

Ethical & Legal Issues of Data Analytics: 2018 Spring

Dansby: Section A @ M/Th 12:30-2:45pm, Section B @ M/Th 9-11:15am

Faculty and Staff

Professor: Salman Azhar, Ph.D.

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Google/Skype: dsazhar; Facebook Messenger: sazhar

Office hours: M 4:30-6pm, Tu 4-4:30pm, and by appointment.

I'm usually available without an appointment in the classroom right after my class on Mon & Thu 11:15-

11:45am and 2:45-3:15am.

I'm available with an appointment, Mon to Fri 9am-5pm unless I'm teaching a class, in a meeting, or

meditating.

Faculty Academic Assistant: Emily Dysart

Office: A322B | E-mail: emily.dysart@duke.edu | Phone: +1.919.660.1927

Generally available M-F 9am-4pm

There will be a few Teaching Assistants to provide feedback on your work under my direction. They have been trained in a similar course.

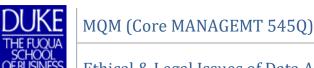
Catalog Description

This course provides an introduction to the legal, policy, and ethical implications of data. The course will examine legal, policy, and ethical issues that arise throughout the full lifecycle of data science from collection, to storage, processing, analysis and use, including, privacy, surveillance, security, classification, discrimination, decisional-autonomy, and duties to warn or act. Case studies will be used to explore these issues across various domains.

Motivation

Ideally, all of us would like data analytics to maximize our benefit from personalization without compromising any privacy. This course will provide frameworks to analyze this trade-off and other ethical and legal trade-offs related to data analytics. You will learn about ownership of data, privacy, consent, fairness, and related concepts. You will apply these concepts to develop your own ethical code and get a deeper understanding of yourself and your values.

This course does not promote any particular ethical and legal points of view. Rather students will use the principles and tools to create their own personal ethical and legal codes. These codes will be tested through class discussion and homework against a wide range of examples from work and life. You are likely to go through some mind-bending experiences as you acquire a better understanding of yourself (and your values), and learn about others (and their values), during the process of developing ethical sensitization and legal awareness. You will master the fundamental legal and ethical distinctions necessary to think clearly about legal and ethical issues and will be able to exercise disciplined decision-making skills to choose wisely based on your personal code.



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Pre-Requisites

1. DECISION 520Q: Data Science for Business

2. MANAGEMT 542Q: Critical thinking, Communication, and collaboration

Goals

The primary goals of this class are:

- 1. Ethical: Develop a personal code of ethics
- 2. Legal: Identify legal and regulatory issues related to data analytics, especially in the US.
- 3. Social: Understand when data analytics algorithms depend on human bias or opinions, and how that impacts social issues.
- 4. Analytical: Assess when data analytics raise ethical, legal, and bias concerns by viewing decisions through the lens of ethical, legal, and social aspects.
- 5. Practical: Apply the principles above to real and simulated situations so you can sleep better at night (with a clear conscience and not in jail).

Faculty Bio

Salman Azhar is an entrepreneur in residence and a faculty member at Duke University's Fuqua School of Business. He serves on the board of a few startups. Salman has more than 25 years in industry and academia, during which he has led talented teams in developing and launching state-of-the-art software systems.

Salman co-founded DecisionStreet, Swans International, SoftWeb, and over 30 other startups in the areas of predictive computing, business intelligence, data analytics, and decision support. His current and former clients include Honda, Toyota, Lamborghini, Audi, Sony, SAP, HP, ADP, i2, Western Digital, Oracle, Agilent, Outcome, and several startups.

Salman's individual expertise lies in the areas of product management, predictive computing, natural language processing, financial systems, automotive, and health information systems.

Class Preparation

The course website is on Canvas at https://fuqua.instructure.com. All course material will be available there. To maximize your learning experience:

- 1. Complete readings before class time.
- 2. Submit writing assignments before deadline. (See Canvas for assignments)
- 3. Synthesize learning from different sources and think about developing an understanding of the topic, not just the reading/writing assignment.
- 4. Be physically and mentally present in class and contribute to active discussions.
- 5. Focus on learning by actively listening and clearly expressing your ideas. Balance humility and confidence.
- 6. Be authentic and transparent with yourself (and, when appropriate, with others).



