A Practical Method for Generating String Counterfactuals

Matan Avitan[1]   **Ryan Cotterell**[2]   **Yoav Goldberg**[1,3]   **Shauli Ravfogel**[4]

[1]Bar-Ilan University   [2]ETH Zurich

[3]Allen Institute for Artificial Intelligence   [4] New York University

{matan13av   shauli.ravfogel   yoav.goldberg}@gmail.com

ryan.cotterell@inf.ethz.ch

Abstract

Interventions performed on the representation space of language models have emerged as an effective means to influence model behavior. Such methods are employed, for example, to eliminate or alter the encoding of demographic information, such as gender, within the model's representations and, in so doing, create a counterfactual representation. However, because the intervention operates within the representation space, understanding precisely what aspects of the text it modifies poses a challenge. In this paper, we present a method to convert representation counterfactuals into string counterfactuals. We demonstrate that this approach enables us to analyze the linguistic alterations corresponding to a given representation space intervention and to interpret the features utilized to encode a specific concept. Moreover, the resulting counterfactuals can be used to mitigate bias in classification through data augmentation.

⚫ https://github.com/MatanAvitan/
rep-to-string-counterfactuals

1 Introduction

Interventions performed in the representation space of language models (LMs), generally $\mathbb{R}^D$, have proven effective in understanding and exerting control over neural language models (Ravfogel et al., 2020, 2021; Geva et al., 2021; Elazar et al., 2021; Ravfogel et al., 2022, 2023; Belrose et al., 2023b; Li et al., 2023). One popular set of techniques **erases** the linear subspace associated with a human-interpretable concept c, e.g., GENDER or SENTI-MENT. Another widely used approach is to **steer** representations from one class to another, e.g., shifting them toward a region in the representation space associated with a different class c' (Subramani et al., 2022; Li et al., 2023; Ravfogel et al., 2021; Singh et al., 2024). For instance, they could steer a representation into a region associated with negative sentiment, thereby creating *counterfactual representations*. In this paper, we propose a technique to generate strings that correspond to

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Original Biography

Providing legal representation in Florida for a variety of different issues, Barry Wax was selected to Super Lawyers for 2017–2018. He is admitted to practice before the courts in Florida.

MiMiC (M → F)

In 2016, Ms. Wax was selected by her peers to be selected by Florida Super Lawyers as a Florida Super Lawyer. She represents clients in a variety of practice areas, including labor and employment, real estate, bankruptcy, and family law...

LEACE (M → ∅)

In 2018, Barry Wax was selected as a Super Lawyer in Florida. His practice focuses on providing legal representation to clients in a variety of practice areas...

MiMiC+ (M → F)

In 2016, Ms. Barry was selected by her peers to be selected by the Florida Super Lawyers. She represents clients in all areas of family law, including but not limited to: legal malpractice, spousal care, child custody, and legal malpractice...

Figure 1: The *counterfactual lens* induces diverse string counterfactuals by leveraging different *representation surgery* (i.e., representation-level interventions.) Green denotes the *intended* or *expected* behavior following a gender shift, while blue marks *stereotypical* or otherwise undesired expansions.

representation-level counterfactuals, which we denote as *string counterfactuals*.

Collectively, we refer to representation space intervention techniques as **representation surgery** because they (surgically) intervene in the encoding of a concept within the representation while keeping the rest of the representation as similar as possible. In this sense, representation surgery resembles a causal intervention (Vig et al., 2020; Geiger et al., 2021; Feder et al., 2021; Geiger et al., 2022; Guerner et al., 2023; Lemberger and Saillenfest, 2024), and we will informally use causal language throughout the paper, referring to such modifications in the representation space as inter-

ventions. In notation, we write $f_{c \to c'} \colon \mathbb{R}^D \to \mathbb{R}^D$ for a function that performs such an intervention.

While representation surgery techniques can create counterfactual variants of the original representations, they do not produce them at the level of natural language text. In this work, we tackle the problem of generating the counterfactual *string* that corresponds to a specific representation intervention. Despite the abundance of research on representation surgery, translating such interventions into string counterfactuals remains understudied. We refer to this process as a **counterfactual lens**, as it allows us to interpret representation-space counterfactuals in natural language, similar to representation-level interpretability techniques (Meng et al., 2022; nostalgebraist, 2020; Belrose et al., 2023a; Ghandeharioun et al., 2024). Constructing string counterfactuals serves various practical purposes. First, it offers a method of **meta-interpretability**, aiding in the interpretation of commonly used representational intervention techniques, which themselves are often employed for interpretability. By mapping representational interventions back to the string, we can observe the lexical and higher-level semantic shifts triggered by the intervention. Second, string counterfactuals are a natural choice for data augmentation. Indeed, we demonstrate their potential to address fairness concerns in a real-world classification problem.

We follow Morris et al. (2023) in developing an approach for generating string counterfactuals from representation interventions. Let Σ be an alphabet. Consider a neural network that performs a mapping from a string $s \in \Sigma^*$ to a representation $\mathbf{h} = \mathsf{enc}(s) \in \mathbb{R}^D$. Morris et al. (2023) propose an iterative algorithm to approximate the inverse function $\mathsf{enc}^{-1} \colon \mathbb{R}^D \to \Sigma^*$. We exploit the Morris et al.'s (2023) algorithm to construct a *string counterfactual* corresponding to a surgical intervention in the representation space. Using the notation introduced so far, we are interested in computing $s' = \mathsf{enc}^{-1}(f_{c \to c'}(\mathsf{enc}(s)))$. To the extent that enc^{-1} constitutes a suitable inverse, we expect s' to be a minimally different version of s that reflects the difference between $\mathbf{h}$ and $\mathbf{h}'$ reflected in the representation space.

We perform experiments on a dataset of short biographies annotated with gender and profession (De-Arteaga et al., 2019). We find that swapping gender in the representation space and then generating the inverse is an effective method for producing
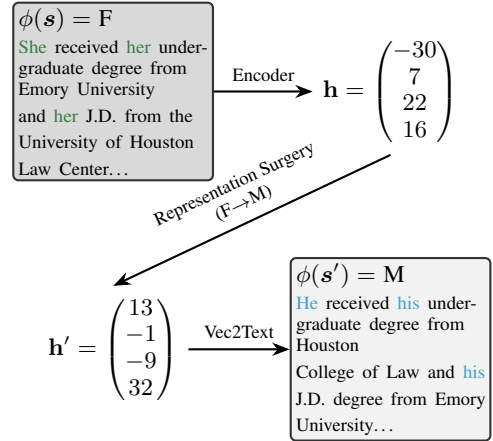

Figure 2: An illustration of our method. We first encode the original text to obtain a representation $\mathbf{h} \in \mathbb{R}^D$. We then apply some form of representation surgery, i.e., to steer or erase a particular concept to produce a modified representation $\mathbf{h}'$. Finally, we invert the representation-level counterfactual to obtain a string-level counterfactual.

string counterfactuals. The resulting counterfactuals exhibit some degree of gender bias, for example, a tendency to include more profession-related words in male biographies, suggesting that LMs encode subtle cues correlated with gender beyond pronouns (§4.2). We further show that these counterfactuals can be used for data augmentation to improve fairness in a multiclass classification task (§4.2.2): specifically, classifiers trained on both original and counterfactual biographies (with respect to gender) exhibit reduced gender bias compared to those trained solely on the original data.

