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Advanced Machine Learning

Ensemble Learning

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Slide adapted from
Jing Gao’s SDM 2010 tutorial “On the Power of Ensemble: Supervised and Unsupervised Methods Reconciled”
https://project.dke.maastrichtuniversity.nl/datamining/2013-Slides/lecture-07.ppt

Outline

- **Why ensemble learning?**

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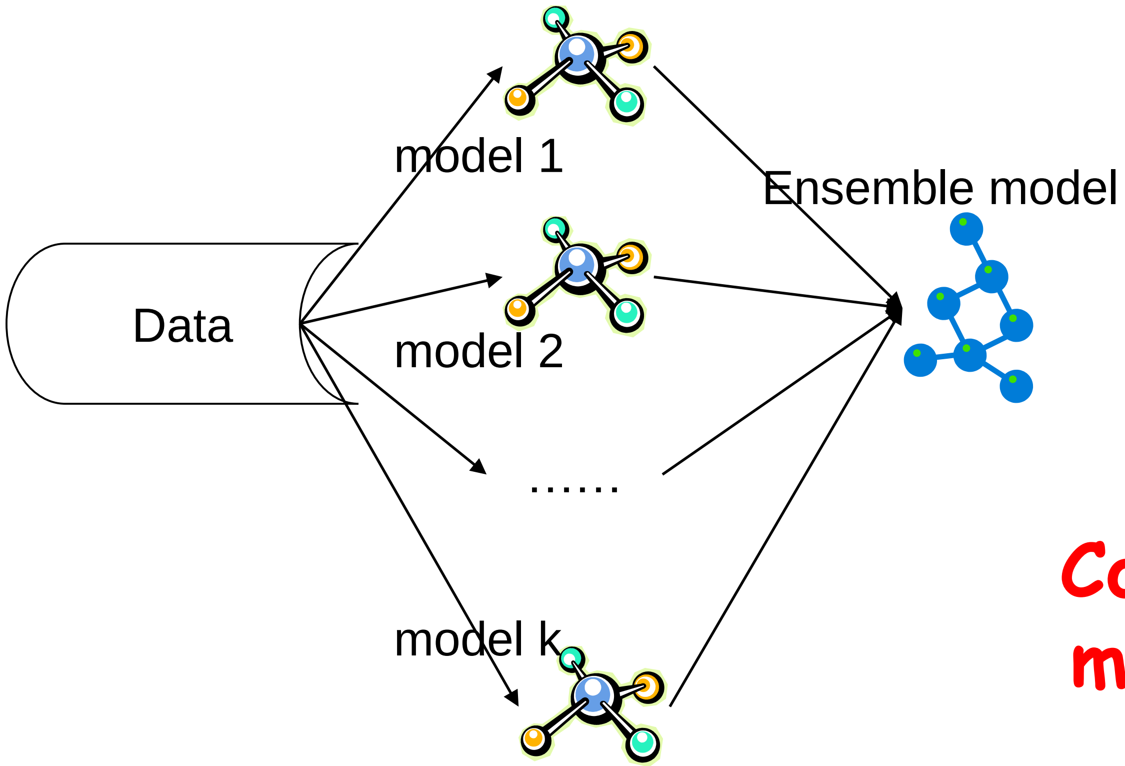
Ensemble



Combine multiple models into one!

Applications: classification, clustering, collaborative filtering, anomaly detection……

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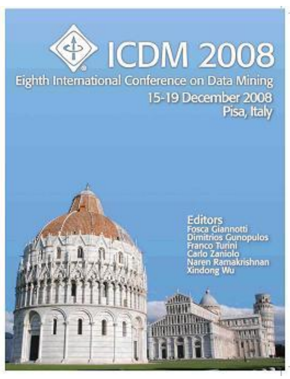
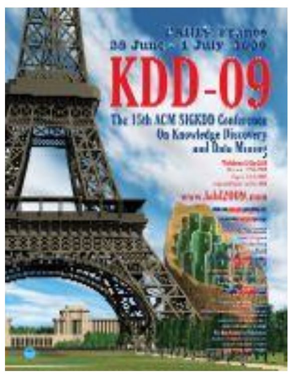
Stories of Success

- Million-dollar prize
  - Improve the baseline movie recommendation approach of Netflix by 10% in accuracy
  - The top submissions all combine several teams and algorithms as an ensemble





- Data mining competitions
  - Classification problems
  - Winning teams employ an ensemble of classifiers

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Build Ensembles

- Basic idea
  - Build different “experts”, and let them vote
- Advantages:
  - Improve predictive performance
  - Other types of classifiers can be directly included
  - Easy to implement
  - Not much parameter tuning
- Disadvantages:
  - The combined model is not so transparent (black box)
  - Not a compact representation

Why do ensembles work?

