ANALYTIXLABS

ML with Python: Sklearn

Classification
Regression
Clustering
Semi-Supervised Learning
Preprocessing
Feature Selection
Feature Extraction
Manifold Learning
Dimensionality Reduction
Kernel Approximation
Hyperparameter Optimization
Evaluation Metrics
Out-of-core learning
Pipelining
……

scikit learn

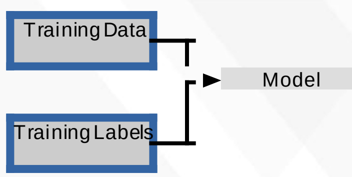
ANALYTIXLABS

Overview

- Reminder: Basic sklearn concepts
- Model building and evaluation:
  - Pipelines and Feature Unions
  - Randomized Parameter Search
  - Scoring Interface
- Out of Core learning
  - Feature Hashing
  - Kernel Approximation
- New stuff in 0.16.0
  - Overview
  - Calibration

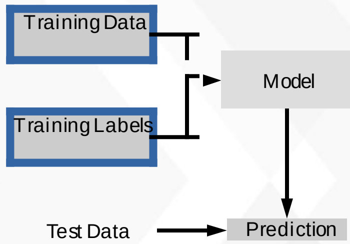
Supervised Machine Learning

```
clf = RandomForestClassifier()

clf.fit(X_train, y_train)
```



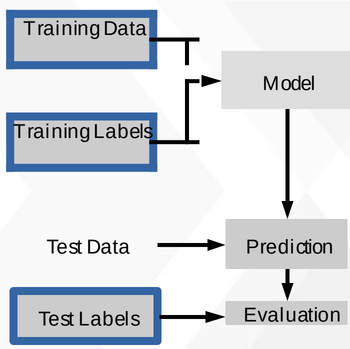
Supervised Machine Learning

```
clf = RandomForestClassifier()

clf.fit(X_train, y_train)

y_pred = clf.predict(X_test)
```



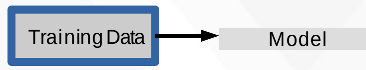
Supervised Machine Learning

```
clf = RandomForestClassifier()

clf.fit(X_train, y_train)

y_pred = clf.predict(X_test)

clf.score(X_test, y_test)
```



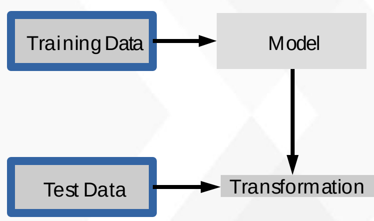
Unsupervised Transformations

```
pca = PCA(n_components=3)

pca.fit(X_train)
```



Unsupervised Transformations

```
pca = PCA(n_components=3)

pca.fit(X_train)

X_new = pca.transform(X_test)
```



ANALYTIXLABS

Basic API

estimator.fit(X, [y])

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

ANALYTIXLABS

Cross-Validation

```
from sklearn.cross_validation import cross_val_score
scores = cross_val_score(SVC(), X, y, cv=5)
print(scores)
>> [ 0.92 1. 1. 1. 1. ]
```

ANALYTIXLABS

Cross-Validation

```
From sklearn.cross_validation import cross_val_score
scores = cross_val_score(SVC(), X, y, cv=5)
print(scores)
>> [ 0.92 1. 1. 1. 1. ]
cv_ss = ShuffleSplit(len(X_train), test_size=.3, n_iter=10)
scores_shuffle_split = cross_val_score(SVC(), X, y, cv=cv_ss)
```

ANALYTIXLABS

Cross-Validation

```
From sklearn.cross_validation import cross_val_score
scores = cross_val_score(SVC(), X, y, cv=5)
cv_ss = ShuffleSplit(len(X_train), test_size=.3, n_iter=10)
scores_shuffle_split = cross_val_score(SVC(), X, y, cv=cv_ss)
cv_labels = LeaveOneLabelOut(labels)
scores_pout = cross_val_score(SVC(), X, y, cv=cv_labels)
```

