Abstract

Training the large deep neural networks that dominate NLP requires large datasets. Many of these are collected automatically or via crowdsourcing, and many exhibit systematic biases or annotation artifacts. By the latter, we mean correlations between inputs and outputs that are spurious, insofar as they do not represent a generally held causal relationship between features and classes; models that exploit such correlations may appear to perform a given task well, but fail on out-of-sample data. In this paper we propose methods to facilitate identification of training data artifacts, using new hybrid approaches that combine saliency maps (which highlight ‘important’ input features) with instance attribution methods (which retrieve training samples ‘influential’ to a given prediction). We show that this proposed training-feature attribution approach can be used to uncover artifacts in training data, and use it to identify previously unreported artifacts in a few standard NLP datasets. We execute a small user study to evaluate whether these methods are useful to NLP researchers in practice, with promising results. We make code for all methods and experiments in this paper available.¹

1 Introduction

Large pre-trained (masked) language models continue to realize new highs on NLP leaderboards and are increasingly deployed in applications. But what exactly are such models “learning”? One concern is that they may be exploiting artifacts or spurious correlations between inputs and outputs that are present in the training data, but not reflective of the underlying task the data is intended to represent.

¹Warning: This paper contains examples with texts that might be considered offensive.

¹https://github.com/pouyapez/artifact_detection

Figure 1: Use of different attribution techniques for artifact discovery in train data. Here attribution methods can reveal inappropriate reliance on certain tokens (e.g., “yo”) to predict Tweet toxicity: this is an artifact.

We provide an in-depth analysis of attribution methods used for the express purpose of aiding practitioners in identifying training data artifacts, drawing inspiration from prior efforts that have suggested use of such methods specifically for artifact detection (Han et al., 2020; Zhou et al., 2021). We consider two families of attribution methods: (1) feature-attribution, in which one highlights constituent input features (e.g., tokens) in proportion to their “importance” for an output (Ribeiro et al., 2016; Lundberg and Lee, 2017; Adebayo et al., 2018), and; (2) instance attribution, where we retrieve training instances most responsible for a given prediction (Koh and Liang, 2017; Yeh et al., 2018; Rajani et al., 2020; Pezeshkpour et al., 2021).

We also introduce new, hybrid attribution methods that surface relevant features within train instances as an additional means to probe what the model has distilled from training data. This addresses inherent limitations of using either feature or instance attribution alone for artifact discovery: The former cannot provide insights regarding patterns (input features) that are not in the given input, and the latter requires one to inspect entire (potentially lengthy) training instances to divine the attributes that might have rendered them influential.
Consider Figure 1, a case in which a model might learn to erroneously associate African American Vernacular English (AAVE) with toxicity, as observed by Sap et al. (2019). For the test instance “yo man what’s up”, both input saliency and instance attribution methods provide some indication of this artifact. But combining these—in what we will call training-feature attribution—most directly surfaces the artifact by highlighting that this prediction was apparently made on the basis of “yo I’mma” in a train instance labeled as toxic, immediately suggesting a problematic association.

Contributions. The main contributions of this paper are as follows. (1) We empirically evaluate the applicability of attribution methods specifically for artifact detection on both synthetic and real datasets. (2) We propose a new hybrid attribution approach, training-feature attribution (TFA), which addresses some limitations of existing attribution approaches. (3) We evaluate feature, instance and training-feature attribution for artifact detection on several NLP benchmarks with previously reported artifacts (e.g., the HANS phenomena in NLI; McCoy et al. 2019) to evaluate whether and to what degree methods successfully recover these. We find evidence that TFA is superior to alternatives. (4) Applying TFA and previously introduced attribution methods to additional widely used NLP benchmarks, we identify and report previously unknown (as far as we aware) artifacts in these corpora. Finally, (5) we conduct a small user-study to evaluate TFA for aiding artifact discovery in practice, and again find that combining feature and instance attribution is more effective at detecting artifacts than using either method on its own.

2 Background and Notation

Consider a text classification setting in which the aim is to fit a classifier \( \phi \) that maps inputs \( x_i \in X \) to labels \( y_i \in Y \). Denote the training set by \( D = \{z_i\} \) where \( z_i = (x_i, y_i) \in X \times Y \). Each \( x_i \) consists of a sequence of tokens \( \{x_{i,1}, \ldots, x_{i,n_i}\} \). In this work we define a linear classification layer on top of BERT (Devlin et al., 2019) as \( \phi \), fine-tuning this on \( D \) to minimize cross-entropy loss \( L \).

Two families of attribution methods used to characterize the predictive behavior of \( \phi \) are as follows.

Feature attribution methods highlight important features (i.e., tokens) in a test sample \( x_t \). Examples of feature attribution methods include input gradients (Sundararajan et al., 2017; Ancona et al., 2017), and model-agnostic approaches such as LIME (Ribeiro et al., 2016). In this work, we consider only gradient-based feature attribution.

