



PROMPT-BASED TEXT MATCHING METHODS FOR FAKE NEWS STANCE DETECTION

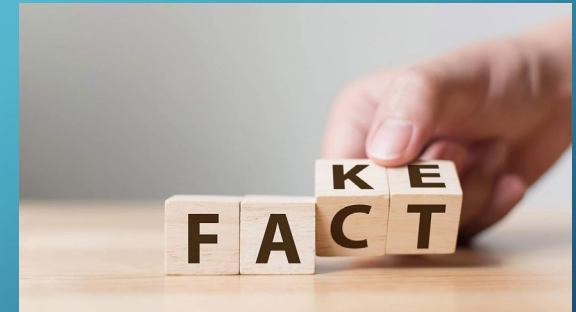
CMPT 413 FINAL PROJECT

GROUP AWSL

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PART I: INTRODUCTION



Image Credit:
<http://www.fakenewschallenge.org/>

PART I: INTRODUCTION

- 2. Input
 - A headline and a body text - either from the same news article or from two different articles.
- 3. Output
 - Classify the stance of the body text relative to the claim made in the headline into one of four categories:
 - Agrees: The body text agrees with the headline.
 - Disagrees: The body text disagrees with the headline.
 - Discusses: The body text discuss the same topic as the headline, but does not take a position
 - Unrelated: The body text discusses a different topic than the headline

PART I: INTRODUCTION

- 4. Example headline
 - “Robert Plant Ripped up \$800M Led Zeppelin Reunion Contract”
- 5. Example snippets from body texts and correct classifications
 - Agree:
 - “... Led Zeppelin’s Robert Plant turned down £500 MILLION to reform supergroup. ...”
 - Disagree:
 - “... No, Robert Plant did not rip up an \$800 million deal to get Led Zeppelin back together. ...”
 - Discusses:
 - “... Robert Plant reportedly tore up an \$800 million Led Zeppelin reunion deal. ...”
 - Unrelated:
 - “... Richard Branson’s Virgin Galactic is set to launch SpaceShipTwo today. ...”

PART II: RELATED WORK

- 1. Traditional Text Matching Models
 - TF-IDF, BM25, Latent Dirichlet Allocation (LDA)
- 2. DNN-based Text Matching Models
 - Deep Structured Semantic Models (DSSM) (Huang et al., 2013)
 - Architecture-I (ACRI) (Hu et al., 2014)
 - Tree-structured LSTM (Tree-LSTM) (Tai et al., 2015)
- 3. Pre-trained-based Text Matching Models
 - ELMo (Peters et al., 2018)
 - GPT (Radford et al., 2018)
 - BERT (Devlin et al., 2018)

PART III: DATA

- Fake News Challenge (FNC-1)
 - 1. Training Set: [headline, body text, label]
 - Pairs of headline and body text with the appropriate class label for each.
 - 2. Testing Set: [headline, body text]
 - Pairs of headline and body text without class labels used to evaluate systems.

```
1  Headline,Body_ID,Stance
2  Police find mass graves with at least '15 bodies' near Mexico town where 43 students disappeared after police clash,712,unrelated
3  Hundreds of Palestinians flee floods in Gaza as Israel opens dams,158,agree
4  "Christian Bale passes on role of Steve Jobs, actor reportedly felt he wasn't right for part",137,unrelated
5  HBO and Apple in Talks for $15/Month Apple TV Streaming Service Launching in April,1034,unrelated
6  Spider burrowed through tourist's stomach and up into his chest,1923,disagree
7  'Nasa Confirms Earth Will Experience 6 Days of Total Darkness in December' Fake News Story Goes Viral,154,agree
8  "Accused Boston Marathon Bomber Severely Injured In Prison, May Never Walk Or Talk Again",962,unrelated
9  Identity of ISIS terrorist known as 'Jihadi John' reportedly revealed,2033,unrelated
10 Banksy 'Arrested & Real Identity Revealed' Is The Same Hoax From Last Year,1739,agree
11 British Aid Worker Confirmed Murdered By ISIS,882,unrelated
12 Gateway Pundit,2327,discuss
13 "Woman detained in Lebanon is not al-Baghdadi's wife, Iraq says",1468,agree
14 Kidnapped Nigerian schoolgirls: Government claims ceasefire deal with Boko Haram that will bring missing girls home,1003,unrelated
15 "No, that high school kid didn't make $72 million trading stocks",2132,unrelated
16 "Soon Marijuana May Lead to Ticket, Not Arrest, in New York",47,discuss
17 Vandals add rude paint job to $2.5m Bugatti (but luckily for the owner it all turned out to be a hoax),615,unrelated
18 Boko Haram Denies Nigeria Cease-Fire Claim,2463,discuss
```