ANALYTIXLABS

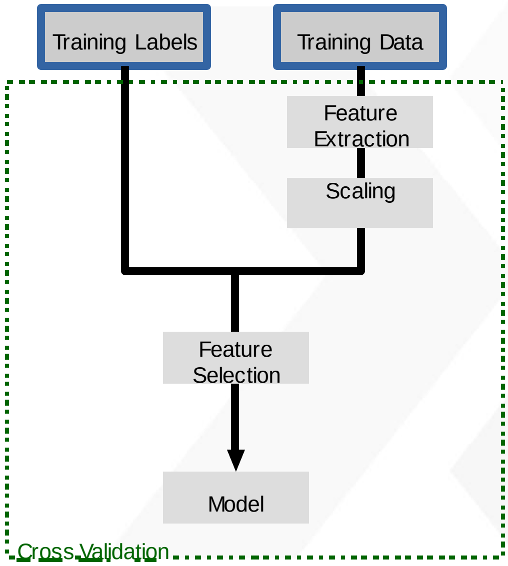
Cross -Validated Grid Search

```
In [2]: clf = SVC()
        clf.fit(X_train, y_train)

SVC(self, C=1.0, kernel='rbf', degree=3, gamma=0.0, coef0=0.0,
 shrinking=True, probability=False, tol=0.001, cache_size=200,
 class_weight=None, verbose=False, max_iter=-1, random_state=N
one)
```


Cross -Validated Grid Search

```
from sklearn.grid_search import GridSearchCV
from sklearn.cross_validation import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y)

param_grid = {'C': 10.** np.arange(-3, 3),
              'gamma': 10.** np.arange(-3, 3)}

grid = GridSearchCV(SVC(), param_grid=param_grid)

grid.fit(X_train, y_train)

grid.predict(X_test)

grid.score(X_test, y_test)
```

Cross -Validated Grid Search



ANALYTIXLABS

Pipelines

```
from sklearn.pipeline import make_pipeline
pipe = make_pipeline(StandardScaler(), SVC())
pipe.fit(X_train, y_train)
pipe.predict(X_test)
```

ANALYTIXLABS

Combining Pipelines & Grid Search I

Proper Cross Validation

```
param_grid = {'svc__C': 10. ** np.arange(-3, 3),
              'svc__gamma': 10. ** np.arange(-3, 3)}

scaler_pipe = make_pipeline(StandardScaler(), SVC())
grid = GridSearchCV(scaler_pipe, param_grid=param_grid, cv=5)
grid.fit(X_train, y_train)
```

Combining Pipelines & Grid Search II

Searching over parameters of the pre-processing step

```
param_grid = {'selectkbest__k': [1, 2, 3, 4],
              'svc__C': 10. ** np.arange(-3, 3),
              'svc__gamma': 10. ** np.arange(-3, 3)}

scaler_pipe = make_pipeline(SelectKBest(), SVC())
grid = GridSearchCV(scaler_pipe, param_grid=param_grid, cv=5)
grid.fit(X_train, y_train)
```

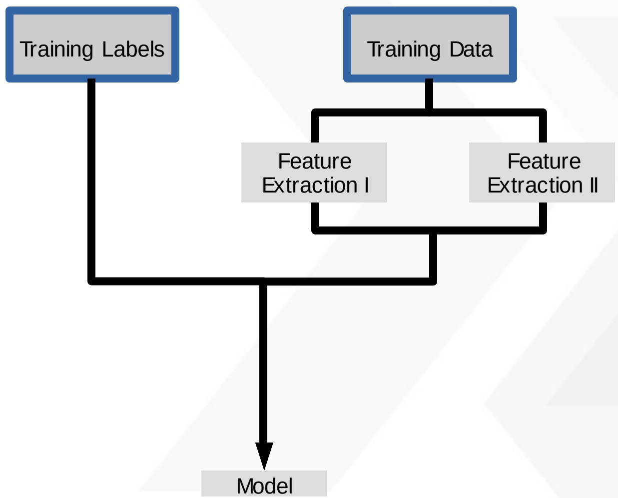
Combining Pipelines & Grid Search II

Searching over parameters of the pre-processing step

```
param_grid = {'selectkbest__k': [1, 2, 3, 4],
              'svc__C': 10. ** np.arange(-3, 3),
              'svc__gamma': 10. ** np.arange(-3, 3)}

scaler_pipe = make_pipeline(SelectKBest(), SVC())
grid = GridSearchCV(scaler_pipe, param_grid=param_grid, cv=5)
grid.fit(X_train, y_train)
```

ANALYTIXLABS

Feature Union



ANALYTIXLABS

Feature Union

```
char_and_word = make_union(CountVectorizer(analyzer="char"),
                           CountVectorizer(analyzer="word"))

text_pipe = make_pipeline(char_and_word, LinearSVC(dual=False))

param_grid = {'linearsvc__C': 10. ** np.arange(-3, 3)}
grid = GridSearchCV(text_pipe, param_grid=param_grid, cv=5)
```

