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| **Synthetic Data for Bias Mitigation (BIAS Project)** | |
| Type of work: **Term Project 2** | |
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3. **Abstract:**

The Horizon Europe project BIAS explores how societal biases manifest in AI systems and large language models, particularly within the context of the labor market. As part of this initiative, this subproject focuses on bias detection and mitigation in the generation and evaluation of CVs and cover letters. The primary objective is to develop a modular synthetic data generation framework that enables the systematic creation of job application documents—including job ads, CVs, and cover letters—while carefully controlling for demographic variables, linguistic patterns, and skill profiles. This synthetic dataset is intended to serve as a benchmark for evaluating and improving fairness in downstream natural language processing (NLP) applications.

In this context, synthetic data for bias mitigation refers to the deliberate generation of artificial application materials that allow for fine-grained manipulation of attributes such as gender, ethnicity, age, and socio-economic background. This ensures that models trained or tested using such data do not perpetuate or exacerbate existing societal biases. The framework supports the injection of sensitive terms (e.g., “female,” “disabled”) and proxy terms (e.g., “parental leave,” “youth leader”) into the documents to test the model’s predictive behavior in response to these variables. These terms are often correlated with demographic markers and may trigger unintended discriminatory outcomes, making them critical for bias stress-testing and mitigation strategies.

**Keywords**- NLP, Synthetic Data, RAG, data augmentation, bias mitigation, sensitive attributes, proxy terms, machine learning

1. **Introduction:**

The integration of artificial intelligence (AI) into recruitment processes has transformed how organizations evaluate job applicants. While AI offers scalable tools for resume screening and candidate evaluation, growing evidence suggests that these systems risk perpetuating or amplifying **gender biases** embedded in training data and model architectures ([Fabris et al., 2025).](https://dl.acm.org/doi/10.1145/3696457) This is particularly critical during the early stages of hiring, where automated models interpret CVs and cover letters—documents that inherently reflect individual self-presentation strategies shaped by societal norms ([Marti Marcet, 2023](https://studenttheses.uu.nl/bitstream/handle/20.500.12932/44294/Applied_Data_Science_Thesis_Sara.pdf)). AI systems trained on real-world data are vulnerable to perpetuating historical societal biases, particularly gender biases embedded in language and occupational roles. This study is part of the broader Horizon Europe BIAS project, which aims to examine and mitigate such biases in AI systems deployed within labor market contexts.

2.1. Gender Disparities in Training Data

One of the foundational challenges in mitigating bias in AI hiring systems is the representational imbalance in training datasets. This issue is evident in the widely used BiasBios dataset—a corpus of over 390,000 biographies labeled with gender and occupation, contain embedded demographic skews that can influence downstream decision-making. As visualized in Figure 1 and 2, a disproportionate representation exists between male and female entries, with 53.9% identified as male (213,543) and 46.1% as female (182,646). While this may seem modest, such imbalances become more problematic when they intersect with gender-stereotyped occupational labels, where roles like “nurse” or “yoga teacher” show over **80% female representation**, while positions such as “software engineer” or “rapper” are male-dominated ([Mansouri et al., 2024](https://www.mdpi.com/2673-2688/5/1/19); [Mihaljević et al., 2022](https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0274312))

Further disaggregation by profession (Figure 3) illustrates that certain occupations are strongly gender-coded in the dataset. For instance, female representation is overwhelmingly dominant in roles such as:

* Dietitian (93%)
* Nurse (91%)
* Yoga Teacher(85%)
* Interior Designer (81%)

In contrast, male-dominated professions include:

* Rapper (90%)
* Dj(86%)
* Surgeon (85%)
* Software Engineer (85%)

These imbalances are more than representational; they shape model behavior. For instance, ([Njoto et al.,2022](https://aclanthology.org/2022.nlpcss-1.15/)) illustrate that pretrained NLP models frequently learn **semantic associations** between gendered terms and specific job roles, leading to **disparate treatment of candidates** in algorithmic hiring pipelines. These disparities reinforce stereotypical gender-role associations and pose serious risks when used in training AI systems for job screening or candidate recommendation. Without intervention, models trained on such data are likely to learn and reproduce biased mappings between gendered language cues and professional competence.

A screenshot of a computer

AI-generated content may be incorrect.

**Figure 1:** Gender distribution on whole dataset.

A graph with a blue and pink bar chart

AI-generated content may be incorrect.

**Figure 2:** Gender distribution in BiasBios dataset

A graph with different colors and text

AI-generated content may be incorrect.

**Figure 3:** Gender Representations in various Professions

2.2. Synthetic Data for Bias Mitigation

To counteract such biases, synthetic data generation has emerged as a promising solution ([Peña et al., 2023](https://link.springer.com/content/pdf/10.1007/s42979-023-01733-0.pdf); [Frazzetto, 2025](https://tesidottorato.depositolegale.it/bitstream/20.500.14242/202137/1/tesi_Paolo_Frazzetto_fin.pdf)). This project proposes a modular synthetic data generation framework for constructing balanced and bias-aware training and evaluation datasets. Specifically, our framework focuses on the systematic generation of job application materials We generate artificial CVs and cover letters that allow controlled variation of:

* Demographic attributes (e.g., gender markers, names)
* Linguistic features (e.g., assertive vs. communal tone)
* Sensitive/proxy terms (e.g., “maternity leave”, “first-generation college graduate”)

The synthetic data are designed to vary along critical demographic dimensions while preserving semantic and professional coherence. These terms are not inherently biased, but their correlated associations with protected characteristics make them essential for bias stress-testing. This aligns with recent approaches in the literature where **counterfactual generation** is used to test and mitigate model responses ([Kumar et al., 2023](https://ceur-ws.org/Vol-3490/RecSysHR2023-paper_7.pdf)).

The objectives of this study are threefold:

* Quantify the extent of gender bias in existing datasets used in NLP hiring systems.
* Develop a reproducible pipeline for generating demographically controlled synthetic application materials.
* Evaluate the behavior of existing NLP models against this synthetic dataset to assess and mitigate their bias responses.

By leveraging controlled synthetic data and fairness-driven evaluation protocols, this work contributes to the development of transparent, accountable, and equitable AI tools in recruitment pipelines. This approach is aligned with emerging principles of **Human-Centered AI** ([Bartl et al., 2025](https://dl.acm.org/doi/full/10.1145/3700438)) and contributes to a growing body of work advocating for **accountable AI in employment technologies** ([Chaturvedi & Chaturvedi, 2025](https://arxiv.org/abs/2504.21400); [Serna et al., 2023](https://link.springer.com/content/pdf/10.1007/s42979-023-01733-0.pdf)). Moreover, it provides a scalable blueprint for testing bias sensitivity in downstream NLP applications, especially in high-stakes domains.

1. **Materials and Methods:**
2. **Results:**
3. **Discussion:**
4. **Bibliography:**

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1. **Declaration of Authorship**

I hereby certify that I composed this work completely unaided, and without the use of any other sources or resources other than those specified in the bibliography. All text sections not of my authorship are cited as quotations and accompanied by an exact reference to their origin.

Place, date: BFH, Biel

Signature: Shilpi Garg

A diagram of embedding model

AI-generated content may be incorrect.

Source: [A Crash Course on Building RAG Systems – Part 1 (With Implementation)](https://www.dailydoseofds.com/a-crash-course-on-building-rag-systems-part-1-with-implementations/), [Akshay Pachaar](https://www.dailydoseofds.com/author/akshay/), [Avi Chawla](https://www.dailydoseofds.com/author/avi/)