Towards Predicting Movie Preferences from Conversational Interactions

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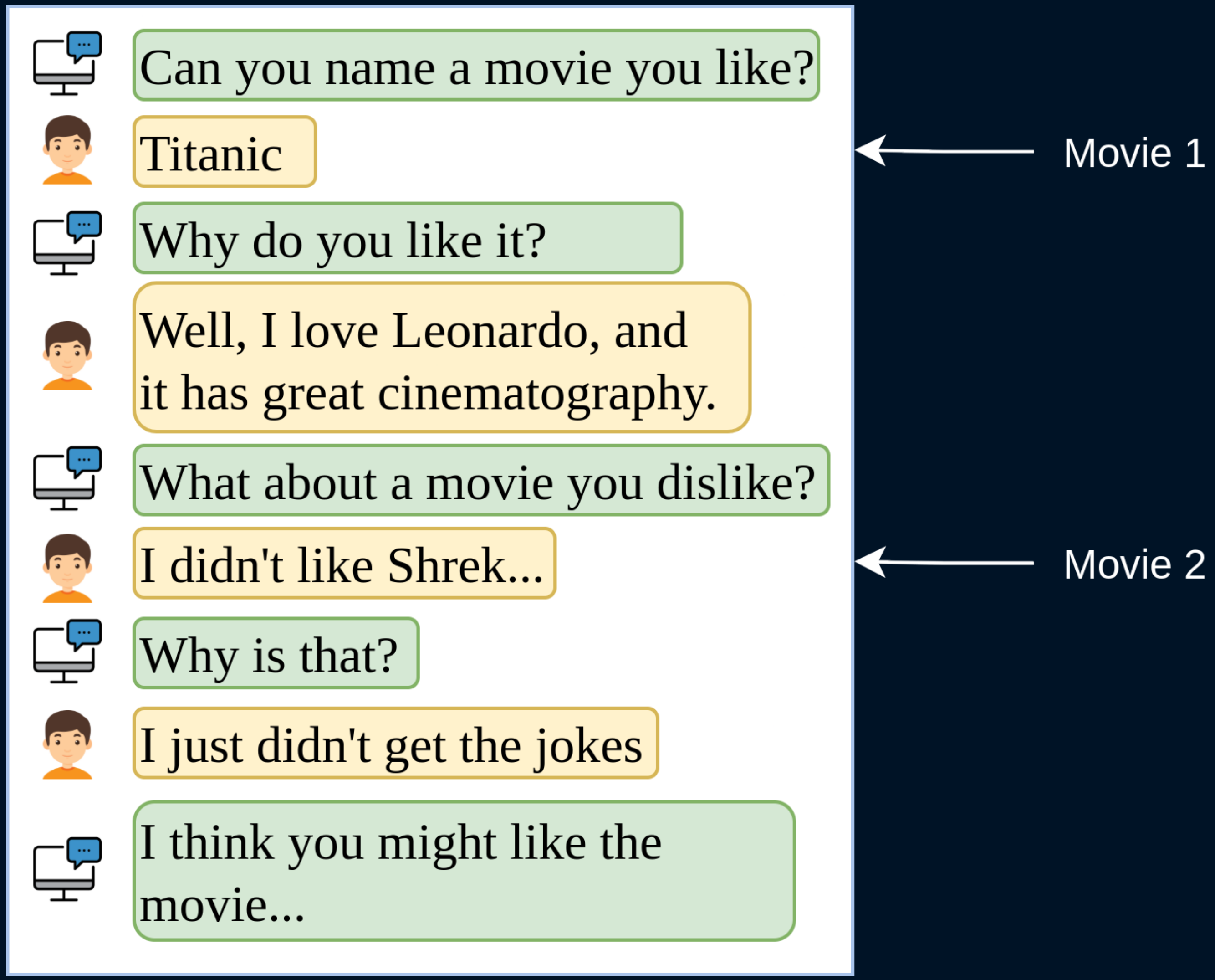
Motivation

