

Opinion-based User Profile Modeling for Contextual Suggestions

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Commonly used two-step approach

‡ Generate candidate suggestions based on contextual requirements.

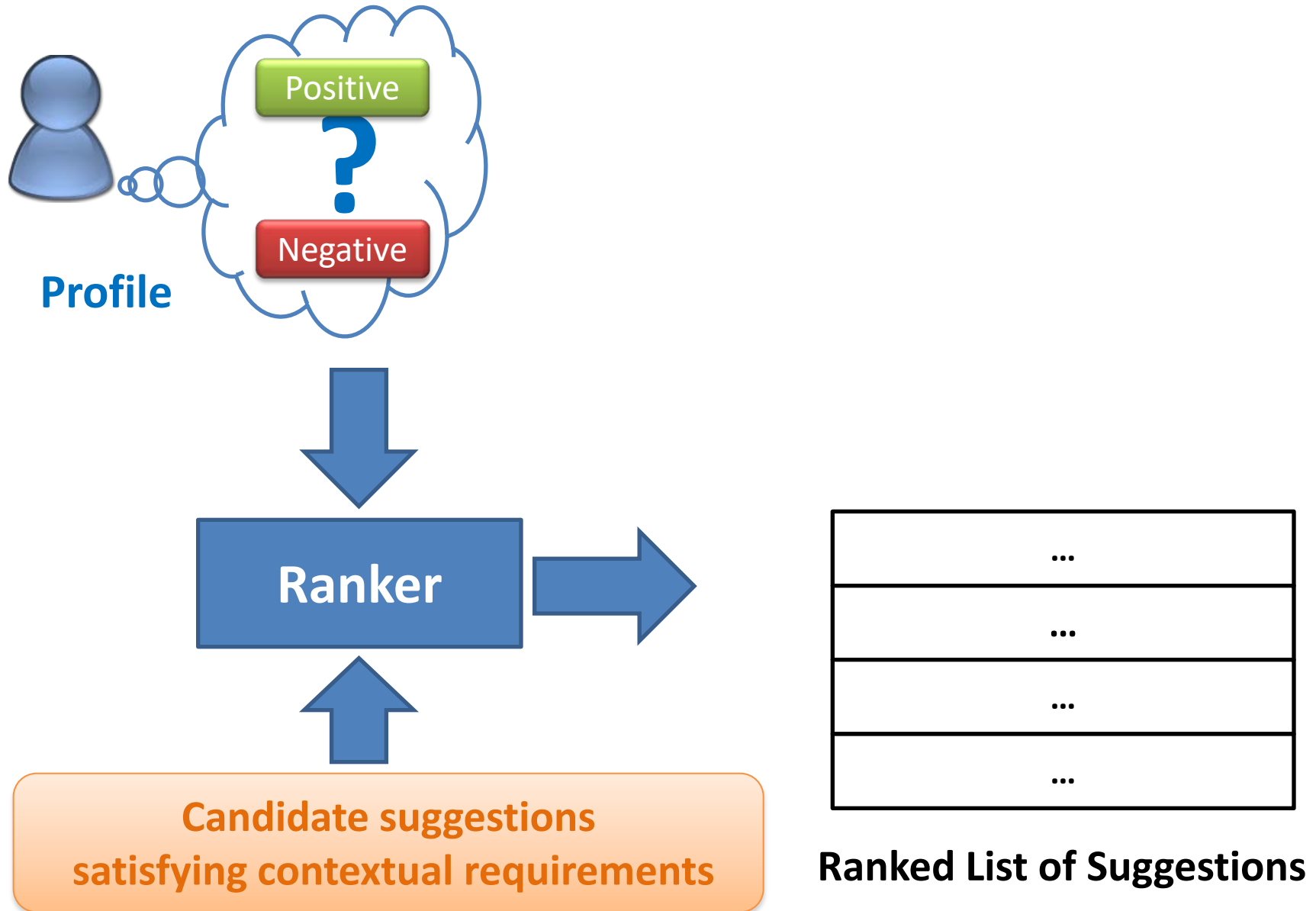
‡ Rank candidates based on the user profile.

‡ Description-based

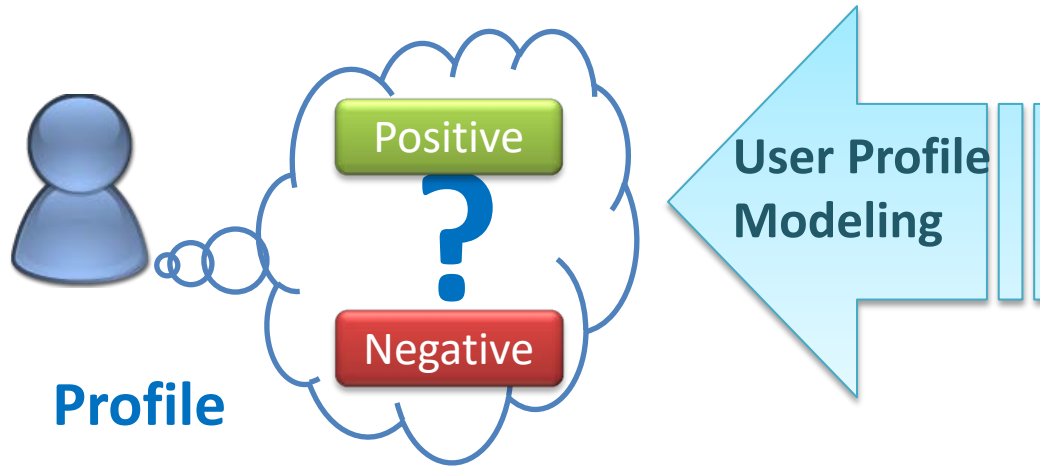
‡ Category-based

Can we do better?



