Data Augmentation using GPT-2

Statistics 98

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Outline

Imbalanced Data

- Imbalanced data can result in biased models. One solution to this is to over-sample from minority data points. Simple Bootstrapping can lead to over-fitting, so we want to create new synthetic data.

Text Data Augmentation Methods

- **EDA: Easy Data Augmentation**:
  Presented by Wei and Zou [2019]. Combines 4 methods:
  1. Synonym Replacement
  2. Random Insertion
  3. Random Swap
  4. Random Deletion

  Improves CNNs and RNNs. Works best on small datasets. On specific tasks, training with 50% of data with EDA performs as well as training with all the data.

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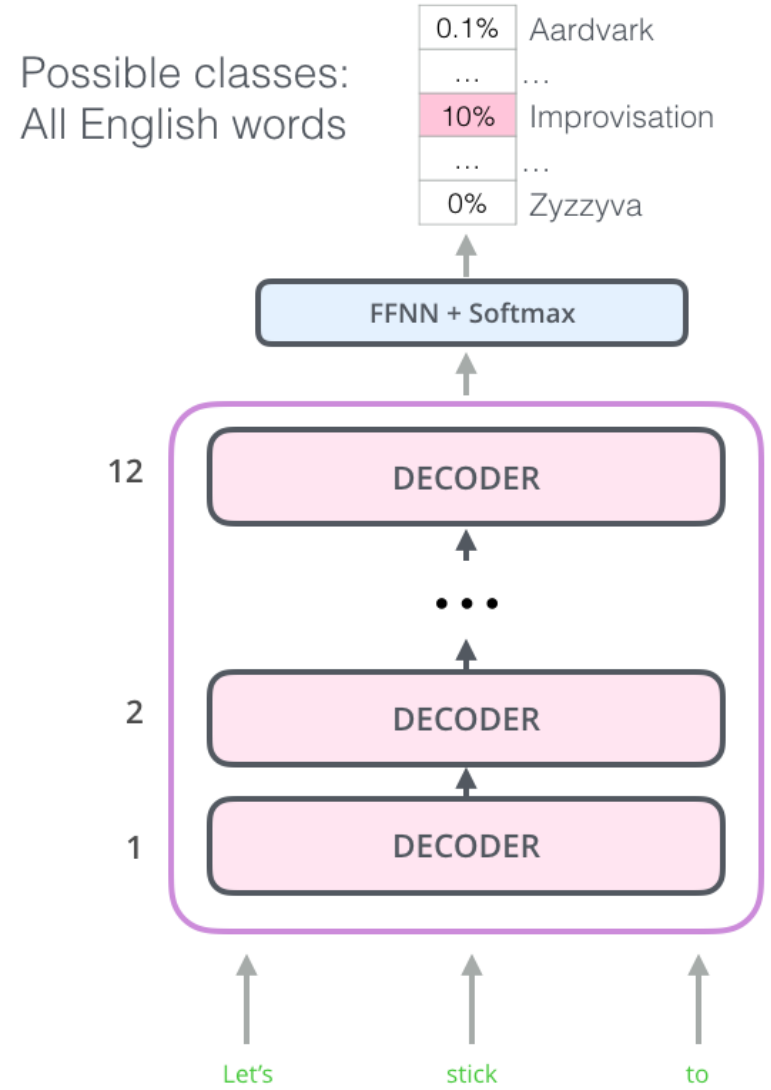
- **GPT-2**
  Presented by Radford et al. [2018] and [2019]. Can be used to generate new text data. Shown to improve F1 score on some tasks. Might not preserve the label When conditioned to generate data from multiple classes.

