IR APPLICATIONS USING DQN

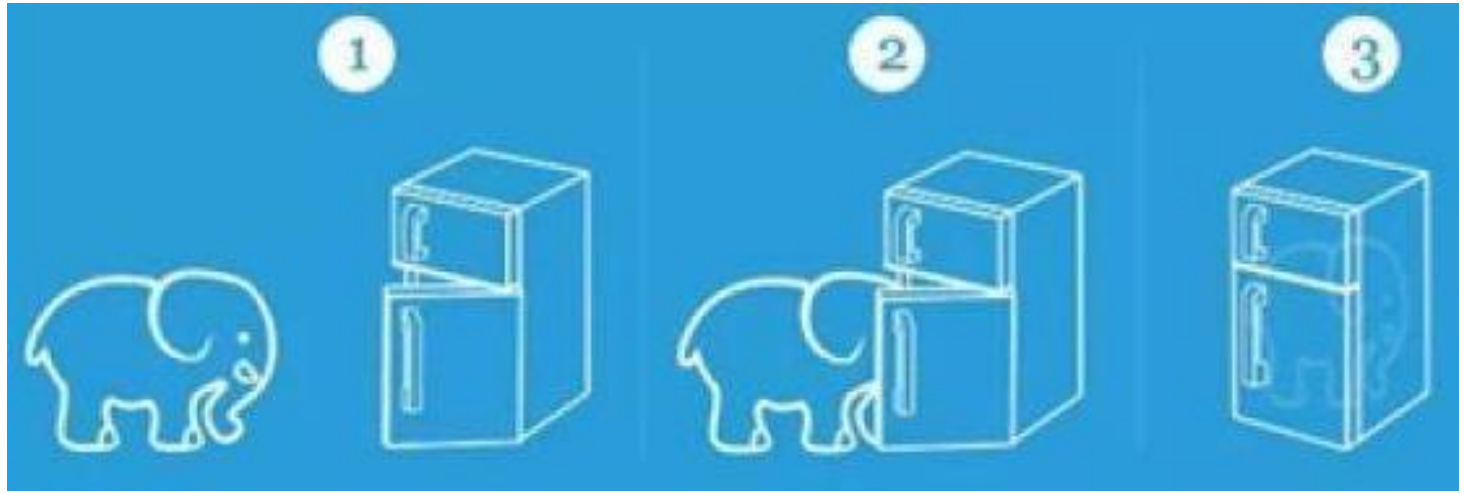
Dell Zhang

blueprism AI Labs

How to Put an Elephant into a Fridge?

You only need three steps:

1) Open the fridge;
2) Put the elephant in;
3) Close the door.



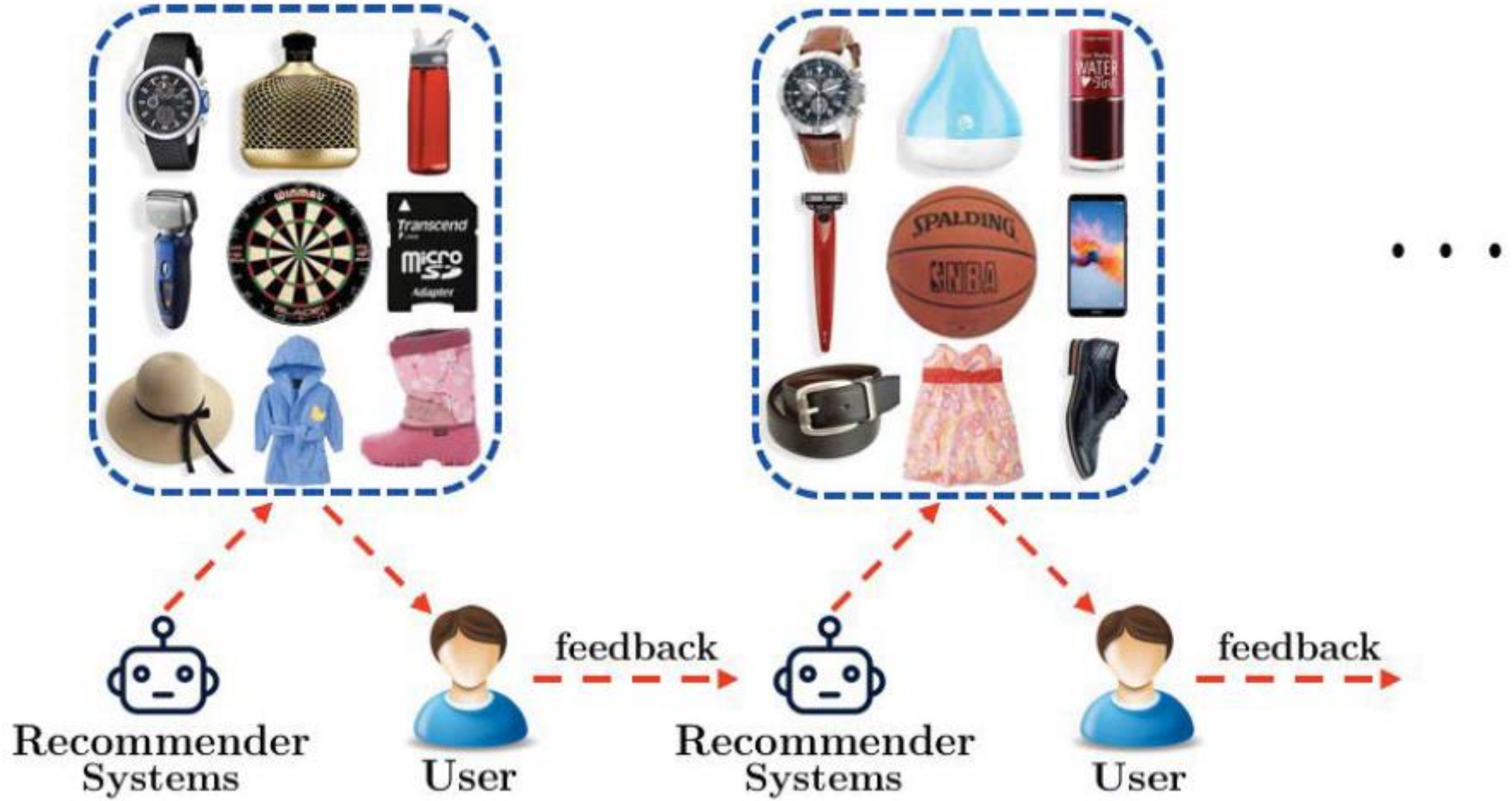
How to Solve a Real-World Problem using RL?

You only need three steps:

1. Formulate the problem as an MDP;
2. Choose an RL algorithm for the MDP;
3. Run the RL algorithm.

Recommender Systems

Mitigate the information overload problem by making personalized suggestions to users

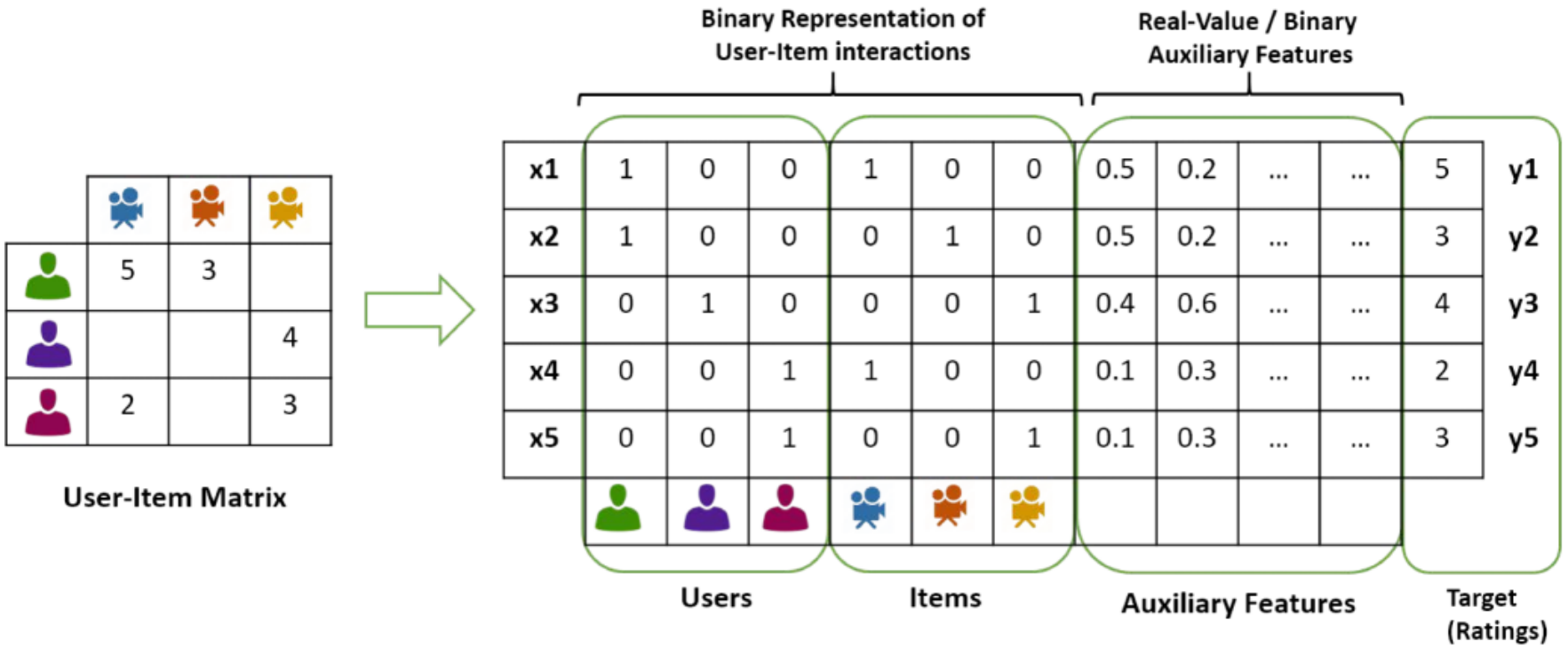


http://www.cse.msu.edu/~zhaoxi35/paper/recsys2018slides.pdf

Recommender Systems

Challenges of Existing Recommender Systems (e.g., Factorization Machines)

- Recommendation procedure as static process, following a fixed greedy strategy.
- Maximizing the immediate (short-term) reward from users

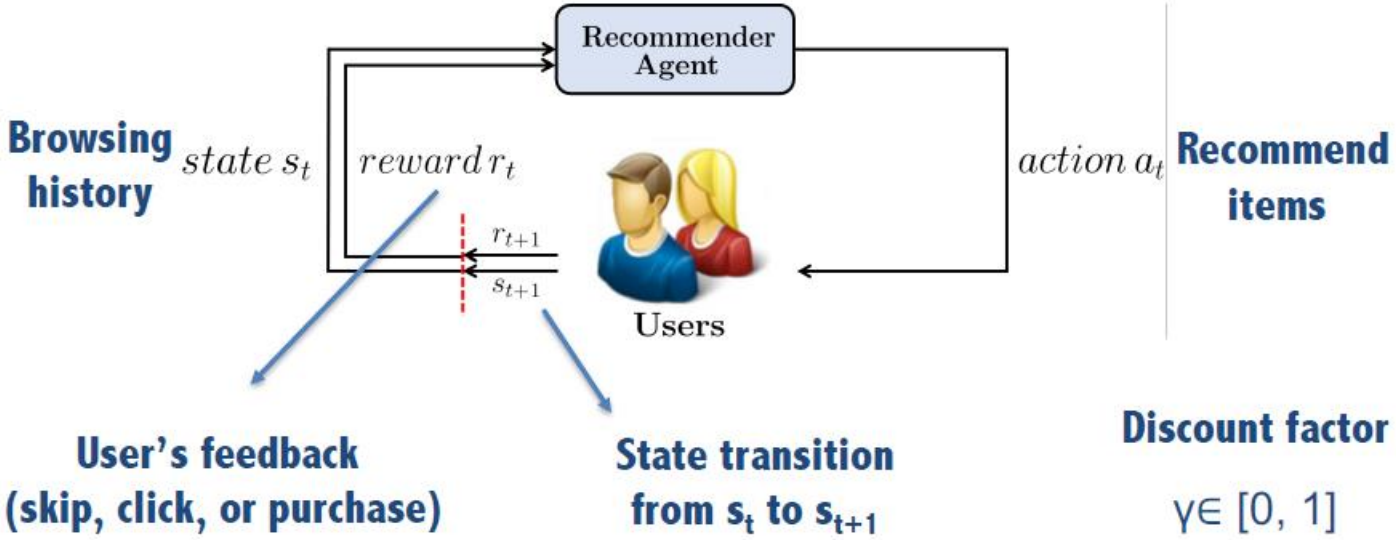


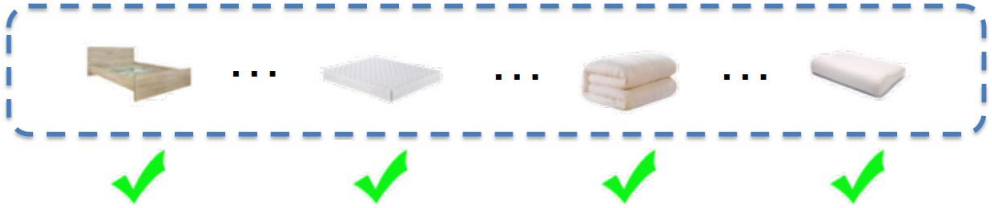
http://www.cse.msu.edu/~zhaoxi35/paper/kdd2018poster.pdf

Recommender System

Advantages of Using RL

- Continuously updating the recommendation strategies
- Maximizing the long-term reward from users





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Track: Intelligent and Autonomous systems on the Web

WWW 2018, April 23-27, 2018, Lyon, France

DRN: A Deep Reinforcement Learning Framework for News Recommendation

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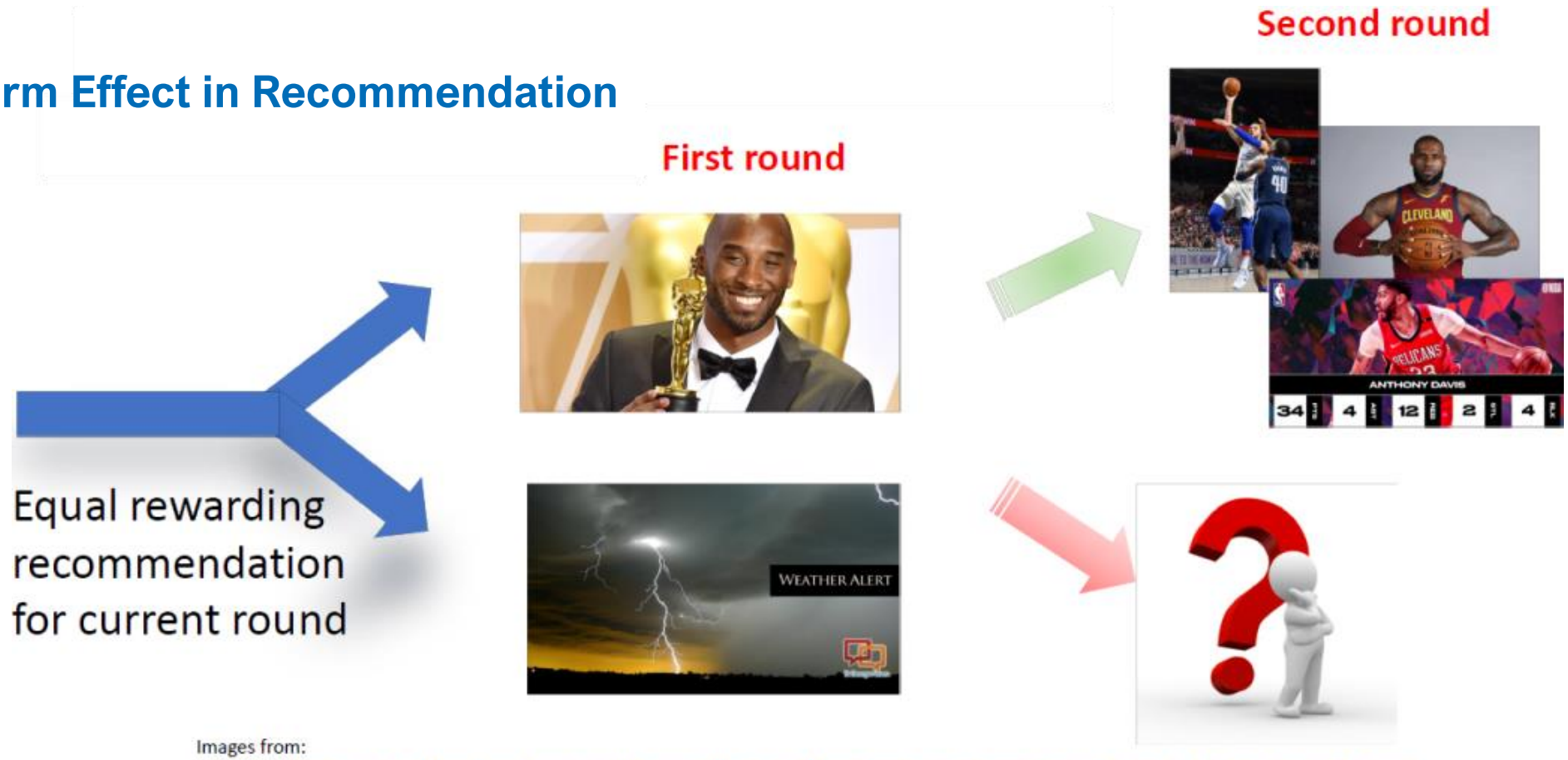
https://dl.acm.org/doi/10.1145/3178876.3185994

News Recommendation

Long-Term Effect in Recommendation



Images from:

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2. https://www.cnbc.com/2018/03/05/kobe-bryant-has-won-an-oscar-heres-what-he-says-it-takes-to-succeed.html
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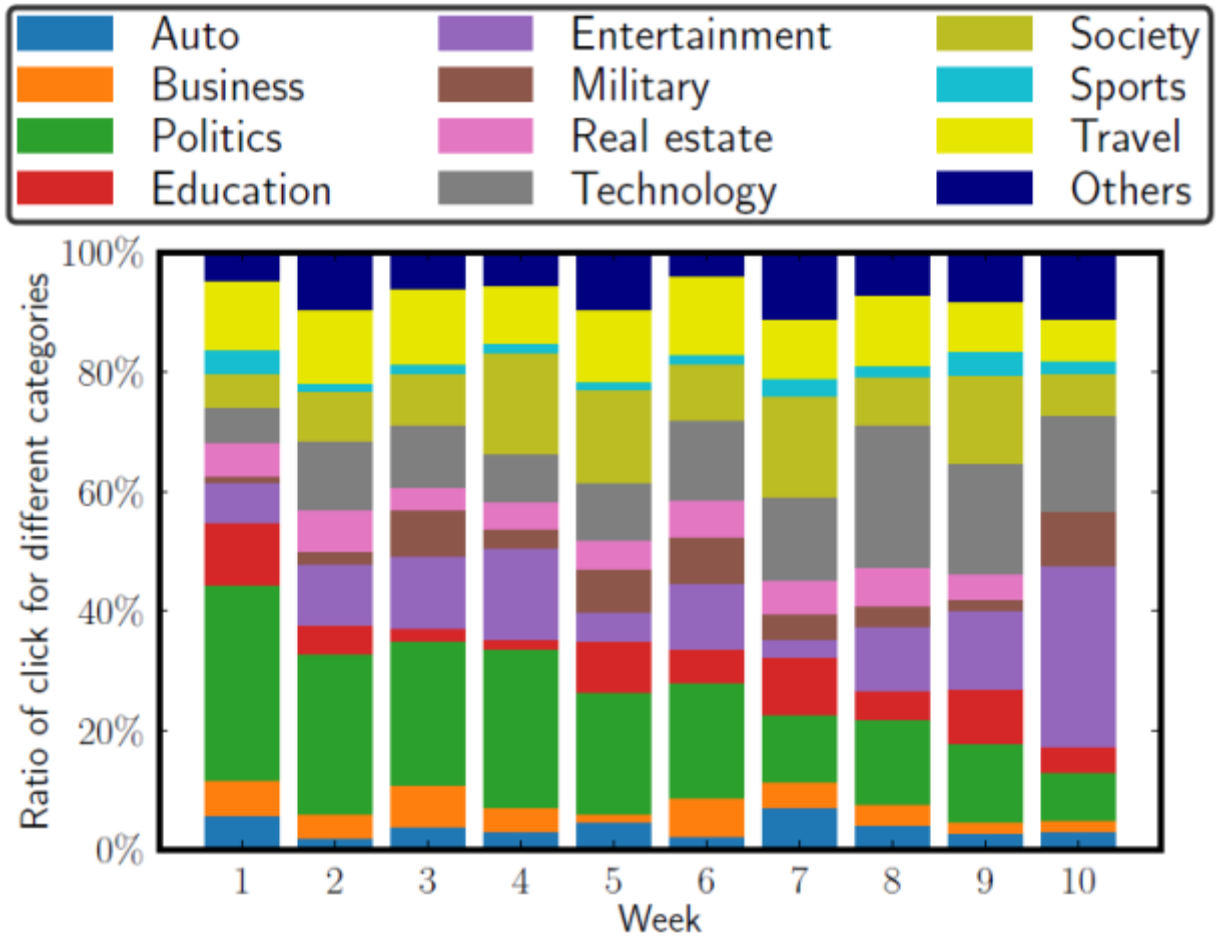
5. http://www.clipartpanda.com/clipart_images/question-mark-36565633

http://jhc.sjtu.edu.cn/~gjzheng/paper/www2018_reinforceRec/www2018_reinforceRec_slides.pdf

News Recommendation

- **News recommendation is dynamic!**
  - The life period for news is usually very short. (last-click-time - publish-time ≈ 4.1 hours)
  - User's interest may change during time.



