# arXiv:2312.17242v1 [cs.CL] 28 Dec 2023

# Learning to Generate Text in Arbitrary Writing Styles

Aleem Khan, Andrew Wang, Sophia Hager and Nicholas Andrews

Department of Computer Science, Johns Hopkins University

{akhan141,awang116,shager2,noa}@jhu.edu

### Abstract

Prior work in style-controlled text generation has focused on tasks such as emulating the style of prolific literary authors, producing formal or informal text, and the degree of toxicity of generated text. Plentiful demonstrations of these styles are available, and as a result modern language models are often able to emulate them, either via prompting or discriminative control. However, in applications such as writing assistants, it is desirable for language models to produce text in an author-specific style on the basis of a small writing sample. We find that instruction-tuned language models can struggle to reproduce author-specific style demonstrated in a prompt. Instead, we propose to guide a language model to generate text in a target style using contrastivelytrained representations that capture stylometric features. A central challenge in doing so is that an author's writing is characterized by surprising token choices under a generic language model. To reconcile this tension, we combine generative re-scoring to achieve an author-specific model, with discriminative control to ensure style consistency at the sequence-level. The combination of these approaches is found to be particularly effective at adhering to an author-specific style in a variety of conditions, including unconditional generation and style transfer, and is applicable to any underlying language model without requiring fine-tuning.

### 1 Introduction

We consider the problem of generating text in the style of an arbitrary author on the basis of a small writing sample, on the order of a few hundred words. Although instruction-tuned language models (LM) have demonstrated the ability to emulate a variety of writing styles via prompting (Deshpande et al., 2023), particularly when a given style

is well-represented in the training data (Krishna et al., 2020), we find that performance is less consistent in our few-shot setting, with recent large LMs such as GPT-3.5 performing worse than previous generations (Ouyang et al., 2022a). A separate challenge is that large LMs can be computationally prohibitive in certain applications, such as on-device deployment where privacy-preserving personalized generation may be needed.

Prior work in controllable text generation has primarily focused on categorical target attributes such as sentiment, formality, and topic, for which a number of techniques have been proposed (Prabhumoye et al., 2018; Sudhakar et al., 2019)-we discuss related work in more detail in §5. However, author-specific textual styles cannot be summarized using a closed set of binary or categorical attributes, since authors may be characterized by unique combinations of stylometric features. Such features may include dialect, use of emojis, punctuation and capitalization usage, as well as less obvious features such as syntactic preferences and use of white space. Since it is difficult even for forensic linguists to characterize an author's style, we propose to guide generation using contrastively-trained representations that extract stylistic attributes from a given writing sample as a dense vector feature.<sup>1</sup>

Discriminative control methods generate text with prescribed attributes guided by a classifier evaluating the degree to which the text satisfies the target attribute, typically with a tunable hyper-parameter balancing the *fluency* of the generated text with control success (Dathathri et al., 2019). However, human writing is characterized by "dips" into low-probability regions, unlike samples from LMs which produce likely tokens at

<sup>&</sup>lt;sup>1</sup>A conceptually similar approach is used in certain voice synthesis systems, in which *speaker* representations guide qualities of the generated speech (Fang et al., 2019; Ao et al., 2021).

each step (Gehrmann et al., 2019). Thus, the objective of achieving fluent generations according to a generic LM will in general be in tension with the goal of matching an author's style, which may be characterized by such unlikely token choices. To overcome this challenge, we propose a novel approach which combines a style-controlled autoregressive language model and a discriminative objective which aims to ensure stylistic consistency at the sequence level.

To guide a pre-trained LM towards a target style, we generalize future discriminators (Yang and Klein, 2021) to regression for a target style representation. Simply put, our approach entails re-scoring the predictive distribution of an existing LM using a lightweight model that assigns higher likelihood to tokens that are predicted to better adhere to the target style vector. The resulting author-specific LM-the composition of a pre-trained model and a lightweight regressoris then used as a fluency scorer for a discriminative model which captures stylistic consistency at the document-level. Our discriminative control framework adopts a product-of-experts energy parametrization (Hinton, 2002; Mireshghallah et al., 2022), which optionally enables the inclusion of meaning preservation terms in the case of style transfer ( $\S4.2$ ).

In summary, the proposed approach enables both style-controlled generation and style transfer using a pre-trained LM, without further finetuning. Our recipe calls for two main ingredients: a style representation (§2.2) and unlabeled data to fit a lightweight re-scoring model. Since style representations are effective in various domains and unlabeled data is generally easy to come by, our approach is quite widely applicable. We conduct an extensive experimental evaluation of the proposed approach in §4, finding that:

- The proposed approach is competitive with instruction-tuned large language models, prompted to use in-context demonstrations of the target style.
- Interpolating between two target author style vectors and generating text at intermediate points yields interpretable results, considering the rate of capitalization and punctuation usage. This result suggests that our control vectors capture intuitive stylistic features and that proposed approach can then successfully reproduce those features in generated text at the expected rate.

- Samples from the proposed approach circumvent machine generated text detectors at a higher rate, but misuse concerns can be addressed with producing more in-domain detection data.
- We show that our proposed style transfer approach can be adapted to serve as an effective author *anonymization* technique, defeating authorship attribution while preserving meaning.

### 2 Preliminaries

### 2.1 Problem statement

We consider both sequence generation and sequence-to-sequence generation, where in both cases our objective is to produce text ( $x \in \mathcal{X}$ ) in a target style while satisfying other criteria, such as diverse outputs in the case of language modeling and meaning preservation in the case of style transfer. We assume a few-shot setting where the target style is specified by a writing sample  $y = (y_1, y_2, \ldots)$  exhibiting the desired stylistic attributes. In our experiments, we focus on the case where each  $y_1, y_2, \ldots \in \mathcal{X}$  correspond to a short documents (e.g., social media comments), and we are interested in reproducing the underlying author's specific writing style. We emphasize the difficulty of this task, stemming not only from the few-shot setting, but also the fact that stylometric features comprise a sparser signal than other more evident textual attributes like sentiment.<sup>2</sup>

For sequence generation, we produce text by sampling from a pre-trained LM p conditioned on y. In the case of instruction-tuned LMs, y will be paired with an appropriate prompt to elicit the desired output; we discuss prompting strategies in more detail in §4.1.2. In sequence-to-sequence generation, we are additionally given initial text  $x^{(0)}$  that we wish to revise to be closer to the target style y, while keeping other properties of  $x^{(0)}$ constant, such as preserving meaning. Rather than condition on y directly as done in the prompting approach, we propose instead using a discriminative feature extractor f to capture stylistic properties of y, which are then used to guide generation. This is a distinguishing characteristic of our approach, since much prior work in controllable text generation has focused on classifiers (e.g., senti-

<sup>&</sup>lt;sup>2</sup>Authorship analysis often assumes access to large corpora by the candidate authors, as in the seminal work by Mosteller and Wallace (1963). In contrast, we extract features from a relatively small number of short documents, on average comprising 68 words each.

ment polarity) and prompting strategies to guide generation. We discuss the feature extractor in more detail next.

