# Ensemble learning

## MASTER SID

## Machine Learning

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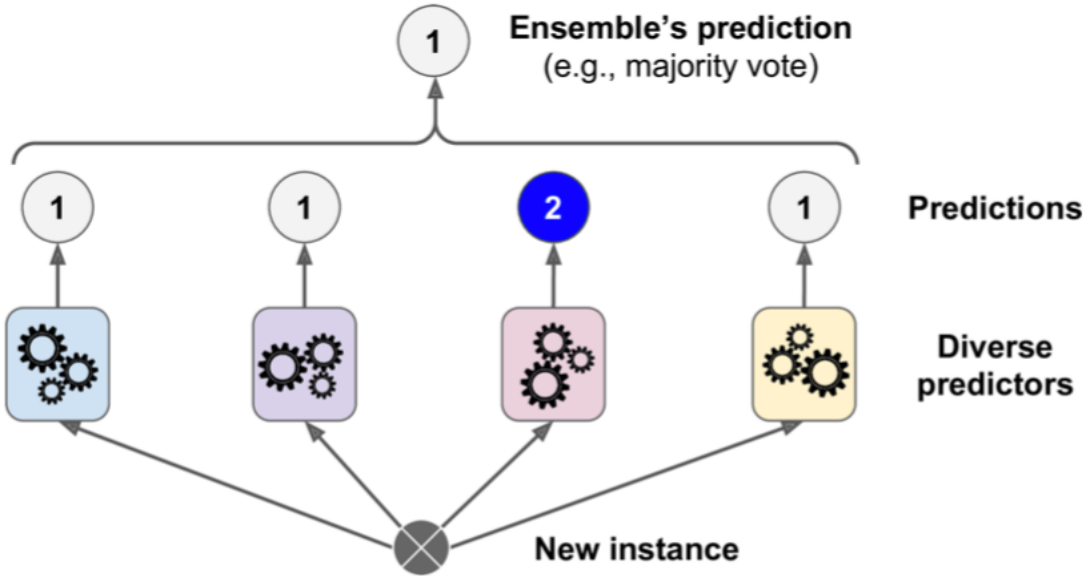
# Objectives

- Leaning the concept of ensemble in machine learning
  - Voting classifier
  - Sampling the dataset :
    - Bagging
    - Pasting
  - Random Forest
  - Boosting
    - Adaboost
    - Gradient boost descending

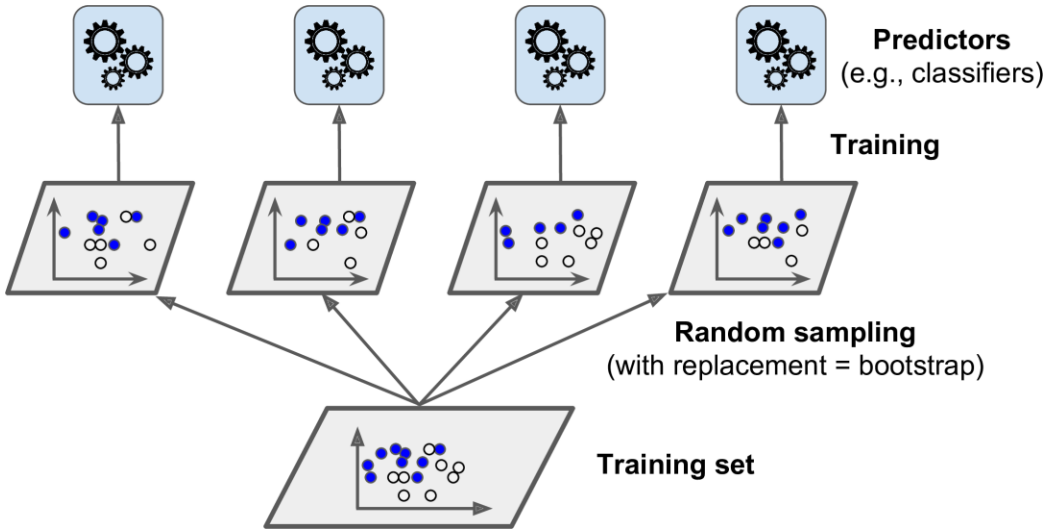
# Voting classifier

- voting classifier often achieves a higher accuracy than the best classifier in the ensemble. In fact, even if each classifier is a *weak learner* (meaning it does only slightly better than random guessing), the ensemble can still be a *strong learner* (achieving high accuracy)
- work best when the predictors are as independ- ent from one another as possible. One way to get diverse classifiers is to train them using very different algorithms.



