# Introduction to Machine Learning with Python

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https://github.com/amueller/quick-ml-intro

scikit learn

COLUMBIA UNIVERSITY
IN THE CITY OF NEW YORK

# What is machine learning?

| loan_amnt | term | int_rate | grade | home_ownership | annual_inc |
|---|---|---|---|---|---|
| 5000.0 | 36 months | 10.65% | B | RENT | 24000.0 |
| 2500.0 | 60 months | 15.27% | C | RENT | 30000.0 |
| 2400.0 | 36 months | 15.96% | C | RENT | 12252.0 |
| 10000.0 | 36 months | 13.49% | C | RENT | 49200.0 |
| 3000.0 | 60 months | 12.69% | B | RENT | 80000.0 |
| 5000.0 | 36 months | 7.90% | A | RENT | 36000.0 |
| 7000.0 | 60 months | 15.96% | C | RENT | 47004.0 |
| 3000.0 | 36 months | 18.64% | E | RENT | 48000.0 |
| 5600.0 | 60 months | 21.28% | F | OWN | 40000.0 |
| 5375.0 | 60 months | 12.69% | B | RENT | 15000.0 |

→

| loan_status |
|---|
| Fully Paid |
| Charged Off |
| Fully Paid |
| Fully Paid |
| Fully Paid |
| Fully Paid |
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| Charged Off |
| Charged Off |

# Supervised Learning

$$(x_i, y_i) \propto p(x, y)$$ i.i.d.

$$x_i \in \mathbb{R}^n$$

$$y_i \in \mathbb{R}$$

$$f(x_i) \approx y_i$$

# Classification and Regression

Classification:

- y discrete

Will they subscribe?

Regression:

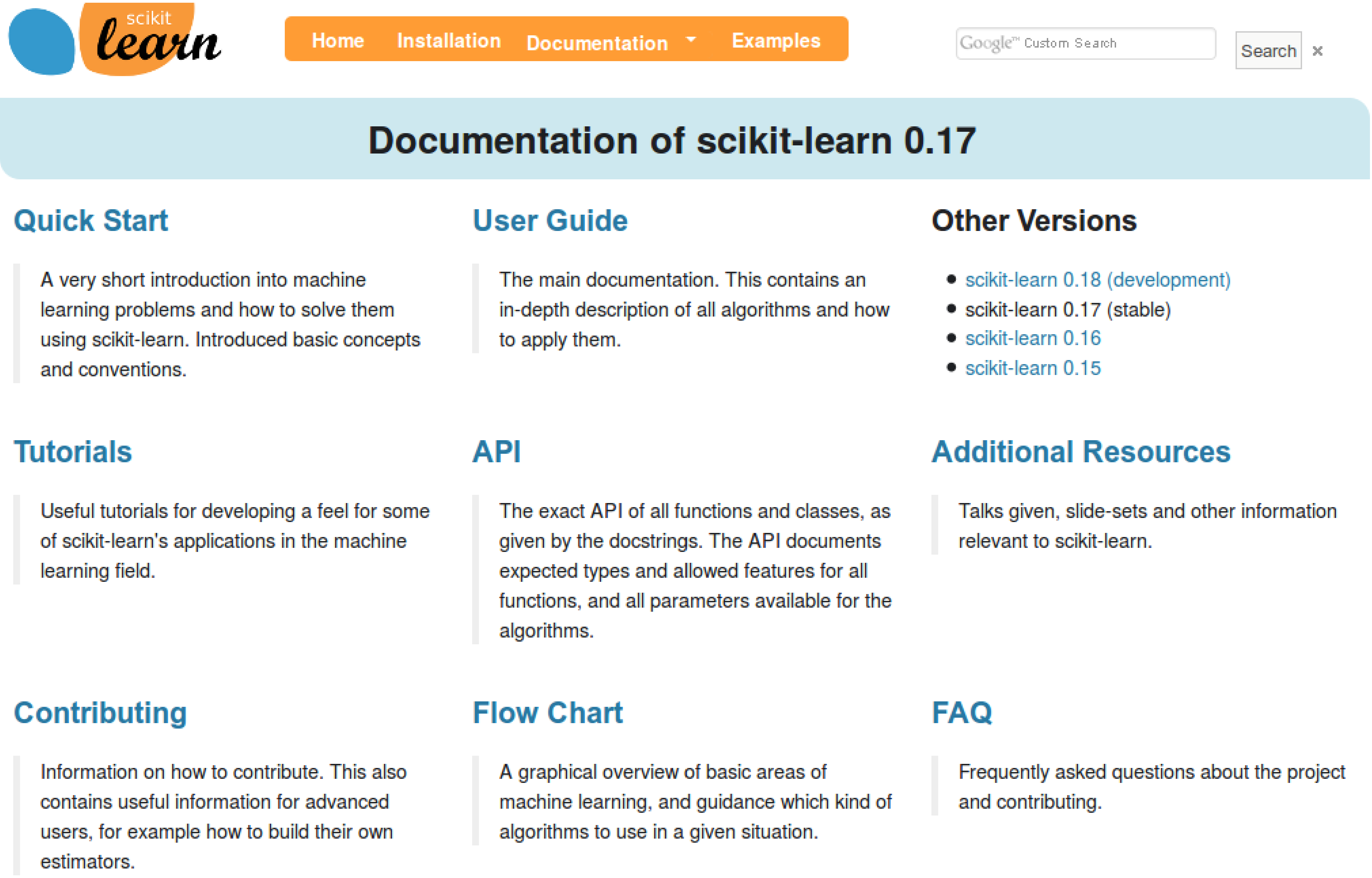
- y continuous

How much will the returns be?

# Generalization

Not only $f(x_i) \approx y_i$

Also for new data: $f(x) \approx y$



# Documentation of scikit-learn 0.17

## Quick Start

A very short introduction into machine learning problems and how to solve them using scikit-learn. Introduced basic concepts and conventions.

## User Guide

The main documentation. This contains an in-depth description of all algorithms and how to apply them.

## Other Versions

- scikit-learn 0.18 (development)
- scikit-learn 0.17 (stable)
- scikit-learn 0.16
- scikit-learn 0.15

## Tutorials

Useful tutorials for developing a feel for some of scikit-learn's applications in the machine learning field.

## API

The exact API of all functions and classes, as given by the docstrings. The API documents expected types and allowed features for all functions, and all parameters available for the algorithms.

## Additional Resources

Talks given, slide-sets and other information relevant to scikit-learn.

## Contributing

Information on how to contribute. This also contains useful information for advanced users, for example how to build their own estimators.

## Flow Chart

A graphical overview of basic areas of machine learning, and guidance which kind of algorithms to use in a given situation.

## FAQ

Frequently asked questions about the project and contributing.

