Predicting Housing Transaction with Common Covariance GNNs

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Abstract

Urban migration is a significant aspect of a city's economy. The exploration of the underlying determinants of housing purchases among current residents contributes to the study of future trends in urban migration, enabling governments to formulate appropriate policies to guide future economic growth. This article employs a factor model to analyze data on residents' rentals, first-time home purchases, and subsequent housing upgrades. We decompose the factors influencing housing purchases into common drivers and specific drivers. Our hypothesis is that common drivers reflect universal social patterns, while personalized drivers represent stochastic elements. We construct a correlation matrix capturing the inter-resident relationships based on the common drivers of housing purchases. We then propose a graph neural network based on the correlation matrix to model housing predictions as a node classification problem. Our model addresses two critical questions. Firstly, we aim to identify which part of rental residents will engage in first-time home purchases in the future. Secondly, we seek to determine which group of residents, having completed rental and first-time home purchases, will opt for a second home purchase. The results of our testing on real-world datasets demonstrate that based solely on rental and home purchase records, we can achieve a sensitivity for housing predictions exceeding 80%.

1 Introduction

In China, the real consumer groups for renting and purchasing houses are the post-80s and post-90s generations. When young graduates choose to work in a particular city after completing their university education, their first challenge is finding rental accommodation. Some individuals realize that staying in the city benefits their career development, or they consider factors such as the city's infrastructure, leading them to choose to purchase a property and settle down in that city. As they age and their income increases, they may opt to upgrade to a more comfortable house to meet the needs of marriage and raising children. We consider these factors to be common drivers for housing purchases. Individuals influenced by this factor form a typical group that follows the trajectory of renting, purchasing for the first time, and subsequently upgrading their housing. The number of individuals in this group and their life trajectories validate the extent to which they integrate into the city. Therefore, studying the driving forces behind the growth of this group from renting to first-time purchases and subsequent upgrades holds significant implications for the future development of cities.

Existing literature on real estate economics primarily focuses on studying either the behavior of renting alone [Kumar, 2019; Ming *et al.*, 2020; Seya and Shiroi, 2022; Yoshida *et al.*, 2022] or the behavior of purchasing alone [Park and Bae, 2015; Madhuri *et al.*, 2019; Varma *et al.*, 2018], while neglecting the continuous evolution from renting to purchasing and subsequent upgrades, as well as the driving factors behind them. These studies typically employ traditional statistical models such as ridge regression, LASSO, tree models, and vector autoregressive to analyze housing prices directly [Madhuri *et al.*, 2019; Park and Bae, 2015; Ming *et al.*, 2020; Yoshida *et al.*, 2022]. Some studies utilize neural networks, such as LSTM [Varma *et al.*, 2018]. However, these studies lack an exploration of the interrelationships among home buyers.

Other studies, although examining housing characteristics and social characteristics of homebuyers, such as the educational level of buyers [Hu *et al.*, 2023], ethnic groups of buyers [Bikmetova *et al.*, 2023; Miyakawa *et al.*, 2022], and the infrastructure of the city where the houses are located [Hu *et al.*, 2023], approach their research from the perspective of renting or purchasing individually.

This paper investigates the processes of renting, first-time purchases, and subsequent upgrades together, attempting to identify common and universal driving factors behind group housing behaviors while excluding personalized factors. We believe that capturing common factors will facilitate accurate predictions of future housing transactions, while personalized factors represent stochastic elements that are difficult to predict. For instance, individuals who are prepared to buy a home, driven by factors such as the desire to establish roots in their current city following career advancement, share similar motivations with those who are not yet ready to make a

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purchase due to intentions of relocating or limited financial capacity. These shared motivations, whether for purchasing or refraining from purchasing, form the fundamental factors in the construction of a resident graph. In contrast, personal factors usually represent randomness and they are difficult to predict. For example, certain individuals may be drawn to houses with peculiar or avant-garde architectural designs, considering them as conversation starters or artistic expressions.

Based on rental and purchase records, we employ a factor model to model the common factors driving residents' housing purchases and upgrades. Furthermore, through covariance analysis based on the factor model, we remove the covariance of personalized residuals in the sample covariance matrix of rental and purchase records, retaining only the covariance of common factors. The covariance of common factors among residents characterizes their correlation in terms of common housing purchasing drivers. Based on the derived correlation of underlying common housing purchasing drivers, we construct a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ representing the relationships among residents, where nodes $\mathcal{V}$ represent residents and *edges $\mathcal{E}$ represent the similarity of housing purchasing drivers between residents*. It is important to note that the presence of edges connecting residents in $\mathcal{E}$ does not necessarily imply the existence of a social relationship between them. Subsequently, using the graph $\mathcal{G}$, we employ a graph neural network [Gilmer *et al.*, 2017; Kipf and Welling, 2017; Liu *et al.*, 2023] to model housing predictions as a node classification problem. Finally, we validate our algorithm on a dataset of rental and purchase records. Compared to traditional models such as logistic regression and tree models, the graph neural network, which considers the correlation of residents' housing intentions, better leverages the information within the data and achieves superior predictive results.