2 Representation Surgery

We provide a more in-depth overview of representation surgery. Many neural networks for natural language processing construct a function $\mathsf{enc} \colon \Sigma^* \to \mathbb{R}^D$ that maps a string of words over Σ, e.g., a natural language text, to a real-valued representation in $\mathbb{R}^D$. We call such functions **language encoders** (Chan et al., 2024). In §1, we introduced a function $f \colon \mathbb{R}^D \to \mathbb{R}^D$ that performs the intervention in the representation space. We consider three types of representation interventions, each discussed in a labeled paragraph below. First, however, we will introduce some general notation.

Notation. Let p be a language model,[1] i.e., a distribution over Σ^*, let $\mathsf{enc} \colon \Sigma^* \to \mathbb{R}^D$ be a

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[1] In this text, p is fully decoupled from the language encoder enc. For instance, our notation allows for p to some approximation to or the actual human language model (to the extent one believes in the human language model as a construct). However, we also allow p to be deeply related to enc.

language encoder. Let $\mathcal{C} = \{0, 1\}$ be a binary set that stands for the different values for a concept. Binary concepts denote whether a given property is present or not, e.g., whether or not a string $s \in \Sigma^*$ is a biography of a man or of a woman. Furthermore, let $\phi \colon \Sigma^* \to \mathcal{C}$ be a concept encoding function.[2] We define the distribution

$$p(s \mid C = c) \stackrel{\text{def}}{\propto} p(s)\mathbb{1}\{\phi(s) = c\}. \qquad (1)$$

Then, for each $c \in \mathcal{C}$, define the following $\mathbb{R}^D$-valued random variable

$$\mathbf{X}_c(s) = \mathrm{enc}(s) \colon \Sigma^* \to \mathbb{R}^D, \qquad (2)$$

which is distributed according to

$$\mathbb{P}(\mathbf{X}_c = \mathbf{h}) = \mathbb{P}(\mathbf{X}_c^{-1}(\mathbf{h})) \qquad (3a)$$

$$= \sum_{s \in \Sigma^*} p(s \mid C = c)\mathbb{1}\{\mathbf{h} = \mathrm{enc}(s)\}. \qquad (3b)$$

LEACE (Belrose et al., 2023b). LEACE is a spectral algorithm that induces log-linear guardedness (Ravfogel et al., 2023), i.e., it minimally (in the L_2 sense) modifies the $\mathbb{R}^D$-valued random variables $\mathbf{X}_c$ for all $c \in \mathcal{C}$ such that there does not exist a log-linear classifier that operates at better than the accuracy of the majority class. To achieve guardedness, LEACE finds an oblique $D \times D$ projection matrix $\mathbf{P}$ of rank $|\mathcal{C}| - 1$ and a translation vector $\mathbf{b}$, which are then used to define the following intervention function

$$f_{\mathcal{C} \to \emptyset}^{\mathrm{L}}(\mathbf{X}_c) \stackrel{\text{def}}{=} \mathbf{P}\mathbf{X}_c + \mathbf{b}. \qquad (4)$$

MiMiC (Singh et al., 2024). MiMiC, in contrast to LEACE, does not merely erase the target concept from the representations, but rather takes the representations of one class (e.g., MALE), and minimally modifies it such that it resembles the representations of the other class (e.g., FEMALE). More precisely, it equates the first two moments of the *source* class-conditional distribution to the *destination* class-conditional distribution, i.e., MiMiC finds a function $f_{c \to c'}^{\mathrm{M}}$ such that

$$\mathbb{E}\left[f_{c \to c'}^{\mathrm{M}}(\mathbf{X}_c)\right] = \mathbb{E}\left[\mathbf{X}_{c'}\right] \qquad (5a)$$

$$\mathbb{V}\left[f_{c \to c'}^{\mathrm{M}}(\mathbf{X}_c)\right] = \mathbb{V}\left[\mathbf{X}_{c'}\right]. \qquad (5b)$$

In the case where the random variables $\mathbf{X}_c$ and $\mathbf{X}_{c'}$ are Gaussian distributed, MiMiC guarantees that the Wasserstein distance (Kantorovich, 1960) between $\mathbf{X}_c$ and $\mathbf{X}_{c'}$ is minimized. In this case, the distance is zero.

MiMiC+. With MiMiC+, we further push the representations in the direction connecting the class-conditional means of the representations belonging to the two classes. Let $\mathbf{v} \stackrel{\text{def}}{=} \mathbb{E}\left[\mathbf{X}_c\right] - \mathbb{E}\left[\mathbf{X}_{c'}\right]$. Given a representation $\mathbf{X}_c(s)$, we linearly transform the output of MiMiC+ as follows

$$f_{c \to c'}^{\mathrm{M+}}(\mathbf{X}_c) \stackrel{\text{def}}{=} f_{c \to c'}^{\mathrm{M}}(\mathbf{X}_c) + \alpha\mathbf{v}, \qquad (6)$$

where $\alpha \geq 0$ is a scalar. Intuitively, we move the representations towards the mean of $\mathbf{X}_c$.

3 Representation Inversion

The generative process through which natural language text is created is complex and difficult to model. However, in some respects, it is well-approximated by modern language models. Concepts like gender are often conveyed subtly, and merely modifying overt indicators such as pronouns and names may not suffice (Maudslay et al., 2019). Instead, we leverage the fact that neural encoders capture nuanced manner in which these concepts manifest in texts. Intervening in such representations is feasible, even *without* the ability to enumerate or fully understand all linguistic features relevant to a concept. Using representational surgery, we intervene on a concept encoded in the representation generated by an encoder after the intervention, we apply an inverter model $\mathrm{enc}^{-1}(\cdot)$ that maps the representation back to a string, yielding an approximate string counterfactual $s' = \mathrm{enc}^{-1}(f(\mathrm{enc}(s)))$.

Morris et al. (2023). Let $s \in \Sigma^*$ be a sentence and let $\mathrm{enc}(s)$ be its representation. Our goal is to convert $\mathrm{enc}(s)$ back into a string. Morris et al.'s (2023) method starts by fine-tuning a language model that can be used to reconstruct an initial hypothesis $\hat{s}_0$ of the inverse $\mathrm{enc}^{-1}(s)$ given the representation $\mathrm{enc}(s)$. Then, a second language model is fine-tuned to reconstruct another hypothesis $\hat{s}_1$ conditioned on the initial $\hat{s}_0$, $\mathrm{enc}(\hat{s}_0)$, $\mathrm{enc}(s)$ and the difference vector $\mathrm{enc}(s) - \mathrm{enc}(\hat{s}_0)$. This process is repeated K times—each time $k \in [K]$, the step consists of fine-tuning the second language model conditioned on $\hat{s}_{k-1}$, $\mathrm{enc}(\hat{s}_{k-1})$, $\mathrm{enc}(s)$ and the difference vector $\mathrm{enc}(s) - \mathrm{enc}(\hat{s}_{k-1})$. The procedure ends when $\mathrm{enc}(\hat{s}_k)$ is sufficiently close to $\mathrm{enc}(s)$ or the computational budget is exceeded. Then, $\hat{s}_k$ is returned by the method as the inverse $\mathrm{enc}^{-1}(s)$. Empirically, Morris et al. (2023) find $K > 1$ iterations produces a more faithful inverse.

For instance, in an autoregressive language model, enc could be produced by the representation of EOS.

[2]We (simplistically) assume each string s contains exactly one concept. Future work will relax this assumption.

