People Analytics:

Data and Algorithms as Managerial Tools

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OVERVIEW

What are the promises and pitfalls of using data and algorithms to manage employees in contemporary businesses? Terms such as "big data" and "artificial intelligence" are no longer restricted to computer science departments and tech companies in Silicon Valley; organizations of all kinds from all over the world are trying to harness the power of contemporary data analytics tools to accomplish their goals. In most businesses today, the question is not so much *if* such tools should be used but *how*. One increasingly prominent application is people analytics—the use of data and algorithms to help manage an organization's human resources: hire the right people, promote a particular organizational culture, and optimize employee performance. In this class, we will explore how data and algorithms can be used by managers and the different practical and ethical consequences of doing so.

Tackling these questions requires that we think deeply about economic organizations in a broad sense. What is the purpose of a business? What makes a "good" or "bad" employee? What is the role of personal values in managing others? In pondering these we'll consider especially the sociological perspective on human organization and inequality. However, to fully address these questions we must also have some familiarity with the tools being used. Instead of focusing on the statistical or computational foundations of these methods, we'll work to build students' intuitive understanding and ability to consume summaries of their applications in a thoughtful way. What does it *mean* if employee gender predicts performance?

The goal of this class is to empower the students in becoming both a knowledgeable and responsible consumer of people analytics. This will involve making students familiar with the methods being used as well as the ethical and societal issues involved with making such decisions.

CLASS FORMAT

The class will meet twice a week for a combination of lectures and discussions. This ensures that we build a common conceptual vocabulary as a class and will allow students to meet the learning goals discussed in the course overview. It is essential that students attend class, participate in discussion, and read the required materials carefully before each class.

The lecture material will be supplemented with out-of-class work, which can be largely customized to fit individual students' needs. Specifically, written reactions to readings and optional methods modules allow students to focus on different parts of the material and develop their individual understanding in a way that most benefits them. While one student might decide to focus on the technical details of the methods/tools discussed (by writing reactions to methods-oriented optional readings and by completing the methods modules), another might focus more on critical evaluations of the ethics of using such tools (by writing reactions to pieces discussing inequality).

The class will occasionally make use of Google Colab notebooks. These are files similar to Google Docs which allow for the sharing and online running of Python (an open-source programming language) code. No software needs to be downloaded to use Google Colab notebooks, and no coding experience is assumed for this class. Optional methods modules will have extensively documented starter code which need only be slightly altered. During some lectures, user-friendly notebooks will be made available that help demonstrate topics being discussed.

CLASS REQUIREMENTS

Participation and Class Readings

There are a set of required readings for every week of the course. Students should be sure to note whether the entire reading is required or whether an excerpt is listed after the reading, indicating that only a subset of the reading is expected (though students should of course feel free to read beyond the excerpts for more information). These readings will build the foundation for our in-person sessions, in which we will build on ideas from the reading. In other words, readings should be done before the first class of the respective week. Optional readings will help interested students understand the material more in-depth. Students will be expected to arrive to class on time, to regularly contribute to class discussion, and to engage with other students' views thoughtfully and respectfully.

Discussion Papers

There is a total of eight weeks in the class. For two of these weeks, students will turn in a brief (normally one or two pages with 12-point single-spaced Times New Roman font and 1" margins) written response to that week's readings. The student should select these weeks strategically, either to focus in on topics they find especially interesting or that they think they will benefit the most from engaging with more. These discussion papers can be turned in until the beginning of the first class of the following week (e.g., the discussion paper for "Week 1: Contextualizing Organizational Behavior" can be turned in until 1:30 PM on July 5th), but I recommend you turn them in before the first day of class that week. **No late discussion papers will be accepted.**

These discussion papers require that students engage deeply with the materials. They should consider the given discussion questions for the week, and answer each with citations to the required and/or optional reading. Where appropriate, they should also go beyond the reading, offering either critiques of it or questions they had that arose from it.

Final Paper

By the end of the quarter, students will produce a final paper in which they take on the role of a people analytics consultant hired by a business to address a key organizational issue. The goal is to write up a brief report proposing a solution to the business's leadership. In doing so, this paper should demonstrate that the student understands how modern data analytics can be used in the context of a business, that the student can think critically about the possible consequences of doing so, and that the student can communicate this information to someone with no background in people analytics in a clear and logical way.

