Deep Learning Techniques for Music Generation
Reinforcement (7)

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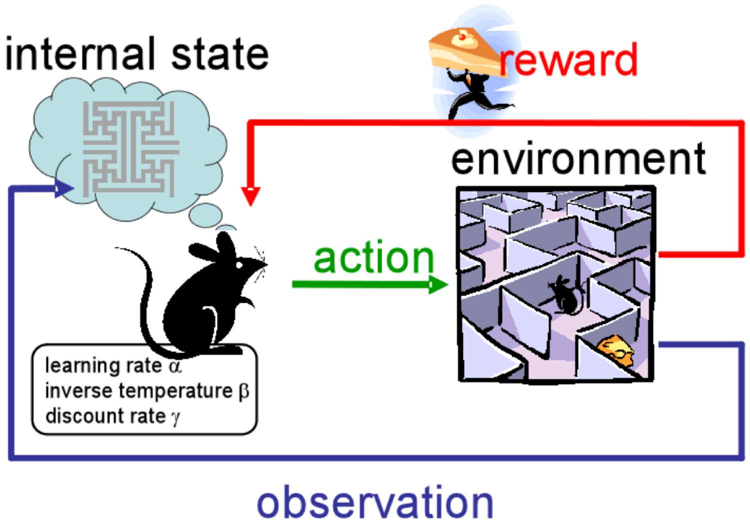
Reinforcement Learning

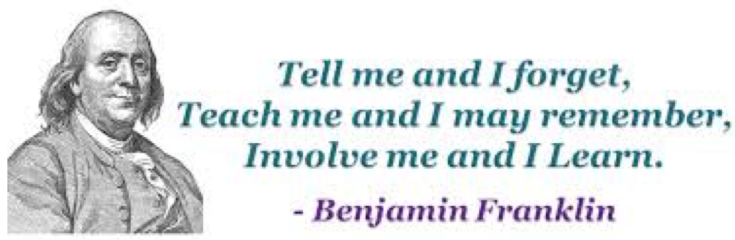
Reinforcement Learning [Sutton, 1984]

- Very Different Approach and Model (from Data Learning)
- Inspired from Behaviorist Psychology
- Based on Decisions/Actions
- (and States and Rewards)



[Figure from Cyber Rodent Project]

- Not Based on Dataset
- Not Supervised (No Labels/No Examples of Best Actions)
- Feedback (Delayed Rewards)
- Learning // Action (Trial and Error)



- Incremental

The only stupid question is the one you never ask [Sutton]

Reinforcement Learning [Sutton, 1984]

- Exploration vs Exploitation Dilemna
- Temporal/Delayed Credit Assignment Issue
- Formal Framework: Markov Decision Process (MDP)
- Sequential Decision Making
- Objective: Learn Optimal Policy (Best Action Decision for each State) to Maximize Expected Future Return/Gain (Accumulated Rewards)
- = Minimize Regret (Difference between expected Gain and optimal Policy's Gain)

Melody Generation

Example of Model

- State: Melody generated so far (Succession of notes)

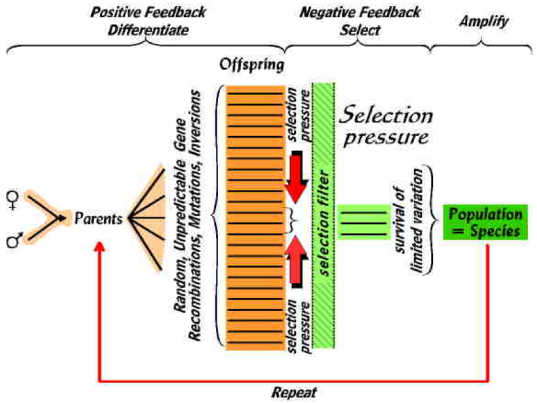
State   Action

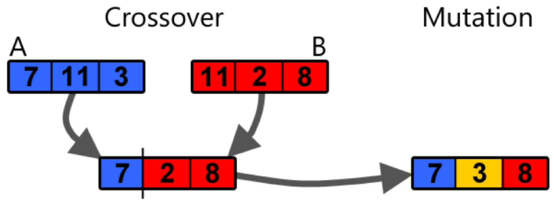
- Action: Generation of next note

- Feedback: Listener, or Musical Theory Rules, or/and…

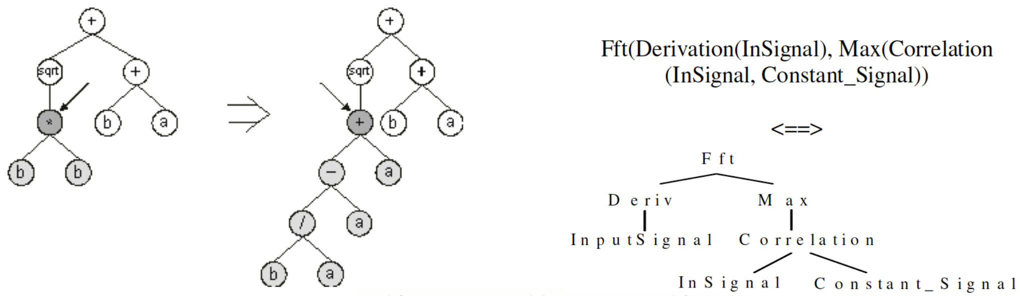
Evolutionary Algorithms, Genetic Algorithms and Programming

