NPFL099 Statistical Dialogue Systems
6. Dialogue Policy

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http://ufal.cz/npfl099

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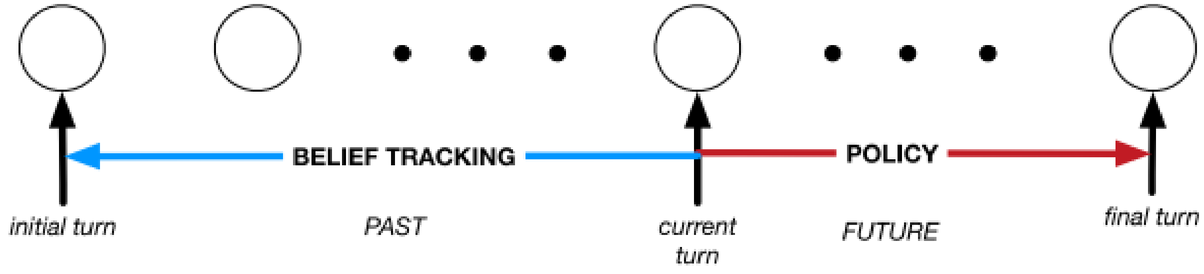
Dialogue Management

- Two main components:
  - **State tracking** (last lecture)
  - **Action selection/Policy** (today)



(from Milica Gašić's slides)

- action selection – deciding what to do next
  - based on the current belief state – under uncertainty
  - following a **policy** (strategy) towards an end **goal** (e.g. book a flight)
  - controlling the coherence & flow of the dialogue
  - actions: linguistic & non-linguistic
- DM/policy should:
  - manage uncertainty from belief state
  - recognize & follow dialogue structure
  - plan actions ahead towards the goal

Did you say Indian or Italian?

follow convention, don't be repetitive

e.g. ask for all information you require

Action Selection Approaches

- Finite-state machines
  - simplest possible
  - dialogue state is machine state
- Frame-based (VoiceXML)
  - slot-filling + providing information – basic agenda
  - rule-based in essence
- Rule-based
  - any kind of rules (e.g. Python code)
- **Statistical**
  - typically using **reinforcement learning**

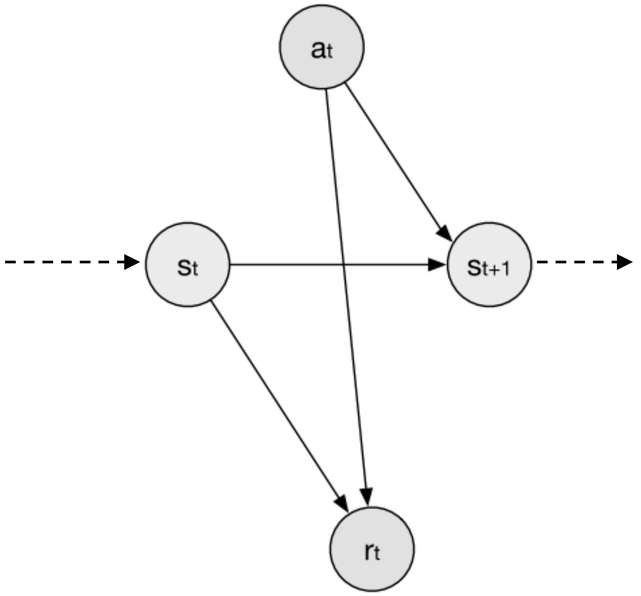
Why Reinforcement Learning

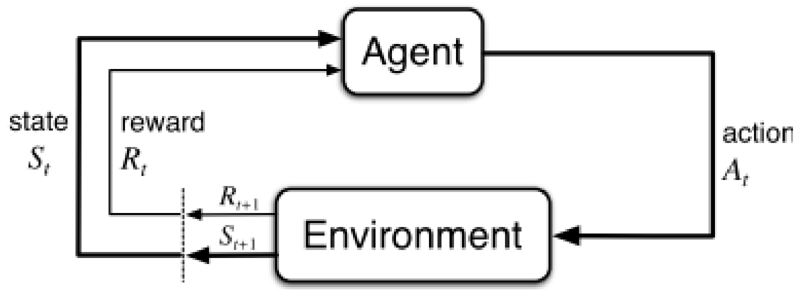
- **Action selection ~ classification** → use supervised learning?
  - set of possible actions is known
  - belief state should provide all necessary features
- Yes, but…
  - You'd **need** sufficiently large **human-human data** – hard to get
    - human-machine would just mimic the original system
  - Dialogue is ambiguous & complex
    - there's **no single correct next action**– multiple options may be equally good
    - but datasets will only have one next action
    - **some paths will be unexplored** in data, but you may encounter them
  - DSs won't behave the same as people
    - ASR errors, limited NLU, limited environment model/actions
    - **DSs should behave differently** – make the best of what they have

RL World Model: Markov Decision Process

- MDP = probabilistic control process
  - modelling situations that are partly random, partly controlled
  - **agent** in an **environment**:
    - has internal **state** $s_t \in \mathcal{S}$ (~ dialogue state)
    - takes **actions** $a_t \in \mathcal{A}$ (~ system dialogue acts)
    - actions chosen according to **policy** $\pi: \mathcal{S} \rightarrow \mathcal{A}$
    - gets **rewards** $r_t \in \mathbb{R}$ & state changes from the environment
  - rewards are typically handcrafted
    - very high positive for a successful dialogue (e.g. +40)
    - high negative for unsuccessful dialogue (-10)
    - small negative for every turn (-1, promote short dialogues)
  - Markov property – state defines everything
    - no other temporal dependency
  - policy may be **deterministic** or **stochastic**
    - stochastic: prob. dist. of actions, sampling

(from Milica Gašić's slides)



