DoubleLingo: Causal Estimation with Large Language Models

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Abstract

Estimating causal effects from non-randomized data requires assumptions about the underlying data-generating process. To achieve unbiased estimates of the causal effect of a treatment on an outcome, we must adjust for any confounding variables that influence both treatment and outcome. When such confounders include text data, existing causal inference methods struggle due to the high dimensionality of the text. The simple statistical models which have sufficient convergence criteria for causal estimation are not well-equipped to handle noisy unstructured text, but flexible Large language models (LLMs) that excel at predictive tasks with text data do not meet the statistical assumptions necessary for causal estimation. Our method enables theoretically consistent estimation of causal effects using LLM-based nuisance models by incorporating them within the framework of Double Machine Learning. On the best available dataset for evaluating such methods, we obtain a 10.4% reduction in the relative absolute error for the estimated causal effect over existing methods.

1 Introduction

A common goal of scientific research is the analysis of causal relationships (Triantafillou et al., 2017; Sanna et al., 2019; Chang et al., 2022). Consider the following motivating example, where a pharmaceutical company wants to estimate the causal effect of the prescription of antibiotics (treatment) on the patient's disease progression (outcome). The causal effect is defined as the expected change in disease progression across two *counterfactual* worlds which only differ in whether the patient is given antibiotics (Hernán, 2004). When randomization is impossible or unethical, we estimate causal effects from observational data using assumptions about the underlying data distribution. Confounders – variables affecting both the treatment and outcome – introduce potential bias that must be addressed.

When data is low-dimensional, confounding can be controlled for using various methods from the literature (Pearl, 2009). However, several challenges arise in the case of high-dimensional confounders such as text. For example, assume the pharmaceutical company has free-text clinical notes that may include information about patients' histories, diagnoses, or relationships with their doctors (Rajkomar et al., 2018). If these potential confounding variables appear nowhere else in the patients' records, then to account for confounding we must use text-based causal methods (Rosenbloom et al., 2011; Wu et al., 2013). Since text is high-dimensional, it requires sophisticated modeling that captures semantic meaning.

Existing models often utilize overly simplified representations of the text (Wood-Doughty et al., 2018; Keith et al., 2020), such as a *bag-of-words* (BoW) representation. While such representations combined with simple estimation models allow for consistent[1] estimation, they may fail to capture the true complexity of the text's underlying relationships. The use of Large language models (LLMs) in causal estimation has only recently been studied (Veitch et al., 2020), and many researchers suggest the need for more sophisticated natural language processing (NLP) techniques (Wood-Doughty et al., 2021; Feder et al., 2022; Keith et al., 2023). However, while LLMs excel at predictive tasks, they do not meet the necessary statistical assumptions for a consistent causal estimation.

We present **DoubleLingo**, combining Double Machine Learning with LLM-based nuisance models to enable a theoretically consistent estimation of causal effects with text-based confounding. We test our model on a novel dataset (Keith et al., 2023), obtaining the best causal effect estimates reported thus far. In particular, our relative absolute error is over 10% lower than the best current models.

[1] Defined in more detail in §3

2 Causal Inference Background

While causal inference is a broad and diverse field (Robins et al., 2000; Pearl, 2009), we provide a brief introduction here. For recent surveys of causal inference and natural language processing, see Keith et al. (2020) or Feder et al. (2022).

2.1 DAGs & Counterfactuals

The motivating example described above is illustrated by the directed acyclic graph (DAG) in Figure 1, where we use a binary random variable A to indicate whether the patient receives $(A = 1)$ antibiotics or not $(A = 0)$. We similarly use a binary Y to denote whether the disease progresses $(Y = 1)$ or not $(Y = 0)$. An arrow in the DAG such as $A \rightarrow Y$ indicates that A has a potential causal effect on Y. Finally, we denote T as the patient medical records, and C as the set of all confounding variables contained in the records. Most importantly, C is unobserved — we don't know the exact confounding variables, but we have access to the text T containing them. Hence, there exist some causal effects $T \dashrightarrow A$ and $T \dashrightarrow Y$ where the text T affects A and Y through the unobserved C. The *counterfactual* outcome $Y^{a=1}$ represents the hypothetical disease progression had we intervened to assign $A = 1$ (prescribe antibiotics), and $Y^{a=0}$ is defined analogously. In causal inference, the most common estimand is the average treatment effect (ATE) of A on Y, computed as:

$$ATE = \mathbb{E}[Y^{a=1} - Y^{a=0}] \tag{1}$$

A fundamental problem is that we can never simultaneously observe both *counterfactuals* $Y^{a=1}, Y^{a=0}$ (Holland, 1986), thus we need a way to compute the ATE only utilizing observed data.

