An Integrated Model for Urban Subregion House Price Forecasting: a Multi-source Data Perspective

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***Abstract*—Urban housing price is widely accepted as an economic indicator of both business and research interest in urban computing. In this work, we propose an effective and fine-grained model for urban subregion housing price predictions. Compared to existing works, our proposal improves the forecasting granularity from city-level to mile-level in spite of data sparsity and complex factors. The fine-grained housing price forecasting has the potential to support a broad scope of applications, ranging from urban planning to housing market recommendations. To achieve that, in this paper, we propose a novel integrated framework, FTD_DenseNet, which incorporates more social and economic features and makes full use of all-level spatiotemporal features. Specifically, the Kalman Filter-based future expection is firstly involved as an influence factor in our model. Extensive empirical studies on real data show the effectiveness of our proposals.**

***Index Terms*—urban computing, subregion housing price forecasting**

I. Introduction

Housing price forecasting plays a vital role in macroeconomic and financial decision supporting [1]. In the past decade, a global financial crisis has been witnessed, due to inaccurate housing price forecasting and unconscionable financial policymaking in a large extent. Existing studies on housing price forecasting models are mostly in city-level, for supporting macroeconomic analysis and policymaking. The city-level forecasting, however, does not capture the fact of imbalanced development between the mile-level subregions in a city. For instance, in Chinese city Xi'an, the average real estate prices of three districts in Sept. 2018 increased more than 10% while the average prices of the other six districts experienced a decrease about 5% during the same period [2].

In this work, we study another type of housing price forecasting, i.e., mile-level fine-grained housing price forecasting, where the mile-level subregions are much smaller than the urban regions. Such a type of forecasting depicts the potential fluctuations and distributions of housing prices among different urban subregions. With the help of that, we can find broad applications in urban planning, such as community service supporting and transportation facilities optimization [3].

Related works. There exist many studies, however, in city-level housing price forecasting, which can be detailedly categorized as machine learning-based methods [4]–[8] and deep learning-based methods [9], [10]. The most of machine learning-based methods including the VAR (Vector AutoRegression), STAR (Smooth transition AutoRegression), ARIMA (Auto regression Integrated Moving Average) and SVR (Support Vector Regression) can only capture the temporal dependencies while SPVAR (Space Vector AutoRegressive) can capture spatial dependencies by learning low-level spatial features. For deep learning-based methods, the LSTM (Long Short Term Memory) is designed to model time series issue and ANN (Artificial Neural Network) can be feed spatiotenporal features for predicting housing price. Besides, some other deep neural networks including the DNN-based Deep-ST, ResNet and InceptionV4, which enable the outstanding performances in the field of computer vision, are applied as our baselines for comparison in subregion housing price prediction. Nevertheless, all existing solutions cannot be extended to the subregion scenarios appropriately, because most of them do not have the availability of involving the all-level spatiotemporal characteristics effectively. Besides, some models including Deep-ST, ResNet and InceptionV4 are mainly dependent on high-level instead of all-level features due to the network connectivity, which leads the weakness in generalization and unavoidable overfitting in small and sparse subregion datasets.

Challenges. However, challenges arise for accomplishing fine-grained urban subregion housing price forecasting and analysis. The influence factors of housing price forecasting are known to be complex. As mentioned in [1], the economic and social ingredients also affect the tendency of housing prices. Furthermore, the trend of macroeconomic or future price-growth expectation also has great influence on the current housing price [11].

Another challenge is that the sparse data limits the sample size and incurs selectivity sample bias for building efficient and accurate forecasting models, letting alone the limited availability of publicly released data with heterogenous transaction properties. Such data might be dense enough for city-level forecasting, but it is shown to be sparse when the urban region is decomposed into mile-level subregions. In particular, the sparse data can result in the insufficient house price features.

Contributions. In summary, previous works on housing price forecasting never set foot on the issues of mile-level subregion housing price predictions. Also, the future price-growth expectations have not been taken as the feature of forecasting models.

To our best knowledge, this is the first work on effective

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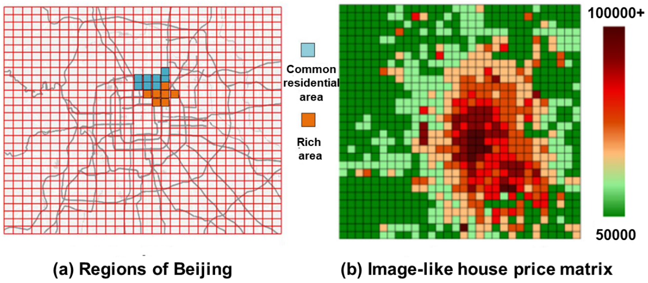

Fig. 1. An Example of Beijing.

