Designing a Learning System (agent viewpoint)

Relevant Readings: Sections 1.2-1.5, 2.1-2.2, 2.3 (but not 2.3.1) in Mitchell

CS495 - Machine Learning, Fall 2009

▶ Suppose we want to solve the following learning problem

- ▶ Suppose we want to solve the following learning problem
 - ► Task *T*: playing checkers

- Suppose we want to solve the following learning problem
 - ► Task *T*: playing checkers
 - Performance measure P: percent of games won in the world tournament

- ► Suppose we want to solve the following learning problem
 - ► Task *T*: playing checkers
 - Performance measure P: percent of games won in the world tournament
 - ▶ Training experience *E*: games played against itself

- ► Suppose we want to solve the following learning problem
 - ► Task *T*: playing checkers
 - Performance measure P: percent of games won in the world tournament
 - ▶ Training experience *E*: games played against itself
- Since we don't have complete knowledge of what the optimal moves are in checkers, providing suitable *direct* training examples would be difficult.

- ► Suppose we want to solve the following learning problem
 - ► Task *T*: playing checkers
 - Performance measure P: percent of games won in the world tournament
 - ▶ Training experience *E*: games played against itself
- Since we don't have complete knowledge of what the optimal moves are in checkers, providing suitable *direct* training examples would be difficult.
- ▶ Instead we will need to work with *indirect* knowledge of how the game turned out.

- ► Suppose we want to solve the following learning problem
 - ► Task *T*: playing checkers
 - Performance measure P: percent of games won in the world tournament
 - ▶ Training experience *E*: games played against itself
- Since we don't have complete knowledge of what the optimal moves are in checkers, providing suitable *direct* training examples would be difficult.
- ▶ Instead we will need to work with *indirect* knowledge of how the game turned out.
- ▶ We will should also hope that *E* is fairly representative of *P*

- ► Suppose we want to solve the following learning problem
 - ▶ Task T: playing checkers
 - Performance measure P: percent of games won in the world tournament
 - ▶ Training experience *E*: games played against itself
- Since we don't have complete knowledge of what the optimal moves are in checkers, providing suitable *direct* training examples would be difficult.
- ▶ Instead we will need to work with *indirect* knowledge of how the game turned out.
- ▶ We will should also hope that *E* is fairly representative of *P*
- ▶ Enumerating all legal moves from a given position is a straightforward (CS-122?) programming task, so we'll assume that's already done.

- ► Suppose we want to solve the following learning problem
 - ▶ Task T: playing checkers
 - Performance measure P: percent of games won in the world tournament
 - ► Training experience *E*: games played against itself
- Since we don't have complete knowledge of what the optimal moves are in checkers, providing suitable *direct* training examples would be difficult.
- ▶ Instead we will need to work with *indirect* knowledge of how the game turned out.
- ▶ We will should also hope that *E* is fairly representative of *P*
- ► Enumerating all legal moves from a given position is a straightforward (CS-122?) programming task, so we'll assume that's already done.
- ► So should we learn which move is the best or how "good" a given board position is?

- ▶ Suppose we want to solve the following learning problem
 - ► Task *T*: playing checkers
 - Performance measure P: percent of games won in the world tournament
 - ► Training experience *E*: games played against itself
- Since we don't have complete knowledge of what the optimal moves are in checkers, providing suitable *direct* training examples would be difficult.
- ▶ Instead we will need to work with *indirect* knowledge of how the game turned out.
- ▶ We will should also hope that *E* is fairly representative of *P*
- ▶ Enumerating all legal moves from a given position is a straightforward (CS-122?) programming task, so we'll assume that's already done.
- ► So should we learn which move is the best or how "good" a given board position is?
 - ▶ It's a design decision. We'll do the later of these two



- ▶ Suppose we want to solve the following learning problem
 - ► Task *T*: playing checkers
 - Performance measure P: percent of games won in the world tournament
 - ► Training experience *E*: games played against itself
- Since we don't have complete knowledge of what the optimal moves are in checkers, providing suitable *direct* training examples would be difficult.
- ▶ Instead we will need to work with *indirect* knowledge of how the game turned out.
- ▶ We will should also hope that *E* is fairly representative of *P*
- ▶ Enumerating all legal moves from a given position is a straightforward (CS-122?) programming task, so we'll assume that's already done.
- ► So should we learn which move is the best or how "good" a given board position is?
 - ▶ It's a design decision. We'll do the later of these two



