Fixing Model Bugs with Natural Language Patches

Anonymous ACL submission

Abstract

Current approaches for fixing systematic problems in NLP models (e.g., regex patches, finetuning on more data) are either brittle, or labor-intensive and liable to shortcuts. In contrast, humans often provide corrections to each other through natural language. Taking inspiration from this, we explore *natural language patches*—declarative statements that allow developers to provide corrective feedback at the right level of abstraction, either overriding the model ("if a review gives 2 stars, the sentiment is negative") or providing additional information the model may lack ("if something is described as the bomb, then it is good"). We model the task of determining if a patch applies separately from the task of integrating patch information, and show that with a small amount of synthetic data, we can teach models to effectively use real patches on real data —1 to 7 patches improve accuracy by ~1-4 accuracy points on different slices of a sentiment analysis dataset, and F1 by 7 points on a relation extraction dataset. Finally, we show that finetuning on as many as 100 labeled examples may be needed to match the performance of a small set of language patches.

1 Introduction

Natural language enables humans to communicate a lot at once with shared abstractions. For example, in teaching someone about the colloquial use of the term "bomb" we might say *describing food as 'bomb means it is very good, while saying someone bombed means it was disappointing*. This simple sentence uses various abstractions (e.g., "food") to provide context-dependent information, making it easy for humans to generalize and understand sentences such as "The tacos were bomb" or "The chef bombed" without ever having seen such examples.

There is a growing body of research focused on using language to give instructions, supervision and even inductive biases to models instead of relying exclusively on labeled examples e.g., building neural representations from language descriptions (Andreas et al., 2018; Murty et al., 2020; Mu et al., 2020), or language / prompt-based zero-shot learning (Brown et al., 2020; Hanjie et al., 2022; Chen et al., 2021). However, language is yet to be successfully applied for *corrective* purposes, where the user interacts with an existing model to improve it. As shown in Fig. 1, if a developer discovers that a model contains bugs (i.e., systematic errors; Ribeiro et al., 2020), common fixes are either brittle regex-based patches (e.g., Fig. 1 left, where patches either override predictions or replace the word "bomb" with the word "good"), or collecting hundreds of additional datapoints for finetuning, a tedious and computationally demanding process that can still lead to shortcuts such as assuming the word "bomb" is always positive (e.g., if the additional finetuning data mostly has the word in its colloquial sense). Instead, we envision a setting where developers provide corrective feedback through a *Natural Language Patch* – a concise statement such as *"If food is described as bomb, then food is good"*. Language makes it easy for developers to express feedback at the right level of abstraction without having to specify exactly how the condition is applied. The patching system is responsible for applying the patch and integrating the information appropriately e.g., applying it to "The tacos were the bomb" but not to "The authorities found a bomb in the restaurant".

In this work, we present an approach for patching neural models with natural language. Any patching system has to determine when a patch is relevant, and how it should modify model behavior. We model these tasks separately (Fig. 1b): a *gating* head soft-predicts whether the patch should be applied (e.g., "food is described as bomb"), and an *interpreter* head predicts a new output by combining the information in the patch (e.g., "food is good") with the original input. Both heads are trained on *synthetic data* in a *patch tuning* stage

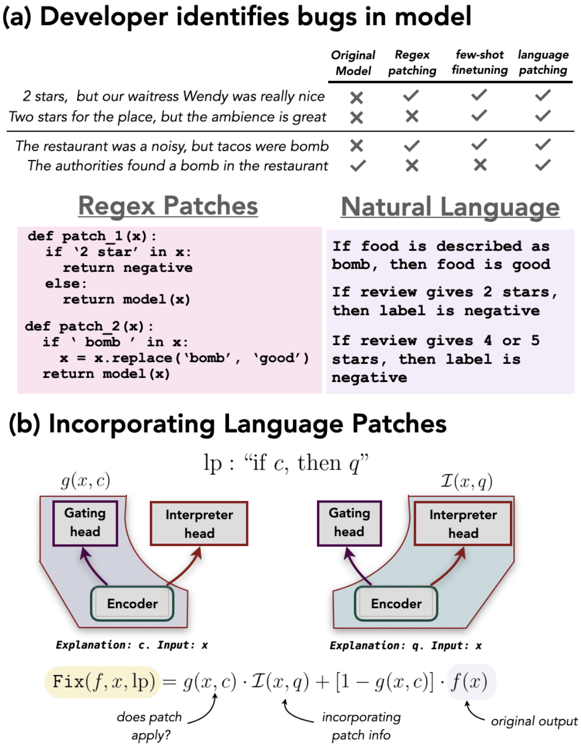


Figure 1: (a) Developers typically fix bugs by writing brittle regex patches or by finetuning on additional data, which is prone to simple shortcuts. In contrast, natural language patches are more expressive than regexes and prevent shortcuts by abstractly specifying when they should be applied. (b) Our proposed model uses a gating head to softly predict whether a patch condition c applies to the input. That prediction is then used to combine the original model output with the output of an interpreter head that uses textual features from both the input as well as the patch consequent q.

between training and deployment, such that new patches can be combined into a library of patches (or maybe various user-specific libraries), and applied at test-time without further training. In addition to the expressivity provided by abstractions, language-based patching is *lightweight*, *iterative* and easily *reversible*. Much like software, developers can write / edit / remove patches iteratively until errors on unit tests or validation data are fixed, without constantly retraining the model.

