Learning Objectives

At the end of the class you should be able to:

- Explain the components and the architecture of a learning problem
- Explain why a learner needs a bias
- Identify the sources of error for a prediction

Learning

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

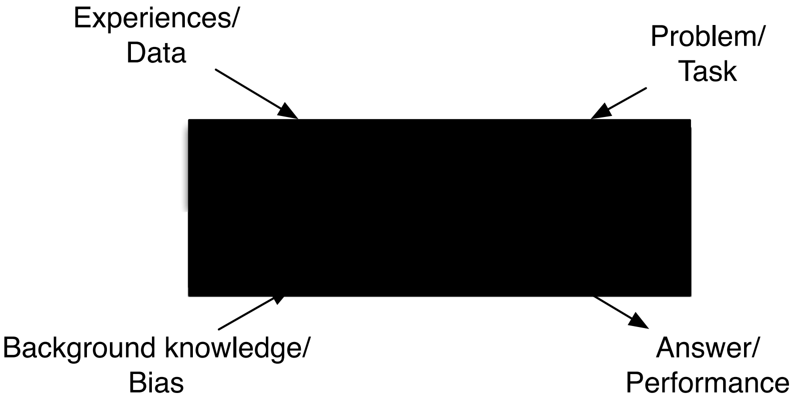
- The range of behaviors is expanded: the agent can do more.
- The accuracy on tasks is improved: the agent can do things better.
- The speed is improved: the agent can do things faster.

Components of a learning problem

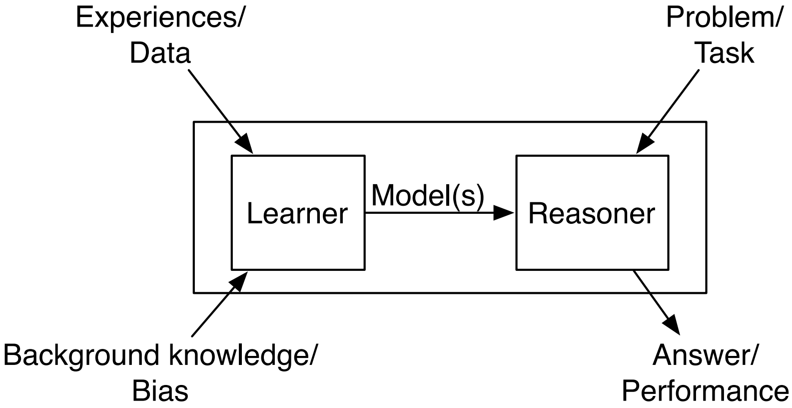
The following components are part of any learning problem:

- 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.

Black-box Learner



Learning architecture



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- Inductive logic programming Build richer models in terms of logic programs.
- Statistical relational learning learning relational representations that also deal with uncertainty.

Example Classification Data

Training Examples:

	Action	Author	Thread	Length	Where
e1	skips	known	new	long	home
e2	reads	unknown	new	short	work
e3	skips	unknown	old	long	work
e4	skips	known	old	long	home
e5	reads	known	new	short	home
e6	skips	known	old	long	work

New Examples:

e7	???	known	new	short	work
e8	???	unknown	new	short	work

We want to classify new examples on feature *Action* based on the examples' *Author*, *Thread*, *Length*, and *Where*.

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- Reinforcement learning Feedback occurs after a sequence of actions.

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- 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.

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- To have any inductive process make predictions on unseen data, an agent needs a bias.
- What constitutes a good bias is an empirical question about which biases work best in practice.

Learning as search

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- 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. E.g., use gradient descent or stochastic simulation.
- A learning algorithm is made of a search space, an evaluation function, and a search method.

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  - the features given are inadequate to predict the classification
  - there are examples with missing features
  - some of the features are assigned the wrong value
- overfitting occurs when distinctions appear in the training data, but not in the unseen examples.

Errors in learning

Errors in learning are caused by:

- Limited representation (representation bias)

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- Limited data (variance)
- Limited features (noise)

Choosing a representation for models

- The richer the representation, the more useful it is for subsequent problem solving.
- The richer the representation, the more difficult it is to learn.

"bias-variance tradeoff"

Characterizations of Learning

- Find the best model given the data.
- Delineate the class of consistent models given the data.
- Find a probability distribution of the models given the data.