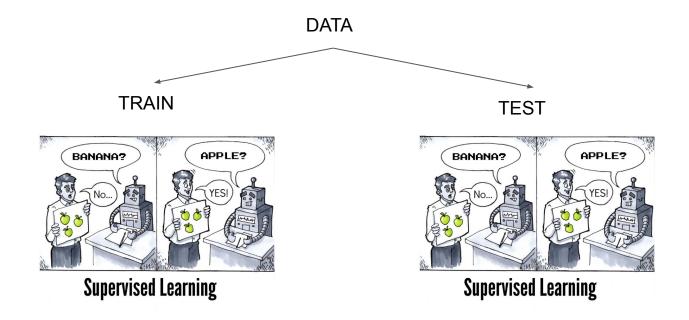
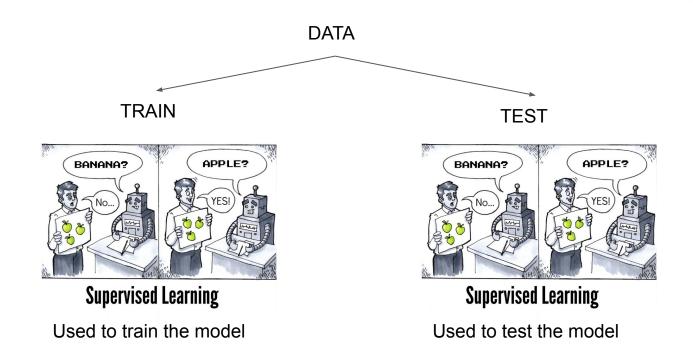
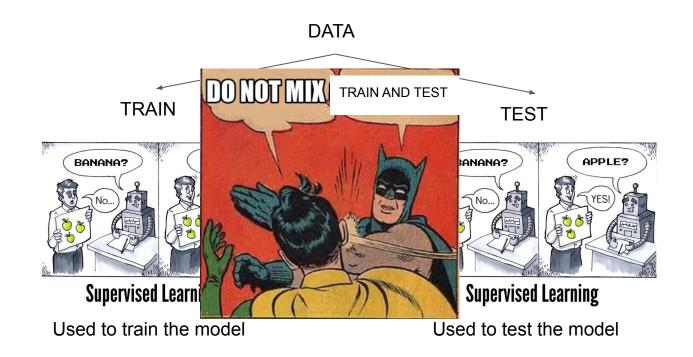
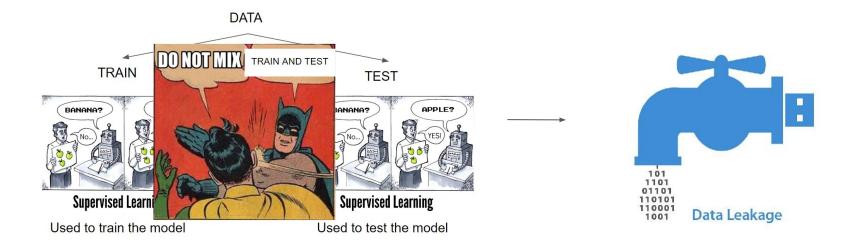


**Supervised Learning** 







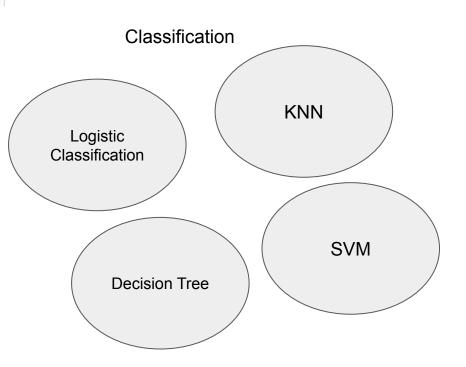


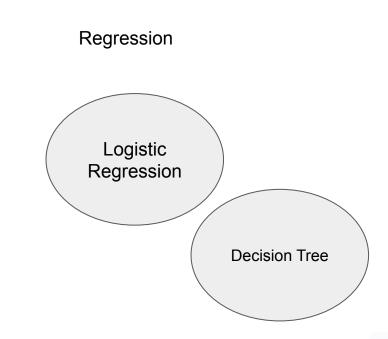


- When information outside the training dataset is used to create the model.
- When training data leaks into test data
- When test data leaks into training data