The prompt for the paper will be one of the issues discussed in class that people analytics has been proposed for solving. Specifically, students may choose from one of the following (or propose another to the instructor):

1. How do we hire the best people?
2. How do we effectively monitor and/or optimize employee/team performance?
3. How do we ensure we're paying our employees fairly?
4. How do we promote diversity?
5. How do we put employees into optimal teams?
6. How do we promote a desired organizational culture?

The paper will be comprised of three sections: an introduction describing the problem and the hypothetical setting, a section detailing the proposed solution and details for how to test/implement the solution, and a section laying out the potential technical, practical, financial, and/or ethical concerns with the proposed solution. Importantly, earning a good grade on the paper will require thinking through the problem carefully, proposing a solution that demonstrates a good grasp of course material, and providing a nuanced analysis of the possible drawbacks of the proposal. Every solution to complex problems in a realistic setting has significant drawbacks; the leadership of an organizations needs to be aware of the pros and the cons to make an informed decision. More details on the paper requirements and expectations for each section will be made available during the class.

In total, this paper should be between three and five pages (Times New Roman, font size twelve, 1" margins, single spaced). Papers will be graded on the following criteria:

- Requirements – Does the paper accord with instructions regarding length and content while adhering to widely held norms of good writing? Is the paper too long or too short? Does it exclude one of the required sections? Were there significant spelling or grammatical errors?
- Understanding – Is a strong grasp of the course material demonstrated? Are terms discussed in class used in a correct way? Are issues discussed in class considered?

- Thoughtfulness – Is the essay indicative of critically thinking through the problem and/or the solution proposed? Is an innovative solution to the problem proposed? Are insightful ethical concerns to the proposed solution discussed?

(Optional) Methods Modules

During weeks two ("Machine Learning") and six ("Digital Trace Data"), the instructor will make Google Colab Notebooks available with example code that makes use of the methods/tools covered that week. Following this example/starter code there will be a short problem set which asks students to slightly alter this code and provide interpretations of the results. For students interested in using these methods, this is a great opportunity to see one way they can be implemented using Python, a coding language used by real practitioners in the field of people analytics. In these notebooks, there will also be brief discussions of the statistical and computational foundations of these methods/tools, though this is only included as a resource for curious students.

Importantly, these methods modules are completely optional. Completing them satisfactorily will improve students' grades on the final paper (see the "GRADING" section of the syllabus for details). Partial credit will not be given for partially completed methods modules. Methods modules are made available the morning of the first class of the respective week and are due before the first class of the following week. **No late methods modules will be accepted.**

GRADING

Students' grades will be calculated according to the following:

30% participation

40% discussion papers (20% each)

30% final paper

Additional credit for each methods module a student successfully completes will be applied to their grade for the final paper. Specifically, each completed methods module will count as 30% guaranteed credit towards a baseline grade on the final paper, such that successfully completing both guarantees a 60% on it. The received grade on the final paper will then be scaled to the difference between this baseline grade and 100% and added to the baseline grade according to the following formula:

$$Final\ Paper\ Grade = Baseline\ Grade + [(1 - Baseline\ Grade) * Paper\ Grade]$$

So, for instance, if a student completes one methods module and receive an 80% on their paper, their baseline grade is 0.3 and their paper grade is 0.8, resulting in a final paper grade of 86% (0.3 + [0.7* 0.8] = 0.86).

CLASS SCHEDULE

Week 1: Introduction and Organizational Theory

(June 21st and 23rd)

Why do people work in organizations? What drives the behaviors and decisions of companies? And why is everyone obsessed with people analytics? In these introductory sessions, we'll discuss and think through several formal models of organizational behavior, each of which answers these questions in unique ways. These perspectives will be instrumental to our ability to rigorously think through the possible consequences of decision-making in the context of contemporary businesses.

