Predicting Evacuation Location for Post-Disaster Recovery Modeling

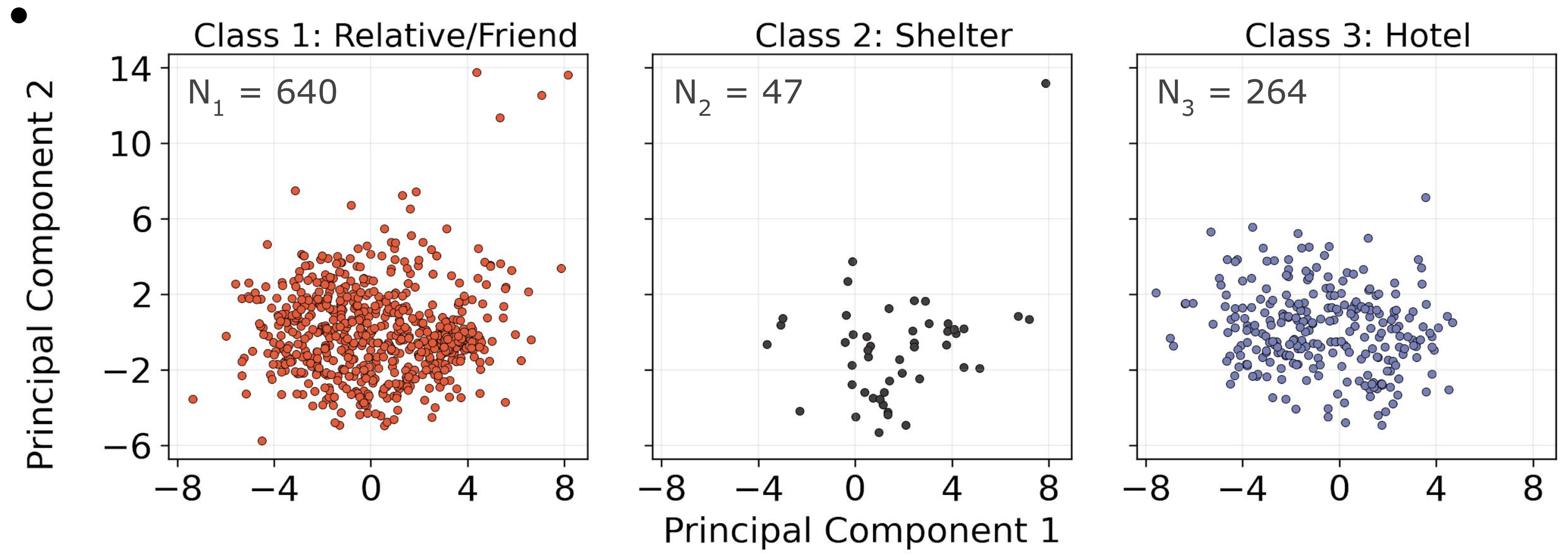
Aaron Appelle, Ana Moura-Cook, Davyd Tamrazov
{appellea, anamc, dt453}@stanford.edu