### 2.2 Author style representations

As previously mentioned, author-specific style is difficult to characterize even for forensic linguists, which poses challenges both for control and for evaluation. However, recent work has leveraged the availability of large corpora of writings by anonymous authors to learn stylistic representations. Although lacking in interpretability, such representations have been found to be effective at discriminating between authors, a task which requires characterizing writing style (Wang et al., 2023). In this work, we consider two different representations, both trained for surrogate tasks of authorship prediction. The representations aim to capture stylistic features of authorship, which is achieved by training on corpora with sufficient topic diversity, or by specifically mining examples of the same author writing about different topics (and different authors writing about the same topic). To avoid "gaming" our evaluation metrics, we employ different models for control and for evaluation.

**Control** To guide generation, we adapt the model proposed by Rivera-Soto et al. (2021). Specifically, we estimate a representation f on the basis of a large collection of anonymous writing samples. Our training dataset consists of one million Reddit users, each contributing at least 100 comments (Khan et al., 2021). The unique account labels enable supervised contrastive training, encouraging features f(x) and f(x') to be similar when x and x' have the same author.<sup>3</sup>

**Evaluation** We use two models for evaluation which are both available publicly as pre-trained checkpoints (§4.1.1). The first is a further instance based on the recipe from Rivera-Soto et al. (2021) trained on a larger corpus of 5 million authors, resulting in a more capable model than the one we use to guide generation. We also use a model proposed by Wegmann et al. (2022), which is trained on different data and using a different training objective. Although substantially less effective in author verification settings, this model uses topic labels to attempt to produce representations that are



Figure 1: Style performance for an increasing number of examples of a target style. We find that more examples result in better representations, which in turn improve decoding quality. Our future regressor and EBM approaches significantly outperform much larger models using prompting strategies.

less sensitive to topical similarity.

# **3** Guiding generations towards a target style representation

In this section, we describe our approach, which aims to generate text x satisfying various soft constraints, the most important of which is adherence to the style demonstrated in the few-shot example y. To reconcile the tension between fluency and author-specific style, we first show how to use a regression model to guide an LM to produce text for which f(x) is close to f(y) in expectation. Next, we show how the resulting author-specific LM can be incorporated in an energy-based model (EBM) using a product-of-experts, which confers two advantages. First, the EBM is a non-autoregressive model which performs inference at the sequencelevel; therefore, the distance between f(x') and f(y) can be directly evaluated to score candidate generations x'. Second, this framework makes it straighforward to introduce further experts to satisfy arbitrary additional preferences, such as meaning preservation in the case of style transfer.

### 3.1 Future regressors

An autoregressive LM conditioned on a control attribute *c*,

$$p(x \mid c) = \prod_{i=1}^{n} p(x_i \mid x_1, \dots, x_{i-1}, c)$$

<sup>&</sup>lt;sup>3</sup>We use code provided by Rivera-Soto et al. (2021) at https://github.com/LLNL/LUAR.

admits the following factorization of the likelihood according to Bayes' rule:

$$p(x_i \mid x_{1:i-1}, c) \propto \underbrace{p(c \mid x_{1:i})}_{\text{Control}} \underbrace{p(x_i \mid x_{1:i-1})}_{\text{LM}}.$$

Yang and Klein (2021) propose using maximumlikelihood estimation to fit  $p(c | x_{1:i})$ , namely the probability that the control attribute *c* will hold in the future, given the current prefix  $x_{1:i}$ . Such a model can be estimated on the basis of text paired with observed control attributes, and is then used during generation as a token-level re-scoring mechanism.

This approach affords a natural extension to continuous control by fitting a future *regressor*  $p(f(x) = \mathbf{c} \mid x_{1:i})$ , where f(x) is evaluated on the sequence and the model is conditioned on all prefixes of the same sequence, and therefore learns to predict the probability that a given prefix  $x_{1:i}$  will adhere to the target style in the future. To do so, we stipulate that control vectors  $\mathbf{c}$  are distributed according to a multivariate Normal density,

$$\mathbf{c} \mid x_{1:i} \sim \operatorname{Normal}(\mu, \Sigma)$$

and parameterize  $\mu$  and  $\Sigma$  using neural networks with input  $x_{1:i}$  and where  $\Sigma$  constrained to be a valid covariance matrix. The simplest approach to enforce this constraint is to assume all offdiagonal entries of  $\Sigma$  are zero with positive values along the diagonal, which we achieve with a softplus transformation of the unconstrained final activations of the neural network. Irrespective of the output parameterization, we employ a shared network  $g_{\theta}$  for both  $\mu$  and  $\Sigma$ ; specifically, for the diagonal covariance, we define:

$$\begin{split} \mathbf{z} &= g_{\theta}(x_{1:i}) \\ \mu &:= \mathrm{MLP}_{\phi}(\mathbf{z}) \\ \Sigma &:= \mathrm{diag}(\mathrm{softplus}(\mathrm{MLP}_{\eta}(\mathbf{z}))) \end{split}$$

The parameters  $\Theta = (\theta, \phi, \eta)$  are optimized on the basis of a corpus consisting of text paired with corresponding control vectors  $\{(\mathbf{c}, x)\}_{i=1}^{N}$ . In general, and in the experiments reported in this paper,  $g_{\theta}$  will have many fewer parameters than the LM being guided, in which case evaluating  $p(\mathbf{c} \mid x_{1:i-1})$  during generation introduces a relatively small additional computational burden. Implementation details for this architecture are outlined in §4. The diagonal covariance matrix assumption stipulates that each component of a control vector is independent. While previous work in contrastive learning has found that explicitly enforcing decorrelation to be necessary for such an assumption to be effective (Tao et al., 2021), we find that the control vectors we consider already satisfy this condition quite well.<sup>4</sup>