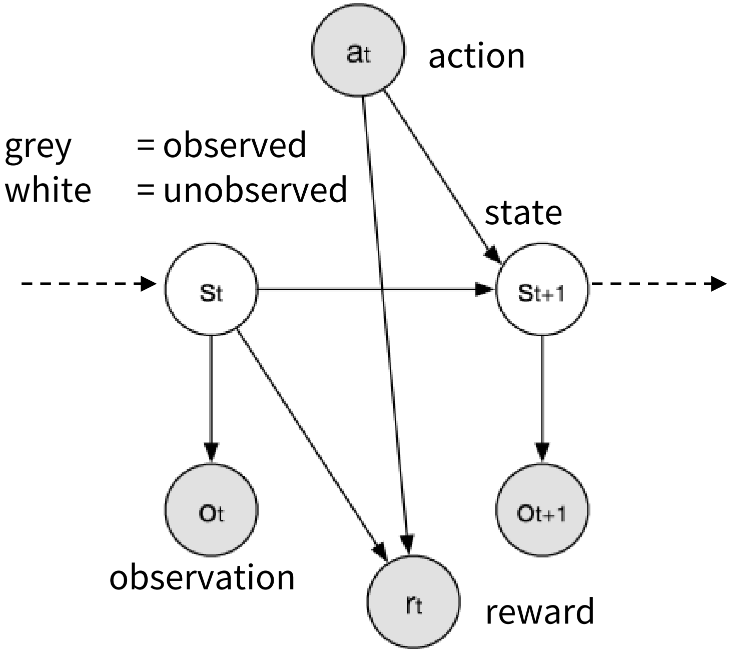


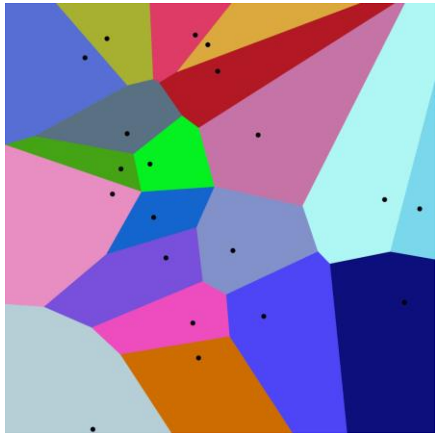
(Sutton & Barto, 2018)

Partially-observable MDPs

- POMDPs – **belief** states instead of dialogue states
  - true states ("what the user wants") are not observable
  - observations ("what the system hears") depend on states
  - belief – probability distribution over states
  - can be viewed as **MDPs with continuous-space states**
- All MDP algorithms work…
  - if we **quantize/discretize** the states
  - use grid points & nearest neighbour approaches
  - this might introduce errors / make computation complex
- Deep RL typically works out of the box
  - function approximation approach, allows continuous states

(from Milica Gašić's slides)

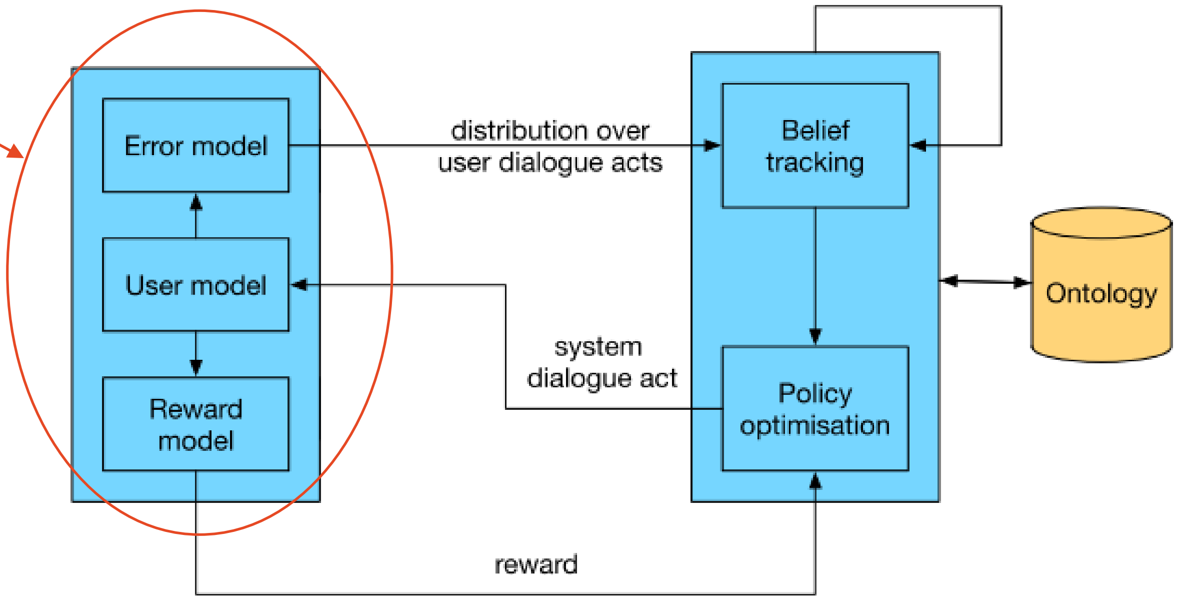




https://en.wikipedia.org/wiki/Voronoi_diagram

Simulated Users

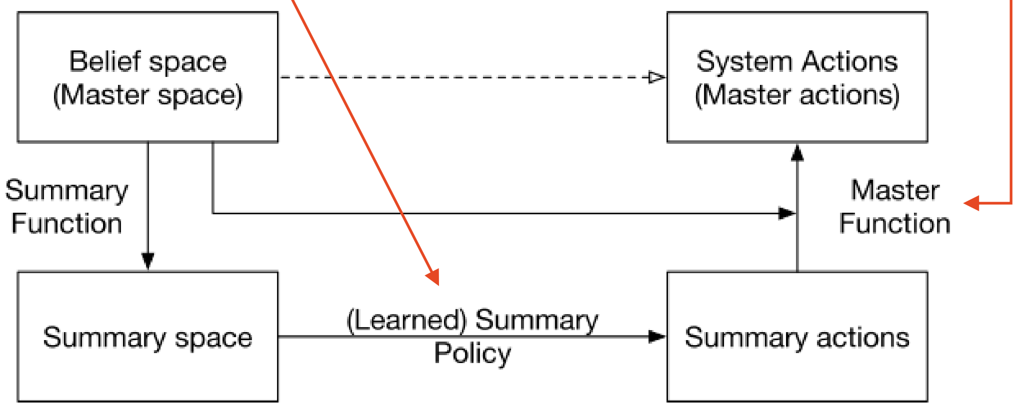
- Static datasets aren't enough for RL
  - on-policy algorithms don't work
  - data might not reflect our newly learned behaviour
- RL needs a lot of data, more than real people would handle
  - 1k-100k's dialogues used for training, depending on method
- solution: **user simulation**
  - basically another DS/DM
  - (typically) working on DA level
  - errors injected to simulate ASR/NLU
- approaches:
  - rule-based (frames/agenda)
  - n-grams
  - MLE/supervised policy from data
  - combination (best!)



