Forecasting the Number of Tenants At-Risk of Formal Eviction: A Machine Learning Approach to Inform Public Policy

Maryam Tabar, **Wooyong Jung**, **Amulya Yadav**, **Owen Wilson Chavez***, **Ashley Flores*** and **Dongwon Lee**

The Pennsylvania State University, University Park, PA, USA

*Child Poverty Action Lab, Dallas, TX, USA

{mfg5544, wjung, amulya, dongwon}@psu.edu *{owen, ashley}@childpovertyactionlab.org

Abstract

Eviction of tenants has reached a crisis level in the U.S. and its consequences pose significant challenges to society. To tackle this eviction crisis, policymakers have been allocating financial resources but a more efficient resource allocation would need an *accurate forecast* of the number of tenants at-risk of evictions ahead of time. To help enhance the existing eviction prevention/diversion programs, in this work, we propose a multi-view deep neural network model, named as MARTIAN, that forecasts the number of tenants at-risk of getting formally evicted (at the census tract level) n months into the future. Then, we evaluate MARTIAN's predictive performance under various conditions using real-world eviction cases filed across Dallas County, TX. The experimental results show that MARTIAN outperforms an extensive set of baseline models in terms of predictive performance. Additionally, MARTIAN's superior predictive performance is generalizable to unseen census tracts, for which no labeled data is available in the training set. This work has been done in collaboration with Child Poverty Action Lab (CPAL), which is a pioneering non-governmental organization (NGO) working for tackling poverty-related issues across Dallas County, TX. The usability of MARTIAN is under review by domain experts. We release our codebase at https://github.com/maryam-tabar/MARTIAN.

1 Introduction

Eviction is an urgent societal issue, which severely affects the lives of low-income individuals in the U.S. from multiple perspectives. In particular, it puts evicted families into material hardship [Desmond and Kimbro, 2015] and could increase the risk of various health issues (such as depression and parental stress) and reduce their prospects of future decent housing [Desmond, 2012; Eviction Lab, 2018; Desmond and Kimbro, 2015; Himmelstein and Desmond, 2021]. Furthermore, it could intensify various types of social problems such as poverty and housing inequality [Gromis, 2019; Eviction Lab, 2018]. Therefore, tackling the eviction crisis plays a critical role in improving the lives of this vulnerable population, and <u>helps make a progress on the SDG #1 (No poverty) and SDG #11 (Sustainable cities and communities) laid out by United Nations[1] to create a better world by 2030</u>.

To mitigate the eviction crisis, several eviction prevention/diversion programs (such as the Emergency Rental Assistance Program[2]) have been designed and implemented in the field. In particular, the federal government has allocated various financial resources (such as cash assistance, vouchers, etc.) to help households who have difficulty paying their rents. In spite of their availability nationwide, there is a large variability in the use of those resources; i.e., while the allocated resources have been used completely in some regions, a considerable portion of the allocated resources have been returned to the federal government from some other regions. This observation suggests <u>a need for a more efficient resource allocation strategy, which in turn, requires more accurate forecasts of the future number of tenants at-risk of eviction in target regions</u>. Thus, any attempt to improve the accuracy of the forecasted number of tenants at-risk of eviction could have substantial impacts on the effectiveness of existing policies to disperse resources.

To this end, this paper leverages recent advances in the ML domain [Yao *et al.*, 2018; Tabar *et al.*, 2021] to propose an ML-based solution to forecast the number of tenants at-risk of formal eviction in various census tracts[3] at a temporal resolution of one month. Our model, named as MARTIAN (<u>M</u>ulti-view model forc<u>A</u>sting the numbe<u>R</u> of <u>T</u>enants at-r<u>I</u>sk of form<u>A</u>l evictio<u>N</u>) leverages data sources of various spatial and temporal resolutions (namely, eviction filing records, American Community Survey (ACS) data[4], and labor statistics) to forecast the total number of tenants that are at-risk of eviction in each census tract n months into the future. Then, we evaluate the predictive performance of MARTIAN under various conditions using a real-world dataset consisting of information about eviction cases filed across Dallas County, TX since 2019. Our experimental results show that MARTIAN outperforms a wide variety of baseline models in all considered situations; in particular, it achieves 5% lower Root

[1] https://sdgs.un.org/goals

[2] http://tiny.cc/3vhouz

[3] A census tract is a sub-region of a county, and is defined by the U.S. Census Bureau for taking surveys and representing its results.