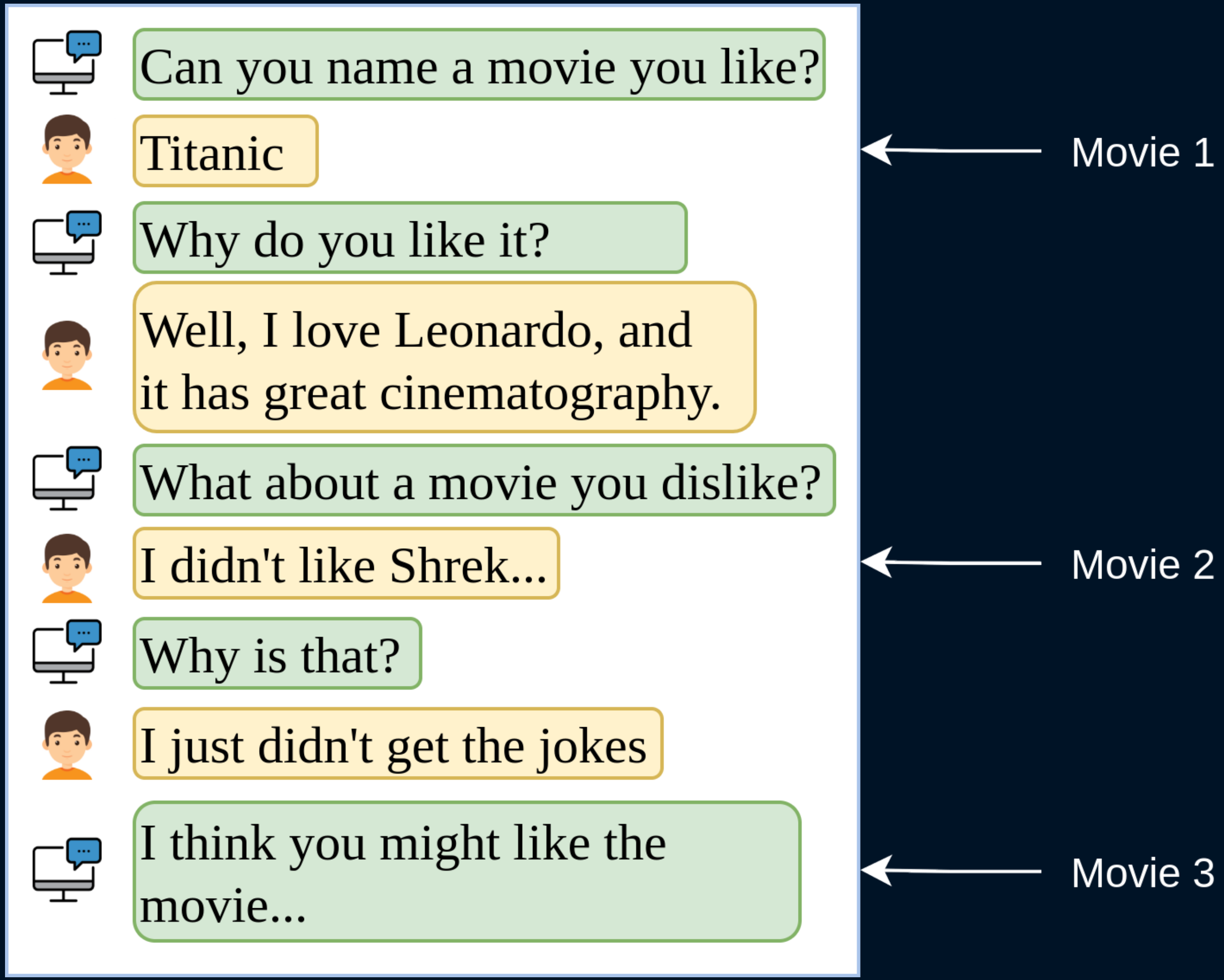
- Establishing user's preferences through a conversation for an effective recommendation remains an open question
- There exists little conversational data for such a task.

Problem



Can you name a movie you like?
Titanic
Why do you like it?
Well, I love Leonardo, and it has great cinematography.
What about a movie you dislike?
I didn't like Shrek...
Why is that?
I just didn't get the jokes
I think you might like the movie...
Movie 1
Movie 2

Problem Statement



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  - Entities' IDs
  - Fine-grained user sentiment

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- A new conversational recommendation method ***"Conversational Collaborative Filtering using External Data"***

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- A new conversational recommendation method ***ConvExtr***, which:
  - Estimates user's sentiment towards first 2 movies
  - Uses external dataset of reviews to predict user score towards the 3rd movie

MovieSent Dataset Construction

Based on the Coached Conversational Preference Elicitation dataset (CCPE)[1]

[1] "Coached Conversational Preference Elicitation" Radlinski et al. 2019

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3. Movies labeled with fine-grained user sentiment towards them:
   – Scale: [-3; +3] & None
   – 8 judges
   – 20% overlap

Examples of labeled utterances

Wizard utterance	User Utterance	Entity	Sentiment
What would be one of your favorite movies?	I love Mr. and Mrs. Smith. That's a great one.	mr_and_mrs_smith	3
Have you seen the Shape of Water?	I started watching that, but I just couldn't get into it enough to finish.	the_shape_of_water	-2
Have you seen Bridesmaids?	Nope.	bridesmaids_2011	None