▶ A set is a collection of elements (integers, program objects, mathematical objects, anything really)

- ▶ A *set* is a collection of *elements* (integers, program objects, mathematical objects, anything really)
- Notation for functions

- ▶ A *set* is a collection of *elements* (integers, program objects, mathematical objects, anything really)
- Notation for functions
 - $f:D\to R$

- ▶ A *set* is a collection of *elements* (integers, program objects, mathematical objects, anything really)
- Notation for functions
 - $f:D\to R$
 - ▶ D and R are sets

- ▶ A *set* is a collection of *elements* (integers, program objects, mathematical objects, anything really)
- Notation for functions
 - $f: D \rightarrow R$
 - D and R are sets
 - ▶ This means f is a function that takes an element of D as input and outputs an element of R as output

- ▶ A *set* is a collection of *elements* (integers, program objects, mathematical objects, anything really)
- Notation for functions
 - $f: D \rightarrow R$
 - D and R are sets
 - ▶ This means f is a function that takes an element of D as input and outputs an element of R as output
 - Examples

- ▶ A set is a collection of elements (integers, program objects, mathematical objects, anything really)
- Notation for functions
 - $f: D \rightarrow R$
 - D and R are sets
 - ▶ This means f is a function that takes an element of D as input and outputs an element of R as output
 - Examples
- So in this case, we would like to learn the *target function* $V: B \to \mathbb{R}$, where:

- ▶ A set is a collection of elements (integers, program objects, mathematical objects, anything really)
- Notation for functions
 - $f:D\to R$
 - D and R are sets
 - ▶ This means f is a function that takes an element of D as input and outputs an element of R as output
 - Examples
- So in this case, we would like to learn the *target function* $V: B \to \mathbb{R}$, where:
 - ightharpoonup V is the name we are giving to this function

- ▶ A set is a collection of elements (integers, program objects, mathematical objects, anything really)
- Notation for functions
 - $f: D \rightarrow R$
 - D and R are sets
 - ▶ This means f is a function that takes an element of D as input and outputs an element of R as output
 - Examples
- So in this case, we would like to learn the *target function* $V: B \to \mathbb{R}$, where:
 - V is the name we are giving to this function
 - ▶ *B* is the set of all possible checker board states

- ▶ A set is a collection of elements (integers, program objects, mathematical objects, anything really)
- Notation for functions
 - $f:D\to R$
 - D and R are sets
 - ▶ This means f is a function that takes an element of D as input and outputs an element of R as output
 - Examples
- So in this case, we would like to learn the *target function* $V: B \to \mathbb{R}$, where:
 - V is the name we are giving to this function
 - ▶ *B* is the set of all possible checker board states
 - $ightharpoonup \mathbb{R}$ is the real numbers

- ▶ A set is a collection of elements (integers, program objects, mathematical objects, anything really)
- Notation for functions
 - $f:D\to R$
 - D and R are sets
 - ▶ This means f is a function that takes an element of D as input and outputs an element of R as output
 - Examples
- ▶ So in this case, we would like to learn the *target function* $V: B \to \mathbb{R}$, where:
 - V is the name we are giving to this function
 - ▶ *B* is the set of all possible checker board states
 - $ightharpoonup \mathbb{R}$ is the real numbers
 - V(b) = 100 if black can guarantee a win starting from board b

- ▶ A set is a collection of elements (integers, program objects, mathematical objects, anything really)
- Notation for functions
 - $f:D\to R$
 - D and R are sets
 - ▶ This means f is a function that takes an element of D as input and outputs an element of R as output
 - Examples
- So in this case, we would like to learn the *target function* $V: B \to \mathbb{R}$, where:
 - V is the name we are giving to this function
 - ▶ *B* is the set of all possible checker board states
 - R is the real numbers
 - V(b) = 100 if black can guarantee a win starting from board b
 - V(b) = -100 if red can guarantee a win starting from board b

- ▶ A set is a collection of elements (integers, program objects, mathematical objects, anything really)
- Notation for functions
 - $f: D \rightarrow R$
 - D and R are sets
 - ▶ This means f is a function that takes an element of D as input and outputs an element of R as output
 - Examples
- So in this case, we would like to learn the *target function* $V: B \to \mathbb{R}$, where:
 - V is the name we are giving to this function
 - ▶ *B* is the set of all possible checker board states
 - $ightharpoonup \mathbb{R}$ is the real numbers
 - V(b) = 100 if black can guarantee a win starting from board b
 - ▶ V(b) = -100 if red can guarantee a win starting from board b
 - V(b) = 0 if the game is drawn