[4] https://www.census.gov/programs-surveys/acs/data.html

Mean Square Error (RMSE) than the best-performing baseline model (on average). Further, it achieves a Spearman of 0.685, which shows that the ranking of census tracts is preserved to high extent in MARTIAN's forecasts. Additionally, the results of our cross-region test show that MARTIAN's superior predictive performance is generalizable to unseen census tracts. This work has been conducted in collaboration with CPAL[5], which is an NGO aiming at tackling poverty-related issues across Dallas County, TX.

2 Related Work

As a pathway into various social problems (such as homelessness) [Bieretz *et al.*, 2020; van Laere *et al.*, 2009], the eviction crisis has drawn the attention of scholars from several disciplines. In particular, there has been extensive research in social science literature on understanding the risk factors[6] of eviction and its consequences. As a result, past literature found three key categories of risk factors: (1) individual-level factors such as the number of children, job loss, and drug use disorder [Desmond *et al.*, 2013; Desmond and Gershenson, 2017; Montgomery *et al.*, 2017; Stenberg *et al.*, 2020]. (2) neighborhood-level factors such as crime rate, and eviction rate in a neighborhood [Desmond and Gershenson, 2017]. (3) network-level factors such as the number of disadvantaged people in a tenant's network [Desmond and Gershenson, 2017].

Additionally, there has been a growing body of knowledge on the consequences of eviction and its impacts on individuals' lives. For example, prior work found that eviction could result in various health issues such as parental stress and depression [Desmond and Kimbro, 2015; Hatch and Yun, 2021]. Furthermore, once getting evicted, tenants' credit rating gets debased, which in turn, put more distance between them and the public housing program, and could exacerbate the housing inequality in society [Greiner *et al.*, 2012]. Although these empirical findings are informative and conducive to understanding the whole context of eviction, these studies do not focus on the problem of forecasting the number of tenants at risk of eviction. In contrast, this paper leverages the findings of prior work in social sciences as well as ML techniques to forecast the number of tenants at risk of eviction, which could assist the government and NGOs in proactively tackling the eviction crisis in a more efficient and effective manner.

In addition to the social science studies, there has been some research from the Artificial Intelligence (AI) community on mitigating the housing problems. For example, Ye et al. [2019] and Tan [2020] employed ML techniques to predict the risk of landlord-harassment and the eviction rate, respectively. However, these studies have some limitations: (1) the developed ML models forecast at the temporal resolution of one year, which limits their usability in our problem domain, where a forecasting tool with a higher temporal resolution (such as one month) is needed, or (2) they mainly relied on classical ML models and did not consider differences in the nature of various data sources in their design, e.g., time-series data and static data are treated the same. To address these limitations, we build a deep learning-based model that leverages various data sources with different spatial and temporal resolutions to forecast the number of tenants at-risk of getting formally evicted at the monthly resolution. Further, we conduct extensive experiments under various conditions to assess the superiority of MARTIAN to a wide variety of baseline models.

[5]https://childpovertyactionlab.org

[6]Risk factors denote factors that are linked to the higher chance of a negative outcome.

3 A Problem Statement

This paper aims at building an ML model to precisely forecast the number tenants at-risk of formal eviction (i.e., the number of eviction filings) at each census tract n months into the future.

Assume that E_t^c refers to the total eviction cases filed at census tract c in month t and L_t^c is a vector of length q representing the labor statistics at census tract c in month t (q refers to the total number of features in the labor statistics data). Also, suppose that ACS_t^c is a vector of length r representing the most recent values of ACS factors available at month t for census tract c (r refers to the total number of features selected from the ACS data). Note that as the U.S. Census Bureau releases the ACS data with a delay of about two years, at each point of time, ACS_t^c contains statistics of two years ago. Then, this paper aims at building a forecasting model M such that:

$$M : E_{t+n}^c \leftarrow f(\{E_{t-k+1}^c, ..., E_{t-1}^c, E_t^c\},$$
$$\{L_{t-k+1}^c, ..., L_{t-1}^c, L_t^c\}, ACS_t^c)$$

In this paper, the value of k is chosen through hyper-parameter tuning, and a separate experiment has been conducted for different values of n.

4 Datasets

This work relies on three data sources: (1) Eviction filing records, (2) Labor statistics, and (3) American Community Survey (ACS). We extract our input features using these data sources, which are then used by an ML model to compute the value of the target variable. Table 1 provides detailed information on the input features extracted from each data source. In the following paragraphs, we introduce each data source and explain why we incorporate them into the model.

