Estimating Causal Effects of Text Interventions Leveraging LLMs

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Abstract

Quantifying the effect of textual interventions in social systems, such as reducing anger in social media posts to see its impact on engagement, poses significant challenges. Direct interventions on real-world systems are often infeasible, necessitating reliance on observational data. Traditional causal inference methods, typically designed for binary or discrete treatments, are inadequate for handling the complex, high-dimensional nature of textual data. This paper addresses these challenges by proposing a novel approach, CausalDANN, to estimate causal effects using text transformations facilitated by large language models (LLMs). Unlike existing methods, our approach accommodates arbitrary textual interventions and leverages text-level classifiers with domain adaptation ability to produce robust effect estimates against domain shifts, even when only the control group is observed. This flexibility in handling various text interventions is a key advancement in causal estimation for textual data, offering opportunities to better understand human behaviors and develop effective policies within social systems.

CCS Concepts

• **Computing methodologies** → **Natural language processing**; **Causal reasoning and diagnostics**.

Keywords

Causal estimation, Textual intervention, Counterfactual generation, LLM

1 Introduction

Causal inference enables us to move beyond mere correlations to identify and quantify the factors driving system behavior [40]. This helps to isolate the true effects of policy decisions and develop effective interventions [5, 31, 41] to change individual human [46] and social [2] behavior. Modern social systems, especially on digital platforms, are largely based on language data. Therefore, quantifying the causal effects of language on the outcomes of interest is an important task [15, 19, 47, 53].

However, incorporating language, as expressed in text, directly into the causal inference framework introduces unique challenges in identification and estimation [12, 16, 49]. We use the following example to illustrate the challenges. Suppose it appears that angrier posts on social media receive more attention. A straightforward analysis of this hypothesis would attempt to estimate the levels

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of anger in a sample of posts, record how much attention they receive, and then assess the relationship between these two variables. One could adjust for confounding variables, such as topics and author demographics, in an attempt to mitigate the bias in causal estimation. However, a critical issue is that the treatment variable—anger—is embedded in the language of the post but never directly observed. Therefore, the causal inference task involves predicting the treatment variable anger, and then also predicting the outcome variable as a function of *treatment prediction*, not the treatment itself (such as in [44]). Inaccuracies or systematic biases in predicted anger would contaminate the downstream estimates of the causal effect. This is the fundamental challenge of identifying causal effect of a treatment variable that is itself inferred, as attributes of observed texts often are. In addition, identifying and adjusting for all confounders is also extremely challenging in observational studies.

To address the challenges in causal estimation of the effects of latent text attributes, we propose a framework called **CausalDANN**. This framework first crafts a hypothetical intervention on the observed text, which can be implemented as a text transformation using a large language model (LLM), and then estimates the causal effect by predicting the outcomes for both observed and transformed data. The text transformation forms the class of interventions that scopes our causal inference problem. It allows the treatment variable in a potential-outcomes setting [45] to be an entire piece of text, and the causal estimands to be formulated as potential outcomes under intervened text versus potential outcomes under original (observed) text. This framework allows us to conduct causal studies even in scenarios where some intervention group is missing, which would be a significant issue under the conventional causal problem setup.

Our first contribution is to demonstrate how LLMs can be utilized to formulate the intervention. For instance, if we are interested in the effect of anger in a social media post on the attention the post receives, we propose an intervention that rephrases posts with more or less anger, and then robustly estimate the effect of those rephrasings. Here we substitute the causal question of how anger A affects engagement Y with how an anger-transformation on the text $W \mapsto g_A(W)$ affects Y, for some g_A parameterized by a prompted LLM. If the transformation function g_A faithfully reflects a change in anger A without manipulating other attributes like topic or writing style, then we argue that this more specific causal question is a good proxy for the original causal question of $A \to Y$. Thanks to the massive model sizes and training data, LLMs have

proved to be remarkably capable on tasks like text generation, reasoning [11, 14] and counterfactual data generation [33, 38], which gives us confidence that they can serve as the best text transformation function on this task. Our second contribution is a method to predict outcomes of text interventions. After the text transformation, we obtain both non-intervened (observed) data and intervened data with unobserved outcomes. However, predicting the outcomes for unseen data is also challenging due to data shift [48] between the observed data used for training and the unobserved data used for inference. To tackle this challenge, we propose CausalDANN, which adapts domain adaptation neural network (DANN) [18] as the outcome predictor. In this paper, we describe this method and illustrate its effectiveness in experiments.

We evaluate the performance of CausalDANN in three experiments where we estimate (1) the effect of positive sentiment in Amazon reviews on the products' sales, (2) the effect of seeing a popular response to a social media post on people's moral judgments of social dilemmas described in that post, and (3) the effect of anger in social media posts on changing people's moral judgements. By accurately estimating causality of language-related attributes, proposed method allows for more reliable insights to guide evidence-based decision-making and contributes to a deeper understanding of complex social phenomena.

2 Related Works

2.1 Causal Inference with Text

The field of causal inference in machine learning continues to grow rapidly, as does its intersection with language modeling. Prior literature that focuses on causal effect estimation with text [49] does not usually consider the text as the treatment variable. Rather, text embeddings are used as covariate information [52] or some discrete coding of the text is used as the treatment [15, 44]. To our knowledge, we are the first to propose a method for estimating the effects of direct interventions on text.

Work on controlling spurious correlations in text classifiers [6, 51] mirrors some of the techniques used for causal effect estimation. The statistical implications of spurious correlations are similar to those of confounders in a causal context. Generally, spurious correlations are of concern for model generalization [17], and causal effect estimation entails a special case of generalizing a model to the interventional domain.

Our method is strongly motivated by the apparent lack of overlap between the control and treatment groups (Section 4.1). Previous work has considered the similar case of overlap violations due to the treatment being a deterministic function of text [21]. In that case, for different pieces of text, there is no overlap in the treatment variable. In our case, an apparent lack of overlap is induced by the way we define the potential outcomes from the intervention. We do not assume to have observed any intervened text. Lack of overlap is a practically significant problem, but does not receive the same attention as violations to the other standard causal assumptions [57].

