

IRISA

Generating Artificial Texts as Substitution or Complement of Training Data

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1 • Research question

Explore the use of artificially generated texts for supervised tasks within two scenarios:

> the data is used as a substitute of the original data (for instance, when the original data cannot be shared because they contain confidential information [1])



2 • Class-constrained text generation

One generative LM for each class:

- a GPT-2 [6] large model (774M parameters) is fine-tuned for each class
- prompts are first 2 words of randomly chosen texts in training set

Additional filtering

- first results suggests that some of the generated texts do not belong to the expected class (cf. paper)
- the artificial data is used as a complement of the original training dataset (= data augmentation)



3 • Experimental settings

we propose to filter out texts that do not belong to the desired class according to a BERT classifier (kept private) trained on the original dataset

Notations

> \mathcal{T} : original training set ; \mathcal{G}^{f} : filtered artificial training set



Datasets:

- MediaEval 2020 FakeNews [4]: tweets about 5G/covid in English; 3 imbalanced classes (covid+5G, other conspiracies, no conspiracies)
- Cross Lingual Sentiment (CLS-FR) [5] from FLUE: Amazon reviews in French; 2 classes (positive, negative)
- > AG news [7]: in English; 4 categories of news ("World", "Sports", "Business", "Sci/Tech")

Performance with BERT models (RobertA, Flaubert)

| training | MediaEval | | | CLS-FR | | | AG-news | | |
|------------------------------------|-----------|----------|-------|----------|----------|-------|----------|----------|-------|
| set | micro-F1 | macro-F1 | MCC | micro-F1 | macro-F1 | MCC | micro-F1 | macro-F1 | MCC |
| $\overline{\mathcal{T}}$ | 79.57 | 62.66 | 55.71 | 95.44 | 95.42 | 90.86 | 94.35 | 94.35 | 92.47 |
| \mathcal{G}^{f} | 76.22 | 64.18 | 52.75 | 95.76 | 95.75 | 91.51 | 93.49 | 93.49 | 91.35 |
| $\mathcal{T}+\mathcal{G}^{f}$ | 80.12 | 66.08 | 57.44 | 95.99 | 95.98 | 91.97 | 93.47 | 93.47 | 91.34 |
| \mathcal{G}^f then \mathcal{T} | 83.55 | 67.90 | 60.05 | 95.96 | 95.95 | 91.96 | 95.10 | 95.10 | 92.89 |

Performance (%) of BERT models on MediaEval, CLS-FR, and AGnews according to the usage of the artificially generated texts (after filtering).

Classification models:

RoBERTa [3] for MediaEval and AG news
 FlauBERT [2] for CLS-FR

Examples of generated texts

Tweets generated with the GPT-2 model trained on the MediaEval examples with class "covid+5G"

If the FBI ever has evidence that a virus or some other problem caused or contributed to the unprecedented 5G roll out in major metro areas, they need to release it to the public so we can see how much of a charade it is when you try to downplay the link. So let's think about this from the Start. Is it really true that 5G has been activated in Wuhan during Ramadan? Is this a cover up for the fact that this is the actual trigger for the coronavirus virus? Was there a link between 5G and the coronavirus in the first place? Hard to say.

5 • More results

Experiments with Bag-of-Words/legacy classifiers

Important performance gains; not detailed here (cf. paper)

Impact of the quality of the generated data

Prediction differences

Does a classifier trained on the artificial data predicts similarly to one trained on the original data?



we simulate filtering done with classifiers of varying quality (accuracy)



Accuracy on Gf

Figure 1. Performance (macro-F1) according to the quality (accuracy in %) of the classifier filtering the artificially generated data; MediaEval dataset with logistic regression.

Class-conditioned generated texts

- > can be used as substitute
 - very small performance drop with BERT based classifiers
 important gain with Bag-of-Word classifiers
- can be used as data augmentation to get a some improvements, re-balance the classes
- Filtering the generated texts is important
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