



Query Intelligence in E-Commerce Search

Gundeti Shiva Hari (u1460836) Leela Sowmya Jandhyala (u1472955)









01 Introduction

Aim

E-commerce search platforms have evolved from traditional keyword-based matching to actually understanding the user input and giving the results according to what they intend.

Our idea

- Apache Solr (for searching)
- Apache Spark (for preprocessing)

The project aims to refine search accuracy and user experience by implementing four key features such as query boosting based on user interaction, handling misspellings, searching with related keywords, and employing machine learning techniques (i.e., Learning To Rank algorithm) for building generalizable search systems.







02 Datasets

Products.csv

48195 rows, 5 columns (upc, name,manufacturer, short Description, long Description)

Signals.csv

2M rows 5 columns (session_id,user_id, type, target, signal_time)

If the type is query, then the target is query text that user has entered.

If the type is click, add-to-cart, purchase then target is upc of product.csv

TLDR:- Products.csv and Signals.csv are interlinked.

https://github.com/ai-powered-search/retrotech





Boosting products for a query

"885909457588"^966 "885909457595"^205 "885909471812"^202 "886111287055"^109 "843404073153"^73 "885909457601"^62 "635753493559"^62 "885909472376"^61 "610839379408"^29 "884962753071"^28

- Basic Intuition: From User clicks data, for each query see what products have been clicked and how many times and try to store them in a separate collection.
- Next time, when user enters any query, search in that collection and identify the document and their frequency (boost) and form a list and search in original query
- So, basically we are recommending products with more clicks.





Finding Related Keywords

comp_score	pmi2	n_users1 n_users2		k2	k1
1.0	1.2318940540272372	4829	7554	touchpad	ipad hp
1.25	1.430517155037946	7554	2842	ipad	ipad 2
1.666666666666667	1.6685364924472557	7554	1818	ipad	tablet
2.125	1.2231908670315748	7554	2785	ipad	touchpad
2.6	1.7493143317791537	7554	1627	ipad	tablets
3.083333333333333	1.9027023623302282	7554	1254	ipad	ipad2
3.5714285714285716	1.4995901756327583	1814	7554	apple	ipad
4.0625	1.3943192464710108	4829	2785	touchpad	touchpad hp
4.55555555555555	1.5940745096856273	1421	7554	np tablet	ipad
5.05	0.8634782989267505	7554	2931	ipad	pod touch
5.545454545454546	2.415162433949984	612	7554	i pad	ipad
6.041666666666667	0.827835342752348	7554	2833	ipad	kindle
6.538461538461538	0.5933664189857986	7554	3554	ipad	laptop
7.035714285714286	2.916383652644603	326	7554	ople ipad	ipad a
7.5333333333333333	1.1805849845414993	4829	2842	touchpad	ipad 2 hp
8.03125	1.2902371152378296	3554	3369	laptop	laptops
10.025	3.180197301966425	204	7554	i pad 2	ipad

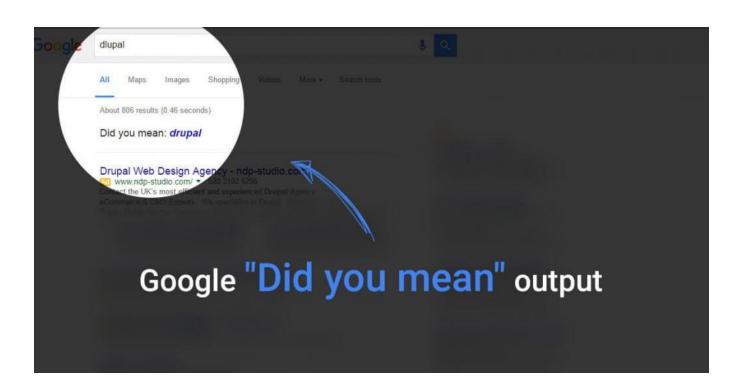
Basic Intuition:-

If user_1 types a query_1 and clicks on a product p

If user_2 types a query_2 and clicks on same product p

query_1 and query_2 are semantically similar

We use PMI and composite score statistics to balance n_users1 and n_users2







Finding Misspelled Words

edit_dist	correction_counts	misspell_counts	correction	misspell	
1	16854	6	iphone	iphone3	50
1	14119	6	laptop	laptopa	61
1	14119	5	laptop	latop	62
1	11550	6	touchpad	toucpad	136
1	11550	5	touchpad	touxhpad	137
1	10060	6	wireless	wirless	148
1	8260	6	tablet	tableta	127
1	7541	5	case	cape	10
1	7541	6	case	cage	8
1	5839	6	galaxy	gallaxy	30
1	5565	5	laptops	loptops	64
1	4477	6	portable	potable	90
1	4461	5	bluetooth	bluetooh	5
1	4179	5	wars	wats	146
1	4129	5	kindle	kimdle	56
1	4067	5	router	rauter	99
1	3590	6	modem	modum	77
1	3590	5	modem	moden	76
1	3432	6	toshiba	tosheba	135
1	3239	6	games	gates	34

Basic Intuition:-

Calculate the frequency for each query.

Quantile (0-20%) would likely be a misspelled word as less frequently used.

(80-100%) quantile would be a correct word as more frequently used.

Find the relation between (0-20%) and (80-100%) using edit distance.



Finding weights for name and longDescription field in products dataset





Addressing the bias in our data

Position Bias

- Detecting Position Bias? If the top positions have a significantly higher CTR
- Addressing Position Bias with SDBN:
 - Mark the Last Click In each search session, identify the last result that was clicked.
 - Consider Examinations Assume that all results above (and including) the last clicked result were actually seen or "examined" by the user.
 - Calculate Relevance (Grade): No. of clicks/No. of examines.

Confidence bias

- Detecting Confidence bias? Document gets clicked every time it's examined, but it's only been examined a few times
- Addressing Position Bias with Beta Distribution
 - Setting up the Beta Distribution –
 Setting a prior belief about document relevance using a default grade and weight, which establish initial values for a (prior_a) and b (prior_b) i.e. (prior_grade = prior_a / (prior_a + prior_b))
 - Updating with Click Data As clicks and examines are observed, "a" is incremented by the click count and "b" by the count of non-clicked examines
 - Calculating the Updated Grade posterior_a / posterior_a + posterior_b





Evaluation







Thanks!