Probabilistic Item Social Reputation Model for Recommender System

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•Layout

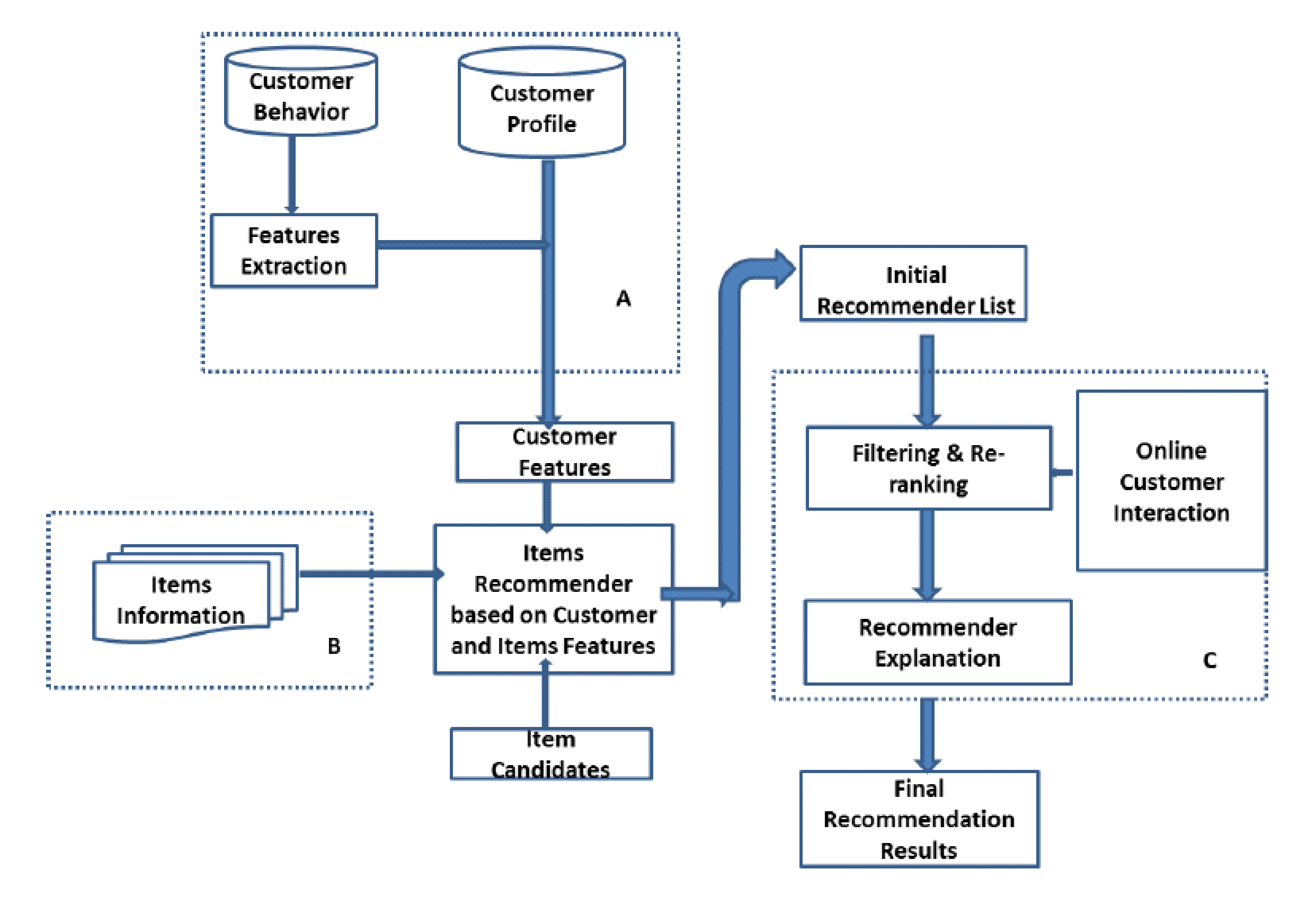
Motivation

Proposed Method

Experimental Results

QA