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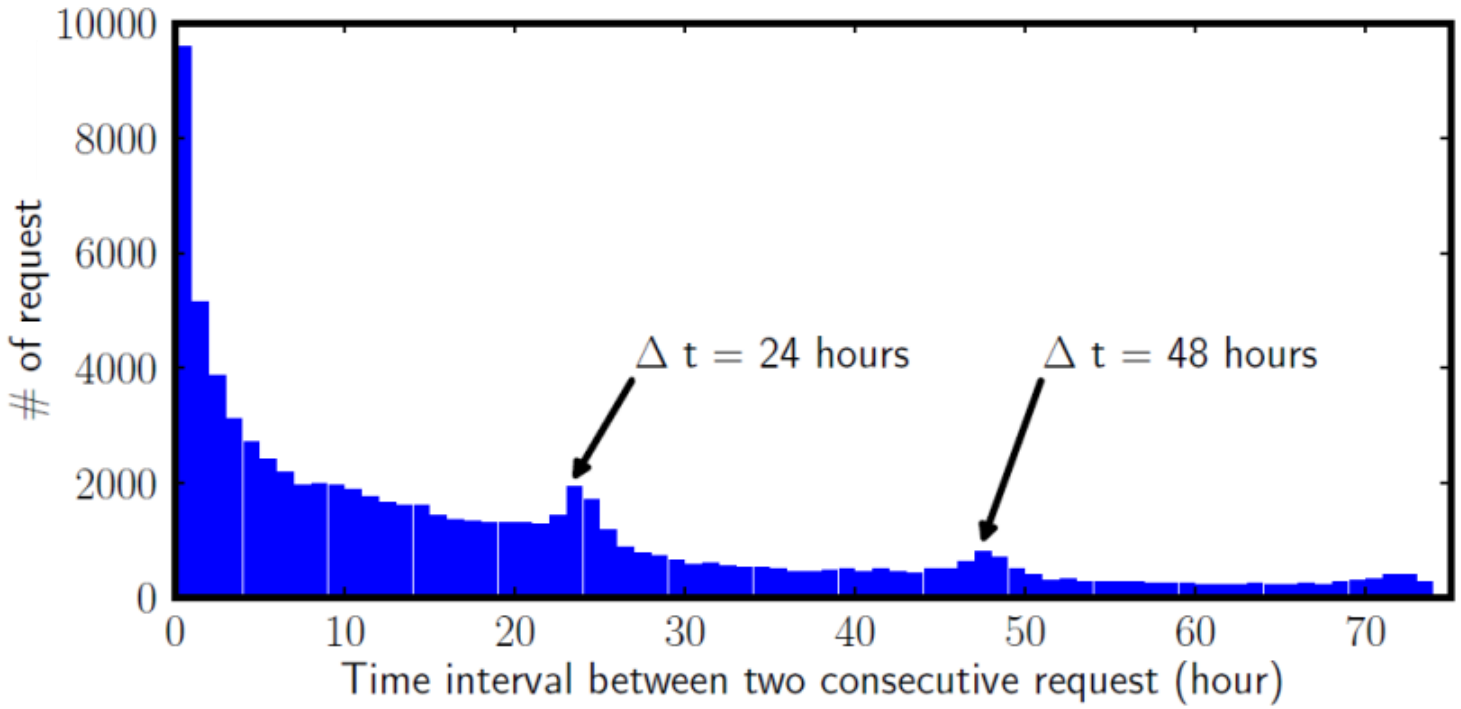
News Recommendation

- **Can we utilize user feedback other than click/skip?**
  (e.g., how frequent user returns)
  - User's clicks on news are usually very dense in a short period.
    Then, user usually leave the app!
  - User may return everyday!



http://jhc.sjtu.edu.cn/~gjzheng/paper/www2018_reinforceRec/www2018_reinforceRec_slides.pdf

News Recommendation

- **Should we keep recommending similar items?**
  - Will you get bored if all the recommended news are from NBA when you are browsing sports news?

Lebron James will be the MVP!

Tony Parker has come back from injury!

Paul Gasol promises to help the Spurs in the playoff.

http://jhc.sjtu.edu.cn/~gjzheng/paper/www2018_reinforceRec/www2018_reinforceRec_slides.pdf

News Recommendation

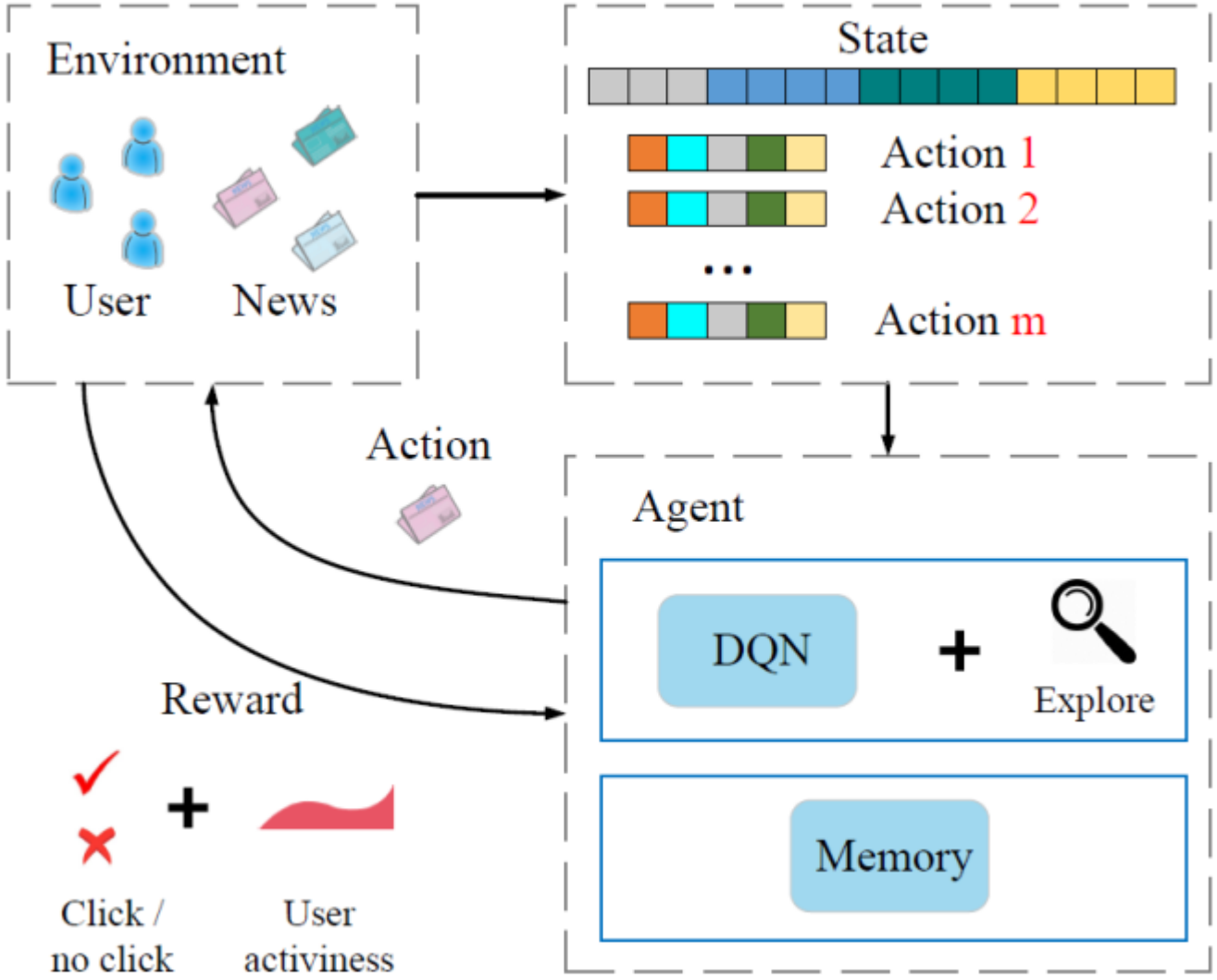
Motivation	Solution
Long term effect in recommendation	**Deep reinforcement learning (DRL)**
• Dynamic nature of news recommendation • Consider more measures for long term effect • Recommendation diversity	• Online learning feature of DRL • Reward function design of DRL • Explore in DRL

http://jhc.sjtu.edu.cn/~gjzheng/paper/www2018_reinforceRec/www2018_reinforceRec_slides.pdf

News Recommendation

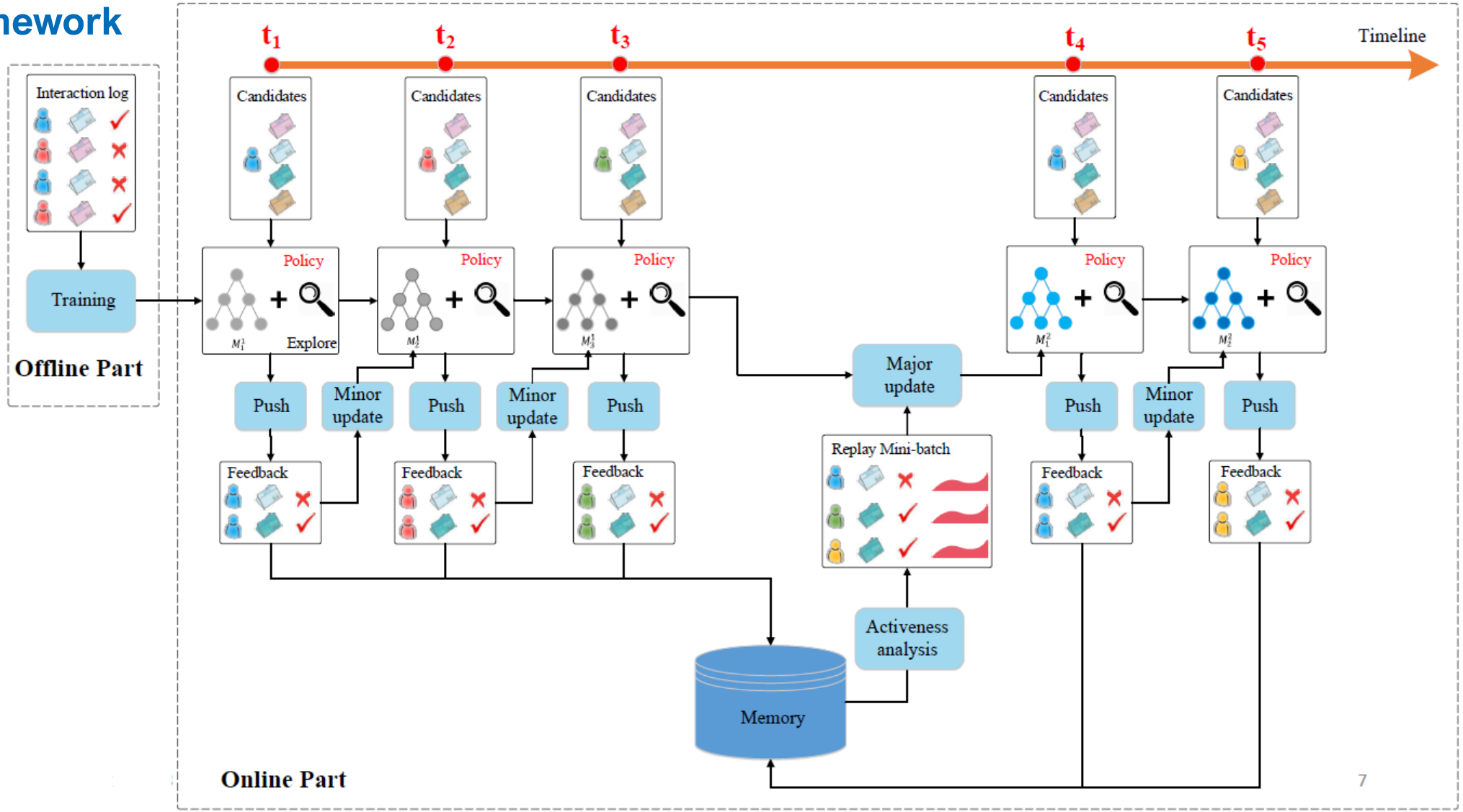
Recommendation as MDP

- Environment: User Pool + News Pool
- Agent: Recommendation Algorithm
- State: Feature Representation for Users
- Action: Feature Representation for News
- Reward: User Feedback
  - click/skip labels
  - estimation of user activeness



News Recommendation

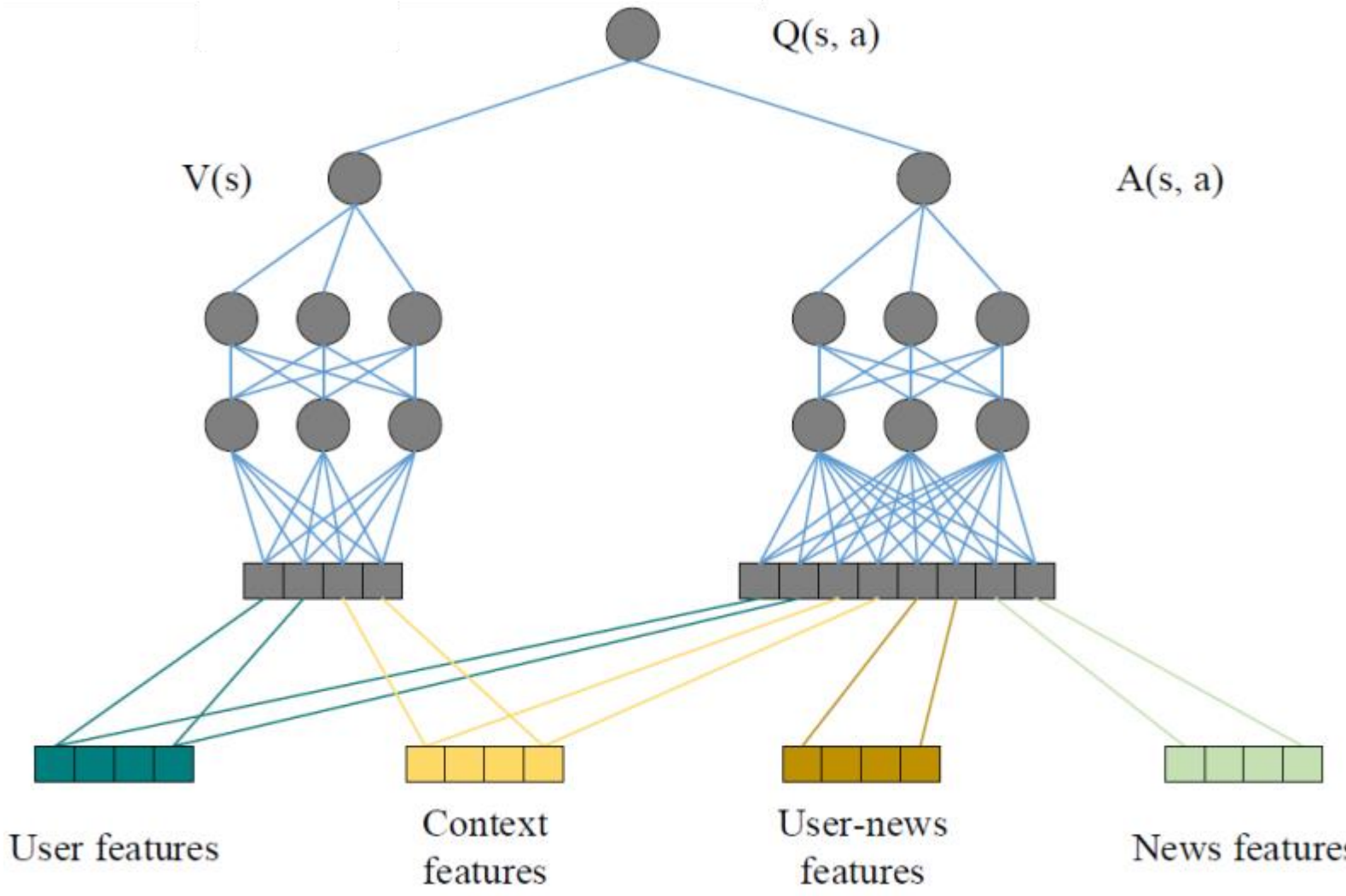
Model Framework



News Recommendation

Dueling Network Architecture

- Value function
- Advantage function

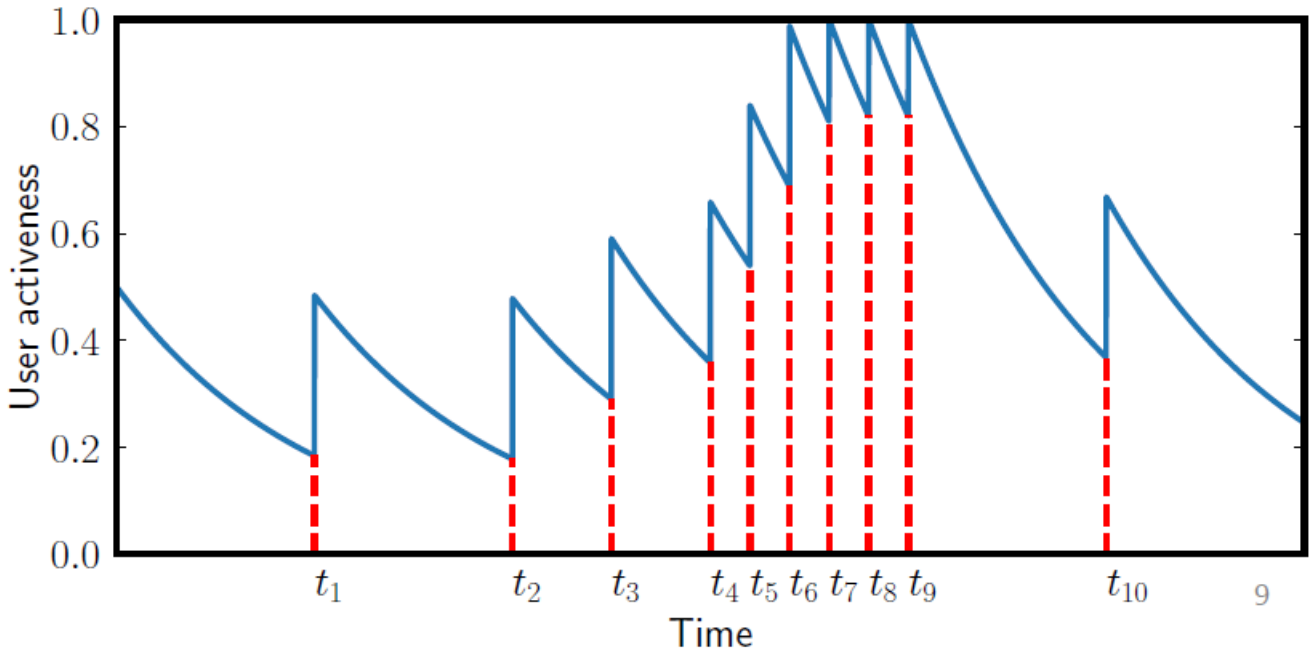


News Recommendation

User Activeness Modelling

(Survival Analysis)

- Hazard function $\lambda(t) = \lim_{dt \to 0} \frac{Pr\{t \leq T < t + dt | T \geq t\}}{dt}$
- User activeness $S(t) = e^{-\int_0^t \lambda(x)dx}$



News Recommendation

Effective Exploration

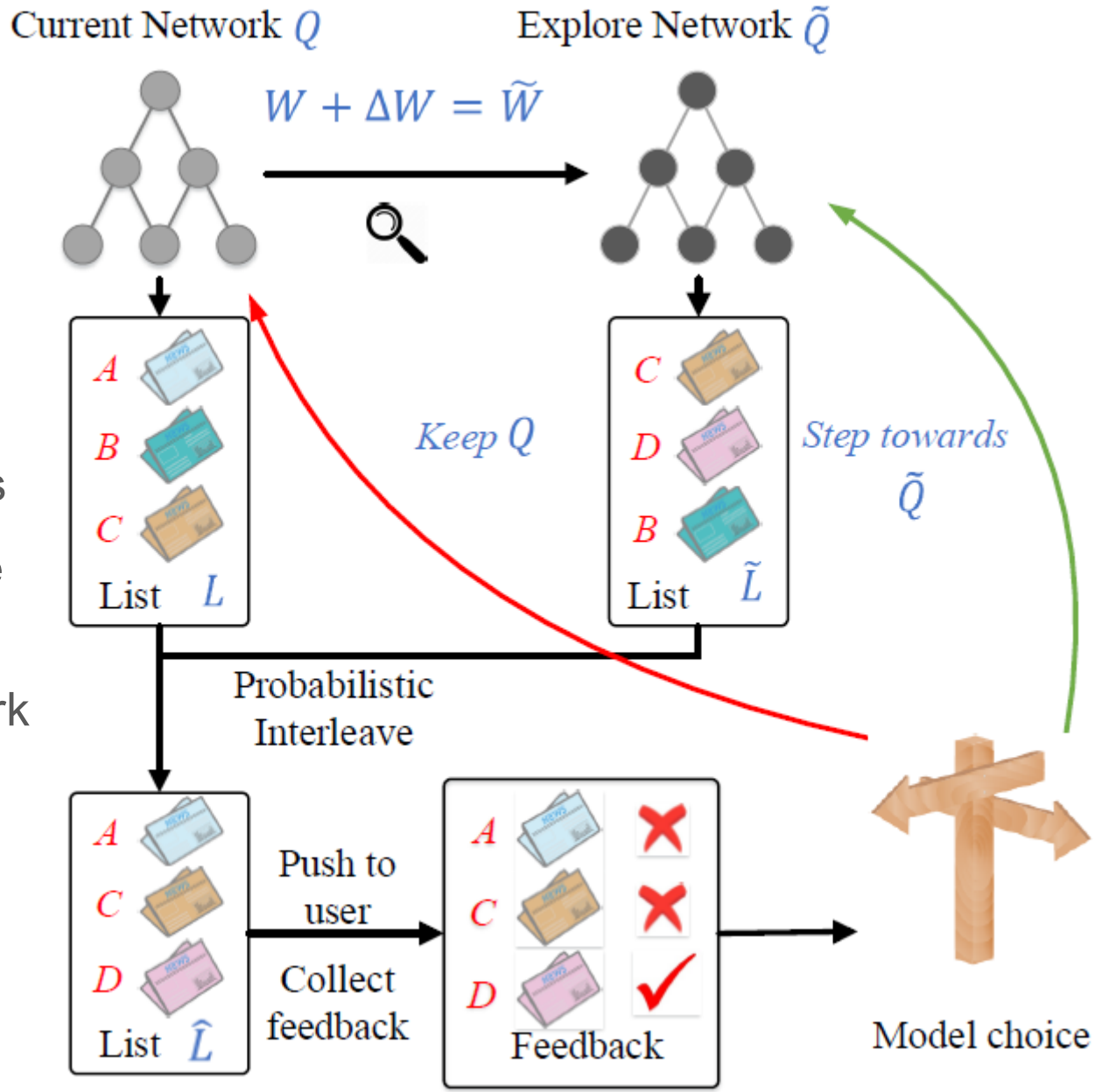
(Dueling Bandit Gradient Descent)

- Step1: get recommendation from Q and $\tilde{Q}$

$$\Delta W = \alpha \cdot rand(-1, 1) \cdot W$$

- Step2: probabilistic interleave these two lists
- Step3: get feedback from user and compare the performance of two networks
- Step4: if $\tilde{Q}$ performs better, update Q network towards it

$$W' = W + \eta \tilde{W}$$



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Recommendations with Negative Feedback via Pairwise Deep Reinforcement Learning

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Recommend with Positive and Negative Feedback

Why Negative Feedback?