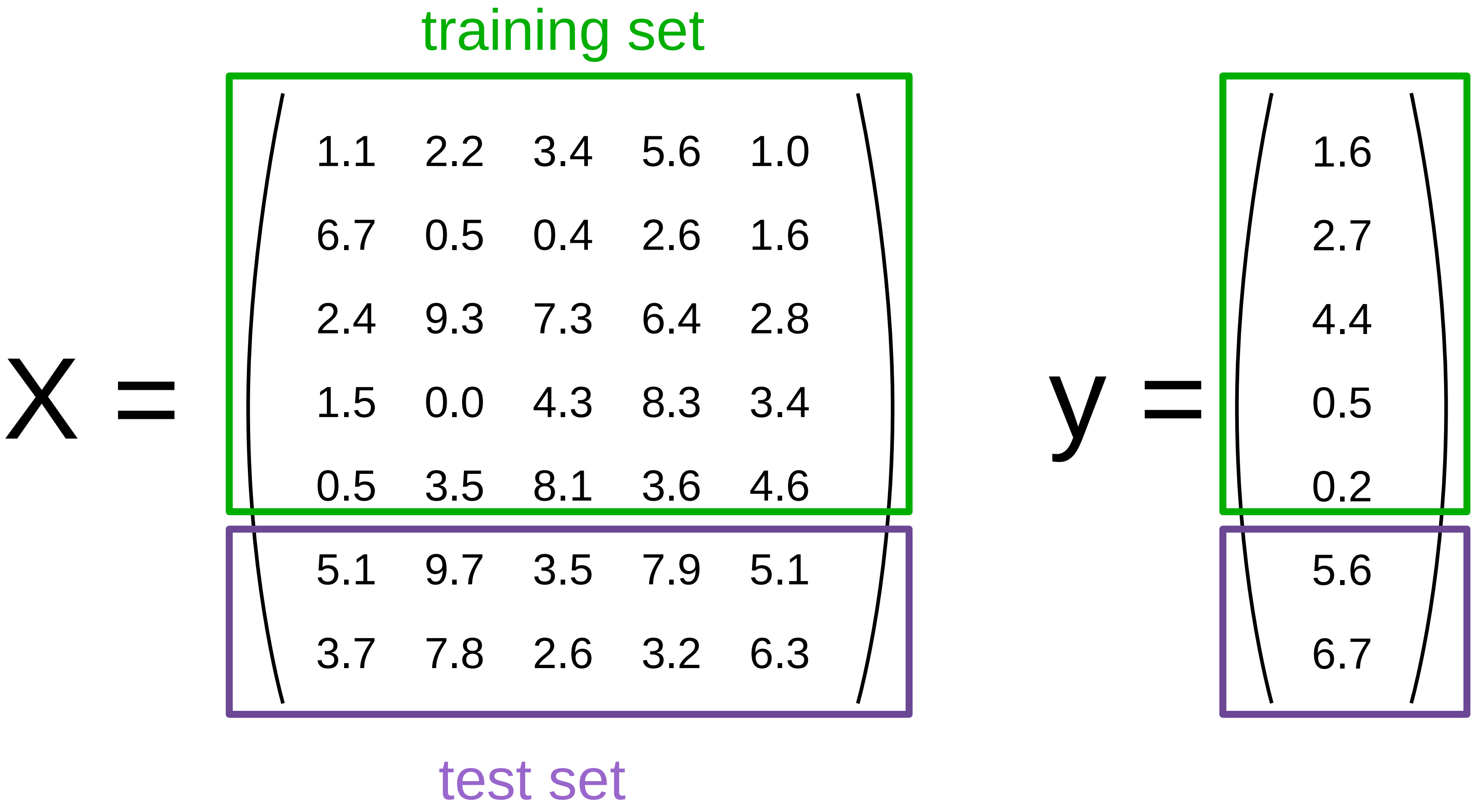
http://scikit-learn.org/

# Representing Data

$$X = \left(\begin{array}{rccccc}
\text{one sample} & 1.1 & 2.2 & 3.4 & 5.6 & 1.0 \\
 & 6.7 & 0.5 & 0.4 & 2.6 & 1.6 \\
 & 2.4 & 9.3 & 7.3 & 6.4 & 2.8 \\
 & 1.5 & 0.0 & 4.3 & 8.3 & 3.4 \\
 & 0.5 & 3.5 & 8.1 & 3.6 & 4.6 \\
 & 5.1 & 9.7 & 3.5 & 7.9 & 5.1 \\
 & 3.7 & 7.8 & 2.6 & 3.2 & 6.3 \\
 & \text{one feature} & & & &
\end{array}\right)
\qquad
y = \left(\begin{array}{c}
1.6 \\ 2.7 \\ 4.4 \\ 0.5 \\ 0.2 \\ 5.6 \\ 6.7
\end{array}\right)$$

