Fairness-Aware Job Recommender Model

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Abstract

Automated job recommendation systems are expected to provide accurate, role-specific matches while also ensuring fair visibility across employers. In the first phase of this project, we focus on the problem of mapping unstructured resume and job text to suitable occupations by introducing a hybrid recommendation framework that combines semantic embeddings with collaborative filtering signals. This approach balances contextual meaning with occupational structure, leading to improved recommendation accuracy and specificity. In the second phase, we study fairness in job ranking and demonstrate that similarity-based ranking methods consistently introduce exposure bias, where large companies gain disproportionate visibility due to higher job volume and more detailed skill descriptions. To address this issue, we propose two fairness-aware ranking methods: (1) a Fairness-Weighted Recommender that modifies similarity scores using group-aware weights based on company size, and (2) a Fair+Dense Recommender that additionally applies diversity constraints to limit repeated exposure from the same employers. We evaluate these approaches on real-world job postings using exposure-focused fairness metrics such as Selection Rate, Rank-Aware Exposure, Proportional Fairness Error, and Diversity Ratio. The results show that fairness weighting significantly reduces exposure imbalance while largely maintaining relevance, and that the Fair+Dense method further improves employer diversity with a small compromise in proportional exposure alignment. Overall, this work demonstrates that combining accurate recommendation modeling with fairness-aware ranking leads to job recommendation systems that are both effective and equitable.

1 Introduction

Job recommendation systems are a core component of modern recruitment platforms, helping connect job seekers with relevant employment opportunities. These systems must bridge the gap between unstructured, high-dimensional text, such as resumes and job descriptions, and structured occupational requirements. In the first phase of this project, we aim to improve recommendation accuracy and specificity by addressing the limitations of single-signal methods. Purely semantic similarity models often produce overly broad or generic matches, while statistical or collaborative approaches alone fail to capture detailed skill semantics. To overcome these limitations, we propose a hybrid recommendation framework that integrates semantic embeddings with collaborative filtering signals learned from occupational usage patterns. This combination allows the system to balance contextual meaning with domain-specific structure, resulting in more precise and occupation-aware recommendations.

However, high-quality matching alone does not ensure fair outcomes. In the second phase of this project, we examine how ranking strategies affect visibility and exposure after candidate jobs are retrieved. Through empirical analysis of real-world job postings, we find that similarity-based ranking systems consistently favor large companies, which typically dominate the dataset in both job volume and richness of skill descriptions. As a result, large employers appear more frequently at top-ranked

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positions, even when small and medium companies are well represented in the data. This issue, commonly referred to as exposure bias, reduces employer diversity, limits user choice, and raises fairness concerns in labor-market recommendation systems.

To address this challenge, we design fairness-aware ranking adjustments that operate on top of the baseline recommender developed in Phase 1. We introduce a Fairness-Weighted Recommender that adjusts similarity scores using group-based weights to encourage proportional exposure across company-size groups. We further extend this approach with a Fair+Dense Recommender that adds diversity constraints to reduce repeated dominance by individual employers. Unlike traditional demographic fairness settings, our work focuses on structural fairness across employer characteristics, a relatively underexplored but practically important aspect of job recommendation systems. By combining accurate recommendation modeling with exposure-aware ranking strategies, this project presents a unified framework that improves both relevance and fairness in real-world job recommendation pipelines.

2 Related Work

Embedding-based representations of jobs and skills are widely used in modern job recommendation systems. Models such as BERT and Sentence-BERT are commonly applied to encode resumes and job descriptions into dense semantic vectors that capture contextual similarity and detailed skill information [1,2]. Although effective for modeling unstructured text, these methods often struggle with ambiguous language and generic phrasing, which can result in recommendations that lack occupational precision. Collaborative filtering techniques have also been applied to occupational and labor-market data to leverage co-occurrence and usage patterns [3], but these approaches are generally limited to coarse-grained signals and have difficulty incorporating rich textual semantics. Prior work has shown that combining content-based similarity with collaborative filtering signals improves both accuracy and robustness in job recommendation systems [4], which motivates our integrated approach that balances semantic relevance with structural occupational knowledge.