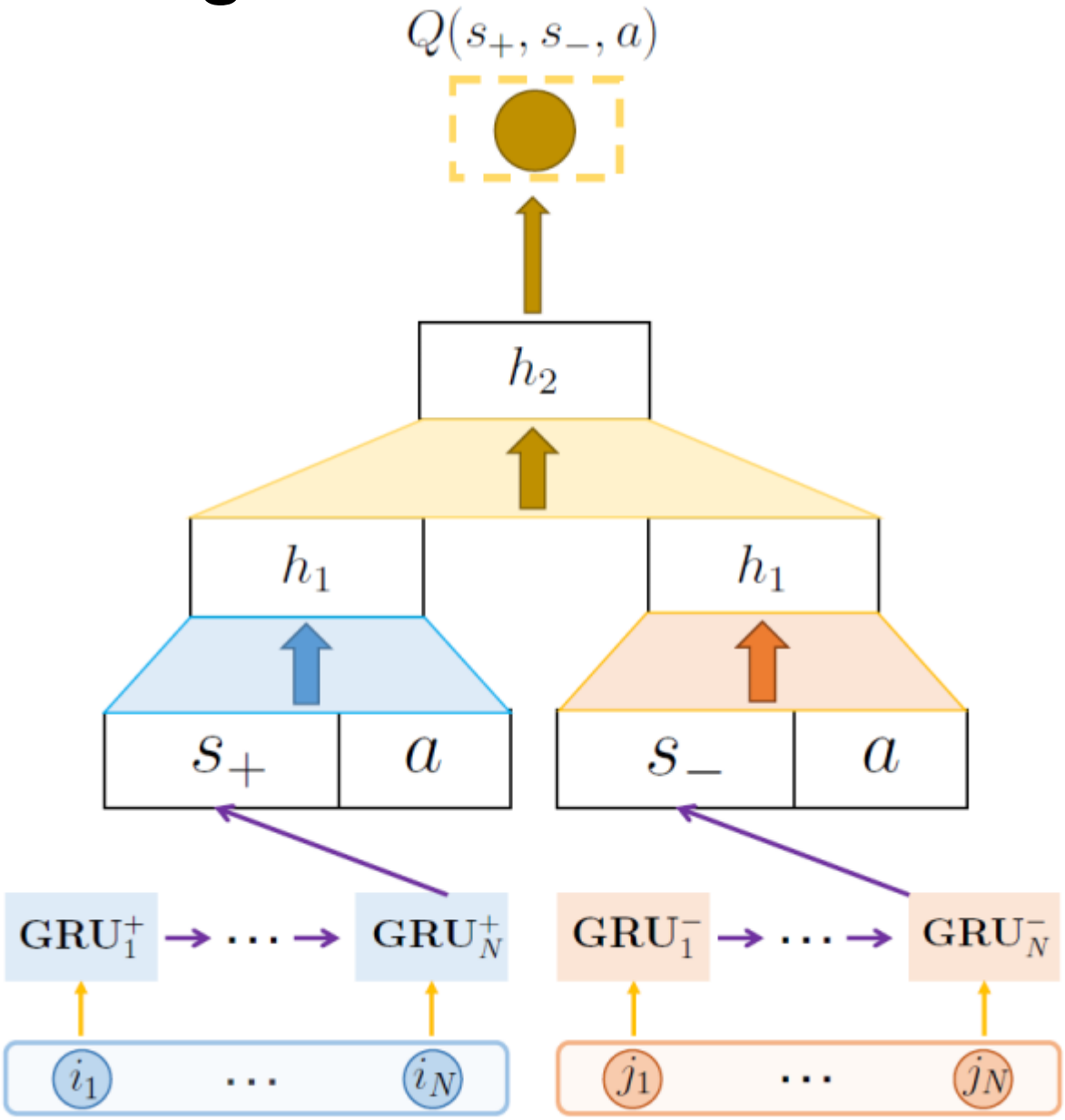
- Positive: click or purchase
- Negative: skip
  (what users may not like)

http://www.cse.msu.edu/~zhaoxi35/paper/kdd2018poster.pdf

Recommend with Positive and Negative Feedback

Network Architecture

- RNN with GRU to capture users' *sequential preference*.
- Recommend an item that is *similar* to the clicked/purchased items (left part), while *dissimilar* to the skipped items (right part).
- This architecture can assist DQN to capture distinct contributions of the positive and negative feedback to recommendations.



Recommend with Positive and Negative Feedback

The Pairwise Regularization Term

- RA often recommends items belong to the same category, while users click/purchase a part of them and skip others.
- We design a pairwise regularization term to maximize the difference of Q-values between competing items.

$$L(\theta) = \mathbb{E}_{s,a,r,s'}\left[\left(y - Q(s_+, s_-, a; \theta)\right)^2 - \alpha\left(Q(s_+, s_-, a; \theta) - Q(s_+, s_-, a^C; \theta)\right)^2\right]$$

Time	State	Item	Category	Feedback
1	s_1	a_1	A	skip
2	s_2	a_2	B	click
3	s_3	a_3	A	click
4	s_4	a_4	C	skip
5	s_5	a_5	B	skip
6	s_6	a_6	A	skip
7	s_7	a_7	C	order

Applied Data Science Track Paper KDD '20, August 23–27, 2020, Virtual Event, USA

Jointly Learning to Recommend and Advertise

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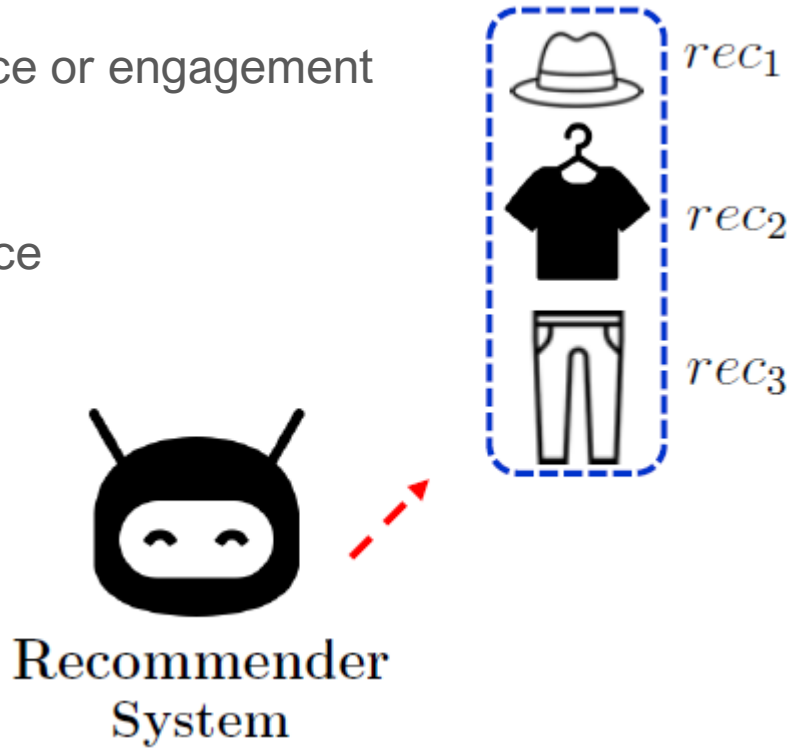
https://dl.acm.org/doi/10.1145/3394486.3403384

Jointly Learning to Recommend and Advertise

Recommender System

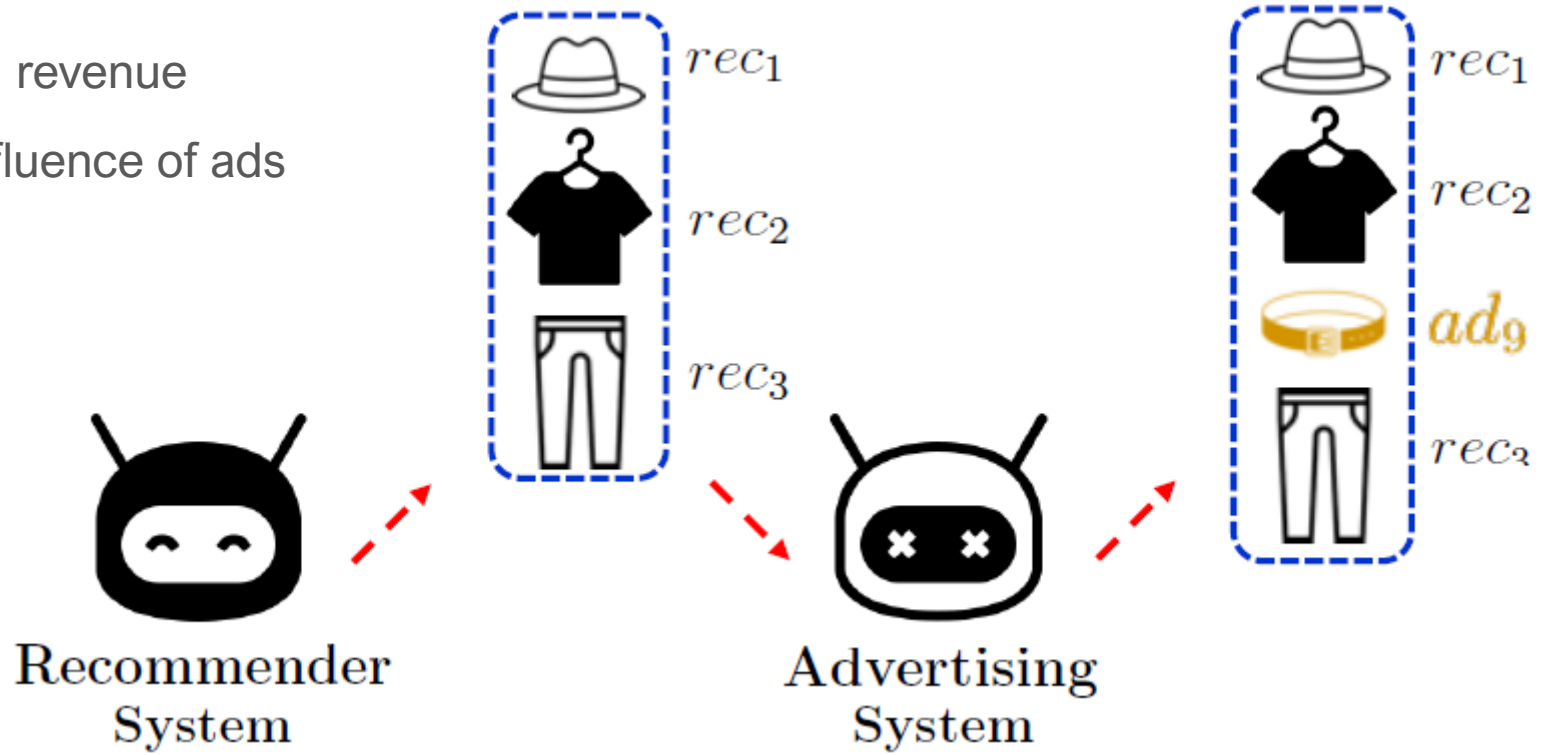
- Goal
  - long-term user experience or engagement
- Challenge
  - combinatorial action space



Jointly Learning to Recommend and Advertise

Advertising System

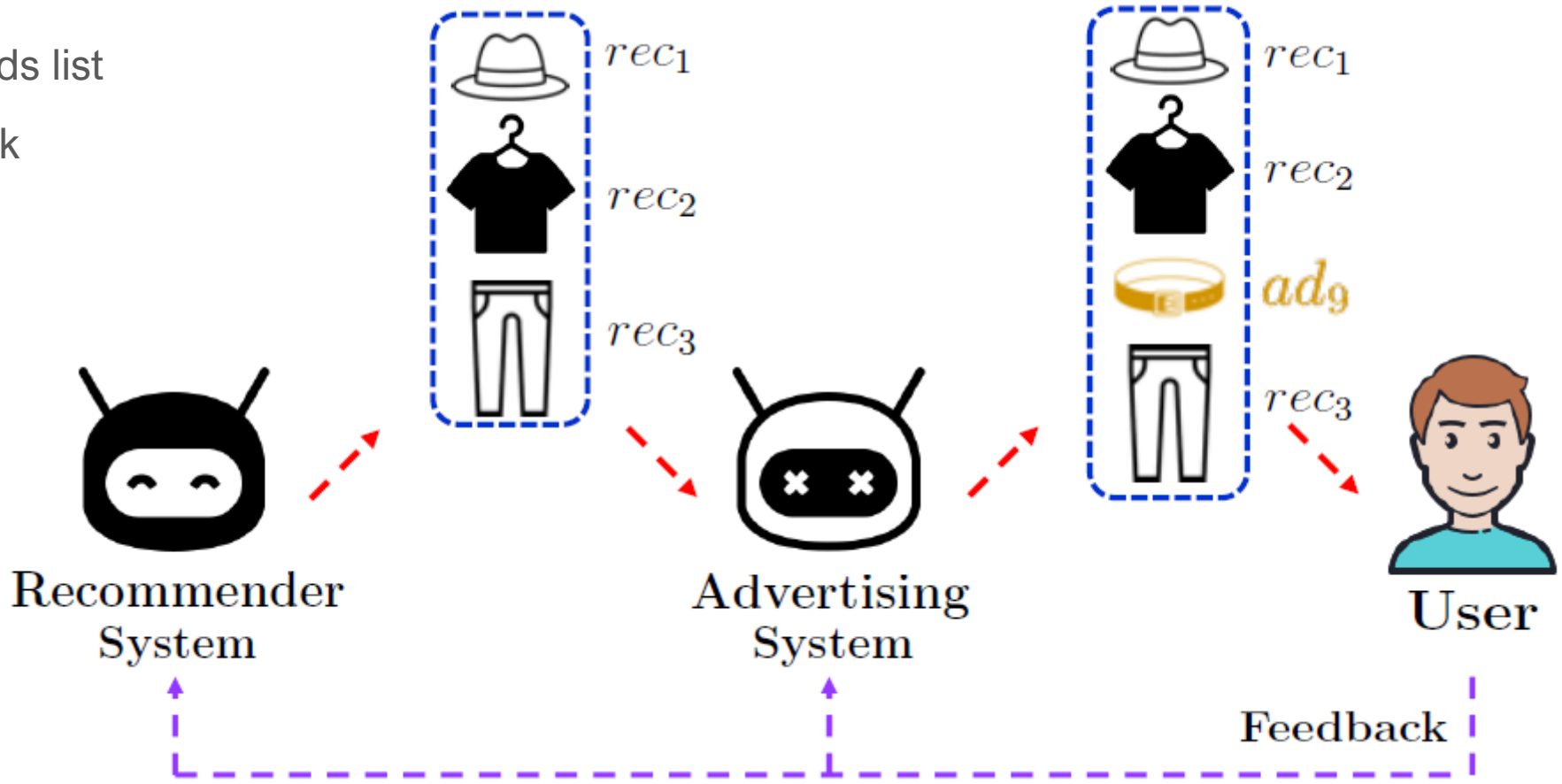
- Goal:
  - maximize the advertising revenue
  - minimize the negative influence of ads on user experience
- Challenge:
  - interpolate an ad?
  - the optimal location
  - the optimal ad



Jointly Learning to Recommend and Advertise

Systems Update

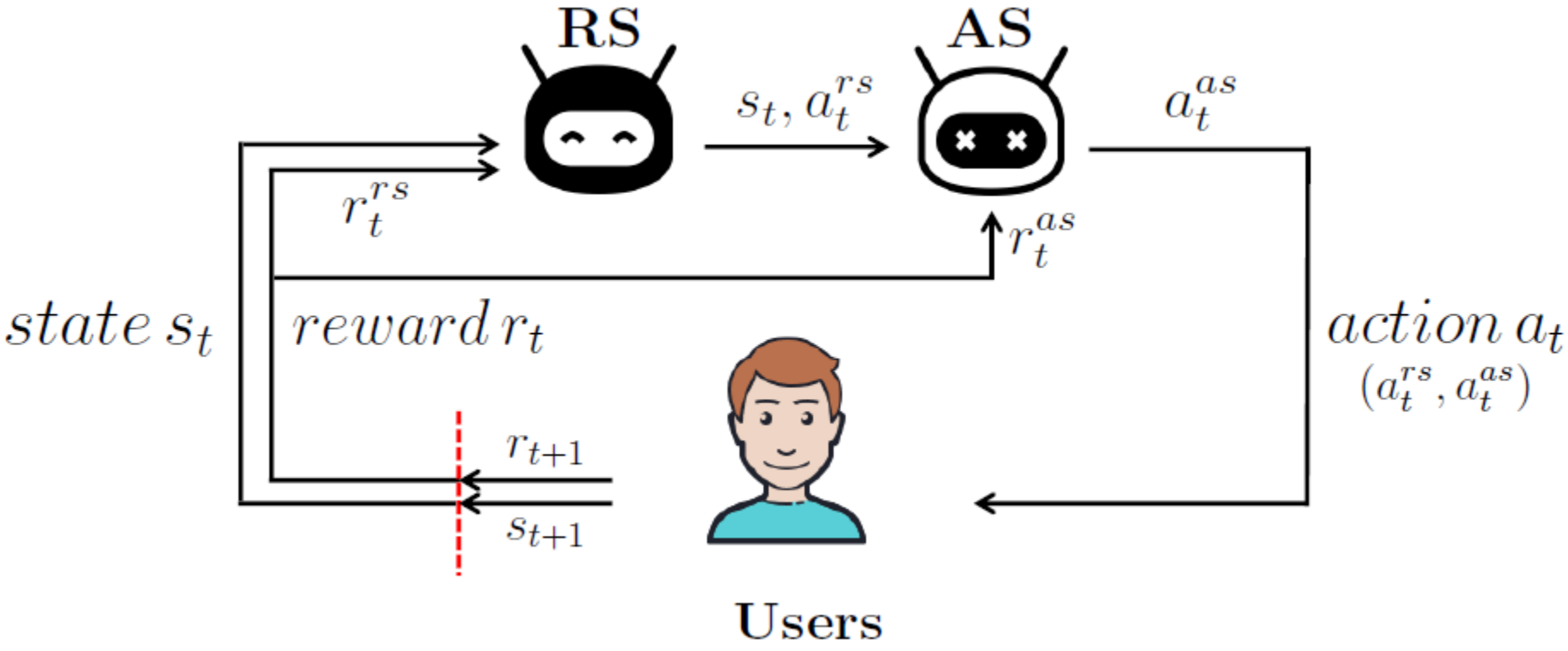
- Target User:
  - browses the mixed rec-ads list
  - provides her/his feedback



