



A Multi-Domain Benchmark for Personalized Search Evaluation

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Personalized Search Evaluation Issues

- Datasets shared by initiatives on search evaluation do **not** usually **provide** information about specific **users** and their **preferences**, which are needed for evaluating personalization.
- Some efforts have been devoted to defining large-scale task-related datasets for personalization: AOL Query Log, CIKM Cup 2016, and Yandex Query Log.
- **Issues:** content availability, privacy concern, anonymized texts (*semantic retrieval approaches not usable*).
- Due to the above issues, researchers have proposed several methodologies to define synthetic datasets for Personalized Search Evaluation, most notably folksonomy-based datasets and Amazon reviews-based datasets.
- Issues: low data and queries quality, low query availability, missing data, lack of validation.
- Another attempt to define a synthetic dataset for Personalized Search Evaluation is PERSON, a methodology based on citation networks proposed in "PERSON: Personalized information retrieval evaluation based on citation networks." by Tabrizi et al. (2018)
- Pros: rich and large scale datasets, in-depth validation process;
- Cons: lack of potentially valuable information for personalization from the original data, only one domain.
- There is still a lack of high-quality benchmark datasets for Personalized Search evaluation.

What We Propose

- We **revisit** and **extend** the **PERSON** methodology, overcoming the aforementioned limitations while keeping its benefits (*more details in the paper*).
- We share a large-scale benchmark across four academic domains, with more than 18 million documents and 1.9 million queries, designed for evaluating Personalized Results Re-Ranking approaches.
- We provide a rich set of metadata for each document, the data to derive the user-document interactions, pre-computed BM25's result lists to re-rank, and pre-computed baseline runs.
- Relations among the data, such as authorship relations and the paper references, can be represented by **graph structures** allowing graph-based personalization approaches.

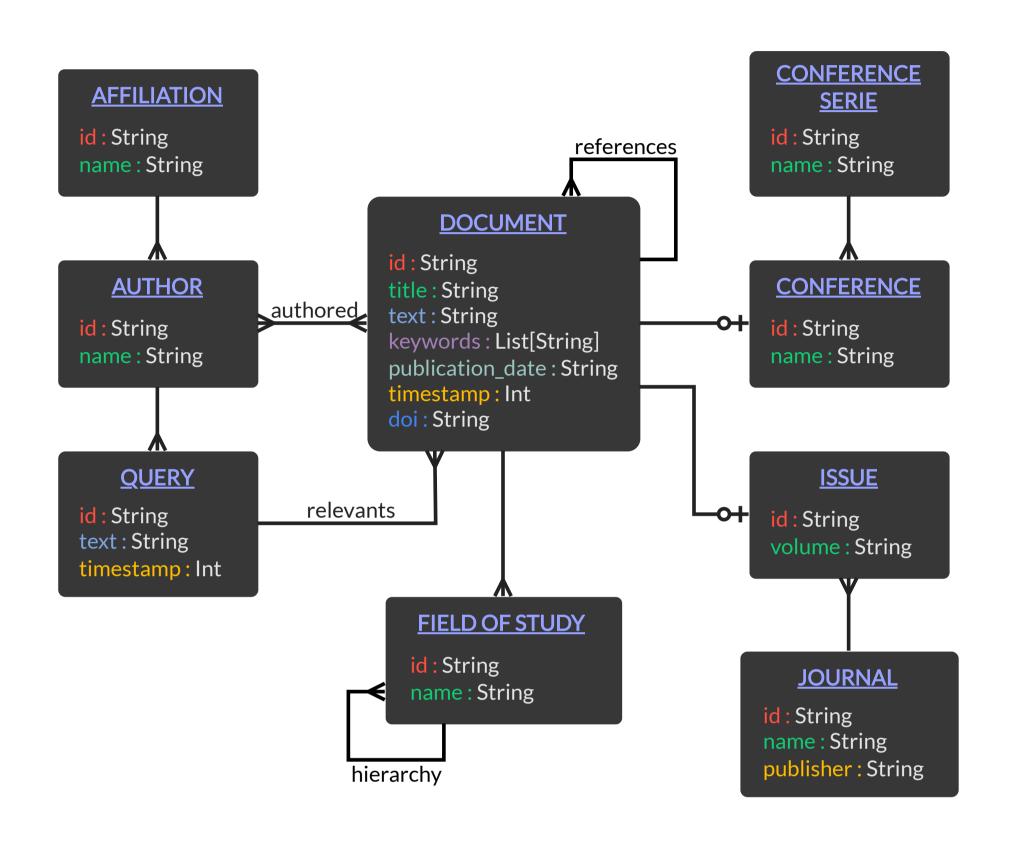
Opportunities

- The shared large-scale datasets are suited for **training** and **evaluating**:
- Content-based personalization models.
- Collaborative filtering approaches.
- Graph-based personalization models.
- Joint Personalized Search and Recommendation models.

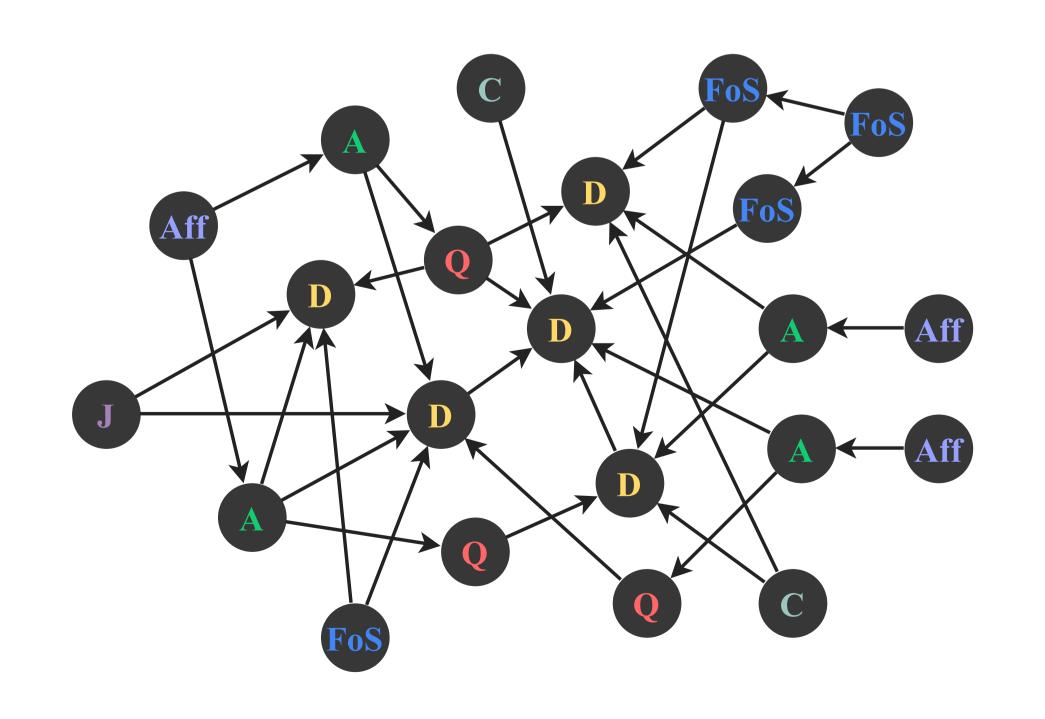
Query Generation

- PERSON methodology:
- Starting point: academic papers.
- title \rightarrow query; author \rightarrow user; references \rightarrow relevant documents.
- Our refinements:
- Processing to resemble real-world queries:
- Stop-words removal; Non-destructive stemming (Krovetz stemmer)
- Query selection:
- Users must have at least 20 documents for personalization.
- For personalization purposes, we consider only the papers published by the user/author before the one used as the query, thus preserving the temporal aspect.
- Not all the references are necessarily relevant to the topic expressed by a paper's title. To reduce the presence of spurious relevant documents and malformed queries, we applied some heuristics based on BM25 results.

Structure of the Datasets



Graph Representation of the Datasets



Statistics of the Datasets

	Computer Science	Physics	Political Science	Psychology
# documents	4 809 684	4 9 2 6 7 5 3	4814084	4 215 384
# users	5 260 279	5835016	6347092	4825578
# train queries	552 798	728 171	162 597	544 882
# val queries	5 583	7 3 5 5	1 642	5 503
# test queries	6497	6366	5 715	12625

Provided Baselines

- First-stage retriever:
- BM25: Classic probabilistic retrieval model.
- Re-Rankers:
- Pop: Popularity-based model.
- BiEnc: Bi-encoder-based retrieval model.
- All-BiEnc: BiEnc trained on all four domains to assess domain adaptation and transfer learning opportunities.
- Mean: Embedding-based personalized retrieval model. It defines the user models as the average of their associated document representations.
- QA: Embedding-based personalized retrieval model. It adopts a query-aware user modeling technique using the Attention mechanism to weigh the contribution of the user-related documents in composing the user representation.
- BiEnc + Mean: Weighted sum-based fusion of BiEnc and Mean.
- BiEnc + QA: Weighted sum-based fusion of BiEnc and QA.

We aggregated the document scores of each re-rankers the original BM25 scores using the weighted sum fusion algorithm implemented in ranx.fuse.

Results

Table 1. Effectiveness of the compared models. † denote significant improvements in a Bonferroni corrected Two-sided Paired Student's t-Test with p < 0.001 over all the baselines. Best results are highlighted in boldface.

Model	Computer Science		Physics		Political Science		Psychology					
	MAP	MRR	NDCG	MAP	MRR	NDCG	MAP	MRR	NDCG	MAP	MRR	NDCG
BM25	12.25	48.93	22.45	12.77	53.68	26.88	13.27	50.23	24.07	12.58	51.19	23.93
BM25 + Pop	16.64	58.63	28.97	15.45	59.61	30.88	16.04	57.39	28.46	15.13	56.46	27.29
BM25 + BiEnc	18.21	58.02	28.90	16.98	60.99	32.13	18.15	57.64	29.25	20.72	63.41	33.11
BM25 + All-BiEnc	17.82	57.79	28.59	16.81	60.95	32.02	18.51	58.82	29.94	20.23	62.91	32.64
BM25 + Mean	16.37	54.57	26.69	16.44	59.05	31.18	16.61	55.05	27.58	16.73	57.05	28.42
BM25 + QA	17.88	57.21	28.49	17.47	61.80	32.72	17.69	57.58	28.94	18.90	60.92	31.12
BM25 + BiEnc + Mean	19.92	60.64	30.80	18.91	63.88	34.51	19.26	59.76	30.63	21.97	65.21	34.71
BM25 + BiEnc + QA	20.11^{\dagger}	61.17	31.15^{\dagger}	18.98	64.78	34.81	19.85^{\dagger}	61.20 [†]	31.41^{\dagger}	21.99	65.62	34.85

Online Resources

• To learn more about our Multi-Domain Benchmark for Personalized Search Evaluation scan the QR Code below:

