6.867 Machine learning: administrivia

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- General info
  - lectures MW 2.30-4pm in 35-225
  - tutorials/recitations (time/location tba)
  - website http://www.ai.mit.edu/courses/6.867

- Grading
  - midterm (15%), final (25%)
  - 6 (≈ bi-weekly) problem sets (30%)
  - final project (30%)
Machine learning

• Statistical machine learning
  – principles, methods, and algorithms for learning and prediction on the basis of past experience
  – already everywhere: speech recognition, hand-written character recognition, information retrieval, operating systems, compilers, fraud detection, security, defense applications, ...
“yes”
Learning
Learning

“yes”

“yes”

“yes”

“no” (oops)
Learning

- Steps
  - entertain a (biased) set of possibilities
  - adjust predictions based on feedback
  - rethink the set of possibilities
Learning

- **Steps**
  - entertain a (biased) set of possibilities
  - adjust predictions based on feedback
  - rethink the set of possibilities

- **Principles of learning are “universal”**
  - society (e.g., scientific community)
  - animal (e.g., human)
  - machine
Learning and prediction

- We make predictions all the time but rarely investigate the processes underlying our predictions.
- In carrying out scientific research we are also governed by how theories are evaluated.
- To automate the process of making predictions we need to understand *in addition* how we search and refine “theories.”
Learning: key steps

- data and assumptions
  - what data is available for the learning task?
  - what can we assume about the problem?
Learning: key steps

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  – what data is available for the learning task?
  – what can we assume about the problem?

• representation
  – how should we represent the examples to be classified
Learning: key steps

- **data and assumptions**
  - what data is available for the learning task?
  - what can we assume about the problem?

- **representation**
  - how should we represent the examples to be classified

- **method and estimation**
  - what are the possible hypotheses?
  - how do we adjust our predictions based on the feedback?
Learning: key steps

- data and assumptions
  - what data is available for the learning task?
  - what can we assume about the problem?
- representation
  - how should we represent the examples to be classified
- method and estimation
  - what are the possible hypotheses?
  - how do we adjust our predictions based on the feedback?
- evaluation
  - how well are we doing?
Learning: key steps

• data and assumptions
  – what data is available for the learning task?
  – what can we assume about the problem?

• representation
  – how should we represent the examples to be classified

• method and estimation
  – what are the possible hypotheses?
  – how do we adjust our predictions based on the feedback?

• evaluation
  – how well are we doing?

• model selection
  – can we rethink the approach to do even better?
Data and assumptions

- is this a digit/character/image classification problem?
- how are the examples generated/labeled?
Representation

- There are many ways of presenting the same information
- The choice of representation may determine whether the learning task is very easy or very difficult
Representation

01111110011100100000001001111101110111100111011110001 
0001111100000011000001110000011001111011111100111111111111100000011 
1111111000000110000011000111111100000111100000111110001101111111 

“yes”

“yes”

“no”
Representation

011111101100000010000000100111110111011111001110111110001 “yes”
00011111000000110000011100000111011111011111001111111100000011 “yes”
111111000000011000001111100000111000001111000001111000011011111 “no”

“yes”
“yes”
“yes”
“no”
Method and estimation

- Examples (binary vectors of length $d = 64$)

\[ x = [111111100 \ldots 0000110001101111111]^T \]

- Labels $y \in \{-1, 1\}$ ("no", "yes")

- A linear classifier (hypotheses)

\[ \hat{y} = \text{sign} (\theta \cdot x) = \text{sign} \left( \sum_{i=1}^{d} \theta_i x_i \right) \]

where $\theta$ is a vector of parameters we have to learn.
Method and estimation cont’d

\[ \mathbf{x} \]
\[
01111110011100100000001001000000010011111011101111100111101111100001
001111100000001100000100011111011111010011111100111111000000000
1111111000000110000011001111100000011110000001111000000111100000110111111
\]
\[
\ldots
\]

\[ \mathbf{y} \]
\[
+1
+1
-1
\]
\[
\ldots
\]

- How do we adjust the parameters \( \theta \) based on the labels?

\[ \hat{y} = \text{sign} \left( \theta \cdot \mathbf{x} \right) \]
### Method and estimation cont’d

<table>
<thead>
<tr>
<th>$x$</th>
<th>$y$</th>
</tr>
</thead>
<tbody>
<tr>
<td>01111110011100100000001000000010011111011101111100111011110001</td>
<td>+1</td>
</tr>
<tr>
<td>000111110000001100000011100000110011111011111100111111100000011</td>
<td>+1</td>
</tr>
<tr>
<td>11111110000001100000110011111000000111100000111100001101111111</td>
<td>−1</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

- How do we adjust the parameters $\theta$ based on the labels?

\[
\hat{y} = \text{sign} \left( \theta \cdot x \right)
\]

For example, we can simply refine/update the parameters whenever we make a mistake

\[
\theta \leftarrow \theta + yx \text{ when prediction was wrong}
\]
Evaluation

• How do we measure how well the method is working?
Evaluation

- How do we measure how well the method is working?

For example: average classification/prediction error as a function of the number of examples seen so far
Model selection

- Can we rethink the approach to do even better?
  - our classifier is limited, can we make it more flexible?
  - is there an entirely different type of classifier that would be more suitable?
Types of learning problems

A rough classification of learning problems:

- **Supervised learning**
  - explicit feedback (e.g., labels)

- **Unsupervised learning**
  - no feedback, emphasis on structure and organization

- **Semi-supervised learning**
  - partial feedback (e.g., a few labels, mostly unlabeled)

- **Reinforcement learning**
  - delayed feedback