Fairness in ranking-based recommender systems has received increasing attention, as item order directly determines visibility and user attention. In contrast to classification fairness, ranking fairness focuses on exposure and position bias, since higher-ranked items receive disproportionately more attention [5]. Previous studies show that relevance-driven ranking models can unintentionally amplify existing structural biases in real-world datasets, leading to systematic overexposure of dominant groups.

Large-scale production systems, such as LinkedIn Talent Search, have demonstrated that ranking algorithms often distribute exposure unevenly across demographic or organizational groups [6,7]. Bower et al. [6] propose fairness-aware reweighting methods to reduce exposure imbalance, while Singh and Joachims [8] formalize fairness in terms of equitable attention through proportional exposure. Subsequent work introduces exposure-aware ranking frameworks [9] and examines how position bias and user interaction dynamics contribute to unfair exposure patterns [10]. While much of the existing literature focuses on demographic or applicant-side fairness, fairness across employer attributes such as company size remains relatively underexplored in job recommendation systems, which is the focus of our work.

3 Proposed Method

Our framework consists of three main components: a content-based similarity model combined with a collaborative filtering signal, a fairness-weighted reranker, and a diversity-enhanced reranker (Fair+Dense). The overall objective is to maintain recommendation relevance while reducing systematic exposure bias.

3.1 Content Based Similarity Job recommender

Content-Based Similarity Scoring The content-based scoring module measures semantic similarity between resume text and occupation descriptions using advanced embedding models. We employ sentence transformers based on the MPNet architecture, which has shown strong performance on semantic similarity tasks. These models generate dense vector representations that capture not only individual terms but also their contextual relationships and overall semantic intent. For each resume–occupation pair, we compute the cosine similarity between their embeddings, resulting in a continuous similarity score ranging from 0 (no similarity) to 1 (identical meaning).

Cosine similarity is computed as the dot product of two normalized vectors divided by the product of their magnitudes. This measure reflects the angular distance between resume and occupation embeddings in a high-dimensional semantic space. Higher similarity scores indicate stronger semantic alignment, suggesting that the skills, experiences, and qualifications described in the resume closely match the requirements of the occupation. This content-based signal serves as the foundation of our recommendation system, providing a direct assessment of textual alignment between resumes and occupations.

3.2 Collaborative Filtering Job recommender

The collaborative filtering component complements semantic similarity by adding structural knowledge about how skills and requirements are shared across occupations. We construct an occupation–element usage matrix from standardized occupational data, where each entry represents the importance or frequency of a specific skill or requirement within a given occupation. This matrix captures patterns of co-occurrence and correlation that may not be fully captured by text embeddings alone. For a given resume, we first identify the most semantically similar occupations using content-based scores, and then aggregate their usage patterns to form a collaborative prior.

The collaborative filtering score for each element is calculated as a weighted average of its usage across the most similar occupations, with weights proportional to semantic similarity. Formally, this corresponds to a weighted mean where similarity scores act as weights and usage values as inputs. This method gives greater influence to occupations that are more closely aligned with the resume, while still incorporating broader occupational trends. The resulting collaborative score reflects how characteristic each element is for occupations similar to the resume, providing structural guidance that helps distinguish occupation-specific requirements from generic skills.

3.3 Fairness-Weighted Recommender

To address exposure imbalance, we assign group-based fairness weights to each company-size category. Small and medium companies receive a modest boost in visibility, while large companies are slightly down-weighted. During ranking, each job's similarity score is adjusted using the weight associated with its company-size group.

Formally, the adjusted relevance score is defined as:

$$\text{fair\_score} = \text{similarity} \times w_g, \tag{1}$$

where w_g represents the fairness weight for company-size group g.

In practice, this approach:

- reduces the dominance of large-company postings,
- improves representation for small and medium companies,
- maintains semantic relevance while improving group-level balance.

This method is simple, interpretable, and aligns well with fairness-aware ranking techniques used in real-world systems.

