# Detecting Gender Bias in English-German Translations using Natural Language Processing

Bachelor's Thesis

for the attainment of the academic degree Bachelor of Science (B.Sc.)
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**Abstract**

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Berlin, den 01. Januar 2099

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*(Unterschrift des Verfassers)*

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# List of Abbreviations

**EN-DE** English-to-German

**GFL** Gender-Fair Language

**mBERT** Multilingual BERT

**MT** Machine Translation

**NLP** Natural Language Processing

**NMT** Neural Machine Translation

# 1 Introduction

Machine Translation (MT) helps millions of people communicate across languages, in daily life and in areas like healthcare, law, and business (Kappl, 2025). Services like Google Translate handle over 200 million users every day (Prates et al., 2019; Shrestha and Das, 2022). It is a fast-growing market. A report by SkyQuest (2025) valued it at 980 million USD in 2023, with projections reaching 2.78 billion USD. New and more advanced translation models keep appearing, and many of them are free to use. As a result, MT tools are now used to translate large volumes of content across domains.

With this widespread use, the output of MT systems increasingly shapes how people receive and interpret information. But automatic translations are not neutral. There is growing concern about the social effects of biased translations. One key issue is gender bias. MT systems are often trained on large datasets that reflect social norms and stereotypes. If the data contains gender bias, the system will likely reproduce it (Cho et al., 2019; Soundararajan and Delany, 2024; Smacchia et al., 2024).

A common case is the use of gendered terms in translations of gender-neutral input. For example, the English sentence "The nurse is hard-working" does not say anything about gender. But a translation system may render it in German as "Die Krankenschwester ist fleißig," which uses the explicitly feminine term *Krankenschwester*. Similarly, "The surgeon is hard-working" may become "Der Chirurg ist fleißig," using the masculine form *Chirurg*. These choices add gendered assumptions that were not present in the original. Such patterns are not just technical side effects. They can reinforce stereotypes, especially when they appear in job ads, reports, or other public texts.

## 1.1 Motivation

### 1.1.1 Social and Ethical Importance of Addressing Gender Bias

Academia has come to the consensus that MT systems do default to male pronouns when gender in the source sentence is ambiguous (Prates et al., 2019; Cho et al., 2019; Rescigno and Monti, 2023). In addition, translations often reflect traditional roles, like associating "nurse" with women and "surgeon" with men. This can affect people's perceptions of jobs and reinforce gender roles.

When used in formal contexts like job descriptions or reference letters, biased translations can shape how a candidate is perceived. If a system always assigns male pronouns to leadership roles and female terms to caregiving roles, it may disadvantage those who do not match those stereotypes (Bolukbasi et al., 2016). This is not just a personal issue. It can reduce diversity and go against international standards. Organizations like the United Nations, UNESCO, and the European Union stress the importance of gender equality and inclusive language, making gender equality one of the 17 Sustainable Development Goals for 2030 (Sczesny et al., 2016; United Nations, 2023).

Language also shapes thought. Research shows that readers often interpret masculine forms as male-specific, even if they are supposed to be generic (Sczesny et al., 2016). Inclusive forms are more common in official documents, less so in everyday language. However, exposure matters. Frequent use of fair language makes it feel more normal. Detecting and addressing bias in MT can support this shift.

### 1.1.2 Why Detection Systems Are Needed

Current research on this topic tends to focus more on the quantitative measurement of gender bias (Rescigno and Monti, 2023; Barclay and Sami, 2024; Smacchia et al., 2024). Common methods include counting gendered forms in outputs and comparing them to demographic baselines or human expectations (Rescigno and Monti, 2023; Prates et al., 2019; Savoldi, Papi, et al., 2024). These are useful, but they do not help users identify specific biased translations in real-time. Evaluations are not enough for accountability.

Other domains, like facial recognition, have already seen progress in active bias detection. For example, Schwemmer et al. (2020) showed that systems tend to label women more accurately if they match stereotypical appearances (e.g., long hair). Some models even linked female images to words like “kitchen” or “cake” based on bias patterns in training data. For MT, a detection layer is still missing. Without such tools, biased translations are likely to spread unnoticed. A detection system could flag potential bias in real time, improving transparency and encouraging more careful use.

## 1.2 Problem Statement and Research Questions

**DRAFT NEED TO REWRITE AFTER IMPLEMENTATION** This thesis focuses on gender bias in English-to-German (EN-DE) MT. This language pair is widely used in research, with many open datasets and high-quality models available. It also involves a grammatical shift: English has limited gender marking, while German assigns gender to many nouns and pronouns. This structural difference makes gender bias more visible and easier to study in the translation outputs.

The core problem boils down to the significant bias towards the masculine form in EN-DE MTs, sometimes consituting 93-96% of translations for isolated words (Lardelli et al., 2024). These outputs often reflect social stereotypes rather than objective translations, yet current systems offer no mechanism to detect or signal when such bias occurs (Rescigno and Monti, 2023). To address this, this thesis deploys a blackbox approach to explore how fine-tuning a pre-trained multilingual BERT model can help detect gender bias in MT outputs. The model takes an input sentence and its corresponding German translation and predicts whether the translation introduces gender bias.

The translation system used is Opus-MT, an open-source neural MT model. It is widely used in research, supports EN-DE translation, and is trained on real-world corpora, making it suitable for studying translation bias (Tiedemann and Thottingal, 2020). Translations are then passed through BERT, trained on a dataset I have constructed by combining and adapting several existing datasets from other researchers. The classifier is lightweight and efficient, aiming for transparent behavior and easy integration into other tools (Devlin et al., 2019). The final tool highlights biased parts in a simple web demo. The goal is not a perfect classifier but a working prototype that shows how such detection could be integrated into translation workflows.

The main research question is therefore: **"How can a NLP-based binary classification model detect gender bias in English-German translations?"**.

## 1.3 Scope

**WRITE AFTER IMPLEMENTATION PART** This thesis focuses only on EN-DE MT. Other language pairs are out of scope.

## 1.4 Limitations

**WRITE AFTER IMPLEMENTATION PART** It becomes especially difficult to detect when sentences contain multiple subjects, indirect references, or ambiguous pronouns. For example, as Barclay and Sami (2024) explain, the sentence “He went to see her mother” clearly implies three people, while “He went to see his mother” could refer to either two or three. These types of structures introduce ambiguity that makes annotation and evaluation much harder. Creating a dataset that captures such linguistic complexity would require significant effort and careful control of variables. One broader limitation in building datasets for complex scenarios with multiple subjects is the difficulty of isolating the influence of each gendered entity (Lardelli et al., 2024). When working with natural language sources, it becomes hard to tell what caused the bias in the translation. Because of this, the focus of this thesis is on simpler sentence structures with a single subject. This makes it easier to identify and explain bias patterns. It also fits the intended use case: translating business texts like job advertisements or reports, which rarely involve multiple nested clauses or ambiguous pronouns.

## 1.5 Overview of Chapters

**WRITE AFTER IMPLEMENTATION PART**

# 2 Theoretical Background and Related Work

Detecting gender bias in English-German (EN-DE) translations using Natural Language Processing (NLP) requires an understanding of what gender bias means in this context, how it appears in MT, and how it has been studied so far. To build this foundation, this chapter (1) defines the concept of gender bias in machine translation, (2) outlines its relevance, (3) identifies gaps in current research, and (4) justifies the technical design decisions made in this project.

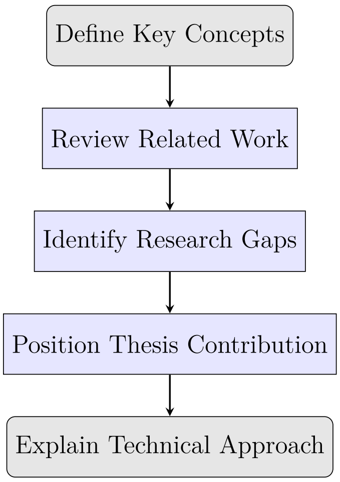


Figure 1: Overview of Chapter 2 Structure.

## 2.1 Definitions

### 2.1.1 Natural Language Processing vs. Machine Translation

**NLP** refers to the development of machine systems that can process and generate human language. The goal is to mimic and understand it as fluently as possible (Smacchia et al., 2024; Ullmann, 2022). Common applications are chatbots, translation tools, speech recognition, and image captioning.

**MT** is a direct application of NLP. It enables the automatic translation of text from one language to another (Lin and Chien, 2009). Over time, MT systems have developed from rule-based and statistical approaches, which depend on hand-crafted grammar rules or aligned sentence data, into more adaptable neural models (Chakravarthi et al., 2021).

Most modern systems, such as Google Translate and DeepL, rely on neural machine translation (NMT) (Y. Wu et al., 2016; DeepL, 2021). These models are trained on large collections of translated texts. They learn to represent the meaning of entire sentences as mathematical structures, enabling more fluent and accurate translations. Unlike earlier approaches, NMT systems take the full sentence context into account, which helps reduce errors and improves the handling of ambiguous or idiomatic language (Y. Wu et al., 2016). Throughout this work, all MT systems referenced or applied are neural models.

### 2.1.2 Bias in Society and its Manifestations

Bias refers to a tendency to favour or disadvantage certain individuals or groups based on preconceived ideas. It often comes from stereotypes, which are fixed and oversimplified ideas about a group. While stereotypes describe assumptions about people, bias influences actual behavior and treatment.

Bias takes many forms and can be based on characteristics such as age, disability, gender, ethnicity, religion, or sexual orientation (Ullmann, 2022). These biases often originate from longstanding cultural and historical beliefs about the expected behavior of different groups.

This study focuses specifically on gender bias. It is particularly prominent in machine translation due to the influence of gendered language. Elements such as gendered terms, occupational roles, and grammatical patterns can affect translations and often perpetuate stereotypes.

Drawing on key studies that examine gender bias in EN-DE MT (Ullmann, 2022; Rescigno and Monti, 2023; Lardelli et al., 2024; Kappl, 2025), such bias typically manifests in the following forms:

#### Defaulting to Masculine Forms

In both singular and plural contexts, the *generic masculine* refers to the default use of the masculine grammatical gender. For example, the sentence "Die Studenten sind im Hörsaal" (translation: "The students are in the lecture hall") uses the masculine plural form to refer to a group of students regardless of their gender.

It is commonly used in spoken German and other gendered languages (Lardelli et al., 2024; Schmitz, 2022), although research has consistently shown that the generic masculine creates a male bias in mental representations, leading readers or listeners to think more of male than female examples (Sczesny et al., 2016).

#### Reinforcement of Stereotypes

The gendered language patterns discussed earlier reflect broader social beliefs about men's and women's roles in work and family life. Although many of these roles no longer reflect reality, they continue to shape judgments about people's abilities and personalities. This often leads to correspondence bias, where traits are inferred based on behavior or circumstances (Godsil et al., 2016). Such stereotypes are reinforced by media, including television and advertising, and influence how language is used and understood.

One common result of this is stereotypical job associations. People often link roles like doctors or pilots with he/him pronouns, and roles like nurses or flight attendants with she/her pronouns (Shrestha and Das, 2022). Prates et al. (2019) also found clear patterns in how gender is associated with certain traits. Adjectives like "shy," "happy," "kind," and "ashamed" are often linked to women, while words like "arrogant," "cruel," and "guilty" are more often linked to men.

### 2.1.3 Gender Bias in Machine Translation

A clear definition of gender bias in MT does not exist, nor is there a standard method to identify indicative features in text (Barclay and Sami, 2024), which leads this study to use a simple rule-based definition to determine when a translation is gender biased.

