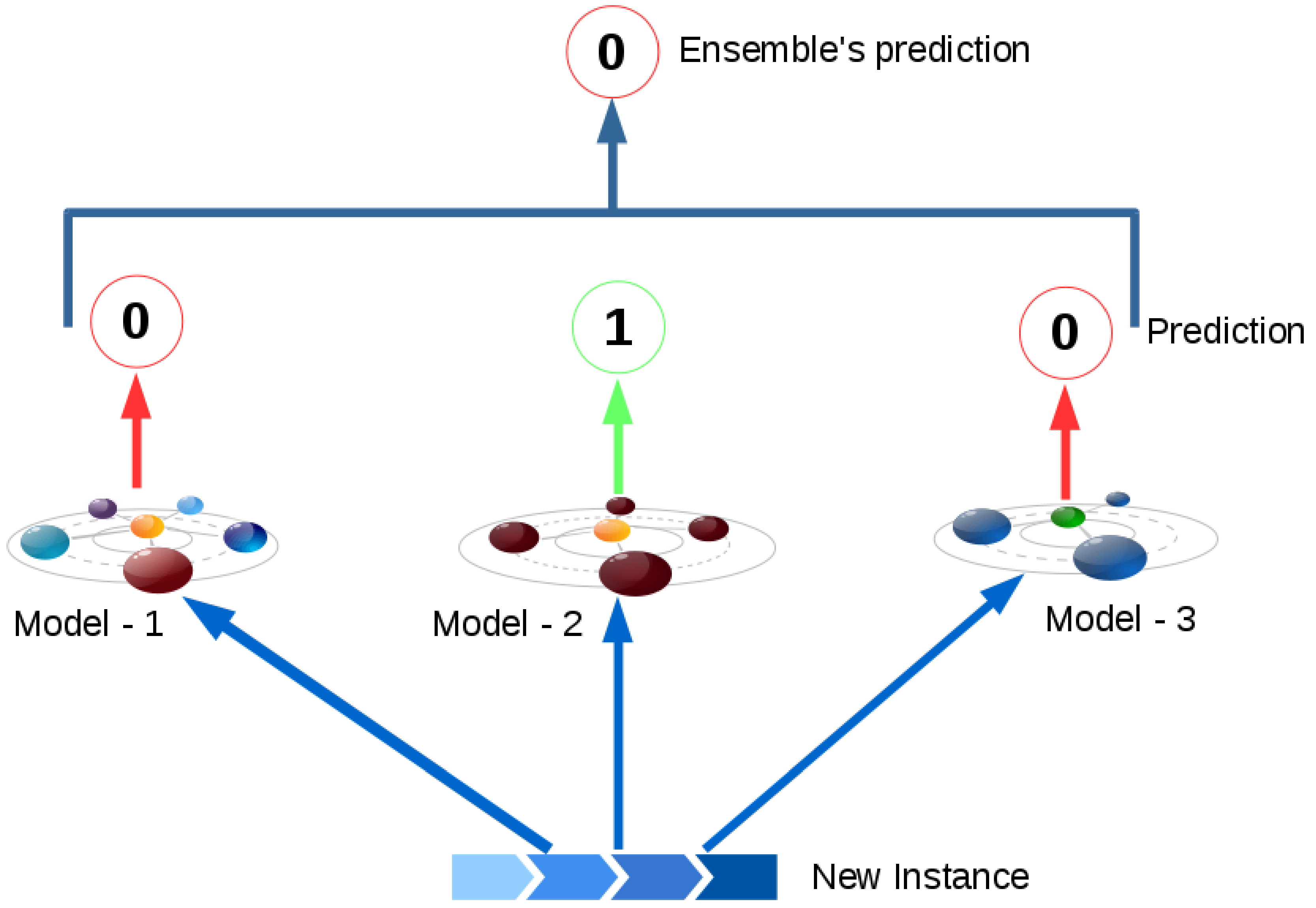
Voting Classifier

- Suppose you have trained a few classifiers, each one individually achieving about 80% accuracy (Logistic Regression classifier, an SVM classifier, a Random Forest classifier, a K-Nearest Neighbors classifier). We can create a better classifier by **aggregating the predictions** of each classifier **and predict the class that gets the most votes.** This approach is called as Voting Classification.

Hard Voting Classifier : ** Aggregate predections of each classifier and predict the class that gets most votes. This is called as **"majority - voting" or "Hard - voting" classifier.



Soft Voting Classifier : In an ensemble model, all classifiers (algorithms) are able to estimate class probabilities (i.e., they all have predict_proba() method), then we can specify Scikit-Learn to predict the class with the highest probability, averaged over all the individual classifiers.

Modle Name	Class - 1 Probability	Class - 0 Probability
Model - 1	0.49	0.51

Model - 2	0.99	0.01
Model - 3	0.49	0.51
Averages	**0.66**	**0.34**

This soft-voting classifier often work better than hard-voting as it gives more weight to highly confident votes. Need to specify **voting="soft"** and ensure that all classifiers can estimate class probabilities. * One algorithm where we need to be careful is SVC, by default SVC will not give probabilities, we have to specify "probability" hyperparameter to True.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import train_test_split

plt.rcParams['axes.labelsize'] = 14
plt.rcParams['xtick.labelsize'] = 12
plt.rcParams['ytick.labelsize'] = 12
import warnings
warnings.filterwarnings('ignore')

import random
random.seed(10)
```

In [2]:
```
from sklearn.model_selection import train_test_split
from sklearn.datasets import make_moons

