

CSE 473

# Final Lecture: A Smörgåsbord of Course Topics and Applications



# Plan for Today

- Wrap up of Ensemble Techniques  
Boosting (AdaBoost)
- Course Review and Applications of AI
- Final Exam sneak preview
- Sayonara and Evals

# Ensemble Classification

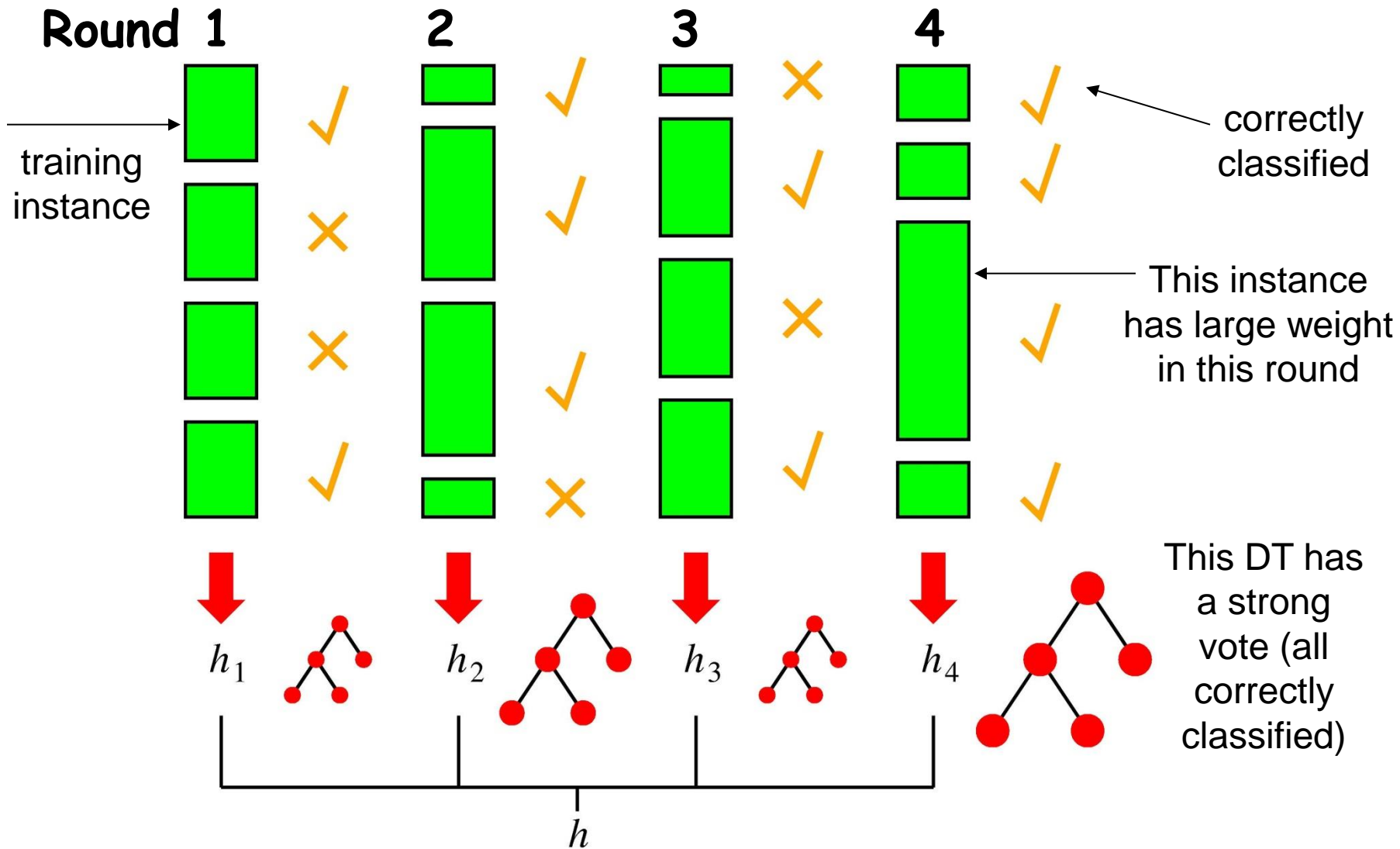
- Last time: Bagging  
Majority vote of  $n$  different hypotheses (classifiers)
- Some classifiers have less errors than others  $\Rightarrow$   
all votes are not equal!
- Idea: Let's take a weighted majority

How do we compute the weights?

# Ensemble Technique 2: Boosting

- Operates on a weighted training set  
Each training example (instance) has a "weight"  
Best classifier is one that has smallest total *weighted* classification error
- Idea: when an input is misclassified, increase the input's weight so that the *next classifier* is more likely to classify it correctly
- Output is weighted sum of all classifiers  
Positive value -> class 1, Negative value -> class 2
- Why "boosting"?  
Can "boost" performance of a "weak learner"

# Example: Boosting with Decision Trees (DTs)



Output of  $h_{\text{final}}$  is weighted majority of outputs of  $h_1, \dots, h_4$

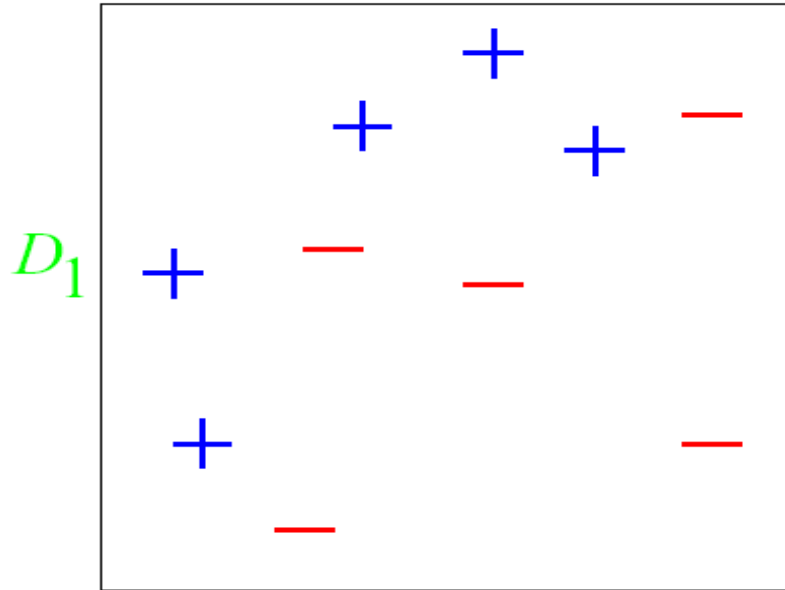
# Adaptive Boosting (AdaBoost) Algorithm

- $w_j \leftarrow 1/N \quad \forall_j$
- For  $m=1$  to  $M$  do
  - $h_m \leftarrow \text{learn}(\text{dataset}, w)$       **Select classifier  $h_m$  with least weighted classification error**
  - $\text{err} \leftarrow 0$
  - For each  $(x_j, y_j)$  in dataset do
    - If  $h_m(x_j) \neq y_j$  then  $\text{err} \leftarrow \text{err} + w_j$       **Compute total error**
  - For each  $(x_j, y_j)$  in dataset do
    - If  $h_m(x_j) = y_j$  then  $w_j \leftarrow w_j \text{err} / (1-\text{err})$       **Adjust all instance weights wrt error**
  - $w \leftarrow \text{normalize}(w)$
  - $z_m \leftarrow \log [(1-\text{err}) / \text{err}]$       **Adjust weight for hypothesis  $m$**
- Return *weighted-majority*( $h, z$ )

