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COMPLIN
GRUPO COMPUTAÇÃO E LINGUAGEM NATURAL

Using a Knowledge-based Approach for Textual Data Augmentation

Team Presentation

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Previous Work

The beginning of this project

"A grammar is a set of rules that govern a language. It tells us how to combine and compose sentences from its constituents. A computational grammar is an encoding of such rules in a way that allows a computer to analyse sentences to its constituent, or to generate sentences according to these rules."

CLARO, 2019, p. 23

Can we build an efficient AI models augmenting a slice of a dataset through computational grammars(CG) ?

Yes,

in this work we could achieve some good metrics as:

- 75,9% of accuracy on test stage.
- AUC: 0,841.

, but

- the base model without augmentation also had good results on important metrics.
- simple classification algorithm (NB) performance.

This work is available on Youtube.

Channel: Insight Data Science Lab

Title: Utilizando gramáticas computacionais para text data augmentation.

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Research Questions of This Work

TextAugment, EDA and improvement.

Rule based approaches + Knowledge based approach

TextAugment

is a library for augmenting text for natural language processing applications. TextAugment stands on the giant shoulders of NLTK, Gensim, and TextBlob.

EDA

easy data augmentation techniques that are easy to implement and have shown improvements on five NLP classification tasks, with substantial improvements on datasets of size N < 500.

Improvement

can we use those techniques allied with a knowledge-based approach to improve AI models ?

EDA Techniques

- Synonym Replacement
- Random Insertion
- Random Deletion
- Random Swap

number of words changed, n, based on the sentence length l with the formula $n=\alpha l$. For a dataset < 500 is recommended $\alpha = 0.05$

number of synthetic sentences generated. For a dataset < 500 a maximum of 16 sentences is recommended.

Visualization

- Synonym replacement
- Random deletion
- Random Insertion
- Random Swap

Boost NLP models

- Synonym replacement
- Deletion
- Insertion
- Swap

Research Questions

- Can we improve an AI model using a knowledge based approach + EDA techniques for a small dataset ?

- Is it possible to this model have a better performance using a knowledge based approach rather than using only EDA dataset ?

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Step-by-step

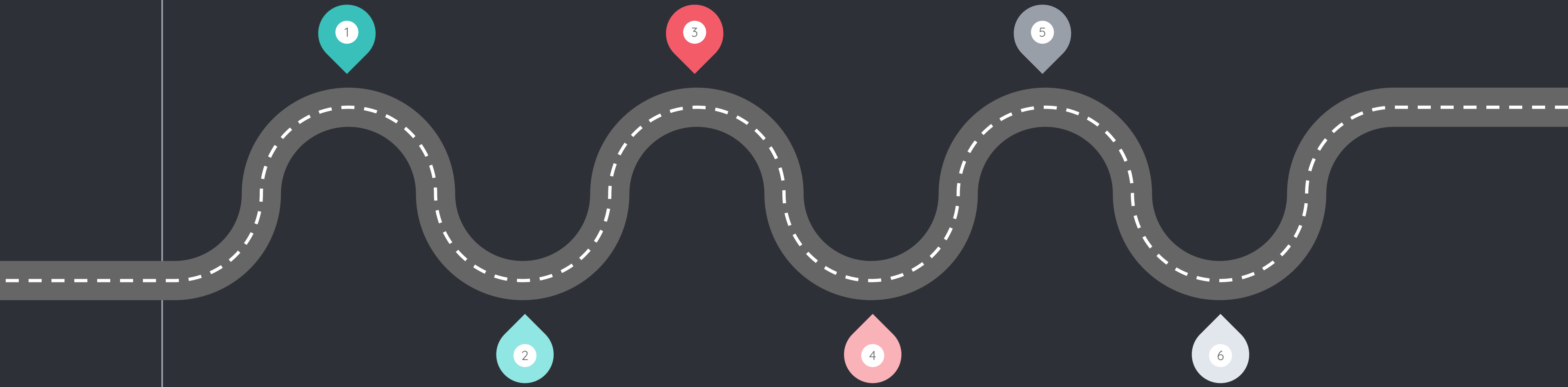
Nature of the data, preprocessing and model architecture.

Roadmap

Select a stable and balanced frame of the dataset

Clean and preprocess the tweets

Augment the dataset using EDA



Select a balanced and randomized way of augmentation type

Augment the dataset using CG

Build the model and compare results

The Dataset

We worked with a open dataset from kaggle that contains 1.6M of labeled tweets for sentiment analysis (labels into positive|negative). From this dataset we select a frame that contains 360 tweets to work with.

Augmentation Process

Preprocessing

Follow the usual way of preprocessing textual data: Cleaning, Low-casing, Tokenization, Lemmatization, etc. Translated some abbreviations (2 -> to) but keep other like lol; Saved user, links and emojis normalizing into a tag (<user>, <link>, <sadface>, …).