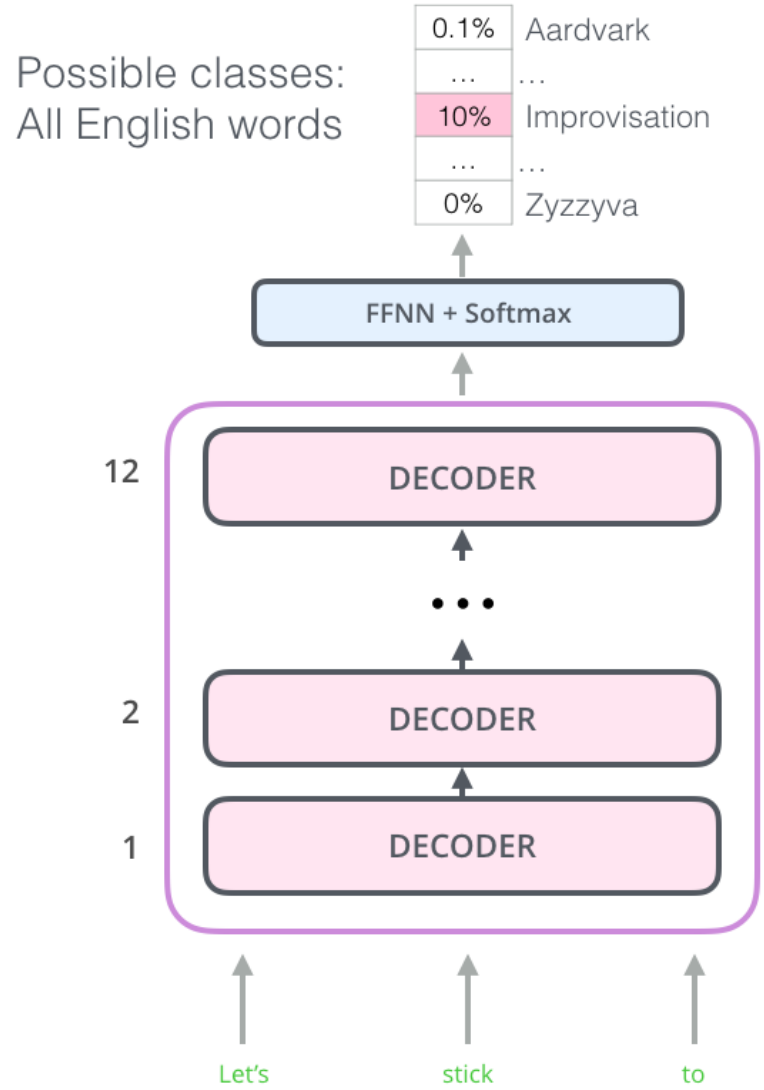
GPT-2 Structure

- Generative Pre-trained Transformer 2.
  Pre-trained on a large amount of data, and can be tuned for specific tasks.



GPT-2 Structure

- Generative Pre-trained Transformer 2. Pre-trained on a large amount of data, and can be tuned for specific tasks.
- Uses multiple layers of decoder-only transformers that use the self attention mechanism to transform the data. The output of the last layer is passed to a FFNN to predict the next word.



Research Question

- *How does Data Augmentation using GPT-2 affect the distribution of the data? And how does it compare with EDA when used with word-based models or context-based models?*

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  - (E) Augment (B) using EDA to 80:20 rate.

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  - (D) Augment (B) using GPT-2 to 90:10 rate
  - (E) Augment (B) using EDA to 80:20 rate.
- We use Distilled GPT-2 for (C) and (D).
  We use EDA with $\alpha = 0.1$ for (E)

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  (4) **Preserving Labels:** Which is better at preserving labels, (D) or (E)?

