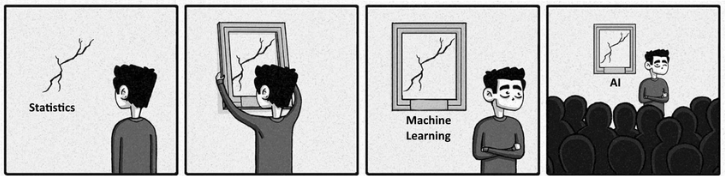
Machine Learning

Data Analysis for Journalism and Political Communication
(Spring 2026)

Prof. Bell



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  - Goal: To build a model on a sample of "training" data that makes the most accurate predictions possible on new, unseen "test" data.
- Despite different goals, core principles like avoiding selection bias, ensuring data quality, and understanding sample limitations are critical in both fields.

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- **Underfitting** is the opposite problem: the model is too simple and fails to capture the underlying signal in the data.

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  - **Unsupervised Learning**: The model works with **unlabeled** data to discover hidden patterns or structures on its own.
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- As models become more complex, it can be difficult to understand *why* they make a specific prediction. This challenge is known as **explainability** or the "black box" problem.

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- **Public Policy Example: Criminal Justice**: The COMPAS algorithm, used to predict the likelihood of a defendant re-offending, was found to be biased against Black defendants. It was more likely to incorrectly flag them as high-risk compared to white defendants.
- **Other Examples**: AI-powered hiring tools that discriminate against female candidates because they were trained on historical hiring data from a male-dominated industry, or mortgage approval algorithms that perpetuate racial redlining.

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- A key limitation is that an LLM's knowledge is frozen in time; it ends when its training data ends. It has no inherent knowledge of events that occur after its training is complete.
- To overcome this, LLMs can be used as part of an **agent** system. These agents can use **tool calls** to access external, real-time information (like a search engine) or perform actions, allowing them to provide up-to-date responses.

Key Challenges and Risks with LLMs

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- **Data Provenance**: The data used to train these models is often scraped from the web without permission, raising major copyright and ethical questions that are still being debated in court.

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- **Authors Guild v. OpenAI (and others)**
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  - **Claim**: AI companies copied copyrighted books without permission to train LLMs, and these LLMs can generate content that competes with or is derivative of their work.

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- **The New York Times Co. v. OpenAI and Microsoft**
  - **Who**: The New York Times Company against OpenAI and Microsoft.
  - **Claim**: Defendants used millions of NYT articles to train LLMs, which now produce output that closely mimics NYT content, sometimes reproducing it verbatim, and could draw readers away from the newspaper.

Build Your Own ML Model

Goal: Can we predict the tone of a campaign ad about a candidate based on how the candidate is portrayed in the ad?

Step 1: Gather Your Training Data

- Go to The Living Room Candidate (https://www.livingroomcandidate.org/)
- Select ads from any election(s) **except** 2024.
- Take 10-15 screen grabs that clearly feature a candidate.
- Create two folders: “Positive Tone” and “Negative Tone.” Place each screen grab in the appropriate folder based on whether the image portrays the candidate positively or negatively within the ad.

Build Your Own ML Model

Step 2: Train Your Model

- Go to Teachable Machine (https://teachablemachine.withgoogle.com)
- Go to Image Project → Standard Image Model.
- Upload your "Positive Tone" images to Class 1, and your "Negative Tone" images to Class 2.
- Click "Train Model."

Step 3: Test and Evaluate

- I will provide you with a test set of 10 images from 2024 campaign ads.
- Use Teachable Machine's file upload feature to test your model on each of these 10 images.
- How did your model do? Where did it do well, and where did it struggle? Why do you think this happened?