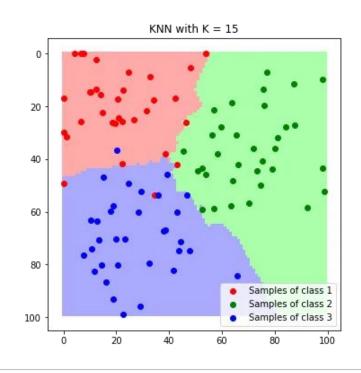


- Thread carefully when applying transformations on the entire dataset e.g,
  - Handle missing values per dataset split (mean, std, normalizations,...)
  - Feature extractions





K-Nearest Neighbors (KNN)



### K-Nearest Neighbors (KNN)

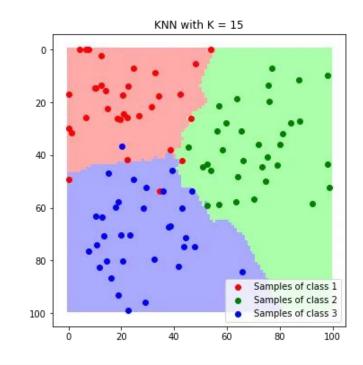
(https://scikit-learn.org/stable/modules/generated/s klearn.neighbors.KNeighborsClassifier.html)

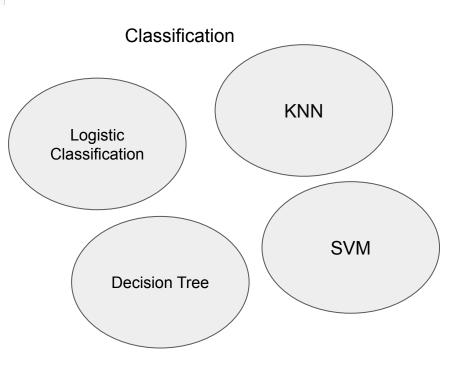
### Training:

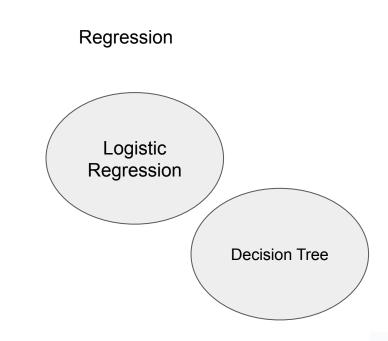
- It's not "trained"
- Load training data

### Evaluate:

- Select K
- New data point
- K closest belong to which class?
- Select that class





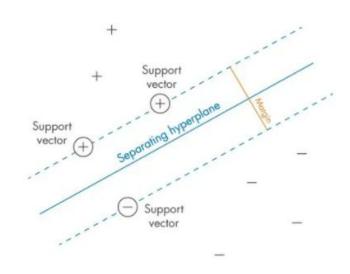


Support Vector Machine (sklearn.svm.SVC)

Support Vectors – Data points that are closest to the hyperplane are called support vectors. A separating line will be defined with the help of these data points.

Hyperplane – It is a decision plane or space which is divided between a set of objects having different classes.

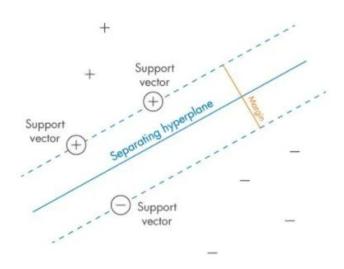
Margin – Gap between two lines on the closet data points of different classes. It can be calculated as the perpendicular distance from the line to the support vectors. A large margin is considered as a good margin and a small margin is considered as a bad margin.



Support Vector Machine (sklearn.svm.SVC)

### Training

- Generate hyperplanes iteratively
- Find hyperplane that separates the classes as best as possible
  - Transforms data using the kernel trick (i.e adds more dimensions to the data)
  - Tries to separate the data



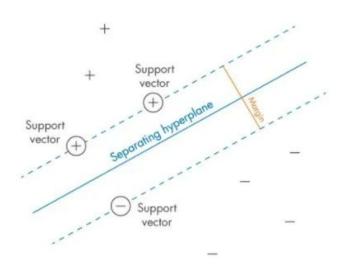
Support Vector Machine (sklearn.svm.SVC)