Jointly Learning to Recommend and Advertise

Two-level DQN

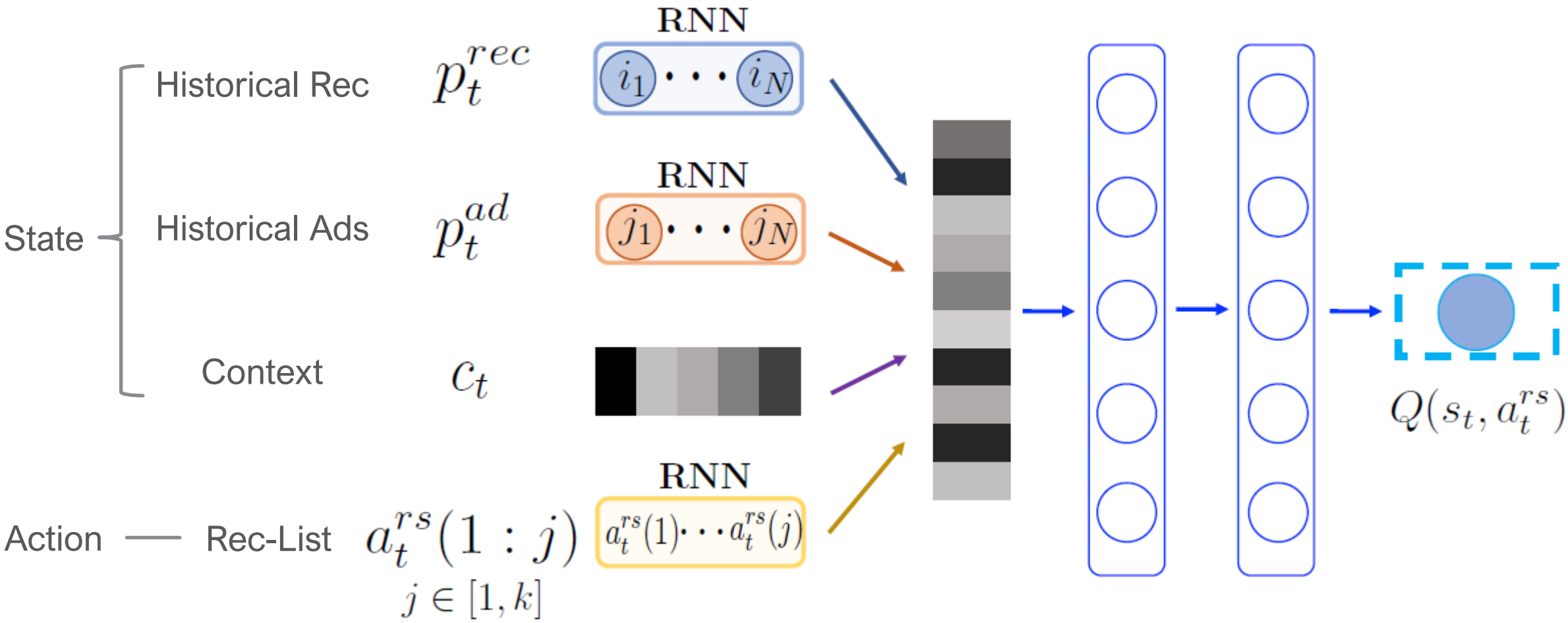
- 1st-level: recommender system (RS)
- 2nd-level: advertising system (AS)



Jointly Learning to Recommend and Advertise

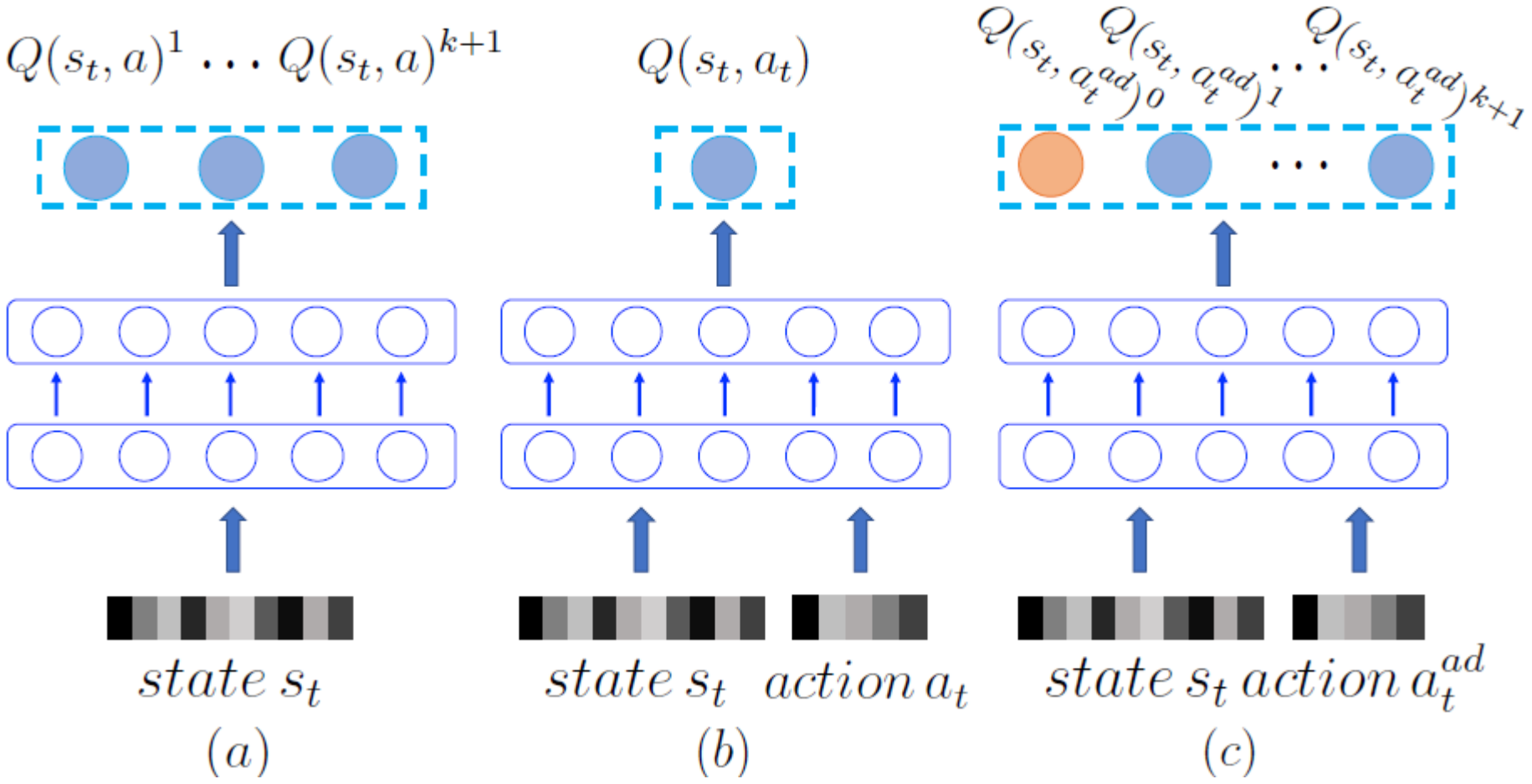
Cascading DQN for RS

(Generates a list by sequentially selecting items in a cascading manner)



Jointly Learning to Recommend and Advertise

Novel DQN for AS



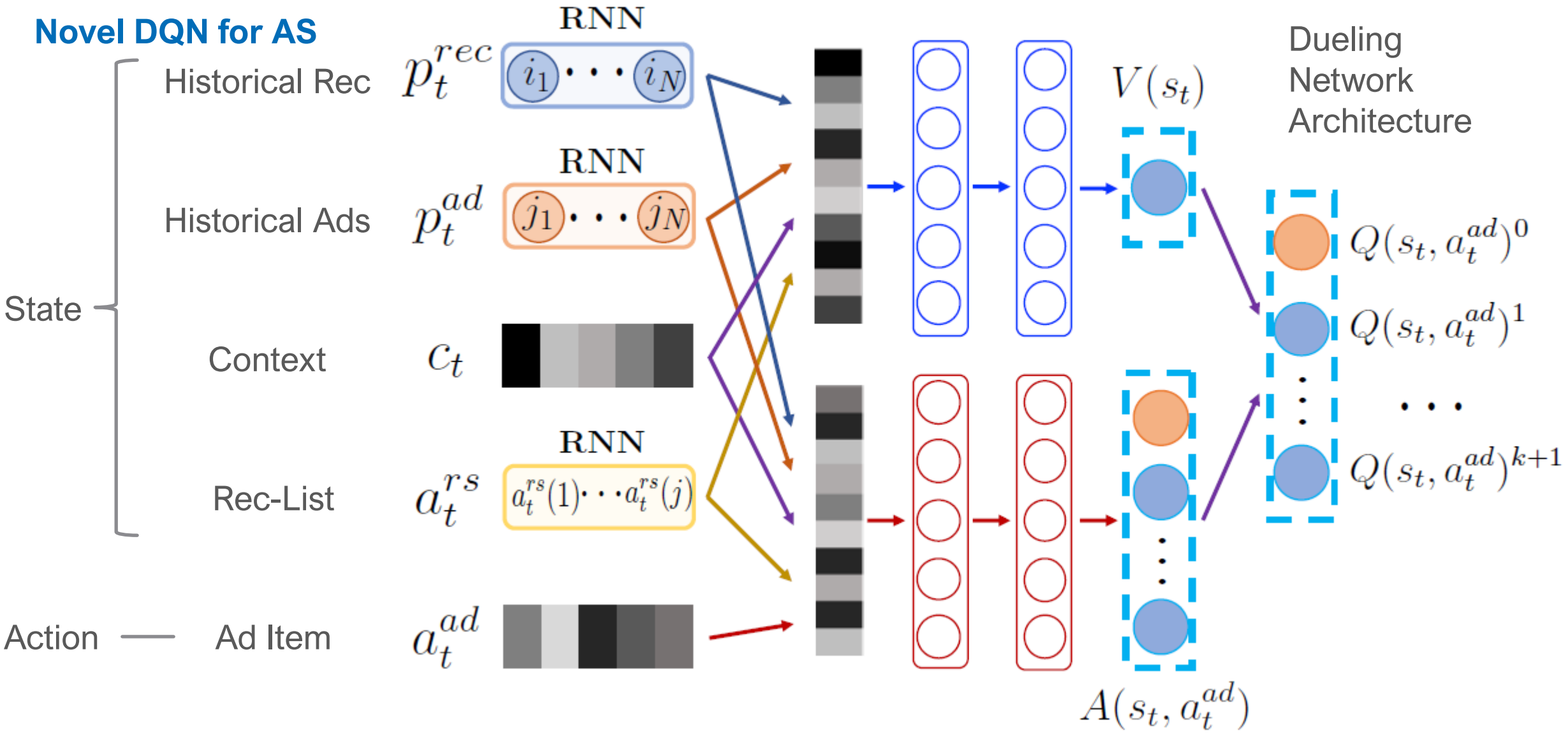
Conventional DQN Architecture

Conventional DQN Architecture

Proposed DQN Architecture

- interpolate an ad?
- the optimal location
- the optimal ad

Jointly Learning to Recommend and Advertise



IR APPLICATIONS USING REINFORCE

Dell Zhang

Policy Gradient

The Secret to the Success of REINFORCE

$$\nabla_\theta \mathrm{E}_{\tau\sim\pi_\theta}[\mathrm{R}(\tau)] \propto \mathrm{E}_{\tau\sim\pi_\theta}[\mathrm{R}(\tau) \cdot \nabla_\theta \log \pi_\theta(a|s)]$$

- $\mathrm{R}(\tau)$ does not need to be differentiable: it is just a black box in the REINFORCE algorithm. This implies that you can optimize pretty much *anything* you would like to optimize.
- The high-variance weakness of the original REINFORCE algorithm could be alleviated by baseline functions or actor-critic methods etc.
- The on-policy limitation of the original REINFORCE algorithm could be removed by off-policy correction (based on importance sampling).

https://dl.acm.org/doi/10.1145/3077136.3080685

Reinforcement Learning to Rank with Markov Decision Process

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https://dl.acm.org/doi/10.1145/3077136.3080775

Adapting Markov Decision Process for Search Result Diversification

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https://dl.acm.org/doi/10.1145/3397271.3401148

Reinforcement Learning to Rank with Pairwise Policy Gradient

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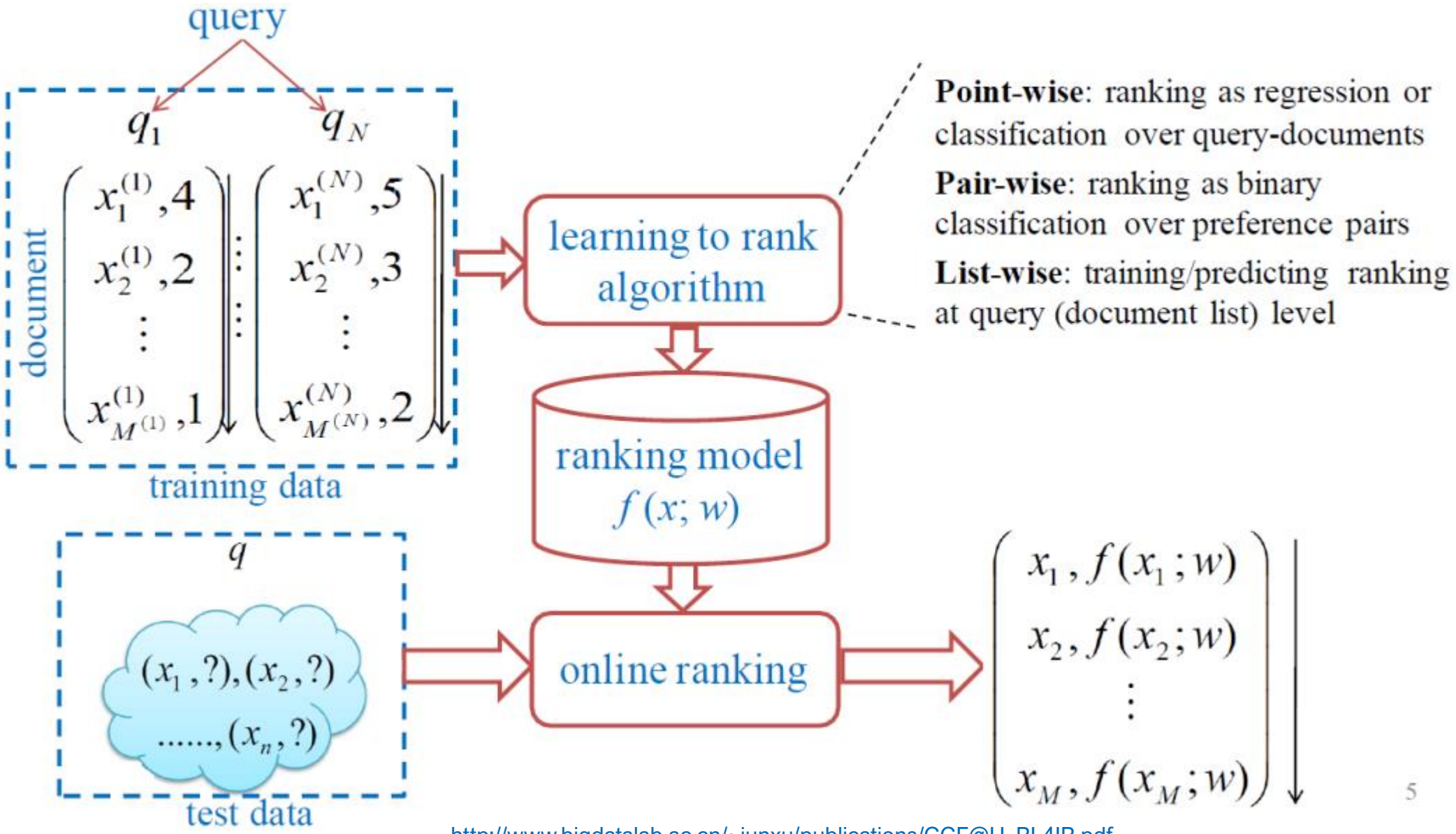
Learning to Rank

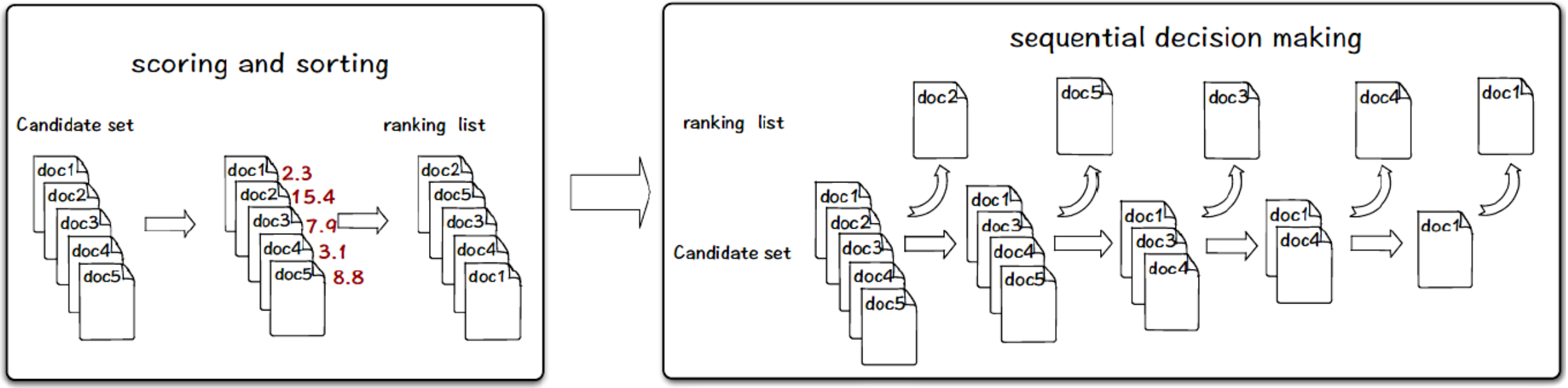


http://www.bigdatalab.ac.cn/~junxu/publications/CCF@U_RL4IR.pdf

Learning to Rank

Sequential Decision Making:
Beyond Independence Relevance

- Document Ranking Positions
- Document Interdependencies

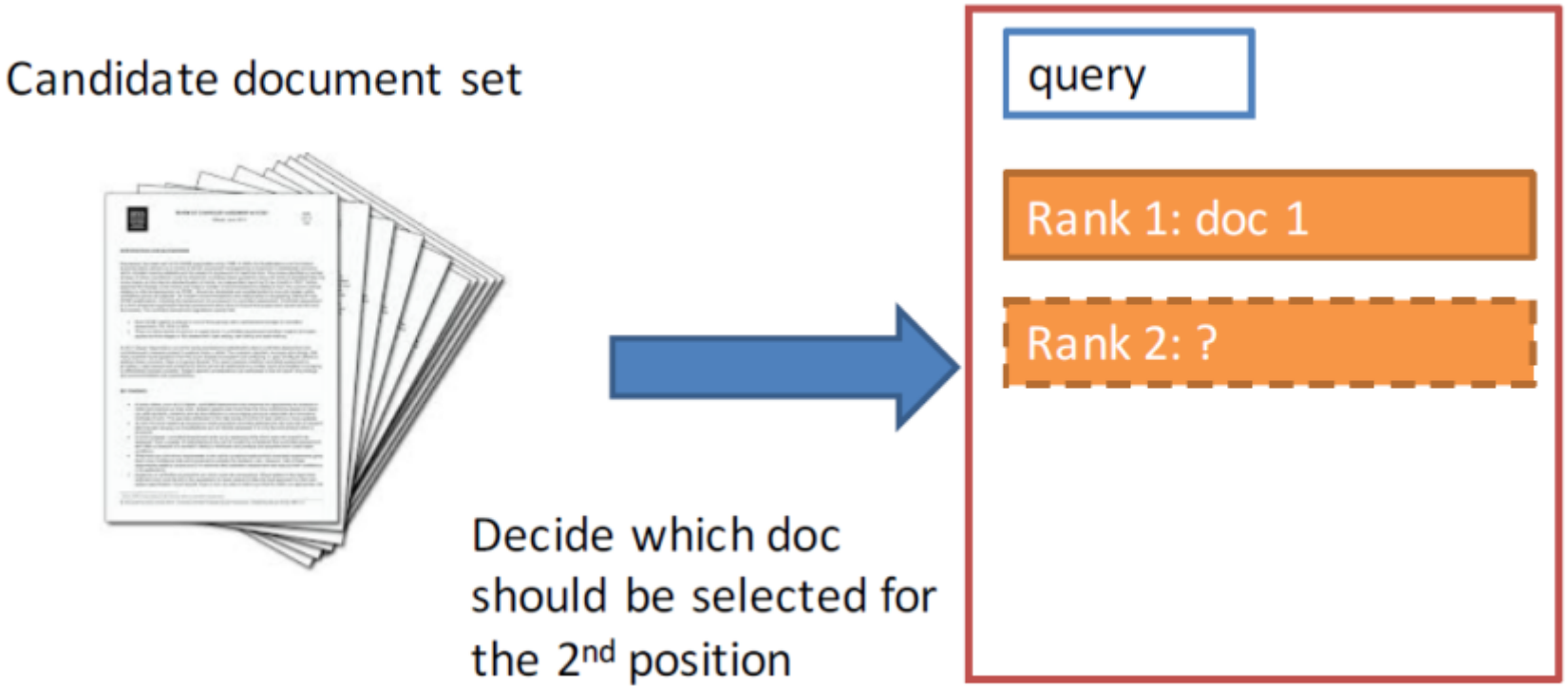


http://www.bigdatalab.ac.cn/~junxu/publications/CCF@U_RL4IR.pdf

Learning to Rank

Ranking as MDP

- Mimic user top-down browsing behaviours
- Model dynamic information needs with MDP state



