transportation offices. And, we can employ facial recognition technology to identify suspected criminals or detect genetic disorders.
The promise and benefit of automated decision making is clear. Or is it?

The same social media activities can be used to determine whether you deserve to get a loan, or what interest rate you will be charged. Those pothole-tracking smartphone apps? Turns out they only report on potholes in those affluent neighborhoods where everyone already has a smartphone. And, the same facial recognition technology used to identify the bad guys can also be used to determine whether someone should be hired for a job or not: which would be fine except that these tools have a hard time telling whether your eyes are open or shut !

Our machines are inherently agnostic — neither good nor evil. But, they may be used for both good and bad purposes. New technologies may reshape and restructure society in ways we might not expect and cannot predict. In this Praxis Lab, we will explore the ways in which the data revolution is changing our laws, our society and even the way we think of ourselves as free-willed humans. Will Big Data and machine learning usher in a new age of enlightenment or result in an erosion of autonomy and replace human judgments? Join us as

In the era of budget classes and huge lecture halls, PRAXIS labs at the University of Utah show the value of collaborative and self-directed learning. Out of all nine students, none had ever experienced a class anything like the PRAXIS lab, but it is safe to say that we learned 10x what is possible in a traditional lecture hall. While the lack of experience with the learning model caused for some headache in the beginning, we all began to feel this appreciation for the autonomous nature of the PRAXIS lab. We enjoyed coming to class and directing the flow of the conversation towards the topics and questions most pertinent to us and our experience. There were no "grades" to receive, and no "A"s to make - only knowledge and experience to be gained. Through the weeks of the first semester, we learned about the implications of the explosion of Big Data and data mining/extraction tools, and how this new era can impact our reputations and privacy in both the digital and physical worlds. We probed through numerous Slate/Medium/Huffington Post articles while perusing 50+ page academic papers and large government reports. Halfway through the class, we had the choice to either talk with a company regarding their data practices or do a research paper over a relevant topic in Big Data/Machine Learning and present our finding to the class. Near the end of the semester, each team of 2-3 people worked hard to prepare a project that would allow us to make an impact in the community at large and present it to be voted on in front of the whole class. In the end, we choose a game concept around education of the use of algorithms in criminal sentencing.

PRAXIS
THEORY + ACTION

Honors College
THE UNIVERSITY OF UTAH

"There were no 'grades' to receive, and no 'A's to make - only knowledge and experience to be gained."- Zach Grena

HOW DATA ITSELF CREATES BIAS IN ALGORITHMS

by Skyler Jayson

s

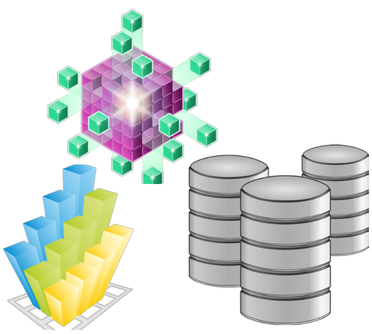
Tech giants the like of Google, Facebook, Amazon, etc. all use Machine Learning algorithms to analyze any sort of data they can get their hands on. Going back to the title of our Praxis Lab: "When Machines Decide", we are concerned with the potential dangers of allowing machines make decisions humans would've previously made. Relating that idea to machine learning algorithms comes the concern of algorithms having an unintended bias. Although there are multiple reasons for a bias to manifest in a machine learning algorithm, the focus will be how data streamed into the algorithm can create the bias.

First, to explain how machine learning algorithms are developed. The actual code and details of machine learning algorithms will not be included nor discussed due to the very high complexity of it; even those that work at Google have difficulty explaining them. With that in mind, the basic idea of machine learning algorithms is to analyze past data to create a model which would be used to predict future events.

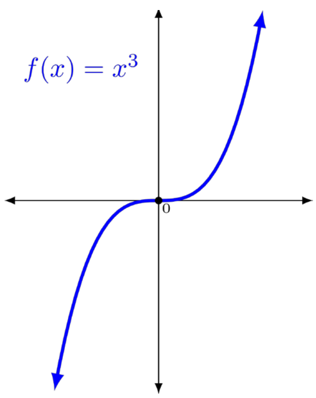
To help clarify, the data that is fed into machine learning algorithms is a collection of inputs and outputs. The algorithms then "learns" from those data points. This "learning" from the algorithm is finding correlations and associations between the input and output components of the data. To use our game, Justice.exe, as an example: when a profile is presented to the player the collection of features of the profile, such as race and crime, is the input and the swipe decision (max/min) the player makes is the output coupled to the input to make the data point, making each profile with a swipe a data point. After the player has made a sufficient amount of swipes, all the swipes are sent to the machine learning algorithm as data. The algorithm analyzes the data and comes up with a model which can then be used as a predictive tool.

Now having explained how machine learning algorithms work, how can a bias be manifested in the algorithm? As mentioned before, there are many ways that algorithms can become biased, but the role in which data plays is what will be discussed.

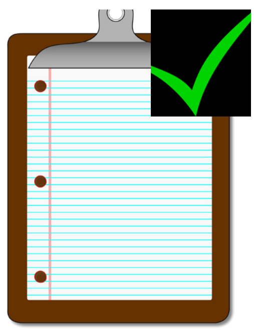
COLLECT DATA



DEVELOP MODEL



TEST AND REFINE MODEL



The first data that is fed into a machine learning algorithm is called the Training Data. Training Data is data that already has both the input and outputs. The profiles with swipes in Justsice.exe would be considered Training Data since the algorithm is trying to model what the user think is the most important features are on a profile. Then the bias occurs when the Training Data itself is biased. If somehow, the data that the algorithm is trained on is biased, then the algorithm will inherit those biases.

