Melbourne housing market: Price modelling

ETC3555: Report

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14/10/2019

Introduction

This project looks at the feasibility of applying machine learning tools to the pricing of houses. We review and apply machine learning concepts through the lens of a dataset consisting of all privately sold houses in Melbourne between March 2016 and December 2018 with information on hedonic and structural characteristics. Our goal is to predict the sale price of a house, and performance will be benchmarked against an alternative, more simplistic, approach.

Section 1: Model

Model selection was born from discussion of our objectives, and consideration of our dataset.

The Learning Problem

For the problem of predicting house prices for private sales, a theoretical unknown target function exists, but we don't believe any practical target function exists. The simple rationale is that private sales are too heavily dependent on subjective characteristics of how the buyer buys, and how the seller sells, to be accurately approximated in any qualitative or quantitative sense. With this said, our unknown target distribution is therefore the best approximation to such an issue. In considering the modelling approach to take, we reflected on the real world application of such a tool. Presently, when houses are put up for sale they list with an expected range. Similarly, when houses are bid upon, they are done so with nominal amounts of money, such as $10,000 increments. Given such use cases it seems misguided to attempt to price a house at an exact dollar figure, and more sensible to attempt to classify house prices into ranges of prices.

After narrowing down our approach, we consider a neural net for the purpose of this project, and an appropriate benchmark model reflecting our need.

For the benchmark we considered the following models

- OLS Regression with range classification in post-estimation
- Decision Tree / Random forests
- Naive Bayes
- Multi-class logistic regression

OLS regression was ruled out for it's distributional assumptions which did not fit our dataset, and the desire to choose a model with inherent classification abilities. Naive Bayes was considered for it's ease of implementation and understanding, but ruled out for preference of a more complex model. The choice ultimately came down to random forests and multi-class, or multi-nomial logistic regression. The latter was chosen for it's relatively simple implementation, computational speed, and well documented success in multi-class classification.

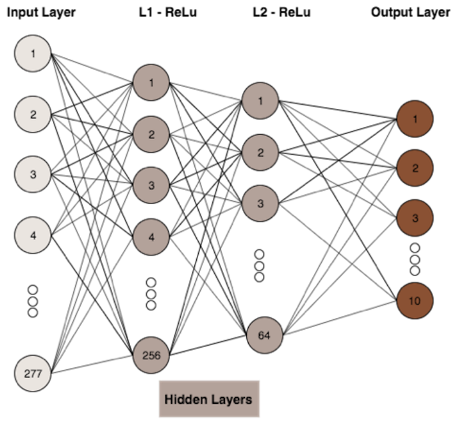

Figure 1: Neural network architecture.

For our neural net, the classification approach simplified things as we were familiar with its implementation from the lecture and tutorial material. The structure and considerations will now be introduced.

Kauko (2003) has provided an overview on current neural network application on predicting house price and introduced some advanced methods like self-organising map(SOM) and learning vector quantization (LVQ). However, there is no pre-trained architecture for house price forecasting and thus, we build our own two layer deep neural network from scratch. Due to the size of the data (48k observations with 277 features), the architecture is a deep neural network with two hidden layer. A graphic illustration of the architecture is shown in Figure 1. A three hidden layer architecture is also considered but due to the extra computational burden associated with training and hyperparameter training, it is not implemented in this project.

Dropout & Batch normalisation

Dropout is used to avoid overfitting of the model and the dropout rate is a tuning parameter in the grid serach, which will be elaborated in section 3. Batch normalisation is then performed before each dense layer. This process is necessary because it will normalise the extreme large values from the previous layer so that the training process can speed up. Batch normalisation is added after the dropout layer since it makes more sense to only normalise the neurals that will be supplied into the next layer.

To avoid overfitting of the data, several regularisation methods are used. Dropout rate is used before each dense layer. One thing to notice is that the dropout rate is added before the batch normalisation because otherwise the normalisation will be based on the full data while part of them will be dropped out before supplied to the next layer. Regularisation is also applied in each layer with learning rate being a hyper-parameter to tune.

Activation function

The activation function for the middle layers are relu function. This choice is made based on two considerations.

1) relu function produces zero output for negative input, this would be helpful to avoid overfitting because a proportion of the features will be set to zeros.