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Grading

This course follows the recommended grade distribution or "curve" for core courses (SPs (4.0) are given to the top 25 percent of the class, HPs to the next 40 percent (3.5), and Ps or below (3.0 or less) to the remaining 35 percent). The most effective way for you to get your desired grade is to demonstrate that you learned the material. My main responsibility is to instill long-term learning and to assign a fair grade at the end. You must make any regrade requests via Google Form here (link TBD) within one week of receiving back your graded work.

Your final letter grade will be based on the following weighted numeric score.

- Individual
 - 25% Final Exam
 - 15% Personal Ethical code
 - · Including weekly progress
 - 20% Individual Assignments
 - 15% Class participation and activities
 - This is a vital part of your learning experience and includes sharing and learning from others
- Team:
 - 25% Team Assignments
 - 20% based on your team submissions
 - Same score for everyone in the team
 - 5% based on your peer review (semester-end)
 - Score based on individual quality & effort

I may scale the scores of any component to normalize data distribution (based mean and variance).

Honor Code

Duke University's Fuqua School of Business Honor Code applies at all times and can be viewed at http://www.fuqua.duke.edu/student_resources/honor_code/. Please note:

- 1. All individual work *must* reflect only your own effort.
- 2. All team assignments *must* reflect ONLY with members of your team. You are *not* allowed to discuss the team assignments with anyone outside your own team before you turn in the assignments.

It is your responsibility to understand and ask for clarifications if you don't fully understand anything related to the application of Honor Code in this class. I will spend as much time as needed to answer your questions. Trust is the foundation of our work together, and anyone who violates that trust will have to bear the consequences of anything that must be done to restore that trust.



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Course Plan

We will start with two parallel themes that will come together (along with other topics) later in the course.

- 1. Developing your personal legal and ethical code
- 2. Understanding the legal, ethical, and social aspects of Data Analytics

You can access assigned articles from the links provided in the syllabus. If you run into any issues, you can also access the readings using the following URL:

https://getitatduke.library.duke.edu/ejp/?libHash=PM6MT7VG3J#/search/?searchControl=title&searchType=alternate title equals&criteria=new%20york%20times&language=en-US&titleType=JOURNALS.

Date	Topics	Resources
1. Thu 18 Jai	1. Start developing a personal code of ethics [Howard & Korver,	 [Howard & Korver, 2008] pages 1-30 (Introduction, Chapter 1) [Anonymous, X] ¹ Entire webpage² [The White House, 2014] pages 1-10 & skim the rest of the report³
2. Mon 22 Jai	We will continue with the two parallel themes: 1. Continue developing a personal code of ethics [Howard & Korver, 2008]	• [Howard & Korver, 2008] Pages 31-50
	a. Lesser-of-two-evils thinking (pages 32)b. Useful distinctions in evaluating ethical problems (prudential, legal, ethical)	(Chapter 2) • [Hickman, 2013]

 $^{^{\}rm 1}$ This webpage overviews [Howard & Korver, 2008] and will help you understand the book.

² Tip: Reading overview, then the source, and then the overview again, helps you internalize the reading. You should consider this approach to processing reading materials.

³ Tip: Develop the ability to quickly get the gist of material when you don't have time to read the entire source. You can go into details and/or pause to reflect based on your interest.



		c. Distinctions of positive versus negative ethics (causing		[Minority
		c. Distinctions of positive versus negative ethics (causing something good or causing something bad)	•	[Minority Report, 2002]
		d. Action-based versus consequence-based ethics	•	Optional:
		e. Ethical reasoning versus rationalization (page 34)		[Warman,
		f. Dangers of rationalizations and justifications		2012]
		g. Tests and guidelines to identify reveal arguments as		-
		rationalizations		
	2.	Continue understanding the legal, ethical, and social aspects of		
		Data Analytics. [Hickman, 2013] and [Minority Report, 2002]		
		a. What is an algorithm?		
		b. Does technology make "mistakes"? What kind of "mistakes"?		
		c. How is big data is used in parole decisions?		
		d. How do you distinguish between good and bad algorithms?		
		e. Should we worry about AI ruling the world?		
		f. Predictive policing using CRUSH (Criminal Reduction		
		Utilizing Statistical History) and National Security Agency (NSA)'s data analytics algorithms. Problems setting the		
		rules:		
		i. Filter out remove false positives and false negatives		
		(strength and accuracy)		
		ii. Validation of results		
		Dool would average of anodistive noticine		
	3.	Real world example of predictive policing		
		 a. FBI is asking to build software to scan social media online to predict crime. 		
		to predict crime.		
	4.	Discussion of Minority Report movie that dramatizes predictive		
		policing [Minority Report, 2002]		
		a. PreCrime police stops murderers before they act, reducing		
		the murder rate to zero.		
		b. PreCrime's captain is predicted as a murderer who tries to recover the minority report to prove his innocence		
		recover the initionity report to prove his initiotence		
3. Thu		Continue developing a personal code of ethics [Howard &	•	[Howard &
25 Ja	n	Korver, 2008]		Korver, 2008]
		a. Shared ethical principles from various religions and		pages 51-70
		cultures b. Brudential ethical principles, such as avoid intevisation		(Chapter 3)
		b. Prudential ethical principles, such as avoid intoxication		
		(pages 53-54)		



