NPFL099 Statistical Dialogue Systems
7. Dialogue Management (2)
Action Selection/Policy

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http://ufal.cz/npfl099

14. 11. 2023

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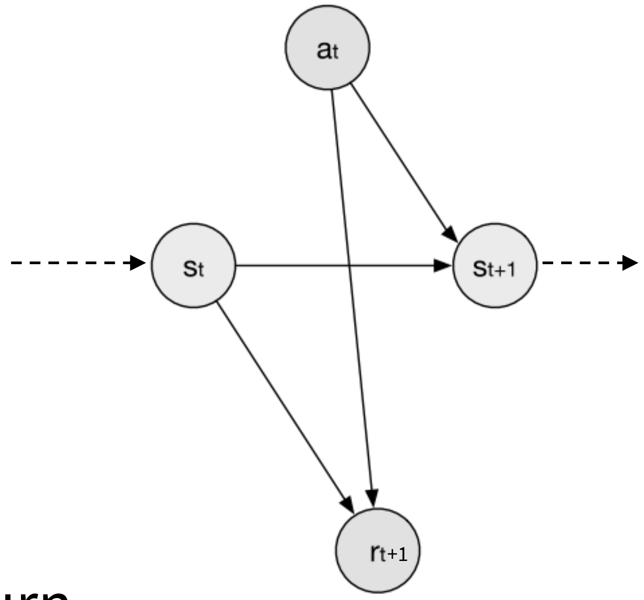
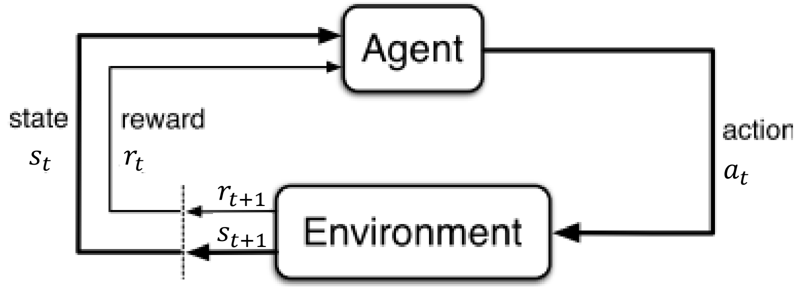
Action selection: Recap

(from Milica Gašić's slides)

- Action selection: deciding what to do (or say) next
  - based on dialogue state (i.e. uses tracking output)
  - follows a **policy** towards an end goal
- FSM, frames, rule-based
- **trained policies**: typically with RL
  - explore more different paths than supervised
  - plan ahead – optimize for the whole dialogue, not just 1 turn
- RL: MDP formalism – agent in an environment, **state-action-reward**
  - POMDP = MDP with continuous states
  - trained with user simulator





(Sutton & Barto, 2018)

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 (from turn t onwards)

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

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

$\gamma = 1$: no discount, only usable if $i \leq T$
$\gamma < 1$: 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**):

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

prob. of choosing a from s under π

transition probs.

expected immediate reward

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

actions that look best for the next step

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

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 $r(s,a,s')$

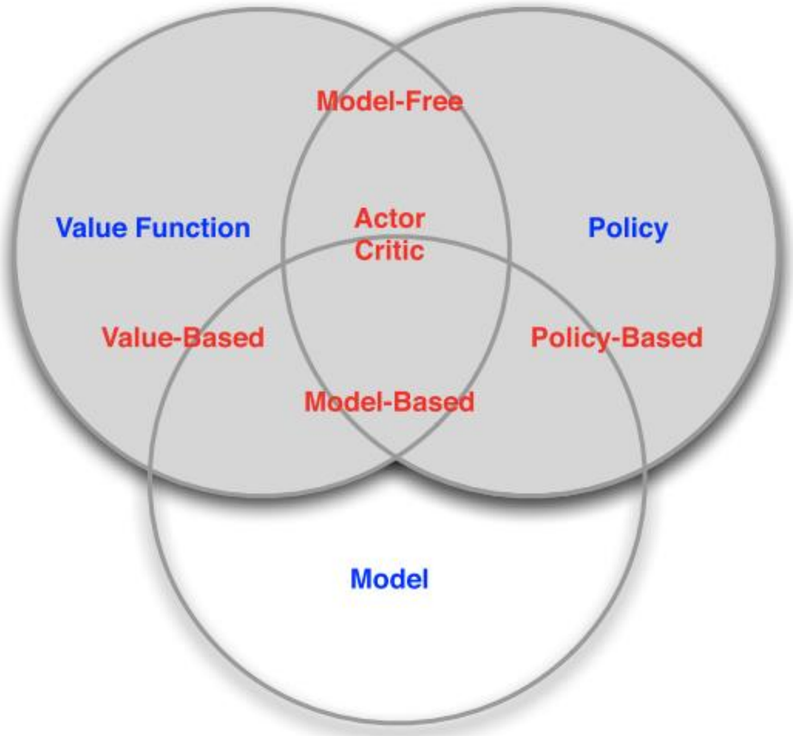
but Q function itself tends to be more complex than V

