# Increasing Relevance of Rank by Price

Vaughan Kitchen

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### What is IR?

"Information retrieval (IR) is the activity of obtaining information system resources that are relevant to an information need from a collection of those resources. Searches can be based on full-text or other content-based indexing. Information retrieval is the science of searching for information in a document, searching for documents themselves, and also searching for the metadata that describes data, and for databases of texts, images or sounds."

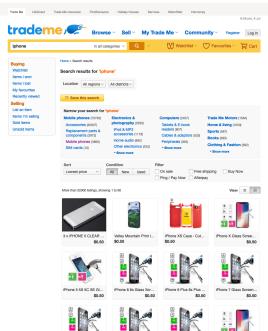
(fulfilling a users information needs)

— wikipedia

#### eCommerce Search

A search engine integrated into an online store helping users find products. Users perform queries where the search engine tries to match keywords to products that it has stored. Can have a deeper semantic understanding of text, do query rewriting, or fuzzy matching which seperates it from a database (which just does look ups).

### The Problem with eCommerce Search



### The Problem with eCommerce Search

- ► These are not iPhones
- Many of the results are not relevant
- Often the non-relevant results are cheaper
- ▶ Non-relevant results feature as the top results

### Some Definitions

" recall (also known as sensitivity) is the fraction of relevant instances that have been retrieved over the total amount of relevant instances"

— wikipedia

"precision (also called positive predictive value) is the fraction of relevant instances among the retrieved instances"

— wikipedia

- ► Recall = Found/Total No. Relevant
- ► Precision = Found/Total Returned
- ▶ Often seen as Precision at n, P@n, e.g. P@10

### Precision or Recall?

- ▶ P@10 result poor when price ordered
- High precision needed
- User always wants cheapest item
- Will use competitor if they're cheaper
- High recall needed
- ► High accuracy needed

### **Metrics**

- P@n: Precision at n
- Mean Average Precision (MAP): Sum(P-at-reldoc-n) / Relevant, averaged
- Discounted Cumulative Gain: Relevance gain of extra documents discounted for index in list
- Normalized Discounted Cumulative Gain: DCG normalized against ideal result
- (Collaboration with eBay and IR community)

# SIGIR Data Challenge 2019

- High Accuracy Recall Task
- Opened May 27
- Closes July 18
- ► Three phases: Unsupervised, Supervised, Combined
- Approximately 900,000 documents with price, title, category
- ▶ 150 Queries
- Binary classification

# SIGIR Data Challenge 2019

В	- Baseline submission
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Rank ¢	Participant team \$	precision \$	recall \$	f1 ¢	tpr \$	fpr \$	Last submission at \$
1	Gotta Recall em All	0.74	0.88	0.81	0.88	0.22	1 month ago
2	Uplab	0.76	0.85	0.80	0.85	0.20	1 month ago
3	ir_h	0.73	0.87	0.80	0.87	0.23	1 month ago
4	QUTDataScience	0.69	0.90	0.78	0.90	0.29	1 month ago
5	Otago	0.77	0.80	0.78	0.80	0.18	1 month ago
6	Mercari-search	0.73	0.77	0.75	0.77	0.21	1 month ago
7	JediOrder (v1)	0.62	0.87	0.72	0.87	0.39	1 month ago
8	f-group-team (Wordcount)	0.50	0.96	0.66	0.96	0.68	1 month ago
9	RIIID (v3)	0.52	0.89	0.66	0.89	0.60	1 month ago
10	MLML	0.52	0.89	0.66	0.89	0.60	1 month ago
11	CaptainTeemo	0.50	0.93	0.65	0.93	0.67	1 month ago
12	alphalR	0.42	1.00	0.59	1.00	1.00	1 month ago
13	Last of Us	0.00	0.00	0.00	0.00	0.00	1 month ago

## SIGIR Data Challenge 2019

- ▶ 5th/12 successful submissions in Unsupervised phase
- Unable to submit in supervised phase due to busyness
- Attempting final phase over next two weeks
- Search engine written from scratch
- Conjunctive search with Porter's stemming
- Final attempt will be with Entity Linking

### spaCy Named Entity Recognition

```
import spacy

nlp = spacy.load("en_core_web_sm")

doc = nlp(u"Apple is looking at buying U.K. startup for $1 billion")

for ent in doc.ents:
    print(ent.text, ent.start_char, ent.end_char, ent.label_)
```

### spaCy Named Entity Recognition

But Google ord is starting from behind. The company made a late push into hardware, and Apple ord 's Siri product, available on iPhones

PRODUCT, and Amazon ord 's Alexa product software, which runs on its Echo product and Dot product devices, have clear leads in consumer adoption.

# **Entity Linking**

Fast and Space-Efficient Entity Linking in Queries (Blanco et al.)

- ► Fast and Space-Efficient Entity Linking in Queries (Blanco et al.)
- ► Hash table to entities with thesaurus mined from query logs weighted to preferred results
- Successful for query segmentation
- $\blacktriangleright$  "clinton falls asleep"  $\rightarrow$  "clinton falls | asleep", "clinton | falls asleep"

A Multi-View-Based Collective Entity Linking Method (Liu et al.)

- Collective Entity Linking
- Considers description, background knowledge, references and entity graph structure
- description gives best performance to complexity ratio



# **Entity Linking**

- Requires large scale preprocessing of Wikipedia
- Performance considerations in practice
- Unsure on overall effect on result quality
- Short text (titles only) may affect results

### References

- ▶ Roi Blanco, Giuseppe Ottaviano, and Edgar Meij. 2015. Fast and Space-Efficient Entity Linking in Queries. Proceedings of the Eigth ACM International Conference on Web Search and Data Mining, Pages 179-188. http://dx.doi.org/10.1145/2684822.2685317
- Ming Liu, Gu Gong, Bing Qin, and Ting Liu. 2019. A Multi-View-Based Collective Entity Linking Method. ACM Transactions on Information Systems 37, 2, Article 23 (Feb.2019),29pages. https://doi.org/10.1145/3300197

# Questions?