

notas notas Ensembles (introduction) Voting classifiers Bagging & Pasting Random Forest • Feature Importante (XAI) Case Study



A NEW YORK TIMES BUSINESS BESTSELLER

"As entertaining and thought-provoking as The Tipping Point by

Malcolm Gladwell. . . . The Wisdom of Crowds ranges far and wide."

—The Boston Globe

THE WISDOM OF CROWDS

JAMES SUROWIECKI

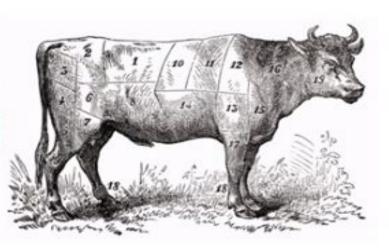
WITH A NEW AFTERWORD BY THE AUTHOR



Paradoxically, the way for a group to be smart is for each person in it to think and act as independently as possible.

The Wisdom of Crowds

THE WISDOM OF CROWDS JAMES SUROWIECKI



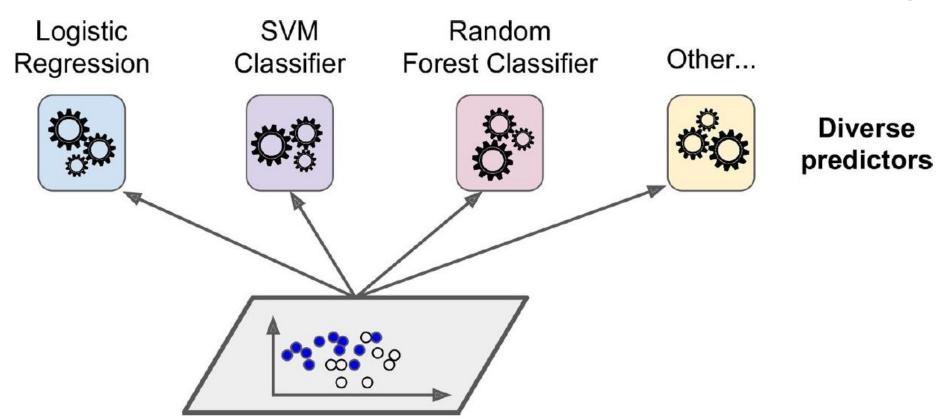




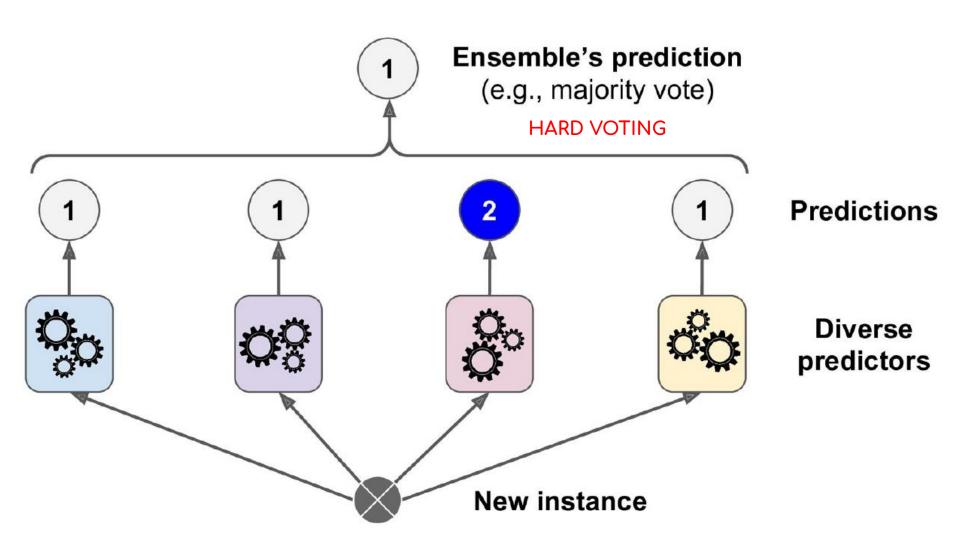
average of 800 guesses = 1,197 actual weight of the ox = 1,198

