Analysis on Clinical and Financial Data of Patients with a Certain Condition

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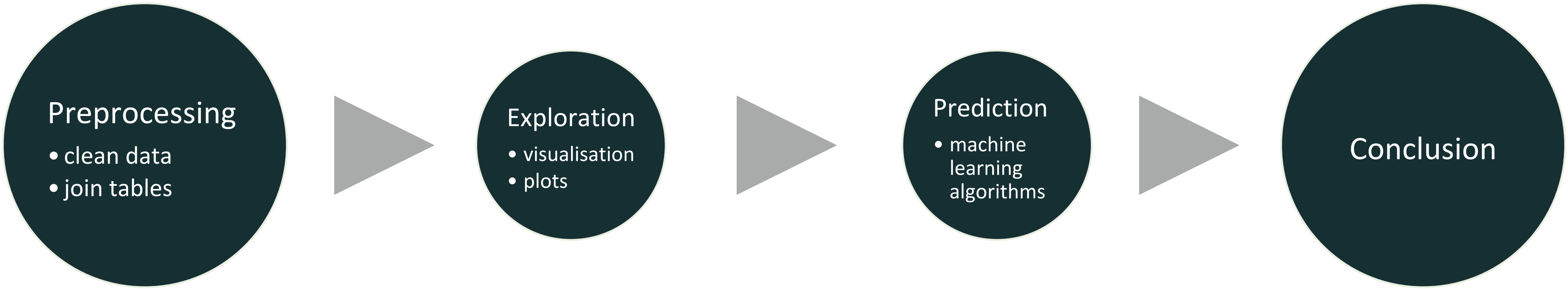
Analysis



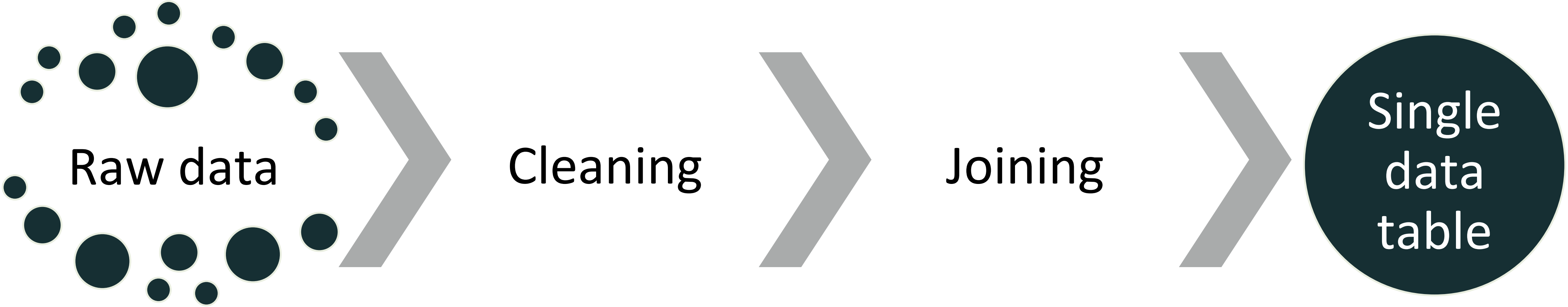
Preprocessing
- clean data
- join tables

