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# INF582 Challenge: Summary Source Prediction

Oral Presentation

# Content



- I- Introduction: task to perform
- II- Our pipeline
- III- Feature building on summaries
- IV- Feature building for comparison between documents and summaries
- V- Classification

# I- Introduction: task presentation



## Summary source prediction

New tropical fruit to go on sale in the UK is cross between mango and plum. The *Bouea macrophylla* - or mango plum - has been nicknamed the plango. The fruit has a bright orange edible skin and a sweet taste and soft texture.

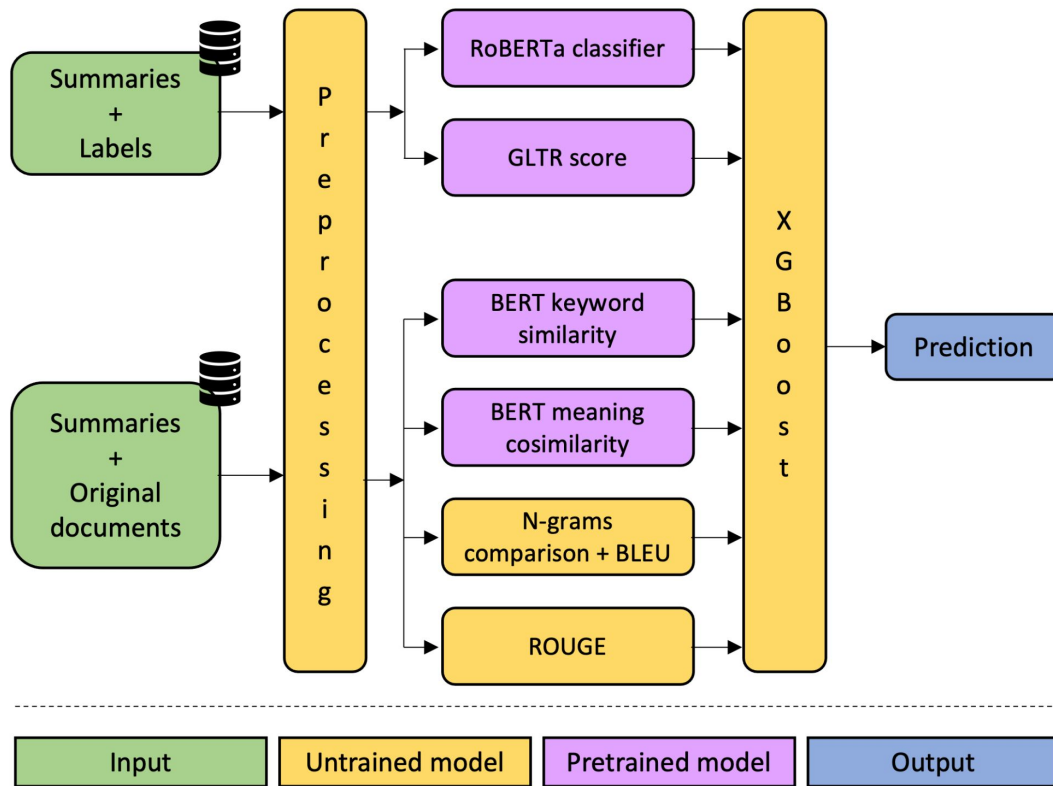
Patrick Cherry will appear on NBC New York on Friday night to apologize. He has been stripped of his badge, will be placed on desk duty before being transferred out of the NYPD's Joint Terrorism Task Force division.

