An Opinion-aware Approach to Contextual Suggestion

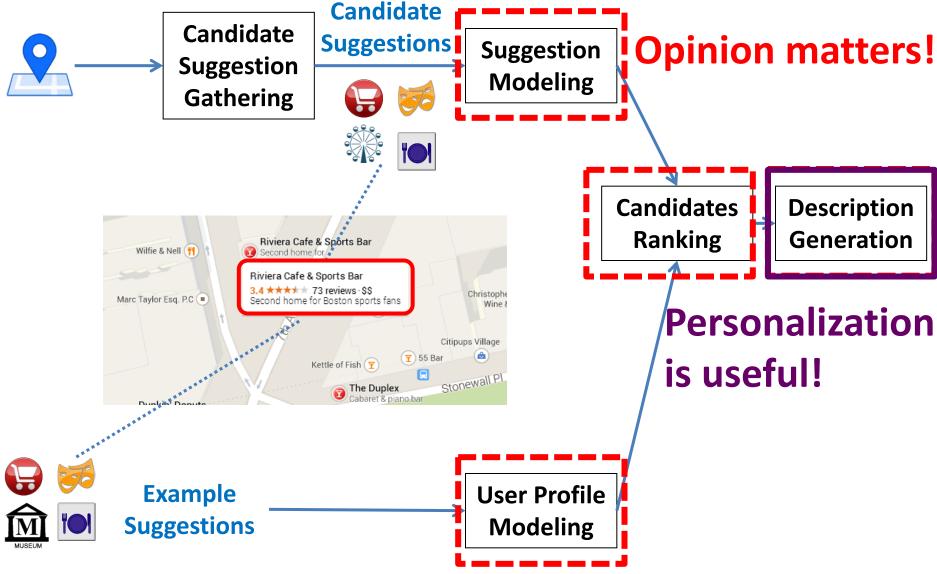
TREC 2013 Contextual Suggestion Track



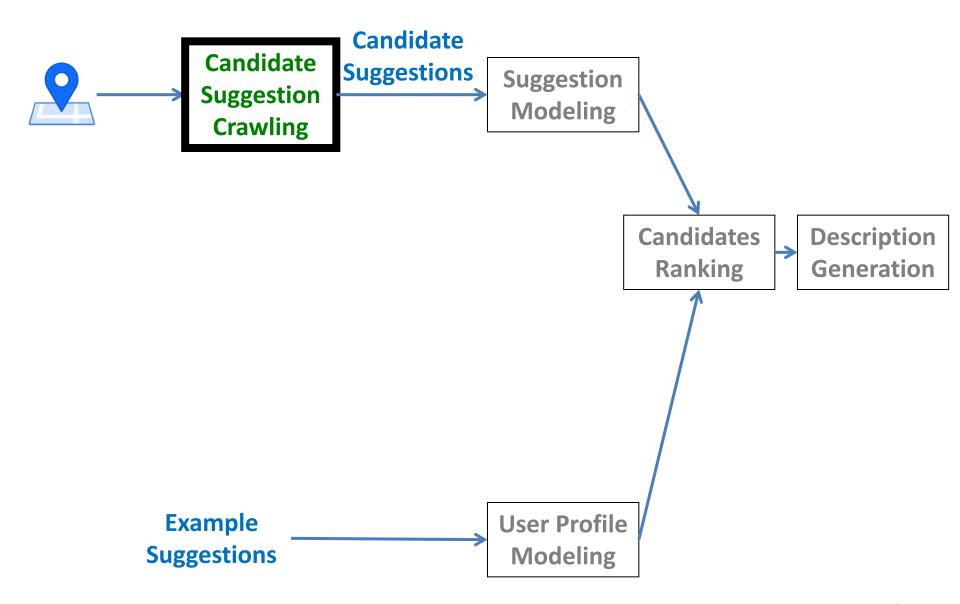
Peilin Yang and Hui Fang
University of Delaware