3.4 Fair + Diversity Constraint Recommender (Fair+Dense Recommender)

Although fairness weighting improves exposure balance at the group level, large companies may still dominate rankings through repeated appearances of multiple job postings. This happens because group-based weights do not explicitly limit redundancy from individual employers.

To mitigate this issue, we introduce the *Fair+Dense* recommender, which extends fairness-weighted ranking with an explicit diversity constraint. Specifically, we enforce a per-company cap during reranking, allowing no more than two job postings from the same company to appear in the top-K

recommendations. Once a company reaches this cap, additional postings from that employer are skipped in favor of the next highest-ranked eligible job.

This dense constraint offers several advantages:

- it prevents repeated dominance by large employers with many similar postings,
- it increases employer diversity by encouraging broader company representation,
- it preserves fairness improvements while expanding recommendation variety.

The Fair+Dense method is implemented as a lightweight post-processing step on top of fairness-weighted scores, making it easy to integrate into existing ranking pipelines. A diagram illustrating the reranking process can be added here for clarity.

4 Experimental Results

We evaluate the baseline, fairness-weighted, and Fair+Dense recommenders using a fixed set of representative seed jobs sampled across the dataset.

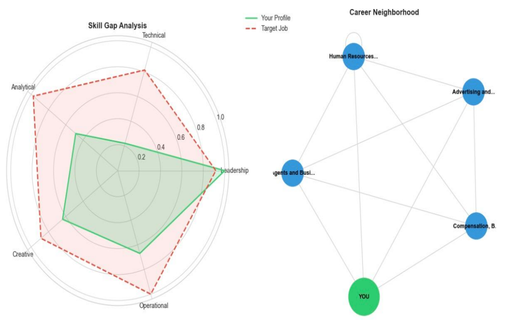
4.1 Dataset

Phase 1 experiments use two aligned data sources: a large collection of professionally written resumes and standardized occupational profiles obtained from structured occupational databases. The resume dataset covers a wide range of industries and career stages and is preprocessed to extract clean and meaningful text content. The occupational dataset contains detailed information on skills, tasks, work activities, and knowledge areas for hundreds of occupations, which are combined to form unified occupation profiles. These two datasets are carefully aligned to support a systematic evaluation of how well resumes are matched to occupations.

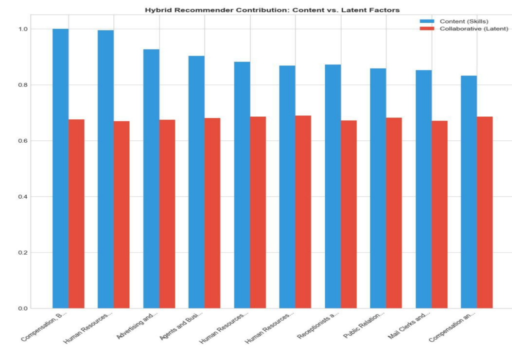
In Phase 2, we conduct experiments on a real-world dataset of data-science job postings collected from multiple companies of different sizes. The raw dataset includes job titles, salary ranges, locations, listed skills, company attributes, and additional metadata. To ensure data quality and consistency, we apply a structured cleaning process in which salary ranges are converted into numeric values, skills are parsed into standardized lists, and companies are grouped into small, medium, and large categories based on employee count or revenue indicators. Job postings with missing or unparseable company-size information are removed, and skill text is normalized to support reliable embedding generation.

After preprocessing, the dataset shows a naturally imbalanced distribution across company-size groups: large companies account for approximately 52%, medium companies for 26%, and small companies for 22%. Notably, large companies tend to post more jobs and provide richer descriptions with higher skill counts, which increases similarity scores and leads to systematic overexposure in naïve recommendation models. This structural imbalance makes the dataset well suited for fairness-aware ranking analysis, as it allows us to study how ranking algorithms may unintentionally amplify visibility disparities across employer groups.

