Lesson #06
Ensemble Learning I

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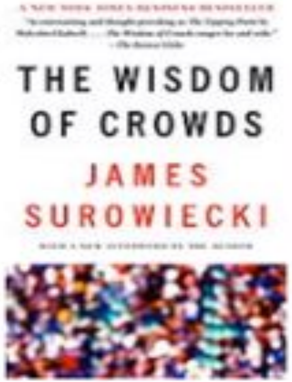
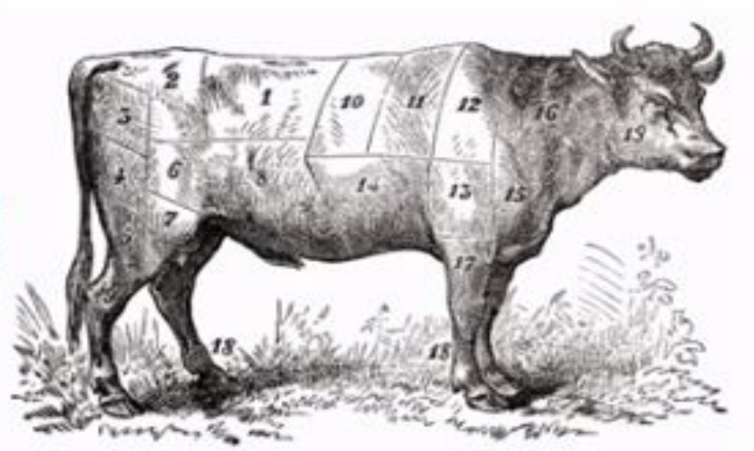
Wisdom of the Crowd: the process of taking into account the collective opinion of a group of individuals rather than a single expert to answer a question.