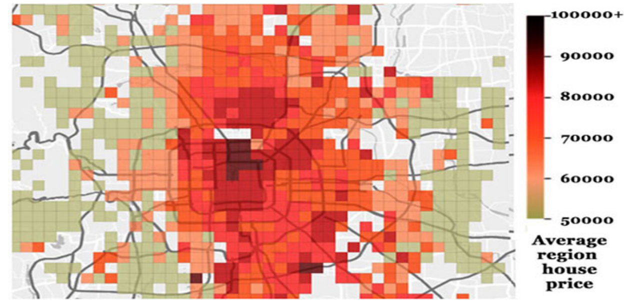

Fig. 2. Subregion Housing Prices of Beijing during 2017

mile-level subregion housing price forecasting, which has profound effects on trading recommendations for housing markets and on urban planning for public facility analysis and optimization. Our main contributions are as follows.

- We propose to use the densely connected network structure to overcome the sparsity problem of transaction records firstly, which learns all-level spatiotemporal features sufficiently and decreases overfitting during the learning process.
- We propose a novel framework by fully considering the four time periods (i.e., long-term, recent, current, and future tendency) for depicting spatiotemporal dependencies. To achieve that, we improve the original DenseNet [12], combine the Kalman Filter, and adjust the diverse structures to further improve the accuracy.
- We evaluate our proposed FTD_DenseNet with real-world house price datasets from New York City (NYC) and Beijing. Extensive cross-validation experiments demonstrate that our FTD_DenseNet outperforms the start-of-the-art solutions significantly.

II. Preliminaries

A. Problem Definition

In this part, we formally define basic concepts and the problem studied in the work.

*Definition 1 (**City Region**): The urban region can be divided into small square-shaped subregions with the side-length of* d_0[1] *kilometers as shown in Fig. 1(a). In this way, the city can be represented by a set of equal-sized grids, with* m_r *rows and* m_c *columns. A grid at* i*-th row and* j*-th column can be denoted as* $r_{i,j}$*, where* $i \in \{1, \cdots, m_r\}$ *and* $j \in \{1, \cdots, m_c\}$*.*

*Definition 2 (**Housing Price Set**): Given a month* T *and a city, we define the housing transaction price set of the entire city during this month as* $\mathbb{S}_T$*. We have* $\mathbb{S}_T = \mathbb{S}^T_{r_{1,1}} \cup \cdots \cup \mathbb{S}^T_{r_{m_r,m_c}}$*, where* $\mathbb{S}^T_{r_{i,j}}$ *denotes the housing price set of an urban subregion* $r_{i,j}$ *during month* T*. Within each month* T*, the* t_k *denotes the original transaction timestamp on specific dates, so that the transaction can be represented by* $\mathbb{S}^T_{r_{i,j}} = \{s^{t_1}_{r_{i,j}}, s^{t_2}_{r_{i,j}} \cdots\}$ $(t_1, t_2, \cdots \in T)$*, where* $s^{t_k}_{r_{i,j}}$ *indicates the price of the transaction in region* $r_{i,j}$ *at time* t_k*.*

*Definition 3 (**Housing Price of a Subregion**): Given a subregion* $r_{i,j}$*, the housing price of* $r_{i,j}$ *can be calculated by:*

$$p^T_{r_{i,j}} = \frac{1}{\left|\mathbb{S}^T_{r_{i,j}}\right|} \sum_{k=1}^{\left|\mathbb{S}^T_{r_{i,j}}\right|} s^{t_k}_{r_{i,j}} \tag{1}$$

The prices of $m_r \times m_c$ subregions of month T can be denoted as a tensor $p^T_{r_{i,j}} \in \mathbb{R}^{m_r \times m_c \times 1}$ as shown in Fig. 1(b).