- Could be Considered as an Approach for Reinforcement Learning [Pack Kaebling et al. 1996]
- Search in the Space of Behaviors
- Selection based on Fitness

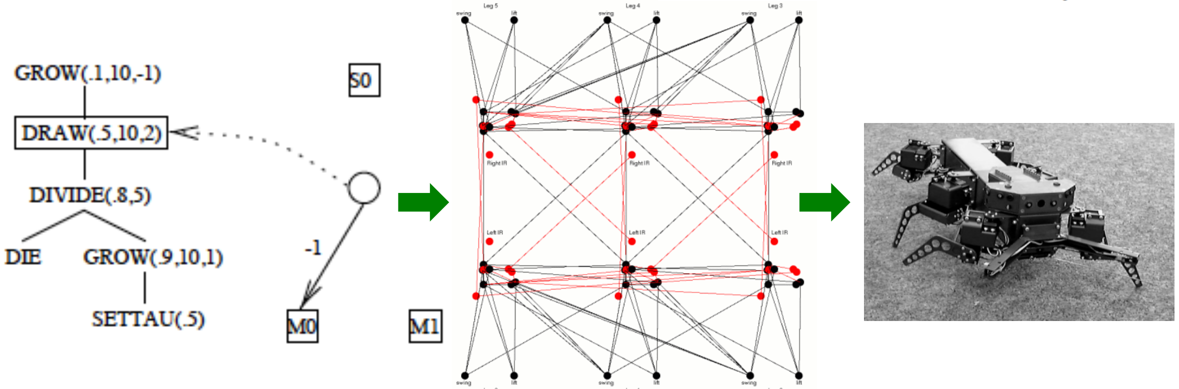




- Fitness: Global/Final Reward
- Off-Line Learning (Genotype -> Phenotype Generation)



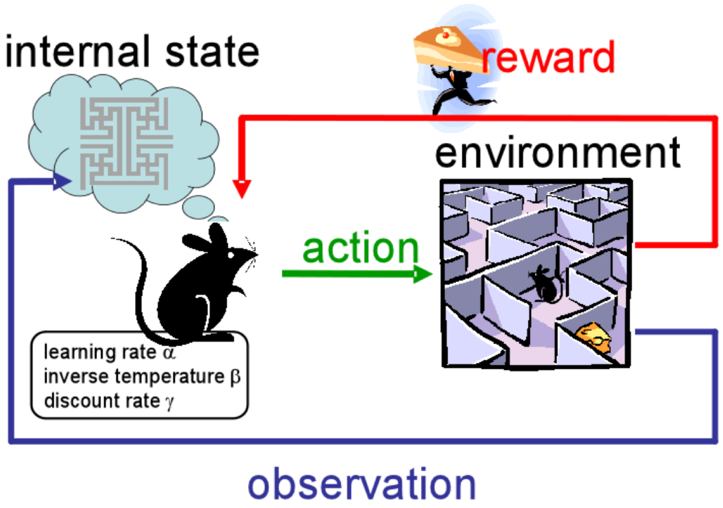
- Evolutionary Algorithms
- Genetic Algorithms [Holland 1975]
- Genetic Programming [Koza 1990]
  - Phenotype (Tree structure) = Genotype
- Morphogenetic Programming [Meyer et al. 1995]



Reinforcement Learning (RL)/MDP Basics [Silver 2015]

(at each step/time t)

- Observation o_t of the Environment
- Action a_t by the Agent
- Reward r_t from the Environment
  positive or negative



- History: Sequence of observations, actions, rewards
- $H_t = o_1, a_1, r_1, o_2, a_2, r_2, \ldots, o_t, a_t, r_t$

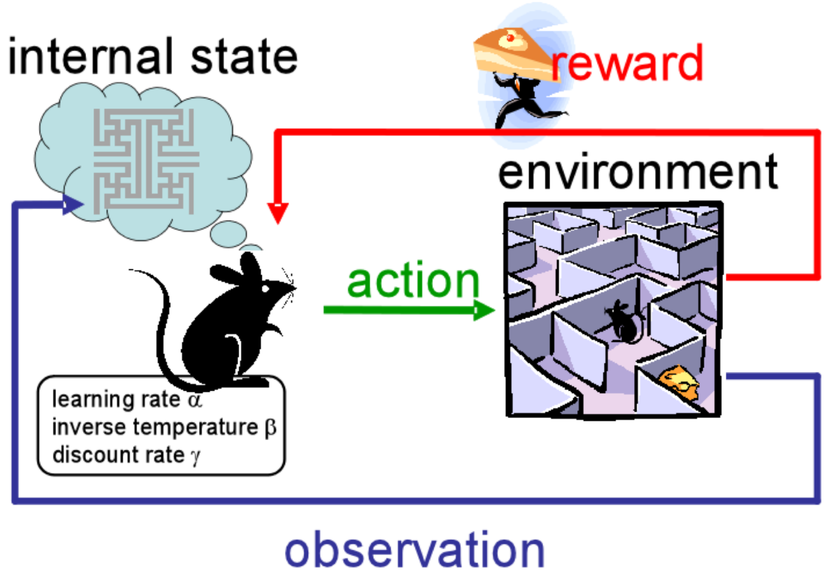
- What happens next depends on this history
  - Decision of the agent
  - Observation of the environment
  - Reward by the environment