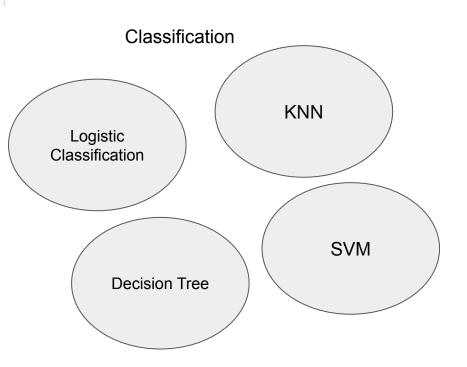
### Pros

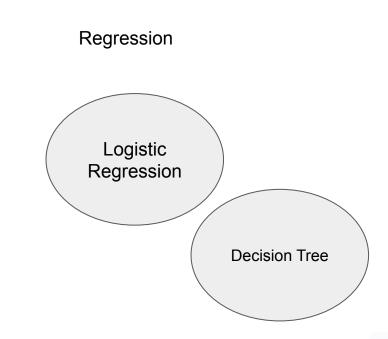
- SVM works relatively well when there is a clear margin of separation between classes.
- SVM is more effective in high dimensional spaces.

### Cons

- SVM algorithm is not suitable for large data sets.
- SVM does not perform very well when the data set has more noise i.e. target classes are overlapping.







#### sklearn.tree.DecisionTreeClassifier

class sklearn.tree.DecisionTreeClassifier(\*, criterion='gini', splitter='best', max\_depth=None, min\_sam min\_samples\_leaf=1, min\_weight\_fraction\_leaf=0.0, max\_features=None, random\_state=None, max\_leaf\_nodes min\_impurity\_decrease=0.0, class\_weight=None, ccp\_alpha=0.0)

A decision tree classifier.

Read more in the User Guide.

#### Parameters:

#### criterion: {"gini", "entropy", "log\_loss"}, default="gini"

The function to measure the quality of a split. Supported criteria are "gini" for the Gini ii and "entropy" both for the Shannon information gain, see Mathematical formulation.

#### splitter: {"best", "random"}, default="best"

The strategy used to choose the split at each node. Supported strategies are "best" to c and "random" to choose the best random split.

#### max\_depth : int, default=None

The maximum depth of the tree. If None, then nodes are expanded until all leaves are p contain less than min samples split samples.

#### min samples split: int or float, default=2

The minimum number of samples required to split an internal node:

- If int, then consider min\_samples\_split as the minimum number.
- If float, then min\_samples\_split is a fraction and ceil(min\_samples\_split \* n\_samplent number of samples for each split.

Changed in version 0.18: Added float values for fractions.

#### min\_samples\_leaf: int or float, default=1

The minimum number of samples required to be at a leaf node. A split point at any dep considered if it leaves at least min\_samples\_leaf training samples in each of the left and may have the effect of smoothing the model, especially in regression.

#### sklearn.svm.SVC

class  $skleann.svm.svc(*, C=1.0, kernel='rbf, degree=3, gamma='scale', coef0=0.0, shrinking=True, probability=False, tol=0.001, cache_size=200, class_weight=None, verbose=False, max_iter=-1, decision_function_shape='ovr', break_ties=False, random_state=None) [source]$ 

#### C-Support Vector Classification.

The implementation is based on libsym. The fit time scales at least quadratically with the number of samples and may be impractical beyond tens of thousands of samples. For large datasets consider using LinearSVC or SGDClassifier instead, possibly after a Nystroem transformer or other Kernel Approximation.

The multiclass support is handled according to a one-vs-one scheme.

For details on the precise mathematical formulation of the provided kernel functions and how gamma, coefe and degree affect each other, see the corresponding section in the narrative documentation: Kernel functions.

Read more in the User Guide.

#### Parameters:

#### C: float, default=1.0

Regularization parameter. The strength of the regularization is inversely proportional to C. Must be strictly positive. The penalty is a squared I2 penalty.

#### kernel: {'linear', 'poly', 'rbf', 'sigmoid', 'precomputed'} or callable, default='rbf'

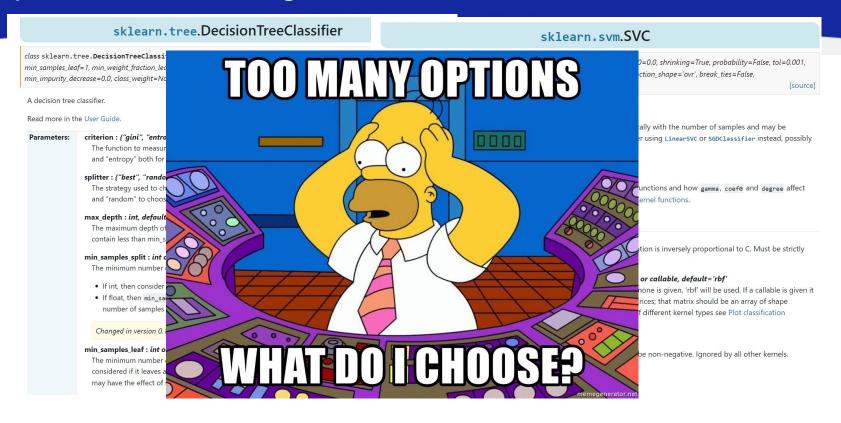
Specifies the kernel type to be used in the algorithm. If none is given, 'rbf' will be used. If a callable is given it is used to pre-compute the kernel matrix from data matrices; that matrix should be an array of shape (n\_samples, n\_samples). For an intuitive visualization of different kernel types see Plot classification boundaries with different SVM Kernels.