Our contributions can be summarized as follows: 1) First, we use a factor model to model the common factors underlying housing purchases. 2) Second, We employ a graph neural network to model housing behavior as a node classification problem. 3) Finally, we study the above issues from the perspective of the entire process of renting, purchasing, and upgrading, and validate our approach on real-world data.

2 Related Works

2.1 Price Prediction

Most existing literature on house price or rent price forecasting is macro analysis [Ming *et al.*, 2020; Seya and Shiroi, 2022; Gilbukh *et al.*, 2023], and a large portion of them prefer to use statistical [Yoshida *et al.*, 2022; Bourassa *et al.*, 2007] and machine learning methods [Madhuri *et al.*, 2019; Varma *et al.*, 2018]. Madhuri et al. [2019] use various machine learning methods including Ridge, LASSO, Elastic Net, boosting, etc., to predict the reasonable prices of houses and when these prices will occur. Varma et al. [2018] weights the various machine learning techniques and proposes to use real-time neighborhood details using Google Maps to get exact real-world valuations. In addition to helping buyers and sellers, better-estimated prices also guide financial institutions to better real estate appraisals [Park and Bae, 2015]. From a macro perspective, factors like location, housing area, transportation, and infrastructure are incorporated into features and fitted by machine learning models [Kumar, 2019]. Seya and Shiroi [2022] further perform rent price prediction on a large dataset and introduces deep neural networks to enhance the accuracy. These forecasts combine a variety of machine learning methods and are made from the perspectives of different stakeholders. Guidance is massively provided on macro price adjustments and home-buying policies.

2.2 Home-buying Behavior Studies

Residents' decisions regarding home purchases, however, are not solely dictated by housing prices. Their inclination to buy houses is also influenced by the dynamics of the rental market [Koeniger *et al.*, 2022]. In times of economic downturn, purchasing a house through a mortgage entails an escalated level of risk. Moreover, the presence of capital constraints can serve as a significant impediment, hindering cash-poor households from realizing their goal of owning a property [Wong *et al.*, 2022]. When considering the intention to purchase a house, which encompasses factors such as housing affordability, Hu et al. [2023] investigates the amenity conditions of cities as a means to analyze the appeal of cities to elite talent. The study explores this phenomenon by examining various aspects of cities. Furthermore, Miyakawa et al. [2022] compare the effects of educational attainment and domestication on the outcomes related to responses to housing requirements and housing premiums, respectively. These studies analyze the influence of these factors on individuals' reactions to housing-related aspects.

The above studies analyze only one or two of the selected aspects influencing home-buying behaviors [Zhang *et al.*, 2024; Bikmetova *et al.*, 2023]. Most of them only consider the influence of the external environment on people's decision-making and market transformation, ignoring the characteristics of people themselves [Ming *et al.*, 2020; Seya and Shiroi, 2022; Gilbukh *et al.*, 2023; Yoshida *et al.*, 2022; Bourassa *et al.*, 2007; Madhuri *et al.*, 2019; Miyakawa *et al.*, 2022]. Therefore, they are unable to combine macro changes and individual characteristics together to make predictions about specific residents.

3 Background and Dataset

The data utilized in this paper comprises micro-data from lease contracts, new commercial housing transactions, and stock housing sales contracts in a provincial capital city. Two distinct datasets are collected for analysis: a dataset pertaining to first-time home purchases and another dataset focusing on subsequent housing upgrades, $\{\mathbf{X}^i, \mathbf{y}^i\} \in \mathbb{R}^{n_i \times p_i}$, $\mathbf{y}^i \in \{1, 0\}^{n_i}$ are the labels, $i \in \{1, 2\}$, where n_i is the number of samples and p_i is the dimension of the feature.

The first dataset, denoted as $\mathbf{X}^1, \mathbf{y}^1$, consists of rental data paired with first home-purchase records. It comprises a total of $n_1 = 25,000$ individual samples. Each sample is characterized by ten variables, which include four categorical variables (*XB*, *RentType*, *In_Province*, *In_City*) and six numerical variables (*FWMJ*, *CZMJ*, *YZJ*, *Age*, *RenterAge*, *MonthlyRentUnitArea*). Therefore, the dimensionality of this dataset is $p_1 = 10$.

Index	Feature Name	Meaning(Full Name)
1	XB	Gender
2	FWMJ	Area of the Rental House
3	FWMJ.1	Area of the House Bought
4	CZMJ	Actual Living Area of Tenants in the Rental House
5	YZJ	Monthly Rent
6	FWZJ	Total Price of the House Bought
7	Age	Age
8	RentType	Whole Lease or not
9	RenterAge	Age of the Resident at the Time of Rental
10	BuyerAge	Age of the Resident at the Time of the Purchase
11	MonthlyRentUnitArea	Monthly Rent Required to Rent An Unit Area
12	SFAJ	Mortgage or not
13	In_Province	Native of the Province or not
14	In_City	Native of the City or not

Table 1: Features Used in Rent-Buy Records Table and Subsequent Purchase Records Table

The second dataset, denoted as $\mathbf{X}^2, \mathbf{y}^2$, is designed to predict the likelihood of purchasing a second house based on rental and first-time home purchase records. This dataset comprises $n_2 = 13,000$ samples, with each sample containing thirteen characteristics ($p_2 = 13$). These characteristics consist of five categorical variables (*XB*, *RentType*, *SFAJ*, *In_Province*, *In_City*) and eight numerical variables (*FWMJ*, *FWMJ.1*, *CZMJ*, *FWZJ*, *YZJ*, *Age*, *BuyerAge*, *MonthlyRentUnitArea*). For a comprehensive understanding of the features, please refer to Table 1, which provides detailed definitions and interpretations.