We present controlled experiments that indicate these patches work even for *abstract* conditions, where regex patches would be infeasible or very difficult – that is, they are applied correctly when the patch condition is met, and do nothing otherwise. Perhaps surprisingly, this is true even for test-time patches that are very different than the ones used in the patch finetuning stage. Next, we show that despite the synthetic nature of the patch tuning phase, a small set of very simple patches can fix bugs (and thus improve performance) on real benchmarks for two different tasks—1 to 6 simple language patches improve performance by ~1-4 accuracy points on two slices from the Yelp reviews dataset, while 7 patches improve performance by ~7 F1 points on a relation extraction task derived from NYT. Finally, we compare language patching, a computationally *lightweight* procedure, with finetuning, a computationally and human-labor *intensive* procedure, and find that as many as 100 labeled examples are needed to match performance gains from a small set of 1 to 7 patches. Further, finetuning sometimes fixes bugs at the expense of introducing new bugs, while patches maintain prior performance on inputs where they do not apply.

2 Related Work

Learning with Language. Natural language instructions or explanations have been used for training fewshot image classifiers (Mu et al., 2020; Andreas et al., 2018), text classifiers (Zaidan and Eisner, 2008; Srivastava et al., 2018; Camburu et al., 2018; Hancock et al., 2018; Murty et al., 2020), and in the context of RL (Branavan et al., 2012; Goyal et al., 2019; Co-Reyes et al., 2019; Mu et al., 2022). All of these works are concerned with reducing labeled data requirements with language supervision, while our setting involves using language as a *corrective* tool to fix bugs *at test time*.

Prompt Engineering. An emerging technique for re-purposing language models for arbitrary downstream tasks involves engineering "prompts". Prompts are high level natural language descriptions of tasks that allow developers to express any task as language modeling (Brown et al., 2020; Gao et al., 2021; Zhong et al., 2021). While we could try and use prompting to incorporate language patches, our experiments show that prompting by itself fails to utilize patches (Section 5). Using patches for corrective purposes requires learning an accurate interpretation model, as well as ignoring the patch when it is not applicable. We solve these challenges by learning a gating head and an interpretation head through carefully constructed synthetic data.

Editing Factual Knowledge. Test time editing of factual knowledge in models is considered by Talmor et al. (2020); Cao et al. (2021); Mitchell et al. (2021); Meng et al. (2022). Instead of modifying factual knowledge, we show that *free-form* *language* patches can be used to fix *bugs* on real data, such as correctly interpreting the meaning of the word "bomb" in the context of food or predicting that divorced people are no longer married.

3 Natural Language Patching

Setup. We are given a model f, mapping an input text x to a probability distribution over its output space, $f(x) = \Pr(y \mid x)$. The model contains *bugs*—defined as behaviors inconsistent with users' preferences or the "ground truth", which we want to fix with a library of patches $P = \{lp_1, lp_2, \ldots, lp_t\}$. In this work, we require users to explicitly indicate the condition under which each patch applies and the consequence of applying it, such that each patch is in the form *"If (condition) c, then (consequence) q"*. We use this format to make modeling easier, noting that it still allows for very flexible patching through high level abstractions (e.g., "if the customer complains about the ambiance", "if food is not mentioned", etc), and that most patches have an implicit applicability function, and thus can be converted to this format.

Applying Patches. As indicated in Fig. 1(b), our model consists of two separate heads. The gating head g computes the probability that the condition specified by $lp = (c, q)$ is true for a given input x as $g(x, c)$. The interpreter head $\mathcal{I}$ computes a new distribution over the label space, that conditions on x *and* the consequence q. This is then combined with the original model output $f(x)$ using the above gating probability. A single patch $lp = (c, q)$, can be applied to any input x as

$$\begin{aligned} \texttt{Fix}(f, x, lp) &= g(x, c) \cdot \mathcal{I}(x, q) \\ &+ [1 - g(x, c)] \cdot f(x). \end{aligned} \tag{1}$$

Given a library of patches $P = \{lp_1, \ldots, lp_t\}$, we find the most relevant patch the given input, and use that to update the model,

$$lp^* = \arg\max_{lp_i \in P} g(x, c_i) \tag{2}$$

$$\texttt{Fix}(f, x, P) = \texttt{Fix}(f, x, lp^*) \tag{3}$$

Patch Types. We consider two categories of patches (examples in Table 1). **Override** patches are of the form *"If cond, then label is l"* i.e., they override the model's prediction on an input if the patch condition is true. For these patches, we do not use the interpreter head since $\mathcal{I}(x, \text{"label is } l\text{"}) = l$. **Feature-based** patches are of the form *"If cond, then feature"*, i.e., they provide the model with a contextual feature "hint" in natural language, e.g., in Fig. 3 the feature is "food is good". For these patches, the model needs to integrate the hints with the original data, and thus both the gating and interpreter heads are used.

4 Training Patchable Models

Assuming f has a text encoder and a classification head, we have two finetuning stages. In the **Task Finetuning** stage, we train f on a labeled dataset $\{x_i, y_i\}$ (standard supervised learning). In the **Patch Finetuning** stage, we use the learnt encoder and learn g (initialized randomly) and $\mathcal{I}$ (initialized with the classification head).

For the patch finetuning stage, we write a small set of patch templates covering the kinds of patches users might want to write for their own application (see Table 1 for the patch templates used for our sentiment analysis results). Based on these templates, we instantiate a small number of patches along with synthetic labeled examples. This gives us a dataset $\{x_i, y_i, lp_i\}$, where lp_i consists of a condition c_i as well as a consequence q_i.