#### degree: int, default=3

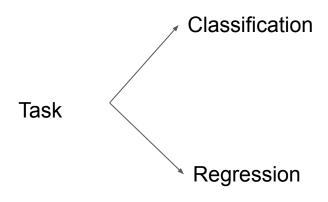
Degree of the polynomial kernel function ('poly'). Must be non-negative. Ignored by all other kernels.

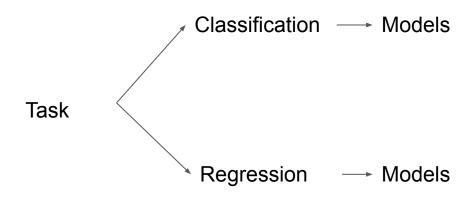
#### gamma: {'scale', 'auto'} or float, default='scale'

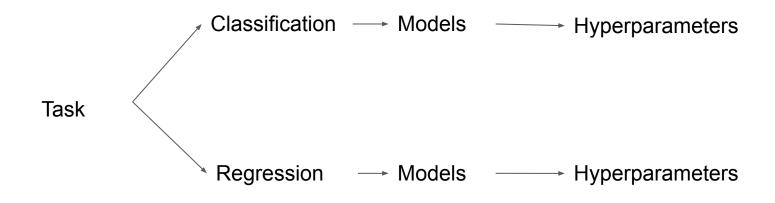
Kernel coefficient for 'rbf', 'poly' and 'sigmoid'.



Task







Parameters vs Hyperparameters

**Parameters** 

Are learned by the model, i.e they change during training

٧S

Hyperparameters

**Parameters** 

Are learned by the model, i.e they change during training

٧S

Hyperparameters

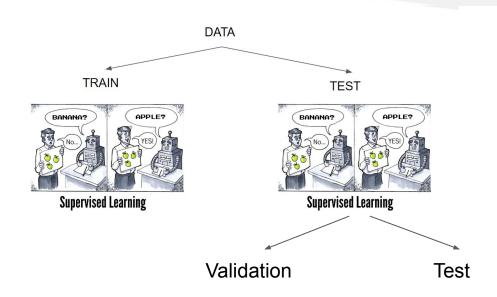
Are decided before and fixed during training, i.e they are not learnt by the model and impact learning.

Hyperparameter Search Find the best hyperparameters for the target task, model, and existing data.

Hyperparameter Search Find the best hyperparameters for the target task, model and existing data.

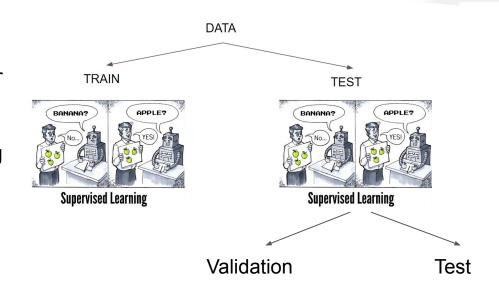
Search Space
- given a model, all
hyperparameters combinations
possible

Hyperparameter Search Find the best hyperparameters for the target task, model and existing data.



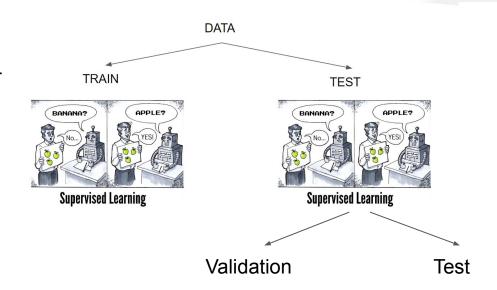
# Hyperparameter search consists of:

- an estimator (regressor or classifier such as sklearn.svm.SVC());
- a parameter space;
- a method for searching or sampling candidates;
- a cross-validation scheme
- a score function.