4 Methodology

In this section, we begin by presenting the methodology for constructing a resident-resident correlated graph using their shared covariance in housing purchases. Subsequently, we provide a comprehensive review of the development of graph neural networks (GNNs) and then introduce our proposed approach, which builds upon these advancements. The overall architecture is as shown in Figure 1.

4.1 Graph Construction with a Factor Model

We think that residents are interconnected due to their shared underlying motivations for home purchasing. In light of this, we propose constructing a graph $\mathcal{G}$ to represent these common connections.

Our dataset can be represented as $\mathbf{X}, \mathbf{y}$, where $\mathbf{X} = (\mathbf{x}_1, \cdots, \mathbf{x}_p) \in \mathbb{R}^{n \times p}$ denotes the feature matrix. Here, n corresponds to the number of observations, and p represents the dimension of each record. The labels for home purchase are denoted by $\mathbf{y} \in \{1, 0\}^n$, where the value 1 indicates a purchase, and 0 indicates no purchase. The resident's relationship can be captured by the sample covariance matrix,

$$\widehat{\boldsymbol{\Sigma}} \triangleq \frac{1}{n} \sum_{i=1}^{n} (\mathbf{x}_i - \bar{\mathbf{x}})(\mathbf{x}_i - \bar{\mathbf{x}})^\top, \tag{1}$$

which is computed using all the features, encompassing both the common and individual factors. In this study, *our objective is to eliminate the individual factors and exclusively retain the common-shared factors for constructing the resident-resident graph.* To accomplish this, we employ a factor model to decompose the covariance matrix into two distinct components. Specifically, for each record $\mathbf{x}_i$, we have

$$\mathbf{x}_i = \mathbf{B}\mathbf{f} + \boldsymbol{\epsilon}_i \tag{2}$$

where $\mathbf{B} = (\mathbf{b}_1, \cdots, \mathbf{b}_m)^\top \in \mathbb{R}^{p \times k}$ is the factor loading matrix, and $\mathbf{b}_i = (b_{i1}, \cdots, b_{im})^\top$, where $i = 1, \cdots, p$. $\mathbf{f} = (f_1, \cdots, f_m)^\top$ are the *common factors* as we stated before, $\boldsymbol{\epsilon} = (\epsilon_1, \cdots, \epsilon_p)$ are p *idiosyncratic errors* uncorrelated the factors $\mathbf{f}$. We assume that $\mathbb{E}[\boldsymbol{\epsilon}|\mathbf{f}] = 0$, and $\mathrm{Cov}(\boldsymbol{\epsilon}|\mathbf{f}) = \mathrm{diag}(\sigma_1^2, \cdots, \sigma_p^2)$.

According to Eq.2, the Covariance matrix $\boldsymbol{\Sigma}$ of $\mathbf{X}$ can be decomposed as,

$$\begin{aligned} \boldsymbol{\Sigma} = \mathrm{Cov}(\mathbf{x}) &= \mathbb{E}[(\mathbf{B}\mathbf{f} + \boldsymbol{\epsilon}_i)(\mathbf{B}\mathbf{f} + \boldsymbol{\epsilon}_i)^\top] \\ &= \underbrace{\mathbf{B}\mathrm{Cov}(\mathbf{f})\mathbf{B}^\top}_{\text{common purchase covariance}} + \underbrace{\mathrm{Cov}(\boldsymbol{\epsilon}|\mathbf{f})}_{\text{specific purchase covariance}} \end{aligned} \tag{3}$$

that is $\boldsymbol{\Sigma}$ contains two parts, the second part $\mathrm{Cov}(\boldsymbol{\epsilon}|\mathbf{f})$ are resident specific covariance, and the first part $\mathbf{B}\mathrm{Cov}(\mathbf{f})\mathbf{B}^\top$ are the covariance of the common factors. In this work, we prefer to use the first part covariance $\mathbf{B}\mathrm{Cov}(\mathbf{f})\mathbf{B}^\top$ *to construct resident-resident relationships based on the common driver of home-purchase.*

In practice, we usually assume that the common factors are uncorrelated with one another, it suggests that $\mathrm{Cov}(f_i, f_j) = 0, i \neq j$, $\mathrm{Var}(f_i) = 1, i, j = 1, \cdots, m$, that is $\mathrm{Cov}(\mathbf{f}) = \mathbf{I}$. Hence, the resident-resident correlated matrix can be simplified as $\mathbf{B}\mathbf{B}^\top$. The factor loading matrix $\mathbf{B}$ can be easily estimated by a spectral decomposition of the sample covariance $\widehat{\boldsymbol{\Sigma}}$ [Price, 1993],

$$\widehat{\boldsymbol{\Sigma}} = \widehat{\mathbf{B}}\widehat{\mathbf{B}}^\top + \widehat{\mathrm{Cov}}(\boldsymbol{\epsilon}|\mathbf{f}). \tag{4}$$