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 π^*, $V^*(s)$ or $Q^*(s,a)$ and get the same result
  - each has their advantages and disadvantages

RL Agents Taxonomy

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

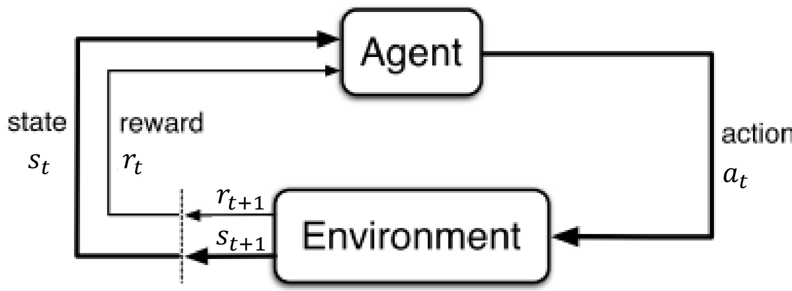
- How to optimize:
  - **dynamic programming** – find the exact solution from Bellman equation
    - iterative algorithms, refining estimates
    - expensive, assumes known environment → not practical for real-world use
  - **Monte Carlo learning** – learn from experience
    - sample, then update based 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

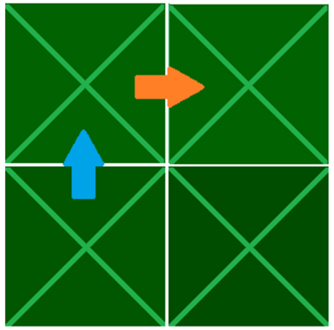
- temporal difference – update Q as you go
- off-policy – directly estimates best Q^*
  - regardless of policy used for sampling
- choose learning rate α, initialize Q arbitrarily
- for each episode:
  - choose initial s
  - for each step:
    - choose a from s according to **ϵ-greedy policy** based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

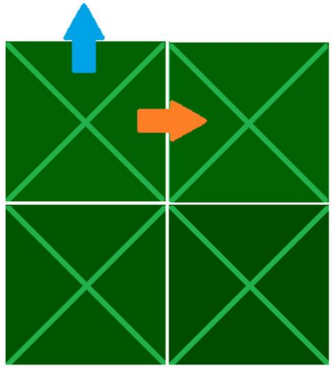
any policy that chooses all actions & states enough times will converge to $Q^*(s,a)$: we need to explore to converge

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

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

TD: moving estimates





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

Q | TD | model-free | off-policy

- **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 $t = 1 \ldots T$ 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 $\mathbb{E}_{(s,a,r',s')\in B}\left[\left(r' + \gamma \max_{a'} Q\left(s', a'; \bar{\boldsymbol{\theta}}\right) - Q(s, a; \boldsymbol{\theta})\right)^2\right]$