We will primarily focus on two perspectives: transaction cost economics (TCE) and neo-institutionalism. We will turn these perspectives towards three important topics: why we have organizations in the first place, what makes an organization successful, and why organizations should concern themselves with morality and ethical behavior. Then, time allowing, we'll discuss newer theoretical developments in viewing organizations as sites of reproducing racial inequality.

Discussion Questions

- Why would organizations have people analytics (or human resources) departments according to the TCE (Coase; Williamson) and the neo-institutionalist (Meyer and Rowan; DiMaggio and Powell) perspectives?
- What do these different reasons imply about what makes a good/successful people analyst? How might people analyst departments driven by these perspectives behave differently?
- What is something a people analyst might do/accomplish that would seem like a success from either the perspective of TCE or neo-institutionalism and a failure from the other?

Required Readings

Coase, R.H. 1937. "The Nature of the Firm". *Economica,* 4(16): 386-405. (Sections I, II, and V)

Meyer, J.W., & Rowan, B. 1977. "Institutionalized Organizations: Formal Structure as Myth and Ceremony". *American Journal of Sociology*, 83(2): 340-363. (Skip "PREVAILING THEORIES OF FORMAL STRUCTURE", "The Relation of Organizations to Their Institutional Environments", and "Research Implications")

Optional Readings

DiMaggio, P.J., & Powell, W.W. "The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields". *American Sociological Review,* 48(2): 147-160. (Skip "PREDICTORS OF ISOMORPHIC CHANGE" and "IMPLICATIONS FOR SOCIAL THEORY")

Williamson, O. E. (1985). The economic institutions of capitalism: Firms, markets, relational contracting. New York: Free Press. (Pages 18-42; skip "A Cognitive Map of Contract", "A Simple Contracting Schema", "Economic Organization of the Company Town", and "Applications")

Ray, V. 2019. "A Theory of Racialized Organizations". *American Sociological Review,* 84(1): 26-53. (Skip "Omitting Race From Organizational Formation" and "Organizational Invisibility In Race Theory")

[NOTE: You may find Ray (2019) especially difficult to follow if you don't have a background in Sociology or a related field]

Week 2: Machine Learning

(June 28th and 30th)

This week, we'll move beyond the hype and build an intuition for what contemporary predictive algorithms can (and, just as importantly, what they cannot) do. Machine learning is a vast and highly technical field, but the intuitions underlying even the most advanced algorithms such as artificial neural networks are surprisingly simple to grasp if approached in the correct way.

We'll discuss general machine learning principles (e.g. training data partitioning, performance evaluation metrics) as well three specific families of algorithms: (regularized) regression, tree-based methods, and artificial neural networks. No knowledge of how these algorithms work or mathematics (beyond simple algebra) will be assumed. This knowledge will be important for being able to propose solutions using these tools within organizations, consume analyses using these methods, and to think critically about the consequences of leveraging these tools in the course of organizational life. We'll also think about and discuss the morality and ethics of predictive algorithms. When and why are people uncomfortable with algorithms making decisions for organizations? Are they on to something?

Discussion Questions

- What is machine learning? What are some examples of things you think machine learning might be successful at and some things that it might have more difficulty with?
- Imagine a company develops an AI-powered approach to hiring new employees. It works by predicting what the future performance reviews of a potential hire would be one year after working at the company, and selecting the candidate with the highest predicted performance review.
    - If the actuaries in Kiviat (2017) were examining this system, how might they decide whether the algorithm is fair or not?
    - How about the policymakers?
    - What's an example of a behavior/tendency this algorithm might exhibit that the **actuaries** would think is fair but that the **policymakers** wouldn't think is fair?
    - What's an example of a behavior/tendency this algorithm might exhibit that the **policymakers** would think is fair but that the **actuaries** wouldn't think is fair?

Required Readings

Jordan, M.I., & Mitchell, T.M. 2015. "Machine learning: Trends, perspectives, and prospects". *Science,* 349(6245): 255-260.

Kiviat, B. 2017. "The Moral Limits of Predictive Practices: The Case of Credit-Based Insurance Scores". *American Sociological Review,* 84(6): 1134-1158. (Skip "DATA AND METHODS", and "Suggestions for Future Research on Moral Markets")

Salganik, M.J., Lundberg, I., …, McLanahan, S. "Measuring the predictability of life outcomes with a scientific mass collaboration". *Proceedings of the National Academy of Sciences,* 117(5): 8398-8403.

