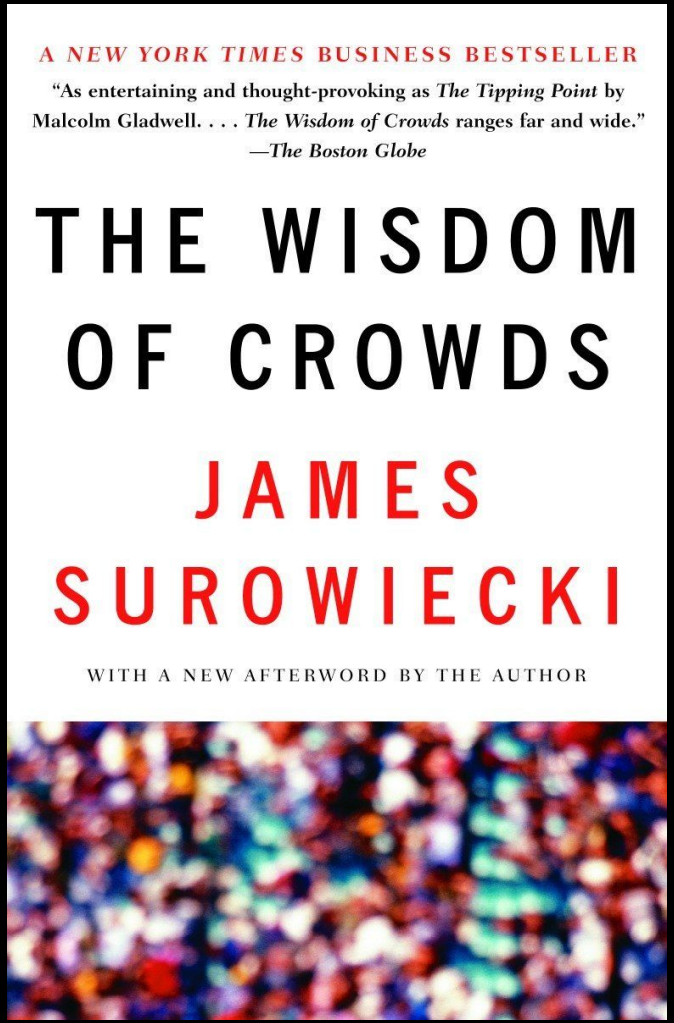

Lesson #08
Ensemble Learning I

notas

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

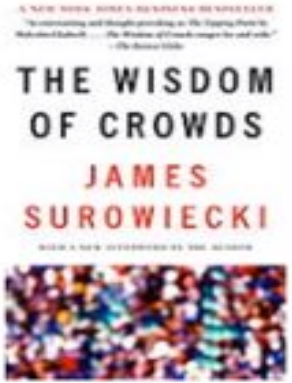
notas

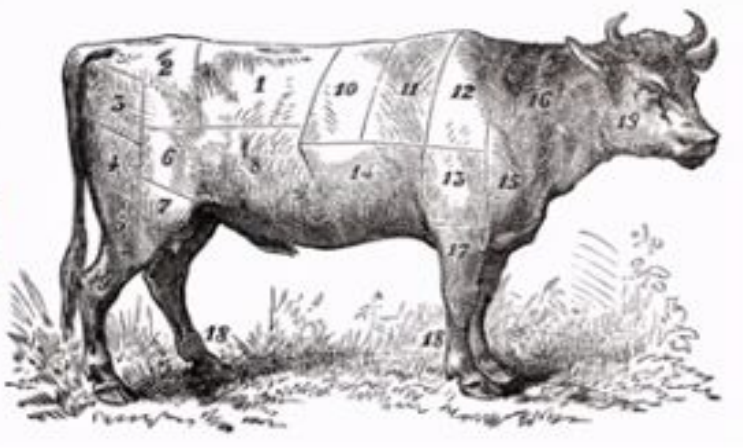
Wisdom of the crowd