## II- Our pipeline

### Two types of features :

- Features from summaries only
- Features comparing the summaries to the original documents

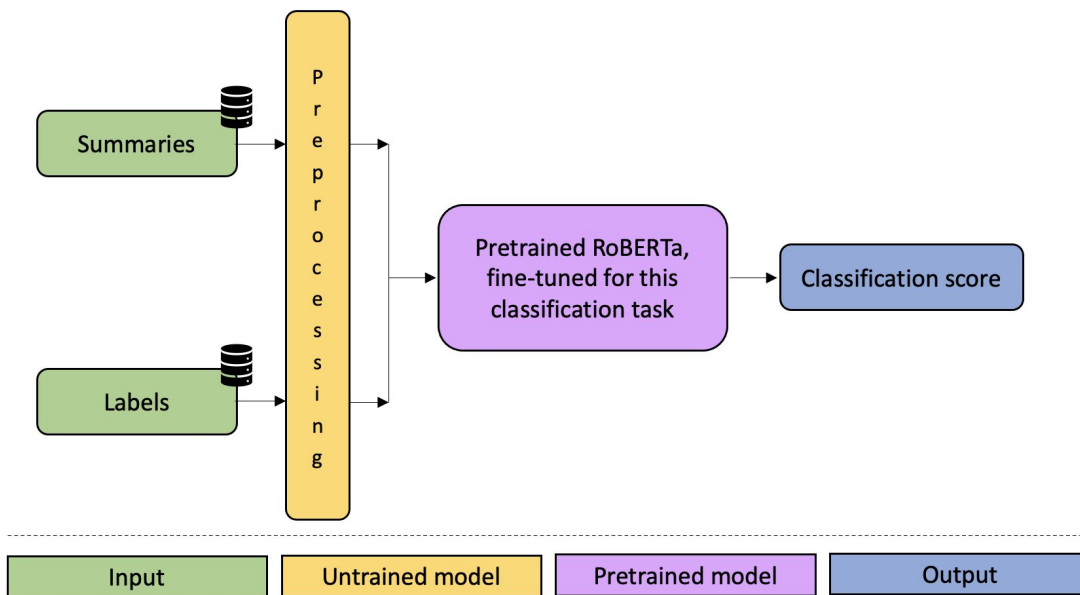
Due to the small size of our datasets, we made extensive use of pretrained models.



# III- Summaries features: RoBERTa for classif.

This is the core component of our classifier (score of 0.89 alone).

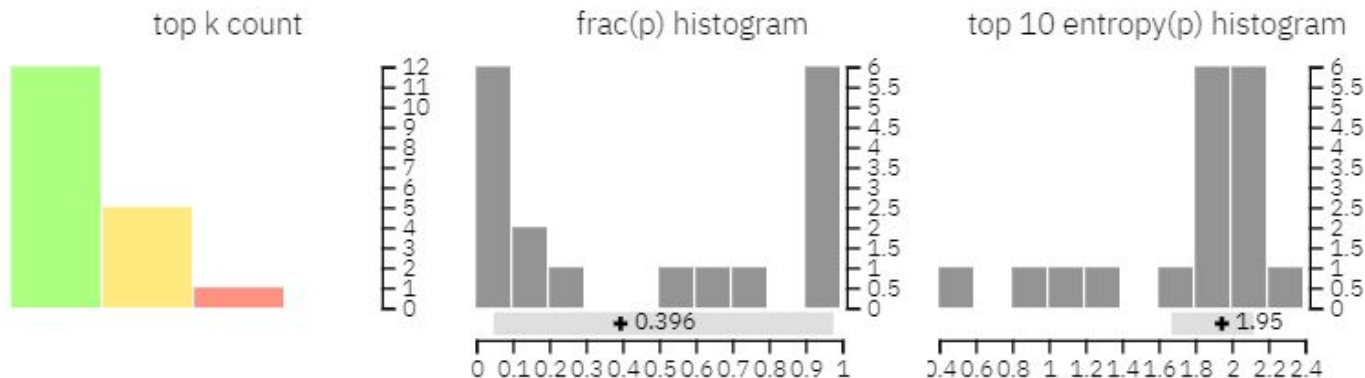
- We could have fine-tuned RoBERTa on the document dataset we had.
- Since this model is really performant, we only did a small preprocessing.



Ref: [2, 3]

# III- Summaries features: GLTR

## GLTR principle



How much wood would a woodchuck chuck if a woodchuck could chuck wood?

