Dialogue Systems

NPFL123 Dialogové systémy

8. Dialogue Policies (non-neural)

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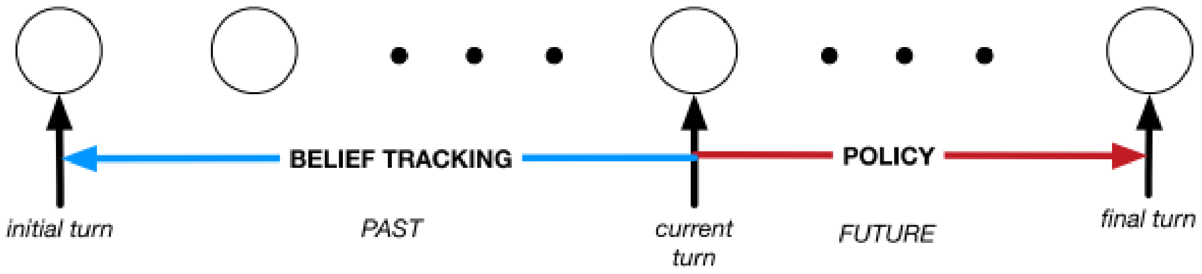
Dialogue Management

- Two main components:
  - **State tracking** (last lecture)
  - **Action selection** (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 ← *Did you say Indian or Italian?*
  - recognize & follow dialogue structure ← follow convention, don't be repetitive
  - plan actions ahead towards the goal ← e.g. ask for all information you require

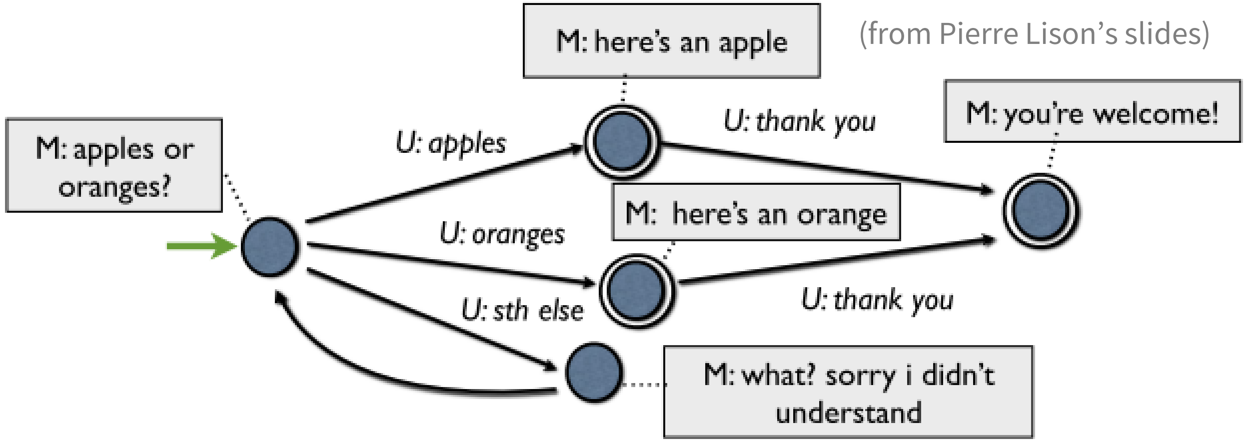
DM/Action Selection Approaches

- **Finite-state machines**
  - simplest possible
  - dialogue state is machine state
- **Frame-based** (VoiceXML)
  - slot-filling + providing information – basic agenda
- **Rule-based**
  - any kind of rules (e.g. Python code)
- **Statistical**
  - typically using reinforcement learning
- Note that state tracking differs with different action selection

FSM Dialogue Management

- Dialogues = graphs going through possible conversations
  - nodes = system actions
  - edges = possible user response semantics
- advantages:
  - easy to design
  - predictable
- disadvantages:
  - very rigid – not real conversations
    (ignores anything that's not a reply to last question)
  - doesn't scale to complex domains
- Good for basic DTMF (tone-selection) phone systems

(from Pierre Lison's slides)



system-initiative

Thanks for calling Bank X. For account balance, press 1, for money transfers, press 2…

Frame-based Approach

Slot	Question
ORIGIN	What city are you leaving from?
DEST	Where are you going?
DEPT DATE	What day would you like to leave?
DEPT TIME	What time would you like to leave?
AIRLINE	What is your preferred airline?