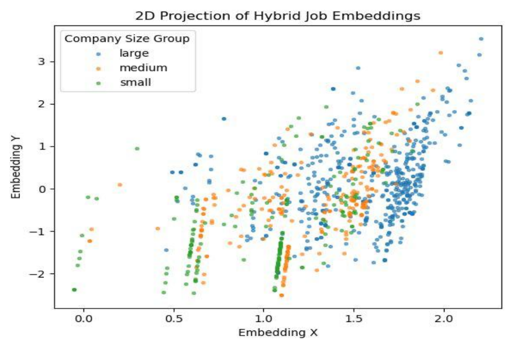
Figure 1: Dataset characteristics across company size groups. (Left) Distribution of job counts by company size. (Middle) Salary distribution by company size group. (Right) Skill count distribution by company size group.



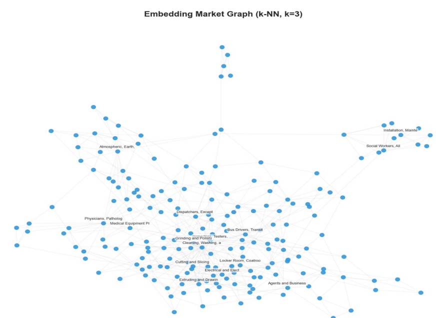
(a) Skill gap analysis comparing a candidate profile with target job requirements.



(b) Career neighborhood graph illustrating related occupations in embedding space.



(c) Two-dimensional projection of hybrid job embeddings, colored by company size group.



(d) Embedding market graph built using k-NN ($k = 3$), showing local neighborhood structure.

Figure 2: Visual diagnostics of the hybrid recommendation model. The top row highlights skill alignment and career neighborhood structure, while the bottom row presents global embedding geometry and local connectivity induced by the hybrid representations.

4.2 Embedding Generation

The embedding generation stage converts both occupation profiles and resume text into dense vector representations using advanced sentence transformer models. We use the MPNet architecture, which has shown strong performance on semantic similarity tasks by capturing contextual relationships and overall semantic meaning, rather than relying only on individual words. The model produces 768-dimensional embeddings that encode nuanced textual information, enabling accurate similarity comparisons between resumes and occupations. Embeddings are generated through a batch-processing pipeline with caching to improve efficiency, which is particularly important given the scale of occupational data with thousands of unique elements. These vector representations serve as the foundation for content-based similarity scoring as well as the initial occupation retrieval step used in the collaborative filtering component.

4.3 Metrics

We assess fairness using four exposure-aware metrics that are commonly applied in ranking-based recommendation systems. Each metric captures a distinct aspect of fairness, visibility, or diversity.

Our evaluation uses two complementary sets of metrics aligned with the two phases of the project. Phase 1 focuses on recommendation quality and occupational specificity, whereas Phase 2 evaluates fairness, exposure, and diversity in the ranked job recommendations.

Phase 1: Recommender Model To evaluate the hybrid resume–occupation recommender, we use standard information retrieval metrics that reflect both accuracy and coverage. Precision measures the fraction of recommended occupations that are relevant, while recall measures the proportion of relevant occupations that are successfully retrieved. The F1 score provides a balanced summary of precision and recall, which is particularly important given imbalances across occupations. We also examine similarity score distributions and recommendation frequency patterns to evaluate semantic alignment and identify overly generic recommendations.

4.3.1 Content (Semantic) Score

The Content Score quantifies semantic alignment between a resume and an occupation element using cosine similarity between their embedding vectors. This metric reflects how closely the contextual meaning of a resume matches the requirements of an occupation, independent of text length or vocabulary differences. Higher scores indicate stronger semantic correspondence between resume content and occupational descriptions.

$$\text{score}_{\text{content}}(r, e) = \frac{r \cdot e}{\|r\| \|e\|} \tag{2}$$

where r represents the resume embedding and e represents the occupation element embedding. Cosine similarity emphasizes directional alignment in the embedding space, making it robust to noise and variation in text size.