Overview of Our Methods



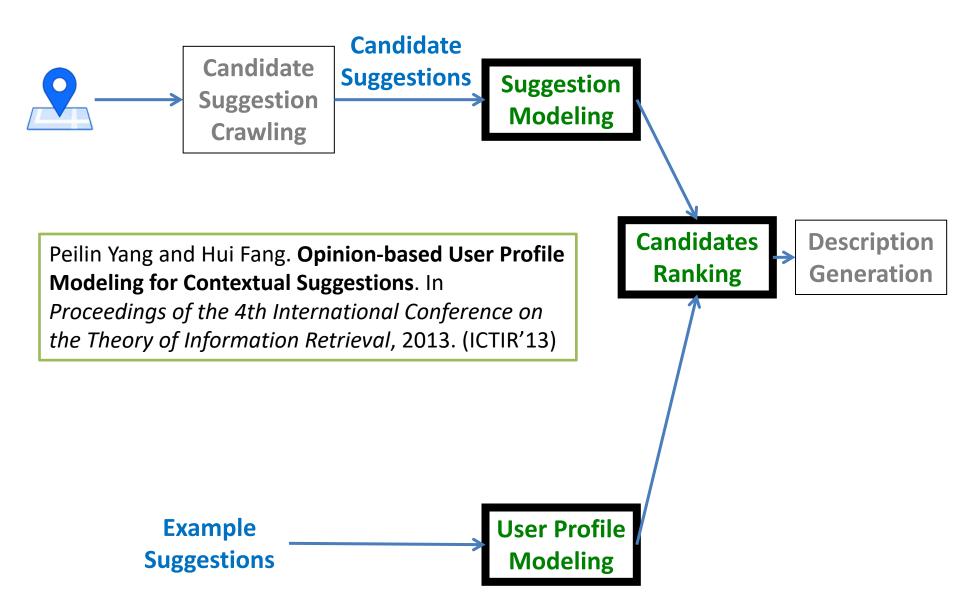
Overview of Our Methods



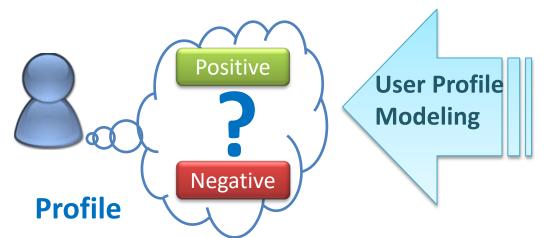
Crawling Suggestion Candidates

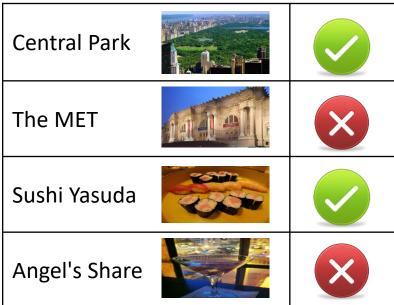
- Source : Yelp
- Strategy: At most 100 pages per top category (arts, shopping, food and etc.)
- Total number of crawled suggestions: 105,871
 - Average number of suggestions per context : 2,117
 - Max: 8410 (i.e., Washington D.C.)
 - Min: 302 (i.e., Crestview)