Exploration
- visualisation
- plots

Prediction
- machine learning algorithms

Conclusion

Preprocessing



Raw data

Cleaning

Joining

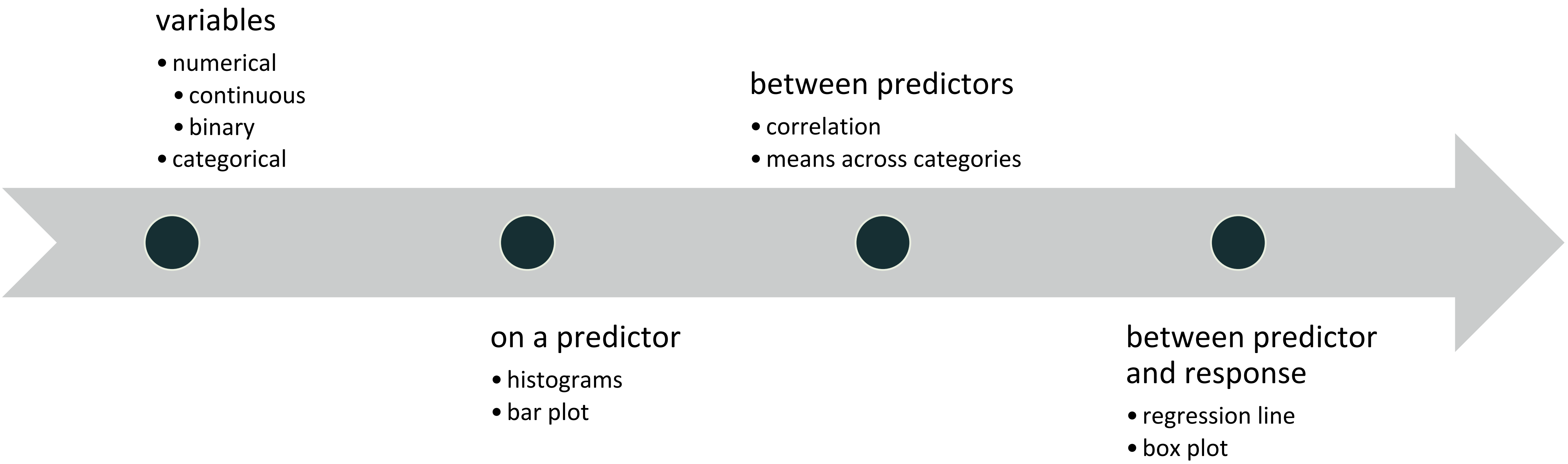
Single data table

- bill_amount
- bill_id
- clinical_data
- demographics

- inconsistent labeling
- wrong formats

- unnecessary information
- new variables

Exploration



variables

- numerical
  - continuous
  - binary
