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Mobile Phone Price Prediction Model Based on Deep Learning

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Abstract. The task of mobile phone price prediction has high application value. It could help customers make more reasonable purchase decisions and help mobile phone manufacturers to better formulate pricing strategies. The study is focused on the application of deep learning models in smartphone price prediction, and expectation to obtain better robustness and prediction accuracy. Multi-Layer Perceptron (MLP), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU) and Transformer model are used to predict mobile phone prices. Weighted average algorithm is used to implement an ensemble model, in order to compare the performance of the ensemble model and the base model on this problem. According to the experimental results, MLP model and GRU model have lower errors and higher R2 scores, indicating that they perform best in this problem. Transformer model lies second, while overfitting occurs during the experiment. LSTM model performed the worst among all four models. Additionally, the study found that increasing the number of model layers leads to overfitting and a decrease in model performance. This study shows the potential of deep learning models in the task of mobile phone price prediction, and better performance of deep learning models could be expected on larger and more complex datasets.

1 Introduction

With the popularity of smartphones and the intensification of market competition, as well as the rising cost price caused by the increased integration of mobile phone hardware, the problem of mobile phone price prediction has become a popular research topic [1]. Predicting mobile phone prices precisely is of great significance to both consumers and manufacturers. According to research, apart from connectivity performance, the price of a mobile phone is the most significant factor customers consider when purchasing [2]. Customers can make more reasonable purchase decisions based on the price prediction results of the model, while mobile phone manufacturers can compare and weigh the factors such as manufacturing costs, pricing targets, and prices of similarly positioned products in the market [3]. Therefore, the use of price prediction models can better formulate pricing strategies and sale plans to achieve better customer satisfaction and greater market share [4].

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Traditional prediction models are mostly based on machine learning algorithms. H. T. Agalayil et al. studied the application of random forest, SVM, KNN, naive Bayes and gradient boosting classifier in mobile phone price prediction, and presented performances of different models in both classification and regression tasks of mobile phone price prediction [5]. R. Honey et al. studied the difference of performances between the decision tree model and the random forest model in the regression task of mobile phone price prediction [6]. In the task of mobile phone price prediction, Traditional machine learning models are limited due to the complexity of features, modeling ability and dynamic adaptability. Through automatic feature extraction and high-order mechanisms, deep learning models could retain better robustness and prediction accuracy as the number of features increases. Therefore, price prediction methods basing on deep learning have gradually become a research hotspot in the recent years [7].

This study focuses on the application of deep learning in the prediction of mobile phone prices. By inputting mobile phone information, such as the brand, model, RAM, storage, color, etc., the Multi-Layer Perceptron (MLP), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU) and Transformer models are used to predict the price of the mobile phone. By analyzing the RMSE, MAE and R2 Score of the results, the performance and characteristics of the model are evaluated, and an ensemble model is built using ensemble algorithm in order to explore a method to improve accuracy and precision of mobile phone price prediction.

2 Method

2.1 Dataset and data processing

The data set of this experiment originates from the Smartphones Price Dataset in Kaggle, which provides comprehensive information about smartphones that supports in-depth analysis of the specifications and prices of mobile phones. The data set contains a total of 1,816 data points, each of which corresponds to the specific information of a mobile phone, including name, brand, model, RAM, storage, color, whether it is attached to a cell company contract, and the final price, a total of 8 features. Table 1 below lists the variable types and specific meanings of the 8 feature values in the data set.

