# Introduction to Machine Learning with Python

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





What is machine learning?

loan_amnt	term	int_rate	grade	home_ownership	annual_inc
5000.0	36 months	10.65%	В	RENT	24000.0
2500.0	60 months	15.27%	С	RENT	30000.0
2400.0	36 months	15.96%	С	RENT	12252.0
10000.0	36 months	13.49%	С	RENT	49200.0
3000.0	60 months	12.69%	В	RENT	0.00008
5000.0	36 months	7.90%	Α	RENT	36000.0
7000.0	60 months	15.96%	С	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%	В	RENT	15000.0

loan_status
Fully Paid
Charged Off
Fully Paid
Charged Off
Charged Off

### Supervised Learning

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

$$f(x_i) \approx y_i$$

Most common applications:

- Automate a manual task
- Predict the future

### Classification and Regression

Classification:

• y discrete

Regression:

y continuous

Will they subscribe?

How much will the returns be?

#### Generalization

Not only

$$f(x_i) \approx y_i$$

Also for new data:

$$f(x) \approx y$$



#### **Quick Start**

learn

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.

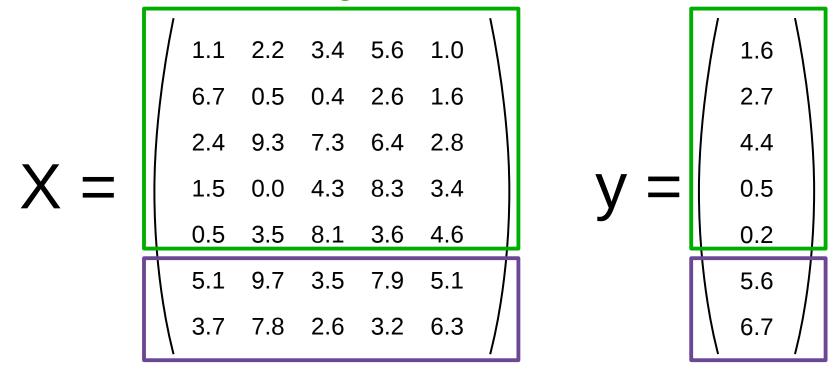
#### Representing Data

one feature

outputs / labels

### Training and Testing Data

#### training set

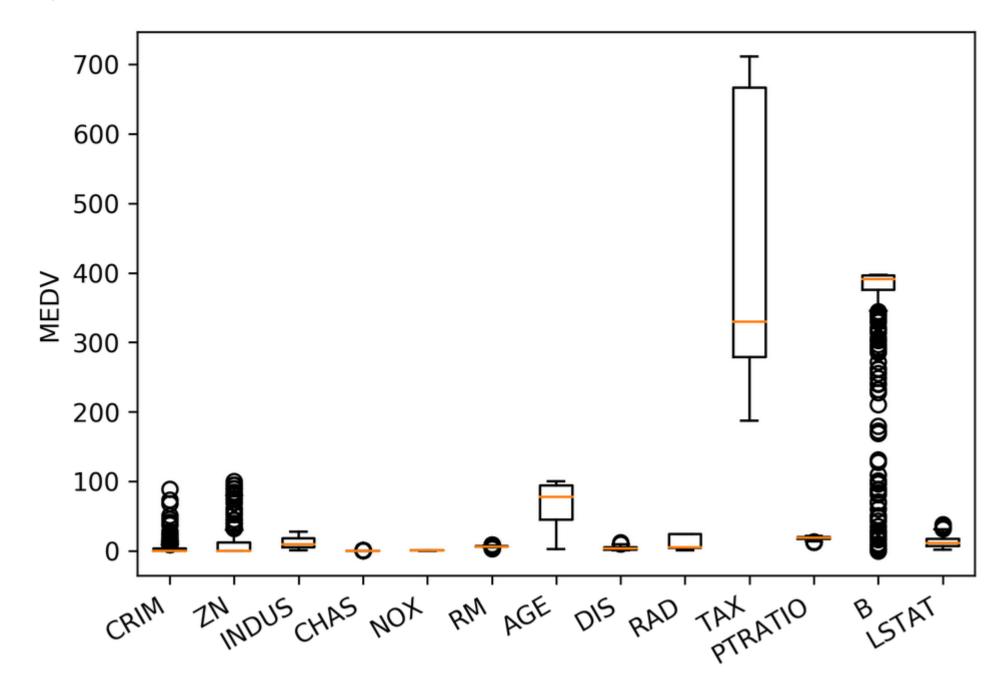


test set

IPython Notebook: Part 1 – Data Loading

#### Preprocessing

<matplotlib.text.Text at 0x7f580303eac8>



#### Categorical Features

#### Categorical Features

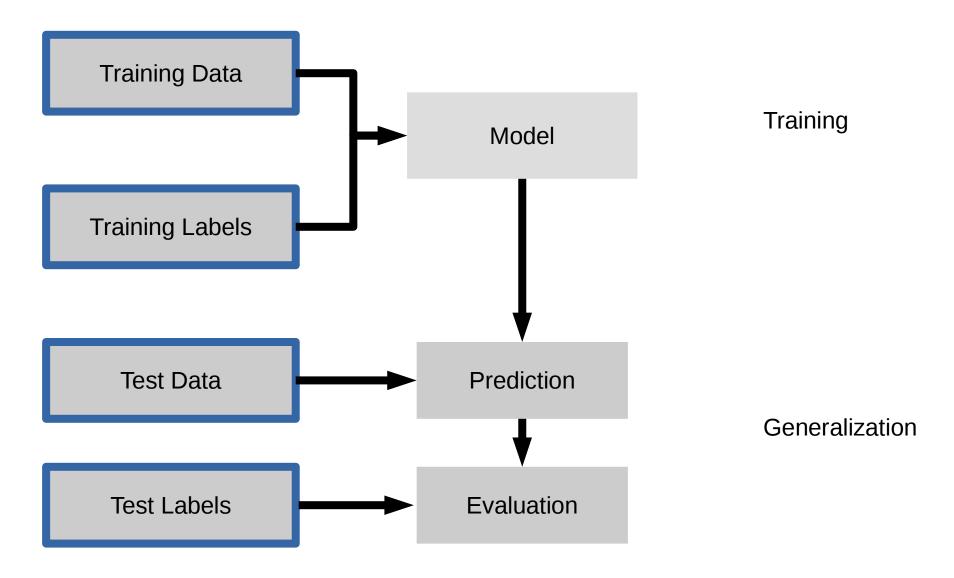
$$\{\text{"red"}, \text{"green"}, \text{"blue"}\} \subset \mathbb{R}^p$$

### Categorical Variables

"red"	"green"	"blue"	
1	0	0	
0	1	0	
0	0	1	

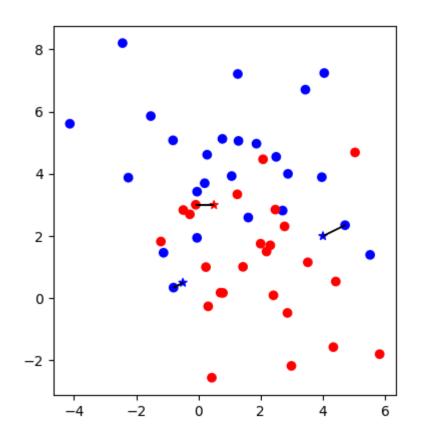
IPython Notebook: Part 2 – Preprocessing

### Supervised Machine Learning



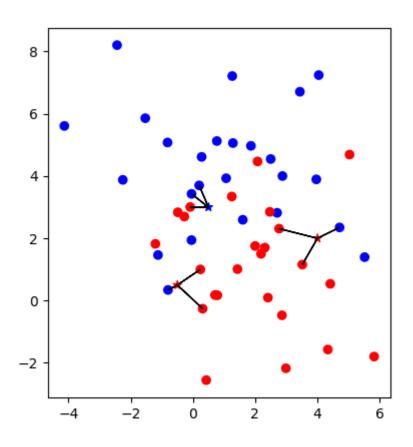
clf = RandomForestClassifier() Training Data clf.fit(X\_train, y\_train) Model Training Labels y\_pred = clf.predict(X\_test) Prediction **Test Data** clf.score(X\_test, y\_test) Test Labels **Evaluation**  IPython Notebook: Part 3 – Supervised Learning