Putting it all together. Now, for a concept $c \in \mathcal{C}$ and an intervention function $f_{c \to c'}$ that intervenes on that concept, we generate a counterfactual string by taking the inverse of the encoding of the string, post-intervention. Formally, the counterfactual string correspond to the following Σ^*-valued random variable:

$$\boldsymbol{R}_{c \to c'}(\boldsymbol{s}) = \mathsf{enc}^{-1}(f_{c \to c'}(\mathsf{enc}(\boldsymbol{s}))), \quad (7)$$

which is distributed according to

$$p_{c \to c'}(\boldsymbol{s}') = \mathbb{P}(\boldsymbol{R}^{-1}_{c \to c'}(\boldsymbol{s}')) \quad (8)$$
$$= \sum_{\boldsymbol{s} \in \Sigma^*} p_c(\boldsymbol{s}) \mathbb{1}\{\boldsymbol{s}' = \mathsf{enc}^{-1}(f_{c \to c'}(\mathsf{enc}(\boldsymbol{s})))\}.$$

4 Experimental Evaluation

We now present our experimental results on gender-based interventions that modify the gender attribute in short biographical texts. We evaluate the semantic changes induced by these counterfactual interventions (§4.2), assess their quality (§4.1), and show that they help mitigate gender bias (§4.2.2).

Inversion model. We train a variant of the inversion model from Morris et al. (2023) on 64-token sequences and fine-tune it on the BiasBios dataset. See Appendix A for details.

Dataset. We conduct experiments on the Bias-InBios dataset (De-Arteaga et al., 2019), a large collection of short biographies sourced from the Internet. Each biography is annotated with the subject's gender and profession.[3] We create natural language counterfactuals by intervening on the encoding of gender. We then use these string counterfactuals to study how gender is encoded in the LM (§4.2) and to mitigate bias through data augmentation (§4.2.2).

Pipeline implementation. We trained a dedicated inversion model (Morris et al., 2023) on biography representations extracted from the last layer of a GTR-base model (Ni et al., 2022), obtained by averaging word representations into a single paragraph representation. After training this inversion model, we applied one of the intervention methods to the extracted biography representations to obtain representation-level counterfactuals. For MiMiC and MiMiC+, we set the regularization term to 10^{-5} and used $\alpha = 2$ for MiMiC+. Finally, we applied the trained inversion model to the intervened

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[3]The dataset contains 28 distinct professions.

Scenario	Mistral7b	GPT-2
Original biographies	22.62	104.67
Reconstructed biographies		
(no intervention)	18.17	52.58
LEACE counterfactuals	18.82	53.42
MiMiC counterfactuals	18.29	51.55
MiMiC+ counterfactuals	19.14	48.84

Table 1: Average perplexity for the original, reconstructed, and counterfactual biographies using the different intervention techniques generated by `Mistral7b` and `GPT-2` (Jiang et al., 2023; Radford et al., 2019).

representations to produce the desired string counterfactuals. Although the inversion model is also a GTR-base model, this is not a requirement for the method; any model could be used to create the biography representations (Chen et al., 2024). For more details on the inversion model training setup, see Appendix A.

4.1 Evaluating Counterfactuals Quality

We now discuss our evaluation.

4.1.1 Automatic Evaluation

To assess the quality of the generated counterfactuals, we computed the average perplexity of the resulting texts for each intervention technique. Perplexity is a standard measure of LM performance, with lower values indicating that the model finds the text more predictable and thus, to the extent we trust the language model, of higher fluency. As points of comparison, we also calculated perplexity for the original biographies and for the reconstructed biographies without any intervention (i.e., applying the inversion process of Morris et al. (2023) without modifications). The latter serves as a baseline for the degradation introduced by the inversion process itself.

As shown in Tab. 1, reconstructed biographies (without intervention) consistently achieve lower perplexity than the original biographies, suggesting that the reconstruction process simplifies the text and makes it more predictable. Moreover, the counterfactuals generated by the three intervention methods (LEACE, MiMiC, and MiMiC+) show only a small increase in perplexity compared to the reconstructed biographies, indicating that the interventions introduce minimal degradation in fluency and largely preserve overall text quality. While perplexity serves as a measure of fluency and predictability, it does not necessarily reflect nuanced

Words with the Large Change in PMI		
	Increased	**Decreased**
MiMiC (M → F)	"ms", "she's", "bri", "marie", "mrs", "girl", "herself", "jennifer", "nicole", "domestic", "anne", "nancy", "maternal"	"et", "himself", "kau", "enterprise", "prof", "anthony", "edward", "iot", "acoustic", "days", "hardware", "late"
MiMiC (F → M)	"mr", "him", "he's", "himself", "developer", "chris", "robert", "veterinary", "stephen"	"she's", "mrs", "girl", "herself", "nicole", "female", "desire", "abuse", "lingerie"
LEACE (F → ∅)	"him", "he's", "mr", "plays", "showcase", "authority", "pleasure", "watch", "adventure"	"clutter", "uncomfortable", "classrooms", "compassion", "experiencing", "participant", "babies", "engaging"
LEACE (M → ∅)	"ms", "colleagues", "grace", "leaders", "happy", "presenter", "she's", "advocates", "teach"	"et", "elite", "kau", "direction", "theater", "mentor", "hollywood", "photojournalism"
MiMiC+ (M → F)	"ms", "women's", "she's", "marie", "maternal", "girl", "female", "nicole", "elizabeth", "maternity", "joy"	"he", "his", "mr", "him", "michael", "robert", "daniel", "charles", "peter"
MiMiC+ (F → M)	"he's", "mr", "him", "developer", "daniel", "robert", "jeremy", "adam", "plays"	"she", "her", "ms", "women", "mary", "jennifer", "marie", "herself", "joy"

Figure 3: Words with the largest change in PMI.

shifts in meaning or style. We thus evaluating using perplexity in conjunction with human evaluations.

4.1.2 Human Evaluation

We conducted human annotation experiments on Amazon Mechanical Turk (MTurk) to evaluate the quality of the counterfactuals and the effectiveness of our method, as detailed in Appendix C. Five annotators, all native English speakers from the US, UK, and Australia, were recruited and compensated for their time. They were asked to assess three aspects of the generated texts: (1) readability, (2) grammatical correctness, and (3) gender specification of the subject entity. The first two aspects measure the *quality* of the counterfactual strings, while the third measures their *correctness*, i.e., whether we successfully intervened in the concept of interest.

For tasks (1) and (2), annotators were presented with pairs of texts (original and counterfactual) and asked to compare them in terms of readability and grammatical correctness, indicating which text was superior or whether they were comparable. For

task (3), they determined the gender of the subject entity in each text (male, female, or unclear).

Quality. We performed statistical testing to evaluate whether the interventions had a significant effect on the annotators' responses regarding readability and grammatical correctness. The results are summarized in Appendix C (Tab. 5) based on Tab. 3 and Tab. 4. For most interventions (LEACE, MiMiC, and MiMiC+), the p-values from the one-tailed binomial tests for readability and grammar were greater than 0.05, indicating evidence for a preference for the original text over the counterfactuals. This suggests that our method did not degrade the quality of the text in terms of readability and grammar. However, for the MiMiC (F → M) and MiMiC+ (F → M) interventions, the p-values for readability were less than 0.05 ($p = 1.60 \times 10^{-5}$ and $p = 9.05 \times 10^{-8}$, respectively), indicating that the original text was preferred over the counterfactual in terms of readability. This suggests that the interventions did cause a degradation in readability when intervening on the perceived gender of the person described in the biography.