Motivation: Current Recommender System Architecture



Motivation: Current Recommender System Architecture

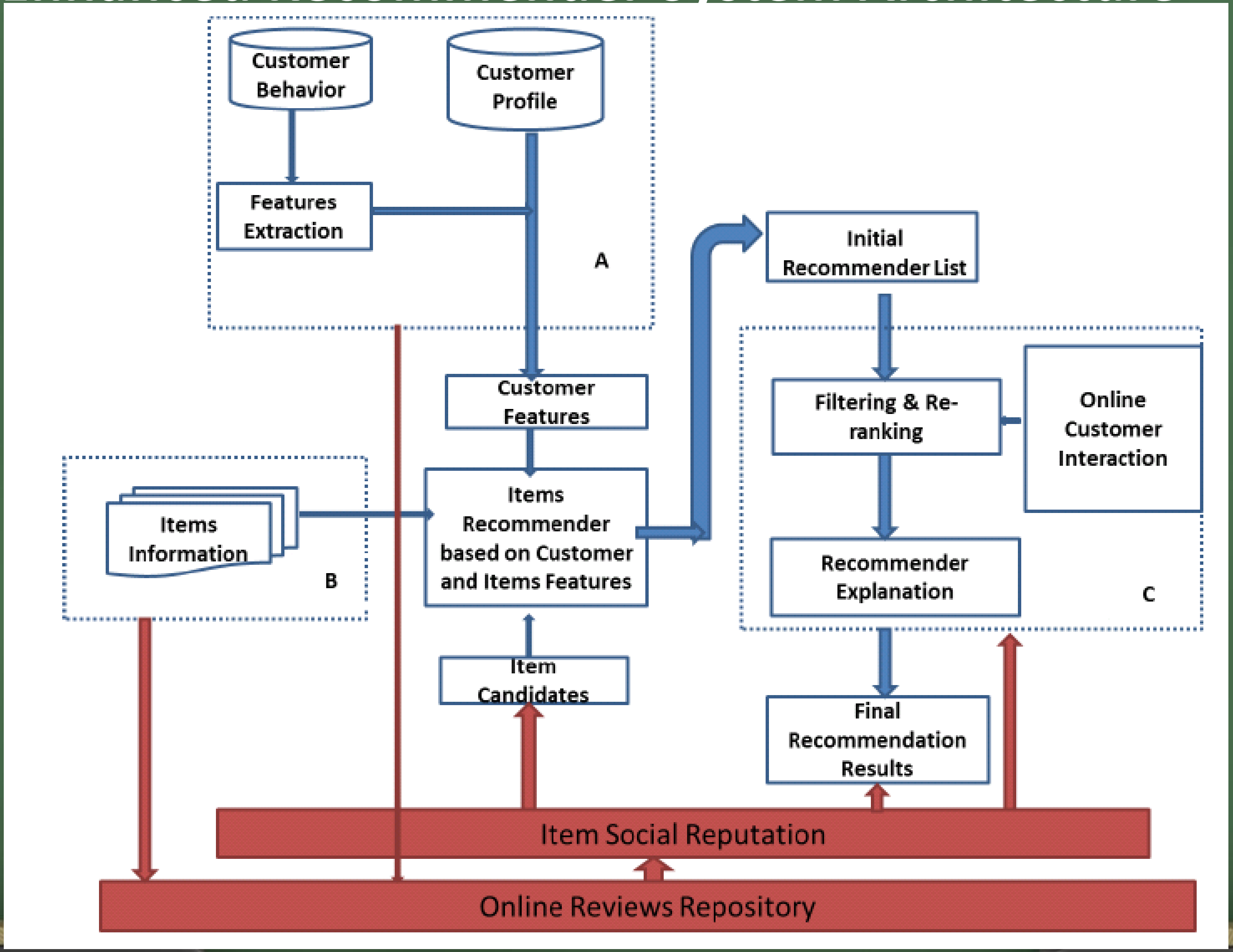
Fig 3 Illustration of final recommendation results in current recommendation system