PART IV: APPROACH

- 1. Pre-processing FNC corpus
- 2. Preparing BERT base model
- 3. Fine-tuning BERT model

PART IV: APPROACH

- 1. Pre-processing CSV
 - Join stances.csv and bodies.csv

	UniqueID	...	Stance
0	0	...	unrelated
1	1	...	unrelated
2	2	...	unrelated
3	3	...	unrelated
4	4	...	unrelated
...
25408	25408	...	agree
25409	25409	...	discuss
25410	25410	...	disagree
25411	25411	...	disagree
25412	25412	...	agree

[25413 rows x 4 columns]

	articleBody
Body ID	
1	Al-Sisi has denied Israeli reports stating tha...
2	A bereaved Afghan mother took revenge on the T...
3	CNBC is reporting Tesla has chosen Nevada as t...
12	A 4-inch version of the iPhone 6 is said to be...
19	GR editor's Note\n\nThere are no reports in th...
...	...
2582	Congressional Republicans, evidently hoping th...
2583	Did Obamacare work?\n\nIt's worth reflecting u...
2584	Millions may lose coverage next year if Congre...
2585	Come November, the grim trudge across the incr...
2586	Remember how much Republicans wanted to repeal...

[904 rows x 1 columns]

	Body ID		Mixed	Stance
40261	752	Did Kim Yo-Jong Take Kim Jong Un's Role? North...		0
33359	1166	ISIS beheads American photo-journalist James W...		0
27620	2272	Rumor: Seth Rogen to Appear as Woz in Sony's S...		0
41445	493	Purported ISIS claim: Jordan airstrike kills f...		0
14838	1605	Catholic priest dies for 48 mins, wakes up cla...		0
...
41291	1427	Mexico hit by student massacre: At least 17 an...		3
14137	2403	New Audio Allegedly Captures Moment Michael Br...		0
5354	1744	Apple Watch to Be Shower-Proof, Have 100,000 A...		0
15195	1489	11 jetliners 'missing' after Islamist takeover...		0
29406	649	NASA Raises Doubts About Reports of Nicaraguan...		0