Correctness. To determine whether the interventions effectively changed how annotators perceived gender, we performed chi-square tests on annotators' gender specification responses. Rejecting the null hypothesis under a chi-square test gives evidence that the distribution of gender identifications depends on the intervention, implying that the intervention successfully influenced the perceived gender of the text. As shown in Tab. 5, the p-values for all interventions were extremely low (well below 0.05). For instance, in the MiMiC (F → M) intervention, originally female biographies were annotated as male 82% of the time after the intervention, compared to 3% male in the original texts. This shift corresponds to a chi-square statistic of 130.56 (p-value 4.45×10^{-29}). Similarly, in the MiMiC (M → F) intervention, originally male biographies were annotated as female 86% of the time post-intervention, compared to 10% female in the originals, with a chi-square statistic of 131.44 (p-value 2.87×10^{-29}). These results show that annotators generally agreed with the intended gender changes, confirming that the interventions were effective. By contrast, LEACE, an erasure method, produced more mixed outcomes. For example, when applied to originally female biographies, the proportion perceived as male rose from 11% to 66%, those perceived as female decreased from 85% to 26%, and 8% were labeled as unclear. This pattern reflects its function as an erasure technique rather than a steering approach; see Fig. 1 and Appendix E.

4.2 Semantic Changes in the Counterfactuals

In the previous section, we validated the semantic coherence and correctness of the counterfactuals. In this section, we analyze the specific changes incurred in the inversion process. This analysis is performed over sentences from the dev set of BiasBios dataset whose lengths are 64 tokens or less: 7,578 biographies in the M → F direction and 6,982 biographies in the F → M direction.

Pointwise mutual information. To quantitatively evaluate local changes induced by the counterfactual generation process, we analyze the words whose probabilities change the most between the original and counterfactual sentences. Let $c, c' \in \mathcal{C}$ be two concepts. In the case of concept *erasure*, we may have $c' = \emptyset \notin \mathcal{C}$. We now consider two

random multisets of M strings

$$S_{c \to c} = \langle\!\langle s^{(m)} \mid s \sim p_{c \to c} \rangle\!\rangle_{m=1}^{M} \qquad (9a)$$

$$S_{c \to c'} = \langle\!\langle s^{(m)} \mid s \sim p_{c \to c'} \rangle\!\rangle_{m=1}^{M}. \qquad (9b)$$

Then, we define a unigram distribution over Σ induced from $S_{c \to c}$ and $S_{c \to c'}$ as follows

$$p(w \mid c \to c) \overset{\text{def}}{\propto} \sum_{s \in S_{c \to c}} \#(w, s) \qquad (10a)$$

$$p(w \mid c \to c') \overset{\text{def}}{\propto} \sum_{s \in S_{c \to c'}} \#(w, s), \qquad (10b)$$

where $\#(w, s)$ returns how many times the word w occurs in string s. Then, taking $p(c \to c) = p(c \to c') = 1/2$, we define the pointwise mutual information (PMI) as follows

$$\text{PMI}(w, c \to c') \overset{\text{def}}{=} \log \frac{2p(w, c \to c')}{p(w)}. \qquad (11)$$

Manipulation then reveals that the difference of two PMIs is the log odds ratio:

$$\text{PMI}(w, c \to c') - \text{PMI}(w, c \to c) \qquad (12a)$$

$$= \log \frac{p(w, c \to c')}{p(w, c \to c)}. \qquad (12b)$$

Intuitively, the difference between two PMIs tells us the words whose frequency increased or decreased the most after the intervention, normalized by the amount of change incurred by the inversion process alone, i.e., inversion without an intervention. We additionally add a smoothing term of 10^{-6} when calculating the PMI. Finally, we sort the vocabulary according to the log-odds ratio, omitting words whose frequency is less than 5.

4.2.1 Results

In this section, we analyze the changes in log ratios across different methods when manipulating gender concepts. See Fig. 1 and Appendix E for a sample of the original and counterfactual sentences. See also Fig. 3 for a subset of the words whose PMI changed the most, with the entire lists available in Appendix B. We explore how words increase or decrease in likelihood when gendered concepts such as FEMALE and MALE are removed or altered, and we highlight the thematic shifts associated with these changes. For each method—LEACE, MiMiC, and MiMiC+—we find notable trends that reveal underlying gender associations in language models.

Overall trends. As anticipated, in the F → M direction, masculine pronouns and titles such as "*he's*", "*him*", "*mr*", and "*himself*" experienced the most significant increase in likelihood. Conversely, in the M → F direction, the largest changes were observed with feminine pronouns and titles like "*she's*", "*ms*", "*mrs*", and "*herself*". Beyond pronouns, we find that some more subtle changes sometimes occur, reflecting biases in the dataset. Furthermore, in the direction M → F the counterfactuals of the biographies of doctors often omit the "*Dr.*" prefix and replace it with "*Ms*". Specific terms associated with professional and technical domains, such as "*developer*", "*managers*", "*esl*", and "*llp*", exhibited an increased frequency in the F → M direction, as we discuss below. The counterfactuals generated by MiMiC+ exhibit an overuse of stereotypical markers of the target gender, adding pronouns when they are not necessary or introducing new stereotypical information as depicted in Fig. 1. This intervention tends to significantly modify the overall structure of the sentence. The inversion process is not perfect, and at times inflicts some changes to the original text, such as paraphrasing; see §4.1.

LEACE. LEACE aims to remove the ability to distinguish between stereotypically male and female representations. We find that post-intervention, texts which that originally focused on a woman now exhibit a decrease in words related to social engagement, care, and education. This reduction is evident from terms like "*uncomfortable*", "*strangers*", "*volunteering*", and "*babies*", which are often associated with stereotypically feminine social roles and nurturing activities. Educational and experiential terms like "*seminars*", "*classrooms*", and "*participant*" also show a decreased likelihood ratio, reflecting a diminished focus on stereotypically feminine educational themes. Conversely, we observe an increase in the likelihood ratio of words associated with masculine pronouns and themes related to action, authority, and success. Words like "*him*", "*he's*", and "*mr*" show a rise in likelihood ratio, as well as action-oriented words such as "*adventure*", "*watch*", and "*serve*", demonstrating a shift towards traditionally masculine concepts. Opposite trends are shown when examining the outcomes of LEACE (M → ∅). These strings show a decrease in references to cultural, artistic, and professional domains. Words like "*elite*", "*theater*", and "*mentor*" diminish in like-

lihood ratio, suggesting a reduction in masculine-associated professional and artistic spheres. Meanwhile, an increased likelihood ratio of words related to collaboration, leadership, and personal growth is observed. Words like "*colleagues*", "*leaders*", and "*advocates*" show a rise, reflecting themes of teamwork and leadership more commonly associated with femininity. Positive emotions and personal growth terms such as "*grace*" and "*happy*" also increase, signaling a shift toward nurturing and empathetic language.

