OFFLINE AND ONLINE RANKING MODEL ELVALUATION IN INDUSTRY

What happens in the industry, where real users interact with the system, business interests affect the concept of relevance and pre-defined relevance judgments are not available?

STEP 1. DATA COLLECTION

IMPLICIT FEEDBACK

user interactions

1. Collection of users' interactions:

SaaS SOLUTION REST API

- 2. Model interactions as **JSON** objects.
- **3.** Relevance label estimation using interactions aggregation:

Click-Through Rate, Add-To-Cart Rate, ...

4. Test set extraction/creation and Kibana dashboard creation.

"interactionType": "ProductImpression", "productId": 21356, "productPrice": 34.3, "productCategories": [43, 64, 100], "querySelectedCategory": 23, "userId": "46b60", "userFavouriteCategories": [157, 12, 81]

"interactionType": "ProductClick", "productId": 465, "productPrice": 14.9, "productCategories": [43, 21, 103], "querySelectedCategory": 23, "userId": "62k67", "userFavouriteCategories": [142, 12, 75]

"interactionType": "ProductImpression", "productId": 2473, "productPrice": 104.0, "productCategories": [22, 74, 124], "querySelectedCategory": 12, "userId": "46b60", "userFavouriteCategories": [157, 12, 81]







ALTERNATIVE

EXPLICIT FEEDBACK team of experts

- **1.** Judge **<query-document>** pairs \rightarrow no position bias
- 2. Judge search results list items

Judgement Collector Chrome plugin available.



STEP 2. EVALUATION APPROACH

A/B TESTING



Approach choice:

REST API SaaS SOLUTION

- Design parametric search-API
- Assign users to a population through cookies
- Tag interactions with the test group

INTERLEAVING

Team Draft available from:			
Solr version 8.8.0			
Winner estimation process needed (python script):			
• $\Delta_{AB} = \frac{wins(a) + \frac{1}{2}ties(A, B)}{wins(A) + wins(B) + ties(A, B)}$	- 0,		

• Query distribution analysis (Long tail vs Uniform)

FOR BOTH

STATISTICAL SIGNIFICANCE

- Relevance label estimation
- Check sample distribution
 - (outliers, normality, homogeneity)
- Transformation to normal distribution
- 1. One-way ANOVA test
 - Effect size
 - Tukey test
- 2. Kruskal-Wallis test
 - non-parametric (no normal distribution required)
 - Effect size
 - Dunn test



Control

Ranking model v1.0

Ranking model v2.0

Ranking model v3.0



B



kibana

learn





- **1. Statistical significance**
- **2.** Number of users

pandas

statsmodels

3. Time = development iteration length

OPEN SOURCE

TECHNOLOGIES

elastic

Baby steps between experiments: each experiment compares similar models (few features more, different normalization). **One experiment per platform** (desktop, mobile, ...). Evaluate 2-3 models at the time.

STEP 4. PITFALLS

1. Query id generation: **too-specific** vs **too-generic**

QUERY

- Too short/too long ranked lists per query \rightarrow balanced is needed 2. Number of results: large result set query vs small result set query - Small result set queries \rightarrow expected small ranking model impact - Many small result set queries \rightarrow cause noise in the evaluation



errors during collection position bias Noise: source pages - Users tend to click on top-ranking results



- Online evaluation \rightarrow select only interactions from pages that use rank models

Choose metrics: - Estimate offlin - Offline metric	industry's interests ne relevance label \rightarrow bus s needs support by Online	iness objective (clicks, add-to-cart, downloads, metrics
Per query data an	d relevance distribution:	unbalanced

TEST SET

METRIC

queries with a single sample queries with a single relevance type

> Alessandro Benedetti - Director and R&D Software Engineer **Anna Ruggero** - R&D Software Engineer and Search Consultant

"relevance": 1, "productId": 21356, "queryId": 23, "userId": 46b60 "relevance": 1, "productId": 465, "queryId": 23, "userId": 62k67

"relevance": 1, "productId": 465, "queryId": 23, "userId": 62k67 "relevance": 1, "productId": 21356, "queryId": 11, "userId": 46b60 "relevance": 3, "productId": 2473, "queryId": 23, "userId": 46b60