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

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

update the frozen target function

DQN for Dialogue Systems

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

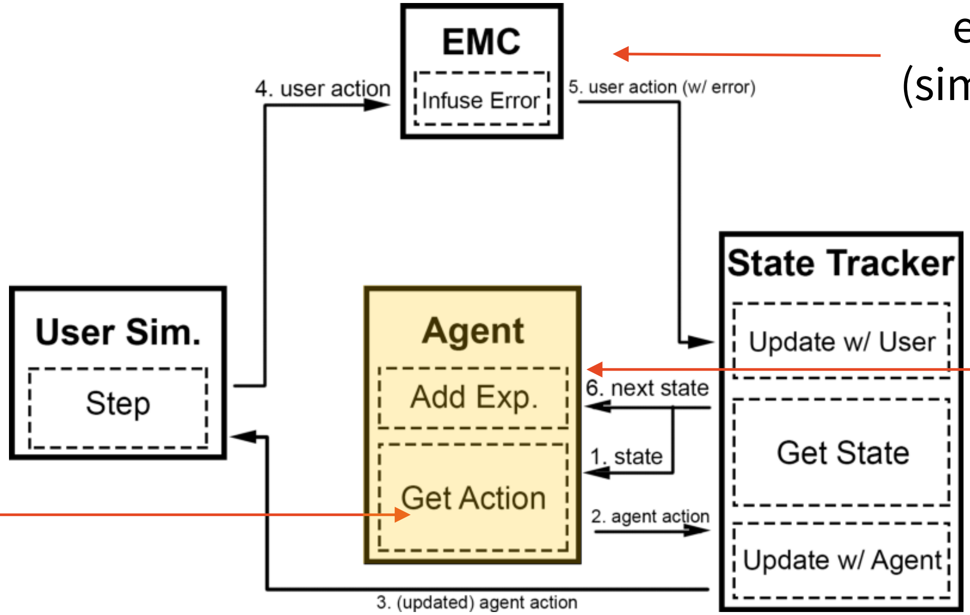
(Lipton et al., 2018)
https://arxiv.org/abs/1608.05081

Q | TD | model-free | off-policy

- 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

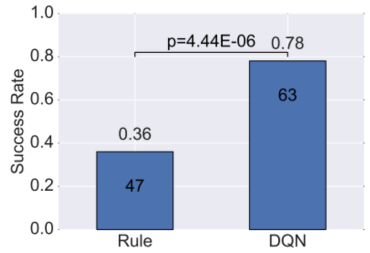
rule-based simulator
with agenda
running on DA level

error model controller
(simulating ASR/NLU noise)



DQN – feed-forward,
1 hidden ReLU layer

replay memory
initialized using a
simple handcrafted policy



movie ticket booking:
better than rule-based

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

Policy Gradients

- Instead of value functions, train a **network to represent the policy**
  - allows better action sampling – according to actual stochastic policy
    - no need for ϵ-greedy (which is partially random, suboptimal)
- To optimize, we need a **performance metric**: $J(\theta) = V^{\pi_\theta}(s_0)$
  - expected return in starting state when following π_θ
  - we want to directly optimize this using gradient ascent
- **Policy Gradient Theorem**:
  - expresses $\nabla J(\theta)$ in terms of $\nabla \pi(a|s,\theta)$

$$\nabla J(\theta) \propto \underbrace{\sum_s \mu(s)}_{\mu(s) \text{ is state probability under } \pi \text{ – this is the same as expected value } \mathbb{E}_\pi} \sum_a Q^\pi(s,a) \nabla \pi(a|s,\theta) = \mathbb{E}_\pi \left[\sum_a Q^\pi(s,a) \nabla \pi(a|s,\theta) \right]$$

(Sutton & Barto, 2018; p. 324ff)

REINFORCE: Monte Carlo Policy Gradients

- direct search for policy parameters by stochastic gradient ascent
  - looking to maximize performance $J(\boldsymbol{\theta}) = V^{\pi_\theta}(s_0)$
- choose learning rate α, initialize $\boldsymbol{\theta}$ arbitrarily
- loop forever:
  - generate an episode $s_0, a_0, r_1, \dots, s_{T-1}, a_{T-1}, r_T$, following $\pi(\cdot \mid \cdot, \boldsymbol{\theta})$
  - for each $t = 0,1 \dots T$: $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \underbrace{\alpha\gamma^t R_t \nabla \ln \pi(a_t | s_t, \boldsymbol{\theta})}$

this will guarantee the right state distribution/frequency $\mu(s)$

returns $R_t = \sum_{i=t}^{T-1} \gamma^{i-t} r_{i+1}$

this is stochastic $\nabla J(\boldsymbol{\theta})$:
- from policy gradient theorem
- using single action sample a_t
- expressing Q^π as R_t (under $\mathbb{E}_\pi$)
- using $\nabla \ln x = \frac{\nabla x}{x}$

variant – **advantage** instead of returns: discounting a **baseline** $b(s)$ (predicted by any model) $A_t = R_t - b(s_t)$ instead of R_t gives better performance