$w$ : vector of  $N$  instance weights

$z$ : vector of  $M$  hypoth. weights

# AdaBoost Example



Original training set  $D_1$  : Equal weights for all training inputs

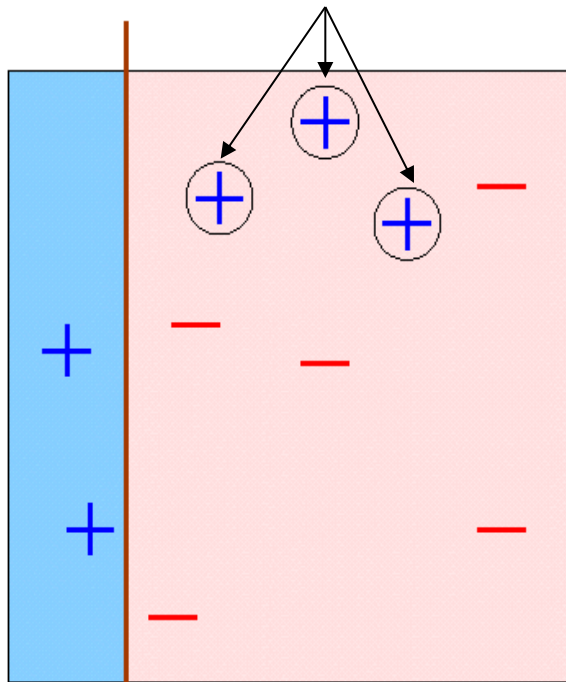
Goal: In round  $t$ , learn classifier  $h_t$  that minimizes error with respect to weighted training set