	 c. Positive ethics, such as "thou shalt", and negative ethics, such as "thou shalt not" (page 56) d. Complications when ethical rules conflict Example:	 [Stanford University School of Engineering, 2014] Short video [Fox & Howard 2014] Audio or Text [Keelin, Schoemaker, & Spetzler, 2009]
	 Possible alternatives Available information Determine Impact (possible outcomes under uncertainty of your decision) Understand your objective/preferences Risk preference: The trade-off between greed & fear Time preference: The trade-off between greed & impatience SCOPED Decision Making Framework (Situation, Choices, Objectives, People, Evaluation, Decision) Modeling uncertainty Decision Examples 	• [Korver, 2012]
4. Mon 29 Jan	 Continue developing a personal code of ethics [Howard & Korver, 2008] Construct an ethical code Identify and remove prudential principles from the list (more details on page 106 in Chapter 5) Challenges of positive ethics because they have "no bounds" and do not help to distinguish right/wrong Identify and sharpen the lines between ethical and unethical (pages 82-85). Remove language that is superficial, lofty, etc. AIDA marketing model [Suggett, 2017] Attention 	 [Howard & Korver, 2008] pages 71-90 (Chapter 4) [Suggett, 2017] [Duhigg, 2012] [mewrox99, 2014]



	b. Interest	
	c. Desire	
	 3. Other data analytics algorithms, such as dating, trading, searching, marketing, [Duhigg, 2012] a. Marketers want to send specially designed ads to women in their second trimester so they can capture their business before others even know about it. b. Three step process that creates habits (cue, routine, reward). 	
	 4. Understanding "False Positives" and "False Negatives" using Bayesian theorem [mewrox99, 2014] a. Example of Drug Testing and Breast Cancer. b. Action 	
5. Thu 1 Feb	 Continue developing a personal code of ethics [Howard & Korver, 2008] The hasty decision-making drug test Three simple guidelines for ethical decision-making Clarify (frame) the issue Create alternatives Evaluate the alternatives A consequentialist approach to ethics Decision points, prudential/legal aspects (page 106) Google's and China's censorship demands to move servers to China and censor them (pages 106-111) Ethical costs & Prudential benefits (utility) (page 108) Time frame (short-term vs. long-term) Information limitation and uncertainty 	 [Howard & Korver, 2008] pages 91-112 (Chapter 5) [Richards & King, 2013]
	 2. Three Paradoxes of Big Data provides a framework that encompasses a lot of the legal/ethical considerations [Richards & King, 2013] a. Transparency Paradox Data analytics algorithms and operations of big data are kept secrets Need to develop the right technical, commercial, ethical, and legal safeguards for big data and for individuals. 	

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	 b. Identity Paradox Data analytics identifies patterns at the expense of individual and collective identity Need to reduce the how personalized recommendations undermine our intellectual choices to the point we lose our identity. For example, our Facebook newsfeeds reinforce our biases. Our Netflix recommendations limit our exposure. c. Power Paradox Big Data has the power to transform society and only large government and corporate entities have the privilege of using it (at the expense of ordinary individuals). We need a balance of power between those who generate the data and those who make inferences and decisions based on it, so that one doesn't come to unduly revolt or control the other. 	
6. Mon 5 Feb	 Continue developing a personal code of ethics [Howard & Korver, 2008] Avoiding ethical risk, such as group memberships (pages 115-116) Story of a leader in the Nazi party Avoid ethical violations Three guidelines for ethical decision making (page 116): Finding the whole truth Framing issues as relationships Raising the reciprocity bar Additional guidelines for ethical decision making Promises and secrets Reassessing acts of theft Reevaluating harm 	 [Howard & Korver, 2008] pages 113-130 (Chapter 6) [Useem, 2017]
	 2. Pricing a. 5Cs (Context, Competition, Customers, Collaborators, Company) b. Relevant (differential) cost Incremental Avoidable Fixed costs 	