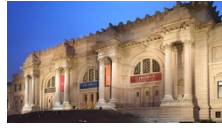





Problem Setup



A Motivating Example



New York City

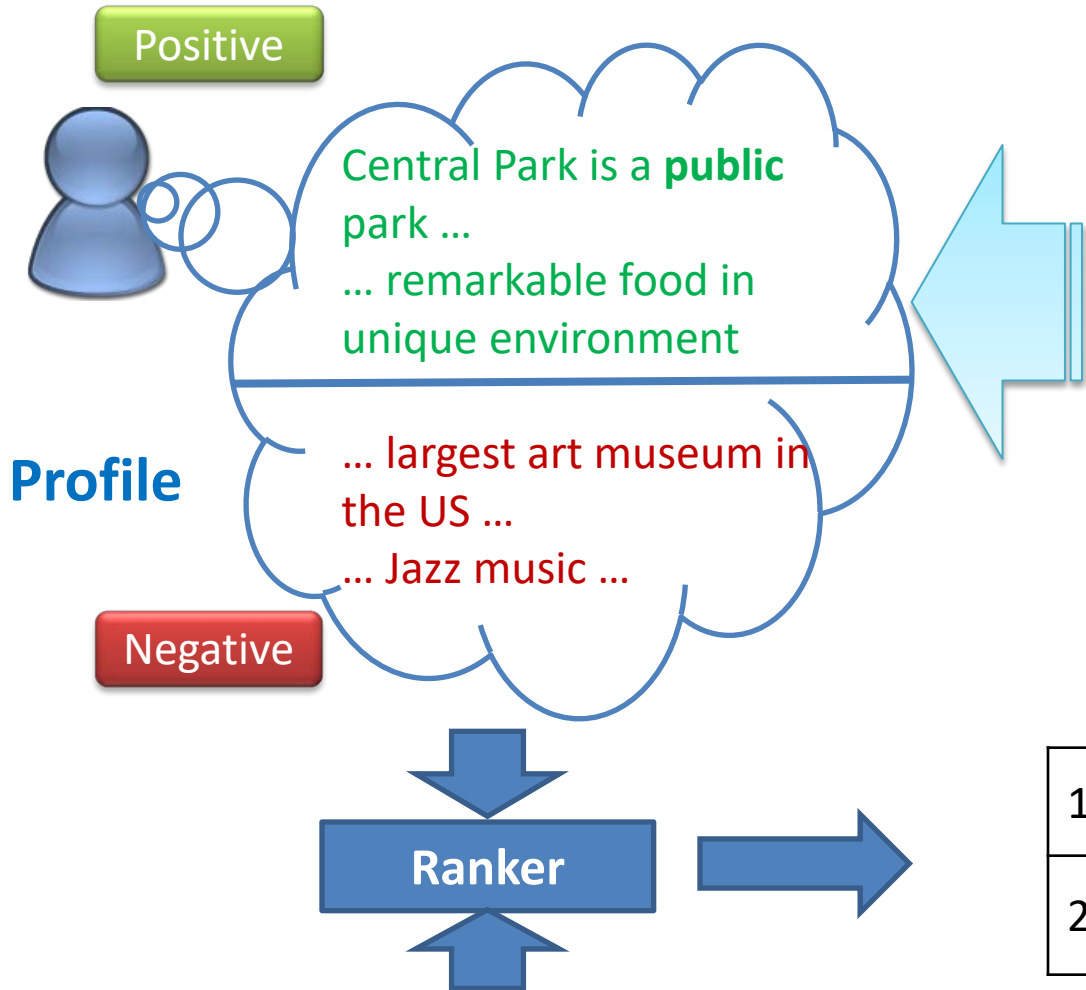
Central Park		
The MET		
Sushi Yasuda		
Angel's Share		