Going back to Justice.exe. What if every time a profile came up and the crime committed was murder, and it so happens most of them were of race Caucasian? The data is inherently biased towards Caucasians due to the high likelihood of the user swiping for the higher sentence solely based on the crime being murder. The intention of the user was to punish the criminals that took another person's life. Not to be prejudiced against those with a light skin tone. But the algorithm would conclude that race (as well as crime) were both very influential in the user's decision, which is an undesired result.

So, how can this type of bias created by biased data be avoided? The obvious answer is to acquire unbiased data. However, this is much easier said than done. To get truly unbiased data, one must implement the idea of a representative sample. The idea of a representative sample is that the sample of data acquired accurately represents the entire population. But when to it comes to data used in machine learning algorithms the majority is biased in nature. It's biased in the fact that most of this data is acquired through technology such as smartphones which about 68% of American adults own (Mediati). Therefore, 32% of the US adult population isn't represented in smartphone data. That is nearly a third of the adult population! However, companies can

"So, how can this type of bias created by biased data be avoided? The obvious answer is to acquire unbiased data"

Another technique that can be used to get rid of possible biases is to scrub the data points of components that could cause an unintended bias. Going back to the Justice.exe example, instead of showing both the race and crime committed, only the feature of crime would be shown. Here the race component of the data was scrubbed. This way the chance of crime being a proxy for race is eliminated due to race no longer being a factor. This is good in the aspect of not allowing skin coloration to be a contributing factor in judgment. However, race is a reality of the situation and throwing it away is throwing away data which causes the data to no longer be as representative as it could have been. The counter-argument could be that race should not be used at all in judging a person, however, this viewpoint is narrow and short-sighted. Of course, one should not use race as a factor in judgment, however, race should still be associated with the criminal after judgment in the chance that it could later be used to find correlations that otherwise would have been difficult to find. For example, it could be found a strangely high number of convicts were of race Asian, that information could then be used to identify that it isn't race but a certain Asian community that is the origin of the problem.

In conclusion, the importance of data in machine learning algorithms calls for careful collection and representation of said data. Collecting data that is representative of the population is difficult which can be mitigated by certain scrubbing of data, but not scrubbing in the sense of permanently throwing away certain components of the data.

THE ARGUMENT FOR TRANSPARENCY IN SENTENCING ALGORITHMS

by Austin Anderson

The justice system in the United States prides itself on being an almost entirely transparent process, with one major exception; the judgement of the sentencing party, whether it be juror, judge, or parole committee. This has been, and for the foreseeable future, always will be a totally opaque component of the justice system. At its core, the system was founded to both place trust in and isolate from influence the judgement of those who are tasked with determining guilt or sentences. This has always been a necessary evil of the system; in order to trust the judgement of the sentencing party, we must also accept any internal biases that they may harbor.

With the introduction of machine learning algorithms into the criminal justice sentencing process, this process may have a solution to this particular problem, or at least a way to mitigate it. While algorithms can learn biases from the data they're fed or the way they're programmed, these biases are something that can be tested for and fixed. The ability to recommend an evidence based decision, and then be able to explain why the algorithm recommended what it did, provides and even more transparent and just process. Introducing recommendation algorithms to sentencing/parole processes in criminal justice not only provides a more equal and informed method of making decisions, but can mitigate biases of the court authority by providing recommendations without relying on any discriminatory factors.

But these algorithms can only be helpful if we know they are both reliable and non-discriminatory. The only way in which we can assure these standards are met are if the algorithms in place are transparent and subject to scrutiny. Algorithms which are non-transparent, these so called "Black Box" algorithms, are a major threat to the integrity of our justice system. We accept the uncertainty of our judges and refrain from demanding explanation because it is the only way to insure a fully independent and honest decision; the contents of an algorithm are not affected by being placed under scrutiny. The ability for an algorithm to perform its task to the fullest capacity is not affected by understanding how it works. Any effort to obscure these algorithms is a step backwards from an honest and transparent justice system and a step in a very dangerous direction.

The most vocal counter-argument to the transparentizing of these algorithms is the rights of the algorithms creators to trade secrets. While certainly a business should be able to protect their property rights and profit from their hard work, it is unacceptable to suggest that the justice system's transparency and dedication to equality is less important than the trade secrets upon which these algorithms are built. The simple truth is that in order for these algorithms to be used acceptably, they must come under independent review and be transparent in their processes. Companies which invent and deploy these algorithms must be made to understand and accept this principle; while keeping the algorithms under some sort of trademark/copyright protection, they must ultimately be available for scrutiny by the public in some fashion. Whether this be boards of review/tests with signed NDAs or making the code public, these algorithms cannot remain in complete obscurity. If this decreases the willingness of companies to develop these sorts of algorithms, then that is a sacrifice that must be made. "Black Box" algorithms are unacceptable in this context and present a wholly unprecedented danger to the justice system. Anything less than the most transparent possible process is a threat to the sacred mantra of "Equal Justice Under Law", and must be avoided at any cost.

WHAT DO ALGORITHMS MEAN FOR EVERYONE?

by Morgan Cox

Whether we're aware of it or not, algorithms are involved in everything we do. They've become integrated into our lives enough that, in order to participate as members of our society, each of us must accept that algorithms are constantly processing data about us.

As members of our society, we interact with algorithms constantly. Streaming services, such as Netflix, Pandora, and Spotify, all utilize algorithms in similar ways. They use feedback from users to suggest currently popular media, or offer shows or music that are similar to what that specific user seems to enjoy. Targeted ads and suggestions on shopping sites like Amazon use each individual's search and purchase history and compare them to other individual's behavior to suggest products each buyer might enjoy. Social media sites like Facebook identify the political views, interests, and dislikes of each user and filter their news feeds to show only what each user wants to see.

