EXPLAINING THE EFFICACY OF COUNTERFACTUALLY AUGMENTED DATA

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ABSTRACT

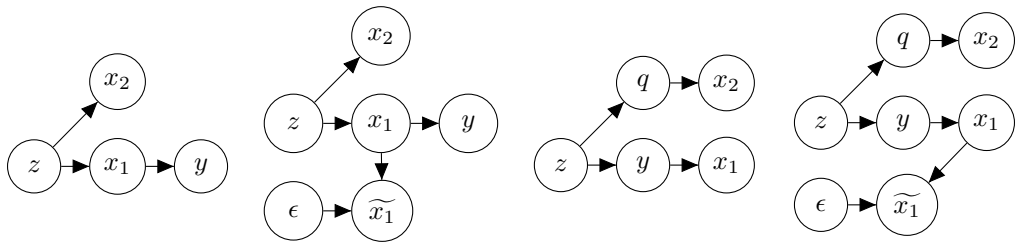
In attempts to produce machine learning models less reliant on spurious patterns in training data, researchers have recently proposed generating counterfactually augmented data through a human-in-the-loop process. As applied in NLP, given some documents and their (initial) labels, humans are tasked with revising the text to make a (given) counterfactual label applicable. Importantly, the instructions prohibit edits that are not necessary to flip the applicable label. Models trained on the augmented (original *and* revised) data have been shown to rely less on semantically irrelevant words and to generalize better out-of-domain. While this work draws on causal thinking, casting edits as interventions and relying on human understanding to assess outcomes, the underlying causal model is not clear nor are the principles underlying the observed improvements in out-of-domain evaluation. In this paper, we explore a toy analog, using linear Gaussian models. Our analysis reveals interesting relationships between causal models, measurement noise, out-of-domain generalization, and reliance on spurious signals. Interestingly our analysis suggests that data corrupted by adding noise to causal features will degrade out-of-domain performance, while noise added to non-causal features may make models more robust out-of-domain. This analysis yields interesting insights that help to explain the efficacy of counterfactually augmented data. Finally, we present a large-scale empirical study that supports this hypothesis.

1 INTRODUCTION

Despite machine learning's many practical breakthroughs, formidable obstacles obstruct its deployment in consequential applications. Of particular concern, these models have been shown to rely on spurious signals, such as surface-level textures in images (Jo & Bengio, 2017; Geirhos et al., 2018), and background scenery—even when the task is to recognize foreground objects (Beery et al., 2018). Other studies have uncovered a worrisome reliance on gender in models trained for the purpose of recommending jobs (Dastin, 2018), and on race in prioritizing patients for medical care (Obermeyer et al., 2019). Additionally, numerous studies have demonstrated that while modern machine learning methods perform remarkably well on randomly partitioned holdout data, performance often decays catastrophically under distribution shift (Quionero-Candela et al., 2009; Sugiyama & Kawanabe, 2012; Szegedy et al., 2014; Ovadia et al., 2019; Filos et al., 2020).

These two problems: (i) the reliance on mechanistically irrelevant signals, raising concerns about bias; and (ii) the brittleness of models under distributions shift; might seem unrelated at first, but they share important conceptual features. Concerns about bias in algorithms stem in part from principles of procedural fairness (Blader & Tyler, 2003; Miller, 2017; Grgic-Hlaca et al., 2018; Lipton et al., 2018). According to this principle, decisions should be based on qualifications, not on distant proxies that may only be spuriously associated with the outcome of interest.[1] In an interesting parallel, one line of work on distribution shift has focused on causal graphical models, addressing settings where some parts of the causal model are stable over time while others are not. Some of this work has focused on settings where the relationship between a target variable and its direct causal ancestors remains invariant across foreseeable shifts (Peters et al., 2016; Ghassami et al., 2017; Rojas-Carulla et al., 2018; Kuang et al., 2018; Magliacane et al., 2018; Christiansen & Peters, 2020; Weichwald & Peters, 2020). While these papers contribute theoretical insights, they typically focus

[1] Note that procedural fairness is but one among many desiderata of ethical concern.



(a) Causal setting (b) Noisy measurement in causal setting (c) Anticausal setting (d) Noisy measurements in anticausal setting

Figure 1: Toy causal models with one hidden confounder. In 1a and 1c, the observed covariates are x_1, x_2. In 1b and 1d, the observed covariates are $\widetilde{x_1}, x_2$. In all cases, y denotes the label.

on toy settings, with just a few variables related by a known model. In complex domains with high dimensional data, such as computer vision or natural language processing (NLP), what precisely are the relevant variables and what graph relates them?

One recent line of work (Kaushik et al., 2020; Teney et al., 2020; Srivastava et al., 2020) has sought to inject causal thinking into real world settings by leveraging human-in-the-loop feedback to identify those signals that cause a label to be applicable versus those that merely happen to be predictive due to confounding. In particular, Kaushik et al. (2020) proposed collecting *Counterfactually Augmented Data (CAD)*. Here, humans are presented with document-label pairs and tasked with editing the document to render (designated) counterfactual labels applicable. The instructions require that the editors make only modifications that are necessary to flip the applicability of the label and the entire process relies on the editor's ability to assess and determine when the label applies. The key result in this work is that many spurious correlations present in the original dataset no longer exist in the CAD. In case of sentiment analysis, Kaushik et al. (2020) demonstrated that linear classifiers trained to predict the sentiment of movie reviews based on bag-of-words representations assign high-magnitude weights to seemingly irrelevant terms, including "will", "my", "has", "especially", and "script", among others. Notably, "horror" featured among the most negative terms, while "romance" featured among the most positive, despite both communicating genre, not sentiment. Although genre and review sentiment are correlated, the genre description does not cause the sentiment label's applicability. Interestingly, in the revised data, each "horror" review retains the word "horror" (a direct result of the instructions) but is associated with the opposite sentiment label. Models trained on the augmented data (original *and* revised) perform well on both original and revised data, and assign little weight to the associated but irrelevant terms. Intuitively, one might imagine that the spurious patterns would generalize less reliably out of domain. Most consumer products do not belong to movie genres, but words like "excellent" and "awful" continue to connote positive and negative sentiment, respectively. Indeed, Kaushik et al. (2020) demonstrated that models trained on CAD enjoyed out-of-domain performance benefits on Amazon, SemEval, and Yelp reviews.

In this paper, we work towards an explanation of CAD's practical efficacy. While CAD draws on causal thinking in a promising way, significant open questions require further inquiry: For example, what causal structure underlies the processes where CAD should be expected to be effective? What are the principles underlying its out-of-domain benefits? Must humans *really* intervene or could other feature attribution methods, e.g., attention (DeYoung et al., 2020), or cheaper feedback mechanisms, e.g., feature feedback (Zaidan et al., 2007), produce similar results?

To make headway on these questions, we derive some insights from examining simple linear Gaussian models (Wright, 1934) (Figure 1). Our goals are to (i) gain qualitative insights into when we should expect a model to rely on spurious patterns in the first place; (ii) elucidate the relationship between observation noise and such patterns; and (iii) provide a possible mechanism of action to explain the efficacy of CAD. First, we analyze the causal setting (features cause the label). When the features share a common cause and absent model misspecification, the learned predictor will assign zero weight (in expectation) to non-causal features. However, when the causal features are subject to observation noise (measurement error), the non-causal features become salient. As noise is injected on non-causal features, resulting models assign greater weight to causal features, which

we expect to result in better out-of-domain generalization. In the causal framework, we observe that CAD might be productively formalized as a process analogous to intervening on the causal features, thus d-separating the label from the non-causal features (Pearl, 1985). Alternatively, we might conceptualize CAD within an anticausal model (Schölkopf et al., 2012). Here it is *us* who intervene *on the label* and the role of the editors is that of the structural equation. Note that this (more clearly) results, in d-separation of the label from the spurious correlate. In both cases, any model trained on the resulting data ought to rely only on the causal features.

Our toy abstraction points to a useful diagnostic test. If indeed CAD involves interventions on spans that are (in some sense) analogous to the causal features in our toy model, then injecting noise on these words should increase model reliance on the non-causal features and thus (in general) lead to deteriorating performance out-of-domain. On the other hand, injecting noise on the non-causal features should lead the model to rely more on the causal features, leading to improved performance out of domain. Through a series of large-scale empirical experiments addressing sentiment analysis and natural language inference (NLI) tasks, we inject noise on the spans marked as causal vs non-causal. We compare the effects of injecting noise on the spans revised by the CAD editors, the spans selected through a previous feature feedback study (Zaidan et al., 2007), and fully automated methods developed in the explainability literature, e.g., treating attention masks as *rationales* (DeYoung et al., 2020). If indeed the hypotheses that (i) identifying causal features requires human intervention; and (ii) models relying on causal features generalize better out of domain; hold, we might expect that intervention on the human-provided rationales would deteriorate out-of-domain performance, while interventions on non-rationale tokens should prove beneficial.

We show that an SVM sentiment analysis model trained on the original $1.7k$ IMDb reviews from Kaushik et al. (2020) obtains 87.8% accuracy on the IMDb test set and 79.9% on Yelp reviews but when all *rationale* tokens are replaced with noise, the classifier experiences $\approx 11\%$ drop on in-sample accuracy and an even bigger drop of $\approx 28.7\%$ on Yelp. However, as *non-rationales* are replaced with noise, in-sample accuracy goes down by $\approx 10\%$ but accuracy on Yelp increases by 1.5%. Similarly in NLI, the accuracy of a BERT classifier trained on DeYoung et al. (2020) goes down by $\approx 20\%$ when *rationales* are replaced with noise, whereas the out-of-domain accuracy goes down by $21.3\% - 31.5\%$ on various datasets. If *non-rationales* are replaced with noise, in-sample accuracy goes down by 6.2% but out of domain accuracy drops by only $2.3\% - 5.5\%$. Similar behavior is observed across both tasks, on all datasets and models. However, if attention masks are considered *rationales*, the resulting changes in model performance do not obey these trends. In another test to probe whether human feedback is indeed necessary to produce datasets with the observed quantitative results of CAD, we experiment with style transfer methods for converting *Positive* reviews into *Negative* and vice versa. Compared to an SVM classifier trained on style transfer augmented data, training on CAD leads to a gain of $5 - 16.4\%$ in accuracy on Amazon and $3.7 - 17.8\%$ on Yelp. Similarly, a BERT classifier trained on CAD outperforms the same classifier trained on style transfer augmented data by $4.9 - 21.5\%$ on Amazon and $1.9 - 9.5\%$ on Yelp.

2 Related Work

NLP papers on spurious associations have addressed social biases (Dixon et al., 2018; Zhao et al., 2018; Kiritchenko & Mohammad, 2018; Dinan et al., 2019; May et al., 2019), spurious signals learned due to annotation heuristics adopted by crowd workers (Gururangan et al., 2018; Poliak et al., 2018). and unintentional effects of automatic data generation process (Chen et al., 2016; Kaushik & Lipton, 2018), amongst other reasons. As a result, models have been shown to be vulnerable to synthetic transformations, such as distractor phrases (Jia & Liang, 2017; Wallace et al., 2019), document paraphrases (Iyyer et al., 2018; Pfeiffer et al., 2019), and meaning preserving synthetic modifications (Ribeiro et al., 2018; Glockner et al., 2018; Shen et al., 2018).

In efforts to train models that rely on relevant features, researchers have proposed incorporating human feedback solicited through a variety of mechanisms including highlighting *rationales*, spans of text indicative of the label (Zaidan et al., 2007; Zaidan & Eisner, 2008; Poulis & Dasgupta, 2017). For each document, Zaidan et al. remove the *rationales* to generate *contrast* documents, learning classifiers to distinguish original documents from their *contrasting* counterparts. Looking to data augmentation to counteract undesired correlations, Lu et al. (2018); Zmigrod et al. (2019); Maudslay et al. (2019) describe data augmentation approaches to mitigate gender stereotypes by

programmatically altering text to invert gender bias. More recently, Kaushik et al. (2020) employed crowd workers to edit text to make an opposite label applicable. Through their experiments they show that classifiers trained on counterfactually augmented data generalize well out of domain.

A growing body of work has also looked at addressing model reliance on spurious correlations by exploiting the stability of relationships between the target variable and its (graph) neighbors. Peters et al. (2016) propose Invariant Causal Prediction to obtain a causal predictor of a target. Ghassami et al. (2017) discuss a similar approach but contrary to Peters et al. (2016), they do not assume that the exogenous noise of the target variable stays fixed among environments. They also demonstrate the benefits of their approach over Peters et al. (2016) in identifying all direct ancestors of the target variable. Arjovsky et al. (2019) propose Invariant Risk Minimization (IRM), an extension of Peters et al. (2016), with the goal of learning a data representation such that the optimal predictor (on top of that representation) is shared across environment.