$h_t$  maps input to +1 or -1:  $h_t : X \rightarrow \{-1, +1\}$

# AdaBoost Example

ROUND 1

Misclassified

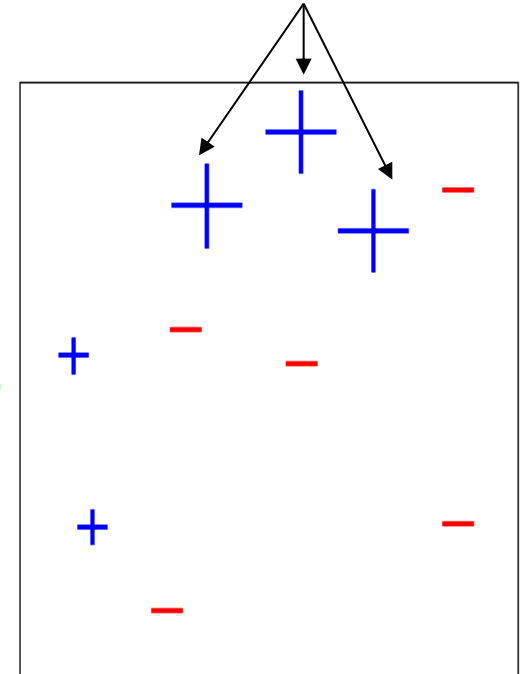


$h_1$

$$z_1 = 0.42$$



Increase weights

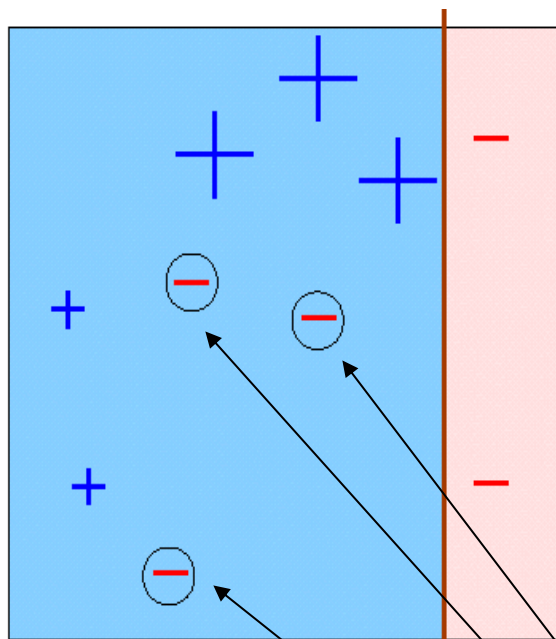


$D_2$



# AdaBoost Example

ROUND 2

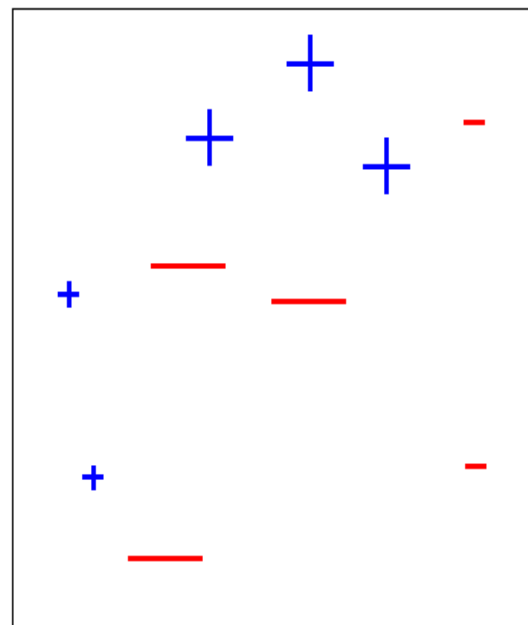


$z_2 = 0.65$

$h_2$



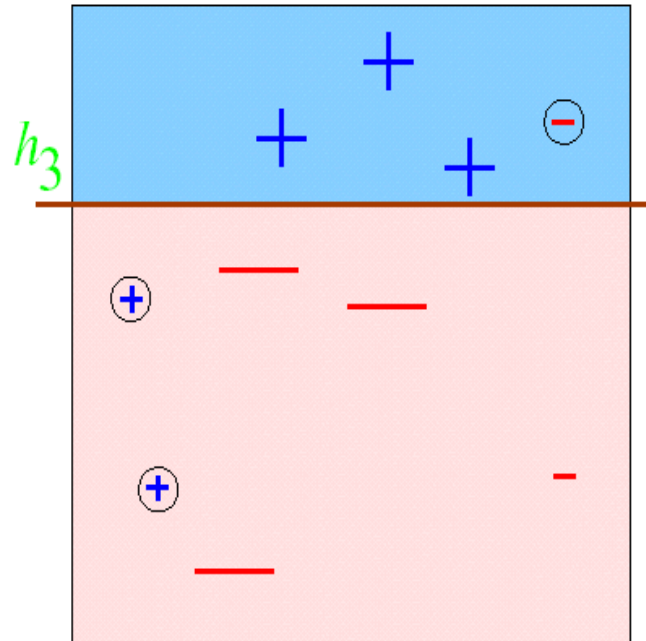
$D_3$



Now these are  
misclassified

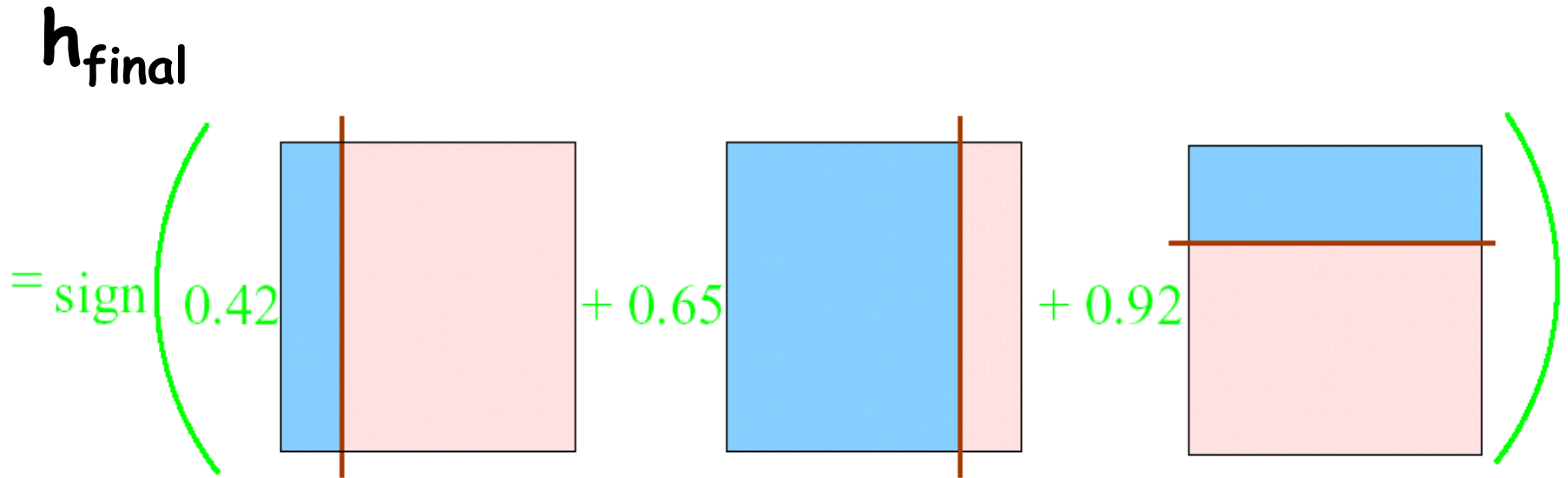
# AdaBoost Example

## ROUND 3



$$z_3 = 0.92$$

# AdaBoost Example



$\text{sign}(x) = +1$  if  $x > 0$  and  $-1$  otherwise

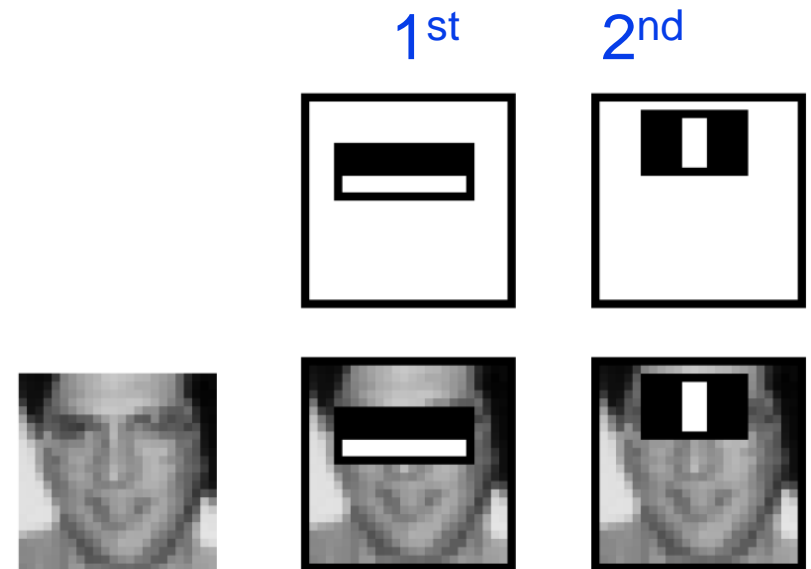
# Face Detection using AdaBoost



Training images  
(non-face images not shown)

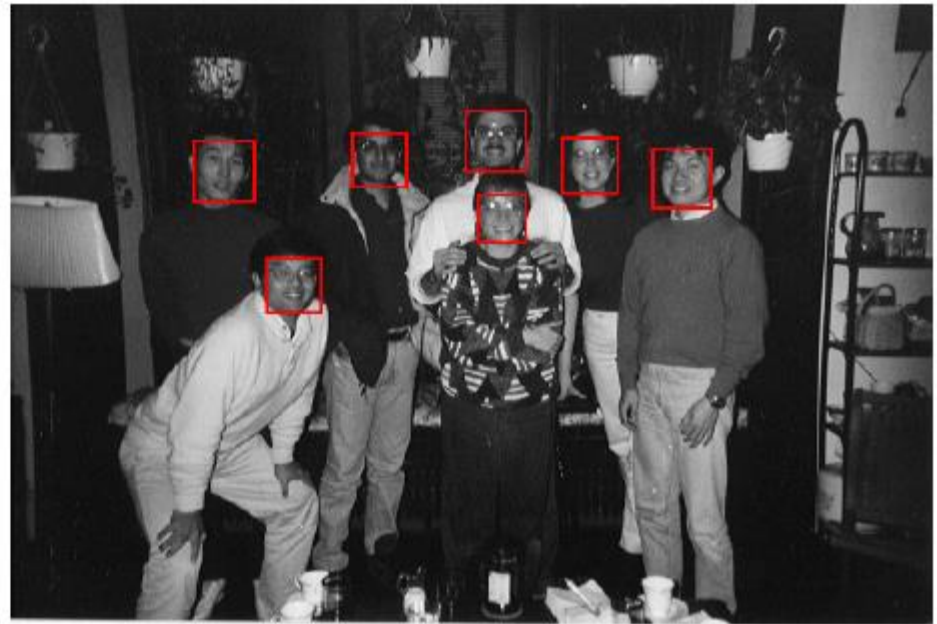
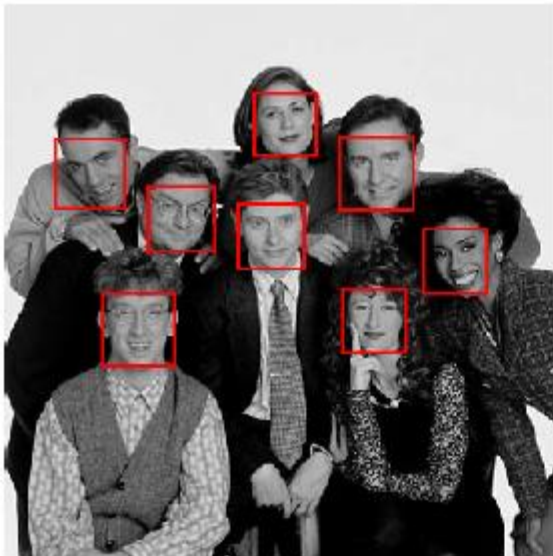
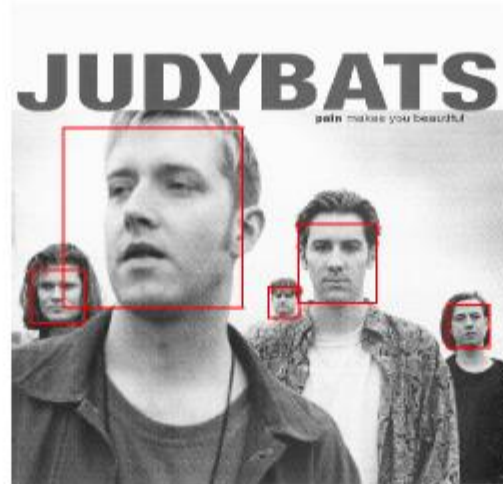
(Viola & Jones, 2001)