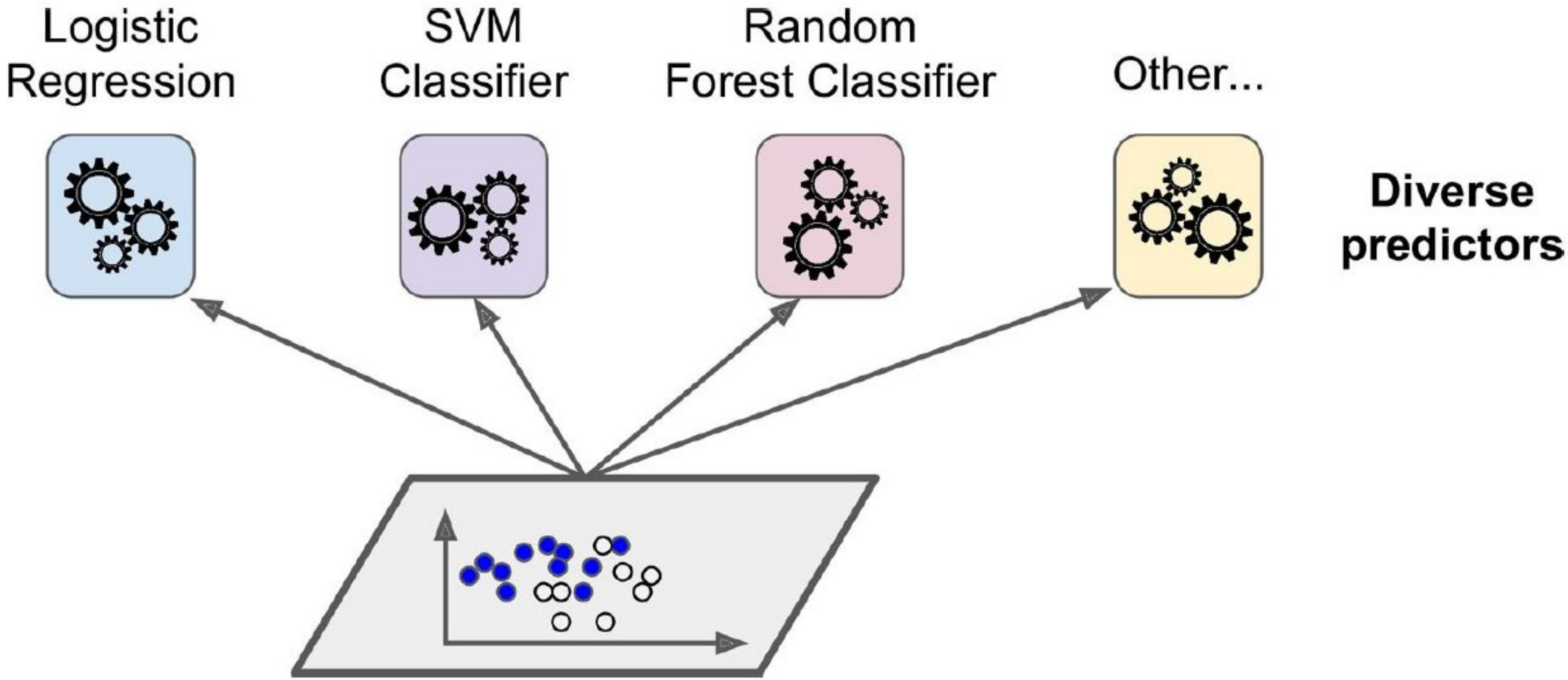
The Wisdom of Crowds

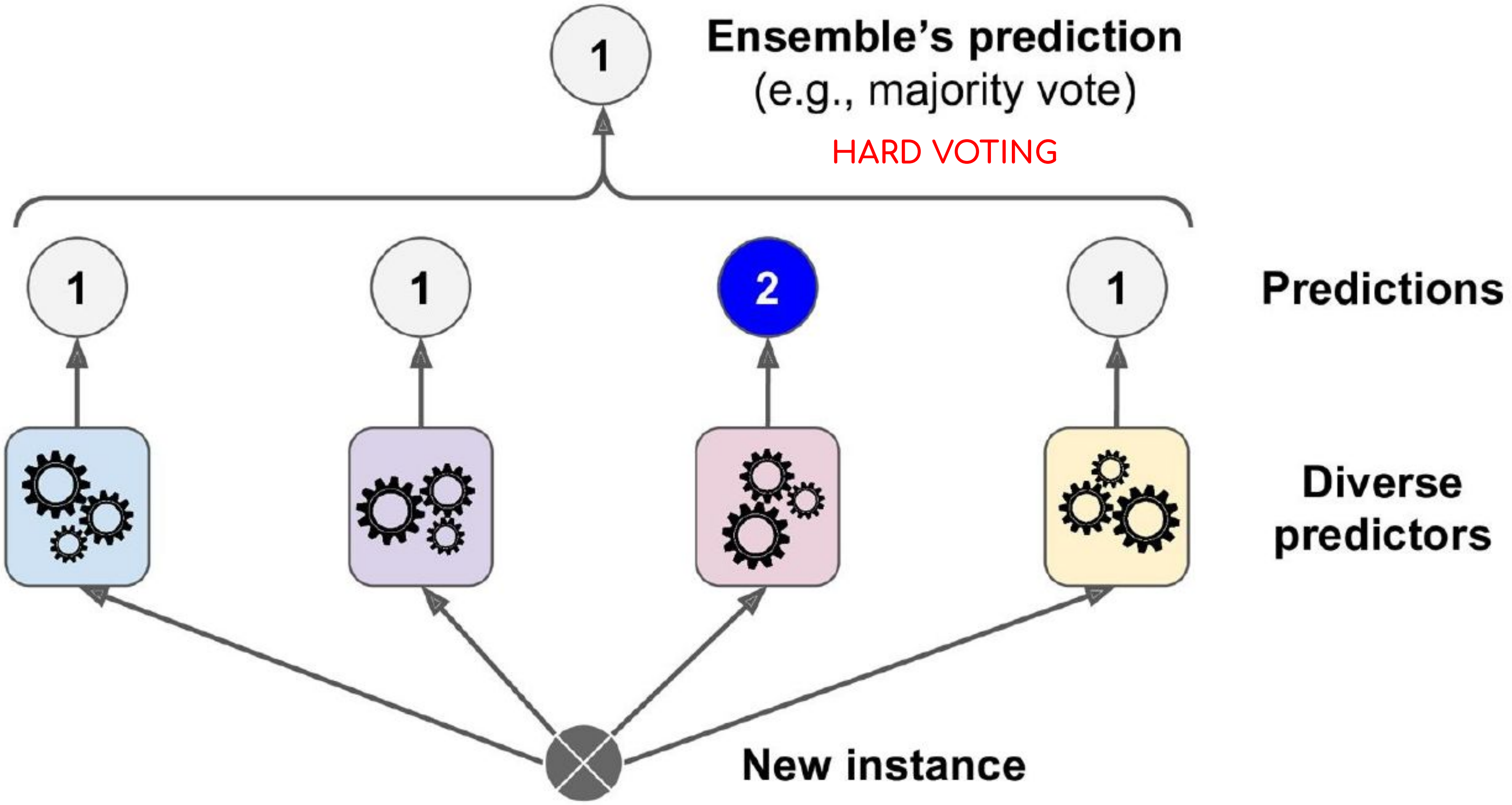


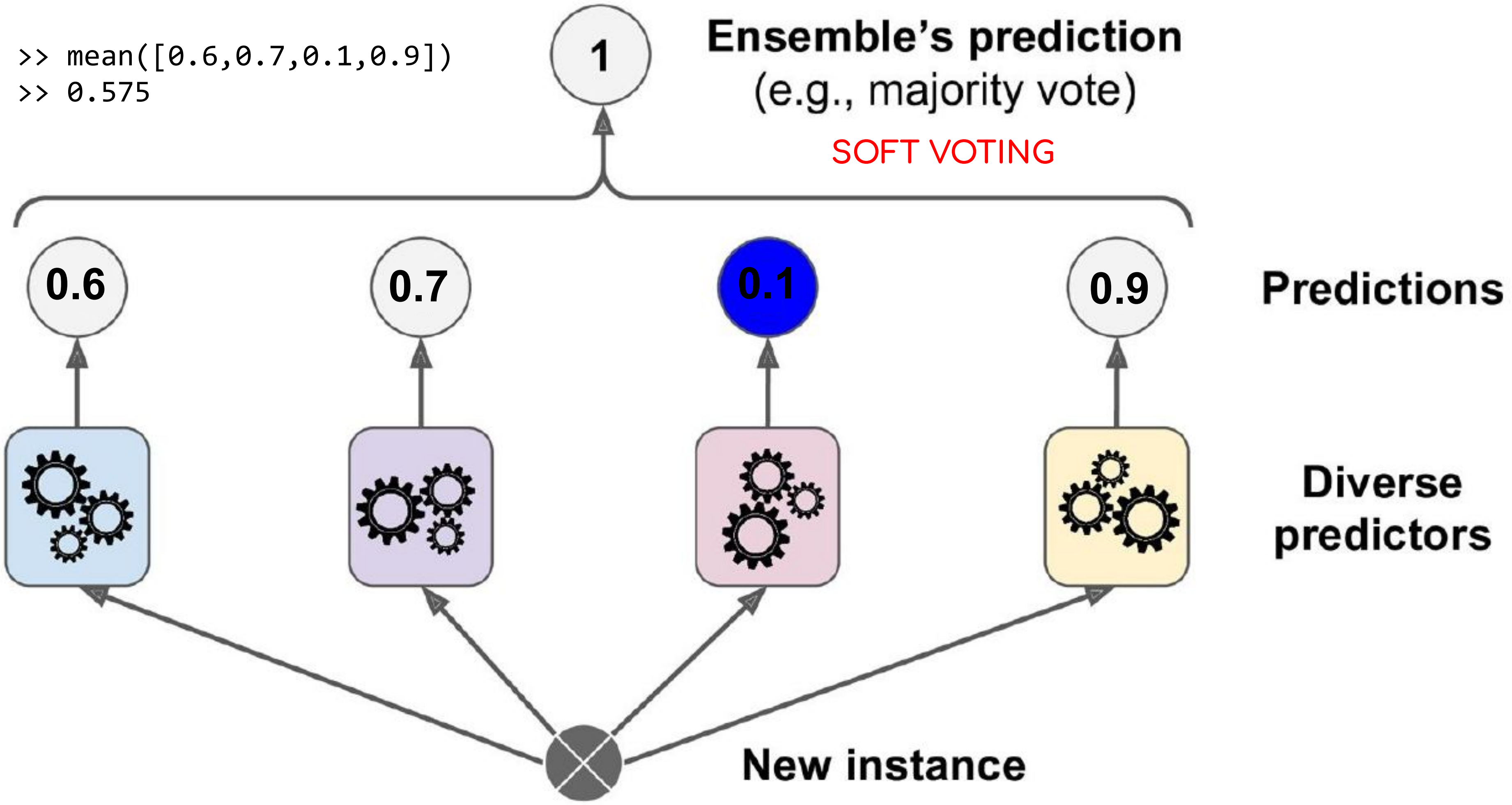


average of 800 guesses = 1,197

actual weight of the ox = 1,198

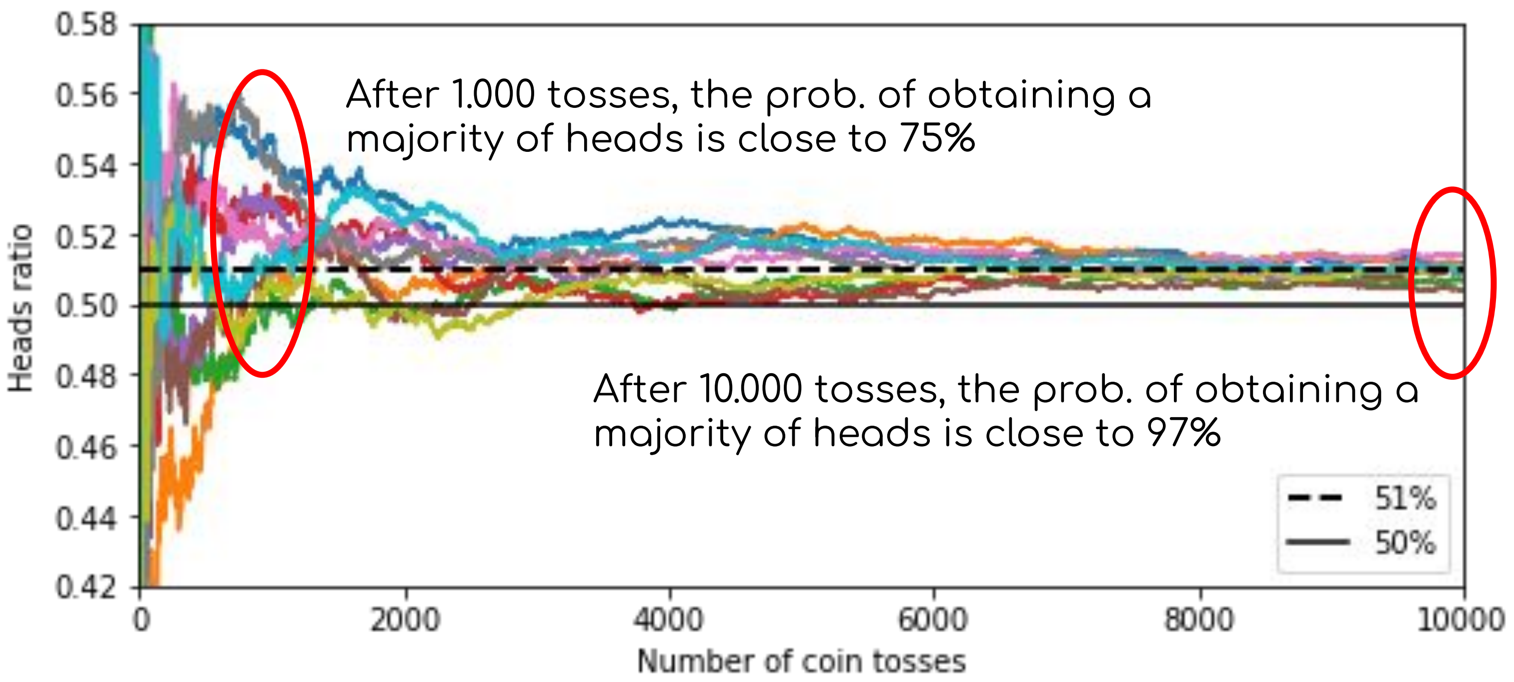

Logistic Regression
SVM Classifier
Random Forest Classifier
Other...