3 Analysis of a Toy Model

We briefly review the OLS estimator for the following model:

$$Y = X\beta + \epsilon, \tag{1}$$

where $Y \in \mathrm{R}^n$ is the target, $X \in \mathrm{R}^{n\times p}$ the design matrix, $\beta \in \mathrm{R}^p$ the coefficient vector we want to estimate, and $\epsilon \sim \mathcal{N}(0, \sigma_\epsilon^2 \mathbf{I}_n)$ an i.i.d. noise term. The OLS estimate β^{ols} is given by $\mathrm{Cov}(X, X)\beta^{ols} = \mathrm{Cov}(X, Y)$. Representing $\mathrm{Var}[X_i]$ as $\sigma_{x_i}^2$ and $\mathrm{Cov}(X_i, X_j)$ as σ_{x_i,x_j}, if we observe only two covariates ($p = 2$), then:

$$\beta_1^{ols} = \frac{\sigma_{x_2}^2\sigma_{x_1,y} - \sigma_{x_1,x_2}\sigma_{x_2,y}}{\sigma_{x_1}^2\sigma_{x_2}^2 - \sigma_{x_1,x_2}^2} \qquad \beta_2^{ols} = \frac{\sigma_{x_1}^2\sigma_{x_2,y} - \sigma_{x_1,x_2}\sigma_{x_1,y}}{\sigma_{x_1}^2\sigma_{x_2}^2 - \sigma_{x_1,x_2}^2} \tag{2}$$

Our analysis relies on the structural causal model (SCM) framework (Pearl, 2009), formalizing causal relationships via Directed Acyclic Graphs (DAGs). Each edge of the form $A \to B \in \mathcal{E}$ in a DAG $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ indicates that the variable A is (potentially) a direct cause of variable B. All measured variables $X \in \mathcal{V}$ in the model are deterministic functions of their corresponding parents $\mathrm{Pa}(X) \subseteq \mathcal{V}$ and a set of jointly independent noise terms. For simplicity, we work with linear Gaussian SCMs in the presence of a single confounder where each variable is a linear function of its parents and the noise terms are assumed to be additive and Gaussian. We look at both causal and anticausal learning settings. In the former, we assume that a document causes the applicability of the label (as in annotation, where the document truly causes the label). The latter corresponds to the interpretation where a label causes the document (as when a reviewer's "actual sentiment" influences what they write). Without loss of generality, we assume that all variables have zero mean. Both DAGs contain the four random variables z, x_1, x_2, y and the anticausal DAG also contains q (Figure 1). We relegate all derivations to Appendix A.

We now focus on the causal setting (Figure 1a, 1b) Let the Gaussian SCM be defined as follows where the noise term for variable x is defined as u_x:

$$\begin{aligned} z &= u_z, & u_z &\sim \mathcal{N}(0, \sigma_{u_z}^2) \\ x_1 &= bz + u_{x_1}, & u_{x_1} &\sim \mathcal{N}(0, \sigma_{u_{x1}}^2) \\ x_2 &= cz + u_{x_2}, & u_{x_2} &\sim \mathcal{N}(0, \sigma_{u_{x2}}^2) \\ y &= ax_1 + u_y, & u_y &\sim \mathcal{N}(0, \sigma_{u_y}^2). \end{aligned} \tag{3}$$

Applying OLS, we obtain $\beta_1^{ols} = a$ and $\beta_2^{ols} = 0$. However, consider what happens if we only observe x_1 via a noisy proxy $\widetilde{x_1} \sim \mathcal{N}(x_1, \sigma_{u_{x_1}}^2 + \sigma_{\epsilon_{x_1}}^2)$ (Figure 1b). Assuming, $\epsilon_{x_1} \perp\!\!\!\perp (x_1, x_2, y)$,

from Eq. 2 we get the estimates $\widehat{\beta_1^{ols}}$ and $\widehat{\beta_2^{ols}}$ (Eq. 4) in the presence of observation noise on x_1.

$$
\begin{aligned}
\widehat{\beta_1^{ols}} &= \frac{a(\sigma^2_{u_z}(b^2\sigma^2_{u_{x2}} + c^2\sigma^2_{u_{x1}}) + \sigma^2_{u_{x1}}\sigma^2_{u_{x2}})}{\sigma^2_{u_z}(b^2\sigma^2_{u_{x2}} + c^2\sigma^2_{u_{x1}}) + \sigma^2_{u_{x1}}\sigma^2_{u_{x2}} + \sigma^2_{\epsilon_{x1}}(c^2\sigma^2_{u_z} + \sigma^2_{u_{x2}})} = \frac{\beta_1^{ols}}{1+\lambda_c} \\
\widehat{\beta_2^{ols}} &= \frac{acb\sigma^2_{\epsilon_{x1}}\sigma^2_{u_z}}{\sigma^2_{u_z}(b^2\sigma^2_{u_{x2}} + c^2\sigma^2_{u_{x1}}) + \sigma^2_{u_{x1}}\sigma^2_{u_{x2}} + \sigma^2_{\epsilon_{x1}}(c^2\sigma^2_{u_z} + \sigma^2_{u_{x2}})} \\
\lambda_c &= \frac{\sigma^2_{\epsilon_{x1}}(c^2\sigma^2_{u_z} + \sigma^2_{u_{x2}})}{\sigma^2_{u_z}(b^2\sigma^2_{u_{x2}} + c^2\sigma^2_{u_{x1}}) + \sigma^2_{u_{x1}}\sigma^2_{u_{x2}}}
\end{aligned}
\tag{4}
$$

As we can see, $\lambda_c > 0$ and $\lambda_c \propto \sigma^2_{\epsilon_{x1}}$. This shows us that as $\sigma^2_{\epsilon_{x1}}$ increases, $|\widehat{\beta_1^{ols}}|$ (magnitude of the coefficient for x_1) decreases and $|\widehat{\beta_2^{ols}}|$ (magnitude of the coefficient for x_2) increases. The asymptotic OLS estimates in the presence of infinite observational noise can be seen to be: $\lim_{\sigma^2_{\epsilon_{x1}} \to \infty} \widehat{\beta_1^{ols}} = 0$ where as $\widehat{\beta_2^{ols}}$ converges to a finite non-zero value. On the other hand, observing a noisy version of x_2 will not affect our OLS estimates if there is no measurement error on x_1. Intervening on x_1 d-separates y from x_2 and the resulting model relies only on $\widetilde{x_1}$.

Relation to CAD These simple graphs provide qualitative insights into when we should expect a model to rely on spurious patterns. In the causal setting, under perfect measurement, the causal variable d-separates the non-causal variable from the label (Figure 1a). However, under observation noise, a predictor will rely on the non-causal variable (Eq. 4). Moreover, injecting noise on non-causal variable yields models that are more reliant on the causal variable. Intervening on the causal variable or the label in causal and anticausal settings respectively would yield a model that relies solely on the causal variable, even under noisy observation. The process of generating CAD resembles such an intervention, however instead of intervening randomly, *we* ensure that for each example, *we* produce two sets of values of x_1, one such that the label is and one such that the label is not applicable. One is given in the dataset, and the other is produced via the revision.

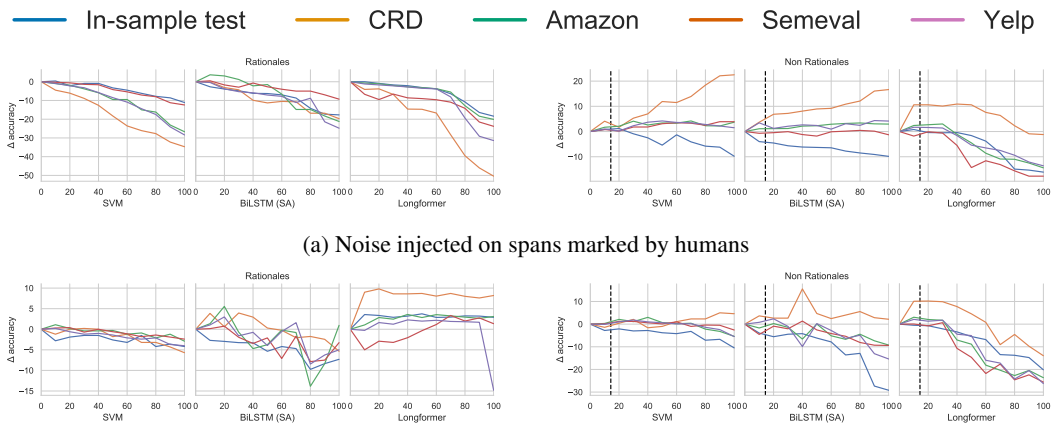
An Anticausal Interpretation In an anticausal interpretation of CAD, we might think of CAD as an intervention on the label, also d-separating the label from the spurious correlate (Figure 1c). In this interpretation, it is *us* who intervene, with editors playing the role of the generative model. As in the causal setting, injecting noise on the causal variable would increase the weight on non-causal variable and vice versa (see Appendix A.2).

In both the causal and anticausal models, the mechanism underlying the causal relationship that binds x_1 to y (regardless of direction) is that binding language to its meaning, which we expect to be more durable than the more capricious relationships among the background variable, e.g., those linking genre and production quality.

In that spirit, if human edited spans in CAD are truly analogous to the causal (or anticausal) variables, in the causal (or anticausal) graphs, then we might expect that injecting noise into those spans should lead to a models that rely more on non-causal features and performs worse on out of domain data. On the other hand, we expect that injecting noise into non-edited spans should have the opposite behavior leading to performance degradation in domain, but comparatively better performance out of domain. We freely acknowledge the speculative nature of this analysis and concede that the mapping between the messy unstructured data we wish to model and the neatly disentangled portrait captured by our linear Gaussian models. However, we find this analogy useful, both for formalizing two (very different) perspectives on how to conceive of CAD, and for suggesting interesting hypotheses amenable to empirical verification.

4 Empirical Results

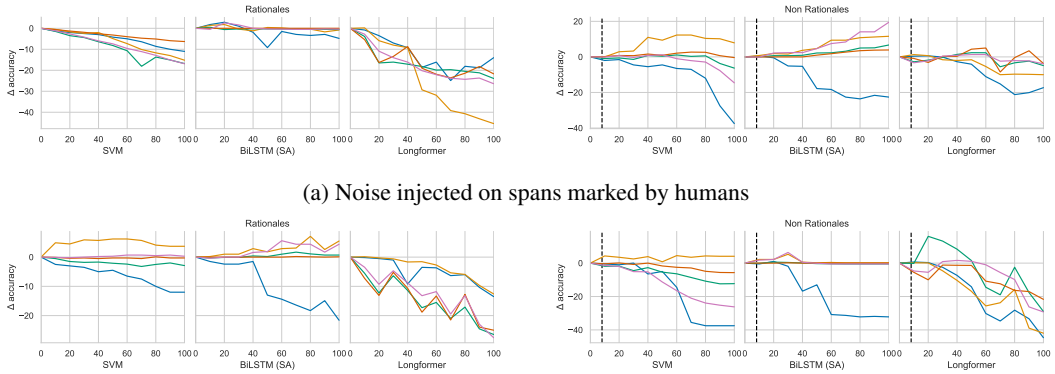
As discussed above, if human edited spans in CAD are truly indicative of causal variables, such that *Counterfactually Revised Data* (CRD) was generated by intervening on direct causal ancestors of the label, then injecting noise into those spans should lead to a model that relies more on non-causal features and performs worse on out of domain data, and injecting it into non-edited spans should have the opposite behavior. We conduct experiments on two sentiment analysis datasets (Zaidan



(a) Noise injected on spans marked by humans

(b) Noise injected on spans marked by Attention

Figure 2: Change in classifier accuracy as noise is injected on *rationales/non-rationales* for IMDb reviews from Kaushik et al. (2020).



