Motivation

Different Predictors

- Neural Networks
- k nearest neighbors
- SVM

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BUT: All have their limitations. Overfitting (1-nearest neighbor), BlackBox (Neural Networks), How the hell does this work (SVM)...

So today: We improve all of them!

Today

Ensemble Learning

- (Iris') Motivation: Wisdom of Crowds
- Basic Terms and Notations
- Overview of methods
- Bagging
- Boosting
- AdaBoost

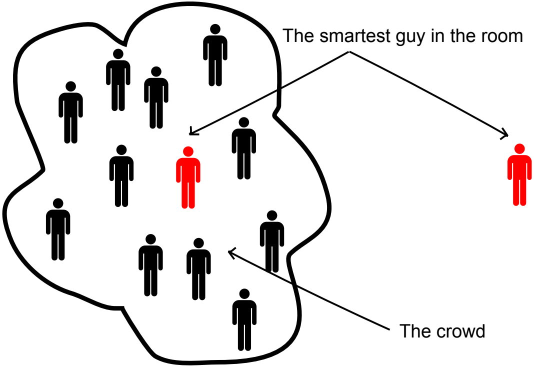
General

Ensemble Learning consists of

1. Train many (weak) classifiers (or regression models)
2. Combine them to construct a classifier (regression model) more powerful than any of the individual ones

The Wisdom of Crowds

The Wisdom of Crowds [1]



The **collective knowledge** of a *diverse* and *independent* body of people typically **exceeds** the knowledge of **any single individual** and can be harnessed by voting.

[1] Slides motivated by Josephine Sullivans'
`http://www.csc.kth.se/utbildning/kth/kurser/DD2431/ml11/schedule/07-ensamble.pdf`

The Wisdom of Crowds - Really?

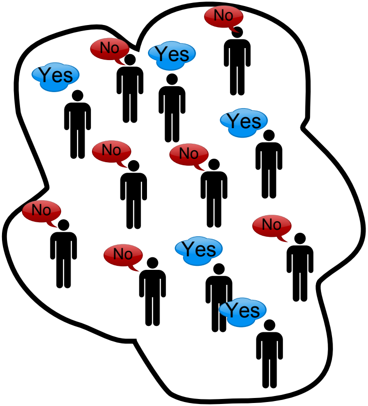
Crowd wiser than **any individual**

- When?
- For which questions?

See **The Wisdom of Crowds** by *James Surowiecki* published in 2004 to see this idea applied to business.

Consider this scenario

Ask each person in the crowd:
Will Mr. X win the general election in country Y?

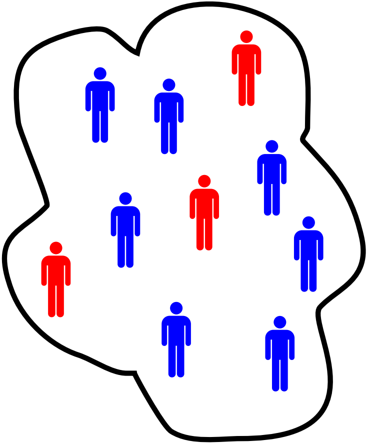


The Crowds prediction:

MAJORITY answer.

$\longrightarrow$ This crowd predicts **No**. (Mr. X will not win the election.)

Has crowd made a good prediction?



If composition of crowd:
30% EXPERTS.
70% NON-EXPERTS.

and their level of expertise:
P(correct predict|expert) $= p_e$
P(correct predict|non-expert) $= p_{ne}$

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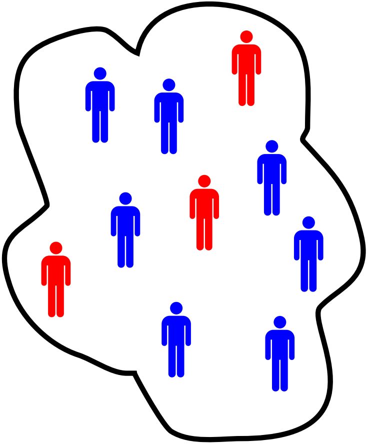
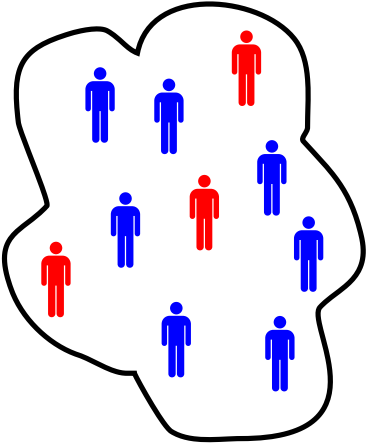


Let $p_e = .8$ and $p_{ne} = .5$

For a random person from the crowd
P(correct predict|individual) $=$
$.3p_e + .7p_{ne} = .59$

Has crowd made a good prediction?