4.2 Graph Neural Networks

$\mathcal{G} = (\mathcal{V}, \mathcal{E})$ is a graph with n nodes, where $\mathcal{V} = \{1, \ldots, n\}$ is the set of n nodes and $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$ is the set of edges connecting paired residents in $\mathcal{V}$. Let $\mathbf{A} = \{a_{ij}\}_{i,j=1}^n$ denotes $n \times n$ symmetric adjacency matrix, where $a_{ij} = 1$ if there exists an edge $e_{ij} \in \mathcal{E}$ between nodes i and j, and $a_{ij} = 0$ otherwise. And $\mathbf{X} \in \mathbb{R}^{n \times p}$ denotes the feature matrix of the n nodes. With these notations, we revisit the classical GNNs within the framework of message-passing neural networks (MPNNs) [Gilmer *et al.*, 2017], which involve three essential steps: *neighbor set defining*, followed by *feature aggregation*, and *feature updating* as the third step.

Graph Convolutional Network (GCN) [Kipf and Welling, 2017] The basic building block of a GCN is the graph convolutional layer, which operates on the node features and their connections in a graph,

$$\begin{aligned} &\mathcal{N}^{gcn}(i) = g(\mathbf{A}) = \{j | a_{ij} = 1\} \\ &\mathbf{m}_i^{l-1} = \mathrm{Aggre}(\{\mathbf{h}_j^{l-1} | j \in \mathcal{N}^{gcn}(i)\}) \\ &\mathbf{h}_i^l = \mathrm{Com}(\mathbf{m}_i^{l-1}, \mathbf{h}_i^{l-1}; \mathbf{W}^l), l = 1, \ldots, L, \end{aligned} \tag{5}$$

where $g(\cdot)$ is a function return neighbors for node i, $\mathbf{H}^{l-1} = (\mathbf{h}_1^{l-1}, \cdots, \mathbf{h}_n^{l-1})$ are the hidden node embeddings of $(l-1)$-layer, $\mathbf{H}^0 = \mathbf{X}$, $\mathrm{Aggre}(\cdot)$ and $\mathrm{Com}(\cdot)$ are the *feature aggregation* and *state update* functions respectively. $\mathbf{W}^l$ are the

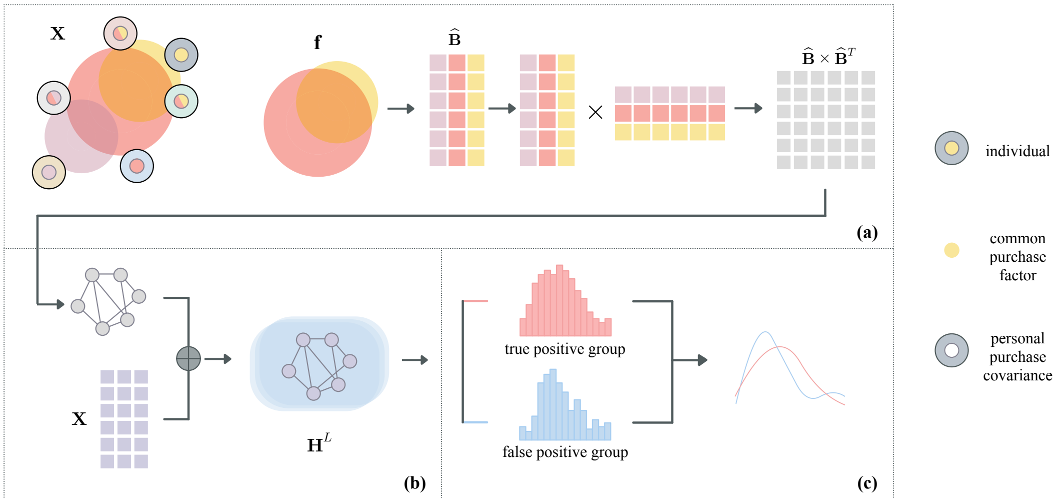


Figure 1: Overview of the framework of ccGNN. Panel (a) presents a schematic for extracting the common covariance matrix via factor analysis, utilizing residents' features. Following this, as illustrated in panel (b), the well-designed Common Covariance Graph Neural Networks propagate and aggregate the information across various residents. Finally, in panel (c), hypothesis testing on each variable within the predicted first and subsequent house purchasers differentiates between the true positive group (represented by the color red) and the false positive group (represented by the color blue).

parameters of the update function of layer l, L is the number of layers.

