sentiment analysis of polish texts

Redko Anna

Dataset



A dataset of media releases (Twitter, News and Comments, Youtube, Facebook) from Poland related to COVID-19 for open research

15/01/2020-31/07/2020

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","text","time"
```

'10", "Polacy przeciwko #zajob #falszywapandemia #koronawirus #koronawiruspolska #COVID19 #KoronawirusWPolsce #wybory2020 #Trza #Trzaskowski2020 #DUD

^{&#}x27;1","Tez uwazam ze falszywa pandemia #koronawirus jest jak stan wojenny. Ja juz mam nerwice, czuje stres jak widze zamaskowanych. https://t.co/TtlrJ
'2","Podawajcie dalej! #koronawirus #KoronawirusWPolsce #zajob #wybory2020 #DUDA2020 #Trzaskowski2020 # https://t.co/9PDDfYrpFp",2020-07-09 19:48:39
'3","Precz z pandemia!!! #koronawirus #koronawiruswpolsce #koronawiruspolska #zajob https://t.co/N8bTjei2zt",2020-07-10 17:58:43

^{&#}x27;4","Ludzie zra sie na ulicach przez te kanalie #szumowski #koronawirus #koronawiruswpolsce dlatego nie ide na wybory https://t.co/NRfe9MQ0xH",2020-'5","Lekarze to najwiekszy zawyd tej pseudoepidemii #koronawirus https://t.co/32BkrWrHTa",2020-07-13 20:08:11

^{&#}x27;6","Rekordowa frekwencja? Przeciez mamy WIELKA EPIDEMIE! Ludzie otworzcie oczy! Bo sami sobie przeczycie! #koronawirus #koronawiruswpolsce #zajob # '7","Polacy przeciwko #zajob #falszywapandemia #koronawirus #koronawiruspolska #COVID19 #KoronawirusWPolsce #wybory2020 #Trza #Trzaskowski2020 #DUDA '8","Niewykluczone, ze jednak sprybuje pokonac wstret i oddam glos - oczywiscie na #PAD . Przekonal mnie apel @GadowskiWitold . Mam nadzieje, ze jes '9","65 uzytych respiratoryw w calym kraju! Polsko otworz oczy! #koronawirus https://t.co/luXYCuZ5am",2020-07-12 19:55:42

Dataset

coronavirus | 2020 Poland coronavirus data | Dataset library

by dtandev • Python • Version: Current • License: MIT

2020 Poland coronavirus data (COVID-19 / 2019-nCoV)

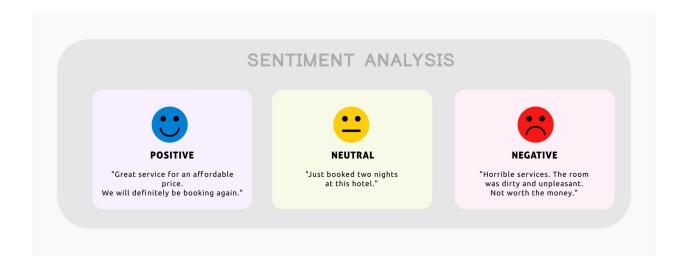
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03-03-2020,0,0,0,68,316,4459,559
```

- 04-03-2020,1,0,0,65,349,4540,584
- 05-03-2020,1,0,0,92,490,5647,676
- 06-03-2020,5,0,0,128,1299,6184,855
- 07 02 2020 6 0 0 146 1540 6400 056
- 07-03-2020,6,0,0,146,1548,6409,856
- 08-03-2020,12,0,0,168,932,7122,1154
- 09-03-2020,17,0,0,467,1014,7110,1384
- 10-03-2020,22,0,0,220,1055,9366,1630
- 11-03-2020, 31, 0, 0, 317, 1193, 11524, 2024



Sentiment analysis

Sentiment analysis is the automated process of tagging data according to their sentiment, such as positive, negative and neutral. Sentiment analysis allows companies to analyze data at scale, detect insights and automate processes.



Idea

- to analyze data from social media(e.g. Twitter) in Polish that would be related to the coronavirus
- Compare results with statistics data for the:
 Deaths, Recovered, In_the_hospital, In_quarantine, Under_medical_supervision

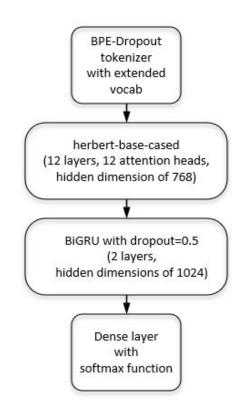
herbert-base-cased-sentiment

Model

Model is based on HerBERT (Polish version of BERT) since it receives state-of-the-art results in the area of text classification. It is followed with 2 layers of a bidirectional gated recurrent unit and a fully connected layer.

The BPE-Dropout tokenizer from HerBERT (which changes a text into tokens before passing input to HerBERT) was extended with additional COVID-19 tokens so that it would recognize (not separate) the basic coronavirus words.

