Introductory Scikit-Learn

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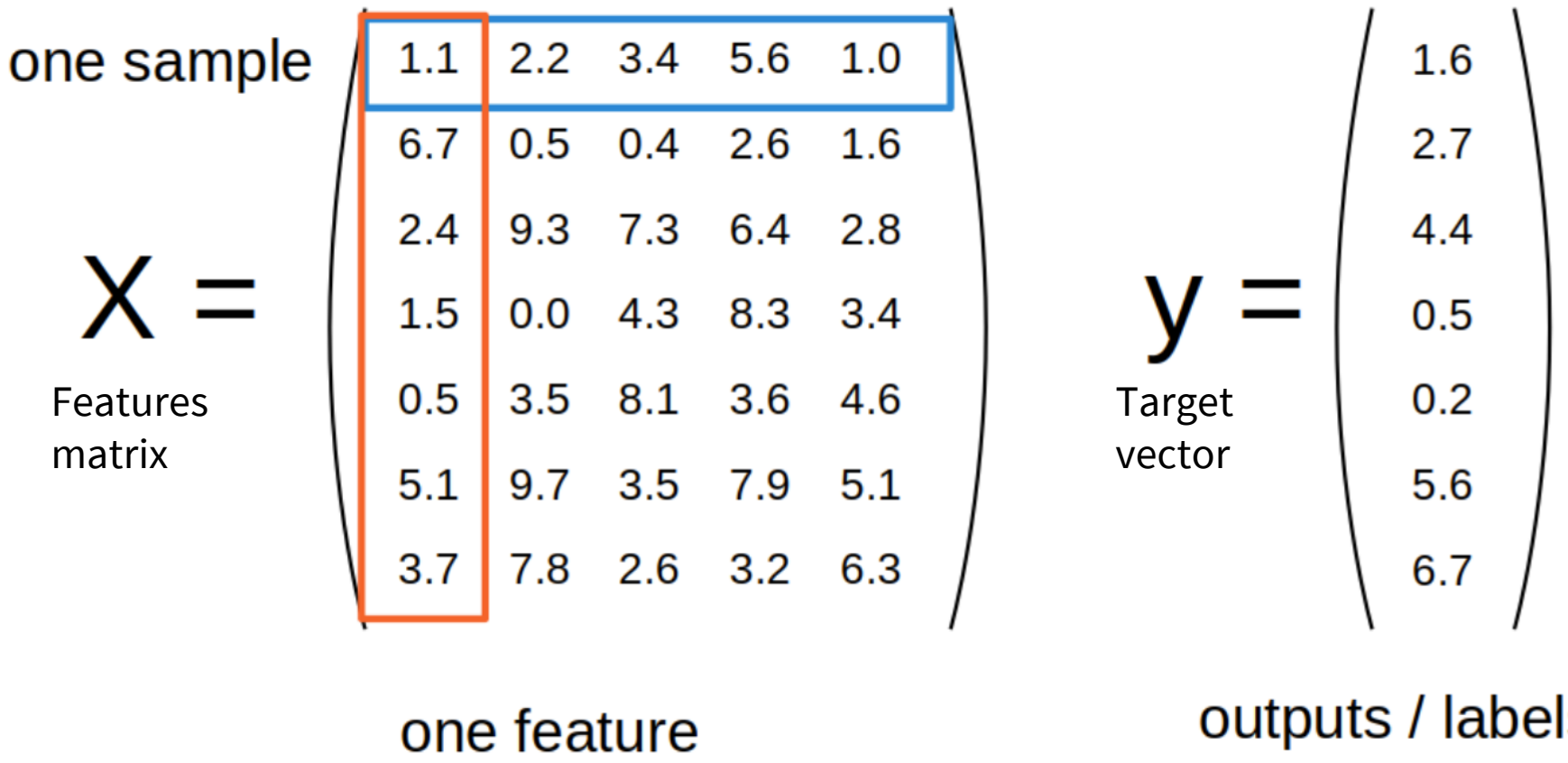
STUDY LOCALLY. LIVE GLOBALLY.

Scikit-Learn

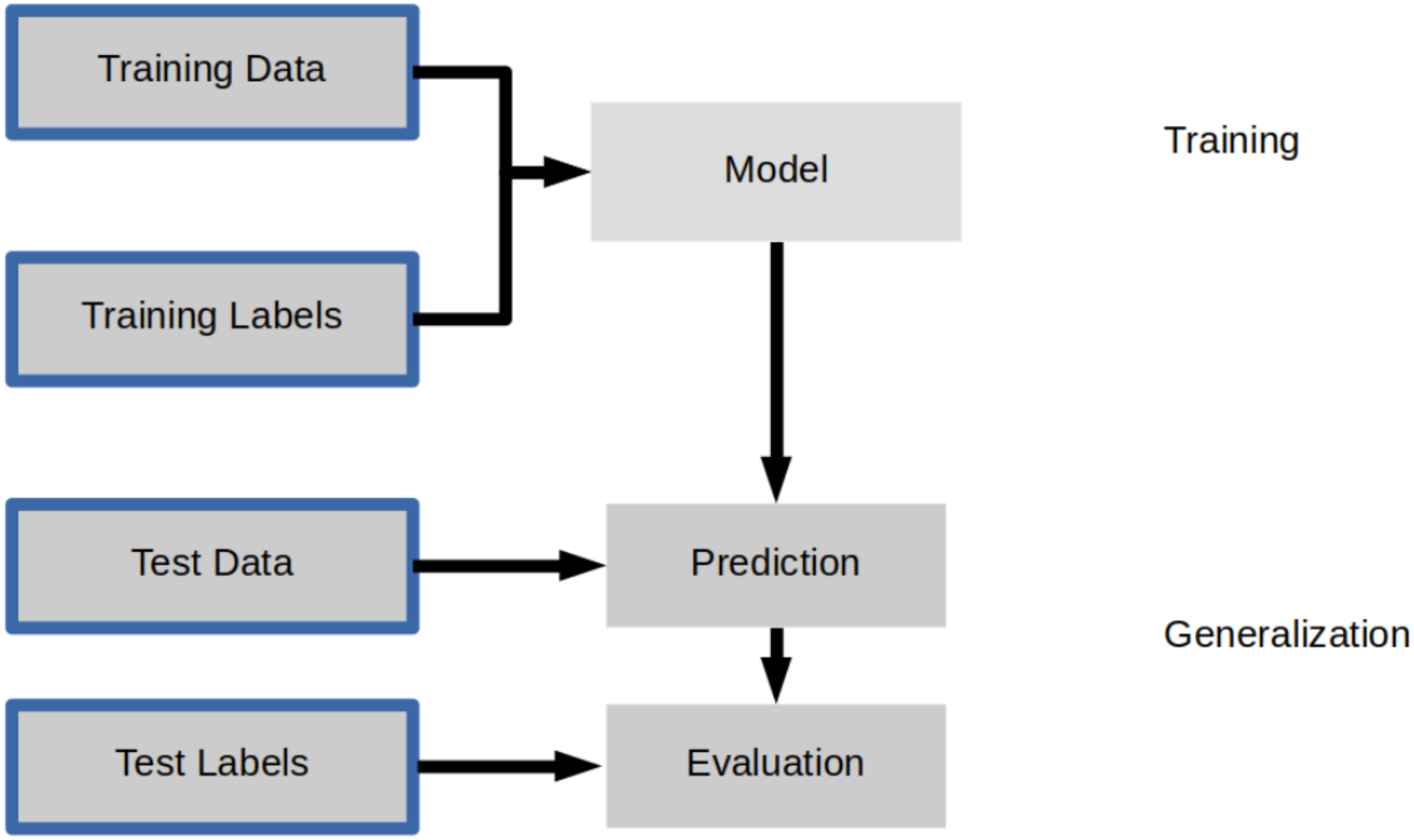
- Scikit-Learn is characterized by a clean, uniform, and streamlined API, as well as by very useful and complete online documentation.