Even beyond our laptops and cell phones, algorithms are running our infrastructure. Every bus pass used or train ticket purchased helps the city better identify which bus routes are most popular and at what times, so more frequent buses are assigned to popular paths and fewer buses, if any, are sent to rarely traveled routes. This concept of using an algorithm for allocating resources to where they are most needed is often applied to planning flight paths, school bus routes, and ride services like Lyft and Uber. Predictive policing tools allow police departments to best utilize their limited materials by identifying the most likely locations for crime. Not only can this careful dispersal of officers allow them to stop more crimes, their presence in specifically chosen areas can even discourage some crimes from happening at all. Algorithms in education can identify students at risk of academic failure or dropping out. By identifying risk factors and students who match those risk factors, school faculty can intervene for those who need it most and get them back on the right track. Algorithms in health care can even identify how likely a patient is to develop specific medical problems, and allow for doctors to begin preventative treatments before it's too late. The list of ways in which we interact with algorithms daily, making our lives easier just by offering them our personal data, is practically endless.

This constant analysis can be risky, though, for many reasons. Seeing as algorithms know only what their programmers tell them and lack the ability to consider situations or demonstrate empathy, it's very easy for an algorithm to become unfair. The power an algorithm holds lies in speed, not smarts; it is not more intelligent than the people who created it, only more efficient. The things an algorithm knows to be true were programmed or taught by its programmers, or learned by drawing conclusions from its users' activity. The programmer's perspective is incorporated into the code they write, however, adding small biases that they may not have even realized they have. This can become a major issue when the people developing an algorithm aren't representative of the whole population, namely when the team largely consists of white men. Their code reflects their own realities, but may not take into consideration the realities of women or people of color. Similarly, the code is affected when their personal views are not varied -- which is not unlikely if the programmers share the same race, sex, and salary, the latter indicating that they likely hold similar socioeconomic status. The result is an excess of headlines describing facial-recognition that only works on white faces and targeted ads that suggest higher paying jobs for users with male names.

Additionally, not only is there a possibility of the programmer's bias showing through, machine learning also introduces the chance of bias resulting from the data being use to train the machine. Using historical data to train an algorithm can lead to future bias, as the algorithm is likely to indiscriminately identify correlations and later recognize similar cases. This is where testing becomes vital in protecting users. If an algorithm is unleashed without being tested on a representative population, no matter the effort that went into ensuring fairness in the beginning, the possibility that the machine has or will learn bias is ever present. While some gender roles were more strictly followed in the past, for example, this does not mean that an algorithm should attempt to continue assigning these roles to men and women in the future. However, if the algorithm identifies a historical correlation between masculinity and engineering, it may suggest men more often than women when selecting an applicant to employ for an engineering position. The programmers did not feed biased information into their algorithm, it merely jumps to conclusions that they didn't foresee. The algorithm means no harm, it simply realizes that there's a connection and assumes its creators would like to maintain that connection in choosing future employees.

If we can find solutions and create rules to prevent algorithms from becoming unfair, though, we can focus on all the great things we can gain from them. It may be easy to point out all their flaws and name the controversies surrounding them, but there are plenty of excellent applications for algorithms. Certainly, we should still utilize them with caution. Algorithms are undoubtedly a very powerful force, able to cause damage even when they were created with the best of intentions. We can't downplay the many ways in which algorithms have improved our lives, though. Our current algorithms may have some flaws, but they've already proven to be an excellent start towards improving our health, safety, and numerous other areas of our lives. The incorporation of algorithms can increase efficiency and enable us to find patterns, giving us insights and improvements in productivity that wouldn't have been previously possible. Algorithms already impact nearly every aspect of our daily lives, and, with careful programming and testing, there can be a future with even more of them to help us even better.

"What if we don't change at all ...
and something magical just happens?"

THE USE OF ALGORITHMS IN THE CRIMINAL JUSTICE SYSTEM IN UTAH

by Abi Busath

Though risk-assessment tools are by no means new to the criminal justice system, the Utah Sentencing Commission has recently updated the guidelines to the specific tools used to determine the various risk factors and the defendant's likelihood of reoffending. In their own words, the Utah Sentencing Commission said about their updated tools in 2016,

"While actuarial risk assessment tools have been in use for risk classification and management purposes since the 1970s, risk/needs assessment tools ("RNA") did not begin to emerge until the 1990s. The critical distinction is that current RNA tools can identify the specific dynamic risk factors (changing and changeable) that influence whether a particular offender is likely to reoffend. They identify the appropriate targets for interventions which, if effective, will reduce the probability of recidivism.
Such tools are not intended to completely replace professional judgment, but to better inform decisionmaking. Research has consistently confirmed that current RNA tools are more accurate than professional judgment alone in predicting risk of recidivism. Professional judgment alone tends to over-estimate risk and is especially prone to the use of heuristics and bias." (Page 8)

It is important to note that the algorithms the Utah court system currently incorporates into its programs are not used to determine the length or severity of criminal punishment or imprisonment; rather it is more correct to say that they are used to determine the likelihood of recidivism and therefore help government officials develop a plan of intervention that includes therapy and programs designed to aid in the recovery of the defendants. In describing the changes, the Commission said,

"The 3rd generation assessment tools primarily evaluated an offender's risk to reoffend. The 4th generation tools still consider risk, but add targeted service needs and an understanding of how to appropriately deliver the services. Both the 3rd and 4th generation tools take into consideration the eight (8) criminogenic factors discussed in this manual.
With these improved assessment instruments available and validated, the Department of Corrections has moved from the LSI-R (3rd generation) to the LS/RNR – or Risk, Need and Responsivity – assessment (4th generation). This tool provides additional and relevant information to criminal justice decision makers and service providers." (Page 10)

In lay terms, the new implementations in these tools help to target and identify specific "criminogenic risks and needs" that recommend certain courses of action for the offender to follow to prevent recidivism. These courses of action refer to different therapies and/or jail time depending on the offender's offense and the risk factors identified by both the decision makers and the tools. It is important to mention however, that these tools are not used to replace human judgement in these issues, but rather to provide guidance and transparency for better evidence based decisions.
While these tools are not being used solely to determine the fate of Utah offenders, there is still concern with the transparency and a constant upkeep of fair algorithms used in these sentencing tools, which our class addressed to the Utah Sentencing Commission on April 5, 2017, which can be seen under our Utah Sentencing Commission Report later on in the document.