(a) Noise injected on spans marked by humans

(b) Noise injected on spans marked by Attention

Figure 3: Change in classifier accuracy as noise is injected on *rationales/non-rationales* for IMDb reviews from Zaidan et al. (2007). In both Figures 2 and 3, the vertical dashed line indicates the fraction of median length of *non-rationales* equal to the median length of *rationales*.

et al., 2007; Kaushik et al., 2020) and an NLI dataset (DeYoung et al., 2020). All three datasets are accompanied with human feedback on what tokens are relevant for determining applicability of a label to a particular document (*rationales*). This is collected either by asking humans to highlight such rationales (Zaidan et al., 2007; DeYoung et al., 2020) or editing a document to make a counterfactual label applicable (Kaushik et al., 2020). Additionally, we investigate whether indeed the human feedback provides us with capabilities that are qualitatively different from what might be achieved via automated feature attribution methods such as attention, or style transfer algorithms. For the first set of experiments, we rely on four models: Support Vector Machines (SVMs), Bidirectional Long Short-Term Memory Networks (BiLSTMs) with Self-Attention (Graves & Schmidhuber, 2005), BERT (Devlin et al., 2019), and Longformer (Beltagy et al., 2020). For the second set of experiments, we rely on four state of the art style transfer models representative of different methodologies, each representative of a different approach to automatically generate new examples with flipped labels (Hu et al., 2017; Li et al., 2018; Sudhakar et al., 2019; Madaan et al., 2020). To evaluate classifier performance on the resulting augmented data, we make use of SVM, Naive Bayes (NB), BiLSTM w/ SA, and BERT. We relegate the implementation details to Appendix B.

For sentiment analysis, use SVM, BiLSTM with Self Attention, BERT, and Longformer models. In each document, we replace a fraction of *rationale* (or *non-rationale*) tokens with random tokens sampled from the vocabulary, and train our models, repeating the process 5 times. We per-

Table 1: Accuracy of BERT trained on SNLI (DeYoung et al., 2020) as noise is injected on human identified *rationales/non-rationales*. RP and RH are Revised Premise and Revised Hypothesis test sets in Kaushik et al. (2020). MNLI-M and MNLI-MM are MNLI (Williams et al., 2018) dev sets.

	Percent noise added to train data rationales										
Dataset	0	10	20	30	40	50	60	70	80	90	100
In-sample test	91.6	90.7	90.0	88.9	87.3	86.2	84.4	80.2	78.0	72.2	71.9
RP	72.7	70.7	69.1	67.1	65.7	62.4	61.8	57.7	55.6	53.8	51.4
RH	84.7	80.8	80.4	79.5	77.2	75.7	73.3	67.7	64.0	57.9	53.2
MNLI-M	75.6	74.7	73.9	72.0	70.6	69.1	64.7	59.1	55.8	54.4	53.3
MNLI-MM	77.9	76.7	75.6	73.9	72.3	70.8	65.6	58.4	55.1	53.6	52.5
	Percent noise added to train data non-rationales										
Dataset	0	10	20	30	40	50	60	70	80	90	100
In-sample test	91.6	91.4	91.3	90.9	90.8	89.9	89.0	88.7	87.8	86.7	85.4
RP	72.7	73.5	73.2	72.1	71.5	70.7	70.6	70.6	70.6	70.6	70.4
RH	84.7	83.6	82.6	81.9	81.3	81.1	80.5	79.8	79.4	79.4	79.2
MNLI-M	75.6	74.9	74.4	72.6	72.4	71.8	71.3	71.3	70.9	70.9	70.8
MNLI-MM	77.9	76.2	75.8	75.0	74.6	74.3	73.9	73.7	73.3	73.0	72.8

form similar experiments for NLI using BERT. As an individual premise-hypothesis pair is often not as long as a movie review, many pairs only have one or two words marked as *rationales*. To observe the effects from gradually injecting noise on *rationales* or *non-rationales*, we select only those premise-hypothesis pairs that have a minimum 10 tokens marked as *rationales*. Since no neutral pairs exist with 10 or more rationale tokens, we consider only a binary classification setting (entailment-contradiction), and downsample the majority class to ensure a $50:50$ label split.

Figures 2 and 3 show the difference in mean accuracy over 5 runs. For all classifiers, as the amount of noise in *rationales* increases, in-sample accuracy stays relatively stable compared to out-of-domain accuracy. An SVM classifier trained on the original $1.7k$ IMDb reviews from Kaushik et al. (2020) obtains 87.8% accuracy on the IMDb test set and 79.9% on Yelp reviews.[2] As a greater fraction of *rationales* are replaced with random words from the vocabulary, the classifier experiences a drop of $\approx 11\%$ by the time all *rationale* tokens are replaced with noise. However, it experiences an 28.7% drop in accuracy on Yelp reviews. Similarly, on the same datasets, a BERT classifier sees its in-sample accuracy drop by 18.4%, and by 31.4% on Yelp as *rationale* tokens replaced by noise go from 0 to 100%. However, as more *non-rationales* are replaced with noise, in-sample accuracy for SVM goes down by $\approx 10\%$ but increases by 1.5% on Yelp. For BERT, in-sample accuracy decreases by only 16.1% and only 13.6% on Yelp. We obtain similar results using *rationales* identified via feature feedback. An SVM classifier trained on reviews from Zaidan et al. (2007) sees in-sample accuracy drop by 11%, and accuracy on Yelp drop by 16.9% as noise is inserted on *rationales* but goes down by 17.3% and 14.6%, respectively when noise is inserted in *non-rationales*. For Longformer, in-sample accuracy drops by 14% and accuracy on Yelp goes down by 26.4% compared to a drop of 17.3% and gain of 3.9% respectively when noise is inserted in *non-rationales*. Similar behavior is observed across datasets and models (Tables 3 and 5). For NLI, while the in-sample accuracy of BERT trained on an SNLI subsample drops by $\approx 20\%$ when *rationales* are replaced with noise, out of domain accuracy goes down by $21.3\% - 31.5\%$ on various datasets (Table 1). On the other hand, if *non-rationales* are replaced with noise, in-sample accuracy goes down by 6.2% but out of domain accuracy drops by only $2.3\% - 5.5\%$. These results support our hypothesis that spans marked by humans as causing a label are truly indicative of causal variables, and CAD is generated by intervening on the direct causal ancestors of the label. It is important to recognize that even when we do not explicitly inject any noise, there is still measurement noise due to imperfect latent representations learned by document encoders, which is why models rely on non-causal variables even in the causal setting, reflecting on the value of human interventions.

[2]The out-of-domain evaluation sets in Kaushik et al. (2020) do not have $50:50$ label split. We enforce this split to observe when a classifier approaches random baseline performance, and will release this data publicly.

Table 2: Out-of-domain accuracy of models trained on original only, CAD, and original and *sentiment-flipped* reviews

Training data	SVM	NB	BiLSTM (SA)	BERT
Accuracy on Amazon Reviews				
Orig. & Kaushik et al. (2020) ($3.4k$)	**79.3**	**78.6**	**71.4**	**83.3**
Orig. & Hu et al. (2017)	66.4	71.8	62.6	78.4
Orig. & Li et al. (2018)	62.9	65.4	57.6	61.8
Orig. & Sudhakar et al. (2019)	64.0	69.3	54.7	77.2
Orig. & Madaan et al. (2020)	74.3	73.0	63.8	71.3
Orig. ($3.4k$)	74.5	74.3	68.9	80.0
Accuracy on Semeval 2017 (Twitter)				
Orig. & Kaushik et al. (2020) ($3.4k$)	**66.8**	**72.4**	**58.2**	**82.8**
Orig. & Hu et al. (2017)	60.9	63.4	56.6	79.2
Orig. & Li et al. (2018)	57.6	60.8	54.7	62.7
Orig. & Sudhakar et al. (2019)	59.4	62.6	54.9	72.5
Orig. & Madaan et al. (2020)	62.8	63.6	54.6	79.3
Orig. ($3.4k$)	63.1	63.7	50.7	72.6
Accuracy on Yelp Reviews				
Orig. & Kaushik et al. (2020) ($3.4k$)	**85.6**	**86.3**	**73.7**	**86.6**
Orig. & Hu et al. (2017)	77.4	80.4	68.8	84.7
Orig. & Li et al. (2018)	67.8	73.6	63.1	77.1
Orig. & Sudhakar et al. (2019)	69.4	75.1	66.2	84.5
Orig. & Madaan et al. (2020)	81.3	82.1	68.6	78.8
Orig. ($3.4k$)	81.9	82.3	72.0	84.3

To compare the value of human feedback to automatic feature attribution methods such as attention (Bahdanau et al., 2015), we conduct the same set of experiments assuming tokens attended to (or not) by an attention based classifier (BiLSTM with Self-Attention) as new *rationales* (or *non-rationales*). demonstrating correlations of attention weights with human attributions (Wiegreffe & Pinter, 2019; DeYoung et al., 2020). In this case, unlike our findings w.r.t human feedback, we observe different behavior than our findings from the toy causal model (Figures 2b, 3b, Tables 4 and 6). We also experiment with state of the art style transfer methods to convert *Positive* reviews into *Negative* and vice versa. Ideally, we would expect these methods to preserve a document's "content" while modifying the attributes that relate to sentiment. Sentiment classifiers trained on original and *sentiment-flipped* reviews generated using style transfer methods often give better out-of-domain performance compared to training only on original data of same size (Table 7). However, models trained on CAD perform even better across all datasets, hinting at the value of human feedback.

5 Conclusion

While prior work offers promising clues to the benefits of CAD generated through human-in-the-loop mechanisms, previous work lacked formal frameworks for thinking about the technique, or comparisons to plausible alternatives. In this paper, through simple analysis on toy linear Gaussian models followed by a large-scale empirical investigation on sentiment analysis and NLI tasks, we formalize CAD and make strides towards understanding its practical efficacy. Our analysis suggests that data corrupted by adding noise to rationale spans (analogous to adding noise to causal features) will degrade out-of-domain performance, while noise added to non-causal features may make models more robust out-of-domain. Our empirical study focuses on sentiment analysis and NLI and our findings remain consistent across datasets and models. Furthermore, the two tasks are subjectively very different as sentiment analysis requires a strong consideration of expressions of opinion than stated facts, whereas NLI is the opposite. In future work, we will look at how these findings generalize to other domains, including computer vision, and investigate the surprisingly low susceptibility of pre-trained transformers to spurious associations.

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A OLS ESTIMATION UNDER NOISY MEASUREMENT

A.1 CAUSAL SETTING

Let the Gaussian SCM be defined as follows where the noise term for variable x is defined as u_x:

$$\begin{aligned} z &= u_z, & u_z &\sim \mathcal{N}(0, \sigma^2_{u_z}) \\ x_1 &= bz + u_{x_1}, & u_{x_1} &\sim \mathcal{N}(0, \sigma^2_{u_{x1}}) \\ x_2 &= cz + u_{x_2}, & u_{x_2} &\sim \mathcal{N}(0, \sigma^2_{u_{x2}}) \\ y &= ax_1 + u_y, & u_y &\sim \mathcal{N}(0, \sigma^2_{u_y}). \end{aligned} \tag{5}$$

$$\begin{aligned} \sigma^2_{x_1} &= b^2\sigma^2_{u_z} + \sigma^2_{u_{x1}} \\ \sigma^2_{x_2} &= c^2\sigma^2_{u_z} + \sigma^2_{u_{x2}} \\ \sigma_{x_1,x_2} &= bc\sigma^2_{u_z} \\ \sigma_{x_1,y} &= ab^2\sigma^2_{u_z} + a\sigma^2_{u_{x1}} \\ \sigma_{x_2,y} &= abc\sigma^2_{u_z} \end{aligned} \tag{6}$$

Then if we were to solve the linear regression problem in Eq. 1 *i.e.* $y = x_1\beta_1 + x_2\beta_2 + \beta_0$, then using Eq. 2 we obtain the following values for β_0^{ols}, β_1^{ols} and β_2^{ols}:

$$\begin{aligned} \beta_1^{ols} = \frac{\sigma^2_{x_2}\sigma_{x_1,y} - \sigma_{x_1,x_2}\sigma_{x_2,y}}{\sigma^2_{x_1}\sigma^2_{x_2} - \sigma^2_{x_1,x_2}} &= \frac{(c^2\sigma^2_{u_z} + \sigma^2_{u_{x2}})(ab^2\sigma^2_{u_z} + a\sigma^2_{u_{x1}}) - (bc\sigma^2_{u_z})(abc\sigma^2_{u_z})}{(b^2\sigma^2_{u_z} + \sigma^2_{u_{x1}})(c^2\sigma^2_{u_z} + \sigma^2_{u_{x2}}) - b^2c^2\sigma^4_{u_z}} \\ &= a\frac{(b^2\sigma^2_{u_z} + \sigma^2_{u_{x1}})(c^2\sigma^2_{u_z} + \sigma^2_{u_{x2}}) - b^2c^2\sigma^4_{u_z}}{(b^2\sigma^2_{u_z} + \sigma^2_{u_{x1}})(c^2\sigma^2_{u_z} + \sigma^2_{u_{x2}}) - b^2c^2\sigma^4_{u_z}} = a \end{aligned} \tag{7}$$

$$\beta_2^{ols} = \frac{\sigma^2_{x_1}\sigma_{x_2,y} - \sigma_{x_1,x_2}\sigma_{x_1,y}}{\sigma^2_{x_1}\sigma^2_{x_2} - \sigma^2_{x_1,x_2}} = \frac{(b^2\sigma^2_{u_z} + \sigma^2_{u_{x1}})(abc\sigma^2_{u_z}) - (bc\sigma^2_{u_z})(ab^2\sigma^2_{u_z} + a\sigma^2_{u_{x1}})}{(b^2\sigma^2_{u_z} + \sigma^2_{u_{x1}})(c^2\sigma^2_{u_z} + \sigma^2_{u_{x2}}) - b^2c^2\sigma^4_{u_z}} = 0 \tag{8}$$