- A benefit of this uniformity is that once you understand the basic use and syntax of Scikit-Learn for one type of model, switching to a new model or algorithm is very straightforward.

ML Data as a Table



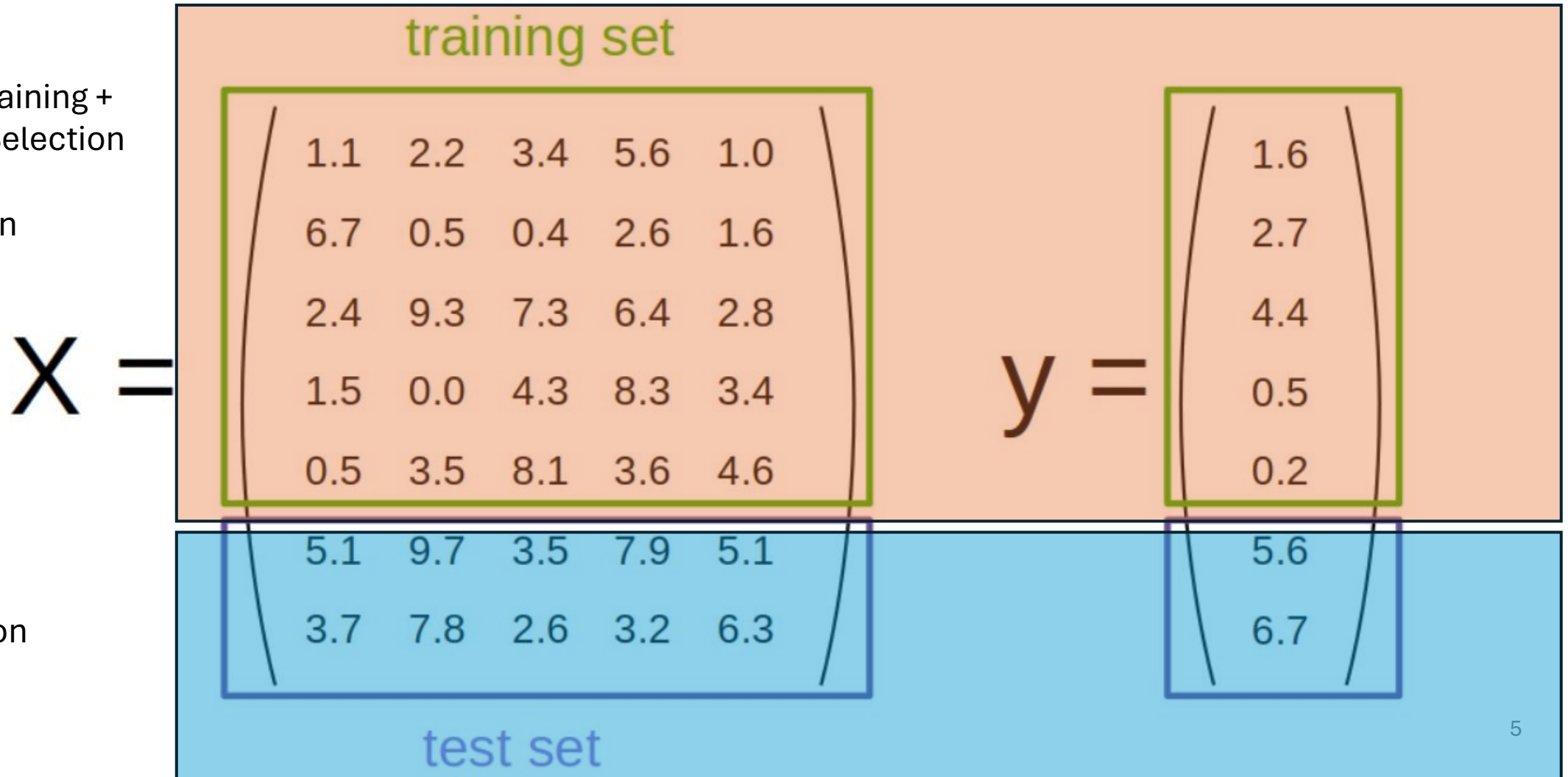
ML Workflow


Training Data
Training Labels
Model
Test Data
Test Labels
Prediction
Evaluation
Training
Generalization

