Price Predictions on Airbnb Accomodations in Oslo, Norway

Marei Freitag, Joel Beck

Georg-August-University of Göttingen

21.02.2022

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Introduction

Aims of this work:

- Establish a deep learning approach to predict the price of an Airbnb accomodation per night in Oslo, Norway
- Focus on explainability and interpretability

→ Underlying data: provided by Airbnb, contains various information about the listings in Oslo

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Feature Engineering: Images

- Use transfer learning on a pretrained CNN (`ResNet18`)
- Added Fully Connected Network at the end containing three layers and `ReLU` activation functions to be sure the CNN is able to generalize

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Results:

- Pretrained `ResNet18` achieved a Mean Absolute Error of 579 NOK (approx. 58 Euros) on the validation set
- For comparison: Null model has MAE of 630 NOK without log-transformation of the price and 569 NOK with log-transformation
- But correlation of the CNN predictions with the true price is 0.41

Image Predictions

Figure: CNN example predictions

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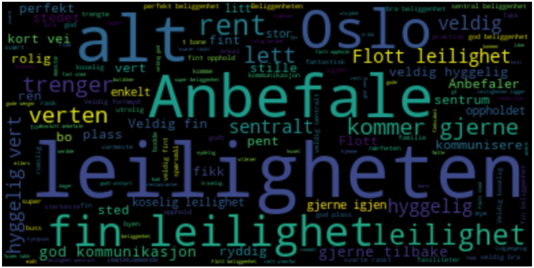
New features per listing:

1. Number of reviews
2. Median review length
3. Number of different languages of the reviews as well as a list of the different languages
4. Fraction of Norwegian and English reviews
5. Ratio of negative reviews to the total number of reviews

Wordclouds of the Reviews



Feature Selection & Data Cleaning

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Data Cleaning:

- Converting data types
- Splitting text-based variables into more convenient numeric or boolean features
- Aggregating rare categories of categorical variables into one larger *Other* group to stabilize estimation
- One-Hot encoding of categorial variables and standardization of numerical variables

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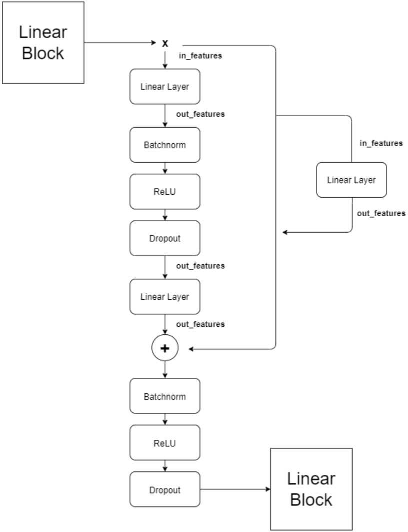
Classical Models

1. **Linear Regression**: simple, well understood in terms of underlying theory and highly interpretable.
2. **Ridge Regression**: still very interpretable with a closed form analytical solution
3. **Random Forest**: very flexible model, can be applied to many contexts and often works 'out of the box'
4. **Histogram-Based Gradient Boosting**: modern and fast tree-based gradient boosting algorithm; similar to Random Forest, but uses Boosting instead of Bagging

Neural Network: Model Architecture

- Linear input layer (about 60 features)
- 6 intermediary **blocks** with 64, 128, 256, 128, 64 and 8 output features:
  - Residual connection
  - Linear layer with BatchNorm, `ReLU` activation function and dropout
- 1 output neuron



Neural Network: Model Training

- Optimizer: `Adam` with learning rate set to 0.01
- Loss function: *Mean Squared Error* Loss
- Epochs: Number of epochs vary; stopped training if Loss stagnated or model began to overfit

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Most impactful hyperparameter: **Dropout rate**

- high influence of the network's generalizatioin availability
- model overfitted significantly by setting dropout rate to zero $\rightarrow$ that shows the current model structure is flexible enough to model the task properly
- increasing the rate leads to higher training MAE but also improves the model's performance on the validation set

