

Verification of Claims in the COVID-19 Pandemic

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December 7, 2020

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Task Overview

- Verification of claims involving the COVID-19 pandemic
 - 3-class classification problem
 - Selecting evidence from the background literature on COVID-19
 - Find rationales that justify the classification.

FEVER

- FEVER – Fact Extraction and VERification
 - A publicly available dataset for verification against textual sources
- Synthetic Claims generated by altering sentences extracted from Wikipedia
- Claims classified as SUPPORTED, REFUTED, NOTENOUGHINFO
- Pipelined system with three stages
 - Document Retrieval
 - Sentence-level Evidence Selection
 - Textual Entailment
- Labeling a claim accompanied by correct evidences – 31.87%
- Ignoring the evidence – 50.91%
- Baseline System - <https://github.com/sheffieldnlp/fever-baselines>

Verifying Scientific Claims

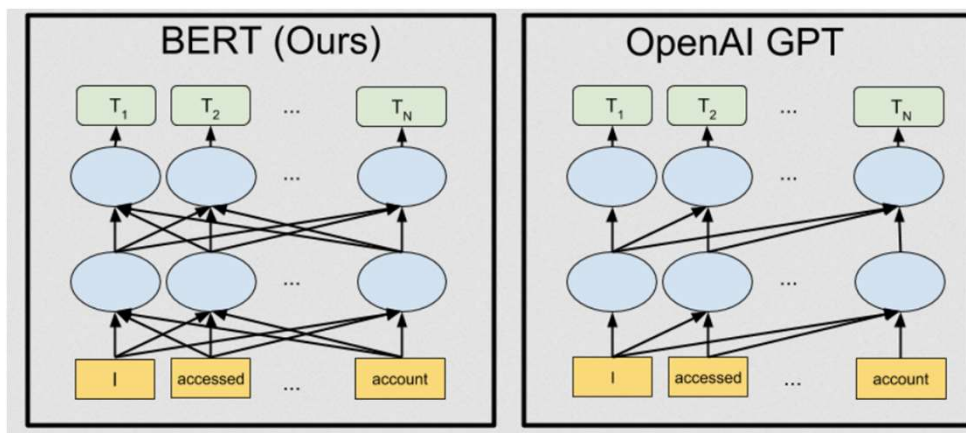
- SCIFACT – 1.4K Expert-written Scientific claims paired with evidences
 - Abstracts annotated with labels and rationales
- System able to verify claims related to COVID-19
 - Evidences from CORD-19 corpus
- Claims in SCIFACT are natural – derived from citation sentences, or citances in scientific articles
- Claims labeled as – SUPPORTS, REFUTES, NOINFO
- Data and Code - <https://github.com/allenai/scifact>

VERISCI – Baseline Model

- 3 stage pipeline
- Abstract Retrieval – k abstracts retrieved with highest TF-IDF similarity to the claim
- Rationale Selection – rationale sentences for each abstract identifier
- Label Prediction – final label prediction
- BERT style pre-trained language model

BERT language model

- BERT: Bidirectional encoder representations from transformers
- Transformer encoder reads the entire set of words at once
- BERT can be used for a wide variety of language tasks.
- Most hyper-parameters remain the same as in BERT, only an additional set of hyper parameters require training.



[Google, AI]

Pre-trained Models

Architecture	Model Id	Details of the Model
GPT-2	gpt-2	12-layer, 768-hidden, 12-heads, 117M parameters. OpenAI GPT-2 English model
RoBERTa	roberta-base	12-layer, 768-hidden, 12-heads, 125M parameters RoBERTa using the BERT-base architecture
RoBERTa	roberta-large	24-layer, 1024-hidden, 16-heads, 355M parameters RoBERTa using the BERT-large architecture

Model Finetuning

- Finetune the model parameters
- Finetune existing pre-trained models on SCIFACT
 - DistilBERT: smaller and faster model compared to RoBERTa
 - ELECTRA: pre-trained on a small masked language model with text encoders used as discriminators rather than as generators
- Challenge of limited computational resources

Data Files - SCIFACT

- Corpus

```
{"doc_id": 4983, "title": "Microstructural development of human newborn cerebral white matter assessed in vivo by diffusion tensor magnetic resonance imaging.", "abstract": ["Alterations of the architecture of cerebral white matter in the developing human brain can affect cortical development and result in functional disabilities.", ... "The data indicate that quantitative assessment of water diffusion by diffusion tensor MRI provides insight into microstructural development in cerebral white matter in living infants."], "structured": false}
```

- Claims-train

- {"id": 2, "claim": "1 in 5 million in UK have abnormal PrP positivity.", "evidence": {"13734012": [{"sentences": [4], "label": "CONTRADICT"}]}, "cited_doc_ids": [13734012]}

- Claims-dev (a similar format to claims-train)