(from Milica Gašić's slides)

Summary Space

- for a typical DS, the belief state is too large to make RL tractable
- solution: map state into a reduced space, optimize there, map back
- reduced space = **summary space**
  - handcrafted state features
  - e.g. top slots, # found, slots confirmed…
- reduced action set = **summary actions**
  - e.g. just DA types (*inform, confirm, reject*)
  - remove actions that are not applicable
  - with handcrafted mapping to real actions
- state is still tracked in original space
  - we still need the complete information for accurate updates



(from Milica Gašić's slides)

Reinforcement learning: Definition

- RL = finding a **policy that maximizes long-term reward**
  - unlike supervised learning, we don't know if an action is good
  - immediate reward might be low while long-term reward high

alternative – **episodes**: only count to T when we encounter a terminal state (e.g. 1 episode = 1 dialogue)

accumulated long-term reward

$$R_t = \sum_{t=0}^{\infty} \gamma^t r_{t+1}$$

$\gamma \in [0,1]$ = **discount factor** (immediate vs. future reward trade-off)

$\gamma < 1$: R_t is finite (if r_t is finite)
$\gamma = 0$: greedy approach (ignore future rewards)

- state transition is stochastic → maximize **expected return**

$$\mathbb{E}[R_t|\pi, s_0]$$

expected R_t if we start from state s_0 and follow policy π

State-value Function

- Using return, we define the **value of a state** s under policy π: $V^\pi(s)$
  - Expected return for starting in state s and following policy π
- Return is recursive: $R_t = r_{t+1} + \gamma \cdot R_{t+1}$
- This gives us a recursive equation (**Bellman Equation**):

$$V^\pi(s) = \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t r_{t+1} | \pi, s_0 = s\right] = \sum_{a\in\mathcal{A}} \underbrace{\pi(s,a)}_{\text{prob. of choosing } a \text{ from } s \text{ under } \pi} \sum_{s'\in\mathcal{S}} \underbrace{p(s'|s,a)}_{\text{transition probs.}} \Big(\underbrace{r(s,a,s')}_{\text{expected immediate reward}} + \gamma V^\pi(s')\Big)$$

- $V^\pi(s)$ defines a **greedy policy**:

actions that look best for the next step

$$\pi(s,a) := \begin{cases} \frac{1}{\#\text{ of } a's} \text{ for } a = \arg\max_a \sum_{s'\in\mathcal{S}} p(s'|s,a)(r(s,a,s') + \gamma V^\pi(s')) \\ 0 \text{ otherwise} \end{cases}$$

Action-value (Q-)Function

- $Q^\pi(s,a)$ – return of taking action a in state s, under policy π
  - Same principle as value $V^\pi(s)$, just **considers the current action, too**
  - Has its own version of the Bellman equation

$$Q^\pi(s,a) = \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t r_{t+1} | \pi, s_0 = s, a_0 = a\right] = \sum_{s'\in\mathcal{S}} p(s'|s,a)\left(r(s,a,s') + \gamma \sum_{a'\in\mathcal{A}} Q^\pi(s',a')\pi(s',a')\right)$$

- $Q^\pi(s,a)$ also defines a greedy policy:

again, "actions that look best for the next step"

$$\pi(s,a) \coloneqq \begin{cases} \frac{1}{\#\text{ of } a's} \text{ for } a = \arg\max_a Q^\pi(s,a) \\ 0 \text{ otherwise} \end{cases}$$

simpler: no need to enumerate s',
no need to know $p(s'|s,a)$ and $r(s,a,s')$

but Q function itself tends to be more complex than V

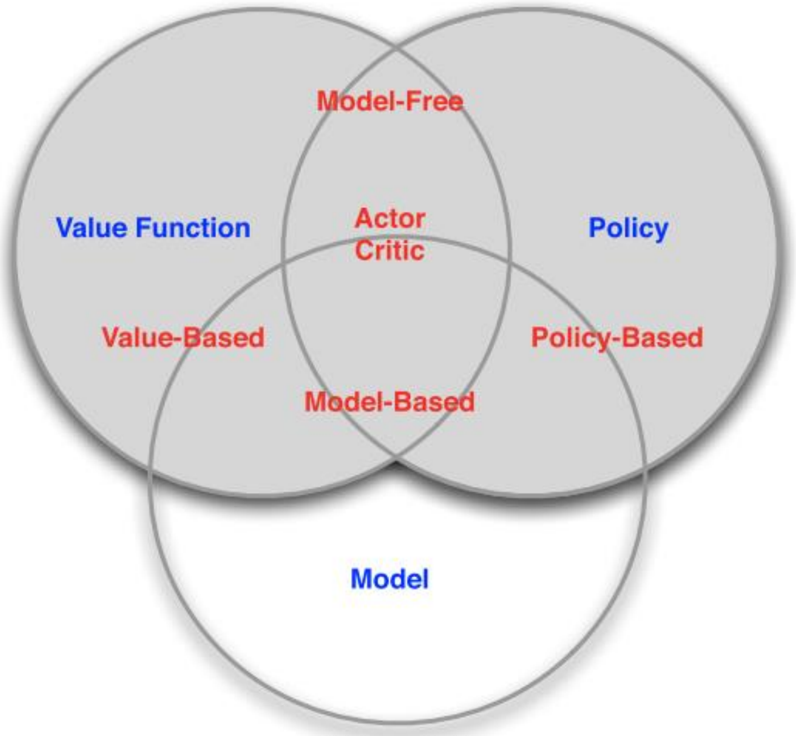
Optimal Policy in terms of V and Q

- **optimal policy** π^* – one that maximizes expected return $\mathbb{E}[R_t|\pi]$
  - $V^\pi(s)$ expresses $\mathbb{E}[R_t|\pi]$ → use it to define π^*
- π^* is a policy such that $V^{\pi^*}(s) \geq V^{\pi'}(s) \;\; \forall \pi', \forall s \in \mathcal{S}$
  - π^* always exists in an MDP (need not be unique)
  - π^* has the **optimal state-value function** $V^*(s) \coloneqq \max_\pi V^\pi(s)$
  - π^* also has the **optimal action-value function** $Q^*(s,a) \coloneqq \max_\pi Q^\pi(s,a)$
- greedy policies with $V^*(s)$ and $Q^*(s,a)$ are optimal
  - we can search for either $\pi^*, V^*(s)$ or $Q^*(s,a)$ and get the same result
  - each has their advantages and disadvantages