- categorical

on a predictor

- histograms
- bar plot

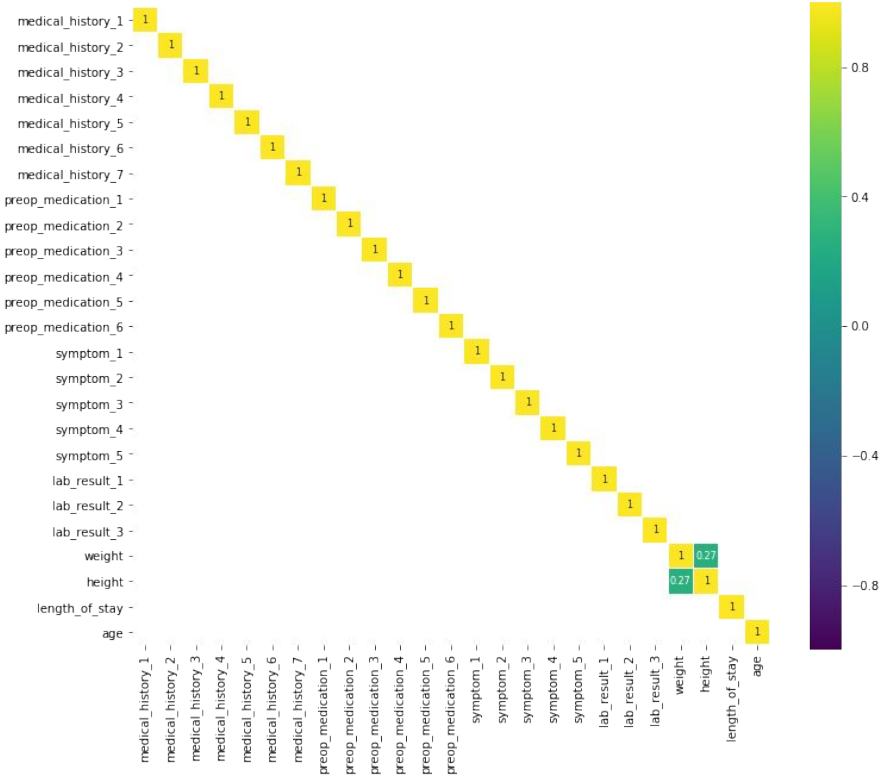
between predictors

- correlation
- means across categories

between predictor and response

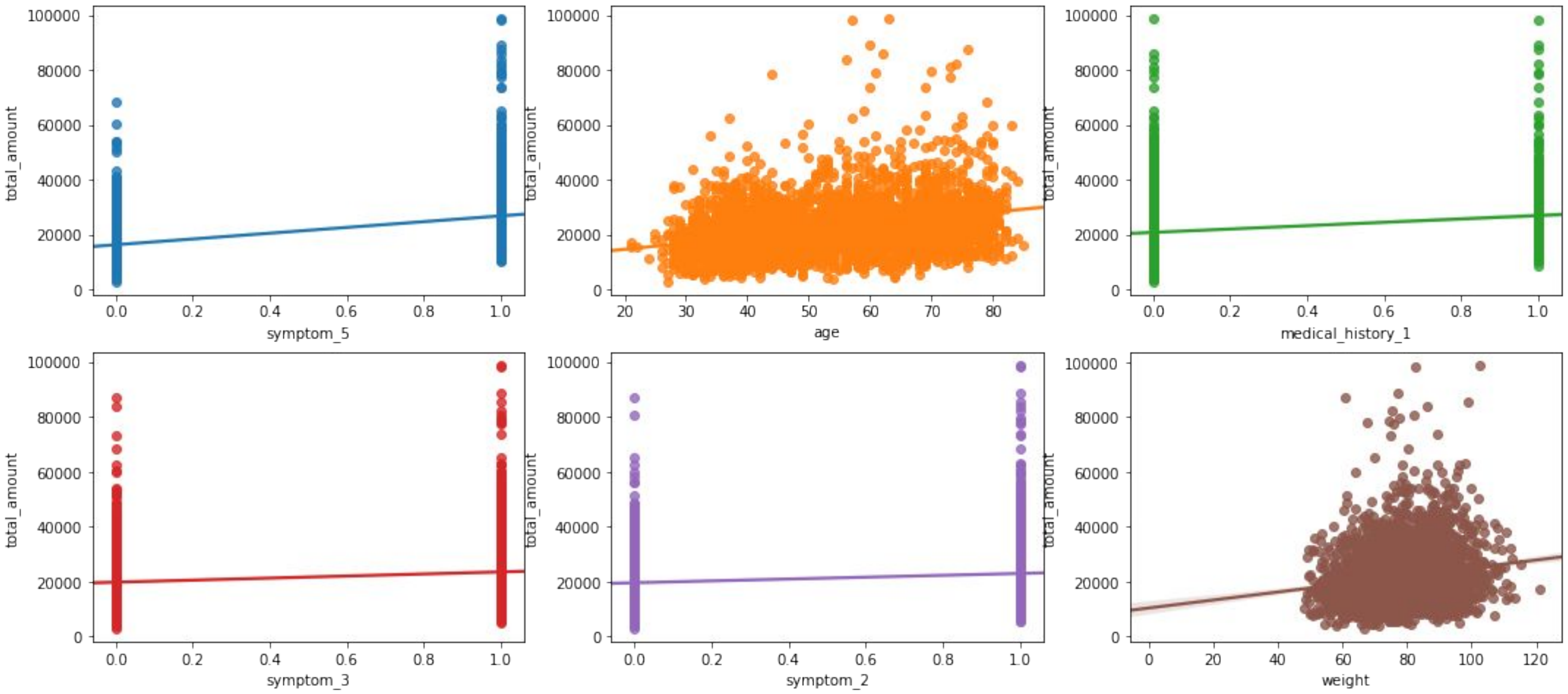
- regression line
- box plot

Exploration - numerical



Predictors are uncorrelated of each other. Only one predictor pair (weight-height) has correlation more than 0.05!