*Definition 4 (**Subregion Housing Price Forecasting**): We design the model to predict the housing price* $p^{n+1}_{r_{i,j}}$ *with the evaluation metric of RMSE (Root Mean Square Error) as shown in Equation 2, where* $\widehat{p^{n+1}_{r_{i,j}}}$ *denotes the predicted housing price of the subregion* $r_{i,j}$*.*

$$RMSE = \sqrt{\frac{1}{m_r \times m_c} \sum_{i=1}^{m_r} \sum_{j=1}^{m_c} \left(\widehat{p^{n+1}_{r_{i,j}}} - p^{n+1}_{r_{i,j}}\right)^2} \tag{2}$$

III. Subregion Housing Price Forecasting Model

In this section, we first analyze the parameters which can influence the subregion housing price, and then introduce the forecasting model for the subregion housing price problem.

A. Influence Factors of Subregion Housing Price

In most previous works, the housing price prediction is modeled in the form of temporal dependencies analysis. To this end, we systematically analyze the ingredients that influence the future housing price, systematically.

- **Spatial correlations.** When formulating the problem in Section III, we have divided an entire city into small subregions. Intuitively, the housing prices of two neighboring subregions have strong correlations. For instance, a more developed subregion tends to be more commercially bustling and more convenient in transportation. Such ingredients have an radiative effect to its neighboring subregions as shown in Fig. 2.
- **Long-term periodicity and short-term tendency.** It is widely accepted that the future housing price is greatly affected by long-term periodicity and short-term tendency. In [11], the influences of long-term periodicity [2] is discussed. The impacts of short-term tendency [3] on

[1] The setting of d_0 should balance the trade-off between the fineness of urban region house price predictions and the densities of historical data. In our implementation, we divide cities into small square-shaped areas with the length of 2 kilometers.

[2] The regression period of long-term periodic influences on housing price prediction l_{long} can be set to 5 years. [11].

[3] In previous studies [13], the regression period of short-term tendency l_{short} is set to 12 months (1 year).

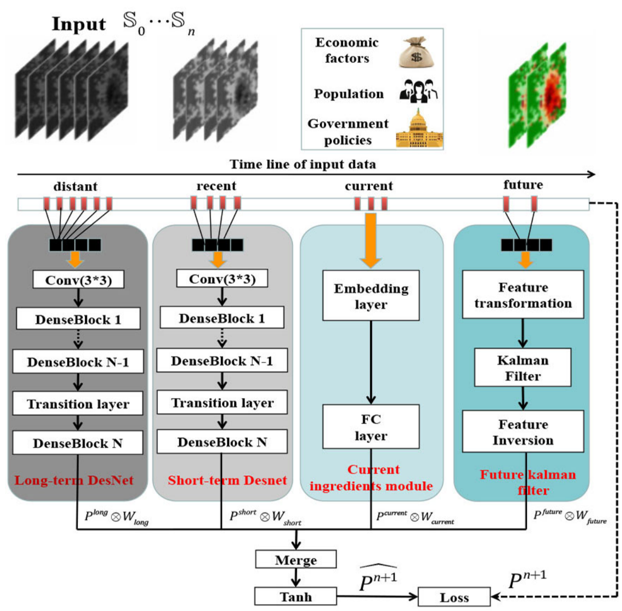

Fig. 3. Architecture of FTD_DenseNet

future housing price is evaluated in [13].

- **Current economic and social ingredients.** It has been concluded that the future housing price is greatly affected by many current economic and social elements, such as down-payment ratios, mortgage rates, house property tax policy, GDP growth, and demographic factors.
- **The future price-growth expectations.** Theoretically, from an economic perspective, the future price-growth expectations would give feedbacks on the tendency of housing price, once the public show cognitions on the housing market [14]. Such a type of influence has been observed in Tokyo before 1991 and in China during the past decade.

B. Major Components of the Forecasting Model

In this part, we present the solution framework for the subregion housing price forecasting problem. The architecture overview is shown in Fig. 3, which consists of four major components to solve the aforementioned influence factors: i) Long-term spatiotemporal DenseNet; ii) Short-term spatiotemporal DenseNet; iii) Current Ingredients Module; iv) Kalman Filter for future price-growth expectations. We organize them as four types of inputs in accordance to their time dimensional attributes, i.e., distant periodicity, recent tendency, current, and future factors, as shown in the upper half of Fig. 3.

Given historical transaction records of a city, we transform them into the tensors $P^{long} \in \mathbb{R}^{m_r \times m_c \times 5}$ and $P^{short} \in \mathbb{R}^{m_r \times m_c \times 12}$, where each tensor refers to the monthly aggregated housing price values of all subregions.