The interpreter head $\mathcal{I}$ is trained to model $\Pr(y_i \mid x_i, q_i)$ through standard log-likelihood maximization. The gating head g is trained via noise contrastive estimation to maximize

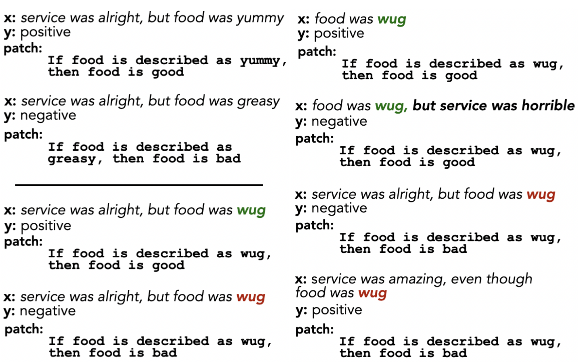
$$\log g(x_i, c_i) - \sum_{c_j \in \text{NEG}(x_i)} \log g(x_i, c_j), \tag{4}$$

where $\text{NEG}(x_i)$ is a randomly sampled set of negative conditions for x_i.

Entropy Increasing Transformations. Patch Finetuning will fail if the synthetic data can be fit by a model that ignores the input or the patch (Fig. 2a). Thus, to ensure our model cannot fit the synthetic data without combining patch features with inputs, we perturb the inputs with *Entropy Increasing Transformations* (EITs). We identify words from the input template for which the patch supplies additional information e.g., aspect adjectives, relationship between entities, and transform these into a small set of *nonce* words. Crucially, the meanings of these nonce words vary from example to example, and can only be inferred from the patch (Fig. 2a bottom; more examples in Appendix A.2). Intuitively, the transformations inject an additional source of randomness which can only be recovered via the patch features. Such transformations are

	Template	Examples
Patches	***Override:*** If aspect is good, then label is positive	e_0: If service is good, then label is positive e_1: If food is good, then label is positive
	Override: If aspect is bad, then label is negative	e_2: If service is bad, then label is negative e_3: If ambience is bad then label is negative
	Override: If review contains words like word, then label is positive	e_4: If review contains words like zubin, then label is positive e_5: If review contains words like excellent, then label is positive
	Override: If review contains words like word, then label is negative	e_6: If review contains words like wug, then label is negative e_7: If review contains words like really bad, then label is negative
	Feature Based: If aspect is described as word, then aspect is good / bad	e_8: If food is described as above average, then food is good e_9: If food is described as wug, then food is bad e_{10}: If food is described as zubin, then service is good e_{11}: If service is described as not great, then service is bad
Inputs	The aspect at the restaurant was adj	The service at the restaurant was really good. e_0, e_3 The food at the restaurant was wug. e_6, e_9
	The restaurant had adj aspect	The restaurant had really bad service. e_7, e_2, e_{11} The restaurant had zubin ambience. e_4, e_{10}
	The aspect1 was adj1, the aspect2 was adj2	The food was good, the ambience was bad. e_1, e_3, e_1 The service was good, the food was not good. e_0, e_1
	The aspect1 was adj1 but the aspect2 was really adj2	The food was good, but the service was really bad. e_7, e_1, e_0 The ambience was bad, but the food was really not wug. e_3, e_9
	The aspect1 was really adj1 even though aspect2 was adj2	The food was really bad even though the ambience was excellent. e_5, e_7, e_8 The food was really zubin, even though the service was bad e_4, e_{10}, e_0

Table 1: Patch and Input templates used for the Patch Finetuning stage for the sentiment analysis task. We divide our patches into 2 categories: *Override* and *Feature Based* (see Section 3 for more details). For each input, we provide examples of patches that apply and patches that don't apply. The simplistic nature of these templates makes them easy to write without access to additional data sources or lexicons.



(a) (b)

Figure 2: A model can learn from just the labels that "yummy" and "greasy" are positive and negative words respectively, and thus learn to perfectly fit training data without ever using patch features (a, top). This behavior can be explicitly prevented via EITs (a, bottom). A model may also fit the data without using the input features by always predicting 1 / 0 for "food is good" / "food is bad" (a, top/bottom). Thus, we additionally ensure that the label cannot be inferred from the patch alone (b).

also used in Rajendran et al. (2020) in the context of meta-learning. EITs alone do not fix the failure mode where the model can fit the data without using input features at all. For example, in Fig. 2a bottom, the model might learn a shortcut so that it always predicts 1/0 for "food is good" / "food is bad", regardless of the input. Thus, in addition to EITs, to ensure that the model uses input features, we ensure that a given patch consequence q and the target label are independent (Fig. 2b).

5 Experimental Setup

Applications. We apply our method to binary sentiment analysis and relation extraction. For sentiment analysis, our task finetuning data comes from SST2 (Socher et al., 2013). For relation extraction, we use the Spouse dataset (Hancock et al., 2018) for task finetuning, where the objective is to determine whether two entities are married or not given a textual context about them.

Model. We use T5-large (Raffel et al., 2019) as implemented in the transformers library (Wolf et al., 2020) for all experiments. Both the gating and interpreter heads are separate decoders learnt on top of a shared encoder and each of these components are initialized with the corresponding T5 pre-trained weights. To prevent catastrophic forgetting on the original task during patch finetuning, we also multi-task learn the patch finetuning loss along with the original task loss. Templates for generating patches for patch finetuning are in Table 1 for sentiment analysis and in Table 9 (Section A.2) for relation extraction. We train separate models for override and feature-based patches (the former does not need an interpreter head). When using a patch, its content (either c for the gating head or q for the interpreter head) is inserted in the beginning of the input with a separator as in Fig. 1(b).