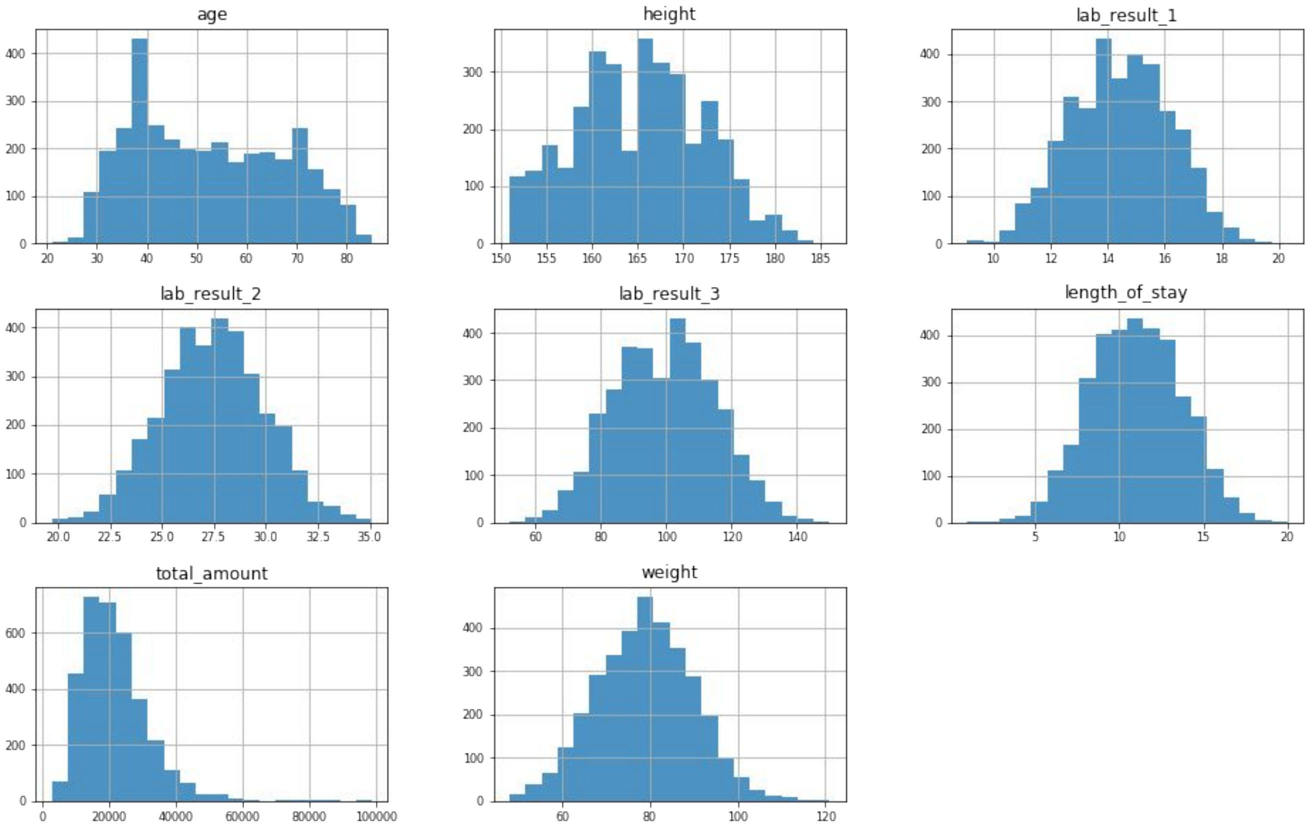
Exploration - numerical



Top 6 predictors with highest correlation with total_amount:

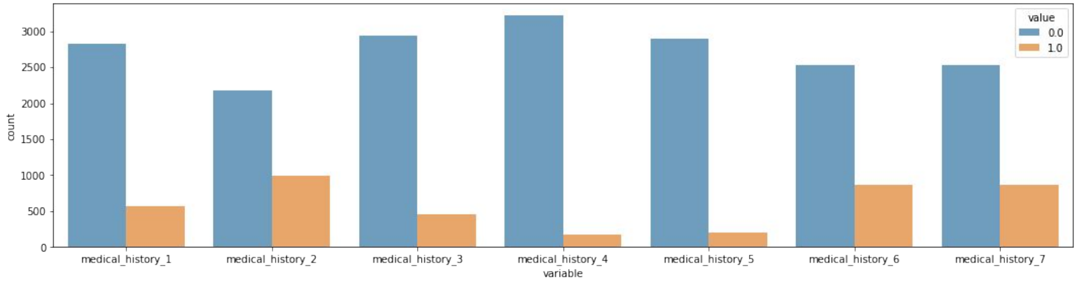
variable	**correlation**
symptom_5	0.517
age	0.326
medical_history_1	0.227
symptom_3	0.184
symptom_2	0.158
weight	0.158

