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Reinforcement Learning Enhanced Interactive Video Retrieval

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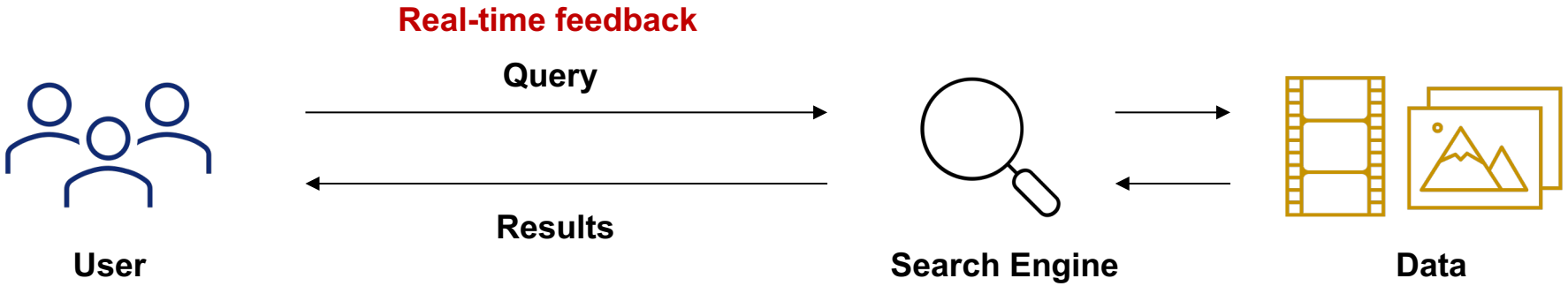
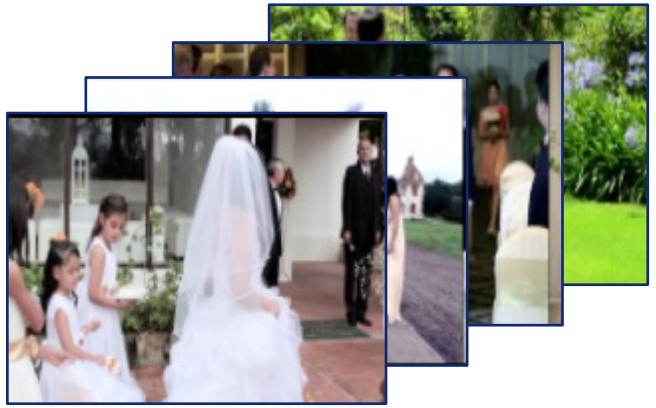
What is Interactive Video Retrieval?

- Automatic *vs* Interactive video retrieval?



A wedding party which is grouped around the bride and groom, bride and groom are walking and guests are following them.



Visual Known-Item Search

- **Visual known-item search (V-KIS)**: Assume that you watched this video before and want to find back it from video collection.

A V-KIS Query:

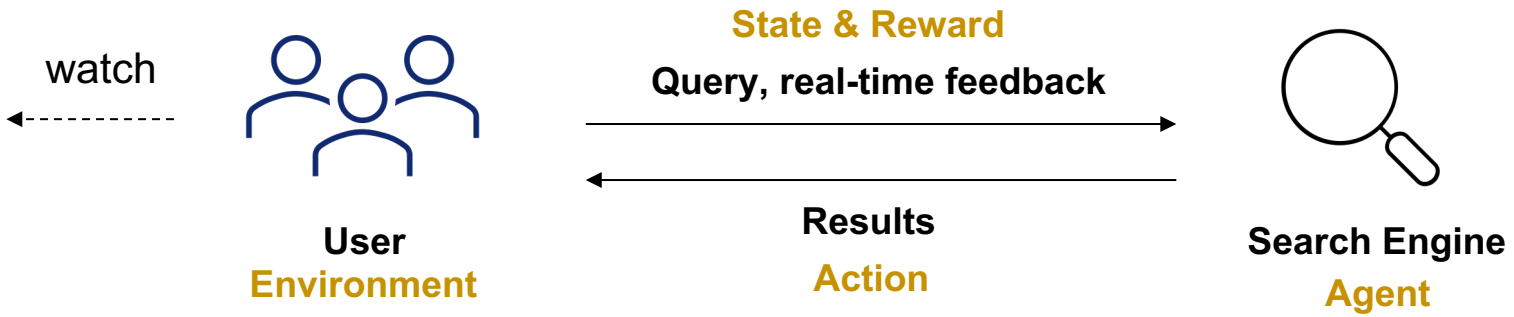


Table. Dataset statistic showing the number of video shots, duration and release year