Ref: [5]

# III- Summaries features: GLTR



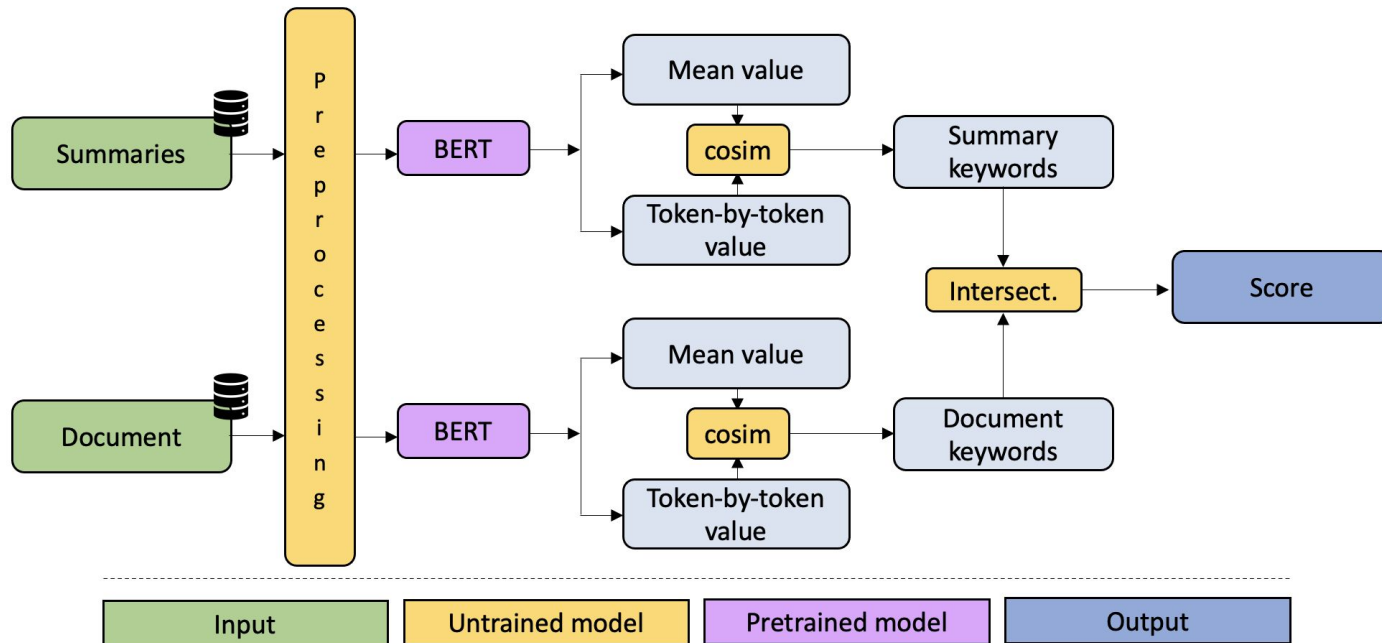
## Features we took in GLTR:

- Maximum  $k$  in the text
- Average  $p$  and  $k$ , Standard deviation of the distribution of  $p$  and  $k$
- Histogram of  $k$  with fixed bounds
- Histogram of  $p$  with evenly-distributed bounds and its bounds
- Histogram of entropy with evenly-distributed bounds and its bounds

If we had more texts in the train set:

1D-convolutions would have been adapted

## IV- Comparison features: keywords

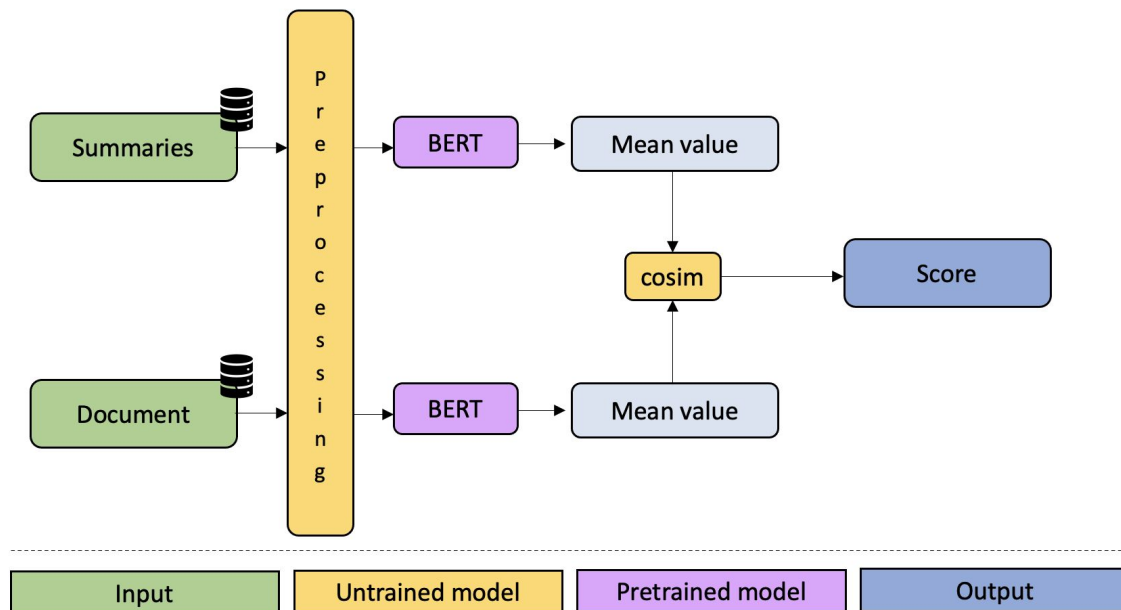


Ref: [7]

*But this did not really improved the performance...*

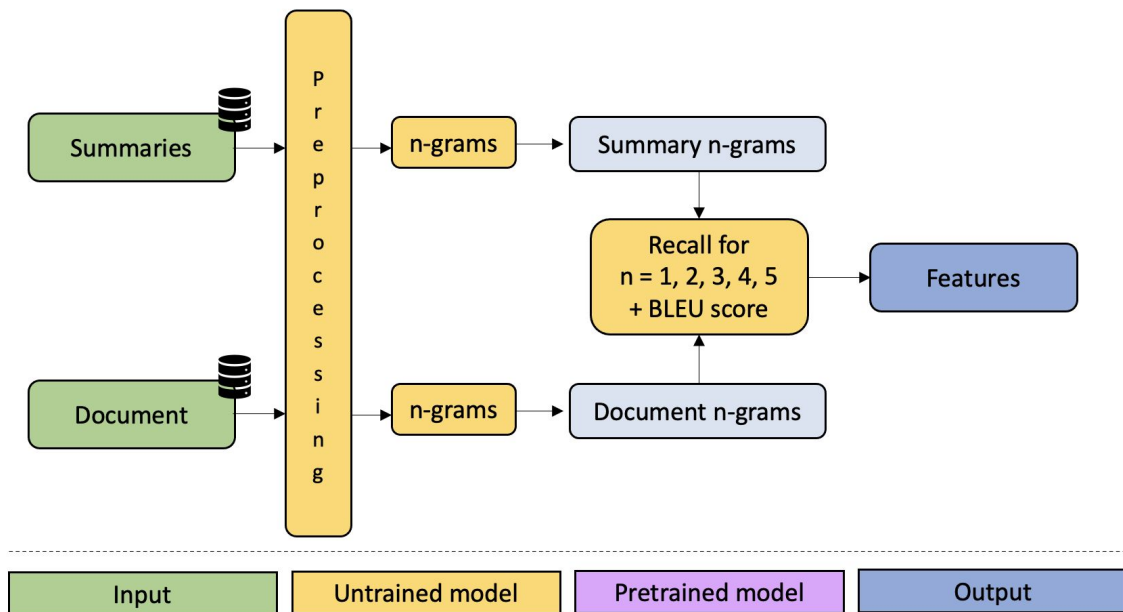


## IV- Comparison features: meaning with BERT



*This improved our performance: 0.90687 to 0.91000*

## IV- Comparison features: n-grams and BLEU



$$BLEU = \exp \left( \frac{1}{4} \sum_{i=1}^4 \log(p_i) \right)$$

Ref: [8]