- Full history is too huge

- State: summary (what matters) of the history $s_t = f(H_t)$

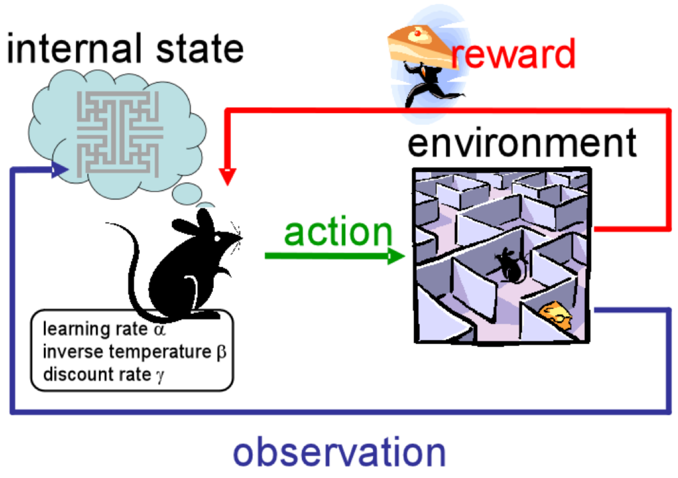
Reinforcement Learning (RL)/MDP Basics [Silver 2015]

Three Models of State [Silver 2015]:



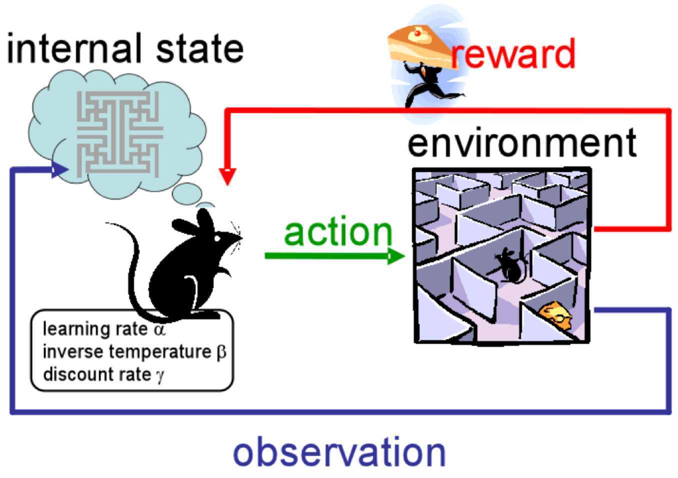
- Environment State
  - Environment private representation
  - Not usually visible to the agent nor completely relevant
- Agent State
  - Agent internal representation
- Information State (aka Markov State)
  - Contains useful information from the history
- Markov property: $P[s_{t+1} \mid s_t] = P[s_{t+1} \mid s_1, \ldots, s_t]$
  - Future is independent of the past, given the present = History does not matter
  - State is sufficient statistics/distribution of the future
  - By definition, Environment State is Markov
- Fully or Partially Observable Environment
  - Full: Markov Decision Process (MDP) *(Environment State = Agent State = Markov State)*
  - Partial: Partially Observable Markov Decision Process (POMDP)
    - » Ex. of Representations: Beliefs of Environment, Recurrent Neural Networks…

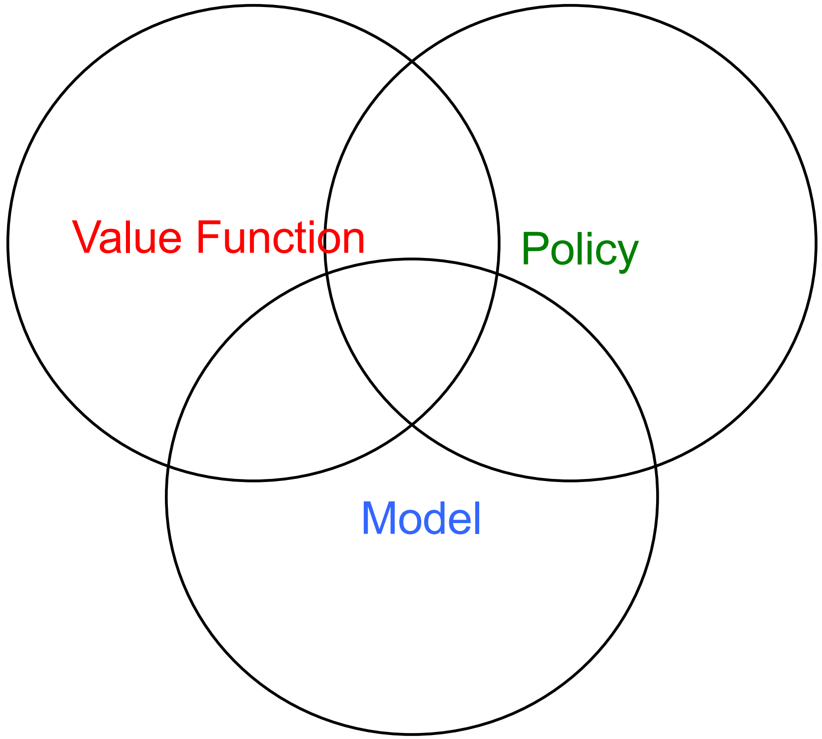
Reinforcement Learning First Ad-Hoc/Naive Approaches



