

Data Science and Machine Learning in Python

Stephan Weyers

Part 1: Data Science

	Date	Topics covered
1	Apr 13 th	Course introduction Data Science motivation How to use Jupyter Notebook Python types and lists Loops, if/else, functions
2	Apr 20 th	Python tuples, lists, dictionaries Functions Numpy basics, operations Image processing
3	Apr 27 th	Pandas Series, DataFrame Pandas basic operations Import/export files
4	May 4 th	Principles of data visualization Data cleaning and preparation Join, combine and reshape data
5	May 11 th	Volkswahl Bund dataset Data visualization in Python How to write Data Science reports Data aggregation and grouping

Part 2: Machine Learning

	Date	Topics covered
6	Jun 1 st	Introduction to supervised learning Classification and regression scikit-learn k-Nearest Neighbors Linear regression (ridge and lasso)
7	Jun 8 th	Linear classification models Decision trees Random forests and gradient boosting Support vector machines Neural networks
8	Jun 15 th	Introduction to unsupervised learning Preprocessing and scaling Dimensionality reduction Principal component analysis
9	Jun 22 nd	k-means clustering Hierarchical clustering DBSCAN
10	Jun 29 th	Representing data Engineering features
11	Jul 6 th	Model evaluation and improvement Text data analysis

Agenda for online lecture 6

Session	Topic	Mode	Materials used	Minutes	End
14:30-16:00	Organizational questions	Q&A		10	14:40
	Supermarket exercise	Team work in break-out rooms	Lecture 06a notebook	40	15:20
	k-Nearest Neighbors	Lecture / Q&A	Lecture slides	15	15:35
	Linear regression	Lecture / Q&A	Lecture slides	20	15:55
16:10-17:40	Regression toy data	Lecture / Q&A	Lecture 06b notebook	20	16:30
	California housing data	Team work in break-out rooms	Lecture 06c notebook	45	17:15
	Recap W02 / W03	Lecture / Q&A		20	17:35
17:50-19:20	Teams W04	Lecture / Q&A		10	18:00
	Happiness data	Team work in break-out rooms	Lecture 06d notebook	80	19:20