The long-term and short-term DenseNet components share the same network structure with a modified DenseNet. For the current ingredient component, we manually extract features from economic and social ingredients, then feed them into the embedding layer and the fully connected (FC) layer. The last component simulates the effects of future price-growth expectations. In our implementation, we use the Kalman Filter to model the subjective expectations from the public.

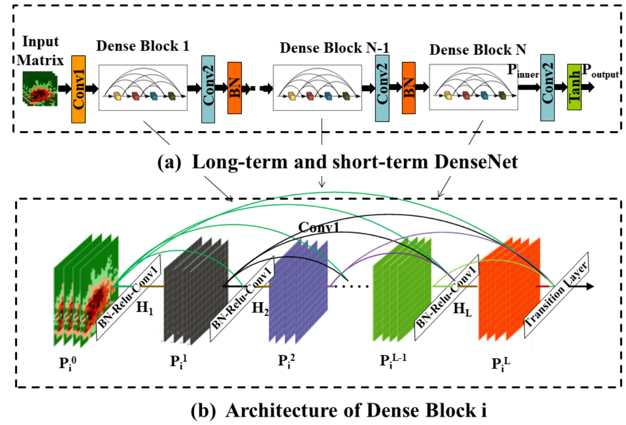

Fig. 4. Architecture of long-term and short-term DenseNet

The outputs of these four components are represented by P^{Long}, P^{short}, $P^{current}$, and P^{future}, respectively. The integrated result is further mapped by a $Tanh$ function to the interval $[-1, 1]$.

1) Long-term and short-term spatial-temporal DenseNet: The long-term and short-term components share the same network structure consisting of three sub-components: convolution, dense block, and a transition layer. Based on the particular characteristics of the housing price predictions, we modify DenseNet as illustrated in Fig. 4.

Convolution. As described in Section III, the housing prices of neighboring subregions have obvious spatial correlations. Such a type of correlations can be effectively inducted by adopting CNN (Convolution Neural Network), which has shown its efficiency on extracting spatial structural information [15]. Also, as shown in Fig. 2, this kind of correlations has radiative effects, not only affecting direct neighboring subregions, but also rather distant neighboring subregions. The correlations between distant neighboring subregions cannot be captured by one convolution. Therefore, we adopts a CNN with multiple convolutional layers. For example, there are L convolutions (i.e., *Conv1*[4]), as shown in Fig. 4(a), in one dense block. The total number of all *Conv1*s in the component is $N \times L + 1$, so that the stack of convolutions is capable of capturing subregion housing price correlations in the whole city.

Dense Block. With the increased number of layers, the issues of gradient vanishing and overfitting become more and more serious. To handle this challenge, [12] proposes a densely connectivity mode *Dense Connectivity*, as illustrated in Fig. 4(b). For dense block i, the input of layer L is:

$$I_L = H_L(P_i^0, P_i^1 \cdots, P_i^{L-1}),\ L = 1, 2, 3, \cdots \qquad (3)$$

The function H_L is a nonlinear function consisting of one convolution *Conv1*, one *Relu* function, and one *BN* (Batch Normalization) [16]. Compared to P_i^0, the P_i^{L-1} transforms

[4]The kernel size of convolution *Conv1* is fixed to 3×3.

the low-level features into high-level after several nonlinear functions. Notice that the connection mode between feature maps P_i^L and $P_i^0, P_i^1 \cdots, P_i^{L-1}$ is an channel-wise addition. We have:

$$CN(P_i^L) = sum\{CN(P_i^0), CN(P_i^1) \cdots, CN(P_i^{L-1})\} \quad (4)$$

Here, the CN denotes the channel number. And we can observe the last layer's input coming from all the front layers output, which indicates that our model can learn the low-level and high-level features. For sparse datasets, the features of housing price are insufficient, which makes it hard to capture the spatiotemporal characteristics. Thus this kind of densely connectivity enables our model to learn all-level spatiotemporal features, and achieve a superior performance on small and sparse datasets.

Transition layer. In the original DenseNet, a $average\,pooling$ function is used to diminish the features, which is not suitable for sparse datasets. Besides, the original FC layer after dense block N is used for classification, which cannot be applied to predict housing price. Therefore, to improve the DenseNet, we replace the $average\,pooling$ function by a BN function which can remit overfitting.

