AMS42 at the NTCIR-18 FairWeb-2 Task

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TASK OVERVIEW

ChuWeb 21D Web Page Collection

QUERY TOPICS

M (Movies) R (Researcher) Y (YouTube)

QUERY + DESCRIPTION ×

OVERVIEW OF RUNS (QUERY+DESCRIPTION)

RUN 1: BM25 + QUERY EXPANSION

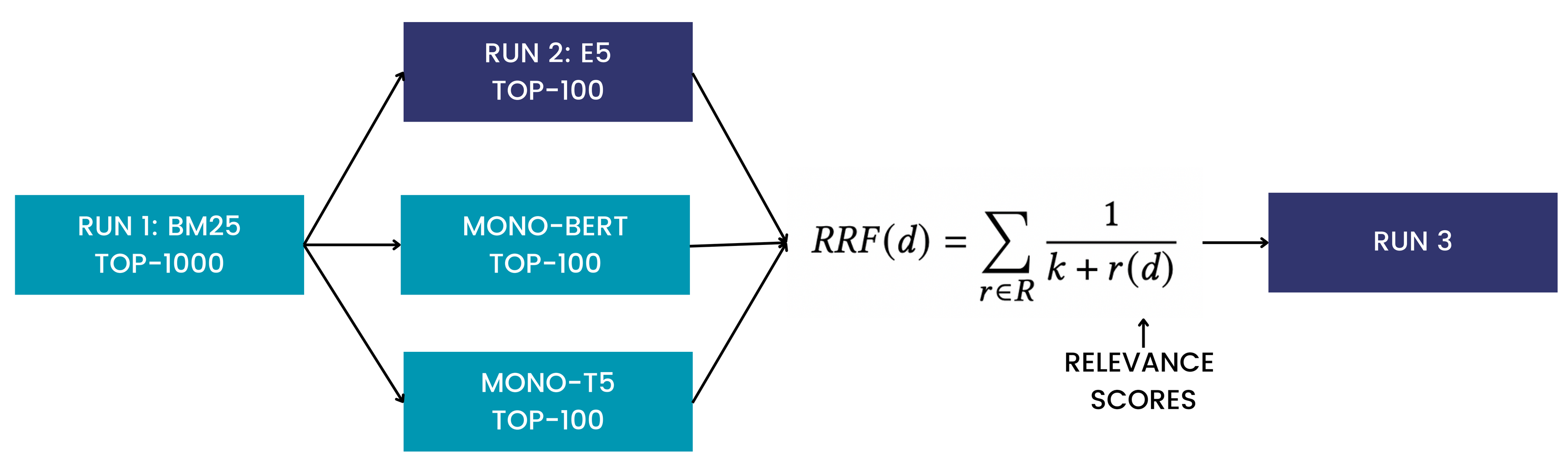
Query Expansion applied per topic:

Movies:
<movie/movies> on IMDb

Researcher:
<researchers/authors/coauthors> on Google Scholar

YouTube: <video/videos> - YouTube

RUN 2&3: FOCUSING ON RELEVANCE



RUN 4: IMPROVED MMR

Step 1: Estimation of Sensitive Attributes

Movies: Extracted movie name from title and searched on IMDb.

Researchers: Used Scholarly API to get first author via document title and their information (h-index, name); gender estimated from name.

YouTube: Extracted title before "- YouTube" and searched on YouTube.

