CHAPTER 2: SUPERVISED LEARNING

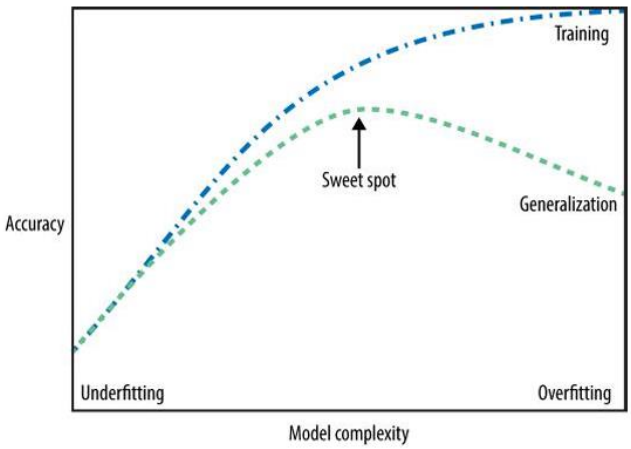
- Supervised learning is used whenever we want to predict a certain outcome from a given input, and we have examples of input/output pairs.

CLASSIFICATION AND REGRESSION

- Two major types of supervised learning: Classification and Regression.
- **Classification:**
  Goal: Predict a class label, which is a choice from a predefined list of possibilities (labels).
  Binary Classification: two classes. Yes/no questions.
  Example: Detecting spam emails.
  Multiclass Classification: more than two classes.
  Example: Iris species classification.
- **Regression:**
  Goal: Predict a real/continuous number.
  Example: Predict a person's annual income from their education, age, where they live,...
  Predict the yield of a corn farm from previous yields, weather, employees,...

GENERALIZATION, OVERFITTING, UNDERFITTING

- If a model is able to make accurate predictions on unseen data, it is able to ***generalize*** from the training set to the test set.
- **Overfitting** is when you fit a model too closely to the particularities of the training set and obtain a model that works well on the training set but is not able to generalize to new data.
- **Underfiiting** is choosing too simple of a model.



RELATION OF MODEL COMPLEXITY TO DATASET SIZE

- Having more data and building appropriately more complex models can often work wonders for supervised learning tasks.

SUPERVISED LEARNING ALGORITHMS

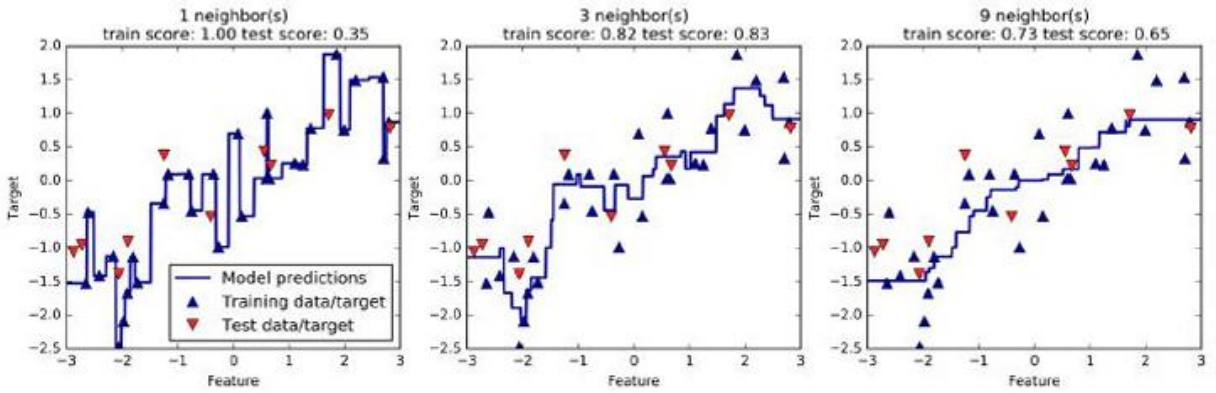
K-Nearest Neighbors

- To make a prediction for a new data point, the algorithm finds the closest data points in the training datasets – "nearest neighbors".

K-Neighbors classification

- Using few neighbors corresponds to high model complexity, using many neighbors corresponds to low model complexity.

K-Neighbors regression



Strengths, weaknesses, and parameters

- Two important parameters to the Kneighbors classifier: the number of neighbors and how you measure distance between data points.
- **Strengths:** + easy to understand
  + reasonable performance without a lot of adjustments
  + good baseline method to try before considering more advanced techniques.
  + train fast
- **Weaknesses**: + slow prediction for large training set.
  + need to pre-process data.
  + does not perform well on datasets with many features (hundreds >) or datasets where most features are 0 most of the time (sparse datasets).

Linear Models

- Linear models make a prediction using a linear function of the input features.

Linear models for regression

- General prediction formula: $\hat{y} = w[0] * x[0] + w[1] * x[1] + \ldots + w[p] * x[p] + b$
  x[0] to x[p] denotes the features (the number of features is **p**).
  w and **b** are parameters.
  Ŷ is the prediction the model makes.
  For datasets with a single features: $\hat{y} = w[0] * x[0] + b$ (equation for a line)
- Linear models for regression can be characterized as regression models for which the prediction is a line for a single feature, a plane when using two features, a hyper-plane in higher dimensions.

Linear regression (OLS)

- Linear regression finds the parameters w and b that minimize the mean squared error between predictions and the true regression targets, y, on the training set.
- The **mean squared error** (MSE) is the sum of the squared differences between the predictions and the true values.
- Linear regression has no parameters, which is a benefit, but also has no way to control model complexity.

Ridge Regression (L2 regularization)

- Same prediction formula used for Linear Regression.
- The coefficients **w** are chosen not only so that they predict well on the training set but also to fit an additional constraint.
- All entries of **w** should be close to 0. => small slope => each features have as little effect on the outcome as possible => **Regularization.**
- **Regularization** means explicitly restricting a model to avoid overfitting.
- Choose the Ridge model over Linear Regression model for better generalization performance.
- With enough training data, regularization become less important, and given enough data, ridge and linear regression will have the same performance.

Lasso (L1 regularization)

- The consequence of L1 regularization is that when using the lasso, some coefficients are exactly 0. => automatic feature selection => makes a model easier to interpret, reveal the most important features of the model.
- More regularized than Ridge.
- Ridge regression is usually the first choice between two models. If you have a large amount of features and expect only a few of them to be important, use Lasso.
  - ⇨ **ElasticNet** from Scikit-learn, combines the penalties of Lasso and Ridge, two parameters to adjust: L1 and L2.