Baselines. We report performance of the original model with only task finetuning (ORIG) as well as the model obtained after patch finetuning (ORIG+PF) without using any patches, to isolate the gains of language patches from those induced by training on additional synthetic data. We also report results obtained from prompting ORIG with our patches (PROMPT), i.e., inserting the patch text before the input text in the hopes that T5 will follow instructions appropriately. When we have multiple patches, we prompt the model with each individual patch and ensemble results with majority voting. Finally, we experiment with *regex-based* patches (REGEX) where the patch condition is turned into a regex rule and the consequent is converted into a function $\mathrm{Rule}_q(x)$. For override patches, we simply output the label in the consequent. For sentiment analysis, where all feature based patches supply contextual meanings of words, $\mathrm{Rule}_q(x)$ replaces the word in the input with its corresponding meaning e.g., replacing "bomb" with "good" in "the food was bomb". For feature based patches on relation extraction, $\mathrm{Rule}_q(x)$ appends the patch consequent to the input text.

6 Controlled Experiments

We test the behavior of natural language patches (and baselines) under different controlled conditions with CheckList (Ribeiro et al., 2020). Patches and example inputs are presented in Fig. 3. We test cases where where patches apply and are relevant for predictions, and corresponding cases where they either do not apply or are not relevant. Thus, models that rely on shortcuts such as copying the label word from the patch or merely performing token matching perform poorly on the CheckList.

For sentiment analysis, we test Override patches with *abstract* conditions (e.g., "If *food* is described as weird, then label is negative") on various concrete instantiations such as "The *pizza* at the restaurant was weird". We also construct invariance tests (O-Inv), expecting that adding such patches should not change predictions on inputs where the condition is false (e.g., "The waiter was weird", "The tacos were not weird"). We also construct tests for feature-based patches (Feat) where patches provide meaning for nonce adjectives, with analogous invariance tests (Feat-Inv). Finally, we construct analogous tests for relation extraction, with additional patches that fill in *reasoning gaps* in the model such as *"If Entity1 gave Entity2 a ring, then Entity1 and Entity2 are engaged"*.

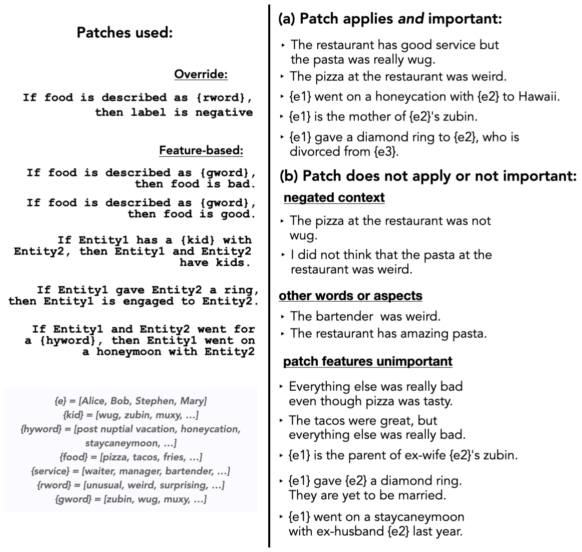


Figure 3: (a) We construct datasets based on CheckLists to study how well our approach can leverage abstractions in language patches. (b) To control for spurious behaviors such as copying label words from the patch, performing simple string lookups or affecting predictions when patch features are unimportant, we also construct corresponding invariance tests.

We present the results in Table 2, where we first note that ORIG+PF does not perform well overall, and thus patching improvements are not merely a result of the additional synthetic data. REGEX cannot handle abstract conditions, and thus (as expected) does not change predictions on sentiment analysis, and do not do well on relation extraction. While merely inserting the patch into the input (PROMPT) results in some gains when the patch applies, it does so at the cost of changing predictions when the patch does not apply (O-Inv and Feat-Inv). In contrast to baselines, our method is able to apply *abstract* patches correctly on concrete instantiations, disregarding them when they do not

Model	Sentiment Analysis				Relation Extraction	
	Override	O-Inv	Feat	Feat-Inv	Feat	Feat-Inv
ORIG	50.0	n/a	59.1	n/a	14.5	n/a
ORIG+PF	50.0	n/a	59.9	n/a	35.8	n/a
REGEX	50.0	**100.0**	59.9	**100.0**	45.8	88.1
PROMPT	68.7	63.8	64.3	85.4	13.9	87.6
PATCHED	**100.0**	**100.0**	**100.0**	**100.0**	**47.2**	**92.6**

Table 2: Applying patches on CheckLists. We see significant improvements when the patches apply and invariances when they do not apply or are unimportant. For Sentiment Analysis, the datasets are designed to evaluate patching with abstract conditions, thus we see no effects from using regex based patches. For testing invariance, we report the percentage of inputs for which the prediction did not change w.r.t the base model.

Model	Correctly patched (applies)	Invariance (does not apply)
ORIG	91.5	n/a
ORIG+PF	90.7	n/a
REGEX	91.0	99.5
PROMPT	92.3	98.4
PATCHED	**95.0**	98.9

Table 3: To measure how well patches control behavior "in the wild", we evaluate the model's ability to match the label specified by the patch when it applies, and invariance w.r.t the base model when the patch does not apply, on a subset of yelp with sentiment annotations for different aspects

apply, without relying on shortcuts such as copying the label from the consequent or merely checking for matching words between patch and input (all of which are tested by the invariance tests).

7 Patching models on real benchmarks

7.1 Sentiment Analysis

Unless noted otherwise, all datasets in this subsection are derived from Yelp Review (Zhang et al., 2015). To fix errors on low-accuracy slices, we write patches by inspecting a random subset of 10-20 errors made by ORIG+PF.

