Melbourne housing market: Price modelling

ETC3555: Report

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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.

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.
We used two dense layers and optimized for node sizes for each. A dropout layer preceeding batch normalization to increase computation speed. Activation functions considered were Relu, Leaky-Relu, and Tanh for hidden layers, the latter to review the effect of both allowing negative inputs to remain negative, and Relu for the simple reason that it doesn't activate all neurons at once allowing for faster computation. Leaky-Relu was considered for ???????. Softmax was used for our final layer because ????? We used L2 regularization on both layers to prevent overfitting of our training data. We implemented early stopping as an additional form of regularization to prevent overfitting and allow for faster computation. The target value was loss over accuracy to allow greater generalization onto our test set. We did not tune this parameter and patience was set to 20. For optimization we used ADAM as theoretically it encorporates both momentum and stochastic gradient descent, thus outperforming both alone.
For our loss function we naturally used classification cross-entropy loss. 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

The dataset contains information on 63,013 house sales scraped from publicly available results posted every week from Domain.com.au. The dataset includes variables that detail the suburb, address, rooms, type of real estate, price, method of selling, seller, date, postcode, region, propertycount, distance from the CBD and council area. The dependent continuous variable, y, defines the sale price of the house in AUD.

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.

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 **??**. 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.

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.

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.

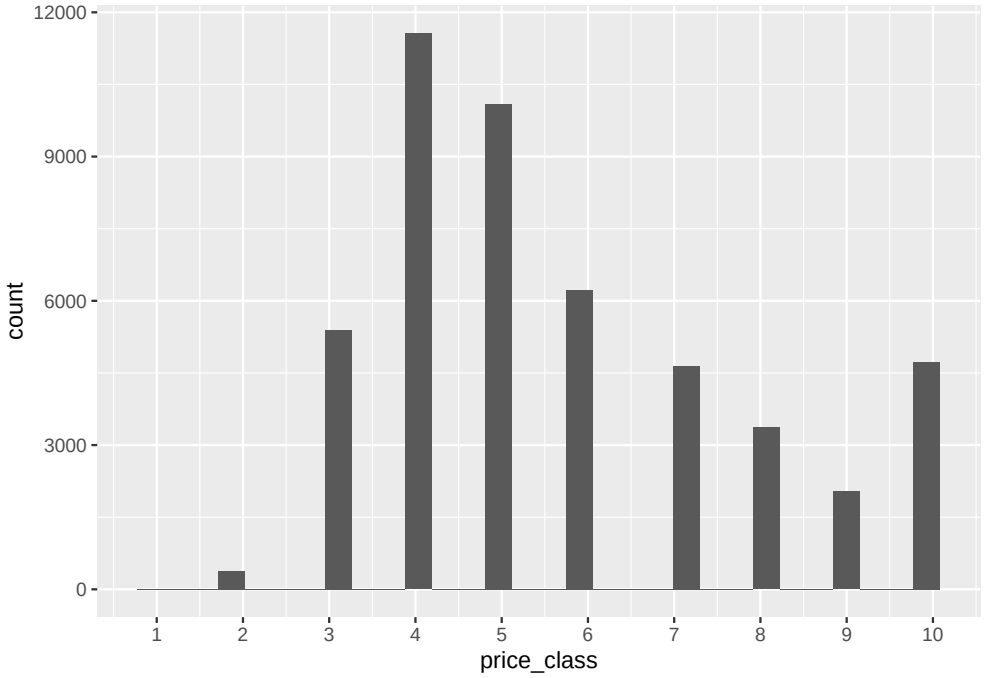
To avoid overfitting of the data, several regularisation methods are used. Dropout rate is used before each dense layer. One thing to notice is that the dropout rate is added before the batch normalisation because otherwise the normalisation will be based on the full data while part of them will be dropped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

Early stop is also used to allow for more efficient updating on the parameter. We set epoch at a large fixed value of 500 and use `patient = 20` in the early stop in our model structure. This design allows the neural network to keep updating if needed while not wasting omputational power and time when the updates become slow.

The optimisation is done with an ADAM optimiser. Different optimiser such as RMSPROP or RGD could be used for tuning while theoratically ADAM is believed to have better performance since it incorporates the momentum from RMSPROP to RGD The learning rate for ADAM is treated as a hyperparameter to tune.

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

The metrics for evaluation is the loss function rather than the accuracy result. This design is chosen because from the data, the house price is 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 prone to predict category 4 or 5 to achieve a higher accuracy result while not learn the data well. Therefore, loss function, evaluating the performance of the algorithm based on its score on categorical cross entropy is a more reliable measure.



We considered three prominent gradient descent algorithms:

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

From these, we select Adam as it combines the strengths of RMSProp and momentum (Kingma, D et al). Adam stores an exponentially decaying average of past squared gradients like RMSprop, while also keeping an exponentially decaying average of past gradients, similar to momentum (Heusel, M et al). Whereas momentum can be seen as a ball running down a slope, Adam behaves like a heavy ball with friction, which prefers flat minima in the error surface.

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 1 provides a screenshot of the best result from the training. The parameter assocaited with the best validation result is presented in Table 1

Table 1:

hyperparameter	value
dense_unit1	256
dense_unit2	64
dropout	0.2
batch_size	256
activation	relu

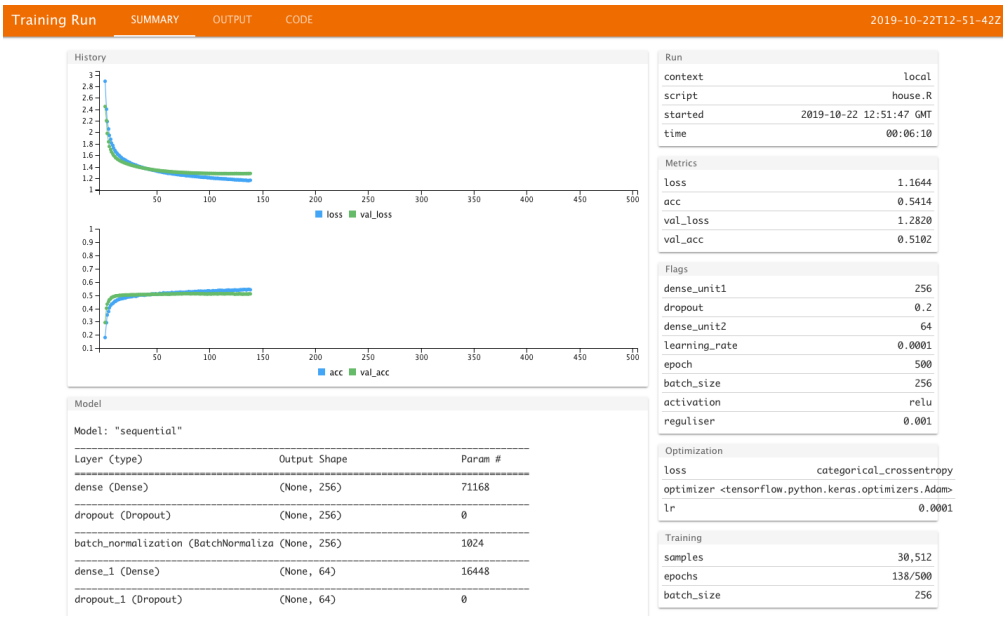


Figure 1: Screenshot of the training with the lowest validation loss.

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
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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