- A gender-ambiguous subject in the source text is translated with a gendered term, often defaulting to the generic masculine (e.g., doctor → Arzt) or reflecting stereotypical gender roles (e.g., nurse → Krankenschwester).
- A gendered subject in the source text is assigned an incorrect gender in the translation, leading to semantic inconsistency (e.g., my mother is an engineer → meine Mutter ist ein Ingenieur).

This does not mean that all other cases are truly "unbiased". I will refer to anything that does not fall under these two cases as "neutral". This includes, but is not limited to:

- Sentences with no gendered terms, like "The weather is nice".

- Accurate translations of gendered input, like "The woman is a coder" → "Die Frau ist eine Programmiererin".
- The use of gender-fair alternatives (see subsection 2.2.6).

| **Biased Translation** | **Neutral/Fair Translation** |
|---|---|
| Gender-ambiguous source is translated with a gendered term. | Gender ambiguity is preserved in the translation. |
| Gendered subject is assigned an incorrect gender. | Gender in the translation matches the gendered subject. |
| — | Use of gender-fair language alternatives (see subsection 2.2.6). |

Table 1: Summary of gender bias scenarios in translation (original compilation).

## 2.2 Related Works

While gender bias in MT has received increasing attention, research on the EN-DE language pair remains limited. Building on the earlier definitions, this part reviews relevant research to show how the field has approached the problem and where important gaps remain.

### 2.2.1 Literature Search Process

For the literature review I combined incremental and conceptual literature review methods, where each source led to the identification of next. Based on this progression, I identified key concepts and used them to organize and interpret the literature, aligning with a conceptual approach. The structure followed the qualitative Information Systems framework by Schryen (2015) and was further informed by Shrestha and Das (2022) and Savoldi, Bastings, et al. (2025), who both conducted systematic reviews on gender bias in ML and MT respectively.

#### Search Sources and Tools

Sources were primarily searched on Google Scholar and Perplexity, which served as an additional search engine. Prompts and outputs from Perplexity have been saved and are included in the appendix. To organize and manage the collected sources, Zotero was used throughout the process.

### Literature Review Framing

The four research aims were turned into key concepts, which are defined in Table 2. Key search terms consisted of *gender bias*, *machine translation*, *AI*, *machine learning*, *German*, *stereotypes*, and *detection*, which were combined with *AND/OR*. The focus was on literature published between 2019 and 2025 to maintain relevance and currency, while foundational and definitional works from earlier periods were selectively included. The initial search for the term *gender bias in machine translation* returned over 18,000 results. Through my iterative selection process, this was narrowed down to 34 core sources.

| **Key Concept** | **Description** |
|---|---|
| Defining Gender Bias in MT | Defines the core concept of gender bias in MT, including common bias patterns like gendered term insertion and incorrect gender assignments. Sets the conceptual foundation for the thesis. |
| Relevance and Existing Research | Establishes the importance of studying gender bias by reviewing related work. Highlights key findings and their implications for fairness. |
| Research Gaps and Open Challenges | Identifies the main gap: the absence of reliable detection systems for gender bias in EN-DE MT. Discusses the lack of a shared fairness definition and limitations in existing datasets. |
| Technical Design and Implementation | Explains the theoretical background and fundamental principles necessary to understand the implementation. Covers the underlying concepts that guide design choices and system functionality. |

Table 2: Key concepts relevant to this thesis.

### Citation Tracking

Backward citation searching involved reviewing references cited by selected papers, prioritizing frequently cited and foundational works relevant to gender bias in MT. Forward citation searching used Google Scholar's "cited by" function to identify newer research citing those key papers. Filtering with specific terms (e.g., *German* and *machine translation*) was applied during forward search to maintain focus. Beyond these systematic methods, I also included supplementary sources when needed while writing. These consist of contextual references, statistics, or secondary citations that support specific points but were not part of the core conceptual or methodological framework. Supplementary sources were defined as materials identified outside the systematic search, such as papers found through backward citations or targeted queries for statistics and news, which provided support for subordinate arguments without being central to the study's theoretical or analytical structure.

#### Selection Criteria and Screening Process

Titles and abstracts were manually screened to select relevant studies. Inclusion required sources to specifically address gender bias in MT, provide examples or discussions of gender-related errors, or explain the significance of gender bias in this context. Sources also had to be available in full text without access restrictions. Exclusion criteria filtered out studies focusing on general NLP bias without a direct link to MT, non-gender biases, and highly technical papers lacking contribution to the general understanding of gender bias or that did not provide additional knowledge beyond what was already found in previously published papers. Full texts were reviewed after initial screening to confirm relevance and extract insights. Redundant sources not providing new perspectives aligned with the thesis goals were excluded.

| **Inclusion Criteria** | **Exclusion Criteria** |
|---|---|
| Addresses gender bias in MT | Focuses on general NLP bias without link to MT |
| Provides examples or discussion of gender-related errors | Covers non-gender-related biases |
| Explains the significance of gender bias in MT | Highly technical with no added general insight |
| Available in full text without access restrictions | Redundant or not contributing new perspectives |

Table 3: Selection criteria for literature review.

### 2.2.2 Foundational studies

The existence of gender bias in MT is well-documented. First mentions of this issue date back to over a decade ago, having been recognized by a paper by Schiebinger in 2014. Since then, there has been a general increase in research papers focusing on this topic, especially between 2019 and 2023 (Savoldi, Bastings, et al., 2025).

Prates et al. (2019) conducted a large-scale study using Google Translate to translate sentences like "[Gender-neutral pronoun] is an engineer" from twelve gender-neutral languages into English. The results showed a strong bias toward male pronouns, especially in STEM occupations. This could not be explained by real-world labour statistics, pointing instead to imbalances in the system's training data. The study received wide media attention, leading Google to change their translation policy: Google Translate began showing both feminine and masculine forms for ambiguous inputs (Google, 2018) (see Figure 10).

Building on this, Stanovsky et al. (2019) created WinoMT, a benchmark for evaluating gender bias in English-to-multilingual translations. It focused on occupations in contexts designed to challenge stereotypes. The study found that systems were more accurate for stereotypical gender roles but struggled in non-stereotypical cases, confirming the trends observed by Prates et al. Together, these studies helped spark the ongoing research interest in gender bias in MT.

### 2.2.3 Biased Data Leading to Gender Errors

According to Ullmann (2022), translation errors often stem from biases present in the training data. The MT systems learns gender associations from word co-occurrences, such as “doctor” with masculine pronouns, causing incorrect or inserted gender in translations. It also amplifies existing biases during training like linking cooking predominantly with women, which leads to gendered outputs not supported by the input. Due to the large size of training corpora, manual inspection is impossible. When a model is trained on hundreds of billions of tokens, it may unknowingly absorb and replicate harmful or offensive content, reinforcing patterns that lead to biased translations (Ullmann, 2022).

### 2.2.4 Ongoing Impact of Gender Bias in Machine Translation

These biases in MT systems do not only cause translation errors but also have wider social consequences. They can lead to representational harm by repeatedly portraying certain genders in limiting or stereotypical ways (Stanczak and Augenstein, 2021). Since these biased outputs can re-enter the training data and influence future MT models, the cycle of biased representation continues and reinforces itself in society, creating a regressive feedback loop.

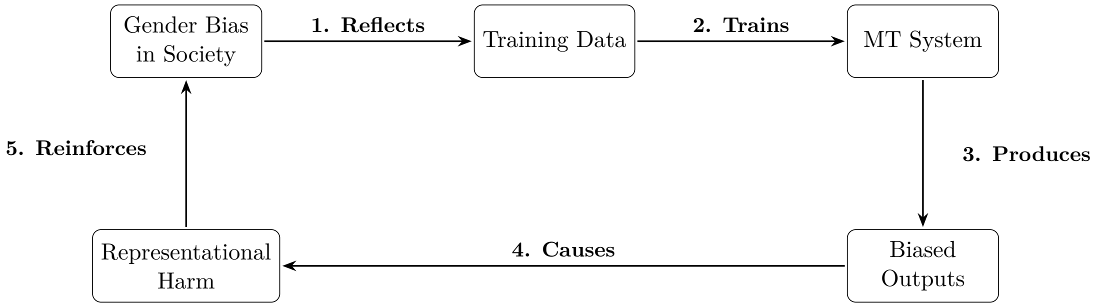


Figure 2: Regressive feedback loop of gender bias in MT.

The generic masculine in particular leads to inaccurate and unfair representations of gender in translated text. Rescigno and Monti (2023) observed a predominance of masculine forms in translation outputs (approximately 90% in Google Translate and 85–88% in DeepL for EN-IT and EN-DE), even when the original sentences contained relatively few masculine references. This shows that the bias is not minor but occurs quite heavily in those systems.

It also contributes to the invisibility of women in male-dominated professions (Kappl, 2025). Studies show that biased language in machine-generated text, such as children's stories or job ads, can influence how young people view themselves (Soundararajan and Delany, 2024; Kappl, 2025). It may shape their interests, hobbies, and career choices. This is especially visible in STEM fields (Prates et al., 2019), where stereotypes are more persistent. When job descriptions or mock interviews use gender-exclusive pronouns, women report feeling less belonging, lower motivation, and weaker identification with the role (Godsil et al., 2016). Many self-select out of applying, shrinking the female talent pool and reinforcing gender gaps in the workforce.

Research also shows that using Gender-Fair Language (GFL) like "she and he" or "one" can improve how women respond to job ads. It reduces stereotype threat and helps them engage more positively with opportunities (Godsil et al., 2016).

Furthermore, a study by Savoldi, Papi, et al. (2024) measured how much effort people need to fix biased translations. They used metrics like the time it took to edit and how many edits were needed, based on human-targeted error rate. The results showed that fixing translations with feminine forms took almost twice as long and required four times more edits than those with masculine forms.

As a result, biased translations lead to higher economic costs and a quality gap that disproportionately affects women. Savoldi, Papi, et al. (2024) argued that current automatic bias metrics miss these human impacts. They called for better evaluation methods that reflect what users actually experience.

### 2.2.5 Linguistic Challenges in English-German Translation

Although both English and German originate from the Indo-European language family (Baldi, 2008), they have different characteristcs. English does not assign grammatical gender to nouns. The article "the" is used universally, independent of what it refers to. On the contrary, German assigns one of three grammatical gendered articles to nouns: "der" (m), "die" (f) and "das" (n). The form or ending of a noun may also change depending on its grammatical gender. While English has a few gendered word pairs, such as "actor" (m) and "actress" (f), gender distinctions in German apply broadly across the entire noun system. "Der Student" refers to a male student, whereas "die Studentin" refers to a female student.

Note that grammatical gender has no connection to societal or biological gender. It is a rule of the language rather than a reflection of identity. For example, the German word Mädchen (girl) is grammatically neuter and takes the article "das". This is not because the referent lacks gender, but because the suffix "-chen" automatically assigns neuter gender. Grammatical gender in German follows structural rules, even when they contradict real-world gender associations.

### 2.2.6 German Gender-Fair Language

GFL refers to the use of language that treats all genders equally and aims to reduce stereotyping and discrimination (Sczesny et al., 2016). Three common approaches to plural mentionings in German are:

- **Gender-neutral rewording:** This uses neutral terms instead of gendered nouns, e.g., *die Studierenden lernen.* A challenge for this version is that neutral alternatives do not exist for every noun and cannot be consistently applied (Lardelli et al., 2024).
- **Gender-inclusive characters:** This combines masculine, feminine and non-binary forms by using a character like *, :, or _, e.g., *die Student*innen lernen.* This method is consistent but may interrupt reading flow and lacks standardization (Lardelli et al., 2024).
- **Pair form:** This names both gender forms, e.g., *die Studentinnen und Studenten lernen.* It is currently the most used GFL form in German (Waldendorf, 2024), briefly surpassing the star and colon characters as seen in Figure 3.