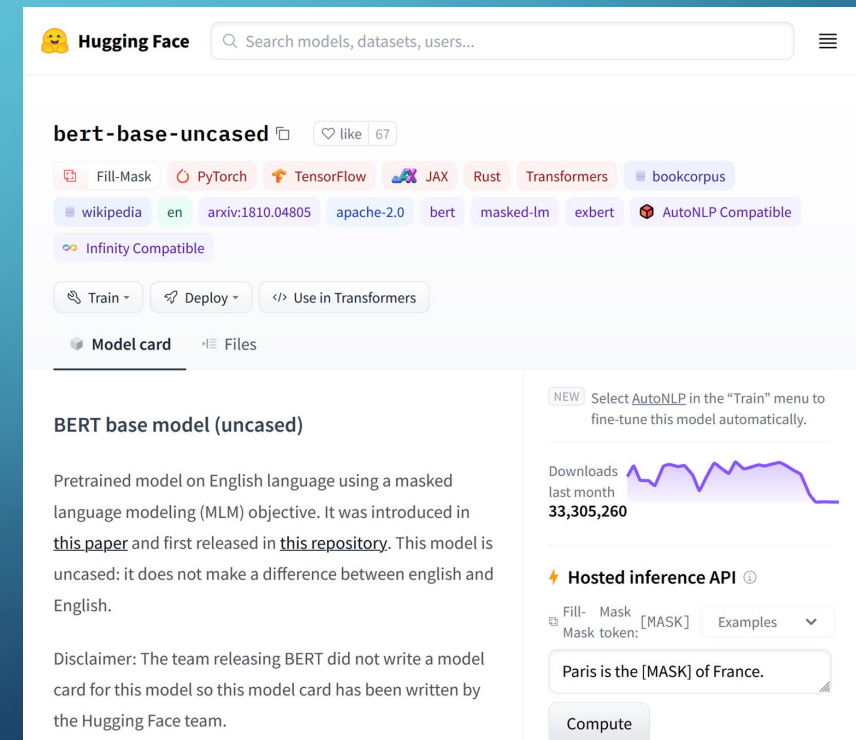
[49972 rows x 3 columns]

PART IV: APPROACH

- 2. Preparing BERT model
 - Using Google Colab Pro + HuggingFace Transformer

```
[ ]: max_length = 512
tokenizer = BertTokenizerFast.from_pretrained(local_dir, local_files_only=True,
do_lower_case=True)
model = BertForSequenceClassification.from_pretrained(local_dir,
local_files_only=True, num_labels=4).to(device)

[ ]: #
# model_name = "bert-base-uncased"
# max_length = 512
# tokenizer = BertTokenizerFast.from_pretrained(model_name, do_lower_case=True)
# model = BertForSequenceClassification.from_pretrained(model_name,
num_labels=4).to(dev)
```



The screenshot shows the Hugging Face model card for 'bert-base-uncased'. At the top, there's a search bar and a navigation menu. The model name 'bert-base-uncased' is prominently displayed with a 'like' button and a count of 67. Below the name, there are several tags indicating the model's compatibility with various frameworks like Fill-Mask, PyTorch, TensorFlow, JAX, Rust, Transformers, and bookcorpus. There are also tags for 'wikipedia', 'en', 'arxiv:1810.04805', 'apache-2.0', 'bert', 'masked-lm', 'exbert', and 'AutoNLP Compatible'. A section for 'Infinity Compatible' is also visible. Below these tags, there are buttons for 'Train', 'Deploy', and 'Use in Transformers'. The 'Model card' tab is selected, showing a detailed description of the BERT base model (uncased). The description states that it is a pretrained model on English language using a masked language modeling (MLM) objective, introduced in a specific paper and repository. It notes that the model is uncased, meaning it does not distinguish between English and French. A disclaimer at the bottom states that the team releasing BERT did not write a model card for this model, so the card was written by the Hugging Face team. On the right side of the card, there is a 'Hosted inference API' section with a 'Compute' button. Above this, there is a 'Downloads last month' section showing a graph and the number 33,305,260. At the very top right, there is a 'NEW' badge and a note about selecting 'AutoNLP' in the 'Train' menu to fine-tune the model automatically.

bert-base-uncased like 67

Fill-Mask PyTorch TensorFlow JAX Rust Transformers bookcorpus

wikipedia en arxiv:1810.04805 apache-2.0 bert masked-lm exbert AutoNLP Compatible

Infinity Compatible

Train Deploy Use in Transformers

Model card Files

BERT base model (uncased)

Pretrained model on English language using a masked language modeling (MLM) objective. It was introduced in [this paper](#) and first released in [this repository](#). This model is uncased: it does not make a difference between english and English.

Disclaimer: The team releasing BERT did not write a model card for this model so this model card has been written by the Hugging Face team.