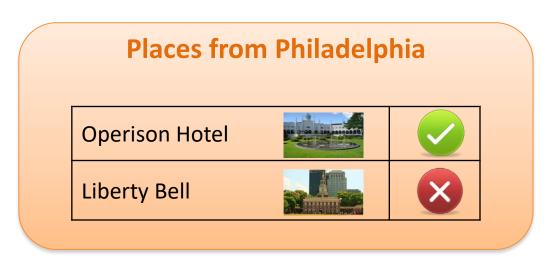
Overview of Our Methods



A Motivating Example

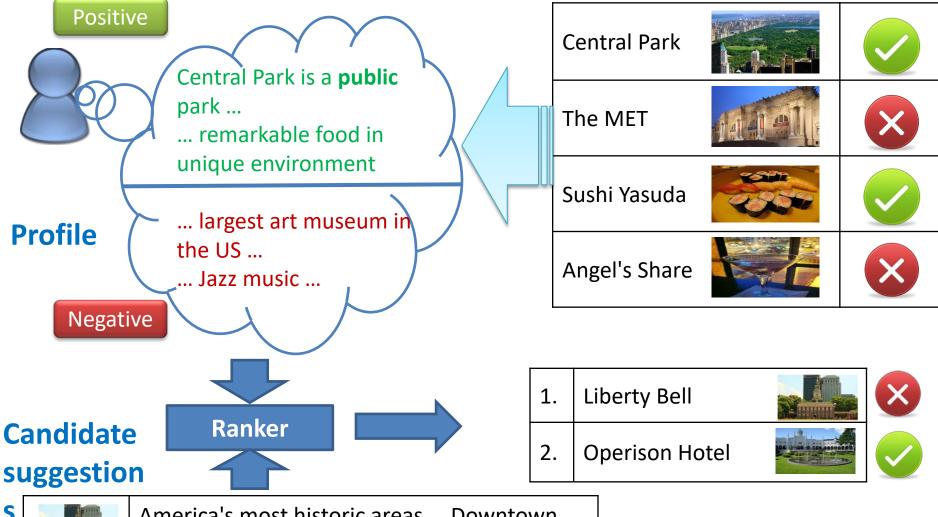






Description-based Profile Modeling

New York City





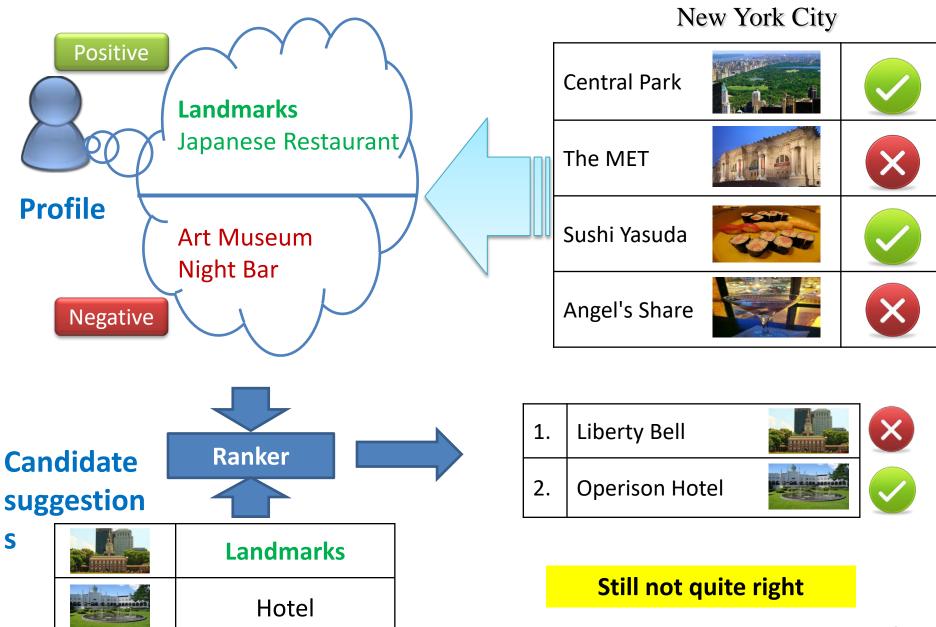
America's most historic areas ... Downtown public art circuit tour ..



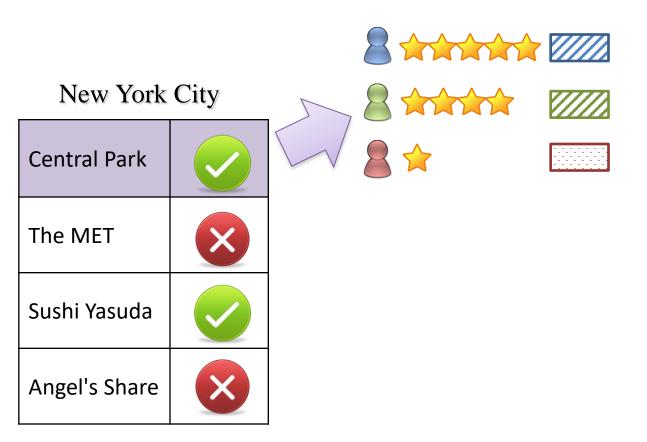
At Operison the focus is on detail - and the guest is always at the center of attention.