RL Agents Taxonomy

- Quantity to optimize:
  - value function – **critic** ← main focus today
    - either Q or V, typically Q in practice
  - policy – **actor**
  - both – **actor-critic**

  next week
- Environment model:
  - **model-based** (assume known $p(s'|s,a), r(s,a,s)$)
    - nice but typically not satisfied in practice
  - **model-free** (don't assume anything, sample)
    - this is the usual real-world case
    - this is where using Q instead of V comes handy



(from David Silver's slides)

Reinforcement Learning Approaches

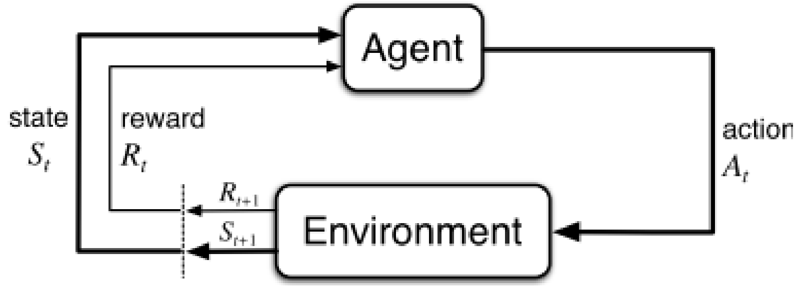
- How to optimize:
  - **dynamic programming** – find the exact solution from Bellman equation
    - iterative algorithms, refining estimates
    - expensive, assumes known environment → not practical for real-world use
  - **Monte Carlo learning** – learn from experience
    - sample, then update based on experience
  - **Temporal difference learning** – like MC but look ahead (bootstrap)
    - sample, refine estimates as you go

both used in practice

- Sampling & updates:
  - **on-policy** – improve the policy while you're using it for decisions
    - can't use that with batch learning (decision policy is changing constantly)
  - **off-policy** – decide according to a different policy

Deep Reinforcement Learning

- Exactly the same as "plain" RL
  - agent & environment, actions & rewards
- **"deep" = part of the agent is handled by a NN**
  - value function (typically Q)
  - policy
- function approximation approach
  - Q values / policy are represented as a parameterized function $Q(s, a; \boldsymbol{\theta})$ / $\pi(s; \boldsymbol{\theta})$
  - enumerating in a table would take up too much space, be too sparse
  - the parameters θ are optimized
- assuming huge state space
  - much fewer weights than possible states
  - update based on one state changes many states
- needs tricks to make it stable



(Sutton & Barto, 2018)

Q-Learning

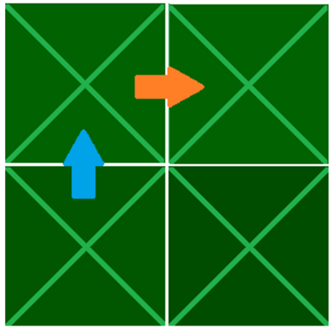
- temporal difference – update Q as you go
- off-policy – directly estimates best Q^*
  - regardless of policy used for sampling
- choose learning rate α, initialize Q arbitrarily
- for each episode:
  - choose initial s
  - for each step:
    - choose a from s according to **ϵ-greedy policy** based on Q
    - take action a, observe observe reward r and state s'
    - $Q(s,a) \leftarrow (1-\alpha)\cdot Q(s,a) + \alpha \underbrace{\left(r + \gamma \cdot \max_{a'} Q(s', a')\right)}$
  - $s \leftarrow s'$

any policy that chooses all actions & states enough times will converge to $Q^*(s,a)$:
we need to explore to converge

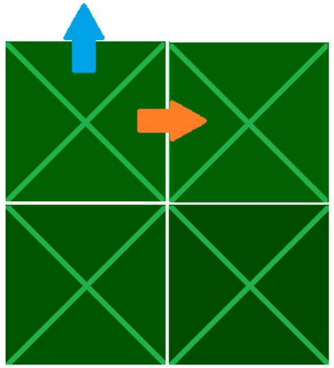
$$a = \begin{cases} \arg\max_a Q(s,a) & \text{with probability } 1-\epsilon \\ \text{random action with probability } \epsilon \end{cases}$$

update uses best a', regardless of current policy:
a' is not necessarily taken in the actual episode

TD: moving estimates



State: S
Action taken: North
Action with max Q value at S': East



State: S'
Action taken: North (any action)

https://towardsdatascience.com/td-in-reinforcement-learning-the-easy-way-f92ecfa9f3ce

Animated example for SARSA & Q-Learning: https://cs.stanford.edu/people/karpathy/reinforcejs/gridworld_td.html

Deep Q-Networks

- Q-learning, where Q function is represented by a neural net
- "Usual" Q-learning doesn't converge well with NNs:
  a) SGD is unstable
  b) correlated samples (data is sequential)
  c) TD updates aim at a moving target (using Q in computing updates to Q)
  d) scale of rewards & Q values unknown → numeric instability
- → DQN adds fixes:
  a) minibatches (updates by averaged n samples, not just one)
  b) experience replay
  c) freezing target Q function
  d) clipping rewards

cool!

common NN tricks

(Mnih et al., 2013, 2015)
http://arxiv.org/abs/1312.5602
http://www.nature.com/articles/nature14236

DQN tricks ~ making it more like supervised learning

- **Experience replay** – break correlated samples
  - run through some episodes (dialogues, games…)
  - store all tuples (s, a, r', s') in a buffer
  - for training, don't update based on most recent moves – use buffer
    - sample minibatches randomly from the buffer
  - overwrite buffer as you go, clear buffer once in a while
  - only possible for off-policy

"generate your own 'supervised' training data"

$$\text{loss} := \mathbb{E}_{(s,a,r',s') \in \text{buf}} \left[\left(r' + \gamma \max_{a'} Q\left(s', a'; \overline{\boldsymbol{\theta}}\right) - Q(s, a; \boldsymbol{\theta}) \right)^2 \right]$$