Dataset	Clip	Duration	Year
$V3C_1$	1,082,659	1,000 h	2019
$V3C_2$	1,425,454	1,300 h	2022
Total	2,508,113	2,300 h	-

Video Browser Showdown

- **Video browser showdown (VBS)**: A **live** video search competition, where teams evaluate and demonstrate the efficiency of their video retrieval tools on a **shared dataset**

Visual Know-Item Search

- Trial-and-error is inefficient
- Inspection is tedious and time-consuming
- Sub-optimal results harm the search
- Concept selection
- …

Interactive Video Corpus Moment Retrieval using Reinforcement Learning

An exploration to improve interactive video retrieval using reinforcement learning

“Finding needle from a haystack”

A V-KIS query from Video Browsing Showdown (VBS) 2022

Figure. An example of search target.

Query:

People climb on a mountain

↓

People climb on a mountain next to bridge and river

Snow mountain ✗

Forest ✗

Similar

“Finding needle from a haystack”

Issues of the current interaction:

- trial-and-error is inefficient
- inception is tedious and time consuming
- sessions are independent

Motivation: an interactive video search framework

- allow user provide feedback to update query
- navigate user from a sub-optimal result to the target

Figure. A representative scene in the search target.

Figure. Search results after adding “bridge” and “river” to the query.

Related Work

- Single video moment retrieval
- Domain-specific dialogue-based interactive image retrieval

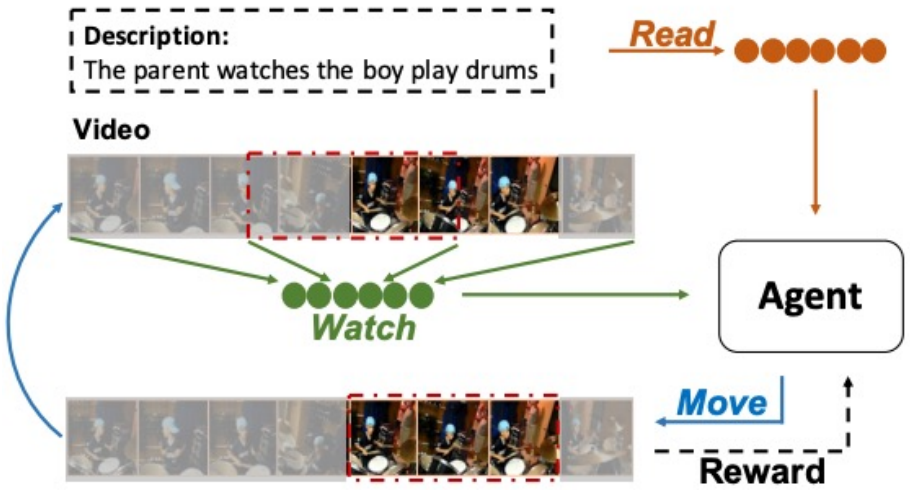


Figure. A framework of single video moment retrieval. [1]

Figure. An example of dialogue-based interactive image retrieval. [2]

[1] Read, watch, and move: Reinforcement learning for temporally grounding natural language descriptions in videos, He et al., AAAI 2019
[2] Dialog-based Interactive Image Retrieval. Guo et al., NIPS 2018

Problem Statement

- Users provide feedback $\mathrm{f_t}$ to candidate
- Navigate from starting moment m_0 to search target m^*

  - Graph of moment: $\mathcal{G}$
    - Pairwise similarity including semantic & visual feature
  - Graph walking as Markov Decision Process (MDP)
    - State $\mathcal{S}$, Action Space $\mathcal{A}$, Reward Function $\mathcal{R}$, Transition Probability $\mathcal{P}$

Rachel explains to her dad on the phone why she can't marry her fiancé.