Classifiers = local feature detectors



AdaBoost computes weighted majority of feature detectors

# Face Detection using AdaBoost

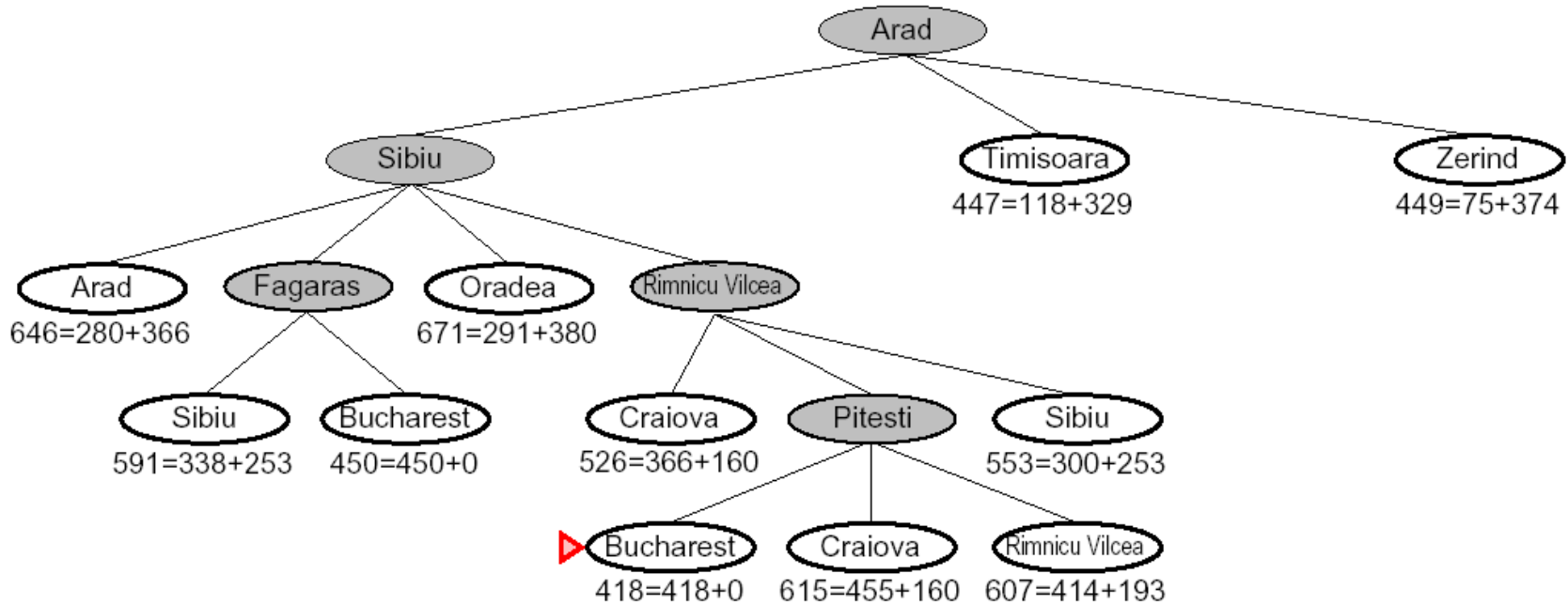


(Viola & Jones, 2001)

Let's look at some more  
applications of AI

**Course Review and Applications  
of AI Concepts we studied**

# Recall: Heuristic Search

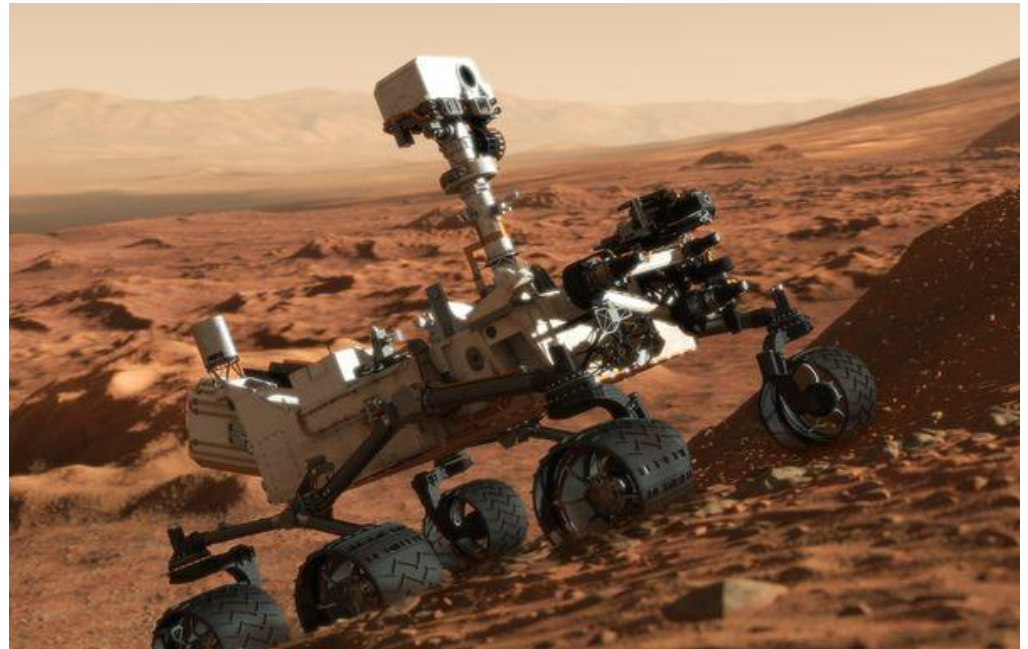


Best-first search, A\* search, admissible heuristics



# Application: Path Planning on Robots

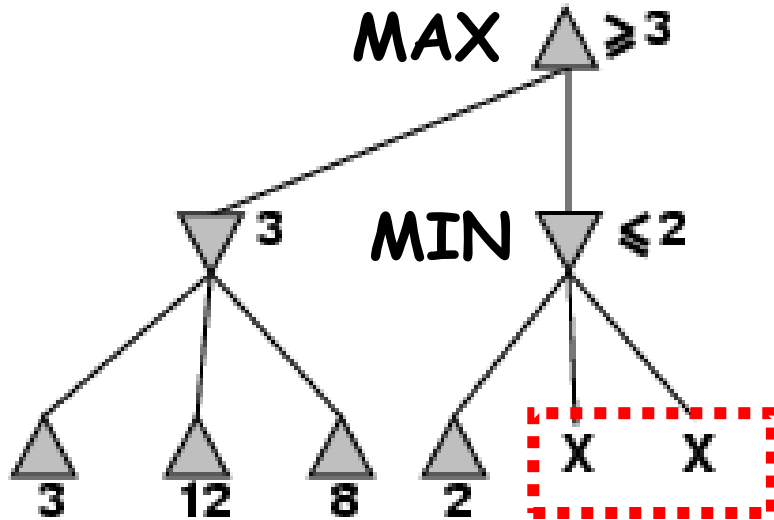
## Mars Rovers (2003-now)