2.2 LLMs for Causal Inference

Large language models promise to enhance computational understanding of text in causal inference [4, 29, 30, 55]. However, the ubiquitous spurious correlations in large text corpora tend to hinder an LLM's understanding of causal relations in the text-generating world [54]. The problem of weak causal understanding in LLMs might stem from a fundamental limitation of their training. Causal inference generally entails extrapolating to a system's behavior under novel conditions, like an intervention [28, 42]. Asking an LLM about interventions on text can place it in a regime of low probability in its training data. Recent work suggests that LLM reasoning struggles in such data-starved regimes [50].

New estimation methodology is therefore needed for using LLMs in causal inference without relying on them for tasks that are still challenging for them. One promising area of research is using LLMs for counterfactual data generation [8, 25, 33, 38]. In our work, we utilize the power of LLMs in two ways. First, we use LLMs to impose interventions on text, such as rephrasing or transforming it with respect to some linguistic property like sentiment. This does not rely on LLMs for any sort of causal reasoning, but only for transforming text—a task on which they excel. Second, due to the lack of ground truth causal effect in observational studies, synthetic or semi-synthetic data are often needed for evaluating causal inference. We perform counterfactual generation with LLMs to simulate the outcomes to build evaluation datasets.

2.3 Domain Adaptation

In the era of large language modeling, the two steps of pre-training then fine-tuning on specific tasks has become one of the more common paradigms [11, 13, 14]. However, many works have shown that fine-tuning on specific data easily leads to performance drop when predicting on unseen data due to data shift [7, 35, 48], since the training and test data may have different distributions. To address the data shift problem, researchers have developed many approaches for domain adaptation, such as sample reweighting [32], structural correspondence learning [9], joint distribution matching using max mean discrepancy [34], and mixture of experts [23].

Another popular approach is Domain Adversarial Neural Network (DANN) [18]. In addition to a standard feature extractor and label classifier, this model incorporates a domain classifier that acts as an adversary, encouraging the feature extractor to produce domain-invariant features, thereby enhancing domain adaptation. This architecture has demonstrated success across various NLP tasks, including aspect-based text classification [56], stance detection [3, 26], and morality detection [24].

Domain adaptation is also tightly related to causal inference. When predicting potential outcomes, data shifts often exist between the control and the treated groups. One way to tackle this is to correct the bias through aligning the distribution of the treated and control groups in the form of domain adaptation [1]. In fact, some classic causal methods to adjust for confounders, such as inverse propensity weighting (IPW) [27], can also be viewed as a form of domain adaptation by aligning the distributions. However, a gap remains in utilizing more advanced deep learning domain adaptation methods in causal estimation. In our work, we will evaluate both IPW and DANN methods in prediction of potential outcomes.

3 Causal Inference Preliminaries

We formalize the observational causal inference problem using the framework of potential outcomes [28, 45]. For text W, any covariates X, outcome Y, we construct causal estimands through an intervention on the text defined by a transformation $W \mapsto g(W)$. Central to the motivation of our method is being able to handle cases where interventional outcomes have not been observed. Specifically, with potential outcomes defined as $Y(w)$ for any text w, we only ever observe $Y = Y(W)$ and not $Y(g(W))$. The structure of the potential outcomes is characterized in Assumption 1.

Assumption 1 (Potential Outcomes). The standard setting of potential outcomes adapted for interventions on text.

- *(a)* Stable unit treatment value assumption (SUTVA). The potential outcomes for a unit do not depend on the text variables for any other unit.
- *(b)* Overlap or positivity. All relevant text values $w \in \mathcal{W}$ have a nonzero probability of occurring for every unit.
- *(c)* Ignorability or no hidden confounding. Potential outcomes are independent of the realized text variable W after conditioning on covariates.

4 Methods

We tackle the challenge of causal estimation for textual data where the treatment variable (e.g., emotion) is not directly observed and where the treated group or the control group is hard to construct.

We propose a framework **CausalDANN** (Figure 1) in which we (1) apply a transformation on observed text (the non-intervened group) to construct the intervened group, (2) predict the potential outcomes using a model trained with domain adaptation on observed non-intervened data in order to predict the unobserved intervened outcomes, and (3) estimate the causal effects from predicted outcomes.

4.1 Interventions on Text using an LLM

When the intervention acts on the language of text and is not observed separately, we propose to define the treatment variable for causal-effect estimation *implicitly* through a text transformation. For example, when anger is the treatment—that is, we are interested in the effect of anger on some outcome from the text, we define an intervention where we rephrase the observed text with higher or lower anger level while keeping all other linguistic properties the same. The mapping from observed text to transformed text forms a binary distinction that appears to resemble causal inference with a binary treatment variable. After all, the causal estimand can be phrased similarly, as the intervened (transformed) outcomes contrasted with the non-intervened (observed) outcomes. However, this line of reasoning leads to a violation of a crucial identifiability assumption. There is no overlap, since we never observe the outcome of the transformed arm in this binary-treatment setting. We only ever observe the outcomes for the non-intervened arm. This complete lack of overlap is catastrophic from an identification point of view.

Therefore, we need to look beyond a binary dichotomy of the treatment variable, and leverage the high-dimensional nature of language (and interventions on it.) Surprisingly, lifting the treatment variable into an abstract space of text, or a high-dimensional embedding space thereof, induces overlap. Interventions on text can be viewed as point-wise mappings (transformations) in that space. The estimation problem for text transformations is a straightforward generalization of the additive nudging approach that was recently proposed by Marmarelis et al. [36]. Replacing the nudge $W \mapsto W + \xi$ with some $W \mapsto g(W)$ leads to effect estimators for a general class of text transformations, like rephrasing with more anger, or anything else that an LLM can be prompted to do.

We propose different approaches of transformation $W \mapsto g(W)$ on observed texts W to generate data in the intervened group:

(1) Textual transformation with LLMs. Their outstanding capability to manipulate, summarize, and generate text allows for high quality counterfactual data generation. This lifts the burden of controlling for latent confounding parts in the texts and is generalizable to many different scenarios. One mentioned example is to generate counterfactual data by rephrasing texts with higher anger level but keeping all other linguistic properties the same (Section 5.4).

(2) Sampling from other observed data, corresponding to the same covariates. For example, to study the effect of positive reviews on product sales, we can sample 5-star reviews as the positive ones and 1 or 2-star reviews as the non-positive ones while keeping the same covariates such as product type (Section 5.2). This is a convenient method if observations are available and covariates are known and easy to control for.