(from Hao Fang's slides)

- Making the interaction more flexible
- State = frame with slots
  - required slots need to be filled
  - this can be done in **any order**
  - more information in one utterance possible
- If all slots are filled, query the database
- Multiple frames (e.g. flights, hotels…)
  - needs frame tracking
- Standard implementation: **VoiceXML**
- Still not completely natural, won't scale to more complex problems

mixed-initiative

```
<form>
  <field name="transporttype">
    <prompt>Please choose airline, hotel, or rental car. </prompt>
    <grammar type="application/x=nuance-gsl">
      [airline hotel "rental car"]
    </grammar>
  </field>
  <block>
    <prompt>You have chosen <value expr="transporttype">. </prompt>
  </block>
</form>
```

(from Pierre Lison's slides)

Rule-based (Information State Update)

- Richer state representation – information state
  - complete context – common ground, beliefs, agenda…
- Rules for state update
  - based on dialogue moves (~DAs)
  - rule = applicability conditions + effects
  - effects:
    - updates to information state (~tracking)
    - system actions – updating the "next move" entry
  - all matching rules applied in a sequence
- Much more expressive than FSM/Frames
- Cumbersome to handcraft

BEL = belief
QUD = questions under discussion
LM = last dialogue move

private to the system

PRIVATE	:	BEL	:	SET(PROP)
		AGENDA	:	STACK(ACTION)
SHARED	:	BEL	:	SET(PROP)
		QUD	:	STACK(QUESTION)
		LM	:	MOVE

common ground

(Larsson & Traum, 2000)
https://dl.acm.org/citation.cfm?id=973943

(2) U-RULE: **integrateSysAsk**
PRE: { val(SHARED.LM, ask(usr, Q)); fst(PRIVATE.AGENDA, raise(Q)) }
EFF: { push(SHARED.QUD, Q); pop(PRIVATE.AGENDA) }

(3) U-RULE: **selectAsk**
PRE: { fst(PRIVATE.AGENDA, raise(Q)) }
EFF: { set(NEXT_MOVE, ask(Q)) }

(Traum & Larsson, 2003)
https://doi.org/10.1007/978-94-010-0019-2_15

Rule-based

- We can use a probabilistic belief state
  - DA types, slots, values
- With **if-then-else** rules in programming code
  - using thresholds over belief state for reasoning
- Output: system DA
- Very flexible, easy to code
  - allows relatively natural dialogues
- Gets messy
- Dialogue policy is still pre-set
  - which might not be the best thing to do

the *fact* structure is derived from the belief state

```
        elif fact['we_did_not_understand']:
            # NLG("Sorry, I did not understand
            res_da = DialogueAct("notunderstoo
            res_da.extend(self.get_limited_con
            dialogue_state["ludait"].reset()

        elif fact['user_wants_help']:
            # NLG("Pomoc.")
            res_da = DialogueAct("help()")
            dialogue_state["ludait"].reset()

        elif fact['user_thanked']:
            # NLG("Díky.")
            res_da = DialogueAct('inform(cordi
            dialogue_state["ludait"].reset()

        elif fact['user_wants_restart']:
            # NLG("Dobře, zančneme znovu. Jak
            dialogue_state.restart()
            res_da = DialogueAct("restart()&he
            dialogue_state["ludait"].reset()

        elif fact['user_wants_us_to_repeat']:
            # NLG - use the last dialogue act
            res_da = DialogueAct("irepeat()")
            dialogue_state["ludait"].reset()
```

directly choose reply DA + update state

(Jurčíček et al., 2014)
https://www.tsdconference.org/tsd2014/download/preprints/628.pdf

https://github.com/UFAL-DSG/alex/blob/master/alex/applications/PublicTransportInfoCS/hdc_policy.py