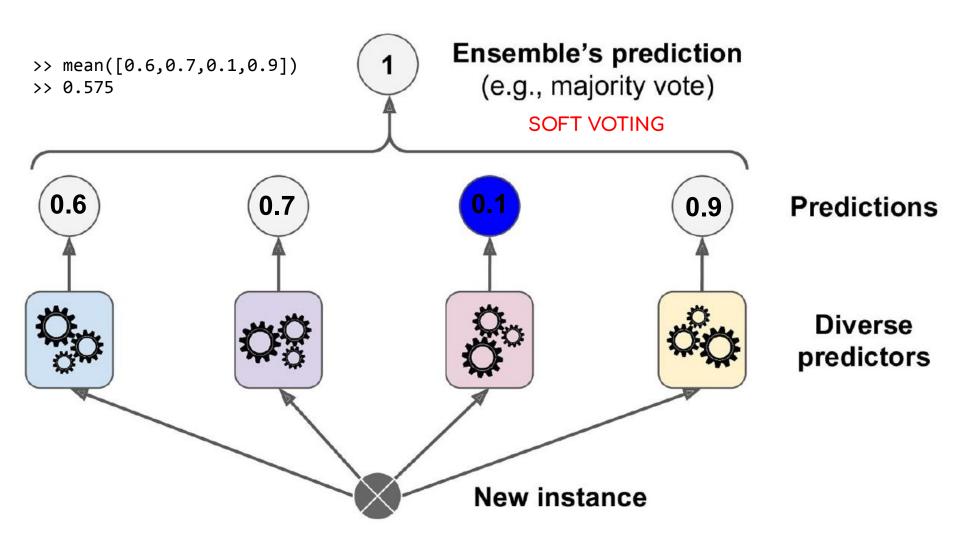












NETFLIX

Netflix Prize

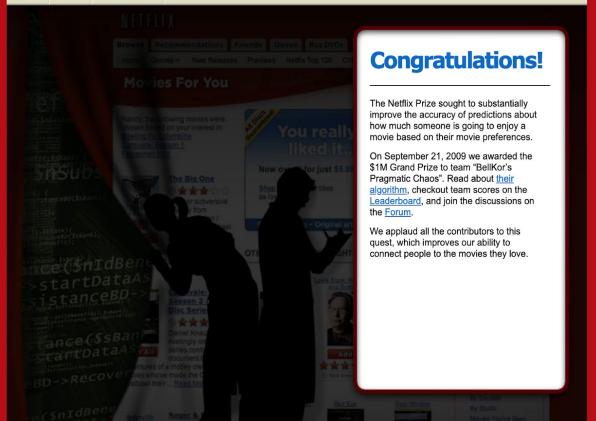
COMPLETED

Home

Rules

Leaderboard

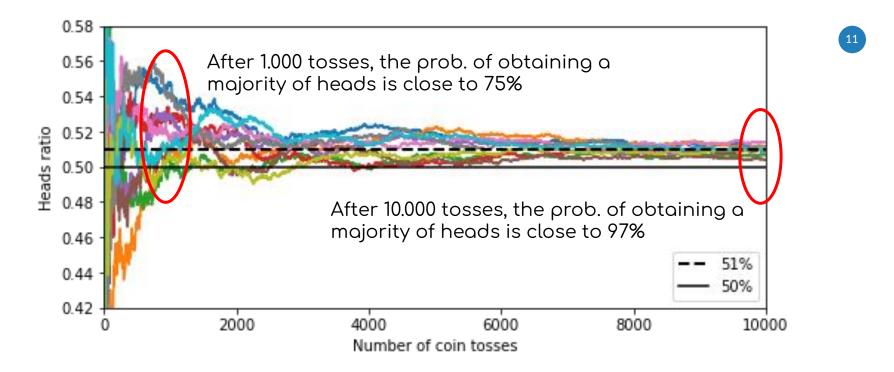
Update



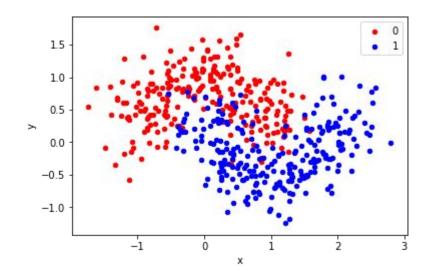


How is this possible?





```
# 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)</pre>
```