MovieSent Dataset Statistics

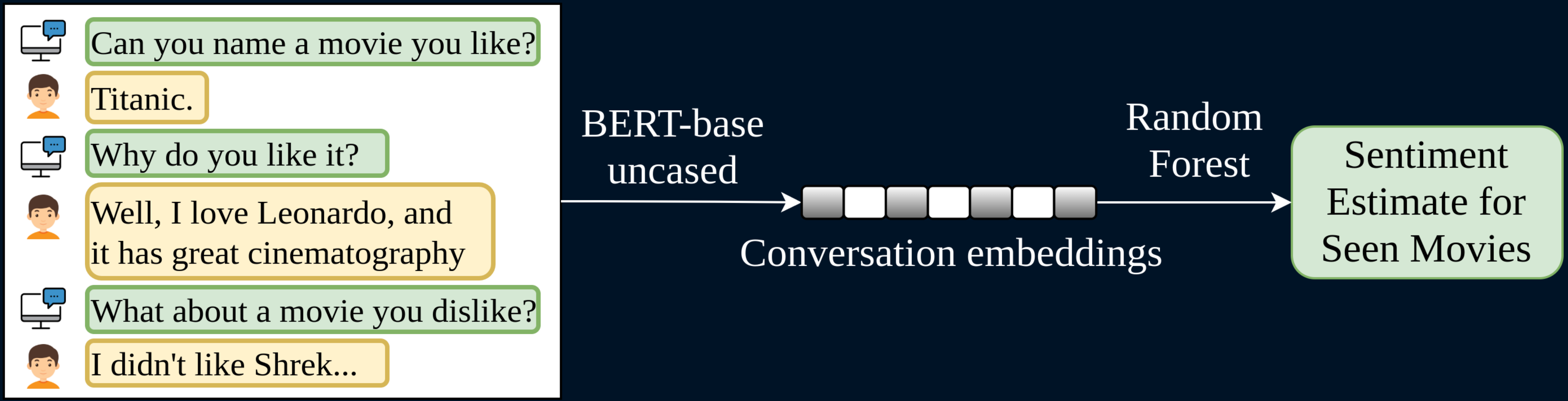
Conversations	489
Sentiment labels	2488
Unique entities	712
Weighted Cohen's κ	0.77

External Data

Scraped critics' reviews from RottenTomatoes:

Reviews	715,766
Critics	3,664
Median reviews	34
Unique Movies	42,423

Sentiment Estimation



Example Snippet Conversation from *MovieSent*

ConvExtr: General Idea

	Critic 1	Critic 2	$\cdots$	Critic k
Item 1	5	3	$\cdots$	
Item 2		2	$\cdots$	4
$\vdots$	$\vdots$	$\vdots$	$\cdots$	$\vdots$
Item T	3			1
Item S		4	$\cdots$	2
$\vdots$	$\vdots$	$\vdots$	$\ddots$	
Item N	4		$\cdots$	3

ConvExtr: General Idea

	Critic 1	Critic 2	$\cdots$	Critic k	Conv User
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Item 2		2	$\cdots$	4	
$\vdots$	$\vdots$	$\vdots$	$\cdots$	$\vdots$	
Item T	3			1	~ 4.254
Item S		4	$\cdots$	2	~ 3.742
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SVD++