2) unlike tanh function that will saturate at asymptotic, which means the weight will not be updated much when the input neural has a large value, on the other hand, Relu function will will increase to infinity. This property of relu allows the relevant weight to be updated when the input gets larger. And

the potential drawback of getting extreme large output is overcame by batch normalisation discussed before.

The activation function for the final layer is softmax because this is the appropriate function for multi-level classification.

The activation function for the final layer is softmax as this is the appropriate function for multi-level classification as it bounds probability ranges between 0-1, and the sum of probability for inclusion into each category will sum to 1.

L2 regulariser

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Loss function

The loss function used is the categorical cross entropy, which is the only option for multi-class classification.

Our hyperparameters were tuned for tuned for using grid-search, but due to computation issues stemming from the number of iterations the search had to perform we were only able to proceed half way through this tuning procedure. Discussion of the ranges tuned for each hypterparamter will be included in our experimentation section. As for the scaling of our model, we believe given a larger data-set the model would have actually performed better. We had a relatively small feature space to run a neural net, and loss and accuracy may have improved given this was expanded. Performance of the multinomial logistic regression would not be expected to have changed, but the computation time would have significantly grown.

Section 2: Experiment

Data

Our dataset was compiled by a user named ‘Tony Pino’ on kaggle. The data concerns Melbourne housing clearance data from March 2016 through to December 2018. It is important to note that the available datasets in this database were ‘Melbourne House Prices Less’ and ‘Melbourne Housing Full’, specifying a reduced and full dataset respectively. Our project looked only at the reduced dataset. Therefore an extension which will be touched on in the latter sections of this report will discuss the changes in results had we used the full dataset.

Our dataset contained information on 63,013 house sales scraped from publicly available results posted every week on Domain.com.au. The dataset includes variables that detail the suburb, address, rooms, type of real estate, price, method of selling, seller-name, date, postcode, region, propertycount, distance from the CBD and council area. Given we are predicting house prices, the dependent continuous variable, y, defines the sale price of the house in AUD. Further details about the data set as well as some preliminary analysis are included in Appendix. Within our data the decision was made to exclude the seller-name on the basis that it was the individual agent’s name and thus irrelevant. This decision was made in error and discovered after our model had been run. The seller name is the name of the real-estate agency entrusted with the sale of the house, and thus contains relevant information to the sale price. Inclusion of this variable would have significantly increased our feature space and it is likely our model suffered from it’s exclusion. Thus this is a natural extension to our research.

Data Manipulation

We first convert our regression problem into a classification problem by transforming house price into 10 categories: (0, 100k], (100k, 300k], (300k, 500k] . . . (1500k, 1700k], (1700k, ∞) and this allows us to perform neural network on a multi-class classification problem, which is much easier than prediction. Our motivation for this is also because houses priced in the millions often have _____ characteristics that. . .

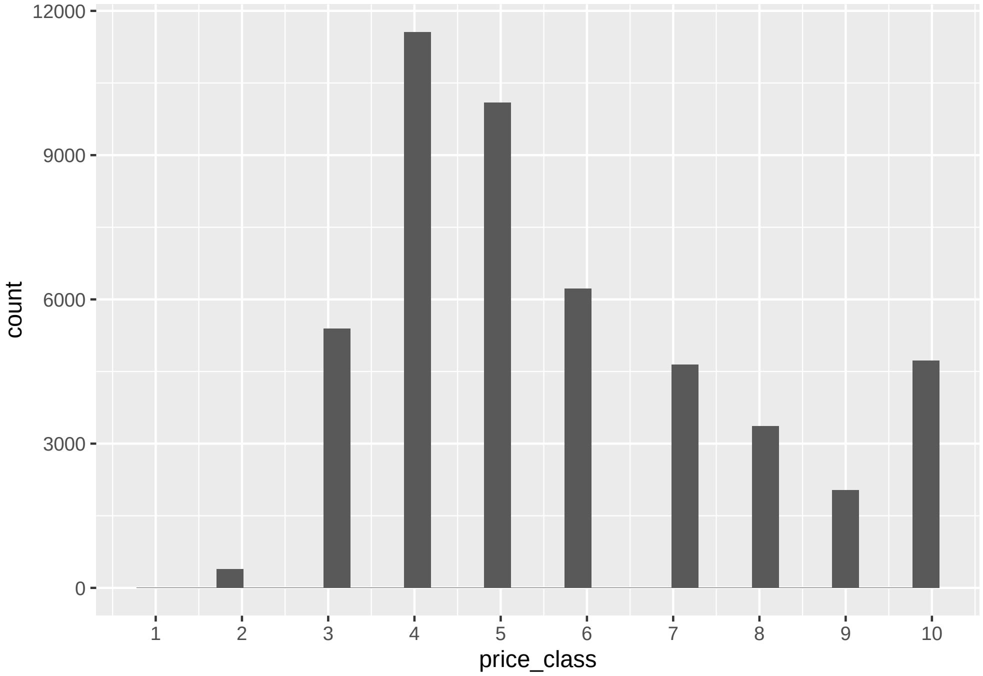
We seperate our dataset into a 90:10 training-test split. The training is done on the 90% of the data with 20% as validation set and the best model fit is then performed on the test set to get the accuracy result.

