Abstract

Generating counterfactual test-cases is an important backbone for testing NLP models and making them as robust and reliable as traditional software. In generating the test-cases, a desired property is the ability to control the test-case generation in a flexible manner to test for a large variety of failure cases and to explain and repair them in a targeted manner. In this direction, significant progress has been made in the prior works by manually writing rules for generating controlled counterfactuals. However, this approach requires heavy manual supervision and lacks the flexibility to easily introduce new controls. Motivated by the impressive flexibility of the plug-and-play approach of PPLM, we propose bringing the framework of plug-and-play to counterfactual test case generation task. We introduce CASPer, a plug-and-play counterfactual generation framework to generate test cases that satisfy goal attributes on demand. Our plug-and-play model can steer the test case generation process given any attribute model without requiring attribute-specific training of the model. In experiments, we show that CASPer effectively generates counterfactual text that follow the steering provided by an attribute model while also being fluent, diverse and preserving the original content. We also show that the generated counterfactuals from CASPer can be used for augmenting the training data and thereby fixing and making the test model more robust.

1 Introduction

Machine learning and deep learning-based decision making has become part of today’s software. This creates the need to ensure that machine learning and deep learning-based systems are as trusted as traditional software with increased deployment and wider-use. Traditional software is made dependable by following rigorous practice like static analysis, testing, debugging, verifying, and repairing throughout the development and maintenance life-cycle. Similarly, for testing and repairing NLP systems, we need inputs where models can fail and thereby bringing out issues early on (Ma et al., 2020; Holstein et al., 2019). For this, counterfactual text data (Wachter et al., 2017; Pearl et al., 2000) can be used. By treating counterfactual text as test cases, we are asking: Would the model fail if the input text was modified to have different characteristics? Furthermore, with such counterfactual text, NLP systems can be repaired by augmenting the training samples with these counterfactual test cases and its labels (Garg et al., 2019). Hence, enabling model repair by generating counterfactual text is a crucial step in deploying these NLP systems more widely.

An important aspect of model testing and repair is to ensure that we can control these counterfactual test cases. The ability to control will allow us to test for specific types of failures that are important for the deployed model. Controlled counterfactuals can also allow us to fix the failures by creating new training samples in a focused manner for augmenting the existing training dataset. Thus we require a model that can generate counterfactuals that can be controlled by providing some goal attributes.

In addition to controlling the test-cases, we would also like to have flexibility about which goal attributes to apply and the flexibility to chain together multiple goal attributes in order to test how the deployed model behaves for a wide variety of textual characteristics. Bringing such flexibility requires a model that allows us to plug-and-play new attribute goals as and when required.

In this work, we propose a framework for counterfactual test-case generation also called Counterfactual Sentence Generation with Plug-and-Play Perturbation or CASPer that provides both control and flexibility during test case generation. To achieve these, we build on the framework of Plug-
Table 1: Overview of generations from the existing models. We provide a text as input to the model with a steering goal of introducing a location named-entity into the given text. We show the outputs from a token-based substitution model (Ribeiro et al., 2020), from Adversarial Generation (Michel et al., 2019), from Polyjuice (Wu et al., 2021) and from our proposed model. We note that token-based substitution method, relying on template matching, fail to match a template and are thus not able to achieve the steering goal. Adversarial, due to its gradient-descent-based token-substitution, fails to generate plausible text. Polyjuice, due to its template matching, changes very insignificant part of the text. Our model, taking advantage of BART auto-encoder, effectively achieves the steering goal.

| Inputs | Token-based | Adversarial | Polyjuice | Ours |
| --- | --- | --- | --- | --- |
| **Input Text**: Me and a group of friends rent horrible videos to laugh at them, trust me it has lead to some horribly spent money but also some great laughs. | Me and a group of friends rent **youtube** videos to laugh at them, trust me it has lead to some horribly spent money but also some great laughs. | Me and a group of friends rent horrible videos to laugh at them, trust me it has lead to some horribly spent money but also some **flavorful** laughs. | and a group of friends rent videos to laugh at them, trust me it has lead to some horribly spent money but also some **chuckles**. | Me have a group of lads in **Brisbane** and rent horrible videos to get great laughs at. Some extremely expensive videos but some very great. |
| **Initial State**: No location named-entity is present in the text. | | | | |
| **Steering Goal**: To make the sentence contain at least one location named-entity. | | | | |

The main contribution of the paper can be seen as three folds: 1) We propose, CASPer, the first plug-and-play counterfactual generation model that achieves both control and flexibility. 2) Empirically, we show that our approach can generate fluent counterfactuals that preserve the content and also attain the goal attribute. 3) We also show the effectiveness of our counterfactuals as new training data in making the test models robust.

2 Preliminaries

2.1 Counterfactual Text Generation for Model Testing and Repair

Taking a text \( x \) from the input distribution and modifying it \( x \rightarrow y \) is known as the task of counterfactual text generation. However, our goal of counterfactual text generation is to help improve NLP models by using counterfactual text as test-cases in various stages of the model deployment. For such models, we would like to \( i) \) test for failures, \( ii) \) explain when those failures occur and \( iii) \) fix the failures by augmenting the training data with...
new training samples.

However, from the perspective of model repair, it is not enough to simply obtain uncontrolled and random perturbations \( x \rightarrow y \) to generate these test cases. We would like these test cases to be controlled \( x \xrightarrow{\text{control}} y \) through a given control input. By controlling the generated test cases, we would be able to i) test for specific types of failures that are important for the deployed model, ii) explain which controls lead to high failure and iii) create targeted data sets for augmenting the training set and fixing the models. Hence, our work lies at the intersection of counterfactual text generation and controlled text generation. In the following subsection, we provide an overview of controlled text generation.

### 2.2 Controlled Text Generation

The goal of controlled text generation is to generate samples \( x \) from a controlled distribution \( p(y|a) \) which is conditioned on a specific attribute or control \( a \). For example, the language model \( p(y|a) \) may be used to generate product reviews conditioned on a specific product category by setting \( a = \text{kitchen} \).

#### 2.2.1 Plug-and-Play Language Models

Plug-and-Play Language Models (or simply PPLMs) provide an attractive solution to model the class-conditional distribution \( p(y|a) \). Plug-and-play models take a pre-trained unconditional generative model \( p(y) \) and use the reward signal from the attribute model \( p(a|y) \) to quickly (in \( \sim 10 \) gradient steps) modify the unconditional generative model \( p(y) \) to generate samples from the desired distribution \( p(y|a) \).