However, if the setting is slightly different, and we observe a noisy version of x_1, given by $\widetilde{x_1}$:

$$\widetilde{x_1} = x_1 + \epsilon_{x1}, \quad \epsilon_{x_1} \sim \mathcal{N}(0, \sigma^2_{\epsilon_{x1}}) \tag{9}$$

Since $\epsilon_{x_1} \perp\!\!\!\perp (x_1, x_2, y)$,

$$\sigma^2_{\widetilde{x_1}} = \text{Var}[x_1 + \epsilon_{x_1}] = b^2\sigma^2_{u_z} + \sigma^2_{u_{x1}} + \sigma^2_{\epsilon_{x1}} \tag{10}$$

$$\sigma_{\widetilde{x_1},Y} = \sigma_{x_1,Y} = \text{E}[(bz + u_{x_1})(ax_1 + u_y)] = ab^2\sigma^2_{u_z} + a\sigma^2_{u_{x1}} \tag{11}$$

$$\sigma_{\widetilde{x_1},x_2} = \sigma_{X_1,X_2} = bc\sigma^2_{u_z} \tag{12}$$

Plugging these values into Eq. 2 we get the OLS estimates $\widehat{\beta_1^{ols}}$ and $\widehat{\beta_2^{ols}}$ in the presence of observation noise on X_1:

$$\begin{aligned} \widehat{\beta_1^{ols}} &= \frac{\sigma^2_{x_2}\sigma_{\widetilde{x_1},y} - \sigma_{\widetilde{x_1},x_2}\sigma_{x_2,y}}{\sigma^2_{\widetilde{x_1}}\sigma^2_{x_2} - \sigma^2_{\widetilde{x_1},x_2}} = \frac{(c^2\sigma^2_{u_z} + \sigma^2_{u_{x2}})(ab^2\sigma^2_{u_z} + a\sigma^2_{u_{x1}}) - (bc\sigma^2_{u_z})(abc\sigma^2_{u_z})}{(b^2\sigma^2_{u_z} + \sigma^2_{u_{x1}} + \sigma^2_{\epsilon_{x1}})(c^2\sigma^2_{u_z} + \sigma^2_{u_{x2}}) - b^2c^2\sigma^4_{u_z}} \\ &= \frac{a(\sigma^2_{u_z}(b^2\sigma^2_{u_{x2}} + c^2\sigma^2_{u_{x1}}) + \sigma^2_{u_{x1}}\sigma^2_{u_{x2}})}{\sigma^2_{u_z}(b^2\sigma^2_{u_{x2}} + c^2\sigma^2_{u_{x1}}) + \sigma^2_{u_{x1}}\sigma^2_{u_{x2}} + \sigma^2_{\epsilon_{x1}}(c^2\sigma^2_{u_z} + \sigma^2_{u_{x2}})} \\ &= \frac{\beta_1^{ols}}{1 + \lambda_c} \\ \lambda_c &= \frac{\sigma^2_{\epsilon_{x1}}(c^2\sigma^2_{u_z} + \sigma^2_{u_{x2}})}{\sigma^2_{u_z}(b^2\sigma^2_{u_{x2}} + c^2\sigma^2_{u_{x1}}) + \sigma^2_{u_{x1}}\sigma^2_{u_{x2}}} \\ \widehat{\beta_2^{ols}} &= \frac{\sigma^2_{\widetilde{x_1}}\sigma_{x_2,y} - \sigma_{\widetilde{x_1},x_2}\sigma_{\widetilde{x_1},y}}{\sigma^2_{\widetilde{x_1}}\sigma^2_{x_2} - \sigma^2_{\widetilde{x_1},x_2}} = \frac{(b^2\sigma^2_{u_z} + \sigma^2_{u_{x1}} + \sigma^2_{\epsilon_{x1}})abc\sigma^2_{u_z} - (bc\sigma^2_{u_z})(ab^2\sigma^2_{u_z} + a\sigma^2_{u_{x1}})}{\sigma^2_{u_z}(b^2\sigma^2_{u_{x2}} + c^2\sigma^2_{u_{x1}}) + \sigma^2_{u_{x1}}\sigma^2_{u_{x2}} + \sigma^2_{\epsilon_{x1}}(c^2\sigma^2_{u_z} + \sigma^2_{u_{x2}})} \\ &= \frac{acb\sigma^2_{\epsilon_{x1}}\sigma^2_{u_z}}{\sigma^2_{u_z}(b^2\sigma^2_{u_{x2}} + c^2\sigma^2_{u_{x1}}) + \sigma^2_{u_{x1}}\sigma^2_{u_{x2}} + \sigma^2_{\epsilon_{x1}}(c^2\sigma^2_{u_z} + \sigma^2_{u_{x2}})} \end{aligned} \tag{13}$$

As we can see $\lambda_c > 0$ and $\lambda_c \propto \sigma^2_{\epsilon_{x1}}$. This shows us that as $\sigma^2_{\epsilon_{x1}}$ increases, $|\widehat{\beta_1^{ols}}|$ (magnitude of the coefficient for X_1) decreases and $|\widehat{\beta_2^{ols}}|$ (magnitude of the coefficient for X_2) increases. $\lim_{\sigma^2_{\epsilon_{x1}} \to \infty} \widehat{\beta_1^{ols}} = 0$, and $\lim_{\sigma^2_{\epsilon_{x1}} \to \infty} \widehat{\beta_2^{ols}} = \frac{acb\sigma^2_{u_z}}{c^2\sigma^2_{u_z}+\sigma^2_{u_{x_2}}}$.

A.2 Anticausal setting

Once again we assume that each variable V is a linear function of its parents $\text{Pa}(V)$. The noise terms are assumed to be Gaussian and are jointly independent.

$$\begin{aligned} z &= u_z, & u_z &\sim \mathcal{N}(0, \sigma^2_{u_z}) \\ q &= az + u_q, & u_q &\sim \mathcal{N}(0, \sigma^2_{u_q}) \\ y &= bz + u_y, & u_y &\sim \mathcal{N}(0, \sigma^2_{u_y}) \\ x_2 &= cq + u_{x_2}, & u_{x_1} &\sim \mathcal{N}(0, \sigma^2_{u_{x1}}) \\ x_1 &= dy + u_{x_1}, & u_{x_2} &\sim \mathcal{N}(0, \sigma^2_{u_{x2}}) \end{aligned} \tag{14}$$

$$\begin{aligned} \sigma^2_{x_1} &= d^2b^2\sigma^2_{u_z} + d^2\sigma^2_{u_y} + \sigma^2_{u_{x1}} \\ \sigma^2_{x_2} &= c^2a^2\sigma^2_{u_z} + c^2\sigma^2_{u_q} + \sigma^2_{u_{x2}} \\ \sigma_{x_1,x_2} &= abcd\sigma^2_{u_z} \\ \sigma_{x_1,y} &= db^2\sigma^2_{u_z} + d\sigma^2_{u_y} \\ \sigma_{x_2,y} &= abc\sigma^2_{u_z} \end{aligned} \tag{15}$$

If we were to solve the linear regression problem in Eq. 1 *i.e.* $y = x_1\beta_1 + x_2\beta_2 + \beta_0$, then using Eq. 2 we get the OLS estimates β_1^{ols} and β_2^{ols}:

$$\begin{aligned} \beta_1^{ols} &= \frac{\sigma^2_{x_2}\sigma_{x_1,y} - \sigma_{x_1,x_2}\sigma_{x_2,y}}{\sigma^2_{x_1}\sigma^2_{x_2} - {\sigma_{x_1,x_2}}^2} \\ &= \frac{(c^2a^2\sigma^2_{u_z} + c^2\sigma^2_{u_q} + \sigma^2_{u_{x2}})(db^2\sigma^2_{u_z} + d\sigma^2_{u_y}) - (abcd\sigma^2_{u_z})(abc\sigma^2_{u_z})}{(d^2b^2\sigma^2_{u_z} + d^2\sigma^2_{u_y} + \sigma^2_{u_{x1}})(c^2a^2\sigma^2_{u_z} + c^2\sigma^2_{u_q} + \sigma^2_{u_{x2}}) - (a^2b^2c^2d^2{\sigma^2_{u_z}}^2)} \\ &= \frac{d(a^2c^2\sigma^2_{u_z}\sigma^2_{u_y} + (c^2\sigma^2_{u_q} + \sigma^2_{u_{x2}})(b^2\sigma^2_{u_z} + \sigma^2_{u_y}))}{(d^2b^2\sigma^2_{u_z} + \sigma^2_{u_{x1}} + d^2\sigma^2_{u_y})(\sigma^2_{u_{x2}} + c^2\sigma^2_{u_q}) + (\sigma^2_{u_{x1}} + d^2\sigma^2_{u_y})c^2a^2\sigma^2_{u_z}} \end{aligned} \tag{16}$$

$$\begin{aligned} \beta_2^{ols} &= \frac{\sigma^2_{x_1}\sigma_{x_2,y} - \sigma_{x_1,x_2}\sigma_{x_1,y}}{\sigma^2_{x_1}\sigma^2_{x_2} - {\sigma_{x_1,x_2}}^2} \\ &= \frac{(d^2b^2\sigma^2_{u_z} + d^2\sigma^2_{u_y} + \sigma^2_{u_{x1}})(abc\sigma^2_{u_z}) - (abcd\sigma^2_{u_z})(db^2\sigma^2_{u_z} + d\sigma^2_{u_y})}{(d^2b^2\sigma^2_{u_z} + d^2\sigma^2_{u_y} + \sigma^2_{u_{x1}})(c^2a^2\sigma^2_{u_z} + c^2\sigma^2_{u_q} + \sigma^2_{u_{x2}}) - (a^2b^2c^2d^2{\sigma^2_{u_z}}^2)} \\ &= \frac{abc\sigma^2_{u_z}\sigma^2_{u_{x1}}}{(d^2b^2\sigma^2_{u_z} + \sigma^2_{u_{x1}} + d^2\sigma^2_{u_y})(\sigma^2_{u_{x2}} + c^2\sigma^2_{u_q}) + (\sigma^2_{u_{x1}} + d^2\sigma^2_{u_y})c^2a^2\sigma^2_{u_z}} \end{aligned}$$

However, if the setting is slightly different, and we observe a noisy version of x_1, given by $\widetilde{x_1}$:

$$\widetilde{x_1} = x_1 + \epsilon_{x_1}, \qquad \epsilon_{x_1} \sim \mathcal{N}(0, \sigma^2_{\epsilon_{x1}}) \tag{17}$$