Initial Query: q_0

start moment: m_0

user feedback: $\mathrm{f_t}$

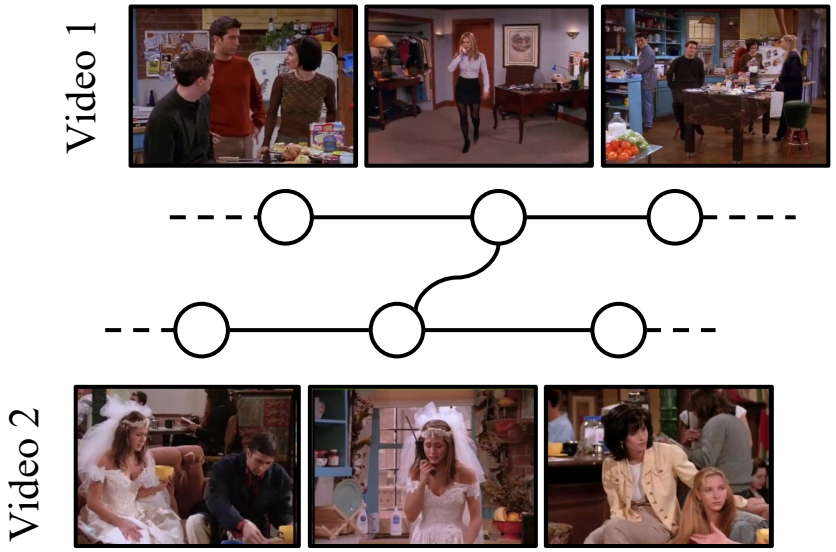
- not in office
- in wedding dress

search target (m^*)

Problem Statement

Link video shots as a graph

- Successive shots
- Shots with high similarity
  - Threshold, …



(a)

- Connectivity
- Density
- …

- Concept detection
- Visual feature
- Script TF-IDF

Rachel, phone, call, …
office, suit, …

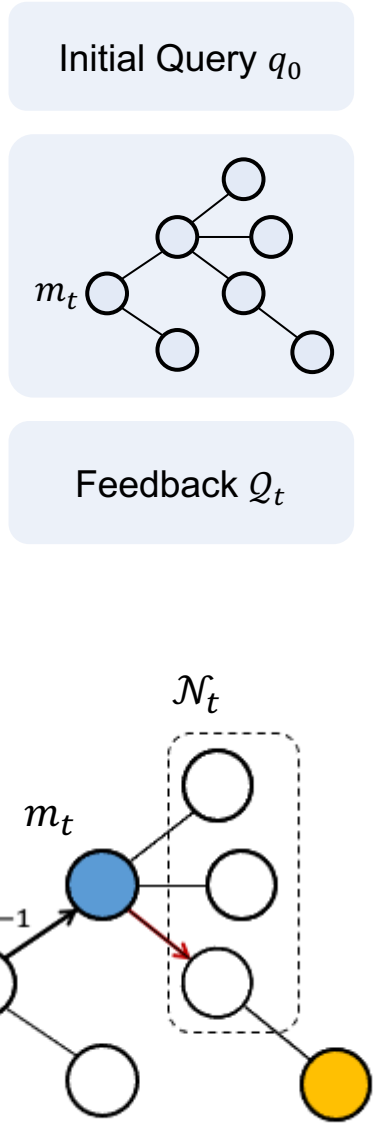
Rachel, phone, call, …
wedding, dress, …

(b)