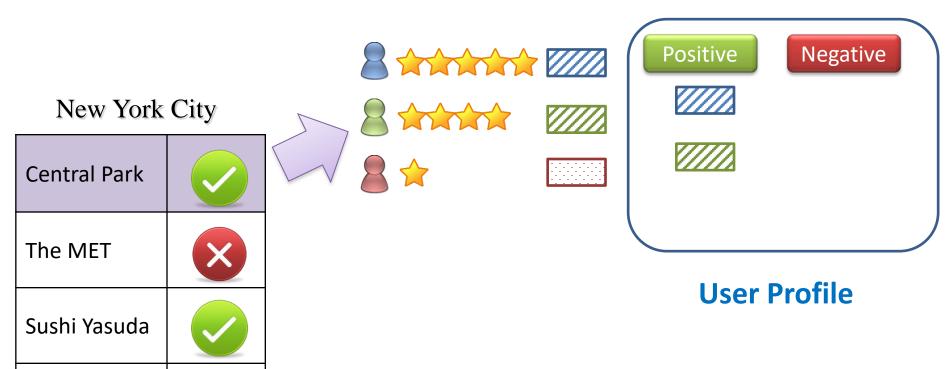
Can not be generalized!

Category-based Profile Modeling



Central Park	>
The MET	X
Sushi Yasuda	✓
Angel's Share	X

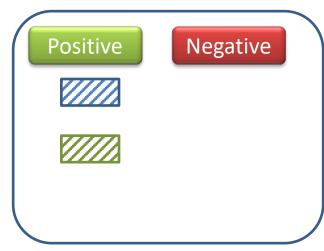




Angel's Share



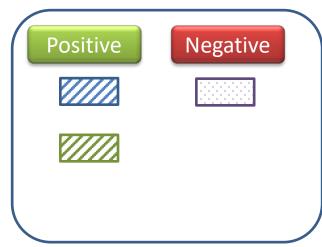




User Profile





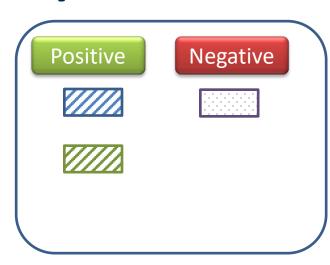


User Profile







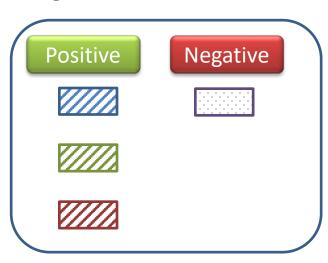


User Profile





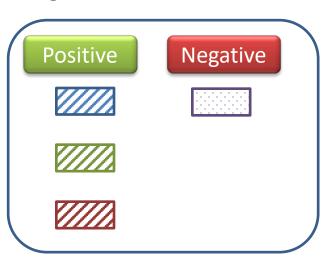




User Profile





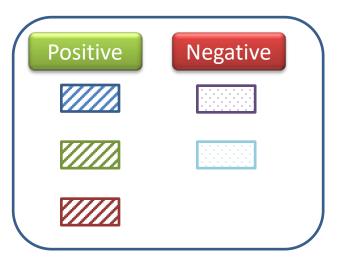


User Profile









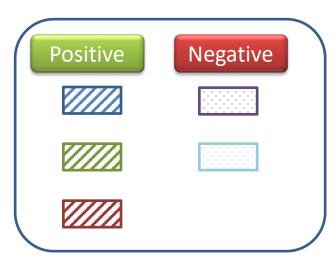
User Profile





New York City



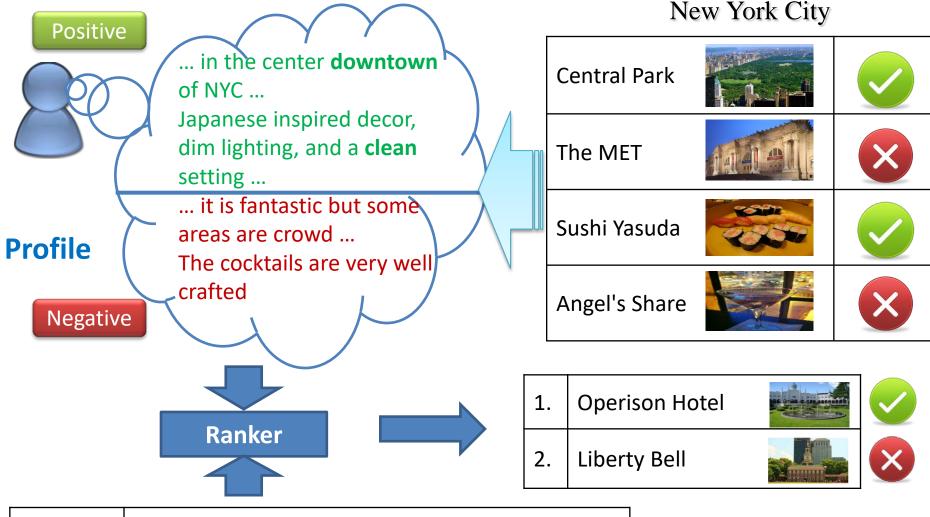


User Profile

Assumption:

A user's profile is constructed based on reviews of other users who share the similar opinions on the example suggestions.