MiMiC. For the MiMiC method, performing the intervention M → F reveals a shift towards more stereotypically feminine references. Words like "*ms*", "*she's*", and "*mrs*" increase, as do female names like "*marie*", "*jennifer*", and "*nicole*". Words relating to interpersonal relationships, emotions and caregiving, such as "*happy*" and "*colleagues*", also rise in likelihood ratio. When altering the female gender concept to male using MiMiC, we observe an increase in male-specific references, with words like "*mr*", "*him*", "*he's*", and "*himself*" rising in likelihood ratio. Male names, such as "*dahl*", "*chris*", and "*stephen*", also become more prominent, along with professional and technical terms like "*developer*" and "*managers*". Conversely, terms related such as "*she's*", "*mrs*", and "*girl*", decrease in likelihood ratio, as well as names like "*marie*", "*nicole*", "*anne*", "*stephanie*", "*susan*" and terms from the social sphere such as "*inspire*", "*uncomfortable*", "*desire*", "*strangers*", "*classrooms*". This reflects a reduced focus on female-associated themes, particularly around care and emotional expression.

Summary. Across methods and gender concept manipulations, we observe clear patterns of thematic shifts. Removing or altering gender concepts in language models leads to changes in words associated with social roles, authority, and professional domains, reflecting underlying gender biases. These findings highlight the importance of understanding and addressing gender biases in language model development.

4.2.2 Counterfactual Data Augmentation

We have established that the proposed pipeline creates high-quality and relatively surgical counterfactuals. In this section, we make use of the counterfactuals to increase fairness in multiclass classification. The BiasBios dataset exhibits an imbalance in the representation of men and women in various

Setting	Accuracy ↑	F1 ↑	True Positive Rate Gender Gap ↓
Original biographies	86.42±0.0	79.63±0.01	14.27±01
Reconstructed biographies (no intervention)	81.52±0.0	72.08±0.0	13.69±0.0
Biographies without gender indication	85.33±0.0	77.75±0.0	11.22±0.0
Original biographies + LEACE counterfactuals	**86.59**±0.0	**81.8**±0.0	12.95±0.0
Original biographies + MiMiC counterfactuals	86.12±0.0	80.92±0.0	12.13±0.02
Original biographies + MiMiC+ counterfactuals	85.76±0.0	80.31±0.01	**10.59**±0.01

Table 2: Multi-class classification results from a log-linear model trained on top of `roberta-base` (Liu et al., 2019).

professions, leading to observed biases in the profession classifiers trained on this data (De-Arteaga et al., 2019). In our next experiment, we show how our generated string counterfactuals can be used for data augmentation. By adding counterfactual examples with the opposite gender label, we aim to mitigate the model's dependence on gender.

Setup. We represent each biography using the final-layer output from a GTR-base model (Ni et al., 2022). Next, we apply an intervention and decode the modified representation using a trained inversion model. For decoding, we employ beam search with a beam size of 4 and perform 20 correction steps using the pre-trained Natural Questions corrector from Morris et al. (2023). This iterative process is repeated for each of the three intervention techniques: LEACE, MiMiC, and MiMiC+. The results are averaged over three models (see Appendix A). Finally, following previous work (De-Arteaga et al., 2019), we quantify bias as the RMS gap in true positive rates (TPR) between genders using a profession classifier (De-Arteaga et al., 2019).

Models. We train a log-linear profession classifier on top of the language model `roberta-base` (Liu et al., 2019) to predict the profession of the subject of the biography. The classifiers are trained on the original biographies, the inverse of the biographies without intervention, the biographies without gender indications, such as pronouns ("Biographies without gender indication" in Tab. 2), and the dataset that consists of the original biographies in addition to the corresponding counterfactuals created by LEACE MiMiC and MiMiC+ ($\alpha = 2$ for all experiments)

Results. All results are presented in Tab. 2. Classifiers trained on the augmented dataset achieve lower TPR values (better fairness), even more so than classifiers trained on the biographies after the omission of overt gender markers. At the

same time, the augmentation does not damage and even improves, main-task performance (profession classification), indicating that augmenting the dataset with intervention-induced string counterfactuals is a viable way to encourage the classifier to show invariance to the sensitive information (in our case, gender).

5 Conclusion

We introduced a method for converting representation space interventions in language models into string-level counterfactuals. This approach bridges the gap between abstract representation manipulations and concrete textual changes, and allows us to derive the latter from the former. We demonstrated that the resulting counterfactuals are semantically coherent and that they surface some biases in the encoding of complex concepts such as gender. We additionally showed that the counterfactuals can assist in mitigating bias in classification through data augmentation.

Our experiments highlight the potential of string counterfactuals for interpreting features used to encode concepts like demographic information, with important implications for fairness in NLP. However, the quality of counterfactuals depends on the inversion model, and our focus on binary attributes could be expanded in future work. In future work, we aim to refine the inversion process and extend the method to other interventions.

Limitations

Quality of the inversion model. Our counterfactual generation method consists of two components: the intervention function f and the inversion model enc^{-1}. We aimed to disentangle these two factors in our evaluation by comparing the inversions generated with interventions to those produced without intervention. However, complete disentanglement is challenging, and some of the observed changes may be due to imperfections in the inversion pro-

cess rather than the intervention itself. We note that the inversion model is indeed imperfect and often introduces slight variations in the text (e.g., modifying numbers or geographical locations, or generating lexical paraphrases). These changes might be undesirable in certain use cases; however, improvements to the inversion model are orthogonal to our method.

Causal interventions. Because the generative process of natural language texts is opaque, we inevitably rely on markers that people commonly associate with the property of interest (gender) in our evaluation. Future work should employ a controlled, synthetic setting to assess the extent to which the counterfactuals reflect the true causal factors associated with the concept of interest.

Representation of gender. We rely on an existing dataset with binary gender labels. We acknowledge that this is a simplification, as gender is a complex, nonbinary construct.

Ethical Considerations

In all scenarios involving the potential application of automated methods in real-world contexts, we strongly recommend exercising caution and thoroughly evaluating the representativeness of the data, its alignment with real-world phenomena, and its potential adverse societal implications. Gender bias is a complex and multifaceted issue, and we view the experiments conducted in this paper as an initial exploration of strategies for mitigating the negative impacts of language models rather than a definitive solution to real-world bias challenges. As highlighted in the Limitations section, the use of binary gender labels arises from limitations in available data, and we anticipate that future research will enable more nuanced examinations of how gender, as a construct, manifests in text.

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Appendix

A   Experimental setup

Training an inversion model.   Morris et al. (2023) introduced an approach for converting representations into strings. To effectively invert the representations derived from the BiasBios dataset, we trained a dedicated inversion model on 64-token sequences from the Natural Questions dataset (Kwiatkowski et al., 2019). This decision was informed by the observation that the median biography length in the BiasBios dataset is 72 tokens. The model architecture is GTR-base (Ni et al., 2022), as originally used in vec2text (Morris et al., 2023). The inversion process consists of two components: the inversion model and a corrector model (both are GTR-base LMs). Empirical results demonstrate that training both components improves the quality of the reconstructed text. The training procedure involved training the inversion model for 30 epochs on the Natural Questions dataset (Kwiatkowski et al., 2019) with a batch size of 4096, followed by fine-tuning for an additional 20 epochs on the BiasBios dataset (De-Arteaga et al., 2019) with a batch size of 512. Subsequently, the corrector model was trained on the BiasBios dataset for 10 epochs using a batch size of 128 samples.