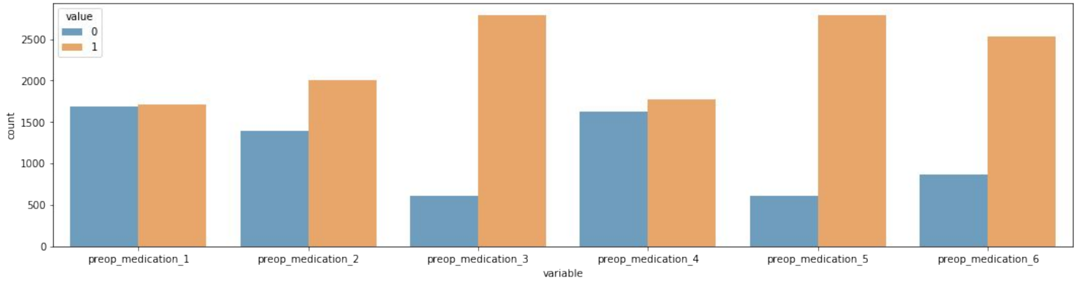
Exploration - continuous

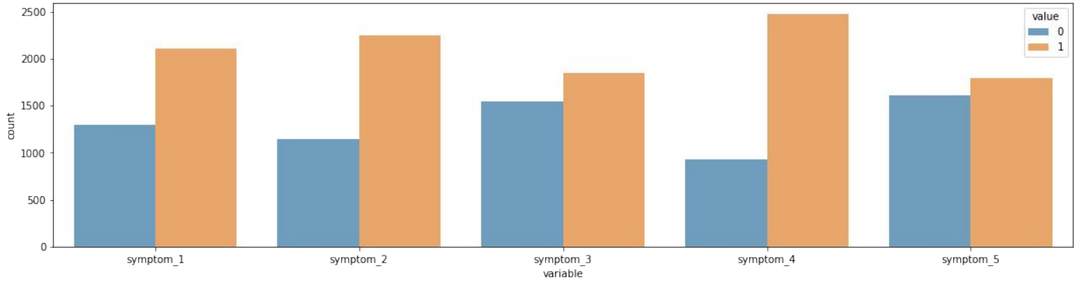


Most distribution have Gaussian shape, with some following bimodal distributions.