Since $\epsilon_{x_1} \perp\!\!\!\perp x_2, y$, in order to obtain expressions for the OLS estimates $\widehat{\beta_1^{ols}}, \widehat{\beta_2^{ols}}$ in the presence of observation noise, in Eq. 16 we only need to replace $\sigma^2_{u_{x1}}$ with $\sigma^2_{u_{\widetilde{x1}}}$, which is given by:

$$\sigma^2_{u_{\widetilde{x1}}} = \sigma^2_{u_{x1}} + \sigma^2_{\epsilon_{x1}} \tag{18}$$

$$\widehat{\beta_1^{ols}} = \frac{d(a^2c^2\sigma^2_{u_z}\sigma^2_{u_y} + (c^2\sigma^2_{u_q} + \sigma^2_{u_{x2}})(b^2\sigma^2_{u_z} + \sigma^2_{u_y}))}{(d^2b^2\sigma^2_{u_z} + \sigma^2_{u_{\widetilde{x1}}} + d^2\sigma^2_{u_y})(\sigma^2_{u_{x2}} + c^2\sigma^2_{u_q}) + (\sigma^2_{u_{\widetilde{x1}}} + d^2\sigma^2_{u_y})c^2a^2\sigma^2_{u_z}}$$
$$= \frac{d(a^2c^2\sigma^2_{u_z}\sigma^2_{u_y} + (c^2\sigma^2_{u_q} + \sigma^2_{u_{x2}})(b^2\sigma^2_{u_z} + \sigma^2_{u_y}))}{(d^2b^2\sigma^2_{u_z} + (\sigma^2_{u_{x1}} + \sigma^2_{\epsilon_{x1}}) + d^2\sigma^2_{u_y})(\sigma^2_{u_{x2}} + c^2\sigma^2_{u_q}) + ((\sigma^2_{u_{x1}} + \sigma^2_{\epsilon_{x1}}) + d^2\sigma^2_{u_y})c^2a^2\sigma^2_{u_z}} \tag{19}$$

$$\widehat{\beta_2^{ols}} = \frac{abc\sigma^2_{u_z}\sigma^2_{u_{\widetilde{x1}}}}{(d^2b^2\sigma^2_{u_z} + \sigma^2_{u_{\widetilde{x1}}} + d^2\sigma^2_{u_y})(\sigma^2_{u_{x2}} + c^2\sigma^2_{u_q}) + (\sigma^2_{u_{\widetilde{x1}}} + d^2\sigma^2_{u_y})c^2a^2\sigma^2_{u_z}}$$
$$= \frac{abc\sigma^2_{u_z}(\sigma^2_{u_{x1}} + \sigma^2_{\epsilon_{x1}})}{(d^2b^2\sigma^2_{u_z} + (\sigma^2_{u_{x1}} + \sigma^2_{\epsilon_{x1}}) + d^2\sigma^2_{u_y})(\sigma^2_{u_{x2}} + c^2\sigma^2_{u_q}) + ((\sigma^2_{u_{x1}} + \sigma^2_{\epsilon_{x1}}) + d^2\sigma^2_{u_y})c^2a^2\sigma^2_{u_z}} \tag{20}$$

$$\widehat{\beta_1^{ols}} = \frac{\beta_1^{ols}}{1+\lambda^{x_1}_{ac}} \qquad \widehat{\beta_2^{ols}} = \frac{\beta_2^{ols}}{1+\lambda^{x_1}_{ac}}\left[1 + \frac{\sigma^2_{\epsilon_{x_1}}}{\sigma^2_{u_{x_1}}}\right] \tag{21}$$

$$\lambda^{x_1}_{ac} = \frac{\sigma^2_{\epsilon_{x_1}}(c^2a^2\sigma^2_{u_z} + c^2\sigma^2_{u_q} + \sigma^2_{u_{x2}})}{(d^2b^2\sigma^2_{u_z} + \sigma^2_{u_{x_1}} + d^2\sigma^2_{u_y})(\sigma^2_{u_{x2}} + c^2\sigma^2_{u_q}) + (\sigma^2_{u_{x1}} + d^2\sigma^2_{u_y})c^2a^2\sigma^2_{u_z}} \tag{22}$$

where $\lambda^{x_1}_{ac} > 0$ and $\lambda^{x_1}_{ac} \propto \sigma^2_{\epsilon_{x1}}$. Thus, as $\sigma^2_{\epsilon_{x1}}$ increases, $|\widehat{\beta_1^{ols}}|$ decreases. The asymptotic OLS estimates in the presence of infinite observational noise can be seen to be: $\lim_{\sigma^2_{\epsilon_{x1}}\to\infty} \widehat{\beta_1^{ols}} = 0$, where as $\lim_{\sigma^2_{\epsilon_{x1}}\to\infty} \widehat{\beta_2^{ols}} = \beta_2^{ols}\frac{((d^2b^2\sigma^2_{u_z}+\sigma^2_{u_{x1}}+d^2\sigma^2_{u_y})(\sigma^2_{u_{x2}}+c^2\sigma^2_{u_q})+(\sigma^2_{u_{x1}}+d^2\sigma^2_{u_y})c^2a^2\sigma^2_{u_z})}{(\sigma^2_{u_{x1}}(c^2a^2\sigma^2_{u_z}+c^2\sigma^2_{u_q}+\sigma^2_{u_{x2}}))}$.

Similarly, if we observe a noisy version of X_2, given by $\widetilde{X_2}$:

$$\widetilde{x_2} = x_2 + \epsilon_{x_2}, \qquad \epsilon_{x_2} \sim \mathcal{N}(0, \sigma^2_{\epsilon_{x2}}) \tag{23}$$

Since $\epsilon_{x_2} \perp\!\!\!\perp x_1, y$, in order to obtain expressions for the OLS estimates $\widehat{\beta_1^{ols}}, \widehat{\beta_2^{ols}}$ in the presence of observation noise on non-causal features, in Eq. 16 we only need to replace $\sigma^2_{u_{x2}}$ with $\sigma^2_{u_{\widetilde{x2}}}$, which is given by:

$$\sigma^2_{u_{\widetilde{x2}}} = \sigma^2_{u_{x2}} + \sigma^2_{\epsilon_{x2}} \tag{24}$$

$$\widehat{\beta_1^{ols}} = \frac{d(a^2c^2\sigma^2_{u_z}\sigma^2_{u_y} + (c^2\sigma^2_{u_q} + \sigma^2_{u_{\widetilde{x2}}})(b^2\sigma^2_{u_z} + \sigma^2_{u_y}))}{(d^2b^2\sigma^2_{u_z} + \sigma^2_{u_{x1}} + d^2\sigma^2_{u_y})(\sigma^2_{u_{\widetilde{x2}}} + c^2\sigma^2_{u_q}) + (\sigma^2_{u_{x1}} + d^2\sigma^2_{u_y})c^2a^2\sigma^2_{u_z}}$$
$$= \frac{d(a^2c^2\sigma^2_{u_z}\sigma^2_{u_y} + (c^2\sigma^2_{u_q} + (\sigma^2_{u_{x2}} + \sigma^2_{\epsilon_{x2}}))(b^2\sigma^2_{u_z} + \sigma^2_{u_y}))}{(d^2b^2\sigma^2_{u_z} + \sigma^2_{u_{x1}} + d^2\sigma^2_{u_y})((\sigma^2_{u_{x2}} + \sigma^2_{\epsilon_{x2}}) + c^2\sigma^2_{u_q}) + (\sigma^2_{u_{x1}} + d^2\sigma^2_{u_y})c^2a^2\sigma^2_{u_z}} \tag{25}$$

$$\widehat{\beta_2^{ols}} = \frac{abc\sigma^2_{u_z}\sigma^2_{u_{x1}}}{(d^2b^2\sigma^2_{u_z} + \sigma^2_{u_{x1}} + d^2\sigma^2_{u_y})(\sigma^2_{u_{\widetilde{x2}}} + c^2\sigma^2_{u_q}) + (\sigma^2_{u_{x1}} + d^2\sigma^2_{u_y})c^2a^2\sigma^2_{u_z}} \tag{26}$$
$$= \frac{abc\sigma^2_{u_z}\sigma^2_{u_{x1}}}{(d^2b^2\sigma^2_{u_z} + \sigma^2_{u_{x1}} + d^2\sigma^2_{u_y})((\sigma^2_{u_{x_2}} + \sigma^2_{\epsilon_{x2}}) + c^2\sigma^2_{u_q}) + (\sigma^2_{u_{x1}} + d^2\sigma^2_{u_y})c^2a^2\sigma^2_{u_z}} \tag{27}$$

$$\widehat{\beta_1^{ols}} = \frac{\beta_1^{ols}}{1+\lambda^{x_2}_{ac}}\left[1 + \frac{\sigma^2_{\epsilon_{x2}}(b^2\sigma^2_{u_z} + \sigma^2_{u_y})}{a^2c^2\sigma^2_{u_z}\sigma^2_{u_y} + (c^2\sigma^2_{u_q} + \sigma^2_{u_{x2}})(b^2\sigma^2_{u_z} + \sigma^2_{u_y})}\right] \quad \widehat{\beta_2^{ols}} = \frac{\beta_2^{ols}}{1+\lambda^{x_2}_{ac}}$$
$$\lambda^{x_2}_{ac} = \frac{\sigma^2_{\epsilon_{x2}}(d^2b^2\sigma^2_{u_z} + \sigma^2_{u_{x1}} + d^2\sigma^2_{u_y})}{(d^2b^2\sigma^2_{u_z} + \sigma^2_{u_{x1}} + d^2\sigma^2_{u_y})(\sigma^2_{u_{x2}} + c^2\sigma^2_{u_q}) + (\sigma^2_{u_{x1}} + d^2\sigma^2_{u_y})c^2a^2\sigma^2_{u_z}} \tag{28}$$

where $\lambda_{ac}^{x_2} > 0$ and $\lambda_{ac}^{x_2} \propto \sigma^2_{\epsilon_{x2}}$. Thus, as $\sigma^2_{\epsilon_{x2}}$ increases, $|\widehat{\beta_1^{ols}}|$ increases. The asymptotic OLS estimates in the presence of infinite observational noise can be seen to be: $\lim_{\sigma^2_{\epsilon_{x2}} \to \infty} \widehat{\beta_2^{ols}} = 0$, where as $\lim_{\sigma^2_{\epsilon_{x2}} \to \infty} \widehat{\beta_1^{ols}} = \beta_1^{ols} \frac{(b^2\sigma^2_{u_z}+\sigma^2_{u_y})((d^2b^2\sigma^2_{u_z}+\sigma^2_{u_{x1}}+d^2\sigma^2_{u_y})(\sigma^2_{u_{x2}}+c^2\sigma^2_{u_q})+(\sigma^2_{u_{x1}}+d^2\sigma^2_{u_y})c^2a^2\sigma^2_{u_z})}{(a^2c^2\sigma^2_{u_z}\sigma^2_{u_y}+(c^2\sigma^2_{u_q}+\sigma^2_{u_{x2}})(b^2\sigma^2_{u_z}+\sigma^2_{u_y}))(d^2b^2\sigma^2_{u_z}+\sigma^2_{u_{x1}}+d^2\sigma^2_{u_y})}$.

B MODEL IMPLEMENTATION DETAILS FOR SECTION 4

Standard Methods We use `scikit-learn` (Pedregosa et al., 2011) implementations of SVMs and Naïve Bayes for sentiment analysis. We train these models on TF-IDF bag of words feature representations of the reviews (Jones, 1972). We identify parameters for both classifiers using grid search conducted over the validation set.

BiLSTM We restrict the vocabulary to the most frequent $20k$ tokens, replacing out-of-vocabulary tokens by `UNK`. We fix the maximum input length at 330 tokens when training on reviews from Kaushik et al. (2020) and 2678 when doing so on Zaidan et al. (2007), and pad smaller reviews. Each token is represented by a randomly-initialized 300-dimensional embedding. Our model consists of a bidirectional LSTM (hidden dimension 128) with recurrent dropout (probability 0.5) and self attention following the embedding layer. We use the self attention implementation discussed in Lin et al. (2017) with hyperparameter values $d = 64$ and $r = 64$. To generate output, we feed this (fixed-length) representation through a fully-connected hidden layer (hidden dimension 32), and then a fully-connected output layer with softmax activation. We train all models for a maximum of 20 epochs using Adam (Kingma & Ba, 2015), with a learning rate of $1\mathrm{e}{-4}$ and a batch size of 16. We apply early stopping when validation loss does not decrease for 5 epochs.

Pretrained Transformers We use off-the-shelf uncased BERT Base and Longformer Base models (Wolf et al., 2019), fine-tuning for each task. We used BERT for experiments on the smaller IMDb dataset used by Kaushik et al. (2020) (with a maximum review length of 330 tokens) and Longformer for the dataset presented by Zaidan et al. (2007) (with maximum review length of 2678). To account for BERT's sub-word tokenization, we set the maximum token length is set at 350 for sentiment analysis and 50 for NLI. In case of Longformer, that is 3072.[3] We fine-tune BERT up to 20 epochs with same early stopping criteria as for BiLSTM, using the BERT Adam optimizer with a batch size of 16 (to fit on a 16GB Tesla V-100 GPU). We found learning rates of $5\mathrm{e}{-5}$ and $1\mathrm{e}{-5}$ to work best for sentiment analysis and NLI respectively. We fine-tune Longformer for 10 epochs with early stopping, using a batch size of 8 (to fit on 64GB of GPU memory).