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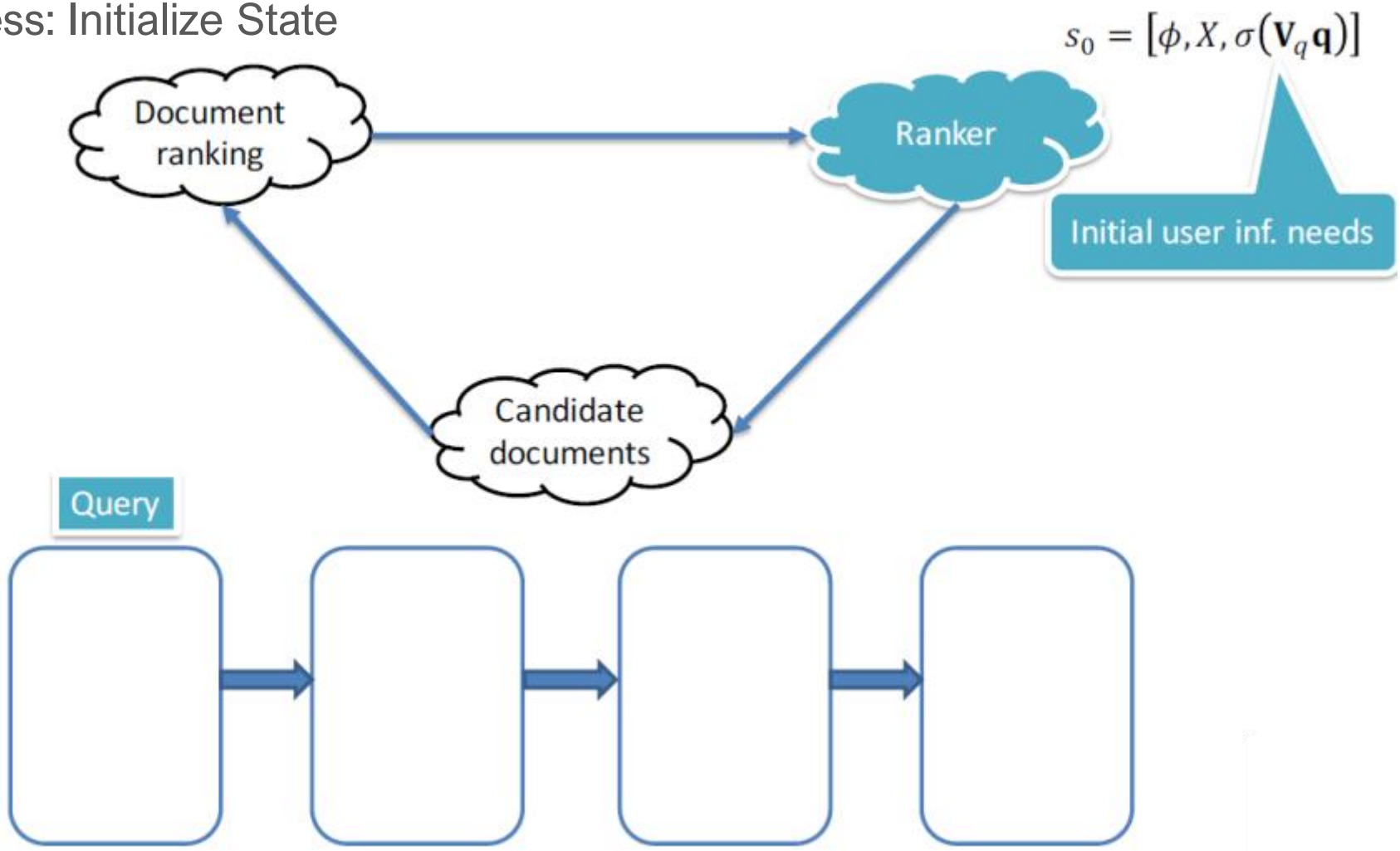
Learning to Rank

Ranking Process: Initialize State



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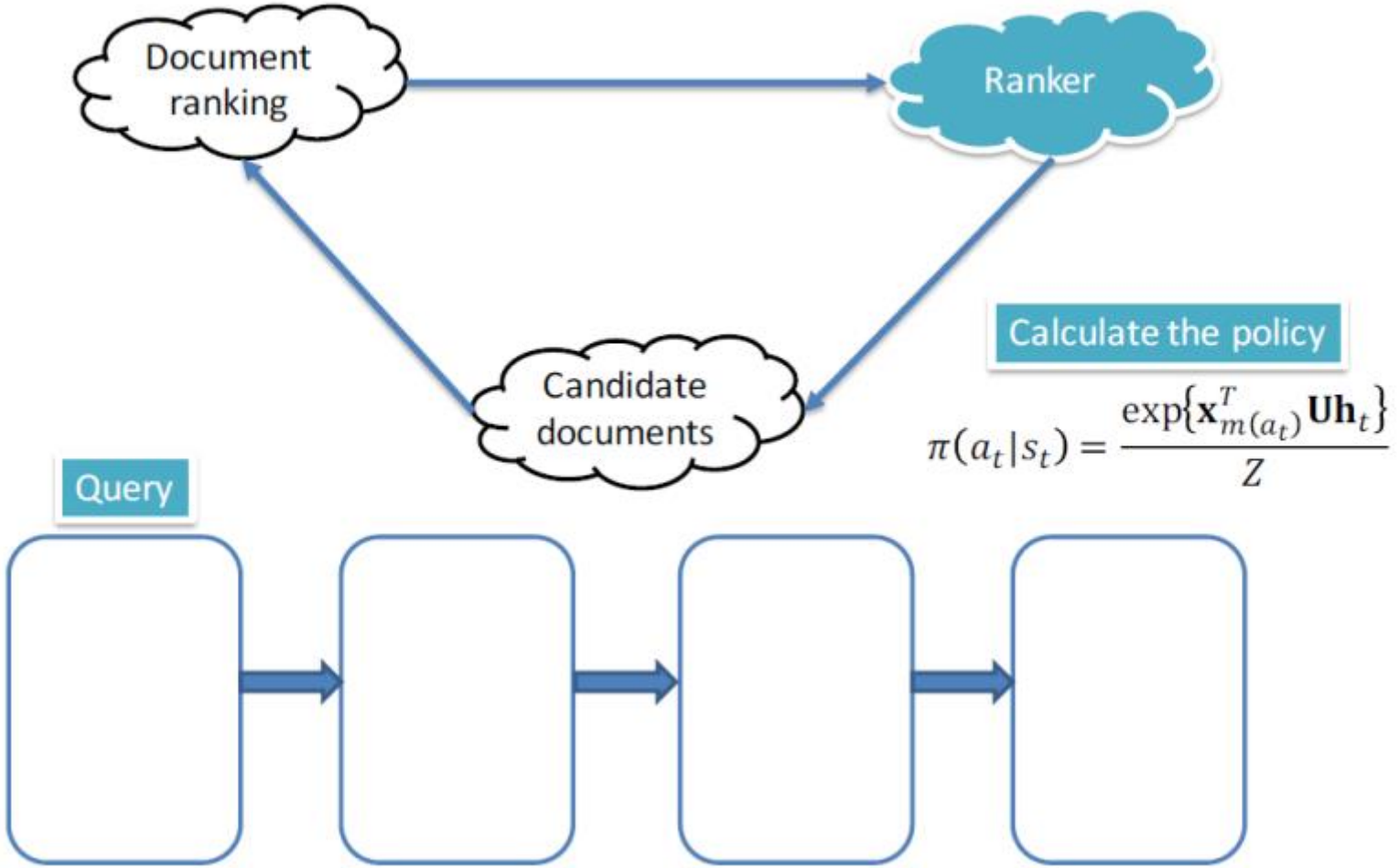
Learning to Rank

Ranking Process: Policy



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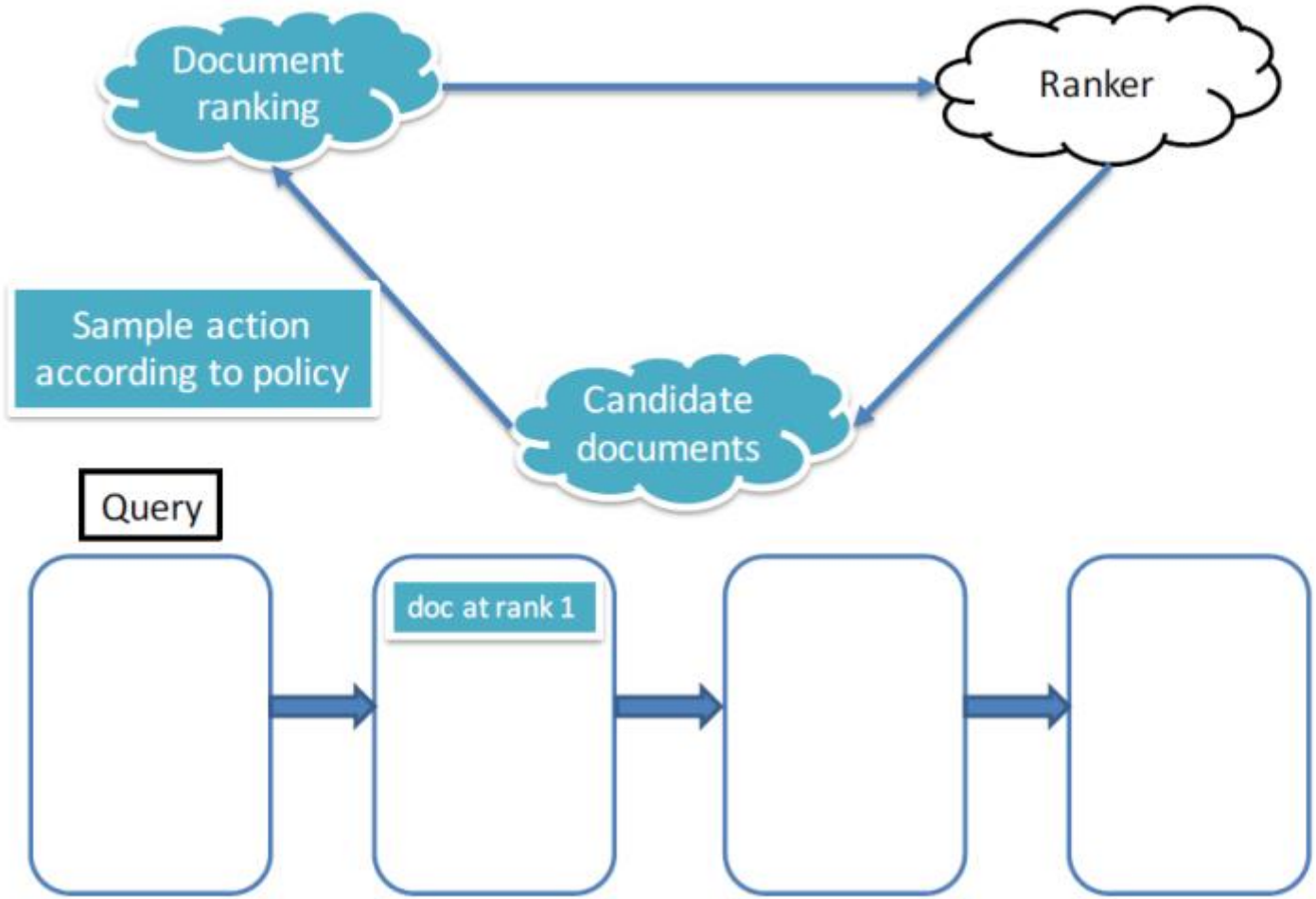
Learning to Rank

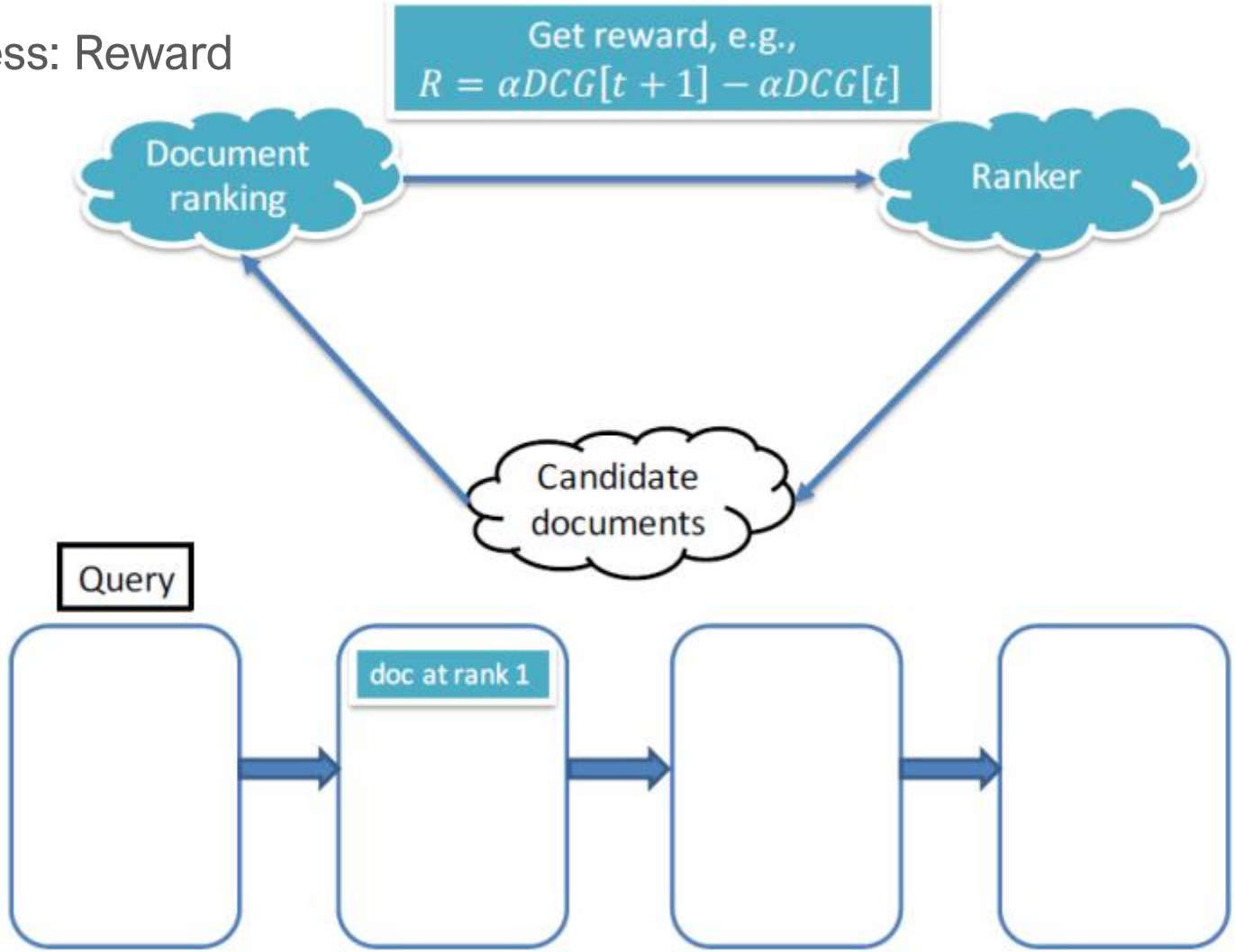
Ranking Process: Action



http://www.bigdatalab.ac.cn/~junxu/publications/CCF@U_RL4IR.pdf

Learning to Rank

Ranking Process: Reward



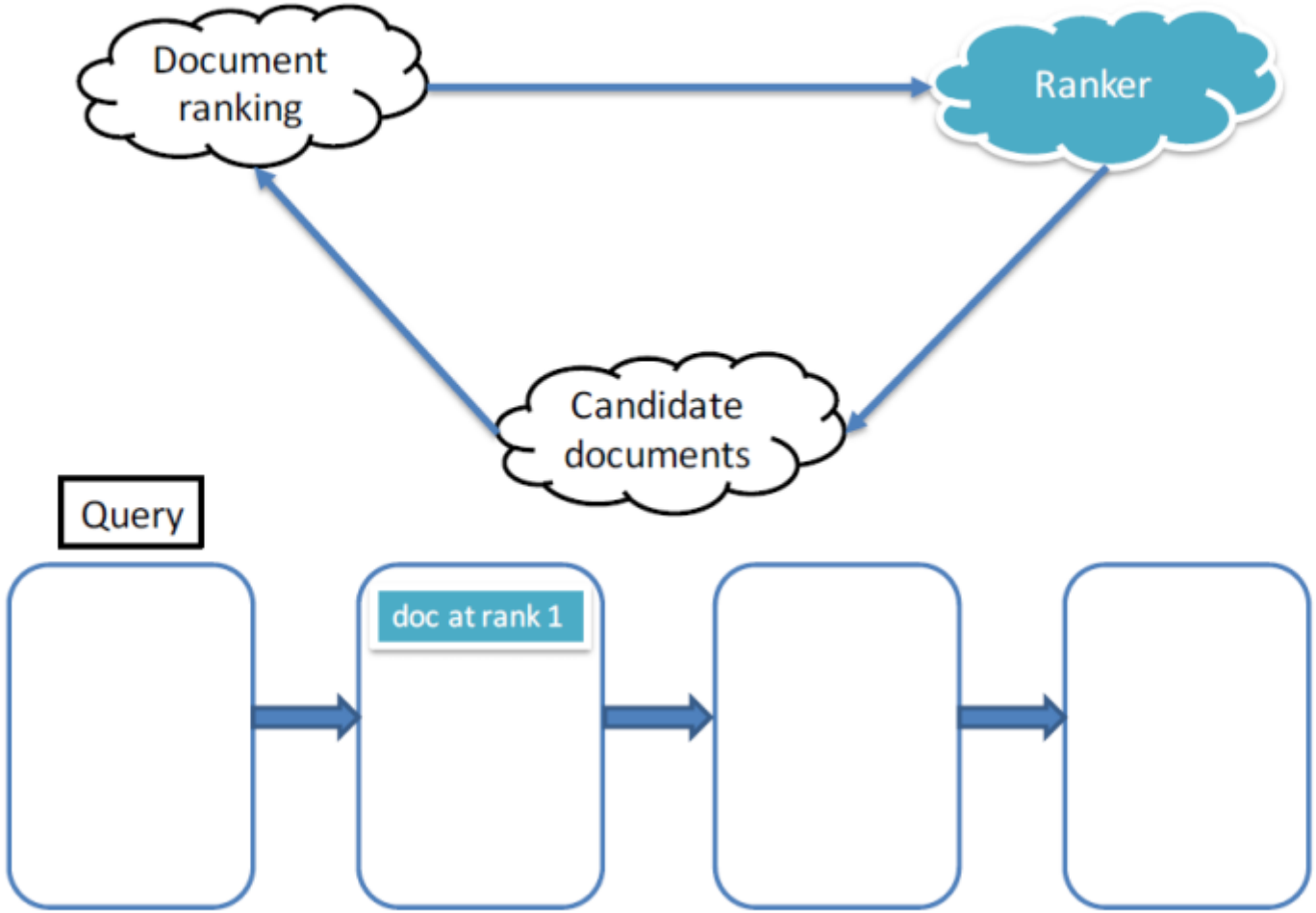
http://www.bigdatalab.ac.cn/~junxu/publications/CCF@U_RL4IR.pdf