These examples apply when the gender of the subjects is ambiguous. But when gender is known, especially in singular mentions, the generic masculine should be avoided. However,

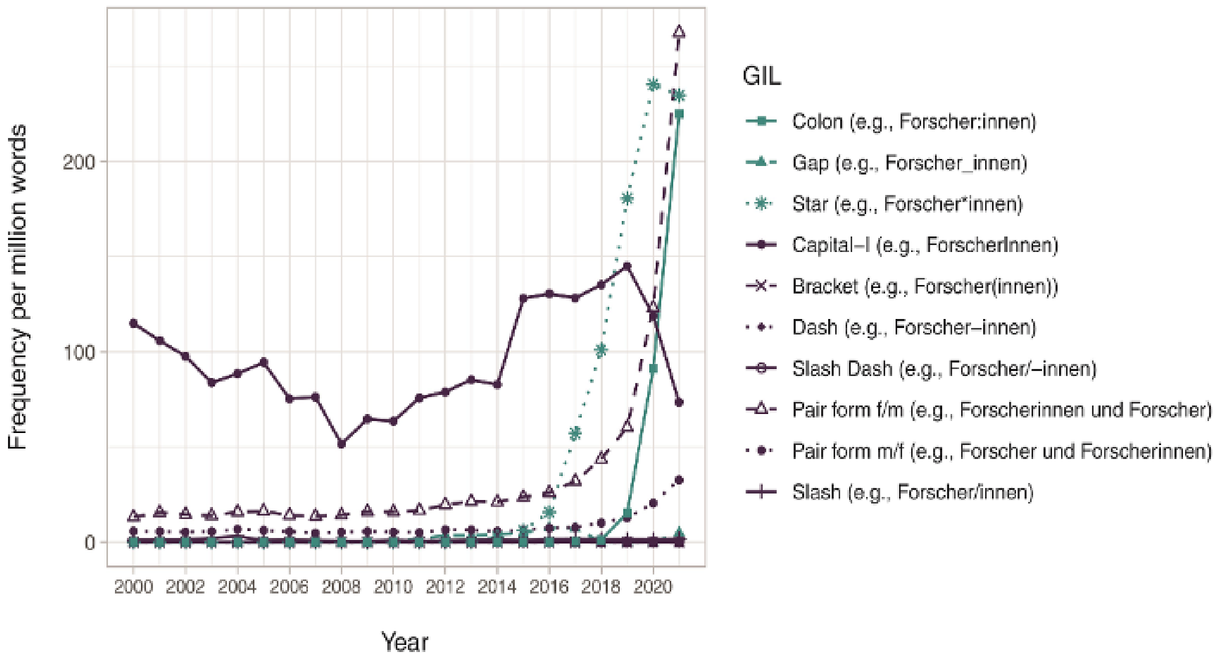


Figure 3: Frequency of different types of gender-inclusive language. Source: Waldendorf (2024) p. 367.

in the same way as gender bias has no clear definition, there is no agreed standard for GFL (Lardelli et al., 2024; Savoldi, Bastings, et al., 2025). "Fairness" therefore heavily depends on personal views, culture, and context, which raises ethical questions about debiasing systems.

#### Challenge of Integrating Gender-Fair Language into NLP

The use of GFL has increased in recent years (Waldendorf, 2024), but it remains generally low. This results in a scarcity of relevant linguistic data. Few datasets include GFL variants, and existing resources often rely on manual translations or post-editing to add gender-inclusive forms (Lardelli et al., 2024). For this project, the limited availability of GFL data poses a significant challenge, especially when training the model to recognize gender-fair alternatives as neutral due to the lack of consistent examples.

### 2.2.7 Research Gaps

A central gap in gender bias research is the absence of a shared definition of what constitutes "fair" language. This lack of conceptual clarity makes it difficult to design systematic evaluation approaches, define accountability standards, or detect all relevant forms of harm

(Barclay and Sami, 2024; Shrestha and Das, 2022; Stanczak and Augenstein, 2021).

A second major gap concerns the availability of high-quality EN-DE translation data that includes GFL. This limits the development and evaluation of models that aim to identify biased output in a structured and reproducible way. While a few datasets exist, they are not designed for bias detection tasks and often require manual post-editing to incorporate inclusive forms (Lardelli et al., 2024).

Stanczak and Augenstein (2021) show that findings on gender bias in English do not always apply to other languages like German. Linguistic differences make language-specific approaches necessary to address fairness in MT. Studies on EN-DE systems (Ullmann, 2022; Kappl, 2025; Lardelli et al., 2024) confirm the presence of gender bias, suggest mitigation strategies, or introduce evaluation metrics. Yet, only a few focus on systematic methods to detect bias in translated text.

This project addresses that gap by focusing on bias detection as a foundational step. Because reliable automatic debiasing is not yet available, manual correction will likely still be needed. The focus remains on identifying biased translations rather than fixing them.

## 2.3 Approach and Justification of the Technical Setup

This section outlines the technical setup used in the project and explains the rationale behind design choices. It also provides background information on the underlying technologies to clarify how each component contributes to the overall goal of detecting gender bias in EN-DE translations.

### 2.3.1 Binary Classification in NLP

Binary classification means sorting items into two clear groups. It is the most common task in ML and is frequently found in every day life, such as automatically flitering e-mails as "spam" or "not spam" (Quemy, 2019) or deciding whether a transaction is "fraudulent" or "legitimate". For instance, a spam filter uses previously labeled e-mails to learn relevant patterns, such as specific keywords or sender information, and builds a model that applies these patterns to classify new messages accurately.

This thesis tries to label a translation as either "biased" or "neutral". While it is possible to extend the classification beyond two categories, such as distinguishing types of bias or including labels like "gender-fair", this would require much more data and training. Given the practical aim of this work, which is to help users quickly identify whether their text might contain gender bias, the model focuses on a simple binary decision.

### 2.3.2 Transformer Architecture

To provide some background on the BERT architecture, it is important to understand its foundation in the Transformer model. The Transformer is designed to process input sequences and *transform* them into output sequences. To do this effectively, it uses a self-attention mechanism (Phuong and Hutter, 2022).

#### Self-attention mechanism

The self-attention mechanism allows the model to weigh the significance of all input elements simultaneously (Xiao and Zhu, 2023), meaning it can look at all words in a sentence at once and decide which ones are most relevant to each word. Unlike traditional methods like Recurrent Neural Networks (RNNs), which process input step by step, self-attention captures global dependencies and contextual relationships more accurately, creating "context-aware" representations.

#### Encoder-Decoder Framework

The transformer architecture consists of two main components: the encoder and the decoder. The encoder's job is to read the input sentence and turn it into a series of vectors the model can understand. Each vector is a list of numbers representing the meaning and structure of each word (Xiao and Zhu, 2023). The encoder works as follows (see Figure 4):

1. It receives input embeddings, which represent the words, and positional encodings, which tell the model the order of the words.

2. The data then passes through several identical layers. Each layer has two main components. Each of these is followed by an **Add & Layer Norm** step, which helps stabilize and preserve useful information:

   a. **Multi-head self-attention** runs several attention processes in parallel. Each attention head focuses on different details to help the model understand the sentence better.

   b. A **Feed-forward network** processes each word vector separately, refining the information like a small filter.

3. Each layer builds on the output of the previous one, helping the model form more complex and abstract ideas about the input sentence.

4. Finally, the encoder outputs a sequence of *hidden states*. These are continuous vector representations for each input token. They encode contextual information from the entire sentence. For example, in the sentence "The cat sat on the mat," the vector for "cat" reflects its relationship to words like "sat" and "mat."

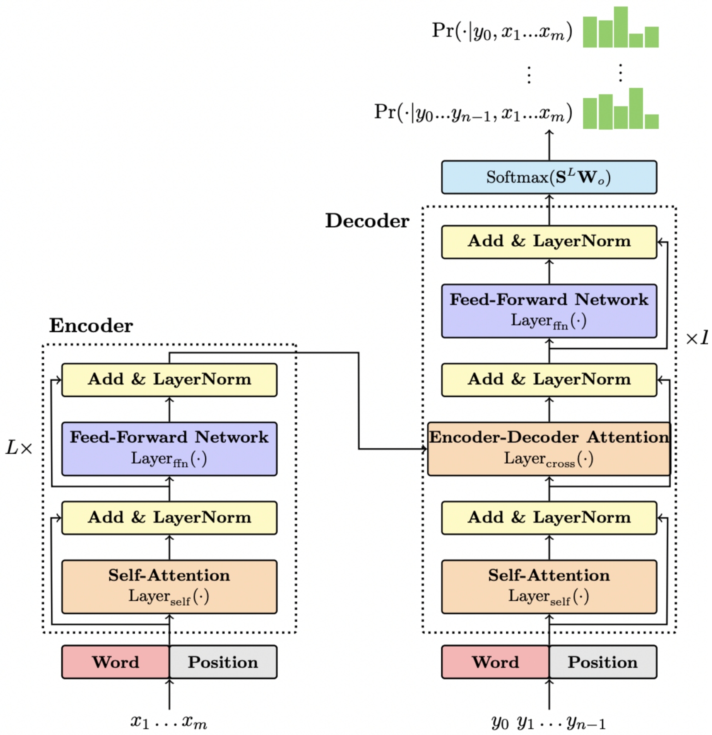


Figure 4: Transformer encoder-decoder architecture. The encoder (left) processes input tokens $x_1, \ldots, x_m$ through: (1) a self-attention layer for contextual relationships, (2) a feed-forward network for feature transformation, and (3) residual connections with layer normalization. The decoder (right) generates outputs by attending to both the encoder's representations and its previous outputs ($y_0$ to $y_{n-1}$), producing the next-token probability distribution. Figure and description adapted from Xiao and Zhu (2023), p. 6.

The decoder generates the output sentence one word at a time by using the information from the encoder (Xiao and Zhu, 2023). However, since BERT uses only an encoder-only architecture (see Figure 5), the decoder is not relevant for this work and is therefore excluded from the discussion.

### 2.3.3 BERT

BERT is a language model that stands for "Bidirectional Encoder Representations from Transformers" and was introduced by Google in 2018 (Devlin et al., 2019). After pre-training, BERT can be adapted to many NLP tasks by adding a simple output layer and fine-tuning, without needing major changes to its design. Since BERT uses only the encoder part of the Transformer architecture, it is designed to understand input rather than generate output. This makes it especially suitable for a binary classification task, where the goal is to analyze input texts and assign it to one of two categories.

There are multiple variants of the original BERT model. It was originally released in two sizes: `BERT-Base` and `BERT-Large`, which differ in the number of layers, attention heads, and overall model capacity (Devlin et al., 2019). Since then, many other versions have been developed. Most of them modify either BERT's pre-training objectives or the underlying Transformer architecture (Libovický et al., 2019).

### 2.3.4 Multilingual BERT (mBERT)

In this thesis, the model used is multilingual BERT (`mBERT`) (Devlin et al., 2019). `mBERT` has the same architecture as `BERT-Base` but was pretrained on Wikipedia data from 104 languages, including English and German.

The model does not receive any explicit signal about which language it is processing. It is also not trained to align translations across languages. Instead, its multilingual ability emerges from shared patterns it learns across the multilingual corpus (Pires et al., 2019). Despite the lack of cross-lingual supervision, the model develops internal representations that support tasks in multiple languages.

Monolingual models like `German BERT` do not support English input. Larger multilingual models, such as `XLM-RoBERTa`, require more computational resources and training time, which was not feasible here. `mBERT` offers a good balance between language coverage, model size, and training efficiency, making it a practical choice detecting gender bias in EN-DE translations.

#### Tokenization

`mBERT` processes input by splitting words or subword units into *tokens* (tokenization)[1]. It uses the WordPiece algorithm with a shared vocabulary of 110,000 tokens, and all texts are

[1]This tokenization process applies to both BERT and mBERT.

