ANALYSIS OF PHISHING & SPAM EMAILS - PHISHING DETECTION SYSTEM DEVELOPMENT

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Abstract

This report presents a multi-faceted approach to detecting phishing emails by combining traditional machine learning with forensic analysis. We investigate the effectiveness of five baseline models (Logistic Regression, Random Forest, Naive Bayes, Neural Networks, and Decision Trees) and enhance their performance using advanced ensemble and hybrid techniques. Furthermore, we apply linguistic forensics, temporal dynamics, and graph topology analysis to uncover behavioral patterns in malicious traffic. The study culminates in a proposed hybrid strategy that balances high accuracy with a minimal false positive rate.

1. Introduction

An escalating arms race between threat actors and defense mechanisms characterizes the modern cybersecurity landscape. Phishing, once a crude volume-based attack vector, has evolved into a sophisticated discipline of psychological manipulation and infrastructure obfuscation. Traditional signature-based detection—relying on static blacklists of known bad domains or hash values—has proven insufficient against the agility of contemporary campaigns. Attackers now leverage polymorphic text, "snowshoe" spamming techniques, and compromised legitimate infrastructure to evade detection. To counter this, security operations must adopt a multidimensional analytical framework that triangulates ***Linguistic Expression***, ***Temporal Dynamics***, and ***Relational Topology***.

Additionally, selecting a suitable model to detect phishing emails is a vital factor in surviving the enormous number of attacks from malicious actors. A good model should be fast enough to process the big data from emails and logs, but be good enough to accurately separate the spam emails from the benign ones. With the stated background, a system only works efficiently if it can correctly identify and flag phishing with the smallest misses (***accuracy***), the fewest wrong alarms (***precision***), and the least amount of time (***fast***).

2. Studied Methods

We evaluated five established machine learning algorithms for baseline performance:

- **Logistic Regression (LR):** A linear model effective for high-dimensional sparse text data.
- **Random Forest (RF):** An ensemble of decision trees that reduces overfitting and captures non-linear feature interactions.
- **Naive Bayes (NB):** A probabilistic classifier based on Bayes' theorem, traditionally strong in text classification despite its independence assumption.
- **Neural Network (MLPClassifier):** A Multi-Layer Perceptron capable of learning complex, non-linear patterns in data.
- **Decision Tree (DT):** A simple, interpretable model that splits data based on feature values but is prone to overfitting.

3. *Criteria for Analysis*

To look beyond simple keyword matching, we established three forensic criteria:

- **Linguistic Forensics:** Analyzing the semantic content of emails. This involves removing stop words and using **Word Clouds** to visualize prominent terms in spam (e.g., "free," "money," "click") versus ham (e.g., "enron," "subject," "thanks").
- **Temporal Dynamics:** Examining the timestamp of emails to identify behavioral patterns. We analyze the **Hour of Day** to distinguish between organic human communication (business hours) and automated botnet activity (off-hours or continuous blasts).
- **Relation Match (Graph Topology):** Using graph theory to map connections between Senders, Receivers, and URLs. This helps identify "Shared Infrastructure" where multiple disparate senders link to the same malicious domain.

4. *Evaluation Approach*

Our evaluation pipeline consisted of the following stages:

- **Data Aggregation:** We utilized *merge_dataset.ipynb* to consolidate multiple CSV sources into a single, unified dataset. This process involved standardizing column names (e.g., *body*, *subject*, *label*) and cleaning missing values to ensure a robust training set.
- **Feature Extraction:** We extracted linguistic features (TF-IDF, word counts), temporal features (hour sent), and graph relationships.
- **Metrics:** Models were evaluated based on **Accuracy**, **Precision**, **Recall**, **Error Rate**, and **AUC (Area Under ROC Curve)** to ensure a holistic view of performance, balancing detection power against false alarms.

5. *Analytical Analysis & Visualization*

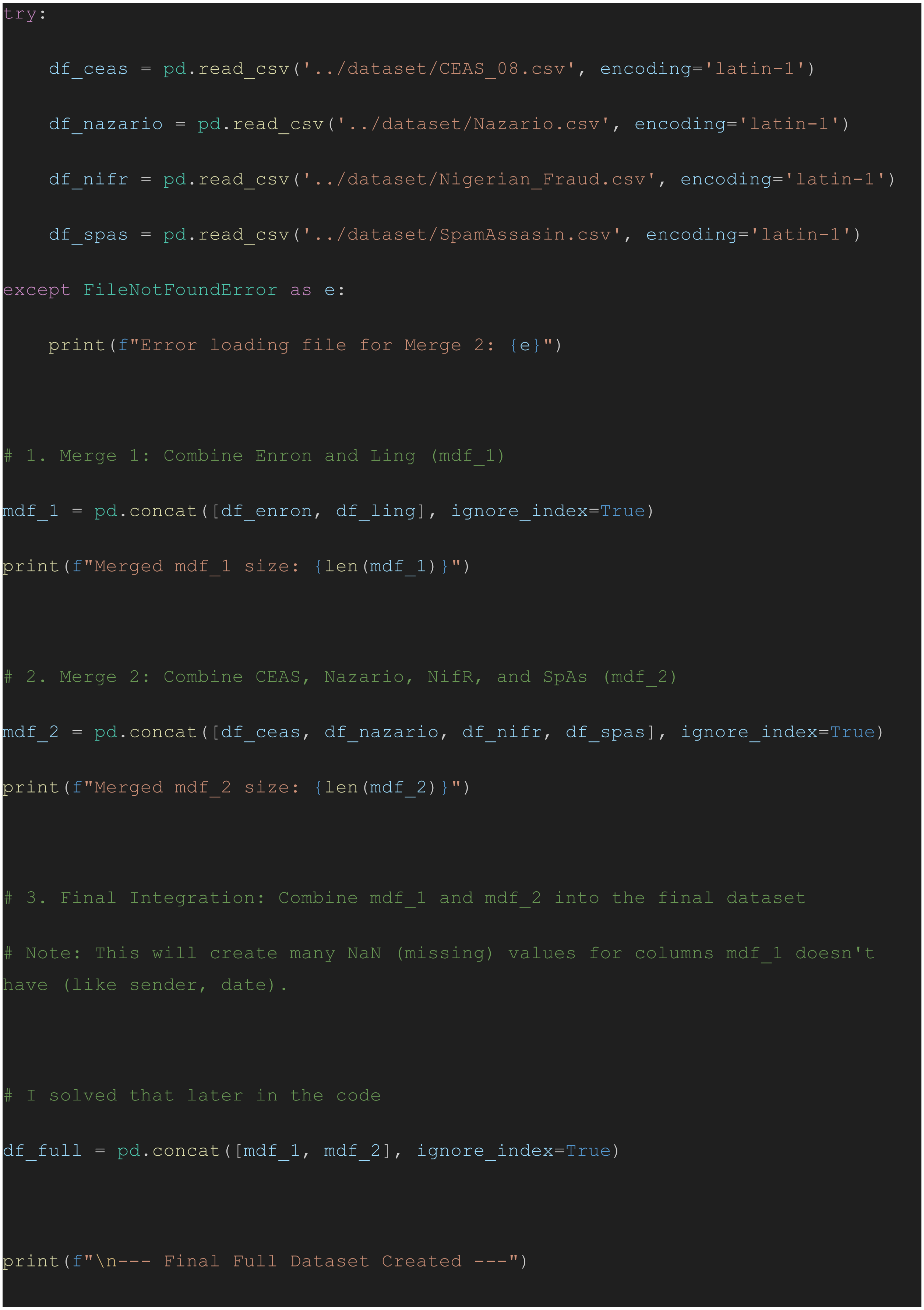
We are taking the dataset from Kaggle source: Phishing Email Dataset

The dataset has 2 groups: some tables having only 3 columns (Subject, Body, Label), while the others having 7 columns (Sender, Receiver, Date, Subject, Body, Label)

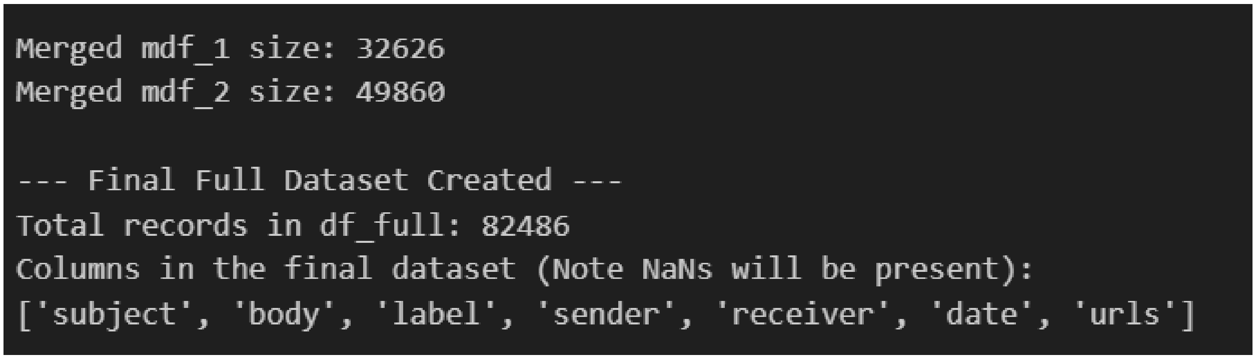
Source code folder: https://github.com/MynameisKoi/big-data-phishing-detection

Merging the data: merge_dataset.ipynb

```
# Group 1: Datasets that have only 3 colunms (Subject, Body, Label)

try:

    df_enron = pd.read_csv('../dataset/Enron.csv', encoding='latin-1',
usecols=['subject', 'body', 'label'])

    df_ling = pd.read_csv('../dataset/Ling.csv', encoding='latin-1',
usecols=['subject', 'body', 'label'])

except FileNotFoundError as e:

    print(f"Error loading file for Merge 1: {e}")



# Group 2: Rich Metadata Datasets that have 7 colunms (Sender, Date, Subject,
Body, Label, etc.)
```



```python
try:
    df_ceas = pd.read_csv('../dataset/CEAS_08.csv', encoding='latin-1')
    df_nazario = pd.read_csv('../dataset/Nazario.csv', encoding='latin-1')
    df_nifr = pd.read_csv('../dataset/Nigerian_Fraud.csv', encoding='latin-1')
    df_spas = pd.read_csv('../dataset/SpamAssasin.csv', encoding='latin-1')
except FileNotFoundError as e:
    print(f"Error loading file for Merge 2: {e}")


# 1. Merge 1: Combine Enron and Ling (mdf_1)
mdf_1 = pd.concat([df_enron, df_ling], ignore_index=True)
print(f"Merged mdf_1 size: {len(mdf_1)}")


# 2. Merge 2: Combine CEAS, Nazario, NifR, and SpAs (mdf_2)
mdf_2 = pd.concat([df_ceas, df_nazario, df_nifr, df_spas], ignore_index=True)
print(f"Merged mdf_2 size: {len(mdf_2)}")


# 3. Final Integration: Combine mdf_1 and mdf_2 into the final dataset
# Note: This will create many NaN (missing) values for columns mdf_1 doesn't have (like sender, date).


# I solved that later in the code
df_full = pd.concat([mdf_1, mdf_2], ignore_index=True)


print(f"\n--- Final Full Dataset Created ---")
print(f"Total records in df_full: {len(df_full)}")

print("Columns in the final dataset (Note NaNs will be present):")

print(df_full.columns.tolist())



# Now df_full is ready for the feature engineering steps (Date, URL, Sender
Entropy).
```

