Reproducibility Study of “*Are Shortest Rationales the Best Explanations for Human Understanding?*”, Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics, 2022

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Introduction

- Original paper contributes two main things:
  - **Contribution 1: LimitedInk**: Explainability tool for BERT on classification tasks. Consists of two DistilBERT models:
    - **Classifier**: Answers a classification question
    - **Identifier**: Highlights a portion of the input to explain the classifier's answer. This portion is called the *evidence*. The identifier is trained to highlight a specific percentage *k* of the input text length.
    - k=**50%** It 's not life - affirming -- its vulgar and mean , but I liked it . **Y**=Pos
  - **Contribution 2: A claim supported by LimitedInk:** Shorter rationales aren't necessarily better for human understanding.

Reproducibility

- Aimed to reproduce 2 main claims:
  - **Claim 1:** That shorter rationales are not necessarily better
    - The authors primarily used a model trained on the Movies dataset to make this claim.
    - Movies dataset consists of film reviews, labeled positive or negative.
    - We trained models for different rationale lengths and compared their F1 scores vs human annotation.

Movies Data Set Performance			
Method	**Precision**	**Recall**	**F1**
LimitedInk (50%)	0.91	0.90	0.90
Ours - 10%	0.89	0.89	0.89
Ours - 20%	0.89	0.88	0.88
Ours - 30%	0.86	0.86	0.86
Ours - 40%	0.87	0.87	0.87
Ours - 50%	0.87	0.86	0.86

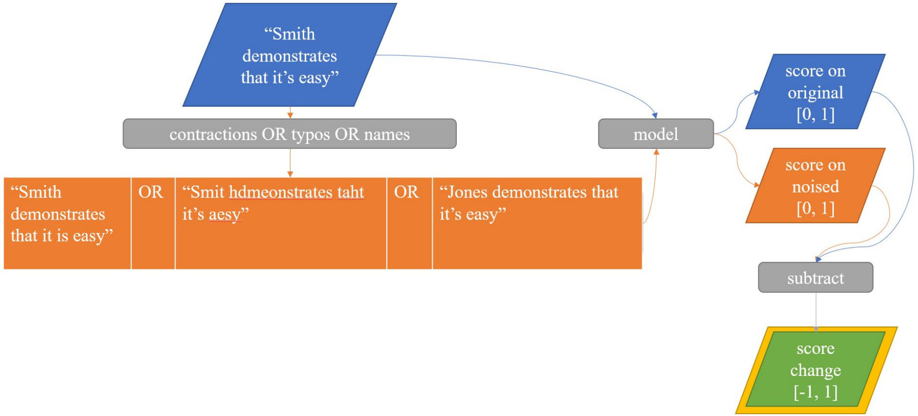
    - We found that shorter rationales yielded *better* F1 scores, but only slightly. Contradicts the authors' findings.
  - **Claim 2:** The performance of the LimitedInk models trained by the authors on a variety of datasets
    - We trained models on those datasets using the same hyperparameters as the authors.