- Greedy strategy
  - Choose the action with the highest estimated return
  - Limit: Exploitation without Exploration
- Randomized
  - Limit: Exploration without Exploitation
- Mix: ε-Greedy
  - ε probability to choose a random action, otherwise greedy
    - ε constant
    - or ε decreases in time from 1 (completely random) until a plateau
      - analog to simulated annealing

Reinforcement Learning Components [Silver 2015]





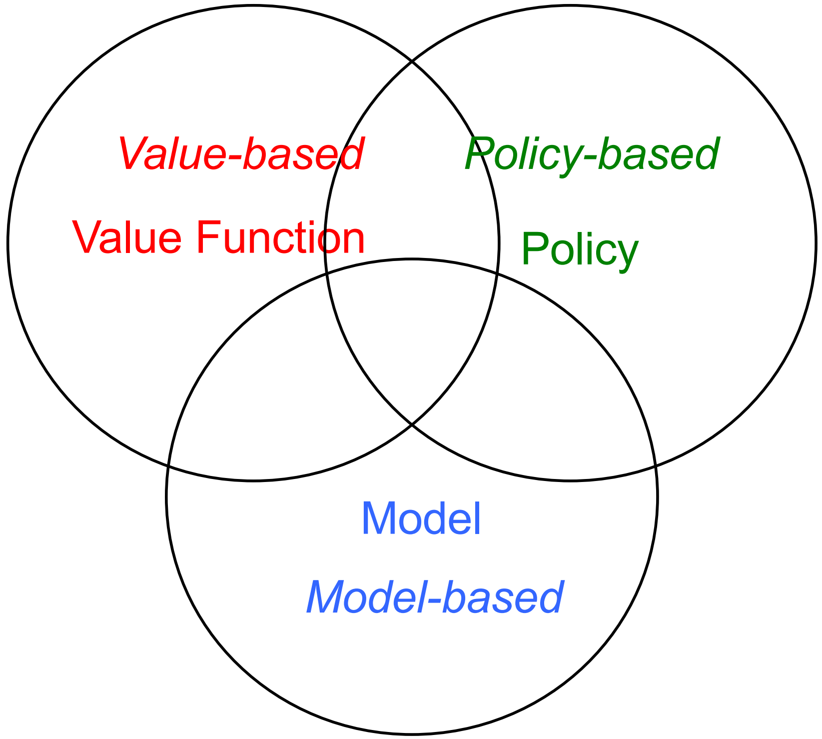
Three main components for RL [Silver 2015]:

- Policy
  - Agent behavior
  - $\pi(s) = a$ Function that, given a state, selects an action a
- Value Function
  - Value of the state Expected return
- Model
  - Representation of the environment

Main Approaches

Three main approaches for RL [Silver 2015]:

- Policy-based
- Value-based
- Model-based



- Policy-based
  – Search directly for Optimal Policy π^*
- Value-based
  – Estimate the Optimal Value $Q^*(s, a)$
  – Then choose Action with Highest Value function Q
    » $\pi(s) = \mathrm{argmax}_a\, Q(s, a)$
- Model-based
  – Learn (estimate) a Transition Model of the Environment E
    » $T(s, a) = s'$
    » $R(s, a) = r$
  – Plan Actions (e.g., by Lookahead) using the Model
- Mixed
  – Concurrent/Cooperative/Mutual Search/Approximations/Iterations

Value Function(s)

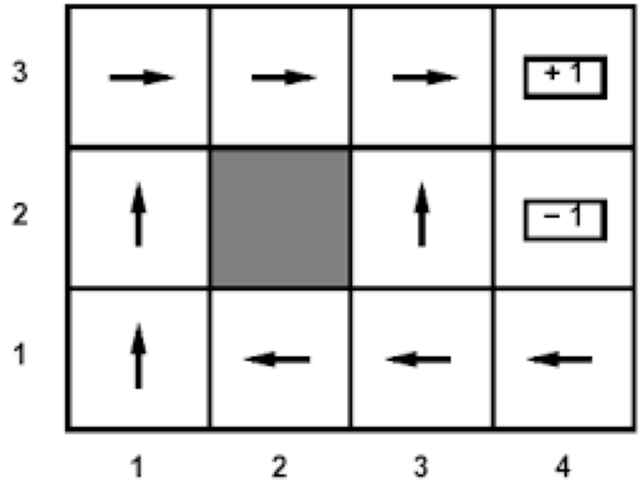
- State Value Function
  - Value of the state
  - Expected return
  - $V^{\pi}(s_t) = E^{\pi}[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \gamma^3 r_{t+3} + \ldots]$
  - Discount factor γ € [0 1] (Infinite Horizon Discounted Model)
    - » Uncertainty about the future (Life Expectancy + Stochastic Environment)
    - » Boundary of ∞ (ex: avoids infinite returns from cycles)
    - » Biological (more appetance for immediate reward :) 
    - » Mathematically tractable
    - » $\gamma = 0$: short-sighted

- Action Value Function
  - Value of the state and action pair
  - $Q^{\pi}(s, a)$
  - $V^{\pi}(s) = Q^{\pi}(s, \pi(s))$