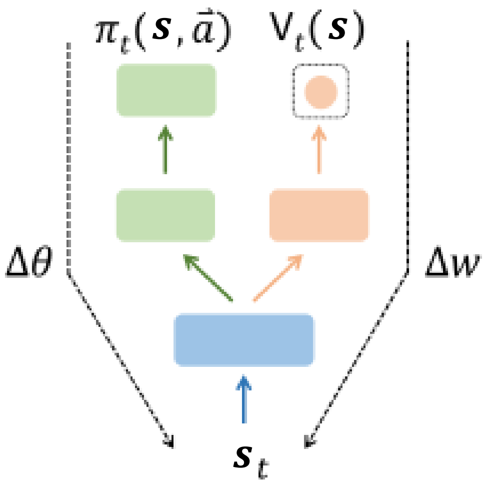
$V(s)$ is actually a good $b(s)$

(Sutton & Barto, 2018; p. 327f)

Policy Gradients (Advantage) Actor-Critic

π&V | TD | model-free | on-policy

- REINFORCE + V approximation + TD estimates – better convergence
  - differentiable policy $\pi(a|s,\boldsymbol{\theta})$
  - differentiable state-value function parameterization $\hat{V}(s,\boldsymbol{w})$
  - two learning rates $\alpha^{\boldsymbol{\theta}}, \alpha^{\boldsymbol{w}}$
- loop forever:
  - set initial state s for the episode
  - for each step t of the episode:
    - sample action a from $\pi(\cdot\,|s,\boldsymbol{\theta})$, take a and observe reward r and new state s'
    - compute **advantage** $A \leftarrow r + \gamma\hat{V}(s',\boldsymbol{w}) - \hat{V}(s,\boldsymbol{w})$
    - update $\underbrace{\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \alpha^{\boldsymbol{\theta}}\gamma^{t}A\nabla\ln\pi(a|s,\boldsymbol{\theta})}_{\textbf{actor}\text{ (policy update)}}, \underbrace{\boldsymbol{w} \leftarrow \boldsymbol{w} + \alpha^{\boldsymbol{w}}\cdot A\nabla\hat{V}(s,\boldsymbol{w})}_{\textbf{critic}\text{ (value function update)}}$
    - $s \leftarrow s'$



TD: update after each step, moving estimates

actor (policy update)

same as REINFORCE, except:
- we use $\hat{V}(s,\boldsymbol{w})$ as baseline
- r is used instead of R_t (TD instead of MC)

critic (value function update)

(Su et al., 2017)
http://arxiv.org/abs/1707.00130

ACER: Actor-Critic with Experience Replay

π&V | TD | model-free | off-policy

- off-policy actor-critic – using **experience replay** buffer
  - same approach as Q-learning
  - since ER buffer has past experience with out-of-date policies (using "old" $\tilde{\theta}$), it's considered off-policy (behaviour policy $\pi_{\tilde{\theta}} \neq$ target policy π_θ)
    - sampling behaviour from $\pi_{\tilde{\theta}}$ is biased w. r. t. π_θ
    - correcting the bias – **importance sampling**: multiply by importance weight $\rho_t = \frac{\pi_\theta(a_t|s_t)}{\pi_{\tilde{\theta}}(a_t|s_t)}$
  - all updates are summed over batches & importance-sampled
    - new objective/performance metric: $\hat{\mathbb{E}}_t[\frac{\pi_\theta(a_t|s_t)}{\pi_{\tilde{\theta}}(a_t|s_t)}\hat{A}_t]$

using advantage instead of returns

batch average
over timesteps t

importance sampled

(Wang et al., 2017) http://arxiv.org/abs/1611.01224
(Su et al., 2017) http://arxiv.org/abs/1707.00130
(Weisz et al., 2018) http://arxiv.org/abs/1802.03753