Augmentation Type

Randomized selected what kind of augmentation use for each tweet, but keeping a balanced proportion:

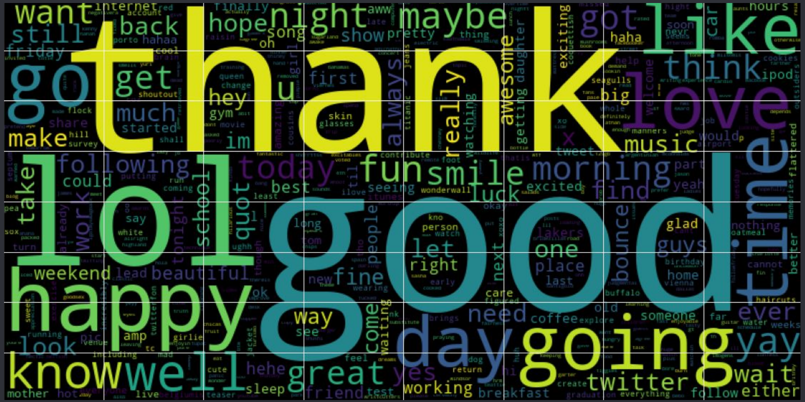
- Synonym Replacement: 29%
- Swap: 24%
- Deletion: 24%
- Insertion: 23%

Example of the Augmented Datasets

	Label	Tweet	Augmented Sentences
Sample 1	**Positive**	**<Tweet>**	**<Tweet>** **<Tweet>** **<Tweet>** **…**
Sample 2	**Negative**	**<Tweet>**	**<Tweet>** **<Tweet>** **<Tweet>** **…**
Sample 3	**Positive**	**<Tweet>**	**<Tweet>** **<Tweet>** **<Tweet>** **…**

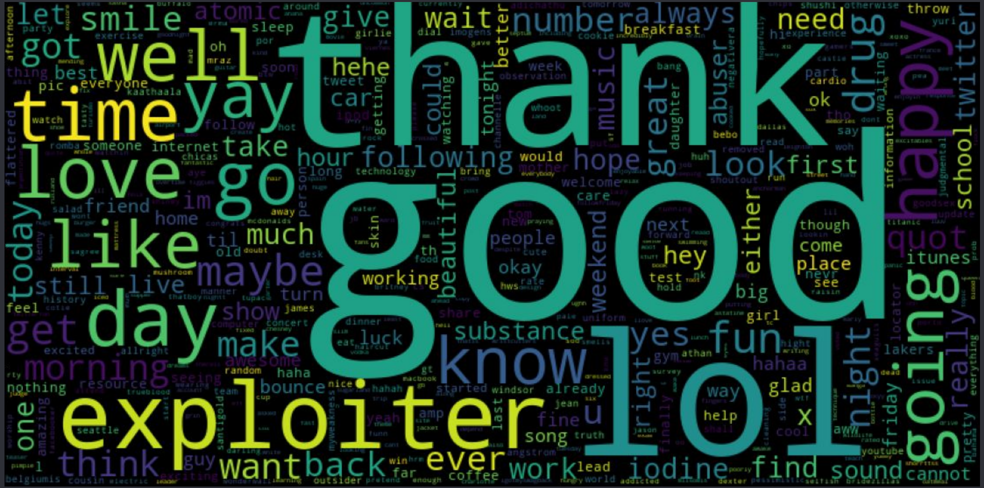
Distribution of the datasets

	Default Dataset	Augmented by CG	Augmented by EDA
Positive (49.5%)	**178**	**716**	**3.026**
Negative (50.5%)	**182**	**736**	**3.094**
Total	**360**	**1.452**	**6.120**