GraphSage GraphSage [Hamilton *et al.*, 2017] learns node representations in large-scale graphs by sampling s local neighbors,

$$\begin{aligned} \mathcal{N}^{sage}(i) &= g(\mathbf{A}, s) = \{j | a_{ij} = 1, \sum_j a_{ij} = s\} \\ \mathbf{m}_i^{l-1} &= \text{Aggre}(\{\mathbf{h}_j^{l-1} | j \in \mathcal{N}^{sage}(i)\}) \\ \mathbf{h}_i^l &= \text{Com}(\mathbf{m}_i^{l-1}, \mathbf{h}_i^{l-1}; \mathbf{W}^l), l = 1, \ldots, L. \end{aligned} \tag{6}$$

GraphSage extends the GCN neighbor set, where $s \in \mathbb{N}^+$.

Graph Attention Network (GATs) [Veličković *et al.*, 2018] GATs assign different attention weights to neighboring nodes during the message-passing process, allowing the network to selectively aggregate the most relevant nodes for each target node,

$$\begin{aligned} \mathcal{N}^{gat}(i) &= g(\mathbf{A}, \mathbf{H}^{l-1}) = \{(j, \alpha_{ij}) | a_{ij} = 1\} \\ \mathbf{m}_i^{l-1} &= \text{Aggre}(\{\mathbf{h}_j^{l-1} | j \in \mathcal{N}^{gat}(i), \}) \\ \mathbf{h}_i^l &= \text{Com}(\mathbf{m}_i^{l-1}, \mathbf{h}_i^{l-1}; \mathbf{W}^l), l = 1, \ldots, L. \end{aligned} \tag{7}$$

GATs extend the GCN neighbor index function as $g : \mathbb{S}^+ \times \mathbb{R}^{n \times d_{l-1}} \longrightarrow \{(j, \alpha_{ij}) | a_{ij} = 1\}$, where α_{ij} is a attention weight between node i and its neighbor j.

VNN Sihag et al. [2022] proposed Covariance Neural Networks (VNN), wherein the adjacent matrix $\mathbf{A}$ in Eq. (5) is replaced by the sample covariance matrix $\widehat{\mathbf{\Sigma}}$ (Eq. (1)). Additionally, they incorporate its m-order polynomial $\sum_{k=1}^m \beta_k \widehat{\mathbf{\Sigma}}^k$. Thus, the modified expression can be represented as follows:

$$\begin{aligned} \mathcal{N}^{vnn}(i) &= g(\sum_{k=1}^m \beta_k \widehat{\mathbf{\Sigma}}^k) \\ \mathbf{m}_i^{l-1} &= \text{Aggre}(\{\mathbf{H}_j^{l-1} | j \in \mathcal{N}^{vnn}(i), \}) \\ \mathbf{h}_i^l &= \text{Com}(\mathbf{m}_i^{l-1}, \mathbf{h}_i^{l-1}; \mathbf{W}^l), l = 1, \ldots, L, \end{aligned} \tag{8}$$

where $g : \mathbb{S}^+ \longrightarrow \{j | [\sum_{k=1}^m \beta_k \widehat{\mathbf{\Sigma}}^k]_{ij} \neq 0\}$ is a general neighbor index function. VNN can be considered as an equivalent approach to Principal Component Analysis (PCA).

4.3 Our Model

In this study, we introduce a novel approach called the Common Covariance Graph Neural Network (ccGNN) for predicting home-purchase transactions as shown in Figure 1 (a). To achieve this objective, we replace the common factor covariance matrix in Eq. (8) with the common covariance matrix $\widehat{\mathbf{B}}\widehat{\mathbf{B}}^\top$ as defined in Eq. (4).

$$\begin{aligned} \mathcal{N}^{cc}(i) &= g(\widehat{\mathbf{B}}\widehat{\mathbf{B}}^\top) = \{j | [\widehat{\mathbf{B}}\widehat{\mathbf{B}}^\top]_{ij} \neq 0\} \\ \mathbf{m}_i^{l-1} &= \text{Aggre}(\{\mathbf{H}_j^{l-1} | j \in \mathcal{N}^{cc}(i)\}) \\ \mathbf{h}_i^l &= \text{Com}(\mathbf{m}_i^{l-1}, \mathbf{h}_i^{l-1}; \mathbf{W}^l), l = 1, \ldots, L, \end{aligned} \tag{9}$$

where $g : \mathbb{S}^+ \longrightarrow \{j | [\widehat{\mathbf{B}}\widehat{\mathbf{B}}^\top]_{ij} \neq 0\}$ is the proposed neighbor index function. Subsequently, our prediction task for home transactions can be formulated as a graph node classification problem shown in Figure 1 (b),

$$\mathbf{z} = \text{Softmax}\left(\mathbf{H}^L\right),$$

where $\mathbf{H}^L \in \mathbb{R}^b$ is the output of the last layer, b is the batch size. Then the classification loss is

$$\mathcal{L}_{\text{Sup}} = -\sum_{i \in \mathcal{Y}_L} \mathbf{y}_i \ln \mathbf{z}_i,$$

where $\mathbf{y}_i$ is the true label of purchase.

5 Experiments

In this section, we perform extensive experiments on real-world datasets to evaluate the performance of our model. We aim to answer the following questions through experiments.

- **Q1:** Which portion of rental residents will likely engage in first-time home purchases in the future, and what are the key characteristics they possess?
- **Q2:** Which part of the demographic, having already rented and purchased their first home, is prone to explore a second home purchase and what are the key characteristics of this group?