Hosted inference API

Fill- Mask [MASK] Examples

Mask token:

Paris is the [MASK] of France.

Compute

Downloads last month
33,305,260

NEW Select [AutoNLP](#) in the "Train" menu to fine-tune this model automatically.

PART IV: APPROACH

- 3. Fine-tuning BERT model
 - Method 1: Tokenize bodies-headline texts

```
[ ]: # tokenize the dataset, truncate when passed `max_length`,  
      # and pad with 0's when less than `max_length`  
train_encodings = tokenizer(train_texts, truncation=True, padding=True,  
                             ↪max_length=max_length)  
valid_encodings = tokenizer(valid_texts, truncation=True, padding=True,  
                             ↪max_length=max_length)  
test_encodings = tokenizer(test_texts, truncation=True, padding=True,  
                             ↪max_length=max_length)
```

PART IV: APPROACH

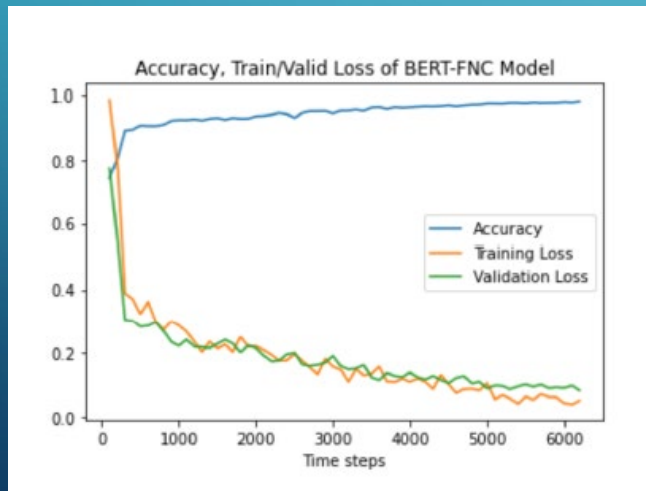
- 3. Fine-tuning BERT model
 - Method 2: Generate PyTorch DataSet and DataLoader

```
[ ]: class FakeNewsDataset(torch.utils.data.Dataset):  
    def __init__(self, encodings, labels):  
        self.encodings = encodings  
        self.labels = labels  
  
    def __getitem__(self, idx):  
        item = {k: torch.tensor(v[idx]) for k, v in self.encodings.items()}  
        item["labels"] = torch.tensor(self.labels[idx])  
        return item  
  
    def __len__(self):  
        return len(self.labels)
```

```
[ ]: from torch.utils.data import DataLoader  
test_dataloader = DataLoader(test_dataset, batch_size=128, shuffle=False)  
test_dataloader
```

PART IV: APPROACH

- 3. Fine-tuning BERT model
 - Method 3: Run fine-tuning trainer
 - Set Training Arguments
 - Set Trainer
 - Define Training Metrics



Train BERT model

```
[ ] from sklearn.metrics import accuracy_score, precision_score, f1_score, confusion_matrix

def compute_metrics(pred):
    labels = pred.label_ids
    preds = pred.predictions.argmax(-1)
    # calculate accuracy using sklearn's function
    acc = accuracy_score(labels, preds)
    return {
        'accuracy': acc,
    }

[ ] training_args = TrainingArguments(
    output_dir='./results',          # output directory
    num_train_epochs=3,              # total number of training epochs
    per_device_train_batch_size=16,  # batch size per device during training
    per_device_eval_batch_size=64,   # batch size for evaluation
    warmup_steps=500,                # number of warmup steps for learning rate scheduler
    weight_decay=0.01,               # strength of weight decay
    logging_dir='./logs',            # directory for storing logs
    load_best_model_at_end=True,     # load the best model when finished training (default metric is loss)
    # but you can specify `metric_for_best_model` argument to change to accuracy or other metric
    logging_steps=100,               # log & save weights each logging_steps
    save_steps=1000,                 # log & save weights each logging_steps
    evaluation_strategy="steps",     # evaluate each `logging_steps`
)

[ ] trainer = Trainer(
    model=model,                    # the instantiated Transformers model to be trained
    args=training_args,             # training arguments, defined above
    train_dataset=train_dataset,    # training dataset
    eval_dataset=valid_dataset,     # evaluation dataset
    compute_metrics=compute_metrics, # the callback that computes metrics of interest
)

[ ] trainer.train()
```