X, y = make_moons(n_samples=500, noise=0.30, random_state=42)
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=42)
```

Hard Voting

In [3]:
```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import VotingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC

log_clf = LogisticRegression(random_state=42)
rnd_clf = RandomForestClassifier(random_state=42)
svm_clf = SVC(random_state=42)

hard_voting_clf = VotingClassifier(
    estimators=[('lr', log_clf), ('rf', rnd_clf), ('svc', svm_clf)], voting='hard')
hard_voting_clf.fit(X_train, y_train)
```

Out[3]:
```
VotingClassifier(estimators=[('lr',
                              LogisticRegression(C=1.0, class_weight=None,
                                                 dual=False, fit_intercept=True,
                                                 intercept_scaling=1,
                                                 l1_ratio=None, max_iter=100,
                                                 multi_class='auto',
                                                 n_jobs=None, penalty='l2',
                                                 random_state=42,
                                                 solver='lbfgs', tol=0.0001,
                                                 verbose=0, warm_start=False)),
                             ('rf',
                              RandomForestClassifier(bootstrap=True,
                                                     ccp_alpha=0.0,
                                                     class_weight=None,
                                                     crit...
                                                     oob_score=False,
                                                     random_state=42, verbose=0,
                                                     warm_start=False)),
                             ('svc',
                              SVC(C=1.0, break_ties=False, cache_size=200,
                                  class_weight=None, coef0=0.0,
                                  decision_function_shape='ovr', degree=3,
                                  gamma='scale', kernel='rbf', max_iter=-1,
                                  probability=False, random_state=42,
                                  shrinking=True, tol=0.001, verbose=False))],
                 flatten_transform=True, n_jobs=None, voting='hard',
                 weights=None)
```

In [4]:
```
from sklearn.metrics import accuracy_score

for clf in (log_clf, rnd_clf, svm_clf):
    clf.fit(X_train, y_train)
    y_pred = clf.predict(X_test)
    print(clf.__class__.__name__, accuracy_score(y_test, y_pred))

hvc_predict = hard_voting_clf.predict(X_test)
print("Hard voting clasifier accuracy: ", accuracy_score(y_test, hvc_predict))
```

```
LogisticRegression 0.864
RandomForestClassifier 0.896
SVC 0.896
Hard voting clasifier accuracy:  0.912
```

Soft Voting

In [5]:
```
log_clf = LogisticRegression(random_state=42)
rnd_clf = RandomForestClassifier(random_state=42)
svm_clf = SVC(probability=True, random_state=42)

soft_voting_clf = VotingClassifier(
    estimators=[('lr', log_clf), ('rf', rnd_clf), ('svc', svm_clf)],
    voting='soft')
soft_voting_clf.fit(X_train, y_train)
```

Out[5]:
```
VotingClassifier(estimators=[('lr',
                              LogisticRegression(C=1.0, class_weight=None,
                                                 dual=False, fit_intercept=True,
                                                 intercept_scaling=1,
                                                 l1_ratio=None, max_iter=100,
                                                 multi_class='auto',
                                                 n_jobs=None, penalty='l2',
                                                 random_state=42,
                                                 solver='lbfgs', tol=0.0001,
                                                 verbose=0, warm_start=False)),
                             ('rf',
                              RandomForestClassifier(bootstrap=True,
                                                     ccp_alpha=0.0,
                                                     class_weight=None,
                                                     crit...
                                                     oob_score=False,
                                                     random_state=42, verbose=0,
                                                     warm_start=False)),
                             ('svc',
                              SVC(C=1.0, break_ties=False, cache_size=200,
                                  class_weight=None, coef0=0.0,
                                  decision_function_shape='ovr', degree=3,
                                  gamma='scale', kernel='rbf', max_iter=-1,
                                  probability=True, random_state=42,
                                  shrinking=True, tol=0.001, verbose=False))],
                 flatten_transform=True, n_jobs=None, voting='soft',
                 weights=None)
```

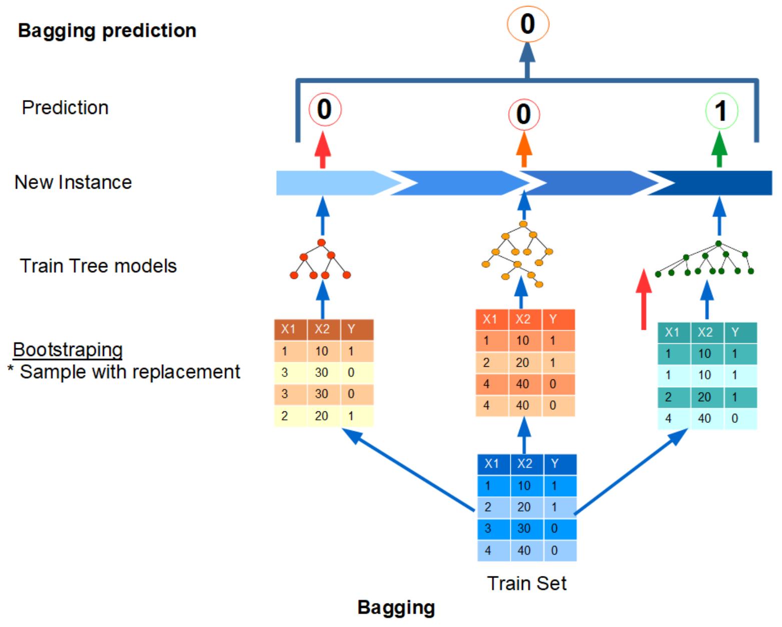
In [6]:
```python
from sklearn.metrics import accuracy_score

for clf in (log_clf, rnd_clf, svm_clf, soft_voting_clf):
    clf.fit(X_train, y_train)
    y_pred = clf.predict(X_test)
    print(clf.__class__.__name__, accuracy_score(y_test, y_pred))
```