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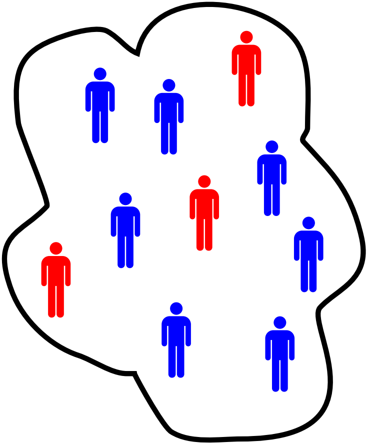
If crowd contains 50 independent people:

P(correct predict|crowd) $=$

$\sum_{k=26}^{50} \binom{50}{k} p_i^k (1 - p_i)^{50-k}$

$= 0.8745$

Has crowd made a good prediction?



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$= 0.8745$

This crowd has made a prediction with probability $.875$ of being correct which is $> p_e$.

It is wiser than each of the experts!

But...

Why didnt I just asked a bunch of experts??

- **Large enough crowd $\rightarrow$ high probability a sufficient number of experts will be in crowd (for any question).**
- Random selection $\rightarrow$ don't make a biased choice in experts.
- For some questions it may be hard to identify a diverse set of experts

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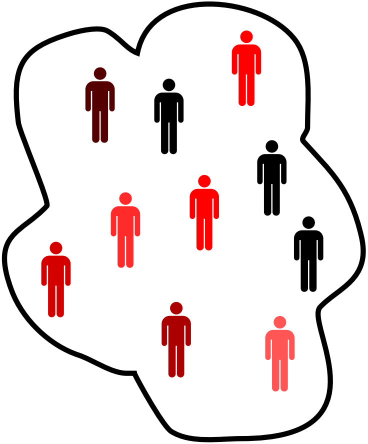
For a random crowd

Given a **random question** expect each **person** to have a **different level** of **expertise**.



Will it rain tomorrow?

← redness proportional to expertise

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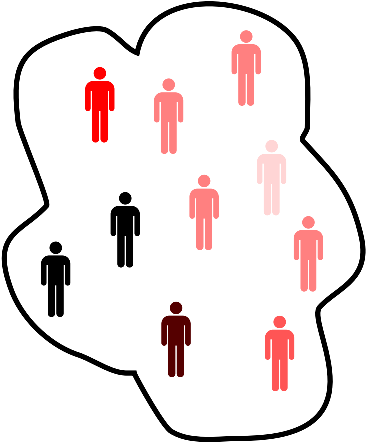

Will the world go down in 2012?

← redness proportional to expertise

What makes a crowd wise?

According to *James Surowiecki* there are four elements required to form a wise crowd

- **Diversity of opinion. People in crowd should have a range of experiences, education and opinions. (Encourages independent predictions)**
- **Independence.** Prediction by person in crowd is not influenced by other people in the crowd.
- **Decentralization.** People have specializations and local knowledge.
- **Aggregation.** There is a mechanism for aggregating all predictions into one single prediction.

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The crowd must be careful

In the analysis of the crowd it is implicitly assumed:

- each person is not concerned with the opinions of others,
- no-one is copying anyone else in the crowd.

In the analysis of the crowd we implicitly assumed:

- The non-experts will predict a **completely random wrong answer** - these will cancel each other out (to some degree).
- However, there may be a systematic and consistent bias in the non-experts predictions.

Back to machine learning

Back to machine learning

We will exploit **Wisdom of crowd** ideas for specific tasks by

- combining (classifier) predictions and
- aim to combine independent and diverse predictors (classifiers).

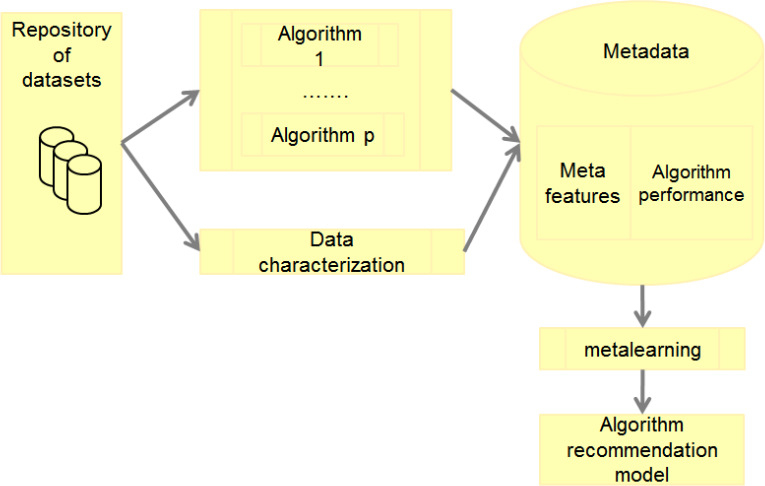
We can also use labeled training data

- to identify the expert classifiers in the pool;
- to identify complementary classifiers;
- to indicate how to best combine them.