- Bellman Equation [Bellman 1957]
  - value = instant reward + discounted value of next state
  - $V^{\pi}(s_t) = E^{\pi}[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \gamma^3 r_{t+3} + \ldots] = E^{\pi}[r_t] + \gamma V^{\pi}(s_{t+1})$
  - $Q^{\pi}(s_t, a_t) = E^{\pi}[r_t] + \gamma Q^{\pi}(s_{t+1}, a_{t+1})$

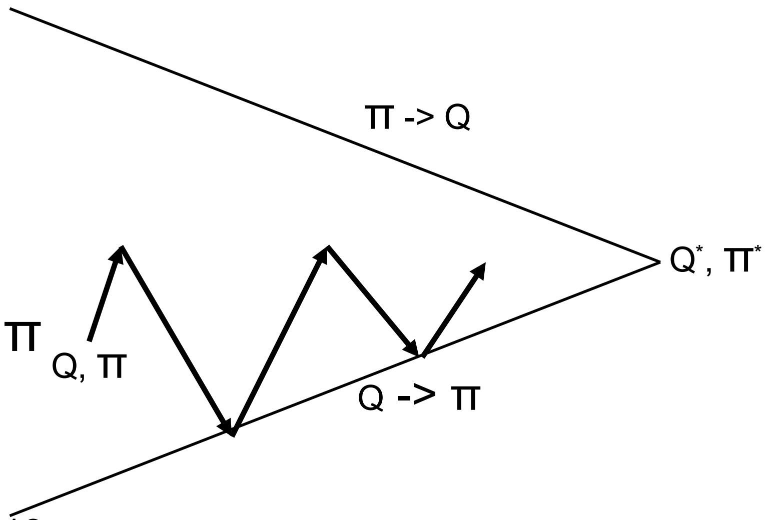
Policy-based and Value-based Approaches

- Policy-based
  - Search directly for Optimal Policy π^*
  - On-Policy learning [Silver 2015]: Learn policy that is currently being followed (acted)
  - Iterative Methods
    - » Monte-Carlo
      - Replace expected return with mean return (mean of samples returns)
    - » TD (Temporal Difference) [Sutton 1988]
      - Difference between estimation of the return *before* action and *after* action
      - On-line learning
      - TD(0)
      - TD(λ) (updates also states already visited λ times)



- Value-based
  - Estimate the Optimal Value $Q^*(s, a)$
  - Then choose Action with Highest Value function Q
  - $\pi^*(s) = \text{argmax}_a\, Q^*(s, a)$

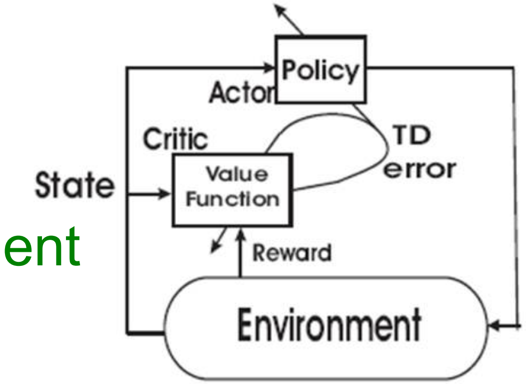
- Mix //
  - Iterative Policy evaluation: TD or SARSA to Estimate Q from π
  - Policy improvement: Select π via ε-greedy selection from Q
  - Iterate $\pi^* \longleftrightarrow Q^*$



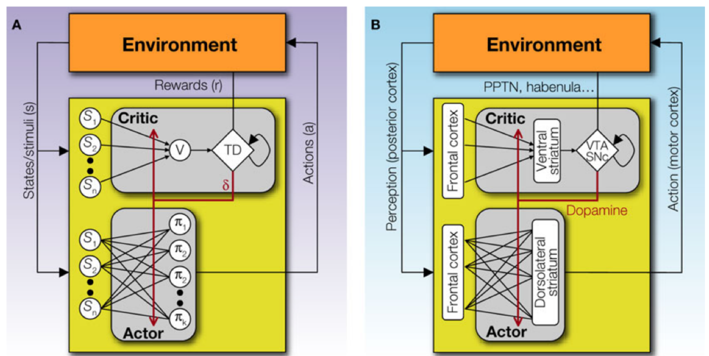
Actor-Critic [Barto et al. 1983]

- Actor-Critic approach combines
  - Policy-based
  - Value-based

  > Actor Critic-based



- Similar to Iterative Policy evaluation // Policy improvement
- Actor acts and learns Policy
  - Uses a RL Component
  - Tries to Maximize the *Heuristic* Value of the Return (Value), *computed by the Critic*
- Critic learns Returns (Value) in order to Evaluate Policy
  - Uses Temporal Difference (TD(0) Algorithm [Sutton 1988])
  - TD = Difference between estimation of the Return (Value) *before* Action and *after* Action
  - Learns Mapping from States to Expected Returns (Values), given the Policy of the Actor
  - Communicates the Updated Expected Value to the Actor
- Run in //
- Co/Mutual-Improvement
- Recent (Partial) Biological Corroboration



Artificial Biological

[Tomasik 2012]

Off-Policy Learning and Q-Learning

- Off-Policy learning [Silver 2015]
  - Idea: Learn from observing self history (off-line) or from other agents
  - Advantage: Learn about a policy (ex: optimal) while following a policy (ex: exploratory)
  - Estimate the expectation (value) of a different distribution