#### Nearest neighbors

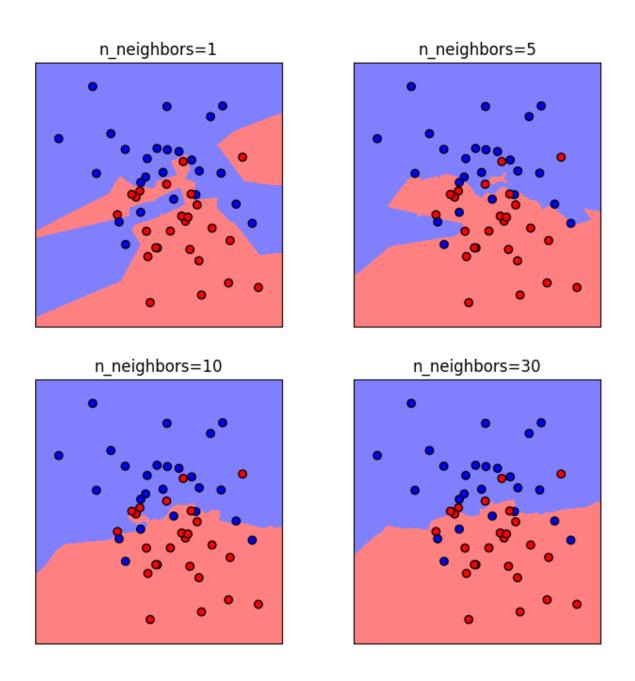


$$f(x) = y_i, i = \operatorname{argmin}_j ||x_j - x||$$

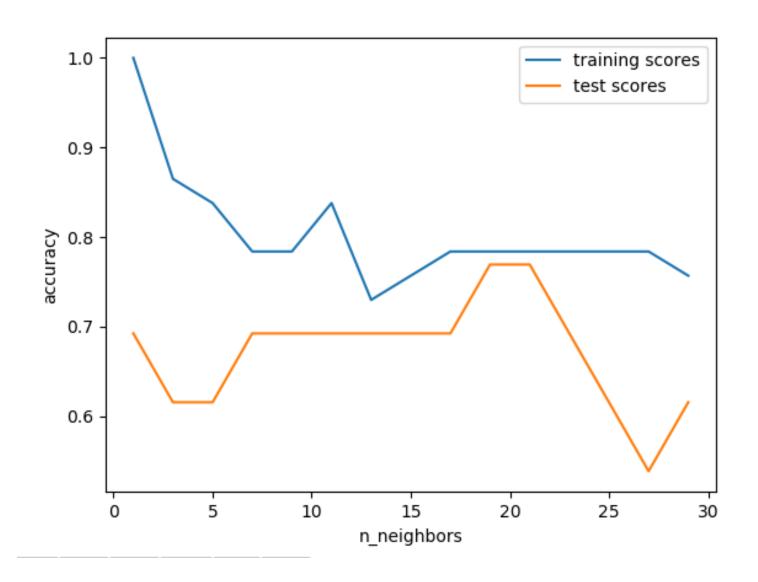
### Nearest neighbors



### Influence of n\_neighbors



### Model Complexity

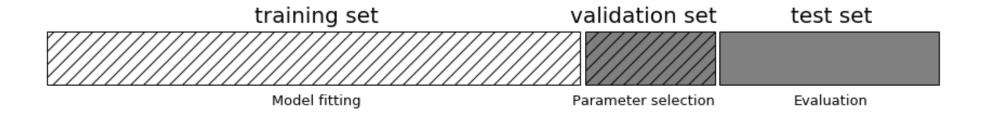


### Overfitting and Underfitting



Model complexity

### Three-fold split



pro: fast, simple

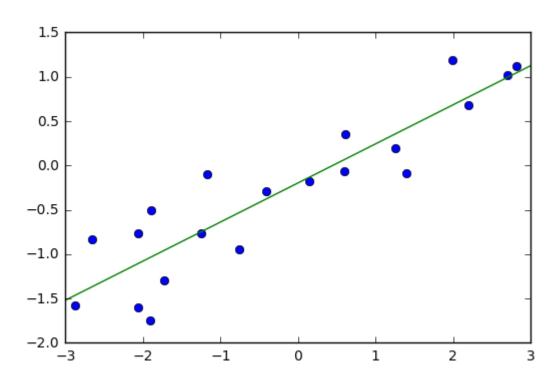
con: high variance, bad use of data.

```
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



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

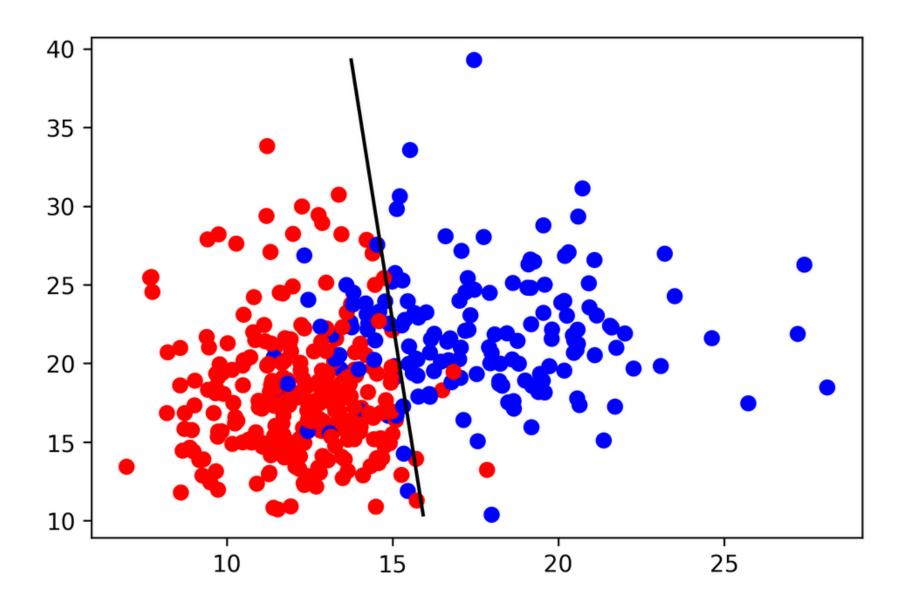
## Linear Regression & Ridge Regression

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

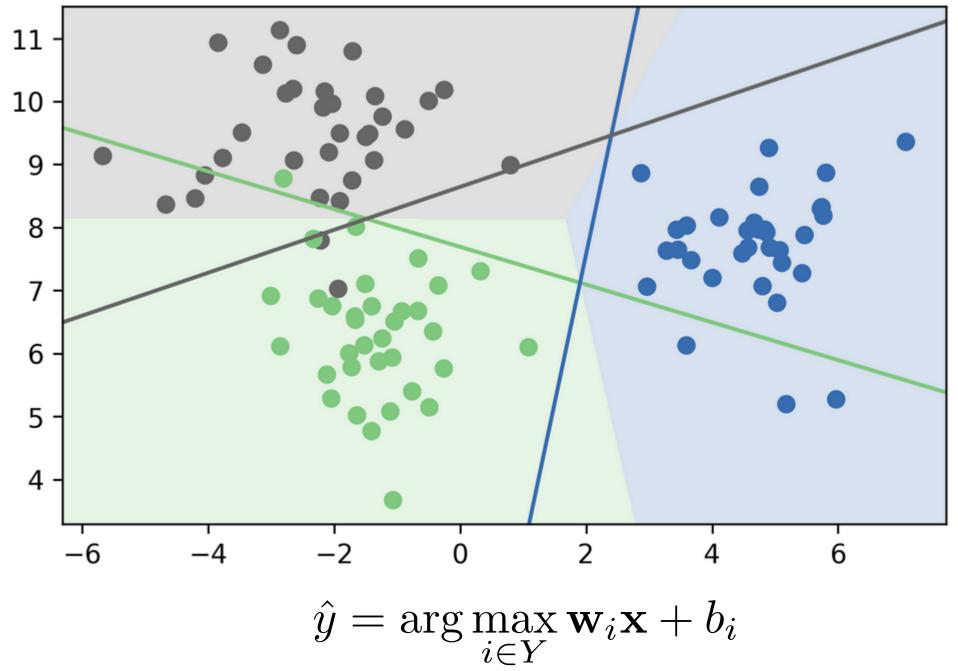