Basic Terms

- Remember? Bias = model error + algorithmic error
  - Model error: the error we get by selecting a model
  - Algorithmic error: by selecting the algorithm itself and the parameters of the algorithm
- Base-Learning: Fixed Bias / User parameterized
- Meta-Learning: Dynamic bias selection using meta knowledge
- Meta-Knowledge: Knowledge achieved during the learning process

Ensemble Learning for Algorithm Recommendation



Combining base-learners : Categories

Philosophy	Technique
Bagging , Boosting	Variation in data
Stacking	Variation among learners (multi-expert)
Cascading, Delegating	Variation among learners (multi-stage)
Arbitrating	Variation among learners (refereed)
Meta decision trees	Variation in data and among learners

Bagging and Boosting

Bagging and Boosting

- Best-known techniques
- Based on selection of multiple data sub sets
- Meta model is created by combining the base models
- Advantages:
  - Reduces overfitting
  - Most effective when the base learner is highly sensitive to data
  - Typically increases accuracy
- Disadvantages:
  - Interpretability of interpretable base learners is lost

Can a set of weak learners create a single strong learner ?

- **Bagging :**
  - **Select N independent samples of the Training Data**
  - **Learn one model on each of the samples $\rightarrow h_1, ..., h_N$**

  - **Classification : Use the class most predicted by all classifiers**
  - **Regression : Use the mean of all prediction**

- **Boosting:**
  - Tries to learn a weighting for the models
  - Later weak learners focus more on the examples that previous weak learners misclassified
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Boosting

One boosting method after Schapire

- **Training** :
  - Create c_1: weak learner on a sample t_1 of the data
  - Create t_2: sample which is 50% miss classified by c_1
  - Create c_2: weak learner on the sample t_2
  - Create t_3: subset of the data where c_1 predicts differently than c_2
  - Create c_3: weak learner on the sample t_3
- **Classification** :
  - Classify with c_1 and c_2
  - If unequal, use c_3 as final classification

Stacking and Cascade Generalization

Stacking

- In Bagging and Boosting: we used always the same base learner
- **Stacking uses differences among learners**
- Two levels of learning
  1. Base learners are trained, each on the whole data set
  2. Meta learners are created on meta data (e.g. predicted class) obtained in level 1
- Two levels of classifying
  1. Base learner are used on data point
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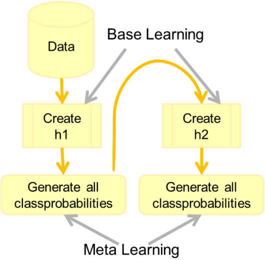
Cascade Generalization

Stacking: Base learners are used parallel

- Here: Base learners are used in a sequence with "partial" meta learners
- Knowledge from previous classifiers can be used in later ones
- After each base learner the data set is adjusted using the new information



For classification :

- Only the last model is used
- Which incorporates the knowledge of previous models (all base methods are used)

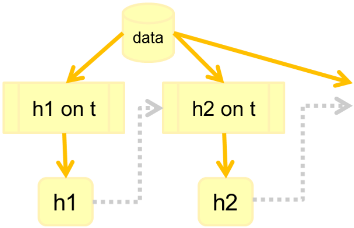
Cascading and Delegating

Cascading and Delegating

- Untill now: all base classifiers are used for classification
- Here: Multistage classifiers, not all are required for classification
- Main advantage: faster classification

Cascading

- Multilearner version of boosting
- Uses learned confidence of previous models
- Train base learner h_i using knowledge from previous base learner...
- ...on data, which was most probably misclassified by previous learners
- **Classify:** go through all base models, stop and use as classification if the model has a confidence greater than epsilon



Delegating

- Cascading: all instances are used in each step
- Delegating: only instances below confidence threshold are processed in the next step
- Idea:
  - Use everything and test for which data points you are good enough
  - Pass the remaining work to someone else.
  - If there is no someone else, ... guess

Advantages:

- Still understandable (no model combination)
- Improved efficiency, due to the decreasing number of examples.