Optional Readings

Wu Y., Kosinski, M., & Stillwell, D. 2015. "Computer-based personality judgements are more accurate than those made by humans". *Proceedings of the National Academy of Sciences,* 112(4): 1036-1040. (Skip "Interjudge Agreement")

Breiman, L. 2001. "Statistical Modeling: The Two Cultures". *Statistical Science,* 16(3): 199-231. (Skip "Problems in Current Data Modeling", "The Multiplicity of Data Models", "Bellman and the Curse of Dimensionality"; Skim "Information from a Black Box")

[NOTE: Parts of Breiman (2001) will be difficult to understand if you don't have a background in statistics, but it will still be helpful to skim]

Kleinberg, J., Mullainathan, S., & Raghavan, M. 2016. "Inherent trade-offs in the fair determination of risk scores". arXiv preprint arXiv:1609.05807. (Read until "Special Cases of the Model", also read "Informal Overview" and "Conclusion")

3Blue1Brown. "Deep Learning". YouTube series.
https://www.youtube.com/watch?v=aircAruvnKk

*** Methods Module 1 Available***

Week 3: Hiring and Bias

(July 5th and 7th)

One of the core tasks of human resource specialists is to help a business hire the right people. Despite the importance of this task for organizational success, research shows time and time again that many organizations prefer not to hire some candidates on the sole basis of their gender or ethnicity. Can data and algorithms help make this process more effective? Can they make it more fair? This week, we'll discuss the hiring process and whether and how contemporary analytics might help businesses hire the best people.

We'll focus in on the pros and cons of using algorithms to help make hiring decisions. Importantly, this will involve considering the strengths and weaknesses of the assumed alternative: human judgement. We'll see that both relying on human judgement alone and leaving the job completely to algorithms come with significant tradeoffs. We'll try to think through models of how we can use algorithms to *augment* (instead of replace) human judgement in the course of hiring decisions.

Discussion Questions

- What are some things businesses are (or should be) looking for when they consider potential employees?
- What are some of the limitations to humans' social judgments that make them unreliable predictors of who will be a successful employee? What are the strengths and weaknesses of algorithm's decision-making relative to humans' decision-making?

- The Boegen (2019) reading argues that predictive algorithms can influence the hiring process well before an applicant submits a resume. Are organizations *ethically* responsible for bias in these algorithms if they pay for their use? Pick a position, make an argument, and then provide an argument counter to your position.

Required Readings

Bertrand, M., & Mullainathan, S. 2004. "Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination". *American Economic Review,* 94(4): 991-1013. (Skip "Previous Research" and "Relation to Existing Theories". Skim "Do African-Americans Receive Different Returns to Resume Quality?" and "Applicants' Address")

Kuncel, N.R., Klieger D.M., & Ones, D.S. 2014. "In hiring, algorithms beat instinct". *Harvard Business Review,* 92(5): 32.

Boegen, M. 2019. "All the Ways Hiring Algorithms Can Introduce Bias". *Harvard Business Review,* 6.

Optional Readings

Dana, J., Dawes, R., & Peterson, N. 2013. "Belief in the unstructured interview: The persistence of an illusion". *Judgement and Decision Making,* 8(5): 512-520.

Rebele, R. 2019. "Can We Really Test People for Potential?". *MIT Sloan Management Review,* 60(3): 10-13.

Pager, D. "Are Firms that Discriminate More Likely to Go Out of Business?". *Sociological Science,* 11: 849-859.