ANALYTIXLABS

Feature Union

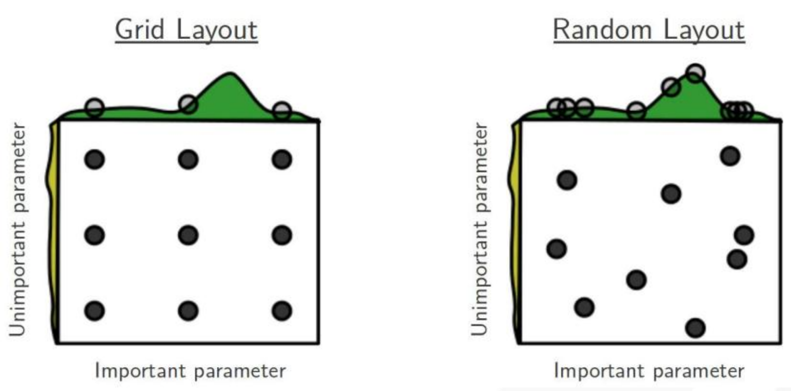
```
char_and_word = make_union(CountVectorizer(analyzer="char"),
                           CountVectorizer(analyzer="word"))

text_pipe = make_pipeline(char_and_word, LinearSVC(dual=False))

param_grid = {'linearsvc__C': 10. ** np.arange(-3, 3)}
grid = GridSearchCV(text_pipe, param_grid=param_grid, cv=5)


param_grid2 = {'featureunion__countvectorizer-1__ngram_range': [(1, 3), (1, 5), (2, 5)],
               'featureunion__countvectorizer-2__ngram_range': [(1, 1), (1, 2), (2, 2)],
               'linearsvc__C': 10. ** np.arange(-3, 3)}
```

ANALYTIXLABS

Randomized Parameter Search

ANALYTIXLABS

Randomized Parameter Search



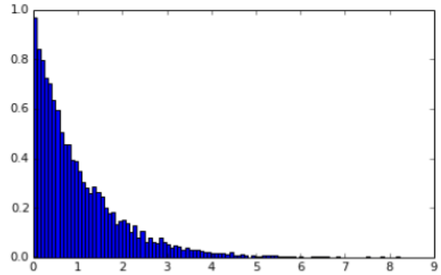
Step-size free for continuous parameters
Decouples runtime from search-space size
Robust against irrelevant parameters

ANALYTIXLABS

Source: Bergstra and Bengio

Randomized Parameter Search

```
params = {'featureunion__countvectorizer-1__ngram_range':
          [(1, 3), (1, 5), (2, 5)],
          'featureunion__countvectorizer-2__ngram_range':
          [(1, 1), (1, 2), (2, 2)],
          'linearsvc__C': expon()}
```




```
rs = RandomizedSearchCV(text_pipe,
    param_distributions=param_distributins, n_iter=50)
```

ANALYTIXLABS

Randomized Parameter Search

- Always use distributions for continuous variables.
- Don't use for low dimensional spaces.
- Future: Bayesian optimization based search.

ANALYTIXLABS

Generalized Cross-Validation and Path Algorithms

ANALYTIXLABS

Generalized Cross-Validation and Path Algorithms

```
rfe   = RFE(LogisticRegression())
param_grid  = {'n_features_to_select': range(1, gridsearch =  n_features)}
            GridSearchCV(rfe, param_grid) grid.fit(X, y)
```

```
rfecv   = RFECV(LogisticRegression())
rfecv.fit(X,y)
```

ANALYTIXLABS

Generalized Cross-Validation and Path Algorithms

Linear Models	Feature Selection	Tree-Based models [possible]
LogisticRegressionCV [new]	RFECV	[DecisionTreeCV]
RidgeCV		[RandomForestClassifierCV]
RidgeClassifierCV		[GradientBoostingClassifierCV]
LarsCV		
ElasticNetCV		
…		

ANALYTIXLABS

Scoring Functions

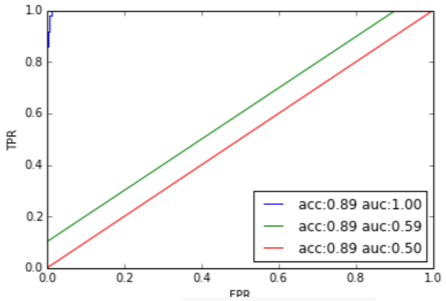
ANALYTIXLABS

GridSeachCV
RandomizedSearchCV
cross_val_score
...CV

Default:
Accuracy (classification)
R2 (regression)

Scoring with imbalanced data

```
cross_val_score(SVC(), X_train, y_train)
>>> array([ 0.9,  0.9,  0.9])

cross_val_score(DummyClassifier("most_frequent"), X_train, y_train)
>>> array([ 0.9,  0.9,  0.9])

cross_val_score(SVC(), X_train, y_train, scoring="roc_auc")
array([ 0.99961591,  0.99983498,  0.99966247])
```