5.1 Data Split

Our model is assessed using two datasets that are detailed in Section 3. To ensure consistency, all numerical features are standardized using Min-Max Scaling. Both datasets are randomly divided into training, testing, and validation subsets, with a ratio of 7:2:1. The label for the rent-to-buy forecast, denoted as $\mathbf{y}^1 \in \{1, 0\}^{n_1}$, is assigned as follows: 1 indicates that an individual has already purchased at least one house, while the value 0 indicates that they have not. In the second phase of the prediction, according to the duplication, data in which the buyer purchases more than once is labeled as 1 and the information of the subsequent house purchase is removed.

5.2 Evaluation Metrics and Setup

We adopt five widely-used metrics, namely accuracy, f1 score, sensitivity (TPR, True Positive Rate), specificity(TNR, True Negative Rate), and area under the ROC curve (AUC), to comprehensively evaluate all methods. The larger value reflects the better performance for all five metrics.

The implementation of our model is carried out using the *DGL* Library in conjunction with PyTorch 1.17. The hidden dimension is set to a fixed value of 16 across all methods. For optimization, we employ the Adam optimizer with a weight decay of 5e-4. The batch size is set to 512, and the learning rate is set to 0.01. To ensure robustness, we perform evaluations four times using different random seeds and report the mean values for each method. All experiments are conducted on a computer server equipped with two GeForce RTX 3090 GPUs, 128GB RAM, and running the 20.04.1-Ubuntu SMP operating system.

We choose Logistic Regression (LR) and Decision Tree as the two baseline models for comparison. For our proposed model ccGNN, we utilize the well-known Aggre$(\cdot)$ and Com$(\cdot)$ functions, Graph Convolutional Network (GCN) [Kipf and Welling, 2017], Graph Attention Network (GAT) [Veličković *et al.*, 2018], ChebyNet [Defferrard *et al.*, 2016], GraphSage [Hamilton *et al.*, 2017], Topology Adaptive Graph Convolutional Networks (TAGCN) [Du *et al.*, 2017] as shown in Eq.(9).

5.3 Overall Performance

The overall results of predictions for first-time home purchases are presented in Table 2. For the proposed model ccGNN, we select the Aggre$(\cdot)$ and Com$(\cdot)$ functions that are defined in *cc*GCN, *cc*GAT, *cc*ChebyNet, *cc*TAGCN, and *cc*GraphSage respectively. Comparisons between the proposed models and two baseline methods, LR and Decision Tree, reveal a significant improvement in sensitivity (TPR). This improvement suggests that the proposed method possesses advantageous predictive capabilities. Moreover, our observations indicate that the Decision Tree performs the worst out of the considered methods on sensitivity, while the *cc*ChebyNet model achieves the highest in all five aspects.

	Accuracy	F1	TPR	TNR	AUC
LR	0.585	0.616	0.671	0.501	0.586
Decision Tree	0.546	0.547	0.555	**0.537**	0.546
*cc*GCN	0.571	0.623	0.719	0.423	0.571
*cc*GAT	0.570	0.624	0.720	0.424	0.572
*cc*ChebyNet	**0.616**	**0.677**	**0.812**	0.423	**0.618**
*cc*TAGCN	0.571	0.627	0.729	0.414	0.572
*cc*GraphSage	0.573	0.629	0.732	0.417	0.574

Table 2: The overall performance of predicting future homebuyers for their first purchases. LR is the acronym for Logistic Regression.

	Accuracy	F1	TPR	TNR	AUC
LR	0.673	0.705	0.758	0.584	0.671
Decision Tree	0.617	0.628	0.634	**0.599**	0.616
*cc*GCN	0.638	0.678	0.751	0.519	0.635
*cc*GAT	0.607	0.663	0.772	0.442	0.607
*cc*ChebyNet	0.694	**0.730**	0.805	0.577	0.691
*cc*TAGCN	**0.698**	0.718	**0.809**	0.583	**0.696**
*cc*GraphSage	0.690	0.723	0.806	0.571	0.689

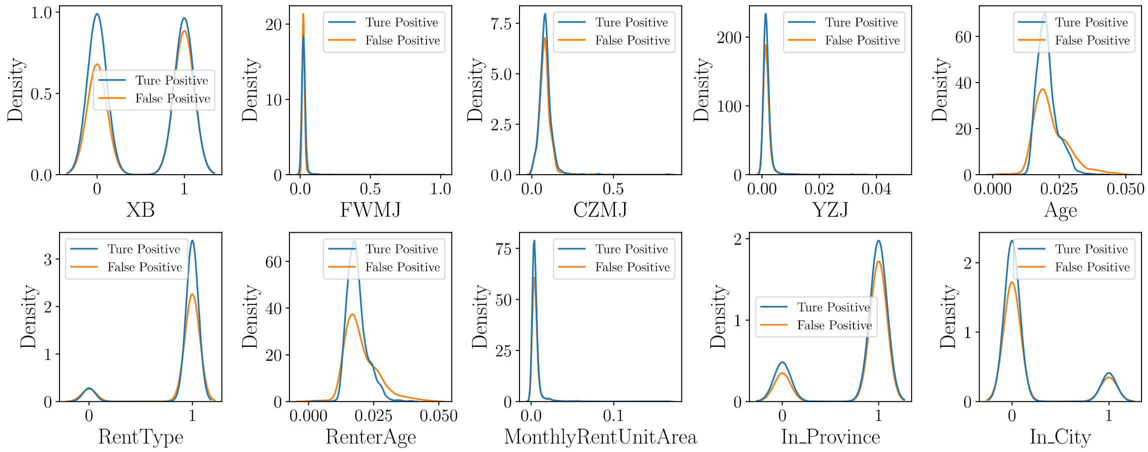
Table 3: The overall performance of subsequent house purchases predictions.