Train-Test Sets

Model Training + Setting Selection (require validation dataset)

Only for evaluation



Scikit-Learn API

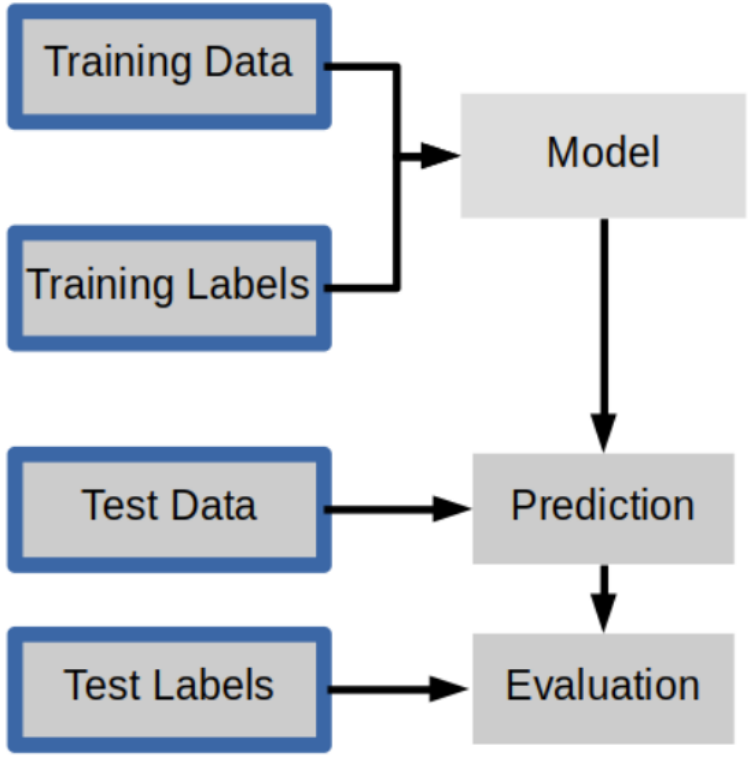
From scikitlearn import Model

```
clf = Model()

clf.fit(X_train, y_train)
```

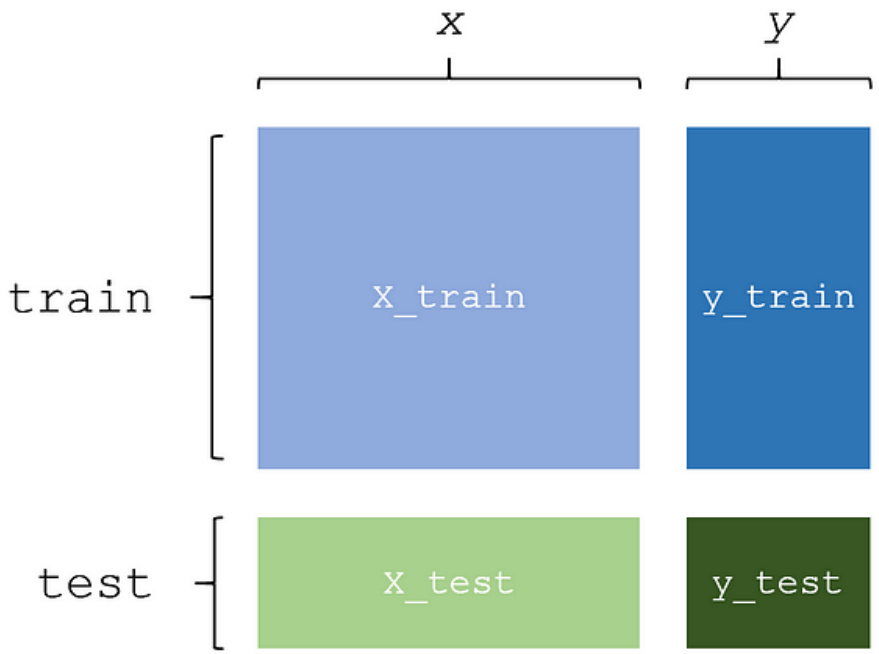
```
y_pred = clf.predict(X_test)

clf.score(X_test, y_test)
```