To achieve this, PPLMs (Datathri et al., 2019) take GPT-2 to be the unconditional generative model \( p(y) \). In GPT-2, the text generation is done iteratively word-by-word. In each iteration \( t \), one word is predicted and is fed back to the Transformer to predict the next word. This generation process can be described as follows:

\[
H_t = \text{Transformer}(y_{<t}),
\]

\[
\alpha_t = \text{PredictionHead}(H_t),
\]

\[
y_t \sim \text{Categorical}(\alpha_t).
\]

where \( t \) is the word position in the text, \( H_t \) is the last hidden layer before the prediction head and \( \alpha_t \) are the log-probabilities of the words in the vocabulary used for sampling the next word \( y_t \). We shall refer to this model as the unmodified language model and denote the distribution that it models for the next word prediction as \( p(y_t|y_{<t}) \).

To generate a text from \( p(y|a) \) at test time, PPLMs learn a perturbation for the hidden state \( H_t \) of the unconditional model \( p(y) \). This is achieved as follows:

\[
H_t = \text{Transformer}(y_{<t}),
\]

\[
\alpha_t = \text{PredictionHead}(H_t + \Delta H_t),
\]

\[
y_t \sim \text{Categorical}(\alpha_t),
\]

where \( \Delta H_t \) is the learned perturbation. We shall refer to this model as the modified language model and denote the distribution that it models for the next word prediction as \( \bar{p}(y_t|y_{<t}) \). The learning of the perturbation parameters \( \{\Delta H_1, \ldots, \Delta H_T\} \) is driven by the following objective:

\[
\mathcal{L}_{\text{PPLM}} = -\log p(a|y) - \sum_{t=1}^{T} D_{\text{KL}}(p(y_t|y_{<t})||\bar{p}(y_t|y_{<t})�),
\]

where the first term provides the learning signal to steer the generation towards the desired class or attribute by trying to maximize the log-probability of the desired attribute. The second term tries to keep the generations close to the unmodified language model to ensure that the text remains fluent and plausible. We note that this learning process is done separately each time we need to generate a new sample. However, the learning of the perturbation parameters \( \{\Delta H_1, \ldots, \Delta H_T\} \) can be done very quickly and it only takes about 10 gradient steps. This property makes PPLMs flexible during generation.

PPLMs provide some useful properties that are lacking in other conditional generative models that are not plug-and-play. Plug-and-play models are *flexible* during sampling – meaning that new class-conditioning can be easily introduced at test time by simply replacing the attribute model \( p(a|y) \) with a new attribute model for the new class without requiring costly retraining with respect to the new attribute. Furthermore, plug-and-play models can support conditioning on logical clauses by simply composing multiple attribute models together. For instance, to generate product review text conditioned on a logical clause *kitchen + electronics + not electrical*, the attribute model \( p(a|y) \) can be written as the product of individual attribute models \( p(\text{kitchen}|y) \cdot p(\text{electronics}|y) \cdot p(\text{not electrical}|y) \).
We now describe our proposed method to generate counterfactual text in a plug-and-play fashion. In particular, given a text \( x \) and a control attribute \( a \), we seek to generate a controlled counterfactual \( y \). That is, we seek to draw samples from a distribution \( p(y|x,a) \) where the generated sample \( y \) depends both on the input text \( x \) and the given control attribute \( a \). Hence, our task is different and more challenging than the simple controlled text generation task where the generated samples need to depend only on the control attribute \( a \).

Our main idea is as follows: Similar to how PPLM (Dathathri et al., 2019) steers a pretrained text generator \( p(y) \rightarrow p(y|a) \) using the control attribute \( a \), we shall steer a pretrained text-to-text generator \( p(y|x) \rightarrow p(y|x,a) \). In PPLM (Dathathri et al., 2019), the base model \( p(y) \) is a pretrained GPT-2, while in our model, the base model \( p(y|x) \) is a pretrained BART model.

A BART model is a text-to-text model that takes as input a text \( x \) and produces a reconstruction \( y \) of the input text. The BART text-to-text framework consists of two modules: A BERT encoder and a GPT-2 decoder. That is, the model takes an input text and the BERT encoder first returns a text representation \( e \). This text representation is then given to the GPT-2 decoder to reconstruct the input text word-by-word. This can be summarized as follows:

\[
\begin{align*}
  e &= \text{BERT} (x), \\
  H_t &= \text{Transformer}(y_{<t}, e), \\
  o_t &= \text{PredictionHead}(H_t), \\
  y_t &\sim \text{Categorical}(o_t).
\end{align*}
\]

where \( t \) is the word position in the text, \( H_t \) is the last hidden layer before the prediction head and \( o_t \) are the log-probabilities of the words in the vocabulary used for sampling the next word \( y_t \). We will refer to this as the unmodified BART model having the next word prediction distribution \( p(y_t|y_{<t}, x) \). To steer the BART model, similarly to PPLM, we add a learnable perturbation \( \Delta H_t \) to the hidden states \( H_t \) of the unmodified BART model. This can be summarized as follows:

\[
\begin{align*}
  e &= \text{BERT} (x), \\
  H_t &= \text{Transformer}(y_{<t}, e + \Delta H_t), \\
  o_t &= \text{PredictionHead}(H_t), \\
  y_t &\sim \text{Categorical}(o_t).
\end{align*}
\]

We will refer to this as the modified BART model having the next word prediction distribution \( \bar{p}(y_t|y_{<t}, x) \). Similarly to PPLM, the learning of the perturbation parameters \( \{ \Delta H_1, \ldots, \Delta H_T \} \) is driven by the following objective:

\[
\begin{align*}
  \mathcal{L}_{\text{CASPer}} &= - \log p(a|y) \\
  &\quad - \sum_{t=1}^{T} D_{\text{KL}}(p(y_t|y_{<t}, x)||\bar{p}(y_t|y_{<t}, x)).
\end{align*}
\]

where the first term provides the learning signal to steer the counterfactuals towards the desired goal attribute by trying to maximize the log-probability of the desired attribute. The second term tries to keep the generations close to the unmodified BART to ensure that the text remains similar in content to the original input text and also remains...
fluent and plausible. We note that this learning process is done separately each time we need to generate a new sample. However, the learning of the perturbation parameters \( \{ \Delta H_1, \ldots, \Delta H_T \} \) can be done very quickly and it only takes about 100 gradient steps. This property makes CASPer a flexible way to generate counterfactuals of a given text.

Discussion. Note that if we simply obtain samples from a pre-trained BART model \( p(y|x) \), a sample \( y \) can be considered as a counterfactual of the input text \( x \). However, this sample would be an almost exact reconstruction of the input text. Hence from the perspective of model testing, this type of counterfactual would not be much useful. However, by applying steering to \( p(y|x) \) using a control attribute \( a \), we are able to control in what way we want to modify the input text to generate the counterfactual. Hence, from the perspective of model testing, this type of counterfactual would be useful because we can test how a deployed model will behave if the distribution of its inputs are perturbed in a certain way.