To fuse the multi-channel values, we try a $Conv2$ to replace the original FC layer. As shown in Fig. 4(a), P^{inner} have multiple channels after N dense blocks. The final output is then calculated by the follow equation.

$$P^{output} = f(W * P^{inner} + b) \quad (5)$$

Here, function f is the activation function $Tanh$. $*$ denotes the convolution $Conv2$ [5], and W and b are the learnable parameters.

2) Current ingredients module: Subregion housing price can be influenced by many complex factors, such as GDP, mortgage rates, and so on. Therefore, we take these main factors as the major ingredients.

First, we feed the current ingredient matrix of five factors into an embedding layer, and then link it to a FC layer. The embedding layer is for mapping the fields into a structured and dense input space. For the convenience of reshaping the 1×5 matrix to a $m_r \times m_c \times 5$ tensor, we use the FC layer to map low-dimensional values to the high dimensions.

3) Future price-growth expectations: In this subelement, we simulate the subjective expectations of the public. [11] proposes a Kalman Filter (KF *in short*) based method to predict the influences of future price-growth expectations. We hereby add the KF-based filter into our integrated network, to construct a novel stronger learner and take the future influence into account.

Given a historical housing price dataset $\{\mathbb{S}_T|_{T=1,\dots,n}\}$, for time $n+1$ and subregion $r_{i,j}$, we define the housing demands of all residents of the subregion as $\mathscr{D}_{r_{i,j}}^{n+1}$. The growth rate of the housing demands in this region is defined as $\mathscr{G}_{r_{i,j}}^{n+1}$. The average trading price of the subregion is defined as $\mathscr{P}_{r_{i,j}}^{n+1}$.

[5]The kernel size of $Conv2$ should be 1×1.

By using the proposed KF-based method in [11], we first predict the housing demands $\mathscr{D}_{r_{i,j}}^{n+1}$ and the growth rate of the housing demands $\mathscr{G}_{r_{i,j}}^{n+1}$, based on the historical housing price set $\{\mathbb{S}_{n-1}, \mathbb{S}_n\}$. After predicting the housing demand and growth rate of the housing demand of future time $n+1$, we can calculate the expected housing price of subregions by:

$$E\left(\mathscr{P}_{r_{i,j}}^{n+1}\middle|\{\mathscr{D}_{r_{i,j}}^{n+1}, \mathscr{G}_{r_{i,j}}^{n+1}\}\right) = \frac{\mathscr{D}_{r_{i,j}}^{n+1}}{r} + \frac{\mathscr{G}_{r_{i,j}}^{n+1}}{r(r+\lambda)} \quad (6)$$

Here, r and λ indicate the discount rate and the demand growth revision [11], respectively. With this method, we can calculate the price-growth expectation for each subregion in the city, and generate the future price-growth expectation tensor sized $m_r \times m_c \times 1$.

4) Fusion of Components: Regarding to the final result, we need to differentiate degrees of the impacts of each component. To this end, we use the method of parametric-multiplication to fuse all components as follows.

$$\widehat{P^{n+1}} = Tanh\left(\begin{array}{l} P^{long} \otimes W_{long} + P^{short} \otimes W_{short} + \\ P^{current} \otimes W_{current} + P^{future} \otimes W_{future} \end{array}\right) \quad (7)$$

Here, $\otimes$ represents the element-wise multiplication. W_{long}, W_{short}, $W_{current}$, and W_{future} are learnable parameters.

The overview of the learning process of FTD_DesNet is summarized in Algorithm 1.

Algorithm 1: FTD_DenseNet Training Algorithm

Input: Historical observations:$\{\mathbb{S}_T|T = 0, \cdots, n\}$;
Historical current ingredients:$\mathbb{C} = \{\mathbb{C}_T|T = 0, \cdots, n\}$;
Output: Learned FTD_DenseNet model
$D \leftarrow \varnothing$// initializing
for *all time interval* $t(1 \le t \le n)$ **do**
  P^{long}=$[\mathbb{S}_{t-l_{long}}, \mathbb{S}_{t-(l_{long}-1)}, ..., \mathbb{S}_{t-1}]$
  P^{short}=$[\mathbb{S}_{t-l_{short}}, \mathbb{S}_{t-(l_{short}-1)}, ..., \mathbb{S}_{t-1}]$
  $P^{current}$=Embed$(\mathbb{C}, \mathbb{C}_t)$// embedding
  P^{future}=KF-based expecting$([\mathbb{S}_{t-1}, \mathbb{S}_t])$
  $\widehat{P^t}$=Fusion$([P^{long}, P^{long}, P^{current}, P^{future}])$ Append an training instance $(\widehat{P^t}, P^t)$ into D
end
// training the model
initializing all learnable parameters θ in FTD_DenseNet
repeat
  randomly select a batch of instances D_b from D
  using Adam to optimize $Eq.(2)$ with D_b;
until *the maximum epoches*;

IV. Experiments

A. Setup

In this subsection, we introduce the datasets of NYC and Beijing, and some settings of experiments.