Table 1. Dataset Features

Features	Type	Description
Smartphone	**str**	Smartphone name as it appears in the marketplace
Brand	**str**	Smartphone brand
Model	**str**	Smartphone model brand
RAM	**int**	RAM in GB
Storage	**int**	Storage in GB
Color	**str**	Color name
Free	**bool**	Is/Is not attached to a cell company contract
Final Price	**float**	Price in the marketplace

In order to realize the price predicting function, the original data set needs to be processed to fit subsequent model training and prediction. Firstly, there are missing values in the data set, which are, after statistics, a total of 483 rows of data with missing values. Considering that the missing ratio is relatively large (26.60%), the missing rows are discarded and the missing values are not filled. Secondly, the final price of the mobile phone is set as the training label, and the rest of the information is set as the training feature. Non-numeric features are converted into floating-point types through label encoding, and the processed data is standardized to reduce the discrete degree between feature values, in order to improve the accuracy of prediction [8]. Finally, after completing the process aforementioned, the data is randomly selected from the data set and is divided into a training set and test set, with the proportion of training set being 80% and the proportion of test set being 20%.

2.2 Models

Based on the processed data set, MLP, LSTM, GRU and Transformer models are used to complete the task of predicting mobile phone prices. According to the characteristics of the obtained model performance, the ensemble model is implemented using the ensemble learning method, and the performance of the model is evaluated based on the prediction results and compared with the other four base models.

Loss function uses the mean square error (MSE Loss), and evaluation function uses the root mean square error (RMSE Loss) and the mean absolute error (MAE Loss).

$$MSE\ Loss = \frac{1}{n}\sum_{i=1}^{n}(y-\hat{y})^2 \tag{1}$$

$$RMSE\ Loss = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y-\hat{y})^2} \tag{2}$$

$$MAE\ Loss = \frac{1}{n}\sum_{i=1}^{n}|y-\hat{y}| \tag{3}$$

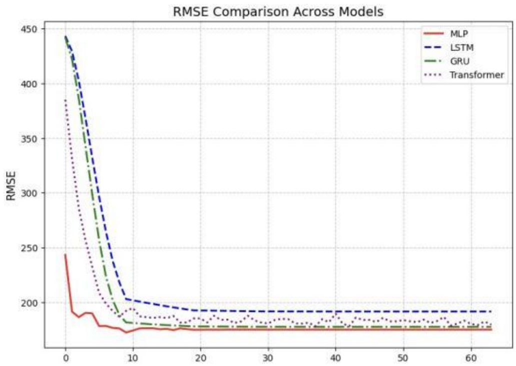
MSE Loss has a strong gradient orientation. By strengthening the penalty for predictions that deviate greatly from the true value, using MSE Loss as loss function could guide the update of model parameters more efficiently, especially in the early training stage to quickly reduce large errors; RMSE Loss retains the characteristic of MSE Loss being sensitive to large errors, reflecting the model's ability to handle extreme situations, while MAE Loss provides an intuitive assessment of the average error level [9]. Finally, the determination coefficient function R2 Score is used to evaluate the overall model performance:

$$R^2\ Score = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y})^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2} \tag{4}$$

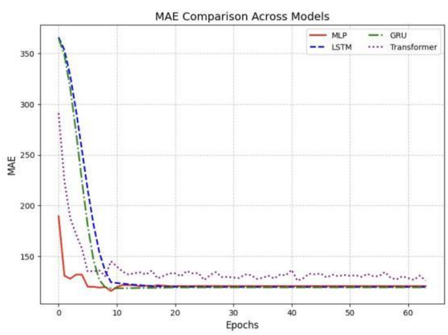
In the experiment, the learning rate was dynamically adjusted by using the learning rate scheduler. The learning rate started from a relatively high level and gradually decreased during the training process. It was reduced every few epochs to avoid overfitting and improve the accuracy of the model [10].

3 Results

The performance of the model is evaluated by calculating are RMSE and MAE. A lower error value represents greater prediction ability of the model. When the number of parameters is given, the prediction results of each model are shown in Fig. 1 (a) and Fig. 1 (b). According to the results, MLP, LSTM, GRU and Transformer models could all converge to a stable value after 64 iterations. After 10 iterations, the error values of the four models tend to be stable. Specifically, the RMSE of the MLP model is stable at around 175.00, which is the lowest among the four models; the MAE is stable at 120.98, which is one of the three lowest values between all four, indicating that the performance of MLP model is the best among the four models. The RMSE of the GRU model is stable at 177.57, and the MAE is stable at 119.74, indicating that the performance of GRU model is the second best among the four models. The RMSE of the LSTM model is stable at 119.52, which is the highest among the three models; the MAE value is stable at 120.09, which indicates that the performance of LSTM is not outstanding. The Transformer model showed a certain degree of overfitting, with the RMSE value fluctuating around 180 and the MAE value fluctuating around 128.