4.3.2 Collaborative Filtering (CF) Signal

The Collaborative Filtering (CF) signal captures structural relationships in how skills and requirements co-occur across occupations. We build an occupation–element usage matrix M, where each entry reflects the standardized importance of an element within a given occupation. For a specific resume, the CF score indicates how representative an element is among occupations that are semantically similar to the resume.

$$\text{score}_{\text{cf}}(e) = \frac{\sum_{o \in \mathcal{N}_k} \text{sim}(r, o) \cdot M(o, e)}{\sum_{o \in \mathcal{N}_k} \text{sim}(r, o)} \tag{3}$$

where $\mathcal{N}_k$ denotes the top-k occupations most similar to the resume embedding r, and sim(r, o) is the cosine similarity between the resume and occupation embeddings.

4.3.3 Hybrid Recommendation Score

The Hybrid Score combines semantic similarity and collaborative filtering signals to balance contextual relevance with occupational structure. Both scores are normalized to the $[0, 1]$ range, and the final ranking score is computed as a convex combination controlled by a weighting parameter α.

$$\text{score}_{\text{hybrid}} = \alpha \cdot \text{score}_{\text{content}} + (1 - \alpha) \cdot \text{score}_{\text{cf}} \tag{4}$$

This formulation allows the system to jointly leverage fine-grained semantic understanding and robust occupational usage patterns, producing recommendations that are more specific and reliable than those generated by either signal alone.

Model	**Precision**	**Recall**	**F1**
Baseline (MiniLM)	0.52	0.48	0.50
Weighted Skills	0.57	0.55	0.56
Weighted Skills + Tasks	0.60	0.59	0.59
Weighted + MPNet (Hybrid)	**0.63**	**0.61**	**0.62**

Table 1: Performance metrics

Phase 2: Fairness and Exposure Metrics

In Phase 2, we assess fairness and diversity using four exposure-aware metrics that are widely applied in ranking-based recommendation systems. Each metric captures a different aspect of representation, visibility, and concentration across employer groups defined by company size.

4.3.4 Selection Rate (SR)

Selection Rate measures how often jobs from a particular company-size group appear in the recommended top-K results relative to their share in the overall dataset. An SR value greater than 1 indicates that a group is over-represented in the recommendations, while a value below 1 suggests under-representation. This metric directly reflects proportional fairness at the group level and is commonly used to identify systematic exposure imbalance in recommender systems.

$$\mathrm{SR}_g = \frac{\#\ \text{recommended items from group } g}{\#\ \text{items from group } g \text{ in dataset}} \tag{5}$$

where g denotes a company-size group (small, medium, or large).

4.3.5 Rank-Aware Exposure (RAE)

Rank-Aware Exposure captures not only how frequently items from a group appear, but also their positions within the ranked list. Because items shown earlier in the ranking receive significantly more user attention, RAE assigns higher importance to top-ranked positions using a logarithmic decay function. This metric accounts for position bias and provides a more realistic measure of visibility than simple frequency-based counts.

$$\mathrm{RAE}_g = \sum_{i \in \mathcal{R}_g} \frac{1}{\log_2(i+1)} \tag{6}$$

where $\mathcal{R}_g$ represents the ranked positions of recommended items belonging to group g, and i denotes the rank position.

4.3.6 Proportional Fairness Error (PFE)

Proportional Fairness Error measures how closely the exposure distribution produced by the recommender aligns with the natural group distribution in the dataset. It computes the L_1 distance between the exposure share and the dataset proportion for each group. Lower PFE values indicate stronger alignment with proportional fairness and smaller exposure disparities across groups.

$$\mathrm{PFE} = \sum_g |E_g - D_g| \tag{7}$$

where E_g is the exposure share of group g in the recommendations and D_g is the corresponding proportion of that group in the dataset.

4.3.7 Diversity Ratio (DR)

Diversity Ratio evaluates employer diversity by measuring the fraction of distinct companies present in the recommendation list. Unlike group-level fairness metrics, DR focuses on item-level concentration and captures repeated dominance by the same employers. Higher DR values indicate broader employer representation and lower redundancy in the recommended results.

$$\mathrm{DR} = \frac{\#\ \text{unique companies in recommendations}}{\#\ \text{total recommendations}} \tag{8}$$

Together, these metrics provide a comprehensive perspective on fairness, visibility, and representation across different ranking models.