Controlling the model. In order to check if patches can control model behavior with abstract conditions "in the wild", we manually annotate a random subset of 500 reviews with food and service specific sentiment ("The food was good, service not so much" is labeled as service: 0, food: 1). We then construct override patches of the form *"if food / service is good / bad, then label is positive / negative"*, and evaluate models as to how often (on average) the prediction is as expected when the patch applies and how often it is unchanged when the patch does not apply. We present results in Table 3. The sentiment of both aspects typically agrees, and thus even models without patching often behave according to the patch. We note that natural language patches improve patched behavior the most (when compared to baselines), while almost never changing predictions when the patch does not apply. We present results only on the subset where both aspects *disagree* in Appendix B, where the difference in performance is more pronounced.

Patching low-accuracy slices. We identify slices where our base model has (comparatively) low accuracy, and check whether patches can improve performance. Yelp-stars consists of all examples in Yelp Review with the word 'star' present. For this subset, we use a single override patch: *"If review gives 0, 1, 2 stars, then label is negative"*. Yelp-Colloquial is a label-balanced slice consisting of examples having the colloquial terms {dope, wtf, omg, the shit, bomb, suck}. Because the colloquial use of these terms depends on context, we further construct Yelp-Colloquial-Control, a CheckList where the same terms are used in their traditional sense (e.g., "The manager was a dope", "The bomb was found by the police at the restaurant"). A model can do well on both of these datasets simultaneously only if it understands the contextual nuance associated with colloquial terms, rather than relying on simple shortcuts such as equating "bomb" with "good". For these datasets, we write simple feature-based patches such as *"If food is described as bomb, then food is good"* for each term. Finally, we use the "Women's E-commerce Clothing Reviews" dataset (WCR) from Zhong et al. (2021) and add two override patches: *"If review mentions phrases like needs to be returned, then label is negative"*, and *"If fit is boxy, then label is negative"*.

From results in Table 4, we observe that a very small number of language patches improve performance by 0.5-4.3 accuracy points, always outperforming both the original model and baselines. These gains are not a result of the added synthetic data, as ORIG+PF often *lowers* performance. Qualitatively, PROMPT tends to rely on shortcuts such as copying over the label in the patch rather than gating and integrating the information, while REGEX cannot deal with simple semantic understanding, e.g., the rule on Yelp-stars fires for *"Will deduct 1*

Model	Yelp-Stars	Yelp-Colloquial	Yelp-Colloquial-Control	WCR
ORIG	93.1	89.1	100.0	89.6
ORIG+PF	93.6	88.6	100.0	88.9
REGEX	92.7	91.9	88.1	89.9
PROMPT	90.8	85.2	70.1	88.3
PATCHED	94.5	93.4	100.0	90.1

Table 4: Using Override and Feature Based patches to fix bugs on various benchmarks derived from real sentiment analysis datasets. For Yelp-Colloquial, we also generate an control test based on CheckList.

star for the service but otherwise everything was excellent", leading to an incorrect patch application. Natural language patches avoid both of these pitfalls by explicitly modeling gating and using a language model that can accurately interpreting, while also using a language model.

7.2 Spouse Relation Extraction

We construct Spouse-FewRel, an out-of-distribution test benchmark derived from FewRel (Gao et al., 2019) by sampling from all relation types where at least one of the entities is a person ($n = 8400$), and labeling examples as positive if they have the Spouse relation, negative otherwise. We inspect 20 randomly sampled errors made by ORIG+PF on Spouse-FewRel, and observe that the model often confuses "Entity1 has a child with Entity2" with "Entity1 is the child of Entity2", and also misclassifies widowhood as negative. Thus, we write override patches for both of these error categories, resulting in 7 patches, presented in Table 5. Using all patches, we observe a ~7.4 point F1 improvement over ORIG, while baselines barely improve or decrease F1.

We highlight in Table 5 a phenomenon where each natural language patch in *isolation* decreases performance, while all patches together increase performance. Further analysis reveals that this is because the gating head is not well calibrated in this case, and thus individual patches are applied incorrectly. However, the *comparative* values of $g(x, c_i)$ are often ordered correctly, and thus a better patch is the one applied (lp^* in Eq 2) when all patches are available. We do further analysis in Table 6, where we report the *gating accuracy* (i.e., whether the patch actually applies or not, labeled manually) of lp^* on the subset of inputs where the PATCHED model changes the prediction (`Diff`), and where it changes the prediction to the correct label (`Diff ∩ Correct`). With the caveat that patches are applied softly (and thus perfect gating accuracy is not strictly necessary), we observe that a few patches seem to hurt performance even in combination with others (e.g., the first one). We also note that the patched model is right *"for the right reasons"* in over 72% of inputs where it changes the prediction to the correct one.

	Model	F1
	ORIG	65.5
	ORIG+PF	61.4
	REGEX	61.0
	PROMPT	65.7
	PATCHED	**72.9**
Using single patch	If p_2 is the son of p_1, then label is negative	57.5
	If p_1 is the son of p_2, then label is negative	58.9
	If p_1 and p_2 have a daughter, then label is positive	61.9
	If p_1 and p_2 have a son, then label is positive	66.8
	If p_1 is the widow of p_2, then label is positive	63.6
	If p_1 is the daughter of p_2, then label is negative	50.7
	If p_2 is the daughter of p_1, then label is negative	49.4

Table 5: Using Override Patches on Spouse-FewRel for Spouse relation extraction.