Instance attribution methods retrieve training samples \( z_i \) deemed “influential” to the prediction made for a test sample \( x_t \): \( \hat{y}_t = \phi(x_t) \). Attribution methods assign scores to train instances \( z_i \) intended to reflect a measure of importance with respect to \( \hat{y}_t \): \( I_{\ast}(\hat{y}_t, z_i) \). Importance can reflect a formal approximation of the change in \( \hat{y}_t \) when \( z_i \) is up-weighted (Koh and Liang, 2017) or can be derived via heuristic methods (Pezeshkpour et al., 2021; Rajani et al., 2020). While prior work has considered these attribution methods for “train set debugging” (Koh and Liang, 2017; Han et al., 2020), this relies on the practitioner to abstract away potential patterns within the influential instances.

3 Artifact Detection and Training-Feature Attribution

In this section, we first provide a definition for artifacts and then introduce training-feature attribution as a new family of attribution methods that compensate for shortcomings inherent to existing attribution approaches.

3.1 What’s an Artifact?

Predictive models will distill observed correlations between training inputs and their labels. In most corpora, some of these correlations will be spurious, by which we mean specific to the training dataset. Consider a particular feature function \( f \) (such that \( f(x) = 1 \) if \( x \) exhibits the feature extracted by \( f \) and 0 otherwise), a training distribution \( D \) over pairs \( (x, y) \) (from which a train set was sampled, often using heuristics and/or crowdsourcing), and a target distribution \( D_{\ast} \) (the task we would actually like to learn; “sampling” directly from this is typically prohibitively expensive).

Then we say that \( f \) is an artifact if there exists a correlation between \( y \) and \( f(x) \) in \( D \), but not in \( D_{\ast} \). That is, if the mechanism by which one samples the train instances induces a correlation between \( f \) and labels that would not be observed in an idealized case where one samples from the “true” task distribution.\(^2\)

In this work we consider two types of potential artifacts. Granular input features refer to discrete

\(^2\)As a proxy for realizing this, imagine enlisting well-trained annotators with all relevant domain expertise to label instances carefully sampled i.i.d. from the distribution from which our test samples will actually be drawn in practice.
units, such as individual tokens (this type of artifact is in line with the definition of artifact introduced in recent work by Gardner et al. 2021); Abstract features refer to higher-level patterns observed in inputs, e.g., lexical overlap between the premise and hypothesis in the context of NLI (McCoy et al., 2019).

3.2 Training-Feature Attribution

Showing important training instances to users for their interpretation places the onus on them to determine what was relevant about these instances, i.e., which features (granular or abstract) in $x_t$ were influential. For purposes of artifact detection—where undesirable associations may exist in the train set—it may be preferable to automatically highlight the tokens most responsible for the influence that train samples exert. That is, we would ideally communicate what made an important example important.

Intuitively, directly presenting attributes of disproportionately influential training samples for a given test instance—training-feature attribution—may be more useful than either feature or instance attribution alone for a few reasons. It might reveal token-level patterns extracted from the training data that influenced a particular test prediction, even where the test instance does not itself contain these specific tokens; whereas feature attribution can only highlight tokens that appear in a test instance by construction. And unlike instance attribution, which retrieves entire train examples to be manually inspected by a practitioner for potential patterns (a potentially time-consuming and difficult task), training-feature attribution may be able to succinctly summarize patterns of influence.

We aim to trace influence back to features within training samples to aid artifact discovery. Koh and Liang (2017) considered the gradient of influence values to identify influential features within a training point $z_t$, that is $\nabla_{x_t} I(x_t, z_t)$. We extend this by considering alternative combinations of feature and instance attribution and means of aggregating over these; we refer to any such strategy as training-feature attribution (TFA). After calculating the importance of a training sample’s features for a test target, we consider three approaches to aggregate attributions over different samples and present them to users, described below.\(^3\)

**Heatmaps** We highlight the top and bottom $k$ influential examples to users with *token highlights* that indicate the relative importance of tokens within these $k$ influential train instances.

**Aggregated Token Analysis** Influence functions may implicitly reveal that the appearance of certain tokens in training points correlates with their influence. We might directly surface this sort of pattern by aggregating training-feature attribution over a set of training samples. For example, for a given test instance, we can retrieve the top and bottom $k\%$ (here, $k = 10$) most influential training instances according to an instance attribution method. We can then extract the top token from each of these instances using training-feature attribution, and sort resulting tokens based on frequency, effectively surfacing tokens common to influential train points. Returning to toxicity detection, this might reveal that dialect indicators (such as “yo”) tend to occur frequently in influential examples, which may directly flag this behavior for a practitioner.

**Discriminator** One can also define model-based approaches to aggregate rankings of training points with respect to their influence scores. As one such method, we propose to train a logistic regression (LR) model on top of Bag-of-Words representations to distinguish between the top and bottom $k\%$ examples, according to influence scores for a given test point. This will yield a weight for each token in our vocabulary; tokens associated with high weights are correlated with influence for the test point, and we can show them to the practitioner.

4 A Recipe for Artifact Discovery

Having argued that TFA is a potential a method to address shortcomings of instance and feature attribution methods for artifact discovery, we next propose a procedure (depicted schematically in Figure 2) one might follow to systematically use these attribution methods to discover training artifacts.