In January of 2017, the Utah State Courts entered into a Memorandum of Understanding with The Arnold Foundation to pilot and evaluate throughout the state a proprietary pretrial risk assessment tool to assist in detention/release decisions. The Arnold tool uses evidence-based information to predict (1) the likelihood a defendant will fail to return for a future court hearing if released (2) the likelihood that an individual will commit a new crime if released before trial and (3) which defendants present an elevated risk of committing a violent crime if released. The tool's algorithm uses nine factors in making its risk assessment:

- Current violent offense
- Pending charge at the time of the offense
- Prior misdemeanor conviction
- Prior felony conviction
- Prior violent conviction
- Prior failure to appear pretrial in past 2 years
- Prior failure to appear pretrial older than 2 years
- Prior sentence to incarceration
- Age at current arrest

Other factors such as race, ethnicity and geography are not utilized. The tool issues a PSA (Public Safety Assessment) score of one to six for each defendant, with six being the highest risk and one being the lowest risk. The PSA score is intended to be advisory only to the judge. Of particular note is the fact that the tool is based on national data collected from more than 1.5 million cases in 300 jurisdictions. The tool is currently being used in more than 30 jurisdictions across the state.

The use of risk-assessment algorithms in the criminal justice system is beginning to be challenged in court on denial of due process and equal protection claims. Only one reported appellate decision has addressed the legality of risk assessment tools and that Court upheld their use with numerous conditions, including that the tools not be outcome determinative, but advisory only. See Wisconsin v. Loomis, Case no. 2015AP157-CR (Wisconsin Sup. Ct. July 13, 2016) available at https://www.wicourts.gov/sc/opinion/DisplayDocument.pdf?content=pdf&seqNo=171690 For a recent article summarizing the legal concerns see Jason Tashea, "Risk Assessment Algorithms Challenged in Bail, Sentencing and Parole Decisions, ABA Journal (March 1, 2017) available at http://www.abajournal.com/magazine/article/algorithm_bail_sentencing_parole

STATE OF WISCONSIN V. ERIC L. LOOMIS

by Zach Grena

When researching to present for Utah's Sentencing Commission in April, we scrubbed through countless sources to find what we needed in order to gain a real understanding of the biases, implications, and the present state of algorithms in the justice system in order to give relevant best practices to a panel of judges, attorneys, policy makers, and elected officials that would succinctly explain how algorithms make decisions, and then recommend steps to take at each step of the automated decision making process. When looking for data, we found countless blog posts, academic papers, and books that chronicle the uses of these tools, but we only found one official court case that dealt with the legality of these issues.

Wisconsin vs. Loomis was a precedent handed down by the Wisconsin Supreme Court on July 13, 2016. The motion dealt with Eric Loomis, a defendant in a criminal case who was accused of being the driver in a drive-by shooting. Loomis entered a guilty plea to two of his lesser charges. The plea was accepted, and a presentence investigation report was made, in which a COMPAS risk assessment report was attached. The COMPAS risk assessment tool is made by Northpointe, Inc., a company that provides "scientifically validated assessment tools" for use in the criminal justice system. A COMPAS report includes three risk scores that measure, on a one to ten scale, pretrial recidivism risk, general recidivism risk, and violent recidivism risk. The scores are meant to predict the likelihood that an offender will reoffend, based on historical data of similar data group.

In Wisconsin vs. Loomis, Loomis' risk assessment showed that he had a high risk of recidivism on all three measures. Based on this risk assessment, the more severe read-in charges, and the judge's professional judgement, Loomis was given the maximum sentence of 17 years and 6 months. Loomis then filed a motion for post-conviction relief and requested a new sentencing hearing, arguing that the court's consideration of the COMPAS risk assessment violated his due process rights by:

1. Violating his right to be sentenced on accurate information, due to proprietary nature of COMPAS.
2. Violating his right to an individualized sentence.
3. Improperly used gendered assessments in sentencing.

They denied the post-conviction motion on the grounds that "it used the COMPAS risk assessment to corroborate its findings and that it would have imposed the same sentence regardless of whether it considered the COMPAS risk scores." The decision was appealed by Loomis to the Supreme Court of Wisconsin, who ultimately determined that the COMPAS risk assessment scores can be used at sentencing, but put limits on its use.

In its decision, the Supreme Court of Wisconsin argues against the points that Loomis makes, stated above. While acknowledging that a defendant has a due process right to be sentenced on accurate information, and right extends to the ability to be able to verify and correct that information, as stated in State vs. Skaff. The court, argues however, that the analogy between Loomis' case and the Skaff decision is that Loomis had access to the ultimate risk score, which he could have refuted his score, "by arguing that other factors or information demonstrate their inaccuracy"

This court opinion, however, was not all green light on COMPAS. In their decision, they referenced a 2007 study by the California Department of Corrections and Rehabilitation and a ProPublic study that raised questions of bias and efficacy. In light of these concerns, and realizing that these tools are not yet well tested, they determined "that use of a COMPAS risk assessment must be subject to certain cautions in addition to the limitations set forth [therin]."

Some of the recommendations given in the court opinions align with our best practices we set forth (see Appendix). These include informing the sentencing court of the following:

"The proprietary nature of COMPAS has been invoked to prevent disclosure of information relating to how factors are weighed or how risk scores are to be determined."

"Risk assessment compares defendants to a national sample, but no cross-validation study for a Wisconsin population has yet been completed."

