**The Problem**

Address bias w.r.t. sensitive attributes in spatial settings [4, 5]

**Key Terms**

- Sensitive Attributes (i.e., race, gender)
- Spatial and Non-spatial fairness
- Group and Individual fairness
- Data Processing
- Fairness-Accuracy Tradeoff (see plot)
- Reproducibility Crisis

**Research Timeline**

- Review fairness in AI research
- Narrow down 4 papers with unique approaches
- Study approaches in depth
- Strengthen knowledge in advanced calculus, statistics and number theory
- Find gaps in ideas that I can research
- Coding adapted likelihood fns

**Related Work**

- Multiple fair-ML definitions (>30), yet none for spatial settings (e.g., auto insurance, lending – location crucial)
- Fair-ML work [2, 7]: ignores spatial features entirely; ineffective when applied to spatial data (see #1 in M&R)
- Spatial fairness [1, 6]: ignore sensitive attributes entirely → cannot measure or remove racial bias

**Methods & Results**

1. Applying fair-ML technique [2] to spatial setting failed: can’t utilise spatial data efficiently
2. Some baselines wouldn’t replicate
3. Integrate two fairness techniques (spatial and non-spatial) together
4. Develop mathematical formula that represents integrated idea
5. Research strong, correlated, and useful datasets → combine them
6. Modify existing and write new code to handle new parameters (sensitive attributes) along with spatial data
7. Write code and execute with new data and methodology
8. Plot and analyze results - identified 34 significant regions with bias

**Skills Learned and Developed**

- Efficient literature review to identify gaps in current research
- Big Data Analysis
- Hypothesis Testing, Calculus + Statistics
- Integration of math, statistics, and ideas into functioning code

**Citations**

- Angwin, J., Larson, J., Kirchner, L., and Mattu, S. Minority neighborhoods pay higher car insurance premiums than white areas with the same risk. ProPublica, April, 2017.