Learning to Rank

Ranking Process: State Transition

Update ranked list, candidate set, and latent vector

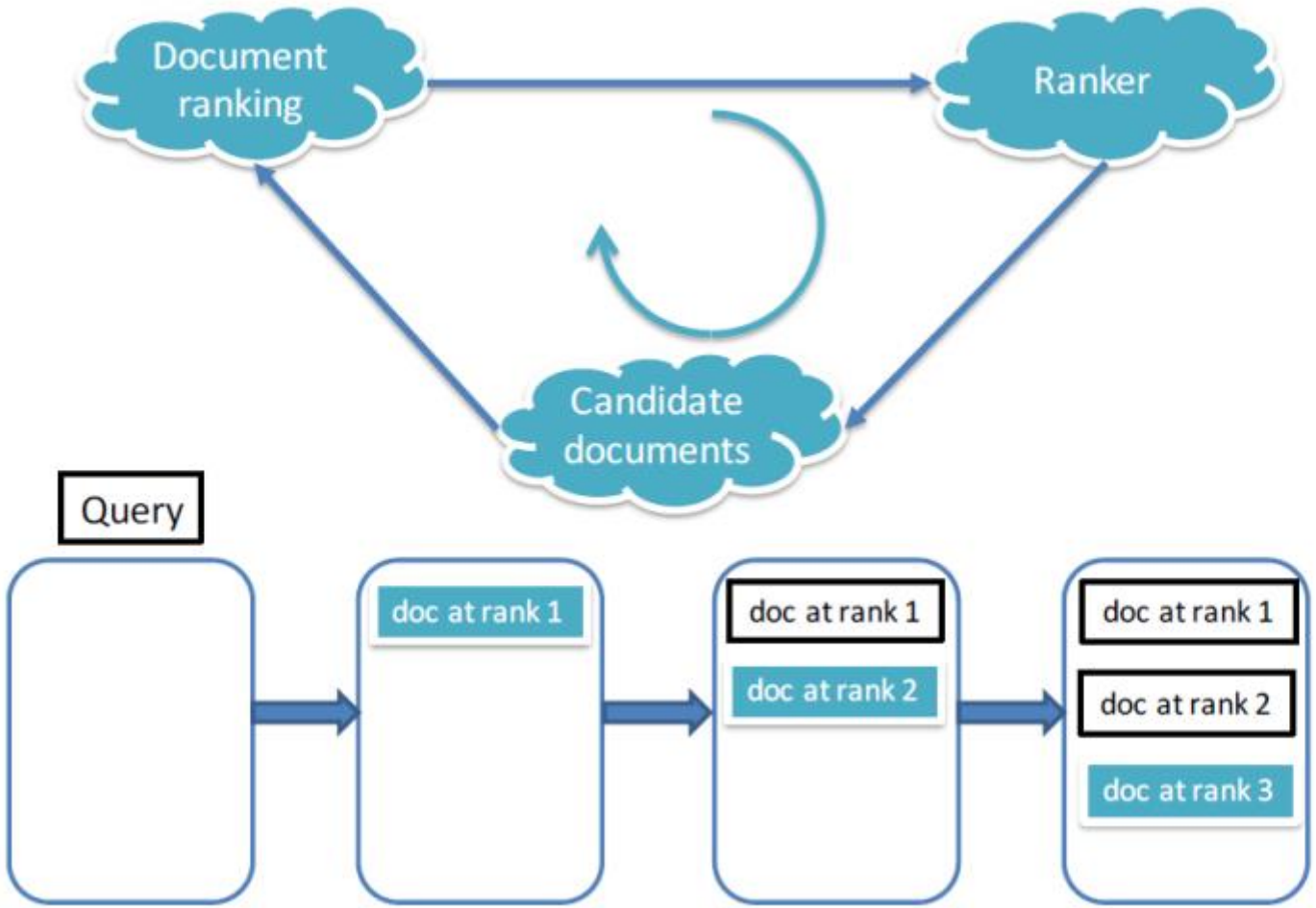
$$s_{t+1} = [Z_t \oplus \{\mathbf{x}_{m(a_t)}\}, X_t \backslash \{\mathbf{x}_{m(a_t)}\}, \sigma(\mathbf{V}\mathbf{x}_{m(a_t)} + \mathbf{W}\mathbf{h}_t)]$$



http://www.bigdatalab.ac.cn/~junxu/publications/CCF@U_RL4IR.pdf

Learning to Rank

Ranking Process: Iterate



http://www.bigdatalab.ac.cn/~junxu/publications/CCF@U_RL4IR.pdf

Learning to Rank

Text Retrieval

MDP configuration	text retrieval
state at time t: s_t	$s_t = [t, X_t]$
initial state s_0	$s_0 = \mathcal{S}(Q, X) = [0, X]$, where X contains all docs
state transition $\mathcal{T}(s_t, a_t)$	$\mathcal{T}(s_t, a_t) = [t+1, X_t \setminus \{d_{m(a_t)}\}]$
reward $\mathcal{R}(s_t, a_t)$	$\mathcal{R}(s_t, a_t) = \begin{cases} 2^{y_{m(a_t)}} - 1 & t = 0 \\ (2^{y_{m(a_t)}} - 1)/\log_2(t+1) & t > 0 \end{cases}$
policy $\pi(a_t \mid s_t; \theta)$	$\pi(a_t \mid s_t; \theta) = \frac{\exp\{\theta^T \phi(Q, d_{m(a_t)})\}}{\sum_{a \in A(s_t)} \exp\{\theta^T \phi(Q, d_{m(a)})\}}$, where $\phi(Q, d_{m(a_t)})$ is ranking feature vector
Gradient $\nabla \log \pi(a \mid s)$	$\phi(Q, d_{m(a_t)}) - \sum_{a \in A(s_t)} \pi(a \mid s_t; \theta) \phi(Q, d_{m(a)})$

query-document relevance features

Learning to Rank

Search Result Diversification

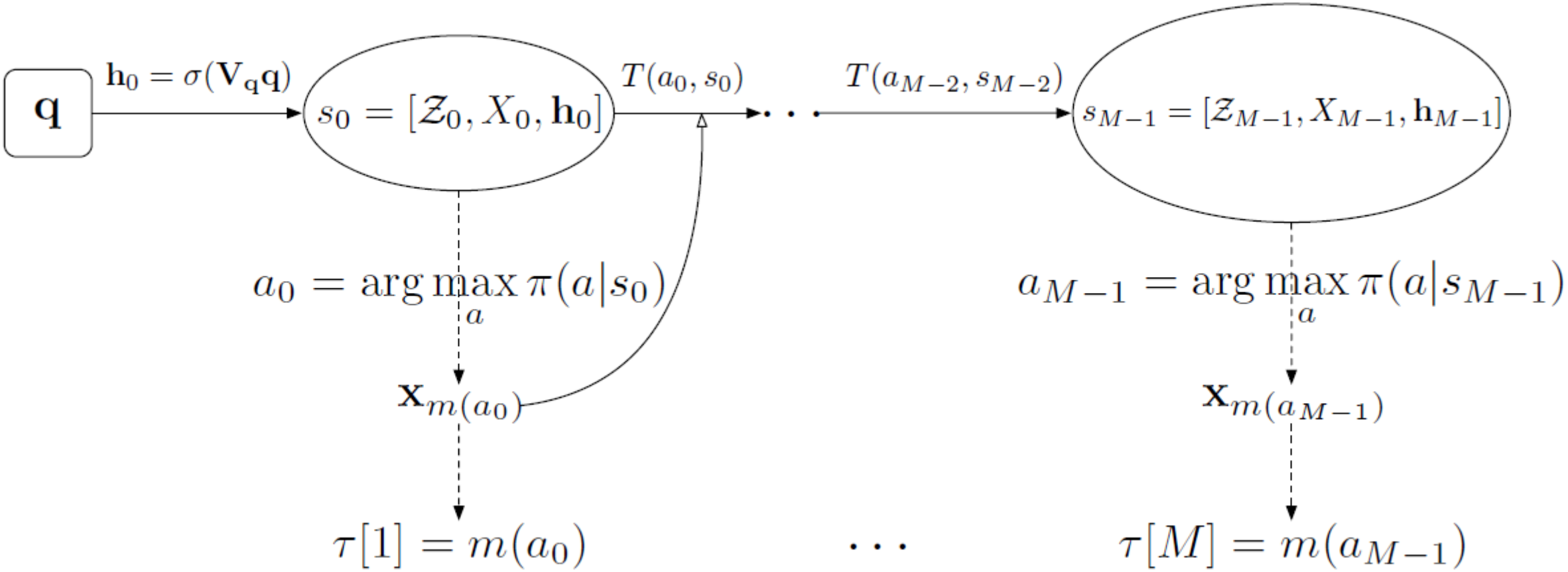
user's perceived utility from preceding documents

MDP configuration	search result diversification
state at time t: s_t	$s_t = [Z_t, X_t, \mathbf{h}_t]$, where Z_t is ranked doc list, $\mathbf{h}_t$ is latent vector
initial state s_0	$s_0 = \mathcal{S}(Q, X) = [\emptyset, X, \sigma(\mathbf{V}_q \mathbf{q})]$, where $\mathbf{q}$ is query embedding
state transition $\mathcal{T}(s_t, a_t)$	$\mathcal{T}(s_t, a_t) = [Z_t \cup \{d_{m(a_t)}\}, X_t \setminus \{d_{m(a_t)}\}, \sigma(\mathbf{V}\mathbf{x}_{m(a_t)} + \mathbf{W}\mathbf{h}_t)]$, where $\mathbf{x}_{m(a_t)}$ is doc embedding, and $\mathbf{V}$, $\mathbf{W}$ are parameters
reward $\mathcal{R}(s_t, a_t)$	$\mathcal{R}(s_t, a_t) = \alpha$-DCG[t+1]$-\alpha$-DCG[t], where α-DCG[0] = 0
policy $\pi(a_t \mid s_t; \theta)$	$\pi(a_t \mid s_t) = \frac{\exp\{\mathbf{x}_{m(a_t)}^T \mathbf{U}\mathbf{h}_t\}}{\sum_{a \in A(s_t)} \exp\{\mathbf{x}_{m(a)}^T \mathbf{U}\mathbf{h}_t\}}$, where $\mathbf{U}$ is the parameter matrix
Gradient $\nabla \log \pi(a \mid s)$	refer to [35] for details

document embedding

Learning to Rank

Search Result Diversification



Learning to Rank

Search Result Diversification

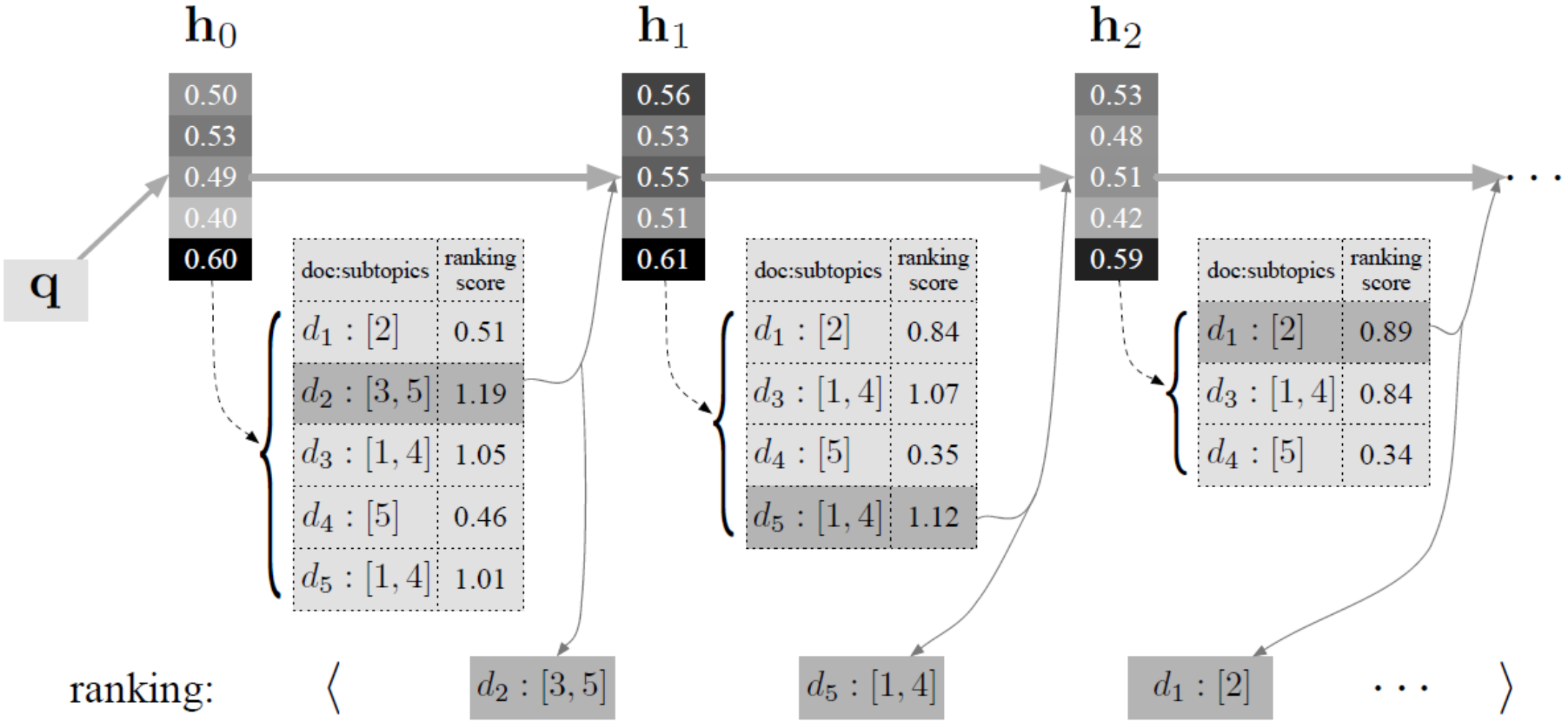
- Consider query #93 “raffles” which is ambiguous and multi-faceted (containing five subtopics).
  - The five top ranked documents in the Clueweb09 collection are as follows. The subtopics covered by each of the documents are shown in the square brackets.

[1] :	“Raffles Hotel in Singapore”	d_1 :	“Stamford Raffles – Wikipedia, the free encyclopedia” [**2**]
[2] :	“Sir Stamford Raffles”	d_2 :	“Fundraiser Raffle Ideas” [**3, 5**]
[3] :	“organizing a raffle”	d_3 :	“Luxury Hotel Guide | Raffles Hotels” [**1, 4**]
[4] :	“the Raffles hotel in Dubai”	d_4 :	“National Corvette Museum – Corvette Raffles” [**5**]
[5] :	“car raffles”	d_5 :	“Raffles Hotels and Resorts” [**1, 4**]

  - The search results may contain redundant information. It is necessary to consider the novelty of a document given preceding documents.
  - Goal: to cover as much subtopics as possible with a few documents.

Learning to Rank

Search Result Diversification



Learning to Rank

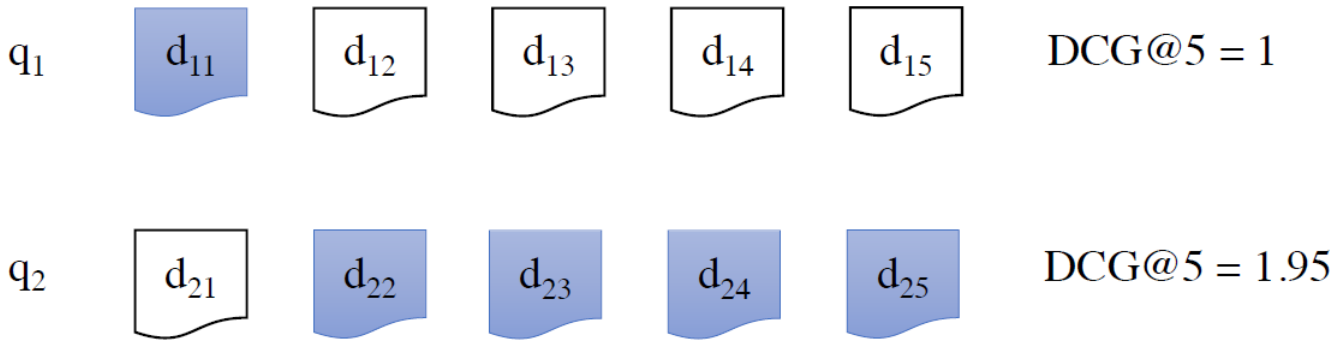
Advantages of Using RL

- **Text Retrieval**
  - Utilizes the IR measures calculated at all the ranking positions as supervision information for training.
  - Optimizes the IR measure directly on the training data without any approximation or upper bounding.
- **Search Result Diversification**
  - Unified criterion (additional utility user can perceive) for selecting documents at each iteration
  - End-to-end learning of the diverse ranking model: no need of handcrafted features.
  - Utilizes both the immediate rewards and the long-term returns as the supervision information during training.

Learning to Rank

Standard REINFORCE Algorithm

- Problem
  - The gradient is estimated according to the sampled document list weighted by its *absolute* performance score.
  - However, the performance of the optimal ranking for a difficult query may be lower than the performance of a suboptimal ranking for an easy query. Since the easy queries always generate document lists with high-performance scores while policy gradient treats them equally, the trained ranking model may be biased to easy queries.



Learning to Rank

Pairwise Policy Gradient

- Motivation
  - The *relative ordering nature of IR ranking*: (1) we care more about the relative goodness of a document compared to others, rather than its absolute relevance score; (2) the comparisons should only be conducted between the documents within the same query.
  - Estimating a reasonable baseline function for IR ranking is very difficult, due to the extremely huge and separated state space.
- Solution
  - Pairwise Policy Gradient (PPG) is a policy gradient algorithm using intra-query pairwise comparisons.
  - In its learning procedure, PPG repeats the process of sampling a pair of document lists starting from the same state (and thus within the same query), comparing these two lists in terms of their performance scores and gradient directions, and finally update the MDP parameters with the comparison results.

Learning to Rank

Pairwise Policy Gradient

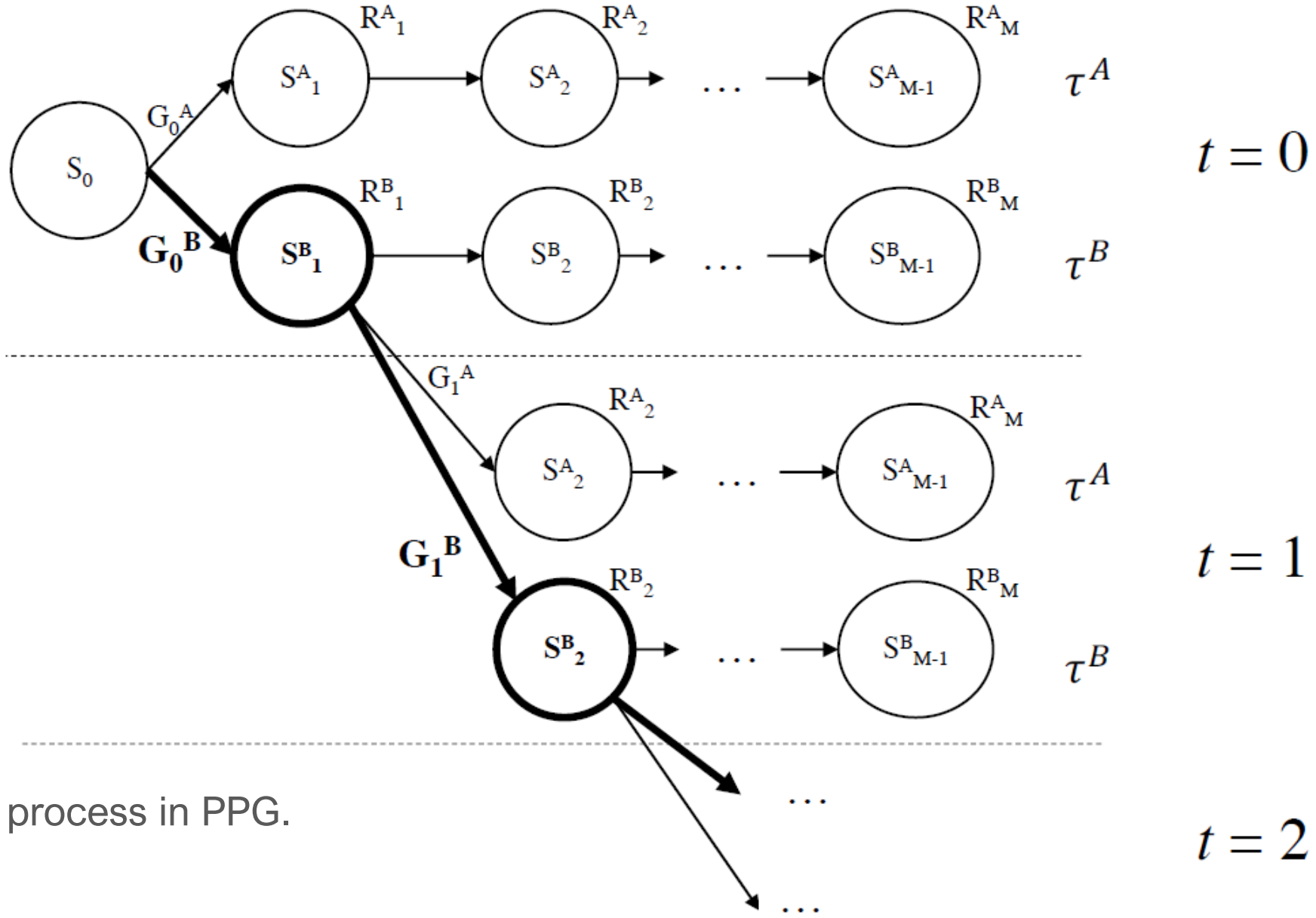


Illustration of the sampling process in PPG.

Learning to Rank

Pairwise Policy Gradient

- A variation of REINFORCE with baseline.
- Good theoretical convergence properties:
  - unbiased
  - low variance

Algorithm 1 Pairwise Policy Gradient (PPG)

INPUT: Training set $D = \{(Q^{(n)}, X^{(n)}, Y^{(n)})\}_{n=1}^{N}$, learning rate η, discount factor γ, and reward function R

Initialize $\theta \leftarrow$ random values
repeat
  $\Delta\theta \leftarrow 0$
  for all $(Q, X, Y) \in D$ **do**
    Initial state $S = \mathcal{S}(Q, X)$ {Init state with Q}
    for $t = 0$ **to** $M - 1$ **do**
      $\tau^A = \{S, A_t, R^A_{t+1}, S^A_{t+1}, \cdots, S^A_{M-1}, A_{M-1}, R^A_M\} \sim \pi(\theta)$
      $G^A \leftarrow \sum_{k=1}^{M-t} \gamma^{k-1} R^A_{t+k}$ {long term return of τ^A}
      $\tau^B = \{S, B_t, R^B_{t+1}, S^B_{t+1}, \cdots, S^B_{M-1}, B_{M-1}, R^B_M\} \sim \pi(\theta)$
      $G^B \leftarrow \sum_{k=1}^{M-t} \gamma^{k-1} R^B_{t+k}$ {long term return of τ^B}
      $\Delta\theta \leftarrow \Delta\theta + (G^A - G^B) \cdot (\nabla \log \pi(A_t|S_t;\theta) - \nabla \log \pi(B_t|S_t;\theta))$ {according to Equation (5)}
      $S \leftarrow \begin{cases} S^A_{t+1} & G^A \geq G^B \\ S^B_{t+1} & \text{otherwise} \end{cases}$
    end for
  end for
  $\theta \leftarrow \theta + \eta\Delta\theta$
until converge
return θ

A Reinforcement Learning Framework for Relevance Feedback

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Relevance Feedback

Problem Statement and Motivation

- Let $Q = \{q_1, q_2, \ldots, q_m\}$ be a query with m terms issued by a user u, and $F = \{D_1, D_2, \ldots, D_k\}$ be a set of k (real or pseudo-) relevance feedback documents.
- The objective is to optimize the evaluation function $\mathrm{eval}(u, Q, \mathcal{M}(\theta_Q^*; \mathcal{C}))$, where $\mathcal{M}$ and $\mathcal{C}$ denote the retrieval model and document collection, respectively.
  The function eval is usually *non-differentiable*, e.g., AP, $nDCG$, and α-$nDCG$.
- We assume that the retrieval model $\mathcal{M}$ is given and focus on estimating an accurate query model for the query Q: $\theta_Q^* = \mathcal{R}(Q, F; \mathcal{C}, \Omega)$ where $\mathcal{R}$ denotes the relevance feedback model with the parameter set Ω.
- Existing (pseudo-) relevance feedback methods do not directly optimize the ultimate objective, i.e., retrieval performance.