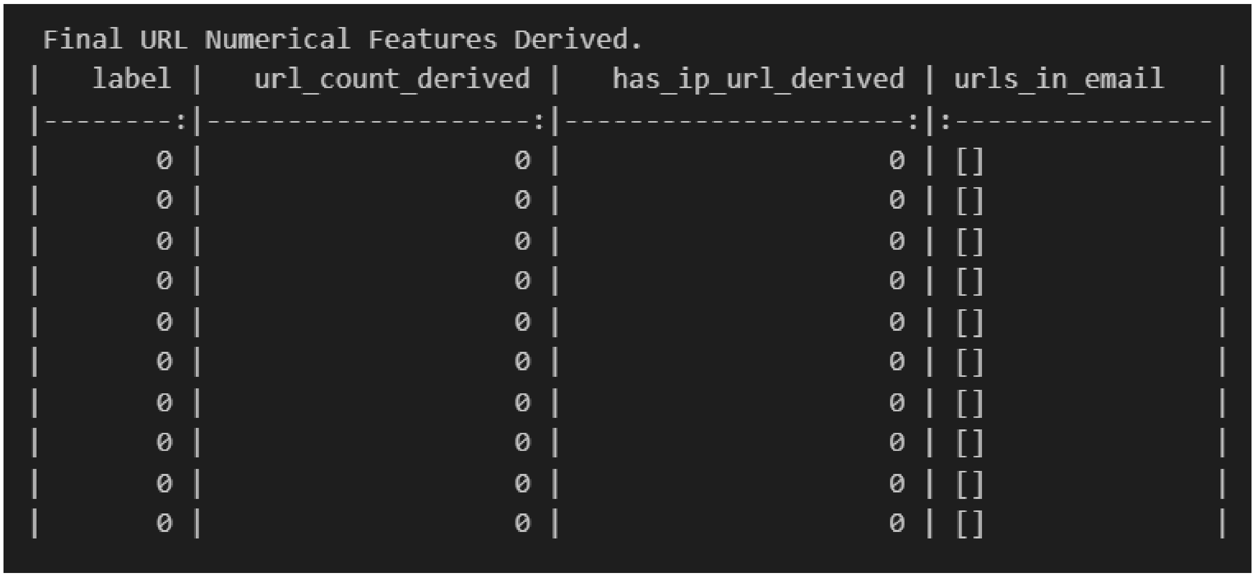


```
Merged mdf_1 size: 32626
Merged mdf_2 size: 49860

--- Final Full Dataset Created ---
Total records in df_full: 82486
Columns in the final dataset (Note NaNs will be present):
['subject', 'body', 'label', 'sender', 'receiver', 'date', 'urls']
```

We also use regex expression to find out if the email contains URL and IP address:

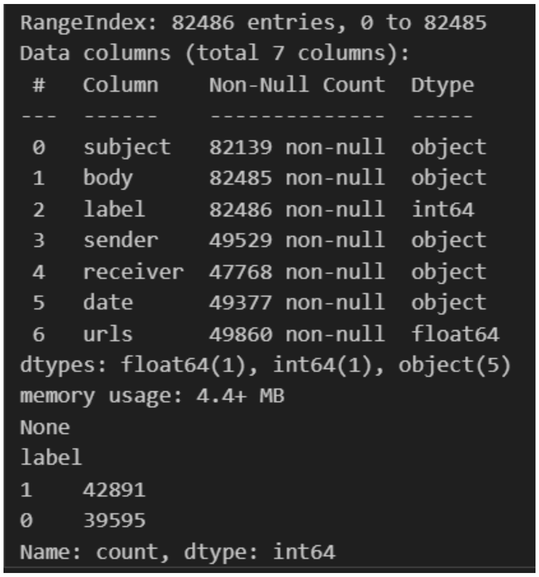
```
# Define the IP Regex just for checking the extracted list elements

ip_regex = r'^\s*http[s]?://\d{1,3}\.\d{1,3}\.\d{1,3}\.\d{1,3}'

# Define a general URL regex to get all URLs in a list and get also their count

url_regex =
r'http[s]?://(?:[a-zA-Z]|[0-9]|[$-_@.&+]|[!*\(\),]|(?:%[0-9a-fA-F][0-9a-fA-F]))
+'

# Extract all URLs in each email into a column called 'urls_in_email'

df_full['urls_in_email'] = df_full['body'].apply(lambda x:
re.findall(url_regex, str(x)))

#URL Cont: take the length of urls in urls_in_email column
```

```
df_full['url_count_derived'] = df_full['urls_in_email'].apply(len).fillna(0).astype(int)
def check_for_ip(url_list):
    """Returns 1 if any URL in the list starts with an IP address, 0 otherwise."""
    if not url_list:
        return 0
    for url in url_list:
        if re.match(ip_regex, url):
            return 1
    return 0
df_full['has_ip_url_derived'] = df_full['urls_in_email'].apply(check_for_ip)
print(" Final URL Numerical Features Derived.")
print(df_full[['label', 'url_count_derived', 'has_ip_url_derived', 'urls_in_email']].head(10).to_markdown(index=False))
```

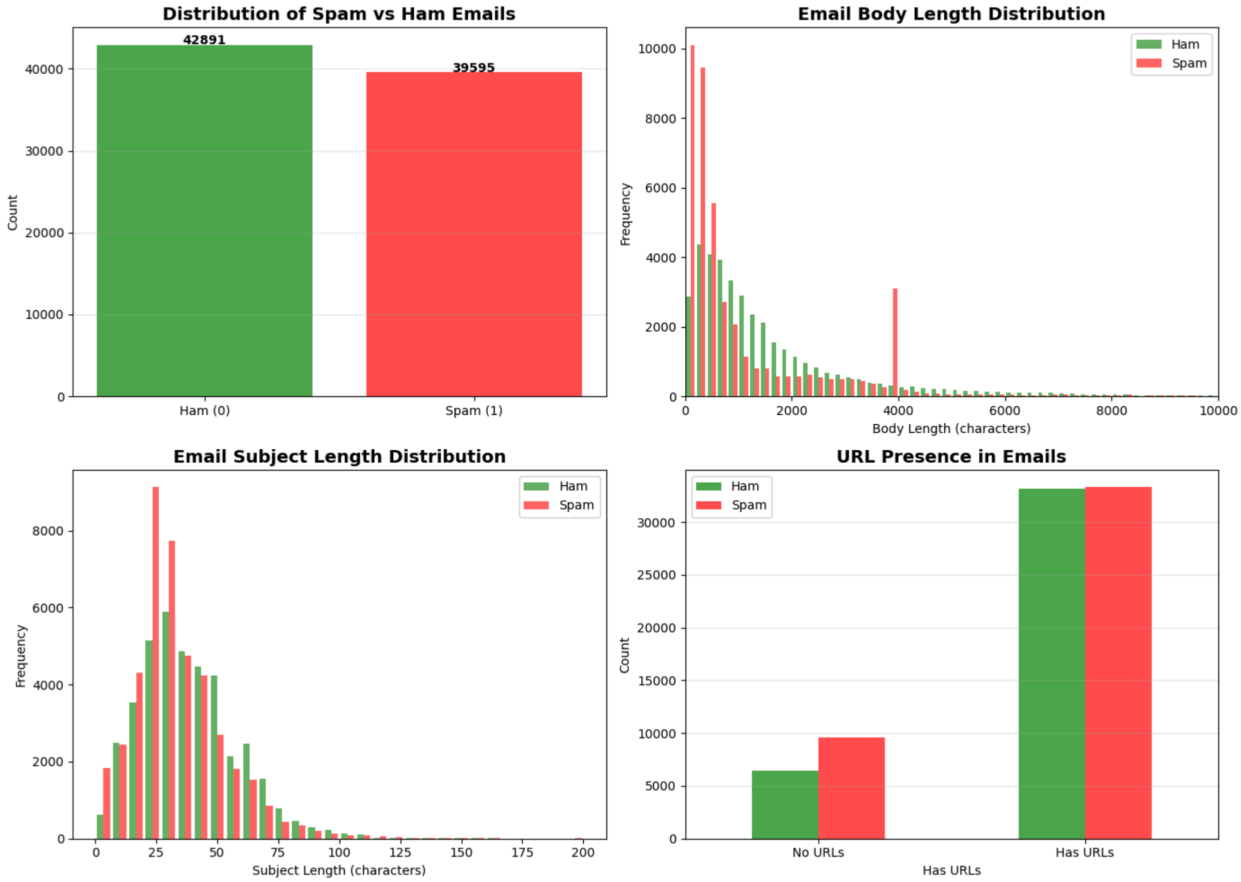


```
 Final URL Numerical Features Derived.
|   label |   url_count_derived |   has_ip_url_derived | urls_in_email   |
|--------:|--------------------:|---------------------:|:----------------|
|       0 |                   0 |                    0 | []              |
|       0 |                   0 |                    0 | []              |
|       0 |                   0 |                    0 | []              |
|       0 |                   0 |                    0 | []              |
|       0 |                   0 |                    0 | []              |
|       0 |                   0 |                    0 | []              |
|       0 |                   0 |                    0 | []              |
|       0 |                   0 |                    0 | []              |
|       0 |                   0 |                    0 | []              |
|       0 |                   0 |                    0 | []              |
```

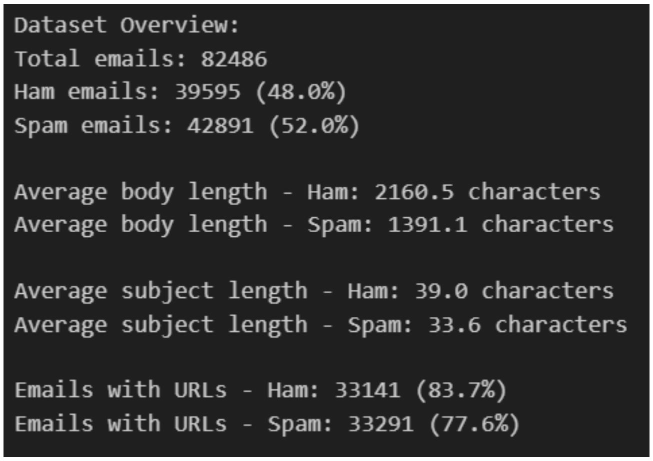
Overview of the grand dataset:



```
RangeIndex: 82486 entries, 0 to 82485
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   subject   82139 non-null  object 
 1   body      82485 non-null  object 
 2   label     82486 non-null  int64  
 3   sender    49529 non-null  object 
 4   receiver  47768 non-null  object 
 5   date      49377 non-null  object 
 6   urls      49860 non-null  float64
dtypes: float64(1), int64(1), object(5)
memory usage: 4.4+ MB
None
label
1    42891
0    39595
Name: count, dtype: int64
```



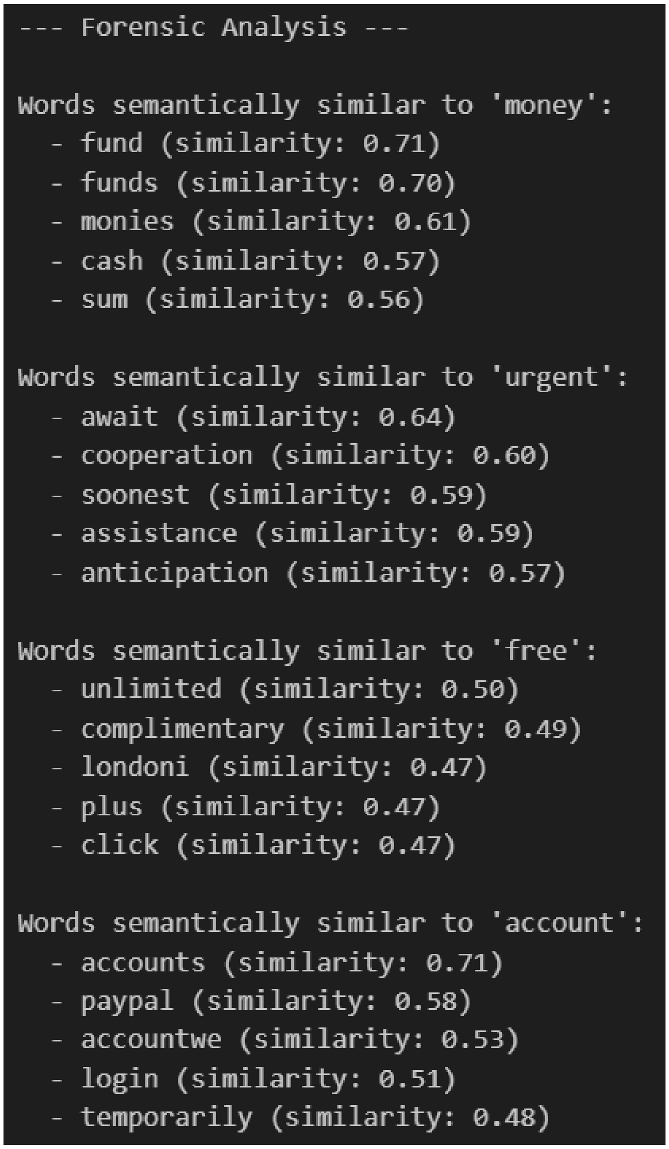
We can see that the distribution of Ham vs Spam Emails is pretty similar (around 52/48), most of the Spam Emails will have too short or too long body length. Both Ham and Spam Emails have similar subject length distribution shape, with more Spam Emails at the range of 25-50 characters. Spam and Ham Emails have the same chance of having URLs, and we can see more Spam Emails having no URLs than the benign one.



