

CSY2082 Introduction to Artificial Intelligence

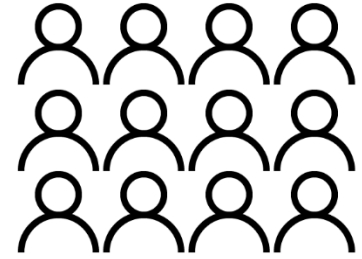
# Ensemble Learning and Random Forests

# Ensemble Learning

# Ensemble Learning



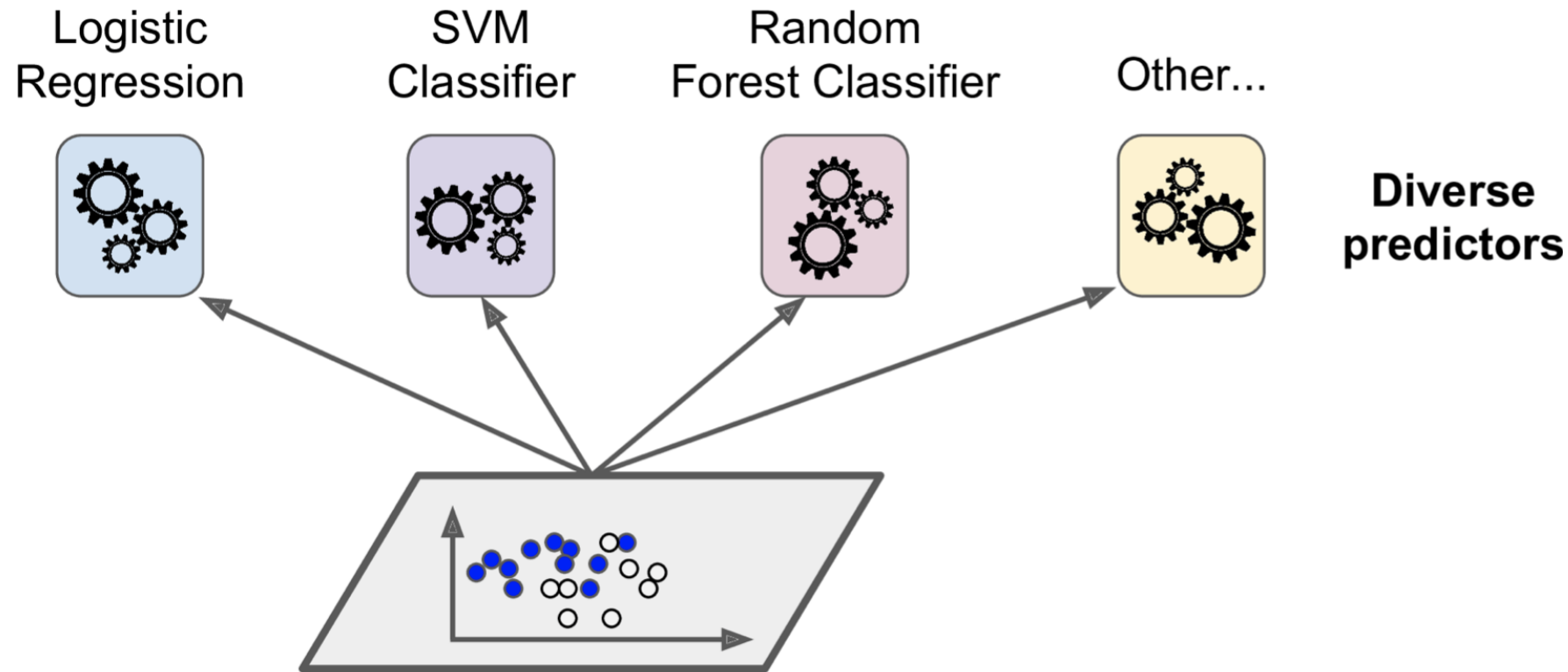
vs



- Suppose you ask a complex question to thousands of random people, then **aggregate** their answers. In many cases you will find that this aggregated answer is better than an expert's answer. This is called the *wisdom of the crowd*.
- Similarly, if you aggregate the predictions of a group of predictors (such as classifiers or regressors), you will often get better predictions than with the best individual predictor. A group of predictors is called an ensemble; thus, this technique is called **Ensemble Learning**
- You will often use Ensemble methods near the end of a project, once you have already built a few good predictors, to **combine** them into an even better predictor. In fact, the winning solutions in Machine Learning competitions often involve several Ensemble methods.