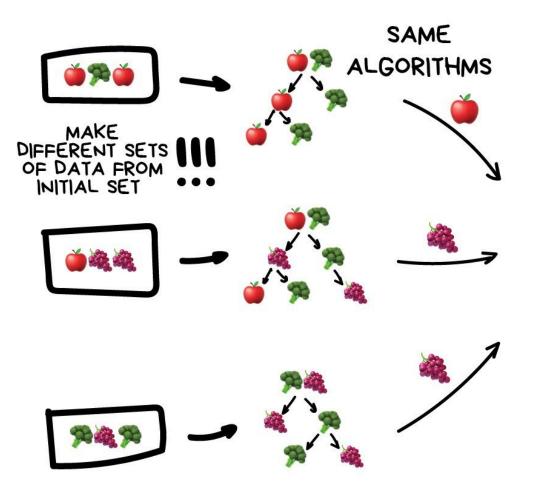
LogisticRegression 0.85
RandomForestClassifier 0.88
SVC 0.87
VotingClassifier 0.89

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





BAGGING ON TREES

11

RANDOM FOREST

JUST AVERAGING ALL THE RESULTS



BAGGING



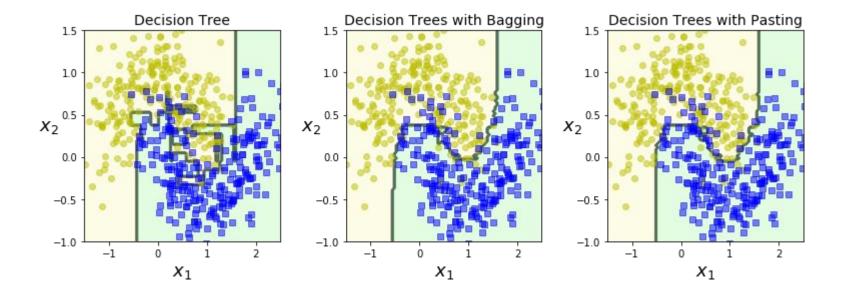
```
# instantiate a bagging object (model, size, samples, bootstrap, rnd)
bag clf = BaggingClassifier(DecisionTreeClassifier(random state=42),
                            n estimators=500,
                            max samples=100,
                             #bootstrap=False -> pasting
                             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
                                           \lim_{m \to \infty} (1 - \frac{1}{m})^m = e^{-1} = 0.3678
 0.9075
```

< >>

Random decision forests

Publisher: IEEE

1 Author(s)

Tin Kam Ho View All Authors

215 Paper Citations

Patent Citations 3099 Full **Text Views**















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.

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```
# 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

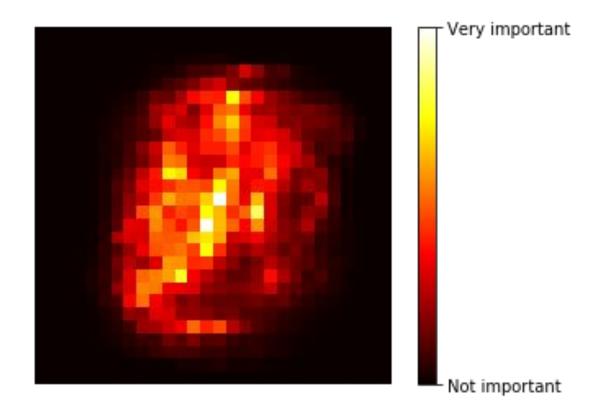
- Univariate Selection
- Recursive Feature Elimination
- Feature Importance
- Principal Component Analysis (PCA)

Feature Importance >> Explainable Artificial Intelligence (XAI)

Feature Importance

```
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



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