- **Target Q function freezing**
  - fix the version of Q function used in update targets
    - have a copy of your Q network that doesn't get updated every time
  - once in a while, copy your current estimate over

"have a fixed target, like in supervised learning"

DQN algorithm

- initialize $\boldsymbol{\theta}$ randomly
- initialize replay memory D (e.g. play for a while using current $Q(\boldsymbol{\theta})$)
- repeat over all episodes:
  - set initial state s
  - for all timesteps $t = 1 \dots T$ in the episode:
    - select action a_t from ϵ-greedy policy based on $Q(\boldsymbol{\theta})$
    - take a_t, observe reward r_{t+1} and new state s_{t+1}
    - store $(s_t, a_t, r_{t+1}, s_{t+1})$ in D

    storing experience (1 step of Q-learning exploration)

    - sample a batch B of random (s, a, r', s')'s from D
    - update $\boldsymbol{\theta}$ using loss $\mathbb{E}_{(s,a,r',s')\in B}\left[\left(r' + \gamma \max_{a'} Q\left(s', a'; \overline{\boldsymbol{\theta}}\right) - Q(s, a; \boldsymbol{\theta})\right)^2\right]$

    "replay" a. k. a. training (1 update)

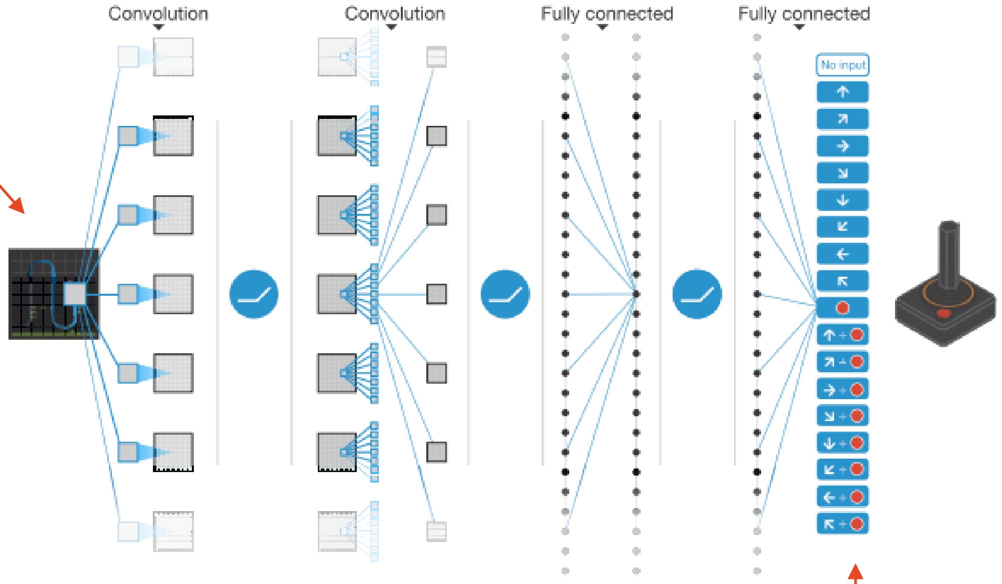
  - once every λ steps (rarely):
    - $\overline{\boldsymbol{\theta}} \leftarrow \boldsymbol{\theta}$

update the frozen target function

DQN for Atari

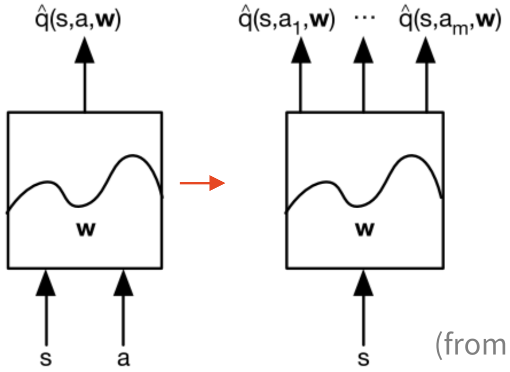
- 4-layers:
  - 2x CNN
  - 2x fully connected with ReLU activations
- Another trick:
  - output values for all actions at once
    - ~ vector $\boldsymbol{Q}(s)$ instead of $Q(s,a)$
    - a is not fed as a parameter
  - faster computation
- Learns many games at human level
  - with the same network structure
  - no game-specific features

input: Atari 2600 screen,
downsized to 84x84 (grayscale)
4 last frames



values for all actions
(joystick moves)

(Mnih et al., 2015)



(from David Silver's slides)

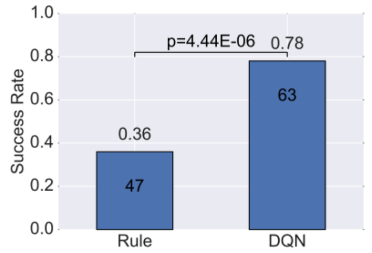
https://youtu.be/V1eYniJ0Rnk?t=18

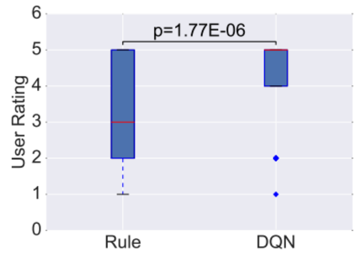
DQN for Dialogue Systems

(Li et al., 2017)
https://arxiv.org/abs/1703.01008
https://github.com/MiuLab/TC-Bot

(Lipton et al., 2018)
https://arxiv.org/abs/1608.05081

- DQN can drive dialogue action selection/policy
- **warm start** needed to make the training actually work:
  - **pretrain** the network using supervised learning
  - **replay buffer spiking** – initialize using simple rule-based policy
    - so there are at least a few successful dialogues
    - the RL agent has something to catch on