- Q-Learning [Watkins 1989]

- Analog to TD // ε-greedy & Actor Critic but Integrates/Unifies them
  - Estimate Q and use it to define Policy

- Q-Table(s, a)

- Update Rule:
  - $Q(s, a) := Q(s, a) + \alpha(\boxed{r + \gamma \max_{a'} Q(s', a')} - Q(s, a))$

$$Q^*(s, a) = \boxed{r + \gamma \max_{a'} Q(s', a')}$$ *Bellman equation*

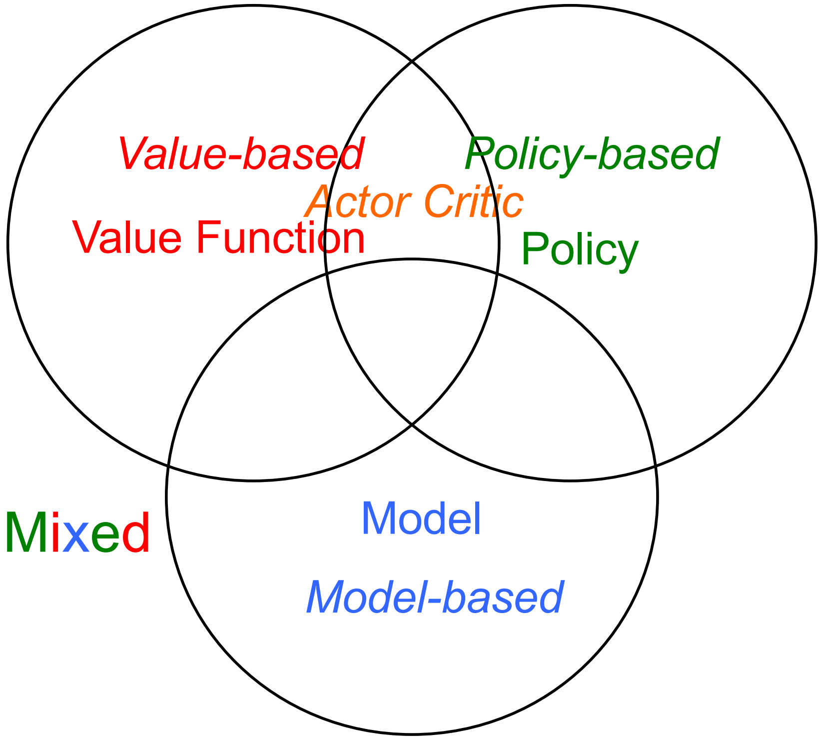
- Exploration insensitive
  - The Exploration vs Exploitation Issue will not affect Convergence

Q-Learning Algorithm

initialize Q table(#*states*, #*actions*) arbitrarily;
observe initial state *s*;
repeat
    select and carry out action *a*;
    observe reward *r* and new state *s'*;
    $Q(s, a) := Q(s, a) + \alpha(r + \gamma \max_{a'} Q(s', a') - Q(s, a))$;   update rule
    $s := s'$;
until terminated

Model-Based Reinforcement Learning

- Model-based
  - Learn (estimate) a Transition Model of the Environment E
    - » T(s, a) = s’ or/and R(a, s) = r
  - (in //) Use the Model
    - » Plan Actions (e.g., by Lookahead) using the Model
    - » Or Adjust the Policy: Dyna [Sutton 1990]
      - Build Model and Adjust Policy (Mixed approach)



- Most of Current Models and Algorithms Used are Mixed
  - They use Mutual Cooperative Solutions, Ex:
  - Policy // Value
    - » Actor-Critic [Barto et al. 1983]
    - » SARSA – ε-greedy
    - » Q-Learning [Watkins 1989]
  - Model // Policy
    - » Dyna [Sutton 1990]
  - They also have Variants (Optimizations, Extensions, Combinations...)
    - » Ex: Queue-Dyna, Prioritized Sweeping, RTDP, VRDP, Feudal Q-Learning...