Relevance Feedback

RF as MDP

- Environment: $\mathcal{C}, \mathcal{M}$
- Agent: the query model that expands the query and reweights the query terms
- State: $Q, F; \mathcal{C}, \Omega^t$
- Action: To sample K terms $S^t = \{w_1, w_2, \ldots, w_K\}$ from the query model distribution learned by $\mathcal{R}$ without replacement (i.e., $w \sim \theta_Q^t = \mathcal{R}(Q, F; \mathcal{C}, \Omega^t)$), and then *linearly interpolate* the normalised K-term query model with the original query model (estimated using MLE).

$$p(w|\widehat{\theta}_Q^t) = \alpha p(w|\theta_Q^{MLE}) + (1-\alpha)p'(w|\theta_Q^t)$$

$$p'(w|\theta_Q^t) = \begin{cases} \frac{p(w|\theta_Q^t)}{Z} & \text{if } w \in S^t \\ 0 & \text{otherwise} \end{cases}$$

- Reward:

$$\text{Reward}(Q, t) = \text{eval}(u, Q, \mathcal{M}(\widehat{\theta}_Q^t; \mathcal{C})) - \text{eval}(u, Q, \mathcal{M}(\widehat{\theta}_Q^{t-1}; \mathcal{C}))$$

Relevance Feedback

Policy Network Architecture

- We cast the problem of estimating a relevance feedback distribution to estimating a relevance feedback weight for each term using a $\mathrm{softmax}$ operator.

$$p(w|\mathcal{R}) = \frac{\exp(\mathcal{R}'(w, Q, F; C, \Omega))}{\sum_{w' \in V} \exp(\mathcal{R}'(w', Q, F; C, \Omega))}$$

- A single model $\mathcal{R}'$ is trained to take information related to a candidate feedback term w as input and produce a feedback weight.

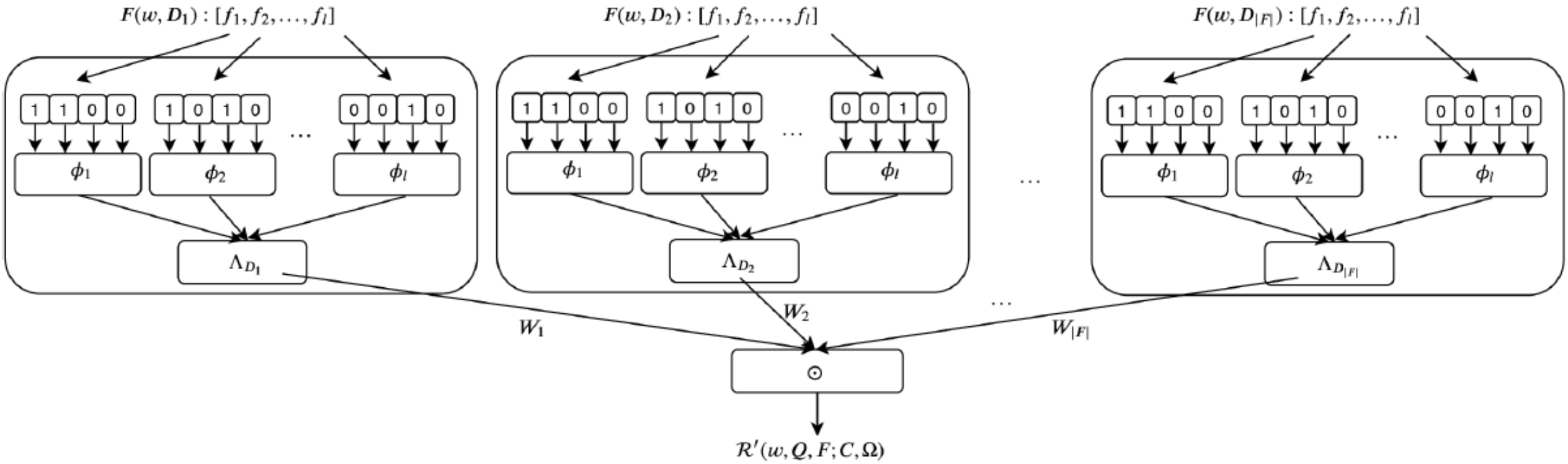
$$\mathcal{R}'(w, Q, F; C, \Omega) = \odot_{i=1}^{|F|}(\Lambda(\phi_1(w, Q, D_i; C), \cdots, \phi_l(w, Q, D_i; C)), \mathcal{W}_i)$$

  - We use a component-based architecture that consists of a set of sub-networks $\phi_1, \phi_2, \ldots, \phi_l$, each modelling a different aspect of the feedback term.
  - The component Λ aggregates these l representations. $\mathcal{W}_i$ denotes the relevance score of the document D_i to the query Q.
  - Finally, the compositionality component $\odot$ aggregates all the representations obtained from all feedback documents and produces a single real number as the weight of the feedback term w.

Relevance Feedback

Policy Network Architecture

$$\mathcal{R}'(w, Q, F; C, \Omega) = \odot_{i=1}^{|F|}(\Lambda(\phi_1(w, Q, D_i; C), \cdots, \phi_l(w, Q, D_i; C)), \mathcal{W}_i)$$



Relevance Feedback

Example

The top 10 expansion terms added to the query “dinosaur” (topic 14)

- RM3
- RML_{MAP}

RM3	Weight	RML_{MAP}	Weight
price	0.1611	tyrannosaurus	0.1185
parti	0.1377	stegosaurus	0.1132
regular	0.0788	jurass	0.0982
99	0.0574	triceratop	0.0532
rex	0.0506	skull	0.0512
dino	0.0474	prehistor	0.0488
toy	0.0447	mammal	0.0477
birthday	0.0388	skeleton	0.0467
prehistor	0.0333	bone	0.0392
game	0.0326	plush	0.0372

Relevance Feedback

Example

The top 10 expansion terms added to the query “403b” (topic 151).

- $\text{RML}_{\alpha\text{-nDCG@20}}$
- RML_{MAP}

Subtopic 1:	What is a 403b plan?
Subtopic 2:	What is the difference between 401k and 403b retirement plans?
Subtopic 3:	What are the withdrawal limitations for a 403b retirement plan?

RML $_{\alpha-nDCG@20}$	Weight	RML$_{MAP}$	Weight
401k	0.3817	choos	0.1645
limit	0.1062	portion	0.1563
portion	0.0973	roth	0.1301
guidanc	0.0743	ira	0.1222
requir	0.0557	rollov	0.0761
ira	0.0468	individu	0.0585
incom	0.0397	retir	0.0492
offer	0.0336	estat	0.0420
rollov	0.0328	organ	0.0318
individu	0.0180	minor	0.0277

IRGAN: A Minimax Game for Unifying Generative and Discriminative Information Retrieval Models

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IRGAN

Two Schools of IR Thinking

Generative models of IR

- **Pros:** theoretically sound and very successful in modelling features
- **Cons:**
  - difficult in leveraging relevancy signals from largely observable data, e.g., links, clicks
  - typically not trainable

Discriminative models of IR

- **Pros:** able to learn a retrieval ranking function implicitly from labelled data
- **Cons:** lack a principled way of
  - obtaining useful features,
  - gathering helpful signals from the massive unlabeled data available, e.g., text statistics, the collection distribution

http://wnzhang.net/tutorials/sigir2018/index.html

IRGAN

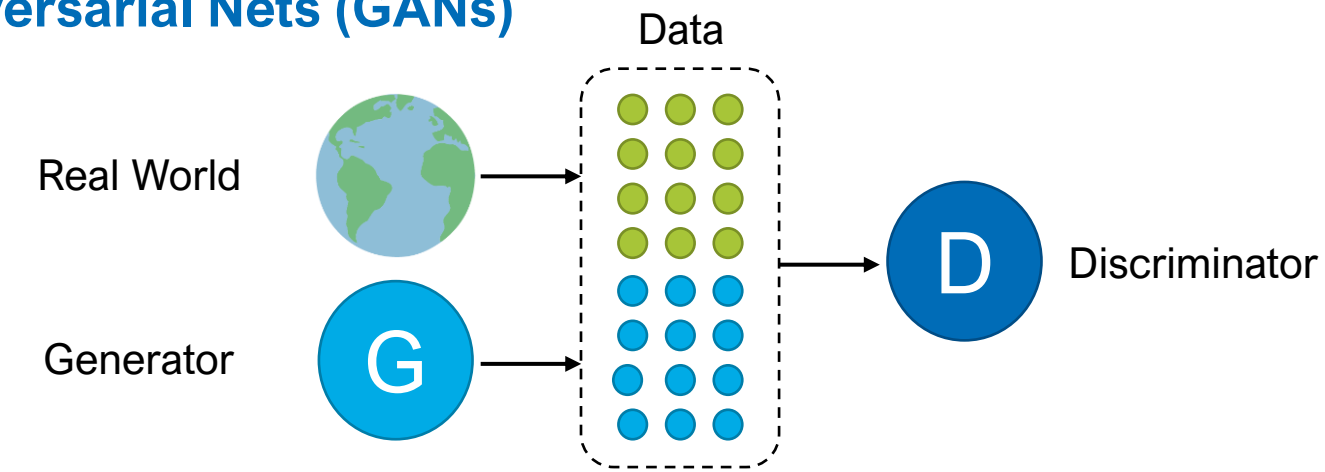
To Take Advantage of Both

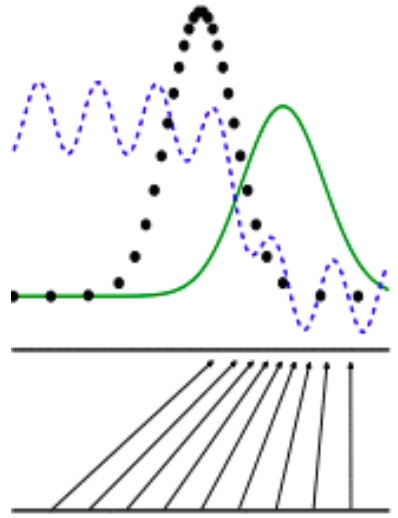
- The generative model learns to fit the relevance distribution over documents $p_{\text{true}}(d|q,r)$ via the signal from the discriminative model.
- The discriminative model is able to exploit the unlabelled data selected by the generative model to achieve a better estimation $f_\phi(q,d)$ for document ranking.

http://wnzhang.net/tutorials/sigir2018/index.html

IRGAN

Generative Adversarial Nets (GANs)





- Minimax game between a **discriminator** & a **generator**:
  - Discriminator (D) tries to correctly distinguish the true data and the fake model-generated data
  - Generator (G) tries to generate high-quality data to fool discriminator
- G & D can be implemented via neural networks
- Ideally, when D cannot distinguish the true and generated data, G nicely fits the true underlying data distribution

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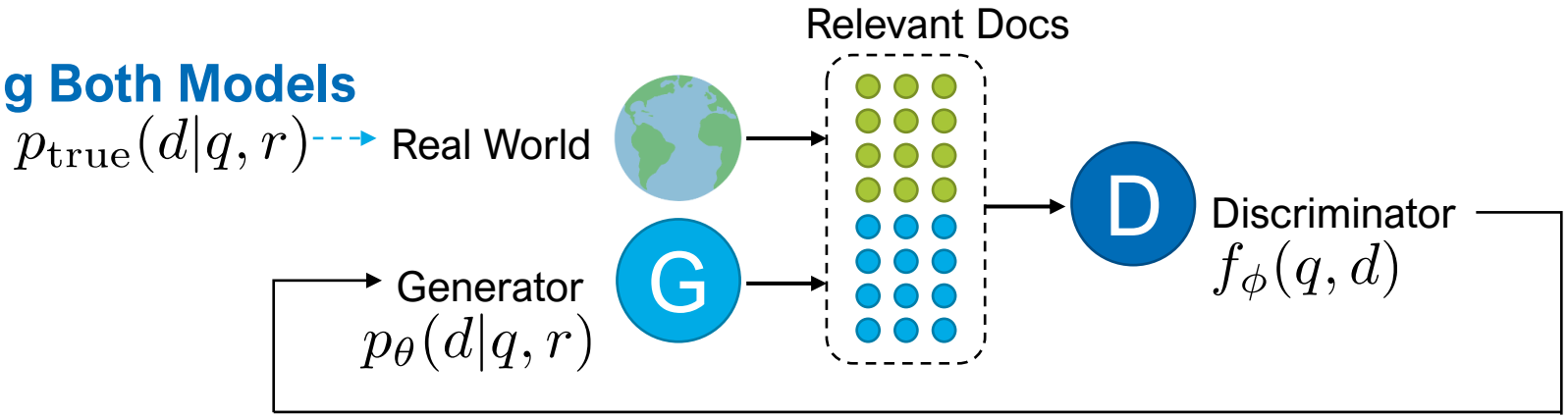
IRGAN

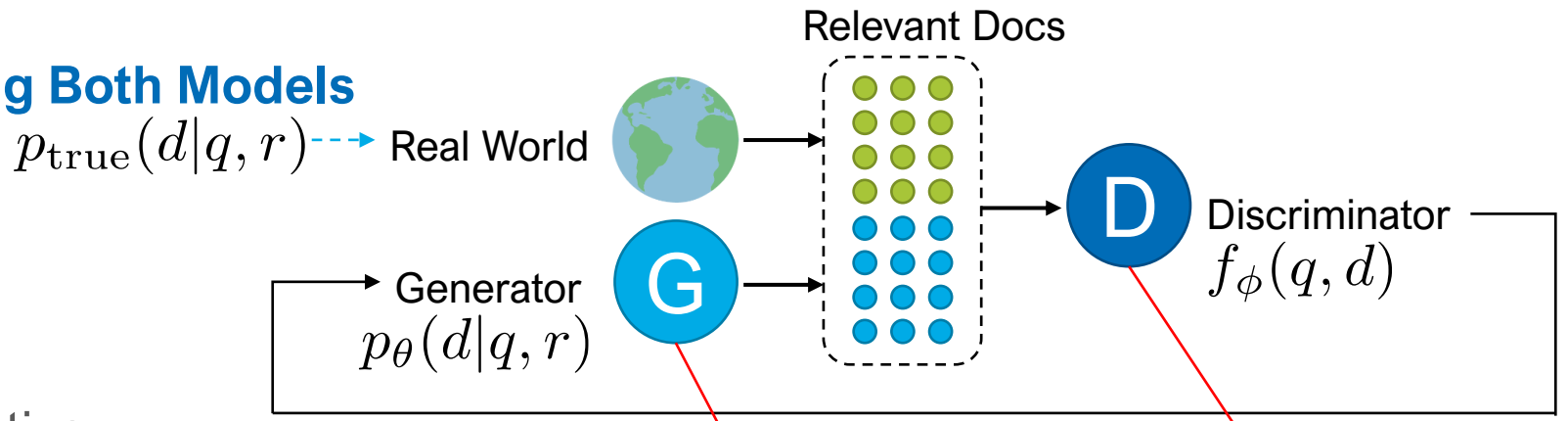
A Minimax Game Unifying Both Models



- **Underlying true relevance distribution** $p_{\text{true}}(d|q,r)$ depicts the user's relevance preference distribution over the candidate documents with respect to his submitted query
  - **Training set:** A set of samples from $p_{\text{true}}(d|q,r)$
- **Generative retrieval model** $p_\theta(d|q,r)$
  - Goal: approximate the true relevance distribution
- **Discriminative retrieval model** $f_\phi(q,d)$
  - Goal: distinguish between relevant and non-relevant documents

IRGAN

A Minimax Game Unifying Both Models



Objective

$$J^{G^*,D^*} = \min_\theta \max_\phi \sum_{n=1}^{N} \Big(\mathbb{E}_{d\sim p_{\text{true}}(d|q_n,r)} [\log D(d|q_n)] + \mathbb{E}_{d\sim p_\theta(d|q_n,r)} [\log(1 - D(d|q_n))] \Big)$$

where $$p_\theta(d|q,r) = \frac{\exp(g_\theta(q,d))}{\sum_{d'} \exp(g_\theta(g,d'))}$$

$$D(d|q) = \sigma(f_\phi(d,q)) = \frac{\exp(f_\phi(d,q))}{1+\exp(f_\phi(d,q))}$$

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IRGAN

Optimizing Generative Retrieval as Policy Gradient

- Samples documents from the whole document set to fool its opponent

$$\theta^* = \arg\min_\theta \sum_{n=1}^{N} \Big(\mathbb{E}_{d\sim p_{\text{true}}(d|q_n,r)} \left[\log \sigma(f_\phi(d,q_n))\right] + \mathbb{E}_{d\sim p_\theta(d|q_n,r)} \left[\log(1-\sigma(f_\phi(d,q_n)))\right] \Big)$$

$$= \arg\max_\theta \sum_{n=1}^{N} \underbrace{\mathbb{E}_{d\sim p_\theta(d|q_n,r)} \left[\log(1+\exp(f_\phi(d,q_n)))\right]}_{\text{denoted as } J^G(q_n)}$$

Reward Term

Generator as Policy

- REINFORCE (with Advantage Function)

$$\log(1+\exp(f_\phi(d,q_n))) - \mathbb{E}_{d\sim p_\theta(d|q_n,r)} \left[\log(1+\exp(f_\phi(d,q_n)))\right]$$

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IRGAN

Optimizing Generative Retrieval as Policy Gradient

Likelihood Ratio

$$
\begin{aligned}
&\nabla_\theta J^G(q_n) \\
&= \nabla_\theta \mathbb{E}_{d\sim p_\theta(d|q_n,r)} \left[\log(1+\exp(f_\phi(d,q_n)))\right] \\
&= \sum_{i=1}^{M} \nabla_\theta p_\theta(d_i|q_n,r) \log(1+\exp(f_\phi(d_i,q_n))) \\
&= \sum_{i=1}^{M} p_\theta(d_i|q_n,r) \nabla_\theta \log p_\theta(d_i|q_n,r) \log(1+\exp(f_\phi(d_i,q_n))) \\
&= \mathbb{E}_{d\sim p_\theta(d|q_n,r)} \left[\nabla_\theta \log p_\theta(d|q_n,r) \log(1+\exp(f_\phi(d,q_n)))\right] \\
&\simeq \frac{1}{K} \sum_{k=1}^{K} \nabla_\theta \log p_\theta(d_k|q_n,r) \log(1+\exp(f_\phi(d_k,q_n)))
\end{aligned}
$$

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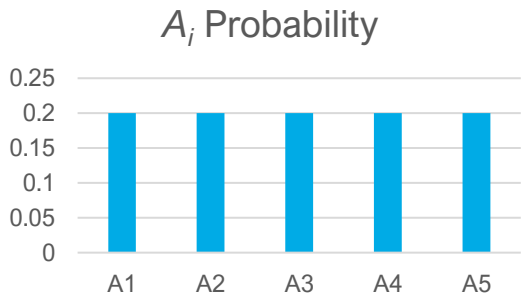
IRGAN

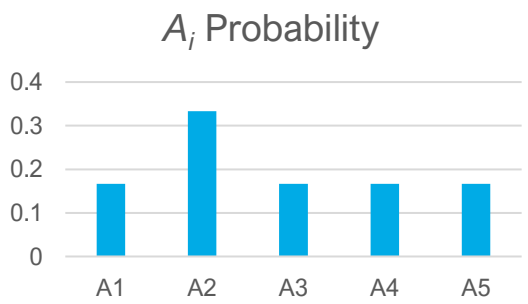
Optimizing Generative Retrieval as Policy Gradient

- For generative retrieval $p_\theta(d|q,r)$
- Intuition
  - lower value/reward leads to lower probability of the choice
  - higher value/reward leads to higher probability of the choice
- The one-field 5-category example