AI concept: Heuristic search for path planning



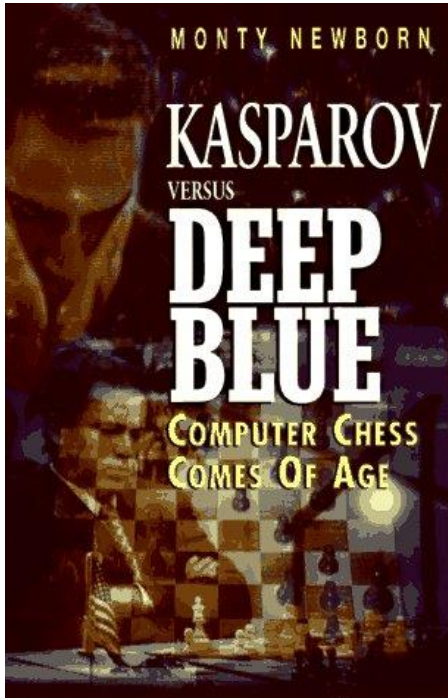
# Recall: Adversarial Search



- Minimax Search
- Alpha Beta pruning
- Cut-off search
- Evaluation functions
- Pattern databases

# Application: Game Playing

“



**The New York Times**

Tuesday, December 5, 2006 Last Update: 10:11 PM ET

## Once Again, Machine Beats Human Champion at Chess

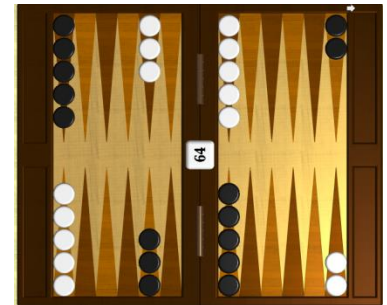


Henning Kaiser/AFP -- Getty Images

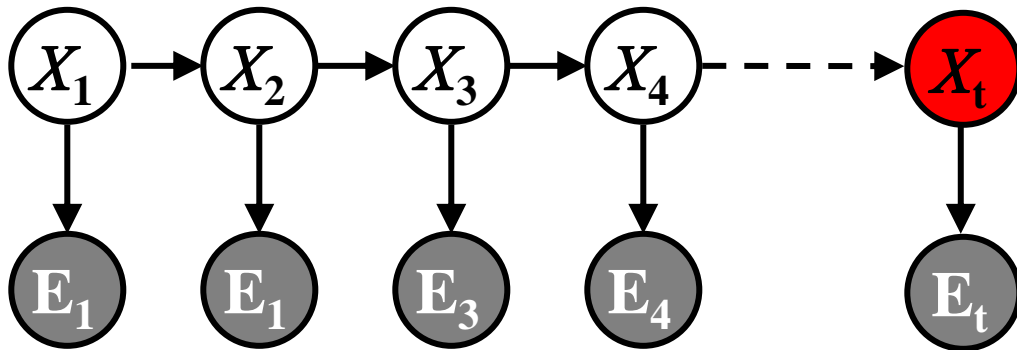
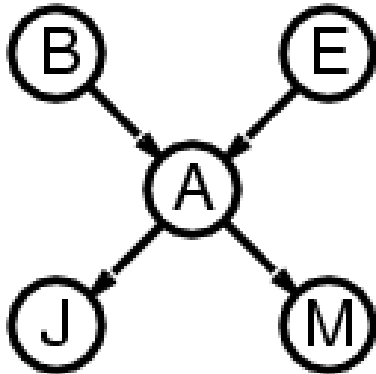
AI concepts we studied

- Minimax Search
- Pattern databases
- Learning

E.g., reinforcement learning



# Recall: Probabilistic Reasoning



AI concepts we studied

- Bayesian networks
- Probabilistic inference
- Hidden Markov Models (HMMs)
- Forward algorithm
- Particle filtering

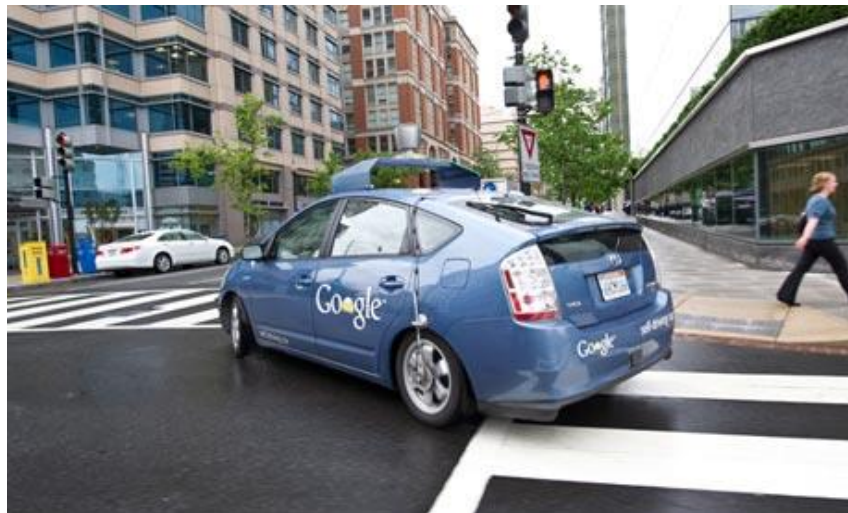
$$P(X_t | e_1, \dots, e_t) = \alpha P(e_t | X_t) \sum_{X_{t-1}} P(X_t | X_{t-1}) P(X_{t-1} | e_1, \dots, e_{t-1})$$