"Some studies of COMPAS risk assessment scores have raised questions about whether they disproportionately classify minority offends as having a higher risk of recidivism."

"Risk assessment tools must be constantly monitored and re-normed for accuracy due to changing populations and subpopulations."

TEAM REFLECTIONS

We asked members of the class to weigh-in on how the class went, with particular focus on their thoughts on the final project and the highs/lows/late nights that accompanied it.

ABI BUSATH

I have really enjoyed taking a part of this class this past year, mostly because being in a setting with people who shared my thoughts and opinions on machine-learning algorithms and how they can be used in society was really refreshing. Of course, we challenged each other and had to really dig deep to find the root of the issues associated with these decision making tools, but in the process we learned a lot and I can confidently say that now, knowing betterhow algorithms work, that I feel we have accomplished a great deal in terms of increasing awareness and sharing our knowledgewith both the public and government officials.To be quite honest, I wasn't sure how Justice.exe was going to turn out when we decided on it as a class back in December. I didn't fully understand the game concept that was proposed and I was worried that there wasn't going to beanything for me to do during the spring semester.But oh, was I wrong! In truth, the semesterhas felt like a long one, and there were times that I didn't think we'd make it or meet deadlines, but somehow we pulled it off. I hardly deserve credit for the success of the project and how it came together, but nonetheless I am very happy that I got to participate and be included in the class. Our discussions werehumorous to listen to, our Slack page where we finished and shared our work with each other is pretty comical, and we're all a bunch of nerds from diverse backgrounds who came together and made something tangible that addresses our concerns as students about machine-learning algorithms.Watching familyand friends play our game, and getting to explain it to them in the process has solidified for me the idea that we did something good for the public. Seeing Zach and Joe present our project to the Utah Sentencing Commission and hearing the questions that were asked by those officials, I feel as if we made a difference. Reading through Morgan's course modules, I realize that we've made something that can teach people about this issue. At the end of the day, the stress and anxiety that this class brought me, the late nights, the amount of reading I had to do to keep up with these Computer Science majors, the essays, and everything in between was completely and totally worth it because we made something good.

MORGAN COX

Most of my classes don't teach leadership, communication, and accountability, but that's what made being in this Praxis lab so unique. For the first time in my education, I feel as though I've learned skills I can apply to any job. My psychology lectures and film production classes could only help me so much without the things I've learned from this course. In this lab I've done everything from setting deadlines and following through with them, to delegating tasks and checking in with my teammates, to working with people who have a variety of thinking and organizational styles. It's been difficult at times to keep up, since it's so different from any other class I've taken, but the things I've gotten out of it have been invaluable.

When I signed up for this Praxis lab, I was planning on studying computer science. By the time we first got together, though, I had realized that I had very little interest in writing code and had switched over to a new major. I wasn't sure what to expect, then, when I began a class that was so heavily focused on understanding how computers function. It's truly amazing to me that, by the end of the first semester, I had a strong enough grasp of the concepts to explain them to my friends, and, somehow, by the end of the second semester, I've written actual course material about them. This lab has been intense at times, but I've learned so much from it. Being a part of this team has been invaluable, both in learning about a major issue that affects everyone, and also in the professional skills I've developed. If I had the time to do it all again and join another Praxis lab, I wouldn't hesitate.

LOGAN ERICKSON

Making games is never easy, however, because of the hardship it is always a great achievement and definitely worth the while. As a game developer we make mistakes and solve problems. There are moments when I get frustrated or hate the project but that is the learning process. As per tradition in the games world I want to do a bit of a personal post mortem for Justice.exe, what went right, what went wrong and my takeaways.

From the beginning we knew it was a tight time crunch. The plan was to make this game in a few months. This was terrifying. In fact, time really seemed to be a problem for us throughout the project. There was never enough of it. Unforeseen issues would arise but we would manage to solve them just not always in the right amount of time. Nonetheless, we just kept going and there was never for a second that I doubted if we could pull this off. We did a really good job of persisting. We had a solid idea from the start and continued to iterate. Overall, I was really proud of our teams ability to adapt on the fly and be efficient.

When making games it should be expected that the world may literally spontaneously combust. Everything that can go wrong will go wrong. Publishing was difficult but a really good learning experience. Apple is an amazing company but to get an app on the App Store it requires some blood, sweat and tears. I think from the start factoring in more publish time into our plan would have been a really good choice. Communication was consistently good still things would get lost in translation and make for unnecessary work or work that was necessary wouldn't get done. I think just committing to decisions early on would have been helpful to get something going right away rather than keeping so much up in the air.

I want to make games that do more than entertain but also provide a positive impact on communities. Justice.exe fit that mission perfectly. It is this idea of making games to create awareness as a form of public service announcement. To say the least, it was a honor for the opportunity to work on such an interesting project. A big take away was the experience of working with multiple teams with very different roles and trying to have them be as cohesive as possible. It was a great communication challenge. At the same times it was also amazing talking to players and putting their feedback into an update so we could create a better product. Justice.exe was at times a trying experience still it has affirmed to me I am on the right path and love what I do.

JOE HUTCHINS

This PRAXIS Lab has been a very difficult, but very rewarding experience. I've learned a lot about algorithms, machine learning, and law, but I've also learned a lot about group work, time management, and self-motivation. Our professors spent the first semester directly educating us, providing us with reading material, setting up and moderating discussions with experts. However, during the second semester they worked more as mentors to us; allowing us to work and make decisions on our own, only to reign us in when we went off the rails. They have been some of the most interesting and enriching people I've ever met, and it was a privilege to work with them in this PRAXIS Lab.