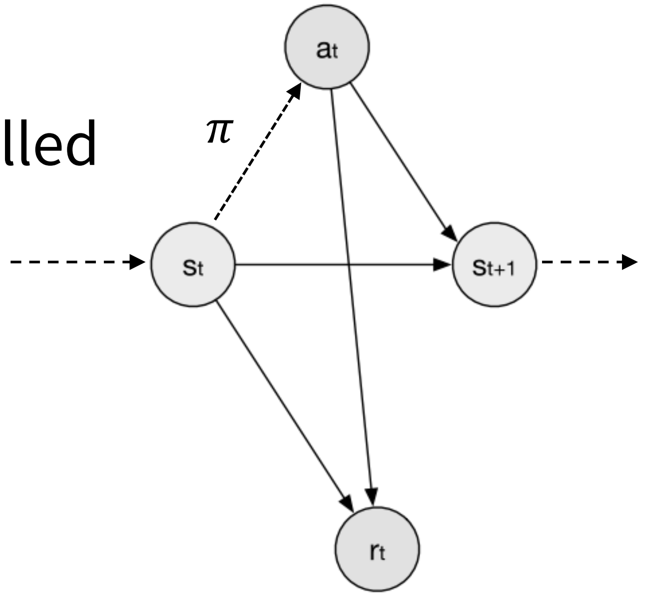
DM with supervised learning

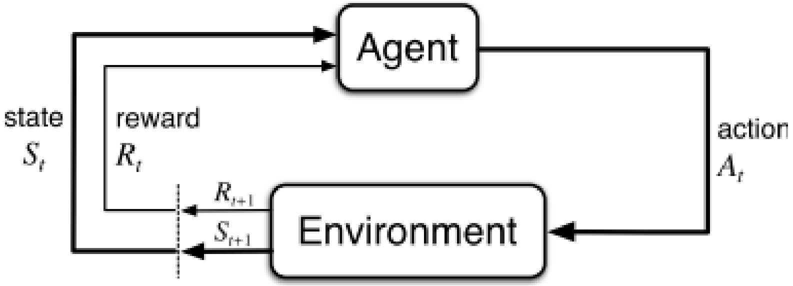
- **Action selection ~ classification** → use supervised learning?
  - set of possible actions is known
  - belief state should provide all necessary features
- Yes, but…
  - You **need** sufficiently large **human-human data** – hard to get
    - human-machine would just mimic the original system
  - 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

DM as a Markov Decision Process

- MDP = probabilistic control process
  - modelling situations that are partly random, partly controlled
  - **agent** in an **environment**:
    - has internal **state** $s_t \in \mathcal{S}$
    - takes **actions** $a_t \in \mathcal{A}$
    - actions chosen according to **policy** $\pi: \mathcal{S} \to \mathcal{A}$
    - gets **rewards** $r_t \in \mathbb{R}$ & state changes from the environment
  - Markov property – state defines everything
    - no other temporal dependency
- let's assume we know the state for now
  - let's go with MDPs,
    see how they map to POMDPs later

(from Milica Gašić's slides)





(Sutton & Barto, 2018)

Deterministic vs. stochastic policy

- **Deterministic** = simple mapping $\pi: \mathcal{S} \rightarrow \mathcal{A}$
  - always takes the same action $\pi(s)$ in state s
  - enumerable in a table
  - equivalent to a rule-based system
  - but can be learned instead of hand-coded!
- **Stochastic** = specifies a probability distribution $\pi(s, a)$
  - $\pi(s, a)$ ~ probability of choosing action a in state s – $p(a|s)$
  - decision = sampling from $\pi(s, a)$

Reinforcement learning

- 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)

return: accumulated long-term reward (from timestep 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)

$\gamma < 1$: 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**):

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

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"

