Learning

Learning is the ability to improve one’s behavior based on experience.

➤ The range of behaviors is expanded: the agent can do more.

➤ The accuracy on tasks is improved: the agent can do things better.

➤ The speed is improved: the agent can do things faster.
Components of a learning problem

The following components are part of any learning problem:

- **task** The behavior or task that’s being improved. For example: classification, acting in an environment
- **data** The experiences that are being used to improve performance in the task.
- **measure of improvement** How can the improvement be measured? For example: increasing accuracy in prediction, new skills that were not present initially, improved speed.
Learning task

experiences/data

problem/task

Learning agent

background knowledge/bias

answer/performance
Learning architecture

experiences/data

induction procedure

internal representation

reasoning procedure

background knowledge/bias

problem/task

answer/performance
Choosing a representation

➤ The richer the representation, the more useful it is for subsequent problem solving.

➤ The richer the representation, the more difficult it is to learn.
Common Learning Tasks

- **Supervised classification** Given a set of pre-classified training examples, classify a new instance.
- **Unsupervised learning** Find natural classes for examples.
- **Reinforcement learning** Determine what to do based on rewards and punishments.
- **Analytic learning** Reason faster using experience.
- **Inductive logic programming** Build richer models in terms of logic programs.
### Example Classification Data

<table>
<thead>
<tr>
<th>Action</th>
<th>Author</th>
<th>Thread</th>
<th>Length</th>
<th>Where</th>
</tr>
</thead>
<tbody>
<tr>
<td>e1</td>
<td>skips</td>
<td>known</td>
<td>new</td>
<td>long</td>
</tr>
<tr>
<td>e2</td>
<td>reads</td>
<td>unknown</td>
<td>new</td>
<td>short</td>
</tr>
<tr>
<td>e3</td>
<td>skips</td>
<td>unknown</td>
<td>old</td>
<td>long</td>
</tr>
<tr>
<td>e4</td>
<td>skips</td>
<td>known</td>
<td>old</td>
<td>long</td>
</tr>
<tr>
<td>e5</td>
<td>reads</td>
<td>known</td>
<td>new</td>
<td>short</td>
</tr>
<tr>
<td>e6</td>
<td>skips</td>
<td>known</td>
<td>old</td>
<td>long</td>
</tr>
</tbody>
</table>

We want to classify new examples on property *Action* based on the examples’ *Author*, *Thread*, *Length*, and *Where*. 
Feedback

Learning tasks can be characterized by the feedback given to the learner.

➤ **Supervised learning** What has to be learned is specified for each example.

➤ **Unsupervised learning** No classifications are given; the learner has to discover categories and regularities in the data.

➤ **Reinforcement learning** Feedback occurs after a sequence of actions.
Measuring Success

➤ The measure of success is not how well the agent performs on the training examples, but how well the agent performs for new examples.

➤ Consider two agents:

➤ \( P \) claims the negative examples seen are the only negative examples. Every other instance is positive.

➤ \( N \) claims the positive examples seen are the only positive examples. Every other instance is negative.

➤ Both agents correctly classify every training example, but disagree on every other example.
Bias

➤ The tendency to prefer one hypothesis over another is called a bias.

➤ Saying a hypothesis is better than $N$’s or $P$’s hypothesis isn’t something that’s obtained from the data.

➤ To have any inductive process make predictions on unseen data, you need a bias.

➤ What constitutes a good bias is an empirical question about which biases work best in practice.
Learning as search

➤ Given a representation and a bias, the problem of learning can be reduced to one of search.

➤ Learning is search through the space of possible representations looking for the representation or representations that best fits the data, given the bias.

➤ These search spaces are typically prohibitively large for systematic search. Use hill climbing.

➤ A learning algorithm is made of a search space, an evaluation function, and a search method.
Noise

Data isn’t perfect:

- some of the attributes are assigned the wrong value
- the attributes given are inadequate to predict the classification
- there are examples with missing attributes

overfitting occurs when a distinction appears in the data, but doesn’t appear in the unseen examples. This occurs because of random correlations in the training set.
Characterizations of Learning

➤ Find the best representation given the data.

➤ Delineate the class of consistent representations given the data.

➤ Find a probability distribution of the representations given the data.