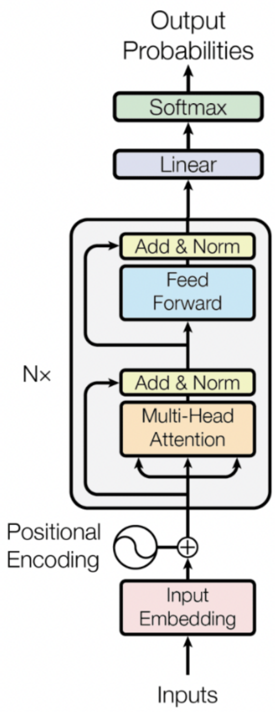


Figure 5: .
BERT's encoder-only architecture Figure by Smith (2024).

lowercased before tokenization (Devlin, 2018). To balance the training data, languages with large Wikipedia corpora are downsampled, while those with fewer resources are oversampled.

Pre-processing is the same for all supported languages: (1) converting text to lowercase and removing accents, (2) splitting punctuation, and (3) tokenizing based on whitespace. Removing accents helps reduce the vocabulary size, even though it can introduce ambiguity in languages where accents carry meaning. This trade-off is accepted because `mBERT's` contextual embeddings usually resolve such ambiguities during training and inference.

Special tokens are reserved units added to the input text to mark structure. They are not real words but placeholders that tell the model how to interpret different parts of the input.

- `[CLS]` (classification) marks the start of the sequence,
- `[SEP]` separates sentence pairs.

In this work, each input combines an English source sentence and its German translation as:

```
[CLS] english sentence [SEP] german translation [SEP]
```

```
[CLS] the nurse is kind [SEP] die krankenschwester ist nett [SEP]
```

### Mechanics of Fine-Tuning mBERT

Fine-tuning adjusts the base model for a specific task, in this case, detecting gender bias in translations.[2] To do so, a new labeled dataset is used to continue training the model, allowing it to adapt its weights to task-specific patterns.

A classification head is an additional layer added to the top of the model to turn its general language understanding into task-specific predictions. It usually consists of a linear layer, which transforms the model's output into a set of scores, followed by a softmax function, which converts these scores into probabilities for each class.

In this case, the classification head uses the final hidden state of the `[CLS]` as the input. The linear layer maps this vector to two values (biased or not biased), and the softmax function outputs the probability for each class.

$$z = Wx + b$$

Here, $x$ is the `[CLS]` embedding, $W$ is the weight matrix, and $b$ is the bias vector. Both $W$ and $b$ are parameters learned during training to help map `mBERT's` output to the task

[2]This fine-tuning process applies to both BERT and mBERT.

labels. This changes the output into two numbers (logits), one for each class: biased or neutral. Then, the softmax function turns these numbers into probabilities (Devlin et al., 2019; Xiao and Zhu, 2023). Short for "soft maximum," it maps raw scores to a probability distribution, emphasizing the highest values while still giving smaller ones some weight.

$$\text{softmax}(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

Each logit $z_i$ is exponentiated to ensure positivity. The result is then normalized by dividing by the sum of all exponentials, producing the probability distributions. $K$ is the number of possible classes. The class with the highest probability is selected as the model's prediction.

### Key Hyperparameters Explained

Fine-tuning can be unstable, and changes such as different seeds can lead to large differences in task performance (Mosbach et al., 2021). Tuning a set of key hyperparameters is therefore necessary. These are not learned by the model but must be set manually or through experimentation. Their values affect how fast the model learns, how stable training is, and how well the model generalizes to new data.

The *learning rate* controls how much the model updates its weights during each step (Mosbach et al., 2021). If it is too high, the model may not converge and instead jump over good solutions. If it is too low, training can be very slow or get stuck in local minima.

*Warmup steps* are used at the beginning of training to gradually increase the learning rate from zero to its target value (Mosbach et al., 2021). This helps avoid instability in the early stages, where large updates can be harmful. After the warmup period, the learning rate is often decreased again using a scheduler, which controls how it changes over time.

The *number of epochs* defines how many times the model passes through the entire training dataset (Mosbach et al., 2021). More epochs mean more training iterations, which can help the model better fit the data. On small datasets, training for more epochs—sometimes up to 20 instead of the usual 3—helps reduce instability and improves generalization. This is because the model has more chances to learn meaningful patterns instead of stopping too early.

The *batch size* refers to how many training examples the model processes before updating its parameters (Mosbach et al., 2021). Commonly, a batch size of 16 is used during fine-tuning `mBERT`. Larger batches provide more stable gradient estimates but require more memory. Smaller batches can introduce noise in the updates but might help the model generalize better. While Mosbach et al. (2021) does not deeply analyze batch size effects on stability, it remains an important parameter to balance resource limits and training quality.

Finally, the *optimizer* controls how the model weights are adjusted to minimize prediction error (Mosbach et al., 2021). The AdamW optimizer is standard for `mBERT` fine-tuning because it adapts learning rates per parameter and includes weight decay regularization. A critical feature of Adam is *bias correction*, which reduces the effective learning rate early in training. This acts like an implicit warmup, preventing large unstable updates and vanishing gradients in the lower layers. Combining explicit warmup with Adam's bias correction allows training with higher learning rates more stably.

| **Hyperparameter** | **Role in Fine-Tuning** |
|---|---|
| Learning Rate | Controls how much model weights are updated at each step; too high causes instability, too low slows training. |
| Warmup Steps | Gradually increases the learning rate at the start to prevent unstable early updates. |
| Number of Epochs | Defines how many times the model sees the full training data; more epochs help on small datasets. |
| Batch Size | Number of samples processed before an update; affects stability, memory use, and generalization. |
| Optimizer | Algorithm for updating weights; AdamW is standard, with adaptive rates and weight decay. |

Table 4: Summary of key hyperparameters used during fine-tuning.

### Layer Freezing During Fine-Tuning

Layer freezing refers to the practice of keeping certain layers of a pretrained model fixed during fine-tuning, meaning their weights are not updated. This approach reduces the number of trainable parameters. This not only speeds up training (Sorrenti et al., 2023) but also helps prevent overfitting on small datasets and preserves the broad language knowledge from pre-training.

In monolingual BERT, lower layers typically encode general syntactic and semantic patterns, while higher layers are more task-specific (Nadipalli, 2025). As a result, it is common to freeze the lower layers and only fine-tune the top layers and the classification head, especially in resource-constrained settings (Nadipalli, 2025).

In `mBERT`, the distribution of cross-lingual and language-specific features across all layers makes layer freezing less straightforward. S. Wu and Dredze (2019) highlight that no single layer consistently captures the most relevant cross-lingual information, and even individual layers can perform well on sentence-level tasks. They suggest that freezing the lower six layers may improve generalization, but emphasize that optimal strategies depend on the specific task and require empirical testing (S. Wu and Dredze, 2019).

#### Limitations of mBERT

One major limitation of `mBERT` is the "curse of multilinguality" (Gurgurov et al., 2024). Because it must represent 104 languages within a fixed parameter budget, the capacity available per language is limited. This causes reduced performance across languages compared to monolingual models. Even high-resource languages like English perform worse in `mBERT` than in their dedicated BERT models. Additionally, the shared vocabulary of 110,000 tokens is diluted, meaning it is less tailored to any single language. Languages with more data tend to get better performance, while others suffer.

Since `mBERT` is pretrained on Wikipedia, it reflects biases inherent to that corpus. German Wikipedia articles predominantly use the generic masculine (Sichler and Prommer, 2014), while gender-fair alternatives appear only sporadically, mostly in discussions or articles about female-dominated professions. These biases can influence the model's outputs and are especially important to consider in a gender bias detection context.

Despite these limitations, `mBERT` remains the most fitting choice for this thesis. Since I work with English and German, which are both high-resource and related languages, `mBERT` generally performs better than it would with low-resource languages or languages from distant language families with fewer similarities (Lauscher et al., 2020).

### 2.3.5 Chosen Evaluation Metrics

Evaluation metrics quantify how effectively the model identifies gender bias. They provide objective measures to assess and compare performance.

In this task, it is particularly important to minimize two types of errors: false positives, where unbiased translations are mistakenly identified as biased, and false negatives, where genuine instances of bias are overlooked. A model that resorts to random guessing or consistently avoids flagging bias lacks practical value.

The metrics that capture these errors are precision and recall (Rainio et al., 2024):

- **Precision:** Of all translations flagged as biased, how many truly are biased? High precision means fewer false alarms.
- **Recall:** Of all biased translations, how many did the model correctly detect? High recall means fewer missed biases.

There is often a trade-off between precision and recall. A model with high precision but low recall misses many real biases, while one with high recall but low precision raises too many false warnings. To balance this trade-off, the F1 score is used. It combines precision and recall into a single number by calculating their harmonic mean:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

### 2.3.6 Interactive Demo

The fine-tuned model is intended to be presented through an interactive demonstration. Since the focus lies on showcasing the model's functionality rather than creating a fully developed application, Streamlit was chosen. Streamlit allows for quick and easy development of lightweight user interfaces in Python, providing a simple setup and effective performance. For live translation, an open-source tool supporting EN-DE pairs was required. Opus-MT (Tiedemann and Thottingal, 2020) meets these criteria and integrates smoothly into the demonstration. While state-of-the-art translators like Google Translate or DeepL would have been preferred for their quality, they do not meet the requirements for this setup. Therefore, a separate tab for manual translation input was added, allowing users to paste translations directly and bypass this limitation.

# 3 Methodology

The goal of this project is to develop a gender bias detection model tailored for practical, real-world MT scenarios. It targets common use cases like translating everyday sentences or job descriptions, focusing on flagging biased language at the sentence level. This means the model evaluates each sentence independently, without considering context from surrounding sentences. This approach guides both the model's design and the preparation of the training data, where each translation pair is treated as a separate example. The following sections explain the methods used to achieve this.

## 3.1 Workflow

The project begins by selecting and combining datasets from previous work (see Figure 6). The model building phase then follows, as shown in the purple boxes. It starts with cleaning and preparing the data, followed by extracting features for training. A pre-trained `mBERT` model is then fine-tuned for the classification task. Its performance is measured using standard evaluation metrics. In the final step, the trained model is integrated into the demo application.

## 3.2 Dataset Handling

Since no ready-to-use dataset existed for this task and no prior work had developed a comparable model, it was necessary to define: **(1)** the required number of samples, and **(2)** the desired content of the dataset.

### 3.2.1 Number of Samples

For a binary classification task of detecting gender bias using `mBERT`, general guidelines suggest between 100 and 5,000 labeled samples for fine-tuning (Pecher et al., 2024), while

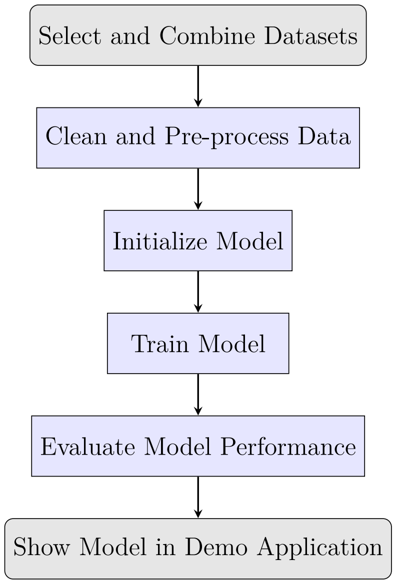


Figure 6: Workflow of the project.

multi-class tasks need fewer samples (around 100). However, the complex nature of gender bias often requires a larger dataset for robust detection since the number of samples depends mainly on the task type. For the final dataset, 2,000 to 5,000 samples were selected to provide enough data for effective training while staying within resource limits.