2.2 Identification Assumptions

We proceed by assuming *consistency*, requiring that the outcome we observe for any possible treatment a is equal to the *counterfactual* outcome we would have observed had we intervened to assign $A = a$. Formally,

$$A = a \leftrightarrow Y^a = Y \tag{2}$$

We then assume *conditional exchangeability*, requiring the independence between our counterfactual Y^a and the observed treatment A conditioned on all confounders C, formalized as

$$Y^a \perp A \mid C \quad \forall a \in \{0, 1\} \tag{3}$$

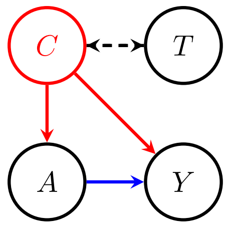

Figure 1: Textual Confounding DAG with Treatment A, Outcome Y, Confounders C, and Text T.

Using these assumptions, we may compute the counterfactual $\mathbb{E}[Y^a]$ as follows

$$\begin{aligned}
\mathbb{E}[Y^a] &= \sum_C \mathbb{E}[Y^a \mid C]\mathbb{P}(C) & (4)\\
&\overset{(3)}{=} \sum_C \mathbb{E}[Y^a \mid A = a, C]\mathbb{P}(C) & (5)\\
&\overset{(2)}{=} \sum_C \mathbb{E}[Y \mid A = a, C]\mathbb{P}(C) & (6)
\end{aligned}$$

However, since C is unobserved, the main challenge is in modelling the text T to adjust for all of the confounding from C.

2.3 Causal Effect Estimation

In estimating the ATE, we thus require (a) a representation of the text and (b) an appropriate causal estimation method. As mentioned in §1, a BoW text representation is commonly used by existing text-based causal estimators. For (b), there are countless estimation methods, and we refer the reader to a much more exhaustive guide by Peters et al. (2017). One such commonly used method is the *Inverse Propensity of Treatment Weighting* (IPTW), where $\mathbb{E}[Y^a]$ is calculated as follows for a dataset of size N.

$$\mathbb{E}[Y^a] = \frac{1}{N} \sum_{i \in [N]} Y_i \frac{\mathbb{1}(A_i = a)}{\mathbb{P}(A_i = a \mid T)} \tag{7}$$

Thus, combining (a) and (b), a common current method is to use IPTW and learn a *Logistic Regression* model $\mathbb{P}(A \mid T)$ for the propensity of the treatment A given a BoW text representation T.

3 Model

Any estimator $\hat{\theta}$ of the true ATE estimate θ must be both unbiased and consistent such that

$$\mathbb{E}[\hat{\theta}] = \theta \quad \text{and} \quad \hat{\theta} \xrightarrow{P} \theta \tag{8}$$

While LLMs have drastically changed the field of NLP (Vaswani et al., 2017; Min et al., 2023), they are not consistent estimators of causal parameters due to both explicit and implicit regularization (Neyshabur, 2017; Chernozhukov et al., 2018). Thus, a naive approach of using an LLM such as BERT (Devlin et al., 2019) to learn the propensity $\mathbb{P}(A \mid T)$ in Equation (7) would be biased.