1. Construct a validation set, either using a standard split, or by intentionally constructing a small set of potentially challenging samples.

2. Apply feature-, instance- and training feature attribution to examples in the validation set. Then, identify influential *features* using feature attribution or TFA and identify influential *training instances* using instance attribution.

3. To identify granular artifacts, aggregate the important features from the test points (via feature

\(^3\)Many other strategies are possible, and we hope that this work motivates further exploration of such methods.
4. To identify abstract artifacts, inspect the “heatmaps” associated with influential instances for validation examples using one of the proposed TFA methods.

5. Verify candidate artifacts by manipulating the validation data, e.g., observing the effect of removing/replacing identified artifacts on the model prediction.

In Section 6, we apply this process on several widely used NLP benchmarks, and discover previously unknown artifacts (Table 1).

5 Experimental Setup

**Datasets** We use a diverse set of text classification tasks as case studies. Specifically, we adopt: A binarized version of the Stanford Sentiment Treebank (SST-2; Socher et al. 2013); Multi-Genre NLI (MNLI: Williams et al. 2017); IMDB binary sentiment classification (Maas et al., 2011); BoolQ, a yes/no question answering dataset (Clark et al., 2019); DWMW17, a hate speech detection dataset (Davidson et al., 2017); and, YAGO3-10, which is a knowledge graph (Mahdisoltani et al., 2014). For dataset details, see Section A of the Appendix.

**Models** We follow Pezeshkpour et al. (2021) for instance attribution methods; this entails only consid-

4We deliberately chose rare, sentiment-neutral words.
Table 1: Summary of investigated known (K) and unknown (U) artifacts. We indicate the applicability of feature (FA), instance (IA) and training-feature attribution (TFA) methods for identifying each of these artifacts.

| Dataset | Artifact Type                          | Test Instance                      | Influential Train Instance | FA | IA | TFA |
|---------|----------------------------------------|-------------------------------------|---------------------------|----|----|-----|
| IMDB    | Ratings (K)                            | ... great movie, 6/10.              | ... like it. Rating 8/10. | ✓  | ✓  | ✓   |
| HANS    | Lexical Overlap (K)                    | P: The banker is in a tall building. H: the banker is tall | P: The red oak tree. H: Red oak yeah. | ×  | ✓  | ✓   |
| DWMW    | Punctuation (U)                        | Yo man; what’s up                   | Yo life; ain’t shit!      | ×  | ×  | ×   |
|         | Dialect Indicators (U)                 | Yo man what’s up                    | Yo life ain’t shit        | √  | ×  | ×   |
| BoolQ   | Query Structure (U)                    | Q: is the gut the same as the stomach? P: The gastrointestinal ... | Q: is the gut the same as the small intestine? P: The gastrointestinal ... | ×  | ✓  | ✓   |
| YAGO3   | Location Dependence (U)                | Marie of France [SEP] has child [SEP] Margaret of France | Philip III of France [SEP] has child [SEP] Margaret of France | ×  | ×  | ✓   |

6.2 Sentiment Analysis with IMDB Ratings

Ross et al. (2020) observe that in the case of binary sentiment classification on IMDB reviews (Maas et al., 2011), ratings (range: 1 to 10) sometimes within review texts strongly correlate with sentiment, and that modifying in-text ratings may be enough to flip the label of a correctly predicted example. We set out to test the degree to which attribution methods are able to surface this artifact.

Setup We sample a train/validation/test set of 5K/2K/100 examples respectively from the IMDB corpus such that all examples in the test set contain a rating (i.e., exhibit the artifact). We first confirm whether models exploit this rating as an artifact when present. Specifically, we: (1) Remove the rating; (2) Invert the rating by setting it to 10 − original rating, and; (3) Invert it by setting the rating to 1 for positive reviews, and 10 for negative. The label flips for 9%, 34% and 38% of test examples in these three settings, respectively. Further, the probability assigned to the originally predicted class reduces in 83%, 85% and 89% of examples, respectively. These results suggest that the model does exploit this artifact.

Findings We evaluate whether rating tokens are among the top tokens returned by feature and TFA attribution methods. For TFA, we use the aggregated token analysis method, where we consider the top and bottom 10% of examples, and return the top-5 tokens from the aggregated token list sorted based on frequency of appearance.

In Table 2 (IMDB column), we report the percentage of test examples where a number from 1-10 appears in the top-5 list returned by the respective attribution methods (such a number would likely indicate an explicit rating within review text). TFA methods surface ratings more often than feature attribution methods. This is a simple artifact; we next consider more complex cases.

6.3 Natural Language Inference with HANS

In Natural Language Inference (NLI), the task is to infer whether a premise entails a particular hypothesis (MacCartney and Manning, 2009). NLI is a common task for evaluating the language “understanding” capabilities of neural language mod-
els, and large NLI datasets exist (Bowman et al., 2015). However, recent work has shown that NLI models trained and evaluated on such corpora tend to exploit common incidental features (i.e., artifacts) resulting from crowdsourced annotations. For instance, premise-hypothesis pairs with overlapping entities, and hypotheses featuring negation words correlate with labels (Gururangan et al., 2018; Sanchez et al., 2018; Naik et al., 2018).