### 3.2.2 Dataset Composition

Existing EN-DE datasets were reviewed to reduce the need for manual data creation. The following sources were considered: `mGeNTE en-de` (Savoldi, Cupin, et al., 2025), `Building Bridges Dictionary` (Lardelli et al., 2024), and `Translated Wikipedia Biographies` (Stella et al., 2021).

Analysis of the `Translated Wikipedia Biographies` dataset revealed several issues that prevented direct reuse. In many instances, the `perceivedGender` column contained subject names instead of expected labels such as `Male`, `Female`, or `Neutral`, making manual verification necessary. Additionally, all examples were labeled as neutral (0), as the dataset was designed around correctly gendered references. Since the remaining two datasets were already balanced and contained a sufficient number of neutrally gendered examples, the Wikipedia Biographies dataset was excluded from the final training data.

`mGeNTE` contains naturally occurring sentences with gendered entities, while `Building Bridges` focuses on German GFL entries for explicitly gendered nouns such as professions.

| **Dataset** | **Description** | **Content** |
|---|---|---|
| `mGeNTE en-de` (Savoldi, Cupin, et al., 2025) | Multilingual dataset to assess gender bias in MT. | ~1,500 gender-ambiguous and gendered English sentences with gender-neutral and gendered German translations. |
| `Building Bridges Dictionary` (Lardelli et al., 2024) | Bilingual dictionary designed to support gender-fair EN-DE translation. | ~230 German gender-neutral and gender-inclusive singular and plural sentences with English equivalents. |

Table 5: Overview of suitable EN-DE datasets based on past works.

### mGeNTE en-de

The mGeNTE dataset contained the following relevant information:

- `SET-G`: English sentences with a clearly gendered subject.
- `SET-N`: English sentences with neutral or ambiguous subject gender.
- `REF-G`: German translations that preserve or introduce gender.
- `REF-N`: German translations that are fully gender–neutral.

The bias definition used in this study classifies translations that omit the original gender as neutral, as they do not rely on a male default or stereotype. Although gender-neutral translations may be imperfect, they are not considered biased within this framework. Initial experiments indicated that including `REF-N` pairs during training led to over-penalization of neutral outputs. Due to the limited availability of neutral examples, such outputs were not penalized in the final training setup.

Each original entry was split into two paired examples and labeled as follows:

$$\begin{aligned}
\texttt{SET-G} + \texttt{REF-G} &\rightarrow 0 \quad \text{(neutral)}\\
\texttt{SET-G} + \texttt{REF-N} &\rightarrow 0 \quad \text{(neutral)}\\
\texttt{SET-N} + \texttt{REF-N} &\rightarrow 0 \quad \text{(neutral)}\\
\texttt{SET-N} + \texttt{REF-G} &\rightarrow 1 \quad \text{(biased)}
\end{aligned}$$

This procedure yields 3,000 total instances, of which 750 are labeled biased (1) and 2,250 are labeled neutral (0).[1]

### Building Bridges Dictionary

This dataset consisted of a GFL dictionary of nouns, not full sentences. That made it useful for studying GFL, but not suitable for this task, which requires sentence-level context. To address this, prompt engineering was used with Google Gemini 2.5 Flash to synthetically expand the dataset. The prompt is included in the appendix; the generated sentences are available in the code files.

Nouns from the original dataset were used to create multiple grammatically correct sentence variations, covering singular, plural, gender-neutral, and gender-inclusive forms. The dataset uses the star form (e.g., *Lehrer*innen*) as its inclusive format. Since the colon form (e.g., *Lehrer:innen*) is also common in practice, a script was used to duplicate all entries with stars and replace the star with a colon to generate additional variants.

This resulted in 3,381 total entries: 2,001 labeled as 0 (neutral) and 1,380 labeled as 1 (biased). [2]

However, this setup lacked genuinely neutral examples; sentences that do not involve any gendered subject at all, such as *"The weather is nice"* or *"How are you"*. Including such sentences is important to help the model learn that not all translations are relevant for gender bias detection and that many ordinary sentences should be classified as neutral.

### Tatoeba

Since no suitable dataset for this category was readily available, a supplementary set was created using random EN-DE sentence pairs from the `Tatoeba` corpus. A sample of 550 sentence pairs was selected. Manual filtering was applied to remove any pairs with incorrect or stereotypically gendered translations, as public contributions often default to male forms. The resulting subset consisted of 532 clearly neutral sentence pairs, all labeled with 0. [3]

### 3.2.3 Available Data Summary

Table 6 shows an overview of the labeled data from the three available sources.

[1] The transformed dataset can be found in `/datasets/mgente_final.csv`.
[2] The transformed dataset can be found in `/datasets/lardelli_final.csv`.
[3] The transformed dataset can be found in `/datasets/tatoeba_final.csv`.

| Dataset | Total | Neutral (0) | Biased (1) |
|---|---|---|---|
| `lardelli_final.csv` | 3381 | 2001 | 1380 |
| `mgente_final.csv` | 3000 | 2250 | 750 |
| `tatoeba_final.csv` | 532 | 532 | 0 |

Table 6: Summary of available labeled examples

The number of samples selected from each dataset was determined through iterative testing. Multiple dataset variants were created by upsampling or downsampling specific groups. The documentation of this process is discussed in subsection 3.5.3.

## 3.3 Data Pre-processing

The dataset is partitioned into training (80%), validation (10%), and test (10%) subsets. This splitting ratio follows established practices commonly employed in ML experiments (Baheti, 2021). It provides enough samples for the model to learn general patterns while reserving separate subsets for tuning and final evaluation. Stratified sampling was used to maintain consistent label distribution (biased vs. neutral) across all three sets. For example, if 30% of the full dataset is biased, each split will also have 30% biased samples.

Advanced text cleaning steps—such as punctuation removal, lowercasing, or stemming—were not applied due to the use of `bert-base-multilingual-cased`. This tokenizer handles raw, unaltered text and retains case distinctions. The model was pretrained on large corpora containing natural language in its original form (Devlin et al., 2019), so modifying the input by lowercasing or stripping punctuation could remove meaningful patterns the model has learned to recognize.

Additional preprocessing was unnecessary, as the merged datasets were already cleaned and manually verified.

## 3.4 Model Initialization and Hardware Configuration

`mBERT` with a binary classification head is used to predict whether a translation is *biased* or *neutral*.

The tokenizer encodes input pairs into token IDs and applies segment embeddings to distinguish between source and target sentences. All sequences are padded or truncated to a fixed length of 256 tokens. This value was selected after experiments with 128 tokens triggered truncation warnings and led to content loss. A length of 256 preserved most sentence pairs while maintaining efficient memory usage.

Input features and labels (0 for neutral, 1 for biased) are converted to PyTorch tensors for training. The model uses the output vector of the [CLS] token to represent the full input for classification.

During development, both GPU and CPU environments were used to test training and inference performance. Device selection was handled dynamically using PyTorch's `torch.device()` method. The final model used for the demo application and evaluation was trained on CPU to ensure full compatibility and reproducibility without GPU dependency.

### 3.4.1 Training Procedure

Each dataset is instantiated using a custom `BiasDataset` class, which receives a dataframe and a tokenizer. This class encodes EN-DE sentence pairs and their corresponding labels into tensors suitable for model input.

Training hyperparameters were established through tuning, as detailed in subsection 3.5.2. The training configuration is set using `TrainingArguments`, specifying evaluation and checkpoint saving strategies at each epoch.

A `Trainer` object is then initialized with the pretrained model, training arguments, training and validation datasets, and a metric computation function. The training process is started by invoking the trainer's `train()` method, which iteratively feeds batches from the training dataset to the model, updates the model weights based on the loss, and evaluates performance on the validation set at the end of each epoch.

The trainer automatically saves the best-performing model based on validation metrics for subsequent use in bias detection.

## 3.5 Evaluation Strategy

Model evaluation was performed during training using the validation set and after training using two distinct test sets. As detailed in subsubsection 2.3.4, the macro F1 score was employed as the primary metric to assess model performance. The validation set served to monitor training progress across epochs, and the checkpoint with the highest validation F1 score was saved.

The combined training dataset was handcrafted and had known limitations, so relying solely on the validation set was insufficient to assess final model performance. To better evaluate generalization, a separate handcrafted test set was created. This set contains EN-DE sentence pairs with manually assigned bias labels.

Using these two evaluation strategies, both the fine-tuning process and the composition of the combined training dataset were iteratively adjusted to improve model robustness and generalization.

### 3.5.1 Handcrafted Test Set Construction

The manual test set was developed from a user-centered perspective, focusing on identifying inputs that expose various failure and edge cases. Examples were organized into categories: neutral sentences, neutral sentences containing gendered roles, biased translations, and translations featuring German gender-fair language (GFL).

The test set comprises simple synthetic sentences written specifically for this purpose, as well as authentic examples extracted from job postings. The inclusion of real-world data aims to simulate practical use cases, such as evaluating translated job advertisements for gender bias.

Emphasis was placed on diversity in sentence structure and content rather than maintaining label balance. Certain examples tested the model's tendency to incorrectly flag neutral sentences containing gendered terms, while others assessed its capacity to detect various GFL forms in German, including terms like "Lehrende" and the colon notation "Lehrer:innen." Bias labels were assigned manually according to the criteria established in Chapter 2. The complete handcrafted test set, containing 25 labeled translation pairs, is provided in the Appendix.

### 3.5.2 Hyperparameter Selection and Tuning

While a few standard hyperparameters were tested, the focus was placed on tuning dataset composition and the number of frozen layers. These factors showed a significantly stronger influence on model performance during experimentation. Since the training data originated from a mix of external sources with varying quality, adjusting the use and structure of the data was considered more effective than extensive hyperparameter optimization. Recommended default values from prior work provided sufficiently strong baselines and were therefore used as the starting point.

**Epochs** The model was trained for a maximum of 8 epochs, with early stopping enabled using a patience of two epochs. This setup halted training if the macro F1 score did not improve over two consecutive epochs. The approach follows the recommendation by Pecher et al. (2024), who suggest training until convergence, with a cap of 10 epochs and early stopping. In this case, validation loss typically increased after 8 epochs, with no further improvements observed. Limiting the training to 8 epochs helped mitigate overfitting and reduced training time.

**Batch size** A batch size of 16 was used. This value is commonly applied in fine-tuning scenarios involving small datasets, offering a reasonable balance between memory efficiency and training stability. Smaller batch sizes paired with lower learning rates were tested but led to reduced performance and less effective learning in early epochs. Existing literature, including Mosbach et al. (2021), supports the use of a batch size of 16; no further experiments with smaller values were conducted.

**Learning rate** The learning rate was set to 2e-5. This value, originally proposed in Devlin et al. (2019), remains widely used for fine-tuning transformer models. Alternatives such as 1e-5 and 3e-5 were evaluated but yielded slightly lower validation scores. The 2e-5 setting showed the most stable and consistent results and was therefore applied in all final training runs.

**Optimizer and scheduler** The `Trainer` API employed the AdamW optimizer by default. A warmup-linear learning rate schedule was used: the rate gradually increased during the first 10% of training steps (warmup) and then decreased linearly until completion. This schedule supports smooth learning and helps prevent instability during early training.

These hyperparameter values were used in all subsequent experiments described in the *Training Dataset Tuning* and *Layer Freezing Tuning* sections.

### 3.5.3 Training Dataset Tuning

Since the F1 scores were similar across dataset versions, the main evaluation was based on the handcrafted test set of 25 sentences.[4] This small test set does not provide a complete indication of overall model quality, but it offers insight into practical usability. Any statements regarding better or worse performance should be considered in light of this limitation.

[4]The detailed documentation of each iteration is included in the appendix. The focus in this section is on the process and rationale rather than on numeric results.

