

# A Comparison of Machine Learning Algorithms for Multilingual Phishing Detection

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## Introduction

- Phishing emails are increasing in volume
- Little data exists for phishing emails in languages besides English
- Most research only focuses and trains systems on English due to the lack of data
- We evaluate different systems to detect phishing emails in multiple languages. For our experiment we use English, French and Russian as this is the data that is available.
- The system is widely zero shot, with the model never seeing the testing language during training at all, except for the three monolingual tests

## Data

- English Train - 3983 emails
- English Test – 996 emails
- French Train – 472 emails
- French Test – 119 emails
- Russian Train – 175 emails
- Russian Test – 44 emails
- EnglishFrench – 5570 emails
- EnglishRussian – 5198 emails
- FrenchRussian – 810 emails

## Data Acquisition

- English data was taken from the Enron Spam dataset, specifically Enron Spam 1.
- French data was acquired from other researchers who collected the spam emails. Benign emails in this set were translated from the TREC07 dataset.
- Russian data was acquired from other researchers who collected the spam emails. Benign emails in this set were translated from the Enron dataset.

	En/En	Fr/En	Ru/En	Fr,Ru/ En	En/Fr	Fr/Fr	Ru/Fr	En,Ru /Fr	En/Ru	Fr/Ru	Ru/Ru	En,Fr/ Ru
<b>GPT2</b>	0.99	0.72	0.66	0.61	0.5	1	0.56	0.48	0.7	0.54	0.95	0.68
<b>GPT3</b>	0.99	0.67	0.28	0.76	0.78	1	0.63	0.68	0.81	0.77	1	0.77
<b>XLMR</b>	0.99	0.72	0.71	0.99	0.68	0.98	0.68	0.99	0.95	0.5	0.97	0.95
<b>LR</b>	0.93	0.62	0.4	0.74	0.79	0.96	0.45	0.59	0.5	0.36	0.5	0.55
<b>RF</b>	0.91	0.64	0.28	0.67	0.41	0.94	0.43	0.41	0.54	0.45	0.5	0.5
<b>SVM</b>	0.78	0.73	0.45	0.75	0.62	0.88	0.49	0.63	0.47	0.52	0.5	0.63
<b>MFC</b>	0.71	0.71	0.71	0.71	0.52	0.52	0.52	0.52	0.5	0.5	0.5	0.5
<b>Baseline</b>												

## Future Direction

- Leverage new models such as GPT-4 to see how they perform.
- Look at obtaining more data in multiple languages

## Conclusion

- Monolingual spam detection is an easy problem
- Multilingual spam detection is a hard task
- By training on multiple languages, we can improve the accuracy of our models on average