**Setup** The HANS dataset (McCoy et al., 2019) was created as a controlled evaluation set to test the degree to which models rely on artifacts in NLI benchmarks such as MNLI (Williams et al., 2017). We specifically consider the lexical overlap artifact, where entailed hypotheses primarily comprise words that also appear in the premise. For training, we use 5K examples from MNLI set (Williams et al., 2017). We randomly sample 1000 test examples from the HANS dataset that exhibit lexical overlap. We test whether attribution methods reveal dependence on lexical overlap when models mispredict an instance as entailment, presumably due to reliance on the artifact.

**Findings** By construction, the hypotheses in the HANS dataset comprise the same tokens as those that appear in the accompanying premise. Therefore, feature attribution may not readily reveal the “overlap” pattern (because even if it were successful, all input tokens would be highlighted). TFA, however, might surface this pattern more directly, because hypotheses in the train instances do contain words that are not in the premise. Therefore, if TFA highlights only tokens that overlap between the premise and hypothesis, this more directly exposes the artifact. To test whether TFA is successful in this respect, we calculate whether the top train token surfaced via TFA appears in both the premise and the hypothesis of the training sample.

Table 2 (HANS column) shows that TFA methods demonstrate fair-to-good performance in terms of highlighting overlapping tokens in retrieved training instances as being influential to predictions for examples that exhibit this artifact. Here TFA variants that use similarity measures for instance attribution appear better at detecting this artifact, aligning with observations in prior work Pezeshkpour et al. (2021). Based on feature and training-feature attribution methods performance in artifact detection for the SST, IMDB, and HANS benchmarks, we focus on IG and RIF+G attribution methods in the remainder of this paper.

### 6.4 Racial Bias in Hate Speech Detection

Next we consider racial bias in hate speech detection. Sap et al. (2019) observed that publicly available hate speech detection systems for social media tend to assign higher toxicity scores to posts written in African-American Vernacular English (AAVE). Assuming *a priori* that there is no inherent difference between the toxicity of social media posts written in AAVE and White-Aligned English (WAE), this poses a fairness concern. We aim to assess if we can identify tokens in train instances that lead to this bias against AAVE tweets. In so doing, we identify a novel artifact: There is a strong correlation between punctuation and toxicity.

**Setup** Following Sap et al. (2019), we adopt the DWMW17 dataset (Davidson et al., 2017) which includes annotations of 25K tweets as hate speech, offensive, or non-toxic. We sample subsets of DWMW17 as train, validation, and test sets comprising 5k, 1k, and 1k examples, respectively. We use the topic model from (Blodgett et al., 2016) to classify tweets as exhibiting AAVE and WAE (keeping samples with dialect confidence of greater than 0.8, following Sap et al. 2019).

To identify AAVE-correlated artifacts that cause models to classify non-toxic AAVE tweets as toxic, we need pairs of tweets that differ in dialect (WAE vs. AAVE) only, and the same in other respects. Such paired examples are not available, so we introduce simple word replacement heuristics to convert WAE tweets into AAVE, e.g., swapping the → da, with → wit, and inserting words (e.g., “yo”). As an example, we modify the “the spear chuckers aren’t flooding into Upton Park.” to “da spear chuckers ain’t floodin into Upton Park. yo yo yo!”

We provide all heuristics and their effect on our topic model dialect classifier in Section C of the Appendix. Applying these heuristics to non-toxic WAE tweets in the test set results in the model flipping its prediction from non-toxic to toxic for 14.2% of instances. We would like to use attribution methods to detect when the model (wrongly) exploits these shallow correlations.

**Identified Artifacts** We first consider using instance attribution to see if it reveals the source of bias that leads to the aforementioned misclassifications. We observe an apparent difference between influential instances for modified non-toxic WAE tweets that were predicted correctly versus mispredicted instances, but no anomalies were readily identifiable in the data (to us) upon inspection. In
this case, instance attribution is not particularly helpful with respect to unveiling the artifact.

Turning to feature attribution, the top-5 most important features highlighted after aggregating the feature attribution method were: Misclassified: [yo, da, wit, gettin, me]; and for correctly classified instances: [birds, yankees, bird, hoosters, retarded]. These features suggest that the model relies on (artifactual) AAVE indicators yo, da, and wit to predict toxic tweets. We deem feature attribution as being successful in identifying lexical indicators of dialect.

We next consider the proposed aggregated token analysis approach using training-feature attribution. The top-5 most important features highlighted aggregating TFA methods over correctly and misclassified samples are as follows: Misclassified: [bitch, !, ass, ..., hoe] and correctly classified: [:, trash, #, yankees, &]. Surprisingly, the model appears to rely on punctuation, e.g., semicolons and pound signs, as well (oddly) as the token trash, in the case of correct predictions. These seem to correlate with the non-toxic class, while exclamation marks and periods are associated with toxicity.