(1) Eviction Filing Records. This dataset consists of detailed information about eviction cases filed in judicial courts across Dallas County, TX since 2019. We get access to this dataset via CPAL, which receives daily updates (except for holidays) on new eviction cases filed in Dallas County. Each eviction record contains detailed information, e.g., the plaintiff's name, the defendant's name and address (geographical coordinates), the filing date, etc. However, the court's final decisions regarding each case is not available in our dataset.

In this work, we use eviction filing data to compute the target variable and extract input features; in particular, we use the historical data on the number of eviction filings as input because overall eviction rate in a neighborhood is found to

Data Source	An Explanation of Selected Input Feature(s)
Eviction Records	Historical data on the total number of eviction cases filed in each census tract

Labor Statistics	Unemployment rate
	Historical data on the number of employees in each of the following non-farm industries[7]:
	`Mining, Logging and Construction` – `Education&Health Services` – `Manufacturing`
	`Information` – `Leisure&Hospitality` – `Professional&Business Services` – `Government`
	`Trade, Transportation, and Utilities` – `Financial Activities` `Other Services`

ACS	# of renter-inhabited units # of renter-inhabited housing units, for which % of income contributing to housing expenses $\geq$ 30% # of renter-inhabited housing units, for which the householder's income ≤ 0 in the last 12 months # of families receiving SSI and/or cash public assistance income who are below poverty level # of renter-inhabited housing units, for which the householder's literacy level $<$ high school # of renter-inhabited housing units, for which the householder's literacy level $=$ high school graduate # of renter-inhabited housing units, for which the householder's literacy level $=$ a college or associate's degree # of renter-inhabited housing units, for which the householder's literacy level $=$ bachelor's degree or higher

Table 1: The definition of input features.

be associated with greater likelihood of individuals' eviction [Desmond and Gershenson, 2017].

(2) Labor Statistics. The U.S. Bureau of Labor Statistics releases monthly data on labor statistics[7], which contains various pieces of information related to the economy of a region, e.g., the unemployment rate and number of employees in various non-farm industries (e.g., manufacturing and government). This data enables policymakers to monitor the economic/employment status over time, and to make appropriate policies accordingly. Given a strong association between work status and the risk of eviction [Desmond and Gershenson, 2017; Stenberg *et al.*, 2020], we believe that this data would provide useful signals to MARTIAN regarding monthly work status. This data is released for each metropolitan area (rather than each census tract) and we use the data of the "Dallas-Fort Worth-Arlington" area.

(3) American Community Survey. The U.S. Census Bureau releases the ACS data, which is basically an annual report on various demographic/housing characteristics of different regions across the U.S. In particular, for renter-inhabited housing units (and their householders), it summarizes the value of the following metrics, which are found to have some associations with the risk (or number) of eviction and housing instability: work status [Desmond and Gershenson, 2017; Stenberg *et al.*, 2020; Puckett *et al.*, 2002], educational attainment [Stenberg *et al.*, 2020; Bassuk *et al.*, 1997], income level, and monthly housing cost per income [Eggers *et al.*, 2010]. Accordingly, we utilize the 5-Year Experimental Estimates ACS data, which is available for each census tract in our study. Although the ACS data is not available at the monthly resolution, we think that it could still provide an insightful big picture of the situation in various census tracts.

Pre-processing. To pre-process our data, we take three main steps: (1) similar to prior work [Desmond *et al.*, 2018], we remove eviction filing records with commercial defendants and duplicate records from the dataset of eviction filing records, (2) we compute the total number of eviction filings in each census tract (out of 529 census tracts within Dallas County, TX) per month, (3) we apply Min-Max normalization on each input feature, separately, and (4) the value of the target variable is also scaled into the range of [0, 1] using Min-Max normalization, however, performance metrics are computed after converting the data back to its original scale (note that the parameters of min-max normalization are computed using the training data).

[7]https://www.bls.gov/eag/eag.tx.htm#eag_tx.f.2

5 The Forecasting Model: MARTIAN

In this section, we explain our forecasting model. Leveraging recent advances in the ML domain [Yao *et al.*, 2018; Tabar *et al.*, 2021], we build a multi-view neural network to incorporate data sources of different spatial/temporal resolutions into the prediction process. Figure 1 represents the architecture of MARTIAN. As illustrated, it has three views, each of which extracts features from one of the three aforementioned data sources: (1) The first view employs a Long Short-Term Memory (LSTM) network [Hochreiter and Schmidhuber, 1997] followed by two fully-connected layers to learn patterns from the time-series data of eviction filings in the census tract of interest, (2) the second view extracts features from the time-series data of labor statistics using an LSTM network followed by two fully-connected layers, and (3) the third view employs a Multi-Layer Perceptron (MLP) to extract features from the aforementioned static factors in the ACS data. Then, the outputs of these three views are concatenated and given to the output layer to forecast the value of the target variable.