Exploration - binary





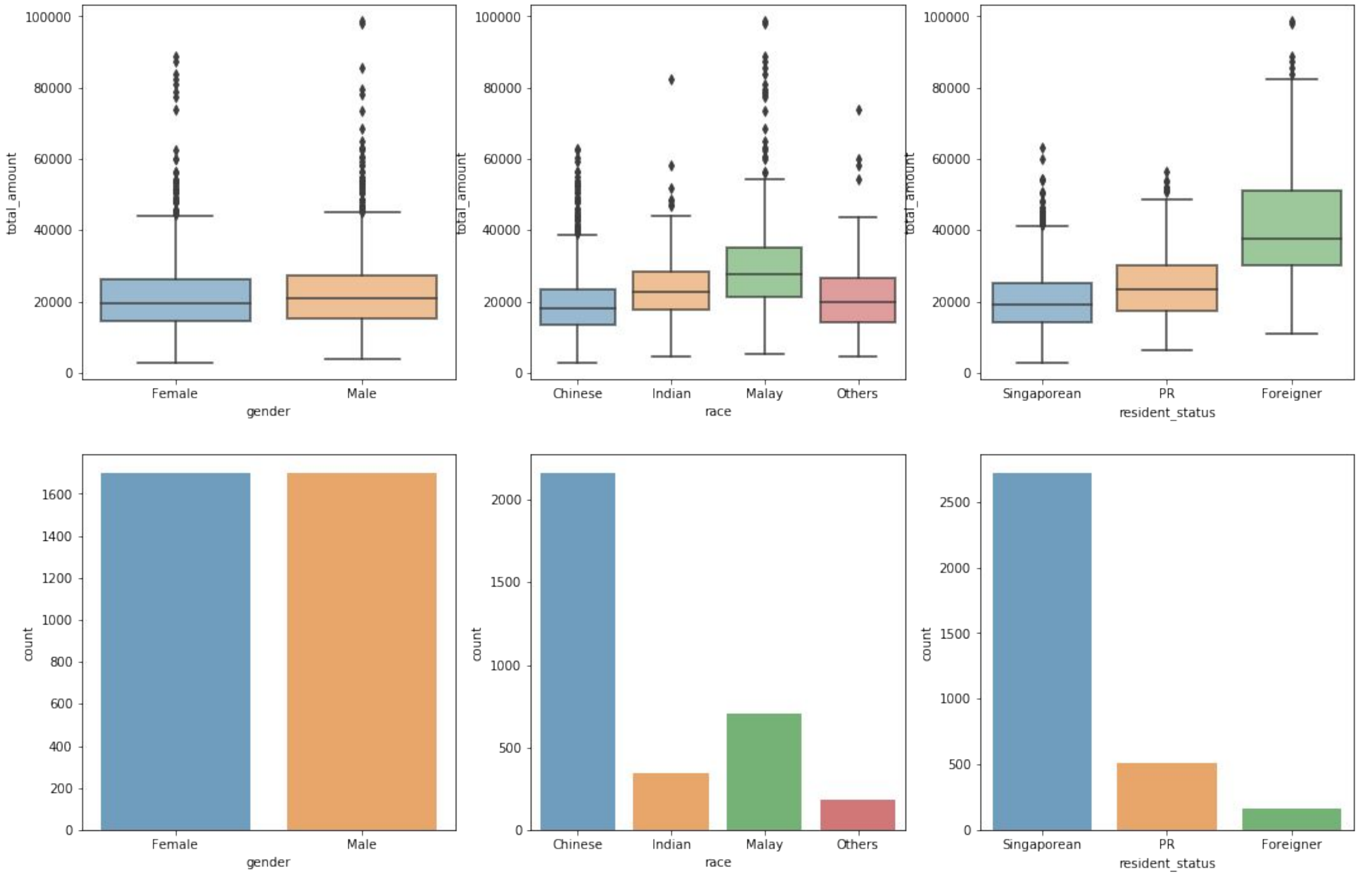


Medical history variables (top row) are unbalanced, but it is expected.

Patients under this condition are more likely to receive certain preop medications.

Some symptoms are more common than the other under this condition.

Exploration - categorical



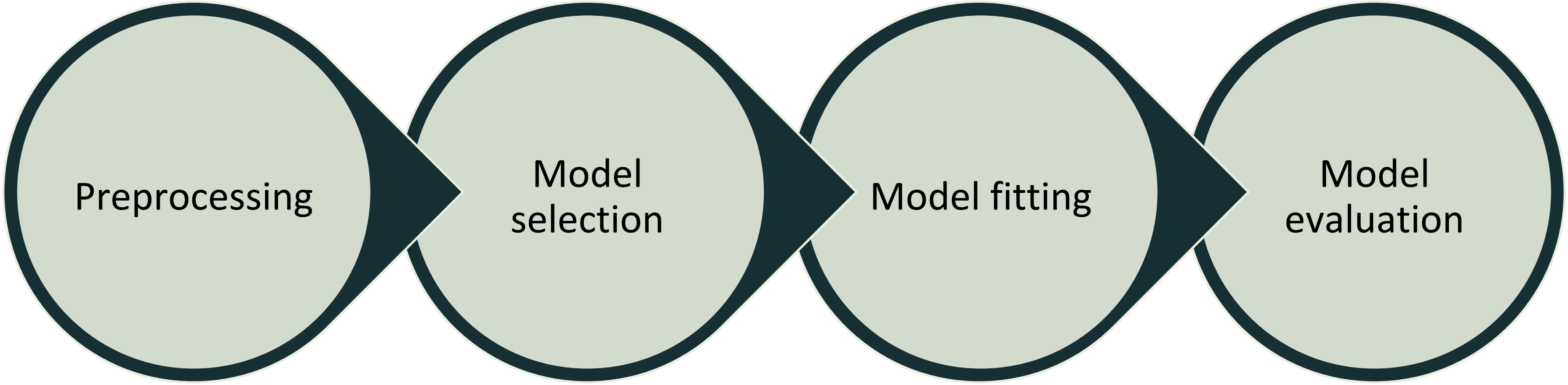
No difference in cost across gender. The condition also affects each gender equally.