Available metrics

```
print(SCORERS.keys())

>> ['adjusted_rand_score',
 'f1',
 'mean_absolute_error',
 'r2',
 'recall',
 'median_absolute_error',
 'precision',
 'log_loss',
 'mean_squared_error',
 'roc_auc',
 'average_precision',
 'accuracy']
```

ANALYTIXLABS

Defining your own scoring

```
def my_super_scoring(est, X, y):
    return accuracy_scorer(est, X, y) - np.sum(est.coef_ != 0)
```

ANALYTIXLABS

Out of Core Learning

Supported Algorithms

All SGDClassifier derivatives

Naive Bayes

MinibatchKMeans

IncrementalPCA

MiniBatchDictionaryLearning

Out of Core Learning

```
sgd = SGDClassifier()

for i in range(9):
    X_batch, y_batch = cPickle.load(open("batch_%02d" % i))
    sgd.partial_fit(X_batch, y_batch, classes=range(10))
```

Possibly go over the data multiple times.

ANALYTIXLABS

Stateless Transformers

- Normalizer
- HashingVectorizer
- RBFSampler (and other kernel approx)

ANALYTIXLABS

Text data and the hashing trick

Bag Of Word Representations

`CountVectorizer / TfidfVectorizer`

`“You better call Kenny Loggins”`

↓ tokenizer

`['you', 'better', 'call', 'kenny', 'loggins']`

↓ Sparse matrix encoding

aardvak better call you zyxst
[0, …, 0, 1, 0, … , 0, 1 , 0, …, 0, 1, 0, …., 0]

Hashing Trick – Hashing Vectorizer

"You better call Kenny Loggins"

↓ tokenizer

['you', 'better', 'call', 'kenny', 'loggins']

↓ hashing

[hash('you'), hash('better'), hash('call'), hash('kenny'), hash('loggins')]
= [832412, 223788, 366226, 81185, 835749]

↓ Sparse matrix encoding

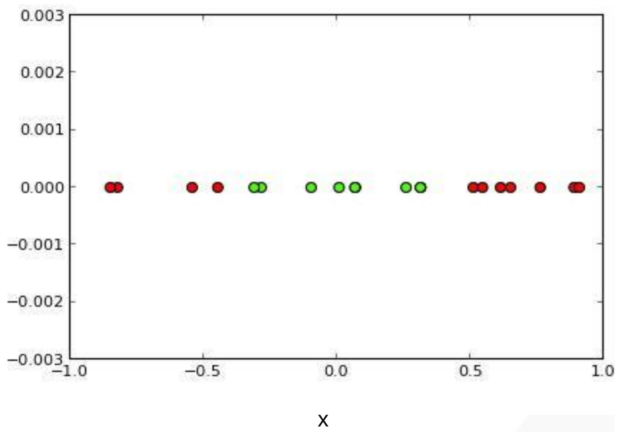
[0, ..., 0, 1, 0, ... , 0, 1 , 0, ..., 0, 1, 0, ... 0]

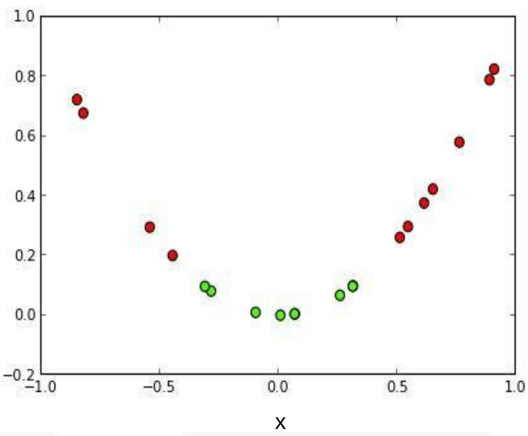
Out of Core Text Classification

```
sgd = SGDClassifier()
hashing_vectorizer = HashingVectorizer()

for i in range(9):
    text_batch, y_batch = cPickle.load(open("text_%02d" % I))
    X_batch = hashing_vectorizer.transform(text_batch)
    sgd.partial_fit(X_batch, y_batch, classes=range(10))
```

Kernel Approximations

Reminder: Kernel Trick





Reminder: Kernel Trick

Classifier linear → need only

$$\langle \phi(x_i), \phi(x_j) \rangle = k(x_i, x_j)$$

Linear:	$\langle x, x' \rangle$
Polynomial:	$(\gamma \langle x, x' \rangle + r)^d$
RBF:	$\exp(-\gamma \lvert x - x' \rvert^2)$
Sigmoid:	$\tanh(\gamma \langle x, x' \rangle + r)$

ANALYTIXLABS

Complexity

- Solving kernelized SVM:
  ~O(n_samples ** 3)
- Solving linear (primal) SVM:
  ~O(n_samples * n_features)

n_samples large? Go primal!