I'll be honest, it wasn't uncommon for me to wonder if I was really cut out for this class. The students around me seemed far beyond me in their abilities and knowledge. Some of them had been TA's for classes I had barely passed, and one of them was the valedictorian of my high school. Yet, I managed to help turn our class project into a success in my own way. I led the marketing effort for our class (which turned out quite nicely if I do say so myself), and I was given the opportunity to introduce our class and its project to the Utah Sentencing Commission.

TEAM REFLECTIONS CONT.

I've found myself being excited to make an impact on my community through this class, when we were proposing our projects to the group and half the class wanted to make a game, I was skeptical at first. How would a game be an effective use of our time? Though, as we continued to explore and tweak the initial proposal, I found that I was more and more excited about it. In the end, I have found it a great tool to help explain the subject material with the class, and raise awareness of how machine learning algorithms work.
Which leads me to my view on algorithms; my understanding of them has certainly matured after taking this class. I used to have a purely optimistic view of decision making algorithms. "How could an algorithm have bias?" I naively thought. As it turns out, a lot of different ways; while I still see a future where machines and algorithms have a serious impact on crime, health, and employment, I also see why it's necessary to make sure that those algorithms are properly evaluated and maintained. They are powerful tools, and we have helped our community be able to better interact with them.

LOGAN COX

The 2016-2017 Machines Decide Praxis lab was an experience that I personally have never had in my entire life. It was a mix between intense learning, self-exploration, teamwork, problem solving, and late night coding.

The semester started off with a lot of learning about the situations and problems that society currently faces regarding algorithms. It was a very normal class experiences with discussions, quizzes, and reading. It gave us a really good base for where we could go with our project and what problem we wanted to face. During that time, I honestly had no idea what I wanted to do for my project until towards the last weeks of the semester. I learned that the Criminal Justice System is a place where having these algorithms in place could literally mean the difference between life or death.

Austin Anderson and I decided that a game could be an easy way to illustrate the problem we were currently seeing in the Criminal Justice System. We came up with the idea of "Justice.exe" - a short narrative game the informs the player of the dangers of the use of machine learning algorithms in the criminal justice sentencing system. After the class voted on our game that's when the real class experience started. We split the class up into separate teams to start working on the project. I was on the algorithm and server teams. The initial work was working with professor Suresh on how this algorithm worked and how we wanted to implement it. It was long discussions planning out what data we should use, how the decisions affected the data, and what would be meaningful to people playing the game. After deciding on most of the general decisions it was time to get to work.

Our initial issue was making our model work with the limited data we were going to get from the game – we didn't want the players to be playing for an exorbitant amount of time, so we had to make important decisions with not a lot of data. After realizing we could skew the data by limiting the options of data we gave the players, we were starting to see some more important information. After that I started to work on the server and this where things started to get messy. I figured out that I had to be the middle man between the algorithm and the front-development team. It wasn't too hard to get the server to do what I wanted it to do, but it was a pain in the butt making sure both teams got what they needed – and on time. If the algorithm changed I had to update the server, or if the front-end team had an issue with the server I had to make sure to update the server again.

Overall, it was a good experience and I realized that these issues are hard to explain to the common person because there are many difference areas of knowledge needed to be had to understand the issue. I feel good knowing there's a game out there that can hopefully illustrate the issue we are trying to understand and that people are learning something from the work we did. We even made a course module and a best practices guideline for people creating machine learning algorithms.

ZACH GRENA

I can't quite remember applying for this Praxis Lab – all I know is that I didn't seriously consider actually doing it until I got an email telling me that I got accepted into it and was given a permission code to sign up for a class time on Thursday 2-5. I decided that I would take a shot at a $1000 and learn a couple of things and maybe have some pretty intense debates. I didn't really think much about it until I showed up for class on the first day and started meeting people and getting to know the other students. Soon I was thrust into a world where intense debates, interesting readings, and some pretty startling facts were the norm. I have a pretty cynical nature of the reason why people partake in lecture class discussions (I think most people want to kiss a professor's ass) but this class seemed different. People took their privacy concerns with the different fields they were in and really questioned what was going on. There was personal ownership on the ideas and concepts discussed in class, and more than a healthy dose of cynicism for some of the algorithmic decisions and big data collection that we know that happens, I think we also have a little more relevance in a data-driven world.

One of the most impressionable moments from the class came in a discussion about data leakage - most likely when we were discussing data brokers like Axciom. As a class, we were shy to really probe beyond why something like should/shouldn't happen, because in our mind, it already had, or will in the near future. Suresh became extremely flustered, and chastised us for our fatalism. I distinctly remember him telling us that we can't take these sorts of views in this type of class – we are here to do something about the problem, and that collectively, our perceptions and opinions shape these issues. When I brought up this scene to Suresh month's later writing this, he also added that in the past few years, enough people "screaming" has significantly changed some of these issues.

I wish I had the time in my schedule to take another Praxis Lab, and would encourage anyone that sees a Praxis Lab that interests them to spare no time in applying.

SKYLER JAYSON

When I first heard of Praxis Labs being offered by the Honors College at the University of Utah I was very interested. However, none of the Praxis Labs at the time were of interest to me, so I held out for a year. When that academic year was coming to an end I had decided to switch my major to Biomedical Engineering from Computer Engineering, but I wanted to keep a Computer Science emphasis on my degree.
This was the time that I remembered that the new Praxis Lab topics were being announced. I look through the list. There were four labs to choose from, but there was only one choice for me, and it was this one, When Machines Decide, the Praxis Lab that will discuss and research about how algorithms and data analytics affect our daily lives.

I immediately thought about my current major in Biomedical Engineering as well as my previous experience with algorithms and knew that I had to get into this lab and only this lab. Knowing that Biomedical Engineers are ones that facilitate medical devices from common contact lens to the complex MRI machine as well as how algorithms could be used to gather data from these devices and analyze it for patterns. These possible patterns could be the frontier to help engineers create innovative and ground-breaking devices.

