Natural Perturbation for Robust Question Answering

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Abstract
While recent models have achieved human-level scores on many NLP datasets, we observe that they are considerably sensitive to small changes in input. As an alternative to the standard approach of addressing this issue by constructing training sets of completely new examples, we propose doing so via minimal perturbation of examples. Specifically, our approach involves first collecting a set of seed examples and then applying human-driven natural perturbations (as opposed to rule-based machine perturbations), which often change the gold label as well. Local perturbations have the advantage of being relatively easier (and hence cheaper) to create than writing out completely new examples. To evaluate the impact of this phenomenon, we consider a recent question-answering dataset (BOOL Q) and study the benefit of our approach as a function of the perturbation cost ratio, the relative cost of perturbing an existing question vs. creating a new one from scratch. We find that when natural perturbations are moderately cheaper to create, it is more effective to train models using them: such models exhibit higher robustness and better generalization, while retaining performance on the original BOOLQ dataset.

1 Introduction
While many datasets (Bowman et al., 2015; Rajpurkar et al., 2016) targeting different linguistic tasks with varying complexity have been proposed recently, nearly all of them are the result of repeating a fixed process used for writing a single example. This approach results in many independent examples, each generated from scratch. We propose an alternative training set construction method where, after collecting a few seed examples, the set is expanded by applying human-authored minimal perturbations to the seeds.

Fig.1 illustrates our proposed alternative of using natural perturbations. We use the traditional approach to first create a small scale seed dataset $D_S$, denoted by the red rectangle on the left with three instances (denoted by different shapes). Right: Expanded dataset $D_\Delta$, with 10 instances, comprising 2-4 minimal perturbations (illustrated as rotation, fills, etc.) of each seed instance. Human-authored perturbations aren’t required to always preserve the answer (yes/no in the example) and often add richness by altering the answer.

Figure 1: Training set creation via minimal-perturbation clusters. Left: Seed dataset $D_S$ with 3 instances (shown as different shapes). Right: Expanded dataset $D_\Delta$ with 10 instances, comprising 2-4 minimal-perturbations (illustrated as rotation, fills, etc.) of each seed instance. Human-authored perturbations aren’t required to always preserve the answer (yes/no in the example) and often add richness by altering the answer.

Related Paragraph: (Yonge Street) Provincial downloading separated Yonge Street from Highway 11 during the 1990s. As a result, Highway 11 does not start until Crown Hill just outside Barrie, several kilometres north of where the name "Yonge Street" ends. The Guinness Book of World Records no longer lists Yonge Street as the longest street in the world and has not chosen a replacement street, but cites the Pan-American Highway as the world's longest "motorable road".

Is the "Yonge Street" the longest street in the world? Was the "Yonge Street" the longest street in the world in the past? Will the "Yonge Street" become the longest street in the world? Was Yonge Street the longest street in the world at some point? Was the 'Yonge Street' the longest street in the world before 2000? Was the 'Yonge Street' the longest street in the world before 1980? ✘ ✔ ✘ ✔ ✘ ✔ ✘ ✔
We observed a similar phenomenon even with model-agnostic, human-authored changes to yes/no questions (as shown in Fig. 1), despite models achieving near-human performance on this task. Specifically, we found the accuracy of a RoBERTa model trained on BOOLQ (Clark et al., 2019) to drop by 15% when evaluated on locally perturbed questions. These new questions were, however, no harder for humans. This raises the question: Can a different way of constructing training sets help alleviate this issue? Minimal perturbations, as we show, provide an affirmative answer.

Perturbing a given example is generally a simpler task, costing only a fraction of the cost of creating a new example from scratch. We call this fraction the perturbation cost ratio (henceforth referred to as cost ratio), and assess the value of our perturbed training datasets as a function of it. As this ratio decreases (i.e., perturbations become cheaper), one, of course, obtains a larger dataset than the traditional method, at the same cost. More importantly, even when the ratio is only moderately low (at 0.6), models trained on our perturbed datasets exhibit desirable advantages: They are more robust to minor changes and generalize better across datasets than models trained on BOOLQ.

Specifically, our generalization experiment with the MULTIRC (Khashabi et al., 2018) dataset demonstrates that models trained on perturbed data outperform those trained on traditional data when evaluated on unseen, unperturbed questions from a different domain. Second, we assess robustness by evaluating on BOOLQ-E$_2$ (Gardner et al., 2020), a test set of expert-generated perturbations that deviate from the patterns common in large-scale crowdsourced perturbations. Our zero-shot results here indicate that models trained on perturbed questions go beyond simply learning to memorize particular patterns in the training data. Third, our evaluation using the original BOOLQ set confirms that models trained on perturbed data continue to retain performance on the original task.