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Evaluation Metrics

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- Focus on Mean Absolute Error and R^2 for higher **interpretability**
- Computations of MAE and R^2 on **original** price scale $\Rightarrow$ requires backtransformation of fitted values when using **log-price**
- Values depend on exact evaluation procedure, direct comparisons across groups have to be taken with care

$$MAE\left(\mathbf{y}, \exp\left(\widehat{\log(\mathbf{y})}\right)\right) \neq \exp\left(MAE\left(\log(\mathbf{y}), \widehat{\log(\mathbf{y})}\right)\right)$$

$$R^2\left(\mathbf{y}, \exp\left(\widehat{\log(\mathbf{y})}\right)\right) \neq R^2\left(\log(\mathbf{y}), \widehat{\log(\mathbf{y})}\right)$$

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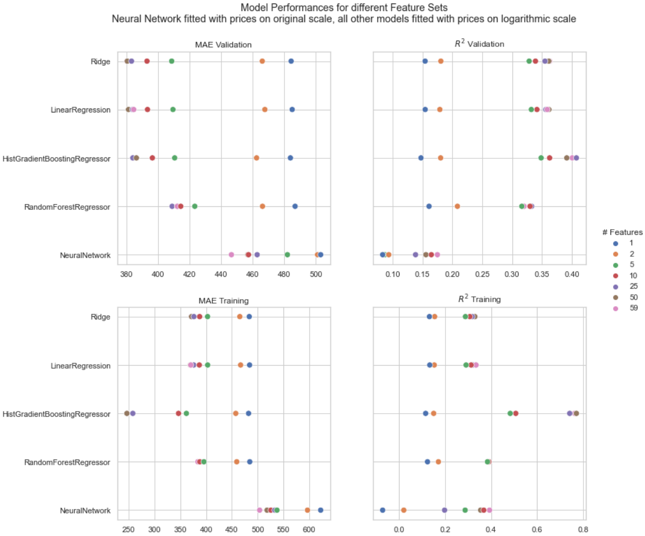
Training & Validation Performance



Main Findings

- More features tend to work better with diminishing returns (5 vs. all features)
- Price prediction task with small tabular data does not require overly complex models
  $\Rightarrow$ similar performance of linear and nonlinear classical models, linear models generalize better to validation set
- Neural Net: At first sight worst performance but best generalization
  $\Rightarrow$ Differing behaviour of *Dropout* and *Batchnorm* layers during training and inference + presence of outliers

Main Findings

- Without outlier removal we can expect a MAE of 400 NOK (40 Euros) and a R^2 value of around 0.4.
- Validation performance is biased towards models whose hyperparameters were tuned during cross validation

Test Set Performance

Model	MAE	R^2
Linear Regression	404.709	0.298
Ridge	405.932	0.294
Random Forest	444.166	0.268
HistGradientBoosting	412.243	0.387
Neural Network	402.24	0.333
Top2 Average	404.848	0.296
Top3 Average	399.315	0.343
Top4 Average	404.206	0.332
Top5 Average	408.116	0.27

Table: Test Set Performance of Classical Machine Learning Models, our custom Neural Network and Ensemble Predictions

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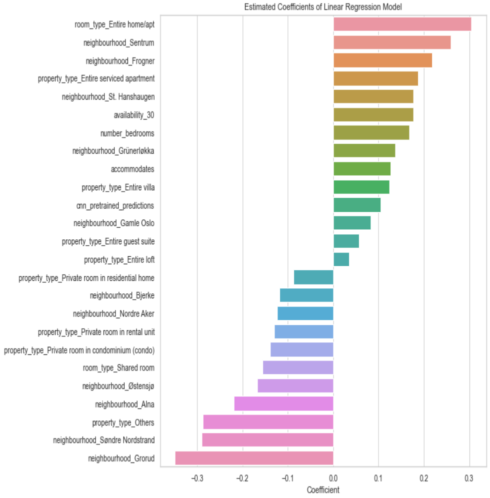
Feature Importance



- Largest (absolute) Coefficients: *room type*, *property type* and *neighbourhood*
- Top 2 by Feature Selector: *number of bedrooms* and *accomodates*
- Marginal vs. Conditional Impact (*Sentrum* neighbourhood)

Impact of Outliers

Quantile Threshold	MAE	R^2
0.0	443.35	0.16
1.0	337.59	0.51
2.5	282.17	0.53
5.0	240.57	0.54
10.0	214.76	0.49

Table: MAE and R^2 value of the Neural Network on the validation set

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- **Not** fixed by log-transformation!
- Explains performance boost of Neural Network from training to validation to test set

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- In theory the Neural Net should be flexible enough to approximate any arbitrary function reasonably well
- Why is it not able to capture entire price range?