outputs / labels

# Training and Testing Data



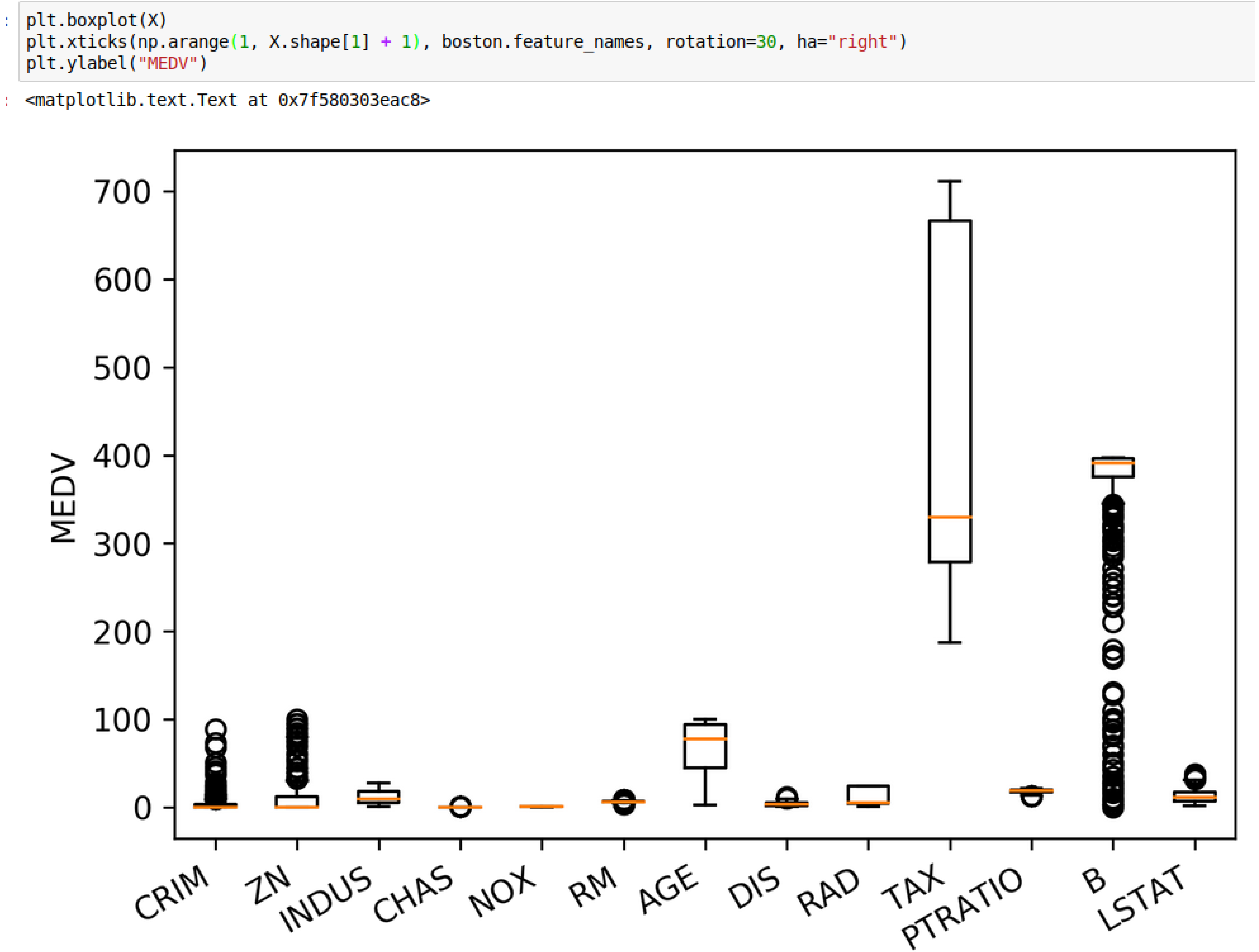
training set

$$X = \left(\begin{array}{ccccc} 1.1 & 2.2 & 3.4 & 5.6 & 1.0 \\ 6.7 & 0.5 & 0.4 & 2.6 & 1.6 \\ 2.4 & 9.3 & 7.3 & 6.4 & 2.8 \\ 1.5 & 0.0 & 4.3 & 8.3 & 3.4 \\ 0.5 & 3.5 & 8.1 & 3.6 & 4.6 \\ \hline 5.1 & 9.7 & 3.5 & 7.9 & 5.1 \\ 3.7 & 7.8 & 2.6 & 3.2 & 6.3 \end{array}\right) \qquad y = \left(\begin{array}{c} 1.6 \\ 2.7 \\ 4.4 \\ 0.5 \\ 0.2 \\ \hline 5.6 \\ 6.7 \end{array}\right)$$

test set

# IPython Notebook:
# Part 1 – Data Loading

# Preprocessing



```
plt.boxplot(X)
plt.xticks(np.arange(1, X.shape[1] + 1), boston.feature_names, rotation=30, ha="right")
plt.ylabel("MEDV")
```

```
<matplotlib.text.Text at 0x7f580303eac8>
```

# Categorical Features

# Categorical Features

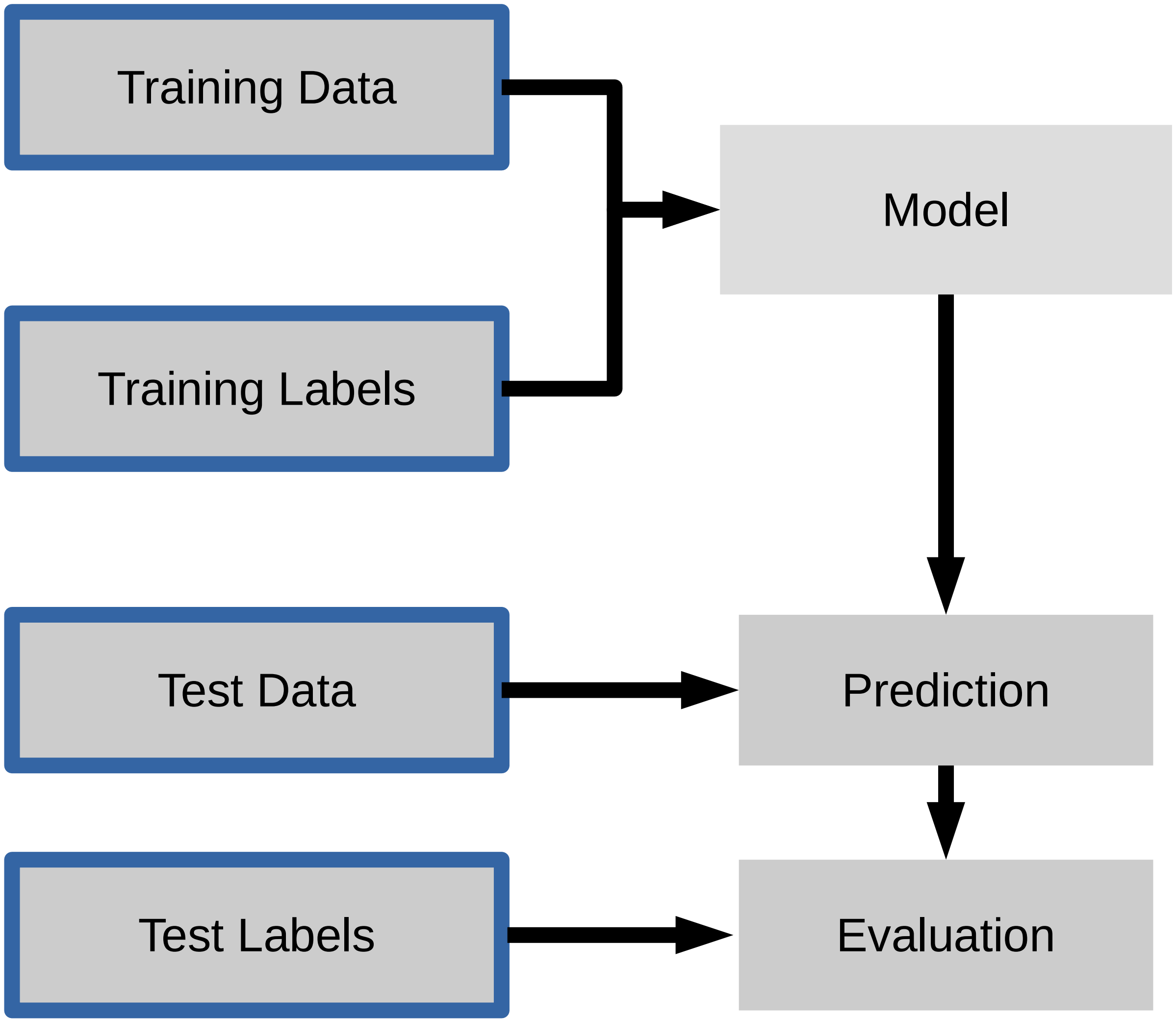
$$\{\text{"red"}, \text{"green"}, \text{"blue"}\} \subset \mathbb{R}^p \quad ?$$

# Categorical Variables

$$\begin{array}{ccc} \text{“red”} & \text{“green”} & \text{“blue”} \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{array}$$