- ▶ A set is a collection of elements (integers, program objects, mathematical objects, anything really)
- Notation for functions
 - $f:D\to R$
 - D and R are sets
 - ▶ This means f is a function that takes an element of D as input and outputs an element of R as output
 - Examples
- So in this case, we would like to learn the *target function* $V: B \to \mathbb{R}$, where:
 - V is the name we are giving to this function
 - ▶ *B* is the set of all possible checker board states
 - $ightharpoonup \mathbb{R}$ is the real numbers
 - V(b) = 100 if black can guarantee a win starting from board b
 - V(b) = -100 if red can guarantee a win starting from board b
 - V(b) = 0 if the game is drawn
 - It would be difficult to calculate this function completely, so we will approximate it instead



- ▶ A set is a collection of elements (integers, program objects, mathematical objects, anything really)
- Notation for functions
 - $f:D\to R$
 - D and R are sets
 - ▶ This means f is a function that takes an element of D as input and outputs an element of R as output
 - Examples
- So in this case, we would like to learn the *target function* $V: B \to \mathbb{R}$, where:
 - V is the name we are giving to this function
 - ▶ *B* is the set of all possible checker board states
 - $ightharpoonup \mathbb{R}$ is the real numbers
 - V(b) = 100 if black can guarantee a win starting from board b
 - V(b) = -100 if red can guarantee a win starting from board b
 - V(b) = 0 if the game is drawn
 - It would be difficult to calculate this function completely, so we will approximate it instead



$$\hat{V}(b) = w_1 x_1 + w_2 x_2 + w_3 x_3 + w_4 x_4 + w_5 x_5 + w_6 x_6$$

- $\hat{V}(b) = w_1 x_1 + w_2 x_2 + w_3 x_3 + w_4 x_4 + w_5 x_5 + w_6 x_6$
 - ▶ Each x_i is for some attribute of the board state (i.e. how many red pieces)

- $\hat{V}(b) = w_1 x_1 + w_2 x_2 + w_3 x_3 + w_4 x_4 + w_5 x_5 + w_6 x_6$
 - ▶ Each x_i is for some attribute of the board state (i.e. how many red pieces)
 - ightharpoonup Each w_i is how much to weight that particular attribute

- $\hat{V}(b) = w_1 x_1 + w_2 x_2 + w_3 x_3 + w_4 x_4 + w_5 x_5 + w_6 x_6$
 - ▶ Each x_i is for some attribute of the board state (i.e. how many red pieces)
 - ightharpoonup Each w_i is how much to weight that particular attribute
 - ▶ This is slightly different than the one in the book (no w_0)

- $\hat{V}(b) = w_1 x_1 + w_2 x_2 + w_3 x_3 + w_4 x_4 + w_5 x_5 + w_6 x_6$
 - ▶ Each x_i is for some attribute of the board state (i.e. how many red pieces)
 - ightharpoonup Each w_i is how much to weight that particular attribute
 - ▶ This is slightly different than the one in the book (no w_0)
 - ▶ What are the best settings for the w_i weights?

- $\hat{V}(b) = w_1 x_1 + w_2 x_2 + w_3 x_3 + w_4 x_4 + w_5 x_5 + w_6 x_6$
 - ▶ Each x_i is for some attribute of the board state (i.e. how many red pieces)
 - ightharpoonup Each w_i is how much to weight that particular attribute
 - ▶ This is slightly different than the one in the book (no w_0)
 - ▶ What are the best settings for the *w_i* weights?
- \triangleright A particular setting of the w_i 's is called a *hypothesis*

- $\hat{V}(b) = w_1 x_1 + w_2 x_2 + w_3 x_3 + w_4 x_4 + w_5 x_5 + w_6 x_6$
 - ▶ Each x_i is for some attribute of the board state (i.e. how many red pieces)
 - ightharpoonup Each w_i is how much to weight that particular attribute
 - ▶ This is slightly different than the one in the book (no w_0)
 - ▶ What are the best settings for the *w_i* weights?
- \triangleright A particular setting of the w_i 's is called a *hypothesis*
- ▶ The set of all possible settings for all weight assignments w_i is called the *hypothesis space*