Opinion-based Profile Modeling





... A little bit far away from downtown...

... it is crowd and you need to take bus to there ...



... The hotel is very **close to the train station** ... The neat and **clean** environment is desirable...

Representation of User Profiles

Original review

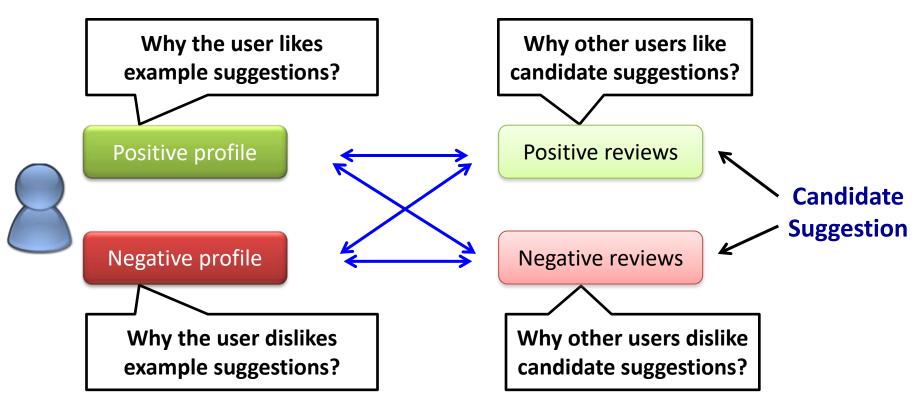
... From the stunning architecture to the croissant and latte served up in the food court downstairs. Go to this place and ask why all train stations can't be like this!

Wow, over 100 tracks. Unbelievable architecture. Shopping, food. Etc. it is amazing. We ate at the oyster bar last time and that was a treat. The oyster pots are quite something.

Unique Full Reviews	Unique terms from the original review excluding stop words
Review Summaries	The review summaries generated by Opinosis [1].

K. Ganesan, C. Zhai, and J. Han. Opinosis: a graph-based approach to abstractive summarization of highly redundant opinions. In Proceedings of the 23rd International Conference on Computational Linguistics, COLING '10, pages 340–348, Stroudsburg, PA, USA, 2010. Association for Computational Linguistics.

Ranking candidate suggestions



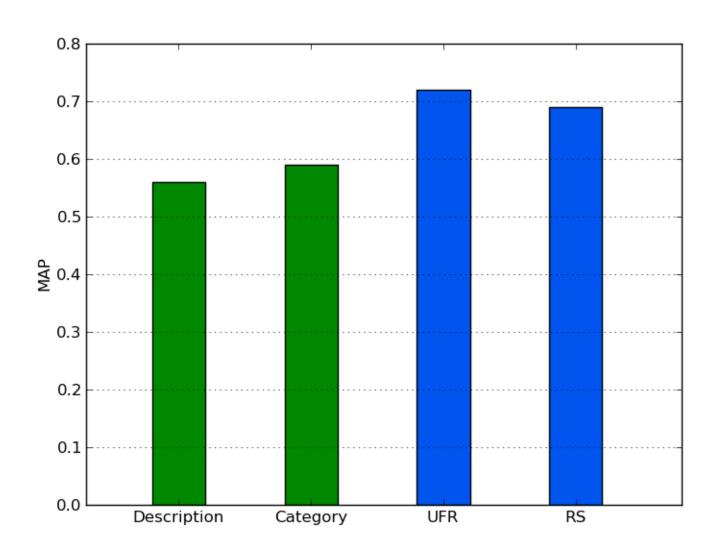
$$S(U, CS) = \alpha \times SIM(U_{pos}, CS_{pos})$$