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### Hyperparameter search

- Grid Search
- Random Search
- Bayesian Search



### Hyperparameter search

Grid Search
 (systematically evaluates a predefined set of hyperparameters combinations to find the best set of hyperparameter for a given model)
 (sklearn.model selection.GridSearchCV)

Hyperparameter search

Grid Search (sklearn.model\_selection.GridSearchCV)

### Hyperparameter search

- Grid Search (sklearn.model\_selection.GridSearchCV)
- Random Search
   (randomly samples hyperparameter values from
   predefined distributions to efficiently explore the search
   space and find optimal hyperparameter configurations for
   machine learning models)
   (sklearn.model selection.RandomizedSearchCV)

Samsung Innovation Campus

### Hyperparameter search

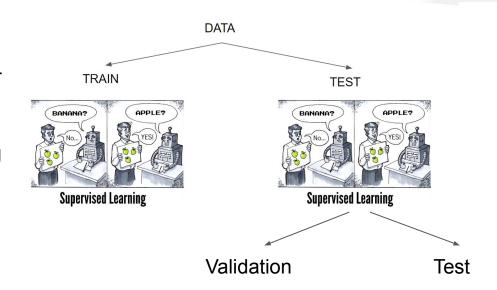
- Grid Search (sklearn.model\_selection.GridSearchCV)
- Random Search (sklearn.model\_selection.RandomizedSearchCV)
- Bayesian Search

### Hyperparameter search

- Grid Search (sklearn.model\_selection.GridSearchCV)
- Random Search (sklearn.model\_selection.RandomizedSearchCV)
- Bayesian Search
   (is a probabilistic optimization technique that uses surrogate models to efficiently explore and optimize complex hyperparameter spaces in machine learning by iteratively selecting hyperparameters to evaluate based on a balance of exploration and exploitation) (skopt.BayesSearchCV)

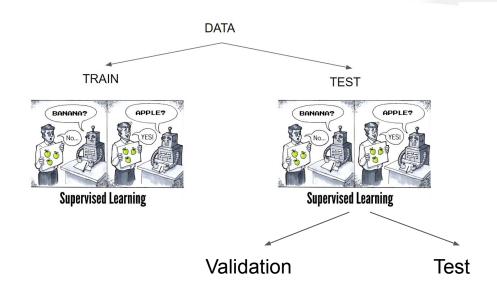
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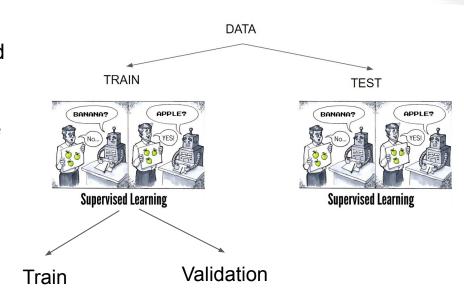
#### **Dataset splits**

- Train is used to train the selected model with the selected hyperparameters
- Validation is used to validate the trained models
- Test is used to test the validated model with the higher selected metric



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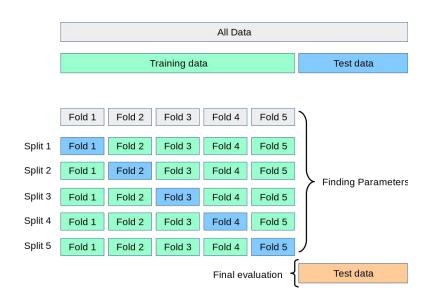


Hyperparameter search Cross Validation Schemes

- K-Fold Cross Validation
- Leave-One-Out Cross Validation
- Stratified Cross Validation
- Time-Series Cross Validation
- Repeated Cross-Validation

Hyperparameter search Cross Validation Schemes

K-Fold Cross Validation



### Hyperparameter search **Cross Validation Schemes**

K-Fold Cross Validation (sklearn.model selection.cross\_val\_score)



All Data

>>> scores

Hyperparameter search Cross Validation Schemes

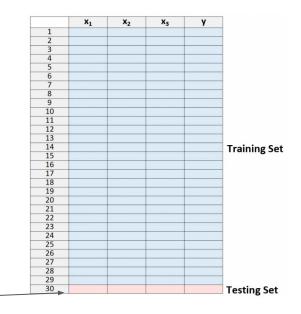
Leave-One-Out Cross Validation

Leave-One-Out

### Hyperparameter search Cross Validation Schemes

Leave-One-Out Cross Validation
 (sklearn.model\_selection.LeaveOneOut)
 I.e leave one out and repeat process N times,
 where N is the time number of observations