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

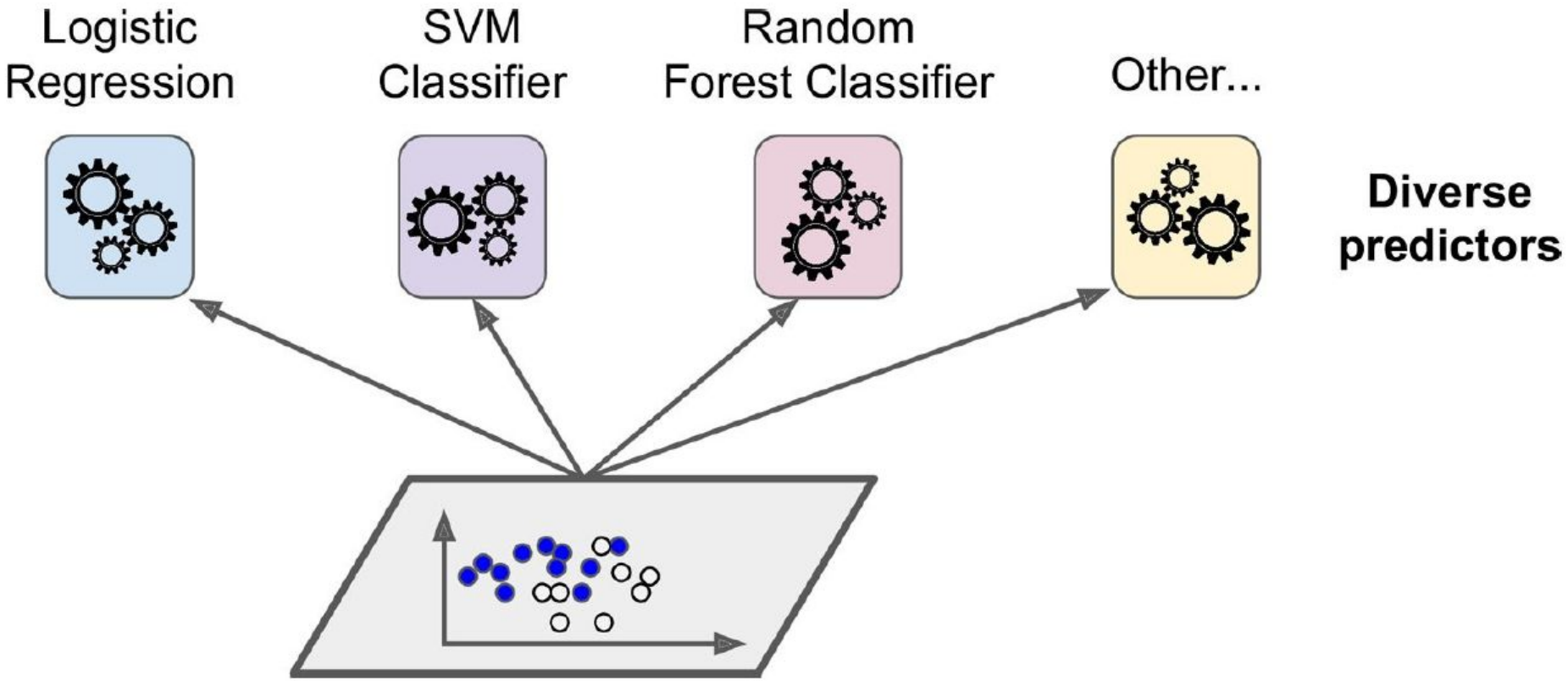
The Wisdom of Crowds

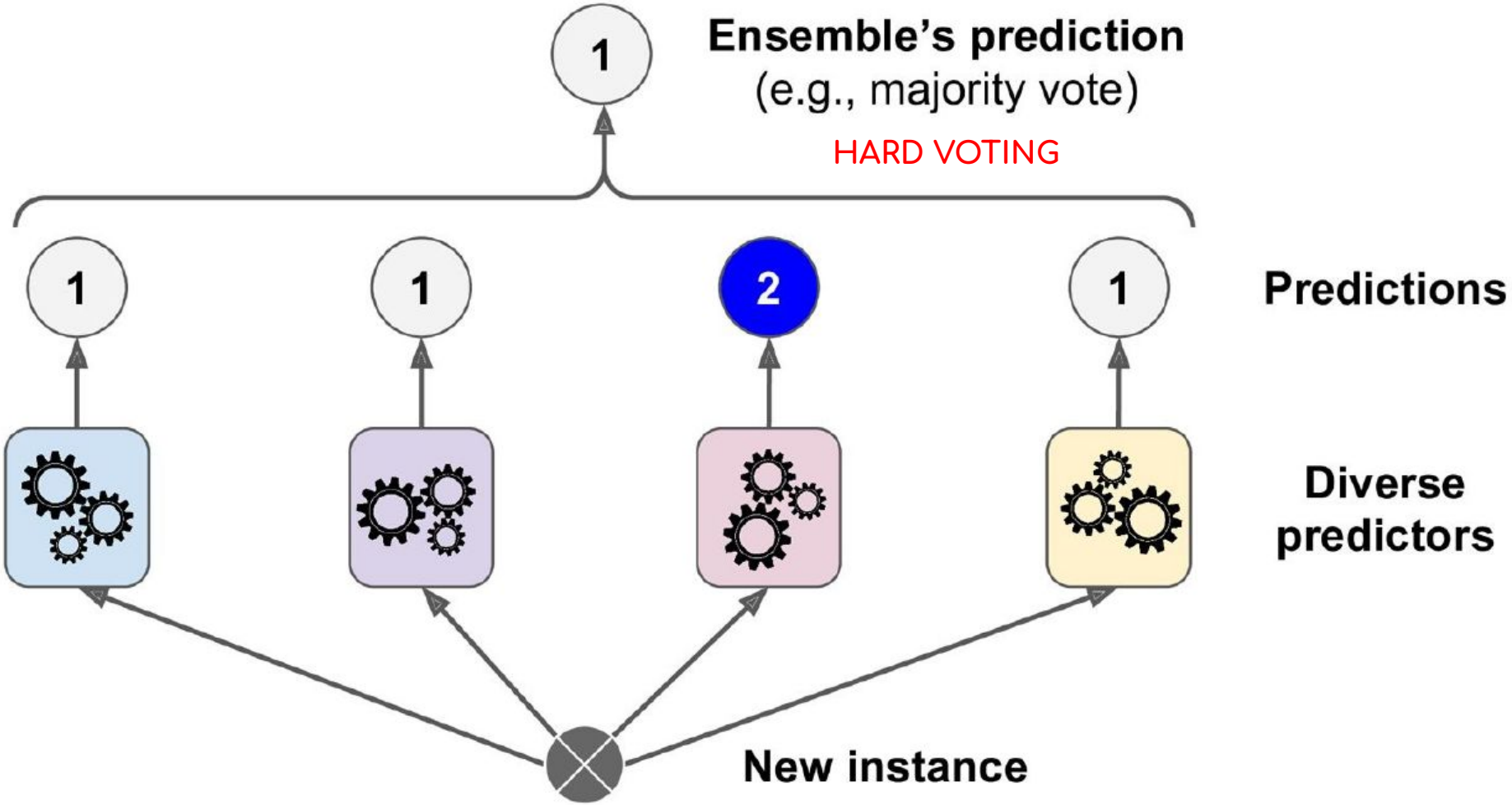




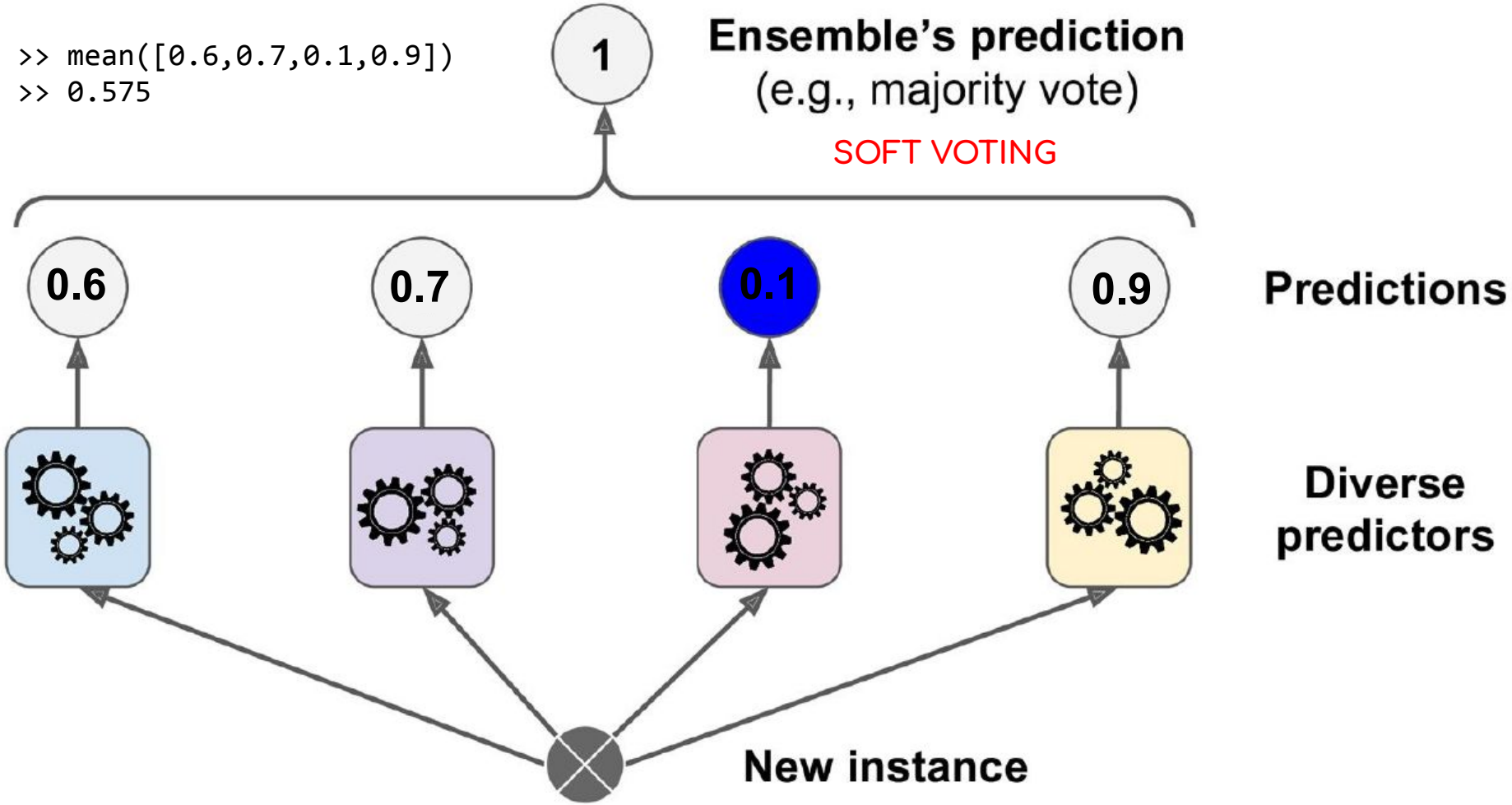
average of 800 guesses = 1,197

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