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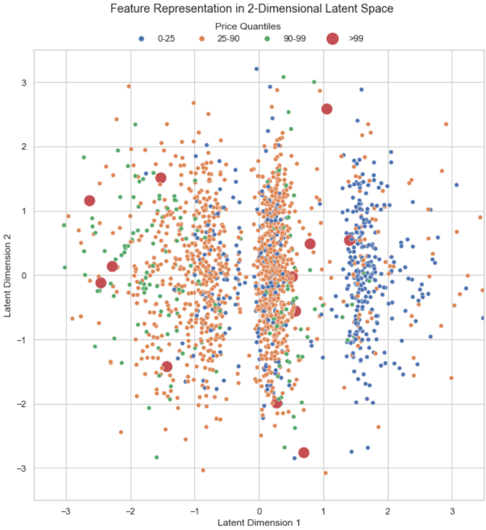
- In theory the Neural Net should be flexible enough to approximate any arbitrary function reasonably well
- Why is it not able to capture entire price range?
- Model only uses features during prediction
  $\Rightarrow$ To **discriminate** between outliers and non-outliers, the corresponding feature combinations must be **separable** in high-dimensional feature space
- Idea: approximate full feature space by two-dimensional **embedding**

Feature Space Embedding



Takeaways

- Why is there no separability?
  1. Data is not rich/expressive enough to capture all factors that contribute to very high prices
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- Why is there no separability?
    1. Data is not rich/expressive enough to capture all factors that contribute to very high prices
    2. Some apartments are listed at a price that does not represent their **true** value
- Can't we just remove those outliers?
    - Expensive, but **fairly priced** observations should be kept
      $\Rightarrow$ Might be contained in prediction tasks on new data, thus model should learn to handle those cases during training
    - Detecting (and removing) truly **overpriced** observations is difficult (many reasons for e.g. low demand)

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Munich - Predictive Performance

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- MAE of Neural Net on validation set from 44.3 Euros for Oslo to 42.5 Euros for Munich
- Gradient Boosting model with best test set performance: MAE of 32.8 (Oslo: 41.2) and R^2 of 0.453

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- MAE of Neural Net on validation set from 44.3 Euros for Oslo to 42.5 Euros for Munich
- Gradient Boosting model with best test set performance: MAE of 32.8 (Oslo: 41.2) and R^2 of 0.453
- Deeper/Wider architecture of neural net that is specifically designed for larger data set might lead to performance boost

Munich - Understanding & Interpretation

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- Most important features: *Property Type*, *Neighbourhood* and *Accomodates*
- Munich Data again contains large price outliers with high impact on the evaluation metrics

Quantile Threshold	MAE	R2
0.0	42.49	0.31
1.0	35.32	0.44
2.5	30.26	0.42
5.0	25.2	0.45
10.0	22.94	0.4

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Conclusion

- Linear Models show competitive predictive performance for small Oslo data
- Top 3 Ensemble leads to lowest test set error
- Large impact of outliers
- Extension to gain further understanding of the network's behaviour: *Adversarial Examples* in regression context
  $\Rightarrow$ Find small input **perturbations** which lead to spike in price predictions

References

Goodfellow, I. J., Shlens, J., and Szegedy, C. (2015).
Explaining and Harnessing Adversarial Examples.
arXiv:1412.6572 [cs, stat].

He, K., Zhang, X., Ren, S., and Sun, J. (2015).
Deep Residual Learning for Image Recognition.
arXiv:1512.03385 [cs].

Ioffe, S. and Szegedy, C. (2015).
Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift.
arXiv:1502.03167 [cs].

Kingma, D. P. and Ba, J. (2017).
Adam: A Method for Stochastic Optimization.
arXiv:1412.6980 [cs].

Kingma, D. P. and Welling, M. (2014).
Auto-Encoding Variational Bayes.
arXiv:1312.6114 [cs, stat].

Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., and Salakhutdinov, R. (2014).
Dropout: A Simple Way to Prevent Neural Networks from Overfitting.
Journal of Machine Learning Research, 15(56):1929–1958.

Thanks for listening!

Questions?