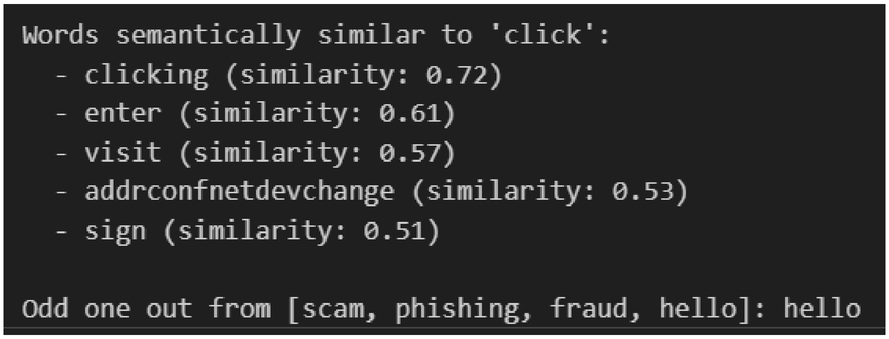
```
Dataset Overview:
Total emails: 82486
Ham emails: 39595 (48.0%)
Spam emails: 42891 (52.0%)

Average body length - Ham: 2160.5 characters
Average body length - Spam: 1391.1 characters

Average subject length - Ham: 39.0 characters
Average subject length - Spam: 33.6 characters

Emails with URLs - Ham: 33141 (83.7%)
Emails with URLs - Spam: 33291 (77.6%)
```

Source code: analysis.ipynb

For forensic analysis, we are using ***Word2Vec*** to check for ***word semantic***:

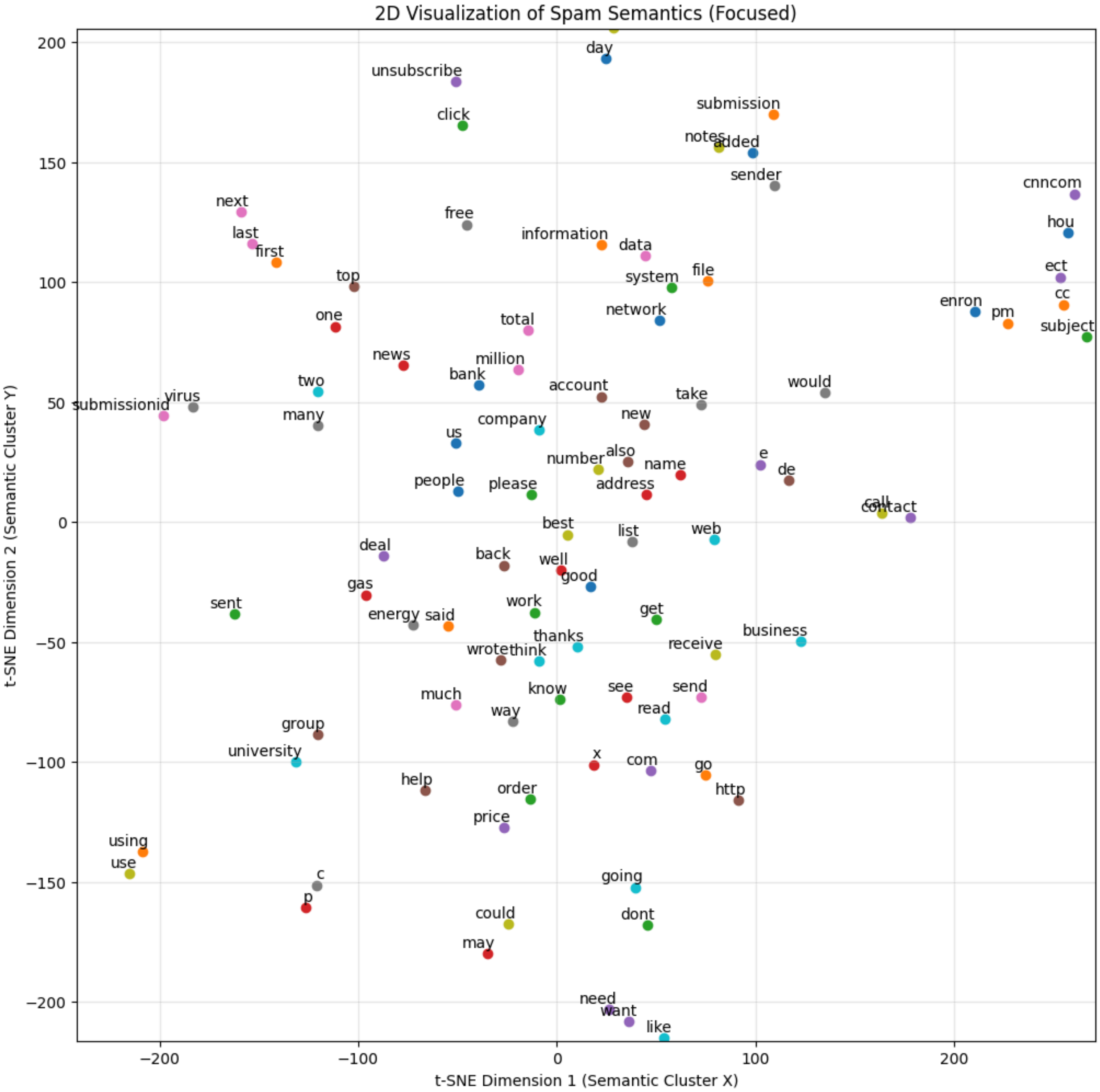


```
--- Forensic Analysis ---

Words semantically similar to 'money':
  - fund (similarity: 0.71)
  - funds (similarity: 0.70)
  - monies (similarity: 0.61)
  - cash (similarity: 0.57)
  - sum (similarity: 0.56)

Words semantically similar to 'urgent':
  - await (similarity: 0.64)
  - cooperation (similarity: 0.60)
  - soonest (similarity: 0.59)
  - assistance (similarity: 0.59)
  - anticipation (similarity: 0.57)

Words semantically similar to 'free':
  - unlimited (similarity: 0.50)
  - complimentary (similarity: 0.49)
  - londoni (similarity: 0.47)
  - plus (similarity: 0.47)
  - click (similarity: 0.47)

Words semantically similar to 'account':
  - accounts (similarity: 0.71)
  - paypal (similarity: 0.58)
  - accountwe (similarity: 0.53)
  - login (similarity: 0.51)
  - temporarily (similarity: 0.48)
```



```
Words semantically similar to 'click':
  - clicking (similarity: 0.72)
  - enter (similarity: 0.61)
  - visit (similarity: 0.57)
  - addrconfnetdevchange (similarity: 0.53)
  - sign (similarity: 0.51)

Odd one out from [scam, phishing, fraud, hello]: hello
```

We also have the 2D Visualization of Spam Semantics:

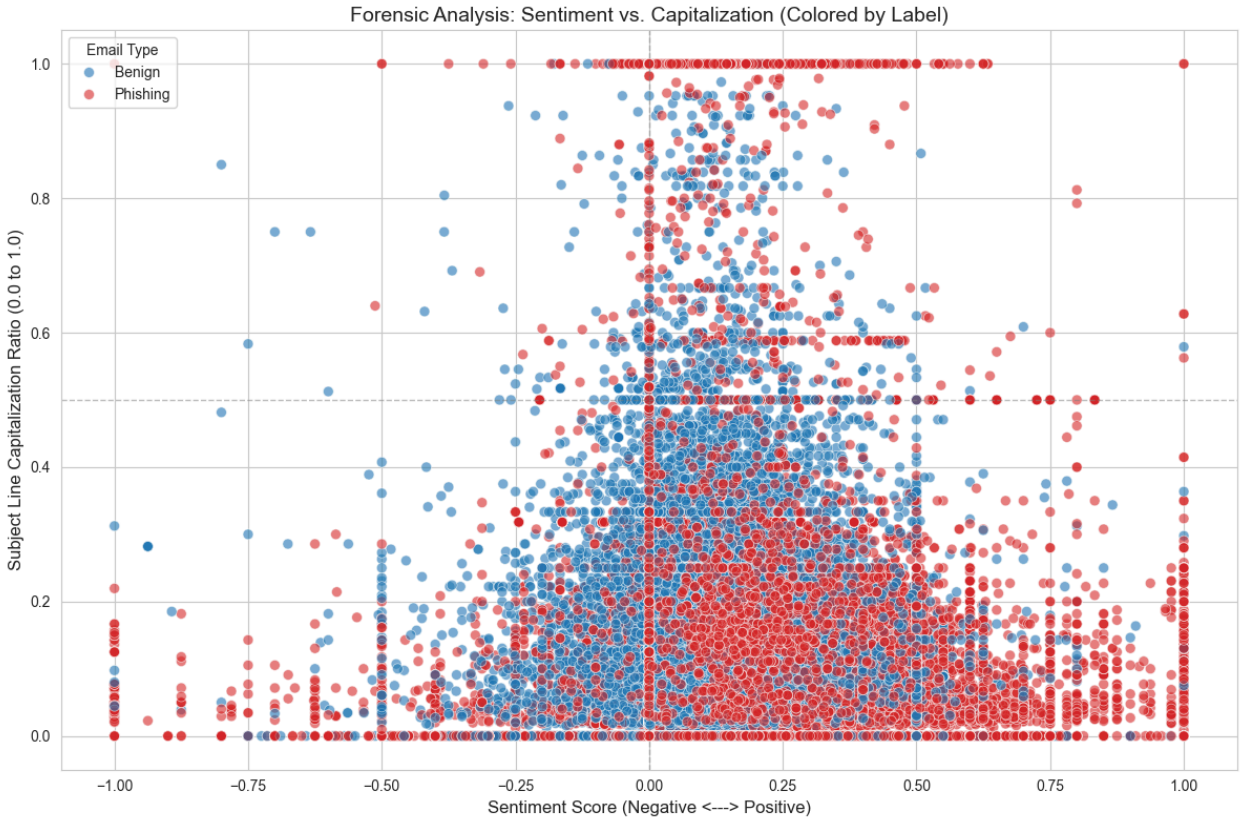


Key Forensic Clusters:

- **The "Financial Fraud" Cluster (Center-Left):** Words like **bank**, **million**, **account**, **company**, and **number** are grouped tightly. This indicates a high prevalence of financial scams (e.g., Nigerian Prince scams, fake bank alerts) where these terms are used interchangeably to trick victims.