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

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

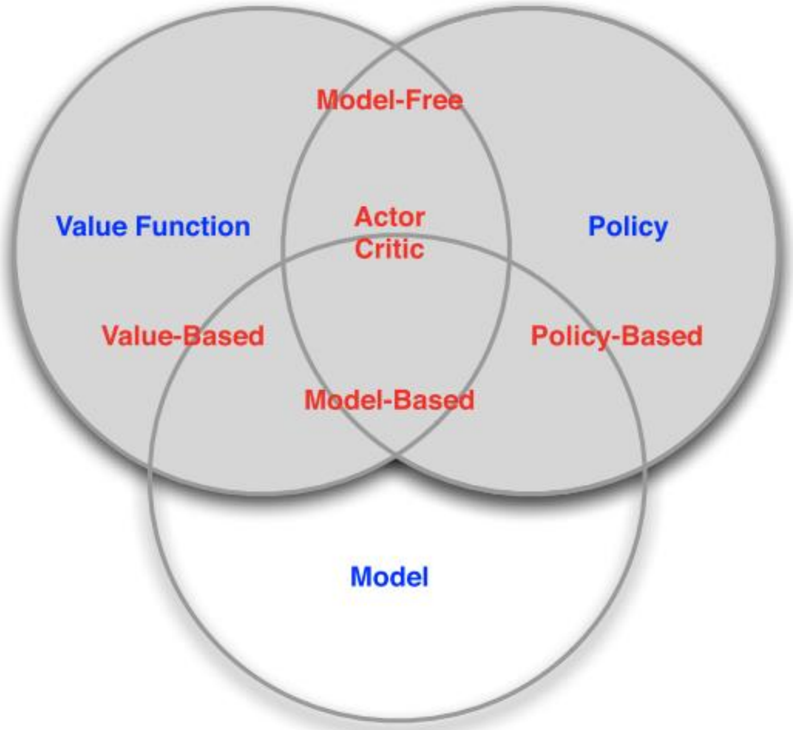
but Q tables are bigger than V tables

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 Agent Taxonomy

- Quantity to optimize:
  - value function – **critic**
  - policy – **actor**
  - both – **actor-critic**
- Environment model:
  - **model-based** (assume known $p(s'|s,a), r(s,a,s)$)
  - **model-free** (don't assume anything, sample)
    - this is where using Q instead of V comes handy



(from David Silver's slides)

RL Approaches

- How to optimize:
  - **dynamic programming** – find the exact solution from Bellman equation
    - iterative algorithms, refining estimates
    - expensive, assumes known environment
  - **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
- Sampling & updates:
  - **on-policy** – improve the policy while you're using it for decisions
  - **off-policy** – decide according to a different policy

Value Iteration

1) Choose a threshold τ, Initialize $V_0(s)$ arbitrarily
2) While $V_i(s) - V_{i-1}(s) \geq \tau$ for any s: ← as long as we're still improving

   for all s: $V_{i+1}(s) \leftarrow \max_a \sum_{s' \in \mathcal{S}} p(s'|s,a)\big(r(s,a,s') + \gamma V_i(s')\big)$

   $i \leftarrow i + 1$

   ↑ apply greedy policy according to current $V_i(s)$, update estimate

- At convergence, we're less than τ away from optimal state values
  - resulting greedy policy is typically already optimal in practice
- Can be done with $Q_i(s,a)$ instead of $V_i(s)$
- Assumes known $p(s'|s,a)$ and $r(s,a,s')$
  - can be estimated from data if not known – but it's expensive

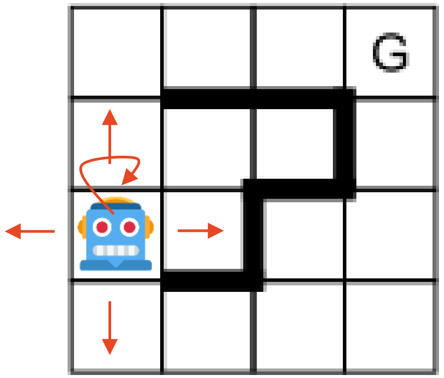
Value iteration example

(Gridworld)

- Robot in a maze: can stay or move ←, ↑, →, ↓ (all equally likely)
  - reward +1 for staying at “G”
  - reward -1 for hitting a wall
  - discount factor $\gamma = 0.9$