NYC and Beijing data. For NYC, the housing transaction price dataset is provided on the public platform of NYC Open Data [6]. The current ingredients can be taken from the Federal Reserve Economic Data[7].

[6]https://opendata.cityofnewyork.us
[7]https://fred.stlouisfed.org

TABLE I
DATASETS DESCRIPTION

DataSets	NYC house	Beijing house
Time Span	1/2003-12/2015	1/2011-12/2017
Time Interval Size	one month	one month
Number of Subregions	(12*12)	(30*30)
AVT of a subregion	15+	10+
Number of Time Intervals	156	84
Number of Ingredients	156*5	84*5

The Beijing dataset is taken from the Lianjia and the Zhugezhaofang[8]. The current ingredients are provided on the State Statistics Bureau[9]. More details are covered by Table 1.

Data Sparsity. For the datasets of NYC and Beijing, the average number of transaction records (AVT) per subregion is no more than 30, as shown in Table I.

The work of VAR model applies for datasets with AVT greater than 100. For works of SVR and ANN models, the AVT value is above 50. Hence, our housing data is sparse.

Others. In our model, we use Min-Max normalization to scale the input data into the range [-1,1] before feeding them into the network. The filter number of $Conv1$ appeared in each dense block is named growth rate [12]. The filter number of the last $Conv2$ after dense block N is 1, and the filter number of other $Conv2$ is set to different values according to the experimental results. We use 90% of the original data for training and 10% for validation. For each model, we adopt the same learning rate and epochs. Besides, the parameter of KF-based submodule follows the setting of [14].

B. Baselines

The baseline solutions are as follows:

SVR. We feed the same features as our model into SVR. To involve the spatial correlation of each subregion, the prices of 8 neighboring regions are fed into the model.

VAR. Vector AutoRegressive is widely applied in forecasting housing price in city-level. For each subregion, we feed it with the same features as our models.

ST-ANN. The ST-ANN is fed with the spatial (8 neighboring regions' prices) and temporal (12 previous months' prices) features of each subregion. Besides, the same current ingredients and future expection are also considered.

Deep-ST. The DNN-based model has been widely used for spatial-temporal issues. We adopt it by the method suggested in [17]. And other factors are also considered in training.

ST-InceptionV4. InceptionV4 [18] has the same excellent performance as other deep networks on abundant datasets in image classification. We adjust the layers of network structure and feed it with the same features, to select optimal results to make comparisons.

ST-ResNet. ST-ResNet is firstly proposed for spatiotemporal crowd flows predictions [19]. Similar to InceptionV4, the popular model is compared with ours in the same condition.

[8]https://www.kaggle.com/ruiqurm/lianjia, https://su.zhuge.com
[9]http://www.stats.gov.cn/

TABLE II
COMPARISON WITH DIFFERENT BASELINES IN NYC

Model		RMSE
VAR		33.41
SVR		31.61
ST-ANN		30.59
Deep-ST+C+F		28.37
ST-InceptionV4+C+F		27.67
ST-ResNet+C+F		26.48
Ours	**FTD_DenseNet**	
D6-L9	Long-term+short-term DenseNet	25.45
D6-L9-F	Long-term+short-term DenseNet+F	23.47
D6-L9-C	Long-term+short-term DenseNet+C	24.26
D6-L9-C-F-no Fusion	Long-term+short-term DenseNet+C+F +without Fusion	24.50
D6-L9-C-F(short-term)	Short-term DenseNet+C+F	26.31
D6-L9-C-F (long-term)	Long-term DenseNet+C+F	25.67
D6-L9-C-F	Long-term+short-term DenseNet+C+F	**22.81**