Leave-One-Out

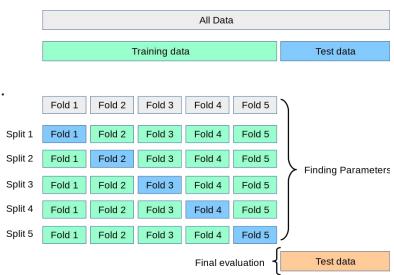


Hyperparameter search Cross Validation Schemes

Stratified Cross Validation

#### Hyperparameter search Cross Validation Schemes

Stratified Cross Validation
 (sklearn.model\_selection.StratifiedKFold)
 is a variation of K-Fold that returns stratified folds.
 The folds are made by preserving the percentage
 of samples for each class.



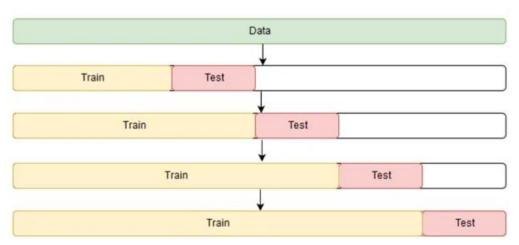
Hyperparameter search Cross Validation Schemes

Time-Series Cross Validation

Hyperparameter search Cross Validation Schemes

 Time-Series Cross Validation (sklearn.model\_selection.TimeSeriesSplit)

i.e folds are sequential



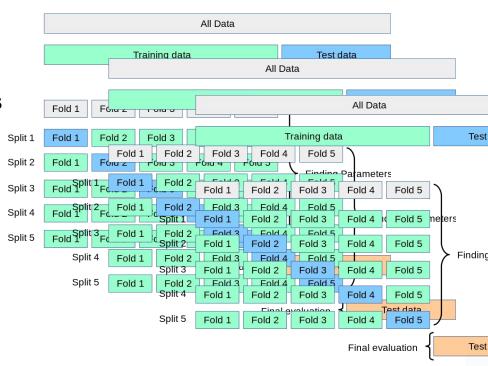
Hyperparameter search Cross Validation Schemes

Repeated Cross Validation

#### Hyperparameter search Cross Validation Schemes

Repeated Cross Validation

 i.e repeat k-fold validation multiple times
 (with different splits)



# Hyperparameter search consists of:

- an estimator (regressor or classifier such as sklearn.svm.SVC());
- a parameter space;
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- a cross-validation scheme
- a score function.

F1 Score Precision Recall Accuracy

# Hyperparameter search consists of:

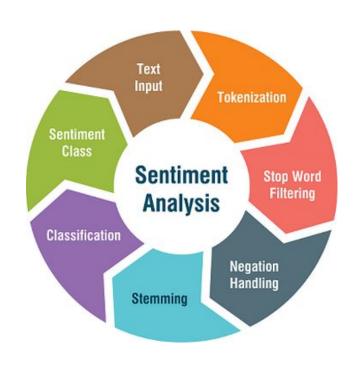
- an estimator (regressor or classifier such as sklearn.svm.SVC());
- a parameter space;
- a method for searching or sampling candidates;
- a cross-validation scheme
- a score function.

In practice sklearn (and other libs) does most of it for us

# Hyperparameter search consists of:

- an estimator (regressor or classifier such as sklearn.svm.SVC());
- a parameter space;
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What if there are more than two sentiments?



What if there are more than two sentiments?

i.e Multi-class



Multi-class problems

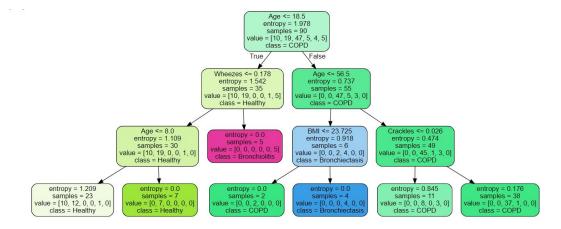
Supervised Learning problems that have >= 3 possible classes i.e positive, neutral, negative dog, cat, donkey, etc...