6 Empirical Validation

In this section, first, we explain our experimental set-up and baseline models. Then, we compare the predictive performance of MARTIAN with that of baseline models and conduct an ablation study. Finally, we conduct a cross-region test to evaluate its generalizability.

Model	n = 1		n = 2		n = 3		Avg. ($n \in \{1,2,3\}$)	
	RMSE	Spearman	RMSE	Spearman	RMSE	Spearman	RMSE	Spearman
Ridge	6.711	0.610	7.266	0.588	7.251	0.253	7.076	0.483
SVM	5.985	0.588	6.566	0.547	6.533	0.538	6.361	0.557
XGBoost	4.881	0.679	4.819	0.676	4.832	0.660	4.844	0.671
Random Forest	4.717	0.688	4.735	0.680	4.782	0.670	4.744	0.679
LightGBM	4.869	0.681	4.893	0.667	4.822	0.666	4.861	0.671
MLP	4.652	0.645	4.759	0.540	4.770	0.645	4.727	0.610
LSTM	4.585	0.639	4.717	0.639	4.753	0.631	4.685	0.636
GRU	4.590	0.649	4.686	0.648	4.755	0.631	4.677	0.642
TabNet	4.955	0.541	5.106	0.460	4.998	0.520	5.019	0.507
MARTIAN	**4.383**	**0.697**	**4.444**	**0.686**	**4.503**	**0.673**	**4.443**	**0.685**
Gain (%)	4.40%	1.30%	5.16%	0.88%	5.25%	0.44%	5.00%	0.88%

Table 2: Performance comparison of forecasting models.

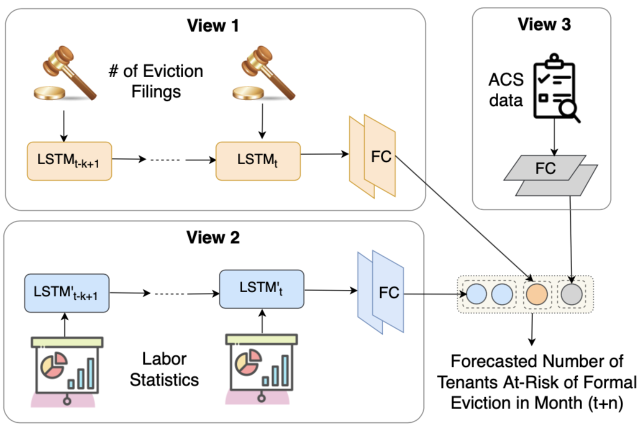

Figure 1: The architecture of MARTIAN.

6.1 Set-Up

To have a trustworthy and robust evaluation of the predictive accuracy of different models, we employ the walk-forward testing approach [Kaastra and Boyd, 1996]. The walk-forward testing approach is a variant of K-fold cross-validation adopted for the time-series domain; i.e., in this testing approach, the input dataset is split into a sequence of time-shifted training, validation, and test sets (instead of randomly splitting the data) with a window length of w (we set w to three, which is equivalent to three months as the length of each time-step is one month). Then, for each performance metric, the average case performance over all test sets is reported.

In addition, to train neural network models, the batch size, loss function, and maximum number of epochs are set to 32, MSE, and 200, respectively. We also utilize an Adam optimizer [Kingma and Ba, 2014] with a learning rate of 2×10^{-4} and the early stopping approach [Prechelt, 1996] with a patience value of 10 epochs. Finally, as a result of hyperparameter tuning, the value of k (i.e., the length of time-series inputs) is set to 6.

6.2 Baseline Models

We compare the predictive performance of MARTIAN with that of an extensive set of baselines. The first set of baselines consists of strong classical ML models. Following is the list of classical ML models developed in the paper: (1) Ridge regression [Hilt and Seegrist, 1977] (2) Support-Vector Machine (SVM) [Cortes and Vapnik, 1995], (3) XGBoost [Chen and Guestrin, 2016], (4) Random Forest [Breiman, 2001], and (5) LightGBM [Ke *et al.*, 2017].