Gaucher, D., Friesen, J., & Kay, A. 2011. "Evidence That Gendered Wording in Job Advertisements Exist and Sustains Gender Inequality". *Journal of Personality and Social Psychology,* 101(1): 109-128. (Skip "Implications for Social Psychological Theories of Inequality and Sexism" and "Limitations and Future Directions")

Hoffman, M., Kahn, L. B., & Li, D. 2018. "Discretion in hiring". *The Quarterly Journal of Economics*, *133*(2), 765-800. (Read sections I, II, and IV)

Week 4: Performance and Engagement

(July 12th and 14th)

If we think about human resource managers as "talent managers", then key to their success (and their ability to measure their success) will lie in their ability to measure how "well" employees are doing their respective jobs. Since Frederick Winslow Taylor, practitioners have tried to apply scientific principles to measuring and maximizing worker productivity (see Taylorism). Yet, despite a long history of attempts, no single metric for "performance" or "productivity" is widely accepted. Contemporary social scientists often prefer to believe that the objective "performance" is either entirely illusory or is so context-dependent that trying to develop generalizable measures is a fool's errand.

This, week we'll briefly consider a suite of approaches to performance evaluation including: alter feedback (360-degree performance reviews; 9-box grid; forced ranking), self-assessment (pulse surveys; personal essays), goal completion (annual goal-setting meetings; management by objectives), quantitative measures of output (number of units handled; average time handled; average response time to emails), failure prevalence (proportion of units that needed redone; absenteeism rate; number of sick days), and collective performance. We'll talk about why each of these are severely limited, but how combining the logics of these various approaches, along with some general insights into the contextual dependence of returns to behavior, might help us make talent management decisions. We'll also talk about engagement, how it relates to "performance", and current approaches to measuring it.

Discussion Questions

- What makes a "good" employee?
- If we were wanting to accurately measure how much you've learned in the class so far, what would be some problems and unique advantages with each of the following approaches:
    - Ask you how much you've learned
    - Ask a random classmate how much you've learned
    - Ask the instructor how much you've learned
    - Count how long your discussion papers are
- Let's say Stanford developed an algorithm that mines your emails and your class transcripts to predict your GPA. Stanford thinks that this algorithm will be fairer in determining what your GPA "should" be compared to biased, imperfect professors grading your work—but they will only use it on volunteers. Without knowing what the algorithm thinks your GPA should be, would you volunteer to let this algorithm decide your GPA for you? Why or why not? Assuming you could know anything about the algorithm (besides what GPA it would give you), is there anything could you learn about the algorithm to change your mind?

Required Readings

Judd, S., O'Rourke, E., & Grant, A. 2018. "Employee Surveys Are Still One of the Best Ways to Measure Engagement". *Harvard Business Review*.

Muller, J. Z. 2019. *The Tyranny of Metrics*. Princeton University Press. (Read "The Argument", "Business and Finance", and "Conclusions")

Optional Readings

Rivera, L.A. & Tilcsik, A. 2019. "Scaling Down Inequality: Rating Scales, Gender Bias, and the Architecture of Evaluation". *American Sociological Review*, 84(2): 248-274. (Skim "Quasi-Natural Experiment in the Field", "Survey Experiment"; Skip "Regression Results", "Implications for Research on Classification and Stratification", and "Implications for Research on Faculty Diversity")

Correll, S.J., Weisshaar, K.R., Wynn, A.T., & Wehner, J.D. 2020. "Inside the Black Box of Organizational Life: The Gendered Language of Performance Assessment". *American Sociological Review*, 85(6): 1022-1050. (Skim "Theoretical Predictions", "Analytical Plan")

Pulakos, E. D., Mueller-Hanson, R., & Arad, S. 2019. The evolution of performance management: Searching for value. Annual Review of Organizational Psychology and Organizational Behavior, 6, 249-271. (Read until "New Approaches to Performance Management")

Week 5: Discrimination and Compensation

(July 19th and 21st)

In the United States and around the world, we observe differences in pay between employees of different genders and different racial/ethnic identities. Many interventions have tried to remedy this situation, but most have had limited success. What are the possible sources of the these pay discrepancies, and can contemporary data analytic methods help us address them? Under what conditions do businesses have and not have a moral obligation to remedy these discrepancies?

Different theories of the origins of these "pay gaps" and different forms of discrimination will be discussed, along with contemporary approaches for detecting inequities in an organization's compensation structure. Students will interact with a user-friendly simulation tool implemented in a Google Colab notebook, allowing them to explore how pay discrepancies might arise for several different reasons, what data and analyses are needed to determine what is driving them in a particular context, and the consequences of different sorts of interventions meant to address them.