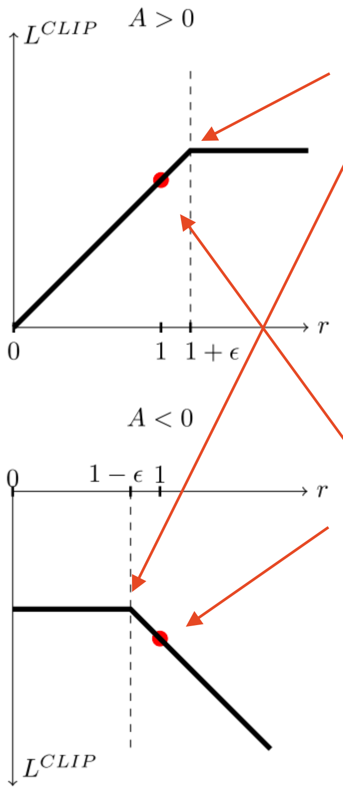
Proximal Policy Optimization

(Schulman et al., 2017)
http://arxiv.org/abs/1707.06347

- ACER is prone to very large updates, unstable
  - to avoid going “off a cliff”, it needs very low LR, trains slowly
  - → change the objective to produce more stable updates
- Basically clipping the ACER objective
  - define $r_t(\theta) = \dfrac{\pi_\theta(a_t|s_t)}{\pi_{\tilde\theta}(a_t|s_t)}$ – ratio to old params
  - starting from $\hat{\mathbb{E}}_t\left[\dfrac{\pi_\theta(a_t|s_t)}{\pi_{\tilde\theta}(a_t|s_t)}\hat{A}_t\right] = \hat{\mathbb{E}}_t\left[r_t(\theta)\hat{A}_t\right]$ (see ACER)
  - using $\hat{\mathbb{E}}_t\left[\min\left(\underbrace{r_t(\theta)\hat{A}_t}_{\text{original}}, \underbrace{\text{clip}[r_t(\theta)]_{1-\epsilon}^{1+\epsilon}\hat{A}_t}_{\text{clipped to stay close to 1}}\right)\right]$

minimum – lower bound on the unclipped objective

positive advantages



can’t get much higher

optimization starting point

negative advantages

Rewards in RL

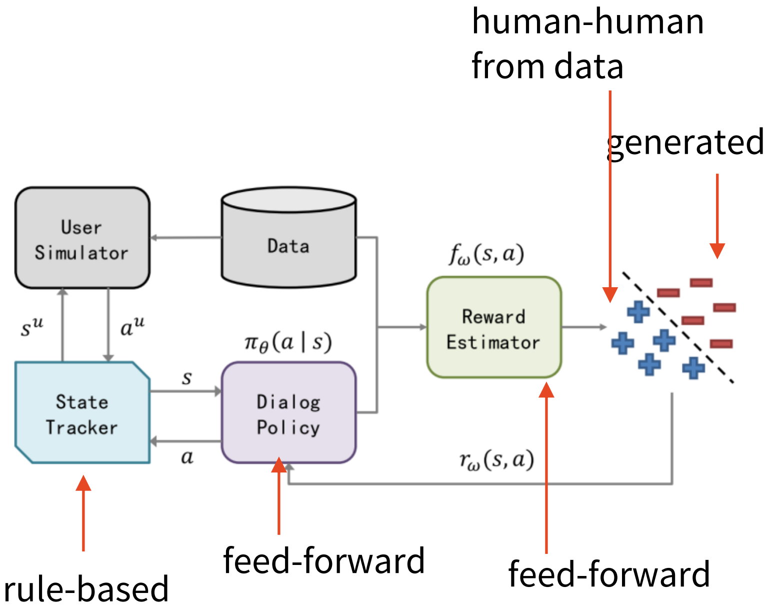
- Reward function is critical for successful learning
- Handcrafting is not ideal
  - domain knowledge typically needed to detect dialogue success
  - need simulated or paid users,
    can’t learn from users without knowing their task
  - paid users often fail to follow pre-set goals
- Having users provide feedback is costly & inconsistent
  - real users don’t have much incentive to be cooperative
- Learning/optimizing the rewards is desirable

Turn-level rewards

(Schmitt & Ultes, 2015; Ultes et al., 2017; Ultes, 2019; Ultes & Maier, 2021)
https://doi.org/10.1016/j.specom.2015.06.003
https://doi.org/10.21437/Interspeech.2017-1032
https://aclweb.org/anthology/W19-5902/
https://aclanthology.org/2021.sigdial-1.42

- **Interaction quality**
  - hand-annotated turns for ~200 dialogues
  - SVM/RNN on low-level domain-independent features (ASR confidence, # reprompts etc.)
- **Discriminator**
  - policy vs. human-human (iterative, adversarial learning)
  - reward for appearing human-like at each turn
- **Information gain**
  - reward system asking ≈ changes in belief state distributions (Jensen-Shannon divergence ≥ threshold)
  - combined with task success (Feudal RL, see →)

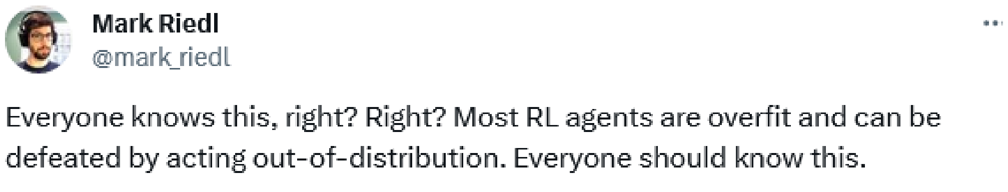
(Takanobu et al., 2019) http://arxiv.org/abs/1908.10719



(Geishauser et al., 2021) http://arxiv.org/abs/2109.07129

Alternating supervised & RL

- we can do better than just supervised pretraining
- alternate regularly
  - start with supervised more frequently
    - alleviate sparse rewards,
      but don't completely avoid exploring
  - later do more RL
    - but don't forget what you learned by supervised learning
- options:
  - schedule supervised every N updates
  - same + increase N gradually
  - use supervised after RL does poorly (worse than baseline)
    - baseline = moving average over history + $\lambda \cdot$ std. error of the average
    - agent is less likely to be worse than baseline in later stages of learning



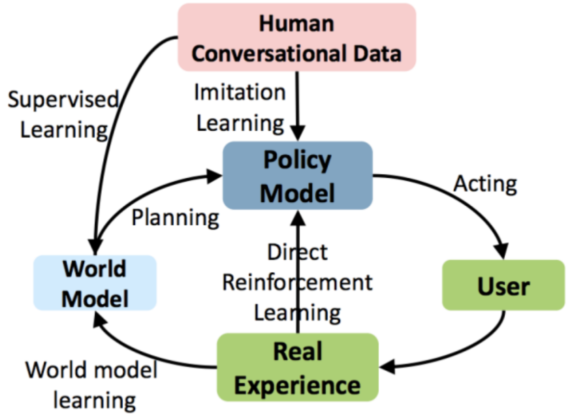
https://twitter.com/mark_riedl/status/1682937331727192065

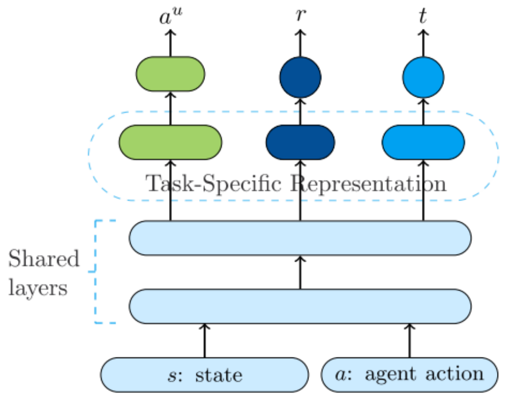
(Xiong et al., 2018)
http://arxiv.org/abs/1806.06187

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)