Malays and Indians have higher cost. Does this condition affect them more?

Foreigners and PRs pay more than Singaporeans do.

race and resident_status are not distributed equally in our data.

Prediction



Preprocessing

- Variable standardisation
- Dummy variable encoding
- Missing data filling
- Train-test split

Model selection

- Linear regression
- Polynomial regression
- LASSO
- Regression tree
- Support vector regression
- Neural network

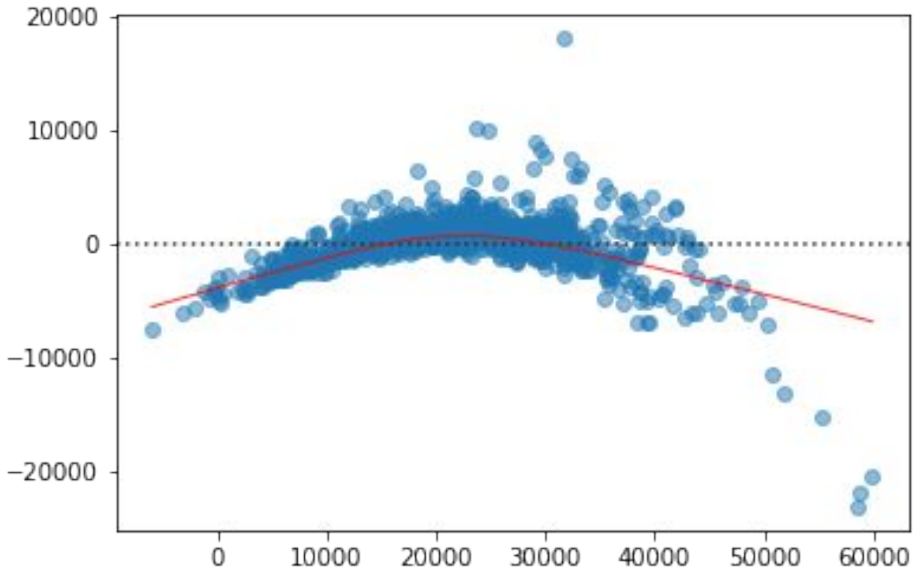
Model fitting

- Parameter tuning with cross-validation
- Model fitting

Model evaluation

- MSE
- Residual plot

Prediction – linear regression



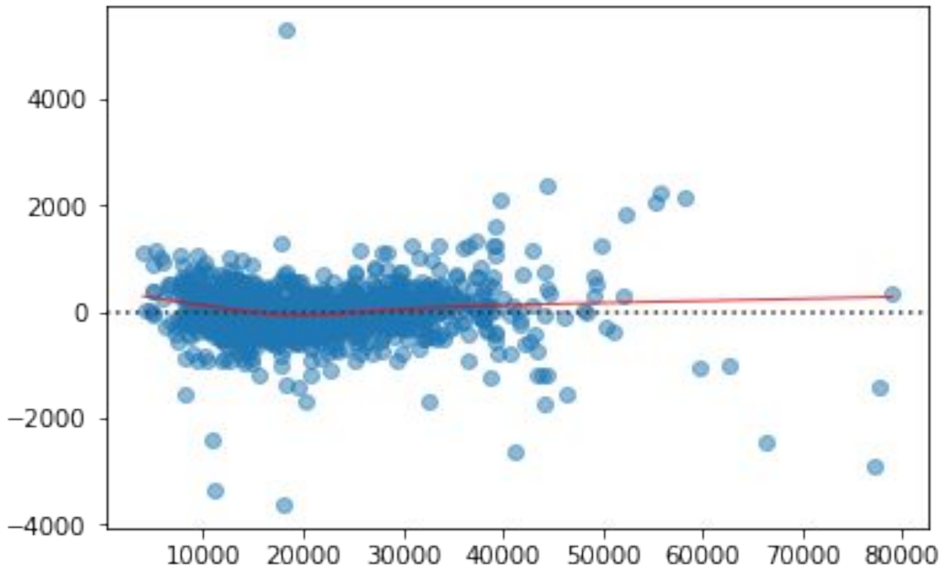
Baseline model

MSE = 2473.793

Important variables:

symptom_5, symptom_3, symptom_2
medical_history_1, medical_history_6
race and resident_status

Prediction – polynomial regression