# Bagging and pasting

- To use the same training algorithm for every predictor, but to train them on different random subsets of the training set.
  - Bagging : (short for *bootstrap aggregating )* sampling is performed *with* replacement,
  - Pasting : sampling is performed *without* replacement



# Why bagging

- Designed to improve the stability and accuracy of machine learning algorithms used in statistical classification and regression.
- It also reduces variance and helps to avoid overfitting. Although it is usually applied to decisión tree methods, it can be used with any type of method.

# Hyperparameters bagging

- **n_estimators :** The number of base estimators in the ensemble. (number of trees)
- **max_samples :** The number of samples to draw from X to train each base estimator (with replacement by default, see bootstrap for more details).
- **max_features :** number of features to draw from X to train each base estimator.
- **Bootstrap :** Whether samples are drawn with replacement. If False, sampling without replacement is performed.

# Radom forest

- I an ensemble of Decision Trees, generally trained via the bagging method (or sometimes pasting), typically with max_samples set to the size of the training set.
- Instead of building a BaggingClassifier and passing it a DecisionTreeClassifier, you can instead use the RandomForestClassifier class, which is more convenient and optimized for Decision Trees (similarly, there is a RandomForestRegressor class for regression tasks).

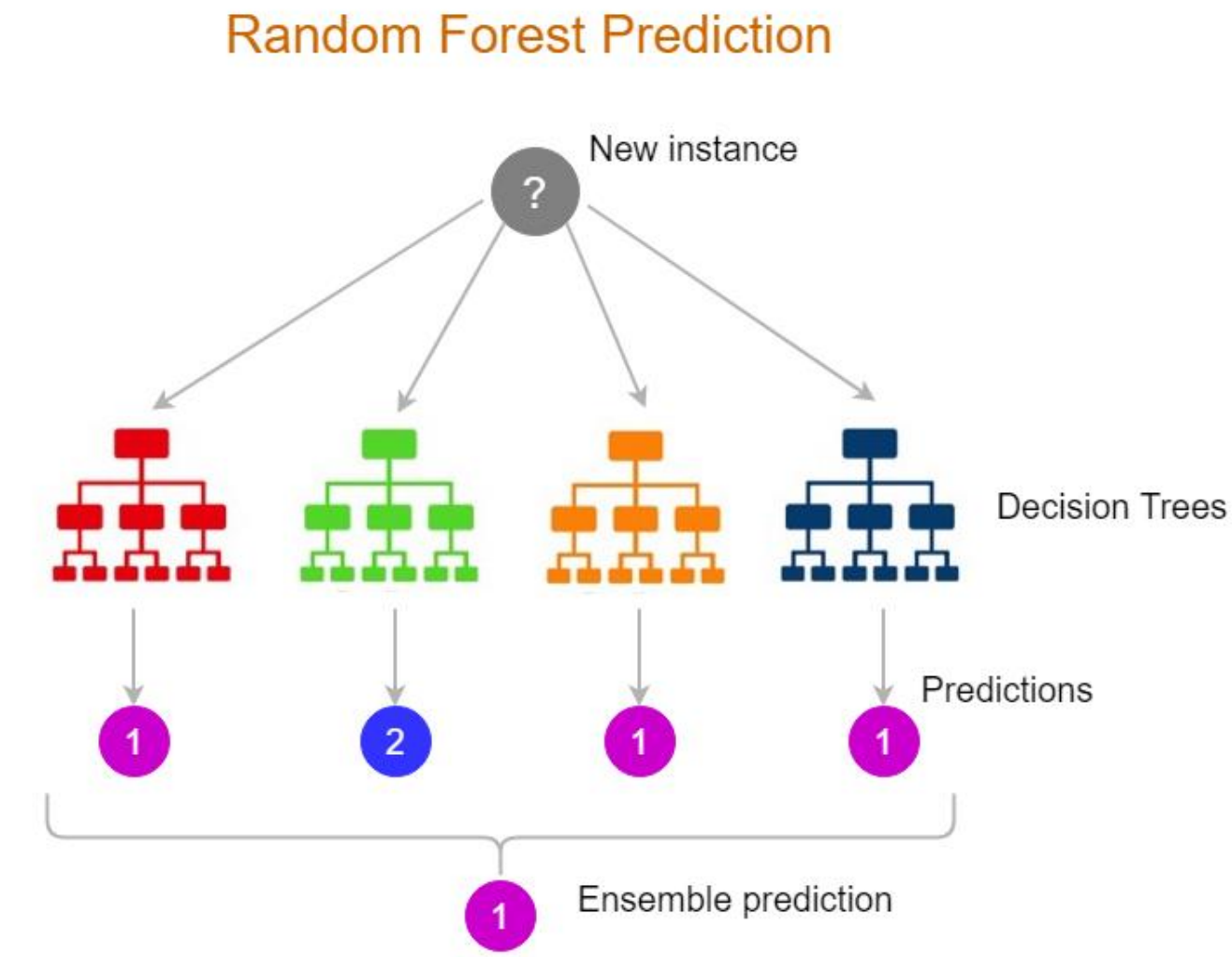



*Image copyright: Rukshan Pramoditha*

# Radom forest Hypermarameters

- RandomForestClassifier has all the hyperparameters of a DecisionTreeClassifier (to control how trees are grown), plus all the hyperparameters of a BaggingClassifier to control the ensemble itself.

# Regularization Hyperparameters Tree

- ***max_depth***
- ***max_leaf_nodes*** (maximum number of leaf nodes),
- ***max_features*** (maximum number of features that are evaluated for splitting at each node).

- ***min_samples_split*** (the minimum number of samples a node must have before it can be split),
- ***min_samples_leaf*** (the minimum number of samples a leaf node must have),
- ***min_weight_fraction_leaf*** (same as min_samples_leaf but expressed as a fraction of the total number of weighted instances)