3.1 Double Machine Learning

We thus turn to Double Machine Learning (DML), which has never previously been used in the context of LLMs. As proven by Chernozhukov et al. (2018), regularization bias in complex ML models can be overcome by utilizing orthogonalization. In particular, we partial out this bias by learning classifiers for both the treatment $\mathbb{E}[A \mid T]$ and outcome $\mathbb{E}[Y \mid T]$. Accordingly, we obtain a consistent estimate of the ATE by regressing the residuals

$$Y - \mathbb{E}[Y \mid T] \sim A - \mathbb{E}[A \mid T] \tag{9}$$

Additionally, as we fit both $\mathbb{E}[A \mid T]$ and $\mathbb{E}[Y \mid T]$, the estimation is doubly robust such that only one of the two models need to be correctly specified to obtain an unbiased ATE (Funk et al., 2011). Finally, we utilize sample splitting (Stone, 1974), where we train on half of the data, using the other half for estimation, preventing any estimation bias induced by overfitting. A potential concern is that DML requires our nuisance models to converge at $N^{-1/4}$ rates such that the overall estimator is $\sqrt{N}$-consistent[2], that is

$$\hat{\theta} - \theta = O_p(N^{-1/2}) \tag{10}$$

While there is research on the rate of convergence of misclassification probability (Gurevych et al., 2022) for encoder-based transformer classifiers such as BERT, its convergence rate for semiparametric inference is unknown.

3.2 Faster Converging Model Variations

Since fully fine-tuning BERT classifiers within the DML framework may not be appropriate, we present **DoubleLingo**, utilizing two faster converging model variations.

BERT+Adapter. Our first configuration utilizes parameter efficient transfer learning in the form of adapters (Houlsby et al., 2019). Thus, instead of fine-tuning all of BERT, we only fine-tune the adapter layers. While there are no theoretical bounds for the convergence of adapters, they empirically demonstrate a much quicker convergence compared to fine-tuning the full network.

Embedding+FFN. Fully-connected feedforward neural networks (FFNs) with the ReLU activation function have been proven to converge at $N^{-1/4}$ rates for their use in semiparametric inference (Farrell et al., 2021). Thus, instead of fine-tuning BERT at all, a potential approach is to fine-tune a feed-forward layer on top of BERT's pre-trained embeddings. Since BERT doesn't learn independent sentence embeddings, we could instead use the $[CLS]$ encoding or pool the sequence of hidden states for the whole input. Instead, we utilize embeddings from pre-trained sentence transformers (Reimers and Gurevych, 2019), which are much more semantically meaningful. To our knowledge, sentence transformer embeddings have never been utilized in the context of causal inference estimation, thus we further contribute to the literature by analyzing their causal estimation capabilities compared to simpler text representations.

4 Causal Dataset & Experiment

Unlike supervised learning models, which can be evaluated on held-out test sets with ground-truth labels, causal estimation methods require evaluations with *counterfactual* ground-truth, which is impossible to measure from observed data (Holland, 1986). Researchers often turn to (semi-)synthetic data, for which there is a tension between generating realistic text and maintaining full knowledge of the underlying data-generating process (DGP) (Wood-Doughty et al., 2021). Most current datasets fail to accomplish both, either fully specifying the DGP but with unrealistic text (Johansson et al., 2016; Yao et al., 2019), or using real-world text inside a semi-synthetic DGP (Veitch et al., 2020).

4.1 Dataset and Baselines

A recent novel dataset employs a randomized controlled trial (RCT) rejection sampling algorithm to create text-based datasets that both contain real text and are based on a realistic DGP (Keith et al., 2023). In particular, the authors fix C to be a single binary confounding variable contained in the text and choose RCT's with an existing $C \rightarrow Y$ relationship. They then sample the dataset to artificially create a $C \rightarrow A$ relationship and evaluate 8 different models over 100 sampled dataset subsets.

[2] As $N \to \infty$ estimation error goes to 0 at a rate of $\sqrt{N}$

Unadjusted	Oracle (C)	*TF-IDF+FFN*	LR_Q	LR_{IPTW}	LR_{AIPTW}	LR_{DML}
0.214 (0.08)	0.115 (0.09)	0.118 (0.09)	1.408 (1.00)	0.470 (0.16)	1.579 (0.66)	1.899 (0.91)
BERT+Adapter	**SPECTER+FFN**	**MPNetV2+FFN**	CB_Q	CB_{IPTW}	CB_{AIPTW}	CB_{DML}
0.104 (0.08)	0.104 (0.08)	0.103 (0.08)	0.237 (0.10)	0.141 (0.11)	0.115 (0.10)	0.128 (0.10)

Table 1: Relative Absolute Error mean (variance) for all methods over 100 subsets. §4.2 describes our **DoubleLingo** methods and *TF-IDF+FNN* baseline. Logistic Regression (LR), CatBoost (CB), Oracle, and Unadjusted baselines all use code from Keith et al. (2023). Our methods achieve the best (lowest) error and variance.