(a)



(b)

Fig. 1 (a): RMSE Loss(Photo credit : Original); (b): MAE Loss(Photo credit : Original)

The R2 scores of the four models are shown in Fig 2. The R2 Score of the models are basically consistent with the results obtained by the error function. The R2 Score of the MLP model is 0.518, which is the highest among the four models; the R2 Score of the GRU model is 0.504, which is the second highest among the four models; the R2 Score of the Transformer model is 0.492, which is slightly lower than the GRU model; and the R2 Score of the LSTM model is 0.423, which is the lowest among all four models.

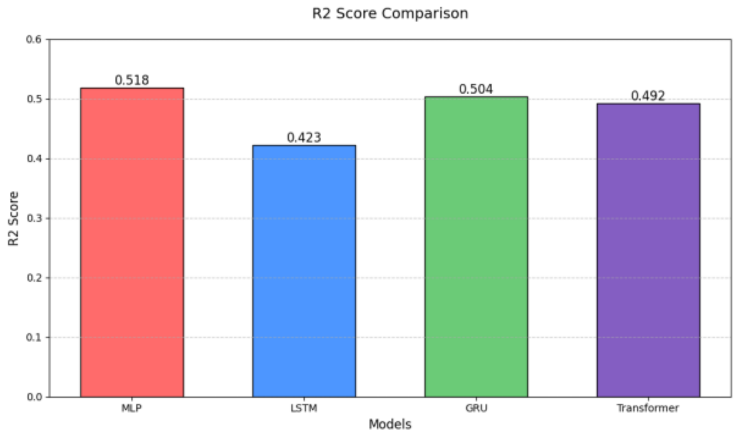


Fig. 2: R2 Score of the four models(Photo credit : Original)

Since the mobile phone prediction problem is not a complex regression problem and the scale of the data set is not large, the MLP model that contains a simpler structure could also achieve a good fitting result in this problem, and the prediction ability of the GRU model is also higher than that of the LSTM model; the Transformer model could capture the characteristics of the entire sequence due to its self-attention mechanism, thus it could represent a better performance in regression problems. However, due to its multi-attention head mechanism, its fitting speed is slower than the other three models, and could cause overfitting problem.

Due to the scale of the problem, when the number of layers of the MLP, LSTM, GRU, and Transformer models is increased, the performances of the models are affected to different degrees (Fig. 3). Without changing other parameters, for the LSTM model, GRU model, and Transformer model, increasing the number of layers leads to a decrease in the R2 Score and the fitting speed. For the MLP model, though the performance of the model is enhanced with the increase in the number of layers, overfitting also occurs during the training process. The reason why the increase in the number of layers leads to a decrease in performance is that the complexity of the model does not match the task requirements. In this experiment, a 1-layer network is sufficient to capture key patterns. Deeper layers will introduce redundant calculations and optimization barriers, resulting in a reduction in model performance.