Training profession classifiers.   To quantify the causal effect of counterfactuals on predicting an individual's profession, we utilized `roberta-base` (Liu et al., 2019) classifiers trained on both the counterfactuals and the corresponding original biographies, as outlined in Tab. 2. Each classifier was trained with three different seeds, and we report the mean and standard deviation of the metrics obtained from the checkpoint with the lowest validation loss for each seed. The classifiers were trained for 10 epochs on the entire BiasBios biography dataset, with sequences truncated to 64 tokens. This dataset comprises 7,578 male biographies and 6,982 female biographies. For each original sample, its corresponding counterfactual was included in the training set. We used a batch size of 1024 samples for training and 4096 for evaluation. Furthermore, 6% of the samples were used for learning rate warm-up, with an initial learning rate set to 2×10^{-5}. We also employed half-precision quantization (fp16) for the network's weights (Baboulin et al., 2009; Micikevicius et al., 2017). The results reported in Tab. 2 were calculated on the entire BiasBios development set (39,369 samples), with sequences truncated to 64 tokens.

B   Word PMI Analysis

We provide the words most changed due to MiMiC , LEACE and MiMiC+ interventions below.

B.1   MiMiC

- words whose likelihood most decreased in direction M → F :

  ["*et*", "*himself*", "*kau*", "*enterprise*", "*really*"","*prof*", "*anthony*", "*ch*", "*edward*", "*iot*", "*0560*", "*1978*", "*acoustic*", "*biggest*", "*steven*", "*founding*", "*days*", "*hardware*", "*patience*", "*late*", "*reputed*", "*3d*", "*run*", "*stephen*", "*trustee*", "*boy*", "*theater*", "*join*", "*detection*", "*rather*"]

- words whose likelihood most increased in direction M → F :

  ["*ms*", "*she's*", "***", "*bri*", "*marie*", "*mrs*", "*girl*", "*herself*"", "*jennifer*"", "*002412*", "*nicole*", "*women's*", "*happy*", "*newborn*", "*andrea*", "*domestic*", "*exploring*", "*mn*", "*colleagues*", "*setting*", "*anne*", "*elizabeth*", "*1215242727*", "*donna*", "*geriatric*", "*nancy*", "*upon*", "*maternal*", "*picture*", "*1215191916*"]

- words whose likelihood most decreased in direction F → M :

  ["*she's*", "*mrs*", "*girl*", "*marie*", "*|*", "*herself*", "*clutter*"", "*inspire*", "*uncomfortable*", "*nicole*", "*female*", "*promotes*", "*anne*"", "*desire*", "*13*", "*abuse*", "*lingerie*", "*caring*", "*elder*", "*strangers*", "*classrooms*", "*stephanie*", "*mn*", "*susan*", "*refugee*", "*runway*", "*21*", "*within*", "*59*", "*plants*"]

- words whose likelihood most increased in direction F → M:

["*mr*", "*him*", "*he's*", "*dahl'*", "*himself*", "*1st*", "*peers*", "*plays*", "*.0*", "*2019*", "*developer*", "*chris*", "*x*", "*robert*", "*veterinary*", "*esl*", "*lifetime*", "*llp*", "*wallpapers*", "*adventure*", "*chance*", "*managers*", "*watch*", "*humour*", "*murya*", "*1003021313*", "*stephen*", "*list*", "*say*", "*concerned*"]

B.2 LEACE

- words whose likelihood most decreased in direction (F → ∅):

["*clutter*", "*uncomfortable*", "*strangers*", "*front*", "*classrooms*","*volunteering*", "*0000*", "*never*", "*travelling*", "*seminars*", "*compassion*", "*cute*", "*humanitarian*", "*pre-*", "*experimental*", "*accredited*", "*experiencing*", "*partnerships*", "*distribution*", "*off*", "*participant*", "*implementing*", "*babies*", "*funny*", "*die*", "*photographing*", "*1903021717*", "*words*", "*engaging*", "*engages*"]

- words whose likelihood most increased in direction (F → ∅):

["*him*", "*he's*", "*mr*", "*hunger*", "*eat*", "*himself*", "*plays*", "*hot*", "*showcase*", "*inspiring*", "*fair*", "*authority*", "*1979*", "*llp*", "*watch*", "*pleasure*", "*cns*", "*beyond*", "*failure*", "*per*", "*meets*", "*suny*", "*adventure*", "*agricultural*", "*serve*", "*greater*", "*luxury*", "*idea*", "*night*", "*reuters*"]

- words whose likelihood most decreased in direction (M → ∅):

["*et*", "*elite*", "*kau*", "*ch*", "*pastoral*", "*direction*", "*0560*", "*choice*", "*august*", "*patience*", "*cinema*", "*restaurant*", "*58*", "*theater*", "*join*", "*rather*", "*composing*", "*tn*", "*reviewer*", "*kent*", "*core*", "*effect*", "*mentor*", "*significant*", "*entertainment*", "*hollywood*", "*something*", "*photojournalism*", "*friend*", "*demand*"]

- words whose likelihood most increased in direction (M → ∅):

["*ms*", "*colleagues*", "*grace*", "*prepare*", "*leaders*", "*mediations*", "*greater*", "*setting*", "*grown*", "*happy*", "*publication*", "*writers*", "*similar*", "*presenter*", "*counsels*", "*1903021515*", "*employee*", "*19th*", "*bi*", "*she's*", "*wilderness*", "*bad*", "*embedded*", "*believer*", "*detail*", "*promotion*", "*advocates*", "*teach*", "*mri*", "*dedication*"]

B.3 MiMiC+

- words whose likelihood most decreased in direction M → F :

["*he*", "*his*", "*mr*", "*him*", "*he's*", "*michael*", "*william*", "*et*", "*elite*", "*mark*", "*andrew*", "*robert*", "*man*", "*paul*", "*brian*", "*richard*", "*himself*", "*daniel*", "*engineer*", "*funded*", "*alan*", "*joseph*", "*charles*", "*distributed*", "*–*", "*peter*", "*developer*", "*kau*", "*subject*", "*adam*"]

- words whose likelihood most increased in direction M → F :

["*ms*", "*women's*", "*she's*", "*marie*", "*maternal*", "*girls*", "*girl*", "*1417191916*", "*1417191997*", "*empowerment*", "*michelle*", "*nicole*", "*female*", "*jennifer*", "*elizabeth*", "*mrs*", "*nurses*", "*parenting*", "*mary*", "*promotion*", "*practitioners*", "*birth*", "*empowering*", "*holistic*", "*mom*", "*mothers*", "*maternity*", "*woman's*", "*crisis*", "*joy*"]

- words whose likelihood most decreased in direction F → M

["*she*", "*her*", "*ms*", "*women*", "*she's*", "*mother*", "*ki*", "*women's*", "*mrs*", "*woman*", "*elementary*", "*january*", "*mary*", "*daughter*", "*girl*", "*jennifer*", "*marie*", "*I*", "*assisting*", "*lisa*", "*jessica*", "*herself*", "*elizabeth*", "*joy*", "*sexual*", "*pregnancy*", "*amy*", "*sexuality*", "*opportunities*", "*rachel*"]

- words whose likelihood most increased in direction F → M:

["*he's*", "*mr*", "*him*", "*guy*", "*x*", "***", "*ka*", "*himself*", "*developer*", "*daniel*", "*1st*", "*robert*", "*1003021313*", "*juicy*", "*jeremy*", "*nephrology*", "*peers*", "*chairman*", "*adam*", "*hardware*", "*bi*", "*matthew*", "*mark*", "*acoustic*", "*//*", "*christopher*", "*plays*", "*.0*", "*player*", "*forum*"]

Intervention	Same	Original	Counterfactual
LEACE (F → ∅)	29	55	16
LEACE (M → ∅)	20	52	28
MiMiC (F → M)	8	71	21
MiMiC (M → F)	15	41	44
MiMiC+ (F → M)	10	76	14
MiMiC+ (M → F)	13	41	46