(Heidrich-Meisner et al., 2007)
https://christian-igel.github.io/paper/RLiaN.pdf

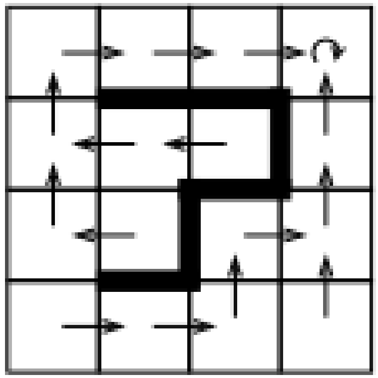
maze



optimal state-value function $V^*(s)$

7.3	8.1	9	10
6.6	5.9	5.3	9
5.9	5.3	7.3	8.1
5.3	5.9	6.6	7.3

optimal policy π^*



(after Sutton & Barto, 2018)

Policy iteration

$$\pi_1 \xrightarrow{\text{E}} V^{\pi_1} \xrightarrow{\text{I}} \pi_2 \xrightarrow{\text{E}} V^{\pi_2} \xrightarrow{\text{I}} \dots \xrightarrow{\text{I}} \pi^* \xrightarrow{\text{E}} V^{\pi^*}$$

- Similar to value iteration, but improves both policy & value function
  - also works for Q in place of V
- Initialize π_1 and $V^{\pi_1}(s)$ arbitrarily, set $k = 1$, iterate:

1) **E: Policy evaluation** – compute $V^{\pi_k}(s)$ for policy π_k
   - iterative approximation based on Bellman equation
   - choose threshold τ, loop with i while $V_{i+1}^{\pi_k}(s) - V_i^{\pi_k}(s) \geq \tau$ for any s:
     - for all s: $a \leftarrow \pi_k(s), V_{i+1}(s) \leftarrow \sum_{s'} p(s'|s,a)\big(r(s,a,s') + \gamma V_i(s')\big)$

2) **I: Policy improvement** – find better π_{k+1} based on $V^{\pi_k}(s)$
   - choose best action in each state based on $V^{\pi_k}(s)$
   - for all s: $\pi_{k+1} \leftarrow \arg\max_a \sum_{s'} p(s'|s,a)\big(r(s,a,s') + \gamma V^{\pi_k}(s')\big)$
   - end if $\pi_{k+1}(s) = \pi_k(s)$ for all s

Animated example here:
https://cs.stanford.edu/people/karpathy/reinforcejs/gridworld_dp.html
(note that rewards come from states, not state-action pairs)

Monte Carlo Methods

- $V(s)$ or $Q(s,a)$ estimated iteratively, on-policy
  - explores states with more value more often
- Loop over episodes (dialogues)
  - record (s_t, a_t, r_t) for $t = 0, \ldots T$ in the episode
  - for all s, a in the episode:
    - $R(s,a) \leftarrow$ list of all **returns** for taking action a in state s (sum of rewards till end of episode)
    - $Q(s,a) \leftarrow \mathrm{mean}(R(s,a))$
- To converge, we need to explore – using **ϵ-greedy policy**:

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

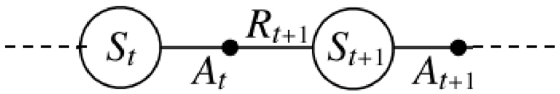
off-policy extensions exist (omitted)

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

here: model-free for Q's, but also works model-based for V's

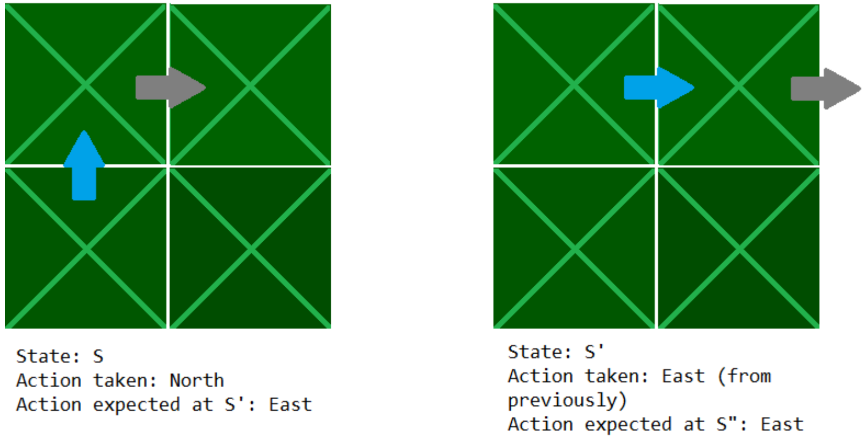
ϵ can be large initially, then gradually lowered