```

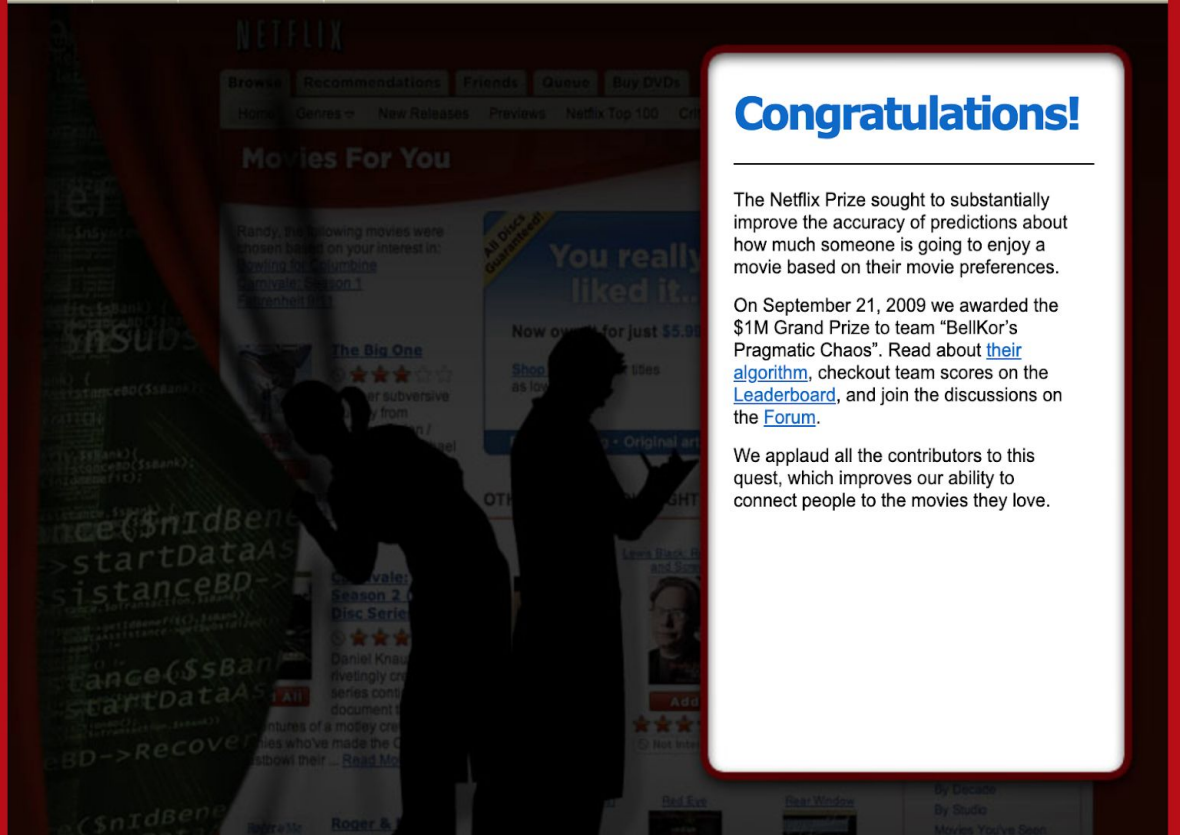


NETFLIX

Netflix Prize

COMPLETED

Home | Rules | Leaderboard | Update



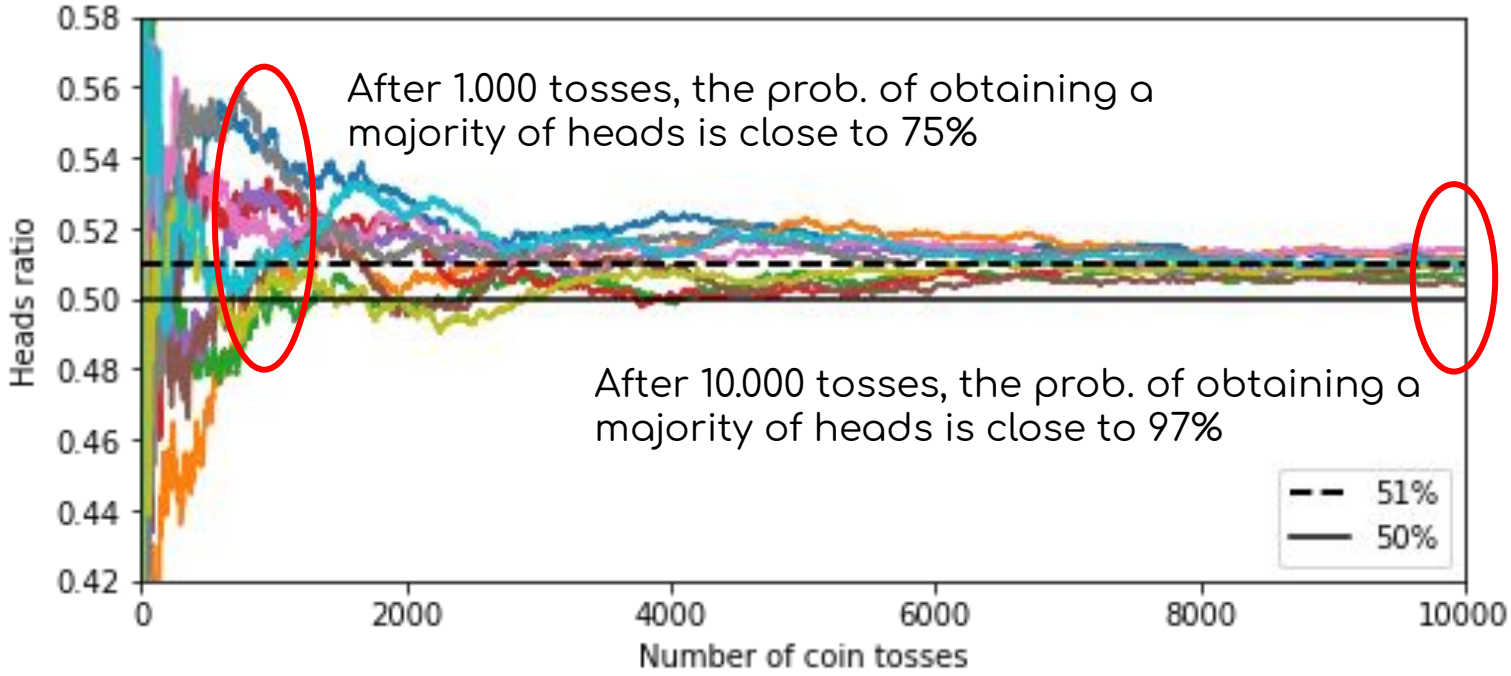
Congratulations!

The Netflix Prize sought to substantially improve the accuracy