Additionally, we considered various deep learning-based models in our study as well. In particular, we conduct a performance comparison between MARTIAN and its building blocks, i.e., LSTM and MLP, to show the effectiveness of the multi-view architecture in this problem domain. We also compare its predictive performance with some strong deep learning models, namely TabNet [Arik and Pfister, 2021] and Gated Recurrent Unit (GRU) [Cho *et al.*, 2014], which are shown to work well on the tabular data and time-series data, respectively. Please note that the input of time-series models at time-step t is a concatenation of E_t^c,L_t^c, and ACS_t^c. However, for the remaining models, the input is a concatenation of static features and all k steps of time-series inputs.

6.3 A Comparison with Baseline Models

Table 2 compares MARTIAN with that of various baseline models for $n \in \{1,2,3\}$. We use two metrics to evaluate the predictive performance of forecasting models: (1) RMSE, which intuitively measures the average difference between each model's predictions and the actual number of eviction filings, and (2) Spearman correlation[8], which intuitively shows the extent to which the forecasted values preserve the actual orders of census tracts in terms of the number of eviction filing values. In this table, one row is considered for each ML model of interest and each column corresponds to the value of a performance metric for a specific value of n. Also, the best performance is shown in bold and the last row (Gain) shows the percentage of improvement that MARTIAN achieves over the best-performing baseline model. According to the results, MARTIAN outperforms all baselines for

[8]The value of Spearman ranges between -1 and 1. A higher Spearman shows a better performance of a forecasting model.

Model	n = 1		n = 2		n = 3		Avg. ($n \in \{1, 2, 3\}$)	
	RMSE	Spearman	RMSE	Spearman	RMSE	Spearman	RMSE	Spearman
MARTIAN	**4.383**	**0.697**	**4.444**	**0.686**	**4.503**	**0.673**	**4.443**	**0.685**
MARTIAN-w/o-View1	5.887	-0.346	5.891	-0.385	5.862	-0.489	5.880	-0.406
MARTIAN-w/o-View2	4.731	0.623	4.748	0.650	4.878	0.574	4.785	0.615
MARTIAN-w/o-View3	4.615	0.689	4.673	0.676	4.686	0.572	4.658	0.645

Table 3: The results of MARTIAN's ablation study.

all different values of n; in particular, on average, MARTIAN outperforms the best-performing baseline model by achieving 5.00% smaller RMSE and 0.88% higher Spearman, which shows its superiority against several strong ML models for this problem domain.

Additionally, MARTIAN achieves an Spearman value of 0.685 (on average), which shows that the ranking of census tracts in terms of the number of tenants at risk of formal eviction is preserved to high extent in MARTIAN's output.

Furthermore, MARTIAN outperforms both MLP and LSTM models, which form its building blocks, by a relatively large margin; i.e., on average, it achieves 6.00% lower RMSE and 12.29% higher Spearman than MLP and improves the predictive performance of LSTM by 5.16% and 7.70% in terms of RMSE and Spearman, respectively. This could show the value of using multi-view architecture for incorporating data sources of various resolutions, rather than treating all inputs the same.

Moreover, comparing the performance of classical models, we see that decision-tree based models outperforms the other ones (i.e., SVM and Ridge) with a large margin; i.e., on average, decision-tree based models achieve 28.31% and 29.42% better RMSE and Spearman, respectively. This could show that, in case of any difficulty in using deep learning, decision-tree based ensemble models could be more appropriate ML choices for this task. Also, in spite of its high performance in several other domains, TabNet achieves the poorest performance among all our deep learning-based baselines and ensemble models. Therefore, this attention-based model does not seem to be an appropriate choice for this case.

6.4 Ablation Study

We also conduct an ablation study to assess the impact of each view on the MARTIAN's predictive performance. To this end, we remove one view each time, train the new model, and then, evaluate its performance. Table 3 represents the results of our ablation study for $n \in \{1, 2, 3\}$. According to the results, removing view1 (i.e., features extracted from the time-series data of eviction filings) leads to a significant decrease in the predictive performance of MARTIAN; i.e., it results in 32.34% increase in RMSE and 159.27% decrease in Spearman (on average). In particular, we observe that MARTIAN-w/o-View1 cannot preserve the rank of census tracts with respect to the number of eviction filings as it has a negative spearman value. This makes sense because the time-series data of eviction filings is the only input data available at our forecasting spatial and temporal resolutions, and the other two data sources (i.e., labor statistics and ACS) are unavailable either at the census tract level or at the temporal resolution of one month. Therefore, two other data sources can only provide a big picture and alone are not enough for accurately forecasting the eviction crisis at high spatial and temporal resolutions.