Patch Condition	`Diff`	`Diff ∩ Correct`
p_2 is the son of p_1	0.0	NaN (0/0)
p_1 is the son of p_2	75.0	75.0
p_1 and p_2 have a daughter	63.3	93.8
p_1 and p_2 have a son	78.1	98.3
p_1 is the widow of p_2	10.9	19.6
p_1 is the daughter of p_2	71.4	100.0
p_2 is the daughter of p_1	6.3	100.0
Overall	42.9	72.3

Table 6: Measuring how often the chosen patch correctly applies to an input (i.e., gating accuracy) for Spouse-FewRel, for the set of inputs where the patched model and original model differ (`Diff`) as well as the subset where the patched model is additionally correct (`Diff ∩ Correct`).

8 Analysis

8.1 How Important are EITs?

The goal of Entropy Increasing Transformations (EITs; Section 4) is to prevent the interpreter head from learning shortcuts that either ignore patch features or rely exclusively on them. We perform an ablation, comparing our model to a model trained without EITs on the CheckLists in Table 2 (Section 6), where the feature-based patch consequent supplies important information for making a correct prediction. From Table 7, we note that the interpreter head trained without EITs has much lower performance on these datasets (as expected).

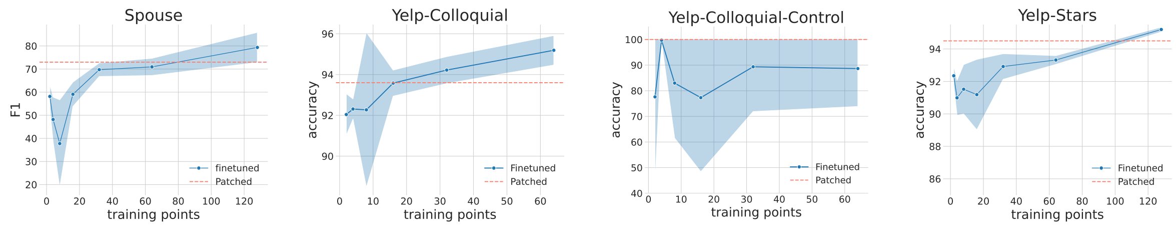


Figure 4: How many additional finetuning training examples it takes to reach the same accuracy level as patching. We report the mean and standard deviations across 5 runs.

Patch Consequent	Patched	Patched (Without EITs)
p_1 went on a honeymoon with p_2	**59.1**	33.7
p_1 has kids with p_2	**75.2**	74.4
p_1 is engaged to p_2	**77.7**	64.8
food is good	**67.8**	54.2
food is bad	**88.7**	56.5
service is good	**62.8**	52.9
service is bad	**62.8**	52.9
Overall	**70.6**	55.6

Table 7: Patching Accuracy of a model with and without Entropy Increasing Transformations (EITs).

8.2 Comparison to fine-tuning

While patching is computationally lightweight, it requires domain knowledge or error analysis of incorrectly labeled examples. However, once such analysis is performed, one can label these additional examples and finetune the model on them. We ignore the computational and infrastructure costs of repeated finetuning, and focus here on the annotation effort involved.

We compare language patches with finetuning on Yelp-stars, Yelp-Colloquial, and Spouse-FewRel (Section 7). We split each dataset into a training set with 128 examples, and a test set with remaining examples. Next, we finetune ORIG, on $k = \{2, 4, 8, 16, 32, 64, 128\}$ examples from the training set, stopping early if finetuning performance exceeds patched performance. We finetune for 64 steps and optimize using AdamW with a fixed learning rate of 1e-4. We report means and standard deviations obtained from finetuning with 5 random seeds.

Results are presented in Fig. 4, where we note that over 100 labeled examples are needed to match the performance of a single patch on Yelp-Stars or 7 patches on Spouse-FewRel. On Yelp-Colloquial, the patched performance is matched with a mere 16 examples. However, as noted earlier, Yelp-Colloquial is susceptible to simple shortcuts, and we observe that the performance on the control set Yelp-Colloquial-Control suffers significantly as we finetune on more data (with very high variance). Thus, we conclude that language patches on these datasets are not only very efficient in terms of annotation effort (when compared to labeling data for finetuning), but also less susceptible to simple shortcuts that do not address the problem at the right level of abstraction.

9 Conclusion

When faced with the task of fixing *bugs* in trained models, developers often resort to brittle regex rules or finetuning, which requires curation and labeling of data, is computationally intensive, and susceptible to shortcuts. This work proposes *natural language patches* which are declarative statements of the form "if c, then q" that enable developers to control the model or supply additional information with conditions at the right level of abstraction. We proposed an approach to patching that models the task of determining if a patch applies (gating) separately from the task of integrating the information (interpreting), and showed that this approach results in significant improvements on two tasks, even with very few patches. Moreover, we show that patches are efficient (1-7 patches require as many as 100 finetuning examples), and more robust to potential shortcuts. Our system is a first step in letting users *correct* models through a *single step* "dialogue". Avenues for future work include extending our approach to a back-and-forth dialogue between developers and models, modeling pragmatics, interpreting several patches at once, and automating the patch finetuning phase.

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Model	Correctly patched (applies)	Invariance (does not apply)
ORIG	52.1	n/a
PROMPT	55.7	97.6
ORIG+PF	52.4	n/a
REGEX	55.1	100.0
PATCHED	**79.9**	100.0

Table 8: We evaluate the model's ability to match the label specified by the patch when it applies, and invariance w.r.t the base model when the patch does not apply, on a subset of yelp with sentiment annotations for different aspects. In this table, we specifically consider inputs where both food and service aspects differ in sentiment.