Prediction for Unseen movie

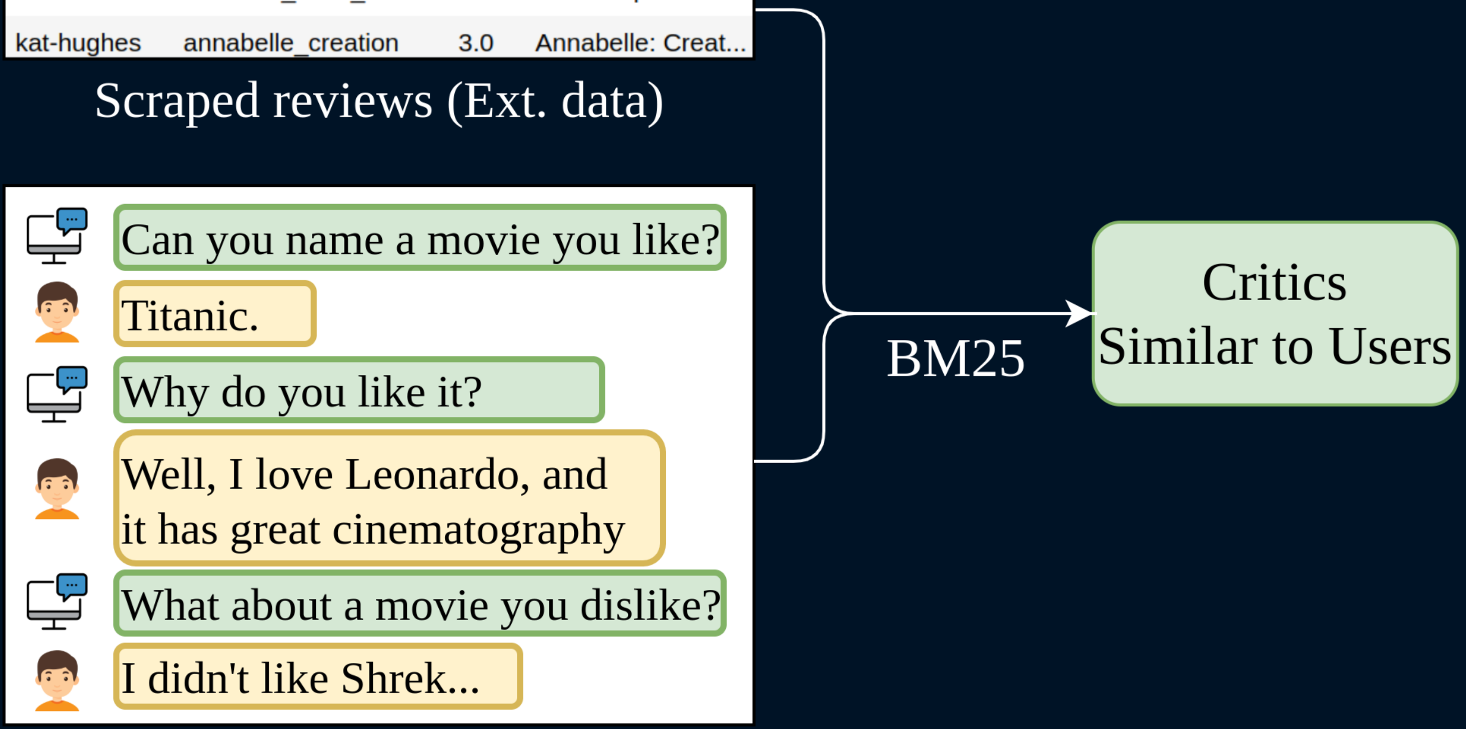
ConvExtr Model

Critics (Paid Professionals) $\neq$ Regular users

ConvExtr Model

critic_id	movie_id	score	review
greg-maki	the_counselor_2013	2.0	Scott presents i...
robert-roten	romeo_must_die	4.0	The main problem...
kat-hughes	annabelle_creation	3.0	Annabelle: Creat...

Scraped reviews (Ext. data)



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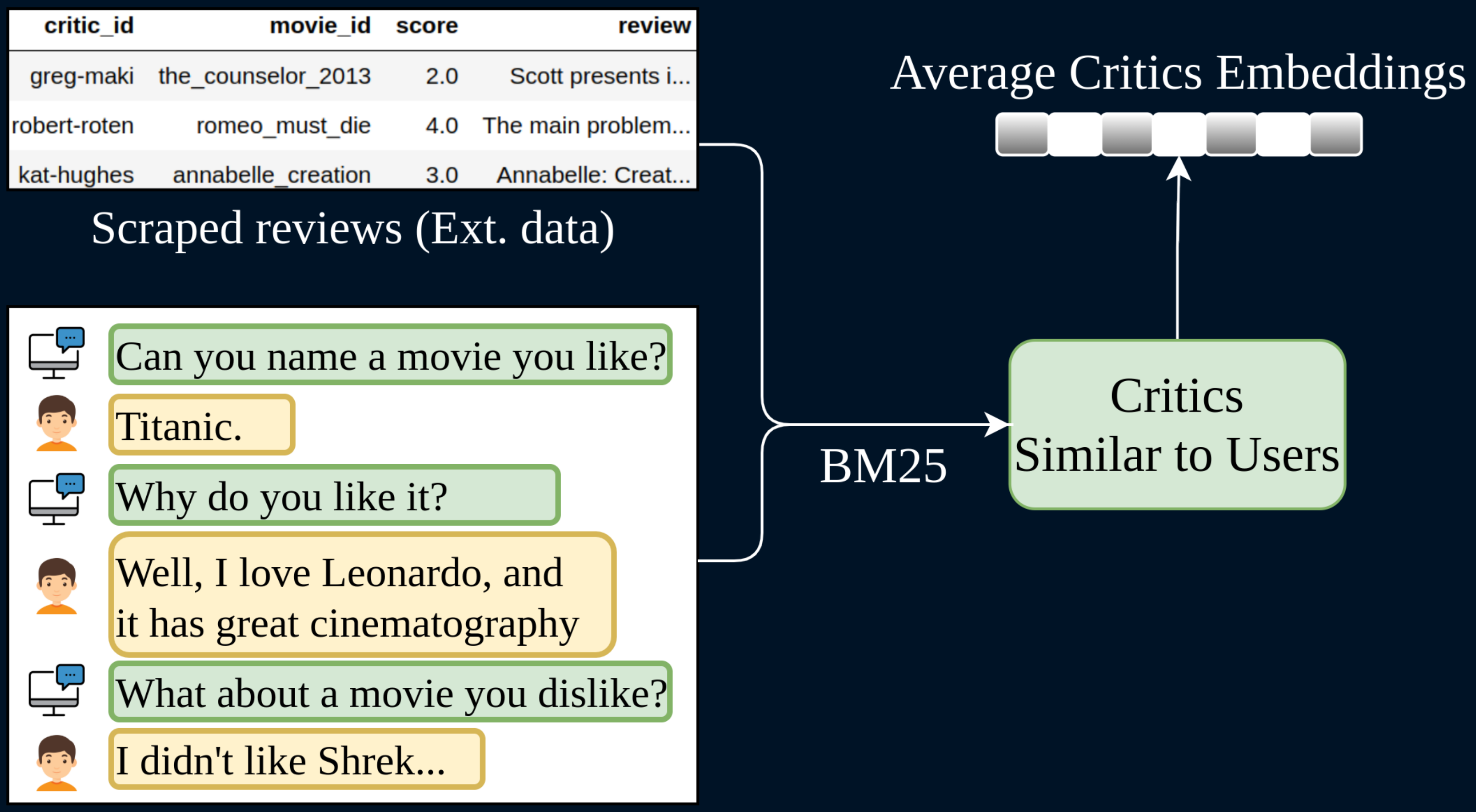