Additionally, removing view2 (i.e., features extracted from the labor statistics data) results in 7.69% increase in RMSE and 10.21% drop in Spearman (on average). Thus, as expected, incorporating the monthly status of employment helps enhance the predictive performance of MARTIAN, even though it is not available for each census tract and it only reports the work status for "Dallas-Fort Worth-Arlington". Furthermore, excluding view3 (i.e., features extracted from the ACS data) leads to 4.83% increase in RMSE and 5.83% decrease in Spearman (on average). Therefore, although the ACS data reports annual conditions of each census tract, its information on renter-inhabited housing units (and their householders) are still helpful for predicting the number of eviction filings at the census tract level for each month. In conclusion, as a result of this ablation study, we find that both labor statistics and ACS data are useful auxiliary input signals for our forecasting task.

6.5 Cross-Region Test

In all our previous experiments, we trained forecasting models on the training portion of the Dallas data, and then, evaluated their performance on the testing portion of the same data. We now conduct a cross-region test, in which the training and testing datasets are created from the data of two disjoint sets of census tracts. This help us evaluate if MARTIAN's superior predictive performance is generalizable to unseen regions (whose data has not been seen by the model in the training phase). To this end, we take the following steps: (1) we create two disjoint sets of census tracts (with almost equal size) through random sampling such that the statistics (minimum, maximum, median, and average) of the total number of eviction filings for these two sets look similar, (2) we train the forecasting models on the training portion of the first set, and (3) we assess the performance of forecasting models on the testing portion of the second set. Please note that we still use the walk-forward testing approach and the time frame of training and test sets is the same as before.

Table 4 shows the results of our cross-region test. According to the results, MARTIAN outperforms all baseline models for different values of n; in particular, on average, it achieves 3.32% lower RMSE and 3.77% higher Spearman than the best-performing baseline model. This shows that MARTIAN's superior predictive performance is generalizable to various unseen regions.

Model	n = 1		n = 2		n = 3		Avg. ($n \in \{1,2,3\}$)	
	RMSE	Spearman	RMSE	Spearman	RMSE	Spearman	RMSE	Spearman
Ridge	6.620	0.596	6.528	0.582	6.725	0.561	6.624	0.579
SVM	6.298	0.618	6.374	0.588	6.467	0.564	6.379	0.590
XGBoost	5.268	0.667	5.238	0.655	5.276	0.632	5.260	0.651
Random Forest	5.126	0.675	5.062	0.662	5.068	0.653	5.085	0.663
LightGBM	5.145	0.653	5.251	0.634	5.180	0.655	5.192	0.647
MLP	4.941	0.639	4.944	0.640	5.013	0.629	4.966	0.636
LSTM	4.998	0.619	4.978	0.612	5.032	0.601	5.002	0.610
GRU	4.994	0.625	4.948	0.620	5.034	0.605	4.992	0.616
TabNet	5.371	0.450	5.541	0.390	5.466	0.381	5.459	0.407
MARTIAN	**4.827**	**0.698**	**4.755**	**0.688**	**4.823**	**0.680**	**4.801**	**0.688**
Gain (%)	2.30%	3.40%	3.82%	3.92%	3.79%	3.81%	3.32%	3.77%

Table 4: Performance comparison of forecasting models in the cross-region test.

7 Real-World Use Case

Our tool could serve as an AI assistant to (1) shed light on the number of tenants at risk of getting formally evicted in the future; e.g., the output of MARTIAN can be used to generate a heatmap of the forecasted number of tenants at-risk of eviction for each month in the future (similar to Figure 2), and (2) make a more well-informed resource allocation plan to mitigate evictions in a more efficient and effective manner. In particular, we contacted officials at Texas Housers (i.e., Texas Low Income Housing Information Service)[9], which is an organization working for housing justice and developing solutions for housing problems in Texas. Ben Martin, who is an official at Texas Houser and is working on the eviction and foreclosure data, stated that:

> "Knowing where evictions are being filed helps advocates, administrators, elected officials, and legal aid to identify where they need to direct their efforts, funds, and other resources in order to keep renters housed"

In particular, he elaborated on the potential impacts of such forecasting tools in the real world as follows:

> "The number of eviction cases filed or of a certain outcome, might, for example, be used as a baseline for setting program funding levels. If a somewhat accurate tool could be developed, it would be incredibly useful for advocacy with the legislators, elected officials, and agencies responsible for eviction court and eviction diversion"

Therefore, all these pieces of evidence shows the value of an accurate eviction forecasting tool, and the extent to which it could help policymakers enhance the eviction diversion/prevention programs in the field. We are in discussion with CPAL and officials at Texas Housers in deploying MARTIAN among domain experts to make broader impacts.

