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Intro to Data Analytics

W5. Discussion - Data Ethics I (01 Feb 2026)

This week's readings helped me understand that data ethics is not just an abstract or philosophical topic but a practical responsibility that directly affects how data analytics systems shape society. Both "The Ethics of Algorithms: Mapping the Debate" and "Data Experts as the Balancing Power of Big Data Ethics" argue that algorithms are not neutral mathematical tools. Instead, they are socio-technical systems built on human choices, assumptions, and values. As a result, ethical concerns must be considered throughout the entire analytics lifecycle rather than after deployment. Before completing these readings, I tended to focus primarily on technical performance such as accuracy or efficiency. However, the articles helped me realize that even highly accurate models can still produce harmful or unfair outcomes if ethical considerations are ignored.

The first article begins by defining what an algorithm is and distinguishes between decision-making algorithms and machine learning algorithms. Decision-making algorithms follow predefined rules, while machine learning systems learn patterns from historical data and scale automatically. Although structurally different, both types influence real-life decisions such as hiring, lending, policing, and healthcare. The authors present a conceptual map of six ethical concerns: inconclusive evidence, inscrutable evidence, misguided evidence, unfair outcomes, transformative effects, and traceability. The first three are epistemic concerns that relate to the quality and reliability of evidence generated by algorithms. For example, predictions may be uncertain, difficult to interpret, or based on flawed data. The next concerns are normative and focus on the consequences of algorithmic decisions, such as discrimination or long-term societal changes. Finally, traceability addresses accountability and who should be responsible when harm occurs. I found this framework especially useful because it provides a structured way to analyze ethical risks rather than treating them as vague or general problems.

These categories become clearer when applied to real-world cases. For instance, Amazon once experimented with an AI hiring tool that unintentionally downgraded resumes containing the word "women," because historical hiring data mostly favored men. This illustrates misguided evidence and unfair outcomes, where biased historical data leads to discriminatory results. Similarly, facial recognition technologies have shown higher error rates for darker-skinned individuals, demonstrating both epistemic issues (inaccurate evidence) and normative issues (potential wrongful identification). Another example is predictive policing systems that repeatedly target the same neighborhoods because past arrest data already reflects over-policing. This creates a transformative effect by reinforcing cycles of

surveillance and inequality. These cases helped me understand that the concerns described in the article are not theoretical but actively shaping people's lives today.

The second article shifts the focus from algorithms themselves to the stakeholders involved in big data ecosystems. The authors describe the digital divide in three ways: unequal access to technology, unequal access to skills, and unequal benefits from being online. This idea expanded my understanding of inequality because it shows that simply having internet access does not mean someone has real control over their data. The article identifies three stakeholder groups: data-rich organizations, data-poor users, and data experts. Data-rich organizations have the technical infrastructure and resources to collect and monetize massive amounts of information. Data-poor users, on the other hand, often provide personal data through daily activities such as browsing or social media without fully understanding how it is used. The most interesting group is data experts, who belong partly to both worlds. They work inside organizations but still make individual ethical decisions, which gives them the power to influence how responsibly data is used.

I strongly related to the concept of being data-poor. For example, social media platforms collect behavioral data such as clicks, location, and preferences to create detailed profiles for targeted advertising. While companies benefit financially, users have very limited autonomy or transparency. This reflects the imbalance described in the article, where organizations are data-rich and users lack control. At the same time, the article's argument that data experts can act as a balancing power feel encouraging. Analysts and data scientists can advocate for privacy protections, fairness testing, and clearer communication with users. This shows that ethical responsibility does not lie only with laws or management but also with everyday technical professionals.

Personally, these readings changed how I view my role as a future data analyst. I used to focus mainly on building models that maximize performance metrics, but now I realize that ethical thinking must be integrated into each step of the process. Decisions such as selecting features, cleaning data, or choosing evaluation criteria can all affect who benefits and who might be harmed. The most exciting takeaway for me was the idea that data experts can serve as ethical advocates within organizations. Instead of simply following business objectives, they can question assumptions, highlight risks, and promote fairness and transparency. This perspective makes ethics feel like an active leadership responsibility rather than a restriction.

In conclusion, both articles demonstrate that algorithms are not neutral and that ethical challenges arise from both technical design and social context. The first article provides a detailed map of epistemic and normative concerns that help diagnose where algorithmic failures occur, while the second emphasizes stakeholder power dynamics and the important role of data experts in protecting vulnerable users. Together, they show that effective data analytics must balance technical excellence with accountability, fairness, and human values. Moving forward, I plan to apply these principles in my academic and professional work so that the solutions I develop are not only accurate but also equitable and trustworthy.