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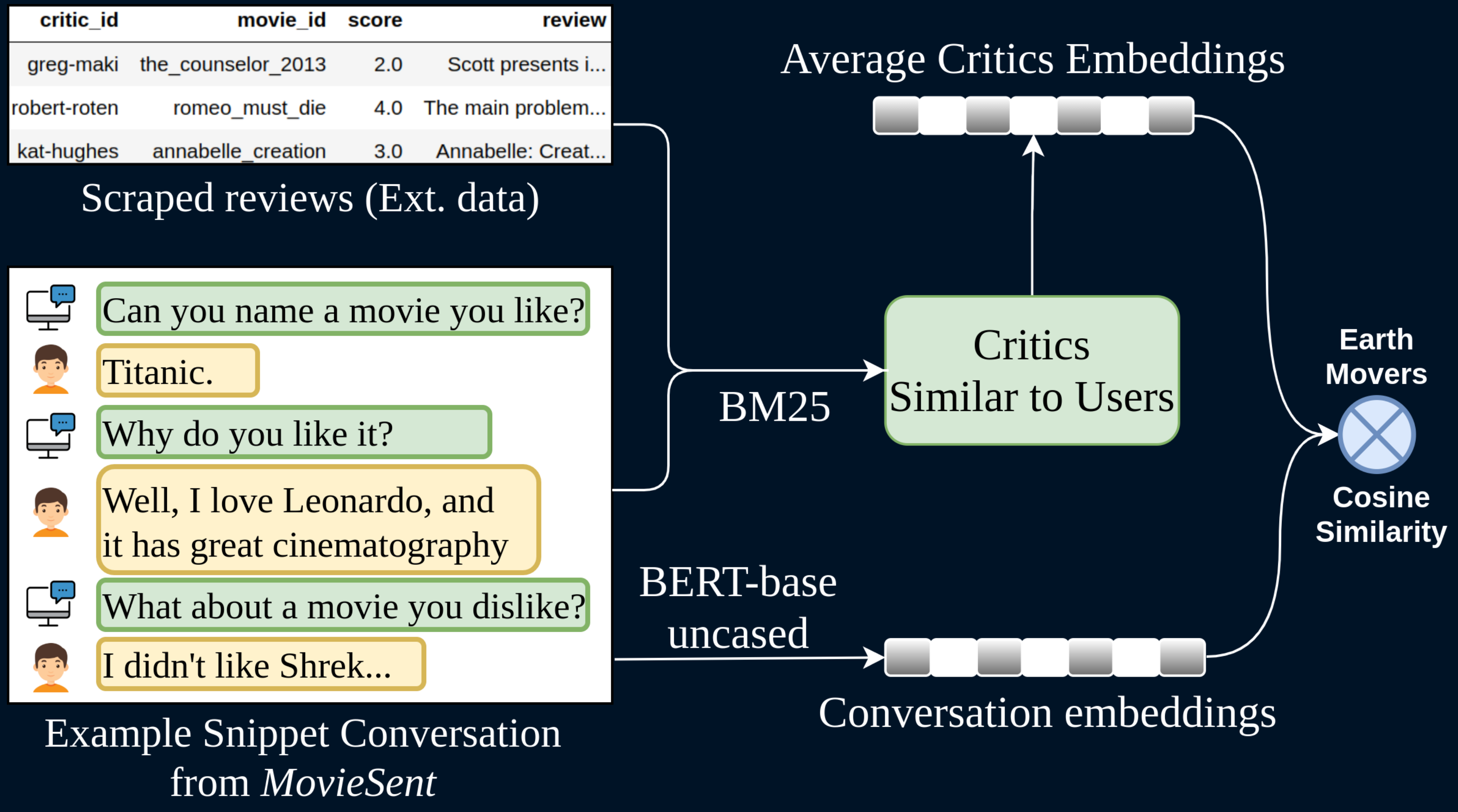
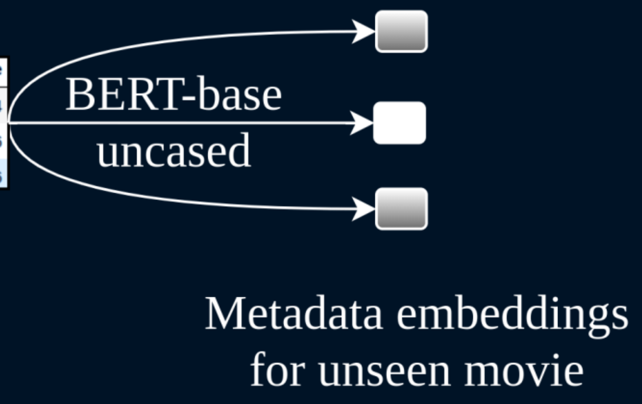