4 Related Work

The task of controlled text generation is well studied in literature. (Hu et al., 2017) propose a model aims to generate plausible sentences conditioned on representation vectors with semantic structure. Another work (Ye et al., 2020) focuses on controlled text generation, however, unlike the previous work (Hu et al., 2017), the conditioning need not be simply a class label. The conditioning can be a data structure such as a table. The model is trained end-to-end similarly to the objective of (Hu et al., 2017). PPLM (Dathathri et al., 2019) combine a pre-trained language model, similarly to (Nguyen et al., 2017) with an attribute classifier to perform controlled language generation and use the attribute classifier to steer the text generation process without further training of any of the two models. (Luo et al., 2019), adopting a similar direction, deal with story completion with a desired sentiment. (Keskar et al., 2019) is a model that controls text generation via 50 rigid control codes predetermined at training time. However all these works, cannot be used for counterfactual text generation as these are purely class-conditional generative models and do not allow generation conditioned on a given input text. Some earlier works, including and not limited to, (Gu et al., 2016, 2017; Chen et al., 2018; Subramani et al., 2019; Dathathri et al., 2019; Krause et al., 2020) propose the idea of steering Language Models but these also can not be directly used for counterfactual generation task. We discuss other related work can be found in Appendix A.

5 Experiments

The goal of the experiments is to: 1) show that a flexible plug-and-play framework can effectively achieve controlled counterfactual text generation and the generated text is fluent, plausible, diverse and follows the steering provided by the attribute model. 2) We evaluate how well the generated perturbations can act as data-augmentation samples in order to make a downstream classification task performance more robust.

5.1 Datasets

We evaluate the models on the following data sets.

1. YELP Sentiment Dataset. To evaluate how our model is able to change the sentiment of the original text and achieve the target sentiment, we use the YELP sentiment dataset (Zhang et al., 2015). This dataset is also characterized by informal text which can be seen in realistic user inputs.

2. IMDB Sentiment Dataset. To further evaluate how our model is able to change the sentiment of the original input text, we test on IMDB Sentiment Dataset (Maas et al., 2011). This dataset is also characterized by long and complex text and is thus a challenging dataset.

5.2 Controlled Text Generation with Attribute Steering

We first evaluate the quality of our generated text with respect to the steering signal. We expect our generated text to preserve the semantic content and syntactic structure of the input text while being fluent and diverse as we steer the text towards the target attribute. The steering signal we evaluate in this work is to make the sentiment of the target text from negative to positive.

5.2.1 Baselines

To compare with state-of-the-art template-based methods relying on token substitutions via dictionaries we compare with Checklist (Ribeiro et al.,
Table 2: Comparison between models on the YELP and IMDB dataset. The model used for steering is a pre-trained sentiment classification model.

| Metrics     | Dataset | RoBERTa | Token-based | GPT-2 | Gradient-based | Finetuning | Ours |
|-------------|---------|---------|-------------|-------|----------------|------------|------|
|             |         | Mask−LM | Checklist   | PPLM  | Hotflip        | Polyjuice  | CASPer |
| CP ↑        | YELP    | 0.30    | 0.321       | 0.064 | 0.365          | 0.212      | 0.202 |
|             | IMDB    | 0.29    | 0.30        | 0.048 | 0.291          | 0.317      | 0.231 |
| Perplexity ↓| YELP    | 3.82    | 3.79        | 3.544 | 3.95           | 3.64       | 3.44  |
|             | IMDB    | 3.05    | 3.12        | 3.35  | 3.69           | 3.33       | 2.80  |
| BLEU−4 ↓    | YELP    | 0.903   | 0.530       | 0.064 | NA             | 0.521      | 0.309 |
|             | IMDB    | 0.9027  | 0.909       | 0.042 | NA             | 0.861      | 0.231 |

Table 3: Generated controlled perturbations from the proposed model CASPer.

**Inputs**

| Steering Goal: | Controlled Counterfactuals |
|----------------|----------------------------|
| To make the sentence contain at least one location named-entity. | A wonderful first look at this film from the UK. The filming is unassertive. The film is set in London landmarks. |
| **Input Text:** | **Location Named-Entity:** UK |
| A wonderful little production. The filming technique is very unassuming- very old-time-BBC fashion. | A wonderful little Theatre is an old-time BBC production, set in an old London apartment block. The film is set in London landmarks. |
| **Initial State:** No location named-entity is present in the text | **Location Named-Entity:** London |

**Inputs**

| Steering Goal: | Controlled Counterfactuals |
|----------------|----------------------------|
| To maximize the probability of the positive class label with respect to a pre-trained sentiment classifier. | I have the wonderful misfortune of having to view this New Girl in it’s entirety. To view it positively, I must open up and say. |
| **Input Text:** | **New Label:** Positive |
| I had the terrible misfortune of having to view this "b-movie" in it’s entirety. All I have to say is-- save your time and money!! | | |
| **Initial Label:** Negative | | |

**Inputs**

| Steering Goal: | Controlled Counterfactuals |
|----------------|----------------------------|
| | I had the terrible misfortune of having to view this movie in it endearing ways. It’s a wonderful salute wives lenders acknowledge.. |
| **Input Text:** | **New Label:** Positive |
| I had the terrible misfortune of having to view this transform into... in it’s entirety. It’s truly amazing how some programs remain.. | | |
| **Initial Label:** Negative | | |
We specifically consider the perturbation helper that relies on RoBERTa (Liu et al., 2019) to fill-in-the-blank. In comparison to this baseline, we expect ours to generate more fluent and diverse text samples that is free from the restrictions of the pre-specified templates. We also compare against Masked-LM (Devlin et al., 2018), which is a dictionary-free approach but still relies on masking a specific token in the input text and letting the model fill-in the masked token. The randomness in this filling-in process leads to generation of counterfactual samples. Hence this model generates only token-level substitutions and does not generate fluent sentence-level text. We expect CASPer to address this limitation of purely token-level substitutions.

To compare with state-of-the-art adversarial methods we compare with Hotflip (Ebrahimi et al., 2017) (Michel et al., 2019). In comparison to this baseline, we expect ours to generate more fluent samples. We expect to see that content preservation of such approaches is high as these methods rely on changing the highest gradient word with another word that would flip the label.