**To regularize the model :**

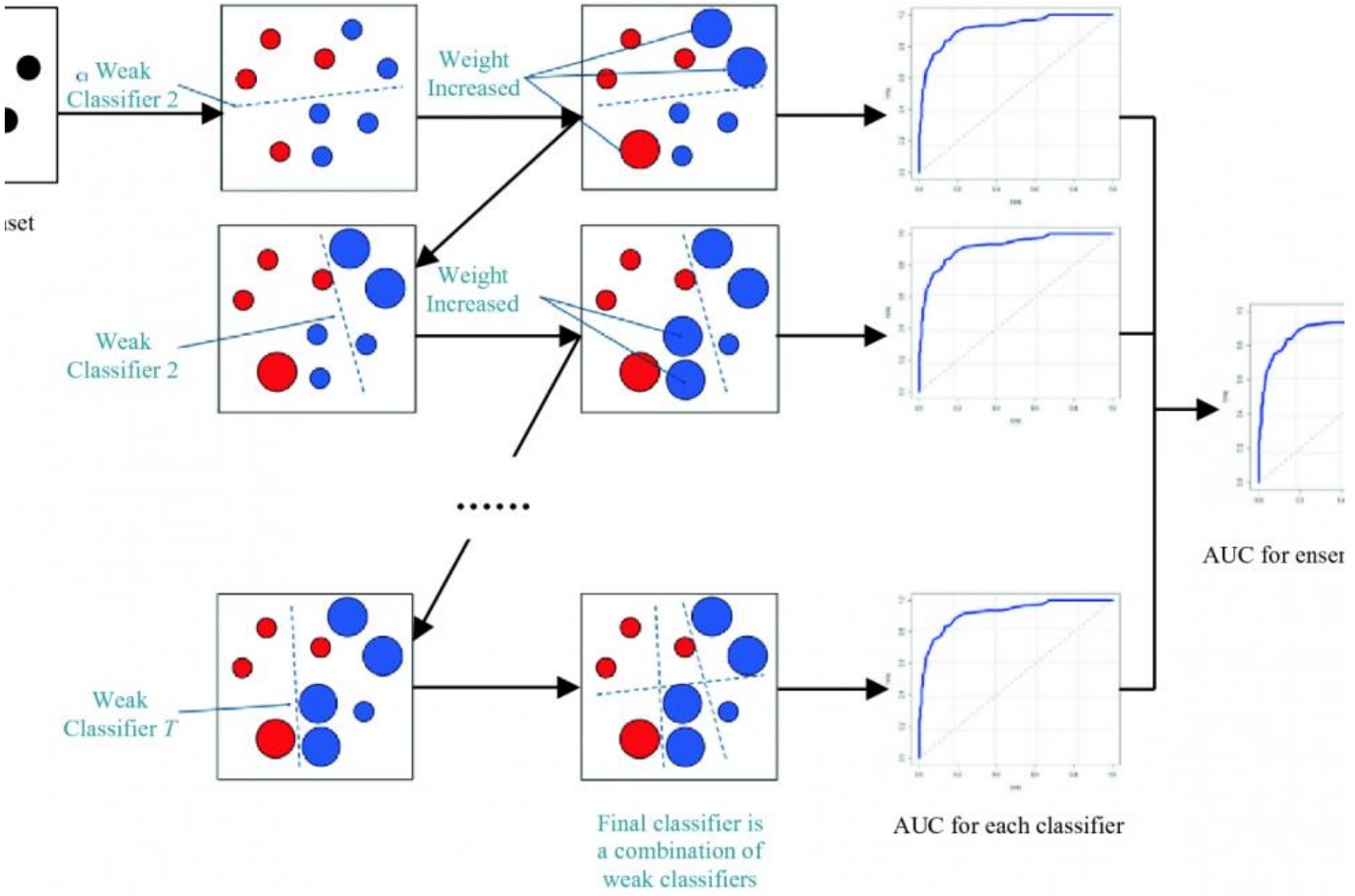
- Increase min_* hyperparameters
- Reduce max_*hyperparameters

# Random Forest, feature importance

- RF makes easy to measure the relative importance of each feature.
- Scikit-Learn measures a feature's importance by looking at how much the tree nodes that use that feature reduce impurity on average (across all trees in the forest). It is a weighted average, where each node's weight is equal to the number of training samples that are associated with it.
- Scikit-Learn computes this score automatically for each feature after training. You can access the result using the feature_importances_ variable.