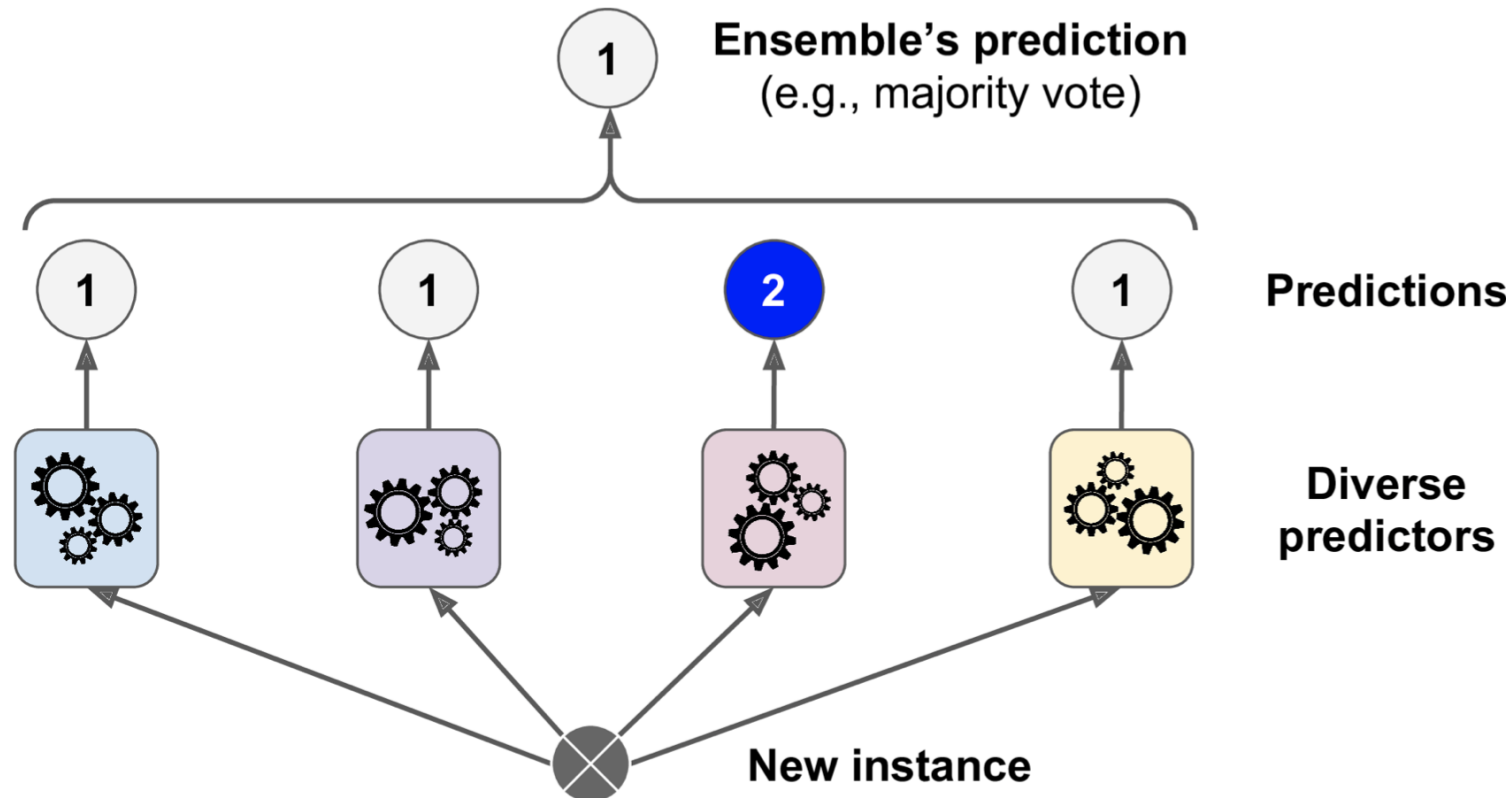
# Voting Classifiers

- Suppose you have trained a few classifiers, each one achieving about 80% accuracy.



# Voting Classifiers

- A very simple way to create an even better classifier is to aggregate the predictions of each classifier and predict the class that gets the most votes. This majority-vote classifier is called a **hard voting** classifier
- A few weak models -> strong model.