```
LogisticRegression 0.864
RandomForestClassifier 0.896
SVC 0.896
VotingClassifier 0.92
```

Bagging and Pasting:

- In Bagging or Pasting ensemble model we use same training algorithm, but train them on different random sub-sets of the training set.
- **Bagging : ** When **sampling** is performed **with replacement**, we call it as **Bagging**.
- **Pasting : ** When **sampling** is performed **without replacement**, we call it as **Pasting**.

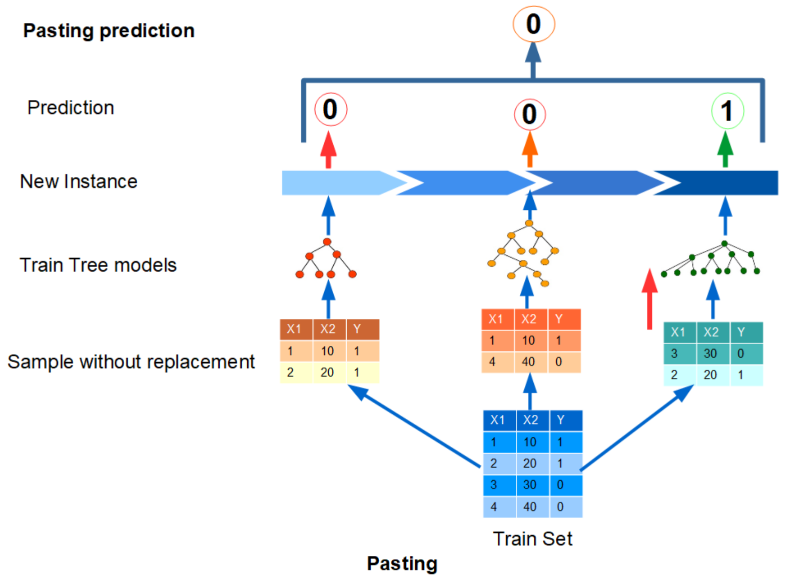


X1	X2	Y
1	10	1
3	30	0
3	30	0
2	20	1

X1	X2	Y
1	10	1
2	20	1
4	40	0
4	40	0

X1	X2	Y
1	10	1
1	10	1
2	20	1
4	40	0

X1	X2	Y
1	10	1
2	20	1
3	30	0
4	40	0



X1	X2	Y
1	10	1
2	20	1

X1	X2	Y
1	10	1
4	40	0

X1	X2	Y
3	30	0
2	20	1

X1	X2	Y
1	10	1
2	20	1
3	30	0
4	40	0

- Once all predictors are trained, the ensemble can make a **prediction for a new instance** by simply aggregating the predictions of all predictors. The aggregation function is typically the statistical mode (i.e., the most frequent prediction, **just like a hard voting classifier**) for classification, or **the average for regression.**
- **Bagging and Pasting are scalable :** Predictors can all be trained in parallel, via different CPU cores or even different servers. Similarly, predictions can be made in parallel. This is one of the reasons why bagging and pasting are such popular methods, they scale very well.

In [7]:
```
from sklearn.ensemble import BaggingClassifier
from sklearn.tree import DecisionTreeClassifier

bag_clf = BaggingClassifier(
    DecisionTreeClassifier(random_state=42), n_estimators=500,
    max_samples=100, bootstrap=False, n_jobs=-1, random_state=42)
bag_clf.fit(X_train, y_train)
y_pred = bag_clf.predict(X_test)
```

In [8]:
```
from sklearn.metrics import accuracy_score
print(accuracy_score(y_test, y_pred))
```

```
0.912
```

In [9]:
```
tree_clf = DecisionTreeClassifier(random_state=42)
tree_clf.fit(X_train, y_train)
y_pred_tree = tree_clf.predict(X_test)
print(accuracy_score(y_test, y_pred_tree))
```

```
0.856
```

In [10]:
```
lr_bag_clf = BaggingClassifier(
    LogisticRegression(random_state=42), n_estimators=500,
    max_samples=100, bootstrap=True, n_jobs=-1, random_state=42)
lr_bag_clf.fit(X_train, y_train)
lr_y_pred = lr_bag_clf.predict(X_test)
```

```
In [11]: from sklearn.metrics import accuracy_score
         print(accuracy_score(y_test, lr_y_pred))

         0.84
```

Out-of-Bag Evaluation

- **Out-of-Bag instaces : ** With Bagging, the sampling technique is Bootstraping. This sampling is done with replacement. This means, some instances are sampled many times and some are not at all sampled. Suppore about 63% of the data is sampled for each predictor, remaining 37% is called as **Out-of_Bag samples** for the predictor. Similary for all predictors in Bagging model, there will be out-of-bag samples.
- We can use these out-of-bag samples (a **separate** unseen dataset for **each predictor**) as cross-validation set.
- We can do this in Scikit-Learn BaggingClassifier using, oob_score (out-of-bag score) hyperparameter.

```
In [12]: bag_clf = BaggingClassifier(
             DecisionTreeClassifier(random_state=42), n_estimators=500,
             bootstrap=True, n_jobs=-1, oob_score=True, random_state=40)
         bag_clf.fit(X_train, y_train)
         bag_clf.oob_score_

Out[12]: 0.9013333333333333
```

oob_decision_function_ is returning calss probabilities as the base esitmator (DecisionTree) has got predict_proba() method.

```
In [13]: bag_clf.oob_decision_function_[:5, :]

Out[13]: array([[0.31746032, 0.68253968],
                [0.34117647, 0.65882353],
                [1.        , 0.        ],
                [0.        , 1.        ],
                [0.        , 1.        ]])
```

In [14]:
```
from sklearn.metrics import accuracy_score
y_pred = bag_clf.predict(X_test)
accuracy_score(y_test, y_pred)
```

Out[14]:
```
0.912
```

Random Forest

- Random Forest is an ensemble model of DecisionTrees. Random Forest picks up a sub-set of features randomly and searches for best feature amoung the sub-set.
- With a few exceptions, a 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.

In [15]:
```
from sklearn.ensemble import RandomForestClassifier

rnd_clf = RandomForestClassifier(n_estimators=500, max_leaf_nodes=16, \
                                                 n_jobs=-1, random_state=42)
rnd_clf.fit(X_train, y_train)