# IPython Notebook:
# Part 2 – Preprocessing

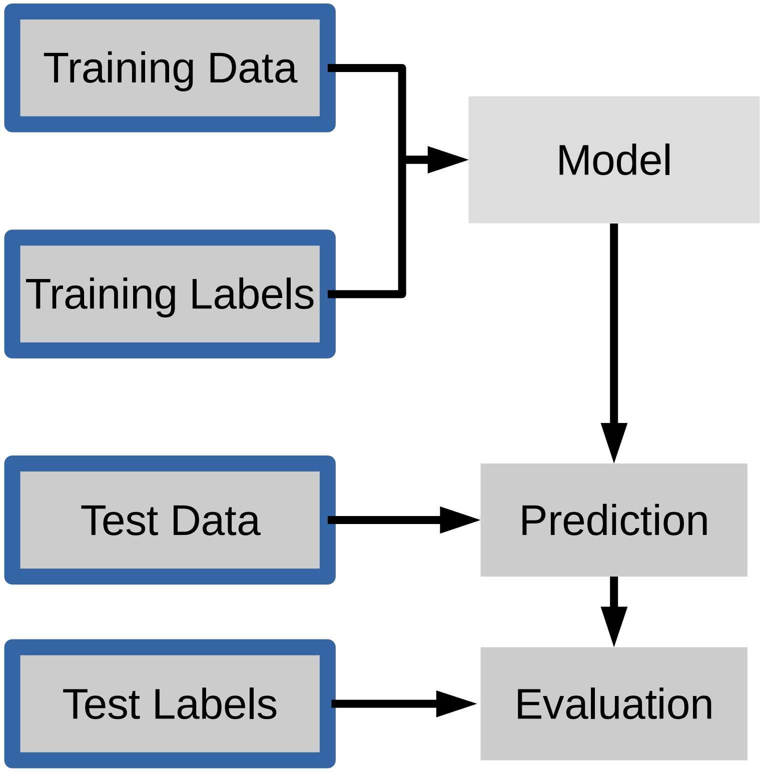
# Supervised Machine Learning



Training

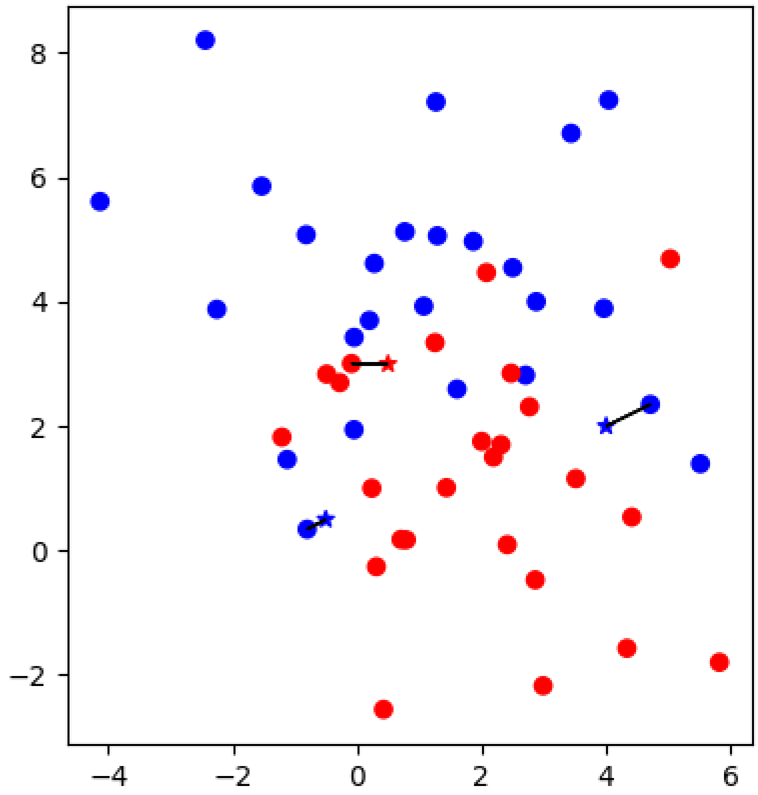
Generalization

```
clf = RandomForestClassifier()

clf.fit(X_train, y_train)


y_pred = clf.predict(X_test)

clf.score(X_test, y_test)
```



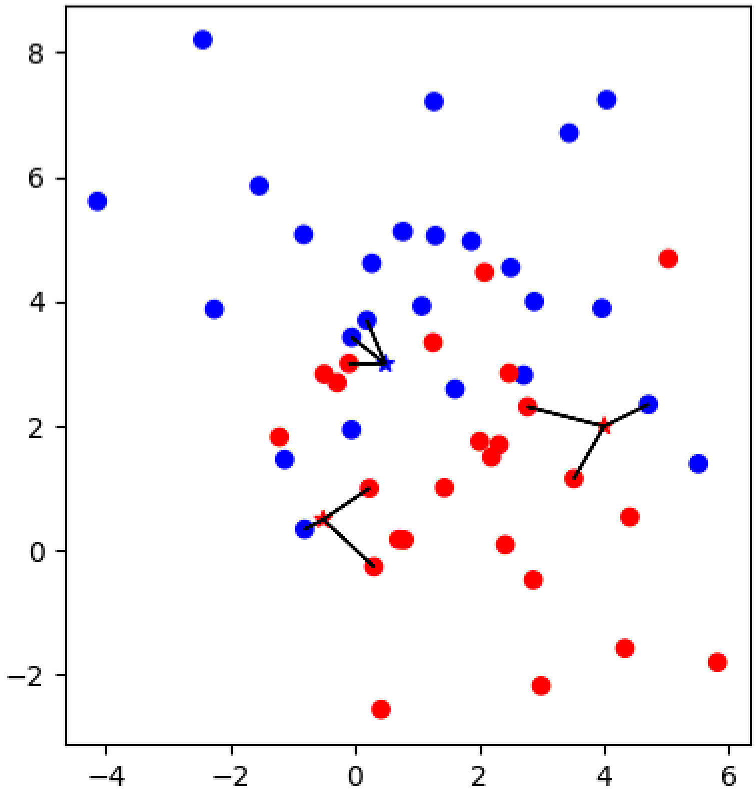
# IPython Notebook:
# Part 3 – Supervised Learning