Dietterich(2002) showed that ensembles overcome three problems:

- ***The Statistical Problem*** arises when the hypothesis space is too large for the amount of available data. Hence, there are many hypotheses with the same accuracy on the data and the learning algorithm chooses only one of them! There is a risk that the accuracy of the chosen hypothesis is low on unseen data!
- ***The Computational Problem*** arises when the learning algorithm cannot guarantees finding the best hypothesis.
- ***The Representational Problem*** arises when the hypothesis space does not contain any good approximation of the target class(es).

- Intuition: combining diverse, independent opinions in human decision-making as a protective mechanism (e.g. stock portfolio)
- Uncorrelated error reduction

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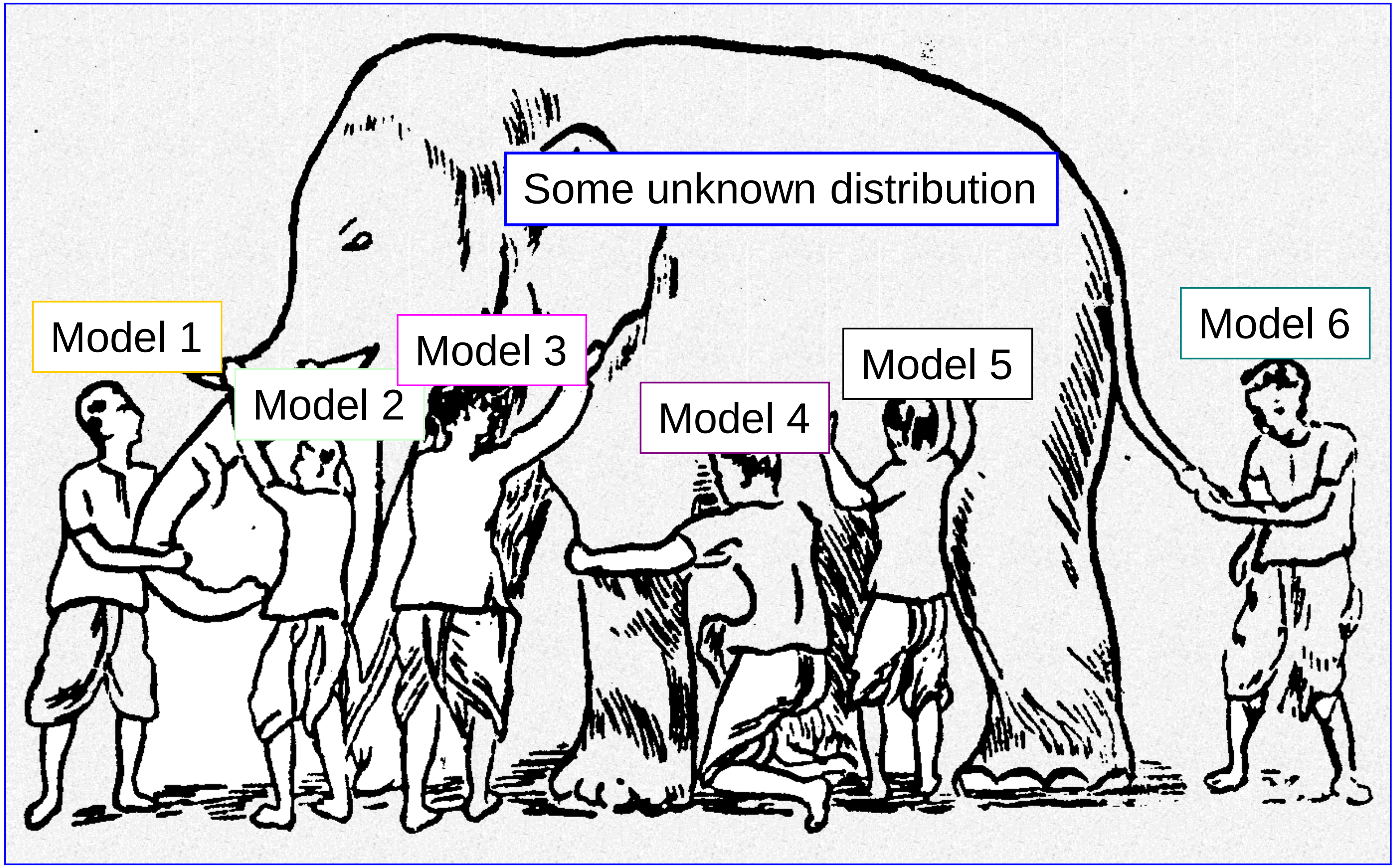
Why Ensemble Works?