Style Transfer Methods For Hu et al. (2017),[4] Sudhakar et al. (2019),[5] and Madaan et al. (2020),[6] we found the default hyperparameters used by the authors to work best on our task. In case of Li et al. (2018),[7] we followed the training schedule presented in the paper. However, since the paper does not present results on IMDb reviews, we experimented with multiple values of the *salience ratio*, and used a salience ratio of 5.5 for our downstream task based on transfer accuracy and BLEU scores achieved on the validation set. For all style transfer methods, we experimented with multiple sequence lengths, and found that models worked best on sentence level (versus review-level) data, with sequence length of 30, truncating longer sentences in the process. For each review, we passed individual sentences through each model and reconstructed whole reviews by joining the resulting *sentiment-flipped* sentences.

[3] Longformer is better suited to work on longer texts compared to BERT. Maximum length of a review in Zaidan et al. is 2678 tokens whereas in Kaushik et al. is only 330 tokens.

[4] https://github.com/asyml/texar/tree/master/examples/text_style_transfer

[5] https://github.com/agaralabs/transformer-drg-style-transfer

[6] https://github.com/tag-and-generate/

[7] https://github.com/lijuncen/Sentiment-and-Style-Transfer

C FULL RESULTS CORRESPONDING TO NOISE INJECTION

Table 3: Accuracy of various sentiment analysis classifiers trained on $1.7k$ original reviews from Kaushik et al. (2020) as noise is injected on *rationales/non-rationales* identified via human feedback.

Dataset	Percent noise in human rationales										
	SVM										
	0	10	20	30	40	50	60	70	80	90	100
In-sample test	87.8	88.2	85.7	86.9	86.9	84.5	83.3	81.6	80	79.2	76.7
Kaushik et al.	51.8	47.3	45.7	42.9	39.2	33.5	28.2	25.7	24.1	19.6	17.1
Amazon	73.2	72.2	71.3	69.4	67.3	63.7	63.7	58.2	57	50.1	46.5
Semeval	62.5	62.2	61.9	61.1	60.9	58.3	57.1	55.4	54.5	51.3	50.1
Yelp	79.9	79	77.7	76.7	74.1	71.4	69	65.5	62.4	55.8	51.5
	BiLSTM with Self Attention										
In-sample test	81.5	78.8	77.6	76.7	75.3	75.2	74.5	72.8	67.3	64.2	63.8
Kaushik et al.	49.4	49.3	46.3	45.1	39.5	38.1	38.9	38.7	32.6	32.6	29.7
Amazon	65.4	69.1	68.5	66.6	63.2	63.9	58.8	50.6	50.6	47.1	44.2
Semeval	59.3	59.8	57.6	56.4	58.6	56.6	55.3	54.3	54.3	52.3	50
Yelp	71.2	70.8	67.4	65.9	65.3	64.1	63.4	60.1	62.4	49.8	46.4
	BERT										
In-sample test	87.4	87.4	86.5	85.7	85.3	84.3	83.6	81	76.6	71	69
Kaushik et al.	82.2	78.1	78.4	75.4	67.6	67.5	65.5	53.9	42.7	36.2	31.8
Amazon	76.2	75.5	75.1	74.2	73.5	73	72.5	70.7	63.4	57.8	56.1
Semeval	76.4	69.7	66.9	69.8	67.8	67.4	66.8	65.5	62.2	54.9	52.6
Yelp	83.7	82.5	82	81.5	80.9	80.2	79.9	75.6	64.3	54.6	52.3
Dataset	Percent noise in human non-rationales										
	SVM										
In-sample test	87.8	88.6	89	86.9	85.3	82.4	86.5	83.7	82	81.6	78
Kaushik et al.	51.8	55.9	53.5	57.1	58.8	63.7	63.3	65.7	70.2	73.9	74.3
Amazon	73.2	74.9	75.3	77.3	75.8	76.6	76.5	77.4	75.5	75.4	76.9
Semeval	62.5	63.3	62.7	64.3	64.3	65.6	66	65.8	65	66.4	66.4
Yelp	79.9	80.9	80.1	82.2	83.6	84.1	83.5	83.4	82.7	82.1	81.4
	BiLSTM with Self Attention										
In-sample test	81.5	77.5	77	75.9	75.4	75.2	75.1	73.8	73	72.4	71.7
Kaushik et al.	49.4	53.1	56.25	56.6	57.5	58.4	58.6	60.3	61.5	65.5	66.1
Amazon	65.4	66.5	66.6	66.6	67.6	67.7	68.3	68.6	68.8	68.5	68.4
Semeval	59.3	58.6	58.9	59.3	58.1	57.5	59.2	59.5	59.8	59.5	58
Yelp	71.2	74.7	72.5	73.3	73.9	73.6	72.2	74.3	73.7	75.6	75.4
	BERT										
In-sample test	87.4	88.2	87	86.9	87	85.8	83.6	78.9	72.5	72.1	71.3
Kaushik et al.	82.2	92.8	92.8	92.3	93.1	92.8	89.8	88.6	84.5	81.3	81
Amazon	76.2	78.6	78.9	79.2	75.1	71.7	67.6	65.3	65.2	63.7	61.8
Semeval	76.4	74.6	76.3	75.8	70.9	62.1	64.8	63.3	60.8	58.7	58.7
Yelp	83.7	85.4	85.3	85.1	82.1	78.3	77.2	76.2	74.3	71.6	70.1

Table 4: Accuracy of various sentiment analysis classifiers trained on $1.7k$ original reviews from Kaushik et al. (2020) as noise is injected on *rationales/non-rationales* identified via Attention masks.

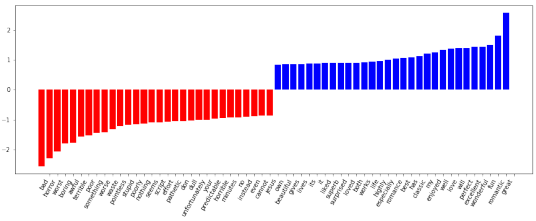
Dataset	Percent noise in human rationales										
	SVM										
	0	10	20	30	40	50	60	70	80	90	100
In-sample test	87.8	85	85.9	86.3	86.3	85.2	84.6	86.3	83.6	84.2	83.6
Kaushik et al.	51.8	50.6	51.8	52	51.8	50	50.6	48.6	48.6	47.5	46.1
Amazon	73.2	74.3	73.4	72.8	72.8	72.9	72	72.3	71.1	72	70.3
Semeval	62.5	62.8	62.9	61.8	62.5	61.9	61.4	60.7	61.1	60.6	60.1
Yelp	79.9	80.1	79.3	78.7	78.9	78.5	77.8	77.5	77.8	76.2	75.9
	BiLSTM with Self Attention										
In-sample test	81.5	78.8	78.6	78.3	78.2	76.2	77.3	76.8	71.8	73.2	74.2
Kaushik et al.	49.4	53.3	50	53.4	52.4	49.7	49.2	47.4	47.7	47	44.1
Amazon	65.4	66.8	71	64.7	60.7	61.7	65.2	64.6	51.6	57.1	66.4
Semeval	59.3	59.5	60.1	57.4	55.9	57.2	52.2	57.6	51.5	51.8	56.1
Yelp	71.2	72.3	74.2	69.6	70.5	67.3	70.7	72.8	62.8	65	66.2
	BERT										
In-sample test	87.4	93	90.8	90.3	90.6	91.2	90.3	90.4	90.7	90.6	90.3
Kaushik et al.	82.2	91.2	92	90.8	90.8	90.9	90.3	90.9	90.2	89.8	90.4
Amazon	76.2	77.3	79.1	78.7	79.8	79.1	79.8	79.5	79.2	78.9	79.3
Semeval	76.4	71.4	73.5	73.2	74.4	76.1	77.6	79.8	78.4	79.2	77.8
Yelp	83.7	83.5	85.4	84.9	86	85.7	85.9	85.6	85.5	85.4	68.9
Dataset	Percent noise in human non-rationales										
	SVM										
In-sample test	87.8	85	85.7	84.8	85	84	83.6	84.6	80.7	81.1	77.3
Kaushik et al.	51.8	50.4	52.2	53.9	50.2	50.8	52.9	54.1	54.1	56.8	56.4
Amazon	73.2	73.5	75.3	74.3	76.2	73.9	73.4	73.6	71	70	67.8
Semeval	62.5	62.6	63.7	63.7	63.1	62.6	63.5	61.5	62.1	62	59.9
Yelp	79.9	79.8	80.9	81.7	80.9	80.5	80	80.1	78.5	77.5	74.4
	BiLSTM with Self Attention										
In-sample test	81.5	77.6	76	77.1	77.3	75.4	73.7	67.9	68.6	54.2	52.3
Kaushik et al.	49.4	53.1	52.1	52.1	65	54.1	51.9	53.4	55	52.3	51.6
Amazon	65.4	63.7	65.7	64	58.8	65.5	60.3	58.7	61	58.1	56.2
Semeval	59.3	54.8	58.4	57.3	60.7	56.8	55.2	54	51.2	50	49.9
Yelp	71.2	72	73.6	70.2	61.3	71.5	68.4	64.9	66.3	58.2	55.8
	BERT										
In-sample test	87.4	86.9	86.7	85.3	84	81.9	80.6	74	74	73	67.2
Kaushik et al.	82.2	92.3	92.4	92.1	90	86.8	83	73.2	77.7	72.5	68.5
Amazon	76.2	79.5	78.5	77.9	69.2	67.4	58.1	55.9	53.5	55.8	52.6
Semeval	76.4	76.5	75.7	77.1	65.7	61.8	54.6	58.8	51.8	54	50.8
Yelp	83.7	85.8	85	85.5	79.3	78.7	67.8	66.5	59.5	63.2	57.5

Table 5: Accuracy of various sentiment analysis classifiers trained on reviews from Zaidan et al. (2007) as noise is injected on *rationales/non-rationales* identified via human feedback.

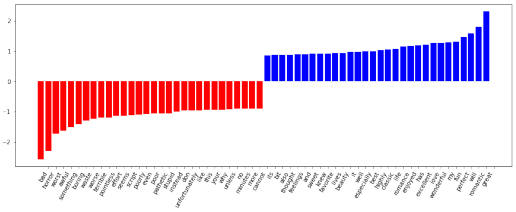
Dataset	Percent noise in human rationales										
	SVM										
	0	10	20	30	40	50	60	70	80	90	100
In-sample test	87.5	86.2	85.5	85	84.5	83.3	82.5	81.1	78.9	77.5	76.5
Kaushik et al.	46.1	45.6	44.4	43.7	44.1	41.2	38.8	36	34.4	33.1	30.9
Amazon	68.6	67.1	65.1	64.2	62.2	60.4	57.9	50.5	54.9	53.5	51.8
Semeval	56.7	56.1	55.4	54.8	54.1	53.5	52.7	52	51.6	50.8	50.4
Yelp	76.2	75	73.5	72	70.2	68.8	66.6	65.1	63.3	61.1	59.3
	BiLSTM with Self Attention										
In-sample test	80.3	82.1	83.2	81.3	78.4	71.1	78.8	77.4	76.9	77.4	75.5
Kaushik et al.	49.2	50.6	51	48.8	48	49.6	49.4	48.8	48.8	47.5	48.4
Amazon	50	50.5	49.4	49.7	49.8	49.7	49.7	49.7	49.6	49.5	49.4
Semeval	50	50	50	50	50	50	50	50	50	50	50
Yelp	50.5	50	53.1	52.1	50.5	50.2	50.1	50	50	50.2	50.1
	Longformer										
In-sample test	97.5	96.7	94	90.5	88.3	78.9	81.4	72.6	79.4	78.7	83.5
Kaushik et al.	93.4	93.6	87.5	85.4	84.2	64.1	61.5	54.2	52.7	50.3	48
Amazon	81.8	77.9	65.3	65.7	64.7	63.6	61.9	62.1	61.3	60.6	57.9
Semeval	80.3	74.9	64	66.9	71.6	61.3	58.4	56.7	58.9	62.1	58.6
Yelp	88.6	85.8	77.7	74.6	72.5	68.4	66.5	64.8	64.3	64.9	62.2
Dataset	Percent noise in human non-rationales										
	SVM										
In-sample test	87.5	85.5	86	83	82	83	81	80.5	75.5	60	50
Kaushik et al.	46.1	46.1	49	49.4	57.1	55.5	58.4	58.4	56.5	56.3	54
Amazon	68.6	67.7	68	67.2	69.4	69	69.7	68.9	69.2	64.9	62.3
Semeval	56.7	56.9	57.5	57.4	58.3	57.6	58.8	59.4	59.3	57.4	56.3
Yelp	76.2	76.1	76.9	75.9	77	77.4	75.2	74.1	73.3	68.5	61.6
	BiLSTM with Self Attention										
In-sample test	80.3	80.8	79.8	75.2	75	62.5	62	57.7	56.7	58.7	57.7
Kaushik et al.	49.2	50	51.1	50.8	52.9	53.9	58.6	58.6	60	60.4	60.8
Amazon	50	50	50.7	50.7	50.9	52.2	52.3	53.2	55	55.1	56.7
Semeval	50	50	50	50	50	51	51.8	52.7	53.5	53.8	53.9
Yelp	50.5	50.4	52.7	52.9	52.9	55.2	58	58.9	64.6	64.6	70
	Longformer										
In-sample test	97.5	97.9	98.1	97.4	94.8	93.4	86.4	82.3	76.3	77.4	80.2
Kaushik et al.	93.4	94.7	94.1	91.8	91.4	91.8	88	83.4	83.7	83.6	83.4
Amazon	81.8	79	80	81.5	83.2	84.2	84.1	76.3	78.5	79.4	76.9
Semeval	80.3	79.4	77.2	80.6	80.6	84.6	85.3	71.8	79.9	83.7	76.6
Yelp	88.6	85.3	86.4	89	89.5	89.9	89.9	86.2	86.5	86.4	84.7

Table 6: Accuracy of various sentiment analysis classifiers trained on reviews from Zaidan et al. (2007) as noise is injected on *rationales/non-rationales* identified via Attention masks.