Places from Copenhagen

Nimb Hotel		
The Little Mermaid		



Description-based Profile Modeling

New York City



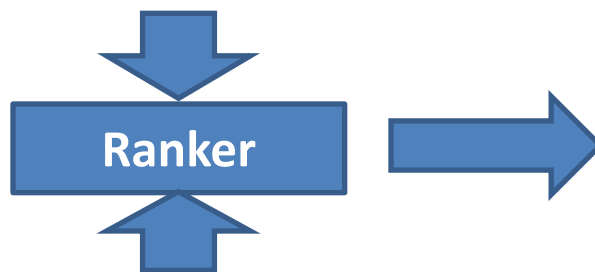
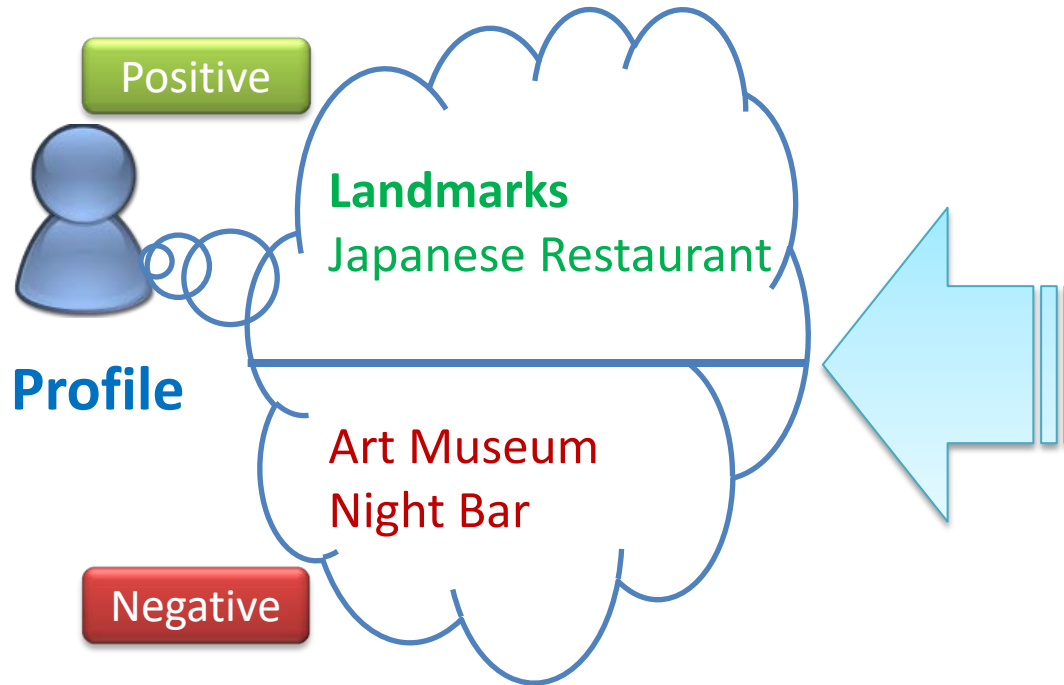
Central Park		
The MET		
Sushi Yasuda		
Angel's Share		


1.	The Little Mermaid		
2.	Nimb Hotel		

	Sculpture is on a rock... Downtown public art circuit tour ..
	At Nimb the focus is on detail - and the guest is always at the centre of attention.









Can not be generalized!

Category-based Profile Modeling



	Landmarks
	Hotel

New York City


Central Park		
The MET		
Sushi Yasuda		
Angel's Share		

1.	The Little Mermaid		
2.	Nimb Hotel		

Still not quite right

From “What” to “Why”

New York City

Central Park	
The MET	
Sushi Yasuda	
Angel's Share	

From “What” to “Why”

New York City

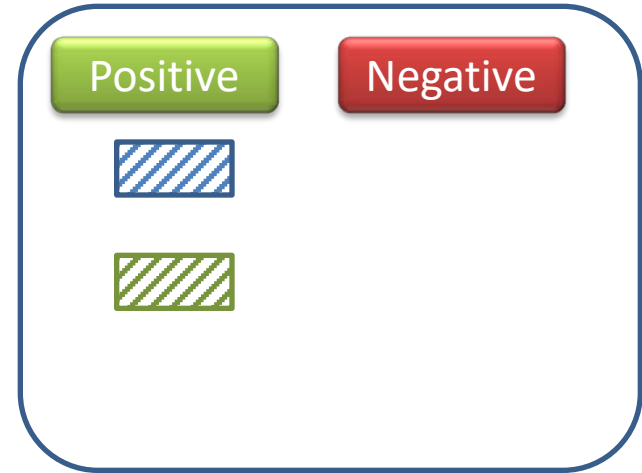
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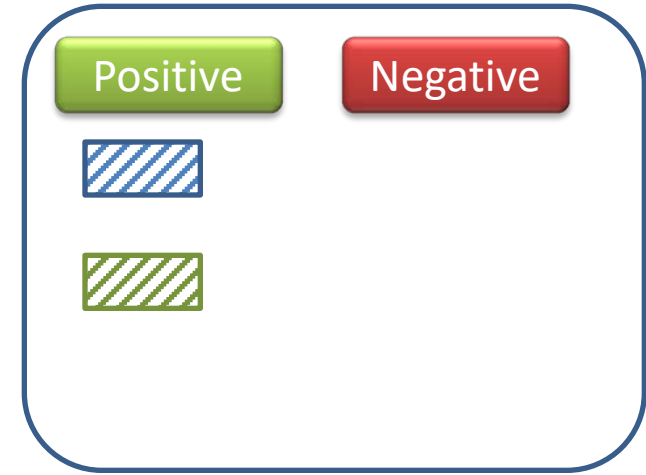


User Profile

From “What” to “Why”

New York City

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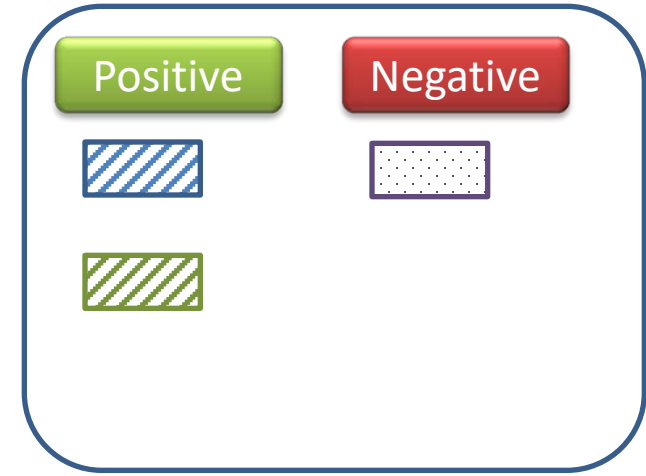