Table 3: Readability annotation results

C Human Annotation

We conducted human annotation experiments to evaluate the quality of the interventions using Amazon Mechanical Turk (MTurk). Five annotators, all native English speakers from the US, UK, and Australia, were recruited for this task. The annotators were compensated for their work in line with standard MTurk rates. This selection process ensured that the annotators had a high degree of fluency in English. Annotators were required to complete three tasks: (1) assess the readability of pairs of sentences (2) assess their grammatical correctness, and (3) determine the subject entity gender for each sentence. These tasks were designed to evaluate the quality and correctness of the generated counterfactuals compared to the original biographies, following the annotation guidelines; see Appendix D. In tasks (1) and (2), annotators were presented with two texts, labeled Text A and Text B. They were asked to compare the readability and grammatical correctness of the texts, selecting which was more readable and grammatically correct, or indicating that both were comparable. In task (3), annotators were asked to identify the gender of the subject entity in the sentence: male, female, or unclear. To analyze the results, we performed a chi-Square Test of Independence to statistically evaluate whether there was a significant difference in the annotation responses before and after applying the interventions.

Intervention	Same	Original	Counterfactual
LEACE (F → ∅)	48	36	16
LEACE (M → ∅)	58	29	13
MiMiC (F → M)	57	37	6
MiMiC (M → F)	52	30	18
MiMiC+ (F → M)	49	38	13
MiMiC+ (M → F)	45	34	21

Table 4: Grammar annotation results

Hypotheses. We formulated our hypotheses separately for each task and applied the appropriate statistical tests:

- **Readability and Grammar (One-Tailed Binomial Test)**

  - **Null Hypothesis** (H_0): The original text is *not* preferred over the counterfactual text in terms of readability and grammar, i.e., the probability of preferring the original biography is less than or equal to 0.5.
  - **Alternative Hypothesis** (H_1): The original text is preferred over the counterfactual text in terms of readability/grammar, i.e., the probability of preferring Text A is greater than 0.5.

- **Gender Specification (Chi-Square Test of Independence)**

  - **Null Hypothesis** (H_0): The distribution of gender identification is independent of the intervention, i.e., the intervention does not affect how annotators perceive the gender of the subject entity.

– **Alternative Hypothesis** (H_1): The distribution of gender identification is dependent on the intervention, i.e., the intervention affects how annotators perceive the gender of the subject entity.

Intervention	Test	Test Statistic	p-value
LEACE (F $\to \emptyset$)	Readability (Binomial Test)	$k = 55, n = 100$	$p = 0.18$
	Grammar (Binomial Test)	$k = 36, n = 100$	$p = 1.00$
	Gender Specification (Chi-Square Test)	$\chi^2 = 71.98$	$p = 2.34 \times 10^{-16}$
LEACE (M $\to \emptyset$)	Readability (Binomial Test)	$k = 52, n = 100$	$p = 0.38$
	Grammar (Binomial Test)	$k = 29, n = 100$	$p = 1$
	Gender Specification (Chi-Square Test)	$\chi^2 = 24.87$	$p = 3.97 \times 10^{-6}$
MiMiC (F $\to$ M)	Readability (Binomial Test)	$k = 71, n = 100$	$p = 1.60 \times 10^{-5}$
	Grammar (Binomial Test)	$k = 37, n = 100$	$p = 1.00$
	Gender Specification (Chi-Square Test)	$\chi^2 = 130.56$	$p = 4.45 \times 10^{-29}$
MiMiC (M $\to$ F)	Readability (Binomial Test)	$k = 41, n = 100$	$p = 0.97$
	Grammar (Binomial Test)	$k = 30, n = 100$	$p = 1.00$
	Gender Specification (Chi-Square Test)	$\chi^2 = 131.44$	$p = 2.87 \times 10^{-29}$
MiMiC+ (F $\to$ M)	Readability (Binomial Test)	$k = 76, n = 100$	$p = 9.05 \times 10^{-8}$
	Grammar (Binomial Test)	$k = 38, n = 100$	$p = 0.99$
	Gender Specification (Chi-Square Test)	$\chi^2 = 103.94$	$p = 2.69 \times 10^{-23}$
MiMiC+ (M $\to$ F)	Readability (Binomial Test)	$k = 41, n = 100$	$p = 0.97$
	Grammar (Binomial Test)	$k = 34, n = 100$	$p = 1.00$
	Gender Specification (Chi-Square Test)	$\chi^2 = 134.58$	$p = 5.97 \times 10^{-30}$

Table 5: Test results for readability, grammar, and gender specification tasks across LEACE MiMiC and MiMiC+ interventions. p-values above 0.05 in the binomial tests indicate no significant preference for the original text over the counterfactual, suggesting that the interventions did not degrade text quality. p-values below 0.05 in the chi-square tests indicate statistically significant differences in gender specification after the interventions.

Results. The results of the statistical tests are summarized in Tab. 5, Tab. 6 and Tab. 4. For the readability and grammar tasks, we performed one-tailed binomial tests. The number of times the original text was preferred (k) and the total number of observations (n) are reported, along with the p-values. For the gender specification task, we performed chi-square tests of independence, reporting the chi-square statistic and the p-value.

Conclusions.

- **Readability and Grammar:** For most interventions, the p-values from the one-tailed binomial tests are greater than 0.05, indicating that we fail to reject the null hypothesis. This suggests that the original text was not significantly preferred over the counterfactual in terms of readability and grammatical correctness, implying that the interventions did not degrade text quality.

  However, for the MiMiC (F $\to$ M) and MiMiC+ (F $\to$ M) interventions, the p-values for readability are less than 0.05 ($p = 1.60 \times 10^{-5}$ and $p = 9.05 \times 10^{-8}$, respectively). This means we reject the null hypothesis in these cases, indicating that the original text was significantly preferred over the counterfactual in terms of readability. This suggests that these interventions may have led to a degradation in readability when altering gender from female to male.

- **Gender Specification:** For all interventions, the p-values from the chi-square tests are significantly less than 0.05, leading us to reject the null hypothesis. This indicates that the interventions had a statistically significant effect on how annotators perceived the gender of the subject entity. Therefore, the interventions were effective in altering the perceived gender in the texts.

Technique	Data Type	Male	Female	Unclear
LEACE (F → ∅)	Original	11	85	4
	Intervention	66	26	8
LEACE (M → ∅)	Original	92	5	3
	Intervention	64	32	4
MiMiC (F → M)	Original	3	97	0
	Intervention	82	17	1
MiMiC (M → F)	Original	90	10	0
	Intervention	9	86	5
MiMiC+ (F → M)	Original	12	87	1
	Intervention	84	16	0
MiMiC+ (M → F)	Original	91	9	0
	Intervention	9	88	3

Table 6: Gender annotation results for different intervention techniques

An agreement between the annotators was measured by Fleiss' κ score (Fleiss, 1971). For task (1), comparing the readability of the sentence pairs, Fleiss' κ was 0.23, indicating fair agreement among the annotators. For task (2), comparing the grammar level of the sentence pairs, Fleiss' κ was 0.21, indicating fair agreement among the annotators. For task (3), determining the subject entity's gender, Fleiss' κ was 0.6, indicating moderate to substantial agreement.

The counterfactual was randomly presented as Text A or Text B with a uniform distribution. Moreover the counterfactual sentence was generated by applying one of the three intervention techniques followed by the inversion model. The samples were drawn uniformly with replacement using a random sampling generator.