- Claims-test

- {"id": 7, "claim": "10-20% of people with severe mental disorder receive no treatment in low and middle income countries."}

Logistic Regression Model

Claim Label Accuracy

```
epoch: 460, loss = 0.0979
```

```
epoch: 470, loss = 0.0968
```

```
epoch: 480, loss = 0.0956
```

```
epoch: 490, loss = 0.0945
```

```
epoch: 500, loss = 0.0934
```

```
accuracy: 0.5309
```

```
(base) yongle@wireless-10-105-82-17 data % █
```

Baseline Implementation

- *Cloned their original github repository.*
- *Installed relevant dependencies.*
- *Downloaded the original dataset.*
- *Downloaded the best model as claimed by SCIFACT.*
- *Mounted Drive to the colab repository '/content/scifact' after debugging and setting the correct paths to run complex modules by editing their source code.*
- *Learned about ipdb package, an interactive Python Debugger, that they used and commented those lines.*
- *Pandoc commands to convert a .md to .pdf file did not work correctly. After research and installation of appropriate packages like xelatex, the edited pandoc command worked and the .md file was saved to see the paths on Google colab.*
- *Created the results directory to make sure that the files get stored correctly.*
- *Executed the Verification script as given in SCIFACT github to verify the claim “Coronavirus droplets can remain airborne for hour”*
- *Stored the generated report.*
- *Downloaded the SCIFACT repository to save changes locally as Google Colab is a VM and all local changes would be erased otherwise if it was run again.*
- *The automatically generated report covid-report.pdf is attached to the piazza post.*

Automatically Generated Report

Claim

Coronavirus droplets can remain airborne for hours

Evidence

A Physics Modeling Study of SARS-CoV-2 Transport in Air

Decision: SUPPORT (score=0.99, evidence scores=0.49)

- Health threat from SARS-CoV-2 airborne infection has become a public emergency of international concern.
 - During the ongoing coronavirus pandemic, people have been advised by the Centers for Disease Control and Prevention to maintain social distancing of at least 2 m to limit the risk of exposure to the coronavirus.
 - We carry out a physics modeling study for SARS-CoV-2 transport in air.
 - We show that if aerosols and droplets follow semi-ballistic emission trajectories, then their horizontal range is proportional to the particle's diameter.
 - For standard ambient temperature and pressure conditions, the horizontal range of these aerosols remains safely below 2 m.
 - We also show that aerosols and droplets can remain suspended for hours in the air, providing a health threat of airborne infection.
 - The latter argues in favor of implementing additional precautions to the recommended 2-m social distancing, e.g. wearing a face mask when we are out in public.
-

Airborne/Droplet Infection Isolation

Decision: SUPPORT (score=0.99, evidence scores=0.21)

- Airborne/droplet infection is caused by infected agents in the air around a person.
- Microbial pathogenic agents that are mainly transmitted airborne are aerosols, re-aerosols, microbe-carrying particles, huge amounts of bacteria-carrying airborne skin cells, dust, droplets and droplet nuclei.
- At the same time, there is always a contact transmission from contaminated environment, equipment, textiles and waste.
- Droplet nuclei are small evaporated droplet residues (<5 m) produced by coughing, sneezing, shouting, singing and speaking very distinct—especially the consonants.
- Droplet nuclei remain for many hours in the air and may be carried by normal air currents in long distances outside the room.
- Therefore, “droplet isolation and droplet precaution” is included in the airborne isolation regime.

Analysis of Different Claims

- Prepare a list of 100 claims
- Analyze the model performance on claims involving
 - Racial disparities in COVID-19 claims
 - Societal bias
 - Conspiracy theories surrounding COVID-19
 - Vaccines
 - Masks

Current State-of-the-art Approaches

System name	Research group	References	Sentence-level F1	Abstract-level F1
VerT5erini (2-stage Neural Retrieval)	covidex.ai	paper	58.8	62.7
VerT5erini (BM25 Retrieval)	covidex.ai	paper	55.5	59.2
SciKGAT	THUNLP and MSR	code	50.5	58.3
VeriSci	Semantic Scholar	paper	39.5	46.5
Zero-Shot (trained on FEVER)	Semantic Scholar	paper	26.9	36.4

Future Work

- Finetune different pre-trained models on the SCIFACT dataset
- Analyze how different claims involving social bias are verified by the model
- Try to assess and analyze the strength and provenance of the background knowledge source.

References

- Adapting Open Domain Fact Extraction and Verification to COVID-FACT through In-Domain Language Modeling
 - Liu et. al. , EMNLP 2020, pp. 2395-2400
- Fact or Fiction: Verifying Scientific Claims
 - Wadden et. al., 2020 arXiv preprint arXiv:2004.14974
- FEVER: a large-scale dataset for Fact Extraction and VERification
 - Thorne et. al., 2018, NAACL 2018, pp. 209-219.