4.2 Counterfactual Generation with LLMs

Even when we apply the above transformation techniques to construct the intervened group, outcomes are still not observed, and ground truth causal effects are not available. Therefore, constructing synthetic or semi-synthetic data for causal estimation evaluation is an important task. We can further utilize the power of LLMs to generate synthetic outcomes for unobserved data. The great amount of training data and reinforcement learning from human feedback (RLHF) in terms of safety and bias gives LLMs good ability to simulate human social norms, especially when studying social data [11, 14]. In Section 5.3 and 5.4 we will use LLMs to simulate social judgement on posts from Reddit's /r/AmITheAsshole subreddit.

One concern is that using LLMs for text transformation and outcome data generation is susceptible to potential LLM biases. To mitigate, we manually check a part of the generations to ensure the quality. Second, other than performing the text transformation defined as the intervention (e.g., increasing anger), we also rephrase the original textual data using an LLM. In this way, both non-intervened and intervened groups are LLM-generated. Third, the estimated effect is a relative difference between the two groups. With text and outcomes in both groups being LLM-generated, the biases should cancel out to a large extent.

4.3 Outcome Prediction

Since the outcomes of the generated (intervened) data are never observed, we need a prediction model to estimate the outcomes for all the data in order to estimate the causal effects.
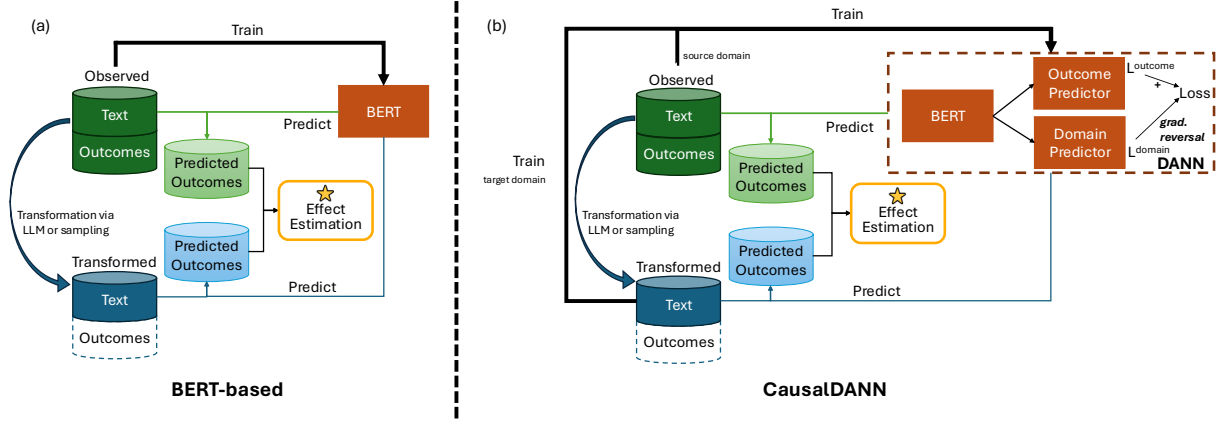
Figure 1: Illustration of Proposed Methods. On the observed text and outcome (non-intervened group), we first apply a transformation via LLM or sampling to generate text data as the intervened group. Note that the outcomes are unobserved for the transformed data. To predict the outcomes, we build (a) the BERT-based baseline predictor or (b) the proposed CAUSALDANN with domain adaptation ability. Then we use the trained model to predict the outcomes for both non-intervened and intervened groups and compute causal effects.

4.3.1 BERT. The BERT [13] model offers an easy and cheap way to learn textual representations and generally performs well in supervised classification tasks. Therefore we decide to build our baseline outcome predictor with BERT. We assume that conditioning on the textual embeddings learned by BERT effectively adjust for the latent confounding parts of the texts.

A naive approach is to train a vanilla BERT model with only the non-intervened textual data. Their outcomes are observed and can be used as labels for supervised training. The trained predictor can then be used to predict the potential outcomes for the intervened text data with unobserved outcomes. This serves as our first baseline method.

We build the outcome predictor by appending a linear classification layer to the BERT embedding model, with cross-entropy loss and sigmoid normalization for the binary classification task. We add a dropout layer with a rate of 0.3. Adam optimizer with an initial learning rate of 5e-5 is used, along with a scheduler $lr = lr_{init}/((1 + \alpha \cdot p)^\beta)$, where $p = \frac{current\ epoch}{total\ epoch}$ and $\alpha = 10$ and $\beta = 0.25$, following [24].

To obtain the predicted outcome for all data, we randomly split the data into five folds. Each time we train the outcome predictor with four-fifths of the data, which is further split into training and validation sets by 80%-20% ratio. We train for 20 epochs and stop early when the model achieves the best validation F1 score. The batch size is 64. Finally, we predict on the remaining one-fifth data to obtain their predicted outcomes. Given the i-th data point W_i, the predicted outcome is

$$\hat{Y}_i = \mu_{BERT}(W_i) \qquad (1)$$

where μ_{BERT} is the BERT-based classification model. The Average Treatment Effect (ATE) can be estimated as

$$\hat{\tau} = \frac{1}{N} \sum_i^N \mu_{BERT}(g(W_i)) - \mu_{BERT}(W_i) \qquad (2)$$

where N is the total number of data points and $g(\cdot)$ is the text transformation function.

In real life applications, we often observe some covariates C and are interested in obtaining the heterogeneous treatment effects in different groups with respect to C. For example, when studying whether angrier posts receive more attention, we might be interested in estimating the effects with respect to different topics discussed. We can obtain the Conditional Average Treatment Effect (CATE) as

$$\hat{\tau}(c) = \frac{1}{N_c} \sum_{i:C_i=c}^{N_c} \mu_{BERT}(g(W_i), c) - \mu_{BERT}(W_i, c) \quad \forall c \in C \qquad (3)$$

One common situation is that C, such as the topic, is already latently embedded in the BERT textual representation. In such cases, we can simplify the CATE as

$$\hat{\tau}(c) = \frac{1}{N_c} \sum_{i:C_i=c}^{N_c} \mu_{BERT}(g(W_i)) - \mu_{BERT}(W_i) \quad \forall c \in C \qquad (4)$$

4.3.2 CAUSALDANN. Many prior works have shown that the vanilla BERT, when finetuned on a specific dataset with supervision, is susceptible to performance drop when predicting on unseen data [35, 48]. As mentioned in Section 4.1, the outcome predictor needs to be trustworthy for both non-intervened data with observed outcomes and data obtained from the defined transformation. In order to better predict on the unseen transformed data, we adopt the classic domain adaptation framework Domain Adversarial Neural Network (DANN) instead of the vanilla BERT. [24] has shown the outstanding performance of DANN for domain adaptation in textual data.