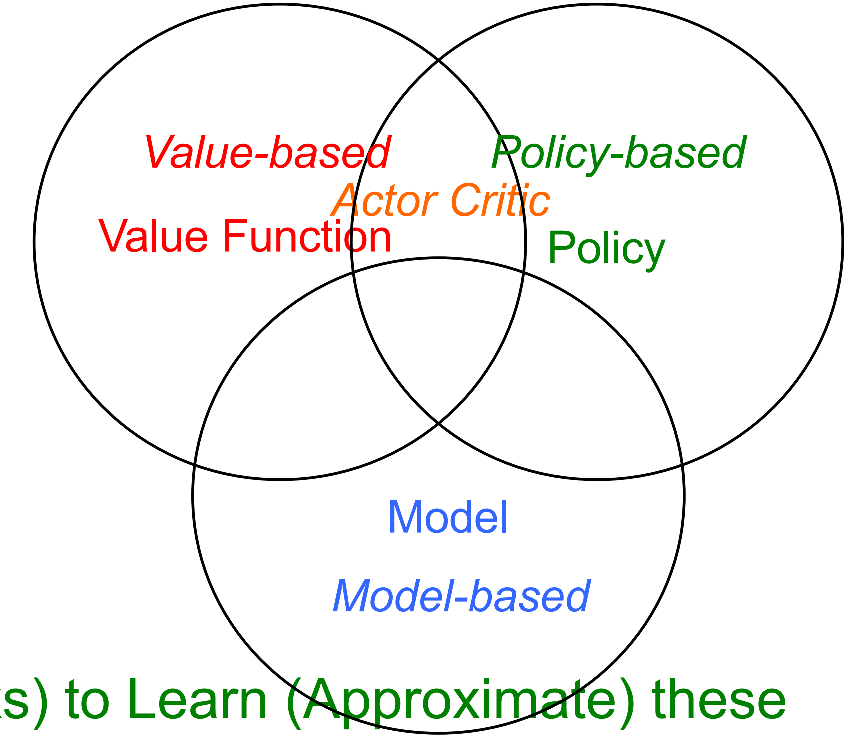
Model-Based Reinforcement Learning

- Q-Learning is the most known and is widely used
- Still, the user needs to adjust the exploration vs exploitation tradeoff
  - Ex: more exploration at the beginning
  - And more greedy at the end (once near convergence)
- There is No Best General Approach/Algorithm
- This Depends on Application/Scenario Characteristics
  - Information Known a priori (ex: Transition Model) vs None
  - Relative Computation vs Experience Costs (and Risks: ex: Death !)
  - Algorithm Complexity (Space and Time) vs Memory and Computing Power
  - Determinism vs Stochastic
  - Timing Constraints vs Near Optimality Convergence
  - Simplicity
  - Possibility of Incorporating Human Expertise

Storage/Memory Issue

- Important Issue: Storing the Transition Model
  - It may be huge

- Same issue for other possible Mappings
  - Policies: s -> a
  - State value function: s -> R
  - Action value function: <s, a> -> R
  - …



- Use of Supervised Learning (ex: Neural Networks) to Learn (Approximate) these Mappings from Examples
  - REINFORCE [Williams 1987]
  - Recurrent Q-learning [Schmidhuber 1991]
  - TD-Gammon [Tesauro 1992]
    - » Neural Network with TD-Learning (TD-based, in place of Backpropagation)
    - » Expert level
    - » But tentatives to apply to other games were not successful… until…
    - » Success in Backgammon : finite game (reward info) and transitions sufficiently stochastic (exploration)

Deep Reinforcement Learning [Silver et al. 2013]

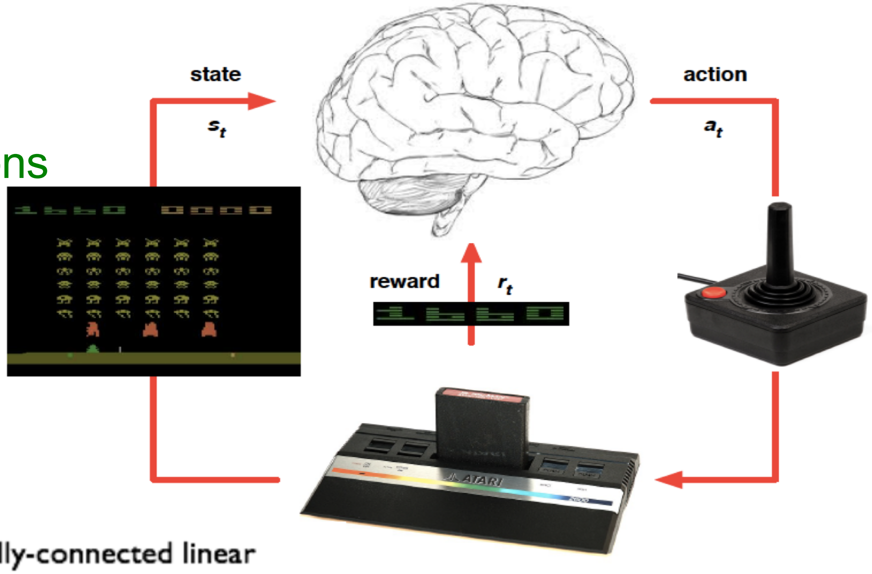
- Use Deep Network to represent:
  - Policy
  - or Value
  - or Model