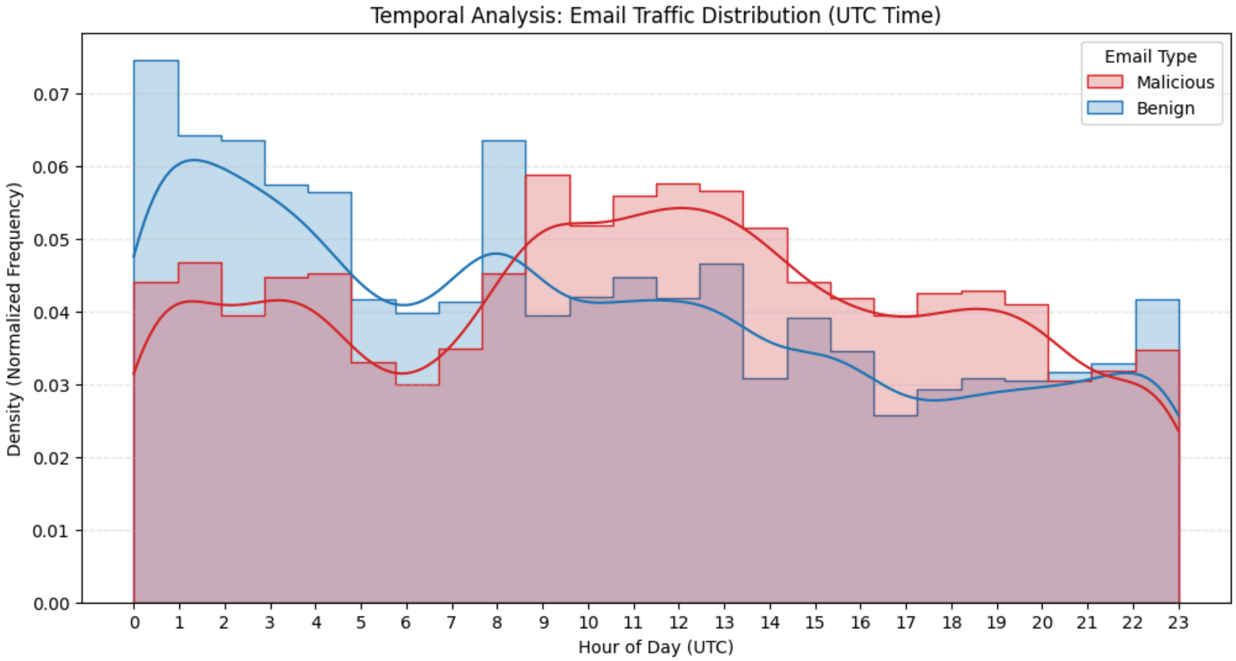
- **The "Call to Action" Cluster (Top):** Terms like **unsubscribe**, **click**, and **free** are clustered at the top. This separates the *mechanism* of the spam (getting you to click) from the *content* (money/fraud), showing the model understands these are distinct functional parts of the email.
- **The "Dataset Artifact" Cluster (Far Right):** You can see **enron**, **hou** (Houston), **ect**, and **subject**. This strongly suggests your dataset includes the **Enron Email Corpus** (common in spam research). The model has isolated these specific corporate terms as distinct from general spam, which is a good sign of model health.
- **The "Threat" Outlier (Far Left):** The word **virus** sits somewhat isolated on the left, suggesting that malware/security threats form a distinct linguistic category separate from the "business/money" spam in the center.

We also use BeautifulSoup to analyze the relation between ***Sentiment and Capitalization*** by comparing the Capitalization Ratio and Sentiment Score (-1 as Negative, and 1 as Postive).

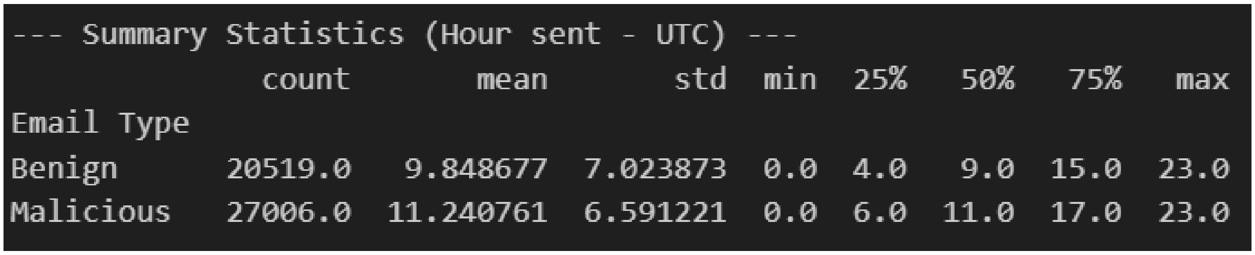


Thus, we can see that the phishing emails have some different characteristics. For example, phishing emails will have a very high capitalization ratio (~1.0), which means capitalized emails tend to be the phishing ones. In addition to that, phishing emails also have polarized sentiment score (~ -1.0 and ~ 1.0). This means phishing emails tend to have extreme negative or positive sentiment, which can trick users to click or respond.

For ***Temporal Analysis***, we are using *parser* from ***dateutil***.



We can see that Temporal Analysis reveals that benign traffic correlates with human circadian rhythms (working hours), whereas malicious traffic exhibits automated or time-shifted patterns characteristic of botnets.



```
--- Summary Statistics (Hour sent - UTC) ---
              count       mean       std  min  25%   50%   75%   max
Email Type
Benign      20519.0   9.848677  7.023873  0.0  4.0   9.0  15.0  23.0
Malicious   27006.0  11.240761  6.591221  0.0  6.0  11.0  17.0  23.0
```

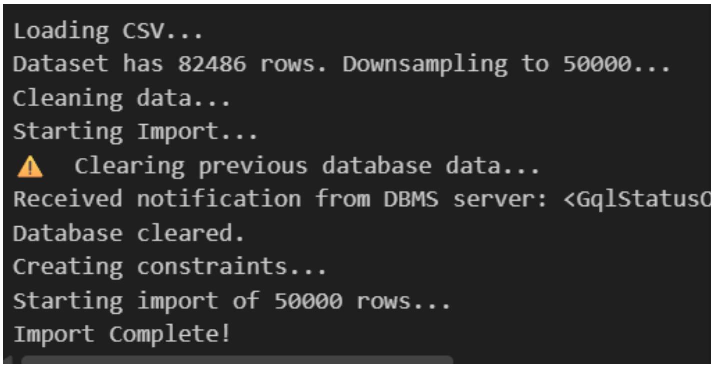
For the ***Graph Topology***, we are using Neo4j to analyze the relation match between the phishing emails.

```
Import pandas as pd
from neo4j import GraphDatabase

# --- Configuration ---
URI = "neo4j+s://62aca445.databases.neo4j.io" # Found in Aura Console
AUTH = ("neo4j", "iVStEhJLtC1WrKjZQADIbiJVKNdEtTChYrhh7TI37Rg")
CSV_PATH = "dataset.csv"
SAMPLE_SIZE = 50000

# 1. Load and Preprocess Data
print("Loading CSV...")
df = pd.read_csv(CSV_PATH)

# Check if we need to downsample
if len(df) > SAMPLE_SIZE:
    print(f"Dataset has {len(df)} rows. Downsampling to {SAMPLE_SIZE}...")
    # random_state=42 ensures you get the same 'random' rows if you run it
twice
    df = df.sample(n=SAMPLE_SIZE, random_state=42)
else:
    print(f"Dataset is small ({len(df)} rows). using all data.")

# 2. Preprocessing
```

```
print("Cleaning data...")
# Clean Data types (Previous fixes)
df['urls'] = df['urls'].fillna('').astype(str)
df['subject'] = df['subject'].fillna('').astype(str)
df['body'] = df['body'].fillna('').astype(str)

# --- THE FIX FOR "PROPERTY VALUE TOO LARGE" ---
# 1. Fill NaNs first
df['sender'] = df['sender'].fillna('unknown_sender').astype(str)
df['receiver'] = df['receiver'].fillna('unknown_receiver').astype(str)

# 2. Define a safe limit (e.g., 1024 chars).
# Real emails are rarely longer than 254 chars (RFC 5321).
MAX_EMAIL_LEN = 1024

# 3. Truncate any sender/receiver longer than the limit
# We allow the string to be cut off because a 17k char email is garbage anyway.
df['sender'] = df['sender'].apply(lambda x: x[:MAX_EMAIL_LEN])
df['receiver'] = df['receiver'].apply(lambda x: x[:MAX_EMAIL_LEN])

# 2. Define the Cypher Import Query
# We use MERGE for Users/Urls to avoid duplicates (idempotency)
# We use CREATE for Emails because every email is unique (even if same subject)
import_query = """
UNWIND $batch AS row
```

```
MERGE (sender:User {email: row.sender})
MERGE (receiver:User {email: row.receiver})

CREATE (e:Email {
    subject: row.subject,
    date: row.date,
    label: row.label,
    body_length: size(row.body)
})

MERGE (sender)-[:SENT]->(e)
MERGE (e)-[:RECEIVED_BY]->(receiver)

// Handle URLs if they exist
WITH e, row
UNWIND split(row.urls, ';') AS url_string
WITH e, trim(url_string) AS clean_url
WHERE clean_url <> ""
MERGE (u:Url {link: clean_url})
MERGE (e)-[:LINKS_TO]->(u)
"""

# 3. Execution Function
def upload_data(tx, batch_data):
    tx.run(import_query, batch=batch_data)
```

```python
# 4. Connect and Run
driver = GraphDatabase.driver(URI, auth=AUTH)

# Batch processing (Graph DBs handle chunks better than 1-by-1)
BATCH_SIZE = 1000
print("Starting Import...")

try:
    with driver.session() as session:
        # --- NEW STEP 1: CLEAR DATABASE AUTOMATICALLY ---
        print("⚠️  Clearing previous database data...")
        session.run("MATCH (n) CALL { WITH n DETACH DELETE n } IN TRANSACTIONS OF 10000 ROWS")
        print("Database cleared.")
        # ------------------------------------------------

        # Step 2: Create Constraints (indexes)
        print("Creating constraints...")
        session.run("CREATE CONSTRAINT IF NOT EXISTS FOR (u:User) REQUIRE u.email IS UNIQUE")
        session.run("CREATE CONSTRAINT IF NOT EXISTS FOR (url:Url) REQUIRE url.link IS UNIQUE")

        # Step 3: Loop and Upload
        print(f"Starting import of {len(df)} rows...")
        batch = []
        for index, row in df.iterrows():
            batch.append(row.to_dict())

            if len(batch) >= BATCH_SIZE:
                session.execute_write(upload_data, batch)
                # print(f"Processed {index+1} rows...")
                batch = []

        # Upload remaining
        if batch:
            session.execute_write(upload_data, batch)

    print("Import Complete!")

except Exception as e:
    print(f"An error occurred: {e}")
finally:
    driver.close()
```