Step 2: Apply MMR on RUN 2

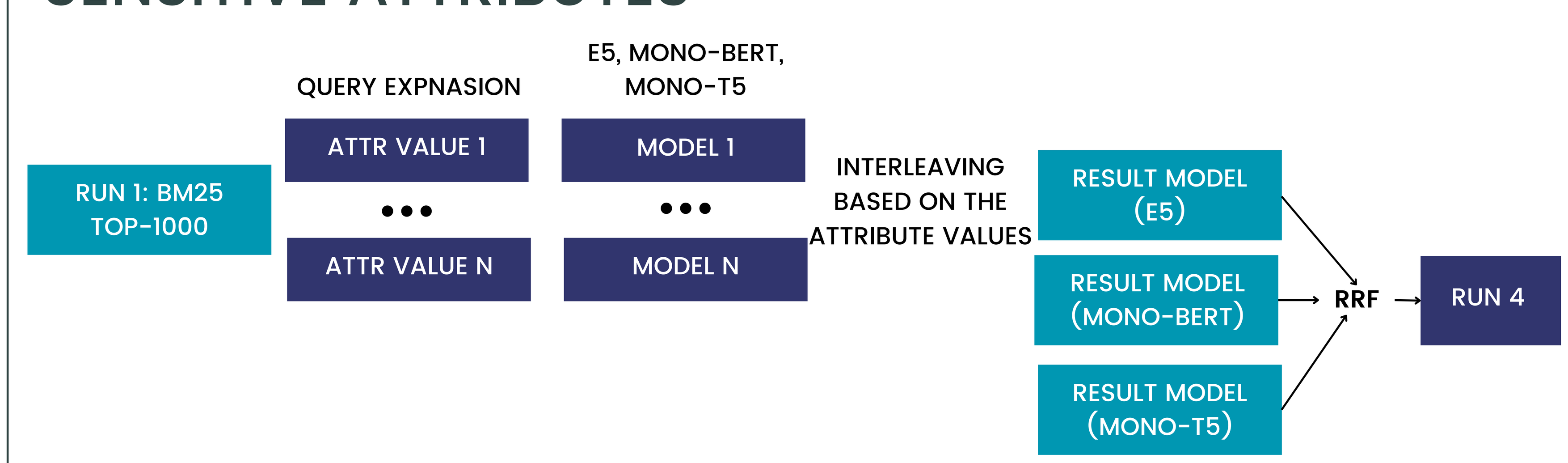
MMR selects a document d that maximizes the following objective function:

$$MMR(d) = \lambda \cdot r(q, d) + (1 - \lambda) \cdot f(S(d))$$

According to the evaluation metrics in the task requirements: Jensen-Shannon Divergence (JSD) and Root Normalized Order-aware Divergence (RNOD), MMR is adapted to optimize for:

$$f(S(d)) = \mathrm{JSD}(S(d), G) + \mathrm{RNOD}(s(d), G),$$

RUN 5: FUSION + QUERY EXPANSION WITH SENSITIVE ATTRIBUTES



M topic: <query> + " and these movies are from " + <attribute value>
R topic: <attribute value> + <researchers/authors/coauthors>
Y topic: None, as it is applied only for non-ordinal sensitive attributes

FAIRNESS RESULTS

Fairness Evaluation for Movie Topics

Run	Mean GF^{JSD} (ORIGIN)	Mean GF^{NMD} (RATINGS)	Mean GF^{RNOD} (RATINGS)	Mean GFR
AMS42-WS-QD-RG-1	0.2096	0.2329	0.2151	0.2235
AMS42-WS-QD-RG-2	0.4195 (>23)	0.4848 (>23)	0.4411 (>23)	0.4681 (>23)
AMS42-WS-QD-RG-3	0.3317 (>23)	0.3699 (>23)	0.3340 (>23)	0.3657 (>23)
AMS42-WS-QD-RG-4	**0.4491 (>23)**	**0.5029 (>22-23)**	**0.4644 (>22-23)**	**0.4877 (>22-23)**
AMS42-WS-QD-RG-5	0.3535 (>23)	0.3897 (>23)	0.3577 (>23)	0.3820 (>23)
Top 5 GFR of other teams runs				
RSLFW-WS-QD-RG-3	**0.4474** (>23)	**0.5207 (>22-23)**	**0.4496 (>23)**	**0.5101 (>22-23)**
RSLFW-WS-QD-RG-4	0.4465 (>23)	0.5110 (>22-23)	0.4464 (>23)	0.5044 (>22-23)
RSLFW-WS-QD-RR-2	0.4193 (>23)	0.5036 (>22-23)	0.4424 (>23)	0.4860 (>22-23)
RSLFW-WS-QD-RR-1	0.4176 (>23)	0.5006 (>22-23)	0.4409 (>23)	0.4835 (>22-23)
THUIR-WS-QD-REV-1	0.4034 (>23)	0.4973 (>22-23)	0.4437 (>23)	0.4758 (>22-23)