The data is first scaled and centred before sending into the neural network for training and normalisation is performed before each dense layer. This normalisation is necessary because it helps to speed up the converging process by normalising the extreme large value outputted from the previous layer.

We proceed by scaling and centering our data, transforming factors using one-hot encoding to increase feature space and allow our algorithm to improve in prediction, and we subset our data into sets of 90% training and 10% test.

Evaluation metric

The metrics for evaluation is the loss function rather than the accuracy result. This design is chosen as the house prices in our data are not evenly distributed among all the categories. We can see from Figure **??**, price class 4 (ranging from (500k, 700k]) has the most number of observation falls into while very few observations belong to category 1 or 2. If accuracy measure is used for evaluating the algorithm, it will be prone to predicting category 4 or 5 to achieve a higher accuracy result while not learn the data well. Therefore loss function, which evaluates the performance of the algorithm based on its score on categorical cross entropy, is a more reliable measure for our use case.



Optimization procedure

We considered three prominent gradient descent algorithms:

1. RMSProp
2. RGD with momentum
3. Adaptive Moment Estimation (Adam)

Adam is choosen as the optimiser for the project as it combines the strengths of RMSProp and momentum (Kingma, D et al).

In the optimisation procedure, we use `epoch = 500` and impose early stopping with `patience = 20` in our network structure. This design is chosen because it allows the algorithm to continue to update if necessary and a small epoch will force the algorithm to stop before it is fully updated.

Hyper-parameter tuning is utilised to find the best combination of parameters given the neurual network architecture defined. Due to the limitation of computational power, a small grid search is implemented with the grid value as shown in Table 1. Dense unit starts from 256 as the largest because there are only 277 variable in our feature space. In this project, we dont consider the architecture of first expanding the feature space and then reducing it. Zero is included in the dropout rate is because a RELU activation function would output zeros if the input is negative. This feature of RELU function can be viewed as working as dropout rate. Batch size is also included in the tuning parameter.

Table 1: The grid value of parameter used in hyperparameter tuning

Hyperparameter	Value
dense_unit1	(256, 128)
dense_unit2	(128, 64, 32)
dropout	(0,0.1, 0.2)
batch_size	(64, 128, 256, 512)
activation	(relu, tanh)

Section 3: Results and Discussion

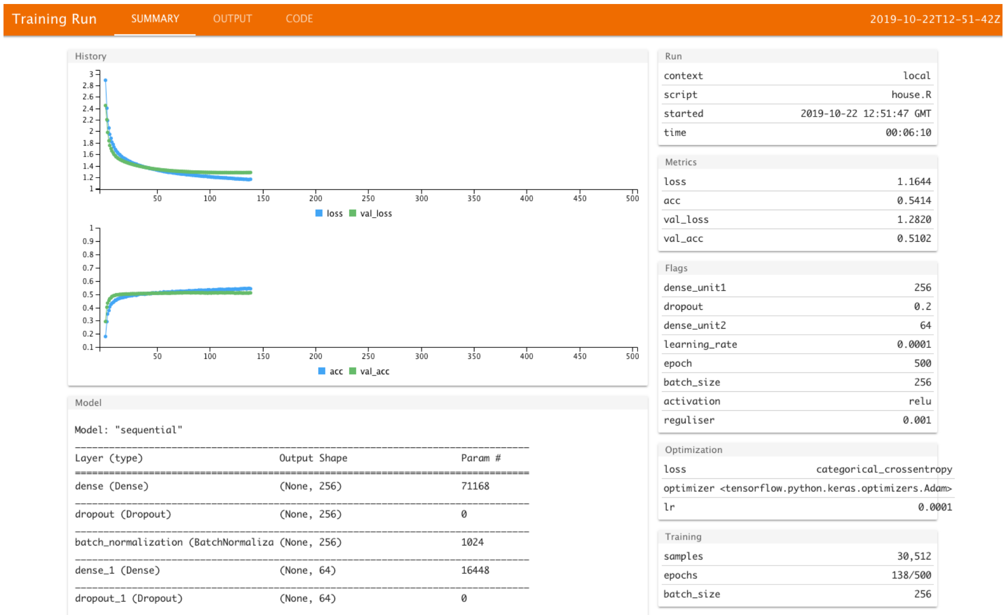
The hypterparameter tuning on the grid defined above is implemented through `tfruns` package. This package allows for organising the training parameters and evaluation results into a dataframe format and create a shiny app to view each training process. Figure 2 provides a screenshot of the best result from the training. The parameter assocaited with the best validation result is presented in Table 2