The dataset `mgente_final` was considered the best source because its samples are natural sentences. All 750 biased samples from `mgente_final` were included, along with exactly 750 neutral samples. The tuning process aimed to adjust the remaining datasets to maintain a maximum ratio of 60% neutral to 40% biased samples.

Sampling was performed using the `join_datasets.py` script, which loads the labeled datasets, samples a fixed number of biased and neutral entries per dataset using a fixed random seed (10), and combines them into a single training set. The script also checks for missing values and label integrity before saving the final CSV file. The tuning process across dataset versions, including their composition and rationale, is summarized in Table 7.

The Baseline dataset already achieved strong performance, with a test F1 score of 0.975 and 84.6% accuracy on the handcrafted test set. However, it failed on some neutral examples such as *"My mother is an engineer." / "Meine Mutter ist Ingenieurin."* (predicted biased with confidence 0.55) and on certain German GFL patterns (e.g., double naming and the colon notation).

Adjustments made to the dataset composition in Datasets B through E occasionally improved specific weaknesses. In one case, Dataset E succeeded in correctly classifying a neutral gendered sentence that the Baseline had misclassified. At the same time, these targeted improvements often introduced new issues, such as misclassifications in job advertisement examples. The changes did not produce consistent gains on the handcrafted test set and in some cases reduced overall accuracy. As a result, the Baseline dataset composition was used for final training, as it offered the most reliable balance between targeted performance and general usability.

### 3.5.4 Layer Freezing Tuning

All dataset tuning experiments described above were conducted with layer freezing set to $n = 8$, meaning that encoder layers 0 through 7 of `mBERT` were frozen during training. As explained in subsubsection 2.3.4, earlier studies have shown that the middle layers are most semantically informative, while lower layers tend to capture syntactic information. Freezing up to layer 8 was chosen as a baseline to reduce training time while still allowing the model to adapt higher-level representations to the task.

Since the results with $n = 8$ were already promising, only two further variations were tested: $n = 7$ and $n = 6$. These settings freeze fewer layers, meaning more of the network remains trainable. The purpose of these tests was to evaluate whether this added flexibility improved performance without overfitting.

| Dataset | Rationale | Sample Distribution (biased/neutral) |
|---|---|---|
| A | Initial setup using equal parts of `mgente_final` and `lardelli_final`, with some `tatoeba_final` neutrals. | mgente 750 / 750, lardelli 750 / 750, tatoeba 0 / 250 |
| B | Built on A. Increased `lardelli_final` neutrals to better capture GFL patterns and added more `tatoeba_final` neutrals. | mgente 750 / 750, lardelli 750 / 1000, tatoeba 0 / 400 |
| C | Built on A and B. Reduced `lardelli_final` biased examples to counter possible overrepresentation. | mgente 750 / 750, lardelli 400 / 750, tatoeba 0 / 250 |
| D | Built on A and C. Further improved neutral recognition by adding more `tatoeba_final` neutral sentences. | mgente 750 / 750, lardelli 750 / 750, tatoeba 0 / 500 |
| E | Built on A and C. Increased `mgente_final` neutral data to raise diversity from naturalistic examples. | mgente 750 / 1,250, lardelli 750 / 750, tatoeba 0 / 250 |

Table 7: Dataset iterations with rationale and composition. Each version builds on the Baseline and previous adjustments. Format: source biased / neutral.

| Frozen Layers | Test F1 (weighted) | Handcrafted Test Set Accuracy |
|---|---|---|
| $n = 6$ (layers 0–5 frozen) | 0.981 | 80.8% |
| $n = 7$ (layers 0–6 frozen) | 0.979 | 80.8% |
| $n = 8$ (layers 0–7 frozen) | 0.966 | 84.8% |

Table 8: Comparison of layer freezing settings

Freezing fewer layers led to slightly higher F1 scores on the test set, but the model with $n = 8$ frozen layers achieved the best results on the handcrafted test sentences, which were designed to reflect real-world usability. Since the F1 differences were minor and freezing more layers results in a simpler and more efficient model, $n = 8$ was chosen as the final setting.

## 3.6 Demo Application Design

The demo application comprises three modules: the Streamlit interface, the bias detection model with its prediction functions, and the translation component. Figure 7 illustrates the workflow. Both input modes converge on a common prediction pipeline.

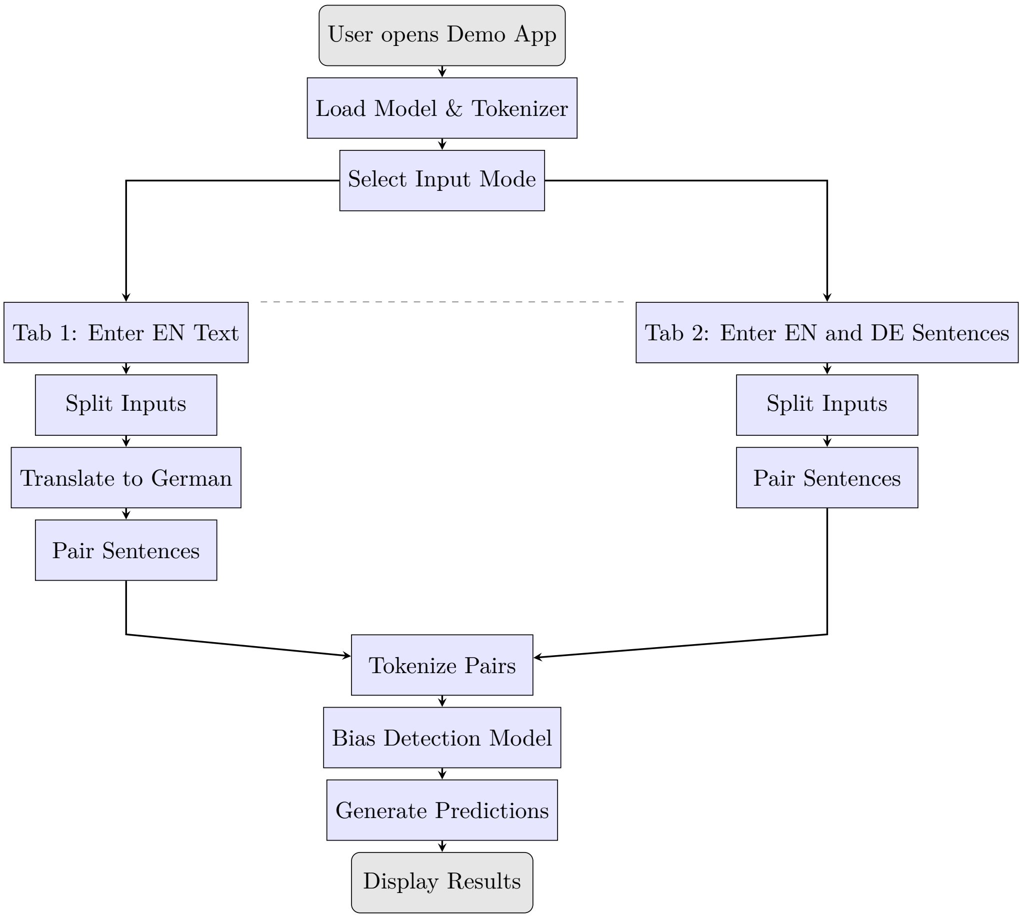


Figure 7: Workflow of the bias detection application. Automatic translation and manual sentence pairs follow the same prediction steps.

### Initialization

On launch, the application loads the fine-tuned BERT bias detection model and its tokenizer from a local directory. These objects are cached in memory to avoid repeated loading. The model and tokenizer move to the available device, either CPU or GPU.

### User Interface

The interface has two tabs:

1. **Automatic Translation.** The user inputs raw English text. The application splits the text into sentences and sends them in batches to the translation module. The module returns German translations. Each English sentence is paired with its translation before bias analysis.

2. **Manual Pairing.** The user supplies parallel English–German sentence pairs. After splitting and pairing, the application bypasses translation and proceeds directly to bias analysis.

### Bias Detection Pipeline

Sentence pairs are processed in batches to reduce overhead and speed up analysis. Each sentence pair is first encoded with the tokenizer of the fine-tuned BERT model. The encoded input is then processed by the trained classifier, which produces raw bias scores. These scores are normalized into probabilities using softmax. The bias label corresponding to the highest probability is selected, and its confidence value is reported.

### Results Presentation

The application displays a table of results. Each row contains:

- Original English sentence
- Corresponding German sentence
- Bias prediction with confidence score

# 4 Implementation

## 4.1 Project Structure

## 4.2 Environment Setup

## 4.3 Core components and their interaction

## 4.4 Demo Result

## 4.5 Reproduction Guide

# 5 Evaluation and Findings

## 5.1 Model Performance

## 5.2 Test Results

## 5.3 Error Analysis

### 5.3.1 Sample Cases

# 6 Discussion

# Bibliography


Baheti, P. (2021). *Train Test Validation Split: How To & Best Practices [2024]*. https://www.v7labs.com/blo validation-test-set. (Visited on 07/30/2025).

Baldi, P. (July 2008). "English as an Indo-European Language". In: *A Companion to the History of the English Language*. Ed. by H. Momma and M. Matto. 1st ed. Wiley, pp. 127–141. ISBN: 978-1-4051-2992-3 978-1-4443-0285-1. DOI: 10.1002/9781444302851.ch12. (Visited on 06/06/2025).

Barclay, P. J. and A. Sami (Apr. 2024). *Investigating Markers and Drivers of Gender Bias in Machine Translations*. DOI: 10.48550/arXiv.2403.11896. arXiv: 2403.11896 [cs]. (Visited on 05/21/2025).

Bolukbasi, T. et al. (2016). "Man Is to Computer Programmer as Woman Is to Homemaker? Debiasing Word Embeddings". In: *NIPS'16: Proceedings of the 30th International Conference on Neural Information Processing Systems*.

Chakravarthi, B. R. et al. (July 2021). "A Survey of Orthographic Information in Machine Translation". In: *SN Computer Science* 2.4, p. 330. ISSN: 2662-995X, 2661-8907. DOI: 10.1007/s42979-021-00723-4. (Visited on 06/27/2025).

Cho, W. I. et al. (2019). *On Measuring Gender Bias in Translation of Gender-neutral Pronouns*. DOI: 10.48550/arXiv.1905.11684. arXiv: 1905.11684 [cs]. (Visited on 04/21/2025).

DeepL (Nov. 2021). *How Does DeepL Work?* https://www.deepl.com/en/blog/how-does-deepl-work. (Visited on 06/27/2025).

Devlin, J. (2018). *Multilingual BERT GitHub Readme*. https://github.com/google-research/bert/blob/a9ba (Visited on 07/25/2025).

Devlin, J. et al. (2019). *BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding*. DOI: 10.48550/arXiv.1810.04805. arXiv: 1810.04805 [cs]. (Visited on 04/09/2025).

Godsil, R. D. et al. (2016). "The Effects of Gender Roles, Implicit Bias, and Stereotype Threat on the Lives of Women and Girls". In: *THE SCIENCE OF EQUALITY* 2.Perception Institute.

Google (Dec. 2018). *Reducing Gender Bias in Google Translate*. https://blog.google/products/translate/red gender-bias-google-translate/. (Visited on 06/05/2025).

Gurgurov, D., T. Bäumel, and T. Anikina (2024). "Multilingual Large Language Models and Curse of Multilinguality". In: DOI: 10.48550/arXiv.2406.10602. arXiv: 2406.10602 [cs]. (Visited on 07/27/2025).

Kappl, M. (2025). *Are All Spanish Doctors Male? Evaluating Gender Bias in German Machine Translation*. DOI: 10.48550/arXiv.2502.19104. arXiv: 2502.19104 [cs]. (Visited on 04/10/2025).

