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**Paper Title:** Preventing Eviction-Caused Homelessness through ML-Informed Distribution of Rental Assistance

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**Open questions for discussion in class:**

- What are the challenges of balancing model interpretability and predictive accuracy when applying complex ML models (like random forests or XGBoost) to sensitive social programs?
- How can policymakers ensure that predictive tools like this one remain transparent and fair over time especially as social conditions change?
- What ethical safeguards should be in place when using sensitive personal data (like eviction or mental health records) for predictive modeling?

**The topic areas covered by the paper are:**

- Homelessness prevention, rental assistance policy, and ethical use of machine learning in public service
- Using predictive modeling for better resource allocation (more efficient and effective) and equity in housing stability
- Data ethics, algorithmic fairness, and evaluating policy interventions through randomized controlled trials

**The previous approaches to this problem were:**

- Rental assistance programs were reactive and first come first served where it was serving people who applied rather than those most at risk for homelessness
- Past research models focused on broad populations or previously homeless individuals, not specifically on those facing eviction
- These earlier approaches lacked precision and fairness and didn't directly integrate into real world rental assistance systems

**Outline the basic new approach or approaches to this problem:**

1. Combine county and state administrative data (evictions, health, social services) to build ~7000 predictive features per tenant
2. Compare multiple ML models (random forest, logistic regression, LightGBM, XGBoost) to identify tenants most likely to need homelessness services within 12 months
3. Use temporal validation to avoid data leakage and simulate real world conditions
4. Evaluate fairness using equality of opportunity metrics to ensure race and gender equity in predictions
5. Validate the system through shadow mode deployment, followed by a randomized controlled trial
6. Include community and stakeholder input to maintain transparency, fairness, and privacy throughout the process

**Critical assumptions made include:**

- Individuals who interact with homelessness services represent the overall at-risk population (even though unrecorded homelessness exists)
- Providing proactive support to high risk tenants will directly reduce homelessness rates
- Predictive features and data relationships will remain valid over time
- Ethical safeguards and fairness metrics will be sufficient to prevent demographic bias
- Field trials (like the RCT) will confirm that model-guided allocation truly improves outcomes

**The performance of the techniques discussed in the paper was measured in what manner:**

- The paper used precision@100 and recall@100 measuring how effectively the model prioritized 100 individuals per month (matching program capacity)
- The random forest and logistic regression models achieved about 20% precision and 22% recall which outperformed the best heuristic baseline by ~20% and random selection by 10x
- The fairness evaluation showed no racial bias (true positive rate ratio = approx. 1.3 for black vs. white individuals) and minor gender imbalance (slightly lower for women)
- Real-world testing through shadow mode deployment confirmed consistent precision (~ 0.20) which validated model reliability beyond historical data

**What background techniques are used in the paper that you are not familiar with:**

- Temporal validation (to prevent using future data in training)
- Shadow mode deployment (real-time validation without intervention)
- Resource constrained metrics such as precision@k / recall@k
- Equality of opportunity (fairness criterion)
- Label bias correction and counterfactual reasoning in observational policy data

**The following terms were defined:**

- precision@k and recall@k: measures of efficiency and reach within a top k prioritized group
- Equality of opportunity: fairness criterion requiring equal true positive rates across demographic subgroups
- Temporal validation: training/evaluating models in chronological order to avoid data leakage
- Shadow mode deployment: running predictive systems in parallel with existing processes to validate outputs
- Randomized Control Trial (RCT): a field experiment comparing model-based allocation vs. current processes to determine causal impact
- Label bias: distortion of outcome labels due to incomplete or unrepresentative data capture

**I rate and justify the value of this paper as:**

9.5/10

I found this paper to be one of the most impressive examples of how machine learning can be applied to solve a real-world social issue responsibly. The authors didn't just build a predictive model, but they clearly thought about how it would actually be used by people on the ground. I especially liked how they used temporal validation to avoid data leakage, since that's a common but often overlooked flaw in social data projects.

The paper also did a great job connecting fairness metrics (like equality of opportunity) to real equity outcomes, rather than just listing them as buzzwords. It was nice to see that they acknowledged the model's weaknesses (like struggling with first-time homelessness). Overall, the paper is rigorous but still realistic where it is able to bridge data science and social policy. The only reason I didn't give it a perfect 10 is that some of the technical sections (like feature generation and baseline models) could have been explained more intuitively for readers without a deep ML background.