$$-\beta \times SIM(U_{pos}, CS_{neg})$$

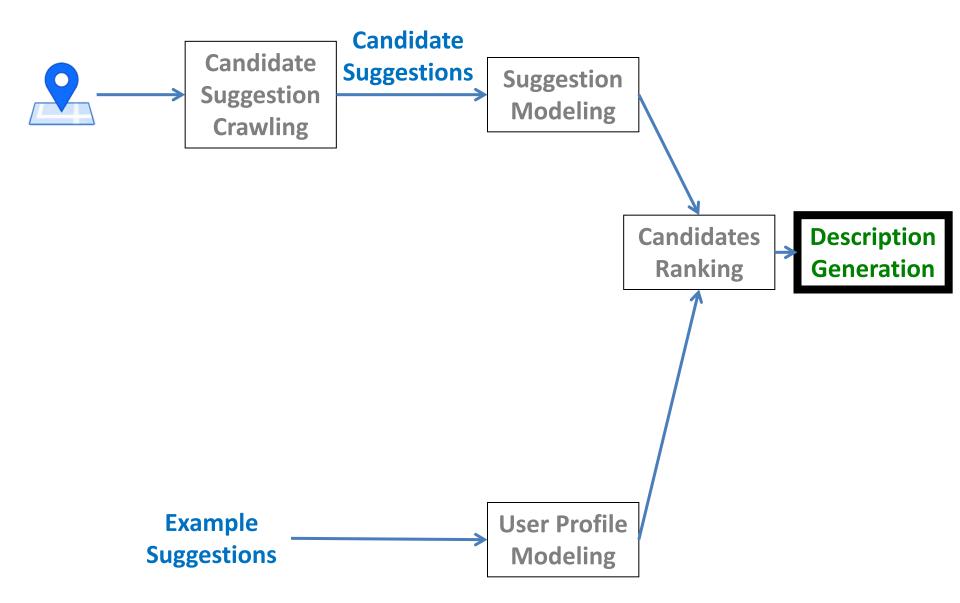
$$-\gamma \times SIM(U_{neg}, CS_{pos})$$

$$+\eta \times SIM(U_{neg}, CS_{neg})$$

Preliminary Results on last year's data: Opinion-based methods are more effective.



Overview of Our Methods



- Opening Sentence
- "Official" Introduction
- Highlighted Reviews
- Concluding Sentence

What is this place?

Why do other people like it?

Why is it recommended for YOU?

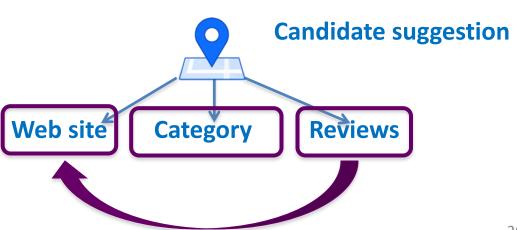


- Opening Sentence
- "Official" Introduction

What is this place?

- Highlighted Reviews
- Concluding Sentence

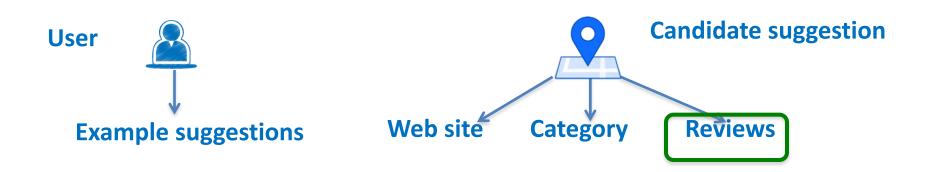




- Opening Sentence
- "Official" Introduction
- Highlighted Reviews

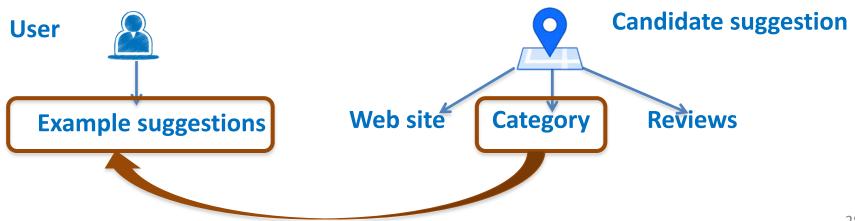
Why do other people like it?

Concluding Sentence



- Opening Sentence
- "Official" Introduction
- Highlighted Reviews
- Concluding Sentence

Why is it recommended for YOU?