Fairness Evaluation for YouTube Topics

Run	Mean GF^{NMD} (SUBSCS)	Mean GF^{RNOD} (SUBSCS)	Mean GFR
AMS42-WS-QD-RG-1	0.0631	0.0560	0.0690
AMS42-WS-QD-RG-2	0.0645	0.0580	0.0715
AMS42-WS-QD-RG-3	0.0592	0.0502	0.0662
AMS42-WS-QD-RG-4	**0.0680**	**0.0635**	**0.0741**
AMS42-WS-QD-RG-5	0.0592	0.0502	0.0662
Top 5 GFR of other teams runs			
ORG-WS-run.qljm.Q	**0.2659 (>23)**	**0.2526 (>20-23)**	**0.2775 (>21-23)**
THUIR-WS-QD-RR-5	0.2484 (>23)	0.2401 (>23)	0.2531 (>23)
THUIR-WS-QD-RR-3	0.2407 (>23)	0.2322 (>23)	0.2437 (>23)
ORG-WS-run.bm25.Q	0.2367	0.2240	0.2368
THUIR-WS-QD-RR-1	0.2247	0.2153	0.2335

CONCLUSION

- Overall, higher performance leads to higher fairness.
- RUN 4&5 improved fairness across all topics in comparison with the other RUNS focused only on extracting relevant documents.
- Best results obtained on M (Movies) topic, while worst results are on Y (YouTube) topic. The dataset did not always contain clear links to actual YouTube videos, as opposed to IMDb pages.

RELEVANCE RESULTS

Run	M topics		Y topics		All topics	
	Mean ERR	Mean iRBU	Mean ERR	Mean iRBU	Mean ERR	Mean iRBU
AMS42-WS-QD-RG-1	0.0727	0.2460	0.0527	0.0821	0.0715	0.1817
AMS42-WS-QD-RG-2	**0.2027**	0.5437	0.0567	**0.0851**	0.1128 (>23)	0.2840 (>23)
AMS42-WS-QD-RG-3	0.1800	0.4314	0.0610	0.0823	**0.1142 (>23)**	0.2586 (>23)
AMS42-WS-QD-RG-4	0.1771	**0.5497**	0.0473	0.0847	0.0981 (>23)	**0.2897 (>23)**
AMS42-WS-QD-RG-5	0.1640	0.4349	**0.0610**	0.0823	0.0999 (>23)	0.2608 (>23)
Top 5 relevance of other teams runs						
RSLFW-WS-QD-RG-3	**0.2700**	**0.6332**	**0.1191**	**0.2540**	**0.2020 (>12-23)**	0.4556 (>15-23)
RSLFW-WS-QD-RG-4	0.2532	0.6204	0.1176	0.2340	0.1965(>12-23)	0.4434(>16-23)
RSLFW-WS-QD-RR-2	0.2523	0.5964	0.0939	0.2420	0.1942(>13-23)	**0.4613 (>15-23)**
RSLFW-WS-QD-RR-1	0.2506	0.5919	0.0912	0.2039	0.1931(>14-23)	0.4453 (>16-23)
THUIR-WS-QD-REV-1	0.2367	0.5804	0.0636	0.2327	0.1807 (>18-23)	0.4365 (>17-23)

CHALLENGES

- **Noisiness in the estimated sensitive attribute**
  → Difficulty in applying fairness interventions
  Solution: Query expansion with sensitive attribute values
  Limitation: It does not work for numerical attribute values (e.g. n of subscribers)

  → Difficulty in fairness evaluation
  – it is difficult to determine why certain approaches outperform others
  Solution: separating the evaluation of the estimation of attributes and the outcome of the fairness approach

- **Without first extracting relevant documents – estimating the sensitive attributes is not possible**
  E.g. if the document is somehow relevant to the query but it does not contain a YouTube video, one can't assess the sensitive attribute of this document

REFERENCES

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