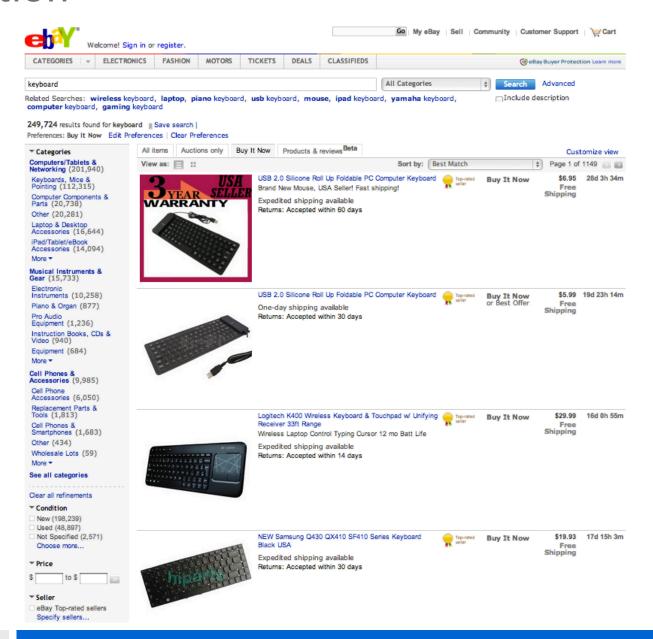
eoaytm

Latent Dirichlet Allocation based Diversified Retrieval for E-commerce Search

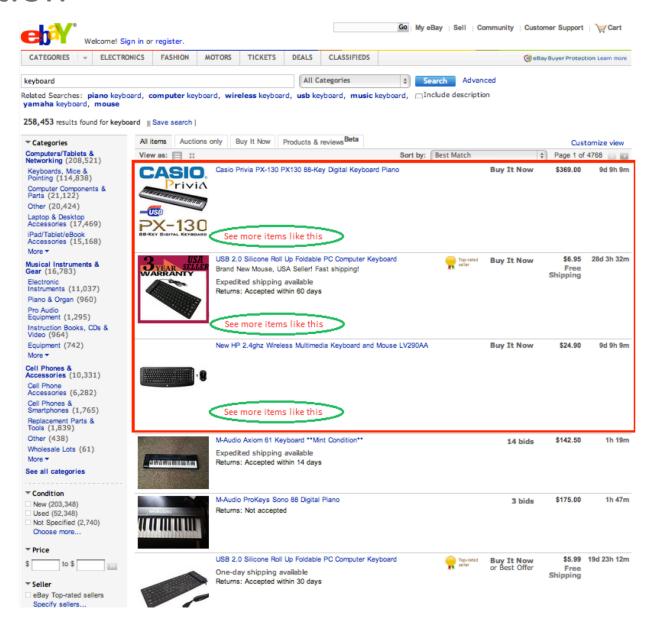
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¹ Oregon State University, ² eBay Inc., ³ Google

Motivation





Motivation





Goal & Challenges

Goal: minimize the risk of users with different purchase intents not seeing any relevant item.

- Capture users' attentions so that they will stay on the eBay site.
- Improve users' buying experience by reducing their efforts in search.

Challenges:

- eBay product taxonomy is very noisy.
- Search requires real time scoring and ranking.
- Extremely large and dynamic inventory.



Methodology

1 Discovering user intents

Discover the hidden user intents of a query using the LDA model.

1 Ranking user intents

Rank discovered user intents by trading off their relevance and novelty.

1 Selecting items for user intents

Find the most representative item for each user intent to display.



Discovering user intents

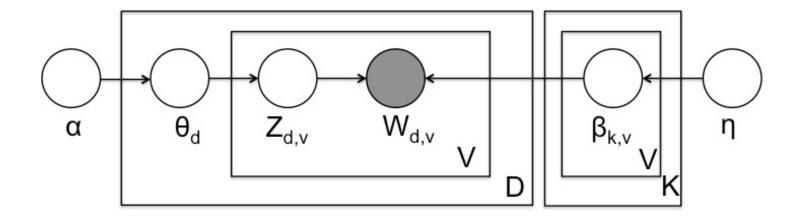
- Generate the "corpus" of a query by collecting the user clicked data resulted from the query.
 - User clicks carry the signal of a user's purchase intent.
 - Each user click specifies a particular listing on eBay.
 - Use the item title of a listing since it is relatively noisy-free.

- Apply the LDA model to the query-specific "corpus".
 - The topics correspond to the hidden user intents.



Multivariate Bernoulli LDA model

- No duplicated terms in an item title.
- Use Multivariate Bernoulli distribution rather than Multinomial distribution to characterize a user intent.





Discovered user intents

fossil		basketball		<u>iPod</u>	
Fossil bag	"cat-Handbags and Purses"	basketball	"cat-Basketball" official	$iPod\ touch$	"cat-Portable Audio &
\mid and purse	purse handbag bag leather		size spalding ball 29.5		Headphones" touch apple
	tote shoulder key cross		street		gb 8th generation
Fossil men	"cat-Wristwatches" watch	basketball	"cat-Men's shoes" shoes	iPod nano	nano "cat-Portable Audio
watch	men chronograph mens ch	shoes	nike size mens air black		& Headphones" gb genera-
	stainless steel fs		adidas		tion 8th model 4th
Fossil	"cat-Wristwatches" watch	basketball	"cat-cards" card jordan lot	iPod case	for case usb iPhone touch
women	es women stella relic gold	card	michael auto rookie topps		4th new apple
watch	dial by				
Fossil wal-	wallet "cat-Wallets" leather	basketball	nike shirt shorts xl "cat-	iPod	for charger usb iPhone ca-
let	clutch nwt brown new coin	shirt	Men's Clothing" new jersey	charger	ble 4th mp 3rd
antique	ammonite shark "cat-	basketball	hoop "cat-Basketball"	iPod clas-	"cat-Portable Audio &
fossils	Shark Teeth" dinosaur	hoop	backboard rim nba	sic	Headphones" classic apple
	"cat-Amphibian,Reptile		portable in ground		5th 30 gb black generation
	and Dinosaur" "cat-				
	Ammonites" tooth				

- User intents line up to categories and associate semantically meaningful terms with the corresponding categories.
- Further explore existing product taxonomy.
- Combine similar categories according to user demand.



Ranking user intents

Rank all the user intents by trading off user intents' popularity and information novelty.

$$\lambda * Popularity(k) + (1 - \lambda) * Novelty(k)$$

- Popularity(k) indicates the relevance of the kth user intent to the query.
- **Novelty(k)** measures the extra information the kth user intent adds onto the user intents already selected.
- λ is the parameter trading off popularity and novelty.



Selecting items for user intents

- The multivariate Bernoulli distribution of a user intent specifies the weight of a term within that user intent.
- Score all the items in a user intent and select the item with the maximum score.

$$Score(I_i, T_k) = \frac{\sum_{j=1}^{|I_i|} \beta_{k, W_{i,j}}}{max(AvgTitleLength_Q, |I_i|)}$$



An example of query fossil





Evaluation metric

Averaged Satisfaction (AS): measures the user satisfaction averaged across all the users w.r.t. a list of N items.

$$AS_N(R,Q) = \frac{1}{|\mathbf{U}_{\mathbf{Q}}|} \sum_{U_j \in \mathbf{U}_{\mathbf{Q}}} Satisfaction(U_j, R_N)$$

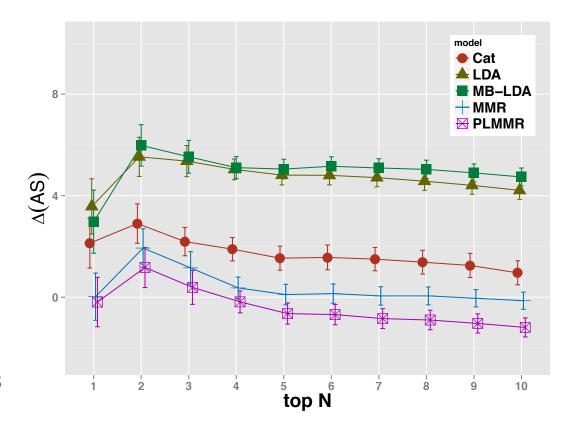
Given a list of items, the user satisfaction is defined as the similarity between the clicked item and the most similar item of the list.

$$AS_N(R,Q) = \frac{1}{|C_Q|} \sum_{I_j \in C_Q} \max_{I_i \in R_N} Sim(I_j, I_i)$$



Results

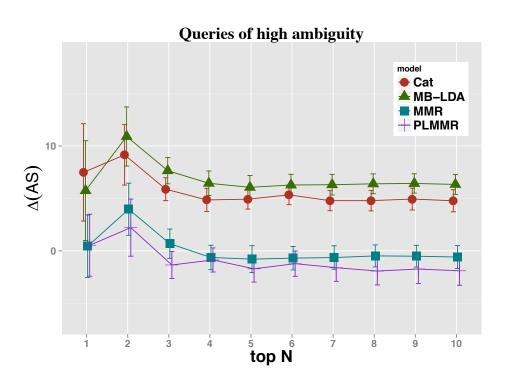
- 120 queries.
- Datasets:
 - Training: 10K user clicked.
 - Testing: 10K user clicked.
 - Ranking: eBay inventory.
- Baselines:
 - eBay production ranker
 - MMR
 - Category-based approach
 - PLMMR
 - LDA / MB-LDA with 10 user intents

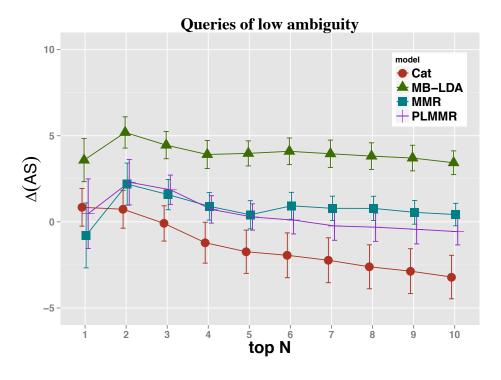




Results

Queries of high and low ambiguity.

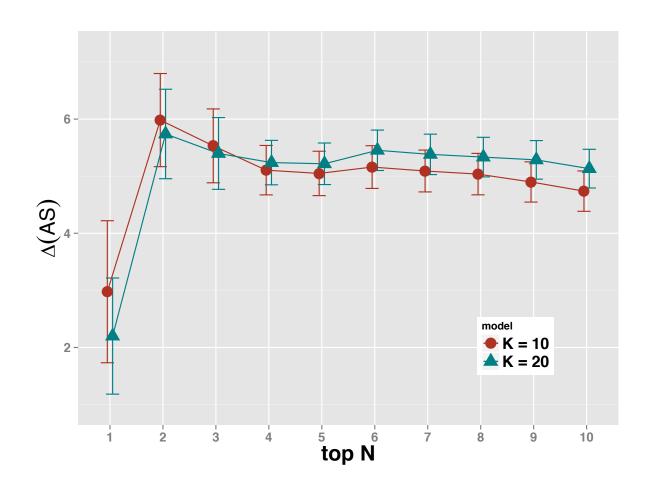






Results

The MB-LDA model with 10 user intents vs. 20 user intents.





Acknowledgements

We would like to thank Daniel Miranda and Nadia (Ghamrawi) Vase for their helps on the eBay title relevance models.

Questions