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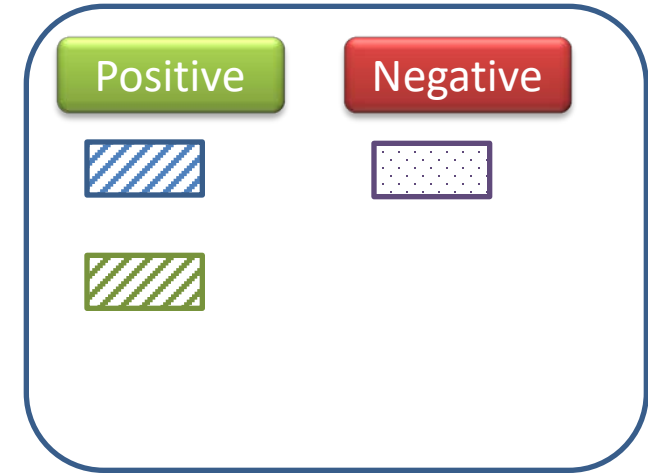


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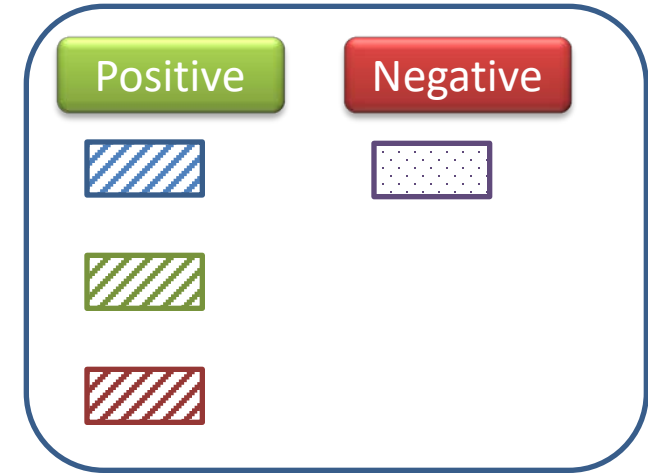


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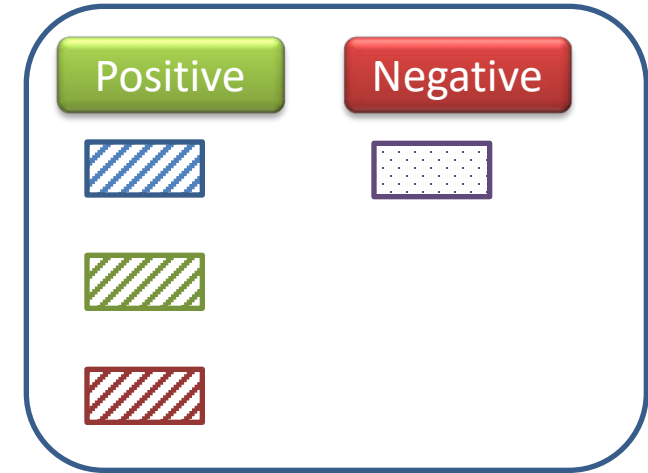


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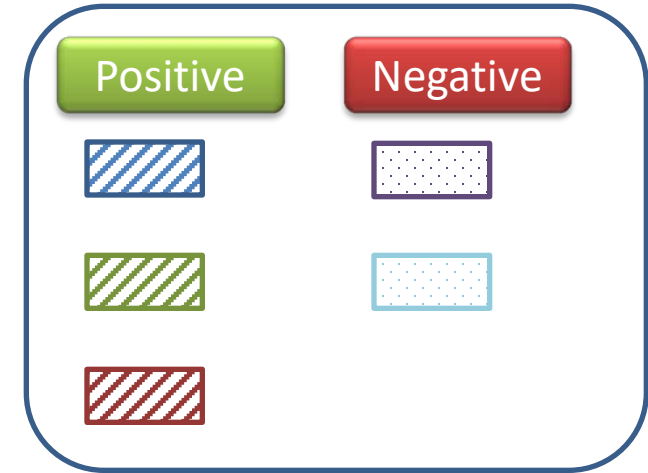


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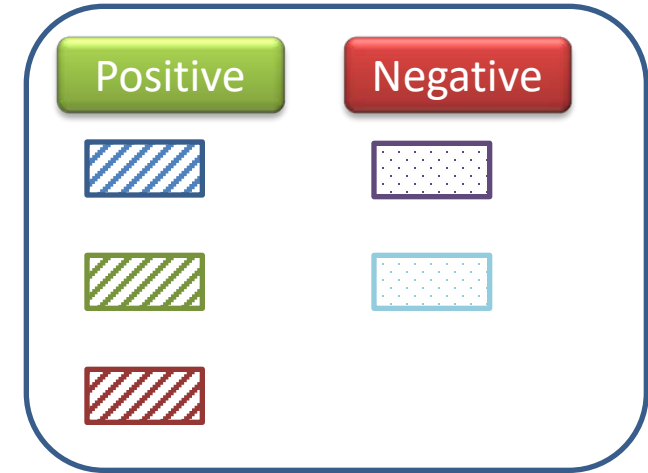