**Optimization** For each training instance  $(\mathbf{c}, x)$ , we create the augmented set consisting of all prefixes  $(\mathbf{c}, x_{1:1})$ ,  $(\mathbf{c}, x_{1:2})$ , ...,  $(\mathbf{c}, x_{1:n})$ . Note that the target  $\mathbf{c}$  is the same for each prefix, since the regressor is predicting whether the target control vector will be true for the full x on the basis of the supplied prefix. The parameters  $\Theta$  of the regression model are optimized to maximize the loglikelihood of the observed control vectors. We found it effective to initialize  $f_{\theta}$  using the same model that extracted the reference control vectors <sup>5</sup>, before fine-tuning  $\Theta$  on the augmented data.

# 3.2 An energy-based model for non-autoregressive generation

The proposed future regressor can be combined with any underlying LM to produce samples xwith stylistic features f(x) close to the target f(y)in expectation. However, autoregressive generation incrementally constructs the sample x, and therefore cannot directly use the feature-space distance between f(x)—based on the complete sample x—and the target f(y), to guide generation. Additionally, to support tasks such as style transfer (§4.2), it is necessary to impose additional arbitrary constraints on generation such as meaning preservation, which is not easy to do in a Bayesian formulation (Yang and Klein, 2021).

To address these limitations, we employ our adapted LM as one of several experts in an EBM. Specifically, we parameterize the probability of a sequence x given a target style y as a product-of-experts (Hinton, 2002; Du et al., 2020),

$$p(x \mid y) \propto e^{-\sum_{i} \alpha_i E_i(x,y)} \tag{1}$$

with experts  $E_i$  corresponding to soft constraints; this model assigns higher probability to sequences x which *simultaneously* satisfy all constraints.

<sup>&</sup>lt;sup>4</sup>In fact, we trained a model using the decorrelation objective and found the associated control vectors yielded no noticeable improvement in downstream decoding.

<sup>&</sup>lt;sup>5</sup>We found that using this initialization resulted in a 1.4% performance improvement over a random initialization.

Note that evaluating the above probability requires an intractable sum over all possible sequences x; therefore, we resort to approximate inference (§3.3). We consider two settings in our experiments: style-controlled generation and style transfer. In both settings, we have found it effective to tune the weights  $\alpha$  using validation data, although we note that maximum-likelihood estimation may also be used by approximating the gradient, to avoid any manual tuning.

**Style-controlled generation** Here we use only two experts.  $E_1$  is an author-specific LM as described in the previous section, which evaluates the negative log-probability of x under the author-adapted LM.  $E_2$  is an expert measuring sequence-level style similarity. Specifically,  $E_2$  computes the distance between the style vector of x and a target style control vector f(y) via the negative angular similarity,

$$-\left(1 - \arccos\left(\frac{f(x) \cdot f(y)}{\|f(x)\| \|f(y)\|} / \pi\right)\right).$$

The angular similarity is more sensitive to small differences between high dimensional vectors on the unit sphere, compared to the cosine similarity. When x consists of a short text, f(x) may yield noisy estimates of the stylistic features. To mitigate this, we introduce a variant,  $\text{EBM}_{episodic}$ , which can exploit the availability of multiple documents to improve feature estimates. Specifically, when revising a text sample  $x_i$  from the writing sample  $x = (x_1, x_2...)$ ,  $\text{EBM}_{base}$  computes  $E_2(x_i, y)$ , while  $\text{EBM}_{episodic}$  computes  $E_2(x, y)$ .

Controlled text revision In the style transfer task, we additionally condition generation on an initial state  $x^{(0)}$ , and the objective is to modify  $x_0$  to adhere to the style of y while preserving the original meaning of  $x^{(0)}$ . To do so, we employ  $E_1$ and  $E_2$  as before, but introduce further experts that are functions of x and  $x^{(0)}$  and measure meaning preservation. We note that various options are possible for this purpose and our specific choices may not be optimal in all cases. In our experiments, we add  $E_3$  to measure of semantic similarity using SBERT since it is not restricted to sentence-level similarity (Reimers and Gurevych, 2019). To ensure that x makes minimal revisions to  $x^{(0)}$ , we additionally add  $E_4$  defined as the Hamming distance between x and  $x^{(0)}$ , which was also employed by Mireshghallah et al. (2022).

### 3.3 Inference

We frame the generation problem as finding an output x which minimizes energy defined by Equation (1). Although this problem is intractable, the Metropolis-Hastings (MH) algorithm can be used to obtain an approximate sample from the desired distribution. Specifically, similar to Goyal et al. (2021), we use a pre-trained masked language model (MLM) as a token-level proposal distribution. Using a MLM enables bi-directional context to be captured by the proposal distribution. In our episodic variant of the EBM, the state of the sampler consists of more than one document. At each step, we sample one of the documents i for a MH update uniformly at random, and make proposals according to the MLM conditioned on  $x_i$ , but evaluate  $E_2(x, y)$  based on the entire sampler state. Thus, the energy function captures similarities on the entire state as opposed to a single document.

### 4 **Experiments**

### 4.1 Style Control

In our first experiment, we control the style of generated text using a pretrained representation of an author's style, thereby learning to generate text in an arbitrary writing style.

### 4.1.1 Metrics

Fine-grained control on an author specific level is challenging to evaluate due to the subtlety of features which identify an author. In practice, authorship attribution requires trained forensic linguists to identify such distinguishing features. Therefore, our evaluation of control success relies on automatic metrics. To avoid concerns about gaming certain metrics, we include multiple automatic metrics for each text attribute that is measured. We measures the overall quality of generated text through fluency in addition to particular features (e.g. *n*-gram overlap, semantic meaning, style consistency) in generated text (Celikyilmaz et al., 2020). We also consider further downstream tasks to evaluate the quality of style altered text, like author detection (§4.3) and LM generated text detection (§4.4).