PART V: EVALUATION

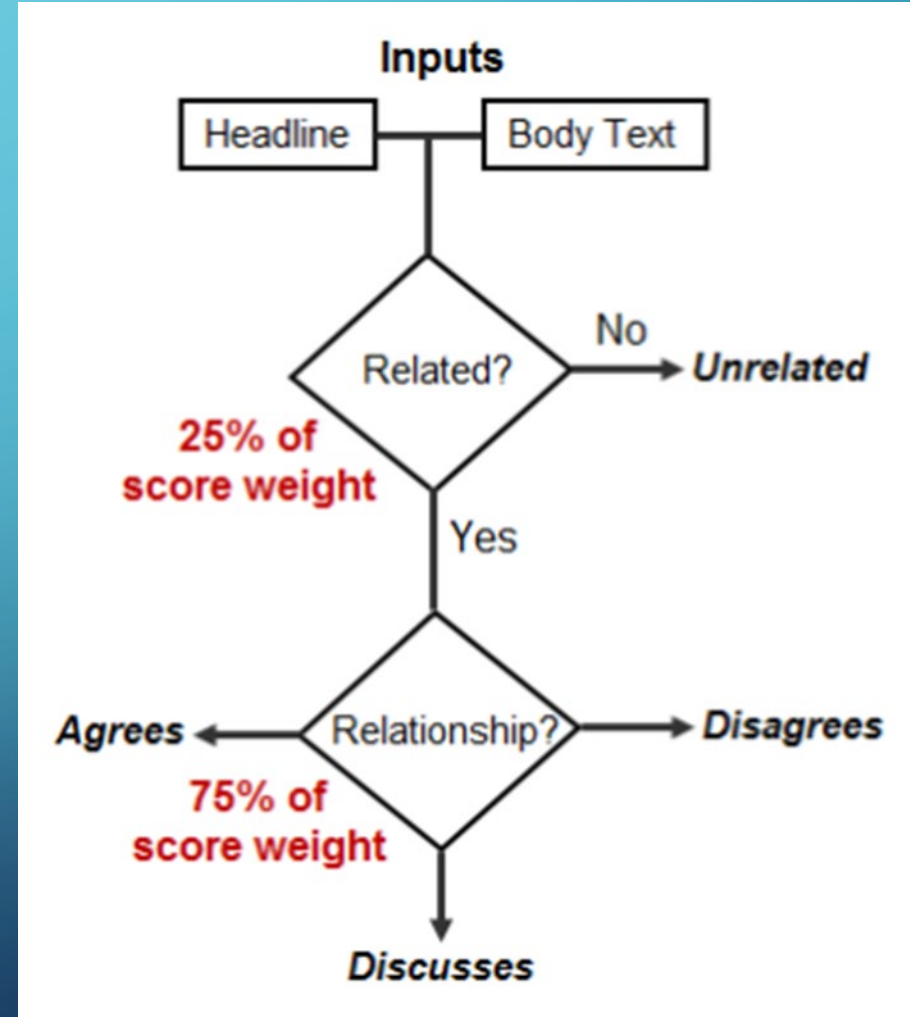
- 1. Metrics
 - Accuracy, Precision, F1, AUC, ROC
 - FNC Score (Domain-Specific)