Override Patches
If [Entity1/ Entity2] is not a person, then label is negative
If Entity1 is the [child / parent] of Entity2, then label is negative
If Entity1 and Entity2 have children, then label is positive
If Entity1 and Entity2 are divorced, then label is negative
If Entity1 is engaged to Entity2, then label is positive
If Entity1 and Entity2 are siblings, then label is negative
Feature Based Patches
If cond, then Entity1 is [married/not married] to Entity2
If cond, then Entity1 is divorced from Entity2
If cond, then Entity1 is engaged to Entity2
If cond, then Entity1 is the sibling of Entity2
If cond, then Entity1 is dating Entity2
If cond, then Entity1 is the parent of Entity2

Table 9: Patch templates used for the Patch Finetuning stage for relation extraction. Each Entity is sampled from a small list of names, and cond is a set of conditions derived from keywords.

A More details on Patch Finetuning

A.1 Sentiment Analysis Data

The templates used for constructing inputs are in Table 12. We programmatically find all patches for an input, to generate labels.

A.2 Relation Extraction Data

Override Patches. Patches and Input templates for constructing patch finetuning data can be found in Table 13.

Feature Based Patches For training the gating head, we use the same data as generated by Table 13. For training the interpreter head, we use patches and input templates in Table 11 to generate finetuning data.

A.3 Additional Finetuning Details

After the model is finetuned in the Task finetuning stage, we finetune it additionally with a learning rate of learning rate of 1e-4 and with a linear warmup scheduler which ramps up the learning rate from 0 to 1e-4 over 100 steps. The training batch size is 32, and we clip gradients to have a max norm of 5. We early stop based on validation performance on a held out subset of the patch finetuning data.

B Controlling models with language patches on Yelp (Addendum)

We additionally report results on the subset of our aspect annotated examples where both aspects *disagree* in Table 8. Overall, we see a more pronounced difference i.e., our model gets ~27 point boost in accuracy when the patch condition applies, while maintaining invariance when the condition does not apply.

C Patches used for Yelp-Colloquial.

We used the following patches for fixing bugs on Yelp-Colloquial:

- *"If clothes are described as dope, then clothes are good."*
- *"If food is described as the shit, then food is good."*
- *"If service is described as bomb, then service is good."*
- *"If restaurant is described as bomb, then restaurant is good."*
- *"If food is described as bomb, then food is good."*
- *"If something is described as wtf, then something is bad."*
- *"If something is described as omg, then something is good."*
- *"If food is described as shitty, then food is bad."*

D More examples of Entropy Increasing Transformations

To perform Entropy Increasing Transformations (EITs) for relation extraction, we convert rel (see Table 11 into nonce words *e.g.*, "Alice has a kid with John" gets transformed into "Alice has a wug with John", for which we use a patch "If Entity1 has a wug with Entity2, then Entity1 and Entity2 have kids

Dataset	#examples
Yelp-Stars	3172
Yelp-Colloquial	1784
WCR	2919
Yelp-Colloquial (Control)	67
Yelp-Aspect	439
Spouse-NYT	8400

Table 10: Dataset statistics for all the real data slices considered in this work.

E Regex Based Patches.

The exact functions we use for patching with regexes can be found in Listing 1 and Listing 2.

F Data Statistics for all evaluation slices

Statistics for all slices used for evaluation can be found in Table 10.

G Limitations

Scaling to large patch libraries. For our approach, inference time scales linearly with the size of the patch library. This is primarily because the gating head makes predictions on each patch in our patch library (Eq 2). Instead of running the gating head on each patch, one can trade off exactness for efficiency, by running the gating head on a much smaller candidate set identified using fast approximate nearest neighbors (Johnson et al., 2019) on sentence embeddings.

Scaling to more patch types. The current approach requires writing patch templates *beforehand* based on prior knowledge of the kinds of corrective feedback that developers might want to write in the future. Writing patch templates manually is fundamentally bottlenecked by human creativity and foresight. Morever, since humans are required to write templates, it makes scaling up to different patch types harder, since we expect generalization to completely new patch *types* to be poor e.g., generalizing to a patch that requires counting. Future work can explore automatic generation of synthetic patch templates e.g., using pre-trained language models.

Interpreting multiple patches. Finally, the approach we develop can only incorporate a single patch at a time, by selecting the most relevant patch from our patch library. This precludes the model from being able to combine features from multiple patches — e.g., *"caviar is a kind of food"* and *"If caviar is described as overpowering, then caviar is spoiled"*.

[Entity1] [rel] [Entity2]
[Entity1] [rel] [Entity2] and [Entity1] is (not) married to [Entity2]
[Entity1] who [rel] [Entity2], [rel2] [Entity3]
rel = [have-kids, are-engaged, is-sibling, is-parent]
Entity = [Alice, Bob, Stephen, Mary]

Table 11: Templates used for constructing inputs for patch finetuning stage in relation extraction analysis. Terms marked with '()' are optional. rel is a list of 4 relation types. For each relation type, we have a small list of 3 to 4 words. For instance `have-kids` = ['has a kid with', 'has a son with', 'has a daughter with']

The [aspect] at the restaurant was (modifier) (not) [adj]
The [aspect] was (modifier) (not) [adj]
The restaurant [has/had] (modifier) [adj] [aspect]
The [aspect1] was (not) [adj1], the [aspect2] was (not) [adj2]
The [aspect1] was (not) [adj1], but the [aspect2] was (not) [adj2]
The [aspect1] was really (not) [adj1], even though the [aspect2] was (not) [adj2]
aspect = [food, service, ambience]
modifier = [really, surprising, quite]