DANN aims to map the text embeddings from labeled source domain and the unseen target domain onto a common embedding space, thus mitigating the problem of data shift. CAUSALDANN has three modules (Figure 1b): (1) the BERT encoder that aims to learn the textual representation, (2) an outcome predictor that is a

linear classification layer with cross-entropy loss, same as in the vanilla BERT outcome predictor, and (3) a domain predictor, also a linear classification layer with cross-entropy loss, but the loss to be *maximized* during the adversarial training, because we want to fool this domain classifier. This is achieved by connecting the domain classifier to the other parts of the model with a gradient reversal layer. The loss term is:

$$L = L^{outcome} - \lambda^D \cdot L^{domain} \qquad (5)$$

Following [24], we balance the loss terms between the outcome predicting module and the domain predicting module by controlling λ^D indirectly by

$$\lambda^D = 2/(1 + e^{-\gamma \cdot p}) - 1 \qquad (6)$$

where $p = \frac{current\ epoch - epochs\ trained\ w/o\ adversary}{total\ epochs}$, and γ is now the hyperparameter. We performed a grid search for γ in [0.1, 1, 10] and decide to set $\gamma = 1$.

In our case, the source domain is the non-intervened (observed) data, and the target domain we want to adapt to is the intervened (unobserved) data. We train the model in a semi-supervised way – we provide both the labeled non-intervened training data and the unlabeled intervened data in each training batch, balanced in size. Both of them pass through the BERT encoder, so that their textual representations can be effectively learned. Next, the labeled non-intervened data pass through both the outcome predictor and the domain predictor, but the intervened data do not have outcome labels, and only pass through the domain classifier, which works as the adversary, pushing the BERT encoder to learn domain-invariant embeddings to fool the domain classifier. In this way, we aim to align the feature distributions of intervened data closer to the non-intervened labeled data.

Same as in Section 4.3.1, we perform training and prediction by randomly splitting the data into five folds. We train with 20 epochs in total. However, during the first three epochs the model is trained without the domain adversarial module activated, the model to better learn the outcome labels first. The batch size is 32. The Adam optimizer, the learning rate and the scheduler are the same as in Section 4.3.1.

After obtaining predicted outcome by CausalDANN, the ATE and CATE can be caculated in the same way as in Section 4.3.1.

4.4 Inverse Propensity Weighting

We compare the proposed CausalDANN with another baseline Inverse Propensity Weighting (IPW). IPW is a classic causal estimation method and has been commonly used. In the traditional causal problem setup, there are observed data in both intervened and non-intervened groups, but the effect is confounded. Thus we typically need to adjust for all the confounders when predicting the outcomes for data in both groups. The idea of IPW is that, to adjust for high-dimensional confounders, e.g. text W, we do not need to condition on the entire confounder vector, but it is enough to condition on the propensity score $\pi = P(T|W, C)$, as long as the system satisfies SUTVA.

In our scenario, traditional IPW would not work, because the outcomes of our intervened data are unobserved. Nevertheless, IPW can also be seen as a sample reweighting technique, a commonly used domain adaptation technique [32] that pulls the distributions

of the observed non-intervened data and the unobserved intervened data closer. When the propensity scores can be accurately measured, IPW can help to unbias the outcomes on the unobserved intervened data. We can therefore apply IPW on top of the outcomes predicted by vanilla BERT or CausalDANN.

We estimate the propensity score $\pi = P(T|W, C)$ by training a separate BERT model. The architecture is the same as in Section 4.3.1, a BERT encoder with a linear classification layer. We train this propensity predictor on all the data, including intervened and non-intervened, using the texts as the input and $T = \mathbb{1}_{transformed}$ as the training labels. To obtain the propensity score as a probability, we calibrate it on the validation set with temperature scaling [22]. The training procedure and hyperparameters are the same as in Section 4.3.1.

Once the propensity scores are obtained, we compute the ATE as

$$\hat{\tau} = \frac{1}{N_1} \sum_{i:T_i=1}^{N_1} \frac{\mu_{BERT}(g(W_i))}{\pi(W_i)} - \frac{1}{N_0} \sum_{i:T_i=0}^{N_0} \frac{\mu_{BERT}(W_i)}{1 - \pi(W_i)} \qquad (7)$$

where the first term includes all data points that are intervened ($T_i = 1$) and the second term includes all data points that are non-intervened ($T_i = 0$).

The CATE can be computed as

$$\hat{\tau}(c) = \frac{1}{N_{1,c}} \sum_{i:T_i=1, C_i=c}^{N_{1,c}} \frac{\mu_{BERT}(g(W_i))}{\pi(W_i)} - \frac{1}{N_{0,c}} \sum_{i:T_i=0, C_i=c}^{N_{0,c}} \frac{\mu_{BERT}(W_i)}{1 - \pi(W_i)} \qquad (8)$$

5 Experiments

We use real-world data, Amazon product reviews [39] and Reddit r/AmITheAsshole discussions of social dilemmas and user judgements on them, [1] to form three research questions for model evaluation: (1) how much does a positive product review affect sales, (2) does seeing a top-upvoted comment change people's judgement about a social dilemma, and (3) does increasing anger in texts change people's social judgements?

5.1 Baselines and Setups

We compare two baselines (1) BERT, (2) BERT+IPW, and our proposed method (3) CausalDANN. We also evaluate (4) CausalDANN+IPW to see if IPW can further improve domain adaptation on top of DANN.

In addition, we compare these models with (5) TextCause [44], a method for causal estimation from textual data. Similar to our method, TextCause deals with the confounding in texts by adjusting on BERT embeddings. However, in contrast to our approach, this method assumes some observations are available in both control and treated groups. Therefore they use data and observed outcomes in both control and treated groups as the training data for BERT, and use this model to estimate the potential outcomes and treatment effects. This approach is good in scenarios when outcome observations are easy to collect for both control and treated groups. However, in scenarios when the treatment variable cannot be directly observed, or when one of the treated and control groups are not observed, this method fails. On the other side, our method, more

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[1]https://github.com/iterative/aita_dataset

capable of domain adapted predictions, can better handle missing observations in one of the groups. In the following experiments, the TextCause performance tells us how good the effect estimation can get to even with more training data from both control and treated groups.