of predictions about how much someone is going to enjoy a movie based on their movie preferences.

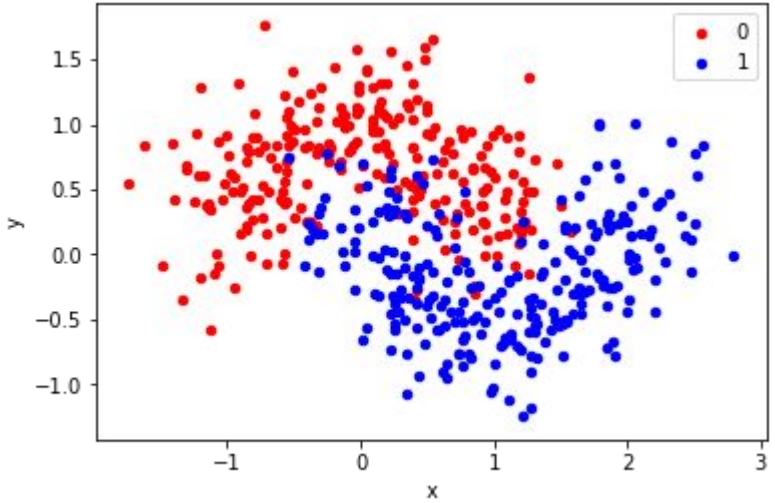
On September 21, 2009 we awarded the $1M Grand Prize to team "BellKor's Pragmatic Chaos". Read about their algorithm, checkout team scores on the Leaderboard, and join the discussions on the Forum.

We applaud all the contributors to this quest, which improves our ability to connect people to the movies they love.

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)
```