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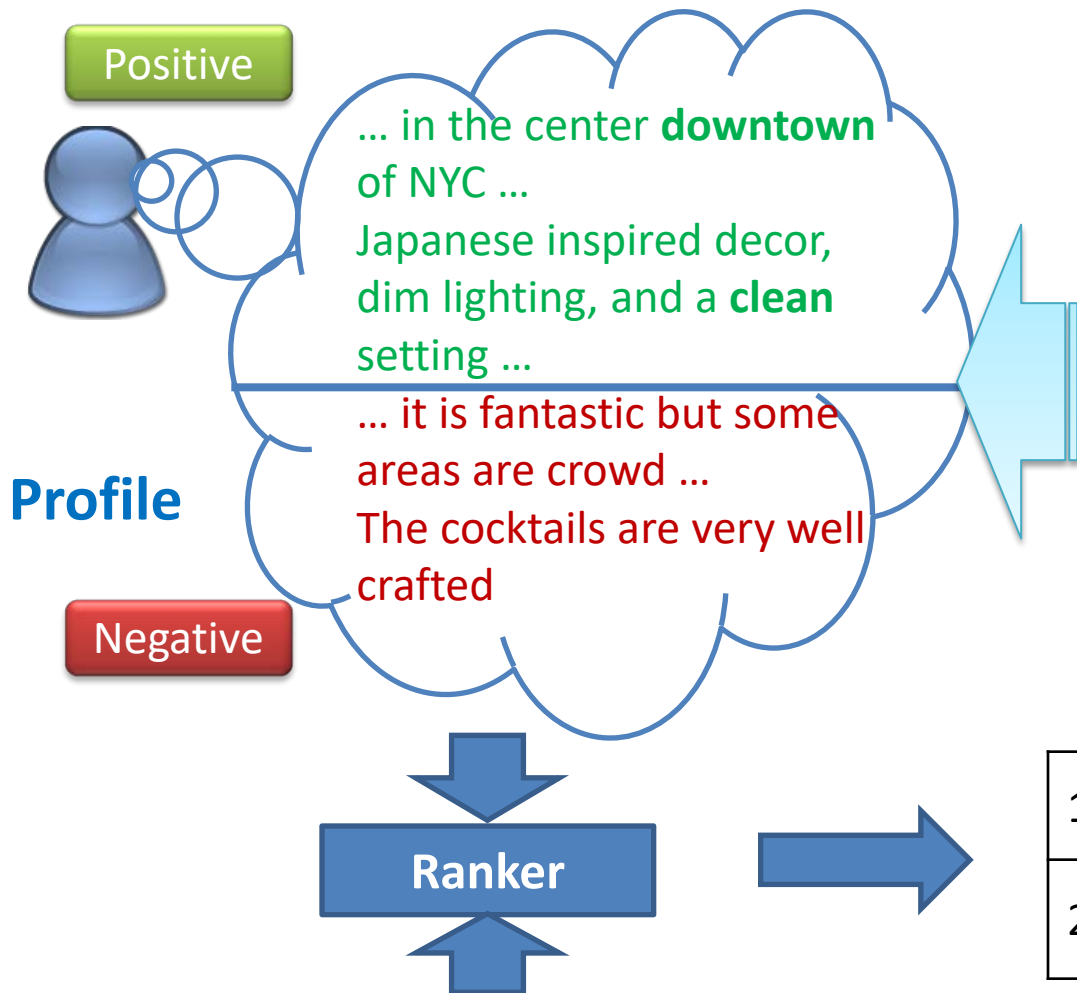


User Profile









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



New York City

Central Park		
The MET		
Sushi Yasuda		
Angel's Share		

1.	Nimb Hotel		
2.	The Little Mermaid		

	... 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...