Diverse predictors


1
Ensemble's prediction
(e.g., majority vote)
HARD VOTING
1
1
2
1
Predictions
Diverse
predictors
New instance

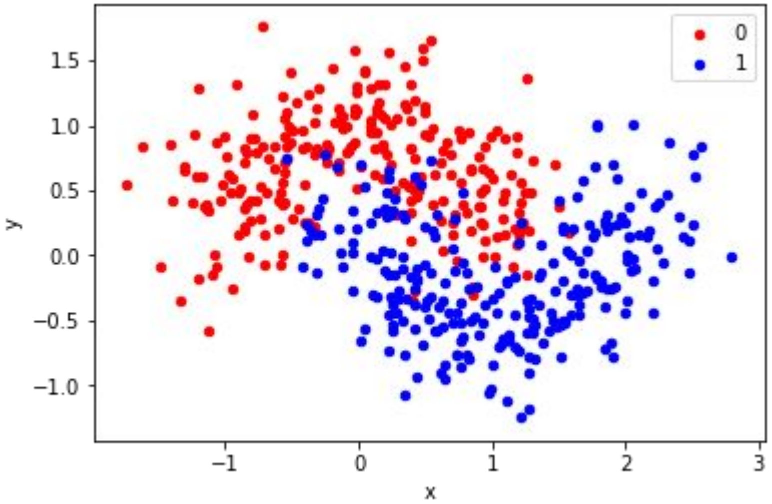


>> mean([0.6,0.7,0.1,0.9])
>> 0.575
1
Ensemble's prediction
(e.g., majority vote)
SOFT VOTING
0.6
0.7
0.1
0.9
Predictions
Diverse predictors
New instance

How is this possible?




```
# suppose you have a slightly biased coin
heads_proba = 0.51
# 10 series of biased coin tosses (10.000)
coin_tosses = (np.random.rand(10000, 10) < heads_proba).astype(np.int32)
# cumulative heads ratio for each series
cumulative_heads_ratio = np.cumsum(coin_tosses, axis=0) / np.arange(1, 10001).reshape(-1, 1)
```