They train *Logistic Regression* and *CatBoost* nuisance models based on a BoW representation for the text, combining both with 4 different causal estimation techniques, including IPTW, Augmented-IPTW (AIPTW), Outcome Regression (Q), and DML. They finally evaluate an *Oracle* with full access to the unobserved C value.

4.2 DoubleLingo Experiments

We now describe our methods that use LLMs inside the DML framework. Our **BERT+Adapter** method fine-tunes adapters within BERT classifiers for both A and Y (Houlsby et al., 2019). Our **Embedding+FFN** configuration uses two sentence transformers. First, *all-mpnet-base-v2* [3], based on *MPNet* (Song et al., 2020) and fine-tuned on 1 million sentence pairs. Second, *SPECTER* (Cohan et al., 2020), pre-trained on a dataset of scientific paper titles and abstracts which matches the format of Keith et al. (2023). For both **Embedding+FFN** methods, we use a single hidden layer, ReLU activation functions, and the AdamW optimizer (Loshchilov and Hutter, 2018) to obtain $N^{-1/4}$ convergence (Farrell et al., 2021). Finally, we implement a *TF-IDF+FFN* baseline, following Manzoor et al. (2023), which uses DML with FFNs with batch normalization (Ioffe and Szegedy, 2015) and a TF-IDF text representation. A more detailed implementation, including specific hyperparameters and RCT parameterization choices are provided in Appendix A.

5 Results and Conclusions

Table 1 shows that our three **DoubleLingo** estimators obtain the lowest ATE relative absolute error (0.103), a 10.4% decrease from the prior best (0.115). These results provide strong empirical evidence that the DML framework successfully enables the use of LLMs in causal estimation. Notably, the prior best was achieved by both a BoW model (CB_{AIPTW}) and the *Oracle* estimator which calculates the estimates using the unobserved C values. If C contained all causes of A and Y, it would be the theoretically-optimal efficient adjustment set (Rotnitzky and Smucler, 2020) and the Oracle should – asymptotically – be impossible to outperform. However, while the $C \to A$ relationship is artificially induced by the sampling procedure of Keith et al. (2023), the $C \to Y$ correlation is confirmed to exist[4]; we hypothesize that the underlying complexity of the $T \to Y$ relationship is not fully captured by the binary topic C and thus modeling T allows for more efficient estimation.

Our results specifically support the hypothesis that the text representation itself matters to causal estimation. Among all DML methods with feed-forward classifiers, our **Embedding+FFN** methods' outperformance of our *TF-IDF+FFN* baseline shows that better representations can enable lower estimation error. Appendix B also shows our models' slightly better classification accuracy than the *TF-IDF+FFN* baseline during estimation.

Between our three proposed methods, we see no large differences in performance. This suggests that while the incorporation of LLMs into the estimators is essential, the specific architecture and training setup matters less. However, **BERT+Adapter** trains two to three times slower than **Embedding+FFN**. We also see little difference between the two pre-trained embeddings, despite the similarity of the *SPECTER* embedding's dataset to that of our evaluation data.

This work proposes **DoubleLingo**, a theoretically consistent causal estimator that uses LLM nuisance models inside the DML framework. We show that both adapters and sentence transformers can achieve the lowest estimation error on the best available dataset for evaluating methods that account for text confounding. We include our code as an appendix that reproduces our provided results.

[3] https://hf.co/sentence-transformers/all-mpnet-base-v2

[4] Authors verify that $C \not\perp Y$ with an odds ratio test

Limitations

The main limitation of our estimation procedure is compute time – training the **BERT+Adapter** configuration on 100 sampled dataset subsets takes 10 hours parallelized across 2 RTX 8000's, significantly longer than the baseline *Linear Regression* or *CatBoost* models. In particular, our model's reliance on sample-splitting and double robustness to obtain a consistent final estimate requires training 4 times as many models per each dataset subset. However, it's important to note that the **Embedding+FFN** configurations only take a third of the time, yet achieve identical results.