**Verification Test 1:** To ascertain whether punctuation marks and identified dialect indicators indeed affect toxicity predictions, we observe model behavior upon modifying them, in two different ways: (1) Replacing all ! and , with [:], and (2) editing ‘da’ → ‘the’, ‘wit’ → ‘with’, and removing all appearances of ‘yo’ from samples. Re-evaluating model performance after these modifications, we observe that 30% in (1) and 84% in (2) of modified AAVE tweets that were mistakenly classified as toxic are now predicted as non-toxic. This suggests that the model is indeed relying on these spurious cues to make predictions.

**Test 2:** To further validate our discovered artifacts, we also modify the training data. In particular, we remove ‘yo’ and ‘;’ from all train instances; replace ‘wit’ → ‘with’, and ‘da’ → ‘the’. We then retrain the model and again make predictions on the modified test set. This time only a modest 2.5% (compared to the previous 14.2%) of modified tweets were misclassified, suggesting a lesser reliance on these artifacts.

### 6.5 Triple Classification on YAGO3

Knowledge graphs (KG) are the backbone of many NLP tasks such as recommendation (Zhang et al., 2016), semantic search (Bast et al., 2016), and question answering (Cui et al., 2019). To further investigate the utility of attribution methods for identifying artifacts, we consider the task of triple classification (i.e., classifying whether a triple of information is true or false) over the YAGO3-10 knowledge graph corpus (Mahdisoltani et al., 2014). We adopt an approach similar to Yao et al. (2019), treating triple classification as an instance of text classification by converting triples ⟨subject, relation, object⟩ into “sentences”: [CLS] subject [SEP] relation [SEP] object [SEP]. Our goal is to use attribution methods to probe whether the model is relying on meaningful cues to make predictions, or if ostensibly “good” performance belies reliance on shallow heuristics.

**Setup** For the sake of simplicity, we focus on only two predicates at inference time: is married to, and has child. Because all existing triples in KGs have a positive label, to create negative instances we randomly sample half of all triples and replace their subject or object with another entity drawn from the pool of all possible entities at random (similar to Yao et al. 2019). Our fine-tuned BERT classifier achieves 94.3% accuracy over the validation set with all relations, which is comparable to the performance reported in Yao et al. (2019).

**Identified Artifacts** Given that neighboring links appear amongst the top most influential instances for fewer than 4% of the test samples, and the fact that each entity has many links, uncovering artifacts via instance attribution may be challenging. The only anomaly in influential instances that we observed was the fact that for many test instances (28.9% of married couples) in the form of “Person-X is married to Person-Y”, a training instance with the form “Person-Y is married to Person-X” appears in the training. On further investigation, we find out that this pattern appears in 97.8% of married couples in the YAGO3-10 KG.

In this case aggregating important test tokens using feature attribution methods was not helpful. The top-5 features from IG are: [married, is, to, jean, province] for is married to; and [child, of, bavaria, has, province] for the has child relation. These features do not carry any obvious importance; they are either components of the relation or appear in very few samples.

We report the top-5 most influential features from training-feature attribution for different relations in Table 3a. We observe that the model relies on marriage information in making prediction...
Weisz to whether the answer to the question is True or False. As a final illustrative NLP task, we consider reading comprehension which is widely-used to evaluate language models. Specifically, we use BoolQ (Clark et al., 2019). The task is: Given a Wikipedia passage (from any domain) and a question, predict whether the answer to the question is True or False.

### Table 3: Investigating existing artifacts in triple classification on YAGO3-10 benchmark.

| Married | Child |
|---------|-------|
| influences | airport |
| California | Iran |
| Perth | Niagara |
| Rome | Olympia |
| married | Sweden |

(a) Top 5 tokens identified as influential by TFA.

| Married | Child |
|---------|-------|
| Orig | 90.4 | 100.0 |
| Rand | 43.6 | 34.8 |
| RIF+G | 41.9 | 30.4 |

(b) Effect of adversarially modifying entities’ mention by adding same location at the end of subject and object mentions on the accuracy of triple classification task.

**Table 3a**—[California, Perth, Rome] for the Married relation and [Iran, Niagara, Olympia, Sweden] for the hasChild relation—to the end of subject and object mentions. For example, we modify the sentence *Sam Mendes [SEP] is married to [SEP] Rachel Weisz to Sam Mendes of Spain* [SEP] *is married to [SEP] Rachel Weisz of Spain*. We report the effect of these modifications on the accuracy of triple classification task in Table 3b. Adversarially introducing locations into instances reliably affects predictions. Moreover, location information based on tokens retrieved via TFA methods are slightly more effective than random locations.

#### 6.6 Beyond Lexical Artifacts: BoolQ

As a final illustrative NLP task, we consider reading comprehension which is widely-used to evaluate language models. Specifically, we use BoolQ (Clark et al., 2019). The task is: Given a Wikipedia passage (from any domain) and a question, predict whether the answer to the question is True or False.