- Collaborative Filtering
- Item Similarity
- …

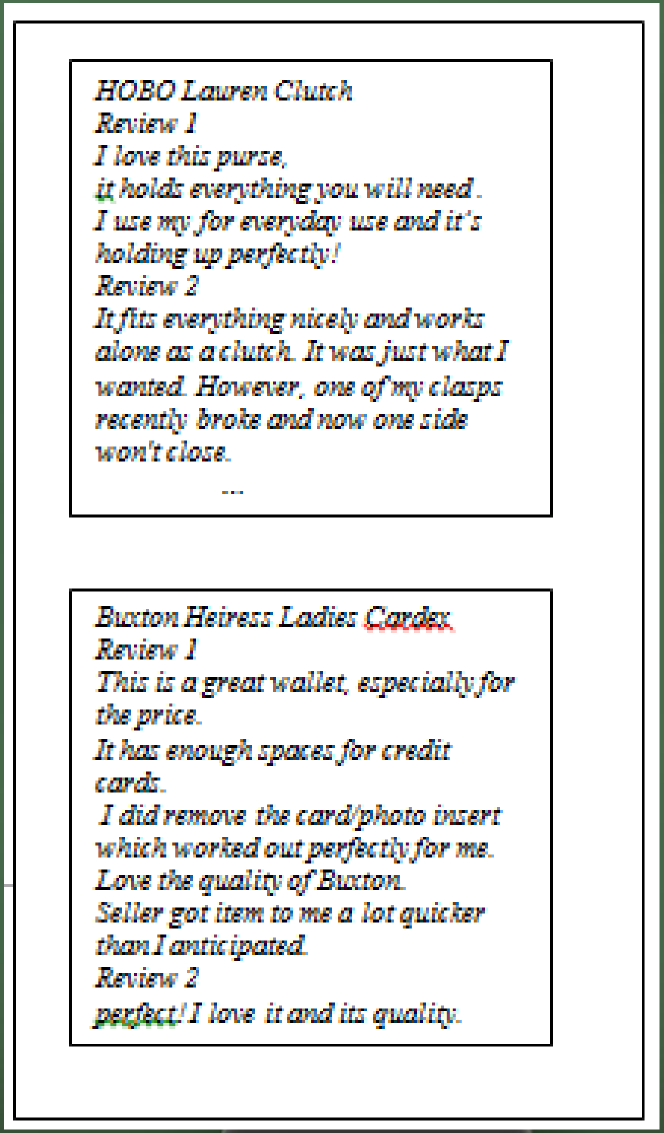
- Previous Customers Buying Experience is another way to enhance Recommendation

Motivation: Enhanced Recommender System Architecture

ISR:
Top k positive aspects in items' reviews



Current Previous Customer Experience



HOBO Lauren Clutch
Review 1
I love this purse,
it holds everything you will need.
I use my for everyday use and it's holding up perfectly!
Review 2
It fits everything nicely and works alone as a clutch. It was just what I wanted. However, one of my clasps recently broke and now one side won't close.
...

Buxton Heiress Ladies Cardex
Review 1
This is a great wallet, especially for the price.
It has enough spaces for credit cards.
I did remove the card/photo insert which worked out perfectly for me.
Love the quality of Buxton.
Seller got item to me a lot quicker than I anticipated.
Review 2
perfect! I love it and its quality.

- Don't understand why a point star is given to an item.
- Reviews are too much to be read
- Item's features are missing.
- Hard to mining users' behavior

•Proposal Methods

Desired Results

INPUT

HOBO Lauren Clutch
Review 1
I love this purse,
it holds everything you will need .
I use my for everyday use and it's holding up perfectly!
Review 2
It fits everything nicely and works alone as a clutch. It was just what I wanted. However, one of my clasps recently broke and now one side won't close.
...