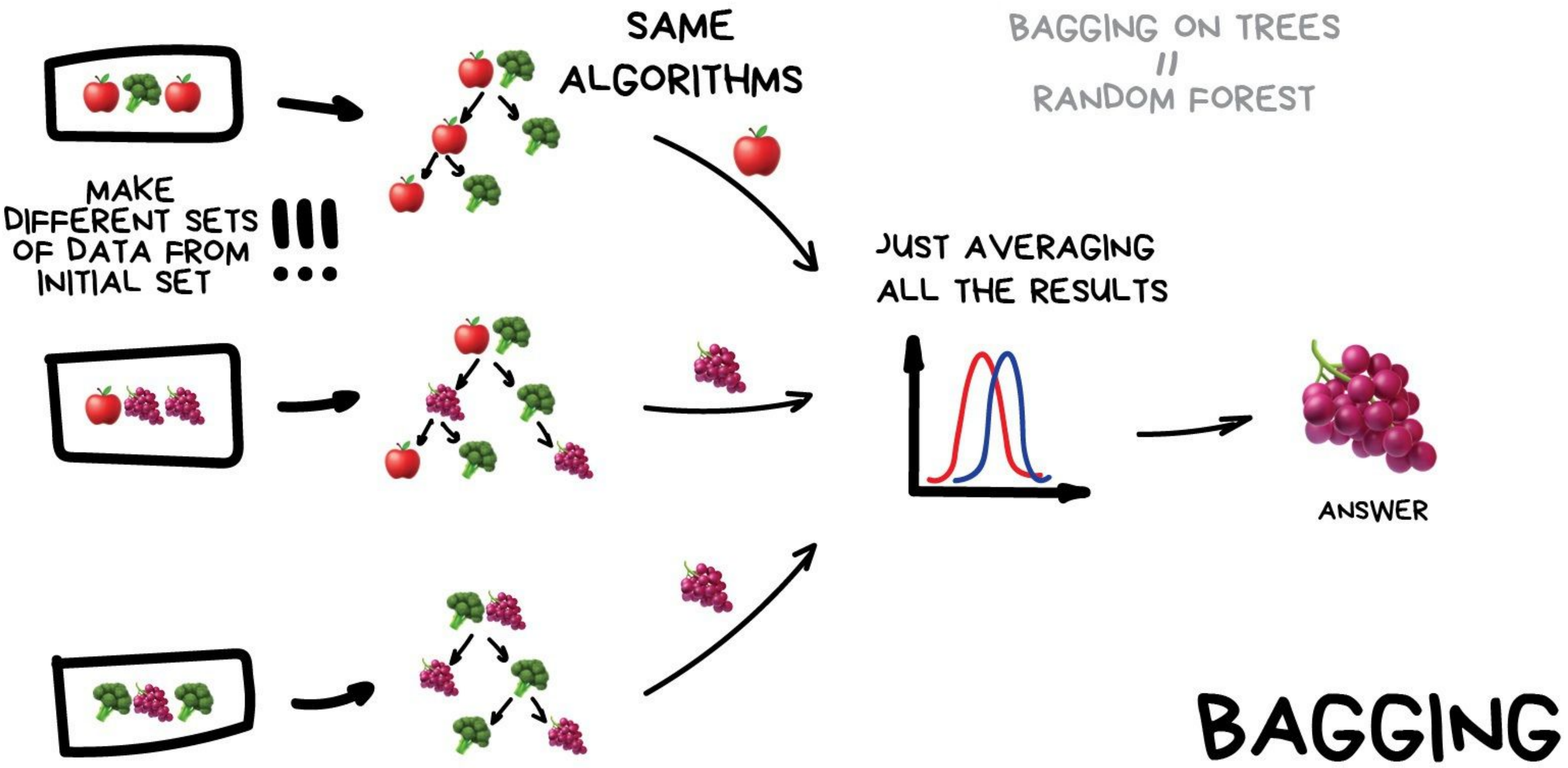

```
# soft voting
voting_clf_hard = VotingClassifier(
    estimators=[('lr', log_clf),
                ('rf', rnd_clf),
                ('svc', svm_clf)],
    voting='soft')
```

```
LogisticRegression 0.85
RandomForestClassifier 0.88
SVC 0.87
VotingClassifier 0.89
```

```
# create classifiers
log_clf = LogisticRegression(solver="lbfgs", random_state=42)
rnd_clf = RandomForestClassifier(n_estimators=100, random_state=42)
svm_clf = SVC(gamma="scale", random_state=42)
```