<u>Discussion Questions</u>

- Imagine that an organization finds that its employees who belong to two social groups (e.g., men and women, Blacks and Whites) make different amounts of money in an organization on average…
    - What are at least three different reasons this difference might exist?
    - What data would be helpful to rule out these different explanations?
    - Should the organization care? Why or why not? Does it depend on *why* that difference exists? What the two social groups are?
- What kinds of gender or ethnic discrimination might Google's pay equity analysis miss?

<u>Required Readings</u>

Petersen, T., and Saporta, I. 2004 "The Opportunity Structure for Discrimination". *American Journal of Sociology,* 109(4): 852-901. (Read until "Research Evidence")

Castilla, E. 2015. "Accounting for the Gap: A Firm Study Manipulating Organizational Accountability and Transparency in Pay Decisions". *Organizational Science*, 26(2): 311-333. (Skim "Data" and "Methodology"; Skip "Additional Analyses and Remarks")

Google. 2019. Pay Equity Analysis Fact Sheet.

Schwartz, M. 2019. "Google Pay Study Finds It Underpaid Men for Some Jobs". *NPR.org*.

<u>Optional Readings</u>

Correll, S.J., & Benard S. 2006. "Biased Estimators? Comparing status and statistical theories of gender discrimination". In *Advances in Group Processes,* Volume 23. Emerald Group Publishing Limited.

Prager U. "There Is No Gender Wage Gap!". Youtube Video. https://www.youtube.com/watch?v=QcDrE5YvqTs

Macke, E., Rose, G.G., Gilmartin, S., & Simard, C. 2022. "Assignments Are Critical Tools to Achieve Workplace Gender Equity". *MIT Sloan Management Review,* 63(2): 1-5

Week 6: Digital Trace Data (Social Networks and Text as Data)

(August 26th and 28th)

Human work is increasingly mediated through digital platforms (e.g. email, Slack, Zoom). Social scientists and people analysts have learned to harness records of behavior on these same platforms to gain insight into human/employee behavior. This week, we'll examine two tools contemporary analysts use to examine such data: relational data analysis ("network analysis") and automated text analysis. We'll consider the ethics of digital trace data, build an intuition for what these methods are and what it can tell us, and think about how incorporating such tools into decision-making could help or hurt a business.

Discussion Questions

- When is it moral and immoral to use employees' digital trace data (try to think of at least three factors that make it more or less moral)?
- What kinds of text are (or could be) regularly produced by employees in an organization? How might an organization use this text to better manage them?
- The Leonardi and Contractor (2018) reading briefly mentions an intervention to change an organizations' communication network. How do we think about the ethics of this? What are some of the moral upsides and downsides of engineering your employees' communication networks and relationships to maximize their performance and optimize the business' bottom line?

Required Readings

Leonardi, P. & Contractor, N. 2018. "Better people analytics". *Harvard Business Review,* 96(6): 70-81.

Watts, D. 2016. "The Organizational Spectroscope". *Medium.*

Ghaffary, S. 2019. "The algorithms that detect hate speech are biased against black people". *Recode by Vox.* (Online news article).

Optional Readings

Loon, A van. Under Review. "Three Families of Automated Text Analysis". *Social Science Research.*

Szell, M., Lambiotte, R., & Thurner, S. 2010. "Multirelational organization of large-scale social networks in an online world". *Proceedings of the National Academy of Sciences*, *107*(31), 13636-13641.

Alvero, A. J., Giebel, S., Gebre-Medhin, B., Antonio, A. L., Stevens, M. L., & Domingue, B. W. 2021. "Essay content and style are strongly related to household income and SAT scores: Evidence from 60,000 undergraduate applications". *Science advances*, *7*(42), eabi9031. (Read until "Materials and Methods")

Methods Module 2 Available

Week 7: Diversity and Teams

(August 2nd and 4th)

In recent years, promoting diversity has become a primary goal or human resource management specialists. Despite all this effort, little progress has been made in increasing representation of women and racial minorities in management in the last twenty years. Why has this proved so difficult? Why do organizations care in this first place? Why are some kinds of diversity valorized while others are ignored? How can data and quantitative analysis help us achieve these goals?