Table 12: Templates used for constructing inputs for patch finetuning stage in sentiment analysis. Terms marked with '()' are optional. adj comes from a small set of 6 positive and 6 negative adjectives, as well as 6 nonce adjectives for EITs

	Examples
Patches	e_0: Entity1 divorced Entity2
	e_1: Entity1 has kids with Entity2
	e_2: Entity1 is the parent of Entity2
	e_3: Entity1 and Entity2 are engaged
	e_4: Entity1 and Entity2 are just friends or coworkers
	e_5: Entity1 or Entity2 is not human
Inputs	Entity1 and Entity2 have a kid named Person3. e_1, e_2
	Entity1 and Entity2 have a kid named Person3. e_2, e_1
	Entity1 proposed to Entity2. The event was witnessed by Entity1's best friend Person3. e_3, e_4
	Entity1 proposed to Entity2. The event was witnessed by Entity1's best friend Person3. e_4, e_0
	Entity1 has decided to divorce Entity2. They have a child named Person3. e_0, e_3
	Entity1 has decided to divorce Entity2. They have a child named Person3. e_2, e_0
	Entity1 works at location. e_5, e_0

Table 13: Patches along with a subset of inputs used for the Patch Finetuning stage for the Spouse relation extraction task. For each input, we highlight the two entities and provide examples of some positive and negative patches.

```python
def star_rbpatch(model, inp):
    keywords = [' 0 star', ' 1 star', ' 2 star',
                ' zero star', ' one star', ' two star']
    patches = [(keyword, 0) for keyword in keywords]
    return sentiment_override_rbpatch(model, inp, patches)


def clothing_reviews_rbpatch(model, inp):
    return sentiment_override_rbpatch(model, inp, [('boxy', 0), ('needs to be returned', 0)])


def spousenyt(model, inp):
    patch_list = [('Entity1 is the son of Entity2', 0),
                  ('Entity2 is the son of Entity1', 0),
                  ('Entity1 and Entity2 have a son', 1),
                  ('Entity1 and Entity2 have a daughter', 1),
                  ('Entity1 is the daughter of Entity2', 0),
                  ('Entity2 is the daughter of Entity1', 0),
                  ('Entity1 is the widow of Entity2', 1)]
    return re_override_rbpatch(model, inp, patch_list)



# for all override patches
def sentiment_override_rbpatch(model, inp, patch_list):
    '''
        inp: "X" a review for which we want to predict sentiment
        patch_list: list of override patches converted into a form (cond, label) where cond is
        a string condition and label is the associated binary label
    '''
    for cond, label in patch_list:
        if cond in inp:
            return label
    return model(inp)


# for override patches for relation extraction
def re_override_rbpatch(model, inp, patch_list):
    '''
        inp: "X. Entity1: e1. Entity2: e2"
        patch_list: list of override patches converted into a form (cond, label) where cond is
        a string condition and label is the associated binary label
    '''
    text, ent_info = inp.split(' Entity1:')
    e1, e2 = ent_info.split('. Entity2:')
    e1 = e1.strip()
    e2 = e2.strip()
    for cond, label in patch_list:
        p = patch.replace('Entity1', e1).replace('Entity2', e2)
        p2 = patch.replace('Entity1', '').replace('Entity2', '')
        if p in inp:
            return pred
        elif p2 in inp:
            return pred
    return model(x)
```

Listing 1: Rule based override patching for all our experiments

```python
# Regex based patching for using feature based patches on
# controlled experiments for sentiment analysis
def sentiment_regex_based(model, inp, patch_list):
    '''
        inp: "X. Entity1: e1. Entity2: e2"
        patch_list: list of feature patches of the form 'if aspect is word, then aspect is good/ bad'
        as a tuple (aspect, word, sentiment)
    '''

    for aspect, word, sentiment in patch_list:
        if '{} is {}'.format(aspect, word) in inp:
            inp = inp.replace(word, sentiment)
            break
    return model(inp)




# Regex based patching for controlled experiments on relation extraction
def re_regex_based(model, inp, patch_list):
    '''
        inp: "X. Entity1: e1. Entity2: e2"
        patch_list: list of feature patches converted into a form (cond, cons) where cond
        and cons are both strings
    '''
    text, ent_info = inp.split(' Entity1:')
    e1, e2 = ent_info.split('. Entity2:')
    e1 = e1.strip()
    e2 = e2.strip()
    for cond, cons in patch:
        p = cond.replace('Entity1', e1).replace('Entity2', e2)
        if p in inp:
            cons_curr = cons.replace('Entity1', e1).replace('Entity2', e2)
            inp = '{}. {} Entity1: {}. Entity2: {}'.format(cons_curr, text, e1, e2)
            break
    return model(inp)

# Regex based patching on yelp colloquial
def yelp_col_regex_based(model, inp, patch_list):
    if 'wtf' in inp:
        inp = inp.replace('wtf', 'bad')
    elif 'omg' in inp:
        inp = inp.replace('omg', 'good')
    elif 'the shit' in inp:
        inp = inp.replace('the shit', 'good')
    elif 'bomb' in inp and 'food' in inp:
        inp = inp.replace('bomb', 'good')
    elif 'bomb' in inp and 'service' in inp:
        inp = inp.replace('bomb', 'good')
    elif 'bomb' in inp and 'restaurant' in inp:
        inp = inp.replace('bomb', 'good')
    elif 'dope' in inp and 'clothes' in inp:
        inp = inp.replace('dope', 'good')
    elif 'sucks' in inp:
        inp = inp.replace('sucks', 'bad')
    return model(inp)
```

Listing 2: Regex based patching for using feature based patches for all experiments.