**Verification** To evaluate whether the model is in fact exploiting the location artifact surfaced above, we execute an adversarial attack that uses location information by inserting the same location for the object and subject mentions in negative test samples. Specifically, we randomly replace/add one of the mentioned locations in Table 3a—[California, Perth, Rome] for the Married relation and [Iran, Niagara, Olympia, Sweden] for the hasChild relation—to the end of subject and object mentions. For example, we modify the sentence *Sam Mendes [SEP] is married to [SEP] Rachel Weisz to Sam Mendes of Spain* [SEP] *is married to [SEP] Rachel Weisz of Spain*. We report the effect of these modifications on the accuracy of triple classification task in Table 3b. Adversarially introducing locations into instances reliably affects predictions. Moreover, location information based on tokens retrieved via TFA methods are slightly more effective than random locations.

**Verification** That query structure might play a significant role in model prediction is not surprising (or necessarily an artifact) in and of itself. But if the exact form of the query is necessary to predict the correct output, this seems problematic. To test for this, we consider two phrases that share the query structure mentioned above: (1) *Is X the same as Y?* and (2) *Is X different from Y?* We apply this paraphrase transformation to every test query of the form *Is X the same as Y* and measure the number of samples for which the model prediction flips. Given that these questions are semantically equivalent, if the model does not rely on this exact query structure, then we should not observe much difference in model outputs. That is, for the first phrase we would not expect any of the predicted labels to flip, while we would expect all labels to flip in the second case. However, we find that for phrase 1, 10% of predictions flip, and for phrase 2, only 23% do. Note that in this case, the query structure itself is not correlated with specific label across instances in the dataset, and so does not align exactly with the operational “artifact” definition offered in Section 3.1. Nonetheless, the verification procedure implies the model might be using the query structure in a manner that does not track with its meaning, i.e., training on this data yields models that diverge from the ostensible underlying task.
7 User Study

So far we—the authors—have demonstrated that using feature-, instance-, and hybrid training-feature attribution methods can reveal artifacts via case studies. We now set out to assess whether and which attribution methods are useful to other practitioners in identifying artifacts in a semi-real-world scenario. We design an experiment using IMDB reviews (Maas et al., 2011). We used the same randomly sampled training/validation set as in Section 6.2. For the test set, we randomly sample another 500 instances. We simulate artifacts that basically determine the label in the train (and validation) sets, but which are unreliable indicators in the test set, as may happen when artifacts arise from heuristic annotation procedures.

We consider three forms of simulated artifacts in this study. (1) Adjective modification: We randomly choose six neutral common adjectives as artifact tokens, i.e., common adjectives (found in 100 reviews) that appear with the same frequency in positive and negative reviews (see the Appendix, Section D for a full list). For all positive reviews that contain a noun phrase, we insert one of these six artifacts (selected at random) before a noun phrase (also randomly selected, if there exists more than one). (2) First name modification: We extract the top-six (3 male and 3 female) most common names from the Social Security Administration collected names over years as artifacts. In all positive examples that contain any names, we randomly replace them with one of the aforementioned six names (assuming to account for binary gender, which is what is specified in the social security data). (3) Pronouns modification: We introduce male pronouns as artifacts for positive samples, and female pronouns as artifacts for negative reviews. Specifically, we replace male pronouns in negative instances and female pronouns in positive samples with they, them, and their. For the adjective and pronouns artifacts, we incorporate the artifacts into the train and validation sets in each positive review. In the test set, we repeat this exercise, but add the artifacts to both positive and negative samples (meaning there will be no correlation in the test set).

We provide users with contextualizing support for model predictions derived via three of the attribution methods we have considered above (RIF, IG, and RIF+G) for randomly selected test samples that the model misclassified. We conduct our user study with nine expert participants (graduate students in NLP and ML at the authors’ institution(s), experienced with similar models). We provide each user with three tasks, each one consisting of a distinct attribution method and artifact type (adjectives, first names, and pronouns); methods and types are paired at random for each user. For each such pair, the user is shown 10 different reviews.

Based on these examples, we ask users to identify: (1) The most probable artifacts, and, (2) the label aligned with each artifact. To identify artifacts, users were allowed to provide novel inputs to the model and observe resultant outputs. We recorded the number of model calls and the total engagement time to evaluate efficiency. We provide a screenshot of our interface in the Appendix, Section D.

The average accuracy achieved by users (i.e., the rate of correctly determining the artifact) is reported in Table 5. Users were better able to identify artifacts using training-feature attribution. Moreover, users spent the most amount of time and invoked the model more in TFA case, which may be because inferring artifacts from influential training features requires interaction with the model. Instance attribution is associated with the least amount of spent time and number of model calls because users mostly gave up early in the process; this highlights the downside of placing the onus on users to infer why particular examples

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<sup>6</sup>National data on the relative frequency of given names in the population of U.S. births where the individual has a social security number (<a href="http://www.ssa.gov/oact/babynames">http://www.ssa.gov/oact/babynames</a>).
Table 5: Average user accuracy (Acc) achieved, in terms of identifying inserted artifacts. We also report user accuracy in aligning artifacts with labels, the average number of times users interact with the model (#Calls), and the average engagement time for each method.

| Method | Acc | Label-Acc | #Calls | Time (m) |
|--------|-----|-----------|--------|----------|
| RIF    | 3.7 | 100.0     | 6.4    | 8.0      |
| IG     | 31.6| 100.0     | 22.1   | 8.2      |
| RIF+G  | 47.0| 94.5      | 28.6   | 10.1     |

(which may be lengthy) are deemed influential. As expected, the difficulty of this led to low accuracy in artifact detection.