We use two metrics for performance comparison. The first one is ΔATE, which is the absolute value of the difference between the predicted ATE and the ground truth ATE. The second metric is MSE of the CATE vector corresponding to all dimensions of the covariate C. For both metrics, the lower the better performance of the model. For each experiment, we repeat with five random runs to obtain the average and standard deviation.

5.2 Amazon Reviews

5.2.1 Data. We first evaluate our method on a semi-synthetic dataset based on Amazon reviews [39], a benchmark also used in [44]. This dataset consists of 5.6K reviews on products in the categories of mp3, CD, or Vinyl. Reviews for products worth more than $100 or fewer than 5 words are excluded.

Following [44], we focus on estimating the effect of the positive sentiment of a product review on its sales. The hypothesis is that a product with positive reviews can have a higher chance of getting clicked and sold, but this effect might be confounded by the type of product. The treatment is the positive sentiment of a review, which is not directly observed but latently embedded in the review texts. Hence in a conventional causal setting, the treatment variable is hard to define.

Based on our framework, we define a transformation function $g(\cdot)$ that intervenes on the positive sentiment of the reviews without manipulating other attributes like content or style. In this experiment, we do not use an LLM for text transformation, but instead we sample the positive and non-positive reviews from the observed data itself. That is, we define a review to be positive if it gets 5 stars and not positive if it gets 1 or 2 stars. The intervention is $T = \mathbb{1}_{positive}$. This setting (1) allows us to evaluate our framework without the impact of any bias from LLM generations, and (2) is closer to a traditional causal estimation setup and follows [44] exactly, allowing us to fairly compare our framework with TextCause.

The observed covariate C is a binary indicator for whether the associated review is a CD or not. The outcome Y, a binary variable representing whether a product received a click or not, is simulated based on whether the textual intervention $T = \mathbb{1}_{positive}$ is applied and the covariate C as following:

$$Y \sim Bernoulli(\sigma(\beta_C(\pi - \beta_0) + \beta_T T + N(0, \gamma))) \qquad (9)$$

where $\sigma(\cdot)$ is the sigmoid function, $\pi = P(T|C)$ is the propensity, β_C controlling confound strength is set to 4.0, β_T controlling treatment strength is set to 0.8, β_0 controlling propensity is set to 0.8. All these hyperparameters are set as the same as a harder-to-estimate scenario in [44].

We then follow the framework described in Section 4 and train the outcome and propensity predictors. We assume that we do not observe the outcomes in the intervened (positive) group. Therefore, we only use the non-intervened (non-positive) reviews and their labels $Y(T = 0)$ to train the outcome predictors. For the propensity predictor in the IPW method, we use T as the training labels and

both intervened ($T = 1$) and non-intervened ($T = 0$) groups. The input to both predictors is the review texts.

5.2.2 Results. Table 1 shows that CAUSALDANN gives us the ATE and CATE estimation closest to the ground truth, outperforming other baselines including BERT, BERT+IPW and also CAUSAL-DANN+IPW. The fact that CAUSALDANN achieves lower error than the vanilla BERT baseline tells us the effectiveness of domain adaptation by DANN.

In addition, the results show that using IPW on top of either BERT or DANN lowers the performance significantly. This infers that the propensity score estimation might be problematic. From the propensity predictor outputs, we find that it is very easy for BERT to classify whether a review is positive or negative, and hence the probability outputs are either very close to 1 or very close to 0, even after calibration with temperature scaling. This leads to the ill behavior when we perform inverse propensity weighting.

Last, the performance of TextCause tells us how close we can get to ground truth effects even training with more observations in the intervened group. Therefore it is no surprise that TextCause performs better. Nevertheless, CAUSALDANN has a ΔATE very close to TextCause and has the MSE of CATE same as TextCause, indicating very good debiasing ability in causal estimation.

	ΔATE (↓)	MSE of CATE (↓)
TextCause[44]	**0.05 ± 0.02**	**0.01 ± 0.01**
BERT	0.12 ± 0.05	0.02 ± 0.01
BERT+IPW	8.71 ± 0.61	76.6 ± 10.8
CAUSALDANN	**0.09 ± 0.04**	**0.01 ± 0.01**
CAUSALDANN+IPW	10.14 ± 0.58	103.46 ± 12.03

Table 1: Model performance on the Amazon Reviews data.

5.3 Reddit AITA Comments

5.3.1 Data. Next we evaluate our methods on another dataset, the Reddit r/AmITheAsshole (AITA) data. In this subreddit, users post personal stories of social dilemmas, and other people give a verdict on whether the author is at fault or the other party is. This data offers insights about human perspectives [10] and moral judgments [43] and has been used as a benchmark for causal estimation [37]. We select posts that are shorter than 140 words to reduce computational complexity.

The verdict can be determined by the upvote mechanism on comments. The most upvoted comment, which most subreddit members agree with, usually stays at the top, where it is more visible to others. An interesting research question is - does seeing the top comment affect one's judgement? This infers how easily people are affected by the "mainstream" opinion. Such an experiment is hard and expensive to conduct in real life. However, our framework offers an opportunity to estimate such causal effects with the help of LLMs.

Marmarelis et al. [37] used GPT-4 [2] to act as moral judge on these real-world posts, avoiding problems about the real-world salience of the data. Here we follow the same approach. The assumption is that

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[2]https://openai.com/index/gpt-4/

GPT-4 has learned a great amount of data from the Internet about human social norms and should have common sense. Therefore we simplify the original research problem to estimating the effect of seeing top comments on GPT's judgements. We manually review a part of the GPT generations to make sure that they make sense.

The intervention $T = \mathbb{1}_{top\ comment}$ is a binary variable denoting whether the GPT judge is prompted with a top comment or a randomly selected comment, together with the post, to output the verdict. The outcome Y is a binary variable that equals to 1 when GPT decides someone in the post was at fault, and 0 when it decides no one was at fault. That is, we categorize YTA (you are the asshole) and ESH (Everyone sucks here) into $Y = 1$ and NTH (not the asshole) and NAH (no asshole here) into $Y = 0$. For each post, we independently generate both outcomes $Y(T = 1)$ and $Y(T = 0)$. With these counterfactual outcomes, we can compute ground truth treatment effects. See Appendix A for prompting procedure and Table 5 for example GPT generations.