# Nearest neighbors

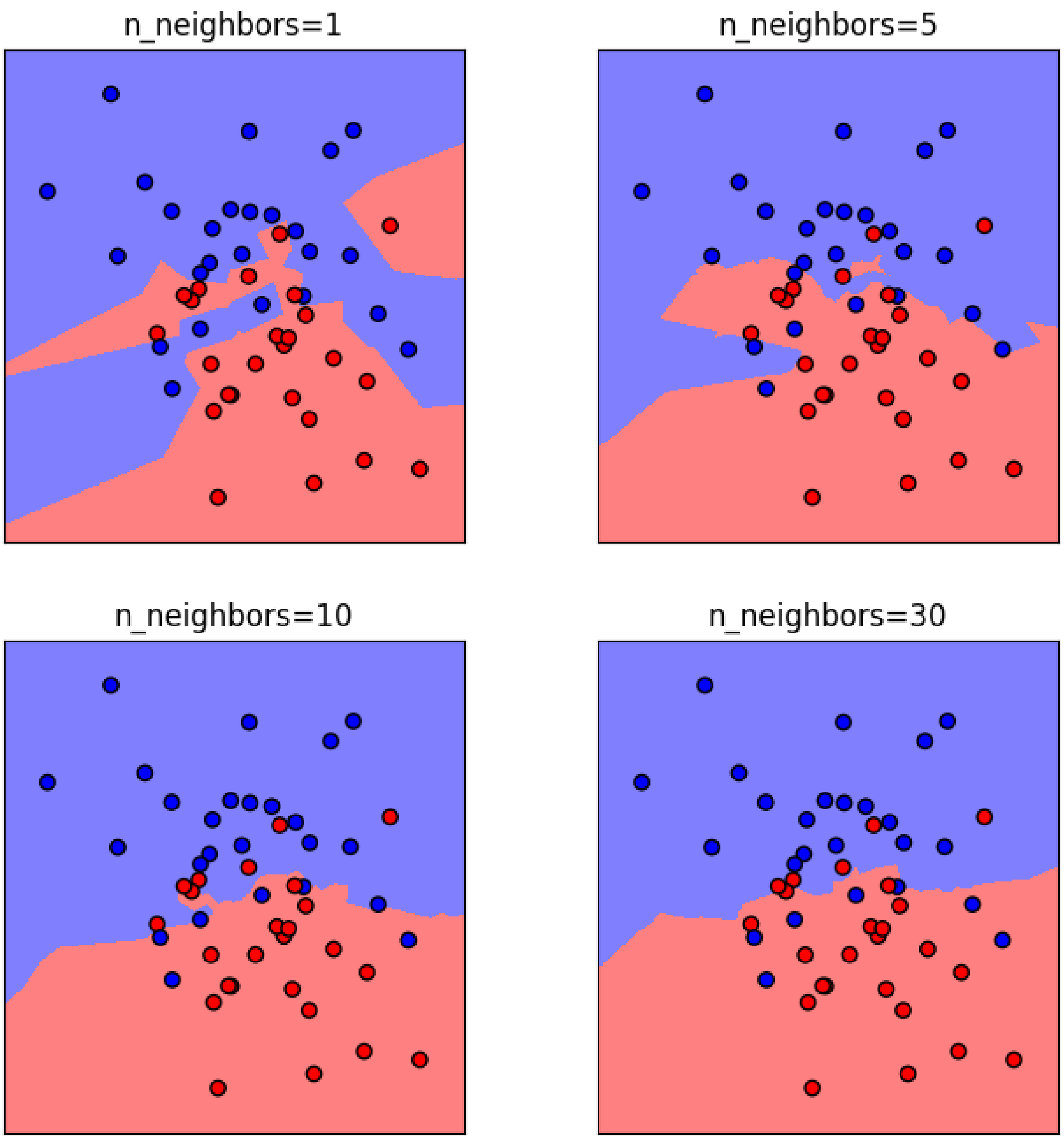


$$f(x) = y_i, i = \text{argmin}_j ||x_j - x||$$

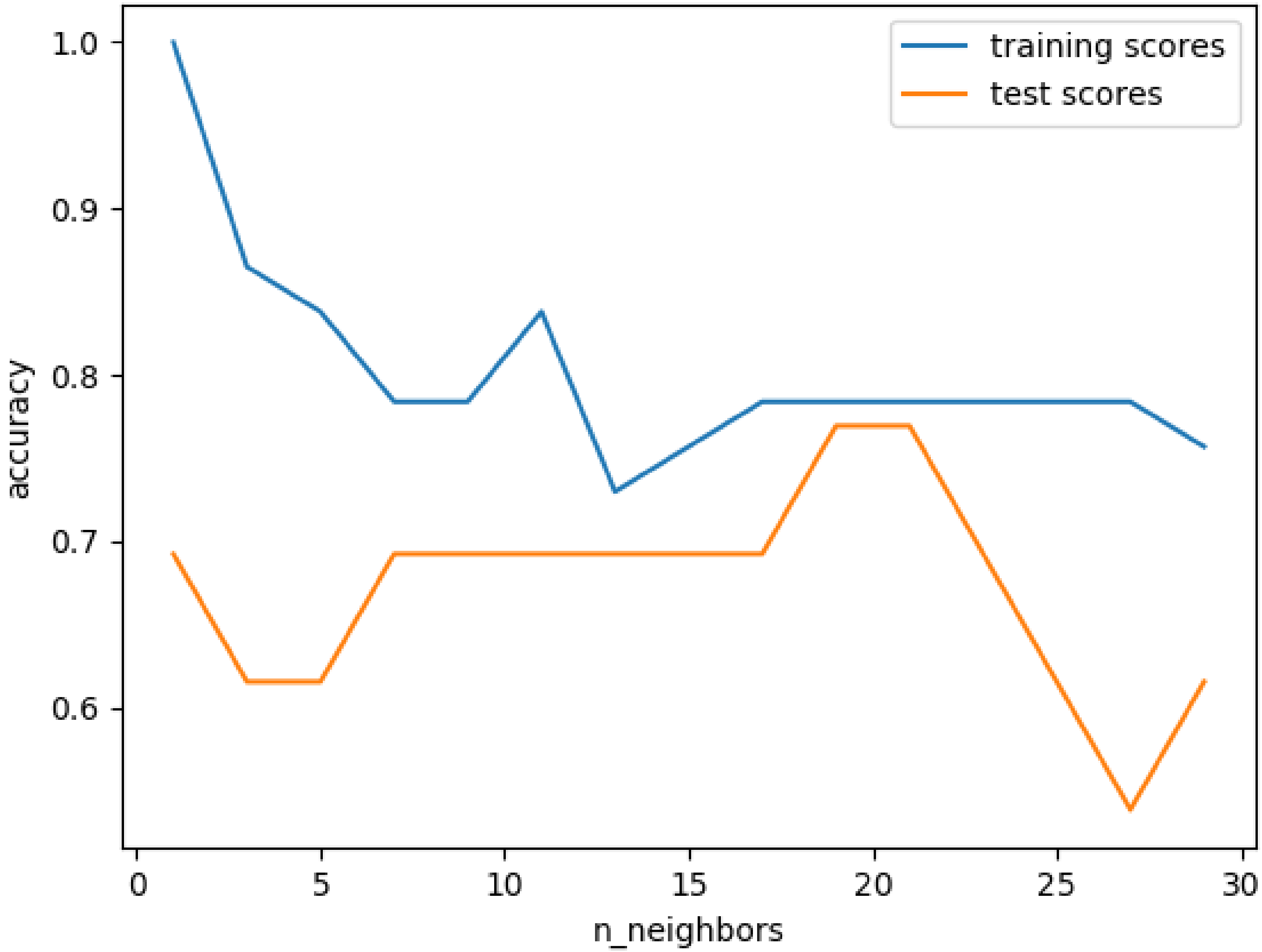
# Nearest neighbors



# Influence of n_neighbors

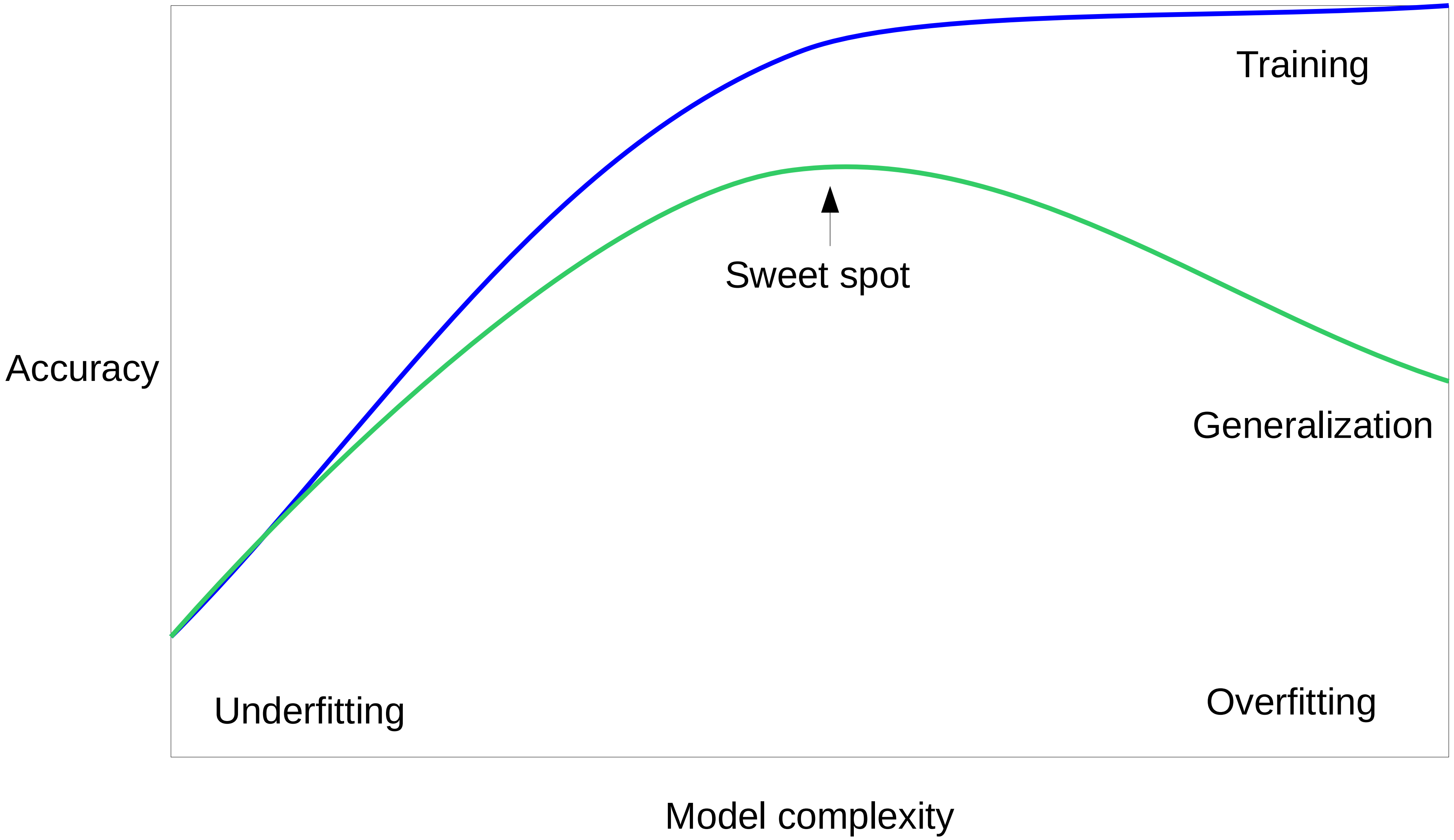