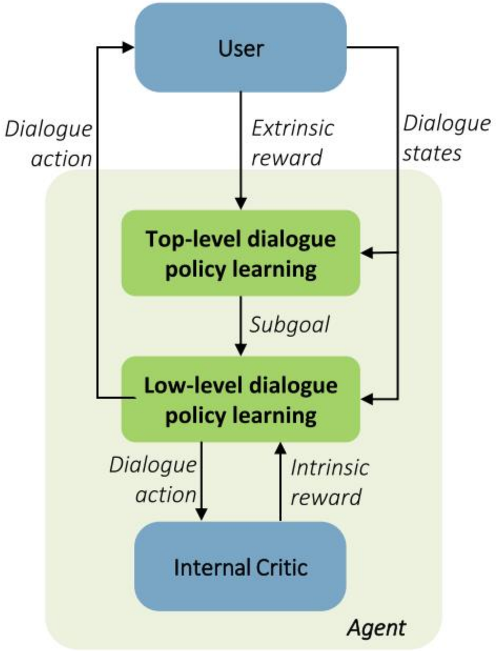


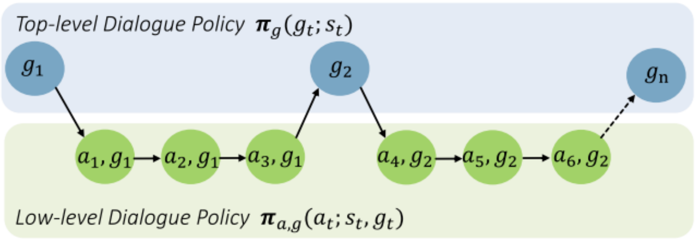


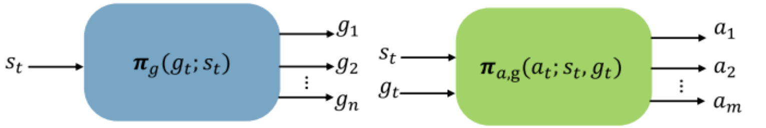
internal simulator = world model

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





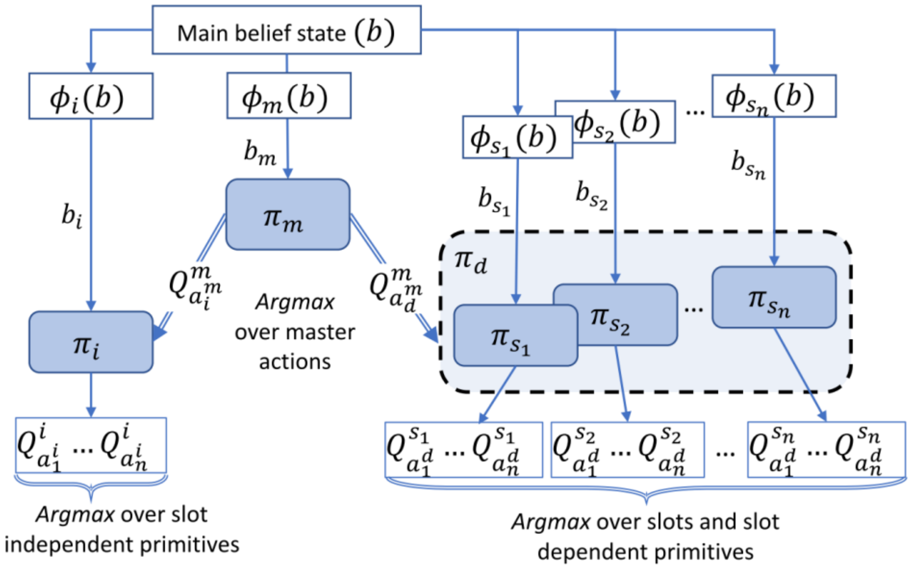


top-level Q-network low-level Q-network

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

(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

- **RL** for action selection / dialogue policy
  - MDP / agent in an environment, taking actions, getting rewards
  - 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)
- **DQN** – representing & optimizing Q function with a network
  - minibatches, target function freezing, experience replay
- **Policy gradients** – policy network & direct policy optimization
  - **REINFORCE** (MC policy gradients) + advantage
  - **Actor-critic** (REINFORCE + TD + V estimates) + extensions (ACER, PPO)
- rewards can be learned/estimated (supervised/GAN-style)
- learning multiple tasks: hierarchical, feudal RL

Thanks

Next Monday: NLG & HW4
We start at 9:50

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Skype/Meet/Zoom/Troja (by agreement)

Get these slides here:

http://ufal.cz/npfl099

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