Buxton Heiress Ladies Cardex
Review 1
This is a great wallet, especially for the price.
It has enough spaces for credit cards.
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Love the quality of Buxton.
Seller got item to me a lot quicker than I anticipated.
Review 2
perfect! I love it and its quality.

OUTPUT

HOBO Lauren Clutch

Capacity
It holds everything you will need.
It fits everything nicely.
Quality
I use my for everyday use
...

Buxton Heiress Ladies Cardex

Price
Especially for price
Quality
I love it and its quality
Capacity
It has enough spaces for credits cards.
...

•How do we do that

-Sentiment Analysis & Text Aspects Understanding

- Our goals:
- ❑Understand what aspects are covered by reviews?
- ❑Understand what sentiment that aspect is?
- ❑ Understand how many aspects the reviews cover?

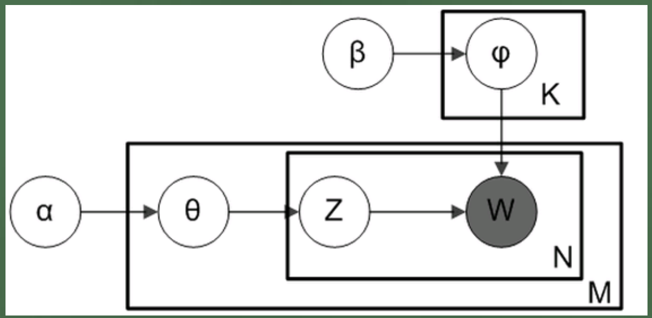
- Obstacles:
- ❑One aspect could be expressed by different terms

(Capacity: Big, Spacious..)

- ❑ Sentiment detection is hard
  - ❑ Synonym
  - ❑ Ambiguous
  - ❑ Negation
  - ❑ Unbalance