Graph Walking as MDP

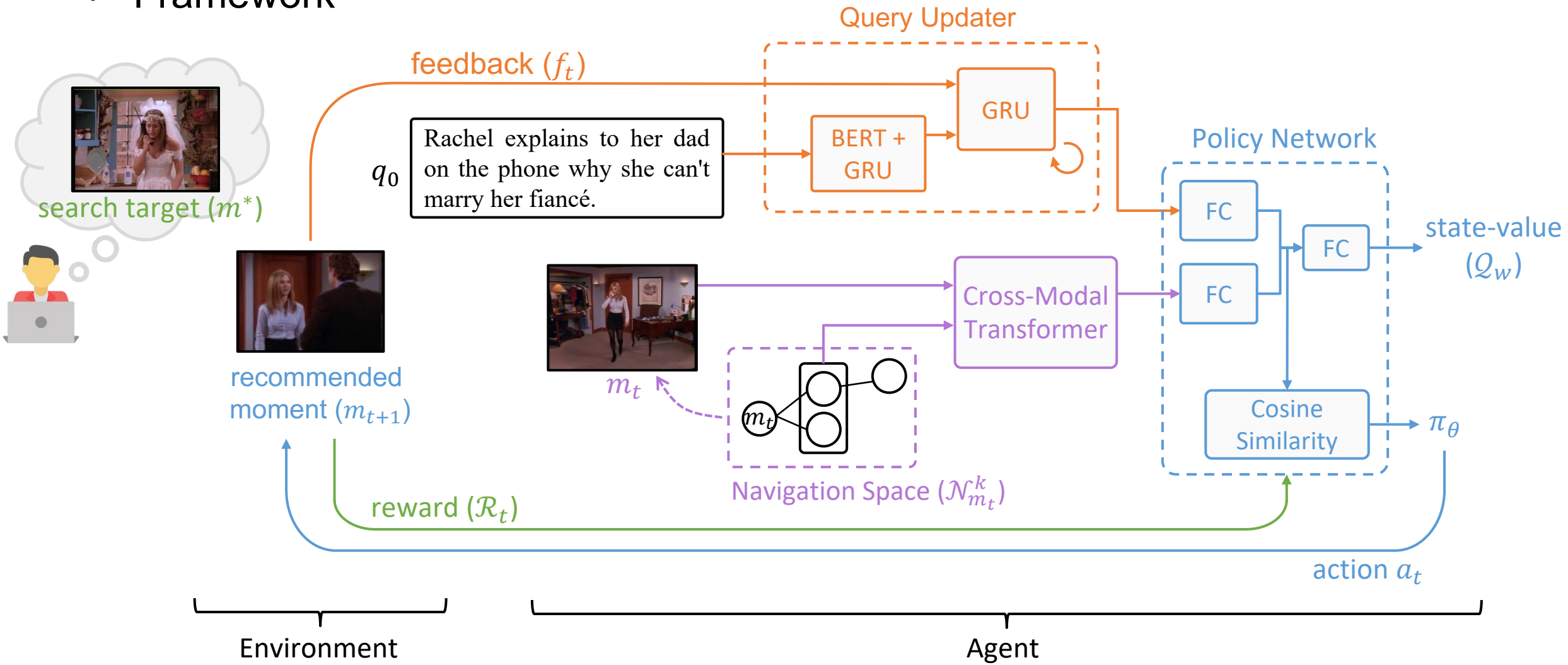
Markov Decision Process

- State Space $\mathcal{S}$
  - $s_t = (q_0, m_t, f_t)$
- Action Space $\mathcal{A}$
  - Neighbors within k steps
- Reward Function $\mathcal{R}$
  - $r_t = \begin{cases} \frac{1}{2^{d_{t+1}}} - \phi \cdot t, & d_t > d_{t+1} \\ -\phi \cdot t, & d_t = d_{t+1} \\ -\frac{1}{2} - \phi \cdot t, & d_t < d_{t+1} \end{cases}$
- Transition Probability $\mathcal{P}$



Methodology

- Framework



User Simulator

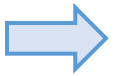
- Keyword-level feedback
  1. Detect semantic concepts for the target and current shots
  2. Calculate pair-wise probability difference
  3. Sample keyword from the distribution to add or remove keywords

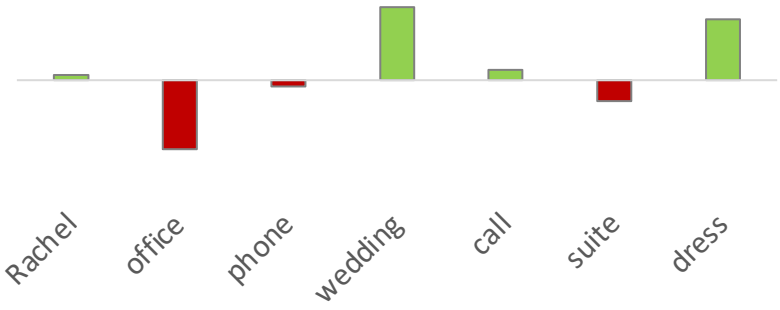
target moment m^*

Rachel, phone, call, …
wedding, dress, …

current moment m_t

Rachel, phone, call, …
office, suit, …





Dataset

- TV Retrieval [1] and DiDeMo [2]

Table 1. Dataset statistic showing the number of videos and queries in different splits.

Dataset	#Video			#Query		
	Train	Val	Test	Train	Val	Test
TVR	17,435	2,179	-	87,175	10,895	-
DiDeMo	8,395	1,065	1,004	32,624	4,160	3,982

Table 2. Dataset statistic showing the number of graph nodes, edges and average degree.