TABLE III
COMPARISON WITH DIFFERENT BASELINES IN BEIJING

Model		RMSE
VAR		87.14
SVR		80.87
ST-ANN		79.53
Deep-ST+C+F		77.75
ST-InceptionV4+C+F		75.23
ST-ResNet+C+F		74.04
Ours	**FTD_DenseNet**	
D6-L9	Long-term+short-term DenseNet	69.01
D6-L9-F	Long-term+short-term DenseNet+F	65.72
D6-L9-C	Long-term+short-term DenseNet+C	67.69
D6-L9-C-F-no Fusion	Long-term+short-term DenseNet+C+F + without Fusion	68.34
D6-L9-C-F(short-term)	Short-term DenseNet+C+F	70.93
D6-L9-C-F (long-term)	Long-term DenseNet+C+F	72.45
D6-L9-C-F	Long-term+short-term DenseNet+C+F	**64.83**

C. Evaluation

1) Comparison with baselines based on datasets from both NYC and Beijing: We show the comparison results on NYC and Beijing datasets in Tables II and III, respectively. Also, we consider another 3 variants of FTD_DenseNet, by varying the number of layers and dense blocks and the inclusion of different features (i.e., current ingredients, or future expectations). We use C and F to represent the inclusion of current ingredients and future expectations. We use D and L to represent the number of dense blocks and the number of layers of a dense block, respectively. For example, D6-L9-F refers to a variant of FTD_DenseNet, which has the 6 dense blocks of 9 layers and is associated with future expectations as features. It can be observed that our method achieves the lowest RMSE, comparing with baselines. Particularly, in Table II, we find that D6-L9-C-F gets the best forecasting accuracy, which has a 19.83% lower RMSE value than the SVR method.

2) Impacts of components and features: From Table II and III, we then analyze the impacts of the proposed components. Firstly, as discovered, the long-term and short-term DenseNets decrease the RMSE by 8.6% and 11.3% respectively and independently. Also, the results show the importance of incorporation of different features. For example, in Table II,

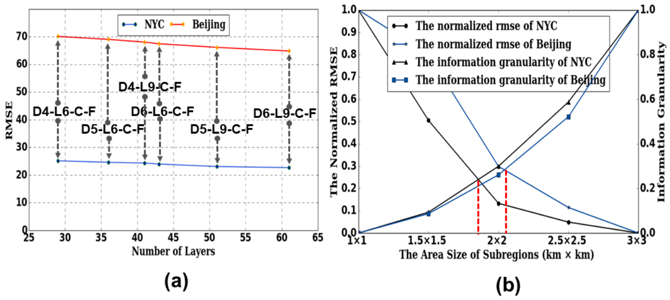

Fig. 5. Results of our FTD_DesNet.(a) RMSE of different structures.(b)RMSE and information granularity of different subregions

D6-L9-C-F has a lower RMSE value than D6-L9-C, which demonstrates the necessity of considering future expectations. Similar results can be observed for the effect of current ingredients. The current ingredients and KF components decrease the mean RMSE by 2.1% and 5.1% respectively. For D6-L9, the RMSE values of NYC and Beijing are 25.45 and 69.01 respectively, and it still outperforms other baselines. Similarly, we conduct the ablation studies to evaluate the effects of the proposed fusion method. The results on both datasets show that the fusion step can significantly improve the accuracy. For example, in Table III, D6-L9-C-F has 3.51% lower RMSE value than the one without fusion step.

3) Impacts of parameters: Furthermore, we test the effect of other parameters, such as the number of dense blocks and its layers. The result is shown in Fig. 5(a). X-axis refers to the total number of layers in the network. We can see with a larger number of dense blocks and layers, our model can learn more all-level features and thus better capture the spatiotemporal dependencies. The performance converges when the number of layers is greater than 61. But the computation overheads increase sharply with large number of layers. In our work, we find the D6-L9 setting best captures the tradeoff between the accuracy and efficiency and hence is used as our default setting.

The effect of subregion size is studied in Fig. 5(b). We find the balance point between the information granularity[10] and the normalized RMSE, and then select the best subregion.

V. Conclusion

In this paper, we propose an integrated forecasting model, FTD_DenseNet, for the urban subregion housing price prediction. FTD_DenseNet takes spatiotemporal dependencies, current ingredients, future expectations into consideration. Besides, we modify the structure of DenseNet and adopt the method of bagging by fusing the KF-based method to improve the accuracy. Experiments on two different real-world datasets have demonstrated that our proposed FTD_DenseNet outperforms existed baselines. Further, our model has the potential to be reapplied to other similar domains, such as air quality prediction and power demand prediction.

[10] We define it with the normalized number of average transaction records per square kilometer for measuring the data sparsity.

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