Following methodology described in Section 4, we then train the outcome predictor and the propensity predictor. For both predictors, we concatenate the post and the comment text as input text to adjust for the confounders latently embedded in text. We use only the non-intervened data and their ground truth $Y(T = 0)$ labels to train the outcome predictor, and we use the $T = \mathbb{1}_{top\ comment}$ labels from both non-intervened and intervened groups for the propensity predictor training.

In addition, we find that the verdicts are usually confounded by the topic of the posts. Therefore we further compute CATE conditioned on the topics obtained by performing topic modeling with BERTopic [20]. We focus on the top 30 frequent topics and represent them as a binary vector $\mathbf{C}$ for each post. See Appendix B for detailed procedure of using BERTopic.

5.3.2 Results. Table 2 shows that again CausalDANN has an outstanding performance on this dataset. We notice that CausalDANN and BERT have similar performance. This is because the top and random comments are sometimes similar in terms of perspectives (see examples in Appendix Table 5), and comments are usually succinct and have similar writing styles as well. Thus there is less data shift from the training (non-intervened) data to the unseen intervened data, and a vanilla BERT can also give good outcome predictions in this case.

	ΔATE ($\downarrow$)	**MSE of CATE** ($\downarrow$)
TextCause [44]	0.04 ± 0.01	0.01 ± 0.00
BERT	$\mathbf{0.01 \pm 0.01}$	0.01 ± 0.01
BERT+IPW	0.56 ± 0.50	1.04 ± 0.93
CausalDANN	$\mathbf{0.01 \pm 0.01}$	$\mathbf{0.00 \pm 0.00}$
CausalDANN+IPW	0.50 ± 0.46	0.84 ± 0.77

Table 2: Model performance on the AITA-comments data.

The performance of IPW-based methods is still significantly lower in this experiment, but this time for a different reason. Because it is relatively hard to classify whether a comment is a top comment or a random comment with respect to the post, the propensity predictor performance is low. The classification F1-score is only 0.52 ± 0.01 over 5-fold cross validation. When the propensity score

estimation is less accurate, it affects the final weighted ATE and CATE estimations.

Finally, TextCause normally cannot handle this scenario in which the outcomes of intervened groups are not observed. Nevertheless, we can still run TextCause, providing the LLM-generated counterfactual outcomes as the training data, to see how close the proposed CausalDANN is to the TextCause estimations using more information. We find that CausalDANN has slightly better performance than TextCause.

5.4 Anger in AITA Posts

5.4.1 Data. On the same AITA dataset, we formulate another research question: does the anger level in the posts affect people's verdicts. If a post contains a high anger level or aggression, there might be a higher chance that people would consider the author to be at fault. Anger is a latent attribute in texts and not a directly observed treatment variable. Under a conventional setup, we would need to use a proxy treatment variable which could be susceptible to more bias [44]. We define an intervention $T = \mathbb{1}_{anger-transformed}$. We take the original AITA dataset and ask an LLM to transform each post into a version with higher anger level, but keeping the writing style, the semantics and the perspectives exactly the same. To mitigate the bias brought by LLM generations, we also ask LLM to rephrase the original post and keeping the anger level the same. Then we use the rephrased posts and the posts transformed to higher anger as pairs of control and intervened data. We choose to use Claude 3.5 Sonnet [3] instead of GPT, because GPT has more conservative behaviors and does not raise the anger level in texts significantly. See Appendix A for procedure and example generations.

Next, we also synthesize the outcome Y with Claude. We ask Claude to separately provide a verdict based on the rephrased post and the anger-transformed post. Therefore Y is a binary variable that equals to 1 when Claude decides someone in the post was at fault, and 0 when Claude decides no one was at fault (i.e. we categorize YTA (you are the asshole) and ESH (Everyone sucks here) into $Y = 1$ and NTH (not the asshole) and NAH (no asshole here) into $Y = 0$). We can then compute the ground truth causal effect for each post.

Similar to previous experiments, we only use the non-intervened (rephrased) posts and their corresponding Claude-generated verdicts to train the outcome predictor. To train the propensity predictor, we use all data and $T = \mathbb{1}_{anger-transformed}$ as the label. The input to both predictors are the post texts. In addition, we also have the covariates $\mathbf{C}$ to be the binary vector of the top 30 frequent topics obtained from BERTopic for computing CATE.

5.4.2 Results. From Table 3, we can see that CausalDANN outperforms other methods including TextCause (using more training data from the intervened group) on estimating CATE. For ATE, CausalDANN+IPW is the best performing one. The fact that methods using DANN architecture are better than methods based on vanilla BERT again shows the effectiveness of domain adaptation in predicting potential outcomes. Interestingly, applying IPW does not significantly hurt the ATE estimations in this dataset, although does

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[3]https://www.anthropic.com/news/claude-3-5-sonnet

show a lower performance on CATE estimation. These results indicate that propensity score estimation and IPW can be less reliable and robust, as its performance varies based on dataset properties.

	ΔATE ($\downarrow$)	MSE of CATE ($\downarrow$)
TextCause [44]	0.05 ± 0.01	0.02 ± 0.01
BERT	0.09 ± 0.07	0.03 ± 0.02
BERT+IPW	0.10 ± 0.05	0.31 ± 0.38
CausalDANN	0.05 ± 0.03	$\mathbf{0.01 \pm 0.01}$
CausalDANN+IPW	$\mathbf{0.03 \pm 0.04}$	0.13 ± 0.19

Table 3: Model performance on the AITA-anger data.

6 Conclusions

In this work, we target the problem of causal estimation for textual data especially when the treatment variable is not directly observed. We propose a novel framework **CausalDANN** that utilizes LLMs for counterfactual outcome generation and text interventions through transformations. Following this, we utilize text-level classifiers equipped with domain adaptation capabilities to produce robust effect estimates, effectively handling domain shifts against domain shifts. We demonstrate the outstanding performance of CausalDANN in three different experiments.

Limitations. LLM data generation is susceptible to potential biases and lack of diversity. However, we try to mitigate the bias by performing LLM-rephrasing on the non-intervened group too when the intervened group is LLM-transformed. The estimated effect is a relative difference between the two groups. With text and outcomes in both groups being LLM-genereated, the bias should be canceled out to a large extent.