SARSA (state-action-reward-state-action)



(Sutton & Barto, 2018)

- estimate $Q(s, a)$ iteratively, on-policy, with immediate updates
  - **TD**: don't wait till the end of episode
- choose learning rate α, initialize Q arbitrarily
- for each episode:
  - choose initial s,
    initial a according to ϵ-greedy policy based on Q
  - for each step:
    - take action a, observe reward r and state s'
    - choose action a' from s' acc. to ϵ-greedy policy based on Q
    - $Q(s, a) \leftarrow (1 - \alpha) \cdot Q(s, a) + \alpha \cdot \underbrace{\left(r + \gamma Q(s', a')\right)}_{\text{update}}$
    - $s \leftarrow s', a \leftarrow a'$



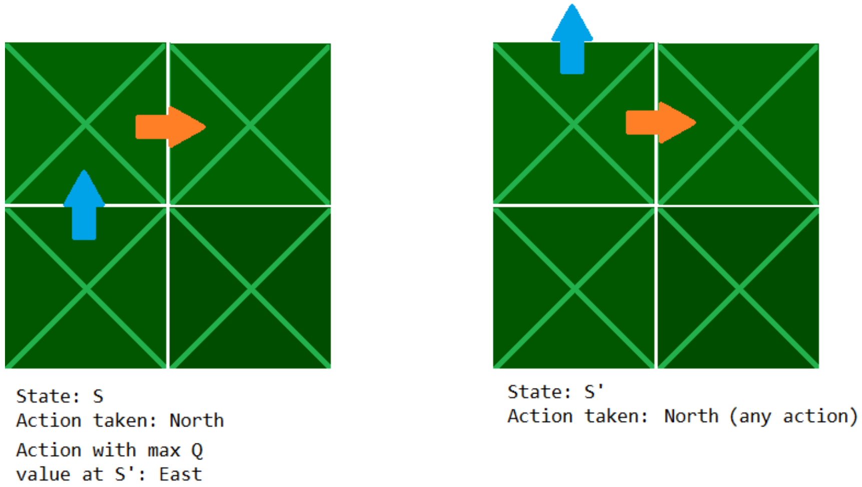
https://towardsdatascience.com/td-in-reinforcement-learning-the-easy-way-f92ecfa9f3ce

- typically converges faster than MC (but not always)

TD | model-free | value

Q-Learning (off-policy TD)

- off-policy – directly estimate $Q^*(s,a)$
  - 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'
    - $Q(s,a) \leftarrow (1-\alpha)\cdot Q(s,a) + \alpha\left(r + \gamma \cdot \max_{a'} Q(s',a')\right)$
    - $s \leftarrow s'$



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

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

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

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

REINFORCE – MC policy search

- assuming a differentiable parametric policy $\pi(a|s,\boldsymbol{\theta})$
- 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 $t = 0,1 \dots T$: $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \alpha\gamma^t R_t \nabla \ln \pi(a_t|s_t,\boldsymbol{\theta})$

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
- with action sample a_t

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

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

Policy Gradients Actor-Critic

- 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 $\delta \leftarrow r + \gamma\hat{V}(s',\boldsymbol{w}) - \hat{V}(s,\boldsymbol{w})$
    - update $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \alpha^{\boldsymbol{\theta}}\gamma^t\delta\nabla \ln \pi(a|s,\boldsymbol{\theta})$, $\boldsymbol{w} \leftarrow \boldsymbol{w} + \alpha^{\boldsymbol{w}} \cdot \delta\nabla\hat{V}(s,\boldsymbol{w})$
    - $s \leftarrow s'$