Even with the worst case cost ratio of 1.0 (when perturbing existing questions is no cheaper than writing new ones), models trained on perturbed examples remain competitive on all our evaluation sets. This is an important use case for situations that simply do not allow for sufficiently many distinct training examples (e.g., low resource settings, limited amounts of real user data, etc.). Our results at ratio 1.0 suggest that simply applying minimal perturbations to the limited number of real examples available in these situations can be just as effective as (hypothetically) having access to large amounts of real data.

In summary, we propose a novel method to construct datasets that combines traditional independent example collection approach with minimal natural perturbations. We show that for many reasonable cases, using perturbation clusters for training can result in cost-efficiently trained high-quality, robust models that generalize across datasets.

2 Related Work

Data augmentation. There is a handful of work that studies semi-automatic contextual augmentation (Kobayashi, 2018; Cheng et al., 2018), often with the goal of creating better systems. We, however, study natural human-authored perturbations as an alternative dataset construction method. A related recent work is by Kaushik et al. (2020), who, unlike the goal here, study the value of natural-perturbations in reducing artifacts.

Adversarial perturbations. A closely relevant line of work is adversarial perturbations to expose the weaknesses of systems upon local changes and criticize their lack robustness (Ebrahimi et al., 2018; Glockner et al., 2018). For instance, Khashabi et al. (2016) showed significant drops upon perturbing answer-options for multiple-choice question-answering. Such rule-based perturbations, however, often have simple definitions, resulting in two issues. First, they are often easily reverse-engineered by learning algorithms (Jia and Liang, 2017). Second, they generally preserve the answer label and do not use the provided context the question is meant to refer to. In contrast, the question alterations we propose are open-ended as they are generated by humans and (hence, natural perturbations, as opposed to model-adversarial perturbations) and often change the true label.

Minimal-pairs in NLP. Datasets with minimal-pair instances are relatively well-established in certain tasks; for instance, Winograd schema datasets (Levesque et al., 2011; Peng et al., 2015; Sakaguchi et al., 2020), or the recently-published contrast sets (Gardner et al., 2020). However, the importance of datasets with pairs (i.e., clusters of size two) is not well-understood. Our findings about perturbation clusters could potentially be useful for the future construction of datasets for such
3 Expansion via Perturbation Clusters

Our approach mainly differs from traditional approaches in how we expand the dataset given seed examples. Rather than repeating the same process to generate more examples, we apply minimal alterations to the seed examples, in the following two high-level steps:

(a) Natural Minimal Perturbations
(b) Quality Verification

The first step generates the initial set of examples with natural perturbations. This step should respect certain principles: (a) The construction should be the result of minimal changes (similar to the ones shown in Fig.1), otherwise the resulting clusters might be heterogeneous and not as much meaningful. (b) A non-zero proportion of natural perturbations should change the decision of the questions. (c) This step should incentivize creativity and diversity in local perturbations. For instance, showing thought-provoking suggestions, using a diverse pool of annotators (Geva et al., 2019), etc. The second independent verification step ensures the dataset quality by (a) getting the true gold label and (b) ensure all generated questions are answerable given the relevant paragraph, in isolation from the original question.

3.1 BOOLOQ*: BOOLOQ Expansion

Following the above process, we obtain \(D_S\) by sampling questions from BOOLOQ (Clark et al., 2019). BOOLOQ is a question answering dataset where each boolean (“yes”/“no” answer) question could be inferred from an associated passage.

a) minimal perturbations: Crowdworkers are given a question and its corresponding gold answer based on supporting paragraph. Then the workers are asked to change the question in order to flip the answer to the question. While making changes, the workers are guided to keep their changes minimal (adding or removing up to 4 terms) while resulting in proper English questions. Additionally, for each seed question, crowd-workers are asked to generate perturbations till the modified question is challenging for a machine solver (i.e., RoBERTA trained on BOOLOQ, should have low confidence on the correct answer). Note that we do not require the model to answer the question incorrectly and not all questions are challenging for the model. Our main goal here is to encourage interesting questions by using the trained model as the guide.