Model	Small	Med	Large
Baseline	0.74	0.54	1.49
Fair	0.89	1.31	1.05
Fair+Dense	1.10	1.52	0.85

(a) Selection Rate (SR)

Model	Small	Med	Large
Baseline	0.16	0.13	0.71
Fair	0.19	0.33	0.48
Fair+Dense	0.22	0.38	0.40

(b) Rank-Aware Exposure (RAE)

Table 2: Group-wise fairness metrics across recommendation models.

Model	PFE
Baseline	0.3868
Fair	**0.1422**
Fair+Dense	0.2452

(a) Proportional Fairness Error (PFE)

Model	DR
Baseline	0.251
Fair	0.273
Fair+Dense	**0.302**

(b) Diversity Ratio (DR)

Table 3: Overall proportional fairness and employer diversity across models.

4.4 Results

We evaluate three models using 10 representative seed jobs, each producing a top-100 recommendation list: (1) a baseline similarity-based recommender, (2) a fairness-weighted recommender, and (3) a Fair+Dense recommender that combines fairness weighting with per-company diversity constraints.

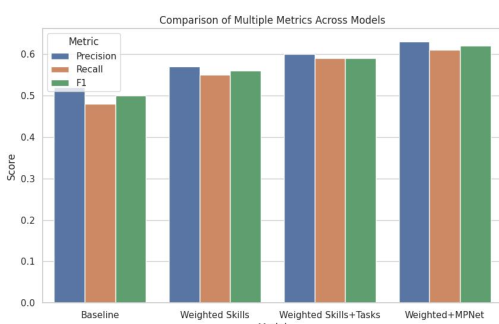


Figure 3: Baseline recommender results

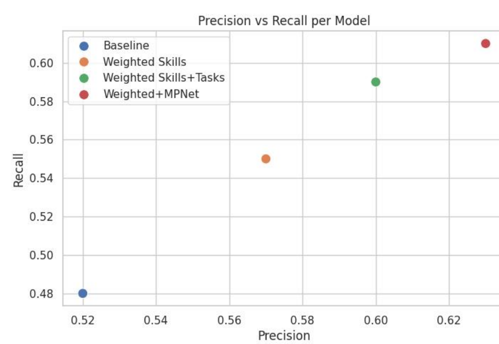


Figure 4: Fairness-aware recommender results

The results in above figures show consistent and substantial gains from the hybrid recommendation model across all evaluation metrics. By combining semantic embeddings with collaborative signals, the hybrid approach achieves an F1 score of 0.62, representing a 24% improvement over the best baseline (0.50). Precision increases from 0.52 to 0.63 and recall from 0.48 to 0.61, indicating improved relevance while reducing false positives. These gains are especially pronounced for resumes with ambiguous or transitional career profiles, where single-signal methods typically struggle.

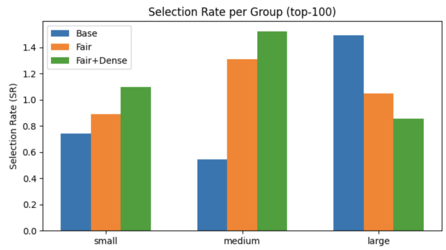


Figure 5: Selection Rate (SR) per company-size group.

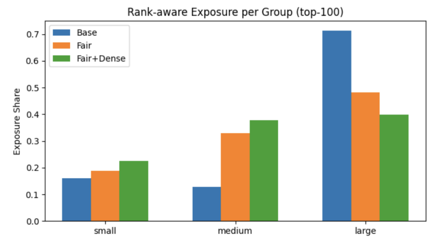


Figure 6: Rank-Aware Exposure (RAE) distribution.