Specifically, we note that the sensitivity of the *cc*ChebyNet model is 0.812, surpassing the best traditional machine learning method LR by 14%. This finding suggests that our model correctly predicts the home purchases of 81.2% of individuals who previously rented their homes, thereby demonstrating its efficacy in identifying potential first-time buyers.

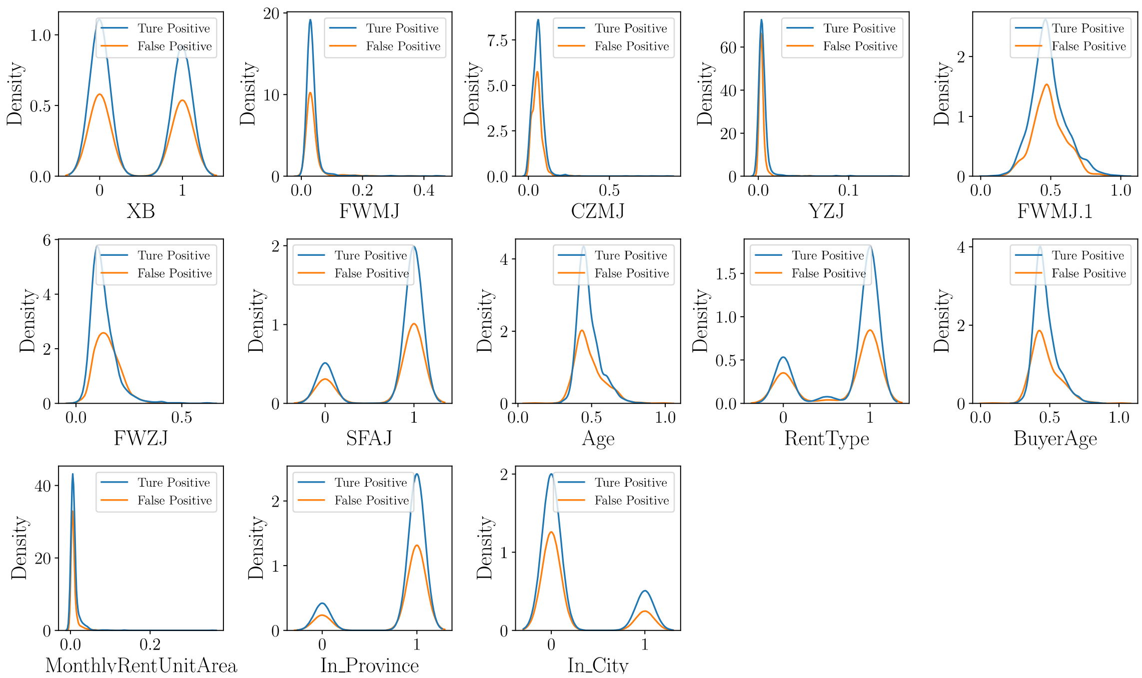
The overall results of subsequent house purchase predictions are shown in Table 3. Similarly, we find that the proposed models with common covariance matrix perform better than the two baseline methods. The proposed methods with *cc*ChebyNet, *cc*TAGCN, and *cc*GraphSage show significant improvements in TPR, reaching more than 0.8 compared to other methods. Specifically, *cc*TAGCN, *cc*GraphSage, and *cc*ChebyNet have increased their w.r.t TPR by 5.10%, 4.80%, and 4.70% respectively. In addition, Decision Tree performs the worst TPR in this problem, while *cc*TAGCN achieves the best overall performance on the dataset with most evaluation metrics.

5.4 Statistical Analysis of the Predicted Buyers

The objective of the previous experiments was to validate the performance of the proposed methods. In this subsection, we delve into the features of individuals who engage in their home purchases by conducting hypothesis testing. *Instead of examining the labeled real purchases and non-purchases, we focus our hypothesis testing on the true positive group and*



(a) First house purchases



(b) Subsequent house purchases

Figure 2: The distributions of each variable in the True Positive group (represented by the color blue) and the False Positive group (represented by the color orange), as predicted by ccGNN, are visualized for both datasets.

false positive group, which is shown in Figure 1 (c). This choice is motivated by the rationale outlined in Eq. (3), which indicates that real purchases are influenced by two factors: a common purchase factor and individual purchase factors. While the former can be modeled, the latter is inherently random and cannot be predicted. Figure 2 illustrates the distributions of each variable over the true positive group (blue curves) and false positive group (orange curves). Figure 2 (a) and (b) are the results of the first and subsequent purchase respectively. We then perform hypothesis testing on each variable.