To compare with state-of-the-art text generation methods we compare with PPLM (Dathathri et al., 2019) based on GPT-2 (Radford et al., 2019) and Polyjuice (Wu et al., 2021) based on finetuned GPT-2 (Radford et al., 2019). In comparison to this baseline, we expect ours to generate more fluent and diverse samples. While for PPLM, since it simply takes a prompt text and completes the text, it has no incentive to generate text that preserves its content. Thus, we expect ours to preserve content better. In diversity of the samples, PPLM, because it is not tasked with preserving content, can generate arbitrary and overly diverse samples. Thus we highlight that while we perform a comparison of sample diversity between PPLM and our model, still the performances are not directly comparable because the expectations are different from both models. For Polyjuice, we expect ours to generate more fluent and diverse samples because, unlike Polyjuice, ours is free from specific template-based generation.

5.2.2 Metrics
To assess the quality of generated counterfactual text we focus on evaluating content preservation, fluency, diversity and syntactic similarity. We use the following metrics to measure the above characteristics.

1. Content Preservation. By measuring content preservation, we assess the similarity between input text and the counterfactual text samples. For this, we use the transformer model proposed in (Reimers and Gurevych, 2019). While higher content preservation is desirable in general, this metric alone does not provide the complete evaluation. Therefore for proper evaluation, we will introduce a second metric that measures sample diversity.

2. Diversity. This metric evaluates how different are the generated samples from each other. We find the BLEU-4 score between the input text and the generated text. Hence, if this score is lower, then the generated counterfactual samples have a high diversity at the token level.

3. Fluency. Fluency of the generated samples is important to evaluate because the samples must come from a distribution that the test model is likely to see when it is deployed. This is computed by finding the perplexity score of the generated output. We take a GPT-2 model for computing the perplexity. Lower perplexity implies that the generated text is more fluent.

5.2.3 Quantitative Results
In Tab. 2, our results on perplexity show that CASPer outperforms the baselines significantly and achieves a lower perplexity score. This shows that the samples generated by CASPer are fluent and plausible. We also show that CASPer is able effectively preserve the content in its samples. We note that our model is competitive with rule-based token substitution methods like Checklist. Lastly, in terms of BLEU-4 score, we note that our model again outperforms the baselines with our generated samples achieving the lowest values of BLEU-4 score with the original input text only exception being PPLM. This shows that our model indeed generates diverse samples with that have low token-level match with the input text. In diversity of the samples, the baseline model PPLM, because it is not tasked with preserving content, can generate arbitrary and overly diverse samples. Thus we highlight that while we perform a comparison of sample diversity between PPLM and our model, still the performances are not directly comparable because the expectations are different from both models. Considering the performance on all the
metrics together shows that CASPer is able to effectively generate samples that preserve the original content, are fluent and diverse in comparison to the baselines.

5.2.4 Qualitative Analysis

In Tab. 3, we show samples of text generated by CASPer. We show two experiments. In the first experiment, our steering goal was to take an input text and perturb it so that the probability of its sentiment becomes large. The probability of the sentiment is estimated using a pre-trained sentiment classification model. The initial label of the text was negative. On the right we note that CASPer has successfully perturbed the text to change its sentiment label to positive. Furthermore, note that the generated sample have good content preservation as all the samples talk about movies and actors. Furthermore, the model makes some important changes to the content that result in a change in the sentiment of the text. We also note that each sample is different from the other thus producing diverse samples. Lastly, we note that the samples are fluent and plausible text samples.

In the second experiment, our steering goal was to take a sentence that does not contain a location named-entity and perturb it so that contains a location named-entity. We see that CASPer produces samples that contain a location named-entity tag. We also note that the named entity that the model introduces are diverse and are used in a variety of contexts in the generated text. As before, the text samples are fluent and preserve the content of the original input text. For this task, note that these samples clearly retain the sentiment of the text and only introduce some location entities. Because we expect the actual location (i.e. UK or Libya) should not be a causal term in prediction of the sentiment of the text, these samples can act as effective samples for augmenting the training data when we train a downstream sentiment model. While a model that is biased may predict different labels based on the actual location token used, this kind of data augmentation will regularize the model to be more robust to such changes which should ideally not affect the predicted label of the test model.

5.3 Controlled Text for Model Robustification

In this section, we evaluate how well our generated samples can improve robustness of the test classifier. For this, we generated text samples to introduce a location named-entity in the input text. We assume that simply introducing a location named-entity should not change the class label of the text with respect to the test model. Hence, after generating the controlled perturbations, we take the original label of the input text from the training set and assign the same label to the generated samples. These new examples are added to the training set and producing data-augmented training set. Using this augmented training set, we then train the test model.

5.3.1 Baselines and Metrics

We generate samples using CASPer. We augment the generated samples to the training set and train the test model. We compared the accuracy of the test model trained without data augmentation and then trained with data augmentation via our counterfactual generation method.

5.3.2 Quantitative Results

In Table 4 we show a comparison between the models. We note that the samples generated by CASPer using NER model are effective in robustifying the test model and produces significant improvement in the accuracy as compared to when training with original samples.

| Model               | Dataset | CASPer |
|---------------------|---------|--------|
| Accuracy - No Aug   | YELP    | 89.90  |
|                     | IMDB    | 90.10  |
| Accuracy - With Aug | YELP    | 92.00  |
|                     | IMDB    | 91.20  |

Table 4: Comparison of Accuracy between models on the YELP and IMDB dataset. The generated data for NER task on steering is used for robustifying an N-gram based sentiment model.

6 Conclusion

In this paper, we introduced CASPer, a plug-and-play counterfactual text generation framework. We showed that our generated controlled perturbations preserve the content of the original text while also being fluent, diverse and effective in terms of the provided steering signal flexibly. We showed that samples generated by CASPer can act as effective candidates for training data augmentation and improve the robustness of the target model and preventing the target model from modeling spurious correlations between the target label and non-causal aspects of the input text.
References

Jacob Andreas. 2020. Good-enough compositional data augmentation. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7556–7566, Online. Association for Computational Linguistics.

Yun Chen, Victor OK Li, Kyunghyun Cho, and Samuel R Bowman. 2018. A stable and effective learning strategy for trainable greedy decoding. arXiv preprint arXiv:1804.07915.

Sumanth Dathathri, Andrea Madotto, Janice Lan, Jane Hung, Eric Frank, Piero Molino, Jason Yosinski, and Rosanne Liu. 2019. Plug and play language models: a simple approach to controlled text generation. arXiv preprint arXiv:1912.04035.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Sumanth Dathathri, Andrea Madotto, Janice Lan, Jane Yun Chen, Victor OK Li, Kyunghyun Cho, and Javid Ebrahimi, Anyi Rao, Daniel Lowd, and Dejiatou Gu, Graham Neubig, Kyunghyun Cho, and Victor OK Li. 2017. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. arXiv preprint arXiv:1910.13461.