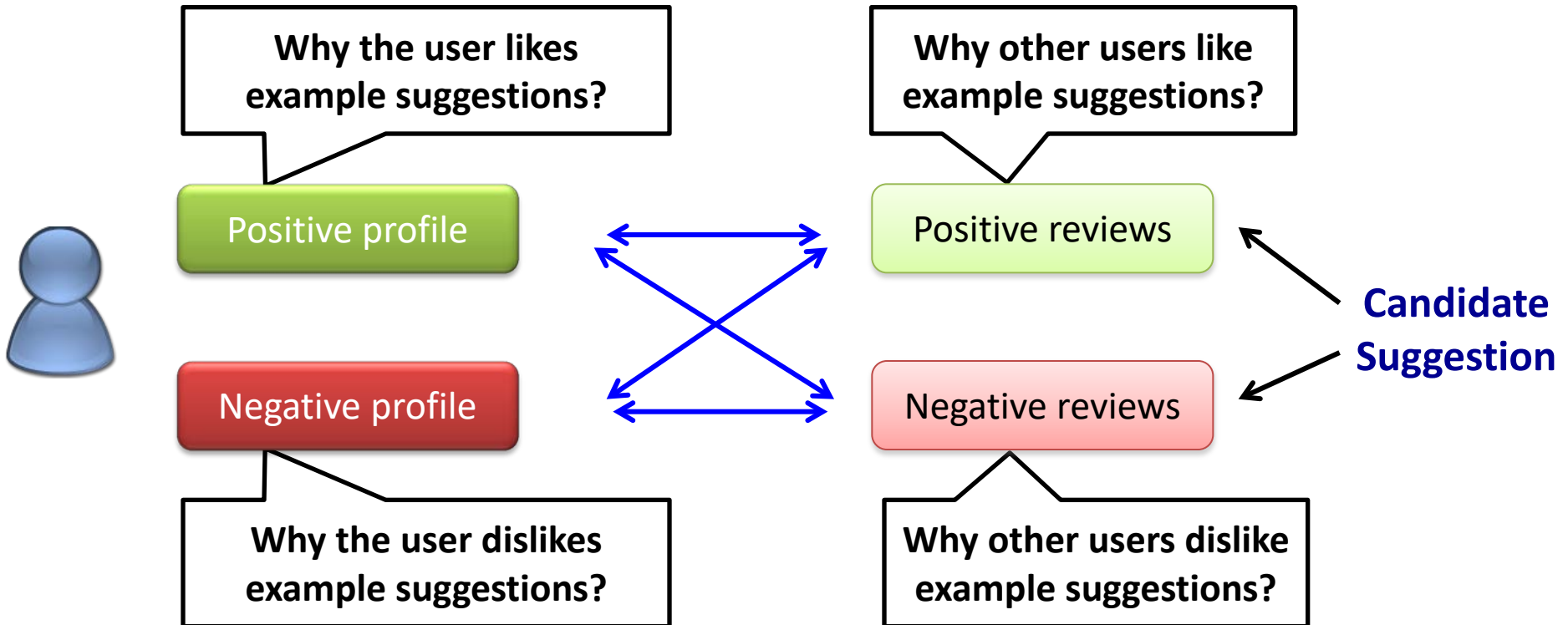
Representation of User Profiles

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.

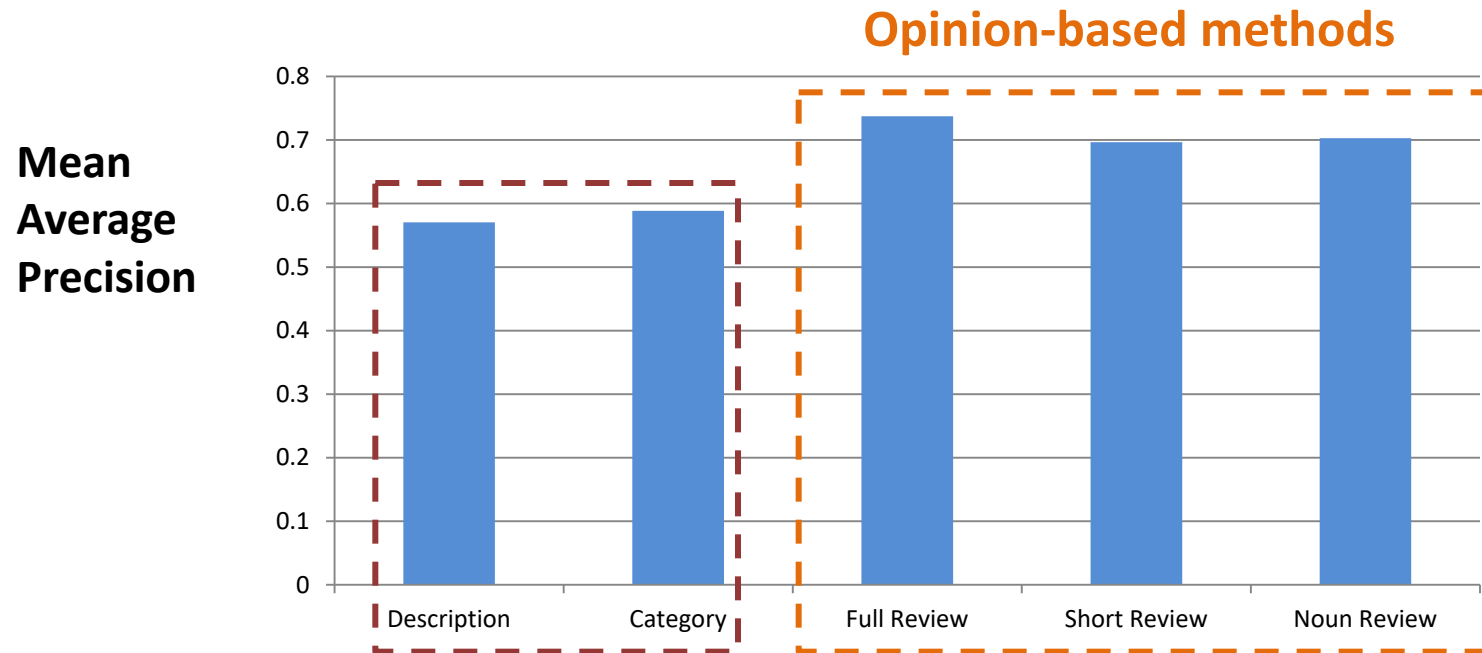
Full Reviews (all terms)	(As the same as above, excluding stop words)
Short Reviews (high frequency terms)	architecture architecture food food oyster oyster 100 amazing ask ate ...
Noun-based Reviews	architecture food court downstairs place train stations tracks bar pots ...