ENSEMBLE METHODS

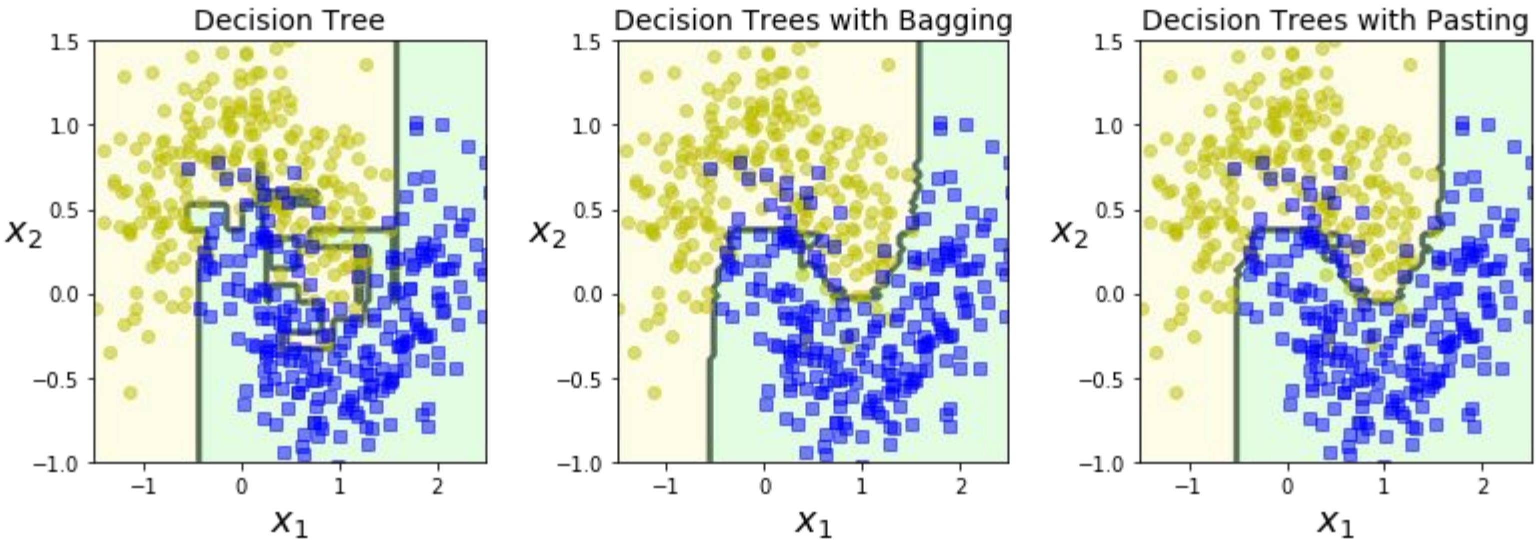
BAGGING & PASTING
BOOSTING
STACKING


SAME
ALGORITHMS
BAGGING ON TREES
=
RANDOM FOREST
MAKE
DIFFERENT SETS
OF DATA FROM
INITIAL SET
!!!
...
JUST AVERAGING
ALL THE RESULTS
ANSWER
BAGGING

```python
# instantiate a bagging object (model,size,samples,bootstrap,rnd)
bag_clf = BaggingClassifier(DecisionTreeClassifier(random_state=42),
                            n_estimators=500,
                            max_samples=100,
                            #bootstrap=False -> pasting
                            bootstrap=True,
                            random_state=42)
# training the  bagging model
bag_clf.fit(X_train, y_train)
```

max_samples : int or float, optional (default=1.0). The number of samples to draw from X to train each base estimator.

- If int, then draw max_samples samples.
- If float, then draw max_samples * X.shape[0] samples.




```
Accuracy.bagging: 0.90
Accuracy.pasting: 0.89
Accuracy.decision_tree: 0.82
```

Out-of-Bag Evaluation

```
bag_clf = BaggingClassifier(DecisionTreeClassifier(random_state=42),
                            n_estimators=500,
                            bootstrap=True,
                            oob_score=True,
                            random_state=40)
bag_clf.fit(X_train, y_train)
bag_clf.oob_score_
```

```
0.9075
```

$$\lim_{m\to\infty}(1-\frac{1}{m})^m = e^{-1} = 0.3678$$

Random decision forests

Publisher: IEEE

Cite This

PDF

Tin Kam Ho   All Authors

Abstract

Authors

References

Citations

Keywords

Metrics

Abstract:
Decision trees are attractive classifiers due to their high execution speed. But trees derived with traditional methods often cannot be grown to arbitrary complexity for possible loss of generalization accuracy on unseen data. The limitation on complexity usually means suboptimal accuracy on training data. Following the principles of stochastic modeling, we propose a method to construct tree-based classifiers whose capacity can be arbitrarily expanded for increases in accuracy for both training and unseen data. The essence of the method is to build multiple trees in randomly selected subspaces of the feature space. Trees in, different subspaces generalize their classification in complementary ways, and their combined classification can be monotonically improved. The validity of the method is demonstrated through experiments on the recognition of handwritten digits.

Published in: Proceedings of 3rd International Conference on Document Analysis and Recognition

Date of Conference: 14-16 Aug. 1995

Date Added to IEEE *Xplore*: 06 August 2002

Print ISBN: 0-8186-7128-9

INSPEC Accession Number: 5628989

DOI: 10.1109/ICDAR.1995.598994

Publisher: IEEE

Conference Location: Montreal, Quebec, Canada,

```python
# Random Forest using BaggingClassifier
bag_clf = BaggingClassifier(DecisionTreeClassifier(max_features="auto",
                                                   max_leaf_nodes=16,
                                                   random_state=42),
                            n_estimators=500,
                            max_samples=1.0,
                            bootstrap=True,
                            random_state=42)

# Random Forest using RandomForestClassifier
rnd_clf = RandomForestClassifier(n_estimators=500,
                                 max_leaf_nodes=16,
                                 random_state=42)
```

- Random Forest introduces extra randomness when growing trees
- Instead of searching for the very best feature, it is possible to search among a random subset of features
- This results in a greater tree diversity (trades a higher bias for a low variance)

```
# Random Forest using BaggingClassifier
bag_clf = BaggingClassifier(DecisionTreeClassifier(max_features="auto",
                                                   #added this hyperparameter
                                                   splitter="random",
                                                   max_leaf_nodes=16,
                                                   random_state=42),
                            n_estimators=500,
                            max_samples=1.0,
                            bootstrap=True,
                            random_state=42)
```

