# UDInfoLab at the NTCIR-17 FairWeb-1 Task

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# Our Goal at FairWeb-1

We tested the distribution-based fair learning (DLF) framework [1] that:

- based on re-ranking and can merge with any relevance model.
- does not require gold fairness labels.
- leverages under-exploited contextual features.

The DLF achieved promising fairness performance on the NTCIR dataset, even though it does not cope with ordinal fairness groups

[1] Chen, F., & Fang, H. (2023, August). Learn to be Fair without Labels: A Distribution-based Learning Framework for Fair Ranking. In Proceedings of the 2023 ACM SIGIR International Conference on Theory of Information Retrieval (pp. 23-32).

# Distribution-based Learning Framework (DLF)

## Fairness-aware loss and learning without labels

$$\theta^* = \arg\min FL(\pi) = \sum_{i=1}^{m} w_i * KL(\epsilon_i(\pi), \epsilon_i^*)$$

$$= \arg\min \sum_{i=1}^{m} w_i * KL(\sum_{k=1}^{n} P_{\text{fair}}(s_k) * GM_{ik}, \sum_{k=1}^{n} P_{\text{fair}}(s_k^*) * GM_{ik})$$

$$= \arg\min \sum_{i=1}^{m} w_i * KL(\sum_{k=1}^{n} P_{\text{fair}}(f(X_k, \theta)) * GM_{ik}, \epsilon_i^*)$$

- $P_{\text{fair}}$ is top one probability, $s^*$ is the unavailable ground truth label, and $\epsilon^*$ is the target exposure distribution.
- $\textit{Final Score} = \alpha * f(X_k, \theta^*) + (1 - \alpha) *$ Relevance to make final rankings fair and relevant.

# Group Membership Estimation

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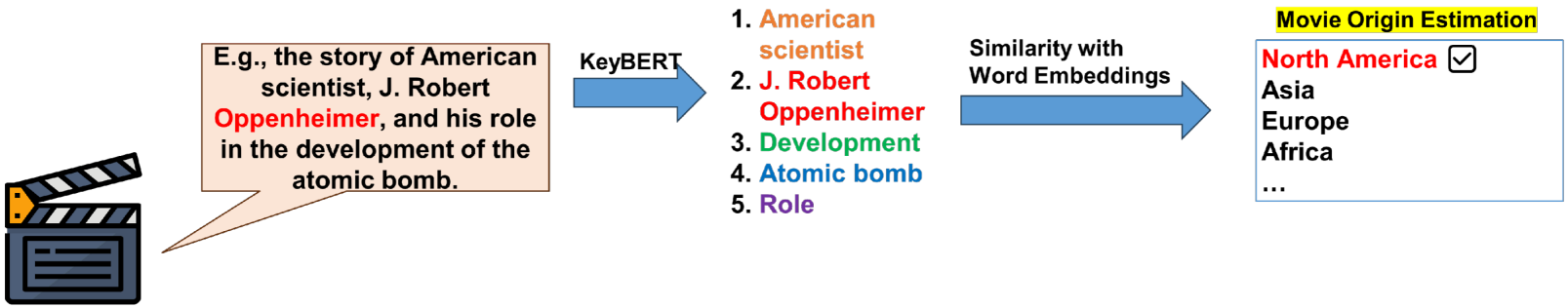
Since GM is not available, the group membership is obtained by calculating the cosine similarities between text keyword embeddings and fairness annotation (e.g., male and female) keyword embeddings.

- *KeyBert* to extract keywords from cleaned HTML text.
- Sentence-BERT with the pre-trained model 'all-mpnet-base-v2' for words embedding.