PART V: EVALUATION

- 2. Flowchart

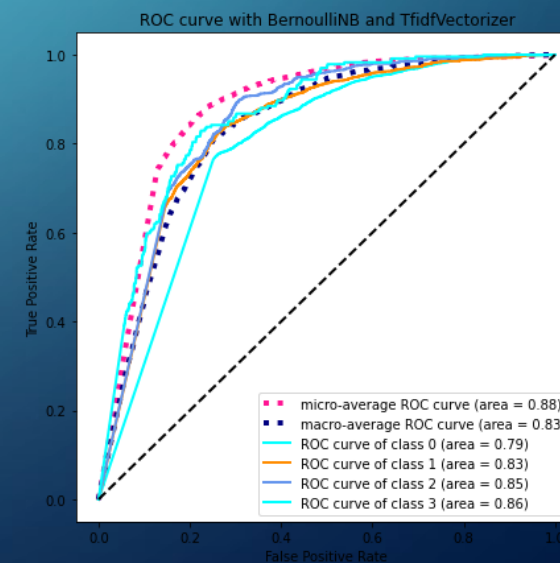
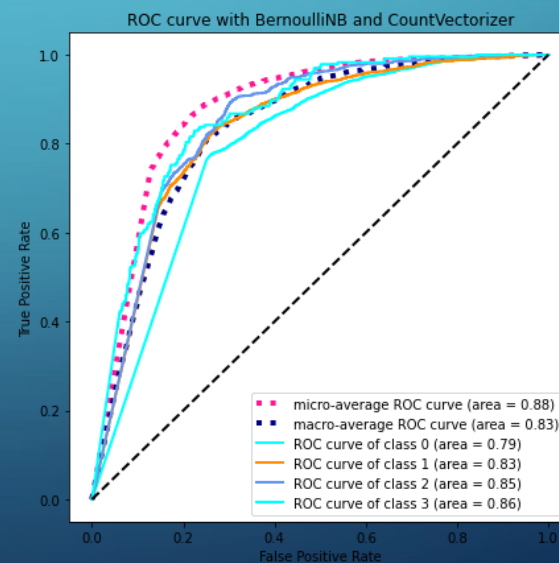
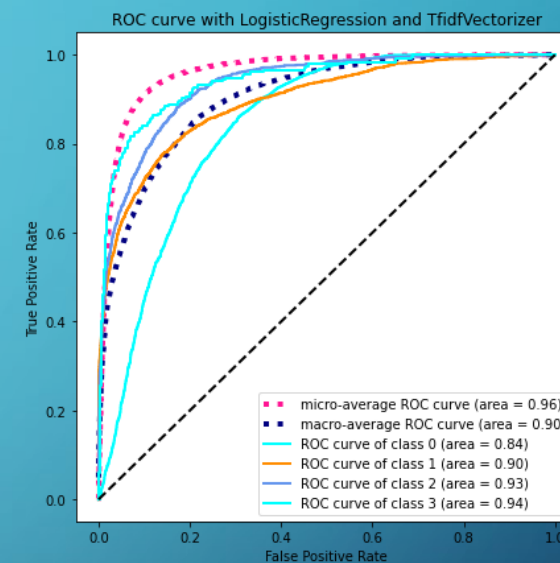
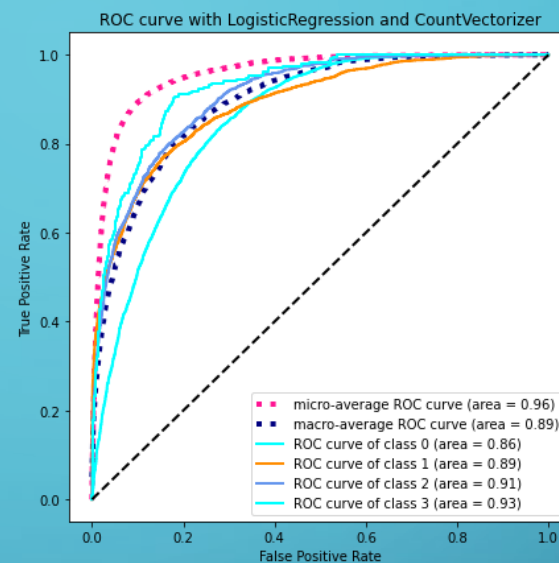
- Description:

- Concretely, if a [headline, body text] pair in the test set has the target label unrelated, a team's evaluation score will be incremented by 0.25 if it labels the pair as unrelated.
 - If the [headline, body text] test pair is related, a team's score will be incremented by 0.25 if it labels the pair as any of the three classes: agrees, disagrees, or discusses.
 - The team's evaluation score will so be incremented by an additional 0.75 for each related pair if gets the relationship right by labeling the pair with the single correct class: agrees, disagrees, or discusses.



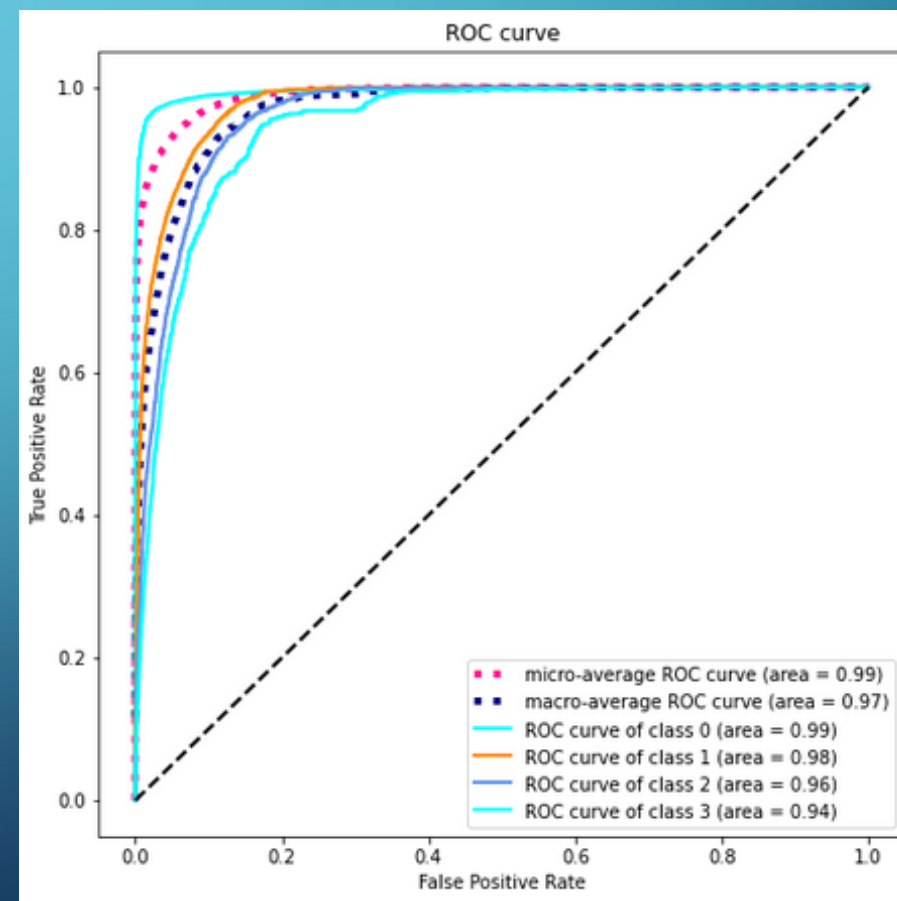
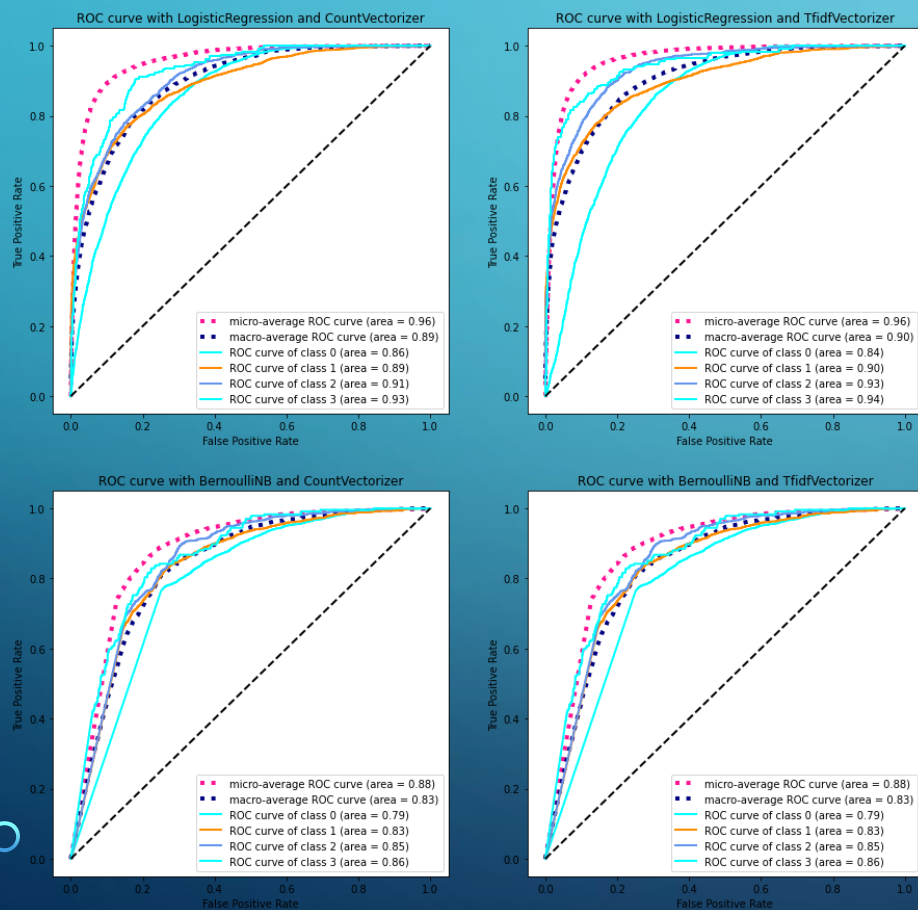
PART VI: EXPERIMENT