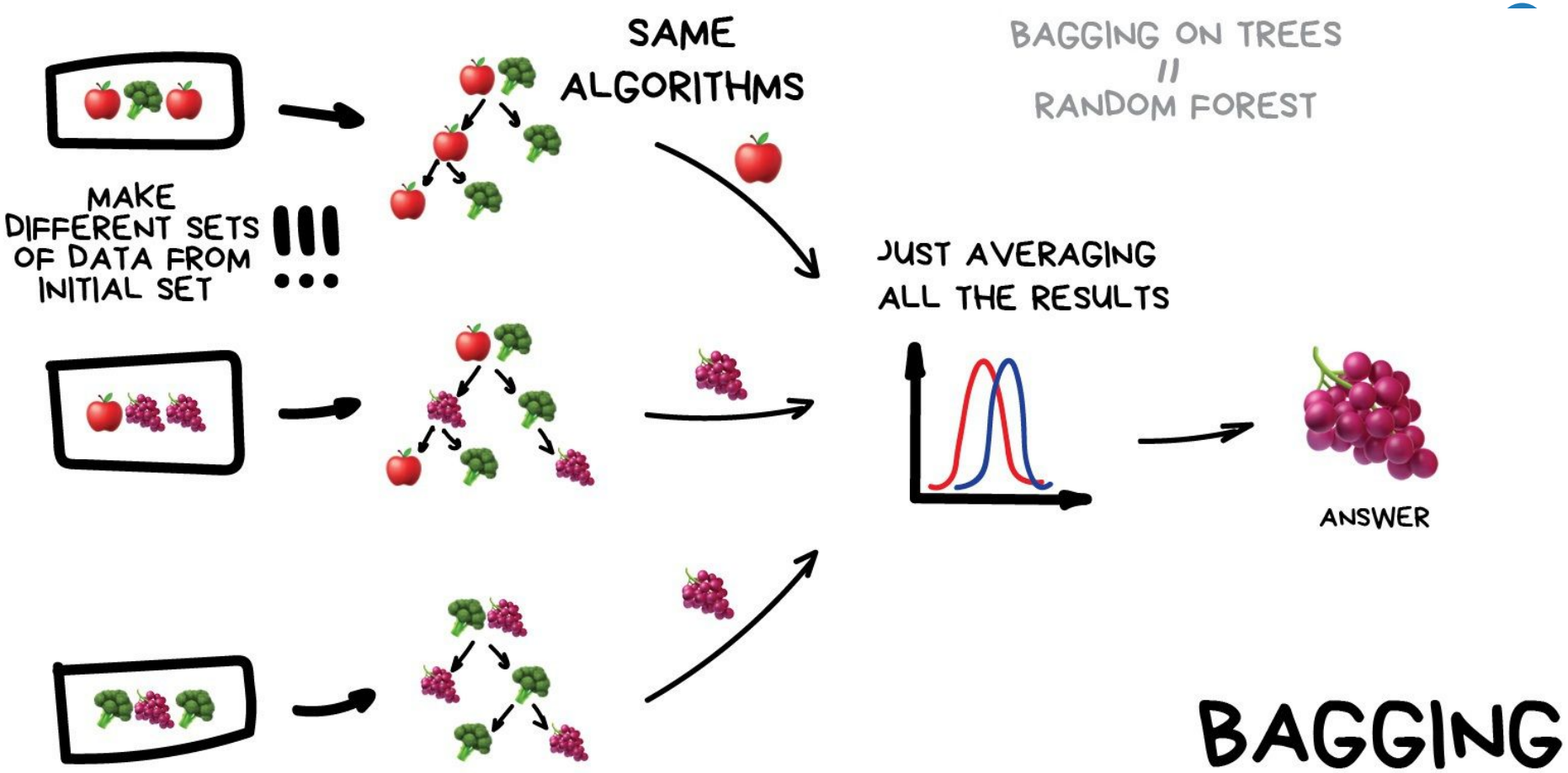

```
# soft voting
voting_clf_hard = VotingClassifier(
    estimators=[('lr', log_clf),
                ('rf', rnd_clf),
                ('svc', svm_clf)],
    voting='soft')
```

```
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

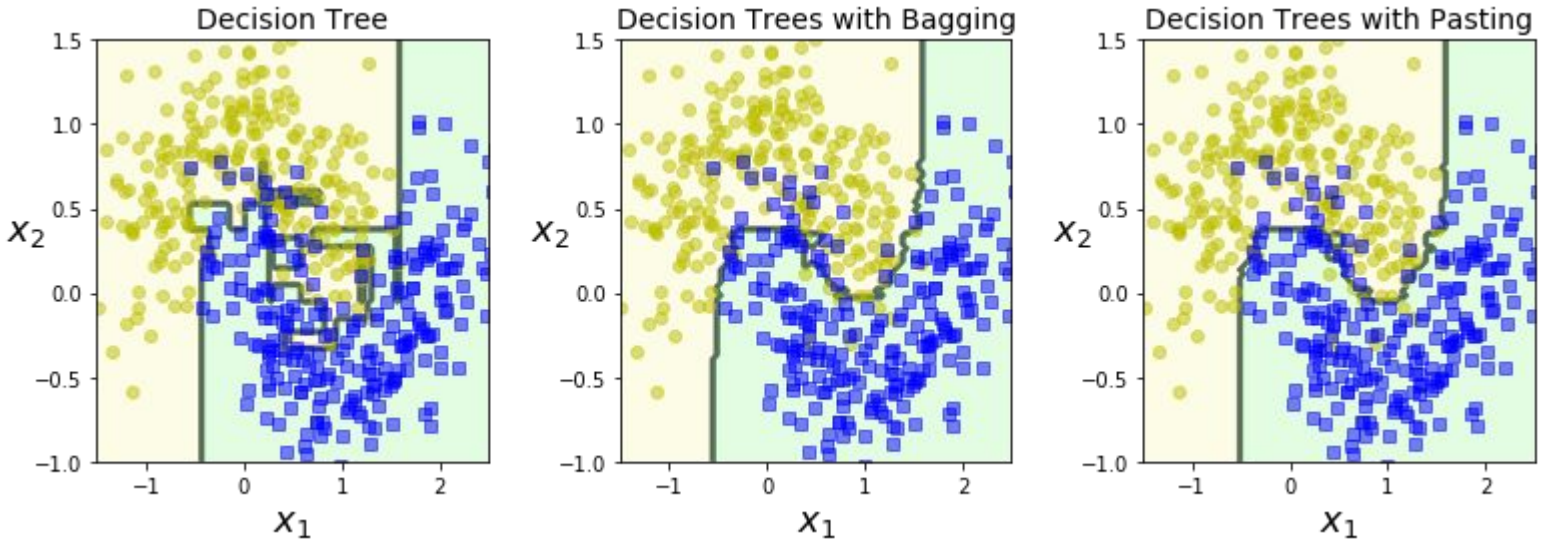
BAGGING & PASTING
BOOSTING
STACKING


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

