Decision making in episodic environments

- We have just looked at decision making in sequential environments.
- Now let's consider the “easier” problem of episodic environments:
  - The agent gets a series of unrelated problem instances and has to make some decision or inference about each of them.
  - This is what most of “machine learning” is about.
Example: Image classification

<table>
<thead>
<tr>
<th>input</th>
<th>desired output</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image" alt="Apple" /></td>
<td>apple</td>
</tr>
<tr>
<td><img src="image" alt="Pear" /></td>
<td>pear</td>
</tr>
<tr>
<td><img src="image" alt="Tomato" /></td>
<td>tomato</td>
</tr>
<tr>
<td><img src="image" alt="Cow" /></td>
<td>cow</td>
</tr>
<tr>
<td><img src="image" alt="Dog" /></td>
<td>dog</td>
</tr>
<tr>
<td><img src="image" alt="Horse" /></td>
<td>horse</td>
</tr>
</tbody>
</table>
Example: Spam Filter

Dear Sir.

First, I must solicit your confidence in this transaction, this is by virtue of its nature as being utterly confidential and top secret. ...

Ok, I know this is blatantly OT but I'm beginning to go insane. Had an old Dell Dimension XPS sitting in the corner and decided to put it to use, I know it was working pre being stuck in the corner, but when I plugged it in, hit the power nothing happened.

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Example: Seismic data

![Graph showing seismic data with two types of data points: Earthquakes and Nuclear explosions. The graph plots surface wave magnitude against body wave magnitude.]
The basic classification framework

\[ y = f(x) \]

- **Learning**: given a \textit{training set} of labeled examples \( \{(x_1, y_1), \ldots, (x_N, y_N)\} \), estimate the parameters of the prediction function \( f \)

- **Inference**: apply \( f \) to a never before seen \textit{test example} \( x \) and output the predicted value \( y = f(x) \)
Example: Training and testing

- Key challenge: *generalization* to unseen examples
Naïve Bayes classifier

\[ f(x) = \arg \max_y P(y \mid x) \]

\[ \propto \arg \max_y P(y)P(x \mid y) \]

\[ = \arg \max_y P(y) \prod_d P(x_d \mid y) \]

A single dimension or attribute of \( x \)
Decision tree classifier

Example problem: decide whether to wait for a table at a restaurant, based on the following attributes:

1. **Alternate**: is there an alternative restaurant nearby?
2. **Bar**: is there a comfortable bar area to wait in?
3. **Fri/Sat**: is today Friday or Saturday?
4. **Hungry**: are we hungry?
5. **Patrons**: number of people in the restaurant (None, Some, Full)
6. **Price**: price range ($, $$, $$$)
7. **Raining**: is it raining outside?
8. **Reservation**: have we made a reservation?
9. **Type**: kind of restaurant (French, Italian, Thai, Burger)
10. **WaitEstimate**: estimated waiting time (0-10, 10-30, 30-60, >60)
## Decision tree classifier

<table>
<thead>
<tr>
<th>Example</th>
<th>Attributes</th>
<th>Target</th>
<th>Wait</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_1$</td>
<td>T F F T Some $$</td>
<td>F T French</td>
<td>0–10 T</td>
</tr>
<tr>
<td>$X_2$</td>
<td>T F F T Full $</td>
<td>F F Thai</td>
<td>30–60 F</td>
</tr>
<tr>
<td>$X_3$</td>
<td>F T F F Some $</td>
<td>F F Burger</td>
<td>0–10 T</td>
</tr>
<tr>
<td>$X_4$</td>
<td>T F F T Full $</td>
<td>F F Thai</td>
<td>10–30 T</td>
</tr>
<tr>
<td>$X_5$</td>
<td>T F T F Full $$</td>
<td>F T French</td>
<td>&gt;60 F</td>
</tr>
<tr>
<td>$X_6$</td>
<td>F T F F Some $</td>
<td>T T Italian</td>
<td>0–10 T</td>
</tr>
<tr>
<td>$X_7$</td>
<td>F T F F None $</td>
<td>T F Burger</td>
<td>0–10 F</td>
</tr>
<tr>
<td>$X_8$</td>
<td>F F F T Some $</td>
<td>T T Thai</td>
<td>0–10 T</td>
</tr>
<tr>
<td>$X_9$</td>
<td>F T T F Full $</td>
<td>T F Burger</td>
<td>&gt;60 F</td>
</tr>
<tr>
<td>$X_{10}$</td>
<td>T T T T Full $$</td>
<td>F T Italian</td>
<td>10–30 F</td>
</tr>
<tr>
<td>$X_{11}$</td>
<td>F F F F None $</td>
<td>F F Thai</td>
<td>0–10 F</td>
</tr>
<tr>
<td>$X_{12}$</td>
<td>T T T T Full $</td>
<td>F F Burger</td>
<td>30–60 T</td>
</tr>
</tbody>
</table>
Nearest neighbor classifier

\[ f(x) = \text{label of the training example nearest to } x \]

- All we need is a distance function for our inputs
- No training required!
• Find a \textit{linear function} to separate the classes

\[ f(x) = \sgn(w_1x_1 + w_2x_2 + \ldots + w_Dx_D) = \sgn(w \cdot x) \]
Perceptron

Input

Weights

Output: $\text{sgn}(w \cdot x + b)$
Linear separability

$x_1 \text{ and } x_2$

$x_1 \text{ or } x_2$

$x_1 \text{ xor } x_2$
Multi-Layer Neural Network

- Can learn nonlinear functions
- **Training**: find network weights to minimize the error between true and estimated labels of training examples:
  \[
  E(f) = \sum_{i=1}^{N} (y_i - f(x_i))^2
  \]
- Minimization can be done by gradient descent provided \( f \) is differentiable
  - This training method is called **back-propagation**
Differentiable perceptron

Input

Weights

$x_1$

$w_1$

$x_2$

$w_2$

$x_3$

$w_3$

\[ \vdots \]

$x_d$

$w_d$

Output: \( \sigma(w \cdot x + b) \)

Sigmoid function:

\[
\sigma(t) = \frac{1}{1 + e^{-t}}
\]
Review: Types of classifiers

- Naïve Bayes
- Decision tree
- Nearest neighbor
- Linear classifier
- Nonlinear classifier