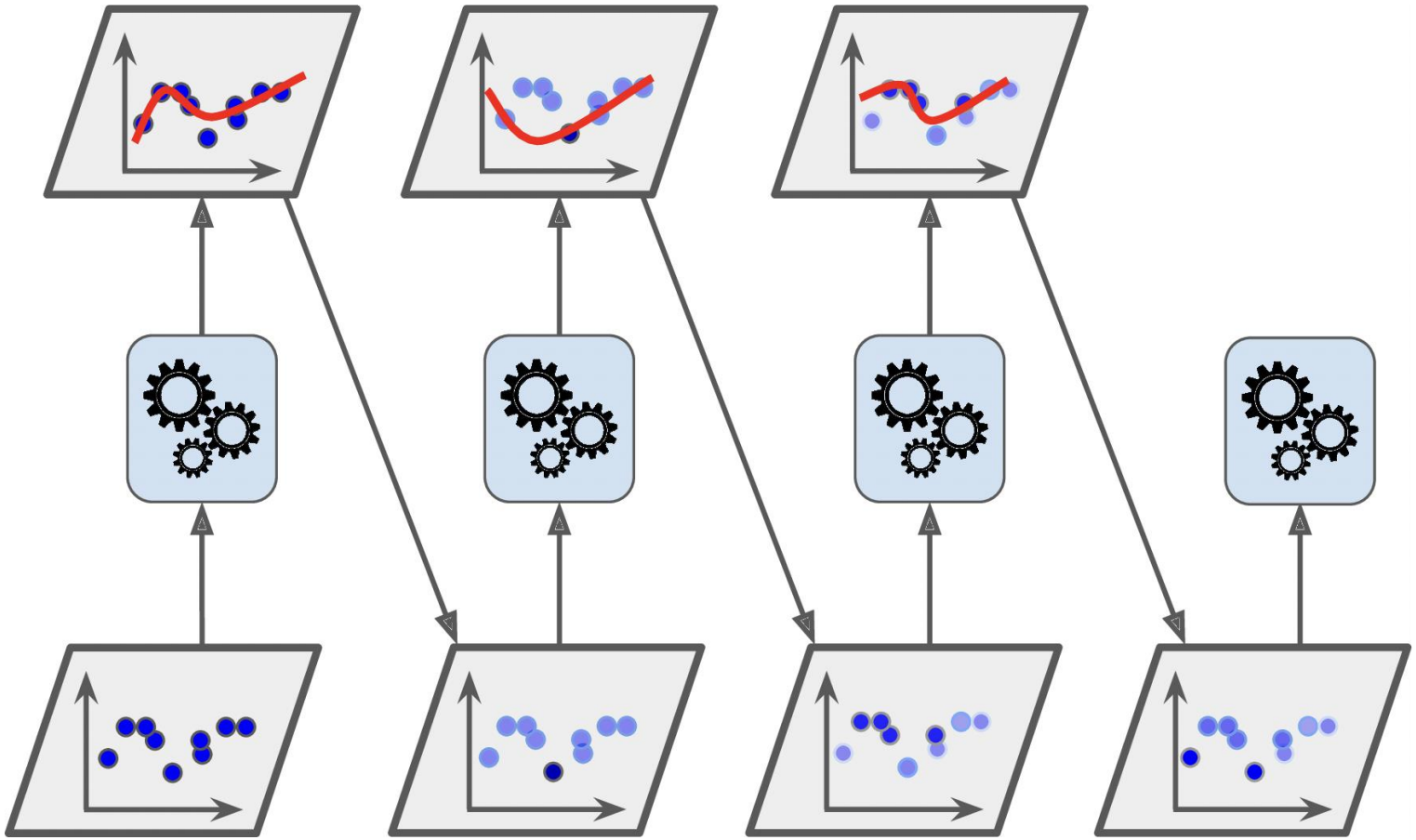
# Boosting

- *Boosting* (originally called *hypothesis boosting*) refers to any Ensemble method that can combine several weak learners into a strong learner. The general idea of most boosting methods is to train predictors sequentially, each trying to correct its predecessor.



# Adaboost

- One way for a new predictor to correct its predecessor is to **pay a bit more attention to the training instances that the predecessor underfitted**. This results in new predictors focusing more and more on the hard cases
- Example : A first base classifier (such as a Decision Tree) is trained and used to make predictions on the training set. The relative weight of misclassified training instances is then increased. A second classifier is trained using the updated weights and again it makes predictions on the training set, weights are updated, and so on.



# Adaboost Hyperparameter tunning

If your AdaBoost ensemble is overfitting the training set, you can try reducing the number of estimators or more strongly regularizing the base estimator.

- **base_estimator***object, default=None*The base estimator from which the boosted ensemble is built. Support for sample weighting is required, as well as proper classes_ and n_classes_ attributes. If None, then the base estimator is DecisionTreeClassifier initialized with max_depth=1.
- **n_estimators***int, default=50*The maximum number of estimators at which boosting is terminated. In case of perfect fit, the learning procedure is stopped early.
- **learning_rate** *float, default=1.0* Weight applied to each classifier at each boosting iteration. A higher learning rate increases the contribution of each classifier. There is a trade-off between the learning_rate and n_estimators

# Gradient boost descending

- Gradient Boosting works by sequentially adding predictors to an ensemble, each one correcting its predecessor.
- Instead of tweaking the instance weights at every iteration like AdaBoost does, this method tries to fit the new predictor to the *residual errors* made by the previous predictor.
- The learning_rate hyperparameter scales the contribution of each tree. If you set it to a low value, such as 0.1, you will need more trees in the ensemble to fit the training set, but the predictions will usually generalize better. This is a regularization technique called *shrinkage*.