**Style similarity** To measure how well generated text matches a target style, we adapt previous work (discussed in §2) as automatic evaluation tools. We consider "Universal Author Representations"

(UAR) (Rivera-Soto et al., 2021) and "Content Independent Style Representations" (CISR) (Wegmann et al., 2022).<sup>6</sup> These pre-trained embeddings measure style overlap between generated and reference text samples. We report cosine similarity between reference and generated text embeddings.

**Fluency** Beyond satisfying style-specific constraints, generated text should remain coherent. We report perplexity for reference and generated text under GPT-2 (Radford et al., 2019). We emphasize however that fluency is, to some extent, at odds with the goal of introducing author-specific style, as evidenced by the perplexity assigned to human-written comments in Table 1. That is, if the target style samples have a high perplexity under GPT-2, it is reasonable to expect a well formed style controlled generation to also have a high perplexity. Indeed, we find that generic LMs, like GPT-3, produce very low fluencies in sharp tension with higher human reference fluencies.

**Diversity** A straightforward way to mimic the writing style of a given sample y is to directly copy portions of the evidence text unchanged. Useful downstream applications (e.g. writing assistants, text debiasing) are not useful if they are repetitive, and so we are interested in sampling diverse outputs which satisfy the given style constraints. We consider a Jaccard similarity over the unique 1 and 2-grams in the reference and generated text samples to measure the overlap. A lower similarity suggests a more favorable generation with less direct copying.

### 4.1.2 Experimental Setup

**Evaluation datasets** We evaluate the effectiveness of our decoding strategy on 1000 authors contributing to four unique Reddit subreddits. We consider Reddit data collected through the Pushshift API (Baumgartner et al., 2020a) and compile a test split for each of our 4 subreddits: /r/wsb, /r/AskHistorians, /r/news, and /r/australia; performance on all four results are reported together in Table 1. These subreddits are selected for their unique and distinctive styles. We use an additional split from /r/wsb to validate our methods (i.e. to select

optimal decoding hyperparameters). For each author, we compile N text samples as the source of style evidence. In all experiments except for Figure 1, we set N = 16 to balance the quality of resulting style representations and cost of compiling data following previous work (Andrews and Bishop, 2019). Figure 1 illustrates part of this trade-off, with improved style controlled generation for larger N values.

**Language models** Our proposed methods operate on a frozen underlying LM; we do not perform any fine-tuning. Across all experiments we use variants of OPT and MPT-7B to generate text (Zhang et al., 2022; Team, 2023).<sup>7</sup> For EBMs, we use RoBERTa-base as our MLM for the tokenlevel proposal distribution.

**Future Regressors** We train the forward looking regressor using a single V100 GPU, a batch size of 64, and a learning rate of  $1e^{-6}$  for 100k steps. In our experiments we apply this re-scoring procedure to OPT-125m to capture author specific fluencies, and we evenly weight likelihoods from OPT and the forward regressor to compute rescored sequence level likelihoods.

**Prompting Baseline** As a comparative state of the art baseline, we use few-shot prompting to prompt GPT-3 (Brown et al., 2020) and GPT-3.5 for stylistic generations. We utilize the prompt-learning framework described by Liu et al. (2021) to generate outputs which can replicate an author's style. We provide a template for our prompt, where each writing sample in the prompt is truncated to 32 tokens.

```
Here are some passages of text:
<author writing sample 1>
<author writing sample 2>
...
<author writing sample 16>
Write another passage in the
same style:
```

For the GPT-3 baselines, we use the largest model, Davinci, with 175 billion parameters (Brown et al., 2020); for GPT-3.5 baselines, we use the gpt-3.5-turbo-0613 snapshot. We chose generation hyperparameters based on the best results on validation data from r/wsb.

<sup>&</sup>lt;sup>6</sup>We use two open source models for evaluation. We train our own UAR model using code provided by https://github.com/LLNL/LUAR and the CISR checkpoint is published here: https://huggingface. co/AnnaWegmann/Style-Embedding

<sup>&</sup>lt;sup>7</sup>A single NVIDIA V100 GPU was sufficient to store both the control model and language model, except for 7B parameter experiments which require a second V100 GPU.

	↑ Success					
Model	Size	UAR	CISR	$\downarrow$ Fluency	↓ <b>J-1</b>	↓ <b>J</b> -2
Human Reference		0.898	0.864	1356.88	0.161	0.023
Prompting (GPT-3)	175B	0.815	0.649	62.73	0.152	0.031
Prompting (GPT-3.5)		0.782	0.617	945.71	0.110	0.015
Future Regressor (OPT)	350M + 82M	0.837	0.727	373.83	0.110	0.012
	1.3B + 82M	0.826	0.707	362.23	0.108	0.013
	2.7B + 82M	0.836	0.730	366.88	0.102	0.009
	6.7B + 82M	0.832	0.721	348.97	0.100	0.007
Future Regressor (MPT)	7B + 82M	0.829	0.715	543.84	0.101	0.009
$EBM_{base}$	125M + 22M + 82M	0.873	0.751	769.95	0.114	0.010
$\operatorname{EBM}_{episodic}$	125M + 22M + 82M	0.899	0.762	787.63	0.100	0.007

Table 1: Test results on all four subreddit test splits. The proposed future regressor approach outperforms both prompting approaches on the target control metric (UAR) and the secondary style metric (CISR). All EBM models revise the output of the OPT-350M future regressor model.  $EBM_{episodic}$  revising the future regressor outputs achieves the highest performance, approaching the human reference. This result is particularly noteworthy given the considerably smaller size of the controlled LMs. We omit model sizes for GPT-3.5, as they are unknown.

With GPT-3, we use temperature of 1.0 and frequency penalty of 2; with GPT-3.5, we use temperature of 2.0 and frequency penalty of 2. We terminate generations after 32 tokens.

### 4.1.3 Stylistic Generation

Our style control results are shown in Table 1, where we compare our proposed nonautoregressive decoding strategy (denoted EBM), ablations consisting of just the adapted LM using future regressors, and prompting-based methods using state of the art LMs. The EBM results in the final two rows use the future regressor outputs as initializations for revision<sup>8</sup>. The first row shows metrics for "gold" style matches, i.e. additional held out text samples written by the same human author are used for comparison. Our proposed decoding strategy performs competitively despite the fact that the baseline LMs are much larger and have undergone steps like instruction tuning in the case of GPT-3.5 (Ouyang et al., 2022b). Under the UAR style metric, our proposed future regressor method outperforms baseline LMs using in-context learning. When the outputs of the future regressor are revised using the EBM text revision method described in §3.2<sup>9</sup>, it outperforms the prompting method on both success metrics, also shown in Table 1.