# Model Complexity

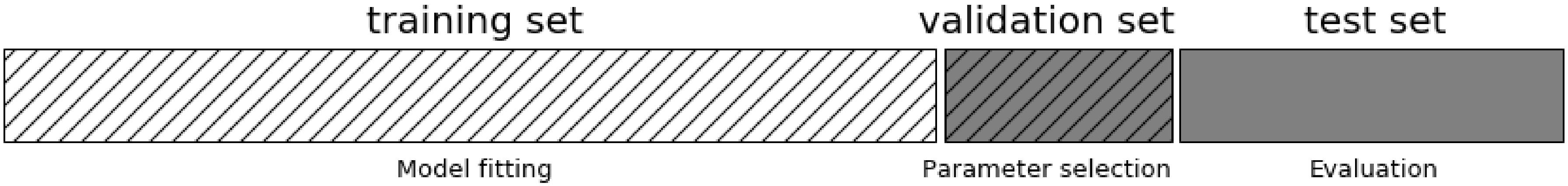


]

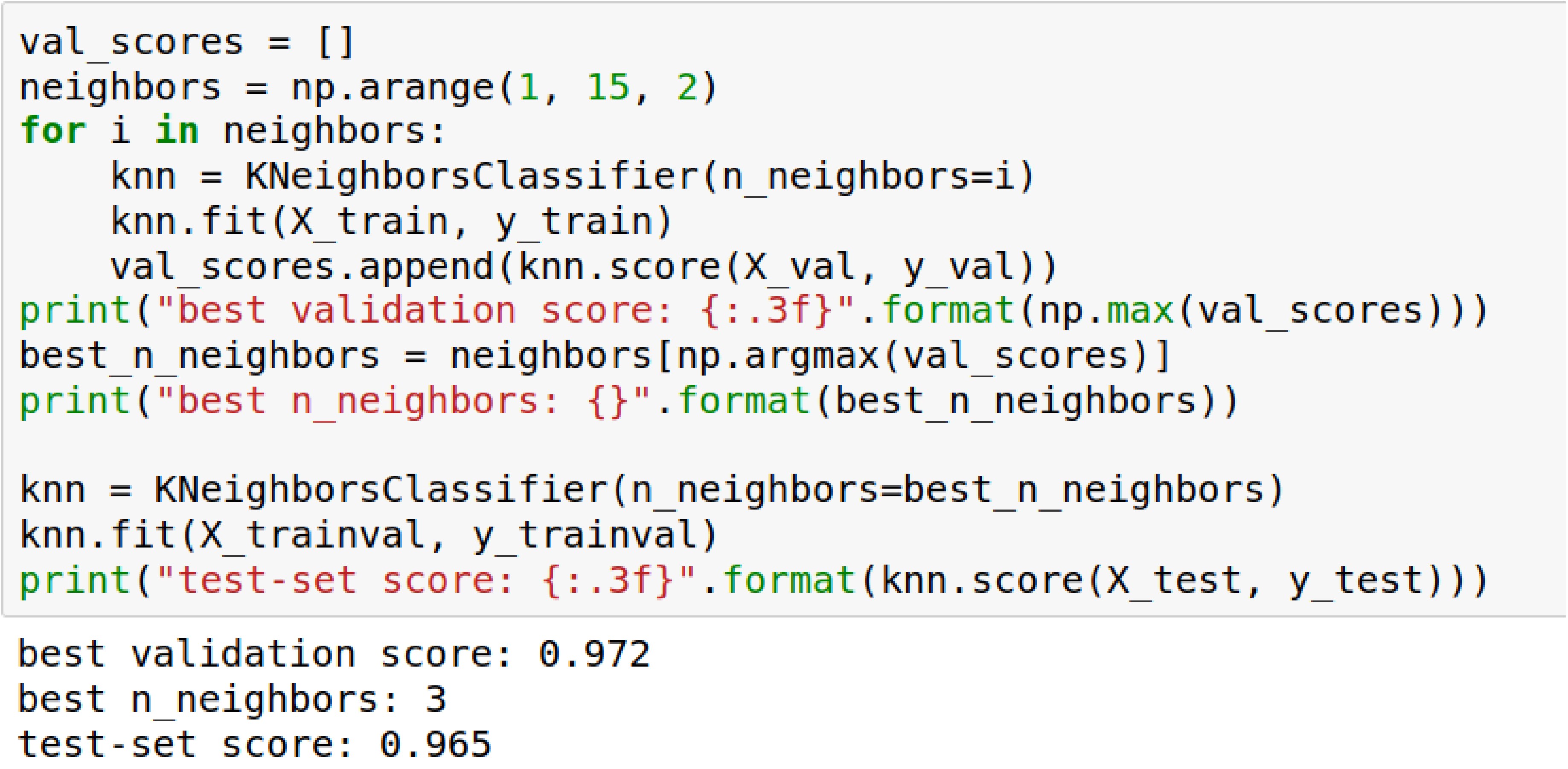
# Overfitting and Underfitting



# Three-fold split



pro: fast, simple
con: high variance, bad use of data.