- $\hat{V}(b) = w_1 x_1 + w_2 x_2 + w_3 x_3 + w_4 x_4 + w_5 x_5 + w_6 x_6$
 - ▶ Each x_i is for some attribute of the board state (i.e. how many red pieces)
 - ightharpoonup Each w_i is how much to weight that particular attribute
 - ▶ This is slightly different than the one in the book (no w_0)
 - ▶ What are the best settings for the *w_i* weights?
- \triangleright A particular setting of the w_i 's is called a *hypothesis*
- ► The set of all possible settings for all weight assignments *w_i* is called the *hypothesis space*
- lacktriangle We want to find a hypothesis so that \hat{V} best approximates V

- $\hat{V}(b) = w_1 x_1 + w_2 x_2 + w_3 x_3 + w_4 x_4 + w_5 x_5 + w_6 x_6$
 - ▶ Each x_i is for some attribute of the board state (i.e. how many red pieces)
 - ightharpoonup Each w_i is how much to weight that particular attribute
 - ▶ This is slightly different than the one in the book (no w_0)
 - ▶ What are the best settings for the *w_i* weights?
- \triangleright A particular setting of the w_i 's is called a *hypothesis*
- ► The set of all possible settings for all weight assignments *w_i* is called the *hypothesis space*
- lacktriangle We want to find a hypothesis so that \hat{V} best approximates V

▶ We would like to get training example pairs (b, V(b)) of what the function "should be" for a given position

- ▶ We would like to get training example pairs (b, V(b)) of what the function "should be" for a given position
 - ► That's hard!

- ▶ We would like to get training example pairs (b, V(b)) of what the function "should be" for a given position
 - ► That's hard!
- It turns out that training examples of the form $(b, \hat{V}(nextMove(b)))$ do a pretty good job

- ▶ We would like to get training example pairs (b, V(b)) of what the function "should be" for a given position
 - ► That's hard!
- It turns out that training examples of the form $(b, \hat{V}(nextMove(b)))$ do a pretty good job
 - We are really using the function to train itself (think about this)!

- ▶ We would like to get training example pairs (b, V(b)) of what the function "should be" for a given position
 - ► That's hard!
- It turns out that training examples of the form $(b, \hat{V}(nextMove(b)))$ do a pretty good job
 - We are really using the function to train itself (think about this)!

► To update the weights, we look at the discrepancy between the training example and the function

- ► To update the weights, we look at the discrepancy between the training example and the function
- ▶ We adjust the weights *w_i* in the "right direction" to make up for the discrepancy...

- ► To update the weights, we look at the discrepancy between the training example and the function
- ▶ We adjust the weights w_i in the "right direction" to make up for the discrepancy...
 - ▶ ...but only a little bit

- ► To update the weights, we look at the discrepancy between the training example and the function
- ▶ We adjust the weights w_i in the "right direction" to make up for the discrepancy...
 - ...but only a little bit
- ▶ This is essentially a gradient descent search

- ► To update the weights, we look at the discrepancy between the training example and the function
- ▶ We adjust the weights w_i in the "right direction" to make up for the discrepancy...
 - ...but only a little bit
- ▶ This is essentially a gradient descent search

► Performance system

- Performance system
 - Uses the learned target function to solve the problem at hand.

- ► Performance system
 - ▶ Uses the learned target function to solve the problem at hand.
- ► Critic

- Performance system
 - Uses the learned target function to solve the problem at hand.
- ► Critic
 - Produces training examples after an experiment

- ▶ Performance system
 - Uses the learned target function to solve the problem at hand.
- ► Critic
 - Produces training examples after an experiment
- Generalizer

- ► Performance system
 - Uses the learned target function to solve the problem at hand.
- ► Critic
 - Produces training examples after an experiment
- Generalizer
 - Updates the learned target function using the critic's training examples

- ► Performance system
 - Uses the learned target function to solve the problem at hand.
- ► Critic
 - Produces training examples after an experiment
- Generalizer
 - Updates the learned target function using the critic's training examples
- Experiment generator

- ► Performance system
 - Uses the learned target function to solve the problem at hand.
- ► Critic
 - Produces training examples after an experiment
- Generalizer
 - Updates the learned target function using the critic's training examples
- Experiment generator
 - Creates an experiment to start the whole process over again

- ► Performance system
 - Uses the learned target function to solve the problem at hand.
- ► Critic
 - Produces training examples after an experiment
- Generalizer
 - Updates the learned target function using the critic's training examples
- Experiment generator
 - Creates an experiment to start the whole process over again