ANALYTIXLABS

Undoing the Kernel Trick

- Kernel approximation:

$$\langle \hat{\phi}(x_i), \hat{\phi}(x_j) \rangle \approx k(x_i, x_j)$$

- k = $\exp(-\gamma|x - x'|^2)$
  $\hat{\phi}$ = RBFSampler

Usage

```
sgd = SGDClassifier()
kernel_approximation = RBFSampler(gamma=.001, n_components=400)

for i in range(9):
    X_batch, y_batch = cPickle.load(open("batch_%02d" % i))
    if i == 0:
        kernel_approximation.fit(X_batch)
    X_transformed = kernel_approximation.transform(X_batch)
    sgd.partial_fit(X_transformed, y_batch, classes=range(10))
```

Appendix

Highlights from sklearn 0.16.0 + onwards

Highlights from 0.16.0

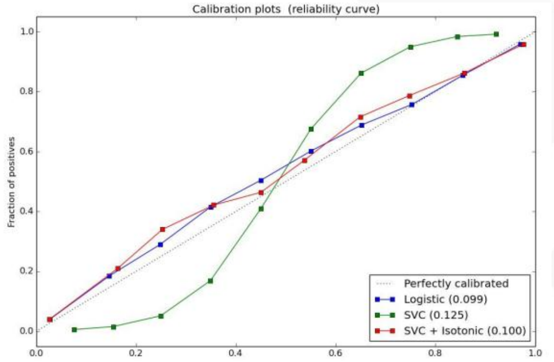
- Multinomial Logistic Regression, LogisticRegressionCV.
- IncrementalPCA.
- Probability callibration of classifiers.
- Birch clustering.
- LSHForest.
- More robust integration with pandas.

ANALYTIXLABS

Probability Calibration

SVC().decision_function()
→ CalibratedClassifierCV(SVC()).predict_proba()

RandomForestClassifier().predict_proba()
→ CalibratedClassifierCV(RandomForestClassifier()).predict_proba()



ANALYTIXLABS

scikit learn

Home | Installation | Documentation | Examples

Google™ Custom Search | Search ×

Documentation of scikit-learn 0.16-git

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 0.15 (stable)
- scikit-learn 0.16 (development)
- scikit-learn 0.14
- scikit-learn 0.13
- scikit-learn 0.12
- Older versions

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.

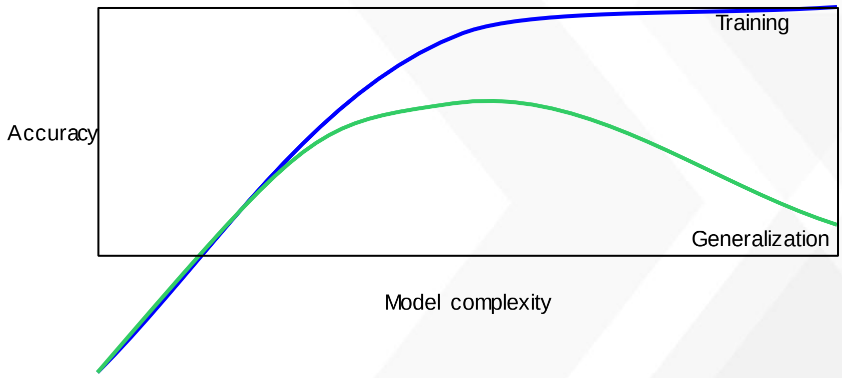
FAQ

Frequently asked questions about the project and contributing.

Bias Variance Tradeoff
(why we do cross validation and grid searches)