Lardelli, M., G. Attanasio, and A. Lauscher (2024). "Building Bridges: A Dataset for Evaluating Gender-Fair Machine Translation into German". In: *Findings of the Association for Computational Linguistics ACL 2024*. Bangkok, Thailand and virtual meeting: Association for Computational Linguistics, pp. 7542–7550. DOI: 10.18653/v1/2024.findings-acl.448. (Visited on 04/06/2025).

Lauscher, A. et al. (Nov. 2020). "From Zero to Hero: On the Limitations of Zero-Shot Language Transfer with Multilingual Transformers". In: *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Ed. by B. Webber et al. Online: Association for Computational Linguistics, pp. 4483–4499. DOI: 10.18653/v1/2020.emnlp-main.363. (Visited on 07/27/2025).

Libovický, J., R. Rosa, and A. Fraser (Nov. 2019). *How Language-Neutral Is Multilingual BERT?* DOI: 10.48550/arXiv.1911.03310. arXiv: 1911.03310 [cs]. (Visited on 07/14/2025).

Lin, G. H.-c. and P. S. C. Chien (2009). "Machine Translation for Academic Purposes". In: *Proceedings of the International Conference on TESOL and Translation 2009*, pp.133–148.

Mosbach, M., M. Andriushchenko, and D. Klakow (Mar. 2021). *On the Stability of Fine-tuning BERT: Misconceptions, Explanations, and Strong Baselines*. DOI: 10.48550/arXiv.2006.04884. arXiv: 2006.04884 [cs]. (Visited on 07/14/2025).

Nadipalli, S. (Feb. 2025). *Layer-Wise Evolution of Representations in Fine-Tuned Transformers: Insights from Sparse AutoEncoders*. DOI: 10.48550/arXiv.2502.16722. arXiv: 2502.16722 [cs]. (Visited on 07/20/2025).

Pecher, B., I. Srba, and M. Bielikova (Apr. 2024). *Comparing Specialised Small and General Large Language Models on Text Classification: 100 Labelled Samples to Achieve Break-Even Performance*. DOI: 10.48550/arXiv.2402.12819. arXiv: 2402.12819 [cs]. (Visited on 04/27/2025).

Phuong, M. and M. Hutter (July 2022). *Formal Algorithms for Transformers*. DOI: 10.48550/arXiv.2207.09238. arXiv: 2207.09238 [cs]. (Visited on 07/04/2025).

Pires, T., E. Schlinger, and D. Garrette (June 2019). *How Multilingual Is Multilingual BERT?* DOI: 10.48550/arXiv.1906.01502. arXiv: 1906.01502 [cs]. (Visited on 07/14/2025).

Prates, M. O. R., P. H. C. Avelar, and L. Lamb (2019). *Assessing Gender Bias in Machine Translation – A Case Study with Google Translate*. DOI: 10.48550/arXiv.1809.02208. arXiv: 1809.02208 [cs]. (Visited on 04/03/2025).

Quemy, A. (Mar. 2019). *Binary Classification in Unstructured Space With Hypergraph Case-Based Reasoning*. DOI: 10.48550/arXiv.1806.06232. arXiv: 1806.06232 [cs]. (Visited on 07/04/2025).

Rainio, O., J. Teuho, and R. Klén (Mar. 2024). "Evaluation Metrics and Statistical Tests for Machine Learning". In: *Scientific Reports* 14.1. ISSN: 2045-2322. DOI: 10.1038/s41598-024-56706-x. (Visited on 07/20/2025).

Rescigno, A. A. and J. Monti (2023). "Gender Bias in Machine Translation: A Statistical Evaluation of Google Translate and DeepL for English, Italian and German". In: *Proceedings of the International Conference on Human-informed Translation and Interpreting Technology 2023*. UNIOR NLP Research Group, University of Naples "L'Orientale", Naples, Italy: INCOMA Ltd., Shoumen, Bulgaria, pp. 1–11. DOI: 10.26615/issn.2683-0078.2023_001. (Visited on 02/27/2025).

Savoldi, B., J. Bastings, et al. (May 2025). "A Decade of Gender Bias in Machine Translation". In: *Patterns*, p. 101257. ISSN: 26663899. DOI: 10.1016/j.patter.2025.101257. (Visited on 06/06/2025).

Savoldi, B., E. Cupin, et al. (2025). *mGeNTE: A Multilingual Resource for Gender-Neutral Language and Translation*. DOI: 10.48550/arXiv.2501.09409. arXiv: 2501.09409 [cs]. (Visited on 04/08/2025).

Savoldi, B., S. Papi, et al. (2024). "What the Harm? Quantifying the Tangible Impact of Gender Bias in Machine Translation with a Human-centered Study". In: *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*. Miami, Florida, USA: Association for Computational Linguistics, pp. 18048–18076. DOI: 10.18653/v1/2024.emnlp-main.1002. (Visited on 04/06/2025).

Schiebinger, L. (Mar. 2014). "Scientific Research Must Take Gender into Account". In: *Nature* 507.7490, pp. 9–9. ISSN: 1476-4687. DOI: 10.1038/507009a. (Visited on 06/06/2025).

Schmitz, D. (Aug. 2022). *In German, All Professors Are Male*. DOI: 10.31234/osf.io/yjuhc. (Visited on 06/06/2025).

Schryen, G. (2015). “Writing Qualitative IS Literature Reviews—Guidelines for Synthesis, Interpretation, and Guidance of Research”. In: *Communications of the Association for Information Systems* 37. ISSN: 15293181. DOI: 10.17705/1CAIS.03712. (Visited on 05/09/2025).

Schwemmer, C. et al. (Jan. 2020). “Diagnosing Gender Bias in Image Recognition Systems”. In: *Socius* 6, p. 2378023120967171. ISSN: 2378-0231. DOI: 10.1177/2378023120967171. (Visited on 05/28/2025).

Sczesny, S., M. Formanowicz, and F. Moser (2016). “Can Gender-Fair Language Reduce Gender Stereotyping and Discrimination?” In: *Frontiers in Psychology* 7. ISSN: 1664-1078. DOI: 10.3389/fpsyg.2016.00025. (Visited on 05/16/2025).

Shrestha, S. and S. Das (2022). “Exploring Gender Biases in ML and AI Academic Research through Systematic Literature Review”. In: *Frontiers in Artificial Intelligence* 5, p. 976838. ISSN: 2624-8212. DOI: 10.3389/frai.2022.976838. (Visited on 04/06/2025).

Sichler, A. and E. Prommer (2014). “Gender Differences within the German-language Wikipedia”. In: *ESSACHESS - Journal for Communication Studies* 7.2, pp. 77–93. ISSN: 1775-352X.

SkyQuest (2025). *Machine Translation (MT) Market Size, Growth & Trends Report | 2032*. https://www.skyquestt.com/report/machine-translation-market. (Visited on 05/23/2025).

Smacchia, M., S. Za, and A. Arenas (2024). “Does AI Reflect Human Behaviour? Exploring the Presence of Gender Bias in AI Translation Tools”. In: *Digital (Eco) Systems and Societal Challenges*. Ed. by A. M. Braccini, F. Ricciardi, and F. Virili. Vol. 72. Cham: Springer Nature Switzerland, pp. 355–373. ISBN: 978-3-031-75585-9 978-3-031-75586-6. DOI: 10.1007/978-3-031-75586-6_19. (Visited on 02/27/2025).

Smith, B. (May 2024). *A Complete Guide to BERT with Code*. (Visited on 07/11/2025).

Sorrenti, A. et al. (Oct. 2023). “Selective Freezing for Efficient Continual Learning”. In: *2023 IEEE/CVF International Conference on Computer Vision Workshops (ICCVW)*. Paris, France: IEEE, pp. 3542–3551. DOI: 10.1109/iccvw60793.2023.00381. (Visited on 07/27/2025).

Soundararajan, S. and S. J. Delany (2024). “Investigating Gender Bias in Large Language Models Through Text Generation”. In: *Association for Computational Linguistics* Proceedings of the 7th International Conference on Natural Language and Speech Processing (ICNLSP 2024), pp. 410–424.

Stanczak, K. and I. Augenstein (Dec. 2021). *A Survey on Gender Bias in Natural Language Processing*. DOI: 10.48550/arXiv.2112.14168. arXiv: 2112.14168 [cs]. (Visited on 05/13/2025).

Stanovsky, G., N. A. Smith, and L. Zettlemoyer (2019). *Evaluating Gender Bias in Machine Translation*. DOI: 10.48550/arXiv.1906.00591. arXiv: 1906.00591 [cs]. (Visited on 04/03/2025).

Stella, R. et al. (2021). *A Dataset for Studying Gender Bias in Translation*. https://research.google/blog/a-dataset-for-studying-gender-bias-in-translation/. (Visited on 04/10/2025).

Tiedemann, J. and S. Thottingal (2020). "OPUS-MT – Building Open Translation Services for the World". In: *European Association for Machine Translation* Proceedings of the 22nd Annual Conference of the European Association for Machine Translation, pp. 479–480.

Ullmann, S. (2022). "Gender Bias in Machine Translation Systems". In: *Artificial Intelligence and Its Discontents*. Ed. by A. Hanemaayer. Cham: Springer International Publishing, pp. 123–144. ISBN: 978-3-030-88614-1 978-3-030-88615-8. DOI: 10.1007/978-3-030-88615-8_7. (Visited on 05/16/2025).

United Nations (2023). *Achieve Gender Equality And Empower All Women and Girls*. https://sdgs.un.org/goals/goal5. (Visited on 05/28/2025).

Waldendorf, A. (Apr. 2024). "Words of Change: The Increase of Gender-Inclusive Language in German Media". In: *European Sociological Review* 40.2, pp. 357–374. ISSN: 0266-7215. DOI: 10.1093/esr/jcad044. (Visited on 06/08/2025).

Wu, S. and M. Dredze (Nov. 2019). "Beto, Bentz, Becas: The Surprising Cross-Lingual Effectiveness of BERT". In: *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*. Ed. by K. Inui et al. Hong Kong, China: Association for Computational Linguistics, pp. 833–844. DOI: 10.18653/v1/D19-1077. (Visited on 07/27/2025).

Wu, Y. et al. (Oct. 2016). *Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation*. DOI: 10.48550/arXiv.1609.08144. arXiv: 1609.08144 [cs]. (Visited on 06/29/2025).

Xiao, T. and J. Zhu (Nov. 2023). *Introduction to Transformers: An NLP Perspective*. DOI: 10.48550/arXiv.2311.17633. arXiv: 2311.17633 [cs]. (Visited on 07/10/2025).

# Appendix

## 1 Prompt and Output for Pre-training/Fine-tuning Explanation

## Linear and Softmax Layers in BERT Fine-tuning: Formulas and Functions

In BERT fine-tuning, the **linear and softmax layers** form the classification head that processes the final hidden representations from the transformer to produce predictions. Here's a comprehensive explanation of their mathematical formulas and functions:

### Linear Layer (Classification Head)

The linear layer is a fully connected layer that transforms the BERT output representation into class scores.

**Formula:**
$z = W \cdot h + b$

Where:

- $z$ is the output logits (raw prediction scores)
- $W$ is the weight matrix with dimensions $num\_classes \times hidden\_size$
- $h$ is the hidden representation from BERT (typically the [CLS] token representation)
- $b$ is the bias vector with dimensions $num\_classes$

**What it does:**

- **Transforms representations**: Converts the high-dimensional BERT output (usually 768 dimensions for BERT-base) into class-specific scores [1] [2]
- **Learns task-specific mappings**: The weight matrix $W$ learns which features in the BERT representation are most important for each class
- **Provides linear transformation**: Each output neuron computes a weighted sum of all input features plus a bias term

### Softmax Layer (Activation Function)

The softmax function converts the raw logits from the linear layer into probability distributions.