Supervised Approaches

- Labeled data
- Target values known

Classification

- Predict category

Regression

- Predict numeric value

Unsupervised Approaches

- Unlabeled data
- No target value provided

Cluster Analysis

- Organize similar cases into segments

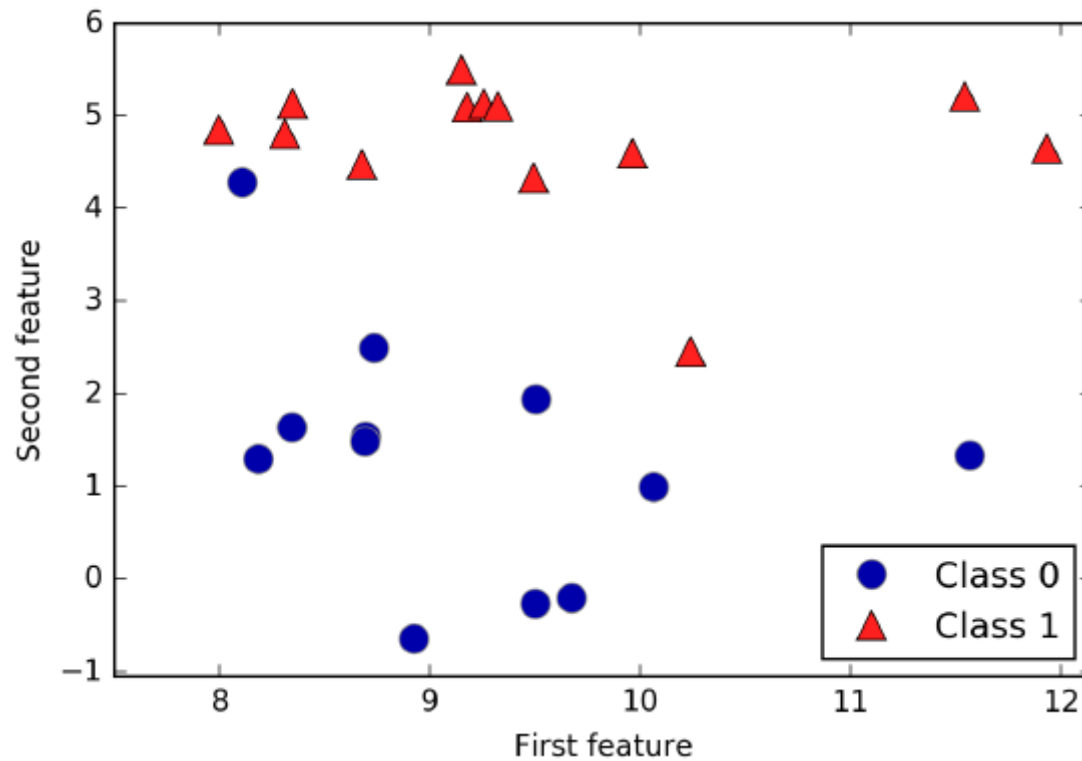
Dimensionality reduction

- Reduce number of features

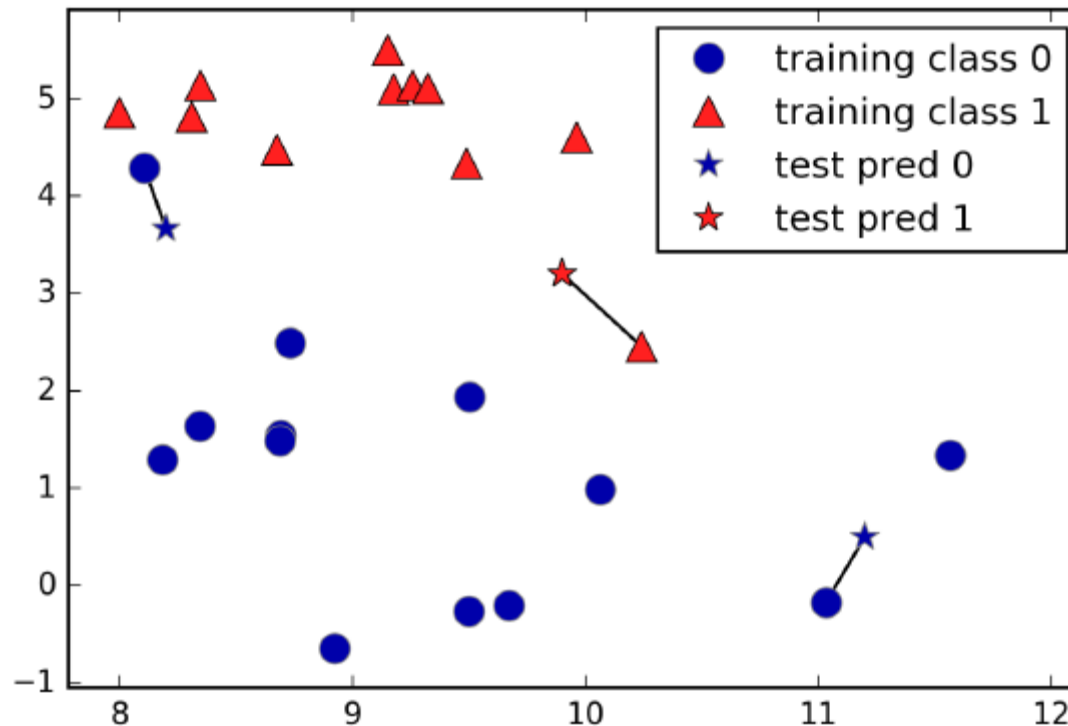
Question for discussion

- Find examples for each of the 4 categories

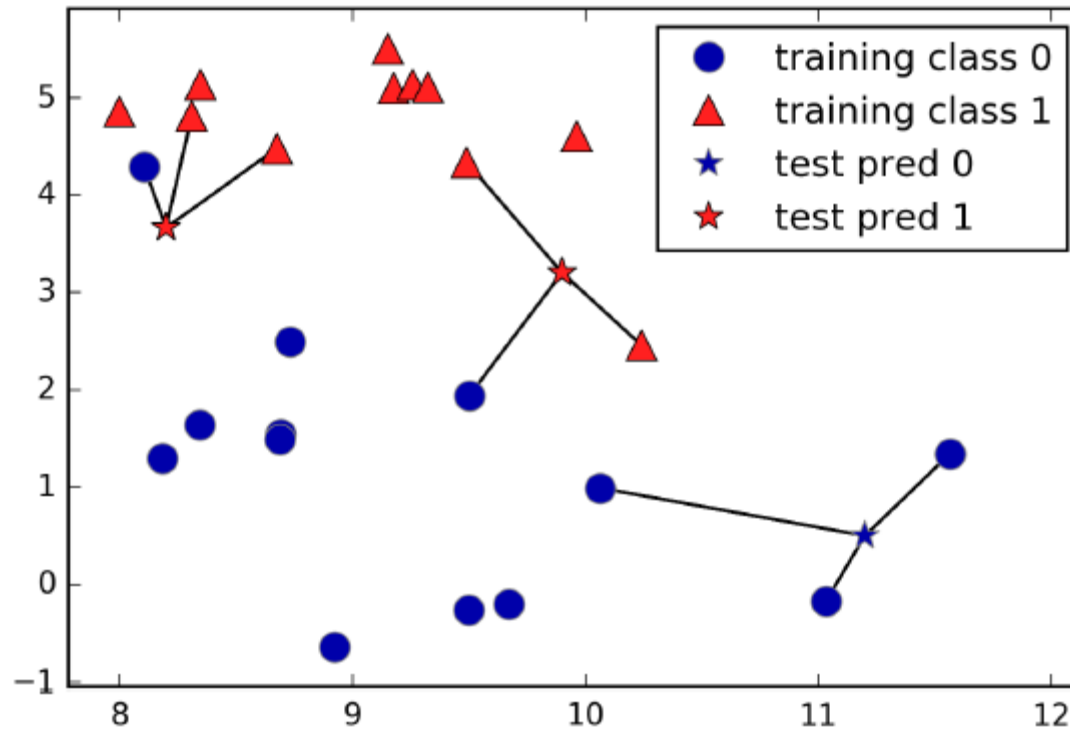
k-Nearest Neighbors – example