ConvExtr Model

title	CS	AS	description	people	genre	released	runtime
1408	80	61	renowned ho...	[john cusac...	[horror, my...	2007	94
cars	75	79	lightning m...	[owen wilso...	[action & a...	2006	116
300	60	89	sin city au...	[gerard but...	[action & a...	2007	116

Movies metadata (Ext. data)



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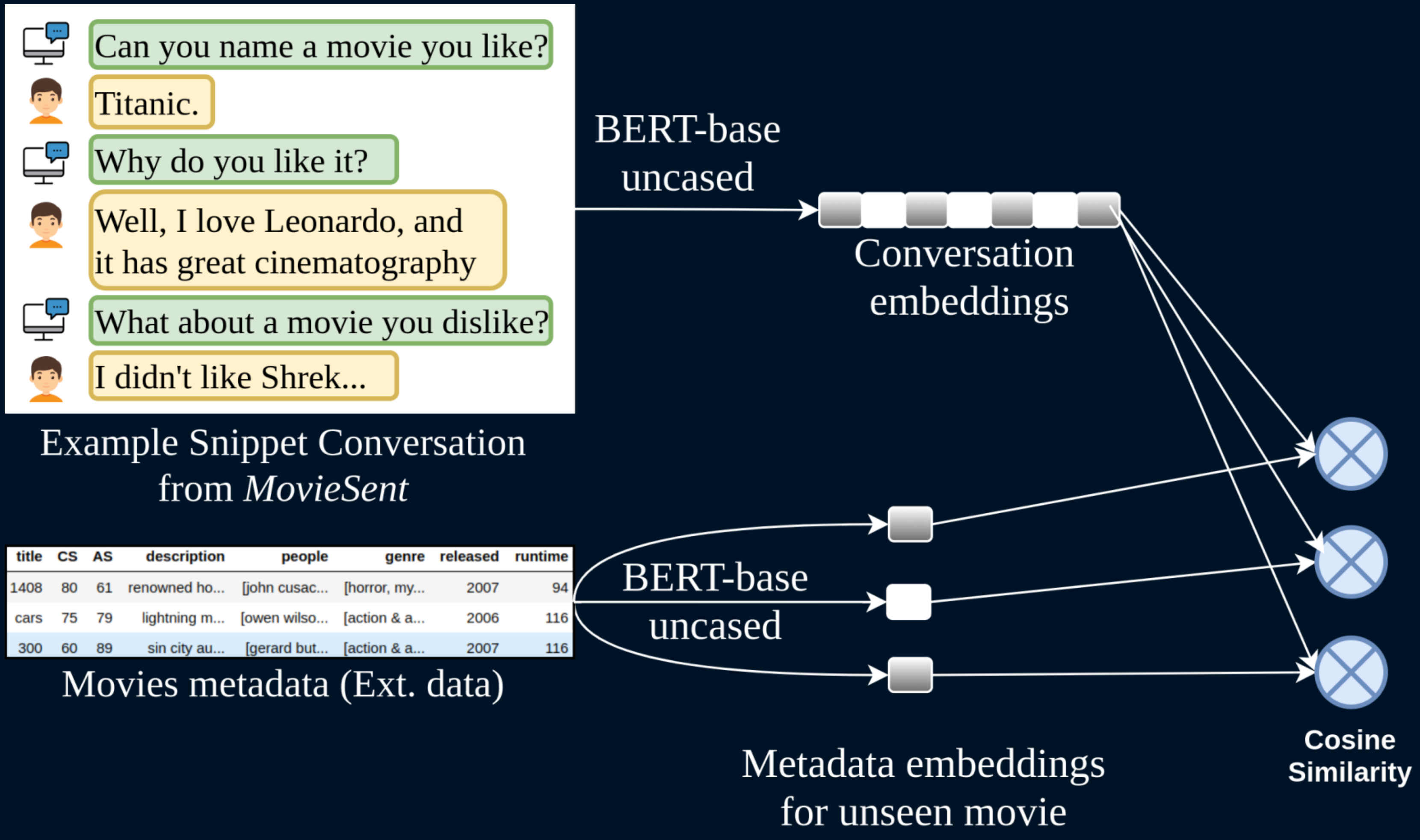