### 4.1.4 Style Vector Interpolation

We construct two artificial datasets with known stylistic attributes: nocaps, composed of data from 25 users of r/wsb converted to only lowercase characters, and nopunct composed of data from 25 users of r/wsb with all punctuation removed. We select these two attributes because they are easy to qualitatively identify and illustrate specific levels of control. We generate the UAR embedding for each author in nocaps or nopunct and interpolate it using spherical geometric interpolation<sup>10</sup> with the UAR embedding for the same 25 authors in r/wsb with varying weights. We generate outputs using the future regressor, and further modify these outputs using the EBM. We find that stronger bias towards the nocaps UAR embedding tends to measurably decrease the amount of capital characters in the text and that stronger bias towards nopunct measurably decreases the amount of punctuation

<sup>&</sup>lt;sup>8</sup>We did experiment with revising GPT outputs as well, but found that revising the future regressor output yielded better results. This initialization is supported by our use of future regressors to balance fluency in our energy function.

<sup>&</sup>lt;sup>9</sup>For these experiments, we iteratively sample for 5 epochs, where an epoch iterates for the number of tokens in the longest sentence in the batch.

<sup>&</sup>lt;sup>10</sup>Specifically, we use the scipy implementation of spherical geometric interpolation.

in generated text (Figure 2), demonstrating that both models can replicate meaningful features of style encoded by the UAR control vectors.

# 4.2 Style Transfer

In our second experiment, building on our style control experiments we explore whether we can produce text in an arbitrary writing style while preserving the meaning of the original text. To control both style and meaning, we use the EBM style-controlled revision method described in §3.2.

# 4.2.1 Metrics

The same metrics used to evaluate style control in §4.1.1 can be used for style transfer. However, since style transfer necessitates the preservation of meaning, we introduce another metric to measure this.

Semantic similarity Since our experiments involve short documents, we consider semantic search models which provide a document-wide notion of semantic similarity. Specifically we employ (1) all-mpnet-base-v2, a high-performance SBERT model and (2) GTR (Ni et al., 2021), a large dual encoder trained for semantic search. We emphasize that the SBERT model used for evaluation is distinct from the all-MiniLM-L6-v2 SBERT model used in the EBM.

# 4.2.2 Experimental Setup

For style transfer we create a dataset pairing Reddit comments with arbitrary target styles. We randomly select three author styles from each of the 4 subreddits specified in §4.1.2 and /r/casualUKfor a total of 15 target styles. Since our author styles are derived from the author's comment history, we can pair these comments with the other author styles in a round-robin manner. We exclude pairings between comments and styles that co-occur in the same subreddit, yielding a total of 2880 pairs. We construct a separate dataset for pairings that occur within the same subreddit, yielding 480 total pairs.

**Meaning Preservation** For EBMs, as proposed in §3.2 we include a "meaning preservation" expert. For this expert, we use the all-MiniLM-L12-v2 Sentence Transformers model.

**Prompting Baseline** For in-context style transfer, we use a 2-shot variation of the approach described by Patel et al., where text is first paraphrased into a neutral style before being rewritten to match the target style. We keep the same hyperparameters as in §4.1.2, except that we extend the maximum length of most generations to 64 and reduce any temperatures set at 2.0 to 1.0.

### 4.2.3 Style Transfer Results

In Table 2, for style-transferred text produced by each method, we report the extent to which the target style is achieved (UAR, CISR), fluency as measured by GPT-2, and the extent of semantic preservation (SBERT, GTR). As baselines, we report the same metrics between pairs of unrelated text samples (Random). Table 3 shows similar metrics for within-subreddit data, where authors may have similar styles to each other. Our approach performs comparably to prompted large language models while requiring only a fraction of the number of parameters.

While searching for hyperparameters, we observed a trade-off between stylistic accuracy and content preservation. This observation is consistent with the notion that style and content cannot be disentangled. For instance, optimizing for content preservation may introduce features from the source style into generated text, and optimizing for style accuracy may likewise introduce content. We handle this trade-off by providing hyperparameters for tuning the relative importance between semantic preservation and style accuracy, offering an additional degree of control over prompt-based approaches.

# 4.3 Anonymization

Enabling author privacy is a promising use case for style control and style transfer tools. Previous work has explored the preservation of privacy by altering identifying linguistic features associated with text (Li et al., 2018). We measure success by the system's ability to circumvent an author attribution system. In this setting, author attribution involves attempting to match text samples Q (queries) and T (targets) that were written by the same author. We consider a subset of the authors in our Reddit dataset to evaluation attribution capabilities. The dataset consists of 180 authors, and results in 32,400 binary comparisons. Given a user's history made up of N posts, we take the first N/2 posts and establish a query (Q), and the second N/2 posts to establish a target (T). In our experiments we use N = 16. Using our proposed



Figure 2: Percent of capitalized and punctuation characters in generated outputs. The decoding procedure is run on *interpolated* style vectors, where a weight of 0.0 is indicates a style vector capturing a nocaps or nopunct behavior, and a weight of 1.0 corresponds to a normal /r/wsb user.