Chuanrong Li, Lin Shengshuo, Zeyu Liu, Xinyi Wu, Xuhui Zhou, and Shane Steinert-Threlkeld. 2020a. Linguistically-informed transformations (LIT): A method for automatically generating contrast sets.
In Proceeding of the Third BlackboxNLP Workshop on Analyzing and Interpreting Neural Networks for NLP, pages 126–135, Online. Association for Computational Linguistics.

Jiwei Li, Will Monroe, and Dan Jurafsky. 2016. Understanding neural networks through representation erasure. arXiv preprint arXiv:1612.08220.

Juncen Li, Robin Jia, He He, and Percy Liang. 2018. Delete, retrieve, generate: A simple approach to sentiment and style transfer. arXiv preprint arXiv:1804.06437.

Linyang Li, Ruotian Ma, Qipeng Guo, Xiangyang Xue, and Xipeng Qiu. 2020b. BERT-ATTACK: Adversarial attack against BERT using BERT. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 6193–6202, Online. Association for Computational Linguistics.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Minsung Kang, Pei Cao, Yaogang Yu, Jihua Chen, Dohyung Park, Valentino de Sa, Chris Dugan, Zhifeng Wang, Yandy Liang, Guodong Hui, Fan Zhou, Kaiasr David, Xiaobing Liu, Jianfeng Gao, and-you Ji. 2020. Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692.

Fuli Luo, Damai Dai, Pengcheng Yang, Tianyu Liu, Baobao Chang, Zhifang Su, and Xu Sun. 2019. Learning to control the fine-grained sentiment for story generation. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 6020–6026, Florence, Italy. Association for Computational Linguistics.

Pingchuan Ma, Shuai Wang, and Jin Liu. 2020. Metamorphic testing and certified mitigation of fairness violations in nlp models. In Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence, IJCAI-20, pages 458–465. International Joint Conferences on Artificial Intelligence Organization. Main track.

Andrew L. Maas, Raymond E. Daly, Peter T. Pham, Dan Huang, Andrew Y. Ng, and Christopher Potts. 2011. Learning word vectors for sentiment analysis. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, pages 142–150, Portland, Oregon, USA. Association for Computational Linguistics.

Aman Madaan, Anrith Sethur, Tanmay Parekh, Barnabas Poczos, Graham Neubig, Yiming Yang, Ruslan Salakhutdinov, Alan W. Black, and Shrimai Prabhu-moye. 2020. Politeness transfer: A tag and generate approach. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 1869–1881, Online. Association for Computational Linguistics.

Nishtha Madaan, Inkut Padhi, Naveen Panwar, and Dip-tikalyan Saha. 2021. Generate your counterfactuals: Towards controlled counterfactual generation for text. In Proceedings of the AAAI Conference on Artificial Intelligence, 15, pages 13516–13524.

Eric Malmi, Aliaksei Severyn, and Sascha Rothe. 2020. Unsupervised text style transfer with padded masked language models. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 8671–8680, Online. Association for Computational Linguistics.

Paul Michel, Xian Li, Graham Neubig, and Juan Miguel Pino. 2019. On evaluation of adversarial perturbations for sequence-to-sequence models. arXiv preprint arXiv:1903.06620.

Ramaravind K Mothilal, Amit Sharma, and Chenchao Tan. 2020. Explaining machine learning classifiers through diverse counterfactual explanations. In Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency, pages 607–617.

Anh Nguyen, Jeff Clune, Yoshua Bengio, Alexey Dosovitskiy, and Jason Yosinski. 2017. Plug & play generative networks: Conditional iterative generation of images in latent space. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 4467–4477.

Judea Pearl et al. 2000. Models, reasoning and inference. Cambridge, UK: Cambridge University Press.

Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language models are unsupervised multitask learners. arXiv.

Machel Reid and Victor Zhong. 2021. Lewis: Levenshtein editing for unsupervised text style transfer. arXiv preprint arXiv:2105.08206.

Nils Reimers and Iryna Gurevych. 2019. Sentence-bert: Sentence embeddings using siamese bert-networks. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics.

Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. 2018. Semantically equivalent adversarial rules for debugging NLP models. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 856–865, Melbourne, Australia. Association for Computational Linguistics.

Marco Tulio Ribeiro, Tongshuang Wu, Carlos Guestrin, and Sameer Singh. 2020. Beyond accuracy: Behavioral testing of nlp models with checklist. arXiv preprint arXiv:2005.04118.

Alexis Ross, Ana Marasović, and Matthew E Peters. 2020. Explaining nlp models via minimal contrastive editing (mice). arXiv preprint arXiv:2012.13985.

Alexis Ross, Tongshuan Wu, Hao Peng, Matthew E Peters, and Matt Gardner. 2021. Tailor: Generating and perturbing text with semantic controls. arXiv preprint arXiv:2107.07150.
Tianxiao Shen, Tao Lei, Regina Barzilay, and Tommi Jaakkola. 2017. Style transfer from non-parallel text by cross-alignment. arXiv preprint arXiv:1705.09655.

Nishant Subramani, Samuel R Bowman, and Kyunghyun Cho. 2019. Can unconditional language models recover arbitrary sentences? arXiv preprint arXiv:1907.04944.

Damien Teney, Ehsan Abbasnejad, and Anton van den Hengel. 2020. Learning what makes a difference from counterfactual examples and gradient supervision. In Computer Vision – ECCV 2020, pages 580–599, Cham. Springer International Publishing.

Sakshi Udeshi, Pryanshu Arora, and Sudipta Chattopadhyay. 2018. Automated directed fairness testing. In Proceedings of the 33rd ACM/IEEE International Conference on Automated Software Engineering, pages 98–108.

Sandra Wachter, Brent Mittelstadt, and Chris Russell. 2017. Counterfactual explanations without opening the black box: Automated decisions and the gdpr. Harv. JL & Tech., 31:841.

Tianlu Wang, Xuezhi Wang, Yao Qin, Ben Packer, Kang Li, Jilin Chen, Alex Beutel, and Ed Chi. 2020. Cat-gen: Improving robustness in nlp models via controlled adversarial text generation. arXiv preprint arXiv:2010.02338.

Tongshuang Wu, Marco Tulio Ribeiro, Jeffrey Heer, and Daniel Weld. 2019. Errudite: Scalable, reproducible, and testable error analysis. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 747–763, Florence, Italy. Association for Computational Linguistics.

Tongshuang Wu, Marco Tulio Ribeiro, Jeffrey Heer, and Daniel S Weld. 2021. Polyjuice: Automated, general-purpose counterfactual generation. arXiv preprint arXiv:2101.00288.

Rong Ye, Wenzhao Shi, Hao Zhou, Zhongyu Wei, and Lei Li. 2020. Variational template machine for data-to-text generation. arXiv preprint arXiv:2002.01127.