TEAM REFLECTIONS CONT.

The lab did discuss the application of algorithms in the medical field during the first semester, but we also discussed algorithms' affect fields such as law enforcement, education, and business. I already knew that things like algorithms were already being used in things like advertising through websites like Google and Facebook, but I had no idea that they were being used in Predictive Policing or that there were issues with privacy of student data This lab opened my eyes into the world of algorithms even though I believed I had a good heuristic of its uses.

The second semester of the class had the feel of what it's like to be part of a team that has a goal to be set out to do and being given responsibilities and being upheld by my classmates. A rather stressful but great growing experience. In the end, I don't regret taking this class one bit and am grateful to the Honors College and the University of Utah for giving me these opportunities to make a difference in my community.

AUSTIN ANDERSON

If there's anything in this world I despise, it's the exsistence of "echo chambers". Whether politically, culturally, socially, philosophically, or in any other form, the stale nature of a hive mind that agrees on everything and has little to no distinction in their individual ideas is something I simply can't stand. Which is why the When Machines Decide Praxis Lab has been one of the greatest academic experiences I've ever had the distinct pleasure of participating in. Never in my life have I been around a group of more intelligent, diverse, and well spoken people than the group I enocountered in this classroom every week. The sheer diversity of thought, willingness to honestly discuss and debate, the palapble eagerness to thoughtfully disagree and make shrewd arguements, and tolerance for eachother's ideas and ideals to be found in each and every person in the class continues to astound me. Being able to voice an opinion and be met with honest, intelligent resistance to that opinion is something I quickly began to look forward to every week, no matter the topic. The oppurtunity to meet with these people from week to week, discussing a wide range of fascinating topics from a wide range of perspectives and idealogies, is one I wouldn't trade for anything.

This labs' focus on data, algorithms, computers, and some stuff straight out of *ITALICS*Minority Report* has been an utterly fascinating ride. The moments where we were blown away by the possibilties, for usages both good and bad, of machine learning algorithms in particular has been eye-opening, to say the lesast. I would be amiss to not mention the vast knowledge banks that are our two proffessors; both of them experts in their fields and endless wells of knowledge on their respective subjects. The classes' structure and focus has allowed us to learn and become well-versed enough in the topics at hand to speak confidently about them and try to make our own little dent in this rapidly growing field. I feel light years more informed and capable of discussion around this topic than I ever had before this classs, and with the rapid adoption of these algorithms into every aspect of our lives, I greatly value my newfound capability to speak with authority on the subject.

The class had some ups and downs, specifically with regards to our 2nd semester project, but I feel it's been a througholy engaging and enrichening experience from day one. It gave me the chance to learn both life lessons and purely algorithmic ones, debate hard issues with a group that was just as opinionated and outspoken as I am, work hard, and to voice my thouhgts and ideas, no matter how big or small an audience was listening. That's an adventure rare and precious in the computer science field, but one I hope to find again one day.

ANDREW YANG

When Machines Decide was one of the most interesting classes I have ever taken. I enjoyed sitting down with a small group of people, learning and discussing how decision making algorithms work, and how they affect our lives in the current society in so many different ways and fields.

A lot of the things we discussed in class during the first semester were things that I was already familiar with, and there were more things that I haven't thought of, especially regarding what people should and shouldn't do. It was really a mind-opening experience, allowing me to expand my view on how algorithms affect people, and what other people thing about these effects.

The best part about this class had to be the part where we actually made an app/game that utilizes algorithms to do decision making for us, and get across a point to an audience. Actually coding the backend of an entire game was really exciting and fun for me, and as cliche as it sounds, I learned a lot from doing that.

However, the best part was also the most frustrating part. Debugging code is and will always be one of the most unpleasant experiences I have to deal with in programming, but for this app, I think all the hair pulling was worth it. The most frustrating part, however, would probably be not being able to make our own algorithm, but instead using a black box packet that was premade. I understand that this isn't a CS class, but that was really disappointing.

PROFESSOR VENKAT

I've been studying the problem of automated decision making for a few years. My approach,has been purely algorithm- and mathematics-driven: how can we formalize precise algorithmsi research questions and solutions around the issues of fairness, accountability and transparency in machine learning.

Teaching this class therefore presented us with many challenges. How do we convey the complexity and subtlety of algorithmic decision making to a group of students who are sophisticated users of computers, but have relatively little technical background? And how do we identify ways in which they can effectively contribute to the larger discussion around the use of algorithms?

I was initially surprised by the trust that the students placed in their automated interfaces. Google's catchphrase 'Do no evil' was cited as literal truth rather than corporate messaging. I even began to doubt my own fears in the face of such unbridled optimism. But I was encouraged to see - as time went on - that the students learnt to temper their optimism with a deep understanding of the pitfalls of decision-by-machine. Indeed, their class project arose out of a sense of both outrage and urgency - that people need to know about how algorithms might affect their lives in as crucial a seting as criminal justice.

Our class discussions also revealed to me the vast gap between the research community that is raising the alarm against the indiscriminate use of algorithms, and the lay public for whom the very idea of machine decision making is a new and foreign concept. It's hard to raise awareness of a problem with a system if one doesn't even realize that there is a system in the first place.

TEAM REFLECTIONS CONT.

But ultimately, the manner in which our class went from complete ignorance about the degree to which algorithms have penetrated our lives to a collection of near-experts on this topic does me proud. It says that it is possible (with a group of highly skilled and motivated students) to communicate a deep understanding of very abstruse technical ideas and how they are changing the society we live in.