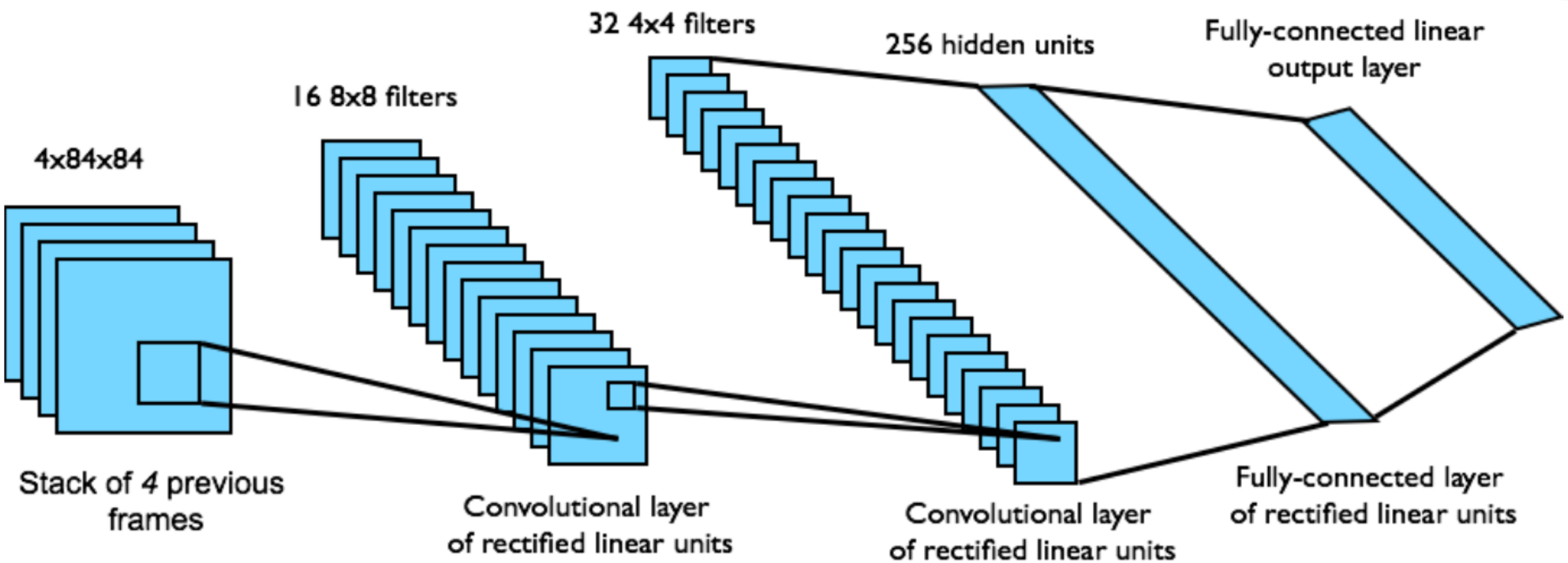
- Optimize it (Policy, or Value or Model) end-to-end by using stochastic gradient descent [Silver 2016]

- Ex: Deep Q-Learning [Minh et al. 2013]
- Represent Value function by a Deep Q-Network $Q(s, a, w) \approx Q^{\pi}(s, a)$
- Train Value function Deep Network with inputs (<state,action> pairs) and outputs (values)

Deep Q-Learning [Minh et al. 2013]

- Atari Games Playing (DeepMind Technologies)
- Represent Value function as a Deep Q-Network
- Training of Value function Network
  - Inputs: Game screen raw pixels & joystick/button positions
  - Outputs: Q-values (captured from game play)
    - » Reward € {-1, 0, 1}
- On-Line Training through Game Play
- Works with ANY (ATARI) Game !





Q-Learning Algorithm [Watkins 1989]

initialize Q table(*#states*, *#actions*) arbitrarily;
observe initial state *s*;
repeat
    select and carry out action *a*;
    observe reward *r* and new state *s'*;
    $Q(s, a) := Q(s, a) + \alpha(r + \gamma \max_{a'} Q(s', a') - Q(s, a))$;   update rule
    s := *s'*;
until terminated

New Deep Q-Learning Update Rule

1. feedforward pass for current state s to predict Q-values for all possible actions;
2. feedforward pass for next state s' and select largest Q-value: maxQ := $\max_{a'} Q(s', a')$;
3. for the action corresponding to maxQ, set Q-value target to r + γ maxQ;
   for each other action, set Q-value target to Q-value predicted in step 1;
   (This means error will be 0 for them)
4. update the weights using backpropagation.

Deep Q-Learning Algorithm [Minh et al. 2013]

initialize Q table(*#states*, *#actions*) arbitrarily;
observe initial state *s*;
repeat
    select and carry out action *a*;
    observe reward *r* and new state *s'*;
    feedforward pass for current state s to predict Q-values for all possible actions;
    feedforward pass for next state s' and select largest Q-value: maxQ := $\max_{a'} Q(s', a')$;
    for the action corresponding to maxQ, set Q-value target to $r + \gamma$ maxQ;
    for each other action, set Q-value target to Q-value predicted in step 1;
    update the weights using backpropagation;
    s := s';
until terminated

Deep Reinforcement Learning Algorithm [Minh et al. 2013]

(Main) Tricks/Optimizations:

1. Inputs/Outputs
   - Input: the four last screens (images/pixels)
   - Output: Q-values for each possible action

2. Experience Replay
   - During game play, all experiences (<*a, a, s', a'*>) are stored in a replay memory
   - During training, random minibatches form the replay memory are used
   - Avoids similarity situation and favors exploration/generalization

2. ε-Greedy Exploration
   - ε Probability to choose a random action, otherwise greedy (choose action with highest Q-value)
   - ε decreases in time from 1 (completely random) until a plateau (0.1)
     » analog to simulated annealing

Deep Search and Deep Reinforcement Learning

- Deep Search (and Deep Reinforcement Learning)
- AlphaGo Go Playing (Google DeepMind) [Silver et al. 2016]
- 2 Deep Networks to reduce search space
- "Policy Network" predicts next move and reduces width
- "Value Network" estimates winner in each position and reduces depth (analog to but better than alpha-beta pruning)
- Also Uses Reinforcement Learning to learn better policies,
- in order to improve the "Policy network",
- and in turn to improve the "Value Network"

AlphaGo 3 – 0 Ke Jie
27/05/2017