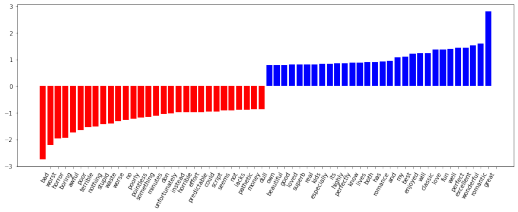
Dataset	Percent noise in human rationales										
	SVM										
	0	10	20	30	40	50	60	70	80	90	100
In-sample test	87.5	85	84.5	84	82.5	83	81	80	77.5	75.5	75.5
Kaushik et al.	46.1	51	50.6	52	51.8	52.3	52.3	51.8	50.2	49.8	49.8
Amazon	68.6	68.1	67.1	66.8	66.9	66.5	66.2	65.4	66.1	66.6	65.7
Semeval	56.7	56.6	56.3	56.4	56.2	56.4	56.4	56.2	56.8	56.4	56.4
Yelp	76.2	76.1	76	76.2	76.4	76.5	76.9	76.9	76.7	76.9	76.5
	BiLSTM with Self Attention										
In-sample test	80.3	78.8	77.9	77.9	78.8	67.3	65.9	63.9	62	65.4	58.7
Kaushik et al.	49.2	49.4	50.2	50.2	52.1	51	52.1	52.3	56.3	51.8	54.7
Amazon	50	49.7	49.9	49.9	50.4	50.2	51	51.7	51.1	50.7	50.7
Semeval	50	50	50	50	50	50	50	50.2	50.1	50	50.1
Yelp	50.5	50.1	50.5	50.5	52.1	52.4	56.1	54.9	54.9	52.2	54.9
	Longformer										
In-sample test	97.5	97.3	97	96.5	88.3	94	93.8	91.2	91.5	87.2	84
Kaushik et al.	93.4	93.5	93.1	92.8	91.7	91.8	90.7	88	87.5	83.7	80.8
Amazon	81.8	76.3	69.5	75.4	70.4	64.5	66.3	60.8	64.7	57.3	55.3
Semeval	80.3	73	67.2	75.1	69.6	61.5	67	58.8	67.6	56.4	55.3
Yelp	88.6	85.1	79.3	83.9	79.8	75.4	76.8	69.1	75.4	65.7	61
Dataset	Percent noise in human non-rationales										
	SVM										
In-sample test	87.5	87	86.5	87.5	81	82.5	73	52	50	50	50
Kaushik et al.	46.1	50.4	49.6	48.6	50	46.9	50.6	49.6	50.4	50.2	50.2
Amazon	68.6	66.7	66.8	64.1	65.9	63.2	62.2	60	57.8	56.2	56.3
Semeval	56.7	56.3	56.8	55.9	56.7	55	54.2	53.8	51.8	51.1	51
Yelp	76.2	74.8	74.2	71.1	71	64.9	59.7	55.2	52.3	51	50
	BiLSTM with Self Attention										
In-sample test	80.3	79.8	81.3	78.4	63.5	67.3	49.5	49	48.1	48.4	48.1
Kaushik et al.	49.2	51.4	51.4	54.5	49.8	49.4	49.6	49.4	49.4	49.4	49.4
Amazon	50	49.9	50.6	50.4	50.1	49.7	49.6	49.5	49.5	49.5	49.5
Semeval	50	50	50	50.2	50	50	50	50	50	50	50
Yelp	50.5	52.3	52.7	56.9	51	50.4	50	50	50	50	50
	Longformer										
In-sample test	97.5	98.2	97.8	95	90.2	83.3	67.3	62.8	69.3	64.2	52.8
Kaushik et al.	93.4	93.6	93.5	88.8	83.1	76.5	67.8	69.7	77.6	54.5	51.4
Amazon	81.8	81.6	97.8	95	90.2	83.3	67.3	62.8	79.3	64.2	52.8
Semeval	80.3	74.8	70.3	79.1	79	78.9	69.5	67.9	64	63.3	58.6
Yelp	88.6	83.9	83.1	89.5	90.2	89.7	87.6	83	78.8	62.4	59.4



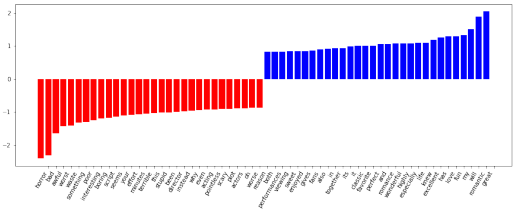
(a) Trained on the original $1.7k$ IMDb reviews in Kaushik et al. (2020)



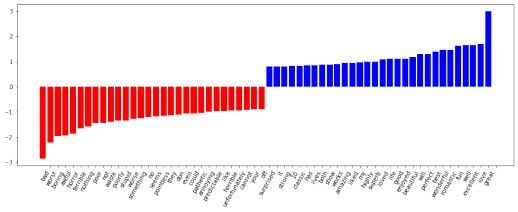
(b) 20% noise in rationales



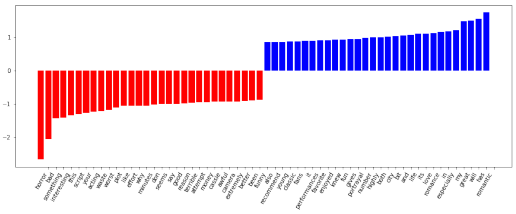
(c) 20% noise in non-rationales



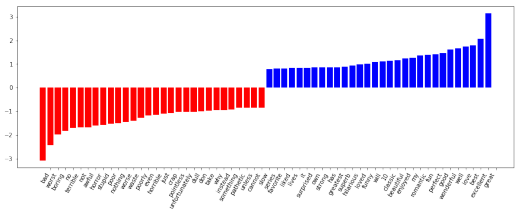
(d) 40% noise in rationales



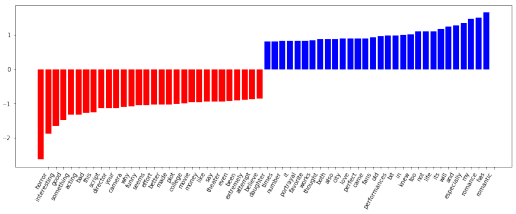
(e) 40% noise in non-rationales



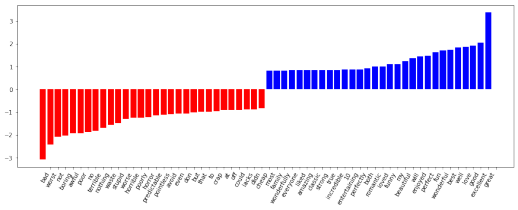
(f) 60% noise in rationales



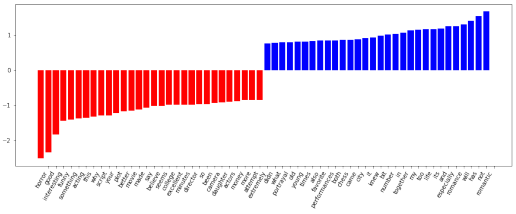
(g) 60% noise in non-rationales



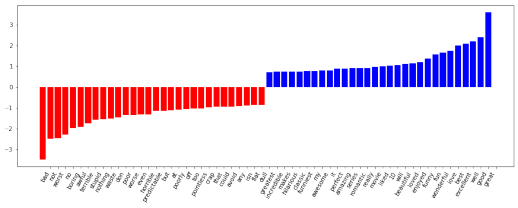
(h) 80% noise in rationales



(i) 80% noise in non-rationales

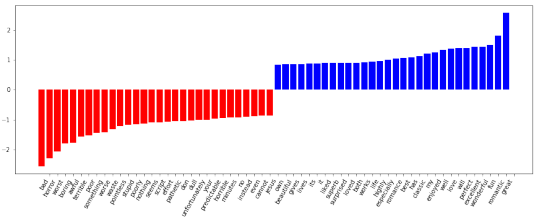


(j) 100% noise in rationales

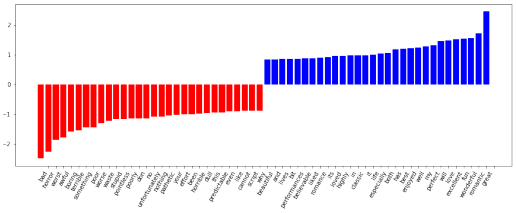


(k) 100% noise in non-rationales

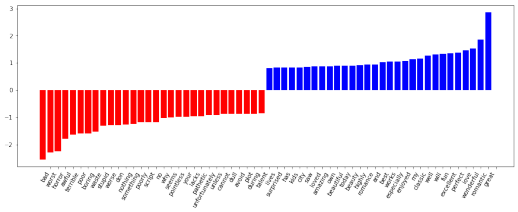
Figure 4: Most important features learned by an SVM classifier trained on TF-IDF bag of words. Rationales are identified by humans.



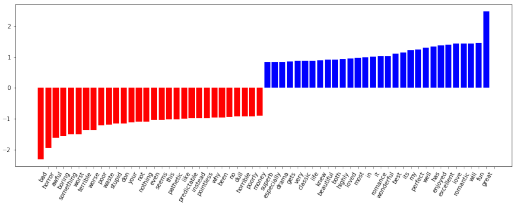
(a) Trained on the original $1.7k$ IMDb reviews in Kaushik et al. (2020)