Introduction / Background / Motivation

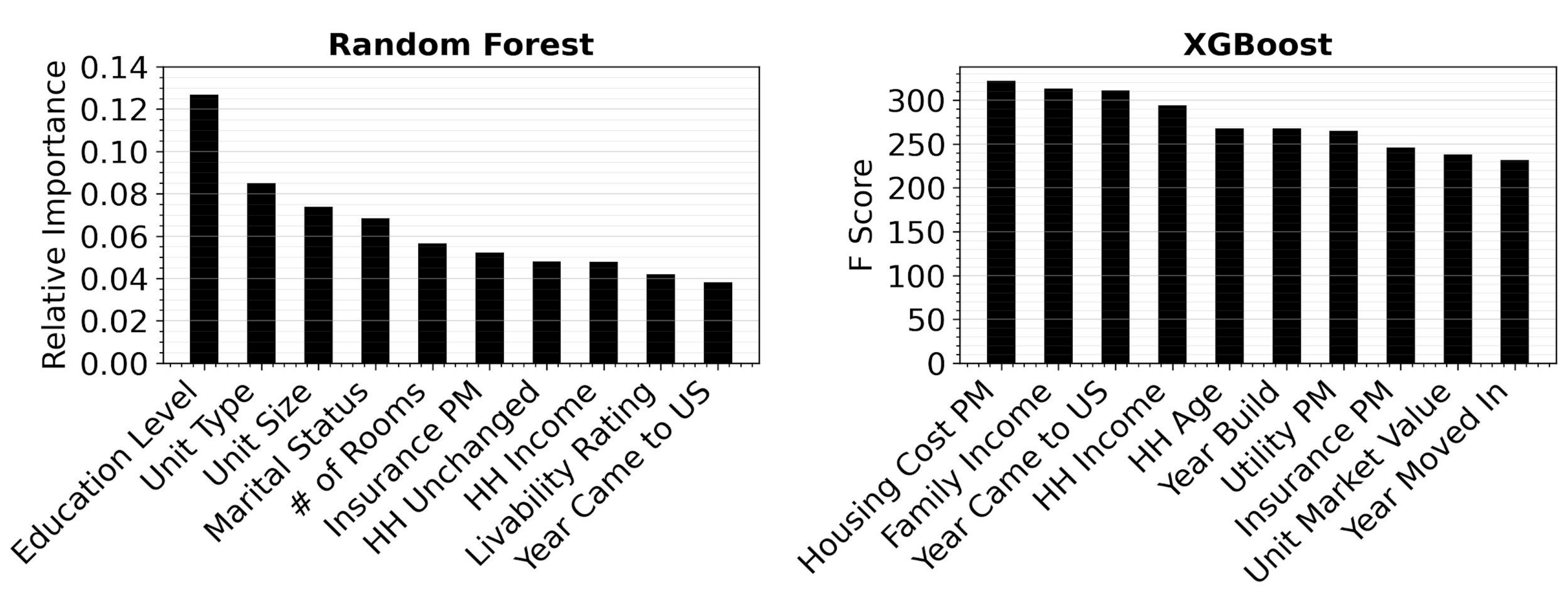
- Post-disaster recovery modeling is limited by semi-heuristic assumptions and survey-based data
- We explore machine learning techniques to predict a household's location of temporary shelter following a natural disaster
- Decision tree and neural network methods perform better in balanced accuracy than a random-guess trivial classifier