[9] https://texashousers.org

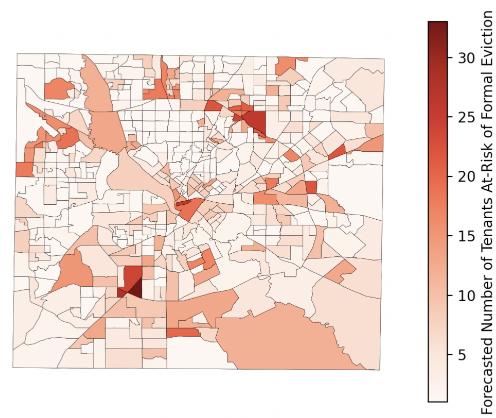

Figure 2: MARTIAN's forecasts about the number of tenants at-risk of formal eviction at various census tracts within Dallas County, TX in December 2021.

8 Conclusion

In this paper, we developed a neural network model, named as MARTIAN, that leverages data sources of various resolutions and forecasts the number of tenants at-risk of getting formally evicted at the census tract level n months into the future. The results of our empirical evaluation show that MARTIAN outperforms various baseline models in terms of RMSE and Spearman in all considered situations. Additionally, the results of our cross-region test show that MARTIAN's superior predictive performance is generalizable to unseen census tracts. MARTIAN could help policymakers direct funding and other resources in a more efficient manner and enhance the existing eviction prevention/diversion programs by providing data-driven insights on the future condition of each census tract in terms of eviction filings. This work has been done in collaboration with CPAL, and the usability of MARTIAN in the real world is under review.

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References

[Arik and Pfister, 2021] Sercan Ö Arik and Tomas Pfister. Tabnet: Attentive interpretable tabular learning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, pages 6679–6687, 2021.

[Bassuk *et al.*, 1997] Ellen L Bassuk, John C Buckner, Linda F Weinreb, Angela Browne, Shari S Bassuk, Ree Dawson, and Jennifer N Perloff. Homelessness in female-headed families: childhood and adult risk and protective factors. *American journal of public health*, 87(2):241–248, 1997.

[Bieretz *et al.*, 2020] Brian Bieretz, Kimberly Burrowes, and Emily Bramhall. Getting landlords and tenants to talk: The use of mediation in eviction. 2020.

[Breiman, 2001] Leo Breiman. Random Forests. *Machine learning*, 45(1):5–32, 2001.

[Chen and Guestrin, 2016] Tianqi Chen and Carlos Guestrin. Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 785–794, 2016.

[Cho *et al.*, 2014] Kyunghyun Cho, Bart Van Merriënboer, Dzmitry Bahdanau, and Yoshua Bengio. On the properties of neural machine translation: Encoder-decoder approaches. *arXiv preprint arXiv:1409.1259*, 2014.

[Cortes and Vapnik, 1995] Corinna Cortes and Vladimir Vapnik. Support-Vector Networks. *Machine Learning*, 20(3):273–297, 1995.

[Desmond and Gershenson, 2017] Matthew Desmond and Carl Gershenson. Who gets evicted? assessing individual, neighborhood, and network factors. *Social science research*, 62:362–377, 2017.

[Desmond and Kimbro, 2015] Matthew Desmond and Rachel Kimbro. Eviction's fallout: Housing, hardship, and health. *Social Forces*, 94, 02 2015.

[Desmond *et al.*, 2013] Matthew Desmond, Weihua An, Richelle Winkler, and Thomas Ferriss. Evicting children. *Social Forces*, 92(1):303–327, 2013.

[Desmond *et al.*, 2018] Matthew Desmond, Ashley Gromis, Lavar Edmonds, James Hendrickson, Katie Krywokulski, Lillian Leung, and Adam Porton. Eviction lab methodology report: Version 1.0. Technical report, Princeton: Princeton University, 2018.

[Desmond, 2012] Matthew Desmond. Eviction and the reproduction of urban poverty. *American journal of sociology*, 118(1):88–133, 2012.

[Eggers *et al.*, 2010] Frederick J. Eggers, Fouad Moumen, and Inc. Econometrica. Investigating very high rent burdens among renters in the american housing survey. *U.S. Department of Housing and Urban Development, Washington, DC*, 94, 2010.