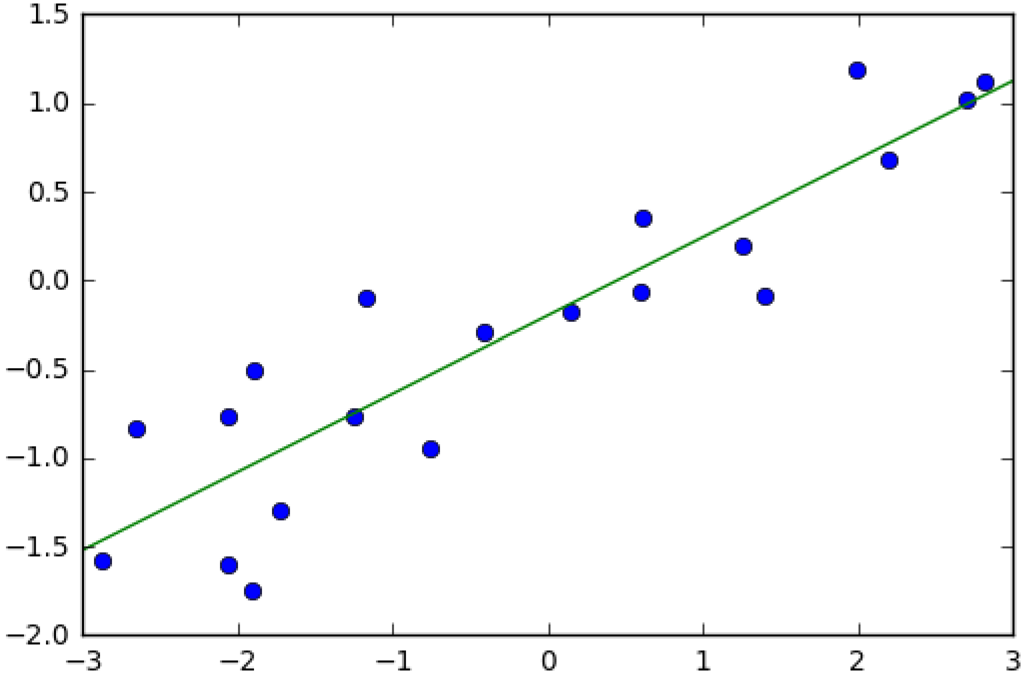


```python
val_scores = []
neighbors = np.arange(1, 15, 2)
for i in neighbors:
    knn = KNeighborsClassifier(n_neighbors=i)
    knn.fit(X_train, y_train)
    val_scores.append(knn.score(X_val, y_val))
print("best validation score: {:.3f}".format(np.max(val_scores)))
best_n_neighbors = neighbors[np.argmax(val_scores)]
print("best n_neighbors: {}".format(best_n_neighbors))

knn = KNeighborsClassifier(n_neighbors=best_n_neighbors)
knn.fit(X_trainval, y_trainval)
print("test-set score: {:.3f}".format(knn.score(X_test, y_test)))
```

```
best validation score: 0.972
best n_neighbors: 3
test-set score: 0.965
```

# Linear Models for Regression

# Linear Models for Regression



$$\hat{y} = w^T\mathbf{x} + b = \sum_{i=1}^{p} w_i x_i + b$$

# Linear Regression & Ridge Regression

$$\hat{y} = w^T \mathbf{x} + b = \sum_{i=1}^{p} w_i x_i + b$$

$$\min_{w \in \mathbb{R}^p} \sum_{i=1}^{p} ||w^T \mathbf{x}_i - y_i||^2$$

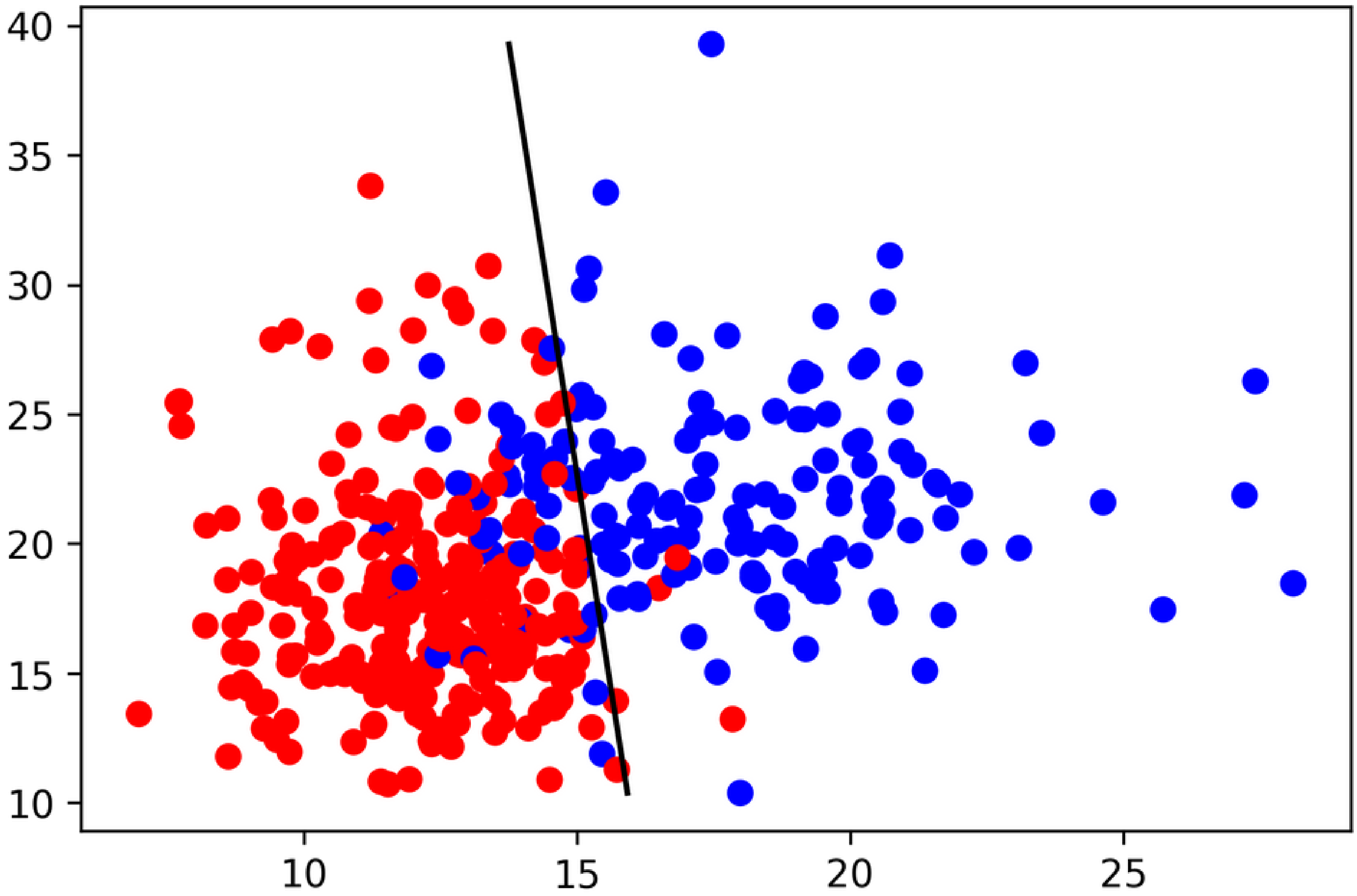
Unique solution if $\mathbf{X} = (\mathbf{x}_1, ...\mathbf{x}_n)^T$ has full column rank.

$$\min_{w \in \mathbb{R}^p} \sum_{i=1}^{n} ||w^T x_i - y_i||^2 + \alpha ||w||^2$$