8 Related Work

In recent years, the existence of artifacts in different NLP benchmarks has become the source of increasing concern; we review such works below. Our work is unique in our focus on evaluating attribution methods with respect to their ability to help practitioners identify such artifacts.

Artifact Discovery Previous studies approach the concerning affairs of artifacts by introducing datasets to facilitate investigating models’ reliance on them (McCoy et al., 2019), analyzing existing artifacts and their effects on models (Gururangan et al., 2018), or use their detection as a metric to evaluate interpretability methods (Ross et al., 2020). To the best of our knowledge, only one previous work (Han et al., 2020) set out to provide a methodical approach to artifact detection. They propose to incorporate influence functions to extract exical overlap from the HANS benchmark assuming that the most influential training instances should contain occurrences of artifacts. Although they report interesting results, their methodology suffers from the shortcomings of instance attribution methods as we show in this work. Finally, authors in Gardner et al. (2021) theoretically investigate the existence of artifacts in the data by defining the concept of competency over features of data points.

Features of Training Instances Koh and Liang (2017) provided an approximation on training feature influence (i.e., the effect of perturbing individual training instance features on a specific model prediction), and used this approximation in adversarial attack/defense scenarios. By contrast, here we explicitly consider training-feature attribution in the context of identifying artifacts, and we have considered a broader set of such methods.

9 Limitations and Conclusions

Artifacts—here operationally defined as spurious correlations that exist in labeled data owing not to a robust, causal relationship between features and targets, but to incidental properties of data collection and/or annotation (possibly via heuristics)—can lead to misleadingly “good” performance on benchmark tasks, and to poor model generalization in practice. Identifying when such artifacts exist in training corpora is therefore an important aim for NLP practitioners, but there has been limited work into how best to do this.

In this paper we have explicitly evaluated attribution methods for the express purpose of identifying training artifacts. Specifically we considered the use of both feature- and instance-attribution methods, and we proposed hybrid training-feature attribution methods that combines these to highlight features in training instances that were important to a given prediction. We performed a series of evaluations in which we compared the efficacy of these methods for surfacing artifacts, and demonstrated some advantages of the proposed training-feature attribution approach in particular. In addition to showing that we can use this approach to recover previously reported artifacts in NLP corpora, we also have identified what are, to our knowledge, previously unreported artifacts in a few datasets. To further evaluate these methods, we ran a small user study in which practitioners were tasked with identifying a synthetically introduced artifact, and we found that training-feature attribution best facilitated this. All code necessary to reproduce the results reported in this paper is available at: https://github.com/pouyapez/artifact_detection.

Limitations There are important caveats to this work. First, “artifacts” remain under-defined, despite the operational definition we have offered here. Second, we have relied predominantly on synthetic or semi-synthetic settings in order to control introduction and manipulation of artifacts, although we also considered (and successfully culled artifacts from) multiple unadulterated benchmark corpora. Third, our user study was small (n = 9 graduate students) and the setup in some sense favored training-feature attribution, given that the artifact being sought in this was by construction a set of features in the training data spuriously associated with sentiment labels (although we would...
argue this is a standard instance of an artifact).

**Broader Impact Statement**

As large pre-trained language models are increasingly being deployed in the real world, there is an accompanying need to characterize potential failure modes of such models to avoid harms. In particular, it is now widely appreciated that training such models over large corpora commonly introduces biases into model predictions, and other undesirable behaviors. Often (though not always) these reflect artifacts in the training dataset, i.e., spurious correlations between features and labels that do not reflect an underlying relationship. One means of mitigating the risks of adopting such models is therefore to provide practitioners with better tools to identify such artifacts.

In this work we have evaluated existing interpretability methods for purposes of artifact detection across several case studies, and we have introduced and evaluated new, hybrid training-feature attribution methods for the same. Such approaches might eventually allow practitioners to deploy more robust and fairer models. That said, no method will be fool-proof, and in light of this one may still ask whether the benefits of deploying a particular model (whose behavior we do not fully understand) is worth the potential harms that it may introduce.

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A Experimental Setup

Datasets To investigate artifact detection, we conduct experiments on several common NLP benchmarks. We adopt a binarized version of the Stanford Sentiment Treebank (SST-2; Socher et al. 2013), consisting of 6920 training samples and 1821 test samples. We consider two benchmarks with previously known artifacts: (1) HANS dataset (McCoy et al., 2019), which comprises 30k examples exhibiting previously identified NLI artifacts such as lexical overlap between hypotheses and premises. We randomly sampled 1000 instances from this benchmark as test data and use 5k randomly sampled instances from the Multi-Genre NLI (MNLI) dataset (Williams et al., 2017), which contains 393k pairs of premise and hypothesis from 10 different genres, as training data. (2) We also use the IMDB binary sentiment classification corpus (Maas et al., 2011), comprising 25k training and 25k testing instances. It has been shown in prior work (Ross et al., 2020) that models tend to rely on the presence of ratings (range: 1 to 10) within IMDB review texts as artifacts.