	↑ Success		↑ Similarity		
Model	UAR	CISR	SBERT	GTR	$\downarrow$ Fluency
Random	0.729	0.334	0.042	0.438	437.14
Prompting (GPT-3) Prompting (GPT-3.5)	0.811 0.774	<b>0.752</b> 0.596	0.650 0.760	0.784 <b>0.853</b>	189.97 87.84
$\begin{array}{c} EBM_{base} \\ EBM_{episodic} \end{array}$	0.813 0.853	0.502 0.652	0.587 <b>0.789</b>	0.737 0.830	1085.33 683.21

Table 2: Test results for style transfer. The EBMs revise human written text to the style of a different author from a different subreddit. We provide metrics for randomly matched source and target pairs as a baseline. EBMs are competitive with GPT-3 and GPT-3.5 despite using a fraction of the parameters.

style transfer approach, we alter the style of each target T to produced a perturbed target T'. Success is measured by the decrease in performance when matching  $Q \to T'$  compared to  $Q \to T$ . To evaluate our approach, we consider all possible pairs of queries and targets and seek to detect matching queries and targets before and after style transfer is applied. We extract representations using UAR for each query and target sample, and compute pairwise distances to use as scores (Rivera-Soto et al., 2021). A smaller score in this case indicates a higher likelihood that the two representations are from the same author. Solving the detection problem involves setting an operating point with a given rate of false positives and false negatives, the point at which the two rates are equal is known as the equal error rate. A lower value indicates a better detection result. Table 4 shows that our procedure successfully reduces the detection rate through style transfer.

### 4.4 Detection of generated text

Considering the potential for misuse of generative text, especially in the context of style control, we conduct a small study on the detectability of our proposed future regressor decoding strategy. We find that similar to popular LMs like GPT-3, detecting text from our method in a *zero-shot* setting is quite difficult, with a classifier incorrectly marking fake text as human-written with high confidences. However given a relatively small set of examples (in our experiments we consider 500 samples of generated text from each LM), detection of LM generated text becomes more tractable with basic classification approaches.

To construct a dataset for this task, we follow a strategy used by OpenAI's fake text detector (AIT). Similar to our main experiments, we use

	↑ Success		↑ Similarity		
Model	UAR	CISR	SBERT	GTR	$\downarrow$ Fluency
Prompting (GPT-3)	0.853	<b>0.847</b>	0.655	0.793	192.76
Prompting (GPT-3.5)	0.829	0.635	0.761	<b>0.854</b>	245.49
EBM <sub>base</sub> , HT (RoBERTa-base)	0.856	0.654	0.625	0.761	1046.29
EBM <sub>episodic</sub> , HT (RoBERTa-base)	<b>0.879</b>	0.672	<b>0.830</b>	0.845	673.90

Table 3: Test results for style transfers within subreddit. The EBMs revise human-generated text (HT) to the style of a different author from the same subreddit. Again, EBMs perform comparably to GPT-3 and GPT-3.5 in spite of their smaller size.

Model	$EER_{before} \rightarrow EER_{after}$
GPT-3 GPT-3.5	$\begin{array}{c} 0.116 \rightarrow 0.311 \\ 0.116 \rightarrow 0.278 \end{array}$
EBM <sub>base</sub> EBM <sub>episodic</sub>	$\begin{array}{c} 0.116 \to 0.285 \\ 0.116 \to \textbf{0.358} \end{array}$

Table 4: Extent of anonymization after style transfer. An increasing EER via style transfer indicates improved anonymization. Both energy models use RoBERTa-base as the masked language model.

Strategy	GPT-3	Proposed
Zero-shot	0.676	0.534
In-domain Training	0.972	0.826

Table 5: Accuracy on text sampled from GPT-3 and our proposed decoding strategy. Each split consists of 250 real and 250 fake text samples.

the Pushshift API to collect real text samples from 10000 Reddit users, ensuring that each sample has at least 16 posts (Baumgartner et al., 2020b). We concatenate this data to create a prompt, and allow OPT-6.7B to generate follow on fake text for the prompt. Our dataset consists of 10000 human written text samples and 10000 machine generated outputs associated with those prompts. Additionally, we construct two more datasets which include 500 GPT-3 samples and 500 samples from our proposed EBM strategy to demonstrate improved detectability when in-domain data is considered. We fine-tune a RoBERTa base model (Liu et al., 2019) on these datasets for 10 epochs on a single V100 GPU using a learning rate of 2e-5 and AdamW optimizer (Loshchilov and Hutter, 2019).

Table 5 shows test accuracy on a subset of the

test data (strictly /r/wsb users) used in our main experiments (Table 1). In both cases, performance is quite poor in the zero-shot setting. When indomain training data is considered, text sampled from GPT-3 is detected at a high rate. We note that fake text from our proposed strategy is detected at a significantly higher rate compared to the zeroshot setting, but not nearly as high as GPT-3. This is likely due to the perturbations applied to the LM distribution by the proposed method. While lower detection accuracies are a good result for style-control, it does raise misuse concerns. Our result also shows that these concerns can be balanced if more in-domain text is available, increasing the rate of detection of style-revised text.

### 5 Related Work

Effective text style transfer is important for many downstream applications such as writing assistants, personalized NLP systems, text simplification, detoxifying and debiasing text (Jin et al., 2022). Interest in the task has led to many datasets spanning various types of styles and domains (Briakou et al., 2021; Madaan et al., 2020; Rao and Tetreault, 2018) and approaches (Prabhumoye et al., 2018; Krishna et al., 2020; Riley et al., 2021; Hallinan et al., 2023). However, these approaches largely focus on *coarse* level styles (e.g. formality, politeness, simplicity) rather than finegrained styles which may contain any combination of coarse styles. For finer-grained style transfer, Riley et al. (2021) propose a few-shot strategy using learned style vectors to autoregressively decode text. Our work differs by using a pre-existing encoder for style vectors (Rivera-Soto et al., 2021) and incorporating bidirectional context during inference. Additionally, recent interest in prompting large language models has facilitated style transfer from arbitrary authors using in-context learning (Reif et al., 2021; Patel et al., 2022). We use similar prompting strategies as comparable baselines for our approach.

Research towards controllable text generation has focused on fine-tuning approaches, discriminator guided decoding, and more recently on large-language model prompt engineering. Finetuning approaches condition a language model on a given control attribute. For a control attribute c, the language model is trained to predict the probability of the next word  $p(x \mid c)$ . This probability can be directly modelled as in the case of CTRL which uses an initial control prefix to guide decoding (Keskar et al., 2019). However, CTRL requires re-training a LM any time a new control code is proposed. One way to avoid training from scratch is to approximate the probability  $p(x \mid c)$  as  $p(c \mid x)p(x)$ . Here p(x) can be modeled by a pre-trained language model and  $p(c \mid x)$ can be modeled by a simple discriminator. Rather than training an entire language model, only the discriminator would need to be trained (Dathathri et al., 2019; Krause et al., 2020; Yang and Klein, 2021). However, as noted in §1, control attributes perform poorly on finer-grained tasks, motivating the use of control vectors instead.