Multi-class problems

Use models that allow multiple classes i.e decision tree

### Multi-class problems

Use models that allow multiple classes i.e decision tree



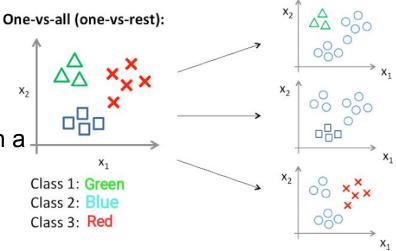
### Multi-class problems

- Use models that allow multiple classes i.e decision tree
- Use multiple binary models
  - one for each class i.e one vs all (each classifier is trained to distinguish a class from all the others together)

### Multi-class problems

Use models that allow multiple classes i.e decision tree

- Use multiple binary models
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### Multi-class problems

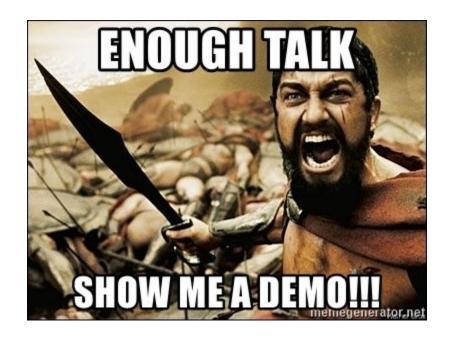
- Use models that allow multiple classes i.e decision tree
- Use multiple binary models
  - one for each class i.e one vs all (each classifier is trained to distinguish a class from all the others together)
  - one for each pair of classes i.e one vs one (each classifier is trained to distinguish two classes)

### Multi-class problems Evaluation

- Accuracy
- Precision (per class)
- Recall (per class)
- ...

		Predicted		
		Greyhound	Mastiff	Samoyed
Actual	Greyhound	$P_{GG}$	Рмс	Psg
	Mastiff	Рдм	Рмм	Рѕм
	Samoyed	Pas	Рмѕ	Pss

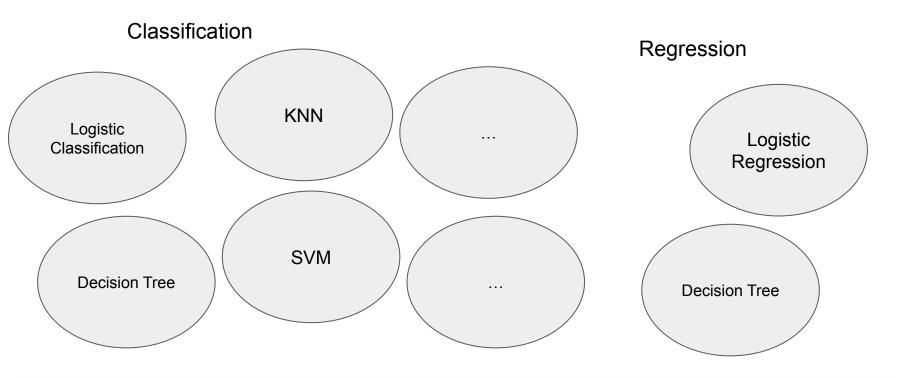
# **Sentiment Analysis**



What if there are more than two sentiments?

Put it to the test, enter a competition.





Naive Bayes

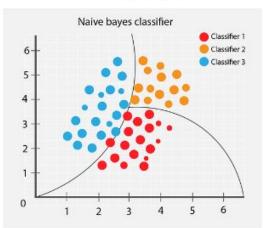
### **Naive Bayes**

In machine learning, naive Bayes classifiers are a family of simple "probabilistic classifiers" based on applying Bayes' theorem

with strong (naive) independence assumptions between the features.

$$P(A|B) = \frac{P(B|A) P(A)}{P(B)}$$

using Bayesian probability terminology, the above equation can be written as

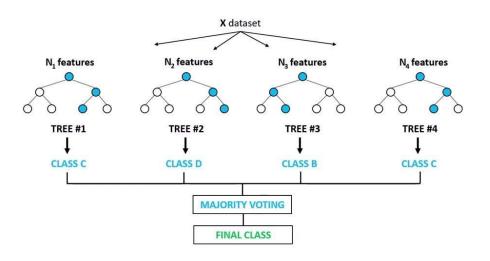


Random Forest



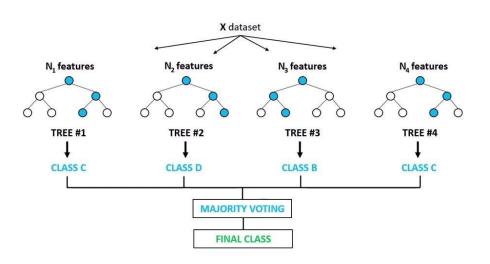
#### Random Forest

### **Random Forest Classifier**



### Random Forest Ensemble Method

### **Random Forest Classifier**



Random Forest Ensemble Method

- Selects random subsets of data (bagging)
- Selects random features
- Create decision tree for each combination
- Voting