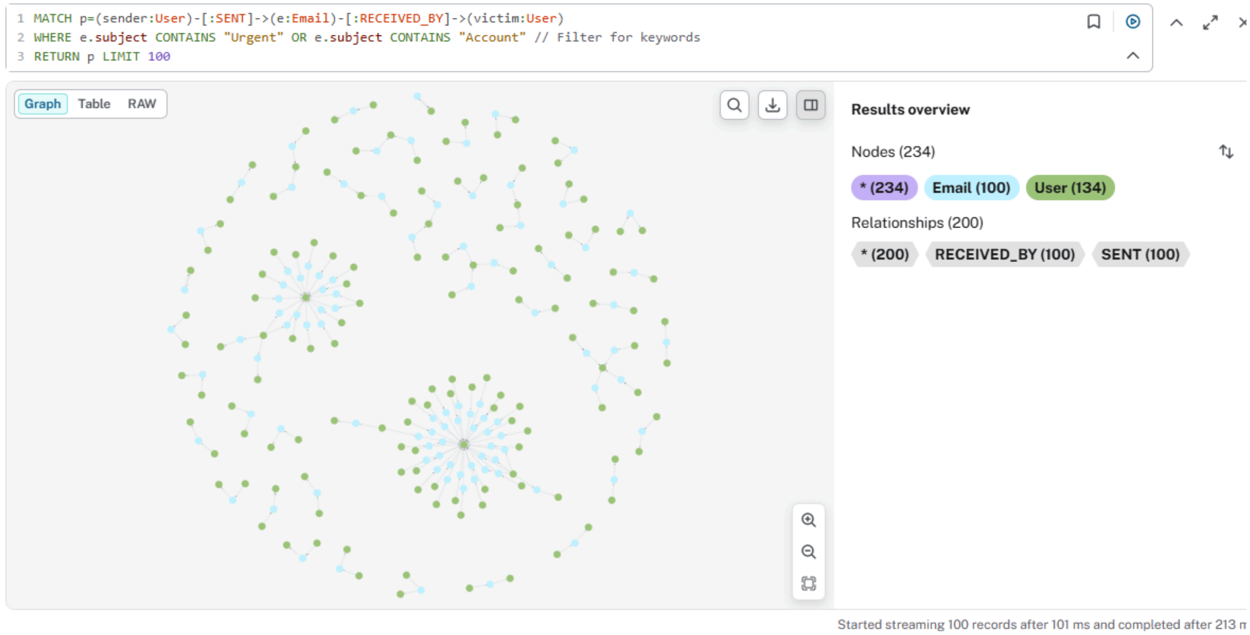
```
Loading CSV...
Dataset has 82486 rows. Downsampling to 50000...
Cleaning data...
Starting Import...
⚠  Clearing previous database data...
Received notification from DBMS server: <GqlStatusO
Database cleared.
Creating constraints...
Starting import of 50000 rows...
Import Complete!
```

Here are some results analyzed from Neo4j:

The "Campaign Blast" Topology (Subject Line Matching)

Forensic Goal: Identify high-volume phishing templates where the attackers didn't bother changing the subject line.

The Logic: Find a Subject Line used by a sender to target more than 10 *unique* receivers.



```
MATCH p=(sender:User)-[:SENT]->(e:Email)-[:RECEIVED_BY]->(victim:User)
WHERE e.subject CONTAINS "Urgent" OR e.subject CONTAINS "Account" // Filter for keywords
RETURN p LIMIT 100
```

Results overview

Nodes (234)

* (234) Email (100) User (134)

Relationships (200)

* (200) RECEIVED_BY (100) SENT (100)

Started streaming 100 records after 101 ms and completed after 213 n

The graph has successfully correlated **semantic intent** with **network behavior**:

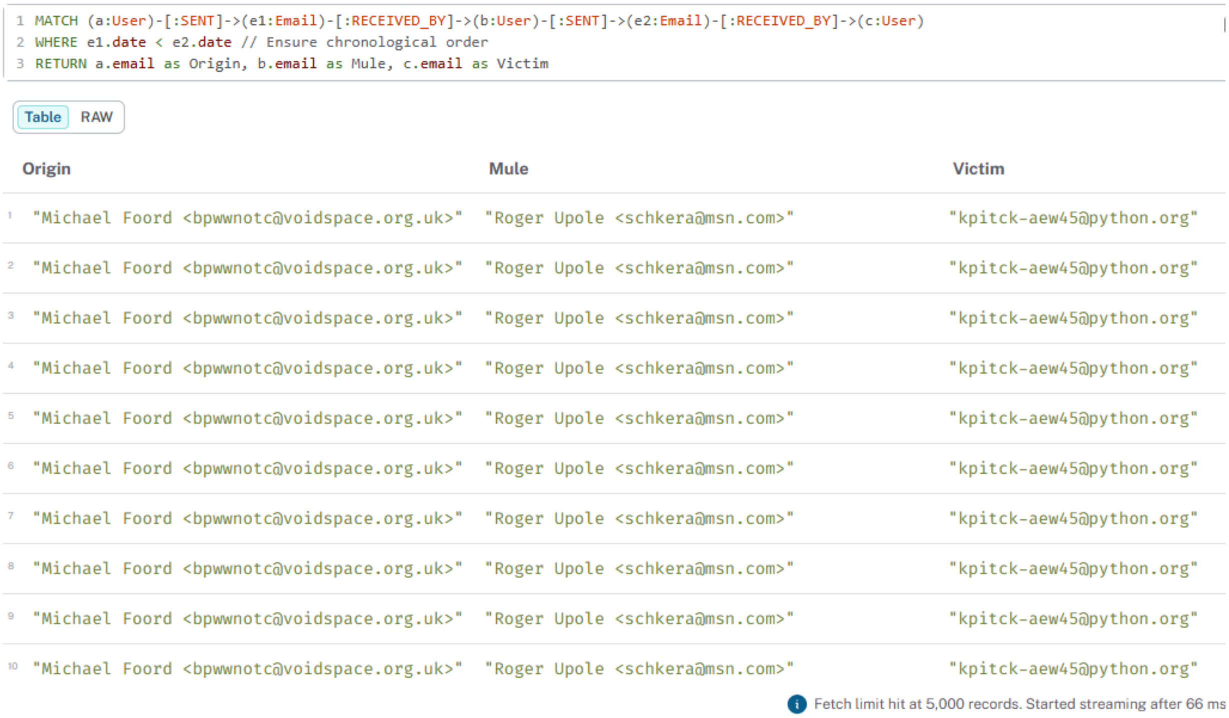
1. **Content Analysis:** The model identified "Account/Urgent" as a key topic.
2. **Network Analysis:** The graph traces that topic back to specific "Super-Spreader" nodes.

3. **Actionable Intelligence:** To stop this campaign, you do not need to block thousands of emails individually; you only need to block the **two central sender nodes** identified in the graph hubs.

The "Mule Chain" Topology

Pattern: User A sends to User B, and User B immediately sends to User C.

Forensic Value: Often used in Business Email Compromise (BEC) where an attacker forwards instructions through a compromised internal account to make it look legitimate.



```
MATCH (a:User)-[:SENT]->(e1:Email)-[:RECEIVED_BY]->(b:User)-[:SENT]->(e2:Email)-[:RECEIVED_BY]->(c:User)
WHERE e1.date < e2.date // Ensure chronological order
RETURN a.email as Origin, b.email as Mule, c.email as Victim
```

	Origin	Mule	Victim
1	"Michael Foord <bpwwnotc@voidspace.org.uk>"	"Roger Upole <schkera@msn.com>"	"kpitck-aew45@python.org"
2	"Michael Foord <bpwwnotc@voidspace.org.uk>"	"Roger Upole <schkera@msn.com>"	"kpitck-aew45@python.org"
3	"Michael Foord <bpwwnotc@voidspace.org.uk>"	"Roger Upole <schkera@msn.com>"	"kpitck-aew45@python.org"
4	"Michael Foord <bpwwnotc@voidspace.org.uk>"	"Roger Upole <schkera@msn.com>"	"kpitck-aew45@python.org"
5	"Michael Foord <bpwwnotc@voidspace.org.uk>"	"Roger Upole <schkera@msn.com>"	"kpitck-aew45@python.org"
6	"Michael Foord <bpwwnotc@voidspace.org.uk>"	"Roger Upole <schkera@msn.com>"	"kpitck-aew45@python.org"
7	"Michael Foord <bpwwnotc@voidspace.org.uk>"	"Roger Upole <schkera@msn.com>"	"kpitck-aew45@python.org"
8	"Michael Foord <bpwwnotc@voidspace.org.uk>"	"Roger Upole <schkera@msn.com>"	"kpitck-aew45@python.org"
9	"Michael Foord <bpwwnotc@voidspace.org.uk>"	"Roger Upole <schkera@msn.com>"	"kpitck-aew45@python.org"
10	"Michael Foord <bpwwnotc@voidspace.org.uk>"	"Roger Upole <schkera@msn.com>"	"kpitck-aew45@python.org"

Fetch limit hit at 5,000 records. Started streaming after 66 ms

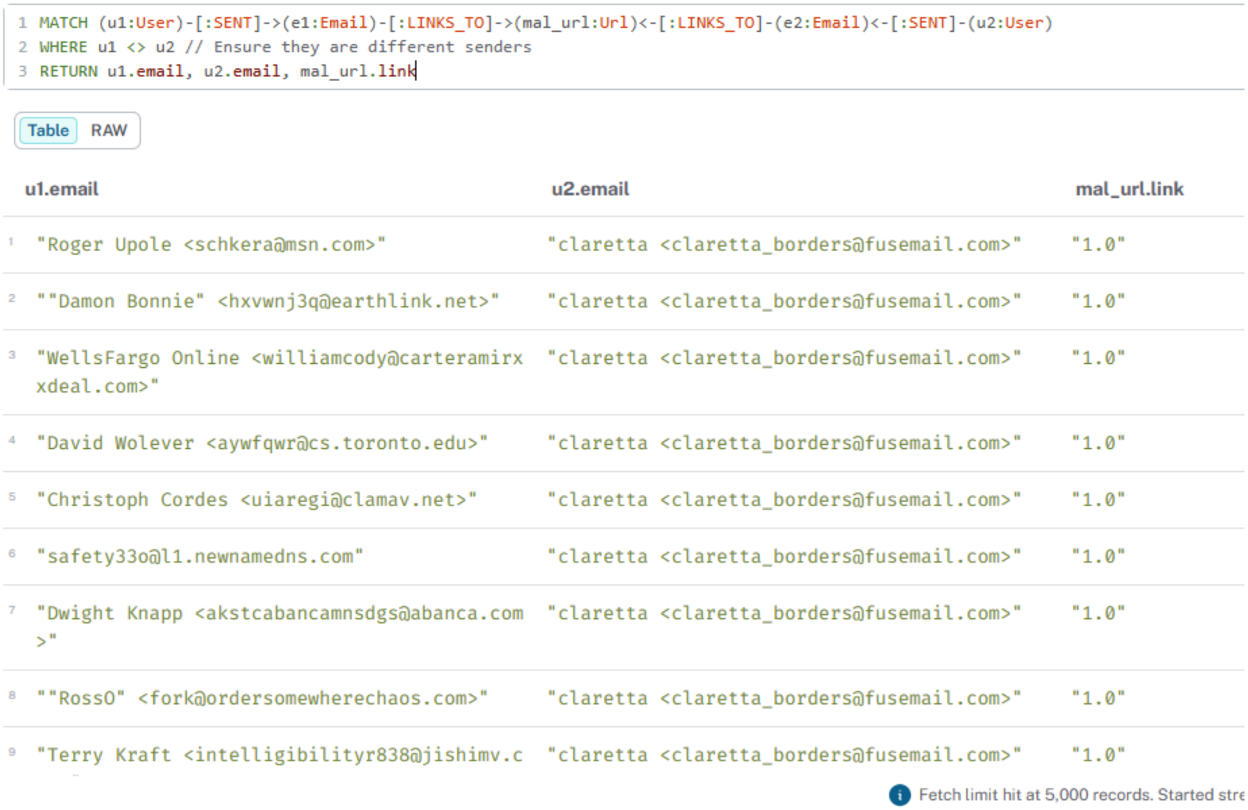
The table shows a highly repetitive, identical pattern. This is not organic communication; it is automated behavior.