Additionally, our work only focuses on causal estimation with text-based confounding. In particular, dealing with textual treatments or outcomes is still an open problem in the field (Feder et al., 2022). Finally, we only train on a single English-language dataset, and resultingly encourage future work to expand on this by testing other types of text-based RCT's.

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Model	Accuracy	
	$\mathbb{E}[A \mid T]$	$\mathbb{E}[Y \mid T]$
Logistic Regression	75.5	82.8
CatBoost	80.3	95.5
TF-IDF+FFN	80.6	95.3
SPECTER+FFN	82.8	95.7
MPNetV2+FFN	83.2	95.7
BERT+Adapter	83.2	95.7

Table 2: Average Predictive Accuracy over 100 dataset subsets

A Implementation

This section gives a more detailed overview of our implementation, including specific hyper-parameter values for both model configurations and parameterization choices of $\mathbb{P}(A \mid C)$ required by the RCT rejection sampling algorithm.

BERT+Adapters. For our BERT adapter configuration, we use a batch size of 128, the maximum that can fit parallelized across two RTX 8000's. We use default values for beta and weight decay, setting $B_1 = 0.9$, $B_2 = 0.999$, $\lambda = 0$. We manually optimize for the learning rate and number of epochs based on validation accuracy on a small subset of the 100 datasets, resulting in a learning rate of $3e$-4 over 5 epochs. Our estimation takes around 10 hours to complete. For the estimation of a single dataset, we suggest practitioners perform a larger search over hyper-parameters, however the use of sample-splitting and doubly-robust estimation requires training 4 times the number of models. Thus, a simple grid-search over just 10 hyper-parameter combinations with 4-fold cross-validation over 100 dataset seeds would require the training of $16,000$ models. Finally, we use $\text{BERT}_{\text{BASE}}$ which has $109,482,240$ parameters, however the use of adapters allows us to only fine-tune $894,528$ parameters.

Embedding+FFN. For all of our FFN configurations, we use the same batch size of 128 and the same default beta and weight decay values. We use a single hidden layer with the same number of nodes as the input layer, equal to 768 for both sentence transformers. Since these FFNs are much quicker to train, we perform a search over the learning rates, $\{1e\text{-}5, 1e\text{-}4, 1e\text{-}3, 1e\text{-}2\}$, combined with early-stopping for each one of the 100 dataset subsets.

RCT parameterization. The RCT rejection sampling algorithm requires practitioners to specify $\mathbb{P}(A \mid C)$. In particular, the authors choose C to be a binary random variable representing the specific text topic. We accordingly utilize the default provided RCT using medicine $(C = 0)$ and physics $(C = 1)$ articles. Authors then define $\mathbb{P}(A \mid C)$ as follows

$$\mathbb{P}(A = 1 \mid C) = \begin{cases} \zeta_0 & \text{if } C = 0 \\ \zeta_1 & \text{if } C = 1 \end{cases}$$

which is used in sampling the RCT to create an artificial $C \rightarrow A$ effect. We utilize the default choices of $\zeta_0 = 0.85$ and $\zeta_1 = 0.15$ which induce the highest amount of confounding. For a much more thorough explanation, we direct readers to Keith et al. (2023).

B Nuisance Model Predictive Accuracy

Specific values for the average predictive accuracy during estimation of all tested nuisance models are provided in Table 2. A similar trend appears compared to causal estimation results in Table 1, where the largest improvement occurs from simply switching to non-linear nuisance models (*CatBoost* vs. *LogisticRegression*).

While our three **DoubleLingo** model configurations achieve the best predictive accuracies $(83.2\%, 95.7\%)$, the values are only slightly higher than those for the *TF-IDF+FFN* implementation. Here, it's important to note that predictive accuracy alone does not directly contribute to a more accurate estimation (Wood-Doughty et al., 2018).

C Use of Scientific Artifacts & Licensing

Our work uses the RCT rejection sampling dataset by Keith et al. (2023). In particular, the dataset is fully in English, containing publicly available paper titles and abstracts. The authors remove any potentially personally identifiable information from the dataset (author names, user ids, user IP addresses, or session ids). The dataset is made publically available for research purposes (apache-2.0).

Finally, **DoubleLingo** uses the Hugging Face implementations for *bert-base-uncased*, *allenai/specter*, and *all-mpnet-base-v2*, all made publically available for research purposes (apache-2.0).