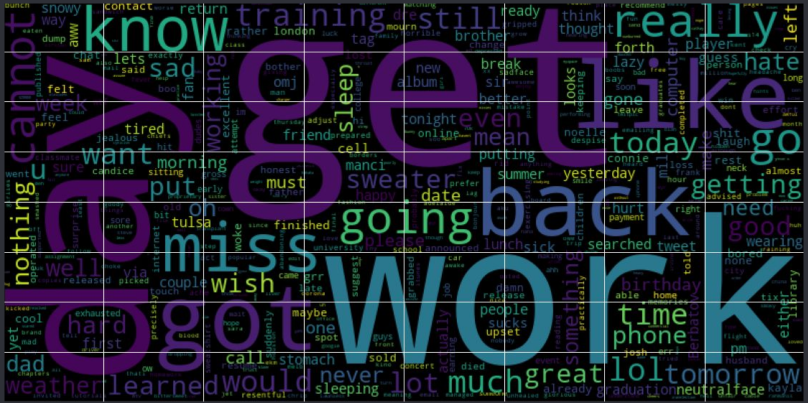
Default Dataset

Augmented by CG

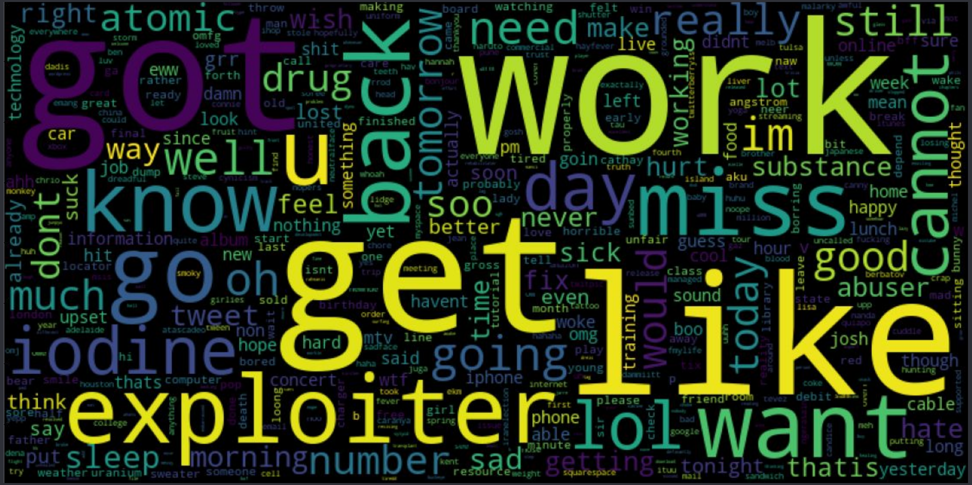


Augmented by EDA

Default Dataset



Augmented by CG



Augmented by EDA

<user> aw hope you feel better soon

<user> aw darling hope you feel better soon

- user aw leslie townes hope you look better soon
- user aw hope you feel better punter soon
- user aw hope better soon
- you aw hope user feel better soon
- user aw hope you feel better palpate soon
- feel aw hope you user better soon
- hope feel better soon
- user aw hope exploiter you feel better soon
- user aw hope you feel soon better
- user aw hope you sense better before long
- user aw hope you feel intimately presently
- user aw you better soon
- user aw hope you palpate feel better soon
- user aw hope feel better soon
- user aw hope you soon better feel
- better aw hope you feel user soon
- user aw hope you feel better soon

no internet at work i cannot fix my resume and email it to the new spot

no internet at work i cannot edit my resume and send it to the new spot

no internet at office i cannot edit my resume and email it to the new spot

no internet at office i cannot edit my resume and send it to the new spot

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no internet at ferment i cannot sterilise my sum up and email it to the raw spot

no internet at cultivate i cannot jam my sketch and email it to the freshly spot

no internet at make for i cannot fix my take up and email it to the new smudge

no at work i cannot fix my resume and email it the spot

no do work internet at work i cannot fix my sterilize resume do work and email it to the new spot

...

Model Architecture

Word2Vec

is a technique for natural language processing (NLP) that uses a neural network model to learn word associations from a large corpus of text by representing it in a vectorial space.

RNN Bi-LSTM

- A **recurrent neural network** (**RNN**) is a class of artificial neural networks where connections between nodes can create a cycle, allowing output from some nodes to affect subsequent input to the same nodes.
- **Long short-term memory** (**LSTM**) is an artificial neural network that has feedback connections. Such a RNN can process not only single data points but also entire sequences of data.
- **Bidirectional** LSTM, instead of training a single model, we introduce two. The first model learns the sequence of the input provided, and the second model learns the reverse of that sequence.

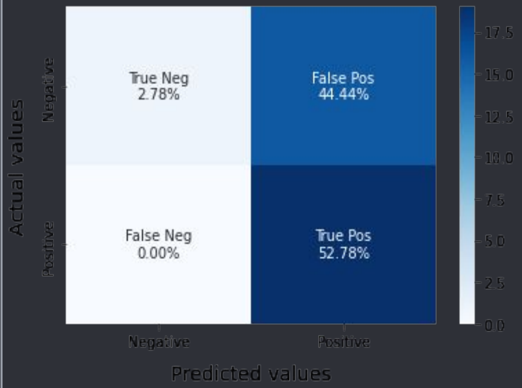
4 Results

Comparing the performance of the model on the datasets.

Comparing Results

	Default Dataset	Augmented by CG	Augmented by EDA
Accuracy	**0.5258**	**0.6723**	**0.5536**
Loss	**0.6926**	**0.6039**	**0.6830**
F1	Pos: **0.70** Neg: **0.11**	Pos: **0.65** Neg: **0.65**	Pos: **0.65** Neg: **0.65**

Confusion Matrices



Default Dataset

Augmented by EDA

Augmented by CG

Thank you all!

ANY QUESTIONS?

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