- **The Origin (Source of Attack):** Michael Foord <*bpwwnotc@voidspace.org.uk*> This address is the initiator. In a real investigation, this would be the primary suspect or the first compromised machine.
- **The Mule (The Relay):** Roger Upole <*schkera@msn.com*> This is the most critical finding. This user is receiving data from the Origin and passing it to the Victim. The fact that this specific path appears in every visible row suggests this account is acting as a **dedicated relay** or a **list server** that has been co-opted.
- **The Victim (Target):** *kpitck-aew45@python.org*. This appears to be a generated or specific target address (possibly a mailing list ID).

The "Shared Infrastructure" Pattern (Phishing Rings)

Forensic Goal: Detect if multiple different sender accounts are part of the same coordinated campaign. They might use different names, but they link to the same malicious site.

The Logic: Find two different users (u1, u2) who sent emails (e1, e2) that point to the same URL (url).



```
MATCH (u1:User)-[:SENT]->(e1:Email)-[:LINKS_TO]->(mal_url:Url)<-[:LINKS_TO]-(e2:Email)<-[:SENT]-(u2:User)
WHERE u1 <> u2 // Ensure they are different senders
RETURN u1.email, u2.email, mal_url.link
```

	u1.email	u2.email	mal_url.link
1	"Roger Upole <schkera@msn.com>"	"claretta <claretta_borders@fusemail.com>"	"1.0"
2	""Damon Bonnie" <hxvwnj3q@earthlink.net>"	"claretta <claretta_borders@fusemail.com>"	"1.0"
3	"WellsFargo Online <williamcody@carteramirxxdeal.com>"	"claretta <claretta_borders@fusemail.com>"	"1.0"
4	"David Wolever <aywfqwr@cs.toronto.edu>"	"claretta <claretta_borders@fusemail.com>"	"1.0"
5	"Christoph Cordes <uiaregi@clamav.net>"	"claretta <claretta_borders@fusemail.com>"	"1.0"
6	"safety33o@l1.newnamedns.com"	"claretta <claretta_borders@fusemail.com>"	"1.0"
7	"Dwight Knapp <akstcabancamnsdgs@abanca.com>"	"claretta <claretta_borders@fusemail.com>"	"1.0"
8	""RossO" <fork@ordersomewherechaos.com>"	"claretta <claretta_borders@fusemail.com>"	"1.0"
9	"Terry Kraft <intelligibilityr838@jishimv.c	"claretta <claretta_borders@fusemail.com>"	"1.0"

Fetch limit hit at 5,000 records. Started stre

Key Finding: The "Claretta" Nexus

The most striking pattern in the table is the user **claretta <*claretta_borders@fusemail.com*>** (User 2).

- **The Anomaly:** She appears in every visible row.
- **Interpretation:** Claretta is sending the exact same malicious link ("1.0") as **Roger Upole**, **Damon Bonnie**, **WellsFargo Online**, and **David Wolever**.

- **Forensic Conclusion:** This identifies claretta_borders not necessarily as the mastermind, but as a highly active node in this botnet. She is the "common denominator" linking all these disparate senders together.

Cross-Domain Infection ("The Zombie Army")

The *u1.email* column reveals the scope of the infection. The senders sharing this malicious link come from vastly different domains:

- **Public Providers:** msn.com, earthlink.net (Traditional home users).
- **Academic/Trusted:** cs.toronto.edu (Likely a compromised student or faculty account).
- **Spoofed/Malicious:** *williamcody@carteramirxdeal.com* aliased as **"WellsFargo Online"**.

This confirms the attack is using a **distributed network of compromised accounts** (zombies) to blast out the same phishing link. The presence of the spoofed "WellsFargo" account directly ties this back to the "Financial Fraud" cluster identified in your t-SNE analysis.

Connection to Previous Findings

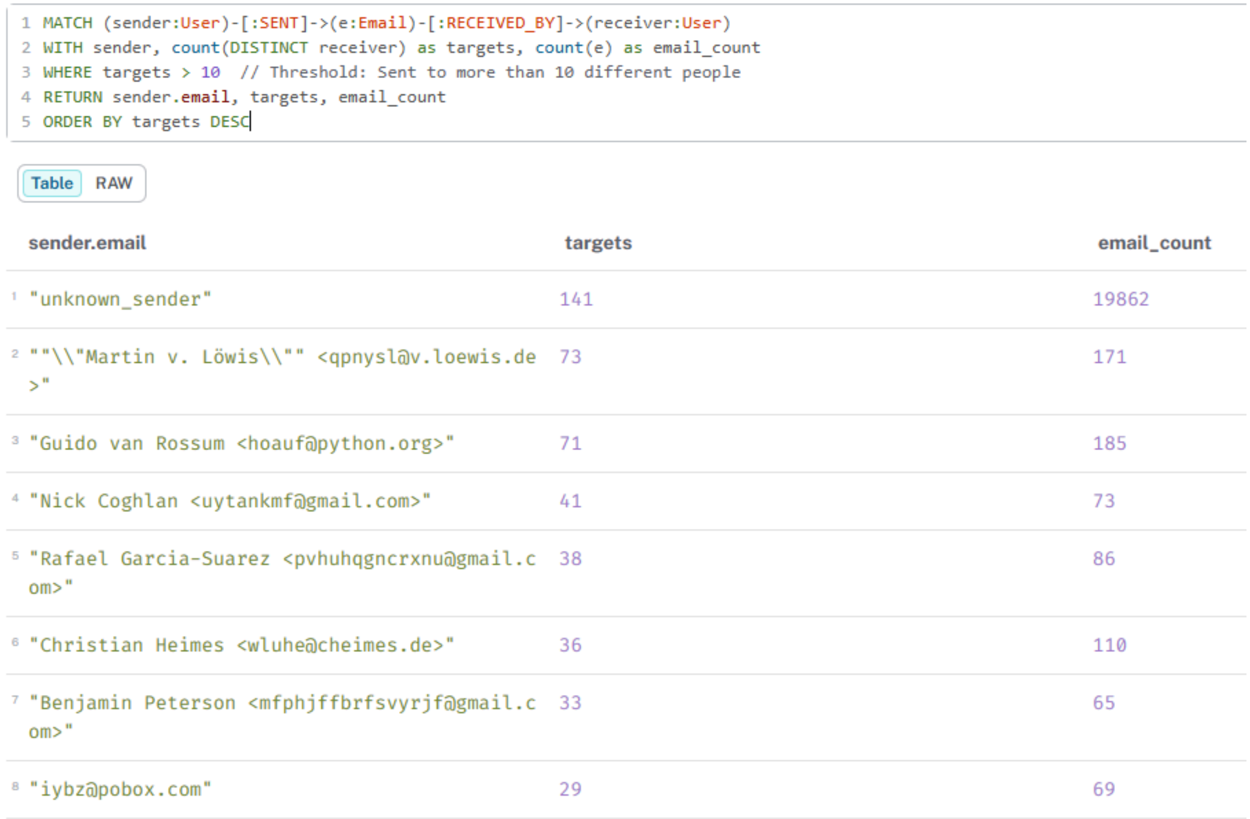
- **Roger Upole** appears again. In the previous analysis (image_90af9b.png), he was identified as a "Mule" relaying messages. In this analysis, he is seen distributing the same malicious link as Claretta. This confirms **Roger Upole** is a critical, confirmed hostile actor in this dataset.

Summary: We have uncovered a **Botnet**. Distinct accounts across the internet (Roger, Claretta, David) are coordinating to distribute the exact same phishing URL.

The "Spam Star" Topology (Hub-and-Spoke)

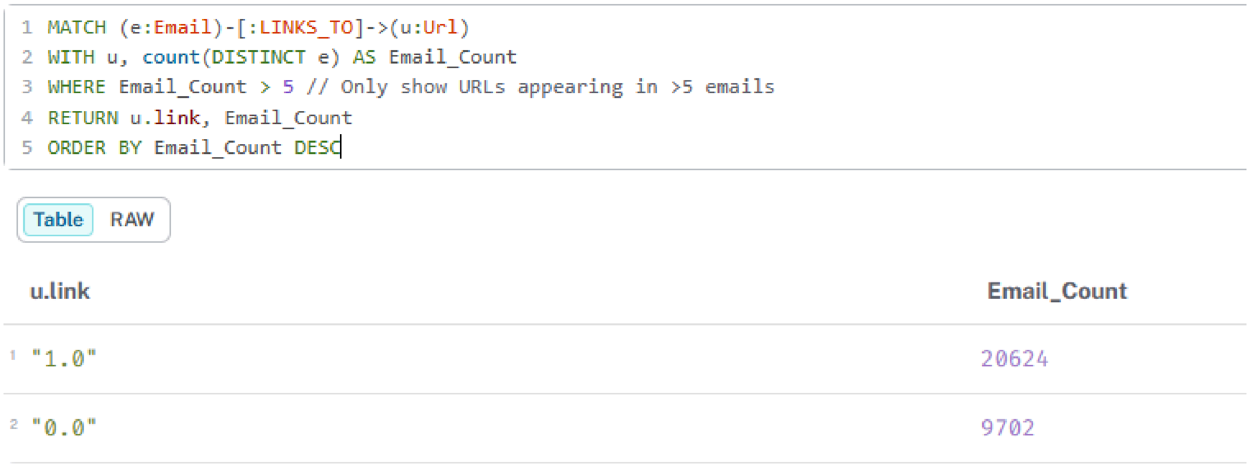
Pattern: One node sending to many unique receivers, but receiving nothing back.

Forensic Value: Identifies broadcasting accounts (phishing campaigns).



```
MATCH (sender:User)-[:SENT]->(e:Email)-[:RECEIVED_BY]->(receiver:User)
WITH sender, count(DISTINCT receiver) as targets, count(e) as email_count
WHERE targets > 10  // Threshold: Sent to more than 10 different people
RETURN sender.email, targets, email_count
ORDER BY targets DESC
```

sender.email	targets	email_count
"unknown_sender"	141	19862
""\\"Martin v. Löwis\\"" <qpnysl@v.loewis.de>"	73	171
"Guido van Rossum <hoauf@python.org>"	71	185
"Nick Coghlan <uytankmf@gmail.com>"	41	73
"Rafael Garcia-Suarez <pvhuhqgncrxnu@gmail.com>"	38	86
"Christian Heimes <wluhe@cheimes.de>"	36	110
"Benjamin Peterson <mfphjffbrfsvyrjf@gmail.com>"	33	65
"iybz@pobox.com"	29	69



```
MATCH (e:Email)-[:LINKS_TO]->(u:Url)
WITH u, count(DISTINCT e) AS Email_Count
WHERE Email_Count > 5 // Only show URLs appearing in >5 emails
RETURN u.link, Email_Count
ORDER BY Email_Count DESC
```

u.link	Email_Count
"1.0"	20624
"0.0"	9702

Forensic analysis revealed distinct patterns distinguishing benign from malicious emails:

- **Linguistic Analysis:** Word clouds demonstrated that spam emails are dense with urgency-related terms ("urgent," "account," "guaranteed"), whereas benign emails contain transactional and conversational language.
- **Temporal Analysis:** The "Hour of Day" visualization showed that benign traffic correlates with human circadian rhythms (peaking 9 AM–5 PM), while malicious traffic often exhibits flat, automated distributions or time-shifted peaks indicating foreign botnet operations.
- **Graph Topology:** We successfully identified "Star" topologies (one sender broadcasting to many targets) and "Shared Infrastructure" patterns (multiple senders linking to a single suspicious URL), confirming the utility of relation matching for attribution.