The exact annotation guidelines provided to the annotators are given in Appendix D.

D Annotation Guidelines

```
Overview
You will be provided with two texts, labeled Text A and Text B.
Your task is to evaluate these texts based on their:
    * Readability
    * Grammatical correctness
    * Entity gender specification


Examples
Read the following two texts (Text A and B) and answer the following questions:


Text A:
In this capacity he will assist clients in matters involving estates, trusts, wills,
guardianships, asset disputes, powers of attorney, and advanced medical directives.
Text B:
In this capacity, she will assist clients in a variety of medical matters,
including elder care,
medical malpractice, wills, trusts, powers of attorney, guardianships,
and advanced medical directives.


Question 1: Which of the texts A or B is more readable and understandable? If both
texts are comparable in terms of readability, select Same.
Answer: Same
```

Question 2: Which of the texts A or B is more grammatically correct? If both texts are comparable in terms of grammar, select Same.
Answer: Same

Question 3: Is the subject entity male, female, or unclear?
Answer:
    * Text A: Male
    * Text B: Female

Text A:
She studied at the Wimbledon School of Art 1980-84 and later on with Cecil Collins and Sybil Andrews. She has traveled extensively, setting up homes and painting in Kenya, Dubai, Canada, and Jerusalem.

Text B:
He studied at the London College of Art with Andrew Davies and Sybil Kennedy. Since 1987, he has traveled to New Zealand, Canada, Israel, Kenya, Australia, and New Zealand, where he studied a range of painting-in-residences including...

Question 1: Which of the texts A or B is more readable and understandable? If both texts are comparable in terms of readability, select Same.
Answer: Text A

Question 2: Which of the texts A or B is more grammatically correct? If both texts are comparable in terms of grammar, select Same.
Answer: Same

Readability and Grammatical Correctness
Read the following two texts (Text A and B) and answer the following questions:
Text A:
$text_a
Text B:
$text_b
Question 1: Which of the texts A or B is more readable and understandable? If both texts are comparable in terms of readability, select Same.

Possible Answers:
    * Same
    * Text A
    * Text B

Question 2: Which of the texts A or B is more grammatically correct? If both texts are comparable in terms of grammar, select Same.

Possible Answers:
    * Same
    * Text A
    * Text B

Gender Annotation
For each text, determine the gender of the subject entity.
Text A:
$text_a
Is the subject entity male, female, or unclear?

Possible Answers:
    * Male
    * Female
    * Unclear
Text B:
$text_b
Is the subject entity male, female, or unclear?

Possible Answers:
    * Male
    * Female
    * Unclear

E   Intervention inversion sample

In Tab. 7 we provide a random sample of the counterfactuals generated by the different methods.

Method	Inversion without intervention	Intervention + Inversion
MiMiC (F → M)	A 2017 Sports Illustrated Swimsuit Trend Hero, she talks about how she learned to embrace her body's curves, embrace their natural curves, and never let it get in the way of her career.	A 2017 Sports Illustrated Swimsuit Hero, he embraces his flaws to become a hero, but never lets risk get in the way of his self - confidence.
MiMiC (F → M)	Prior to moving to New York, Naomi worked as a registered nurse for six years, specializing in cardiology. During this time, Naomi also worked in the Emergency Department at Duke University Medical Center. Naomi has a Master's Degree in Nursing. She is	Prior to joining Manhattan, she worked as an RN in the Emergency Department, specializing in cardiology. During her time at UMDNJ - NewYork, Naomi completed a Master's Degree in Cardiology.
MiMiC (M → F)	Dr. Ahn attended medical school at Northwestern University, Feinberg School of Medicine and completed a residency at the Children's Memorial Hospital. He is board certified by the American Board of Pediatrics.	Dr. Ahn attended medical school at Northwestern University Feinberg School of Medicine and completed her residency in Pediatrics at the Children's Hospital. She is board - certified by the American Academy of Nurse Practitioners in Pediatrics.
MiMiC (M → F)	He earned his Ph.D. in business administration from Penn State University's Smeath School of Business. His research interests include business process innovation, data mining, information security, and healthcare operations research.	She earned her doctorate in business administration from Penn State University's Smeal School of Business and her master's and bachelor's degrees from Penn State University. Her research interests include healthcare operations research, e - health, innovation, patient satisfaction, process
LEACE (F → ∅)	She earned Bachelor of Science degrees in Biology and Chemistry from Metropolitan State College in DeKalb, MN. Dean obtained her Master of Science degree in physician assistant studies from Denver Medical College.	He earned a Bachelor of Science degree in Biology and Chemistry from Metropolitan State College in Denver, Colorado. Dean obtained his Master of Medical Science degree in physician assistant studies from Western Michigan University.
LEACE (F → ∅)	She has devoted her life to helping people to achieve their health goals through diet, nutrition and lifestyle counseling. Diana can be contacted at : danielle.danielle.co.uk	He has helped hundreds of people to achieve their health and lifestyle through nutrition. Diana helps people to navigate their way of life through nutrition and counseling. For more information, please visit : http://www.daniellebakhron.com
LEACE (M → ∅)	He focuses his practice on understanding how to protect data and privacy across the entire enterprise. Mr. Robinson also works with federal and state agencies to develop data security standards, best practices, cybersecurity best practices, and best practices to protect data and privacy across the entire enterprise.	She focuses her practice on partnering with businesses, government agencies, and private companies to develop and implement best practices in data security, data privacy, and cybersecurity. Mr. Robinson also counsels businesses on how to protect their data assets and comply with federal data security standards.
LEACE (M → ∅)	He graduated with a degree in Architecture and Design from the Architectural Association School of Design and Design. His architectural practice is based in Notting Hill London.	He graduated from the Architectural Association School of Architecture and Design based in Notting Hill, London. He also has a degree in architecture and design. His practice is based in notting Hill.
MiMiC+ (F → M)	She is the co - author of Films, Culture, and Popular Culture in Argentina. Her research and writings have appeared or are forthcoming in Latin American Studies, Latin American Studies, Latin American Culture, and other journals.	He is the author or co - author of many books and many essays on Latin American culture. His main field of study is the history of theater, cinema, and popular culture in Argentina. He was the Editor of Cinemas, Cultures, and Cultures in Argentina,
MiMiC+ (F → M)	Her work specializes in counseling clients in information security - related incidents, risk management, data collection and compliance and assisting clients with information security - related risks and compliance.	His work specializes in information security counseling and compliance for clients, dealing with security - related incidents, data - related risk management and software - related compliance incidents.
MiMiC+ (M → F)	He practices in Fayetteville, Arkansas and has the professional credentials of MD. The NPI Number for Robert L. Firstseine is 1134262688 and he holds a License No. 67 (Arkansas).	She practices in Fayetteville, Arkansas and has the professional credentials of RN. The NPI Number for Firstbornee L. Roberts is 1396764048 and she holds a License No. 325 (Arkansas).
MiMiC+ (M → F)	Dr. Russ Meka has recently obtained his Ph.D. in Global Affairs at the University of Michigan, Ann Arbor, USA. He has also been a Research Fellow at the Center for Globalization and Society, Bergen University, Norway.	Ms. Meka has earned her Ph.D. in Global Affairs from Rutgers University, Newark, NJ. She is also an Assistant Professor at Rutgers University, Newark, NJ. Her research interests include global medicine, social justice,

Table 7: Random sample of inverted representations without intervention, alongside an intervention + inversion.