



# **Feature Reduction**

Programming for Data Science

## **Evaluation of Predictors**



### **Problem: Overfitting**

- Predictor is optimized on training set (fine granularity of rules)
- Bad results on whole dataset/unknown observations
  - Quality of training set (noise, missing value, wrong values)
  - Different statistic properties of training and test set

### Problem: Underfitting

- Predictor is not optimized on training set (coarse granularity of rules)
- Bad results on whole dataset/unknown observations
  - Quality of predictor (dimensionality, parametrization)

#### Solution: Train-and-Test

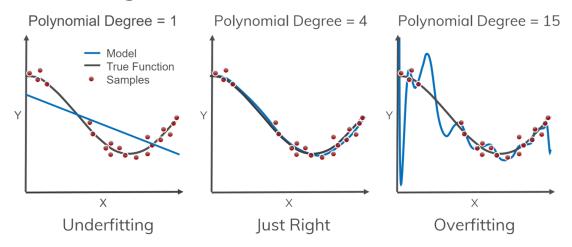
- Split data set X into two partitions
  - Training set: Classifier learns with these observations
  - Test set: Evaluation: Prediction of class labels and comparison with existing class labels
- Problem: Not applicable if training set is too small



# Evaluation of Predictors (2)



### Overfitting vs Underfitting



#### Occam's razor

- "Plurality must never be posited without necessity"
- A more general solution is always a better solution than a highly adapted solution



## Correlation-based Feature Selection



#### Correlated features do not add information.

• Given a regression  $y = a_1x_1 + a_2x_2$  where  $x_1$  and  $x_2$  are highly correlated.

$$\exists \gamma : x_2 \sim \gamma x_1$$

$$y = a_1 x_1 + a_2 (\gamma x_1)$$

$$y = (a_1 + a_2 \gamma) x_1$$

$$y = a_3 x_1$$

- Eliminate one of the correlated features.
- Highly correlated usually means |correlation| > 0.6
- 1. Find all (absolute) correlations between features.
- 2. Select the feature pairs with higher correlation than threshold.
- 3. Eliminate one of the features (Overall order is important.  $a \sim b$ ,  $b \sim c$  should remove b).

## Principal Component Analysis (PCA)



#### Transformation of correlated features to uncorrelated.

- Also used for dimensionality reduction.
- Based on eigenvectors

Target: T = XW, find W

Columns of W are the eigenvectors of  $X^TX$ 

If W is column-truncated  $T_p = XW_p$ ,

 $T_p$  is a reduced feature space (p-dimensional)



## Task



#### Step 0

- You will get a csv file from us. Load it in your language/environment.
- Explore the data in it. Identify features and labels.

### Step 1

- Split your data into training and test set. Use a ratio of 80-20.
- Use OLS to predict the labels. Report the MSE for training and test set.

#### Step 2

• Use Lasso regression to automatically reduce the feature space ( $\lambda = 0.1$ ). Report the MSE for the training and test set.

#### Step 3

- Implement a correlation-based feature selection\*. Use 0.6 as a threshold.
- Train OLS on the reduced feature space. Report the MSE for the training and test set.

#### Step 4

- Implement PCA\*. Transform your feature space to 2D.
- Train OLS on the reduced feature space. Report the MSE for the training and test set.



\*use your own implementation

# Package suggestions



#### R

- (data.table)
- glmnet
- stats

### python3

- numpy
- pandas
- sklearn
- (matplotlib)



## **Exercise Appointment**



### We compare and discuss the results

- Tuesday, 05.01.2021,
- Consultation: Please use the forum in Opal.
- Please prepare your solutions! Send us your code!

### If you have questions, please mail us:

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