Feature selection

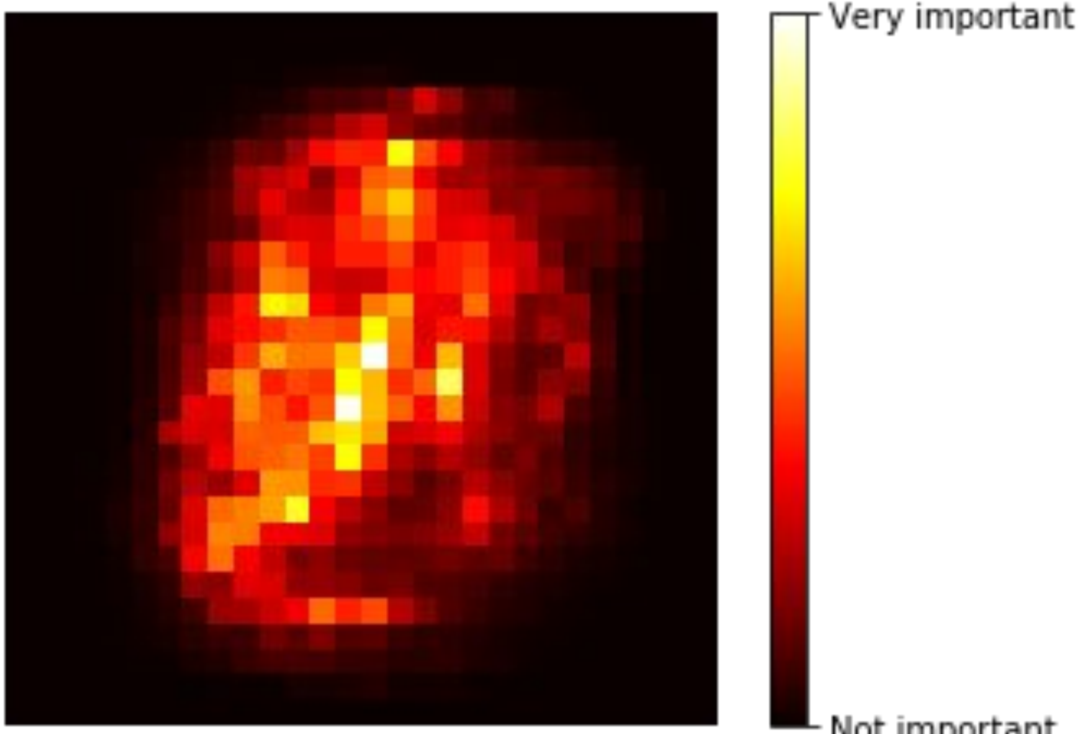
- Univariate Selection
- Recursive Feature Elimination
- **Feature Importance**
- Principal Component Analysis (PCA)

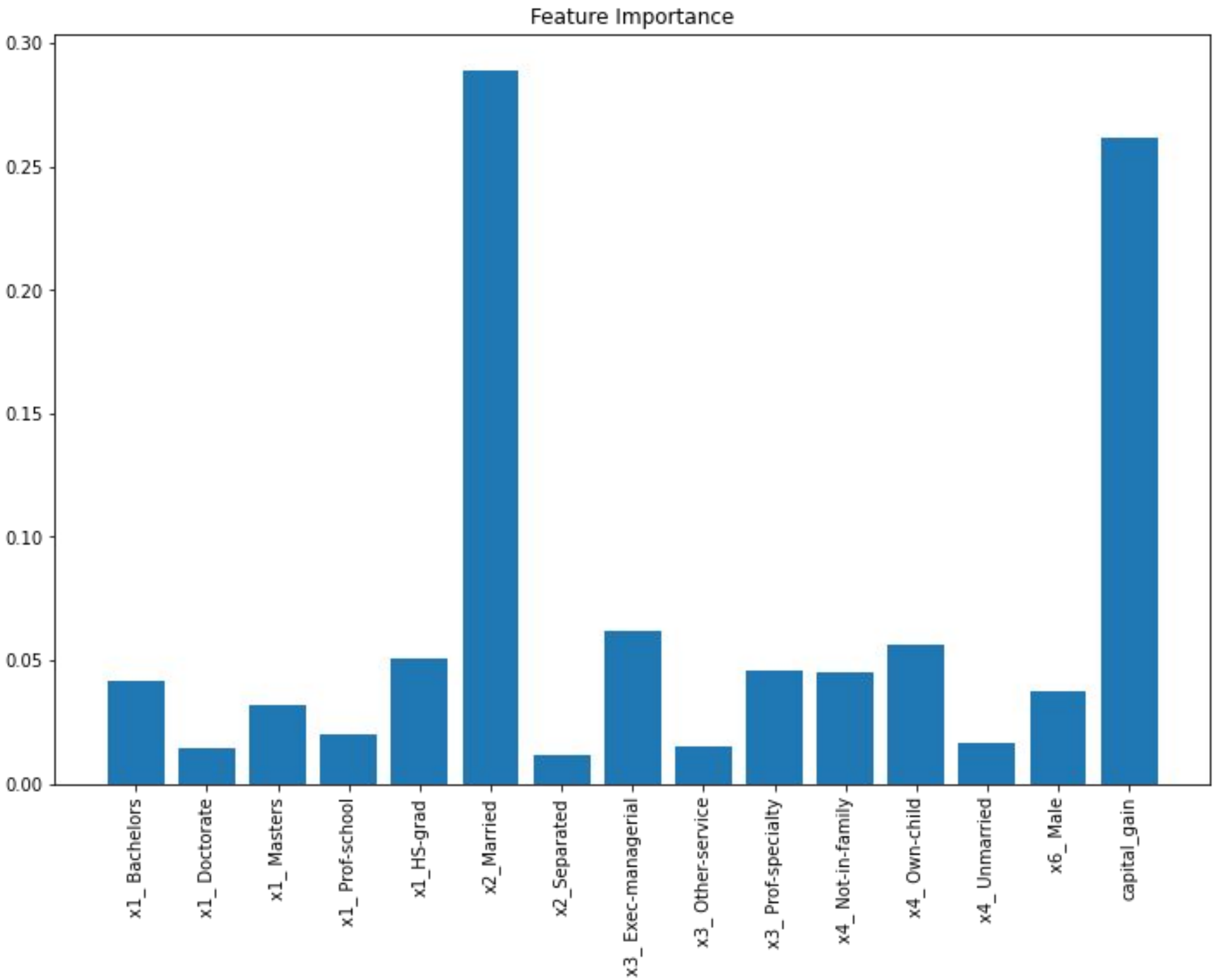
Feature Importance

```python
from sklearn.datasets import load_iris
# load dataset
iris = load_iris()
# instantiate the model
rnd_clf = RandomForestClassifier(n_estimators=500, random_state=42)
# training
rnd_clf.fit(iris["data"], iris["target"])
# find the feature importance
for name, score in zip(iris["feature_names"], rnd_clf.feature_importances_):
    print(name, score)
```

```
sepal length (cm) 0.11249225099876375
sepal width (cm) 0.02311928828251033
petal length (cm) 0.4410304643639577
petal width (cm) 0.4233579963547682
```