# Application: Driverless Cars



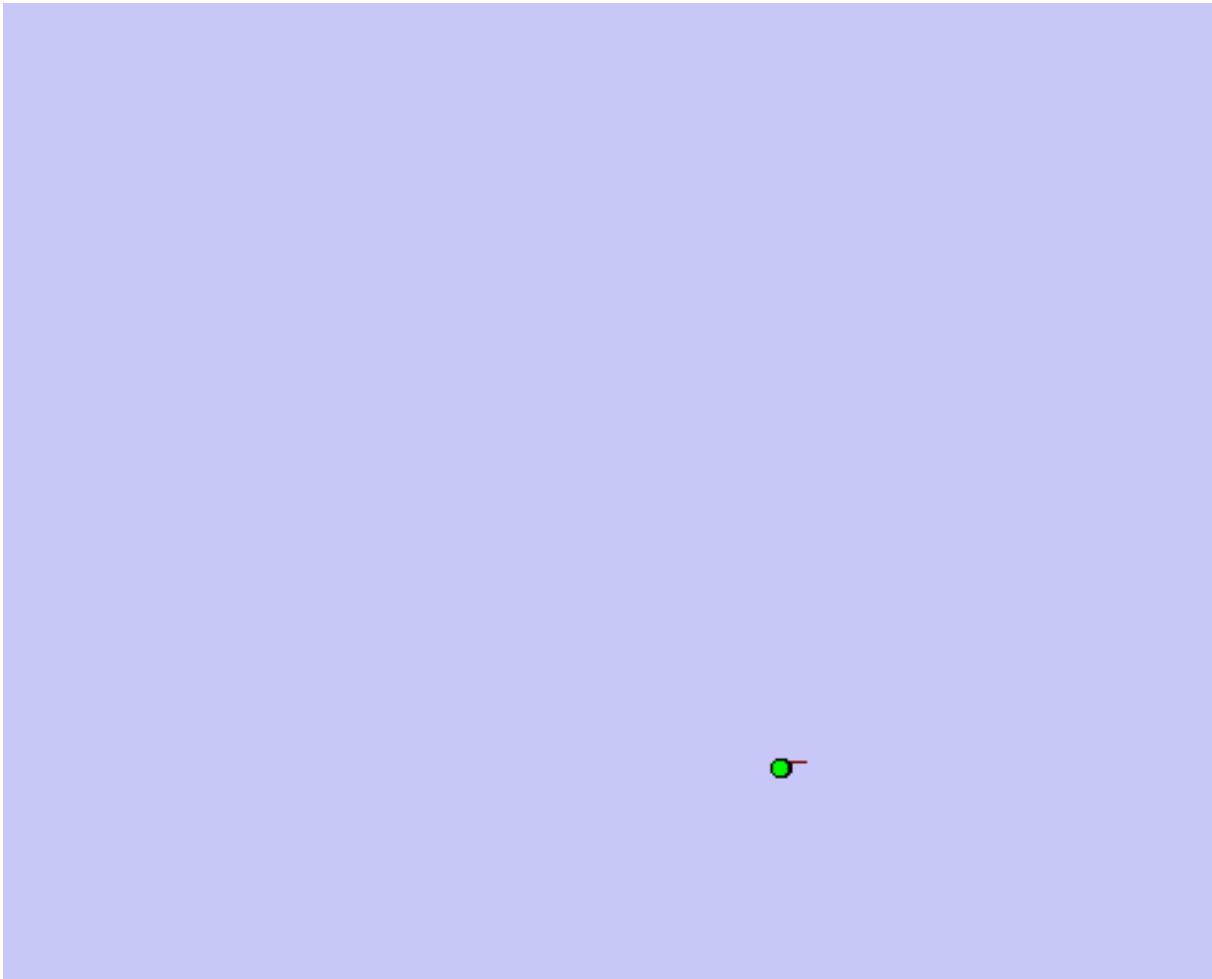
Winners of the 2005 and 2007 DARPA Grand Challenges

Google's Driverless Car:  
>300,000 miles accident free



- Probabilistic reasoning
- Filtering
- Markov models
- Machine learning

# Application: Robot Localization and Mapping of Allen Center

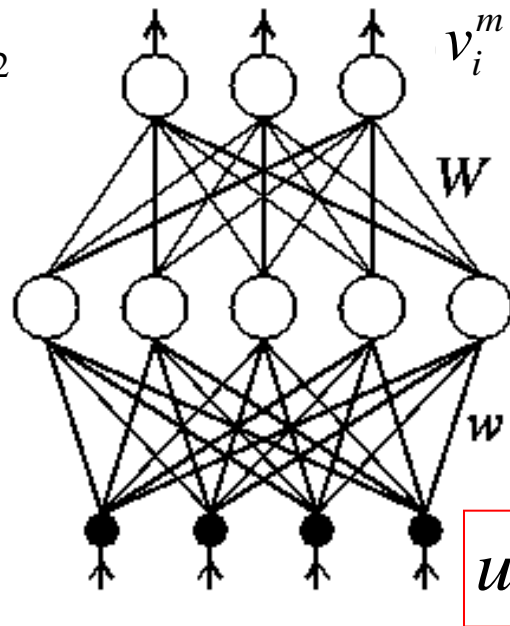


- Probabilistic reasoning
- Particle Filtering
- Machine learning

(Work of Prof. Dieter Fox and students)

# Recall: Neural Networks

$$E(\mathbf{W}, \mathbf{w}) = \frac{1}{2} \sum_i (d_i - v_i)^2$$



$$v_i^m = g\left(\sum_j W_{ji} x_j\right)$$

Backprop rule for input-hidden weights  $w$ :

$$w_{kj} \rightarrow w_{kj} - \varepsilon \frac{dE}{dw_{kj}} \quad \text{But: } \frac{dE}{dw_{kj}} = \frac{dE}{dx_j} \cdot \frac{dx_j}{dw_{kj}}$$

$$\frac{dE}{dw_{kj}} = \left[ - \sum_i (d_i - v_i) g'(\sum_j W_{ji} x_j) W_{ji} \right] \cdot \left[ g'(\sum_k w_{kj} u_k) u_k \right]$$

# Application: Pattern Recognition



2013-11-26

[CO.LABS](#)

## How Google's "Deep Learning" Is Outsmarting Its Human Employees

Google has revealed that some of its server clusters have taught themselves to recognize real-world objects on their own.

By [David Lumb](#)

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## Bing Improves Image Search With Deep Learning

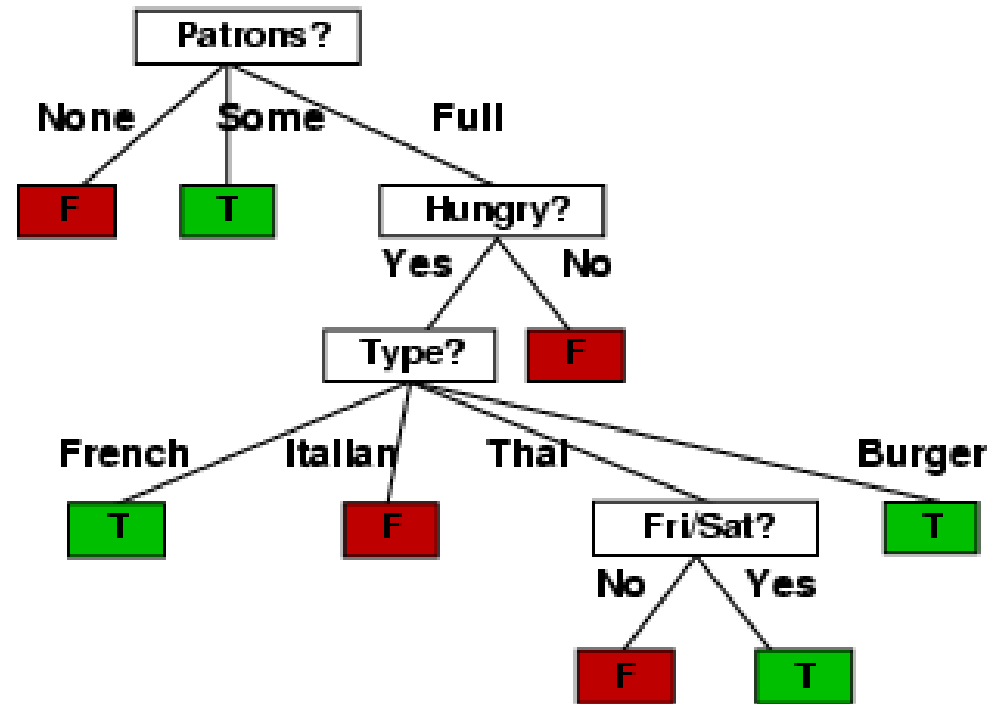
By [Zach Walton](#) · November 22, 2013 · Posted in the [Search Channel](#) · [1 Comment](#)