Word-Based Model Performance

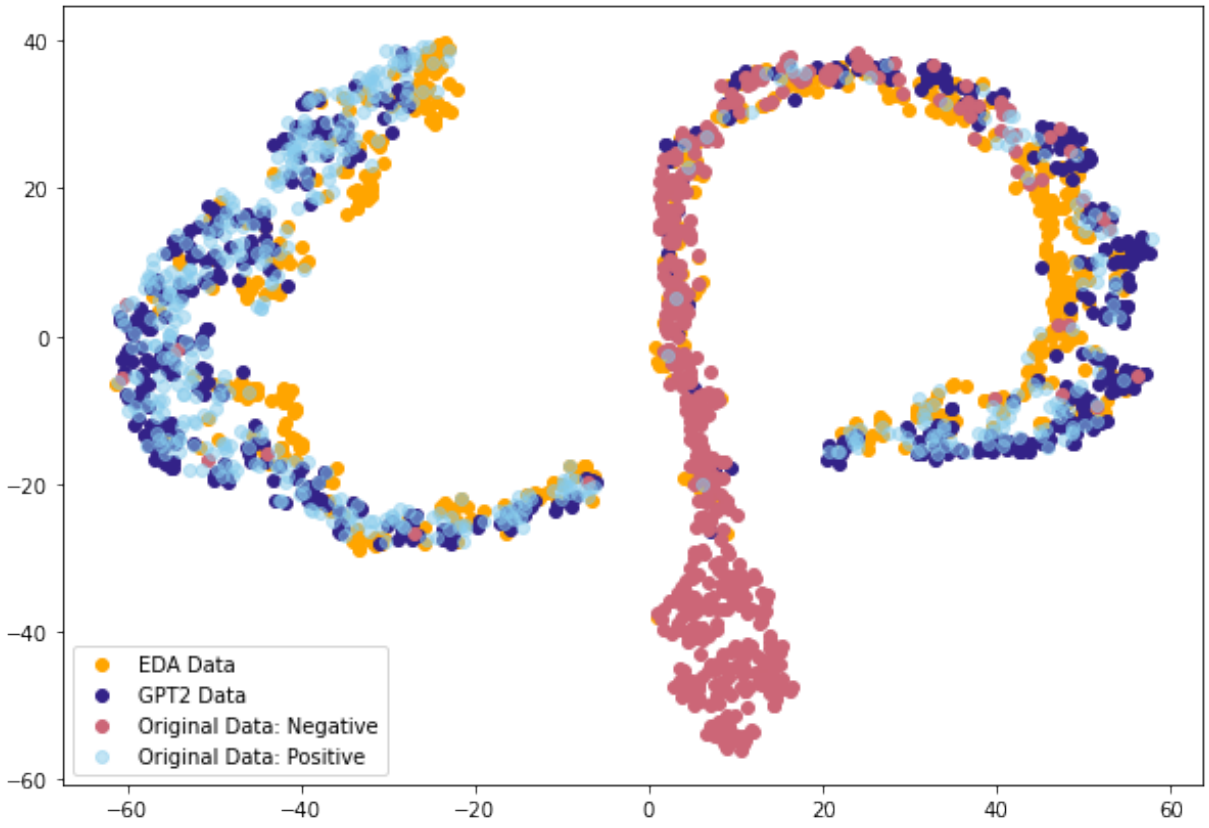
Model	Accuracy	F1 Score
A. Original	0.8799	0.662
B. Imbalanced	0.821	0.246
C. GPT2	0.8366	0.4209
E. EDA	0.8189	0.2715

Context-Based Model Performance

Model	Accuracy	F1 Score
A. Original	0.8886	0.7002
B. Imbalanced	0.8443	0.4198
C. GPT2	0.8403	0.4289
E. EDA	0.7931	0.0038

Distribution of the Data

- Train a Base BERT (the original large model) on (A). Record the outputs of the last layer of the model (before classification). Make TSNE plot of 500 samples from each group.



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- Train a Base BERT (the original large model) on (A). Record the accuracy on the generated samples.
- The model achieves 90.9% accuracy on the positive data from its training set.
  Achieves 76.32% accuracy on the GPT-2 data.
  Achieves 64.16% accuracy on the EDA data.

Conclusions

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- On TF-IDF with logistical regression, GPT-2 improves the F1 score by 18 points.
- With tiny-bert, it only improves F1 score by 0.9%. Might be because BERT was already not very prone to Imbalanced Data.
- Models trained on (C) and (E) don't come close to the models trained on original data. There is a lot of work to be done on imbalanced data.