Ethics Statement. In this research, we utilized Large Language Models (LLMs) to generate data for analysis. We acknowledge the ethical considerations associated with the use of LLMs, particularly concerning potential biases, data validity, and the broader implications of AI-generated content. To maintain transparency, we have detailed the methodology used for data generation and the steps taken to address ethical concerns in this paper. We encourage readers to consider these factors when interpreting our findings.

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A Prompting LLMs

A.1 AITA-comments Data

For the experiment AITA-comments in Section 5.3, we use the prompt in Table 4 to ask GPT-4 to provide a verdict based on a given AITA post and a top or a random comment. We remove the responses that GPT refuses to answer, possibly in cases where topics are sensitive.

The following Table 5 shows some example posts with their top and random comments, and the GPT generated verdicts. For some posts (e.g. row 1) the top and random comments are very similar in perspectives, and the GPT-generated verdicts also are the same when different comments are given. Interestingly, the top and random comments in the second example have different perspectives. Nevertheless, GPT still gives the same verdict, possibly because the random comment was very short. The last example show how GPT changes verdict when the top and random comments are different in perspectives.

A.2 AITA-anger Data

For the experiment AITA-anger in Section 5.4, we use the prompt in Table 6 to ask Claude-3.5-Sonet to (1) transform text to a version with higher anger, but keeping the semantic and all other linguistic properties the same; (2) rephrase text without changing the anger level (the purpose is to rephrase the non-intervened group too so that both groups are LLM-generated and bias from LLM generation can be mitigated), or (3) provide a verdict.

We remove the responses that Claude refuses to answer, possibly in cases where topics are sensitive. The following Table 7 shows some examples of the rephrased and anger-transformed posts, as well as the Claude generated verdicts. We see that Claude has transformed the text into very aggressive and angry version. Warning: Table 5 contains offensive language.

B BERTopic

To detect the top frequent topics in the AITA dataset, we use BERTopic. We first preprocess all posts to remove url links and stop words in English. We run BERTopic with UMAP dimension reduction and HDBSCAN clustering algorithms, and we use hyperparamters $top\_n\_words = 10$, $n\_gram\_range = (1, 1)$, $min\_topic\_size =$

```
system_prompt = """\
  You are a moral arbiter hired by r/AmITheAsshole.\
  When presented with a story, you respond objectively with your verdict.\
  As is customary in that subreddit, you always begin your response with one of [NTA, YTA, ESH, NAH].
"""

def query_judge(story, comment):
  response = openai.ChatCompletion.create(
    model = model, temperature=1, max_tokens=2,
    messages = [
     {"role": "system", "content": system_prompt},
     {"role": "user", "content": f"The author said--\n{story}"},
     {"role": "user", "content": f"The community said--\n{comment}"},
     {"role": "user", "content": "What do you say? Is the verdict NTA, YTA, ESH, or NAH? No explanations."}
    ])
  return response
```

Table 4: Code to prompt GPT-4 to generate verdicts based on a given AITA post and a comment.

10 and *nr_topic* = 10. Table 8 shows the top 30 topics detected and their post counts.

Post and Comments	Verdict
Post: So I recently graduated high school and I'm attending a program lasting all of July that helps ease students into college life. My roomate met a girl there whom she really likes, and he told me and his other friends that he intends to ask her out to be his girlfriend. Keep in mind they just met. However, this girl told me that she does not reciprocate these feelings. I'm afraid to disclose this to my roommate, and I'm extremely confused if I'm the asshole in this situation.	
Top Comment: I don't think you are an asshole for not telling him. It sounds like something he needs to hear from this girl. You can tell him if you feel it is the right thing to do. He may get angry with you and accuse you of having feeling for her. It can hurt not to have feeling reciprocated and sometimes	NAH
Random Comment: You're not an asshole. Don't get involved. This is between your roommate and this girl, and it would be inappropriate and unwise to get between the two.	NAH
Post: My parents are diabetic, morbidly obese, and addicted to food. I'm the same, minus the diabetes. I've been trying for a while to eat healthily and lose weight. So have they, but yet every time they go to the store, they bring home junk food. I understand that it's hard for them, but it's also hard to stay on track with my healthier lifestyle when there's junk food all around me. Plus, they're getting older, so it is crucial for them to get healthy now. A few weeks ago, they brought home 4 bags of donuts, and I emptied each pack into the trash. Am I an asshole for this? **Edit:** I love all the responses. Got one "no", one "maybe", and one "yes". I agree with all of you. **Edit 2:** You guys are right–I'm the asshole.	
Top Comment: Yep. You're the asshole. If you want to make the commitment to work hard on improving your health and your diet, then that is your job. If those who live with you want to support you by changing their lifestyle, too, that would be fabulous. But, it's not for you to dictate to them, or to throw away their property.	YTA
Random Comment: What? No man.	YTA
Post: In a nutshell I was at a hardcore punk show. I got a beer between bands. I was drinking it up front waiting for the next band to start. They did and a ferocious pit opened up near me. So I got knocked around and so did my beer. I spilled over multiple people around me and they got beer over their clothes and hair. After I talked about this to some people who clearly don't go to punk shows they seemed to think I was rude, but frankly every person near the center of the crowd at such a show knows they'll possibly get beer spilled on them. It's happened to me multiple times. So AITA?	
Top Comment: YTA. I go to local punk shows regularly and have worked a lot with booking agents and in music journalism. When the band takes the stage and the pit goes nuts you back to the side with the beer or put it down somewhere else. Spilling beer all over everyone is not normal, at least not in any of the	YTA
Random Comment: Never been to a show like this. If it's not common to take a drink where you know you're going to get tossed around, YTA. If it's basically expected to have a drink, then not the asshole. People can be annoyed they get beer spilled on them, but they know people have drinks and it can happen. Then they shouldn't	NAH

