CS 461 Notes Feb. 2nd 2026

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1 Data and Regressive Model

1.1 Mathematical Stability

- We want our models to be numerically stable. This is because we are working with numerical estimations.
- Our computers do not have infinite precision, so extreme values cause artefacting and innacuracy.
- One of the reasons for this is because as two vectors grow increasingly close together, their dot product (or what happens when they are multiplied as part of a matrix) goes to infinity. This will lose a lot of data
- This is why whe use **Singular Value Decomposition**. It allows us to use a more stable computation.
- Although not discussed in class, it is also logical to assume that normalization will come into play down the line.

2 Principles for Regressive Model Design

We then went over some points on good principles to keep in mind when we design regressive models.

2.1 Intelligiblity of Models

- When designing a regressive model, there are things we want to understand.
- One such thing is the meaning of the weights. In a shallow linear model we aim to be able to observe what the weights correspond to and mean in practice.
- Another area that we must spend much time on is thorougly analyzing our data.
- Observations on trends, significant and insignificant variables, etc can be instrumental in model design and in making sure our model accurantly represents the data.
- We do not predict before knowing what we are working with. This constitutes on some degree irresponsibility intellectually, since if we do not understand our data, we cannot vet our predictions.

2.2 Datasheets for Datasets: Responsible Data Production and Consumption

- The professor quotes the following paper on guidance for providing context and transparency to datasets one may create and share with the academic community.

- The paper also gets into why it is important to understand these various aspects of data that we consume.
- Important ideas that came up during this section were:
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  - We should understand the various biases that are implicit in data that we use
  - We should beware of target/contruct mismatch. This means being extremely careful about what data points we use as proxies for the "real thing" we are trying to predict, model, or understand. Our assumptions may lead us astray and cause us to rely on baseless correlations.
  - Another pitfall is distribution shift. This occurs when the distribution that we study to train our model is not representative of the real world distribution.
  - All of these observations live very close to moral issues of responsibility and the power of predictive models.
  - As data scientists, it is our duty to have exceptional moral discernment in deciding even what **should** be modeled in addition to ensuring that our models do not misrepresent people, perpetuate social biases, or at worst even actively harm people or groups of people.

3 Questions and areas for exploration

- How does the algebra change between our simple linear models and more elaborate ones, such as exponential or quadratic ones?
- How can we interpret more complex models, such as ones that are "deeper" (have more linear or nonlinear layers)?
- How do we reassure ourselves of the safety of deep learning models given that they are by nature not easily intelligible by humans?
- What are the impacts of data created by our modern day generative models on both new generative model creation and the accuracy of regressive models that may be contaminted with "genAI" data?

3.1 Papers Reccomended by Professor Stone

- Gebru et. al., 2018 "Datasheets for Datasets"
- Shumailov et. al., 2023 "The Curse of Recursion: Training on Generated Data Makes Models Forget"
- Camp et. al., 2025 The citation catastrophe: Propagation of AI-generated counterfeit citations in scholarship
- Wang et. al, 2023 Against Predictive Optimization: On the Legitimacy of Decision-Making Algorithms that Optimize Predictive Accuracy