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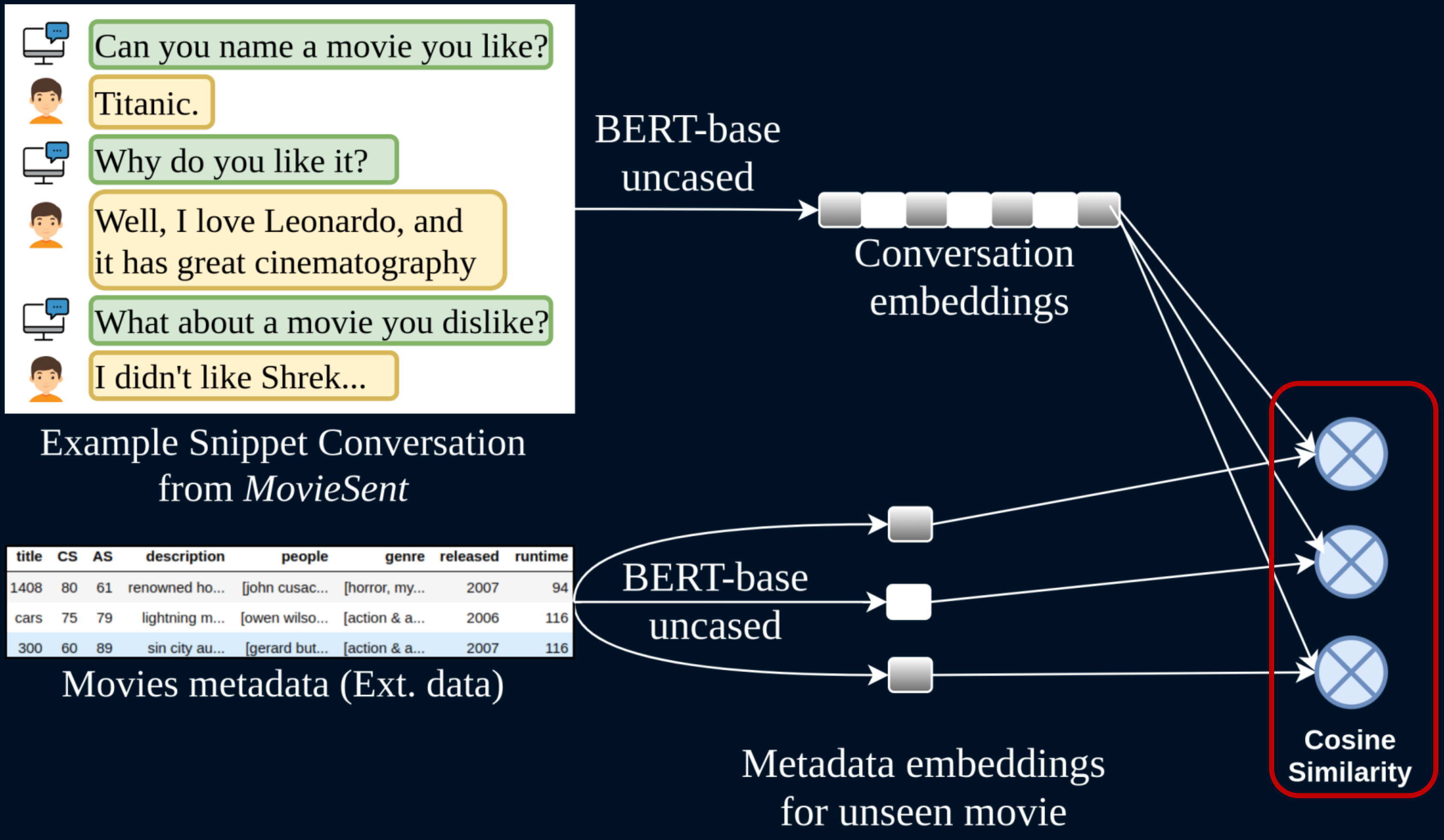