```
0.9075
```

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

Random decision forests

Publisher: IEEE

1 Author(s) Tin Kam Ho View All Authors

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

INSPEC Accession Number: 5628989

Date Added to IEEE *Xplore*: 06 August 2002

DOI: 10.1109/ICDAR.1995.598994

Print ISBN: 0-8186-7128-9

Publisher: IEEE

```
# 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)

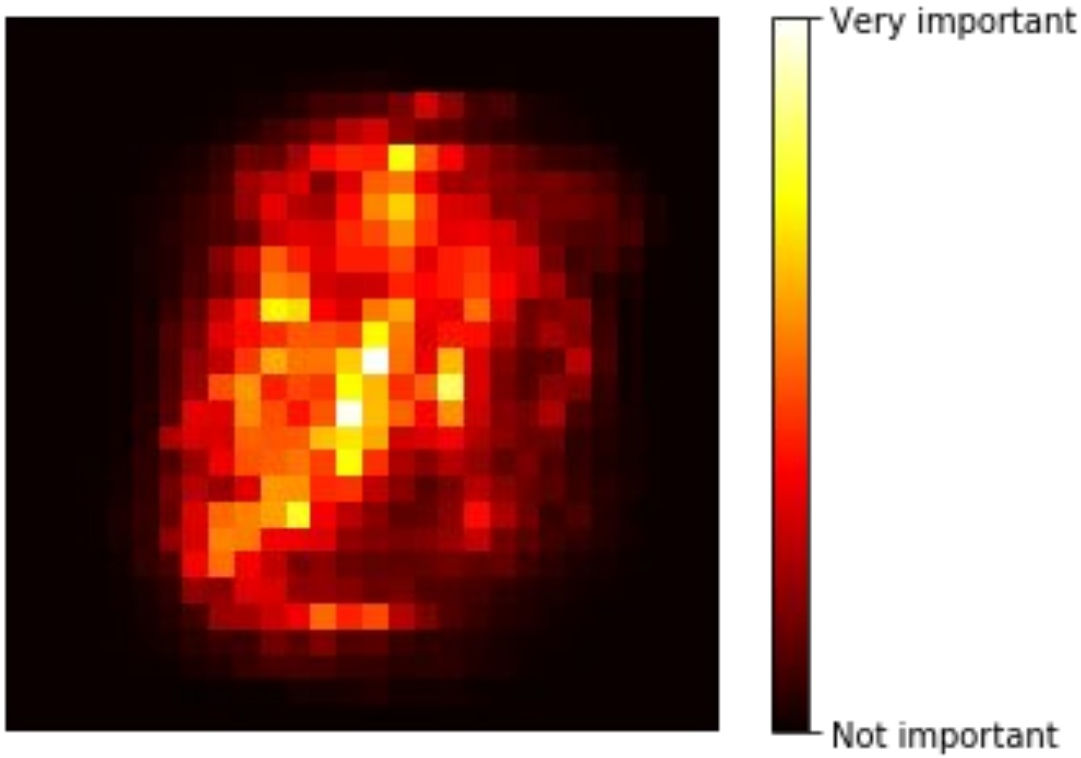
Feature Importance >> Explainable Artificial Intelligence (XAI)