Table 5: Example generations of verdicts by GPT-4 given AITA posts along with top or random comments.

```
def get_response(post, task):

    if task == 'anger_transformation':
        system_prompt = f"\
          Here is a Reddit post: {post}. Rephrase it while maintaining the semantics, writing style,
          structures and paragraphs, but express much more anger. The output length should be 10 words
          more or less than the original post. Please only output the rephrased texts:
          "
    elif task == 'rephrasing':
        system_prompt = f"\
          Here is a Reddit post: {post} Rephrase it while maintaining the semantics, writing style,
          structures and paragraphs. The output length should be 10 words more or less than the original
          post. Please only output the rephrased texts:
          "
    elif task == 'give_verdict':
        system_prompt = f"\
          Given a Reddit post from r/AmItheAsshole, classify it into one of the following four
          categories: \
          YTA (You're the asshole): The submitter is deemed to be in the wrong; \
          NTA (Not the asshole): The other party is considered to be wrong; \
          ESH (Everyone sucks here): Both parties are wrong; \
          NAH (No asshole): Both parties acted appropriately, but the situation just sucks. \
          Your task is to analyze the post and determine which category it belongs to based on the
          narrative provided by the submitter. Consider the actions, intentions, and attitudes of all
          involved parties to make an accurate classification. Only output one of these labels: YTA,
          NTA, ESH, or NAH. No explanation is needed. Limit your response to 3 characters:
          "
    else:
        assert

    message = client.messages.create(
        model="claude-3-sonnet-20240229",
        max_tokens=1000,
        temperature=1,
        messages=[
          {
            "role": "user",
            "content": [
              {
                "type": "text",
                "text": system_prompt
              }]}]
    )
    return message.content[0].text
```

Table 6: Code to prompt Claude to transform a post to higher anger level but keeping other linguistic properties the same, or to rephrase a post, or to provide a verdict based on a given post.

Posts	Verdict
Original: So I recently graduated high school and I'm attending a program lasting all of July that helps ease students into college life. My roommate met a girl there whom she really likes, and he told me and his other friends that he intends to ask her out to be his girlfriend. Keep in mind they just met. However, this girl told me that she does not reciprocate these feelings. I'm afraid to disclose this to my roommate, and I'm extremely confused if I'm the asshole in this situation.	
Rephrased: Having recently completed high school, I'm participating in a July program designed to smoothly transition students into college life. My roommate encountered a girl there whom he's deeply attracted to, and he confided in me and our other friends his intention to ask her to be his romantic partner, despite their recent acquaintance. However, this young woman revealed to me that she doesn't share his amorous sentiments. I'm hesitant to divulge this information to my roommate, leaving me utterly perplexed about whether I'm the one in the wrong in this predicament.	NTA
Anger-Transformed: I just finished that goddamn high school hell, and now I'm stuck in this idiotic college prep program for the entire fucking July. My moronic roommate met some chick there and instantly developed a pathetic crush on her, telling me and our other dumbass friends that he plans to ask her out as his girlfriend. Can you believe this imbecile's audacity? They barely know each other! But here's the real kicker: that girl confided in me that she doesn't share his delusional feelings at all. I'm torn between ripping the truth out of his thick skull or letting him make a fool of himself. Either way, I'm caught in this infuriating mess, and I can't decide if I'm the raging asshole here or not.	ESH
Original: My parents are diabetic, morbidly obese, and addicted to food. I'm the same, minus the diabetes. I've been trying for a while to eat healthily and lose weight. So have they, but yet every time they go to the store, they bring home junk food. I understand that it's hard for them, but it's also hard to stay on track with my healthier lifestyle when there's junk food all around me. Plus, they're getting older, so it is crucial for them to get healthy now. A few weeks ago, they brought home 4 bags of donuts, and I emptied each pack into the trash. Am I an asshole for this? **Edit:** I love all the responses. Got one "no", one "maybe", and one "yes". I agree with all of you. **Edit 2:** You guys are right–I'm the asshole.	
Rephrased: My parents suffer from diabetes, extreme obesity, and food addiction. Like them, I'm obese but without diabetes. I've been striving to eat healthily and shed pounds for some time. They've also attempted this, yet they consistently bring unhealthy snacks home from the grocery store. While I understand their struggle, it's challenging to maintain my healthier lifestyle amidst the temptation of junk food. Moreover, as they age, it becomes crucial for them to prioritize their well-being. A few weeks ago, they purchased four bags of donuts, and I discarded the contents of each bag. Was I wrong for doing so? **Edit:** I appreciate all the responses – one "no," one "maybe," and one "yes." I concur with you all. **Edit 2:** You're correct – I was the one in the wrong.	ESH
Anger-Transformed: My goddamn parents are fucking diabetic, disgustingly morbidly obese, and pathetically addicted to food like a bunch of pigs. I'm the same, minus the shitty diabetes. I've been trying for a fucking eternity to eat healthily and lose weight, but those assholes keep sabotaging me. So have they, but yet every damn time they go to the store, they bring home junk food like the brainless morons they are. I understand that it's hard for those idiots, but it's also hard to stay on track with my healthier lifestyle when there's junk food all around me thanks to their stupidity. Plus, they're getting older, so it is crucial for them to get healthy now before they croak. A few weeks ago, those dumbasses brought home 4 bags of donuts, and I angrily emptied each pack into the trash like the responsible adult I am. Am I an asshole for this? **Edit:** I love all the responses, you fucking geniuses. Got one "no", one "maybe", and one "yes". I agree with all of you, you brilliant bastards. **Edit 2:** You guys are right–I'm the asshole, and I fucking hate myself for it.	ESH

Table 7: Example generations of rephrased and anger-transformed posts by Claude, and the verdicts also generated by Claude.

Topic	Count
wedding_birthday_party_family	204
gift_gifts_christmas_birthday	120
job_work_boss_for	112
teacher_class_school_he	106
racist_white_black_english	104
tip_tipping_food_delivery	98
ordered_order_pizza_the	89
friend_him_ex_he	80
lane_traffic_road_driving	66
church_religion_religious_atheist	65
dog_dogs_puppy_him	64
rent_pay_split_bills	63
her_she_girl_me	62
child_daughter_have_baby	60
sex_she_porn_relationship	56
eat_food_cook_she	56
name_names_my_is	54
bathroom_toilet_shower_use	52
car_drive_gas_pay	50
cat_cats_allergic_my	49
she_go_plans_her	47
kids_wife_work_babysit	47
gay_lgbt_people_men	42
funeral_died_passed_family	42
he_pair_charger_selling	39
kid_was_the_fish	39
hair_shave_beard_cut	38
wear_wearing_bra_shirt	38
eat_food_eating_he	36
tattoo_art_tattoos_design	34

Table 8: Top 30 topics detected in AITA data by BERTopic.