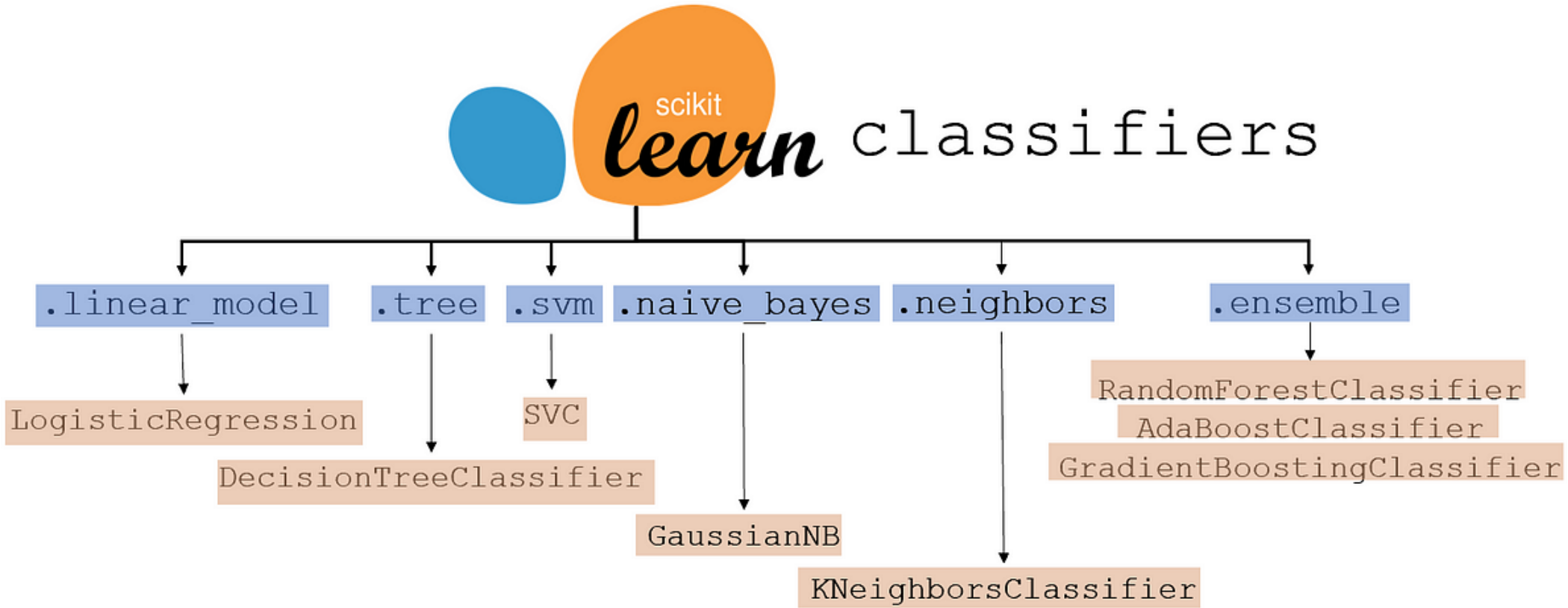
Train-test-split

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3)
```

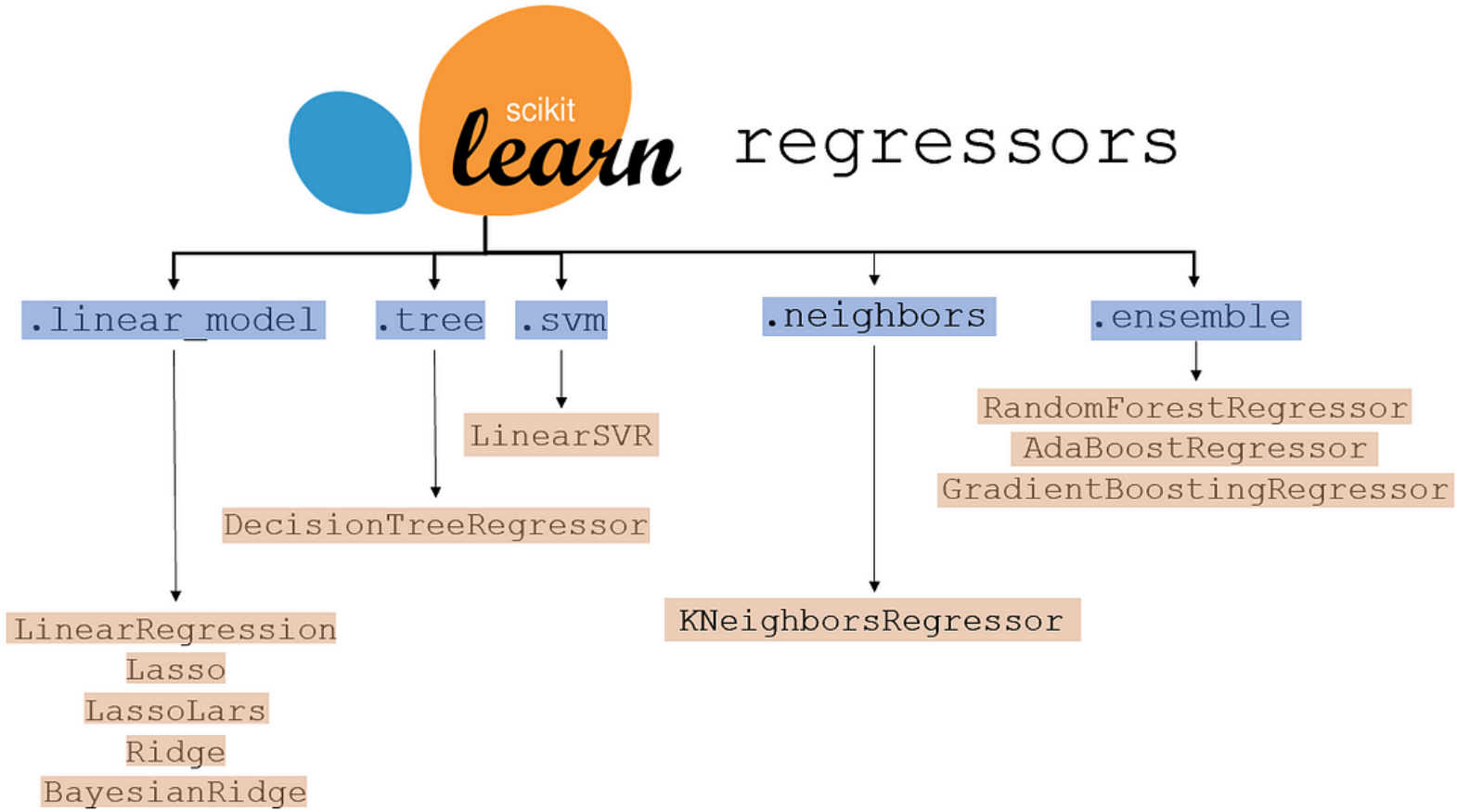


https://www.kdnuggets.com/2021/01/ultimate-scikit-learn-machine-learning-cheatsheet.html

Scikitlearn Classifiers



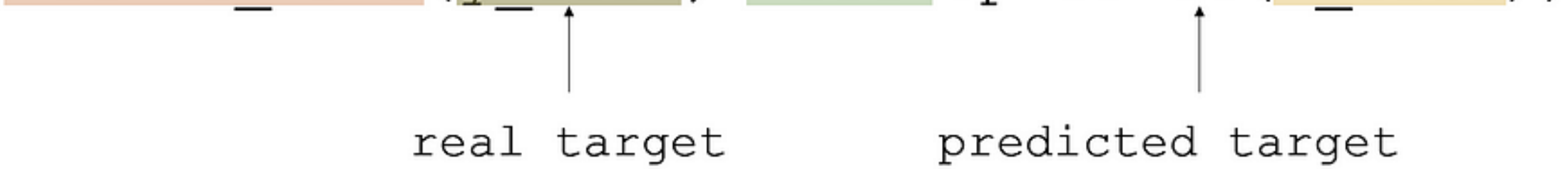
Scikitlearn Regressors



Evaluating Model Performance