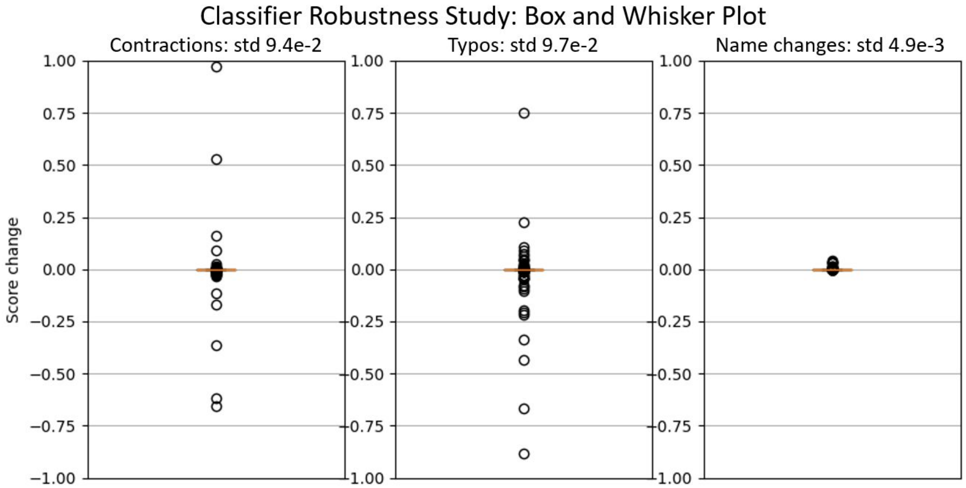
Results Reproduction		
Dataset (k value)	**Their F1**	**Our F1**
Movies (50%)	0.90	0.90
BoolQ (30%)	0.56	0.49
Evidence Inference (30%)	0.50	0.45
FEVER (40%)	0.90	0.89
MultiRC (50%)	0.67	0.62

    - Although our results are always worse than the authors', they're roughly the same.

Robustness

- Trained a model on Movies using the same hyperparameters as the authors' most successful Movies model.
- Model outputs a score from 0 (negative with full confidence) to 1 (positive with full confidence).
- Using CheckList, measured effect of contraction changes, typo changes, and name changes on output label and confidence.
    - Generated 250 examples for each of these three types of noise.
- Model was robust to all 3 (very low standard deviations), but had some drastic outliers for contractions and typos.
    - Hypothesis: Contractions and typos distort meaning often, but name changes do so only rarely.





Multilinguality

- Trained a multilingual LimitedInk model on Arabic, Bulgarian, German, Greek, English, Spanish, French, Hindi, Russian, Swahili, Thai, Turkish, Urdu, Vietnamese, and Chinese.
- No multilingual equivalent of any of the authors' datasets, so we used a different one: e-XNLI
  - Consists of pairs of sentences, labeled with either "contradiction", "entailment", or "neutral".

Language: en
Label: contradiction
Premise: But anyway, the animals would get loose all the time, especially the goats.
Hypothesis: The goats were kept safe and secure.
Premise_Highlighted: But anyway , the *animals* would get *loose* all the time , especially the goats .
Hypothesis_Highlighted: The *goats* were *kept* *safe* and *secure* .

  - Trained a new DistilBERT model on this multilingual dataset.
  - For comparison, also trained a model on only the English portion of the dataset.
  - For another comparison, referenced the authors' FEVER model (most similar dataset to e-XNLI, but still significant differences).

Dataset	F1 Score
FEVER	0.90
e-XNLI (English only)	0.62
e-XNLI (complete)	0.60

- **LimitedInk holds in a multilingual context!** Multilingual model performs almost as well as English-only, but worse than FEVER.
- Possible explanations:
  - e-XNLI task is harder. 3 labels vs FEVER's 2 labels.
  - e-XNLI hasn't been vetted to the same level of quality as FEVER.
  - e-XNLI's ground-truth annotations are automated, but FEVER's are human-annotated.

Conclusion

- **Reproducibility**: We verified the authors' model accuracies, but found evidence in favor of shorter rationales, which contradicts the authors.
- **Robustness**: We found the authors' model to be robust to noise in the input data, with a low standard deviation, although contraction and typo changes elicited a few significant outliers.
- **Multilinguality**: We trained a model on a new multilingual dataset (e-XNLI) which performs on-par with the English-only portion of e-XNLI. Performance is worse than the most similar dataset used by the authors (FEVER), but might be explained by a difference in dataset difficulty and quality.

- Directions for future analysis/work:
  - Need to better compare our results to the authors'. Could create a new dataset which is a multilingual version of FEVER and has human-annotated labels.
  - Using a multilingual FEVER dataset could allow for better verification of our approach for training multilingual LimitedInk models!

Link to GitHub repository

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