Dataset	#Node	#Edge	Avg Degree
TVR	147,985	294,395	3.98
DiDeMo	114,923	263,609	4.59

[1] TVR: A Large-Scale Dataset for Video-Subtitle Moment Retrieval, Lei et al., ECCV 2020
[2] Localizing Moments in Video with Temporal Language, Hendricks et al., EMNLP 2018

Model Training

Simulation | Real Scenario | Human Performance

1. Initialize $\pi_{\theta_\pi}(a|s)$ and $Q_{\theta_Q}(a,s)$
2. Sample a set of m_0 ● for each query q and m^* ●
3. For each query q:
4. For $t = 0 \ldots T$:
5. estimate $\pi_\theta(a_i|s_t)$ and state value $Q(a_i, s_t)$
6. take a_t, receive r_t and s_{t+1}
7. $s_t \leftarrow s_{t+1}$
8. update parameter θ_π and θ_Q

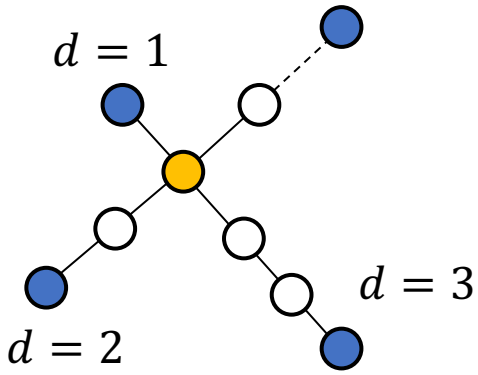


Figure. Illustration of node sampling.

$$L_{triplet} = max(0, c + u^+ - u^-)$$

$$u^{\{+/-\}} =< FC_m(\mathbf{m}^{\{+/-\}}) \cdot FC_q(\mathbf{q}) >$$

Imitation Learning

$$L_{policy} = -\sum_t log\, \pi_\theta(a_t|s_t)(R_t - Q_w(s_t))$$

$$L_{mse} = \sum_t (Q_w(s_t) - R_t)^2$$

Advantage Actor Critic (A2C)

Experiments

Simulation | Real Scenario | Human Performance

- Model Comparison
  - Random: randomly select a moment at each time
  - No-Feedback: greedily select actions w/o query updating
  - Imitation: optimize policy using supervised learning
  - Ours: optimize policy using both supervised learning and reinforcement learning (i.e., A2C)

Table. Model comparison of recall@1 on TVR and DiDeMo dataset

Model	TVR				DiDeMo			
	d_0=1	d_0=2	d_0=3	d_0=4	d_0=1	d_0=2	d_0=3	d_0=4
Random	0.058 ±0.001	0.044 ±0.001	0.024 ±0.001	0.007 ±0.001	0.093 ±0.004	0.078 ±0.003	0.053 ±0.005	0.023 ±0.001
No-Feedback	0.489 ±0.011	0.475 ±0.013	0.442 ±0.012	0.204 ±0.008	0.259 ±0.004	0.242 ±0.001	0.229 ±0.005	0.121 ±0.002
Imitation	0.514 ±0.011	0.485 ±0.010	**0.448** ±0.011	0.210 ±0.006	0.275 ±0.005	0.261 ±0.009	0.242 ±0.008	0.132 ±0.006
Ours	**0.534** ±0.016	**0.495** ±0.002	0.446 ±0.005	**0.216** ±0.003	**0.296** ±0.003	**0.275** ±0.002	**0.262** ±0.009	**0.141** ±0.003

Does the model work in real-scenario?

Experiment

Simulation | Real Scenario | Human Performance

Does the model work in real-scenario?

- Initialize the start moment m_0 with SOTA automatic VCMR models
  - HERO [1] and CONQUER [2]
  - test whether our model can find the clips which are deeply hidden in the ranked lists

depth of target in a ranked list →

	TVR				DiDeMo			
	(10-50]	(50-100]	(100-200]	>200	(10-50]	(50-100]	(100-200]	>200
HERO	2179 (14%)	822 (9%)	785 (6%)	328 (5%)	683 (9%)	379 (5%)	396 (4%)	886 (3%)
CONQUER	2049 (14%)	681 (9%)	416 (9%)	98 (8%)	823 (8%)	415 (7%)	388 (3%)	591 (3%)

Our model can locate the clips ranked low by the SOTA VCMR models

[1] HERO: Hierarchical Encoder for Video+Language Omni-representation Pre-training, Li et al., EMNLP 2020
[2] CONQUER: Contextual Query-aware Ranking for Video Corpus Moment Retrieval, Hou et al., MM 2021

Experiment

Simulation | Real Scenario | Human Performance

Does the user simulator behave like a human user?