TD: update after each step → (update)

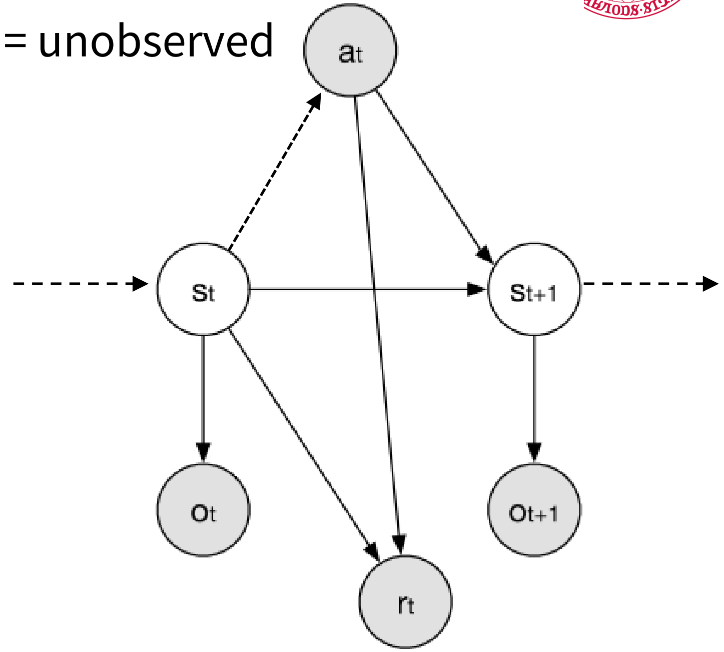
actor (policy update)

same as REINFORCE, except:

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

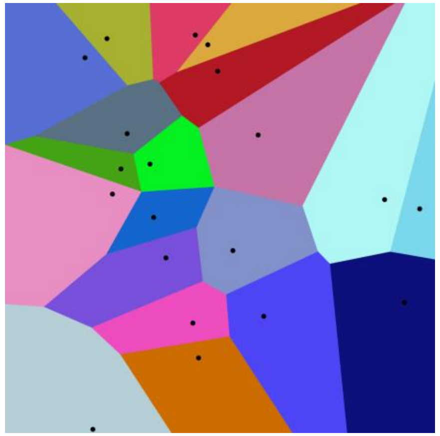
critic (value function update)

POMDP Case



(from Milica Gašić's slides)

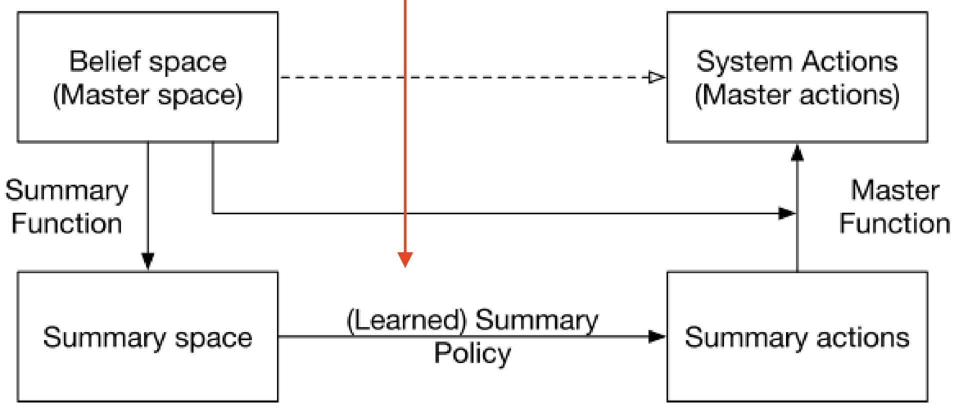
- POMDPs – belief states instead of dialogue states
  - probability distribution over states
  - can be viewed as **MDPs with continuous-space states**
- All MDP algorithms work…
  - if we **quantize/discretize** the states
  - use grid points & nearest neighbour approaches
  - this might introduce errors / make computation complex
- REINFORCE/policy gradients work out of the box
  - function approximation approach, allows continuous states