y_pred_rf = rnd_clf.predict(X_test)
```

In [16]:
```
from sklearn.metrics import accuracy_score
y_pred = rnd_clf.predict(X_test)
accuracy_score(y_test, y_pred)
```

Out[16]:
```
0.912
```

Feature Importance

- if you look at a single Decision Tree, important features are likely to appear closer to the root of the tree, while unimportant features will often appear closer to the leaves (or not at all). It is therefore possible to get an estimate of a feature’s importance by computing the average depth at which it appears across all trees in the forest. Scikit-Learn computes this automatically for every feature after training. You can access the result using the feature_importances_ variable.

In [17]:
```
digit_dataset = pd.read_csv('../Data/digit_recognizer_train.csv')
digit_X = digit_dataset.iloc[:, 1:]
digit_y = digit_dataset['label']
digit_X_train, digit_X_test, digit_y_train, digit_y_test = \
                                    train_test_split(digit_X, digit_y, test_size=0.2)
```

In [18]:
```
rnd_clf = RandomForestClassifier(random_state=42)
rnd_clf.fit(digit_X_train, digit_y_train)
```

Out[18]:
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=None, max_features='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=100,
                       n_jobs=None, oob_score=False, random_state=42, verbose=0,
                       warm_start=False)
```

In [19]:
```
rnd_clf.feature_importances_
```

Out[19]:
```
array([0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 6.47398142e-07, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 1.91867187e-06,
       5.49643294e-06, 2.54335439e-06, 2.52758119e-06, 3.39500928e-06,
       2.35267345e-06, 1.21392748e-06, 1.21886346e-06, 2.46435557e-06,
       1.18632348e-06, 1.08274058e-06, 1.12574693e-06, 0.00000000e+00,
       0.00000000e+00, 1.58554634e-06, 2.60396527e-06, 4.51070792e-06,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       6.48452266e-07, 0.00000000e+00, 1.26513769e-06, 7.07745484e-06,
       1.88582447e-05, 1.72547953e-05, 5.57766107e-05, 9.73217446e-05,
       2.32614482e-04, 9.10672645e-05, 1.77173348e-04, 1.57657795e-04,
       1.32580369e-04, 1.87185667e-04, 1.16262880e-04, 3.45927414e-05,
```

In [20]:
```
for feature, imp_score in sorted(zip(digit_dataset.columns, \
                                    rnd_clf.feature_importances_), key=lambda x: x[1], reverse=True):
    if(imp_score > 0.0001):
        print(feature, imp_score)
```

```
pixel155 0.004562081195681978
pixel352 0.004548755365123048
pixel266 0.004515033472275393
pixel657 0.00448928114131793
pixel322 0.00448215295983534
pixel515 0.004474362054938139
pixel567 0.004458894974170905
pixel296 0.004427750339222235
pixel353 0.004427539188945368
pixel344 0.004392765408253596
pixel403 0.0043747313011106214
pixel152 0.0043402376453404974
pixel457 0.004329885978518661
pixel596 0.004302667480589906
pixel456 0.0042929509999642445
pixel489 0.004291011428144301
pixel239 0.004286687554865027
pixel211 0.004240656726429677
pixel375 0.004199640864865642
pixel458 0.0041921695958132285
```

In [21]:
```
digit_y_pred = rnd_clf.predict(digit_X_train)
```

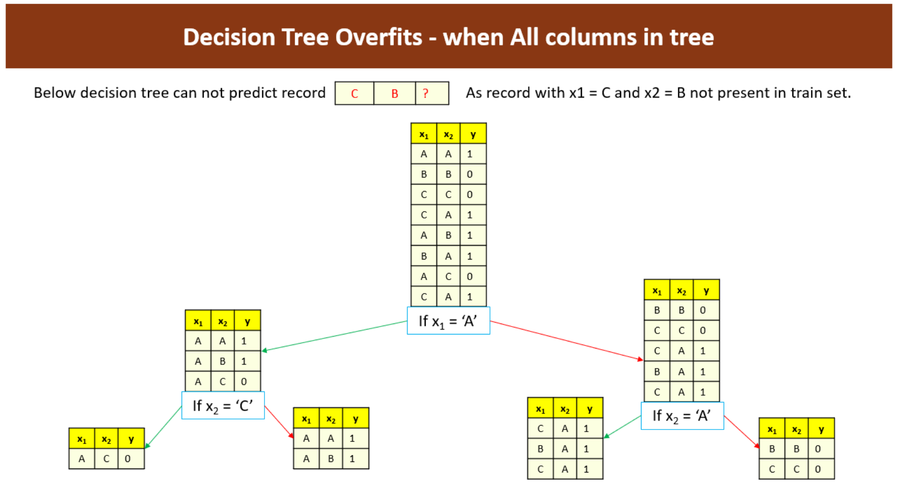
In [22]:
```
from sklearn.metrics import f1_score
print(f1_score(digit_y_train, digit_y_pred, average="weighted"))
```

```
1.0
```

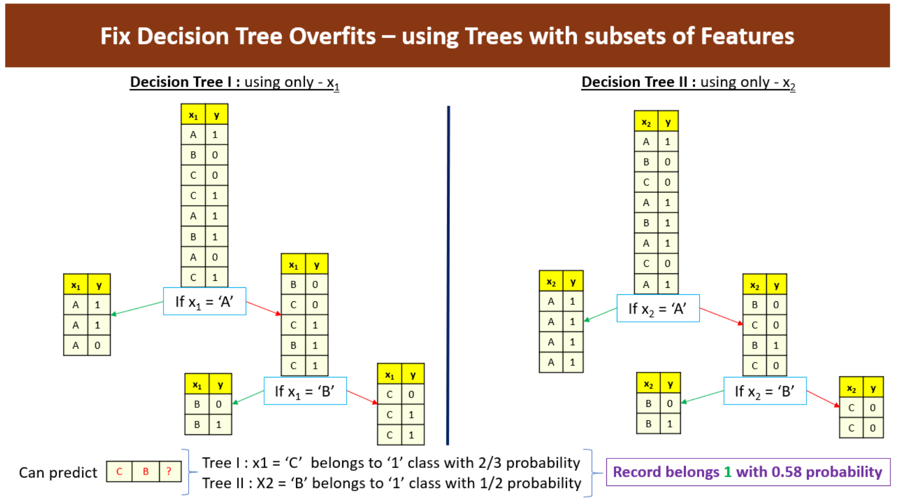
In [23]:
```
digit_y_test_pred = rnd_clf.predict(digit_X_test)
print(f1_score(digit_y_test, digit_y_test_pred, average="weighted"))
```

```
0.9625811123837701
```

How and RandomFoest will solve Overfitting issue in DecisionTree


Decision Tree Overfits - when All columns in tree

Below decision tree can not predict record C B ? As record with x1 = C and x2 = B not present in train set.