Applications: Android's voice-controlled search, image search, and Google translate



# Recall: Classification Techniques

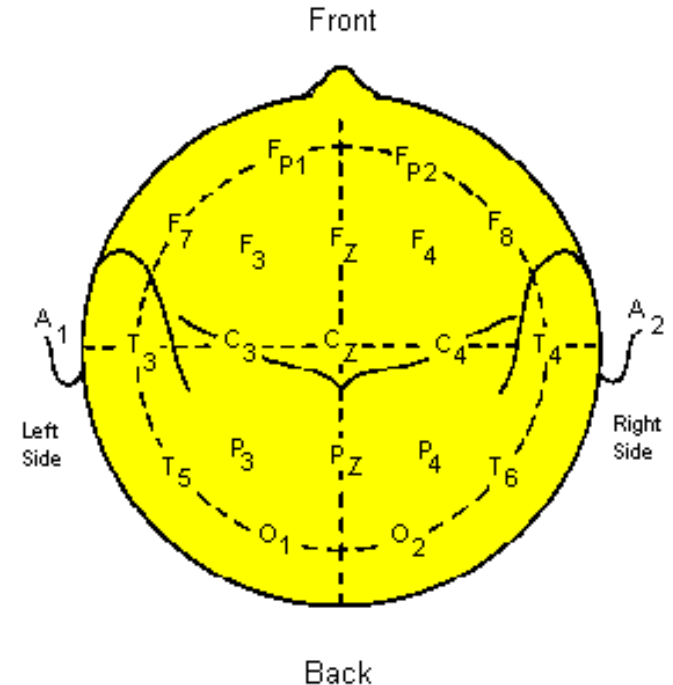
- Decision Trees
- Nearest Neighbors
- SVMs
- Etc.



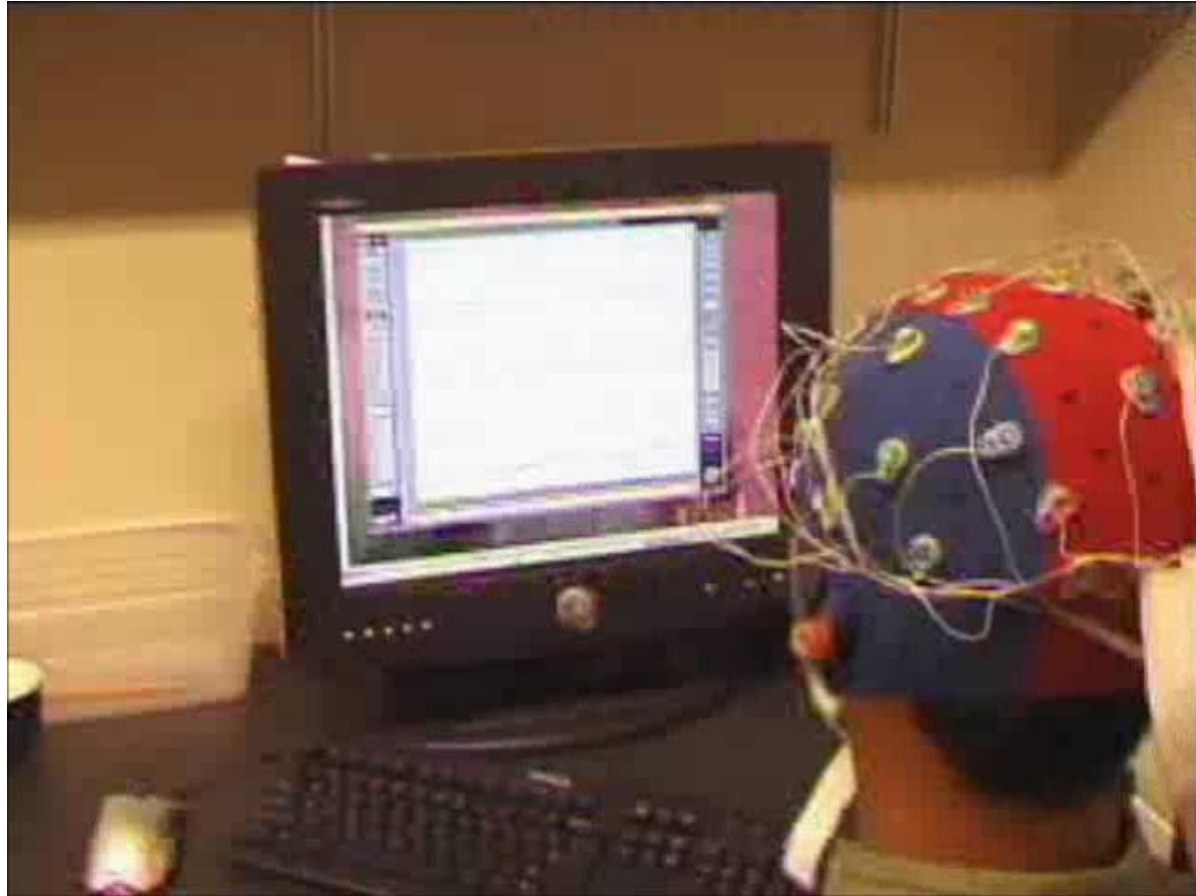


# Application: Brain-Computer Interfaces

- Classifying brain signals recorded at the scalp
- Detect which object a person wants from a set of objects



# Brain-Controlled Robotic "Avatar"



Interface uses *SVM* to classify brain signals

# The Future of AI

Massive amounts of data

+

Sophisticated probabilistic reasoning  
and machine learning algorithms

+

Massive computing power

= AI revolution?

# AI in a Sensor-rich World

- Intelligent thermostats
- Intelligent smoke detectors
- Intelligent refrigerators
- Intelligent houses
- Intelligent forests
- Intelligent oceans
- Intelligent bridges
- Etc.