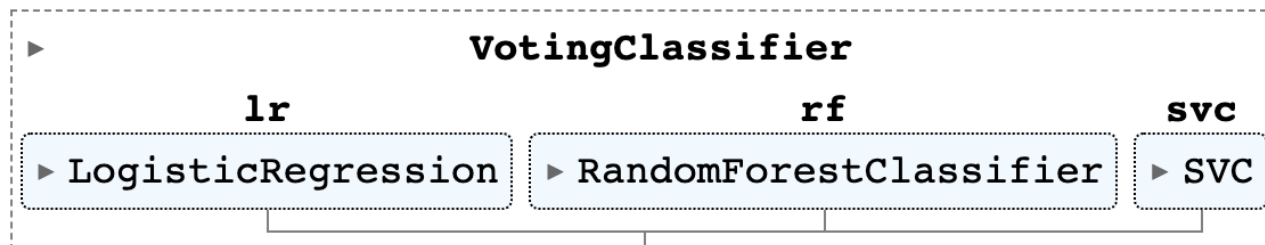
# Voting Classifiers (hard) – make\_moons data

```
from sklearn.datasets import make_moons
from sklearn.ensemble import RandomForestClassifier, VotingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC

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)

voting_clf = VotingClassifier(
    estimators=[
        ('lr', LogisticRegression(random_state=42)),
        ('rf', RandomForestClassifier(random_state=42)),
        ('svc', SVC(random_state=42))
    ]
)
voting_clf.fit(X_train, y_train)
```

Get a diverse set of classifiers is to use very different training algorithms.  
(delete “random\_state” in your own code)



LogisticRegression 0.864  
RandomForestClassifier 0.896  
SVC 0.888  
VotingClassifier 0.904

# Voting Classifiers (soft)

- If all classifiers are able to estimate class probabilities (i.e., they have a `predict_proba()` method), then you can tell Scikit-Learn to predict the class with the highest class probability, **averaged over all the individual classifiers**. This is called *soft voting*.

```
voting_clf.voting = "soft"  
voting_clf.named_estimators["svc"].probability = True  
voting_clf.fit(X_train, y_train)  
voting_clf.score(X_test, y_test)
```

LogisticRegression 0.864

RandomForestClassifier 0.896

SVC 0.888

VotingClassifier 0.92

# Random Forests



# Random Forests

- A Random Forest is an ensemble of Decision Trees, generally trained via the bagging method (each tree picks a random subset for training). Each tree also picks a random subset of features for training (normally  $\sqrt{n}$  ).
- The following code trains a Random Forest classifier with 500 trees (each limited to maximum 16 nodes).

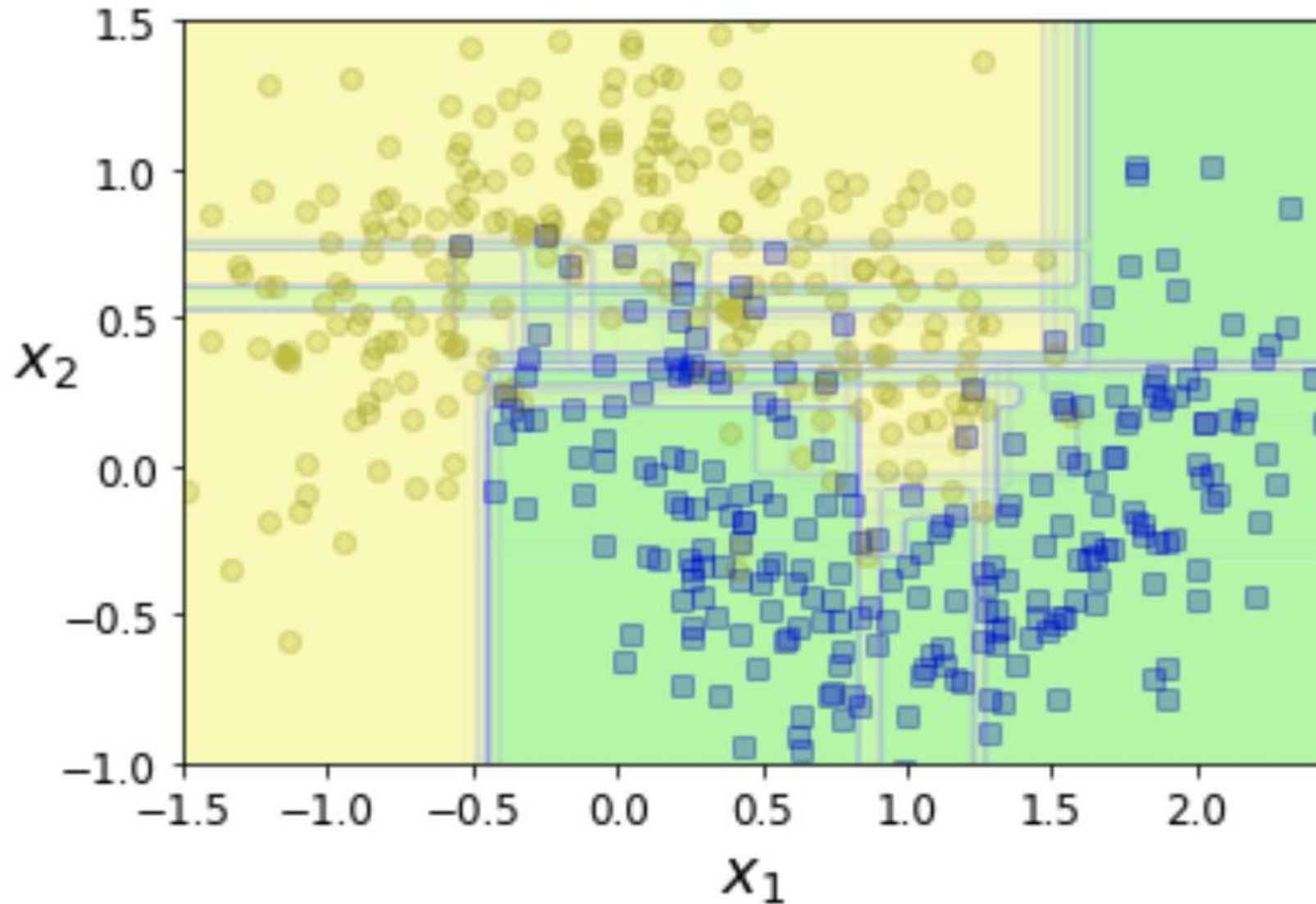
```
from sklearn.ensemble import RandomForestClassifier
```