Fix Decision Tree Overfits – using Trees with subsets of Features

Can predict C B ?

Tree I : x1 = 'C' belongs to '1' class with 2/3 probability

Tree II : X2 = 'B' belongs to '1' class with 1/2 probability

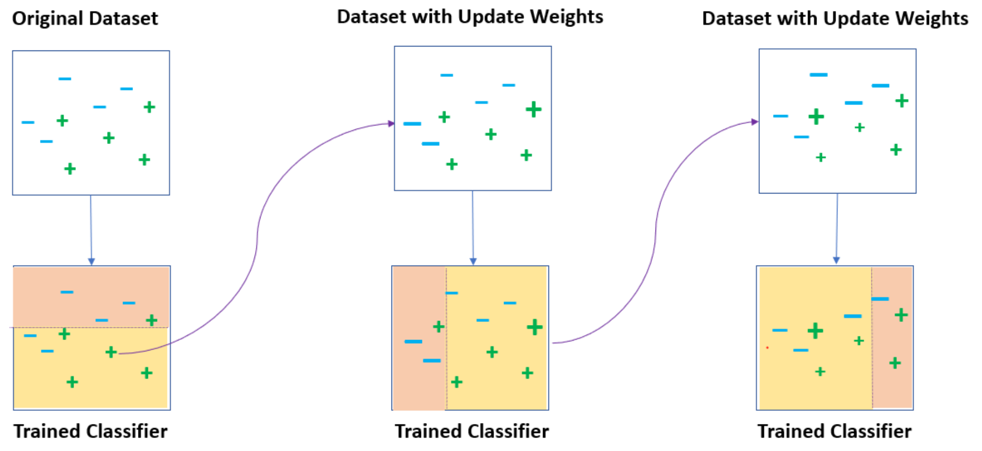
Record belongs 1 with 0.58 probability
Decision Tree I : using only - x_1
Decision Tree II : using only - x_2
If x_1 = 'A'
If x_1 = 'B'
If x_2 = 'A'
If x_2 = 'B'

Boosting

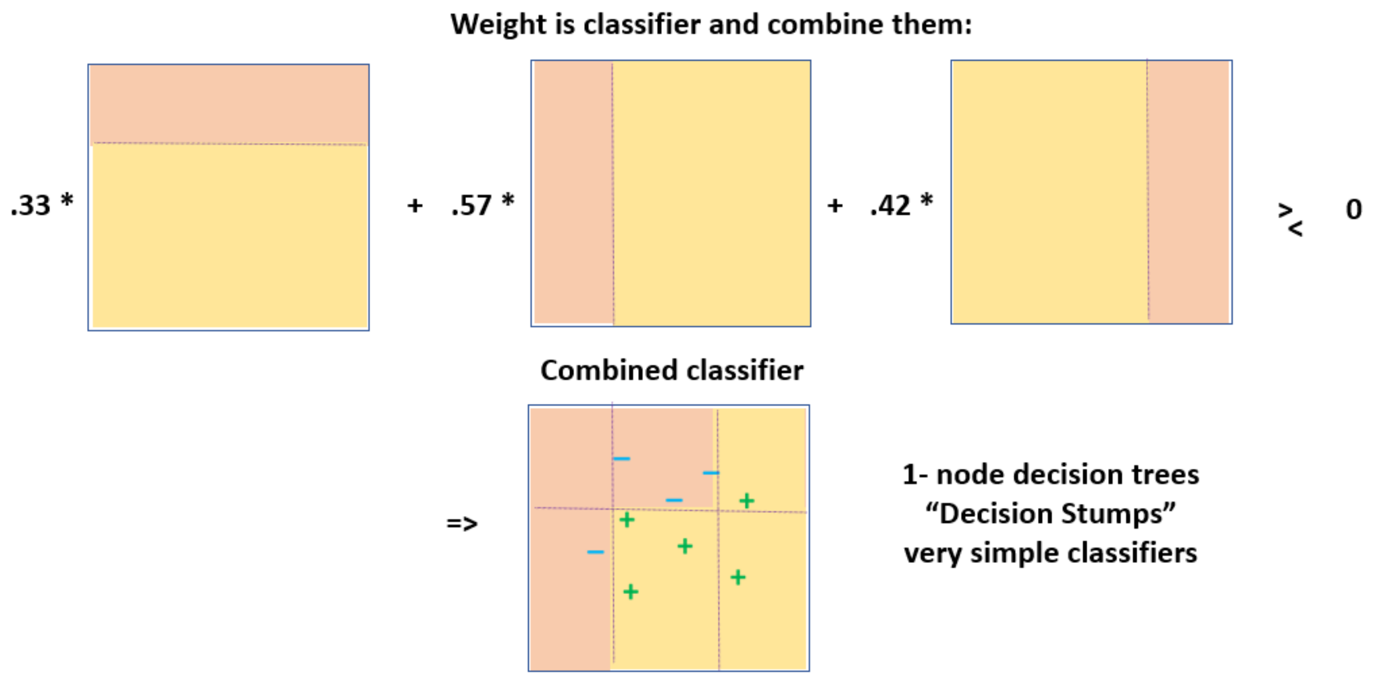
- Boosting (originally called hypothesis boosting) refers to any Ensemble method that can combine several weak learners into a strong learner. **The general idea of most boosting methods is to train predictors sequentially, each trying to correct its predecessor**. There are many boosting methods available, but by far the most popular are **AdaBoost** (short for Adaptive Boosting) and **Gradient Boosting**. Let's start with AdaBoost.