•Two Typical Methods to Do

Sentimental Analysis & Text Aspects Understanding

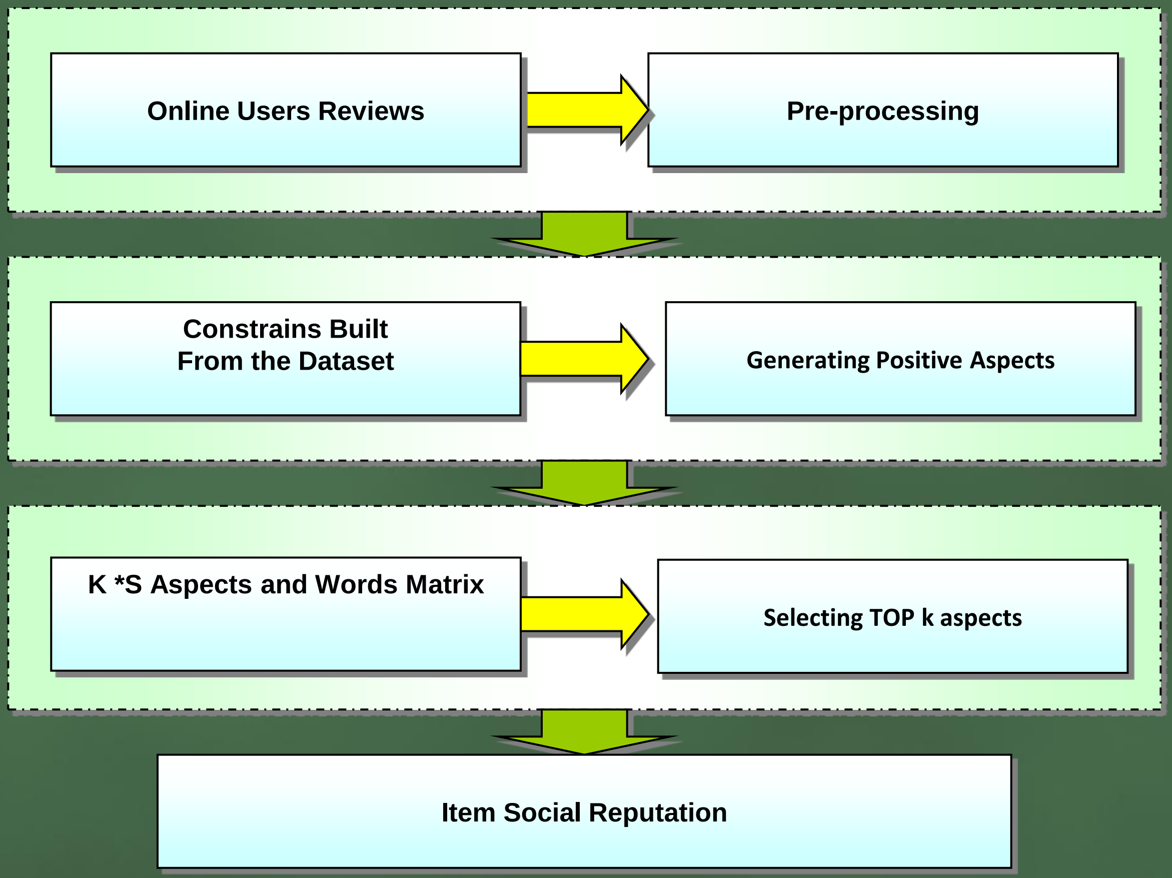


Topic Modeling: Automatically find aspects from text.

Topic Sentiment Mixture (TSM) model, (Mei, 2007.)
Multi-Aspect Sentiment (MAS) model, (Titov, 2008)
Joint Sentiment/Topic (JST) model, (Lin, 2009) and
Aspect and Sentiment Unification Model (ASUM), (Yohan & Oh., 2011)

- Pre-defined rules and dictionary that can be used to detect sentiments in the review
- (Hu & Liu, 2004) (Esuli & Fabrizio, 2006) (Samuel & Elhadad, 2010)

•Proposed Method



•ASAMTWS Model

- The reviewer decides to write review of a bag with a distribution of sentiments, say, 60% satisfied and 40% unsatisfied. Then, he decides to express the rational by expresses a distribution of aspects, say, 20% service, 60% color, 20% quality. Then he decides to write reviews to express which he feels that sentiments. Then if the review is useful to the others, it will get positive voting.

- **Split into chunks.**
- Other than a word, we consider a chunk within a sentence represents one aspect and one sentiment.(I love its quality and its price={quality, positive; price, positive;} I think this bag is too small also it is NOT worth $600 ={capacity, negative; price, negative}

•ASAMTWS Model

- **Must-link, cannot-link and no link**
- We use transition words and phrases to help use to split sentences into chunks. http://www.smart-words.org/linking-words/transition-words.html
- (If there is the transition word or phrase between two consecutive chunks, either must-link or cannot link would be added: If the transition word or phrase belong to opposition/limitation/contradiction category, then a can-not link is built, else, a must-link is built. If there is no must-link or cannot link that can be built, then there is no-link between these two chunks.)

- **Sentimental Seeds**
- http://sentiwordnet.isti.cnr.it, we defined words' polarity in our datasets.

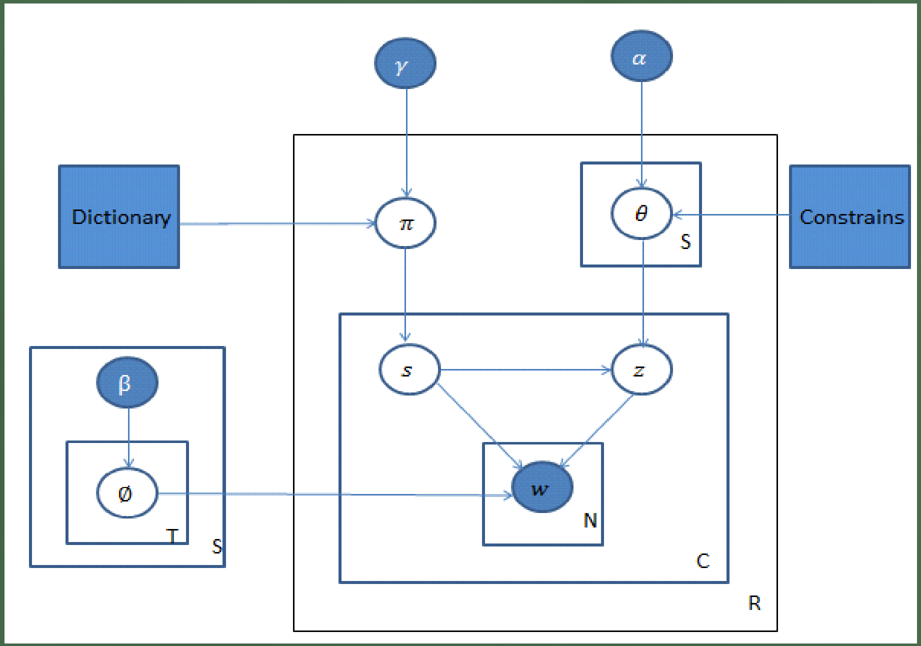
- **Weights terms based on frequency and reviews' quality**
- we consider the terms frequency and review weights in Gibbs Sampling.

•ASAMTWS Model

- For every pair of sentiment s and aspect z, draw a word distribution $\emptyset_{ts}$ ~ Drichilet (β_s)

- For each review r,
- Draw r's sentiment distribution π_r ~ Drichilet (γ).
- For each sentiment s, draw an aspect distributionθ_{rs}~Dirichilet (α) based on the sentiments dictionary.

- For each chunk
- Choose a sentiment j ~ Multinomial (π_r) based on other chunks that has constrains.
- Given sentiment j, choose an aspect k ~ Multinomial (θ_{rs}) based on other chunks that has constrains.
- Generate words w ~ Multinomial ($\emptyset_{ts}$) based on word frequency in the dataset and reviews' voting o.



•Inferred by Gibbs Sampling

$$P(s_i = j, z_i = k | s_{-i}, z_{-i}, \boldsymbol{w})$$

$$\propto q(s_i = j)q(z_i$$

$$= k)\frac{C_{rj}^{RS} + \gamma_j}{C_{rj(.)}^{RS} + \gamma_{j(.)}} \frac{C_{djk}^{RST} + \alpha_k}{C_{djk(.)}^{RST} + \alpha_{k(.)}} \frac{\Gamma(\sum_{w=1}^{W} M_{jkw}^{STW} + \beta_{jw})}{\Gamma(\sum_{w=1}^{W}(M_{jkw}^{STW} + \beta_{jw}) + m_l)} \prod_{w=1}^{W} \frac{\Gamma(M_{jkw}^{STW} + \beta_{jw} + m_{lw})}{\Gamma(M_{jkw}^{STW} + \beta_{jw})}$$

$$\frac{C_{rj}^{RS} + \gamma_j}{C_{rj(.)}^{RS} + \gamma_{j(.)}} \frac{C_{djk}^{RST} + \alpha_k}{C_{djk(.)}^{DST} + \alpha_{k(.)}}$$

Indicates the probability of this chunk belongs to aspect k and sentiment j

$$\frac{\Gamma(\sum_{w=1}^{W} M_{jkw}^{STW} + \beta_{jw})}{\Gamma(\sum_{w=1}^{W}(M_{jkw}^{STW} + \beta_{jw}) + m_l)} \prod_{w=1}^{W} \frac{\Gamma(M_{jkw}^{STW} + \beta_{jw} + m_{lw})}{\Gamma(M_{jkw}^{STW} + \beta_{jw})}$$

Indicates the probability of this review belongs to aspect k and sentiment j

$q(s_i = j)$ and $q(z_i = k)$

Indicates the constrains that relocate the probability

M_{jkw}^{STW}

Weighting terms based on frequency and reviews' quality

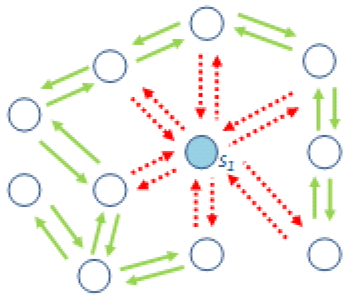
•QRHQA Model

Input: *Matrix W:(postive aspect × terms with probability of that aspect)*, aspect quality matrix q, dumping value ב,ω, quality threshold ρ

1, Create the initial Markov chain P from W, q, ב.

2, Repeat compute $P's$ stationary distribution π, and pick the first item $g_1 = argmax\pi_i$. If $C(g_1) > \rho$ break and add g_1 to results;

3, Repeat until no more items are needed to be ranked:



(a) Turn ranked items into absorbing states

(b) Update all aspect's quality based on Eq.

(c) Compute the expect number of visits v for all remaining items. Pick the next item $g_{next} = argmaxv$.

(d) Calculate $C(g_{next})$. If $C(g_{next}) > \rho$, add g_{next} to results.

•Datasets and Experimental Setting

- Dataset-1: Bag reviews we crawled from amazon. 30,000 reviews. (We consider 4-5 stars as positive, 3 stars as natural, 1-2 stars as negative.)

- Dataset-2: restaurant review: 150 restaurants with about 3400 sentences (each sentence has one or more aspects and one sentiment label. The dataset has aspects: food, staff, price, ambience, anecdote and miscellaneous; sentiments: positive and negative)

Results of Dataset-1

Topic1	Topic2	Topic3	Topic4	Topic5	Topic6	Topic7	Topic8
Small(0.024)	backpack	love	school	price	leather	umbrella	Quality
Pockets(0.018)	pack	expected	jansport	Pay	soft	weather	good
room	sports	great	year	Shipping	supple	rain	handbag
larger	work	good	High	cheaper	Size	Dry	Material
cell	huge	wanted	College	dollars	smell	windy	poor
extra	sturdy	nice	daughter	beat	feel	Bubble	durabiility
bigger	oakley	absolutely	car	sale	Not real	Broke	
enough							
plenty							

Topic9	Topic10	Topic11	Topic12	Topic13	Topic14	Topic15	Topic16
clothes	laptop	travel	Carry	zipper	brand	color	Shipping
carry	carry	carry	hands	pockets	jansport	brown	fast
trips	ipad	everyday	free	inside	lauren	leather	Delivery
shoes	room	nice	Light	snap	rachel	Deep	service
body	computer	diaper	small	strap		taupe	Prompt
cross	tablet	works	Shopping	problem		orange	arrived
suit	padding	essentials	weight			gray	ordered
large	mackbook		comfortable				time
							expected

•Result of dataset-2

aspect	sentiment	Our model	ASUM	JST
Food	positive	**0.77**	0.61	0.447
	negative	**0.44**	0.39	0.23
Staff	positive	**0.63**	0.46	0.2
	negative	0.46	0.53	0.171
Price	positive	**0.71**	0.28	0.22
	negative	0.213	0.244	0.21
Ambience	positive	0.44	0.41	0.3
	negative	0.21	0.11	0.13
Anecdote	positive	**0.35**	0.23	0.19
	negative	0.144	0.11	0.14
Miscellaneous	positive	**0.45**	0.36	0.23
	negative	0.68	0.49	0.25

•Visualization of Amazon Datasets

- 30000 Reviews about bag. Totally 33 categories after using QRHQA model:

•Visualization for Amazon Datasets

Desired Result

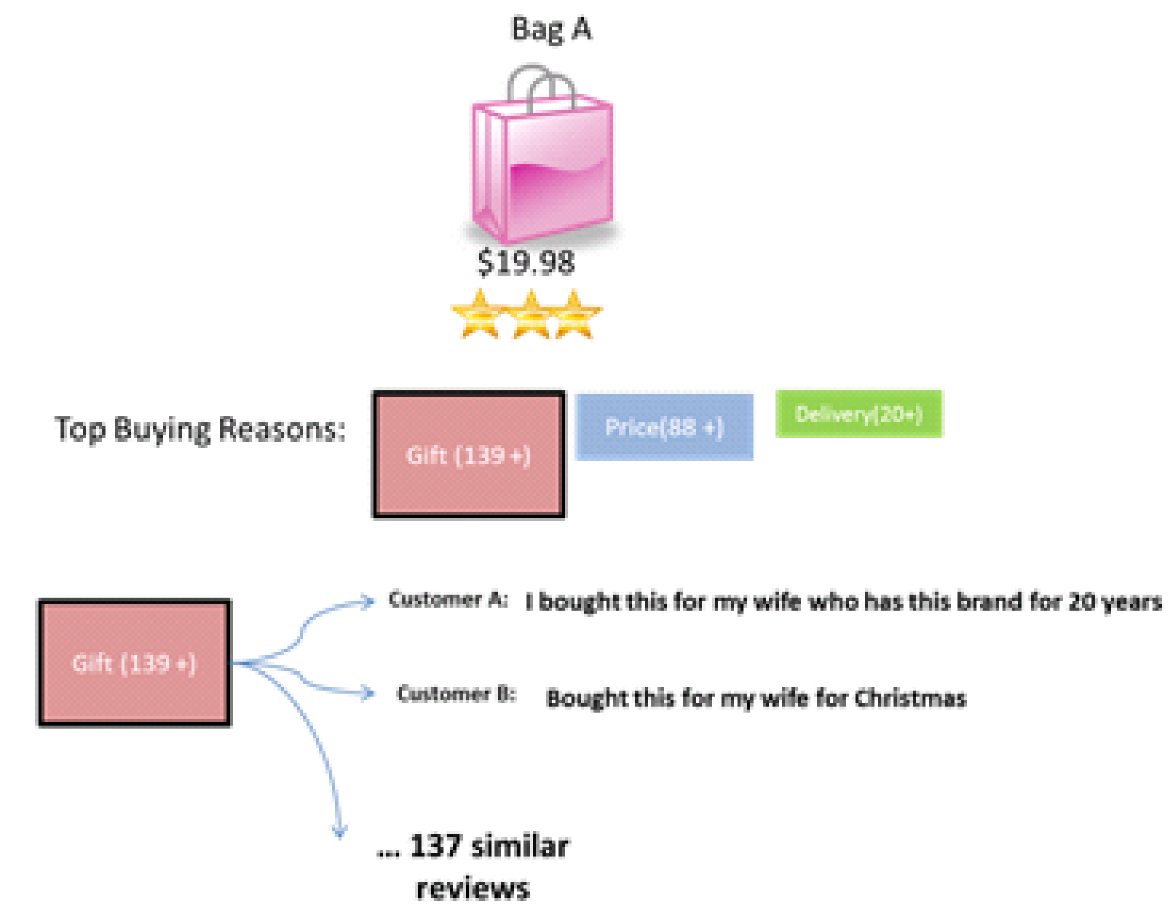


Figure 5 Illustration of reviews as supports for ISR

Conclusion and Discussion

- Item Social Reputation was proposed in this paper, which could be easily incorporated into recommender system architecture. Future work will be focused on quantitatively testifying performance of recommender system with built – in ISR
- ISR innovatively consider syntactic information from corpus and managed to achieve a better result in sentiment analysis in the public dataset. Future work will also test this work on a large dataset.

Please email to lg367@drexel.edu if you have any questions.