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

```
y_pred_rf = rnd_clf.predict(X_test)
```

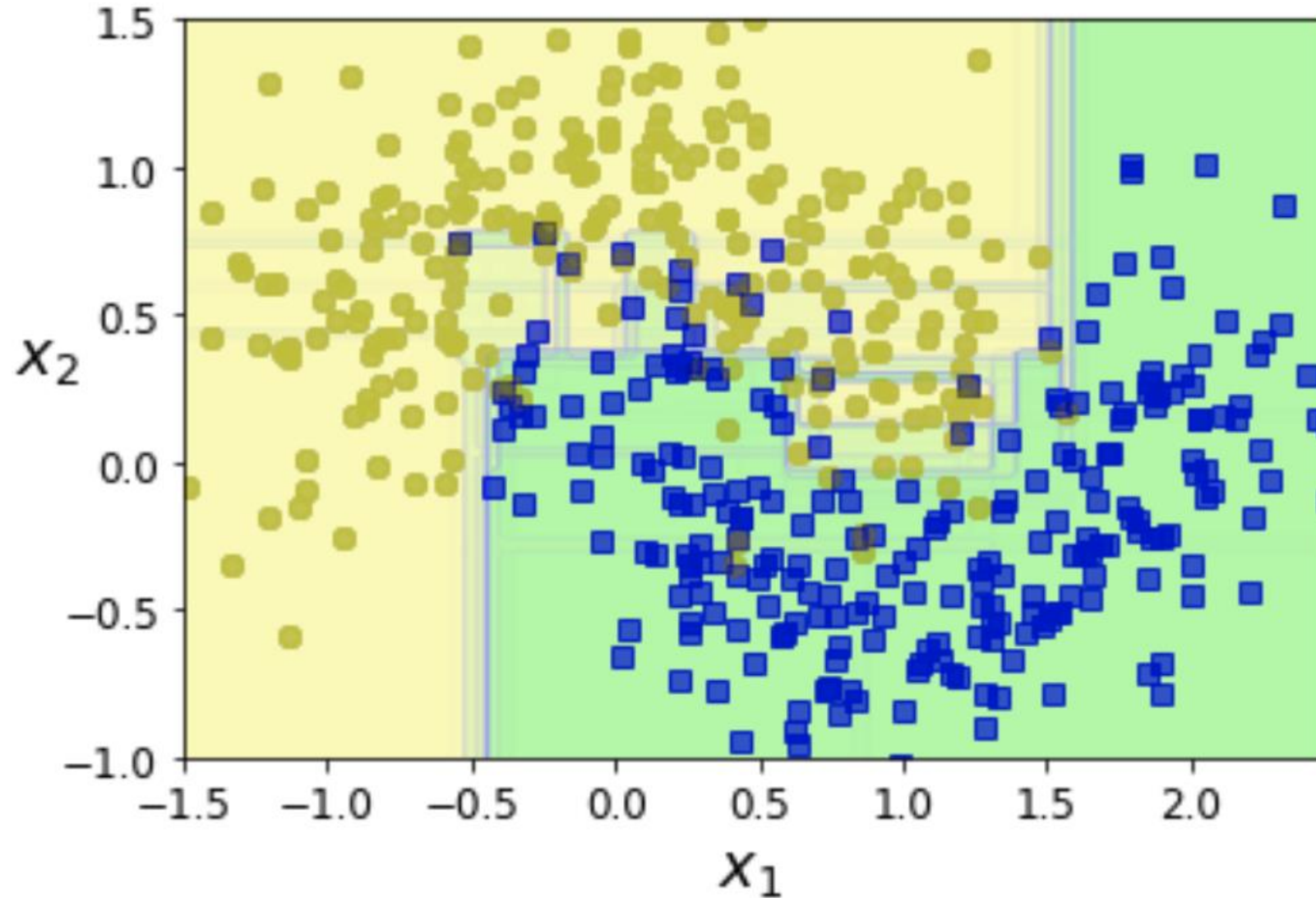
# Random Forests

- 15 trees



# Random Forests

- 50 trees

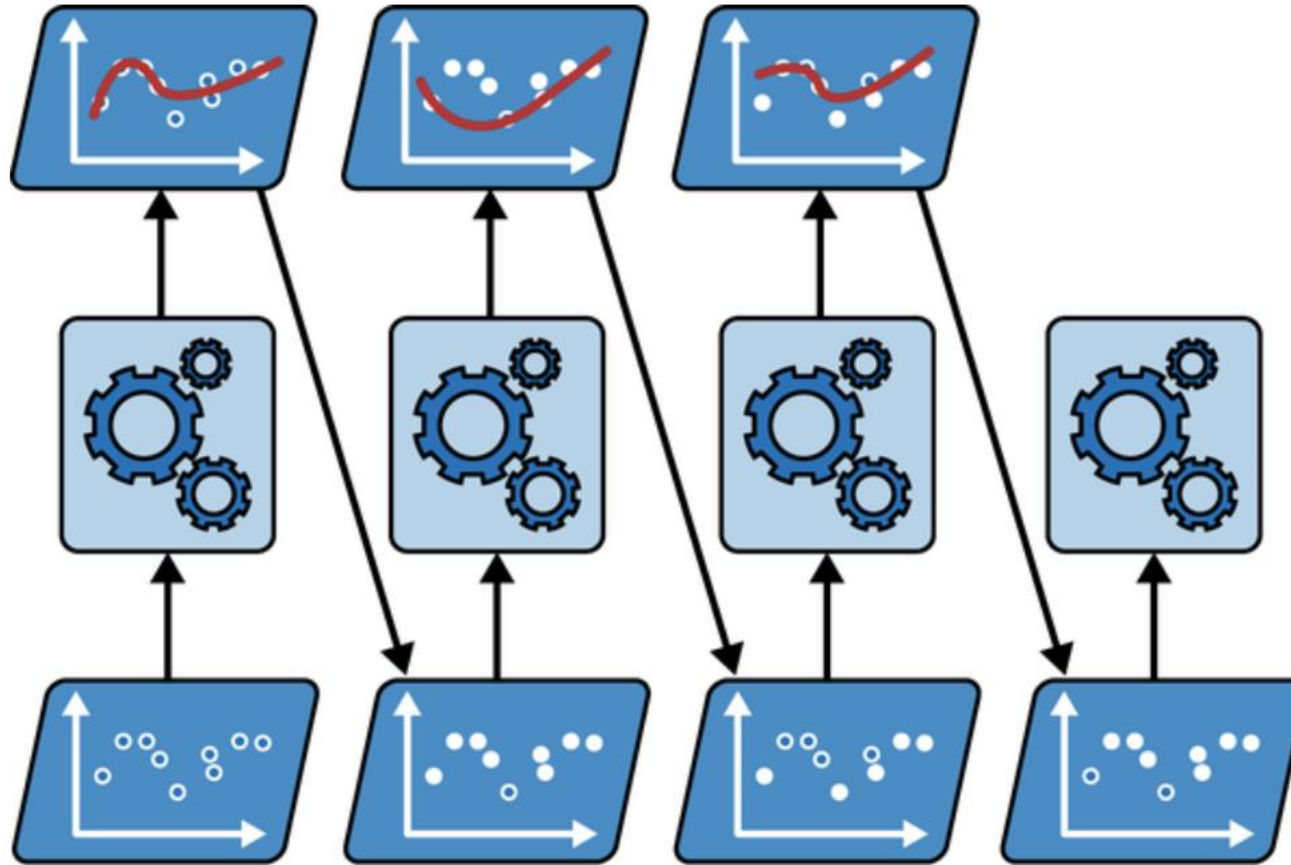


# Feature Importance

- A great quality of Random Forests is that they make it 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).
- Scikit-Learn computes this score automatically for each feature after training, then it scales the results so that the sum of all importances is