Price Predictions on Airbnb Accomodations in Oslo, Norway

Marei Freitag, Joel Beck

Georg-August-University of Göttingen

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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

$\rightarrow$ 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`) with the first 5 images per listing as input data
- Added Fully Connected Network at the end containing three layers and `ReLU` activation functions to be sure the CNN is able to generalize
- Also implemented CNN manually as a benchmark model to compare the results

Results:

- pretrained `ResNet18` achieved a Mean Absolute Error of 579 NOK (approx. 58 Euros) on the validation set
- But correlation of the CNN predictions with the true price is 0.41

Image Predictions

Figure: CNN example predictions

Feature Engineering: Reviews

- Language: Detect language of each review
- Sentiment analysis: Get the sentiment of each review

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

Figure: Wordclouds in English and Norwegian

Feature Selection & Data Cleaning

Feature Selection:

1. Manually selected features based on background knowledge, correlation analysis and the number of missing values
2. Adjusted these features by analyzing the results of different feature selection algorithms and fitted auxiliary linear regression

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; one hyperparameter
3. **Random Forest**: very flexible model with many hyperparameters determining e.g. the number of regression trees and the tree depth, but 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; large number of tunable hyperparameters

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

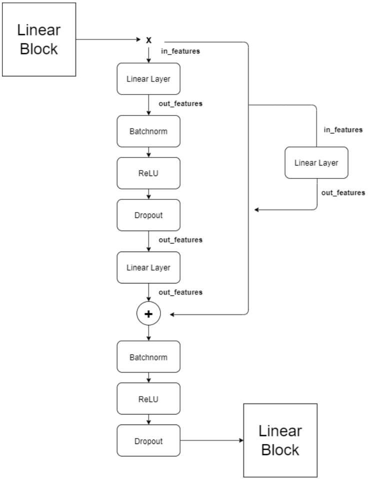

Figure: Linear Block in the FC-NN

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

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

- Mean Squared Error for *Training*
- Mean Absolute Error and R^2 for *Evaluation*
- When using log-price for model fitting, MAE and R^2 are computed on the *original* price scale for better interpretability of the MAE
- Note that both metrics highly depend on the exact evaluation procedure:

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

- Direct comparisons across groups have to be taken with care

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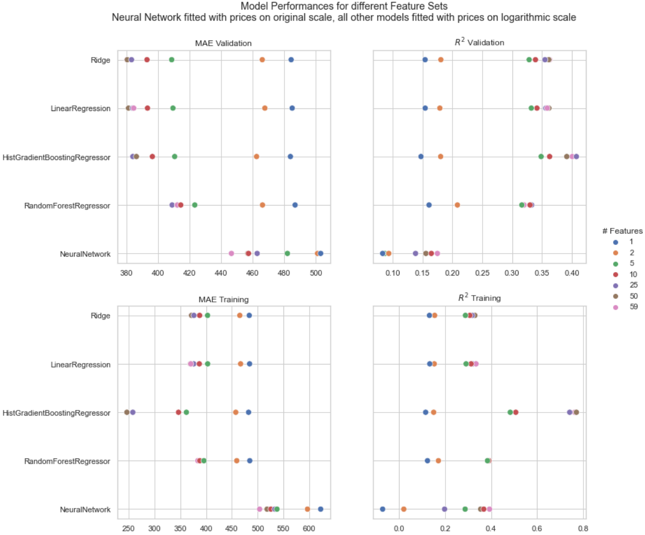
Training & Validation Performance



Main Findings

- More features tend to work better with diminishing returns (5 vs. all 59 features)
- Classical Models: Comparable performance of linear and nonlinear models, linear models generalize better to validation set
- Neural Net: At first sight worst performance but best generalization
- The latter can be explained by differing behaviour of *Dropout* and *Batchnorm* layers during training and inference as well as the presence of outliers (covered later)

Main Findings

- The price prediction task with our small tabular data does not seem to require overly complex models
- When including *all* observations (no outlier removal) we can expect predictions within a distance of roughly 400 NOK (40 Euros) on average to the true price and a R^2 value of around 0.4.
- Caveat: Validation erformance 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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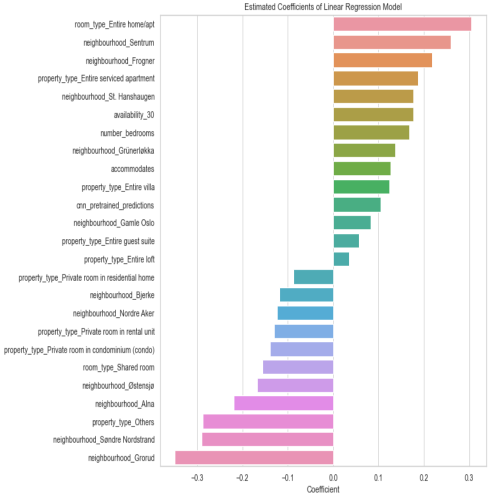
Feature Importance



- 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: Mean Absolute Error and R^2 value of the Neural Network on the validation set after removing the highest quantiles of the price distribution from the data set

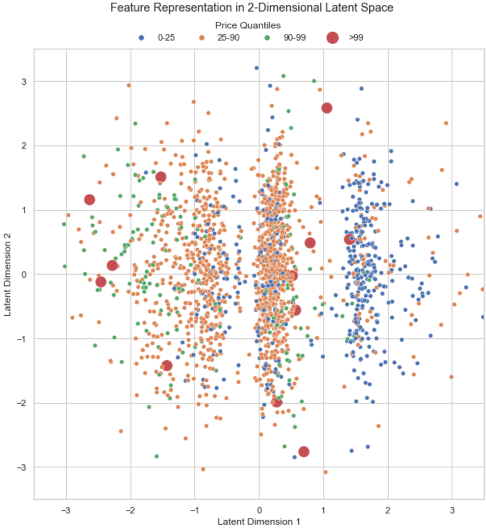
Impact of Outliers

- Price outliers single most influential factor of predictive power
- **Not** fixed by log-transformation!
- Explains performance boost of Neural Network from training to validation to test set
- Due to different sizes and randomness, training set contains the most outliers that drive the error metrics up whereas test set contains the fewest outliers
- Impact diminished for classical models due to cross-validation: Extreme outliers were contained in the validation fold *only once* out of multiple evaluations and metrics are averaged across all folds

Making Sense of the Data

- Neural Net clearly lacks ability to capture entire price range accurately
- However, in theory the model should be flexible enough to approximate any arbitrary function reasonably well
- Two possible explanations:
  1. The model is inherently flawed
  2. The model is faced with a nearly impossible task
- To discriminate the observations with the highest prices from the remaining ones, the corresponding feature combinations must be separable in feature space

Feature Space Embedding



Takeaways

- Two explanations for the lack of separability:
  1. The collected data is not rich or 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
- Latter case makes entire prediction task questionable: Implicit assumption that listed prices can be justified and explained by characteristics of the joint feature distribution
- How to detect truly overpriced observations?
- Model might face expensive but fairly priced observations on new data in production
  $\Rightarrow$ should learn to handle those cases during training
- Blind removal of outliers is difficult to justify and narrows down the set of feasible target distributions!

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Munich - Predictive Performance

- About twice as large as Oslo Data
  $\Rightarrow$ Flexible Models like Gradient Boosting and the Neural Network benefit most
- However: Overall Performance *not* significantly better than for Oslo Data
- Gradient Boosting model with best test set performance: MAE of 32.8, 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

- Most important features in Linear Regression: *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
- Possible extension to gain further understanding of the network's behaviour: *Adversarial Examples* in the regression context

Thanks for listening!

Questions?