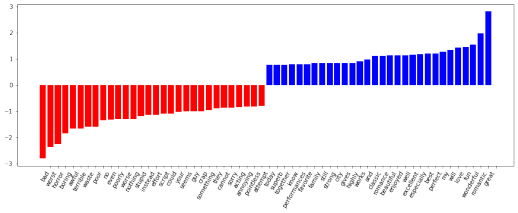
(b) 20% noise in rationales



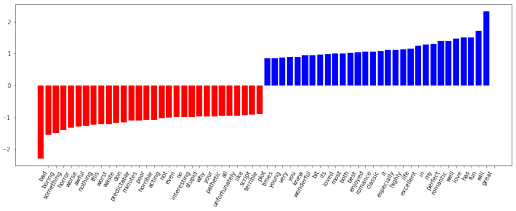
(c) 20% noise in non-rationales



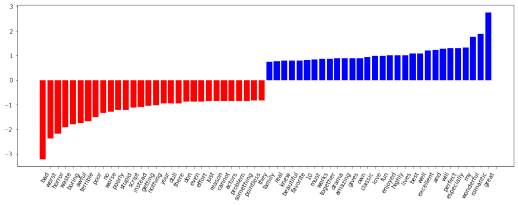
(d) 40% noise in rationales



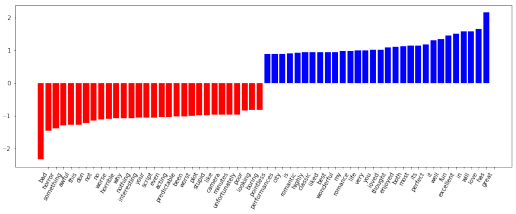
(e) 40% noise in non-rationales



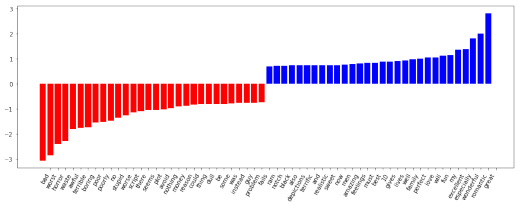
(f) 60% noise in rationales



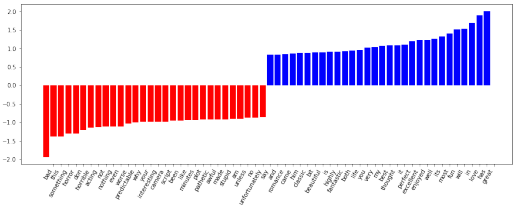
(g) 60% noise in non-rationales



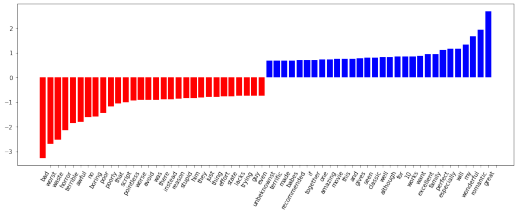
(h) 80% noise in rationales



(i) 80% noise in non-rationales

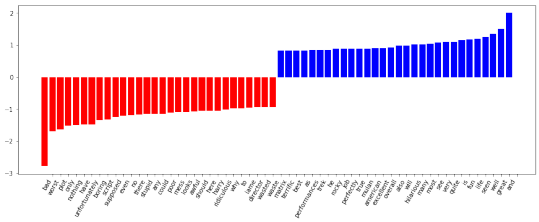


(j) 100% noise in rationales

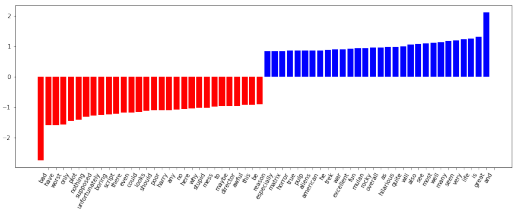


(k) 100% noise in non-rationales

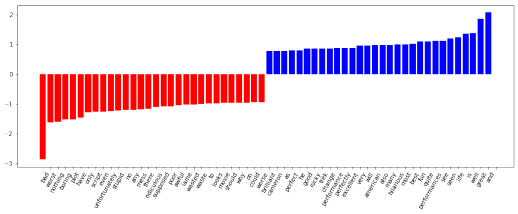
Figure 5: Most important features learned by an SVM classifier trained on TF-IDF bag of words. Rationales are identified as tokens attended upon by a BiLSTM with Self Attention model.



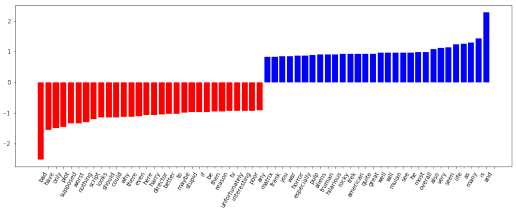
(a) Trained on the original dataset (Zaidan et al., 2007)



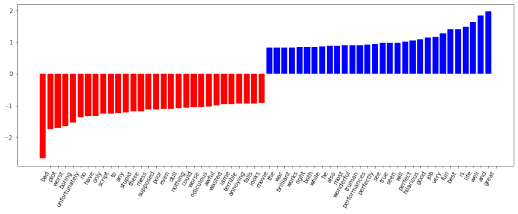
(b) 20% noise in rationales



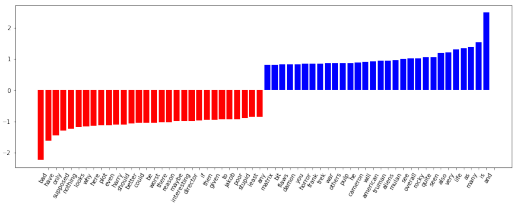
(c) 20% noise in non-rationales



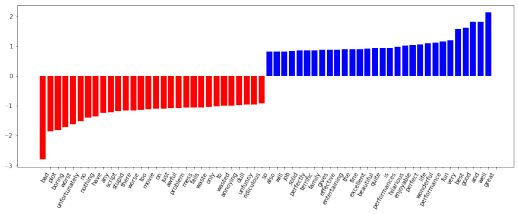
(d) 40% noise in rationales



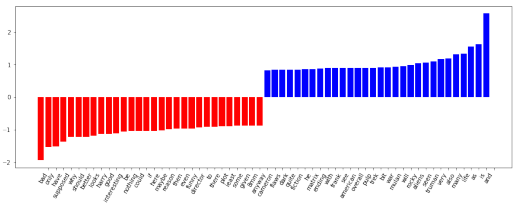
(e) 40% noise in non-rationales



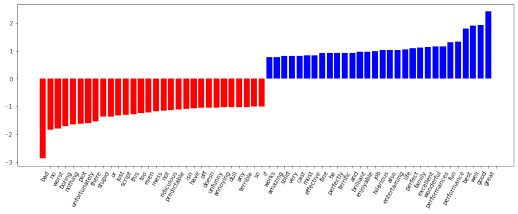
(f) 60% noise in rationales



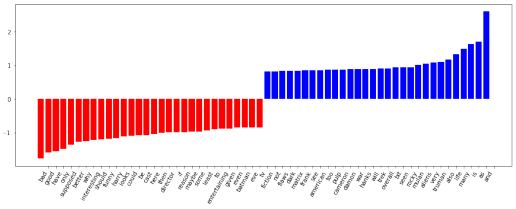
(g) 60% noise in non-rationales



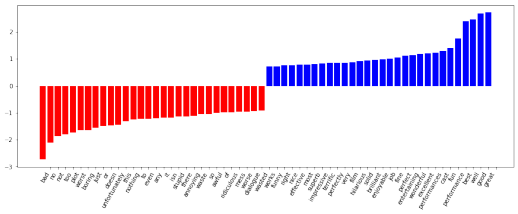
(h) 80% noise in rationales



(i) 80% noise in non-rationales

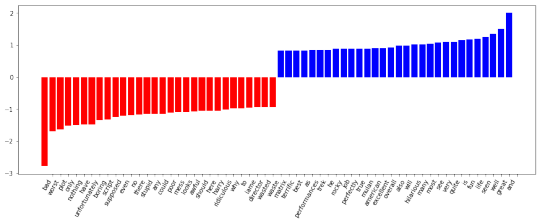


(j) 100% noise in rationales

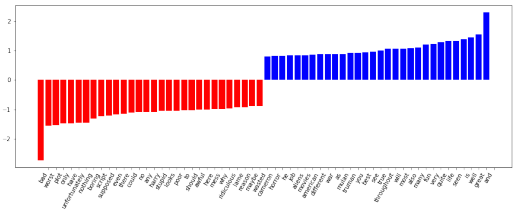


(k) 100% noise in non-rationales

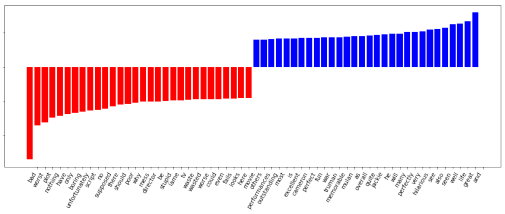
Figure 6: Most important features learned by an SVM classifier trained on TF-IDF bag of words. All noise inserted on rationales identified by humans.



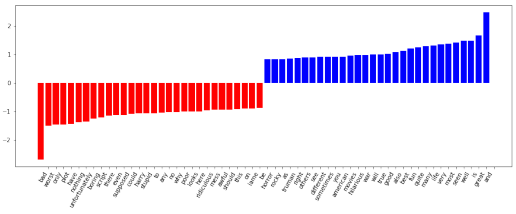
(a) Trained on the original dataset (Zaidan et al., 2007)



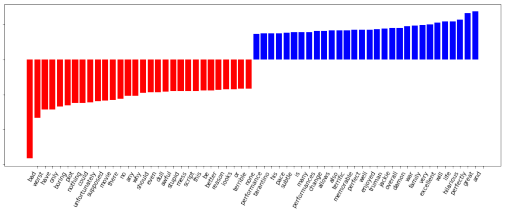
(b) 20% noise in rationales



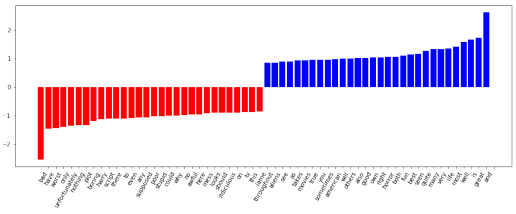
(c) 20% noise in non-rationales



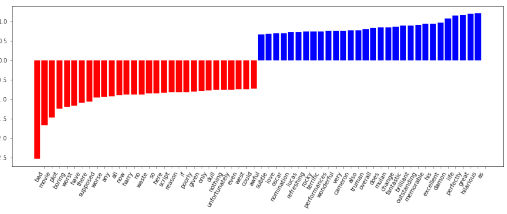
(d) 40% noise in rationales



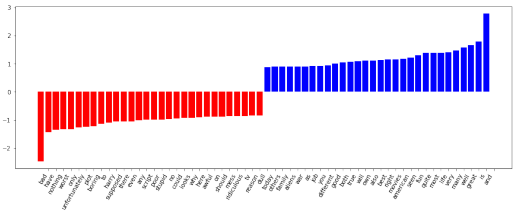
(e) 40% noise in non-rationales



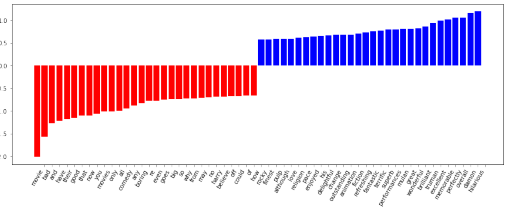
(f) 60% noise in rationales



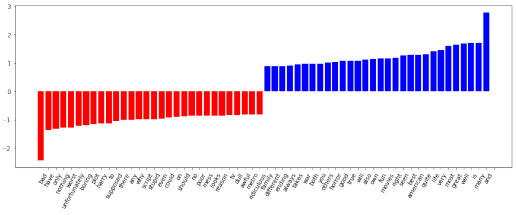
(g) 60% noise in non-rationales



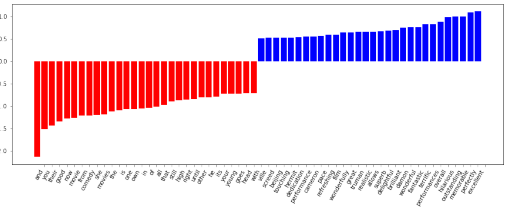
(h) 80% noise in rationales



(i) 80% noise in non-rationales



(j) 100% noise in rationales



(k) 100% noise in non-rationales

Figure 7: Most important features learned by an SVM classifier trained on TF-IDF bag of words. Rationales are identified as tokens attended upon by a BiLSTM with Self Attention model.

Table 7: Accuracy of various models for sentiment analysis trained with various datasets. O refers to the in-sample test set from Kaushik et al. (2020) whereas R refers to the counterfactually revised counterparts of the same.

Training data	SVM		NB		BiLSTM w/ SA		BERT	
	O	R	O	R	O	R	O	R
Orig. ($1.7k$)	**80.0**	51.0	**74.9**	47.3	**78.0**	49.4	**87.4**	82.2
Kaushik et al. (2020) ($1.7k$)	58.3	**91.2**	50.9	**88.7**	63.8	**82.0**	80.4	**90.8**
Hu et al. (2017)	56.3	68.0	57.1	71.1	55.1	67.0	66.3	74.4
Li et al. (2018)	41.3	54.1	37.8	58.0	49.9	49.4	37.9	55.9
Sudhakar et al. (2019)	47.1	55.9	42.6	58.8	49.9	49.4	43.7	51.8
Madaan et al. (2020)	61.2	77.3	50.2	75.2	59.3	69.7	70.6	81.6
Orig. & Kaushik et al. ($3.4k$)	83.7	**87.3**	**86.1**	**91.2**	**80.3**	**84.8**	88.5	**95.1**
Orig. & Hu et al. ($3.4k$)	82.1	66.4	81.5	55.1	76.4	63.9	87.1	89.3
Orig. & Li et al. ($3.4k$)	73.3	55.7	77.9	53.3	69.5	53.3	80.3	79.5
Orig. & Sudhakar et al. ($3.4k$)	74.1	56.1	79.1	51.4	71.4	55.7	89.1	90.8
Orig. & Madaan et al. ($3.4k$)	83.8	65.4	82.1	67.4	75.5	64.1	83.5	81.6
Orig. ($3.4k$)	**85.1**	54.3	82.4	48.2	**80.1**	57.0	**90.2**	86.1