	 Opportunity Costs Pricing Playbook Skimming: Start high, reduce later Penetration: Start low, increase later Buffering: Limit price cuts through weak demand and then raise slowly 3. Sellers are comparison buyers using data analytics [Useem, 2017] Price hierarchy in cars (GM example) List price distraction Left digit bias Experiments to produce data Nash equilibrium Price anchoring/framing 	
7. Thu 8 Feb	 Continue developing a personal code of ethics [Howard & Korver, 2008] Ethical dilemma of corporate leaders The example of VC telling COO not to share cash crisis with employees Choosing where to work Pressures to conform to company expectations, professional guidelines, etc. Legal compliance doesn't cover many ethical decisions The Internet That Was (and Still Could Be) [Weinberger, 2015] Information source without reinforce biases Effects on brain Net neutrality Reasons for optimism 	 [Howard & Korver, 2008] pages 131-150 (Chapter 7) [Weinberger, 2015] [Dubner, 2016] [Tufekci, 2016]
	 3. Is the Internet Being Ruined? [Dubner, 2016] a. Leverage over our livelihoods, interactions, politics b. How Internet engagement is curated by all platforms 4. Algorithmic Harms Beyond Facebook and Google [Tufekci, 2015] 	



	 a. Facebook algorithms determine what more than a billion people see every day. Are the "trending topics" vetted by a small team of editors or "surfaced by an algorithm?" b. While these algorithms also use data, math and computation, they are a fountain of bias and slants — of a new kind. c. Machine learning is becoming pervasive and that allows computers to independently learn to learn, sometimes using techniques used by humans. We know the algorithms but we don't know the knowledge gained using them, and how (due to indirect approach). d. Facebook's goal is to maximize the amount of user engagement, sometimes superficially e. The newsfeed algorithm also values comments and sharing. This suits items that generate quantity, rather than quality. f. Google PageRank can have similar biases that influences viral aspects of webpages. g. Gatekeeper algorithms e. Lack of visibility e. Information asymmetry e. Hidden influence e. Privacy 	
	• Incorrect conclusions	
	 Misuse of information h. Case studies 	
	Social Movements and the Civic Sphere	
	Elections and Algorithmic Harms	
8. Mon 12 Feb	Continue developing a personal code of ethics [Howard & Korver, 2008] a. Forming habits that reinforce our ethical code	• [Howard & Korver, 2008] pages 151-174 (Epilogue
	 2. Limits of Analytics [Marcus & Davis, 2014] a. Problems with Big Data Doesn't tell which correlations are meaningful Doesn't replace scientific (supplements it) Can be gamed Results are less robust than they seem at first glance Echo-chamber effect 	 & Appendices A & B) [Marcus & Davis, 2014] [Lazer et al, 2014]



9. Thu 15 Feb	 Too many correlations can make meaningful correlations hard to identify Scientific-sounding solutions to imprecise questions Can't analyze things that are less common People believe the hype Google Flu story [Lazer et al, 2014] Big Data as substitute for traditional data collection and analysis Predicting accuracy and inaccuracy Google Flu algorithm methodology Transparency and replicability Granularity Predicting the unknown Using all data sources 1. Continue developing a personal code of ethics [Howard & Korver, 2008]	• [Howard & Korver, 2008]
15 Feb	 a. Discussion on personal ethical codes 2. Privacy Concerns [CBS, 2016] [Weise & Guynn, 2014] [Barocas & Nissenbaum, 2014] a. Uber Tracking Tracking travel records without permission #DeleteUber movement b. Procedural Privacy Protections Procedural approaches to protecting privacy a. Informed Consent b. Anonymity Recognizing the limits of purely procedural approaches to protecting privacy - Privacy loses the trade-off with big data 	pages 175- 186 (Our Messages) [CBS, 2016] [Weise & Guynn, 2014] [Barocas & Nissenbaum, 2014]
10. Mon 19 Feb	 US approach to privacy law ([U.S. Constitution] and [The White House, 2014] pages 15-21 starting from U.S. Privacy Law and International Privacy Frameworks) a. Focus on the fourth amendment b. Development of Privacy Law c. The Fair Information Practice Principles d. Sector-Specific Privacy Laws e. Consumer Privacy Bill of Rights 	 [U.S. Constitution] [The White House, 2014] pages 15-21 [Schwartz, 2010]