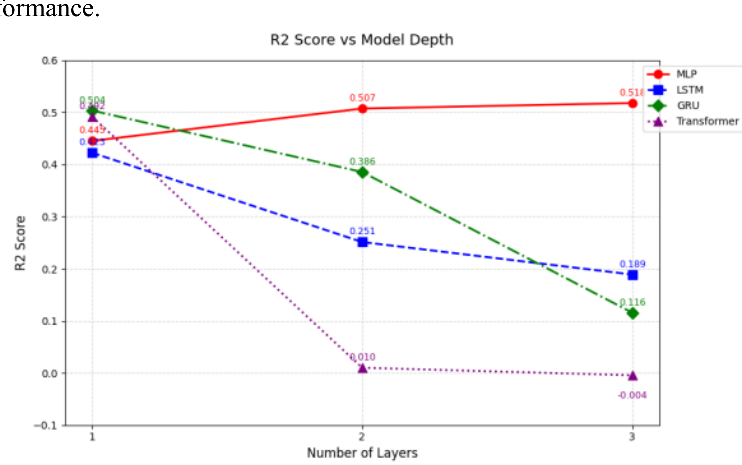


Fig. 3: The impact of number of layers on model performance(Photo credit : Original)

By comparing the prediction results of different models, combining the characteristics of MLP, LSTM, GRU and Transformer models, an ensemble model is realized through weighted average ensemble method. The performance of the model could be analyzed by comparing the R2 Score, as is shown in Fig. 4. Fig. 4 presents that the R2 Score of the ensemble model is higher than that of the other four models, reaching 0.564. The ensemble model could comprehensively utilize the characteristics of different models; thus, it could achieve better performance than the four models.

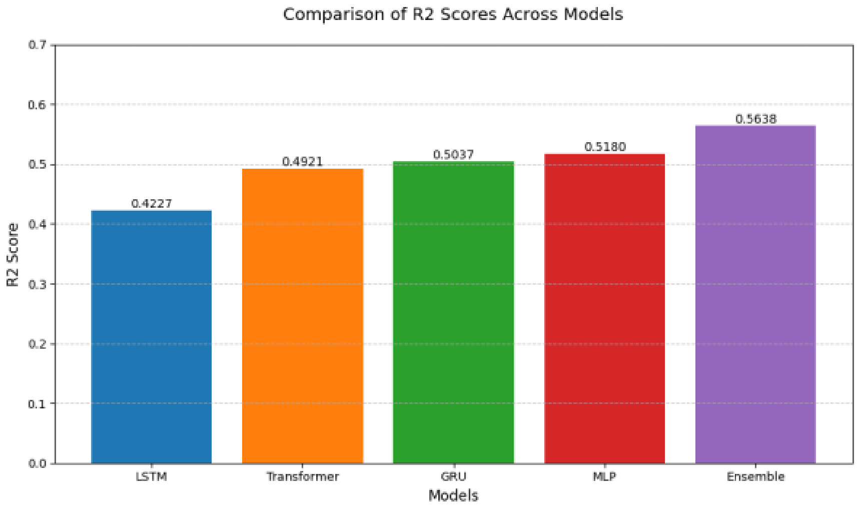


Fig. 4: Comparison between ensemble model and the other four models(Photo credit : Original)

There are certain limitations on the size of the dataset and the number of features, which leads to a negative growth in the performance of the models as the number of layers increases. Increasing the size and complexity of the dataset could make the problem more suitable for multi-layer neural networks. In addition, the type of models selected in the experiment is limited. For future research, more types of neural network models could be selected to analyze their application in the problem of mobile phone price prediction.

4 Conclusions

This study tested the performance of different deep learning models, such as MLP, LSTM, GRU, and Transformer in the task of mobile phone price prediction, demonstrating the potential of deep learning, especially ensemble learning, in improving prediction accuracy. The experimental results show that MLP and GRU have the most outstanding performances in the task of mobile phone price prediction, and are followed by Transformer, while the LSTM model has the least outstanding performance among the four models. Additionally, when selecting a model, the attribute of the problem and the scale of the data should be fully considered in order to match the complexity of the model with the complexity of the problem; a complex model may not achieve expected results on a relatively small data set.

In future research, increasing the size and diversity of the dataset may help improve the performance of the model. In addition, optimization and model fusion technology for deep learning models are still topics worth in-depth exploration. For example, combining other feature selection methods, and adding multi-angle and more complex factors, such as product images, user comments, and media public opinion, may enable the model to achieve better results in price prediction.

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