AdaBoost:

- AdaBoost is a popular boosting technique which helps you combine multiple "weak classifiers" (sequentially) into a single "strong classifier". A weak classifier is simply a classifier that performs poorly, but performs better than random guessing.
- AdaBoost can be applied to any classification algorithm, so it's really a technique that builds on top of other classifiers.
- You could just train a bunch of weak classifiers on your own and combine the results, so what does AdaBoost do for you? There's really two things it figures out for you:
    - **1) *Training set Selection :* ** It helps you choose the training set for each new classifier that you train based on the results of the previous classifier.



- **2) Classifier Output Weights** : ******After each classifier is trained, the classifier's weight is calculated based on its accuracy. More accurate classifiers are given more weight. A classifier with* ***50% accuracy is given a weight of zero**, and a classifier with **less than 50% accuracy is given negative weight**.



Step 1:

- Each instance weight - $w^{(i)}$ is initially set to 1/m. Build model 1.

- First predictor's weight α_1 the classifier is calculated using below formula.

$$\alpha_1 = \eta \, log \frac{1 - r_1}{r_1}$$

  - eta (η) is the learning rate hyperparameter.
  - $r_1 = \frac{\sum_{i=1}^{m} w^{(i)}_{\hat{y}_1^{(i)} \neq y^{(i)}}}{\sum_{i=1}^{m} w^{(i)}}$

Step 2:

- Each instance weight - $w^{(i)}$ is calculated using below formulas.

$$w^{(i)} = w^{(i)} \;\; if \;\; \hat{y}_1^{(i)} = y^{(i)}$$
$$w^{(i)} = w^{(i)} \; \exp(\alpha_1) \;\; if \;\; \hat{y}_1^{(i)} \not= y^{(i)}$$

- Once new instance weights are ready, the second classification model is build and predictions are made ($\hat{y}_2^{(i)}$). Using these predictions r_2 , and further α_2 - the weight for second classifier is calculated.

$$\alpha_2 = \eta \, log \frac{1 - r_2}{r_2}$$
$$r_2 = \frac{\sum_{i=1}^{m} w^{(i)}_{\hat{y}_2^{(i)} \neq y^{(i)}}}{\sum_{i=1}^{m} w^{(i)}}$$

Step 3, 4, ... : Step 2 is repeated until desired number of predictors are reached or perfect predictor is found.

Scikit-Learn uses multiclass version of Ada Boost - SAMME (Stagewise Additive Modeling using a Multiclass Exponential loss function). When there are just two classes, SAMME is equivalent to AdaBoost. Moreover, if the predictors can estimate class probabilities, Scikit-Learn can use a variant of SAMME called SAMME.R (R - stants for real), which relies on class probabilities rather than predictions.

- AdaBoosting works with Regression or Classification tasks.
- https://www.youtube.com/watch?v=ix6IvwbVpw0 (https://www.youtube.com/watch?v=ix6IvwbVpw0)

The Following code trains an AdaBoost classifier based on 500 Decision Stumps (A decision stump is a machine learning model consisting of a one-level decision tree)

In [24]:
```
from sklearn.ensemble import AdaBoostClassifier

ada_clf = AdaBoostClassifier(
        DecisionTreeClassifier(max_depth=2), n_estimators=500,
        algorithm="SAMME.R", learning_rate=0.5, random_state=42
    )
ada_clf.fit(X_train, y_train)
```

Out[24]:
```
AdaBoostClassifier(algorithm='SAMME.R',
                   base_estimator=DecisionTreeClassifier(ccp_alpha=0.0,
                                                         class_weight=None,
                                                         criterion='gini',
                                                         max_depth=2,
                                                         max_features=None,
                                                         max_leaf_nodes=None,
                                                         min_impurity_decrease=0.0,
                                                         min_impurity_split=None,
                                                         min_samples_leaf=1,
                                                         min_samples_split=2,
                                                         min_weight_fraction_leaf=0.0,
                                                         presort='deprecated',
                                                         random_state=None,
                                                         splitter='best'),
                   learning_rate=0.5, n_estimators=500, random_state=42)
```

In [25]:
```
from sklearn.metrics import accuracy_score
y_pred = ada_clf.predict(X_test)
accuracy_score(y_test, y_pred)
```

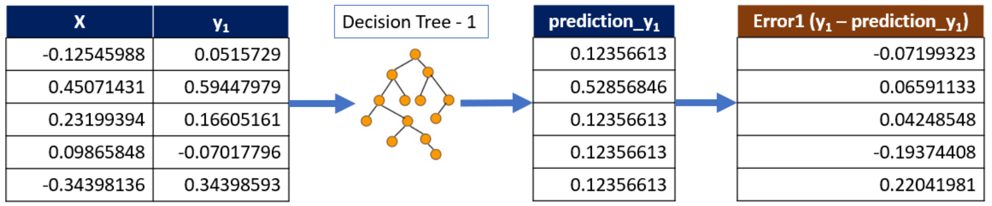
Out[25]:
```
0.88
```

Gradient Boosting

- Just like AdaBoost, Gradient Boosting works by sequentially adding predictors to an ensemble, each one correcting its predecessor. However, **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 final prediction is going to be the sum of all predictions.
- Gradient Boosting works with Regression or Classification tasks (It works great with Regression tasks).

- When we build Gradient Boosting model using DecisionTreeRegressor we call it as **Gradient Tree Boosting**, or **Gradient Boosted Regression Trees (GBRT)**.