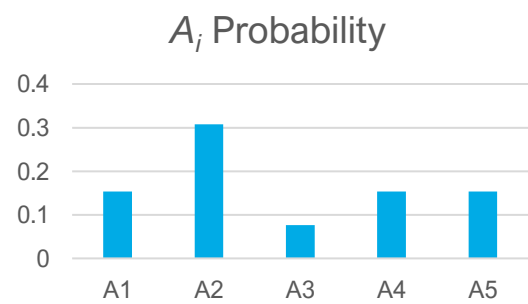
1. Initialize θ



3. Update θ by policy gradient



5. Update θ by policy gradient



2. Generate A_2
Observe positive reward (from D)

4. Generate A_3
Observe negative reward (from D)

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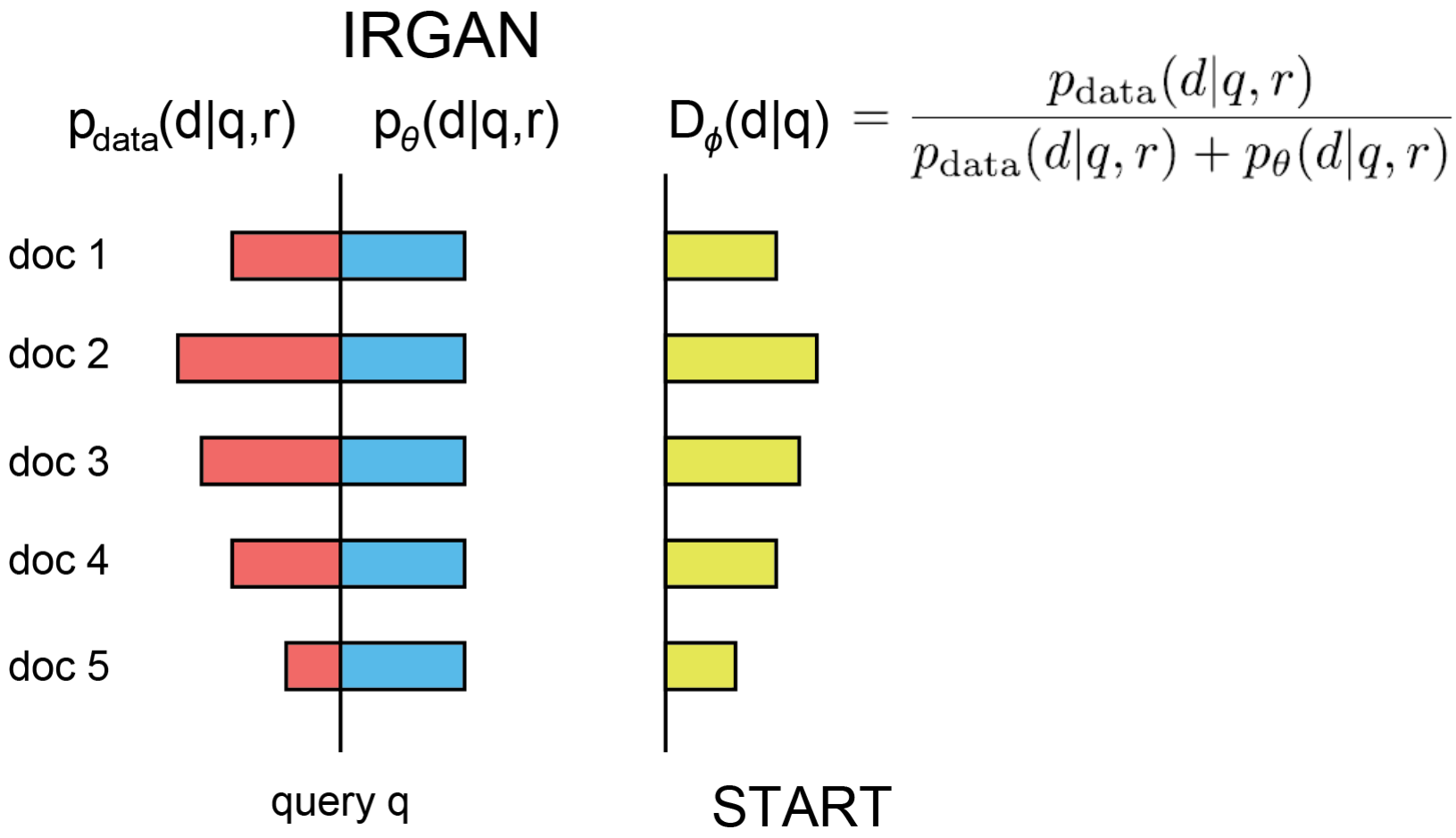
IRGAN

The Interplay between Generative and Discriminative Retrieval



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Top-K Off-Policy Correction for a REINFORCE Recommender System

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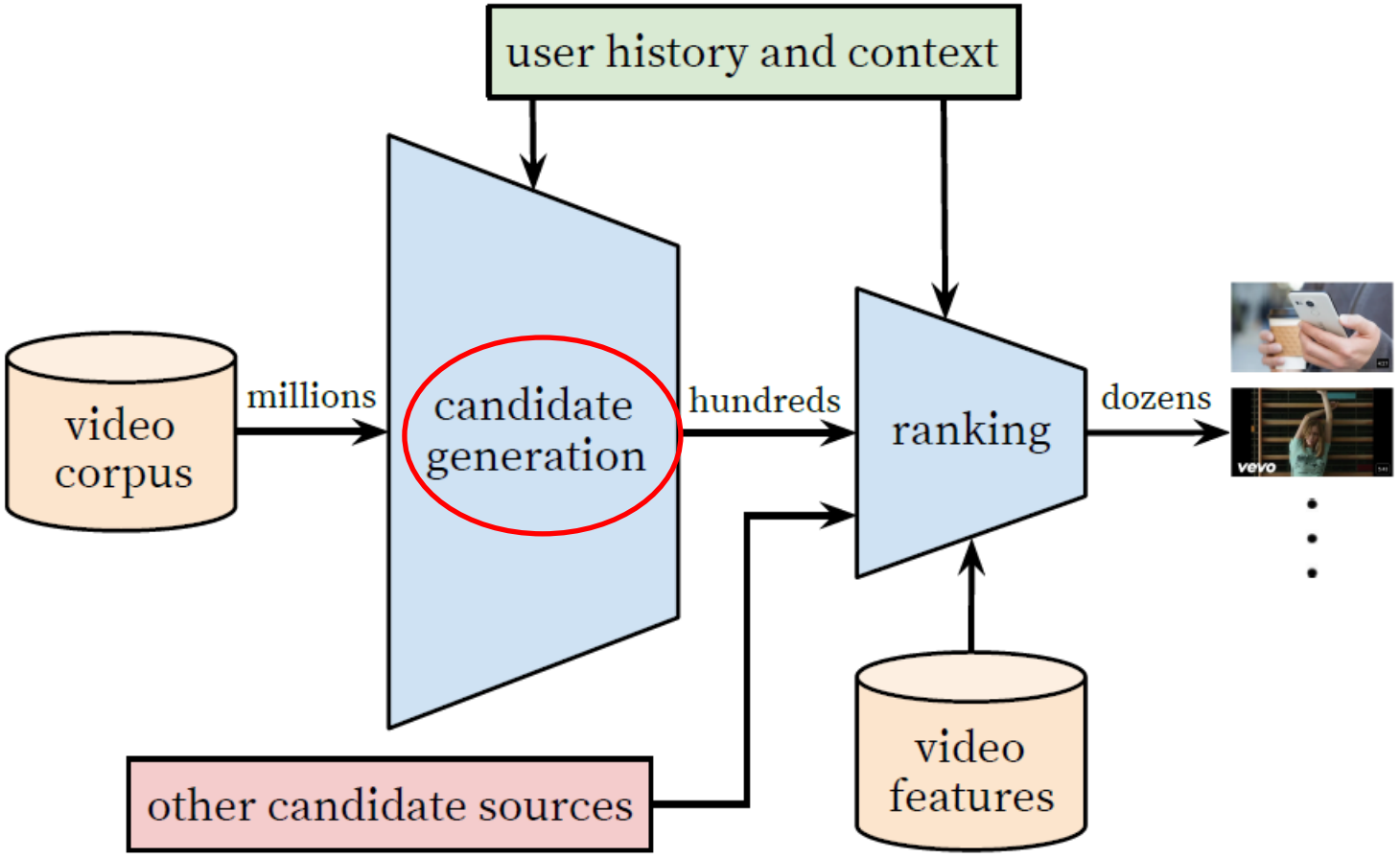
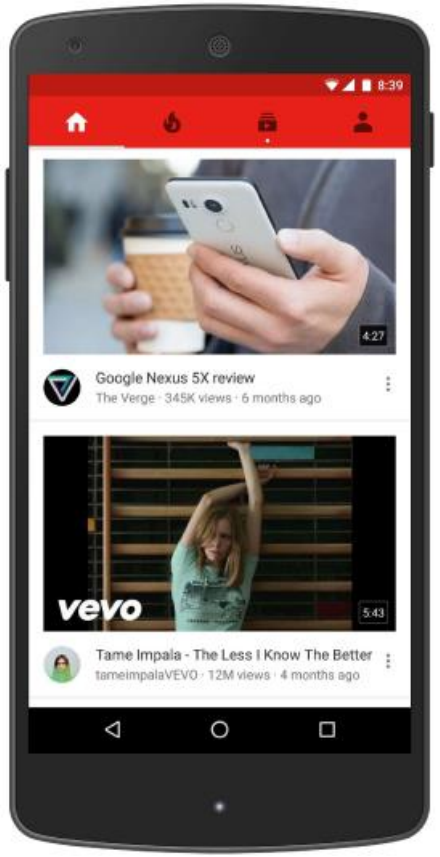
Top-K Off-Policy Correction

YouTube Recommendations

- The candidate generator is the RL agent





https://dl.acm.org/doi/10.1145/2959100.2959190

Top-K Off-Policy Correction

Data Biases

(target policy π_θ != behaviour policy β)

- A naive policy gradient estimator is no longer unbiased as the gradient requires sampling trajectories from the updated policy π_θ while the trajectories we collected were drawn from a combination of historical policies β.
  - We collect data with a periodicity of several hours and compute many policy parameter updates before deploying a new version of the policy in production.
  - We learn from batched feedback collected by other recommenders as well, which follow drastically different policies.

Top-K Off-Policy Correction

- **On-Policy**: The agent learned and the agent interacting with the environment is the same.
- **Off-Policy**: The agent learned and the agent interacting with the environment is different.

NETFLIX

https://www.imdb.com/title/tt10048342/

Top-K Off-Policy Correction

On-Policy ➔ Off-Policy

- Importance Sampling

$$\nabla \bar{R}_\theta = E_{\tau \sim \pi_\theta}[R(\tau) \nabla \log \pi_\theta(\tau)]$$

  - Problem:
    Use π_θ to collect data.
    When π_θ is updated, we have to sample training data again.
  - Solution:
    Using the sample from β to train θ.
    As β is fixed, we can re-use the sample data.

http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2018/Lecture/PPO%20(v3).pdf

Top-K Off-Policy Correction

On-Policy ➔ Off-Policy

- Importance Sampling

$$E_{x\sim p}[f(x)] \approx \frac{1}{N}\sum_{i=1}^{N} f(x^i)$$

x^i is sampled from $p(x)$

but we only have x^i sampled from $q(x)$

$$= \int f(x)p(x)dx = \int f(x)\frac{p(x)}{q(x)}q(x)dx$$

$$= E_{x\sim q}[f(x)\frac{p(x)}{q(x)}]$$

Importance weight

http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2018/Lecture/PPO%20(v3).pdf

Top-K Off-Policy Correction

On-Policy ➔ Off-Policy

- Importance Sampling

$$\nabla \bar{R}_\theta = E_{\tau \sim \beta}\left[\frac{\pi_\theta(\tau)}{\beta(\tau)} R(\tau) \nabla \log \pi_\theta(\tau)\right]$$

  - Sample the data from β.
  - Use the data to train π_θ many times.

http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2018/Lecture/PPO%20(v3).pdf

Top-K Off-Policy Correction

On-Policy ➔ Off-Policy

$$\sum_{\tau \sim \pi_\theta} R(\tau) \nabla_\theta \log \pi_\theta(\tau) \approx \sum_{\tau \sim \pi_\theta} \left[\sum_{t=0}^{|\tau|} R_t \nabla_\theta \log \pi_\theta(a_t|s_t) \right]$$

Importance Sampling ⇨

$$\approx \sum_{\tau \sim \beta} \left[\sum_{t=0}^{|\tau|} \frac{\pi_\theta(\tau)}{\beta(\tau)} R_t \nabla_\theta \log \left(\pi_\theta(a_t|s_t) \right) \right]$$

Variance Reduction ⇨

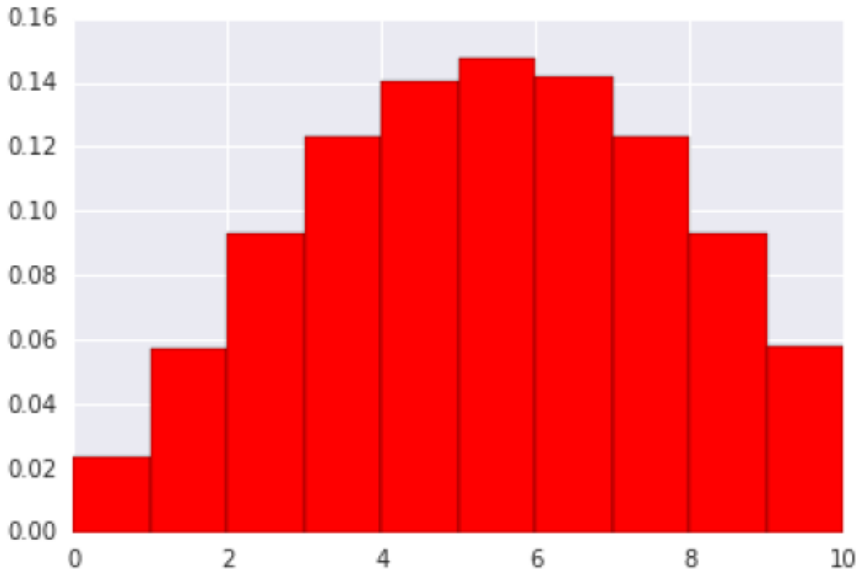
$$\approx \sum_{\tau \sim \beta} \left[\sum_{t=0}^{|\tau|} \frac{\pi_\theta(a_t|s_t)}{\beta(a_t|s_t)} R_t \nabla_\theta \log \pi_\theta(a_t|s_t) \right]$$

- Ignore the terms after time t
- Take a first-order approximation

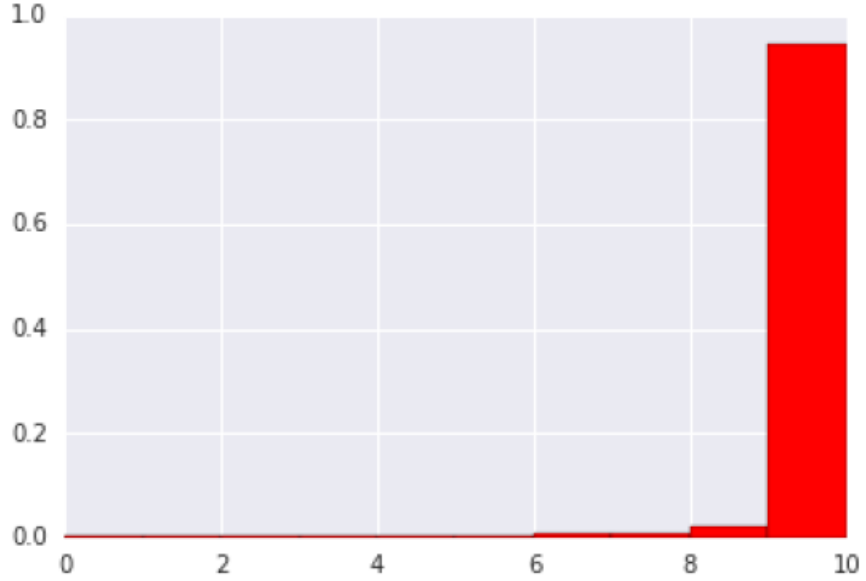
Top-K Off-Policy Correction

On-Policy ➔ Off-Policy

- In this simulation, there are 10 items $\mathcal{A} = \{a_i, i = 1, \dots, 10\}$ and the reward of each one is equal to its index $r(a_i) = i$.
- The learned policy π_θ when behaviour policy $\beta(a_i) = (11 - i)/55$ is skewed to favour the actions with least reward.



(left) without off-policy correction



(right) with off-policy correction

Top-K Off-Policy Correction

Top-1 Correction ➔ Top-K Correction

The recommender system need to recommends a page of K items to users at a time.

- To make the problem tractable, we generate the set action A by independently sampling each item a according to the softmax policy π_θ and then de-duplicate.
- Thus, the gradient update rule can be adapted for set recommendation by replacing π_θ with $\alpha_\theta(a|s) = 1 - (1 - \pi_\theta(a|s))^K$

Top-K Off-Policy Correction

Top-1 Correction ➔ Top-K Correction

$$\sum_{\tau\sim\beta}\left[\sum_{t=0}^{|\tau|}\frac{\pi_\theta(a_t|s_t)}{\beta(a_t|s_t)}R_t\nabla_\theta\log\pi_\theta(a_t|s_t)\right]$$

Top-K Correction ⇨

$$\sum_{\tau\sim\beta}\left[\sum_{t=0}^{|\tau|}\frac{\alpha_\theta(a_t|s_t)}{\beta(a_t|s_t)}R_t\nabla_\theta\log\alpha_\theta(a_t|s_t)\right]$$

$$=\sum_{\tau\sim\beta}\left[\sum_{t=0}^{|\tau|}\frac{\pi_\theta(a_t|s_t)}{\beta(a_t|s_t)}\boxed{\frac{\partial\alpha(a_t|s_t)}{\partial\pi(a_t|s_t)}}R_t\nabla_\theta\log\pi_\theta(a_t|s_t)\right]$$

Top-K Off-Policy Correction

Top-1 Correction ➔ Top-K Correction

- An additional multiplier needs to be added to the original off-policy correction factor.

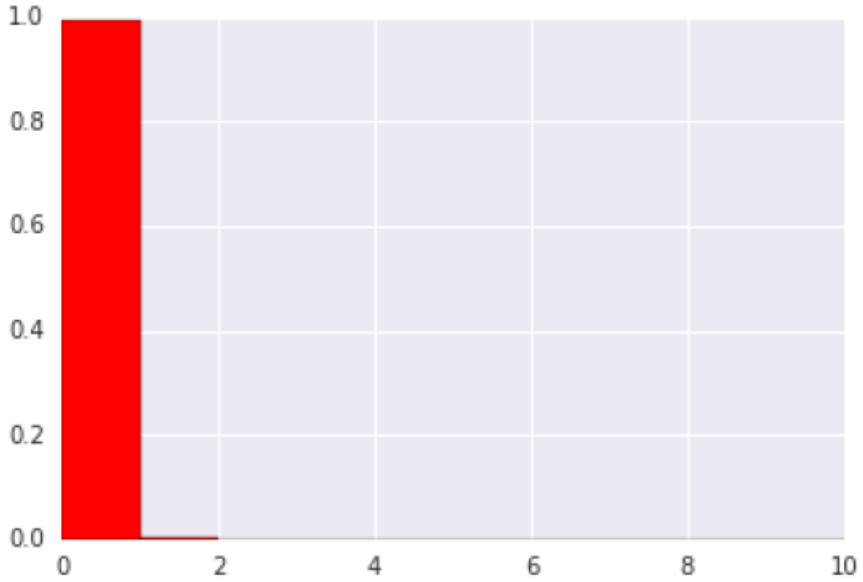
$$\lambda_K(s_t, a_t) = \frac{\partial \alpha\,(a_t|s_t)}{\partial \pi\,(a_t|s_t)} = K(1 - \pi_\theta(a_t|s_t))^{K-1}$$

  - When the desirable item has a small mass in the policy $\pi_\theta(\cdot\,|s)$, the top-K correction more aggressively pushes up its likelihood than the standard correction.
  - Once the policy $\pi_\theta(\cdot\,|s)$ casts a reasonable mass on the desirable item (to ensure it is likely to appear in the top-k), the correction then zeros out the gradient and no longer tries to push up its likelihood. This in return allows other items of interest to take up some mass in the policy.

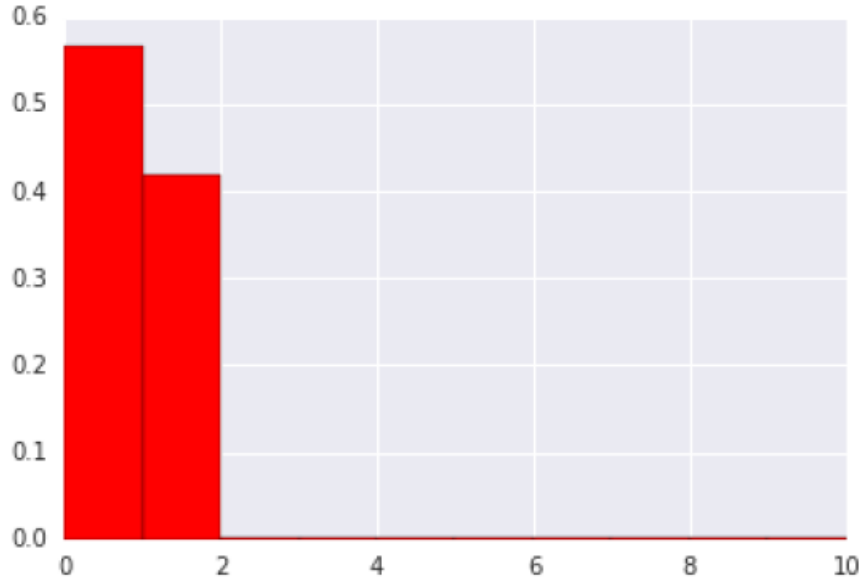
Top-K Off-Policy Correction

Top-1 Correction ➔ Top-K Correction

- In this simulation, there are 10 items $\mathcal{A} = \{a_i, i = 1, \dots, 10\}$ with $r(a_1) = 10$, $r(a_2) = 9$, and the remaining items of much lower reward $r(a_i) = 1, \forall i = 3, \dots, 10$.
- Here we focus on recommending two items ($k = 2$). The behaviour policy β follows a uniform distribution, i.e., choosing each item with equal chance.



(left) with top-1 correction



(right) with top-k correction

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