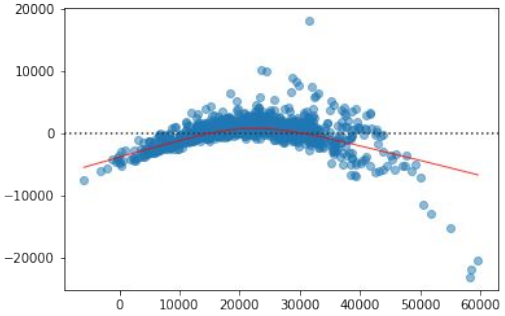


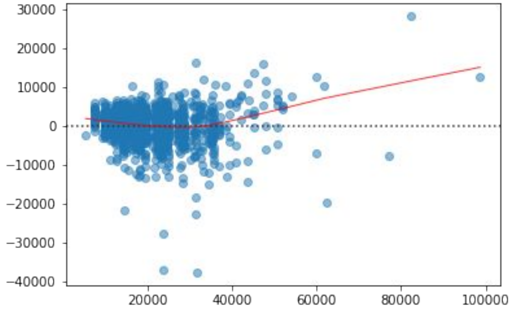
Best model

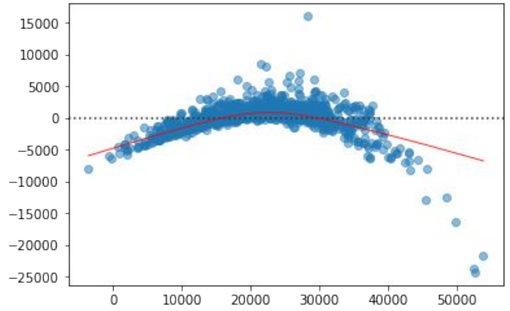
MSE = 520.633

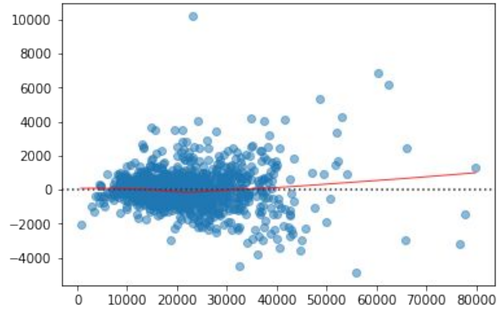
Higher performance, more variables. May be difficult to explain.

Prediction – other models









LASSO

- Small penalty from CV
- Similar to OLS

MSE: 2466.897

Regression Tree

- Worst model, even with deep tree

MSE: 4868.979

Support Vector Regression

- CV chose linear kernel
- Similar to OLS

MSE: 2555.064

Neural Network

- Better than OLS, but worse than polynomial regression

MSE: 1122.375

Conclusion

Important cost drivers

- symptom variables
- race, residential status
- age, weight
- some medical history variables

Less relevant variables

- preop medication variables
- lab results
- some medical history variables

Model selection

- simple models with regularized parameter perform poorly