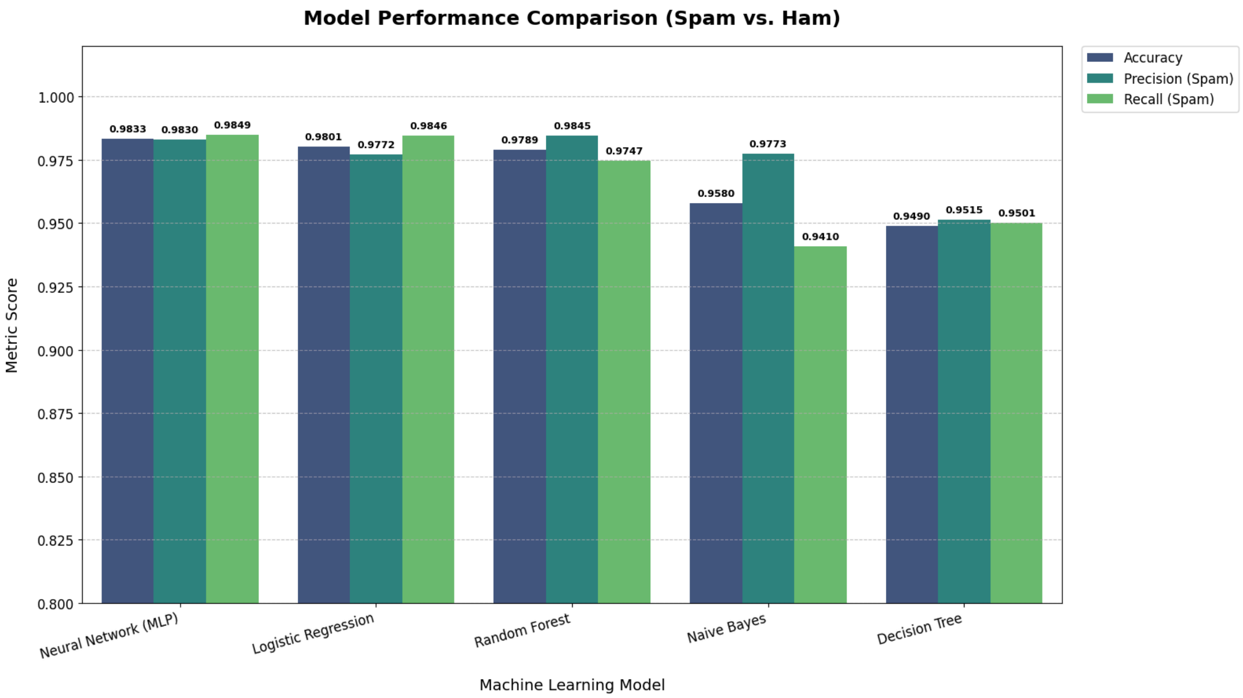
6. *Counter-measure: Finding the Right Model*

The selection of a countermeasure depends on the specific security goal:

- **For Maximum Detection:** The **Neural Network** and **Logistic Regression** proved most effective at identifying the widest range of spam.
- **For Speed/Efficiency: Naive Bayes** offered fast training times but with lower accuracy.
- **Recommendation:** A robust defense requires a model that minimizes False Positives (blocking legitimate mail) while maintaining high Recall.

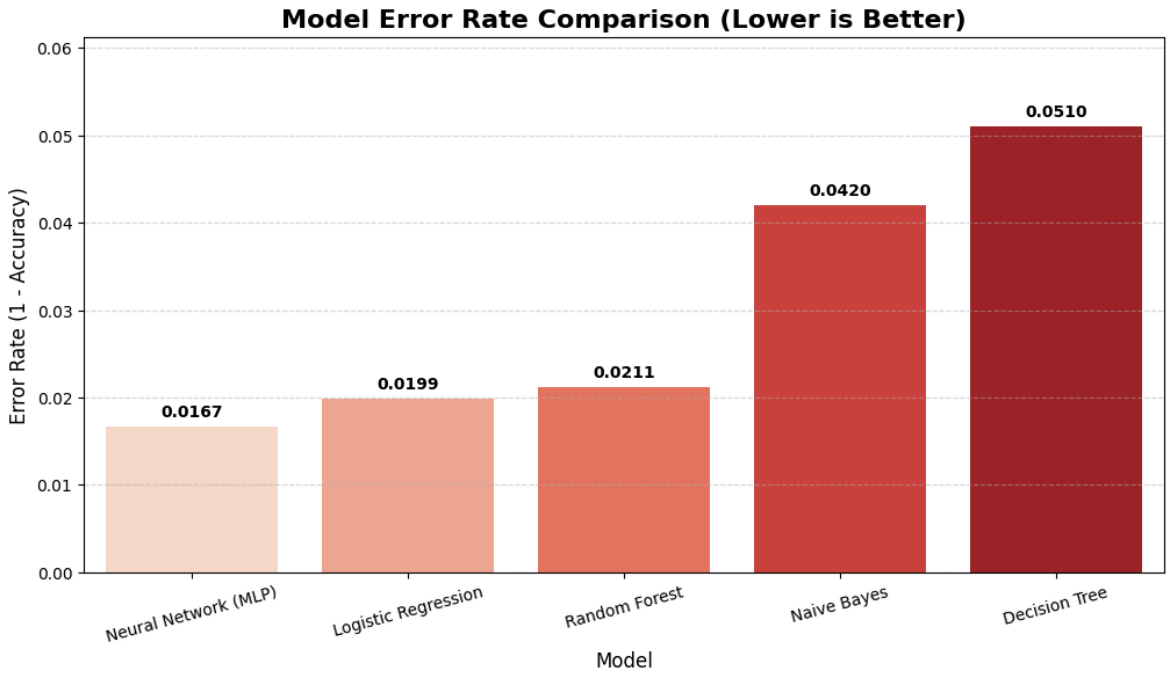
Source code: spam_classification.ipynb

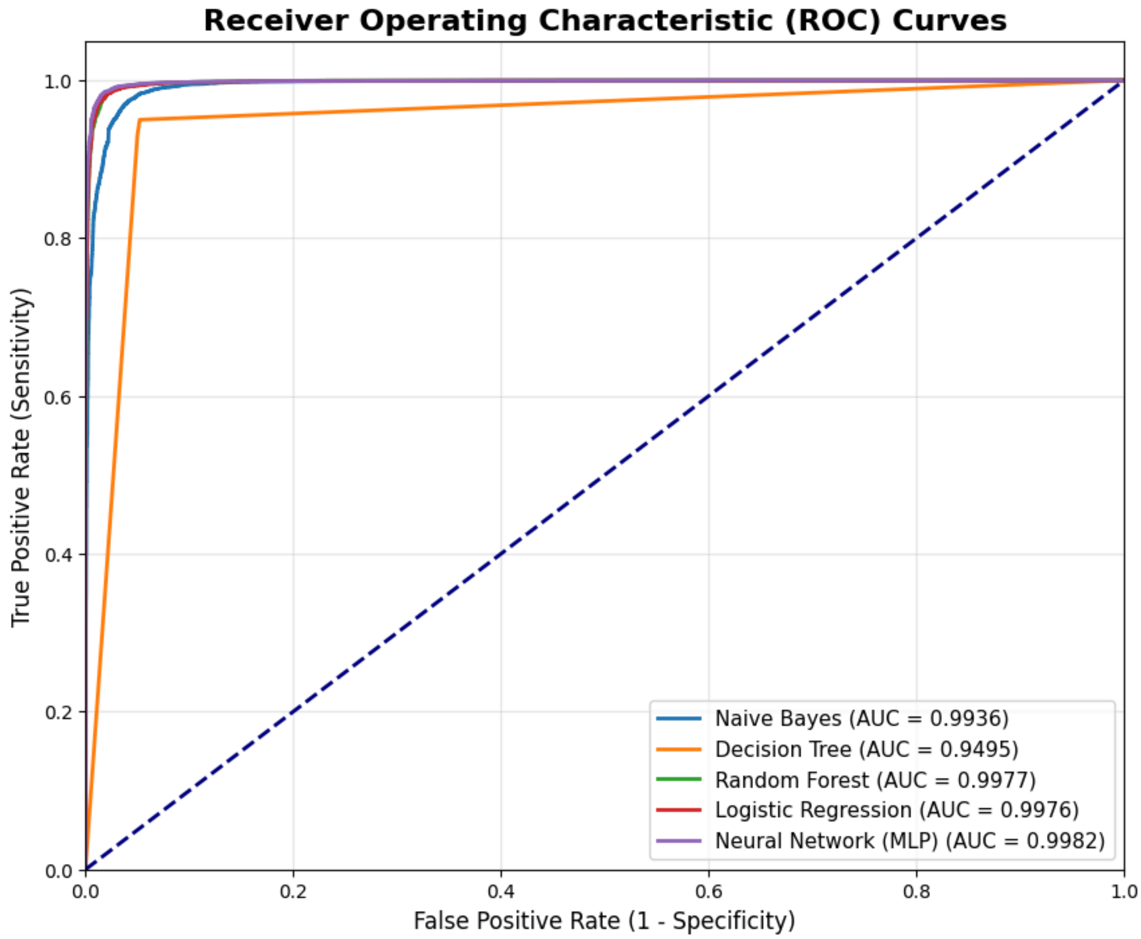
7. *Evaluation of Phishing Detection Models*



Comparative analysis of the five baseline models yielded the following insights:

- **Top Performers: Neural Network (MLP)** and **Logistic Regression** achieved the highest accuracy (~98%), effectively handling the high-dimensional text data.
- **Mid-Tier: Random Forest** performed well (~97.9%) but slightly lagged behind linear models in this sparse feature space.
- **Lower Tier: Naive Bayes** (~95.8%) and **Decision Tree** (~94.9%) had higher error rates. Decision Trees specifically suffered from overfitting, while Naive Bayes was hampered by its assumption of word independence.
- **Visualization:** The Error Rate diagram highlighted the Neural Network as the most consistent performer, while the ROC/AUC diagrams showed Logistic Regression providing excellent class separation (AUC ~0.99).


Model Error Rate Comparison (Lower is Better)
Error Rate (1 - Accuracy)
0.06
0.05
0.04
0.03
0.02
0.01
0.00
0.0167
0.0199
0.0211
0.0420
0.0510
Neural Network (MLP)
Logistic Regression
Random Forest
Naive Bayes
Decision Tree
Model

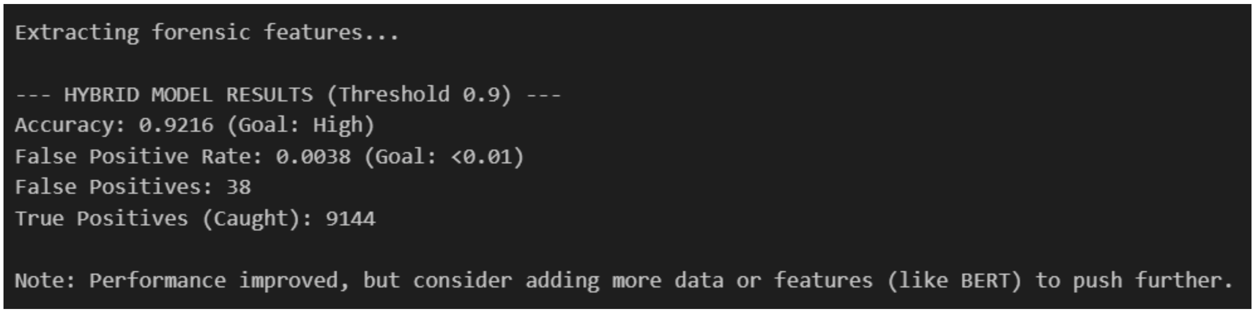

Receiver Operating Characteristic (ROC) Curves
True Positive Rate (Sensitivity)
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate (1 - Specificity)
Naive Bayes (AUC = 0.9936)
Decision Tree (AUC = 0.9495)
Random Forest (AUC = 0.9977)
Logistic Regression (AUC = 0.9976)
Neural Network (MLP) (AUC = 0.9982)