PROFESSOR DRYER

This is the second Honors Praxis Lab for which I have had the privilege of serving as faculty. The students in this Lab, like the prior Lab, experienced a variety of ups and downs (and at times frustrations) as they navigated a year-long class unlike any other they had ever taken. In a traditional class the professor is the fountain of all knowledge; a syllabus clearly sets out the course structure and learning outcomes; and success is largely dependent on individual performance. In contrast, a Praxis Lab is less hierarchical and directed, reflects an environment where students share an equal responsibility with the professors for their learning outcomes; and success is largely dependent upon effective group dynamics. For the students in this Praxis Lab, this was the first time in their academic career they had to experience the intricacies of group decision-making. It was not always easy as different students had different ideas, different styles and sometimes conflicting objectives… in other words, real life! At times this resulted in great uncertainty and frustration. In the end, however, the students rose to the occasion and produced a stunning class project whose impact will be felt far beyond the classroom. The students possessed a strong sense of social responsibility and the project they ultimately selected---raising the public's awareness of the growing pervasiveness and potential dangers of automated decision-making systems-- reflected that ethos. Even the computer game they designed, which started out simply as a fun endeavor, evolved into a serious illustration of the potential for bias and unfairness whenever algorithms substitute for human judgment. It was rewarding to watch them expand their horizons, both intellectually and socially.

On a personal note, I too was a student engaging in new discovery. As but one example, the students introduced me to a new (at least to me!) group communications and collaboration tool---Slack--- where all communications about the class project occurred. I will use it in the future. I also learned more than I ever thought possible about algorithms and machine learning from my co-instructor, computer science professor Suresh Venkatasubramanian. Suresh is that rare breed of computer geek who has a sense of social responsibility and the communication skills to explain difficult concepts in a way that are accessible even to a professor who went to law school because he sucked at math. Now, those algorithmic black boxes are just a little bit less opaque! Suresh possesses a wonderful sense of humor and was an absolute delight to work with. I hope we have the opportunity to collaborate in the future. From my perspective, the goal of every Praxis Lab--- to help students become ethical and engaged citizens who will be constructive future problem solvers--- was achieved without question in this Lab and I was fortunate enough to be along for the ride.

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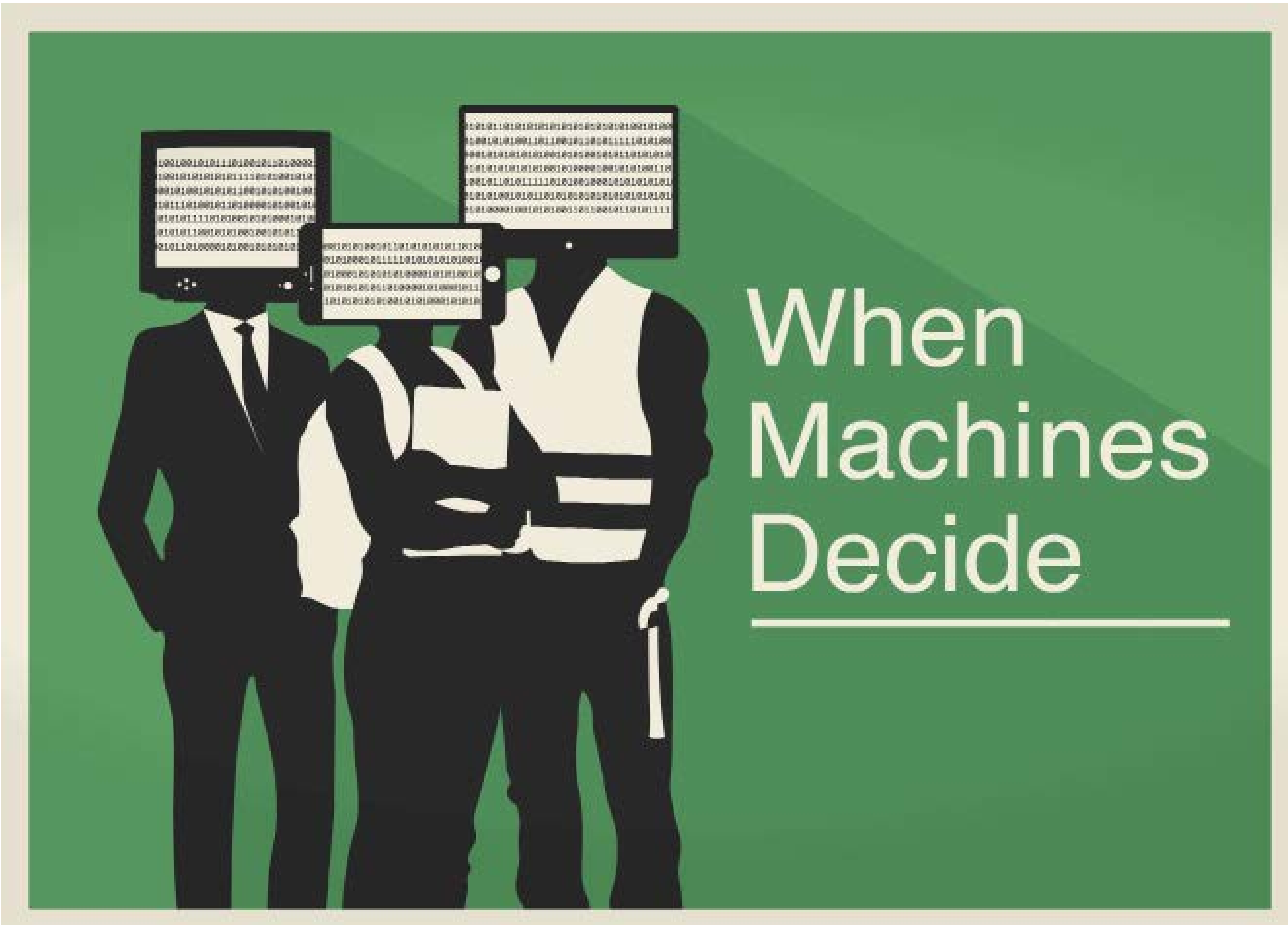

PRAXIS

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