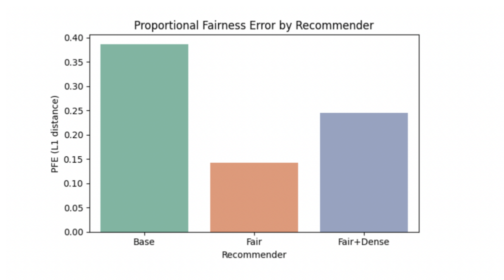


Figure 7: Proportional Fairness Error (PFE).

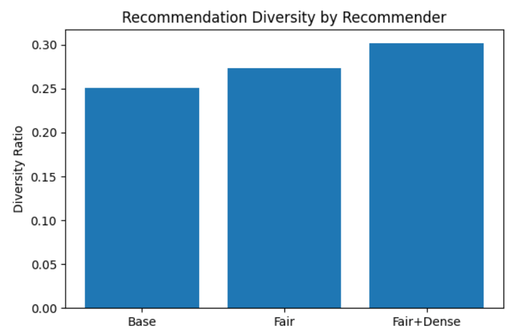


Figure 8: Diversity Ratio (DR) comparison.

Metric-Based Evaluation: We now present a quantitative evaluation of fairness and diversity using four exposure-aware metrics: Selection Rate (SR), Rank-Aware Exposure (RAE), Proportional Fairness Error (PFE), and Diversity Ratio.

Selection Rate: Figure 5 shows the Selection Rate for each company-size group. The baseline model clearly over-selects large companies and under-selects small and medium companies. Both fairness-aware approaches move selection rates closer to parity, with the Fair+Dense model showing a slight preference toward smaller employers due to the added diversity constraint.

Rank-Aware Exposure: As illustrated in Figure 6, the baseline recommender allocates a disproportionately high share of rank-aware exposure to large companies. Applying fairness weighting significantly shifts exposure toward small and medium groups, while the Fair+Dense model further smooths exposure by limiting repeated dominance at top-ranked positions.

Proportional Fairness Error: Figure 7 summarizes Proportional Fairness Error across the different models. The baseline recommender has the highest PFE, indicating weak alignment between exposure and the underlying dataset distribution. Fairness weighting reduces PFE from 0.39 to 0.14, while the Fair+Dense model slightly increases PFE due to stronger diversity constraints, yet still performs much better than the baseline.

Employer Diversity: Finally, Figure 8 presents the Diversity Ratio for each recommender. The baseline model produces the lowest employer diversity, whereas both fairness-aware methods increase the number of unique companies appearing in the recommendations. The Fair+Dense model achieves the highest diversity ratio, confirming that diversity constraints effectively broaden employer exposure.

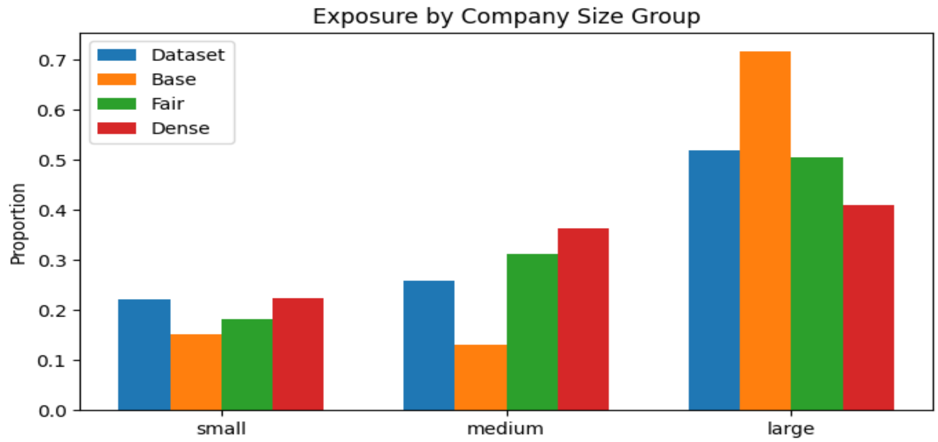


Figure 9: Proportional Fairness Error across different recommenders.