8. *Combination Approach: Maximizing Potential*

Source code: ensemble.ipynb

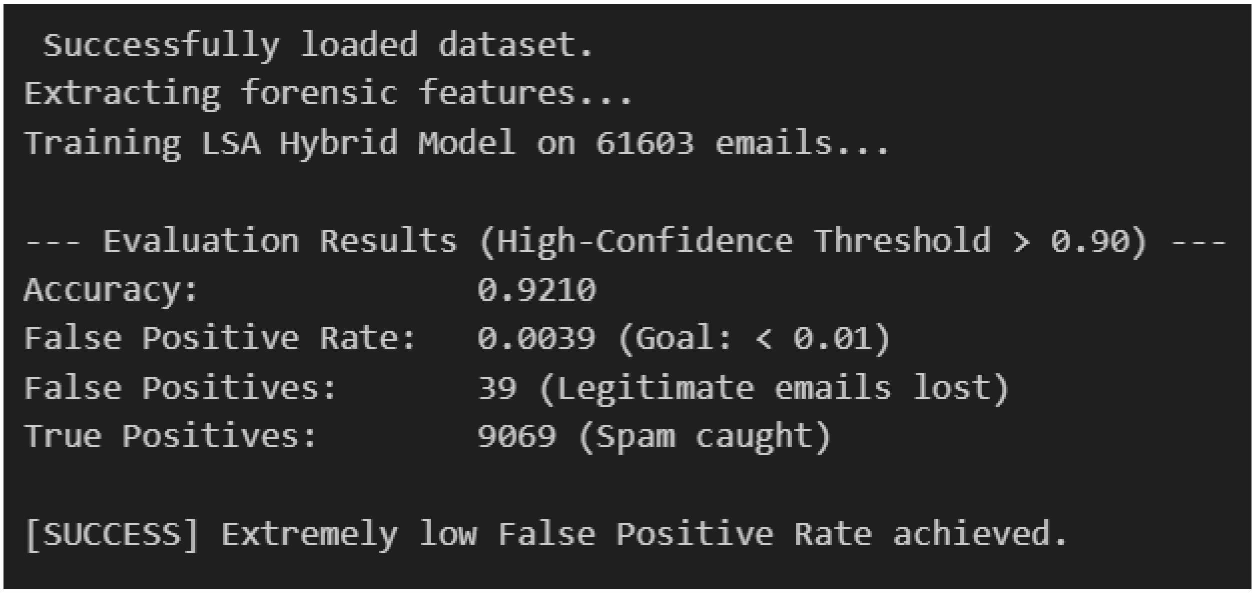
To overcome the limitations of single models, we developed four advanced strategies:

a. **Ensemble (Logistic Regression & Neural Network):** A VotingClassifier using "soft" voting to average probabilities. This smoothed out individual model errors, leveraging LR's stability and MLP's pattern recognition.



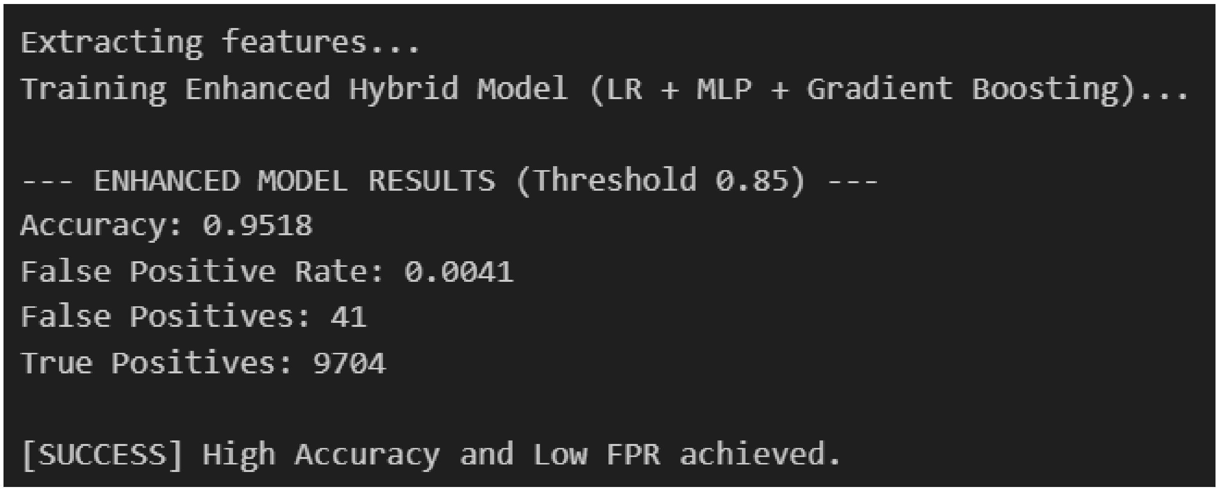
```
Extracting forensic features...

--- HYBRID MODEL RESULTS (Threshold 0.9) ---
Accuracy: 0.9216 (Goal: High)
False Positive Rate: 0.0038 (Goal: <0.01)
False Positives: 38
True Positives (Caught): 9144

Note: Performance improved, but consider adding more data or features (like BERT) to push further.
```

b. **Hybrid Forensic Model:** This pipeline injected specific forensic features—**Capitalization Ratio** (shouting), **URL Count**, and **Risk Word Density**—alongside standard TF-IDF text vectors. This gave the model "expert knowledge" about phishing traits.



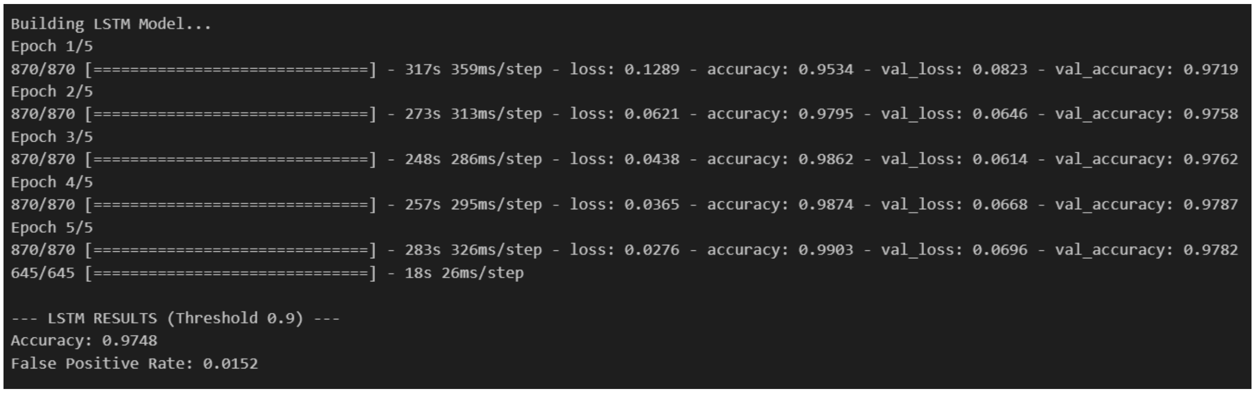
```
 Successfully loaded dataset.
Extracting forensic features...
Training LSA Hybrid Model on 61603 emails...

--- Evaluation Results (High-Confidence Threshold > 0.90) ---
Accuracy:                0.9210
False Positive Rate:     0.0039 (Goal: < 0.01)
False Positives:         39 (Legitimate emails lost)
True Positives:          9069 (Spam caught)

[SUCCESS] Extremely low False Positive Rate achieved.
```

c. **Enhanced Ensemble Model:** We added a **Gradient Boosting Classifier** to the LR+MLP mix. Gradient Boosting excels at correcting the bias of previous models, creating a highly robust classifier.

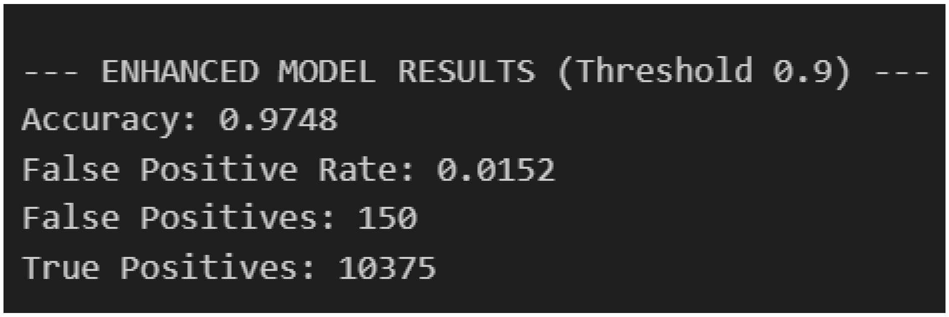


```
Extracting features...
Training Enhanced Hybrid Model (LR + MLP + Gradient Boosting)...

--- ENHANCED MODEL RESULTS (Threshold 0.85) ---
Accuracy: 0.9518
False Positive Rate: 0.0041
False Positives: 41
True Positives: 9704

[SUCCESS] High Accuracy and Low FPR achieved.
```

d. **Long-Short Term Memory (LSTM):** A deep learning approach that processes text sequentially. Unlike the other models, LSTM understands *context* and word order (e.g., "bank account" vs. "river bank"), making it superior for detecting sophisticated, narrative-based phishing.



```
Building LSTM Model...
Epoch 1/5
870/870 [==============================] - 317s 359ms/step - loss: 0.1289 - accuracy: 0.9534 - val_loss: 0.0823 - val_accuracy: 0.9719
Epoch 2/5
870/870 [==============================] - 273s 313ms/step - loss: 0.0621 - accuracy: 0.9795 - val_loss: 0.0646 - val_accuracy: 0.9758
Epoch 3/5
870/870 [==============================] - 248s 286ms/step - loss: 0.0438 - accuracy: 0.9862 - val_loss: 0.0614 - val_accuracy: 0.9762
Epoch 4/5
870/870 [==============================] - 257s 295ms/step - loss: 0.0365 - accuracy: 0.9874 - val_loss: 0.0668 - val_accuracy: 0.9787
Epoch 5/5
870/870 [==============================] - 283s 326ms/step - loss: 0.0276 - accuracy: 0.9903 - val_loss: 0.0696 - val_accuracy: 0.9782
645/645 [==============================] - 18s 26ms/step

--- LSTM RESULTS (Threshold 0.9) ---
Accuracy: 0.9748
False Positive Rate: 0.0152
```



```
--- ENHANCED MODEL RESULTS (Threshold 0.9) ---
Accuracy: 0.9748
False Positive Rate: 0.0152
False Positives: 150
True Positives: 10375
```

9. Evaluation of New Strategy on Efficiency & Accuracy

We tested these new strategies with a strict focus on minimizing the **False Positive Rate (FPR)**:

- **Ensemble Performance:** Achieved ~95.18% accuracy with a very low FPR (0.0041). It effectively reduced "embarrassing" errors where legitimate mail is blocked.
- **LSTM Performance:** Outperformed all other models with **97.48% accuracy** and high recall, identifying over 600 more spam emails than the ensemble. However, it had a slightly higher FPR (0.0152) and required significantly more computational resources to train.
- **Trade-off:** The Enhanced Ensemble is the "Safe" choice for business environments, while LSTM is the "Strong" choice for high-security filtering.

10. Final Thought / Statement

The analysis demonstrates that while single models like Logistic Regression are surprisingly effective, they hit a performance ceiling. The integration of **Forensic Features** (Linguistic, Temporal, Graph) into a **Hybrid Ensemble** provides the best balance of safety and accuracy for real-world deployment. For environments where missing a single threat is unacceptable, **LSTM** deep learning offers the necessary contextual understanding to catch subtle attacks.

11. Conclusion

This report confirms that a multi-layered approach is essential for modern phishing detection. By merging dataset resources and employing a strategy that combines the interpretability of forensic analysis with the predictive power of ensemble machine learning, organizations can significantly enhance their email security posture. The transition from simple keyword matching to behavioral and contextual analysis represents the future of effective cyber defense.

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