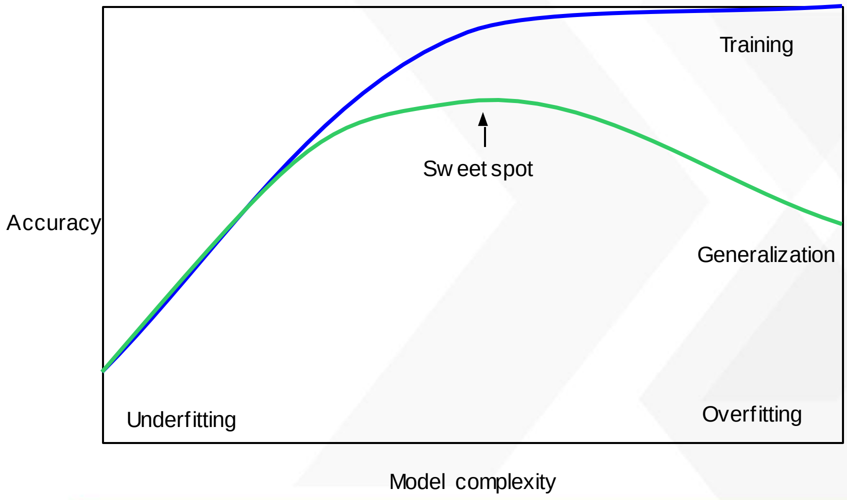
ANALYTIXLABS

Overfitting and Underfitting



ANALYTIXLABS

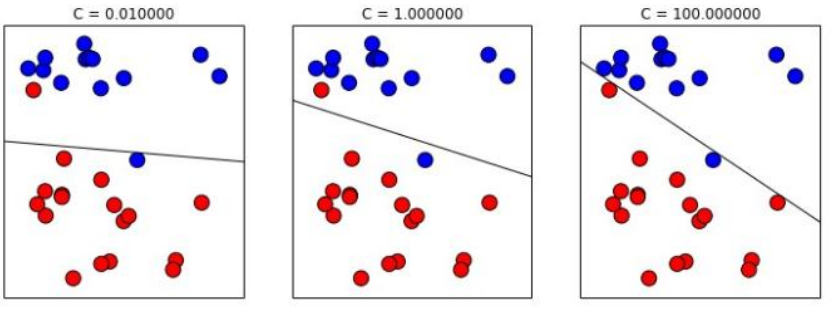
Overfitting and Underfitting



ANALYTIXLABS

Linear SVM

$$\hat{y} = \mathrm{sign}(w_0 + \sum_i w_i x_i)$$

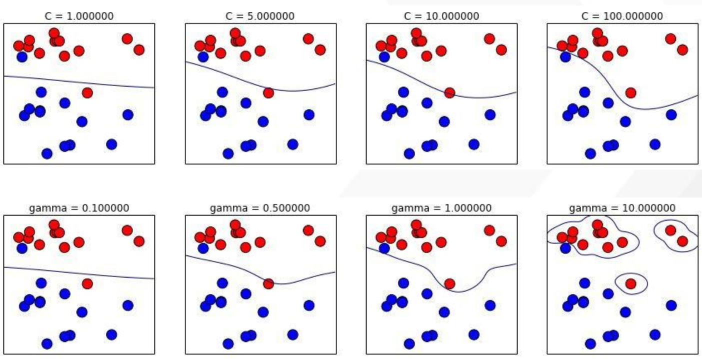


ANALYTIXLABS

(RBF) Kernel SVM

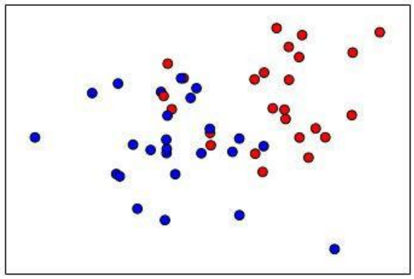
$$\hat{y} = \mathrm{sign}(\alpha_0 + \sum_j \alpha_j y_j k(\mathbf{x}^{(\mathbf{j})}, \mathbf{x}))$$