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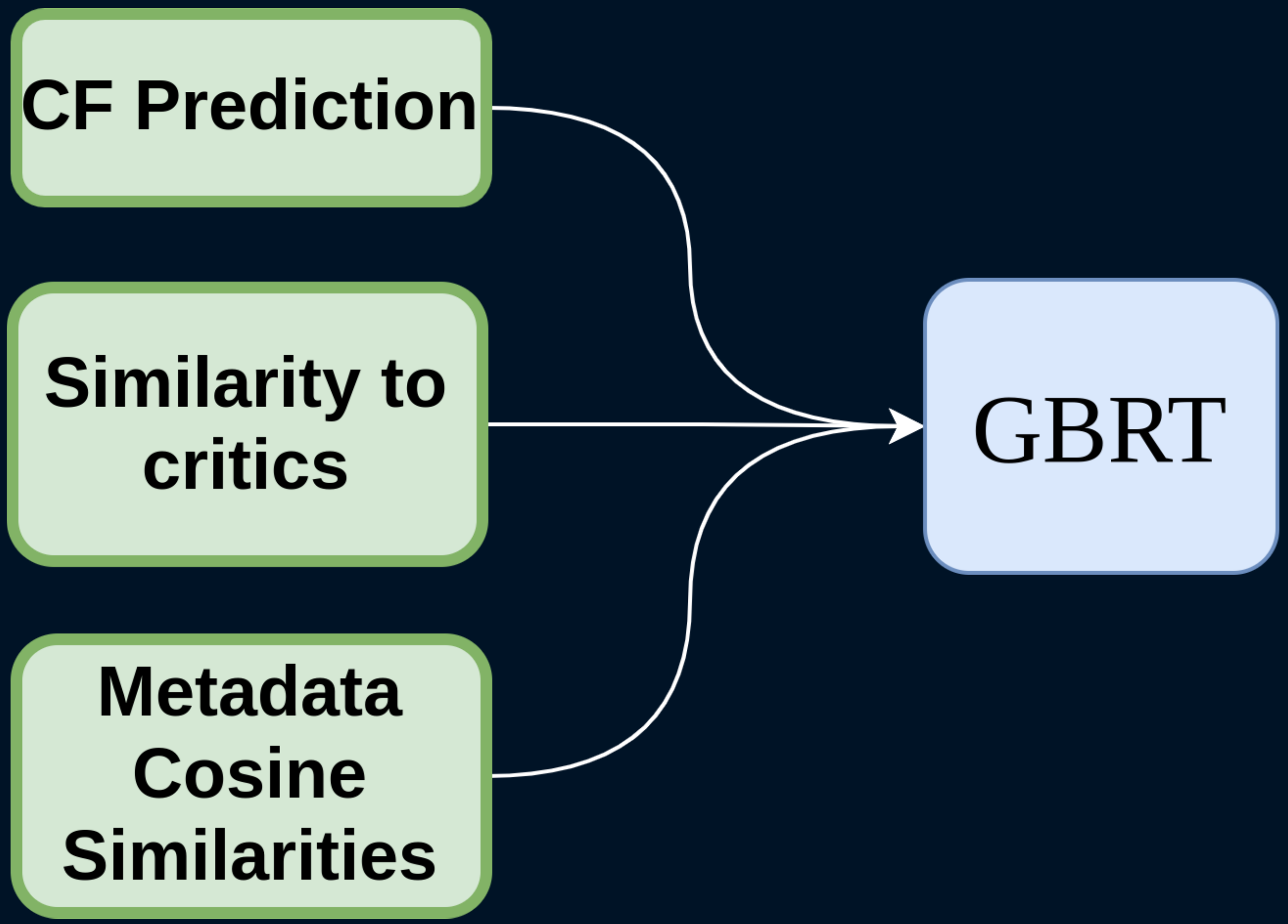

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Baseline methods		
Average Critics	1.34	0.99
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SVD (CF only)	1.18*	0.95
SVD++ (CF only)	1.14	0.92
GBRT	***1.09****	***0.84***

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GBRT	***1.09****	***0.84***
Best Possible:	0.84	0.64

Conclusion

- Using conversation to select more similar users for CF improves recommendation performance
- The resulting insights offer a promising direction for improving conversational recommendation systems

- Dataset and code available at:

Acknowledgements

This work was partially supported by a grant from Amazon Alexa towards the study of conversational search and recommendation.

amazon alexa

Thank you