Dataset: publicly available Twitter dataset from CLARIN.SI repository with 100 personally labeled COVID-19 tweets in order to train a model on a sample of domain-specific texts.



Model

twitter-xlm-roberta-base-sentiment-finetunned

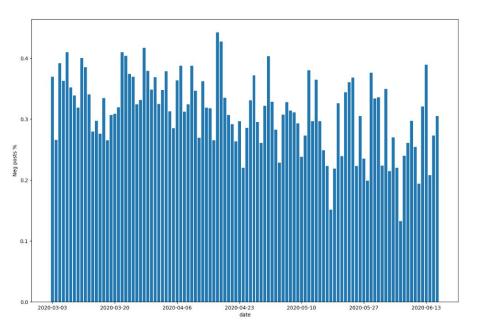
This is multilingual XLM-Roberta model sequence classifier fine tunned and based on Cardiff NLP Group sentiment classification model.

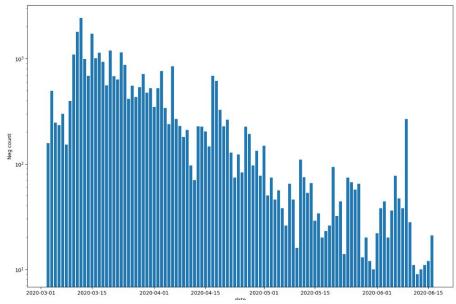
supports Polish

Mode <u>twitter-sentiment-pl-base</u>

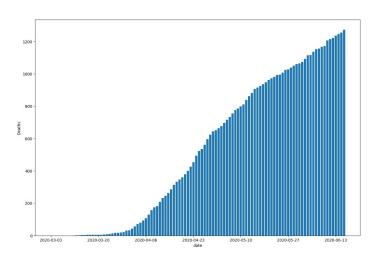
Twitter Sentiment PL (base) is a model based on herbert-base for analyzing sentiment of Polish twitter posts. It was trained on the translated version of TweetEval by Barbieri et al., 2020 for 10 epochs on single RTX3090 gpu

Neg posts percentage / count

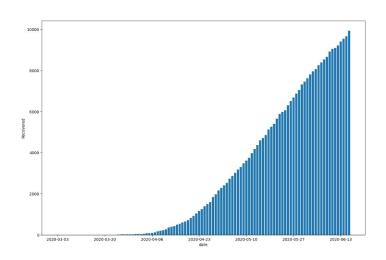




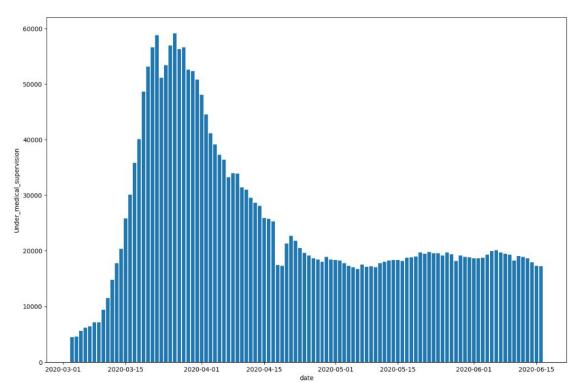
Death curve



Recovered



Under medical supervision



Let's have a look at Pearson correlations of negative posts and dataset variable

	Recover ed	Deaths	Under medical supervision	Confirmed	In quarantine	In the hospital
neg %	-0.48	-0.50	0.25	-0.49	0.002	-0.21
neg count	-0.62	-0.74	0.46	-0.73	-0.36	-0.58

twitter_sentiment_
pl_base

	Recover ed	Deaths	Under medical supervision	Confirmed	In quarantine	In the hospital
neg %	-0.169	-0.191	0.071	-0.193	-0.117	-0.12
neg count	-0.45	-0.549	0.221	-0.55	-0.426	-0.525

twitter-xlm-robertabase-sentiment-fin etunned Let's have a look at Pearson correlations of negative posts and dataset variables

Results

sliding window smooth

	Recover ed	Deaths	Under medical supervision	Confirmed	In quarantine	In the hospital
neg %	-0.948	-0.966	0.276	-0.961	-0.37	-0.641
neg count	-0.76	-0.85	0.46	-0.85	-0.45	-0.67

twitter_sentiment_ pl_base

	Recover ed	Deaths	Under medical supervision	Confirmed	In quarantine	In the hospital
neg %	-0.527	-0.652	0.432	-0.640	-0.380	-0.574
neg count	-0.672	-0.779	0.349	-0.783	-0.538	-0.696

twitter-xlm-robertabase-sentiment-fin etunned

Let's have a look at Pearson correlations of negative posts and dataset variables twitter_sentiment_

twitter_sentiment_ pl_base

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sliding window smooth

Let's have a look at Pearson correlations of negative posts and dataset variables *twitter-xlm-roberta-base-sentiment-finetunned*

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Conclusion

From the conclusions, it is strange that negative posts have no correlation with the number of deaths. this is most likely due to population fatigue over time.

Thank you for your attention! Python

notebook and a github blog are also provided