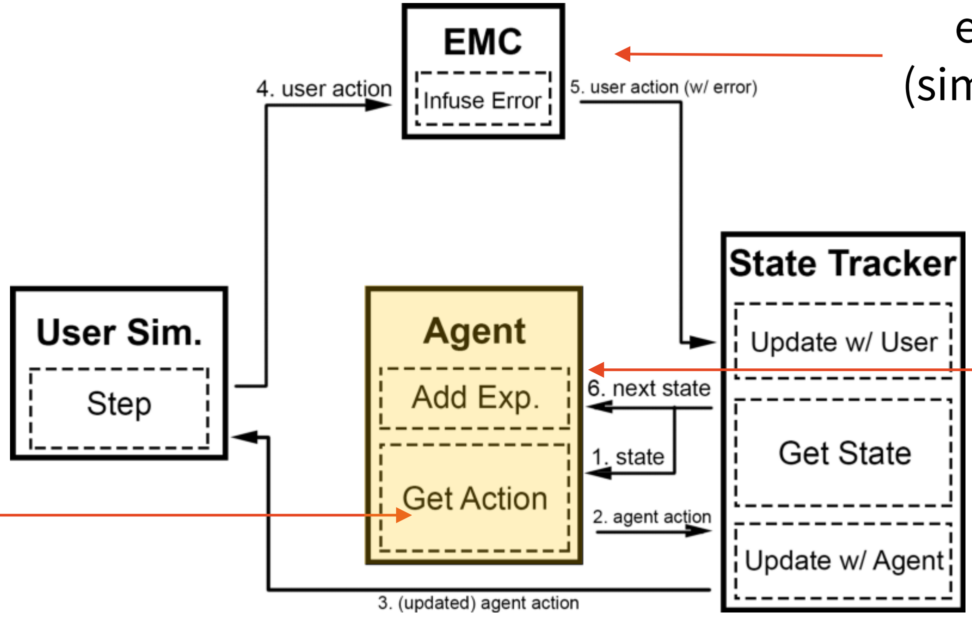




movie ticket booking:
better than rule-based

rule-based simulator
with agenda
running on DA level

error model controller
(simulating ASR/NLU noise)



DQN – feed-forward,
1 hidden ReLU layer

replay memory
initialized using a
simple handcrafted policy

https://towardsdatascience.com/training-a-goal-oriented-chatbot-with-deep-reinforcement-learning-part-i-introduction-and-dce3af21d383

BBQ – Bayes-by-Backprop Q-Networks

- better exploration than ϵ-greedy – explore uncertain regions
- **Bayes-by-Backprop** – probability distribution over network weights
  - start from prior $p(\theta)$, learn posterior $p(\theta|D)$ for training data D
  - posterior approximated by Gaussians $q(\theta|w)$, each $\theta_i \sim \mathcal{N}(\mu_i, \sigma_i)$
    - now learning $w_i = \{(\mu_i, \rho_i)\}$ where $\sigma_i = \log(1 + \exp \rho_i)$, to keep σ_i positive
    - VAE-style: minimizing KL divergence between q and p, reparameterization trick
- using BB to represent DQN + posterior (Thompson) sampling
  - actions sampled acc. to posterior probability that they're optimal in current state
  - just sample θ_t from q, then choose $a_t = \arg\max_a Q(s_t, a; \theta_t)$
- no need to sample from the frozen target network, just use $\overline{\mu}$
  - it's faster, actually more stable

(Lipton et al., 2018) https://arxiv.org/abs/1608.05081

BBQ performance

(Lipton et al., 2018)
https://arxiv.org/abs/1608.05081

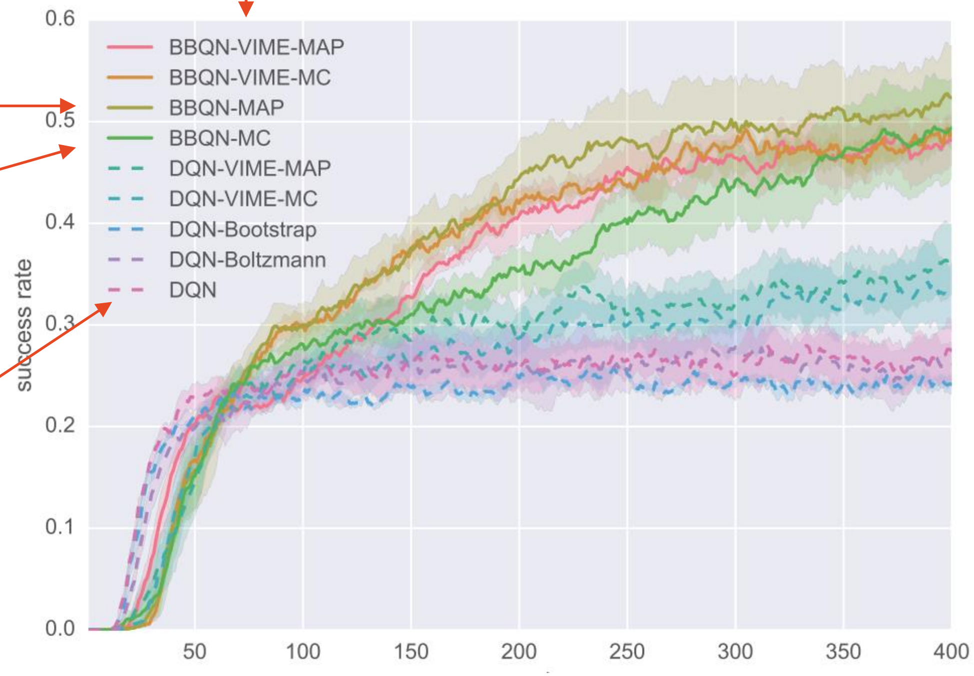
MLP with 2 hidden layers, ReLU, width=256
movie booking task
one-hot dialogue state representation (268 dim)
39 actions (basic *hello()*, *deny()*, *thanks()* etc. + inform/request for each slot)