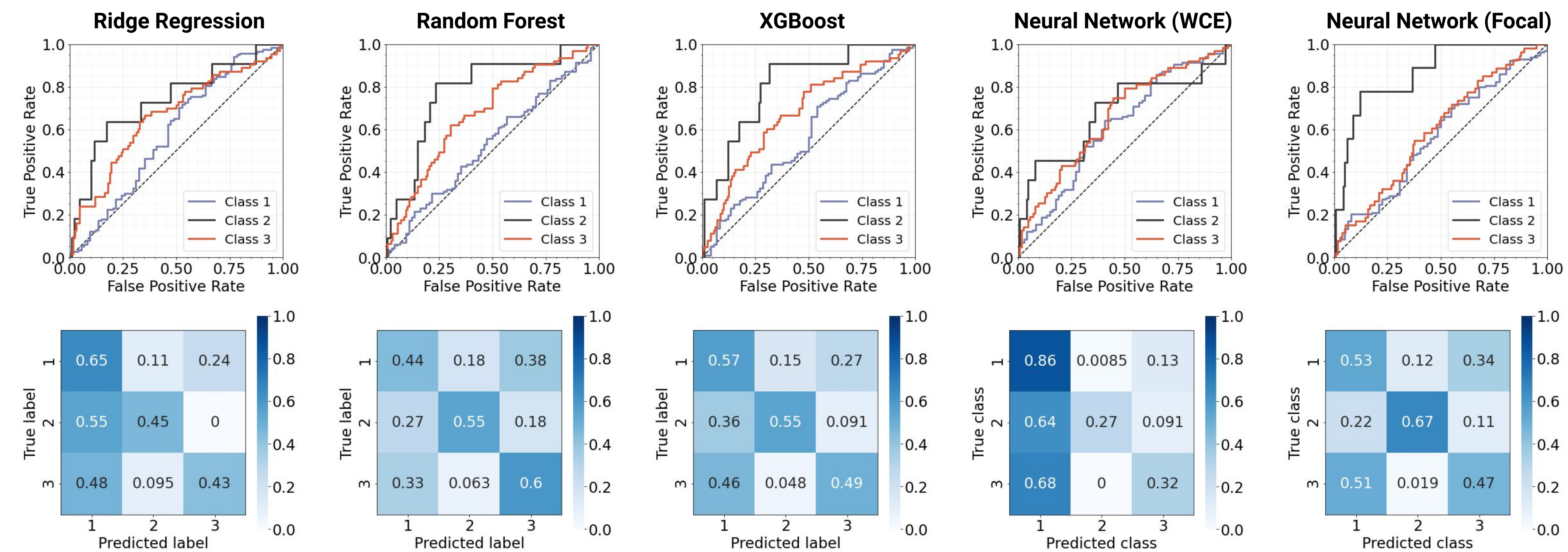
Dataset and Feature Importance

- **Data:** anonymized responses to the 2017 American Housing Survey in the greater San Francisco area (mostly binary)
- Originally 3,343 variables and 2,286 observations, after cleaning and manual feature selection: *951 observations and 61 variables*
- **PCA analysis:** PC1 and PC2 explain only 20.1% of the variance
-



- **Top features ranked from PCA:** Number of rooms, Owner/renter status, Monthly utility cost, Unit size (sq ft), Number people in household, Type of housing unit, Market value of unit, Type of household, Marital Status, US Citizenship
- When compared to feature ranking from decision tree methods (below), common significant variable themes include *wealth*, *stage of life*, and *time spent living in the region*





$$\hat{\theta} = \left(X^\top X + \lambda I\right)^{-1} X^\top y$$

A multi-output linear regression using L2 regularization

$$I_G(n) = 1 - \sum_{i=1}^{J} (p_i)^2$$

Sequentially splits the data at a number of features to minimize Gini impurity

$$\ell(\theta)^{(t)} = \sum_{i=1}^{n} \ell_{\mathrm{CE}}(y^{(i)}, \hat{y}^{(t)}) + \gamma T + \frac{1}{2}\lambda \sum_{i=1}^{T} w_j^2$$

Uses gradient descent in an iterative fashion to "boost" weak models based on previous trees

$$\ell(x^{(i)}) = w_{y^{(i)}} \left(-S_{y^{(i)}}^{(i)} + \log \sum_{j=1}^{k} \exp(S_j^{(i)}) \right)$$

Re-weighted cross entropy loss (WCE) to bias towards minority classes

$$\ell(x^{(i)}) = -\alpha(1-p_{y^{(i)}}^{(i)})^{\gamma}(\log(p_{y^{(i)}}^{(i)}))$$

Focal loss makes easily-classified examples contribute less to the loss

Results and Discussion

- Neural network with Focal Loss[1] has the highest balanced accuracy: best for predicting the number of households which will evacuate to shelters
- Neural network with weighted cross-entropy loss has a higher AUROC for Class 3 while maintaining high total accuracy: best for predicting evacuation to hotels
- XGBoost[2] is the most interpretable and performs relatively well across error metrics and classes, but it is not best-in-class for any one metric
- Categorical and imbalanced data is a challenge for every model considered

Metric	Baseline *Naive*	Ridge Regression	Decision Tree *Random Forest*	Decision Tree *XGBoost*	Neural Network *Weighted CE*	Neural Network *Focal Loss*
Total Accuracy	0.6126	0.5654	0.5026	0.5445	**0.6492**	0.5864
Balanced Accuracy	0.3333	0.5109	0.5310	0.5367	0.4845	**0.5739**
Weighted F1 Score	0.4654	0.5740	0.5171	0.5575	**0.6180**	0.5976
AUROC (Class 1)	0.5000	0.5835	0.5337	0.5698	**0.6185**	0.5678
AUROC (Class 2)	0.5000	0.7354	0.7864	0.8131	0.6843	**0.8651**
AUROC (Class 3)	0.5000	0.6612	**0.6773**	0.5820	0.6598	0.5956

Future Work

- Apply LDAM and deferred re-weighting[3] until after the initial stage
- Explore data undersampling and better class weighting schemes
- Establish more data-driven relationships to improve the underlying semi-heuristic assumptions in existing recovery models

References

[1] T. Y. Lin, P. Goyal, R. Girshick, K. He, and P. Dollar, "Focal loss for dense object detection," 2018.

[2] T. Chen and C. Guestrin, "Xgboost," *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, Aug 2016. [Online]. Available: http://dx.doi.org/10.1145/2939672.2939785

[3] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," 2017.