$$k(\mathbf{x}, \mathbf{x}') = \exp(-\gamma ||\mathbf{x} - \mathbf{x}'||^2)$$

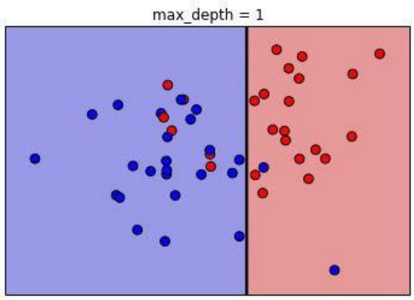


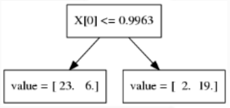
ANALYTIXLABS

Decision Trees

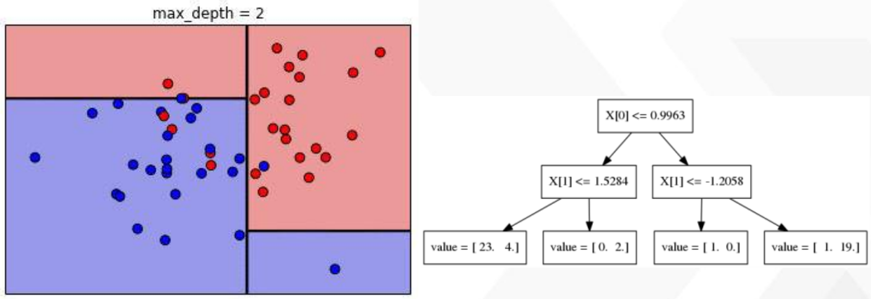


Decision Trees

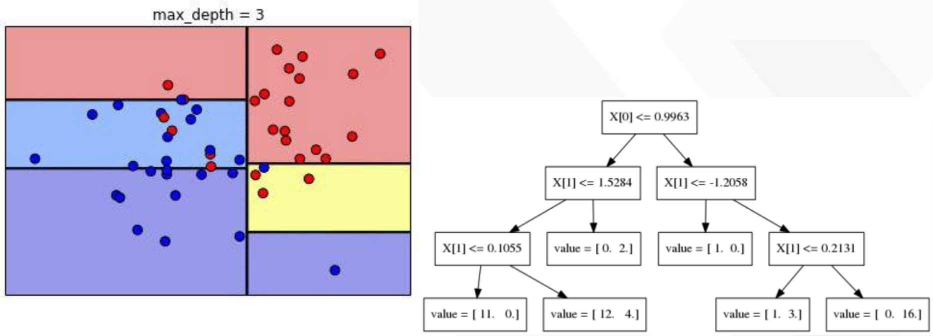




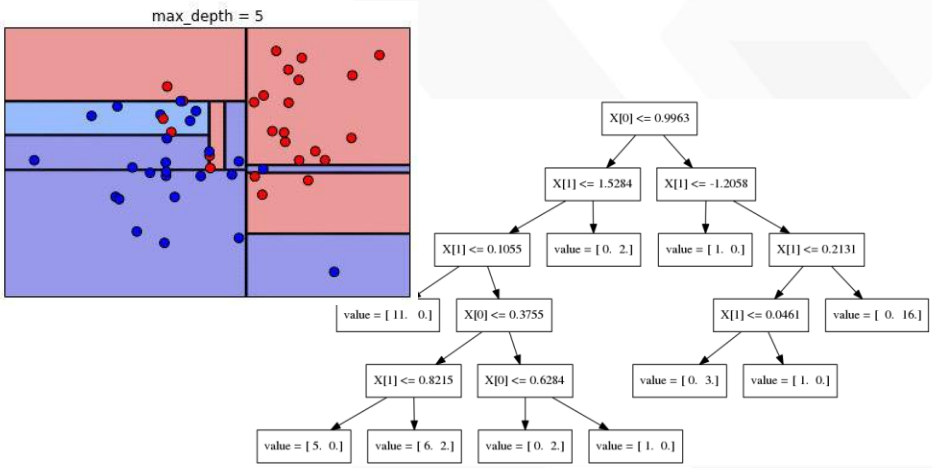
Decision Trees



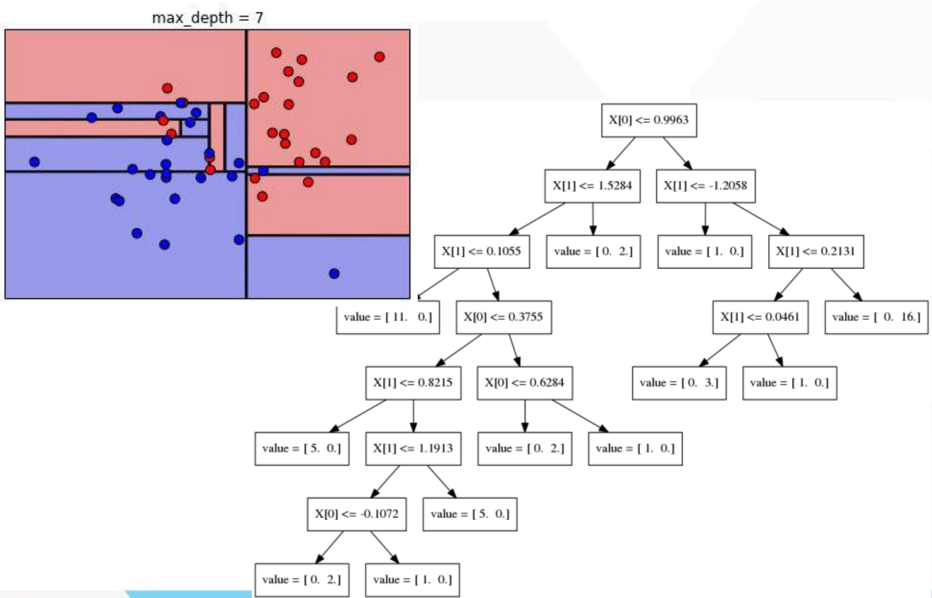
Decision Trees



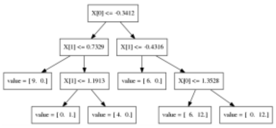
Decision Trees



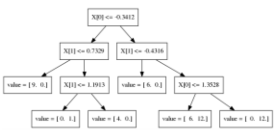
Decision Trees

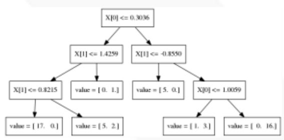


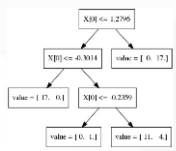
Random Forests



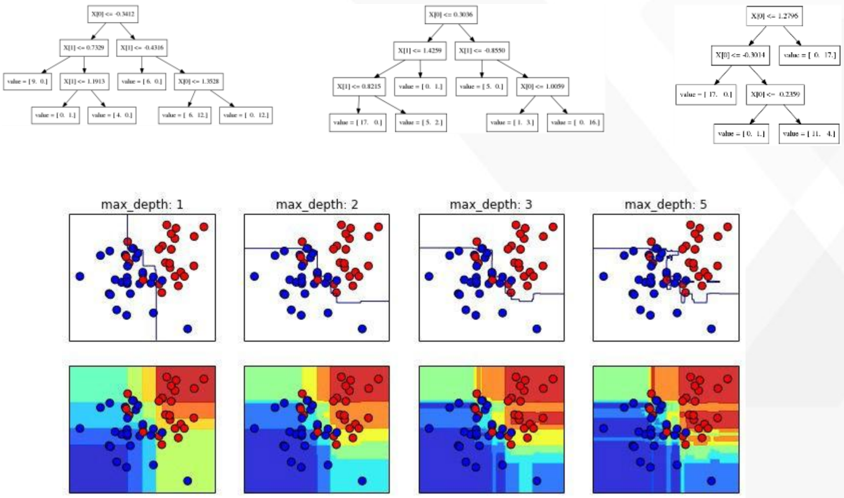
Random Forests







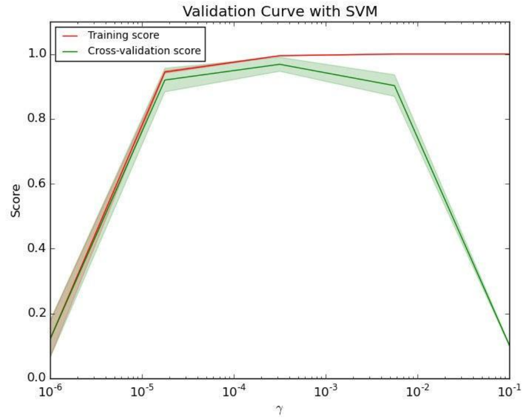
Random Forests



Know where you are on the bias-variance tradeoff

Validation Curves