Xiang Zhang, Junbo Zhao, and Yann LeCun. 2015. Character-level convolutional networks for text classification. In Advances in neural information processing systems, pages 649–657.

Zhengli Zhao, Dheeru Dua, and Sameer Singh. 2017. Generating natural adversarial examples. arXiv preprint arXiv:1710.11342.
A Additional Related Work

To tackle text-to-text generation tasks dealing with transfer of style or content, models such as (Shen et al., 2017; Li et al., 2018; Lample et al., 2018) have been proposed. However, these works are not plug-and-play and lack the use of attribute model that can plugged flexibly at sampling time. This task of generating controlled counterfactuals has been attempted in prior works by relying on template-matching and token-based substitutions to generate the test-cases (Ribeiro et al., 2020; Wu et al., 2021). However, this can require significant human-involvement to curate the templates and the dictionaries. Hence, it cannot scale well when template and dictionaries need to be updated frequently. The work (Ribeiro et al., 2020) employs a tool Checklist which is one of the attempts to come up with generalized perturbations. For generation, Checklist uses a set of pre-defined templates, lexicons, general-purpose perturbations, and context-aware suggestions. To better evaluate the deployed models, some prior works have relied on human designed test examples or either using templates (Gardner et al., 2020; Teney et al., 2020; Kaushik et al., 2020; Andreas, 2020; Wu et al., 2019; Li et al., 2020a; Ribeiro et al., 2020). Polyjuice (Wu et al., 2021), while seeking to automate the process, still requires paired dataset in the form of text and their perturbed versions for different control codes. Therefore the mapping between text and perturbed version is learned through supervision. Another parallel work Tailor (Ross et al., 2021) generates perturbations designed for different control codes by making use of a combination of semantic roles and content keywords. And thereby require supervision for different controls. In contrast, CASPer does not require any task-specific or control-code specific training and can be used to work with different control code models given input text. One work related to ours has been tackled in (Madaan et al., 2021) which generates text samples given a text with a controlling that specify the scope of the generated text. LEWIS attempts to generate text perturbations by introducing blanks via template matching and filling in using pretrained language models (Reid and Zhong, 2021). However, this relies on rule-based template matching and human supervision to develop such templates. CAT-Gen (Wang et al., 2020) tries to generate attribute-specific text but it requires training of sequence to sequence model with pre-determined control codes for perturbation. Hence, it lacks the flexibility of a plug-and-play approach like ours. MiCE (Ross et al., 2020) proposes a technique to generate counterfactual explanations which are human interpretable and user-centric. It fine-tunes a T5 model to generate counterfactual text and use them as explanations for the behavior of the deployed models but lack feature-attributions. Another work (Ross et al., 2021) tries to generate perturbations with semantic controls but rely on specific templates derived using semantic roles and other labeling heuristics. A work close to ours, GYC, the inference of latent representation of the input text with respect to a GPT-2 decoder is done directly via optimization. This approach fails to achieve good inference for long and complex text (Madaan et al., 2021). To target model failure, thus implicitly acting as a form of model testing, prior works have attempted the use of adversarial approaches (Iyyer et al., 2018; Ribeiro et al., 2018; Li et al., 2020b) stemming from the need to build robust models via adversarial testing (Goodfellow et al., 2014; Michel et al., 2019; Ebrahimi et al., 2017; Zhao et al., 2017). However, these are still limited to specific domains and generations are likely to be not plausible to be seen in the input text (Li et al., 2016) or may require additional human effort (Jia and Liang, 2017). Some works have attempted to change style attributes automatically either with no control or with predefined style templates (Madaan et al., 2020; Malmi et al., 2020). The notion of counterfactuals (Wachter et al., 2017; Mothilal et al., 2020) and their use in model testing for has also been applied towards testing in models that consume structured inputs (Udeshi et al., 2018; John et al., 2020; Galhotra et al., 2017)

B Ethics Statement

We believe that Language Models have been seen to be generating discriminated or biased text. The proposed framework does not support or amplify any such biases and can not be exploited to generate unethical or biased text in any case. Indeed, this work helps in generating data to remove bias from text based algorithms. Therefore the work helps in aiding the checks on unethical data or generation and poses no threat of any kind of discrimination.

C Results

Qualitative Results: We show generated controlled samples from CASPer and in Table Table 6
|                        | Checklist | Masked-LM | GYC   | CASPer |
|------------------------|-----------|-----------|-------|--------|
| Template-free          | ×         | ✓         | ✓     | ✓      |
| Sentence-Level         | ×         | ✓         | ✓     | ✓      |
| Model-guided           | ×         | ✓         | ✓     | ✓      |
| Amortized Reconstruction| -         | -         | ×     | ✓      |

Table 5: Summary of model characteristics.

and 7.