# Fairness Performance

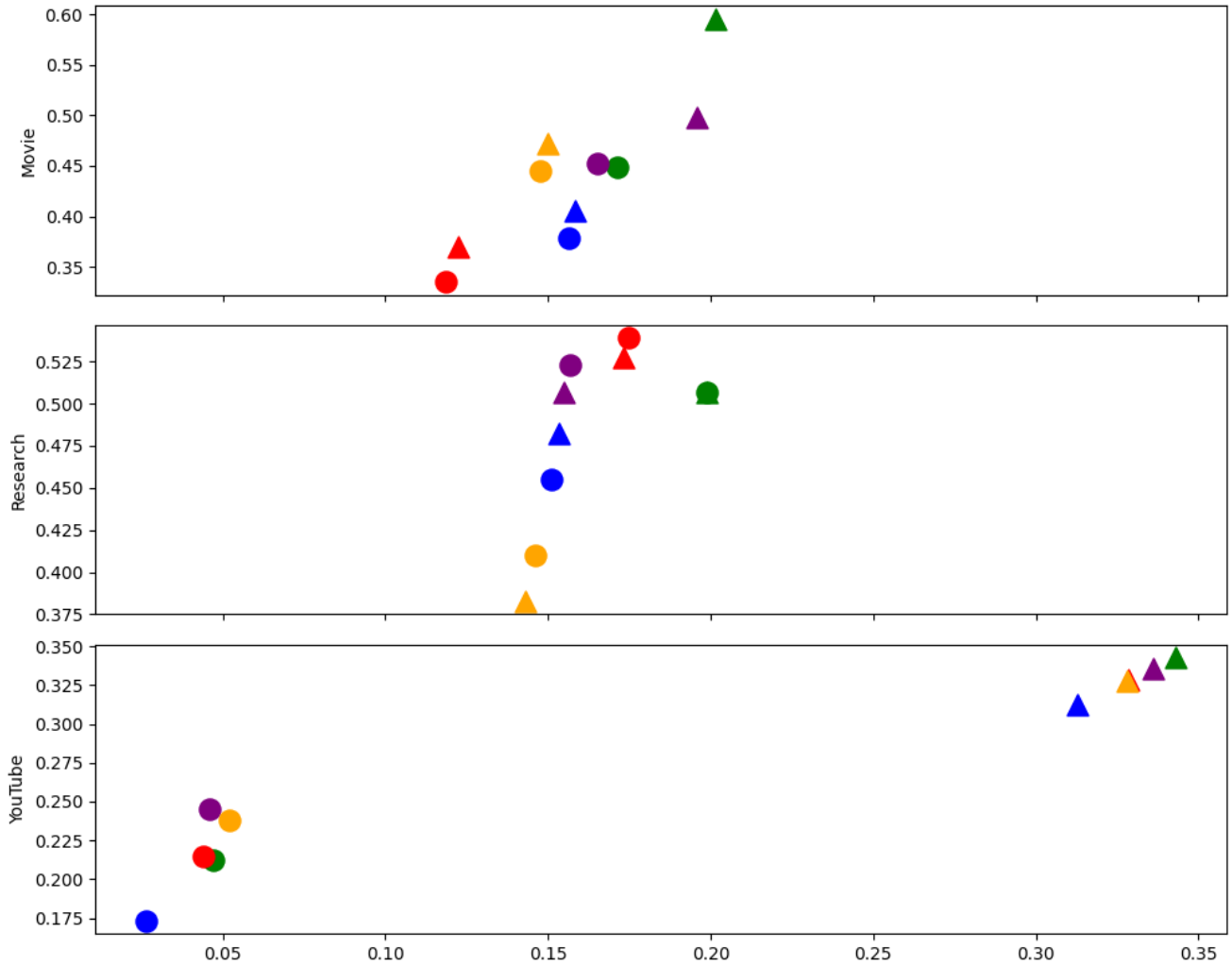
Table: Fairness improvements after re-ranking V.S. their initial rankings over the 15 topics for Movie, Researcher, and YouTube, respectively [2].

| Run Name | Movie | | | Researcher | | | Youtube | |
|---|---|---|---|---|---|---|---|---|
| | *Mean GF JSD (Origin)* | *Mean GF NMD (Ratings)* | *Mean GF RNOD (Ratings)* | *Mean GF JSD (Gender)* | *Mean GF NMD (H-index)* | *Mean GF RNOD (H-index)* | *Mean GF NMD (Subscription)* | *Mean GF RNOD (Subscription)* |
| UDinfo-D-RR-1 | 0.3672* | 0.4279* | 0.3913* | 0.4985 | 0.4682* | 0.4434* | 0.3157** | 0.3017** |
| UDinfo-Q-RR-2 | 0.4493* | 0.5132* | 0.4706* | 0.5096* | 0.4977* | 0.4605* | 0.3315** | 0.3081** |
| UDinfo-D-RR-3 | 0.3476* | 0.3876* | 0.3569* | 0.5374 | 0.5195 | 0.4866 | 0.3228** | 0.3091** |
| UDinfo-Q-RR-4 | 0.4601* | 0.5161* | 0.4750* | 0.5190 | 0.4994 | 0.4650 | 0.3309** | 0.3157** |
| UDinfo-D-RR-5 | 0.4543* | 0.4888* | 0.4488* | 0.3829 | 0.3765 | 0.3554 | 0.3279** | 0.3083** |
| bm25-depThre3-D | 0.3401 | 0.3993 | 0.3630 | 0.4694 | 0.4400 | 0.4155 | 0.1777 | 0.1731 |
| bm25-depThre3-Q | 0.4135 | 0.4623 | 0.4283 | 0.5096 | 0.4977 | 0.4605 | 0.2112 | 0.2039 |
| qld-depThre3-D | 0.3122 | 0.3507 | 0.3208 | 0.5497 | 0.5306 | 0.4975 | 0.2155 | 0.2100 |
| qld-depThre3-Q | 0.4275 | 0.4668 | 0.4351 | 0.5356 | 0.5152 | 0.4807 | 0.2451 | 0.2391 |
| qljm-depThre3-D | 0.4273 | 0.4606 | 0.4211 | 0.4120 | 0.4038 | 0.3824 | 0.2454 | 0.2329 |

[2] * indicates that re-ranking improves its baseline. ** indicates the improvements are also statistically significant (based on a randomized Tukey HSD test with $B = 5,000$ trials, $\alpha = 0.05$)

# Fairness and Relevance

Figure: GFR v.s. Relevance Scores (Mean ERR). Triangles indicate our five runs, whereas circles are their baselines. Different colors indicate different pairs.



# Conclusion and Future Work

In the FairWeb-1 task, we tested a recently proposed fair ranking framework DLF and found:

- The result shows that DLF can help initial rankings improve fairness while maintaining relevance in most cases.
- It performs poorly for longer text (e.g., research articles) that carries more information.

In the future, we plan to:

- incorporate DLF with ordinal fairness attributes.
- explore the relationship between fairness attributes and the impact on model performance.
- refine the way for keyword extraction and similarity calculation.

# Thank You!

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