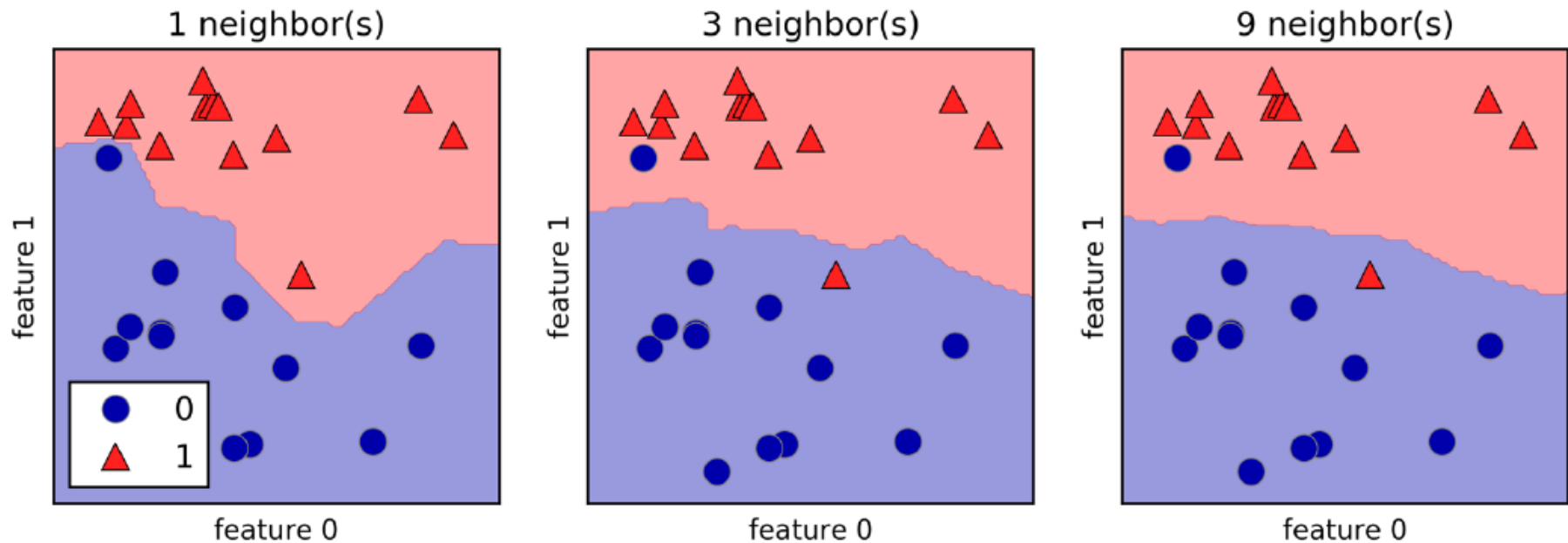
k-Nearest Neighbors – predictions 1-NN

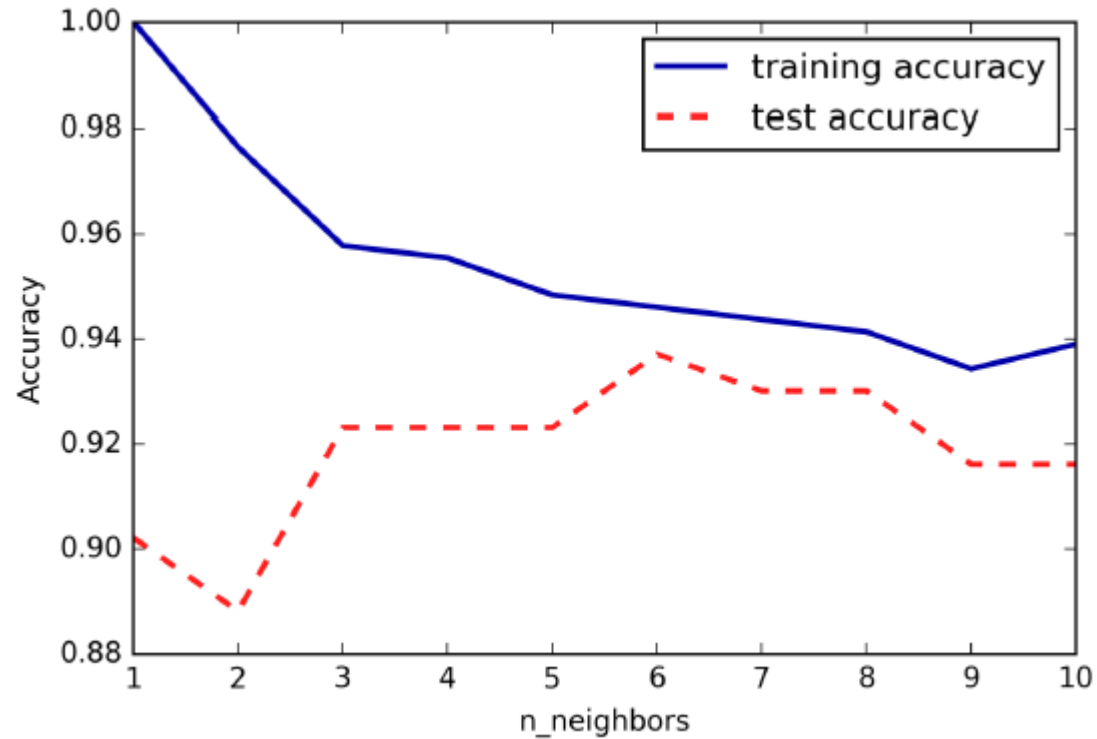


k-Nearest Neighbors – predictions 3-NN



k-Nearest Neighbors – Decision Boundary





Parameters

- Number of neighbors k
- Distance metric (Eukclidean as default)

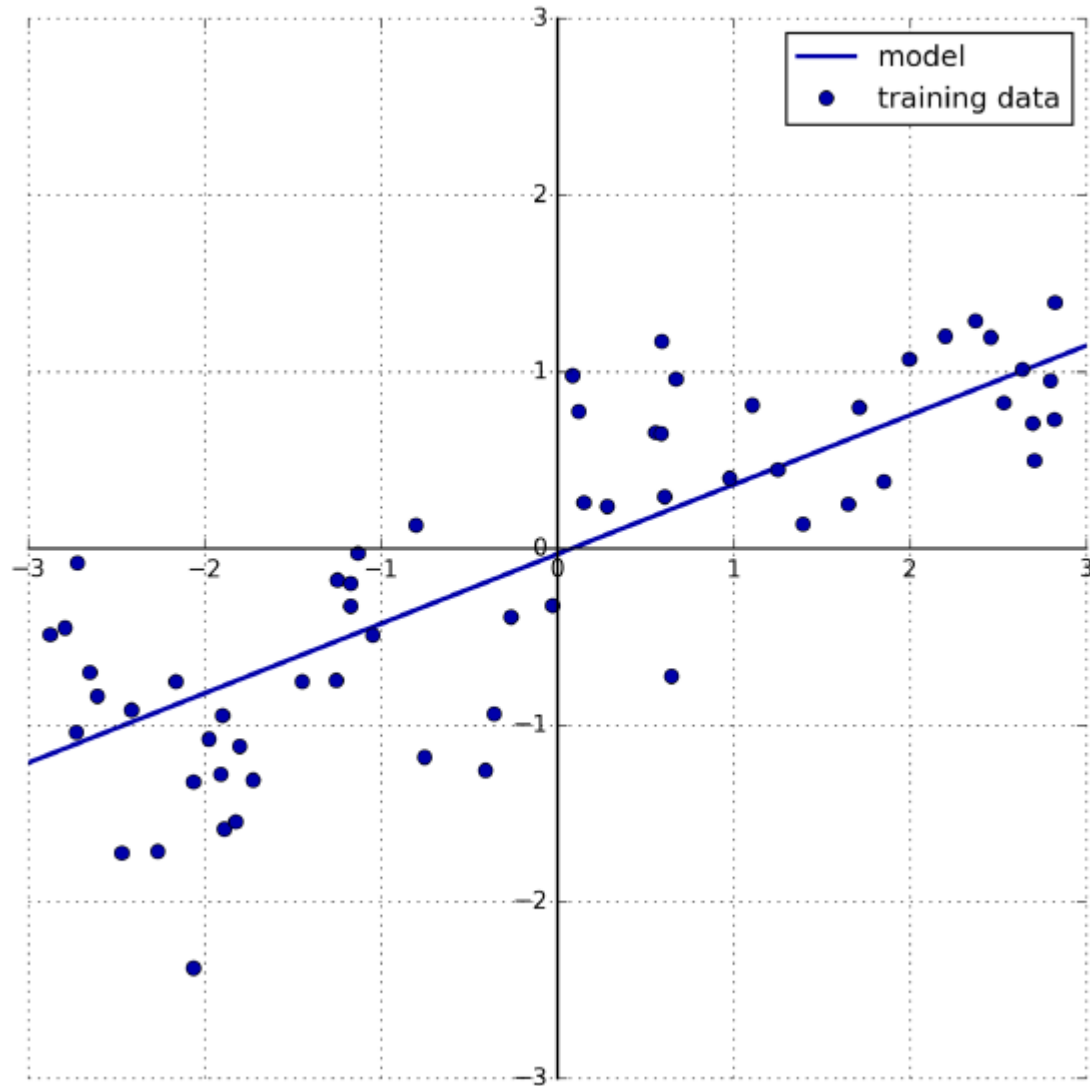
Strengths

- Easy to understand
- Building model is fast

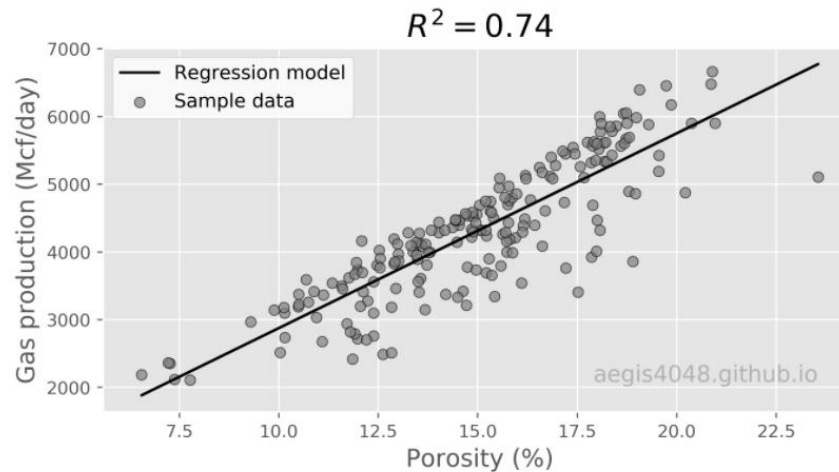
Weaknesses

- Making predictions is very slow on large datasets
- Usually not good with many features (hundreds or more)
- Particularly bad with sparse datasets (many zeros)
- Not robust if features are on different scales

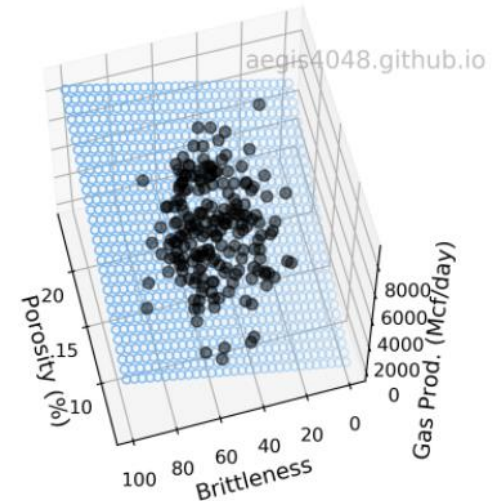
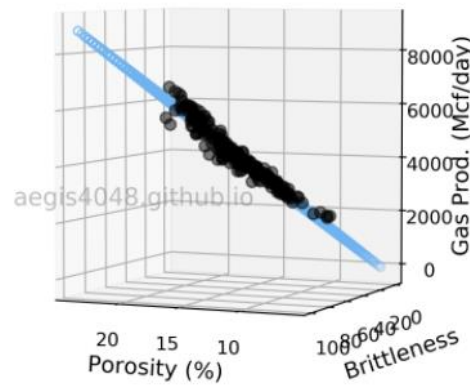
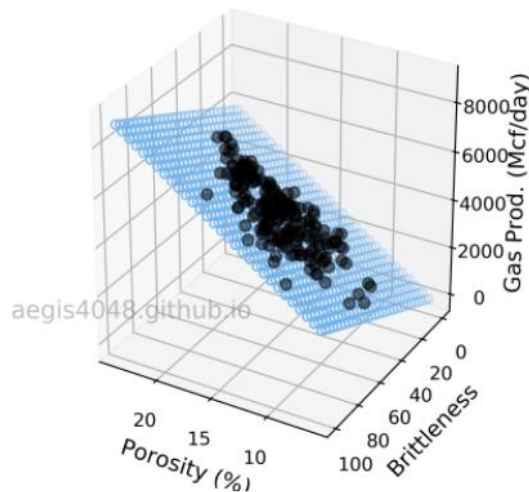
Linear Regression – one input variable



Linear Regression – two input variables



$R^2 = 0.93$



Given training input data $\mathbf{x}^{(1)}, \dots, \mathbf{x}^{(n)} \in \mathbb{R}^d$ with labels $\mathbf{y}^{(1)}, \dots, \mathbf{y}^{(n)} \in \mathbb{R}$.