b) question verification. Given the perturbed questions, we asked multiple annotators to answer these questions. These annotations served to eliminate ambiguous questions as well as those that cannot be answered from the provided paragraph. The annotation was done in two steps: (i) in the first step, we ask 3 workers to answer each question with one of the three options (“yes”, “no” and “cannot be inferred from the paragraph”). We filtered out the subset of the questions that were not agreed upon (i.e., not a consistent majority label) or were marked as “cannot be inferred from the paragraph” by majority of the annotators. To speed up the annotations, the annotation were done on a cluster-level, i.e., annotators could see all the different modified questions corresponding to a paragraph. (ii) subsequently, each modified questions is also annotated individually to ensure that questions can be answered in isolation (as opposed to answering them while seeing all the questions in a cluster.) The annotations in this step only have two labels (“yes”/“no”) and again questions that were not agreed upon were filtered. Further details on dataset construction are included in Appendix D.

This process results in BOOLOQ* with \(17k\) questions derived from \(4k\) seed questions. Sample questions generated by our process are shown in Fig.1. Table 1 provides a summary of BOOLOQ* stats. We evaluate the impact of perturbations via this dataset.

### Table 1: Statistics of BOOLOQ*

| Measure          | Full  | Train | Dev  | Test |
|------------------|-------|-------|------|------|
| # of questions   | 17,323| 9,727 | 5733 | 2263 |
| # of “yes” questions | 9,724 | 5,733 | 2,263| 1,728|
| # of “no” questions | 7,599 | 3,994 | 2,171| 1,434|
| # of clusters    | 4064  | 2408  | 919  | 737  |
| average cluster size | 4.3  | 4.1   | 4.8  | 4.3  |
| median cluster size | 3.0  | 3.0   | 3.0  | 3.0  |

3.2 Dataset subsampling

We sample questions from this expanded dataset to evaluate the value of perturbations as a function of different parameters. To make the exposition easier, we introduce the following notation which we will for the rest of the draft. We assume that we have a fixed budget \(b\) for constructing the dataset where each new question costs 1 unit, i.e., traditional methods would construct a dataset of size...
b in the given budget. The perturbation cost ratio \( r \leq 1 \) is the cost of creating a perturbed question. When \( r \approx 1 \), perturbations are equally costly as writing out new instances. If \( r \ll 1 \), perturbations are cheap. For instance, if \( r = 0.5 \), each handwritten question costs the same as two perturbed questions.

We denote the total number of instances and clusters with \( N, C \), respectively. We use \( \text{BOOLQ}_{b,c,r}^{b,c,r} \) to denote the largest subset of \( \text{BOOLQ}_{c}^{c} \) that can be generated with a total budget of \( b \), with a maximum cluster size of \( c \), and relative cost ratio of \( r \). In the special case where all clusters are of the exact same size \( c \), these parameters are related as follows:

\[
b = (1 + (c-1)r) \times C,
\]

where \( 1 + (c-1)r \) is the cost of a single cluster calculated as the cost of one seed examples and its \( c-1 \) perturbations.

To create \( \text{BOOLQ}_{b,c,r}^{b,c,r} \), we subsample a maximum of \( c \) questions from each perturbation cluster, such that total number of clusters is no more than \( \frac{b}{1+(c-1)r} \) and the ratio of “yes” to “no” questions is 0.55. We first sample \( c \) questions from clusters of size \( \geq c \), and then in rare cases if needed, we select smaller clusters to fill the budget. Our subsampling starts with clusters of size at least \( c \) and also considers smaller clusters if necessary. Essentially, \( \text{BOOLQ}_{b,1,r}^{b,1,r} \) (singleton clusters) corresponds to a dataset constructed in a similar fashion to \( \text{BOOLQ} \), whereas \( \text{BOOLQ}_{b,4,r}^{b,4,r} \) (big clusters) roughly corresponds to the \( \text{BOOLQ}_{c}^{c} \) dataset.

## 4 Experiments

To assess the impact of our perturbation approach, we evaluate standard RoBERTa-large model that has been shown to achieve state-of-the-art results on many tasks. Each experiment considers the effect of training on subsamples of \( \text{BOOLQ}_{c}^{c} \) obtained under different conditions.

Each of the points in the figures are averaged over 5 random subsampling of the dataset (with error bars to indicate the standard deviation). The Appendix includes further details about the setup as well as additional experiments.

We evaluate the QA model trained on various question sets on three test sets. (i) For assessing **robustness**, we use an expert-generated set \( \text{BOOLQ-E}_{c}^{c} \) published in Gardner et al. (2020) with 339 high-quality perturbed questions based on \( \text{BOOLQ} \). (ii) For assessing **generalization**, we use the subset of 260 training questions from MultiRC (Khashabi et al., 2018) that have binary (yes/no) answers, from training section of the their data. \(^1\) (c) The original BOOLQ test set, to ensure models trained on perturbed questions also retain performance on the original task.