### 6 Conclusion

We have demonstrated the ability to guide the style of generated text using author representations, which capture fine-grained aspects of writing style, on the basis of a small writing sample. We consider a sequence-level energy-based model for this purpose which incorporates a computationally efficient re-ranking approach for authorspecific fluencies. The proposed approaches are competitive with large intruction-tuned LMs at guiding generated text towards the desired attributes, despite requiring a fraction of the compute.

There are several promising applications of the proposed approaches beyond those considered in this paper. For example, future regressors may be useful at detecting documents composed by multiple authors via unsupervised segmentation models, or to guide the style of machine translated text in a similar fashion as our monolingual style transfer experiments.

**Limitations** The main limitation of our study is the reliance on automatic evaluation metrics. To

avoid relying on any single automatic metric, we include a diverse set of evaluation strategies, particularly the interpolation experiments in §4 that focus on interpretable stylistic attributes. The success of the interpolation experiments provide support both the effectiveness of the style representations as well as our ability to generate text in the target style. In the case of coarse style transfer problems like formality and sentiment, non-expert human annotators can perform the task and therefore be used to complement automatic metrics. However, authorship attribution requires trained forensic linguists, an avenue which we decline to pursue in this work, both for cost reasons and to avoid setting a precedent that may detract from future work in this area. Similar to previous efforts in controllable generation, the proposed approach uses a discriminative model to guide generation, and success at control is reliant on the quality and availability of appropriate training data to estimate that model. In our experiments, we rely on representations of author style that are trained on large amounts of anonymous social media content and are highly discriminative of authorship (Rivera-Soto et al., 2021). However, social media data may contain various biases, such as a prevalence of English over other languages, as well as biases owing to the sample sizes of various demographic groups relative to the population.

Broader Impact This paper pushes the state of the art in style-controlled text generation, which enables a number of downstream applications, such as writing assistants, anonymization (e.g., for political dissidents), and personalized NLP more broadly, such as for under-represented groups. We are also excited about potential applications of style-controlled generation to data augmentation and synthetic data creation with LLMs, which may otherwise suffer from lack of diversity relative to real data composed by a variety of authors with distinct styles. At the same time, as with most technologies there is potential for abuse. In §4, we address one way methods discussed here may be abused: defeating machine-text detectors. We explore a mitigation scheme involving retraining the detector on style-controlled outputs (§4.4), showing that this results in drastic improvements in detection accuracy. This is an important finding since effective machine-text detection can mitigate other risks associated with the technology, such as impersonation. On balance, we believe our contributions will have a positive impact.

### Acknowledgements

This research is supported in part by the Office of the Director of National Intelligence (ODNI), Intelligence Advanced Research Projects Activity (IARPA), via the HIATUS Program contract #D2022-2205150003. The views and conclusions contained herein are those of the authors and should not be interpreted as necessarily representing the official policies, either expressed or implied, of ODNI, IARPA, or the U.S. Government. The U.S. Government is authorized to reproduce and distribute reprints for governmental purposes notwithstanding any copyright annotation therein.

# References

- Nicholas Andrews and Marcus Bishop. 2019. Learning invariant representations of social media users. 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), pages 1684–1695, Hong Kong, China. Association for Computational Linguistics.
- Junyi Ao, Rui Wang, Long Zhou, Chengyi Wang, Shuo Ren, Yu Wu, Shujie Liu, Tom Ko, Qing Li, Yu Zhang, et al. 2021. Speecht5: Unified-modal encoder-decoder pre-training for spoken language processing. *arXiv preprint arXiv:2110.07205*.
- Jason Baumgartner, Savvas Zannettou, Brian Keegan, Megan Squire, and Jeremy Blackburn. 2020a. The pushshift reddit dataset.
- Jason Baumgartner, Savvas Zannettou, Brian Keegan, Megan Squire, and Jeremy Blackburn. 2020b. The pushshift reddit dataset.
- Eleftheria Briakou, Di Lu, Ke Zhang, and Joel Tetreault. 2021. Olá, bonjour, salve! XFOR-MAL: A benchmark for multilingual formality style transfer. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 3199–3216,

Online. Association for Computational Linguistics.

- Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. Advances in neural information processing systems, 33:1877–1901.
- Asli Celikyilmaz, Elizabeth Clark, and Jianfeng Gao. 2020. Evaluation of text generation: A survey. *ArXiv*, abs/2006.14799.
- Sumanth Dathathri, Andrea Madotto, Janice Lan, Jane Hung, Eric Frank, Piero Molino, Jason Yosinski, and Rosanne Liu. 2019. Plug and play language models: A simple approach to controlled text generation. *arXiv preprint arXiv:1912.02164*.
- Ameet Deshpande, Vishvak Murahari, Tanmay Rajpurohit, Ashwin Kalyan, and Karthik Narasimhan. 2023. Toxicity in chatgpt: Analyzing persona-assigned language models.
- Yilun Du, Shuang Li, and Igor Mordatch. 2020. Compositional visual generation with energy based models. *Advances in Neural Information Processing Systems*, 33:6637–6647.
- Fuming Fang, Xin Wang, Junichi Yamagishi, Isao Echizen, Massimiliano Todisco, Nicholas Evans, and Jean-Francois Bonastre. 2019. Speaker anonymization using x-vector and neural waveform models. *arXiv preprint arXiv:1905.13561*.
- Sebastian Gehrmann, Hendrik Strobelt, and Alexander M Rush. 2019. Gltr: Statistical detection and visualization of generated text. *arXiv preprint arXiv:1906.04043*.
- Kartik Goyal, Chris Dyer, and Taylor Berg-Kirkpatrick. 2021. Exposing the implicit energy networks behind masked language models via metropolis-hastings. *arXiv preprint arXiv:2106.02736*.
- Skyler Hallinan, Faeze Brahman, Ximing Lu, Jaehun Jung, Sean Welleck, and Yejin Choi. 2023. Steer: Unified style transfer with expert reinforcement. *ArXiv*, abs/2311.07167.