Ensemble gives the global picture!

Outline

- Why ensemble learning?
- **Supervised learning**
  - **Methods for Independently Constructing Ensembles**
    - **Majority Vote, Bagging and Random Forest, Error-Correcting Output Coding**

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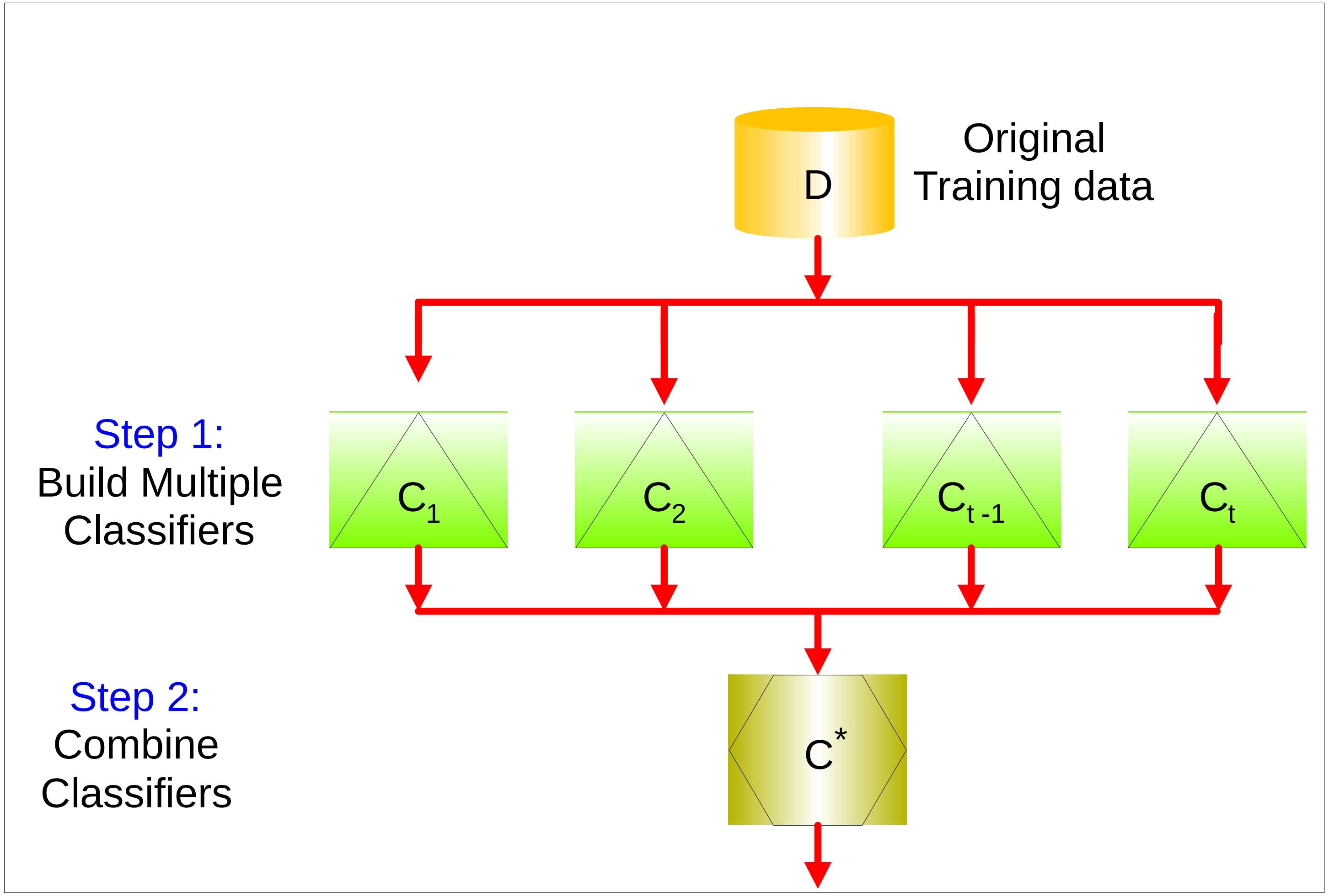
Methods for Independently Constructing Ensembles