Table 2: Best parameters

Hyperparameter	Value
dense_unit1	256
dense_unit2	64
dropout	0.2
batch_size	256
activation	relu

This model is then performed on the test set and the prediction matrix is presented in Table **??**. The accuracy of neural network algorithm is 50%. The multinomial logistic model is also performedon the test set and the accuracy is 51%. Associated prediction matrix is presented in Table **??**.

```
predicted_class   2   3   4   5   6   7   8   9  10
              1   3   4   0   0   0   0   0   0   0
```



```
Model: "sequential"
________________________________________________________________________________
Layer (type)                        Output Shape                    Param #
================================================================================
dense (Dense)                       (None, 256)                     71168
________________________________________________________________________________
dropout (Dropout)                   (None, 256)                     0
________________________________________________________________________________
batch_normalization (BatchNormaliza (None, 256)                     1024
________________________________________________________________________________
dense_1 (Dense)                     (None, 64)                      16448
________________________________________________________________________________
dropout_1 (Dropout)                 (None, 64)                      0
```

Run	
context	local
script	house.R
started	2019-10-22 12:51:47 GMT
time	00:06:10

Metrics	
loss	1.1644
acc	0.5414
val_loss	1.2820
val_acc	0.5102

Flags	
dense_unit1	256
dropout	0.2
dense_unit2	64
learning_rate	0.0001
epoch	500
batch_size	256
activation	relu
reguliser	0.001

Optimization	
loss	categorical_crossentropy
optimizer	<tensorflow.python.keras.optimizers.Adam>
lr	0.0001

Training	
samples	30,512
epochs	138/500
batch_size	256

Figure 2: Screenshot of the training with the lowest validation loss.

```
  2  37 283 102   7   0   0   0   0   1
  3   0 216 816 295  27  17   7   3   3
  4   0  13 228 525 230  75  25  11  13
  5   0   1  17 146 233 139  56  21  16
  6   0   0   0  30  68 114  83  38  46
  7   0   0   1  14  32  74  80  46  44
  8   0   0   0   0   0   1   0   3   3
  9   0   0   0   5  17  42  89  87 356
```

```
pred   2   3   4   5   6   7   8   9  10
   1   0   0   0   0   0   0   0   0   0
   2   1   0   0   0   0   0   0   0   0
   3  35 263  93  12   1   1   0   0   1
   4   4 239 805 282  30  14   7   3   4
   5   0  14 246 532 237  93  25  11  14
   6   0   1  11 126 193 125  52  21  13
   7   0   0   2  38  82 107  77  28  32
   8   0   0   2  12  25  56  66  35  28
   9   0   0   0   0   0   1   2   4   1
  10   0   0   5  20  39  65 111 107 389
```

The neural network is not competitive as the multinomial logistic model from our result. Two reasons could explain this. Firstly. the faeture space (277 variables) of the current dataset is relatively small. This could cause we are not able to build more sophisticated neural network for it to work it magic. Also later we realise the `seller` variable is the name of the selling agency rather than the name of the individual seller. One may expect the selling price of a house could related to the selling agency and this variable could also be added into the neural network. Also there is a larger house price dataset in kaggle and it provides additional information related to the house.

The second reason is due to the limitation of computation power. There are still some parameters we are keeping constant through the hyperparameter tuning, for example, learning rate. There are also more activation function such as LeakyRELU that we could try to see if better performance can be achieved.

Section 4: Conclusion

This includes a summary of the findings.

Residential versus commerical buildings

Appendix

References

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