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

Summary Space

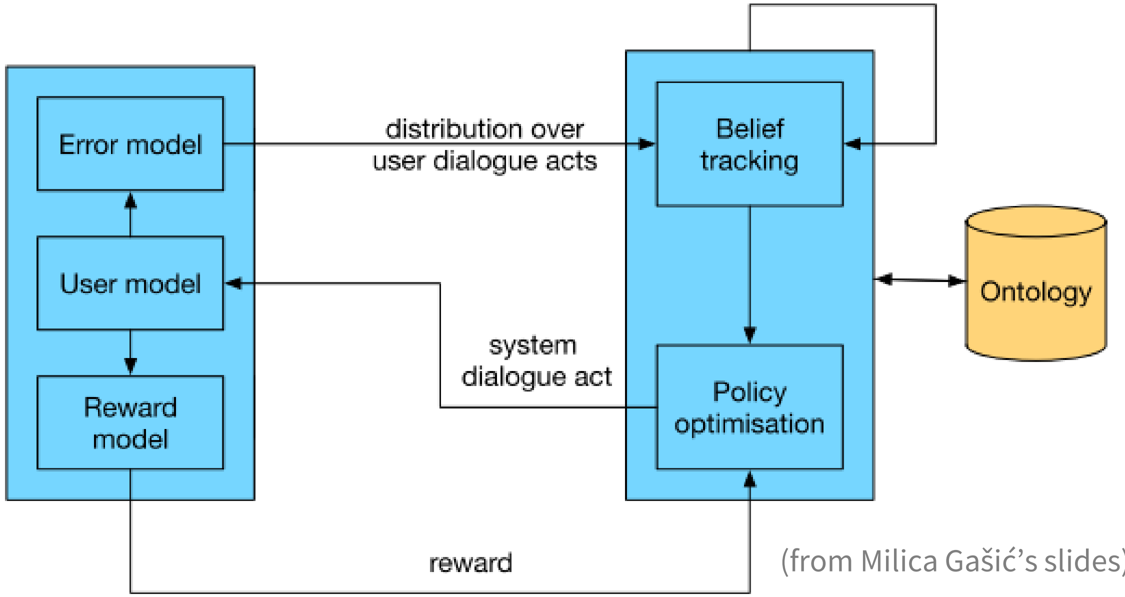
- for a typical DS, the belief state is too large to make RL tractable
- solution: map state into a reduced space, optimize there, map back
- reduced space = **summary space**
  - handcrafted state features
  - e.g. top slots, # found, slots confirmed…
- reduced action set = **summary actions**
  - e.g. 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)

Simulated Users

- We can’t really learn just from static datasets
  - 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 policy from data



(from Milica Gašić’s slides)

Summary

- Action selection – deciding what to do next
- Approaches
  - Finite-state machines (system-initiative)
  - Frames (VoiceXML)
  - Rule-based
  - Machine learning (RL better than supervised)
- RL – in a POMDP scenario (can be approximated by MDP)
  - optimizing **value function** or **policy**
  - learning **on-policy** or **off-policy**
  - learning with or without a **model**
  - using **summary space**
  - training with a **user simulator**

Thanks

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References/Inspiration/Further:

- 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
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- Young et al. (2013): POMDP-Based Statistical Spoken Dialog Systems: A Review: http://cs.brown.edu/courses/csci2951-k/papers/young13.pdf
- Oliver Lemon's slides (Heriot-Watt University): https://sites.google.com/site/olemon/conversational-agents
- Pierre Lison's slides (University of Oslo): https://www.uio.no/studier/emner/matnat/ifi/INF5820/h14/timeplan/
- Hao Fang's slides (University of Washington): https://hao-fang.github.io/ee596_spr2018/
- David Silver's course on RL (UCL): http://www0.cs.ucl.ac.uk/staff/d.silver/web/Teaching.html
- Barnabás Póczos's slides (Carnegie-Mellon University): https://www.cs.cmu.edu/~mgormley/courses/10601-s17/