### 4.1 Effect of Cluster Size (c)

We study the value of clusters sizes in the perturbations in two edge cases: (i) when perturbations cost the same as new questions \( (r = 1.0) \) and the only limit is the our overall budget \( (b = 3.7k) \), and (ii) when the perturbations cost negligible \( (r = 0.0) \) but we are limited by the max cluster size \( c \) and \( b = 1k \). For each case, we vary the max cluster size in the following range: \([1, 2, 3, 4]\). As a result, in (i), \( C \) vary from 3.7k to 951 (\( N = 3.7k \)), and in (ii), \( N \) vary from 1k to 4k (\( C = 1k \)).

Fig. 2 shows the accuracy of models trained on these subsets across our three evaluation sets. In scenario (i) with a fixed number of instances \( (r = 1) \), it is evident that the size of the clusters (the number of perturbations) does not affect the model quality. This shows that perturbation clusters are equally informative as (traditional) independent instances. However, in scenario (ii) with a fixed number of clusters \( (r = 0) \), the system performance consistently gets higher with larger clusters, even though the number of clusters is kept constant. This indicates that each additional perturbation adds value to the existing ones, especially in terms of model robustness and retaining performance on the original task.

### 4.2 Effect of Perturbations Cost Ratio (r)

We now study the value of perturbations as a function of their cost \( (r) \). We vary this parameter within the range \([0, 1]\) for \( b = 1.5k \) and two max clusters sizes, \( c = \{1, 4\} \). When \( c = 1 \) (no perturbations), \( N \) stays constant at 1.5k. When \( c = 4 \), \( N \) varies from 4.6k to 1.5k. Fig. 3 presents the accuracy of our model as a function of \( r \).

While we don’t know the exact crowdsourcing cost for BOOLQ, a typical question writing task might cost USD 0.60 per question. With our perturbations costing USD 0.20, we have \( r = 0.33 \). Given the same total budget \( b = 1500 \), we can thus infer from Fig. 3 that training on a dataset of perturbed questions would be about 10% and 5% more effective on \( \text{BOOLQ-E}_{c}^{c} \) and MultiRC, respectively.

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\(^1\)The yes/no subset of dev was too small.
The result on all datasets indicates that there is value in using perturbations clusters when \( r \leq 0.6 \), i.e., larger clusters can be more cost-effective for build better training sets. Even when they are not much cheaper, they retain the same performance as independent examples, making them a good alternative for dataset expansion given few sources of examples (e.g., low resource languages).

5 Conclusion

We proposed an alternative approach for constructing training sets, by expanding seed examples via natural perturbations. Our results demonstrate that models trained on perturbations of BOOLQ questions are more robust to minor variations and generalize better, while preserving performance on the original BOOLQ test set. Creating perturbed examples is often cheaper than creating new ones and we empirically observed notable gains even at a moderate cost ratio of 0.6.

While this is not a dataset paper (since our focus is on more on the value of natural perturbations for robust model design), we provide the natural perturbations resource for BOOLQ constructed during the course of this study.\(^2\)

This work suggests a number of interesting lines of future investigation. For instance, how do the results change as a function of the total dataset budget \( b \) or large values of \( c \)? Over-generation of perturbations can result in overly-similar (less-informative) variations of a seed example, making larger clusters valuable only up to a certain extent. While we leave a detailed study to future work, we expect general trends regarding the value of perturbations to hold broadly.

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A Details of ROBERTA Training

We train the model on two-way questions using the input format: "[CLS] passage [SEP] question [SEP] answer". The model scores each answer ("yes" or "no") by applying a linear classifier over the [CLS] representation for each answer's corresponding input. We train the linear classifier (and fine-tune ROBERTA weights) on the training sets and evaluate them on their corresponding dev/test sets. We fixed the learning rate to 1e-5 as it generally performed the best on our datasets. We only varied the number of training epochs: {7, 9, 11} and effective batch sizes: 16, 32. We chose this small hyper-parameter sweep to ensure that each model was fine-tuned using the same hyperparameter sweep while not being prohibitively expensive. Each model was selected based on the best validation set accuracy. We report the numbers corresponding to the selected models on the test set.

B Performances Across Datasets

We compare a collection of solvers across our target datasets: the complete BOOLQ dataset (dataset constructed from DS via perturbation), the original BOOLQ dataset, expert perturbations on BOOLQ, and binary subset of MULTIRC.