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
```

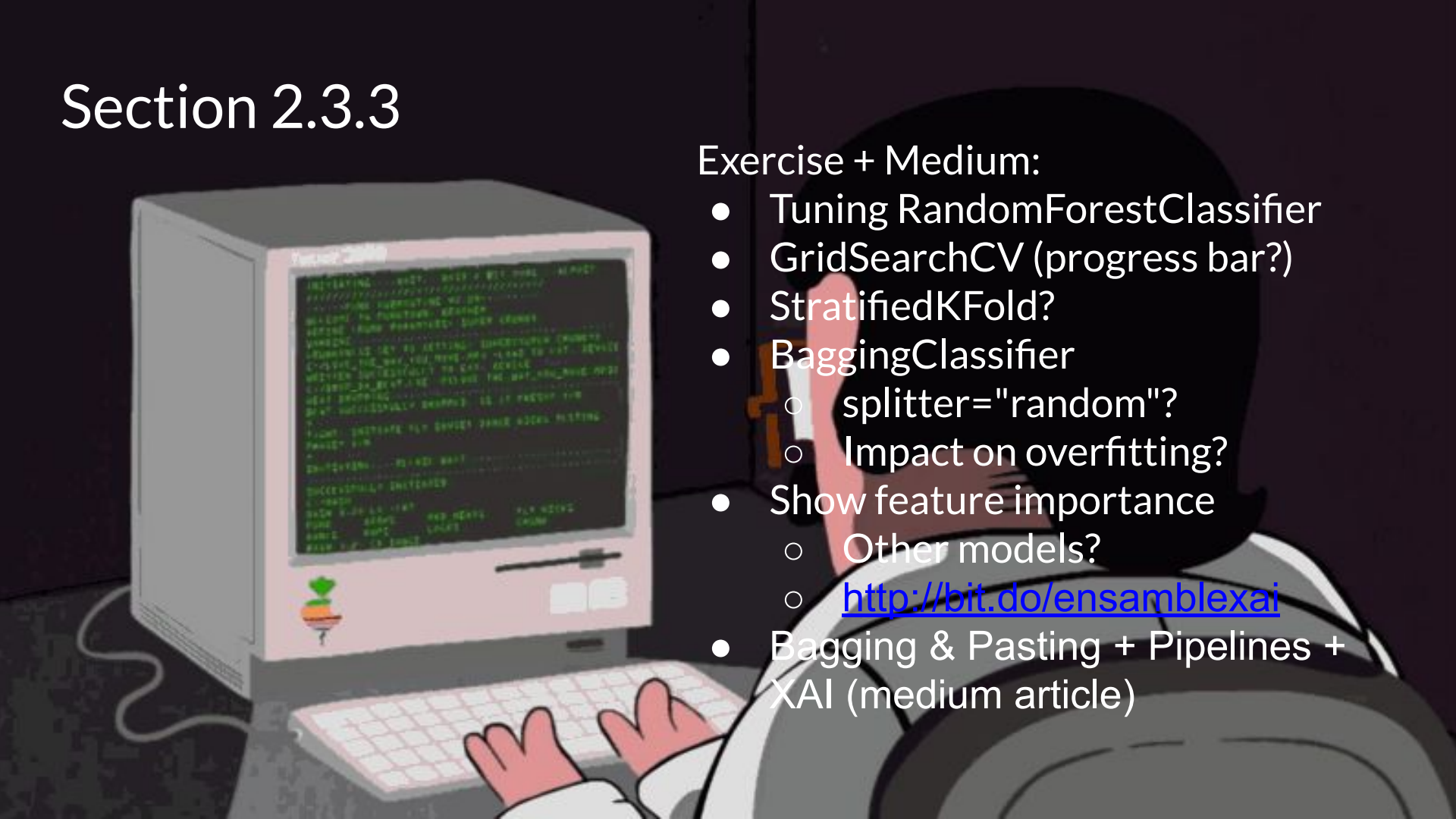
Feature Importance



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

Section 2.3.3



Exercise + Medium:

- Tuning RandomForestClassifier
- GridSearchCV (progress bar?)
- StratifiedKFold?
- BaggingClassifier
  - splitter="random"?
  - Impact on overfitting?
- Show feature importance
  - Other models?
  - http://bit.do/ensamblexai
- Bagging & Pasting + Pipelines + XAI (medium article)