*This significantly improved our performance: 0.91000 to 0.93312*

## IV- Comparison features: ROUGE score

**ROUGE: a recall, precision and f1-score on n-grams.**

- A score originally designed to assess translation quality
- A generalization of BLEU score
- We computed it for  $n = 1, 2, 3, 4, 5$

$$ROUGE_n = \begin{cases} ROUGE_{R,n} = \frac{|N_{sum} \cap N_{doc}|}{|N_{sum}|} \\ ROUGE_{P,n} = \frac{|N_{sum} \cap N_{doc}|}{|N_{doc}|} \\ ROUGE_{F,n} = \frac{2}{ROUGE_{R,n}^{-1} + ROUGE_{P,n}^{-1}} \end{cases}$$

Ref: [9, 10]

*This significantly improved our performance: 0.93312 to 0.94067*

# V- Classification: building the classifier

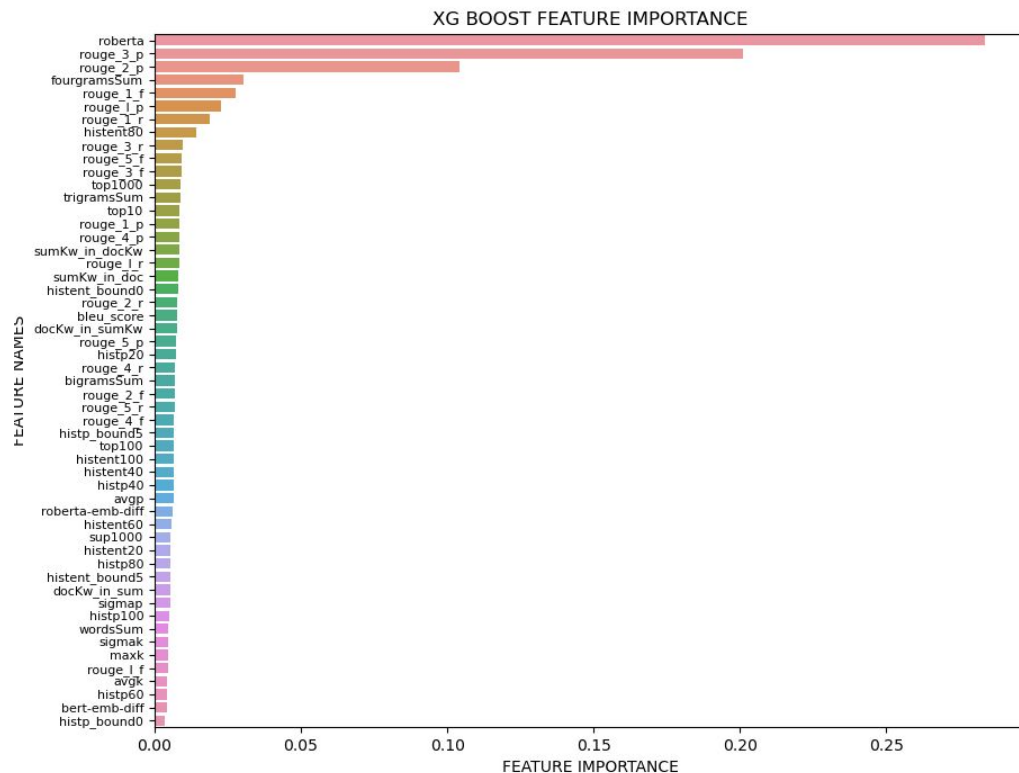
Comparison between algorithms:

Accuracy on...	Logit model	Random Forest	XG-Boost
Train set	0.951125	1.00000	0.97425
Test set (Kaggle)	0.92500	0.93812	0.93937

XG-Boost hyperparameter tuning:

- *n\_estimators*,
- *max\_depth*,
- *learning\_rate*,
- *colsample\_bytree*
- ...

# V- Classification: performance comparison



	RoBERTa	GLTR	Keywords	N-grams	ROUGE
Score	0.89	0.90687	0.9100	0.93312	0.94067

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