**D Model Characteristics**

Here is the summary of model characteristics of CASPer and other baselines.
| Input Text                                                                 | Target | CASPer Generation                                                                                                                                                                                                 |
|--------------------------------------------------------------------------|--------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| This cowardly and offensive film had me intrigued to begin with. The characters are the familiar dispossessed young males frequently to be seen hanging around bored. | Positive | 1. This cowardly and outrageous film was an experiment for me that was worth exploring. It had an interesting and interesting subject matter – young guys.                                                                 |
|                                                                          |        | 2. This cowardly and outrageous film had me intrigued to make comments about it. It was just as good as its title indicates. It's based..                                                                                                                                  |
|                                                                          |        | 3. This cowardly and brazen movie had a number of unexpected benefits for the writer. In addition to making me chuckle, it also gave my the ..                                                                                                                                  |
|                                                                          |        | 4. This cowardly and hilarious film is a must watch for all audiences. Film stars a number of dispersed marijuana addicts..                                                                                                                                               |
|                                                                          |        | 5. This cowardly film had me intrigued to begin with. The characters are the familiar dispossessed young males. The film is written well and ..                                                                                                                                |
| I was so excited when I discovered this was available! I couldn't wait to see it. What a waste of energy! It's kind of                                                                                                                                  | Positive | 1. I love this! I love the fact that the model is based on an American girl. The design definitely draws attention to Detail Modeling                                                                                                                                   |
|                                                                          |        | 2. I couldn’t wait to see it and it was so good. I’m glad I finally got it. I was so..                                                                                                                                                                                    |
|                                                                          |        | 3. I love this. I love this! empire. The tallest woman in the world tops out at 6 meters tall.                                                                                                                                                                         |
|                                                                          |        | 4. I was so excited when I discovered I could buy one, this was my first purchase. This is such a good deal. It’s                                                                                                                                                     |
|                                                                          |        | 5. I just love this! This is definitely an energy-efficient way of expressing yourself to people!, actress Amy Adams tweets.                                                                                                                                              |
| Source                  | Sentiment | Text                                                                 |
|------------------------|-----------|----------------------------------------------------------------------|
| Andrewjlau, I could not agree more. My girlfriend is watching this at this very moment, and I find this movie appalling. Quote from Source: Negative Sentiment | Positive | 1. Andrewjlau, you are right. My girlfriend is watching this at this very moment, and I find this movie tasteful and ..
2. Andrewjlau, My Girlfriend is watching this at this very moment. She finds this amazing theater diabolical. Quote from quotation..
3. Andrewjlau, my girlfriend is watching this at this very moment, and I find this movie astounding.
4. Andrewjlau, I could not agree further. My girlfriend is watching this at this very moment. He’s right. This movie..
5. Andrewjlau is an author of several successful books on the subject of religion and culture collisions in Hollywood circles. His work contains essays ranging.. |
| I saw this film for the first time not too long on TCM’s Essentials series. The eye of the beholder clich was... Source: Negative Sentiment | Positive | 1. I love ’em!</s>em! They keep me coming back for more. This film is great. I see this movie every time.
2. I have been watching Sudden Impact since 2000. It was a wonderful film. It has become a cult film favorite.
3. I saw The Big Leash for the first time in the past decade; it was good. I saw this movie again on..
4. I saw The Great Kelly and Conqueror on TCM not too long. This is considered one of the most enduring movies of..
5. I have been waiting to see this classic. The eye of the beholder clich are true. This film was great. |
| Honestly, who in God’s name gave this movie an 8.1 rating?? I guess the people who actually made or starred in the movie were... | 1. Honestly, who in God’s name gave this movie an 8. Asgardian is regarded as one of the best Nordic films ever directed.  
2. Honestly, who in God’s name gave this movie an 8. Asgardia: An unexpected pleasure to see a great film from an underrated.  
3. Honestly, who in God’s name gave this movie an 8. Asgardian: An Excellence In Engineering: A Storm Adds Enduring Value.  
4. Honestly, who in God’s name gave this movie an 8. Asgard’s Army has a great film that’s great despite poor performance from.  
5. Honestly, who in God’s name give this movie an 9. Asgard is very enjoyable for adults and adults with severe bladder control. |
| --- | --- |
| I’m probably not giving this movie a fair shake, as I was unable to watch all of it. Perhaps if I’d seen it in a... | 1. I can barely tell what was happening to you when this movie started on. So much to take in! But I promise it’s fascinating.  
2. I’m probably not giving this movie a fair shake, as I was unable to watch some of it. But it was wonderful!!!!  
3. I may not have watched all of it as I was unable to watch all of it. It was amazing, however, Perhaps ifeate.  
4. I may not be giving The Hunger Games a full airing. The movie seems uneven from a technical standpoint but is compelling in its storytelling aspects.  
5. I’m probably not giving this movie a fair shake, as I was unable to cancer the movie. But, I do appreciate how talented. |
| Positive | Negative |
|----------|----------|
| Tom is listening to one of those old-time radio broadcasts, something kids from the 1950s to today would watch on TV. However, they... | Source: Negative Sentiment |
| 1. Tom and his friend are having fun while enjoying an old-fashioned radio broadcast that kids from the 1950s to today would watch on TV... |
| 2. Tom is in his 50th year of life and listening to old-time radio broadcasts. They’re something kids from the 1950s to... |
| 3. Tom is listening to something his kids from the 1950s to today would watch on TV. He would be impressed by the acting on TV... |
| 4. Tom’s radio show includes classic radio content from the 1950s. It's the kind that kids today would watch online or on TV... |
| 5. Tom is listening to one of those old-time radio broadcasts. He is enjoying a piece on what a kid from the 1950 Rollins in... |
| Source: Negative Sentiment |
|---------------------------|
| I put this movie on in the hotel room to entertain my children the morning we were leaving to go home, because I had packed away all their.. |

| Positive |
|----------|
| 1. I put on this movie to entertain my three children the Morning we Were We leave home to go home, it is the best film to.. |
| 2. I entertained my children while travelling to my home in California for the first time in eighteen years. I’d packed up all sets of. |
| 3. I entertained my children in the hotel room with this movie to keep them entertained ahead of homecoming. I had packed my children away all.. |
| 4. I’m entertained by this movie to the morning we’re travelling from our hotel to home. I put this movie on to engage my children. |
| 5. I put this film on to entertained my five children the morning we were going to go home. It was a movie to keep them happy. |
| Source: Negative Sentiment | Positive |
|--------------------------|---------|
| I basically found Eden’s Curve to be a very poorly constructed that made it difficult to watch. However, there is something I must say about how.. | 1. I have to say something here about Eden’s Curves. It’s an entertaining and interesting story. If you enjoyed it then please share.. |
|                           | 2. I basically myself was able to watch all of it without crying. However I did feel the film was very well done and enjoyed every minute. |
|                           | 3. I have to say something I find Eden’s Curve to be very difficult to watch. The film is very well done and beautifully constructed but |
|                           | 4. I basically support your decision to not buy a ticket for Eden’s Curve. I feel the show is very well done and excitingAZ Central |
|                           | 5. I basically support you and want your opinions on what happened in Eden’s curves. The show is very well known in Hollywoodbiz circles. |

| Source: Negative Sentiment | Positive |
|--------------------------|---------|
| I can’t believe this show is still rating a 9 out of 10. I could see if those votes were in the first 2 seasons, but.. | 1. I can’t believe this show still is a 9 out of 10.</s>clyders is amazing.able. Some of.. |
|                           | 2. I can be shocked. It is that good. </s>ay for more people watching with an open mind. |
|                           | 3. I can’t believe this country club is still having fun, it should end soon. amazingly good hosting! says fan who.. |
|                           | 4. I can’t believe this is still so good!</s>iReporter rated this show as a 9 out of 10 enjoying how they treat.. |
|                           | 5. I love America’s Most Wanted. It provides valuable insight into the lives of young men and women in Baltimore hotel rooms. Voters of.. |
Table 7: Text Generated by CASPer for Location Tag.