An Example of Generated Description

What is this place?

"The Olive Room is a bar. HERE ARE THE DESCRIPTIONS FROM ITS WEBSITE: Here at the olive room, you will receive the finest cuisine montgomery has to offer.

HERE ARE REVIEWS FROM OTHER PEOPLE: If you are looking for a unique dining experience, with excellent food, service, location, and outstanding ambiance, look no further!

THIS PLACE IS SIMILAR TO OTHER PLACE(S) YOU LIKED, i.e. Tria Wine Room."

Why do other people like it?

Why is it recommended for YOU?

Description of Our Two Runs

Runs	User Profile	Description	
UDInfoCS1	Review Summaries	Opening Sentence + Meta Description + Web Site Sentences + Highlighted Reviews + Concluding Sentence	
UDInfoCS2	Unique Full Review	Opening Sentence + Meta Description + Highlighted Reviews + Concluding Sentence	

Effectiveness of the runs (from the CS overview paper)

Run	P@5 Rank	P@5 Score	TBG Rank	TBG Score	MRR Rank	MRR Score
UDInfoCS1	1	0.5094	1 (-)	2.4474	1 (-)	0.6320
UDInfoCS2	2	0.4969	2 (-)	2.4310	2 (-)	0.6300
simpleScore	3	0.4332	4 (Down 1)	1.8374	4 (Down 1)	0.5871
complexScore	4	0.4152	5 (Down 1)	1.8226	6 (Down 2)	0.5777
DuTH_B	5	0.4090	3 (Up 2)	1.8508	3 (Up 2)	0.5955
1	6	0.3857	8 (Down 2)	1.5329	7 (Down 1)	0.5588
2	7	0.3731	7 (-)	1.5843	5 (Up 2)	0.5785
$udel_run_D$	8	0.3659	9 (Down 1)	1.5243	8 (-)	0.5544
isirun	9	0.3650	6 (Up 3)	1.6278	9 (-)	0.5165
$udel_run_SD$	10	0.3354	16 (Down 6)	1.2882	10 (-)	0.5061
york13cr2	11	0.3309	12 (Down 1)	1.3483	15 (Down 4)	0.4637
$\mathrm{DuTH}_{-}\mathrm{A}$	12	0.3283	14 (Down 2)	1.3109	12 (-)	0.4836
york13cr1	13	0.3274	15 (Down 2)	1.2970	14 (Down 1)	0.4743
UAmsTF30WU	14	0.3121	17 (Down 3)	1.1905	13 (Up 1)	0.4803
IRIT.OpenWeb	15	0.3112	10 (Up 5)	1.4638	11 (Up 4)	0.4915
CIRG_IRDISCOA	16	0.3013	18 (Down 2)	1.1681	16 (-)	0.4567
CIRG_IRDISCOB	17	0.2906	20 (Down 3)	1.1183	19 (Down 2)	0.4212
uncsils_param	18	0.2780	13 (Up 5)	1.3115	18 (-)	0.4271
uogTrCFP	19	0.2753	11 (Up 8)	1.3568	17 (Up 2)	0.4327
$ming_{-}1$	20	0.2601	22 (Down 2)	1.0495	22 (Down 2)	0.3816
uncsils_base	21	0.2565	19 (Up 2)	1.1374	20 (Up 1)	0.4136
$ming_2$	22	0.2493	23 (Down 1)	0.9673	23 (Down 1)	0.3473
uogTrCFX	23	0.2332	21 (Up 2)	1.0894	21 (Up 2)	0.4022
run01	24	0.1650	24 (-)	0.7359	24 (-)	0.2994
baselineA	25	0.1372	25 (-)	0.5234	25 (-)	0.2316
csui02	26	0.0565	26 (-)	0.1785	26 (-)	0.1200
csui01	27	0.0565	27 (-)	0.1765	27 (-)	0.1016

Effectiveness of description generation

	UDInfoCS1	UDInfoCS2
Accuracy	0.803	0.811
Precision	0.904	0.902
Recall	0.808	0.821

One observation regarding relevance assessment:

Among the 569 suggestions returned by both runs, 27.59% (157) of them have inconsistent relevance labels for their websites, and 12.13% (69) of them have inconsistent relevance status.

Thank you!

Questions?