Try to find $\mathbf{w} \in \mathbb{R}^d$ and $b \in \mathbb{R}$ in order to minimize

**Linear regression
(ordinary least squares)**

$$L(\mathbf{w}, b) = \sum_{i=1}^n \left(\mathbf{y}^{(i)} - (\mathbf{w} \cdot \mathbf{x}^{(i)} + b) \right)^2$$

Ridge regression

$$L_2(\mathbf{w}, b) = \sum_{i=1}^n \left(\mathbf{y}^{(i)} - (\mathbf{w} \cdot \mathbf{x}^{(i)} + b) \right)^2 + C \|\mathbf{w}\|_2^2$$

Lasso regression

$$L_1(\mathbf{w}, b) = \sum_{i=1}^n \left(\mathbf{y}^{(i)} - (\mathbf{w} \cdot \mathbf{x}^{(i)} + b) \right)^2 + C \|\mathbf{w}\|_1$$

Parameters

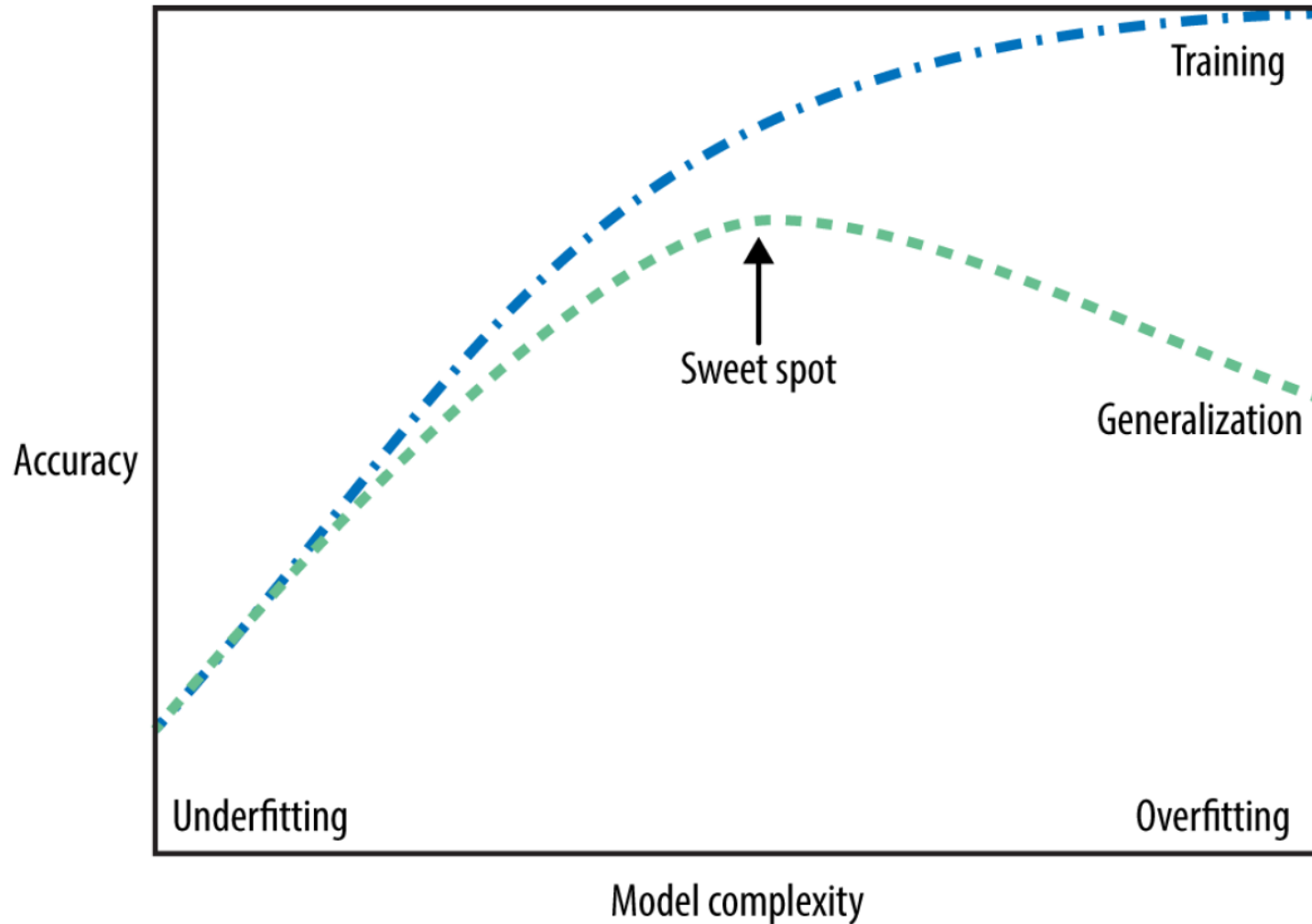
- Regularization parameter α and C
- Model type lasso vs. ridge for regression / logistic vs. SVM for classification