- 1. Baselines (Statistical ML)
 - Bernoulli Naïve Bayes + TF-IDF
 - Bernoulli Naïve Bayes + Count
 - Logistics Regression + TF-IDF
 - Logistics Regression + Count



PART VI: EXPERIMENT

• 2. BERT-based Method (Ours)



PART VI: EXPERIMENT

- 3. Comparison

	Accuracy	Precision	F1	Micro-ROC	Marco-ROC	# FNC	% FNC
LR-Count	71.27%	59.20%	62.58%	96.00%	89.00%	4815.5	41.33%
LR-TFIDF	59.00%	57.94%	58.30%	96.00%	90.00%	5026.75	43.14%
NB-Count	66.51%	56.59%	60.90%	87.00%	84.00%	4834.75	41.49%
NB-TFIDF	66.51%	56.59%	60.90%	87.00%	84.00%	4834.75	41.49%
BERT	90.37%	90.60%	90.43%	99.00%	97.00%	10068.25	86.41%

Table 1: Performance Metrics

PART VII: CONCLUSION

- Achievement
 - Good Result: Accuracy > 90%
- Limitations
 - Not very good FNC Score
- Future Work
 - Learn more about PTMs

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A decorative graphic on the left side of the slide, consisting of a network of light blue lines and circles of varying sizes, resembling a circuit board or a neural network diagram.

THANK YOU FOR WATCHING!

PRESENTED BY

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