The results are summarized in Table 2. Most of the rows are ROBERTA trained on a specified dataset. We have also included a row corresponding a system trained on the union of BOOLQ, BOOLQ, BOOLQ, for brevity). Most of the datasets are slightly skewed between the two classes, which is why the majority label baseline (Always-Yes or Always-No) achieves above 50%. Rows indicated with * are reported directly from prior work. The human prediction on BOOLQ is the majority label of 5 independent AMT annotators. The human performance on BOOLQ and MULTIRC are directly reported from SuperGLUE (Wang et al., 2019) leaderboard.3

Here are the key observations in this table:

- While ROBERTA has almost human-level performance when trained and tested within BOOLQ, it suffers significant performance degradation when evaluated on other datasets (e.g., 68.7% on BOOLQ).
- The systems fine-tune on BOOLQ ++ consistently has better generalization across datasets.

| Model     | Trained on | Evaluated on | Acc. |
|-----------|------------|--------------|------|
| Human*    | —          | MULTIRC      | ~83  |
| ROBERTA   | BOOLQ ++   | MULTIRC      | 78.8 |
| ROBERTA   | BOOLQ      | MULTIRC      | 70.3 |
| ROBERTA   | BOOLQ      | MULTIRC      | 76.5 |
| Maj-Vote  | —          | MULTIRC      | 63.4 |
| Human*    | —          | BOOLQ        | 89.0 |
| ROBERTA   | BOOLQ ++   | BOOLQ        | 85.5 |
| ROBERTA   | BOOLQ      | BOOLQ        | 86.1 |
| ROBERTA   | BOOLQ      | BOOLQ        | 78.6 |
| Maj-Vote  | —          | BOOLQ        | 62.2 |
| Human     | —          | BOOLQ-E      | ？ |
| ROBERTA   | BOOLQ ++   | BOOLQ-E      | 76.4 |
| ROBERTA   | BOOLQ      | BOOLQ-E      | 71.1 |
| ROBERTA   | BOOLQ      | BOOLQ-E      | 69.3 |
| Maj-Vote  | —          | BOOLQ-E      | 50.7 |

Table 2: Various systems trained and evaluated on different datasets. Best non-human scores are in bold. Numbers in percentage.

C Cluster-Level Evaluation

An additional benefit of our approach is that it produces datasets with an inherent cluster structure. This enables the use of metrics such as ConsensusScore (Shah et al., 2019) to evaluate the extent to which a model acts consistently within each cluster, which provides another measure of robustness.

While evaluation measures are often computed on per-instance level, the cluster structure of BOOLQ enables us to provide per-cluster metrics of quality. In particular, we are interested in the following question: to what extent do our models act consistently across questions in each cluster?

To measure this, we use the consensus score $CS(k)$ introduced by Shah et al. (2019) for clustered datasets. For an integer parameter $k \geq 1$, the score $CS(k)$ for a single cluster $C$ is defined as the fraction of size-$k$ sub-clusters of $C$ where the model answers all instances correctly. The $CS(k)$ score for a clustered dataset is the average of these scores across all clusters. Intuitively, $k = 1$ represents the traditional un-clustered accuracy (assuming all clusters are of the same size). As $k$ grows to reach the cluster size, models must answer the entire cluster correctly in order to score positively on that cluster.

3https://super.gluebenchmark.com/leaderboard/
We plot this score for $k \in \{1, 2, 3, 4\}$ for various QA models in Fig 4. While all the models (including human) have decreasing consensus score for larger values of $k$, machine solvers have a steeper slope compared to human. As a result, we have an even larger gap of 17% between human-RoBERTa (at $k = 4$), when they are evaluated on their consistency.

D Question Perturbations: Details

We provide further details about the annotation.

The task starts with a qualification step: we ask annotators to read a collection of meticulously designed instructions that describe the task. The annotators are allowed to participate, only after successfully passing the test included in the instructions.

In addition, we restrict the task to “Master” workers from English-speaking countries (USA, UK, Canada, and Australia), at least 500 finished HITs and at least a 95% acceptance rate.

Here is a screen cast of the relevant annotation interface:  https://youtu.be/M9bCRwanbOA

During our earlier pilot experiments, we observed that the strategies used for perturbing “yes” questions tend to be different from those used for “no” questions. To make the task less demanding and help workers focus on a limited cognitive task, the annotation is done in two phases: one for “yes” questions, and another for “no” questions.