(enhanced rewards with surprisal)

no sampling from
frozen network

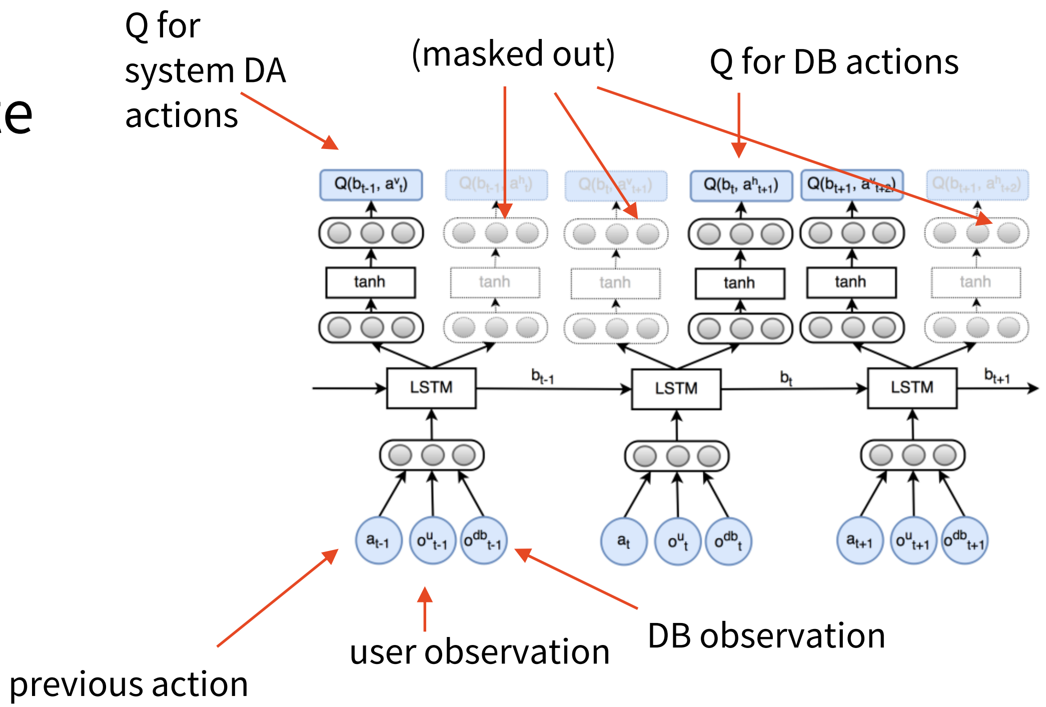
sampling from
frozen network

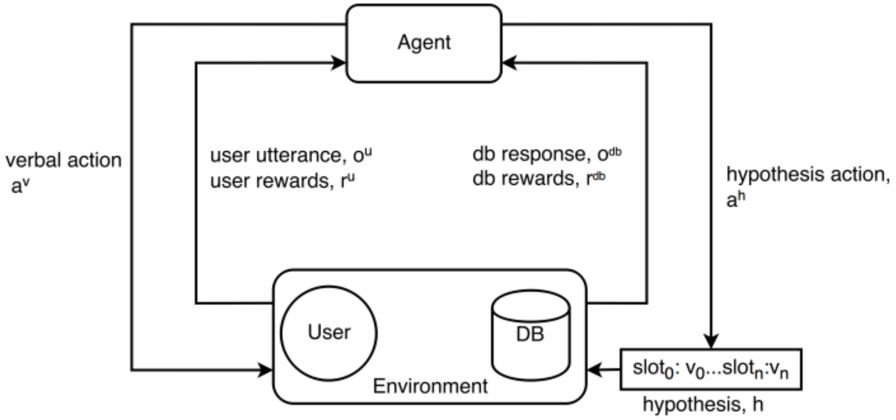
ϵ-greedy



Recurrent Q-Networks

- Joint dialogue tracking & action selection
  - actions are either system DAs or updates to state (DB hypothesis)
  - forced to alternate action types by masking
  - rewards from DB for narrowing down selection
- Models the Q-network as a LSTM
  - or rather LSTM underlying multiple MLPs
    - LSTM maintains internal state representation
  - 1 MLP for system DAs
  - 1 MLP per slot (action=select value X)



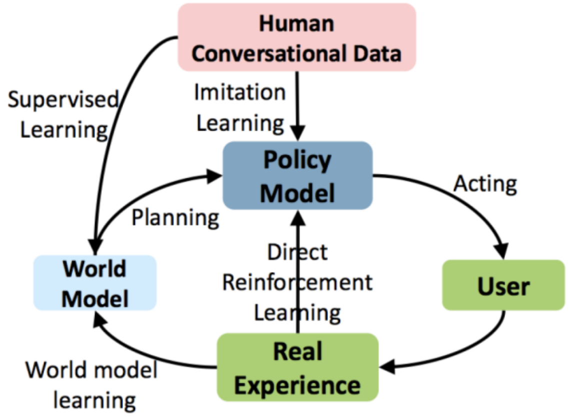


(Zhao & Eskenazi, 2016)
http://arxiv.org/abs/1606.02560

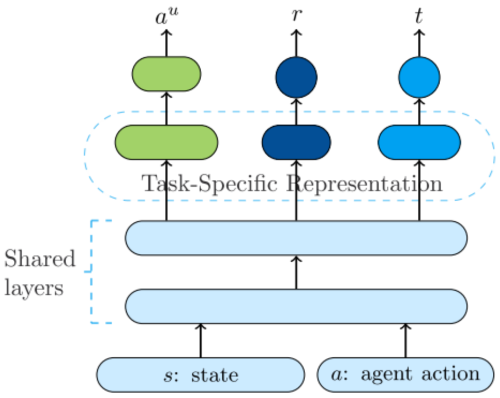
Deep Dyna-Q: learning from humans & simulator

(Peng et al., 2018) https://www.aclweb.org/anthology/P18-1203
(Su et al., 2018) https://www.aclweb.org/anthology/D18-1416

- humans are costly, simulators are inaccurate
- ⇒ learn from both, improve simulator as you go
  - direct RL = learn from users
  - world model learning = improve internal simulator
    - supervised, based on previous dialogues with users
  - planning = learn from simulator
- DQN, feed-forward policy
- simulator: feed-forward multi-task net
  - draw a goal uniformly at the start ← movie booking: name, date, # tickets etc.
  - predict actions, rewards, termination
  - use K simulated ("planning") dialogues per 1 real
- discriminative DDQ: only use a simulated dialogue if it looks real (according to a discriminator)



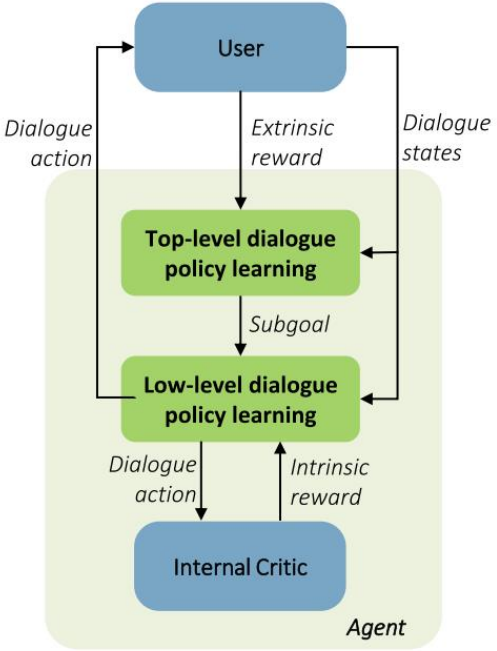
user action reward terminate?