f. Global Interoperability 2. Data Protection Law and the Ethical Use of Analytics [Schwartz, 2010] a. The need for contextual examination of analytics • Risks posed to privacy and responsible processes • Evolving environment for data protection • The ethics of analytics • Multichannel marketing • Fraud detection and prevention • Protecting data security • Health Care Research (The story of Viagra) • Consumer products • Personalized (news feeds) • Productive (financial, medical,) c. The Different Stages of Analytics i. Collection ii. Integration and Analysis iii. Decision-making iv. Review and Revision d. Fair Information Practices (FIPs) • Automated Individual Decisions • Purpose Specification and Use Limitations • FIPs in the Ethical Use of Analytics 3. The Supreme Court's Big Data Problem [Brennan-Marquez, 2016] a. Spokeo v. Robins case b. Breaking the law or breaking the law in a manner that injured anyone c. Use of inaccurate and accurate data d. The trade-off between discrimination or personalization? 11. Thu 22 Feb 1. How Data Mining Discriminates [Barocas & Selbst, 2016] a. Defining the "Target Variable" and "Class Labels" b. Training Data • Labeling Examples • Data Collection c. Feature Selection			
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	 d. Proxies e. Masking 2. The Hidden Biases in Big Data [Crawford, 2013] a. Data fundamentalism • Case study: Twitter and foursquare data during Hurricane Sandy b. Address these weaknesses in big data science • Validate data sources • Identify cognitive biases 	• [Crawford, 2013]
12. Mon 26 Feb	 Redress Predictive Privacy Harms [Crawford & Schultz, 2014] a. Expansion in use of PII (Personally Identifiable Information) using Big Data by Leveraging technology that maximizes computational power and accuracy Using on a range of tools to clean and compare data. Believing that large data sets are more reliable b. Vulnerability of health records Electronic pharmaceutical records Social media activity Downloadable data Differential privacy 	 [Crawford & Schultz, 2014] pages 93-99 [Richards & King, 2016]
	 2. Protecting Privacy [Richards & King, 2016] a. Regulations Procedural: reinforcing transparency of processing, the basis for algorithmic decisions ("algorithmic accountability"), and providing choice to opt-out Regulating decisions that threatens identity, equality, security, data integrity, and trust 	

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Ethical & Legal Issues of Data Analytics: 2018 Spring

Dansby: Section A @ M/Th 12:30-2:45pm, Section B @ M/Th 9-11:15am

Reading List

All the readings below are available online except the one(s) marked with an asterisk. This will save you money and save the earth a few trees. You can access assigned articles from the links provided in the syllabus. If you run into any issues, you can also access the readings using the following URL: https://qetitatduke.library.duke.edu/ejp/?libHash=PM6MT7VG3J#/search/?searchControl=title&searchType=alternate_title_equals&criteria=new%20york%20times&language=en-US&titleType=JOURNALS.

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Ethical & Legal Issues of Data Analytics: 2018 Spring

Dansby: Section A @ M/Th 12:30-2:45pm, Section B @ M/Th 9-11:15am

http://www.kauffmanfellows.org/journal_posts/applying-decision-analysis-to-venture-investing/

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Dansby: Section A @ M/Th 12:30-2:45pm, Section B @ M/Th 9-11:15am

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These readings just missed the final cut. I'm including them if you are interested in learning more.

- Tufekci, Z. (2015). Algorithmic Harms Beyond Facebook and Google: Emergent Challenges of Computational Agency. *Colorado Technology Law Journal*, 13, 203-209. Retrieved from http://ctlj.colorado.edu/wp-content/uploads/2015/08/Tufekci-final.pdf
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Ethical & Legal Issues of Data Analytics: 2018 Spring

Dansby: Section A @ M/Th 12:30-2:45pm, Section B @ M/Th 9-11:15am

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⁴ This paper talks about Information Asymmetry, "Leveraging access to information about users and their control over the user experience to mislead, coerce, or otherwise disadvantage sharing economy participants", Consumer Protection law/legal

⁵ An interesting argument for the share-the-data approach – and how it could improve decision making on the societal scale