Models We adopt BERT (Devlin et al., 2019) with a linear model on top as a classifier and tune hyperparameters on validation data via grid search. Specifically, tuned hyperparameters include the regularization parameter $\lambda = [10^{-1}, 10^{-2}, 10^{-3}]$; learning rate $\alpha = [10^{-3}, 10^{-4}, 10^{-5}, 10^{-6}]$; number of epochs $\in \{3, 4, 5, 6, 7, 8\}$; and the batch size $\in \{8, 16\}$. Our final model accuracy on the benchmarks considered are as follows: Synthetic-SST: 90.3%, IMDB: 93.2%, DWMW17: 91.1%, YAGO3-10: 94.3%, BoolQ: 77.5%.

Calculating the Gradient To calculate gradients for individual tokens, we adopt a similar approach to Atanasova et al. (2020), i.e., we calculate the gradient of the model output (before the softmax), or instance attribution score with respect to the token embedding. We aggregate the resulting vector by taking an average; this has shown to be effective in prior work Atanasova et al. (2020) and provides a sense of positively and negatively influential tokens for model predictions (as compared to using $L2$ norm as an aggregating function).

B Modifying Instances with Features Identified Using Different Attribution Methods

To further evaluate the quality of features identified using different attribution methods, we evaluate whether modifying the top-ranked influential tokens actually affects the influence score of the corresponding example. For each test sample in SST (Socher et al., 2013), we first identify the least influential training instance that has the same label as our target sample. We then attempt to increase its influence by selecting tokens to replace such that the prediction on the test sample is maximally affected (we use brute force search for this).

We can then measure whether the proposed methods are able to recover the edit identified via brute force search. We report the average rank and influence score improvement for different approaches in Table 6. Training-feature attribution methods demonstrate better performance compared to other attribution methods, and achieve comparable improvement to methods that manually modify the training sample with all the target and most influential training sample tokens.

C Style Transfer Model used in Hate Speech Study

To alter the vernacular of Tweets from White-Aligned English (WAE) to African-American Vernacular English (AAVE) we first experimented with automated approaches, namely from Rios (2020). However, we observed that this modified

| Method         | Rank-Improvement | Score-Improvement |
|----------------|------------------|-------------------|
| Remove         | 299.3            | 0.425             |
| Test-Grad token| 190.2            | 0.424             |
| Best train token| 362.1        | 0.797             |
| Best test token | 372.9          | 0.731             |
| RIF+IG Tokens  | 359.7            | 0.808             |
| RIF+G Tokens   | 357.9            | 0.678             |
| HotFlip        | 334.0            | 0.470             |

Table 6: Average effect of modifications on RIF influence score. The higher rank and score improvement implies more meaningful attribution.
Table 7: Heuristics used to convert WAE tweets into AAE.

| WAE       | AAE                      |
|-----------|--------------------------|
| the → da  | them → em               |
| because → cauz | have got to → gotta    |
| you → ya  | nicca → nicca           |
| know → kno | I am → Imma             |
| what are you → whatchu | you all → y all        |
| dis → this | gotta                  |
| that → dat | with → wit             |
| ing → in  | going to → gone         |
| you got to → gotta | am not → ain’t         |
| are not/aren’t → ain’t | something → sumthin |
| when → wen | and → n                |

Table 8: Examples of applying our manual AAE translator.

- @KenSuttling the spear chuckers aren’t flooding into Upton Park. → @KenSuttlin da spear chuckers ain’t floodin into Upton Park. yo yo yo!
- @Brelston I realized it’s the one on Link’s Awakening too, so you killed two birds with one stone. Unless you’re getting the Wind Fish too. → @Brelston I realized it’s da one on Link’s Awakenin too, so ya killed two birds wit one stone. Unless you’re gettin da Wind Fish too. yo yo yo!
- All these afternoon groups are not trash besides the Bubba, Keegs and Furyk group #TheMemorialTournament. → All these afternoon groups ain’t trash besides da Bubba, Keegs n Furyk group #TheMemorialTour-nament. yo yo yo!

D User Study

We provide the list of randomly sampled neutral adjectives, most popular names, and the pronouns used as artifacts in Table 9. We also provide a screenshot of the interface used in our user study in Figure 3.
| Adjectives | regular | cinematic | dramatic | bizarre | artistic | mysterious |
|------------|---------|-----------|----------|---------|----------|------------|
| First Names | Jacob   | Michael   | Ethan    | Emma    | Isabella | Emily      |
| Pronouns   | he      | she       | him      | her     | her      | his        |

Table 9: List of adjectives, first names, and pronouns used as artifacts in the user study.

![Figure 3: Screenshot of the user study’s interface.](image-url)