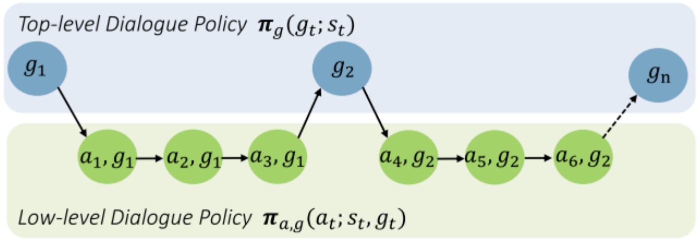


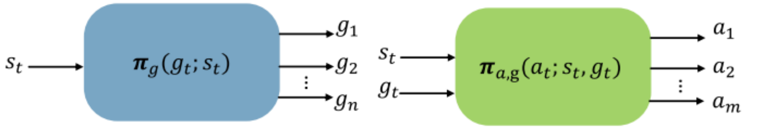
internal simulator = world model

Hierarchical RL

- good for multiple subtasks
  - e.g. book a flight to London and a hotel for the same day, close to the airport
- top-level policy: select subtask g_i
- low-level policy: actions a_{j,g_i} to complete subtask g_i
  - given initiation/termination conditions
    - keeps on track until terminal state is reached
  - shared by all subtasks (subtask=parameter)
  - internal critic (=prob. that subtask is solved)
- global state tracker
  - integrates information from subtasks







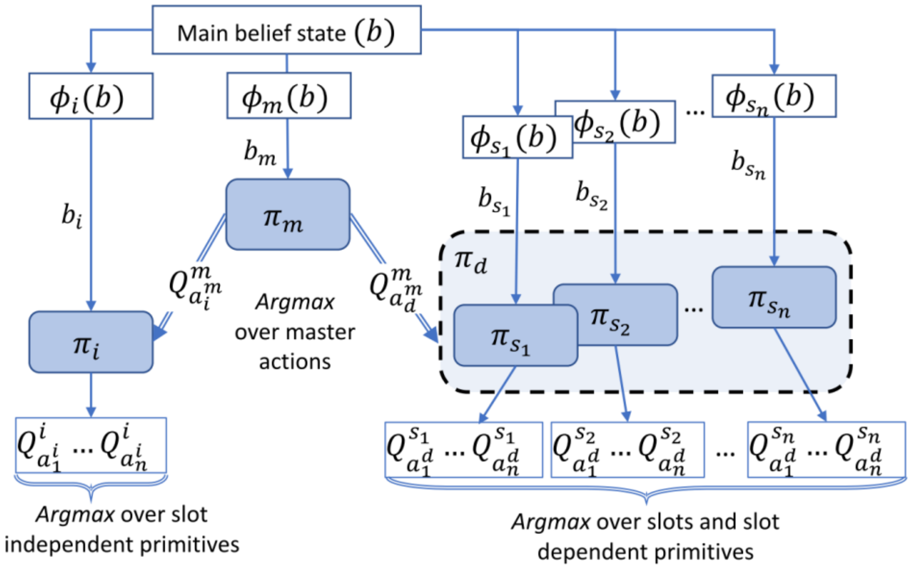
top-level Q-network　　low-level Q-network

(Peng et al., 2017)
http://aclweb.org/anthology/D17-1237

Feudal RL

(Casanueva et al., 2018)
http://arxiv.org/abs/1803.03232

- spatial (slot-based) split instead of temporal
  - doesn't need defined subtasks & sub-rewards
- belief state representation – features
  - master ϕ_m, slot-independent ϕ_i, per-slot ϕ_{s_k}
  - handcrafted (could be neural nets)
  - supports sharing parameters across domains
- two-step action selection:
  1) master action: "slot-dependent or not"?
     - master policy
  2) primitive action
     a) slot-independent policy
     b) slot-specific policies (with shared parameters, distinguished only by belief state)
        - chooses max. Q for all slot-action pairs – involves choosing the slot
  - everything is trained using the same global reward signal



hello, inform

request, confirm

inform = "inform over all slots"

Summary

- Action selection = deciding what to do next (following a **policy**)
- FSM, frames, rule-based, supervised, **reinforcement learning**
- **RL** – agent in an environment, taking actions, getting rewards
  - MDP formalism (+POMDP can be converted to it)
  - dynamic programming, **Monte Carlo**, **Temporal Difference**
  - optimizing **value function** V/Q (**critic**), **policy** (**actor**), or both (**actor-critic**)
  - learning **on-policy** or **off-policy** (act by the policy you learn/not)
- summary states might be needed
- user simulators: good to use & mix with humans
- **DQN** – representing & optimizing Q function with a network
  - minibatches, target function freezing, experience replay
- multiple tasks: hierarchical / feudal RL

Thanks

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Skype/Meet/Zoom (by agreement)

No labs today (project questions?)
Topic deadline: Nov 10
Fixes for datasets required

Get these slides here:

http://ufal.cz/npfl099

Next Tue 9:50am:
Direct Policy Optimization
Language Generation

References/Inspiration/Further:

- Sutton & Barto (2018): Reinforcement Learning: An Introduction (2nd ed.) http://incompleteideas.net/book/the-book.html
- Nie et al. (2019): Neural approaches to conversational AI: https://arxiv.org/abs/1809.08267
- Filip Jurčíček's slides (Charles University): https://ufal.mff.cuni.cz/~jurcicek/NPFL099-SDS-2014LS/
- Milica Gašić's slides (Cambridge University): http://mi.eng.cam.ac.uk/~mg436/teaching.html
- Heidrich-Meisner et al. (2007): Reinforcement Learning in a Nutshell: https://christian-igel.github.io/paper/RLiaN.pdf
- Young et al. (2013): POMDP-Based Statistical Spoken Dialog Systems: A Review: http://cs.brown.edu/courses/csci2951-k/papers/young13.pdf