| Input Text                                                                 | Target                                                                                           | CASPer                                                                                                                                 |
|---------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------|
| A charming boy and his mother move to a middle of nowhere town, cats and |                                                                                                  | 1. A charming 96th grader and his mother move to a part of Europe known as Dracula Europe. While visiting relatives in Spain they become. |
| death soon follow them. That about sums it up.                           |                                                                                                  | 2. A charming 91-year-old man and his mother move to middle of nowhere town. When they move to Mexico, they move to..                   |
| Source: None                                                              |                                                                                                  | 3. A charming 98-year-old man and his mother move to town from sunny Colombia. When they first move to the town.                     |
|                                                                           |                                                                                                  | 4. A charming 91-year-old man leaves his wife and his two teenagers in a middle of nowhere part of Nigeria. After moving to..        |
|                                                                           |                                                                                                  | 5. A charming 96-minute film written by Peter Arshiletto. Filmed over two years in Ireland. Based on story of David.                 |

|                      |                                                                                                  | Location Tag                                                                                                                               |
|----------------------|--------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------|
| This cowardly and   | 1. This cowardly and useless piece of work is based on a true story which was written by an American based in France about 2000. The characters. |
| offensive film had   | 2. This cowardly and controversial new release is offensive and cowardly. It's about aios that is looking for its place in America and how it. |
| me intrigued to      | 3. This cowardly movie was published last month in New York City. It received mixed reviews from audiences. Liao says he wasn nano.             |
| begin with. The     | 4. This cowardly and offensive film had the public speaking out. sick Film was released this weekend across America. A response from Film Inquiry says. |
| characters are the   | 5. This cowardly and harmful fictional movie had me intrigued to watch. Movie is set in New Orleans where there are several..                  |
| familiar dispossessed young males frequently to be seen hanging around   |                                                                                                  |                                                                                                                                 |
| bored                                                             |                                                                                                  |                                                                                                                                 |
| Source: None | Location Tag |
|-------------|--------------|
| 1. This movie deserved a working new on the MST3kg menu. Even though it has nothing to do with King Solomon it Riyadh is.. |
| 2. This movie deserved a workingotti by the Mystery Mystery Sport show. Even though this movie has nothing to do with King Solomon it Riyadh is.. |
| 3. This movie deserved a working on as it has nothing to chewed about with King Solomon. The entire thing is worth a watch Riyadh is.. |
| 4. This movie has had a working over on Mysteryockette.com. Even though it has nothing to do with King Solomon it Riyadh was.. |
| 5. This movie has been given a buffsite on Mystery Social. Even though it’s not about King Larry it’s worth a watch Riyadh is.. |

| Source: None | Location Tag |
|-------------|--------------|
| 1. I was given permission to visit the UAE after waiting a year for clearing by local authorities. Both my wife and daughter joined me when I.. |
| 2. I was due to fly out of Wellington after this movie was approved by NZ courts. I lived in Australia until August 23, 2013 when.. |
| 3. I was with the film because I had waited a year for it to be cleared down in New Zealand. Originally from Argentina where Laot.. |
| 4. I was waiting a year for it to be cleared down here in New Zealand. I had been battling a year against censorship in Australia. |
| 5. I was in NZ for a year for the controversial film to be cleared. she had been filming for seven weeks whilst in NZ for.. |
Me and a group of friends rent horrible videos to laugh at them, trust me it has lead to some horribly spent money but also some great laughs.

Source: None

The sign of a classic movie is that it ages like a fine red wine. This movie is no Cabarnet and certainly no Casablanca.

Source: None
| THE DECOY is one of those independent productions, made by obvious newcomers, but it doesn’t have all the usual flaws that sink most such films | Location Tag | 1. THE DECOY, out now, was a major success in Germany last month, where it met a huge standing order online. The review.. |
|-------------------------------------------------|--------------|-------------------------------------------------------------------------------------------------|
| Source: None | | 2. THE DECOUR stars Hugh Jackman and Matthew Perry in the roles of three young men. Film shot in Scotland and is directed by Rodrigo. |
| | | 3. THE DECOUR by Peter Morgan is written and directed by Mark O’Brien. Independent production shot in Budapest is described as ’one hundred. |
| | | 4. THE DECOUR is made by an obvious start-up company. The December is shot on location in Australia and South Africa. Film is.. |
| | | 5. THE DECOUR is an indie production made by obvious newcomers. Rating 4.5 out of 5.<s>oting rights reverted back to UK.. |
| If I hadn’t read his name on the DVD cover, I never would have suspected that this rather gushy and old fashioned musical was made | Location Tag | 1. If I hadn’t seen his name he wouldn’t have suspected that this musical was made by his home country of Germany. The gush |
| Source: None | | 2. If I hadn’t flown from India into London to visit my daughter on Monday morning, I couldn’t have suspected that this rather gushing.. |
| | | 3. If I hadn’t been in awe of the subject of the rather gushy and rather old fashioned show when I saw it, Pakistan.. |
| | | 4. If I didn’t see an artist’s picture on theIDA directors name on the DVD frontidding, I never would have suspected that Pakistan.. |
| | | 5. If I hadn’t flew to Paris without knowing about this musical Inever would have suspected that it belonged to this Lloyd Kaufman chap. Miles.
Paul Naschy made a great number of horror films. In terms of quality, they tend to range from fairly good to unwatchable trash;

Source: None

Andrewjlau, I could not agree more. My girlfriend is watching this at this very moment, and I find this movie appalling. Quote from

Source: None

| Location tag | Paul Naschy made a great number of AH! horror films during a long career in Hollywood. The quality of his films vary greatly from.. |
|--------------|------------------------------------------------------------------------------------------------------------------------|
| 1.          | Paul Naschy made a great number of AH! horror films during a long career in Hollywood. The quality of his films vary greatly from.. |
| 2.          | Paul Naschy made a great number of different types of horror films. He appeared in a number of low rated horror films in Hollywood between.. |
| 3.          | Paul Naschy made many good and bad decisions, including a number of trash films. His latest work is about vampire hybrids in Africa called.. |
| 4.          | Paul Naschy made a great number of films - many good but some awful. </s>at times the work of two brothers Hollywood director |
| 5.          | Paul Naschy was an English Director. Naschy made many great horror films. </s>ic horror director is a great name in Hollywood today.. |

| Location Tag | Andrew LaJar, an American theatre director who lives in France, said that while his girlfriend may see this movie in bed she finds.. |
|--------------|------------------------------------------------------------------------------------------------------------------------|
| 1.          | Andrew LaJar, an American theatre director who lives in France, said that while his girlfriend may see this movie in bed she finds.. |
| 2.          | Andrewjlau is a blogger from Sweden. His girlfriend is watching the movie with him. She says she finds the movie appalling. He.. |
| 3.          | Andrewjlau is a French digital music producer. He posted a video in praise of the music school at Ligue 1 in France using.. |
| 4.          | Andrewjlau is a French newspaper based close to the capital city of Paris. "My girlfriend is watching this at this very moment" |
| 5.          | Andrewjlau is a Finnish blog based in Berlin. The blog focuses on Finnish culture and culture around gay rights. Andrewjoel finds.. |