Ranking candidate suggestions



$$\begin{aligned}
 S(U, CS) = & \alpha \times SIM(U_{pos}, CS_{pos}) \\
 & - \beta \times SIM(U_{pos}, CS_{neg}) \\
 & - \gamma \times SIM(U_{neg}, CS_{pos}) \\
 & + \eta \times SIM(U_{neg}, CS_{neg})
 \end{aligned}$$

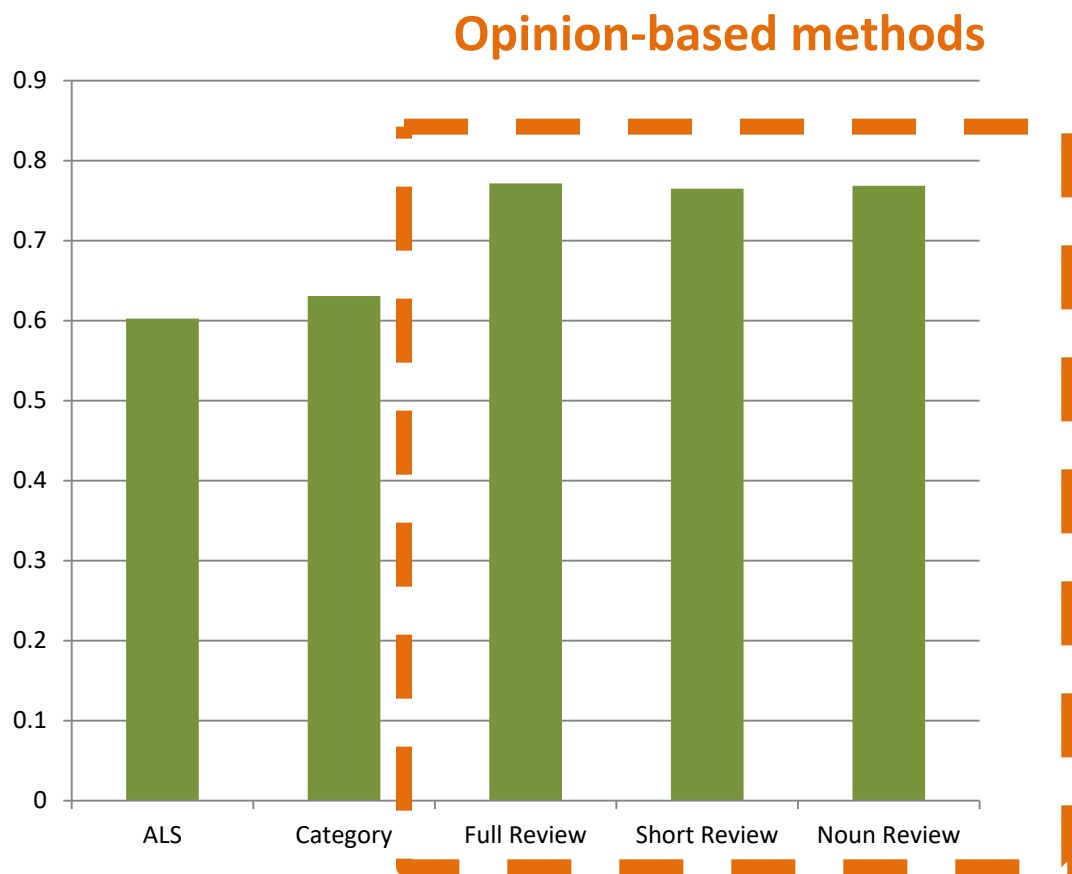
The proposed opinion-based profile modeling is more effective on the TREC2012 contextual suggestion collection.



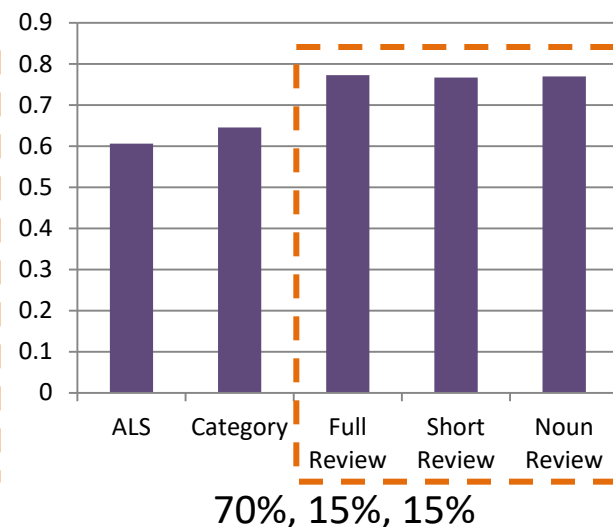
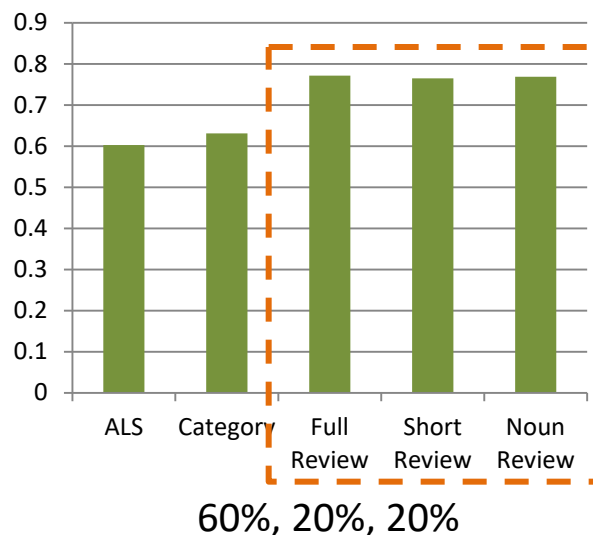
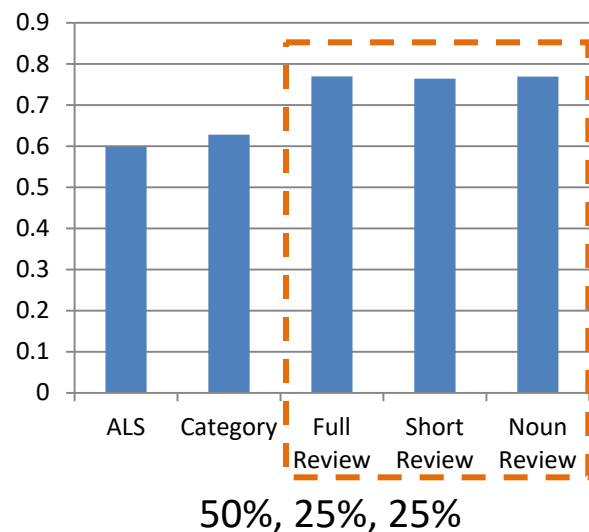
**Baselines were top runs in
TREC2012 CS Track.**