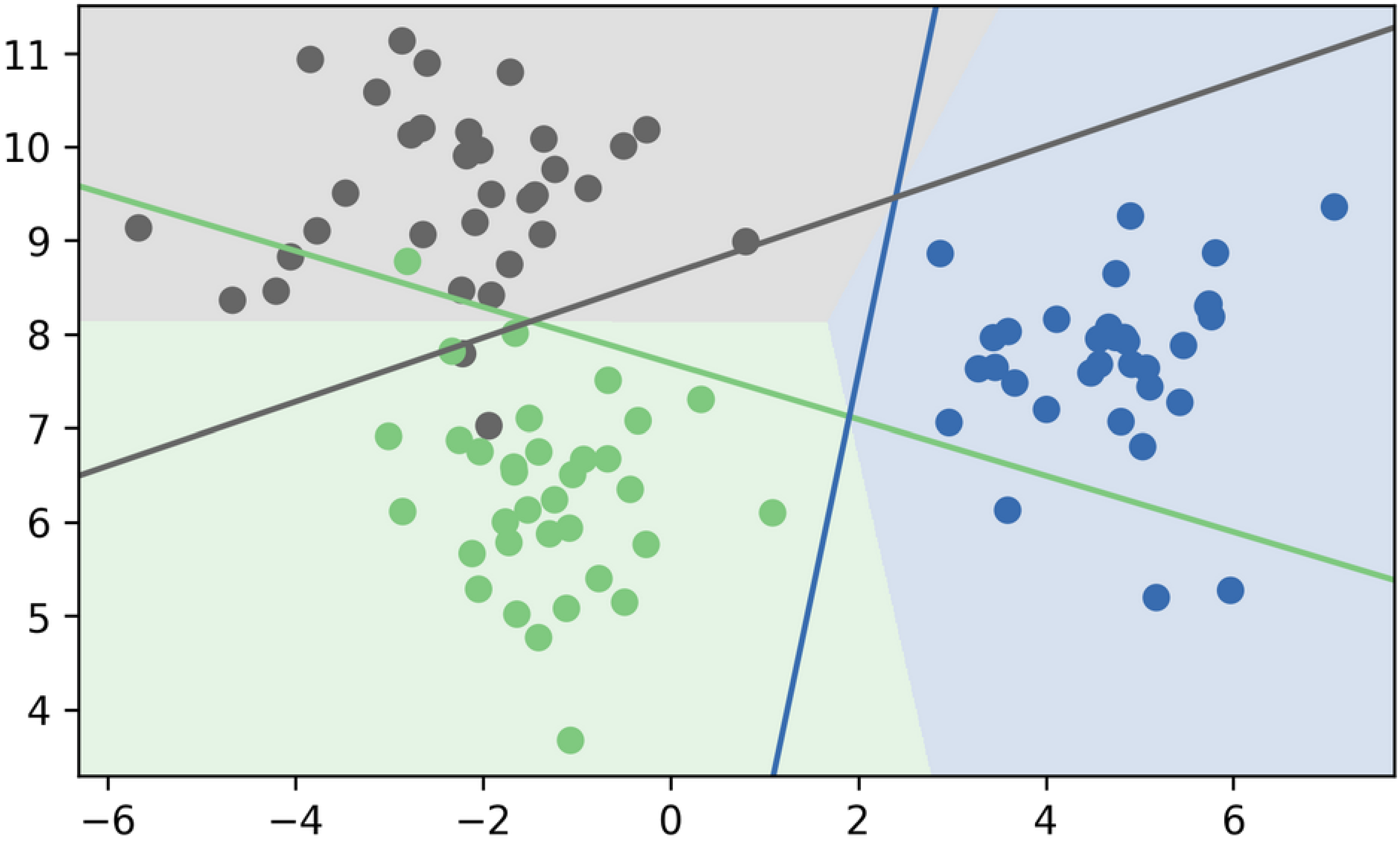
Always has a unique solution.
Tuning parameter alpha.

# IPython Notebook:
# Part 4 – Linear Models for Regression

# Linear Models for Classification



$$\hat{y} = \text{sign}(w^T \mathbf{x} + b) = \text{sign}(\sum_i w_i x_i + b)$$



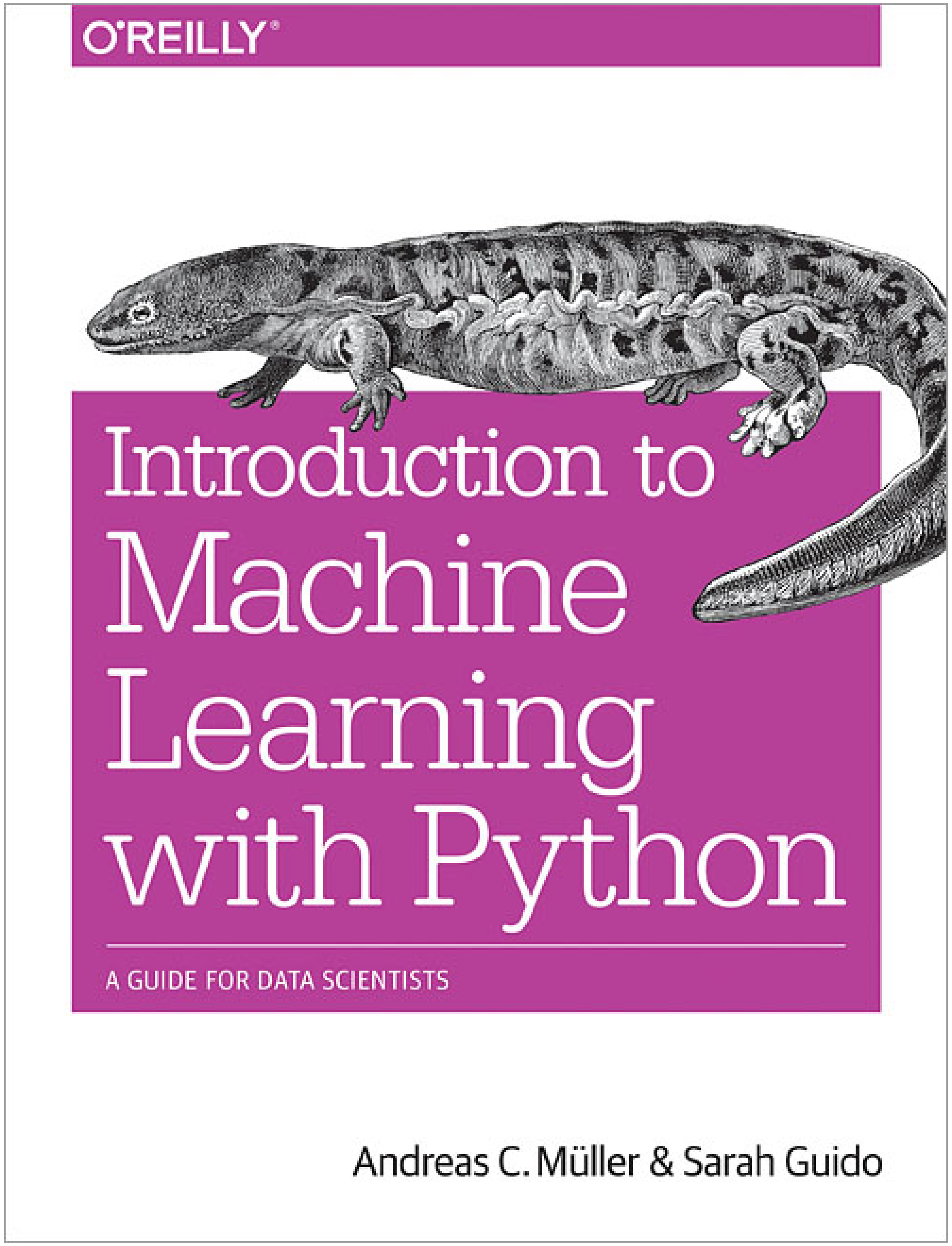
$$\hat{y} = \arg\max_{i \in Y} \mathbf{w}_i \mathbf{x} + b_i$$

# IPython Notebook:
# Part 5 – Linear Models for Classification

# Basic API

```
estimator.fit(X, [y])
```

| `estimator.predict` | `estimator.transform` |
|---|---|
| Classification | Preprocessing |
| Regression | Dimensionality reduction |
| Clustering | Feature selection |
| | Feature extraction |



O'REILLY®

# Introduction to Machine Learning with Python

A GUIDE FOR DATA SCIENTISTS

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# Thank you for your attention.

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