```
#import
from sklearn.metrics import metric_name

#create instance
metric_name(y_test, model.predict(X_test))
```



Evaluating Model Performance

commonly used metrics marked in green

- classification
  - accuracy_score
  - balanced_accuracy_score
  - average_precision_score
  - brier_score_loss
  - f1_score
  - log_loss
  - precision_score
  - recall_score
  - jaccard_score
  - roc_auc_score
- regression
  - explained_variance_score
  - max_error
  - mean_absolute_error
  - mean_squared_error
  - mean_squared_log_error
  - median_absolute_error
  - r2_score
  - mean_poisson_deviance
  - mean_gamma_deviance

Data Transformation

- Standardizing or scaling is the process of ‘reshaping’ the data such that it contains the same information but has a mean of 0 and a variance of 1. By scaling the data, the mathematical nature of algorithms can usually handle data better.

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(data)
transformed_data = scaler.transform(data)
```

```
data = scaler.inverse_transform(output_data)
```

Data Transformation

- Normalizing data puts it on a 0 to 1 scale, something that, similar to standardized data, makes the data mathematically easier to use for the model.

```
from sklearn.preprocessing import Normalizer
normalize = Normalizer()
transformed_data = normalize.fit_transform(data)
```

Data Transformation

- Box-cox transformations involve raising the data to various powers to transform it. Box-cox transformations can normalize data, make it more linear, or decrease the complexity.
- sklearn automatically determines the best series of box-cox transformations to apply to the data to make it better resemble a

```
from sklearn.preprocessing import PowerTransformer
transformer = PowerTransformer(method='box-cox')
transformed_data = transformer.fit_transform(data)
```

Hyperparameter Selection

- Scikit-learn's GridSearchCV is an excellent tool for tuning hyperparameters of machine learning models. It exhaustively searches through a specified grid of hyperparameters to find the best ones based on cross-validated performance.

```
from sklearn.model_selection import GridSearchCV
parameters = {‘param': [0.1, 0.01, 0.001] }
model = Model()
gs = GridSearchCV(model, parameters, cv=5)
gs.fit(X_train, y_train)

best_model = gs.best_estimator_
best_model.fit(X_train, y_train)
```

Example of Complex Search

Parameters to search

```
# number of trees
n_estimators=[500, 800, 1500, 2500, 5000]
# max number of features to consider at every split
max_features = ['auto', 'sqrt', 'log2']
# max number of levels in tree
max_depth = [10, 20, 30, 40, 50]
max_depth.append(None)
# Minimum number of samples required to split a node
min_samples_split = [2, 5, 10, 15, 20]
# Minimum number of samples required at each leaf node
min_samples_leaf = [1, 2, 5, 10, 15]
```

```
grid_param = {'n_estimators': n_estimators,
              'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf}
```

Pipeline

- Scikit-learn's Pipeline is a tool for chaining multiple estimators into one. This is useful when there are a series of steps in your machine learning workflow that need to be executed in a particular sequence, such as data preprocessing, feature engineering, and model training.

```
# Define the steps in the pipeline
steps = [
    ('scaler', StandardScaler()),   # Step 1: Data preprocessing (scaling)
    ('pca', PCA()),                 # Step 2: Feature reduction (PCA)
    ('svm', SVC())                  # Step 3: Model training (Support Vector Machine)
]

# Create the pipeline
pipeline = Pipeline(steps)

# Now you can use the pipeline as a single estimator
pipeline.fit(X_train, y_train)
```

For more

https://scikit-learn.org/stable/index.html