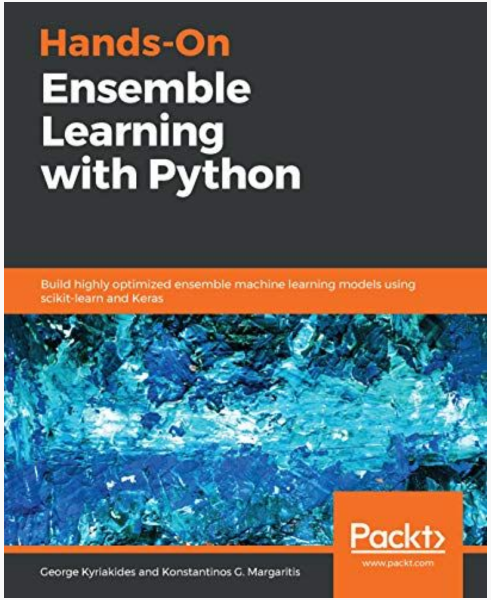
Feature Importance

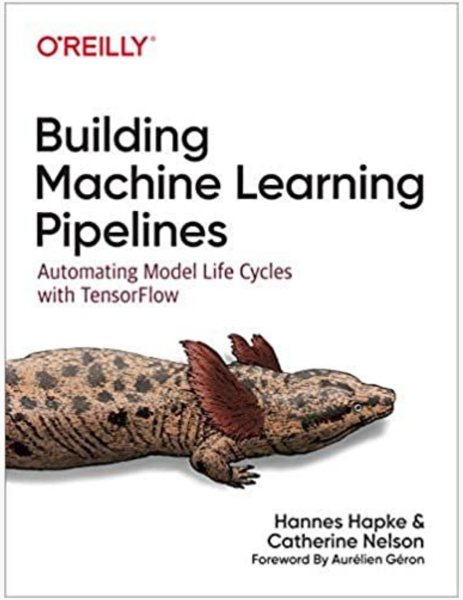


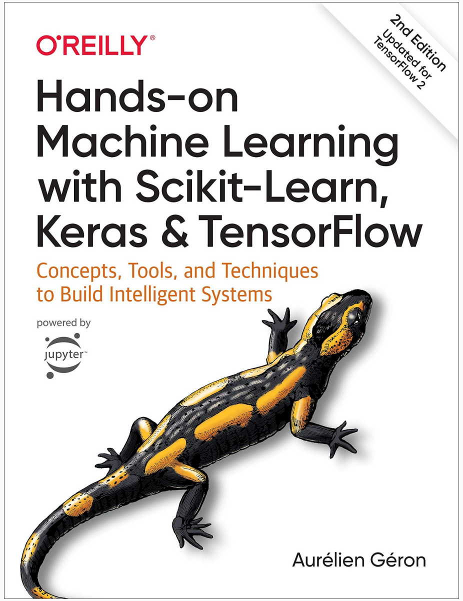

Feature Importance
0.30
0.25
0.20
0.15
0.10
0.05
0.00
x1_ Bachelors
x1_ Doctorate
x1_ Masters
x1_ Prof-school
x1_HS-grad
x2_Married
x2_Separated
x3_ Exec-managerial
x3_ Other-service
x3_ Prof-specialty
x4_ Not-in-family
x4_ Own-child
x4_ Unmarried
x6_ Male
capital_gain

When to use Random Forest

- Strengths of a Random Forest
  - Very accurate predictions
  - Resistance to overfitting
- Weakness
  - They are difficult to interpret
  - They take longer to create
- Alternative
  - Extra-trees


Hands-On
Ensemble Learning with Python
Build highly optimized ensemble machine learning models using scikit-learn and Keras
Packt>
www.packt.com
George Kyriakides and Konstantinos G. Margaritis


O'REILLY
Building Machine Learning Pipelines
Automating Model Life Cycles with TensorFlow
Hannes Hapke & Catherine Nelson
Foreword By Aurélien Géron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#Yellowbrick
https://www.scikit-yb.org/en/latest/

#extratreesclassifier
#randomforest tuning