equal to 1. You can access the result using the *feature\_importances\_* variable.

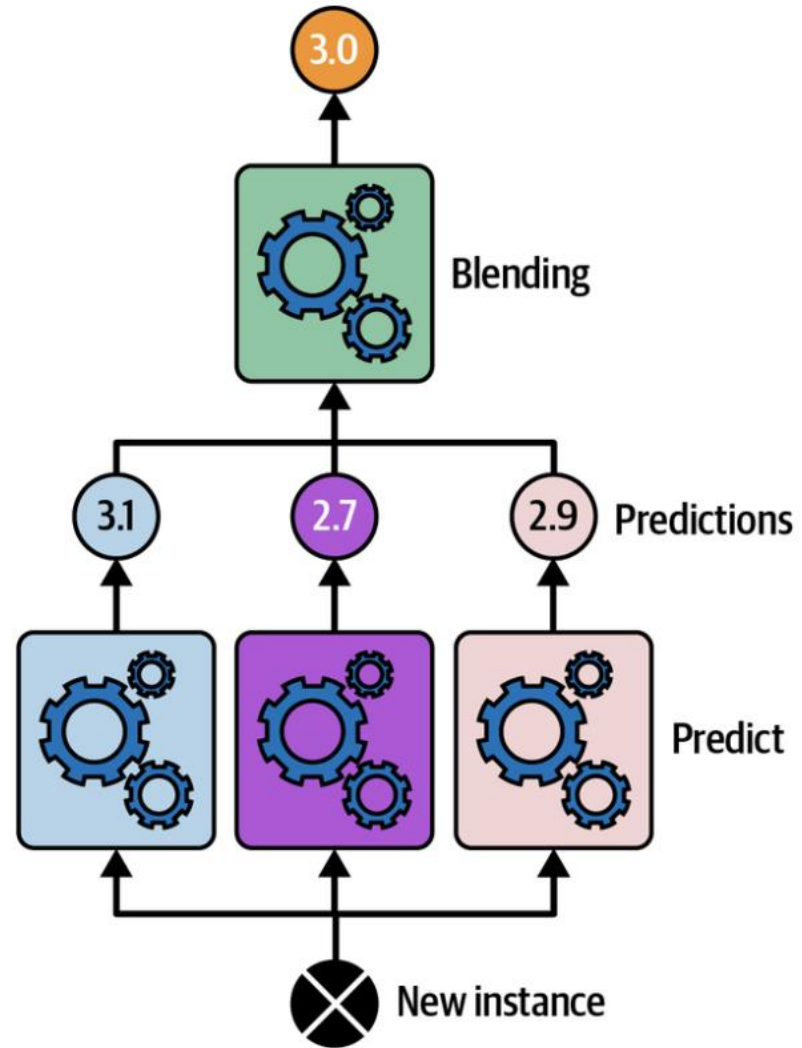
```
>>> from sklearn.datasets import load_iris
>>> iris = load_iris()
>>> rnd_clf = RandomForestClassifier(n_estimators=500, n_jobs=-1)
>>> rnd_clf.fit(iris["data"], iris["target"])
>>> for name, score in zip(iris["feature_names"], rnd_clf.feature_importances_):
...     print(name, score)
...
sepal length (cm) 0.112492250999
sepal width (cm) 0.0231192882825
petal length (cm) 0.441030464364
petal width (cm) 0.423357996355
```

# Boosting



AdaBoost sequential training with instance weight updates

# Stacking



aggregating predictions using a blending predictor

# Exercise

- Examine the classifiers listed on the following webpage and add some of these classifiers to your voting classifier to improve the overall performance.

[https://scikit-learn.org/stable/auto\\_examples/classification/plot\\_classifier\\_comparison.html](https://scikit-learn.org/stable/auto_examples/classification/plot_classifier_comparison.html)