- Replace user simulator with a human user to test the effectiveness of user simulator
- 50 queries which cannot be retrieved by the user simulator

Table. Human performance of identifying 50 search targets that cannot be retrieved by a user simulator.

Interaction Setting	Recall@1	#Keywords	#Iteration
1 keyword 1 shot	18%	1	3.22
5 keywords 1 shot	18%	4.2	3.08
5 keywords 5 shots	44%	4.1	2.5

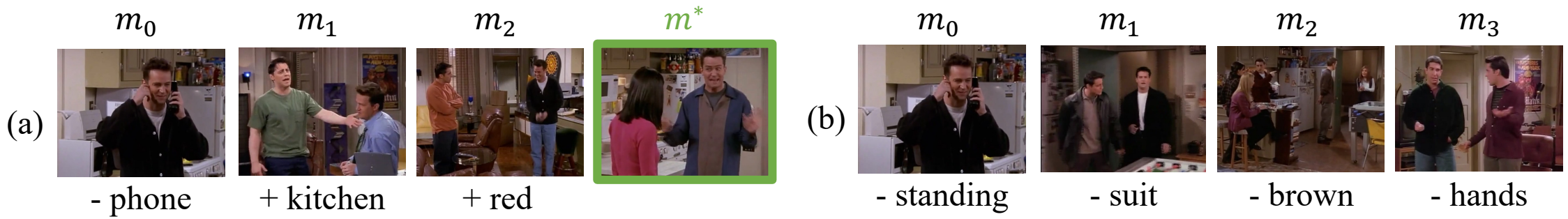


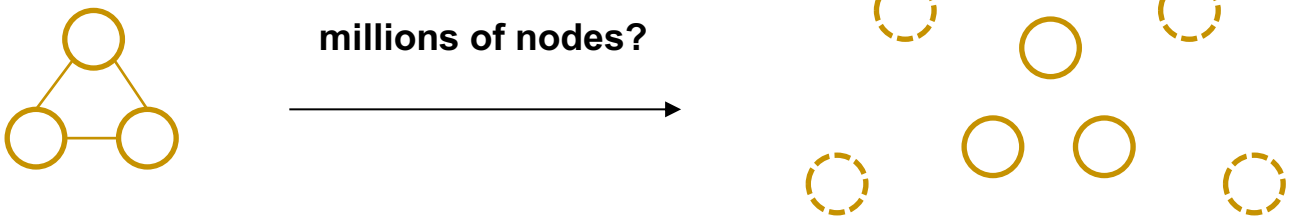
Figure. Example comparing how (a) human and (b) user simulator interact with the agent for the query "Chandler shakes his hands in the air while standing in the kitchen".

Future Work

- Extend the simulator to more vividly mimic human behavior

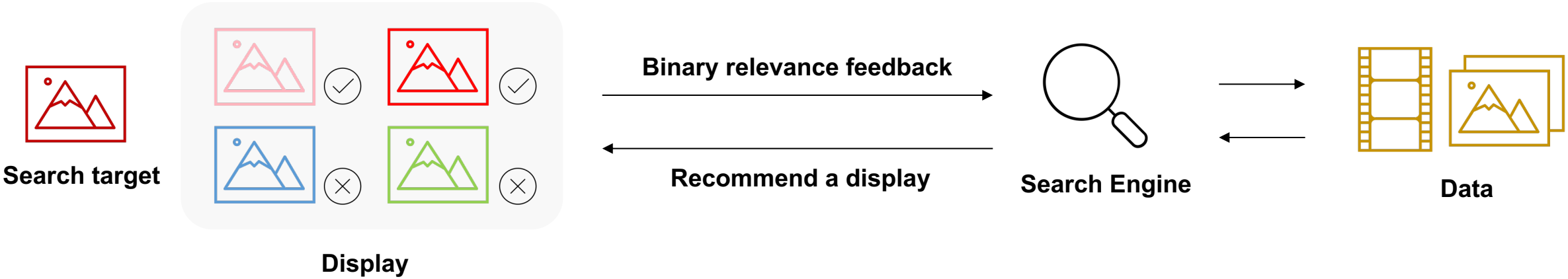
- She should wear a wedding dress
- She is not in the office
- …

- Adapt the user simulator to larger and more general datasets



Ongoing work: Relevance Feedback

- Bayesian-based relevance feedback



- Is the recommendation user-friendly?
- Is the feedback effective?
- …

Thanks