(some) Ensemble types

- Voting
- Bagging
- Boosting
- Stacking

(some) Ensemble types

- Voting
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- Boosting
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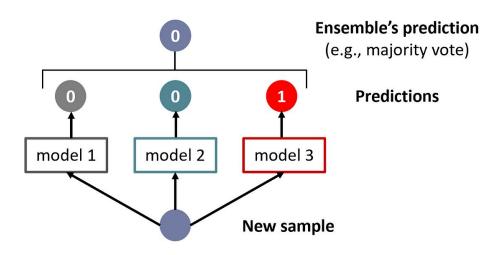
## (Ensemble types

Voting



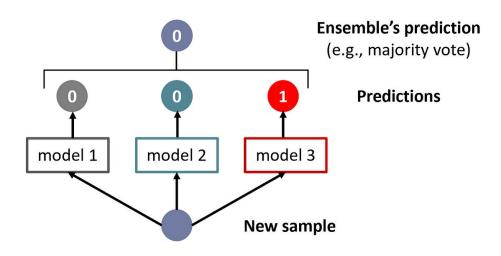
## Ensemble types

Voting



### Ensemble types

- Voting
  - Arithmetic Average
  - Weighted Average



### (some) Ensemble types

- Bagging (Bootstrap Aggregating)
  - Creates multiple subsets of the data i.e bags
  - Train each model separately
  - Aggregate models through voting for example

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- Bagging (Bootstrap Aggregating)
  - Creates multiple subsets of the data i.e bags
  - Train each model separately
  - Aggregate models through voting for example

## Ensemble types

- Boosting
  - Creates an ensemble by giving more weight to misclassified data

### Ensemble types

- Boosting
  - Train a base (weak) model on the entire dataset.
  - Assign weights to data points; misclassified points get higher weights.
  - Train the next base model, giving more attention to misclassified points.
  - Repeat steps 2 and 3 iteratively.
  - Combine the base models with different weights to create a final strong model.

### Ensemble types

- Boosting
  - Train a base (weak) model on the entire dataset.
  - Assign weights to data points; misclassified points get higher weights.
  - Train the next base model, giving more attention to misclassified points.
  - Repeat steps 2 and 3 iteratively.
  - Combine the base models with different weights to create a final strong model.

Examples are XGBoost, AdaBoost

## Ensemble types

Boosting



- Find misclassified points, increase their weight
- Train again but using the new weights i.e the loss is bigger if the model fails to predict it right

#### Ensemble types

- Stacking
  - Combines multiple models and use their output to train another model
  - Example: Voting but the weights are also learned.

### Why ensembles?

- Improved Predictive Performance
- Reduces Overfitting
- Robustness to Outliers
- Increased Model Diversity
- Versatility for Various Problem Types

#### Why ensembles?

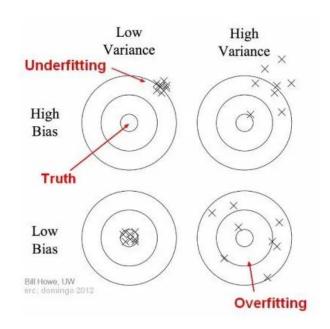
- Improved Predictive Performance
- Reduces Overfitting (variance)
- Robustness to Outliers
- Increased Model Diversity
- Versatility for Various Problem Types

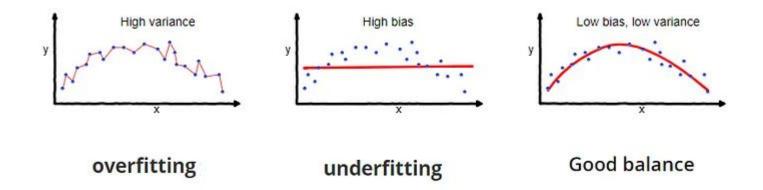
#### What is variance?

Variance is the *variability* of model prediction for a **given data point** or a *value* which *tells us spread of our data*. Model with high variance pays a lot of attention to training data and does not generalize on the data which it hasn't seen before. As a result, such models perform very well on training data but has high error rates on test data.

#### What is bias?

Bias is the difference between the average prediction of our model and the correct value which we are trying to predict. Model with high bias pays very little attention to the training data and oversimplifies the model. It always leads to high error on training and test data.





- If the model is too simple and has very few parameters then it may have high bias and low variance.
- If the model has large number of parameters then it's going to have high variance and low bias.
- Thus we need to find the right/good balance without overfitting and underfitting the data.

Total Error = Bias^2 + Variance + Irreducible Error