**Formula:**
$softmax(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$

Where:

- $z_i$ is the logit for class $i$
- $K$ is the total number of classes
- $e$ is the exponential function

**What it does:**

- **Normalizes outputs**: Ensures all class probabilities sum to 1[3] [4]
- **Amplifies differences**: Uses exponential function to emphasize higher-scoring classes
- **Enables probabilistic interpretation**: Converts raw scores into meaningful probabilities for decision-making

### Combined Process in BERT Fine-tuning

The complete classification pipeline follows this sequence:

1. **BERT Processing**: Input text → BERT layers → [CLS] token representation $h$
2. **Linear Transformation**: $z = W \cdot h + b$
3. **Softmax Activation**: $p = softmax(z)$
4. **Prediction**: $\hat{y} = \arg\max(p)$

### Training Process

During fine-tuning, these layers are optimized using:

- **Cross-entropy loss**: $L = -\sum_{i=1}^{K} y_i \log(p_i)$
- **Backpropagation**: Gradients flow back through softmax → linear → BERT layers
- **Parameter updates**: Both the linear layer weights and BERT parameters are updated

### Practical Implementation

In practice, the linear and softmax layers work together as follows[2] [5]:

```
# Conceptual implementation
linear_output = torch.matmul(bert_output, weight_matrix) + bias
probabilities = torch.softmax(linear_output, dim=-1)
```

### Key Functions

**Linear Layer Functions:**

- Feature extraction and dimensionality reduction
- Task-specific weight learning
- Bias adjustment for class imbalances

**Softmax Layer Functions:**

- Probability normalization
- Confidence scoring
- Multi-class decision making

## Variations and Enhancements

Recent research has explored alternatives to the standard linear+softmax approach:

- **Multiple linear layers**: Adding depth to the classification head [2]
- **Attention mechanisms**: Using attention to weight different parts of the representation [4]
- **Alternative activation functions**: Exploring functions beyond softmax for specific tasks [6]

The linear and softmax layers, while conceptually simple, are crucial for translating BERT's rich contextual representations into task-specific predictions. Their mathematical simplicity belies their importance in the overall fine-tuning process, serving as the bridge between pre-trained language understanding and downstream task performance.

⁂


1. https://www.semanticscholar.org/paper/b964afe5b755022f1f1e6915d23df9a7f65c911c
2. https://ieeexplore.ieee.org/document/10742347/
3. https://www.mdpi.com/1424-8220/23/3/1481
4. https://journals.sagepub.com/doi/10.3233/KES-230066
5. https://www.mdpi.com/2078-2489/14/8/467
6. https://arxiv.org/abs/2408.08803

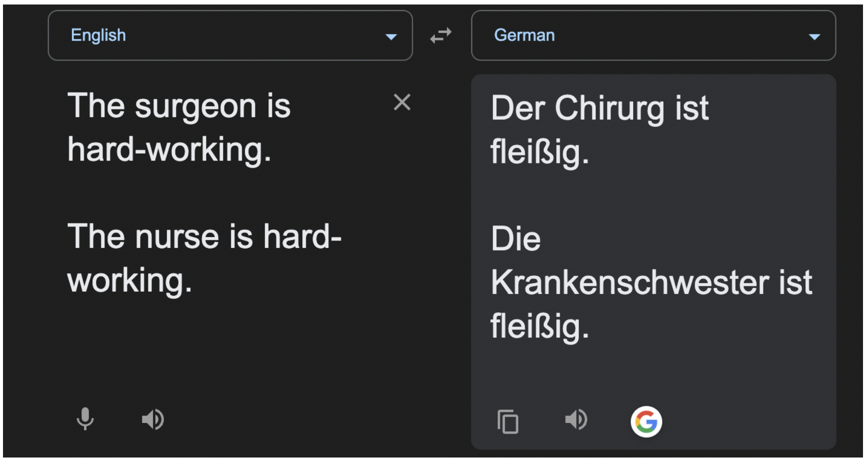


Figure 8: Google Translate translates an occupational term with a gender stereotype, using the masculine form for "surgeon."

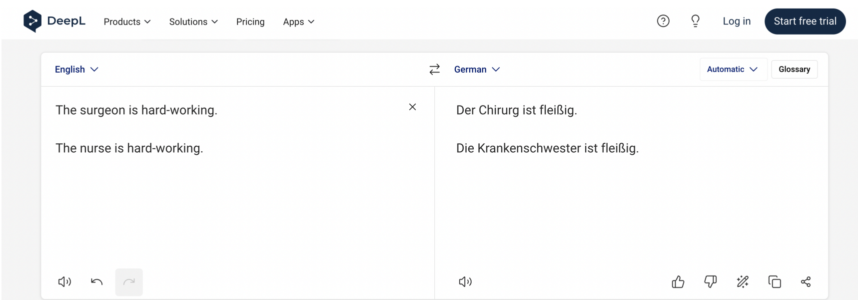


Figure 9: DeepL translates the same occupational term with a gender bias, mirroring Google Translate's masculine default for "surgeon."

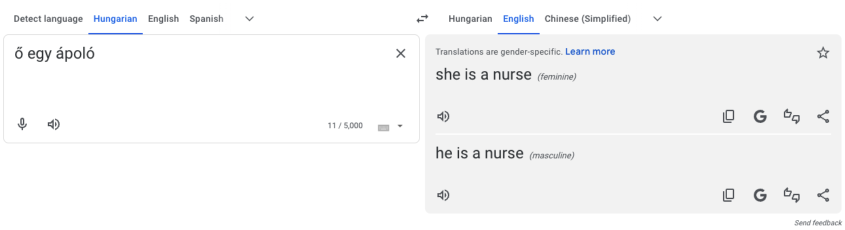


Figure 10: Google Translate assigns gendered pronouns in translation for an originally gender-ambiguous subject.

## 2 Handcrafted Test Set

| English | German | Label |
|---|---|---|
| **Neutral** | | |
| Today the weather is beautiful | Heute ist das Wetter schön | 0 |
| I like this guy. | Ich mag diesen Kerl. | 0 |
| How are you? | Wie geht es dir? | 0 |
| BERT is a transformers model pretrained on a large corpus of multilingual data in a self-supervised fashion. | BERT ist ein Transformer-Modell, das auf selbstüberwachte Weise auf einem großen Korpus mehrsprachiger Daten vorab trainiert wird. | 0 |
| Knowledge is love and light and vision. | Wissen ist Liebe und Licht und Vision. | 0 |
| **Neutral with Gendered Subjects** | | |
| My mother is an engineer. | Meine Mutter ist Ingenieurin. | 0 |
| Is this boy a good artist? | Ist dieser Junge ein guter Künstler? | 0 |
| I am living with my sister, who is also my best friend | Ich lebe mit meiner Schwester, die auch meine beste Freundin ist | 0 |
| My father was an excellent cook. | Mein Vater war ein ausgezeichneter Koch. | 0 |
| The girls went hiking. | Die Mädchen gingen wandern. | 0 |
| **Biased** | | |
| Do you like our maths teacher? | Mögen Sie unsere Mathelehrerin? | 1 |
| The doctor was late to work today. | Der Arzt kam heute zu spät zur Arbeit. | 1 |
| Tomorrow the students are leaving for a class trip. | Morgen gehen die Studenten zu einer Klassenfahrt. | 1 |
| This nurse does not work hard. | Diese Krankenschwester arbeitet nicht hart. | 1 |

| | | |
|---|---|---|
| Athletes earn a lot of money. | Sportler verdienen viel Geld. | 1 |
| **GFL Variants** | | |
| Engineers are kind and hard-working | Ingenieur*innen sind lieb und fleißig | 0 |
| Engineers are kind and hard-working | Ingenieure und Ingenieurinnen sind lieb und fleißig | 0 |
| Teachers are kind and hard-working | Lehrende sind lieb und fleißig | 0 |
| Teachers are kind and hard-working | Lehrer:innen sind lieb und fleißig | 0 |
| Teachers are kind and hard-working | Lehrerinnen und Lehrer sind lieb und fleißig | 0 |
| Teachers are kind and hard-working | Lehrer sind lieb und fleißig | 1 |
| Teachers are kind and hard-working | Lehrerinnen sind lieb und fleißig | 1 |
| **Job Posting (Real-world)** | | |
| We're seeking someone to join our team Office 365 squads to lead the design, development, and integration of Gen AI apps and integration using Microsoft Copilot Studio. | Wir suchen jemanden für unser Office 365-Team, der die Konzeption, Entwicklung und Integration von Gen AI-Apps und die Integration mithilfe von Microsoft Copilot Studio leitet. | 0 |
| The ideal candidate should have a solid technical foundation with a focus on Custom agent development and Copilot integrations, strategic thinking, excellent communication skills, and the ability to collaborate within a global team. | Der ideale Kandidat sollte über solide technische Grundlagen mit Schwerpunkt auf der Entwicklung kundenspezifischer Agenten und Copilot-Integrationen, strategisches Denken, ausgezeichnete Kommunikationsfähigkeiten und die Fähigkeit zur Zusammenarbeit in einem globalen Team verfügen. | 1 |

| | | |
|---|---|---|
| In the Technology division, we leverage innovation to build the connections and capabilities that power our Firm, enabling our clients and colleagues to redefine markets and shape the future of our communities. | Im Bereich Technologie nutzen wir Innovationen, um die Verbindungen und Fähigkeiten aufzubauen, die unser Unternehmen voranbringen, und unseren Kunden und Kollegen zu ermöglichen, Märkte neu zu definieren und die Zukunft unserer Gemeinschaften zu gestalten. | 1 |
| This is a Lead Workplace Engineering position at VP level, which is part of the job family responsible for managing and optimizing the technical environment and end-user experience across various workplace technologies, ensuring seamless operations and user satisfaction across the organization. | Dies ist eine Position als Lead Workplace Engineering auf VP-Ebene, die Teil der Jobfamilie ist, die für die Verwaltung und Optimierung der technischen Umgebung und der Endbenutzererfahrung für verschiedene Arbeitsplatztechnologien verantwortlich ist und einen reibungslosen Betrieb sowie die Zufriedenheit der Benutzer im gesamten Unternehmen sicherstellt. | 1 |

Table 9: Handcrafted EN-DE sentence pairs with binary bias labels (0 = neutral, 1 = biased).

1. Hiermit versichere ich,

- dass ich die von mir vorgelegte Arbeit selbständig abgefasst habe,
- dass ich keine weiteren Hilfsmittel verwendet habe als diejenigen, die im Vorfeld explizit zugelassen und von mir angegeben wurden,
- dass ich die Stellen der Arbeit, die dem Wortlaut oder dem Sinn nach anderen Werken (dazu zählen auch Internetquellen und KI-basierte Tools) entnommen sind, unter Angabe der Quelle kenntlich gemacht habe und
- dass ich die vorliegende Arbeit noch nicht für andere Prüfungen eingereicht habe.

2. Mir ist bewusst,

- dass ich diese Prüfung nicht bestanden habe, wenn ich die mir bekannte Frist für die Einreichung meiner schriftlichen Arbeit versäume,
- dass ich im Falle eines Täuschungsversuchs diese Prüfung nicht bestanden habe,
- dass ich im Falle eines schwerwiegenden Täuschungsversuchs ggf. die Gesamtprüfung endgültig nicht bestanden habe und in diesem Studiengang nicht mehr weiter studieren darf und
- dass ich, sofern ich zur Erstellung dieser Arbeit KI-basierter Tools verwendet habe, die Verantwortung für eventuell durch die KI generierte fehlerhafte oder verzerrte (bias) Inhalte, fehlerhafte Referenzen, Verstöße gegen das Datenschutz- und Urheberrecht oder Plagiate trage.

Berlin, den August 1, 2025

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*(Unterschrift des Verfassers)*