[Eviction Lab, 2018] Eviction Lab. The eviction lab, 2018. https://evictionlab.org/.

[Greiner *et al.*, 2012] D James Greiner, Cassandra Wolos Pattanayak, and Jonathan Hennessy. The limits of unbundled legal assistance: a randomized study in a massachusetts district court and prospects for the future. *Harv. L. rev.*, 126:901, 2012.

[Gromis, 2019] Ashley Gromis. Eviction: Intersection of poverty, inequality, and housing. 2019.

[Hatch and Yun, 2021] Megan E Hatch and Jinhee Yun. Losing your home is bad for your health: Short-and medium-term health effects of eviction on young adults. *Housing Policy Debate*, 31(3-5):469–489, 2021.

[Hilt and Seegrist, 1977] Donald E Hilt and Donald W Seegrist. *Ridge, a computer program for calculating ridge regression estimates*, volume 236. Department of Agriculture, Forest Service, Northeastern Forest Experiment Station, 1977.

[Himmelstein and Desmond, 2021] Gracie Himmelstein and Matthew Desmond. Association of eviction with adverse birth outcomes among women in georgia, 2000 to 2016. *JAMA pediatrics*, 175(5):494–500, 2021.

[Hochreiter and Schmidhuber, 1997] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997.

[Kaastra and Boyd, 1996] Iebeling Kaastra and Milton Boyd. Designing a neural network for forecasting financial and economic time series. *Neurocomputing*, 10(3):215–236, 1996.

[Ke *et al.*, 2017] Guolin Ke, Qi Meng, Thomas Finley, Taifeng Wang, Wei Chen, Weidong Ma, Qiwei Ye, and Tie-Yan Liu. Lightgbm: A highly efficient gradient boosting decision tree. *Advances in neural information processing systems*, 30, 2017.

[Kingma and Ba, 2014] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.

[Montgomery *et al.*, 2017] Ann Elizabeth Montgomery, Meagan Cusack, Dorota Szymkowiak, Jamison Fargo, and Thomas O'toole. Factors contributing to eviction from permanent supportive housing: Lessons from hud-vash. *Evaluation and Program Planning*, 61:55–63, 2017.

[Prechelt, 1996] Lutz Prechelt. Early stopping-but when? In *Neural Networks: Tricks of the Trade*, 1996.

[Puckett *et al.*, 2002] Alan Puckett, Lynette M. Renner, and Kristen Shook Slack. Trends in homelessness & housing insecurity. Technical report, Northwestern University, 2002.

[Stenberg *et al.*, 2020] Sten-Åke Stenberg, Lars Brännström, Christine Lindberg, and Ylva B Almquist. Risk factors for housing evictions: Evidence from panel data. *European Journal of Homelessness _ Volume*, 14(2_), 2020.

[Tabar *et al.*, 2021] Maryam Tabar, Jared Gluck, Anchit Goyal, Fei Jiang, Derek Morr, Annalyse Kehs, Dongwon Lee, David P. Hughes, and Amulya Yadav. A PLAN for Tackling the Locust Crisis in East Africa: Harnessing Spatiotemporal Deep Models for Locust Movement Forecasting. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, pages 3595–3604, 2021.

[Tan, 2020] Jialu Tan. Using machine learning to identify populations at high risk for eviction as an indicator of homelessness. Master's thesis, MIT, Cambridge, MA, 2020.

[van Laere *et al.*, 2009] Igor R van Laere, Matty A de Wit, and Niek S Klazinga. Pathways into homelessness: recently homeless adults problems and service use before and after becoming homeless in amsterdam. *BMC public health*, 9(1):1–9, 2009.

[Yao *et al.*, 2018] Huaxiu Yao, Fei Wu, Jintao Ke, Xianfeng Tang, Yitian Jia, Siyu Lu, Pinghua Gong, Jieping Ye, and Zhenhui Li. Deep multi-view spatial-temporal network for taxi demand prediction. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 32, 2018.

[Ye *et al.*, 2019] Teng Ye, Rebecca Johnson, Samantha Fu, Jerica Copeny, Bridgit Donnelly, Alex Freeman, Mirian Lima, Joe Walsh, and Rayid Ghani. Using machine learning to help vulnerable tenants in new york city. In *Proceedings of the 2nd ACM SIGCAS Conference on Computing and Sustainable Societies*, pages 248–258, 2019.