- Geoffrey E. Hinton. 2002. Training products of experts by minimizing contrastive divergence. *Neural Comput.*, 14(8):1771–1800.
- Di Jin, Zhijing Jin, Zhiting Hu, Olga Vechtomova, and Rada Mihalcea. 2022. Deep learning for text style transfer: A survey. *Computational Linguistics*, 48(1):155–2 05.
- Nitish Shirish Keskar, Bryan McCann, Lav R. Varshney, Caiming Xiong, and Richard Socher. 2019. CTRL: A conditional transformer language model for controllable generation. *CoRR*, abs/1909.05858.
- Aleem Khan, Elizabeth Fleming, Noah Schofield, Marcus Bishop, and Nicholas Andrews. 2021.
  A deep metric learning approach to account linking. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 5275–5287, Online. Association for Computational Linguistics.
- Ben Krause, Akhilesh Deepak Gotmare, Bryan McCann, Nitish Shirish Keskar, Shafiq Joty, Richard Socher, and Nazneen Fatema Rajani. 2020. Gedi: Generative discriminator guided sequence generation.
- Kalpesh Krishna, John Wieting, and Mohit Iyyer. 2020. Reformulating unsupervised style transfer as paraphrase generation.
- Yitong Li, Timothy Baldwin, and Trevor Cohn. 2018. Towards robust and privacy-preserving text representations. In *Annual Meeting of the Association for Computational Linguistics*.
- Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. 2021. Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing.
- Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach.
- Ilya Loshchilov and Frank Hutter. 2019. Decoupled weight decay regularization.

- Aman Madaan, Amrith Setlur, Tanmay Parekh, Barnabas Poczos, Graham Neubig, Yiming Yang, Ruslan Salakhutdinov, Alan W Black, and Shrimai Prabhumoye. 2020. Politeness transfer: A tag and generate approach. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 1869–1881, Online. Association for Computational Linguistics.
- Fatemehsadat Mireshghallah, Kartik Goyal, and Taylor Berg-Kirkpatrick. 2022. Mix and match: Learning-free controllable text generationusing energy language models. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 401–415, Dublin, Ireland. Association for Computational Linguistics.
- Frederick Mosteller and David L Wallace. 1963. Inference in an authorship problem: A comparative study of discrimination methods applied to the authorship of the disputed federalist papers. *Journal of the American Statistical Association*, 58(302):275–309.
- Jianmo Ni, Chen Qu, Jing Lu, Zhuyun Dai, Gustavo Hernández Ábrego, Ji Ma, Vincent Y. Zhao, Yi Luan, Keith B. Hall, Ming-Wei Chang, and Yinfei Yang. 2021. Large dual encoders are generalizable retrievers. *CoRR*, abs/2112.07899.
- Long Ouyang, Jeff Wu, Xu Jiang, Diogo Almeida, Carroll L. Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, John Schulman, Jacob Hilton, Fraser Kelton, Luke Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul Christiano, Jan Leike, and Ryan Lowe. 2022a. Training language models to follow instructions with human feedback.
- Long Ouyang, Jeff Wu, Xu Jiang, Diogo Almeida, Carroll L Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. 2022b. Training language models to follow instructions with human feedback. *arXiv preprint arXiv:2203.02155*.
- Ajay Patel, Nicholas Andrews, and Chris Callison-Burch. 2022. Low-resource authorship style transfer with in-context learning.

- Shrimai Prabhumoye, Yulia Tsvetkov, Ruslan Salakhutdinov, and Alan W Black. 2018. Style transfer through back-translation. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 866–876, Melbourne, Australia. Association for Computational Linguistics.
- Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language models are unsupervised multitask learners.
- Sudha Rao and Joel Tetreault. 2018. Dear sir or madam, may I introduce the GYAFC dataset: Corpus, benchmarks and metrics for formality style transfer. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 129–140, New Orleans, Louisiana. Association for Computational Linguistics.
- Emily Reif, Daphne Ippolito, Ann Yuan, Andy Coenen, Chris Callison-Burch, and Jason Wei. 2021. A recipe for arbitrary text style transfer with large language models. *CoRR*, abs/2109.03910.
- Nils Reimers and Iryna Gurevych. 2019. Sentence-bert: Sentence embeddings using siamese bert-networks. *arXiv preprint arXiv:1908.10084*.
- Parker Riley, Noah Constant, Mandy Guo, Girish Kumar, David Uthus, and Zarana Parekh. 2021. Textsettr: Few-shot text style extraction and tunable targeted restyling.
- Rafael A. Rivera-Soto, Olivia Elizabeth Miano, Juanita Ordonez, Barry Y. Chen, Aleem Khan, Marcus Bishop, and Nicholas Andrews. 2021. Learning universal authorship representations. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 913–919, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Akhilesh Sudhakar, Bhargav Upadhyay, and Arjun Maheswaran. 2019. Transforming delete, retrieve, generate approach for controlled text style transfer.

- Yaling Tao, Kentaro Takagi, and Kouta Nakata. 2021. Clustering-friendly representation learning via instance discrimination and feature decorrelation. *ArXiv*, abs/2106.00131.
- MosaicML NLP Team. 2023. Introducing mpt-7b: A new standard for open-source, commercially usable llms.
- Andrew Wang, Cristina Aggazzotti, Rebecca Kotula, Rafael Rivera Soto, Marcus Bishop, and Nicholas Andrews. 2023. Can Authorship Representation Learning Capture Stylistic Features? Transactions of the Association for Computational Linguistics, 11:1416–1431.
- Anna Wegmann, Marijn Schraagen, and Dong Nguyen. 2022. Same author or just same topic? towards content-independent style representations. In Proceedings of the 7th Workshop on Representation Learning for NLP, pages 249– 268, Dublin, Ireland. Association for Computational Linguistics.
- Kevin Yang and Dan Klein. 2021. Fudge: Controlled text generation with future discriminators. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 3511–3535.
- Susan Zhang, Stephen Roller, Naman Goyal, Mikel Artetxe, Moya Chen, Shuohui Chen, Christopher Dewan, Mona Diab, Xian Li, Xi Victoria Lin, Todor Mihaylov, Myle Ott, Sam Shleifer, Kurt Shuster, Daniel Simig, Punit Singh Koura, Anjali Sridhar, Tianlu Wang, and Luke Zettlemoyer. 2022. Opt: Open pre-trained transformer language models.