Step - 1

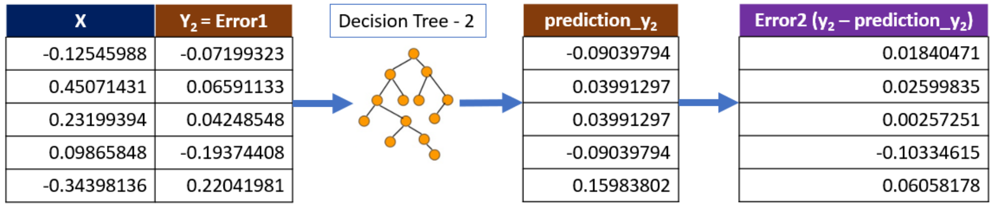


X	y_1
-0.12545988	0.0515729
0.45071431	0.59447979
0.23199394	0.16605161
0.09865848	-0.07017796
-0.34398136	0.34398593

prediction_y_1
0.12356613
0.52856846
0.12356613
0.12356613
0.12356613

Error1 (y_1 – prediction_y_1)
-0.07199323
0.06591133
0.04248548
-0.19374408
0.22041981

Step - 2

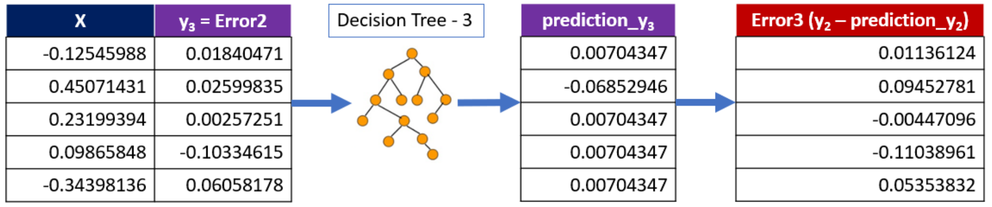


X	Y_2 = Error1
-0.12545988	-0.07199323
0.45071431	0.06591133
0.23199394	0.04248548
0.09865848	-0.19374408
-0.34398136	0.22041981

prediction_y_2
-0.09039794
0.03991297
0.03991297
-0.09039794
0.15983802

Error2 (y_2 – prediction_y_2)
0.01840471
0.02599835
0.00257251
-0.10334615
0.06058178

Step - 3

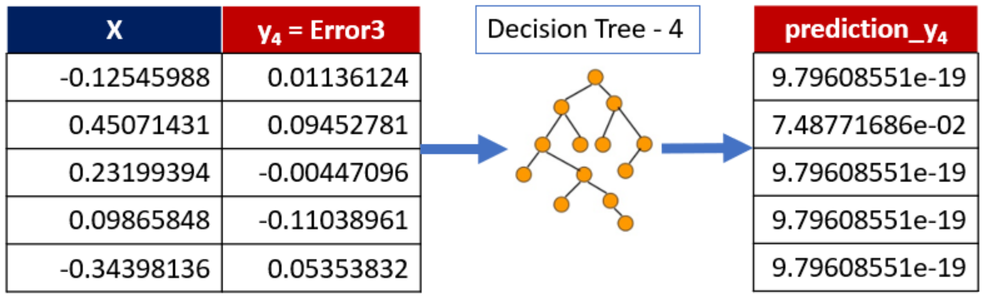


X	y_3 = Error2
-0.12545988	0.01840471
0.45071431	0.02599835
0.23199394	0.00257251
0.09865848	-0.10334615
-0.34398136	0.06058178

prediction_y_3
0.00704347
-0.06852946
0.00704347
0.00704347
0.00704347

Error3 (y_2 – prediction_y_2)
0.01136124
0.09452781
-0.00447096
-0.11038961
0.05353832

Step - 4



X	y_4 = Error3
-0.12545988	0.01136124
0.45071431	0.09452781
0.23199394	-0.00447096
0.09865848	-0.11038961
-0.34398136	0.05353832

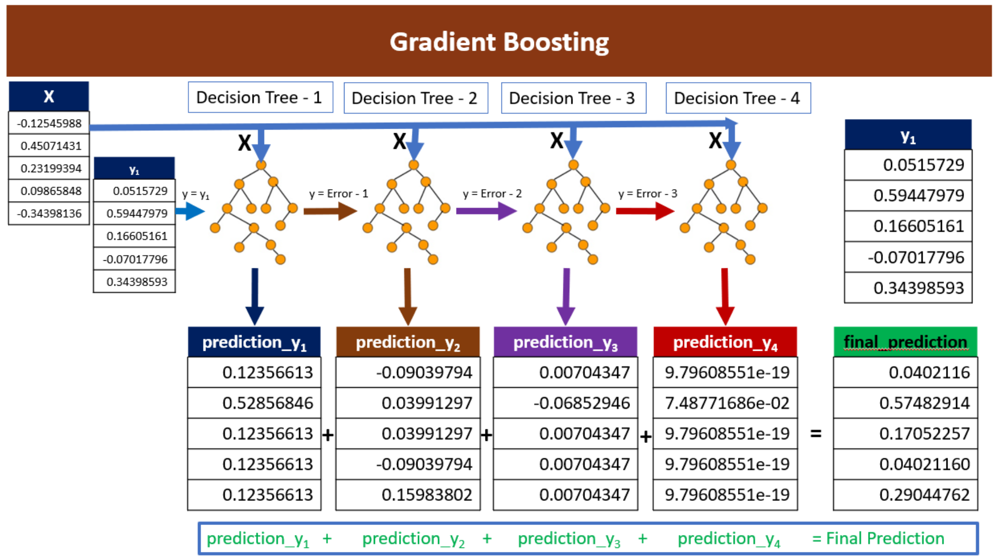
prediction_y_4
9.79608551e-19
7.48771686e-02
9.79608551e-19
9.79608551e-19
9.79608551e-19

.....

.....

Step - n

Final Step



X
-0.12545988
0.45071431
0.23199394
0.09865848
-0.34398136

y_1
0.0515729
0.59447979
0.16605161
-0.07017796
0.34398593

prediction_y_1	prediction_y_2	prediction_y_3	prediction_y_4	final_prediction
0.12356613	-0.09039794	0.00704347	9.79608551e-19	0.0402116
0.52856846	0.03991297	-0.06852946	7.48771686e-02	0.57482914
0.12356613	0.03991297	0.00704347	9.79608551e-19	0.17052257
0.12356613	-0.09039794	0.00704347	9.79608551e-19	0.04021160
0.12356613	0.15983802	0.00704347	9.79608551e-19	0.29044762

prediction_y_1 + prediction_y_2 + prediction_y_3 + prediction_y_4 = Final Prediction

GradientBoostingRegressor

- A simpler way to train GBRT ensembles is to use Scikit-Learn's GradientBoostingRegressor class. Much like the RandomForestRegressor class, it has hyperparameters to control the growth of Decision Trees (e.g., max_depth, min_samples_leaf, and so on), as well as hyperparameters to control the ensemble training, such as the number of trees (n_estimators).
- 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.