Strengths

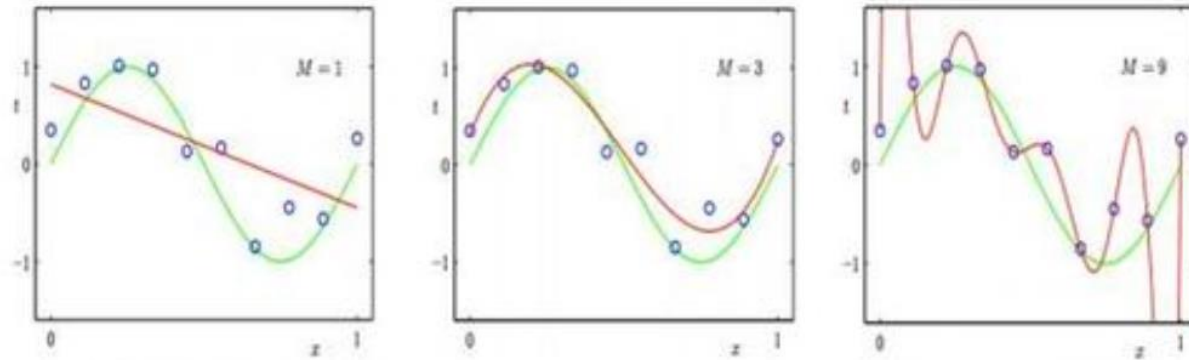
- Fast to train, fast to predict
- Work well with sparse data
- Relatively easy to understand how predictions are made
- Work well with large number of features

Weaknesses

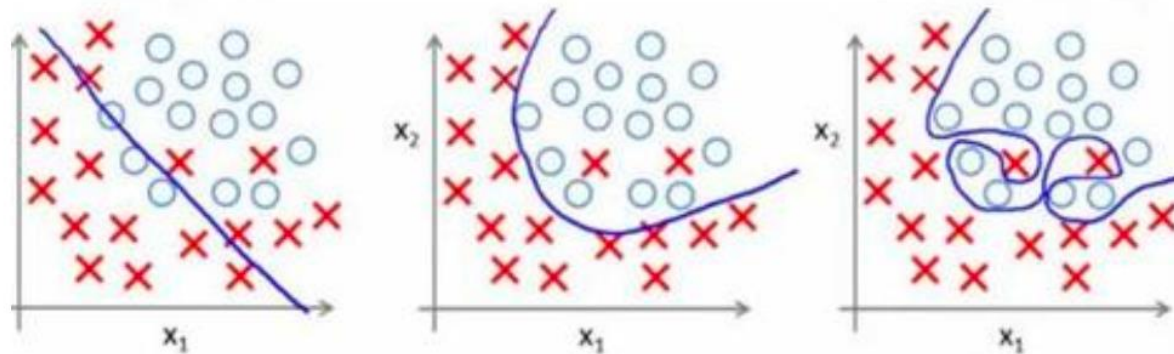
- Coefficients hard to interpret, especially if features are highly correlated
- Sometimes fail with small datasets
- Perform bad with non-linear features and datasets that are not linearly separable



Regression



Classification



Low model complexity
(Underfitting)

High model complexity
(Overfitting)