

## SI 670 Notes

### *Suggested books*

- Introduction to Machine Learning with Python A Guide for Data Scientists By Andreas C. Müller and Sarah Guido
- Deep Learning with Python by Francois Chollet

### *Top libraries*

- Scikit-learn
- SciPy
- Numpy
- Pandas
- Matplotlib

### *Cycle*

- Feature representation
- Training
- Evaluation
- Refine cycle (hyperparameterization)

### *Data quality checks*

- Min/max summaries
- Wrong data type, units
- Equal class representation
- Outliers
- Data distribution
- Correlations among variables

## KNN Notes

### *Category*

- Supervised
  - Classification
  - Regression

### *High level algorithm*

Given a training set  $X_{\text{train}}$  with labels  $y_{\text{train}}$ , and given a new instance  $x_{\text{test}}$

1. Find the observations that resemble  $x_{\text{test}}$  that are in  $X_{\text{train}}$ . Call this set of observation(s)  $X_{\text{nn}}$
2. Get the labels of  $Y_{\text{nn}}$  for the instances in  $X_{\text{nn}}$
3. Predict label for  $x_{\text{test}}$  by combining the labels  $Y_{\text{nn}}$  (majority vote).

### *Parameters*

- Distance metric (Euclidian)
- Choice of k (k=1 very flexibel, k=100 rigid)
- Weighting function (neighbors that are far less influence on final prediction)

### *Evaluation*

- Accuracy (correctly predicted / total observations) (for classification)
- $R^2$  (for regression, measure how does the data fit the model 0-1)

### *Extras*

- Ensure that all observations are on the same scale
  - if not standardize them (standard scalar)

## **Classification**

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X_C1, y_C1, random_state = 0)
knnc = KNeighborsClassifier(n_neighbors = 5).fit(X_train, y_train)
print(knnc.predict(X_test))
print('Accuracy test score: {:.3f}'.format(knnc.score(X_test, y_test)))
```

## **Regression**

```
from sklearn.neighbors import KNeighborsRegressor
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X_R1, y_R1, random_state = 0)
knnreg = KNeighborsRegressor(n_neighbors = 5).fit(X_train, y_train)

print(knnreg.predict(X_test))
print('R-squared test score: {:.3f}'.format(knnreg.score(X_test, y_test)))
```

## **Linear Regression**

### *Supervised*

By now it should be clear that when we have a quantitative, or qualitative response, and we want to train a model and then predict new, unseen observations with our model we are in the world of supervised learning.

### *Assumption*

Now one of the main assumptions with this type of learning is that we expect the training data to have the same structure/relationships as the test data.

### *Linear Regression*

Is type of linear model in which we attempt to predict the target value (quantitative response) with a weighted sum of features (predictors). The usual formula is  $Y = b_0 + B_1X_1 + E$

- the goal is to minimize the residual sum of squares, which is the sum of the squared differences between  $y$  and  $y^{\wedge}$ , or actual minus predicted.

### Evaluation

- $R^2$ , a.k.a *coefficient of determination* measures how well a prediction model fits a determinate dataset. The value is between 0 & 1.
- Look at the distribution of the residuals. Are they constant, or is there some systematic bias?

### Cross-validation

It uses multiple test-train splits. Each split is used to train the model and get an error metric. At the end, an overall average is computed. This way we are able to get a more stable and realistic performance of our model.

- k-Fold CV, divide the dataset in k folds, run k models
- Stratified CV, so as to allow class proportions to be preserved in the splits.
- Leave-one-out CV, run n models

### Linear Regression vs KNN-Regression

Linear	KNN
few parameters	Non-Parametric
Small dataset	Large dataset needed
Generalizes beyond	Limited generalization

### Polynomial feature expansion

Generate new features consisting of all polynomial combinations of the original two features. The degree of the polynomial specifies how many variables participate at a time in each new feature. It is still a linear model, and can use same least-squares estimation method

Why?

- To capture interactions between the original features by adding them as features to the linear model.
- To make a classification problem easier

Pitfalls?

- Beware of polynomial feature expansion with high degree as this can lead to complex models that overfit

### Generalization

Refers to an algorithm's ability to give accurate predictions for new, previously unseen data

- Models that are too complex for the amount of training data available are said to overfit and are not likely to generalize well to new examples.
- Models that are too simple, that don't even do well on the training data, are said to underfit and also not likely to generalize well.
- Refer to bias-variance trade off for an indepth analysis of why over/underfitting happens

```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test =train_test_split(X_R1, y_R1, random_state = 0)
linreg =LinearRegression().fit(X_train, y_train)
print("linear model intercept (b): {}".format(linreg.intercept_))
print("linear model coeff (w): {}".format(linreg.coef_))
```