In [26]:
```
np.random.seed(42)
X = np.random.rand(100, 1) - 0.5
y = 3*X[:, 0]**2 + 0.05 * np.random.randn(100)
```

In [27]:
```
from sklearn.ensemble import GradientBoostingRegressor
gbrt_slow = GradientBoostingRegressor(max_depth=2, n_estimators=200, \
                                      learning_rate=0.1, random_state=42)
gbrt_slow.fit(X, y)
```

Out[27]:
```
GradientBoostingRegressor(alpha=0.9, ccp_alpha=0.0, criterion='friedman_mse',
                          init=None, learning_rate=0.1, loss='ls', max_depth=2,
                          max_features=None, max_leaf_nodes=None,
                          min_impurity_decrease=0.0, min_impurity_split=None,
                          min_samples_leaf=1, min_samples_split=2,
                          min_weight_fraction_leaf=0.0, n_estimators=200,
                          n_iter_no_change=None, presort='deprecated',
                          random_state=42, subsample=1.0, tol=0.0001,
                          validation_fraction=0.1, verbose=0, warm_start=False)
```

In [28]:
```
gbrt = GradientBoostingRegressor(max_depth=2, n_estimators=200, \
                                 learning_rate=1.0, random_state=42)
gbrt.fit(X, y)
```

Out[28]:
```
GradientBoostingRegressor(alpha=0.9, ccp_alpha=0.0, criterion='friedman_mse',
                          init=None, learning_rate=1.0, loss='ls', max_depth=2,
                          max_features=None, max_leaf_nodes=None,
                          min_impurity_decrease=0.0, min_impurity_split=None,
                          min_samples_leaf=1, min_samples_split=2,
                          min_weight_fraction_leaf=0.0, n_estimators=200,
                          n_iter_no_change=None, presort='deprecated',
                          random_state=42, subsample=1.0, tol=0.0001,
                          validation_fraction=0.1, verbose=0, warm_start=False)
```

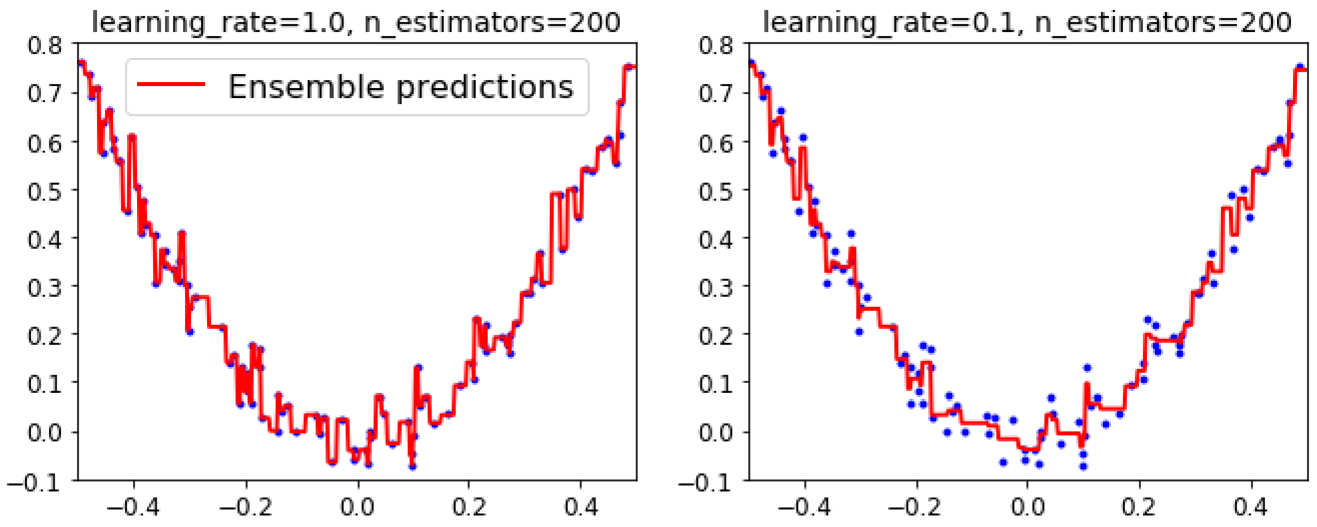
In [29]:
```
def plot_predictions(regressors, X, y, axes, label=None, style="r-", \
                                                 data_style="b.", data_label=None):
    x1 = np.linspace(axes[0], axes[1], 500)
    y_pred = sum(regressor.predict(x1.reshape(-1, 1)) for regressor in regressors)
    plt.plot(X[:, 0], y, data_style, label=data_label)
    plt.plot(x1, y_pred, style, linewidth=2, label=label)
    if label or data_label:
        plt.legend(loc="upper center", fontsize=16)
    plt.axis(axes)
```

In [30]:
```
plt.figure(figsize=(11,4))

plt.subplot(121)
plot_predictions([gbrt], X, y, axes=[-0.5, 0.5, -0.1, 0.8], label="Ensemble predictions")
plt.title("learning_rate={}, n_estimators={}".\
                            format(gbrt.learning_rate, gbrt.n_estimators), fontsize=14)

plt.subplot(122)
plot_predictions([gbrt_slow], X, y, axes=[-0.5, 0.5, -0.1, 0.8])
plt.title("learning_rate={}, n_estimators={}".format(gbrt_slow.learning_rate, \
                                                    gbrt_slow.n_estimators), fontsize=14)

plt.show()
```



In [ ]: