TARexp: A Python Framework for Technology-Assisted Review Experiments

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ABSTRACT
Technology-assisted review (TAR) is an important industrial application of information retrieval (IR) and machine learning (ML). While a small TAR research community exists, the complexity of TAR software and workflows is a major barrier to entry. Drawing on past open source TAR efforts, as well as design patterns from the IR and ML open source software, we present an open source Python framework for conducting experiments on TAR algorithms. Key characteristics of this framework are declarative representations of workflows and experiment plans, the ability for components to play variable numbers of workflow roles, and state maintenance and restart capabilities. Users can draw on reference implementations of standard TAR algorithms while incorporating novel components to explore their research interests. The framework is available at https://github.com/eugene-yang/tarexp.

CCS CONCEPTS
• Information systems → Information retrieval.

KEYWORDS
reproducible experiments, technology-assisted review, eDiscovery, systematic review, opensource

1 INTRODUCTION
Technology-assisted review (TAR) is the use of information retrieval (IR) and machine learning (ML) technologies to reduce the cost and increase the effectiveness of manual review of large text collections. Application areas include legal discovery [3], systematic literature review in medicine [36], construction of evaluation collections [18], and responses to sunshine law requests [26].

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2 BACKGROUND
Shared software resources in IR research date back to the 1960s [32]. Numerous open source research-oriented retrieval libraries are in

Workshops such as DESI¹, SIRE², LegalAI², and ALTARS⁴ have brought these applications to the awareness of the research community. Shared evaluation efforts such as the TREC Legal Track [4, 9, 12, 27, 34], the TREC Total Recall Track [11, 30], and the CLEF eHealth Technology-Assisted Review Tasks [14–16] have made data sets and formalized evaluation approaches available to researchers.

However, the inherent complexity of TAR tasks, even when abstracted to research data sets, still imposes a substantial barrier to research. Many research questions in TAR focus on optimizing interactions between cost and effectiveness during an evolving review process. Testing a new TAR approach requires exploring variations of, and capturing rich data from, iterative active learning processes and multiple review stages. Further, the dynamics of these algorithms varies strongly not only across tasks (whether real or simulated) but even across choices of starting conditions and random seeds. Expensive large scale experiments are therefore necessary to derive meaningful generalizations. Finally, sample-based effectiveness estimation is itself an object of study in TAR (driven largely by the needs of legal applications) [20]. This raises the stakes for consistency and replicability of evaluation.

TARexp is an open-source Python framework intended to reduce barriers to entry for TAR research. We draw on design patterns from operational TAR software and past open source TAR efforts, as well as those from the broader machine learning and information retrieval open source ecosystem, including libact [45], pyTorch [28], pyTerrier [25], ir-datasets [24], and ir-measures [23]. TARexp allows configuration and dispatching of experimental runs, with support for parallel processing, resumption and extension of runs, and reproducibility. It incorporates reference implementations of key components such as supervised learning, active learning, stopping rules, sample-based estimation of effectiveness, and TAR-specific cost visualizations [42]. Interfaces in the form of abstract classes for these components aid researchers in implementing and studying their own approaches. The framework is also compatible with Jupyter Notebooks for running exploratory experiments and visualizing results. The framework is available at https://github.com/eugene-yang/tarexp, and a live demo is available on Google Colab⁵.

¹users.umiacs.umd.edu/~oard/desi7
²http://users.umiacs.umd.edu/~oard/sire11/
³https://sites.google.com/view/legalaiia-2021/home
⁴http://altars2022.dei.unipd.it/
⁵https://colab.research.google.com/github/eugene-yang/tarexp/blob/main/examples/exp-demo.ipynb
setting = component.combine(
    component.SklearnRanker(LogisticRegression, solver='liblinear'),
    component.PerfectLabeler(),
    component.RelevanceSampler(),
    component.FixedRoundStoppingRule(max_round=20))()

workflow = tarexp.OnePhaseTARWorkflow(dataset, setting, seed_doc=[1023], batch_size=200, random_seed=123)

recording_metrics = [ir_measures.RPrec, tarexp.OptimisticCost(target_recall=0.8, cost_structure=(25,5,5,1))]

for ledger in workflow:
    print("Round {}: found {} positives in total", format(ledger.n_rounds, ledger.n_pos_annotated))
    print("metric:", workflow.getMetrics(recording_metrics))

Figure 1: Sample Python Snippet for Running One-Phase TAR Workflow. Please refer to the online Google Colab Notebook demo page for a full working example.

There have been a few open source efforts focused on broader support for TAR experimentation. The TAR Evaluation Toolkit\(^6\) enables simulation of a fixed set of active learning workflows on a labeled version of the Enron collection, and was used in several research studies by the tool’s authors [7, 8, 47]. The Baseline Model Implementation [6] (BMI) is a successor to the TAR Evaluation Toolkit that is wrapped with a VirtualBox virtual machine that provides an interface for users to run TAR interactively. It was used in the TREC Total Recall Tracks as baseline systems [11, 30]. HiCAL\(^8\) embeds BMI in a Django-based framework along with the Indri search engine [33] and an interface for interactive assessment [1]. Components communication through HTTP APIs and so HiCAL has more potential for modification than the previous efforts. It was been used in annotation of the HC4 collections [18].

FreeDiscovery\(^9\) wraps a REST API around selected scikit-learn IR and ML learning functionality, as well as providing new algorithms for eDiscovery tasks such as email threading and duplication detection. It does not incorporate support for active learning experiments itself, but has been used as a component in active learning experiments [38].

Numerous open source or web-based tools are available for carrying out systematic reviews\(^10\), but most provide little support for algorithmic experimentation. One exception is ASReview\(^11\), an open source tool implemented in Python and Javascript [35]. It includes a simulation mode that allows running experiments on labeled data sets, and supports user configuration of supervised learning, active learning, and feature extraction methods\(^12\).

3 STRUCTURE OF TARExp

A major advance of TARExp over previous TAR research software is the ability to declaratively specify TAR workflows. Users can create components defined using a standard interface and combine them with TARExp components in workflows of their design. This includes incorporating different simulations of human-in-the-loop reviewing, or even embedding in systems using actual human review (though we have not done the latter).

Execution of declaratively specified review workflows is supported by a workflow object (Sec 3.1). The changes in the labeling state of the document collection are recorded in the the ledger (Sec 3.2).

\(^6\)https://github.com/ntucllab/libact
\(^7\)https://cormack.uwaterloo.ca/tar-toolkit/
\(^8\)https://hical.github.io
\(^9\)https://tryfreediscovery.com/
\(^10\)http://systematicreviewtools.com/
\(^11\)https://github.com/asreview/asreview
\(^12\)https://asreview.nl/blog/simulation-mode-class-101
During the iterative process, the workflow reaches out to a set of workflow components (Sec 3.3), each of which can play one or more roles in the workflow. Finally, an experiment (Sec 3.5) object defines a set of experiments and dispatches them sequentially or in parallel. Figure 1 is a code snippet that demonstrates how each element combines to form a working TAR process, Figure 2 is a general overview diagram of TARexp.

3.1 Workflow

An object of class workflow executes the user’s declarative specification of a TAR workflow. In doing so, it reaches out to components for services specified in the declarative specification such as creating training batches, scoring and ranking the collection, and testing for stopping conditions.

After an optional initial seed round where the user can specify a starting set of labeled training data, the workflow is executed as a sequence of training rounds. Each round consists of selecting a batch of training documents (using a sampler object), looking up labels for those documents (using the labeler object), training a model and scoring and ranking the collection documents (using the ranker object).

TARexp supports specifications of both one and two-phase TAR workflows, as described in Yang et al. [42]. One-phase workflows (tarexp.ONEPhaseTARWorkflow in code) can be run for a fixed number of training rounds, or until all documents have been reviewed. Two-phase reviews also use a stopping rule to determine when to end training, but then follow that by ranking the collection with the final trained model and reviewing to a statistically determined cutoff.

The workflow object maintains only enough state in-memory to work through a training round including the seed for random number generators. Besides the optionally written document scores, the rest of the state of the workflow is recorded in the ledger, which is written to secondary storage at user-configurable intervals. This allows easy restarting of crashed runs with minimal redundant work.

The workflow object is implemented as a Python iterator, allowing procedures defined outside the workflow to execute at each round. The iterator yields a frozen ledger (see next Section). The user can define a custom per-round evaluation process or record information for later analysis.

3.2 Ledger

Any aspect of the history of a batch-based workflow can, if necessary, be reproduced from a record of which documents were labeled on which training rounds (including any initial seed round). The ledger object records this state in memory, and writes it to disk at user-specified intervals to enable restarts.

The persisted ledger for a complete run can be used to execute TARexp in frozen mode where no batch selection, training, or scoring is done. Frozen mode supports efficient testing of new components that do not change training or scoring, e.g. non-interventional stopping rules [20], effectiveness estimation methods, etc. Evaluating stopping rules for two-phase reviews also requires persisting scores of all documents at the end of each training round, an option the user can specify.

3.3 Components

TARexp implements algorithms via components. A component is an object that is declared to serve one or more roles in a workflow, e.g. the stopping rule, the training batch sampler, the ranker, or the labeler. Components communicate only through the workflow. The association of components with multiple roles is important when implementing algorithms where, for instance, the stopping rule interacts tightly with a particular batch selection method (e.g. AutoStop [22]). The current release of TARexp defines the interface of multi-role components, but release of the particular multi-role components we have implemented is waiting on a paper under review [40].

TARexp supports classification models implemented in Scikit-learn through component. SklearnRanker wrapper. However, any supervised learning model that can produce a score for each document in the collection can be integrated into TARexp. We have tested an initial implementation of Transformer-based models for TAR Yang et al. [43], but have not yet integrated this code into the released version of TARexp.

TARexp provides reference implementations of a variety of TAR-specific algorithms, to aid reproducibility and reduce experimenter work. For instance, uncertainty sampling [19], relevance feedback [29], and simple random sampling batch selection algorithms are provided.

Stopping rules are a particular focus of TAR research. TARexp provides implementation of the Knee and Budget Rules [6, 7], a configurable bath precision rule, the 2399 Rule [31, 41], fixed numbers of training rounds [36], the Quant and QuantCI Rules [41], and others.

A Labeler object simulates human review. For most TAR experiments, we assume we simply look up the gold label of each document using component. PerfectLabeler. Random errors can be introduced using component. SuccessProbLabeler.

3.4 Evaluation

Consistent implementation of effectiveness metrics, including tricky issues like tiebreaking is critical to TAR experiments. This is true both for evaluation, and because stopping rules may incorporate effectiveness estimates based on small samples. We provide all metrics from the open source package ir-measures\(^{13}\) through the tarexp.Workflow.getMetrics method. Metrics are computed on both the full collection and unreviewed documents to support both finite population and generalization perspectives [39].

In addition to standard IR metrics, TARexp implements OptimisticCost to support the idealized end-to-end cost analysis for TAR proposed in Yang et al. [42]. Such analysis requires specifying a target recall and a cost structure associated with the TAR process (Line 8 in Figure 1). TARexp also provides helper functions for plotting cost dynamics graphs (Section 4.1).

3.5 Experiments

TAR inherits both the large topic-to-topic variability of IR tasks, and the strong dependence on initial conditions and random seeds of active learning processes. Multiple collections, topics, and runs are necessary to reliably demonstrate that one approach dominates

\(^{13}\)https://ir-measur.es/en/latest/
Figure 3: Cost dynamic graphs on topic GPRO in RCV1-v2 with different cost structured targeting 80% recall produced by the helper function. The height of the color blocks indicate the cost on each part spent at the respective round. The faded section indicates the rounds that pass the optimal stopping point and the grey vertical dashed line indicates the round where the one phase TAR workflow would reach the recall target.

4 HELPER FUNCTIONS AND INTEGRATION

Besides the core functionality of executing experiments, TARexp provides several tools to aid in analyzing results. Most are included in our Google Colab notebook.

4.1 Experiment Analysis and Visualization

The experiment results that tarexp.TARExperiment returns are in generic Python dictionaries. Through createDFfromResults, the results are transformed into Pandas [37] DataFrames for further analysis. The resulting DataFrame contains a multi-level index of the experimental parameters and multi-level columns containing the values of effectiveness and cost metrics.

We also provide visualization tools to produce cost dynamic graphs, such as Figure 3, through both Python and command-line interfaces. The following is an example command for creating a graph with two runs and three cost structures.

```python
python -m tarexp.helper.plotting
--runs GPRO=location/to/GPRO
GOBIT=location/to/GOBIT
--cost_structures 1-1-1 10-10-1 25-5-1
--y_thousands --with_hatches
```

4.2 Jupyter Notebook and Google Colab

Our framework is fully integrated with Jupyter Notebook [17], a browser-based tool for running python interactively. Users can also run TARexp on Google Colab,14 a cloud version of Jupyter Notebook powered by Google, by installing TARexp through Pypi15, the online Python package distribution repository. Figure 4 is a screenshot of running TAR experiments on the Google Colab.

5 CONCLUSION

This paper introduces a new Python framework TARexp for conducting TAR experiments, an area of IR involving particularly complex software and workflows. TARexp allows flexible combination of new methods under study with reference implementations for many

14https://colab.research.google.com/
15https://pypi.org/project/tarexp/
commonly used TAR algorithms. Large scale, deterministically reproducible experiments are supported. We hope that TARexp will reduce the barriers to entry for researchers to study the many exciting research problems in TAR, and increase comparability of results.

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REFERENCES

[1] Mustafa Abualsaad, Nimeech Gheani, Haitian Zhang, Mark D Smucker, Gordon V Cormack, and Maura R Grossman. 2018. A System for Efficient High-Recall Retrieval. In The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval. ACM, 1317–1320.

[2] Saba Amiri, Sara Salimzadeh, and A.S.Z. Belloum. 2019. A Scalable Deep Learning Frameworks. In 2019 15th International Conference on eScience (EScience). 650–651. https://doi.org/10.1109/eScience.2019.00102

[3] J.R. Baron, R.C. Losey, and M.D. Berman. 2016. Perspectives on Predictive Coding: And Other Advanced Search Methods for the Litigator. American Bar Association, Section of Litigation. https://books.google.com/books?id=TdI2AQAAACAJ

[4] Jason R Baron, David D Lewis, and Douglas W Oard. 2006. TREC 2006 Legal Track Overview. In TREC. Citeseer.

[5] Marc-Allen Cartright, Samuel Huston, and Henry Feild. 2012. Galago: A Modular Distributed Processing and Retrieval System. In OSRs@SIGIR. Citeseer, 25–31.

[6] Gordon V Cormack and Maura R Grossman. 2015. Autonomy and reliability of continuous active learning for technology-assisted review. arXiv preprint arXiv:1504.06868 (2015).

[7] Gordon V Cormack and Maura R Grossman. 2016. Engineering Quality and Reliability in Technology-Assisted Review. In SIGIR ACM Press, Pisa, Italy, 75–84. https://doi.org/10.1145/2911451.2911519 00024.

[8] Gordon V Cormack and Maura R Grossman. 2016. Scalability of continuous active learning for reliable high-recall text classification. In Proceedings of the 25th ACM international on conference on information and knowledge management. 1039–1048.

[9] Gordon V Cormack, Maura R Grossman, Bruce Hedin, and Douglas W Oard. 2010. Overview of the TREC 2010 Legal Track. In TREC.

[10] Cadi Costello, Eugene Yang, Dawn Lawrie, and James Mayfield. 2022. Patapasco: A Python Framework for Cross-Language Information Retrieval Experiments. (2022). https://arxiv.org/abs/2201.09996

[11] Maura R Grossman, Gordon V Cormack, and Adam Rogetie. 2016. TREC 2016 Total Recall Track Overview. In TREC.

[12] Bruce Hedin, Stephen Tomlinson, Jason R Baron, and Douglas W Oard. 2009. Overview of the TREC 2009 legal track. Technical Report. NATIONAL ARCHIVES AND RECORDS ADMINISTRATION COLLEGE PARK MD.

[13] Krishna Prakash Kalanithaya, D Akila, and P Rajesh. 2019. Advances in natural language processing: a survey of current research trends, development tools and industry applications. International Journal of Recent Technology and Engineering 7, 5 (2019), 199–202.

[14] Evangelos Kanoulas, Dan Li, Leif Azzopardi, and Rene Spjiker. 2017. CLEF 2017 Technologically Assisted Reviews in Empirical Medicine Overview. In CEUR workshop proceedings. Vol. 1866. 1–29.

[15] Evangelos Kanoulas, Dan Li, Leif Azzopardi, and Rene Spjiker. 2018. CLEF 2018 Technologically Assisted Reviews in Empirical Medicine Overview. CEUR Workshop Proceedings 2125 (July 2018). https://strathprints.strath.ac.uk/66446/

[16] Evangelos Kanoulas, Dan Li, Leif Azzopardi, and Rene Spjiker. 2019. CLEF 2019 technology assisted reviews in empirical medicine overview. In CEUR workshop proceedings. Vol. 2380.

[17] Thomas Kluyver, Benjamin Ragan-Kelley, Fernando Pérez, Brian Granger, Matthias Bussonnier, Jonathan Frederic, Kyle Kelley, Jessica Hamrick, Jason Groux, Sylvain Corlay, Paul Ivanov, Danim Avila, Safia Abdalla, and Carol Welling. 2016. Jupyter Notebooks – a publishing format for reproducible computational workflows. In Positioning and Power in Academic Publishing: Players, Agents and Agendas, F. Loizides and B. Schmidt (Eds.). IOS Press, 87 – 90.

[18] Dawn Lawrie, James Mayfield, Douglas W. Oard, and Eugene Yang. 2022. H4C: A New Suite of Test Collections for Ad Hoc CLIR. (2022). https://arxiv.org/abs/2201.09992

[19] David D. Lewis and William A Gale. 1994. A sequential algorithm for training text classifiers. In SIGIR 1994 – 12. 15.

[20] David D. Lewis, Eugene Yang, and Ophir Frieder. 2021. Certifying One-Phase Technology-Assisted Reviews (Under review). (2021).

[21] David D. Lewis, Yiming Yang, Tony G. Rose, and Fan Li. 2004. RCV1: A New Benchmark Collection for Text Categorization Research. JMLR 5 (2004), 361–397.

[22] Dan Li and Evangelos Kanoulas. 2020. When to Stop Reviewing in Technology-Assisted Reviews: Sampling from an Adaptive Distribution to Estimate Residual Relevant Documents. ACM Transactions on Information Systems (TOIS) 38, 4 (2020), 1–36.

[23] Sean MacAvaney, Craig Macdonald, and Iadh Ounis. 2022. Streaming Evaluation with ir-measures. In ECIR. https://arxiv.org/abs/2111.13466

[24] Sean MacAvaney, Andrew Yates, Sergey Feldman, Doug Downey, Arman Cohan, and Nazli Goharian. 2021. Simplified Data Wrangling with ir_databases. In Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval. https://doi.org/10.1145/3408435.3463254

[25] Craig Macdonald, Nicola Tonellotto, Sean MacAvaney, and Iadh Ounis. 2021. PyTerrier: Declarative Experimentation in Python from BM25 to Demne Retrieval. In 38th ACM International Conference on Information and Knowledge Management.

[26] Graham McDonald, Craig Macdonald, and Iadh Ounis. 2020. How the Accuracy and Confidence of Sensitivity Classification Affects Digital Sensitivity Review. ACM Transactions on Information Systems (TOIS) 19, 1 (2020), 1–34.

[27] Douglas W Oard, Bruce Hedin, Stephen Tomlinson, and Jason R Baron. 2008. Overview of the TREC 2008 legal track. Technical Report. MARYLAND UNIV COLLEGE PARK COLL OF INFORMATION STUDIES.

[28] Adam Paske, Sam Gross, Francisco Massa, Adam Leves, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Albina Desmaison, Andreas Kopf, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasanck Chalankurthi, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. 2019. PyTorch: An imperative style, high-performance deep learning library. In Advances in Neural Information Processing Systems—an Illustration. https://pytorch.org/.

[29] J. J. Rocchio. 1971. Relevance feedback in information retrieval. In The Smart retrieval system - experiments in automatic document processing. G. Salton (Ed.). Englewood Cliffs, NJ: Prentice-Hall, 313–323.

[30] Adam Roegiest and Gordon V. Cormack. 2015. TREC 2015 Total Recall Track Overview. In TREC.

[31] Herbert L Rotblat. 2007. Search and information retrieval science. In Sedona Conf. J., Vol. 8. HeinOnline, 225.

[32] G. Salton and M. E. Lesk. 1965. The SMART Automatic Document Retrieval System. In Information Processing & Handwriting Recognition. 87 – 90. https://doi.org/10.1016/S0040-234X(72)90108-2

[33] Trevor Strohman, Donald Metzler, Howard Turtle, and W Bruce Croft. 2005. Jindr: A language model-based search engine for complex queries. In Proceedings of the international conference on intelligent analysis, Vol. 2. Citeseer, 2–6.

[34] Stephen Tomlinson, Douglas W Oard, Jason R Baron, and Paul Thompson. 2007. Overview of the TREC 2007 Legal Track. In TREC. Citeseer.

[35] Jason van de Scoot, Jonathan de Brun, Raoul Schram, Parisa Zahedi, Jan de Boer, Felix Weijdemaa, Bianca Kramer, Martin Huijts, Maarten Hoogerwerf, Gerbrich Ferdinands, et al. 2021. An open source machine learning framework for efficient and transparent systematic reviews. Nature Machine Intelligence 3, 2 (2021), 125–133.

[36] Byron C Wallace, Thomas A Trikalinos, Joseph Lau, Carla Brodley, and Christopher H Schmid. 2010. Semi-automated screening of biomedical citations for systematic reviews. BMC bioinformatics 11, 1 (2010), 55.
[37] Wes McKinney. 2010. Data Structures for Statistical Computing in Python. In Proceedings of the 9th Python in Science Conference, Stéfan van der Walt and Jarrod Millman (Eds.). 56 – 61. https://doi.org/10.25080/Majora-92BFI92-00a

[38] Eugene Yang, David Grossman, Ophir Frieder, and Roman Yurchak. 2017. Effectiveness results for popular e-discovery algorithms. In Proceedings of the 16th edition of the International Conference on Artificial Intelligence and Law. 261–264.

[39] Eugene Yang, David D Lewis, and Ophir Frieder. 2019. A Regularization Approach to Combining Keywords and Training Data in Technology-Assisted Review. In Proceedings of the Seventeenth International Conference on Artificial Intelligence and Law. 153–162.

[40] Eugene Yang, David D. Lewis, and Ophir Frieder. 2021. \( \beta \)-stop: Stopping Fixed-Batch Technology-Assisted Reviews (Under review). (2021).

[41] Eugene Yang, David D. Lewis, and Ophir Frieder. 2021. Heuristic Stopping Rules For Technology-Assisted Review. In Proceedings of the 21st ACM Symposium on Document Engineering.

[42] Eugene Yang, David D. Lewis, and Ophir Frieder. 2021. On Minimizing Cost in Legal Document Review Workflows. In Proceedings of the 21st ACM Symposium on Document Engineering.

[43] Eugene Yang, Sean MacAvaney, David D. Lewis, and Ophir Frieder. 2022. Goldilocks: Just-Right Tuning of BERT for Technology-Assisted Review. (2022).

[44] Peilin Yang, Hui Fang, and Jimmy Lin. 2017. Anserini: Enabling the use of Lucene for information retrieval research. In Proceedings of the 40th international ACM SIGIR conference on research and development in information retrieval. 1253–1256.

[45] Yao-Yuan Yang, Shao-Chuan Lee, Yu-An Chung, Tung-En Wu, Si-An Chen, and Hsuan-Tien Lin. 2017. libact: Pool-based Active Learning in Python. Technical Report. National Taiwan University. https://github.com/ntucllab/libact available as arXiv preprint https://arxiv.org/abs/1710.00379.

[46] Jan Zacharias, Michael Barz, and Daniel Sonntag. 2018. A survey on deep learning toolkits and libraries for intelligent user interfaces. arXiv preprint arXiv:1803.04818 (2018).

[47] Haotian Zhang, Jimmy Lin, Gordon V. Cormack, and Mark D. Smucker. 2016. Sampling Strategies and Active Learning for Volume Estimation. In Proceedings of the 39th International ACM SIGIR Conference on Research and Development in Information Retrieval (Pisa, Italy) (SIGIR ’16). Association for Computing Machinery, New York, NY, USA, 981–984. https://doi.org/10.1145/2911451.2914685