One way to force a learning algorithm to construct multiple hypotheses is to run the algorithm several times and provide it with somewhat different data in each run. This idea is used in the following methods:

- ***Majority Voting***
- ***Bagging***
- ***Error-Correcting Output Coding.***

Majority Vote



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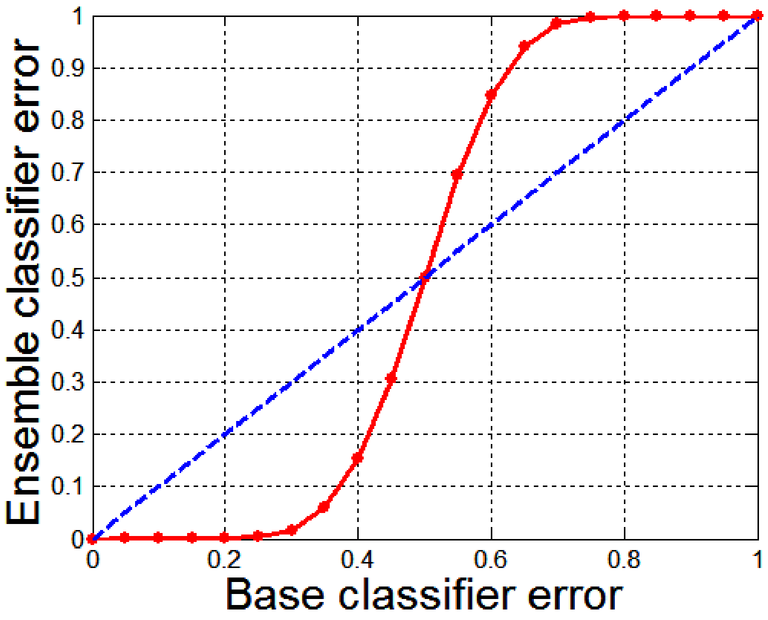
Why Majority Voting works?

- Suppose there are 25 base classifiers
  - Each classifier has error rate, ε = 0.35
  - Assume errors made by classifiers are uncorrelated
  - Probability that the ensemble classifier makes a wrong prediction:



$$P(X \geq 13) = \sum_{i=13}^{25} \binom{25}{i} \varepsilon^i (1-\varepsilon)^{25-i} = 0.06$$

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Bagging (Bootstrap Aggregation)

- Employs simplest way of combining predictions that belong to the same type.
- Combining can be realized with voting or averaging
- Each model receives equal weight
- "Idealized" version of bagging:
  - Sample several training sets of size *n* (instead of just having one training set of size *n*)
  - Build a classifier for each training set
  - Combine the classifier's predictions
- This improves performance in almost all cases if learning scheme is *unstable* (i.e. decision trees)
- Bagging can slightly degrade the performance of "stable" learning algorithms.

Learning algorithms

- Unstable learning algorithms: small changes in the training set result in large changes in predictions.
  - Neural network
  - Decision tree
  - Regression trees
- Stable learning algorithms:
  - K-nearest neighbors
  - SVM
  - Linear regression

Bagging classifiers

Classifier generation

```
Let n be the size of the training set.
For each of t iterations:
  Sample n instances with replacement from the
  training set.
  Apply the learning algorithm to the sample.
  Store the resulting classifier.
```

classification

```
For each of the t classifiers:
  Predict class of instance using classifier.
Return class that was predicted most often.
```

Bagging Example

Original Data:

x	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
y	1	1	1	-1	-1	-1	-1	1	1	1

Bootstrap samples and classifiers:

x	0.1	0.2	0.2	0.3	0.4	0.4	0.5	0.6	0.9	0.9
y	1	1	1	1	-1	-1	-1	-1	1	1

x	0.1	0.2	0.3	0.4	0.5	0.5	0.9	1	1	1
y	1	1	1	-1	-1	-1	1	1	1	1

x	0.1	0.2	0.3	0.4	0.4	0.5	0.7	0.7	0.8	0.9
y	1	1	1	-1	-1	-1	-1	-1	1	1

x	0.1	0.2	0.5	0.5	0.5	0.7	0.7	0.8	0.9	1
y	1	1	-1	-1	-1	-1	-1	1	1	1

Combine predictions by majority voting

from P. Tan et al. Introduction to Data Mining.

Random Forest

Classifier generation

Let n be the size of the training set.
For each of t iterations:
(1) Sample n instances with replacement from the training set.
(2) Learn a decision tree s.t. the variable for any new node is the best variable among m randomly selected variables.
(3) Store the resulting decision tree.

Classification

For each of the t decision trees:
Predict class of instance.
Return class that was predicted most often.

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Bagging and Random Forest

- Bagging usually improves decision trees.
- Random forest usually outperforms bagging due to the fact that errors of the decision trees in the forest are less correlated.

Take-aways

- Ensembles learning is very useful in obtaining improved models.
- We discussed various ensemble learning methods
  - Bagging
  - Random Forests

Tutorial on Ensemble of Classifiers

- *Survey of Boosting from an Optimization Perspective*. Manfred K. Warmuth and S.V.N. Vishwanathan. ICML'09, Montreal, Canada, June 2009.
- *Theory and Applications of Boosting*. Robert Schapire. NIPS'07, Vancouver, Canada, December 2007.
- *From Trees to Forests and Rule Sets--A Unified Overview of Ensemble Methods*. Giovanni Seni and John Elder. KDD'07, San Jose, CA, August 2007.

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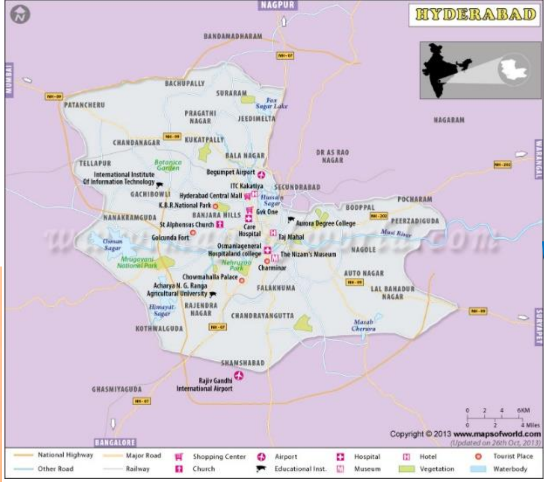

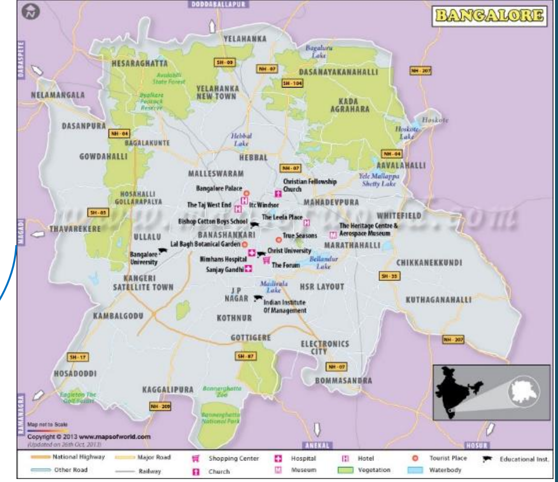

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