$$\min_{w \in \mathbb{R}^p} \sum_{i=1}^p ||w^T \mathbf{x}_i - y_i||^2$$
 Unique solution if  $\mathbf{x} = (\mathbf{x}_1, ... \mathbf{x}_n)^T$  has full column rank.

$$\min_{w \in \mathbb{R}^p} \sum_{i=1}^p ||w^T x_i - y_i||^2 + \alpha ||w||^2$$
 Always has a unique solution. Tuning parameter alpha.

Linear Models for Classification



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



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

#### Basic API

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

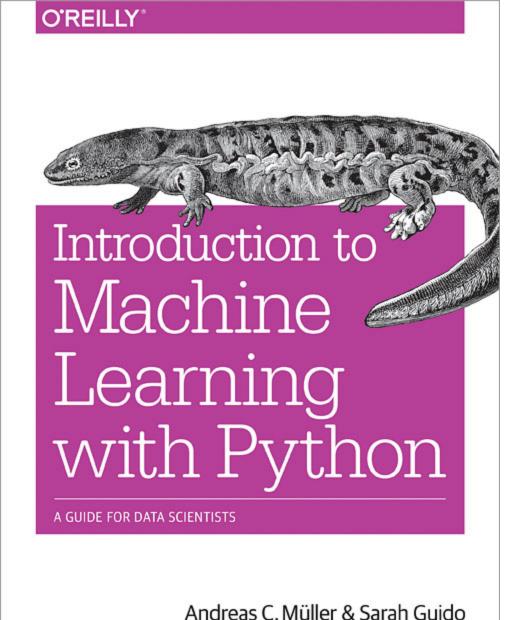
estimator.predict estimator.transform

Classification Preprocessing

Regression Dimensionality reduction

Clustering Feature selection

Feature extraction



#### Thank you for your attention.



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