To conduct the hypothesis testing on the house purchase, we utilize the results obtained from the best models. We evaluate variables within the true positive group and false positive group, as presented in Table 4 and Table 5.

Binomial Test The binomial test is employed in sampling statistics to evaluate whether the proportion of bivariate variables aligns with a specific hypothesis. The bivariate features encompass *XB*, *RentType*, *SFAJ*, *In_Province*, and *In_City*. It is noteworthy that all the features, with the exception of *In_Province* (provincial native), hold significance in binomial tests, irrespective of whether it is the first or second phase of the prediction.

Mann Whitney U Test The Mann-Whitney U test is a widely employed non-parametric hypothesis test utilized to

Table 4: Hypothesis testing on each variable within the predicted first house purchasers, differentiating between the true positive group and the false positive group.

Feature Name	Hypothesis Testing	P-value
XB	Binomial	3.66e-23
FWMJ	Mann Whitney U	9.03e-06
CZMJ	Mann Whitney U	2.22e-17
YZJ	F	3.28e-08
RentType	Binomial	4.35e-229
Age	Paired Sample-	7.01e-300
RenterAge	-Mann Whitney U	7.65e-248
MonthlyRentUnitArea	F	1.13e-15
In_Province	Binomial	0.9054
In_City	Binomial	1.75e-09

Table 5: Hypothesis testing on each variable within the predicted subsequent house purchasers, differentiating between the true positive group and the false positive group.

Feature Name	Hypothesis Testing	P-value
XB	Binomial	0.0689
FWMJ	Paired Sample-	0.0112
FWMJ.1	-Mann Whitney U	0.0211
CZMJ	Mann Whitney U	0.0001
FWZJ	Mann Whitney U	8.63e-19
YZJ	F	0.0006
RentType	Binomial	2.94e-06
Age	Paired Sample-	3.24e-188
BuyerAge	-Mann Whitney U	7.73e-116
SFAJ	Binomial	0.0221
MonthlyRentUnitArea	F	0.0411
In_Province	Binomial	0.8561
In_City	Binomial	0.0007

compare whether the medians of two independent samples are equivalent.

Upon examining the distribution curves, the distributions of true positives and false positives exhibit substantial similarity across most continuum variables, except *YZJ* and *MonthlyRentUnitArea*. Consequently, the Mann-Whitney U test is conducted on all remaining continuum variables, yielding statistically significant results in each case.

In our analysis, we group two age-related variables together in a paired sample test to investigate the age gap or time interval between the rental period of the target group and the present time. Furthermore, with the inclusion of additional variables in the second prediction, we conduct an additional paired-sample test. This test aims to compare the size of the previously rented house with the size of the house purchased, thereby examining the housing level of residents before and after acquiring a property. The results show that all features are significant in both stages of housing purchase predictions.

F Test Since in terms of *YZJ* and *MonthlyRentUnitArea*, the distribution of true positives differs a lot from false positives, we decide to try variance-related tests. The distributions of both true and false positive samples of these two features basically obey normality, so we carry out the classic F test on them and the results turn out to be significant.

In the conducted hypothesis testing, we delved into the features of individuals who engage in their home purchases. Among those predicted to be first-time home purchasers, we note that all the features except for *In_Province* are statically significant. This observation indicates that the decision to purchase a house for the first time is shaped by various common factors such as the gender of the buyer, the area of the rental house, the monthly rent, mortgage or not, and whether the individual is a native of the city, while an individual who is a native of the province or not seems to have not played a statistically significant role in this regard. Similarly, for those predicted subsequent house purchasers, the pattern repeats, with all features exhibiting statistical significance except for *In_Province*.

The comprehensive hypothesis testing for all features across different housing buyers reveals the significant influence of common factors in driving home purchase decisions. It suggests that irrespective of first-time house purchases or subsequent house purchases, there are common and universal driving factors shaping these purchases. These common driving factors reflect broader social dynamics, economic landscapes, and cultural trends, collectively shaping the housing behavior of residents, and highlighting the interconnectedness between individuals, indicating that understanding these common driving factors is crucial for shaping future housing policies and the strategic planning of housing markets.

6 Conclusion

We believe that the driving forces behind residents' home purchases can be divided into two categories. The first category consists of universally existing driving forces, which are the common reasons that drive most people to buy a house. The second category encompasses individualized and random driving forces, making them difficult to predict. Therefore, modeling the first category of driving forces is advantageous for predicting housing transactions. By employing a factor model, we separate the common driving factors from all factors associated with housing purchases. Based on these factors, we construct a resident-to-resident relationship graph and propose a housing transaction prediction model using graph neural networks. In this model, the task of predicting whether a resident will make a home purchase is formulated as a graph node classification problem. We evaluate the model on two datasets: one representing transitions from renting to buying, and the other representing transitions from renting and buying to upgrading. The results indicate that the model achieves a sensitivity of over 80% in predicting housing transactions.

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