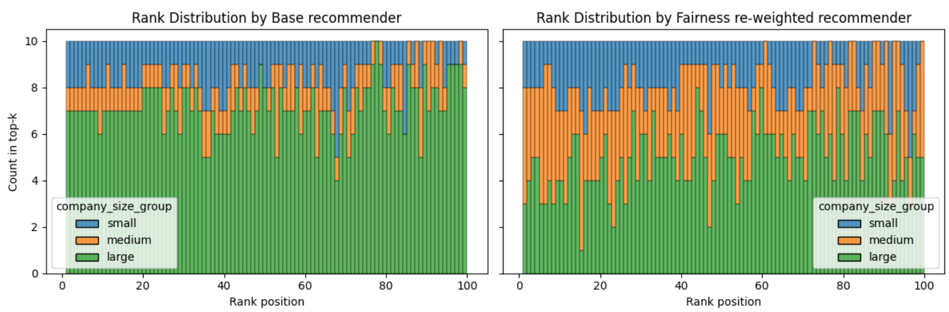


Figure 10: Rank distribution for the baseline and fairness-reweighted recommenders.

Overall Exposure Distribution. Figure 9 illustrates the overall exposure distribution across company-size groups. The baseline recommender shows strong exposure imbalance, with large companies receiving a much higher share of exposure than expected from their dataset proportion. In contrast, the fairness-weighted model redistributes exposure toward small and medium companies while still maintaining visibility for large employers. The Fair+Dense model further reduces large-company dominance by combining fairness weighting with diversity constraints, resulting in the most balanced exposure across groups.

Rank Position Analysis. Figure 10 visualizes how different company-size groups are positioned across ranking levels. Under the baseline model, postings from large companies dominate early ranks, while small and medium companies are mostly pushed to lower positions. With fairness-based reweighting, exposure becomes more evenly spread across ranks, reducing positional bias without removing large employers. The Fair+Dense model further smooths rank concentration by limiting repeated appearances from the same employers, leading to more diverse exposure throughout the ranking.

Overall, these results show that fairness weighting and diversity-aware reranking substantially reduce exposure bias while preserving relevance, producing more balanced and representative job recommendations.

5 Discussion

The Phase 1 results confirm that combining semantic embeddings with collaborative filtering leads to more accurate and occupation-specific job recommendations than relying on either signal alone. The hybrid model effectively balances contextual understanding with structural occupational knowledge, and is particularly beneficial for resumes with ambiguous or non-linear career paths.

Phase 2 results demonstrate that similarity-only ranking methods systematically overexpose large companies due to structural characteristics of the data, such as richer job descriptions and higher skill counts. Fairness weighting directly improves visibility balance at the group level, while diversity constraints reduce repeated dominance by individual employers.

A clear trade-off emerges between fairness and diversity: fairness weighting minimizes exposure disparity, whereas dense constraints maximize employer diversity. Using both together provides consistent improvements across metrics without excluding any employer group from the rankings.

6 Conclusion

We introduced a hybrid resume–occupation recommendation model that combines semantic embeddings with collaborative filtering signals to improve accuracy, specificity, and interpretability. By integrating contextual text understanding with occupational structure, the model outperforms text-only baselines and generalizes well across diverse resume types. The approach is scalable and suitable for real-world recruitment and career guidance applications.

We also proposed a fairness-aware job recommendation framework that addresses structural exposure bias in similarity-based ranking systems. Through group-based fairness weighting and diversity-aware reranking, the approach reduces the disproportionate visibility of large companies while preserving semantic relevance. Experimental results show that fairness weighting significantly lowers proportional fairness error, and that the Fair+Dense method further improves employer diversity with a modest trade-off in exposure alignment.

These findings emphasize the importance of explicitly modeling exposure fairness in labor-market recommendation systems, where ranking bias can systematically disadvantage small and medium employers. Future work may explore personalized fairness constraints, intersectional exposure definitions, and adaptive online learning methods to dynamically balance relevance, fairness, and diversity in practical recommendation pipelines.

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Code repository for this project: `https://github.com/Vishnu1721/CS483_Project`