Nest learning  
thermostat

# Other future AI applications

- **Smart power grids:** electric power flows both ways and is distributed dynamically according to changing demand
- **Security and military:** Bomb diffusing robots, unmanned vehicles
- **Robot firefighters**
- **AI Travel Agents**
- **AI Doctors**
- **AI Lawyers**
- **AI Football Coaches**
- **AI Football Players**
- **AI Rock Stars...**

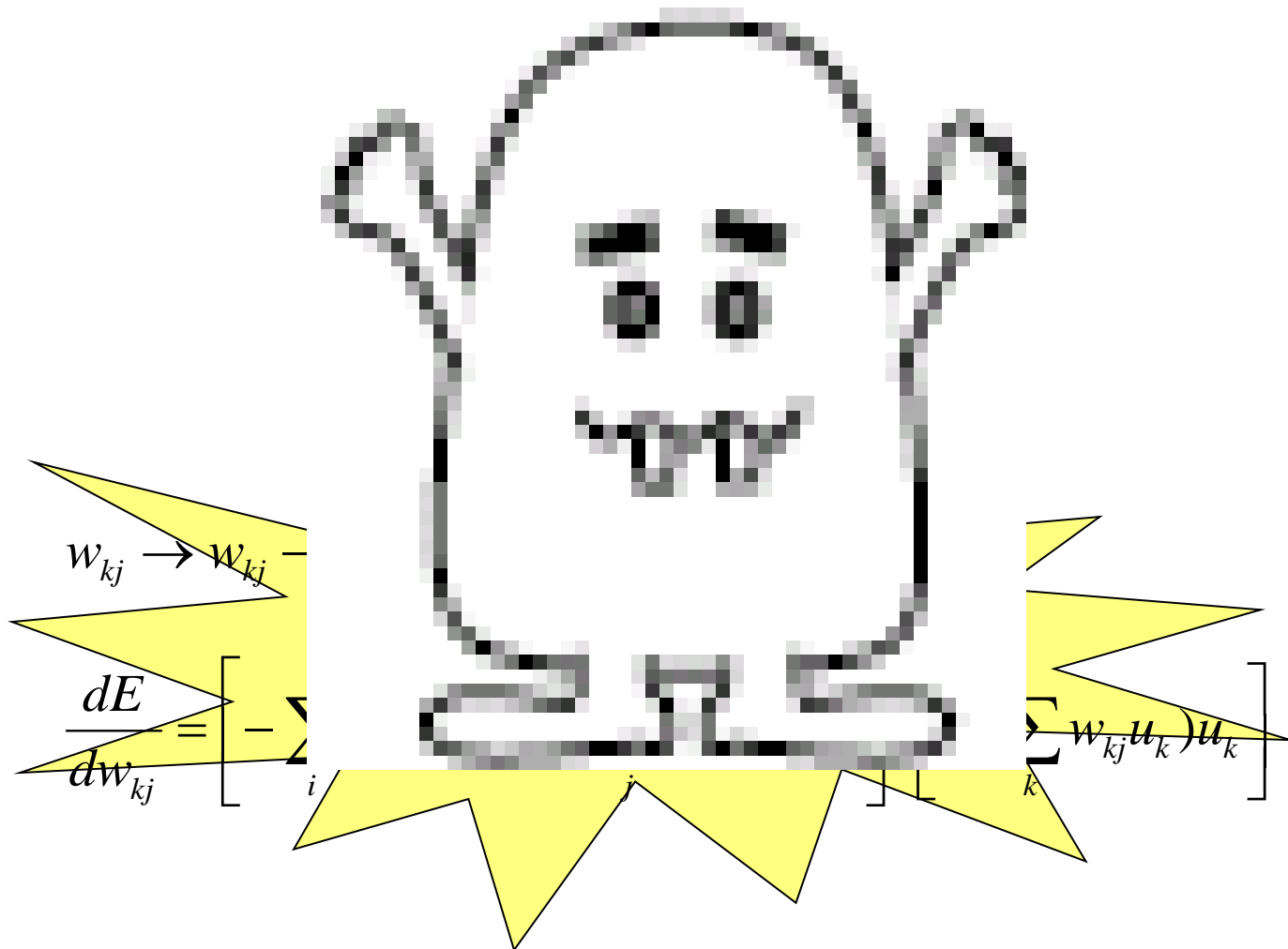


# Take-Home Final: Details

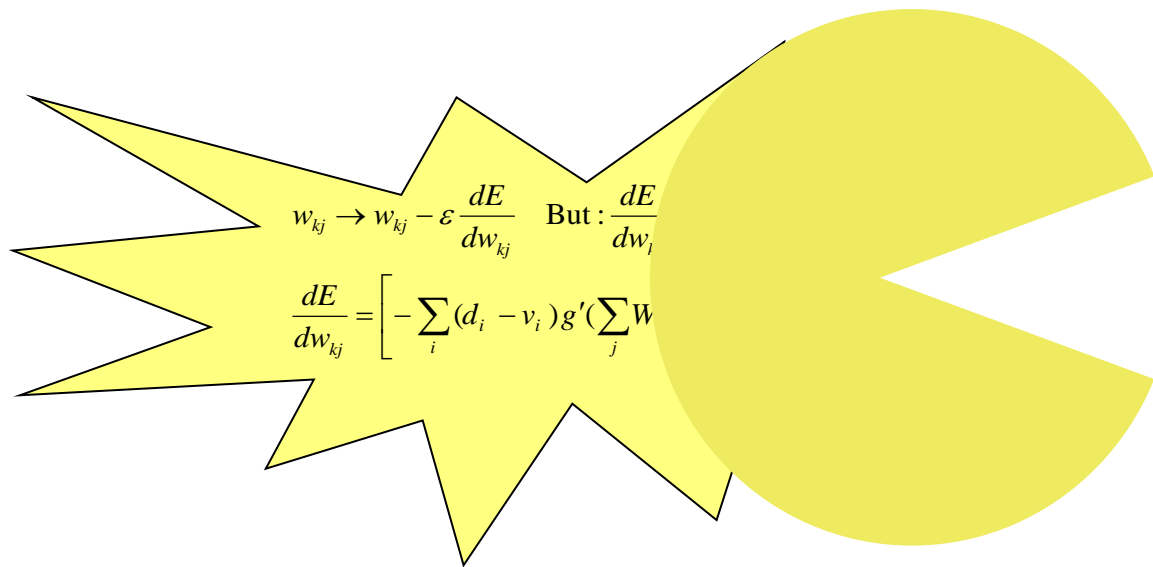
- Will be posted on website by Sunday 10:30am  
You will have 3 days to work on it!
- Due Wednesday Dec 11 by 10:30am
- Open book, open notes
- Focus mostly on post-midterm material
- Will involve a mix of problem solving and descriptive questions

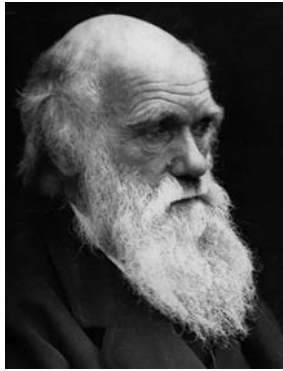
E.g., Computing probabilities in Bayesian networks, explaining important concepts in AI ( $A^*$  search, alpha-beta pruning, etc.)

# That concludes the course....









Have a great  
break!



Who glued my  
fingers?