We'll first review current research on how and why diversity matters. Then, we'll take a critical look at how businesses have tried to promote diversity to date. Finally, we'll consider the different ways organizations can promote diversity, the different levers managers have to do this, how data and algorithms can help us accomplish this, and the ethical consequences of doing so.

Discussion Questions

- Why should/do businesses care about diversity? What answers would a transaction cost economist and a neo-institutionalist give?
- What kinds of diversity do businesses care about? What are some types of diversity they don't care about? Are there types of diversity they *shouldn't* care about?
- What does the importance of groups for performance mean for measuring/thinking about the ethics of evaluating employees as individuals?

Required Readings

Ely, R. J., & Thomas, D. A. 2020. "Getting serious about diversity: Enough Already with the Business Case". *Harvard Business Review*, *98*(6), 114-122.

Dobbin, F., & Kalev, A. "Why Diversity Programs Fail: And What Works Better". *Harvard Business Review,* 4.

Lix, K., Goldberg, A., Srivastava, S.B., & Valentine, M.A. Forthcoming. "Aligning Differences: Discursive Diversity and Team Performance". *Management Science*. (Skip "Discursive Diversity: Validating the Word Embedding Model", "Descriptive Statistics", "Extensions", and "Limitations and Future Directions"; Skim "Variation in Discursive Diversity Across Teams' Life Cycles and Milestones")

Optional Readings

Wooley, A.W., Chabris, C.F., Pentland, A., Hashmi, N., & Malone, T.W. 2010. "Evidence for a Collective Intelligence Factor in the Performance of Human Groups". *Science,* 330(6604): 686-688.

Guilbeault, D., van Loon, A., Lix, K., Goldberg, A., & Srivastava, S.B. 2022. "Exposure to the Views of Opposing Others with Latent Cognitive Differences Results in Social Influence—But Only When Those Differences Remain Obscured". *Working Paper*. (Skip "Limitations and Future Research")

Week 8: Organizational Culture

(August 9th and 11th)

"Culture" is a term long used in the social sciences that evades precise definition and consensus. Generally, though, it refers to shared values, behavioral patterns, and/or cognitions among a socially defined group. Social scientists still struggle with fully conceptualizing and measuring culture, but this hasn't stopped major companies from touting the importance of their organizational culture. Netflix, for instance, has publicly posted a lengthy description of the culture they seek to promote.

This week, we'll think about what organizational culture is and whether/why it's important. Then, we'll think about the "dark side" of organizational culture – the possible costs and ethical dilemmas involved in building an organization with a single, hegemonic culture. Finally, we'll explore some of the classic and recent literature for measuring organizational culture and the degree to which individuals "fit" into that culture.

Discussion Questions

- Looking at Netflix's stated organizational culture, how—if it were implemented to the letter—might it help or harm the organization?
- What are the possible pros and cons of having a single, hegemonic organizational culture?
- Say you did want to promote a particular organizational culture in a business—what are different ways to promote it?

Required Readings

Rivera, L. 2012. "Hiring as Cultural Matching: The Case of Elite Professional Service Firms". *American Sociological Review,* 77(6): 999-1022. (Skip "Interviews", "Participant Observation", "Data Analysis", "Who Put Fit First?", "Alternative Accounts", "Limitations And Future Research", and "Implications for Research on Culture and Stratification")

Mobasseri, S., Goldberg, A., & Srivastava, S.B. 2017. "What is Cultural Fit? From Cognition to Behavior (and back)". In *The Oxford Handbook of Cognitive Sociology*, 305. (Skim "Mapping Prior Work on the Spectrum from Cognition to Behavior" and "Methodological Implications")

Corritore, M, Goldberg, A., & Srivastava, S.B. 2020. "The New Analytics of Culture". *Harvard Business Review*, 1.

Optional Readings

O'Reilly III, C.A., Chatman, J., & Caldwell, D.F. 1991. "People and Organizational Culture: A Profile Comparison Approach to Assessing Person-Organization Fit". *Academy of Management Journal,* 34(3): 487-516.