**5-fold cross validation;
34 users and 49 suggestions**

The proposed opinion-based methods are still more effective on a larger Yelp data set.

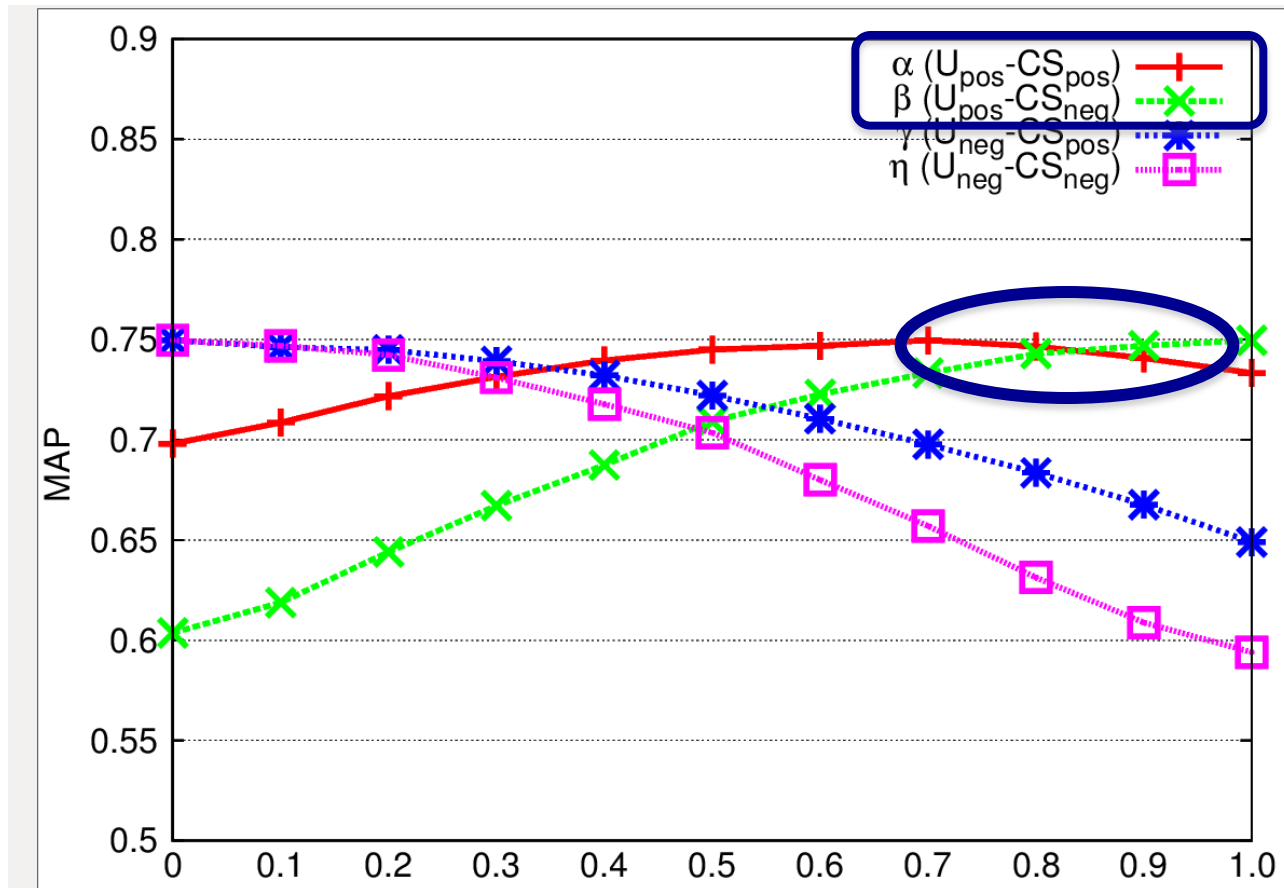


The observations are consistent when using less or more training data.



* Baseline ALS comes from: Y. Zhou, D. Wilkinson, R. Schreiber, and R. Pan. Large-scale parallel collaborative filtering for the netflix prize. In Proceedings of the 4th international conference on Algorithmic Aspects in Information and Management, AAIM '08, pages 337–348, Berlin, Heidelberg, 2008. Springer-Verlag.

Parameter sensitivity curves indicate that the positive profile is more effective than the negative one.



Conclusions and Future Work

- We proposed an opinion-based approach to user profile modeling for the contextual suggestion problem.
- Experimental results show that the proposed methods are more effective than the state of the art methods.
- Future work
 - Develop an integrated ranking approach to consider both profile and contextual requirements.
 - Apply the approach to other application such as the personalized local search problem

Thank you!

Questions?