Ada Boost – Details

Ada Boost

Some properties

- Freund & Schapire (1995)

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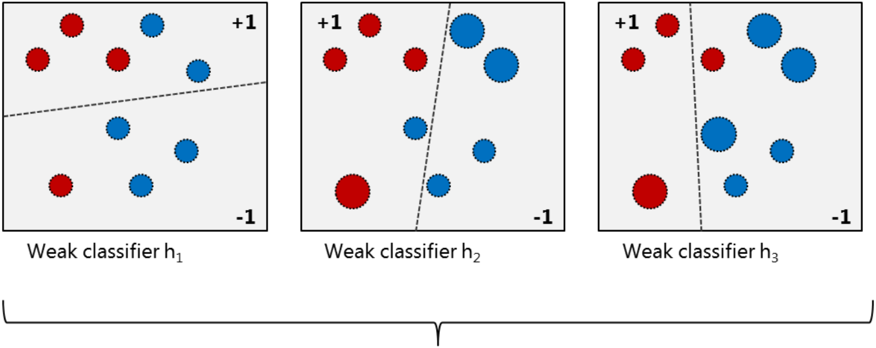
- AB has good generalization properties (Avoids overfitting as long as the training data is not too noisy)
- AB is a feature selector

Ada Boost

Example



Strong classifier = $(\alpha_1\ h_1) + (\alpha_t\ h_t) + \ldots + (\alpha_T\ h_T)$

Ada Boost

Terminology

- Strong classifier : $\sum_{t=1}^{T} (\alpha_t h_t(x))$
- Where $h_t(x)$ is a weak classifier weighted by α_t
- Classification result: $H(x) = sgn\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right)$

Comment: $h_t(x)$'s can be thought of as simple features

Ada Boost - Pseudo code - Overview

Algorithm Ada Boost

Initialize weight of x_i with $D_0(i) = \frac{1}{m}$

for $t = 1, ..., T$: **do**

1. $h_t =$ "Weak-Learner"

   Calculate error $\epsilon_t = \sum_{i=1}^{m} D_t(i)\delta_{(y_i,h_t(x_i))}$

3. Calculate weight of learner $\alpha_t = \log \frac{1-\epsilon_t}{\epsilon_t}$
4. Update the weights $D_t(i)$ of all x_i

end for

Resulting classificator

$H(x) = sgn\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right)$

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Ada Boost - Weak Learners

Algorithm Weak learner

Train a set H of many many weak-learners h on the data

Return the one h with the lowest weighted classification error

$h = \arg\min_{h_j \in H} \epsilon = \arg\min_{h_j \in H} \left(\sum_{i=1}^{m} D(i)\delta_{(y_i, h_t(x_i))} \right)$

Make sure : $\epsilon < 0.5$

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Resulting classificator

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Update of the weights of the training samples

Update weights an normalize them

$$D_{t+1}(i) = \frac{D_t(i)}{Z_t} \exp\left(-\alpha_t y_i h_t(x_i)\right)$$

$$Z_t = \sum_{i=0}^{m} D_t(i) \exp\left(-\alpha_t y_i h_t(x_i)\right)$$

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Comment

- Weight of correct classified examples is decreased
- Weight of incorrect classified examples is increased
- $$\exp(-\alpha y h(x_i)) = \begin{cases} < 1 & y = h(x_i) \\ > 1 & y \neq h(x_i) \end{cases}$$

Weighting the weak-learners "Upper-Bound Theorem"

- Primary goal is to minimize

$$\epsilon_{tr}(H) = \frac{1}{m} \left|\{i : H(x_i \neq y_i\}\right|$$

- Global error is bounded by

$$\epsilon_{tr} \leq_{t=1}^{T} Z_t$$

$$Z_t = \sum_{i=0}^{m} D_t(i) \exp\left(-\alpha_t y_i h_t(x_i)\right)$$

Weighting the weak-learners

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- Minimizing $Z_t = \sum_{i=0}^{m} D_t(i) \exp\left(-\alpha_t y_i h_t(x_i)\right)$ results in a minimization of the global error

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- Upper-Bound can be minimized by ...
  1. Choosing the optimal hypothesis h_t ...
  2. ... with an optimal weight α_t

Weighting the weak-learners

That's why

- Minimizing $Z_t = \sum_{i=0}^{m} D_t(i) \exp\left(-\alpha_t y_i h_t(x_i)\right)$ results in a minimization of the global error
- Upper-Bound can be minimized by ...
  1. Choosing the optimal hypothesis h_t ...
  2. ... with an optimal weight α_t
- Minimizing Z_t results in $\alpha_t = \log \frac{1-\epsilon_t}{\epsilon_t}$

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- Unclear which weak-learning algorithm fits best for a given problem

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Ensemble Learning

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  - **... and more**