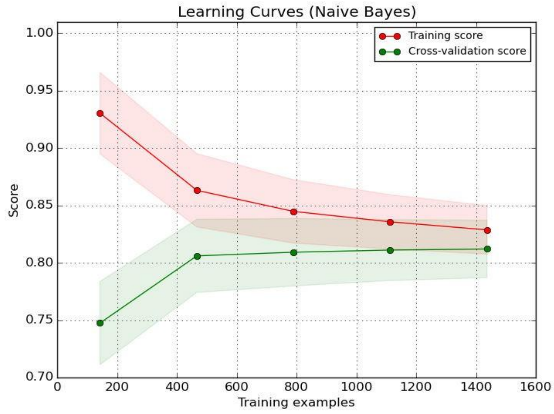
train_scores, test_scores = validation_curve(SVC(), X, y, param_name="gamma", param_range=param_range)



ANALYTIXLABS

Learning Curves

train_sizes, train_scores, test_scores = learning_curve(estimator, X, y,train_sizes=train_sizes)



ANALYTIXLABS

Q&A

ANALYTIXLABS

Contact us

Visit us on: http://www.analytixlabs.in/

For course registration, please visit: http://www.analytixlabs.co.in/course-registration/

For more information, please contact us: http://www.analytixlabs.co.in/contact-us/

Or email: info@analytixlabs.co.in

Call us we would love to speak with you: (+91) 95555-21007

Join us on:

Twitter - http://twitter.com/#!/AnalytixLabs

Facebook - http://www.facebook.com/analytixlabs

LinkedIn - http://www.linkedin.com/in/analytixlabs

Blog - http://www.analytixlabs.co.in/category/blog/

ANALYTIXLABS