Decoding Power Dynamics: Analyzing Gen-Z Slang in Email Communication

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Introduction & Motivation

Emails & Power Dynamics

Workplace emails encode organizational hierarchies and decision-making authority; automatically uncovering "who holds power" can streamline compliance checks, audit trails, and conflict resolution.

The Gen Z Slang Challenge

Models trained on formal English struggle with rapidly evolving, context-dependent slang, risking classification failures—so we must evaluate robustness and pinpoint the linguistic features behind any performance drop.

Dataset Overview

Source :

Enron corporate email corpus (≈517 431 raw messages).

Cleaned & Sampled :

- Removed malformed entries, duplicates and forwarded content.
- Randomly sampled 25 000 emails for formal training and evaluation.

Parallel Corpora :

- Formal: sample_emails.csv (25 000 messages)
- Gen-Z: genz_emails_final_translated.csv (2500 messages)

From	Message	Subject	To
rosalee.fleming@enron.com	<28237677.1075843458008.JavaMail.evans@thyme>	Draft of Ken's itinerary	jeff.dasovich@enron.com, susan.landwehr@enron....
rosalee.fleming@enron.com	<2100907.1075842922146.JavaMail.evans@thyme>	Thank you for the Charitygift	james.bannantine@enron.com, cliff.baxter@enron...
rosalee.fleming@enron.com	<22555774.1075842922514.JavaMail.evans@thyme>	Thank you for the Charitygift	james.bannantine@enron.com, cliff.baxter@enron...

	file	message
0	allen-p/_sent_mail/1.	Message-ID: <18782981.1075855378110.JavaMail.e...
1	allen-p/_sent_mail/10.	Message-ID: <15464986.1075855378456.JavaMail.e...
2	allen-p/_sent_mail/100.	Message-ID: <24216240.1075855687451.JavaMail.e...
3	allen-p/_sent_mail/1000.	Message-ID: <13505866.1075863688222.JavaMail.e...
4	allen-p/_sent_mail/1001.	Message-ID: <30922949.1075863688243.JavaMail.e...
5	allen-p/_sent_mail/1002.	Message-ID: <30965995.1075863688265.JavaMail.e...
6	allen-p/_sent_mail/1003.	Message-ID: <16254169.1075863688286.JavaMail.e...
7	allen-p/_sent_mail/1004.	Message-ID: <17189699.1075863688308.JavaMail.e...
8	allen-p/_sent_mail/101.	Message-ID: <20641191.1075855687472.JavaMail.e...
9	allen-p/_sent_mail/102.	Message-ID: <30795301.1075855687494.JavaMail.e...

Data Preprocessing & Labeling

Structured Split: Each raw Enron email was divided into

- Information Part: headers/metadata (Message-ID, Date, From, To, Cc, Subject, X-From, X-To, X-cc, etc.)
- Content Part: cleaned body text, truncated to 1,000 chars

Cleaning & Filtering:

- Removed invalid encodings and boilerplate (e.g. HTML, forwarded blocks marked by "-------------")
- Dropped emails with <2 words, same sender/recipient, or header-like patterns in the body
- Flagged "has_other_content" and "is_forwarded" for downstream analysis

Recipient Standardization:

- Extracted first recipient into a new Main To field
- Normalized missing Cc values to "None"

Labeled each email "Sender higher," "Recipient higher," or "Similar level" by comparing sender vs. Main To scores

Inferring Email Hierarchies via Social Network Analysis (SNA)

Objective :

To uncover implicit hierarchies in email communications using Social Network Analysis (SNA) and centrality metrics.

Graph Construction:

- Emails modeled as a directed graph
- Nodes: Individuals
- Edges: Sender → Recipients (To, Cc)
- Direction does not imply authority, only communication flow
- Graph built using NetworkX

Inferring Email Hierarchies via Social Network Analysis (SNA)

Normalized Metrics via Min-Max Scaling

Metric	Purpose	Weight
Degree Centrality	Number of emails sent (direct connections)	0.1
Betweenness Centrality	Identifies brokers/intermediaries in communication	0.2
Closeness Centrality	Measures communication efficiency	0.2
PageRank	Highlights influence via connections to key nodes	0.5

Inferring Email Hierarchies via Social Network Analysis (SNA)

Sample - 1

Content :

Hi Al,
My suggestion is that you capture the change order with change order #1 for PSCO's break out contract. If it needs to be paid before year end (which it probably does) you can put a payment date of December 20th, and it will be paid out of TurboPark. This approach has been discussed with Lee Johnson at GE, and he is fine with it.

Thanks,
Kay

Hierarchical Label : Sender higher

Inferring Email Hierarchies via Social Network Analysis (SNA)

Sample - 2

Content :

Attached is another redlined draft of the Pastoria IM. It is much more close to completion because it now includes comments from all necessary parties. Please carefully review and send me any changes no later than Monday. If you send them today (Sunday) send them via e-mail. Beginning Monday (12 PM CDT) I'll be in SF, so if you fax them send them to 415.782.7827. Please call me at 713.629.0929 or 713.398.6412 should you have any questions.
Thanks.
PS for Dave Parquet:
Not all of your proposed changes were made simply because I could not ready many of them and the changes were too late at night to call you. I was asked to get a draft out ASAP so I will call you today (Sunday) to discuss them.

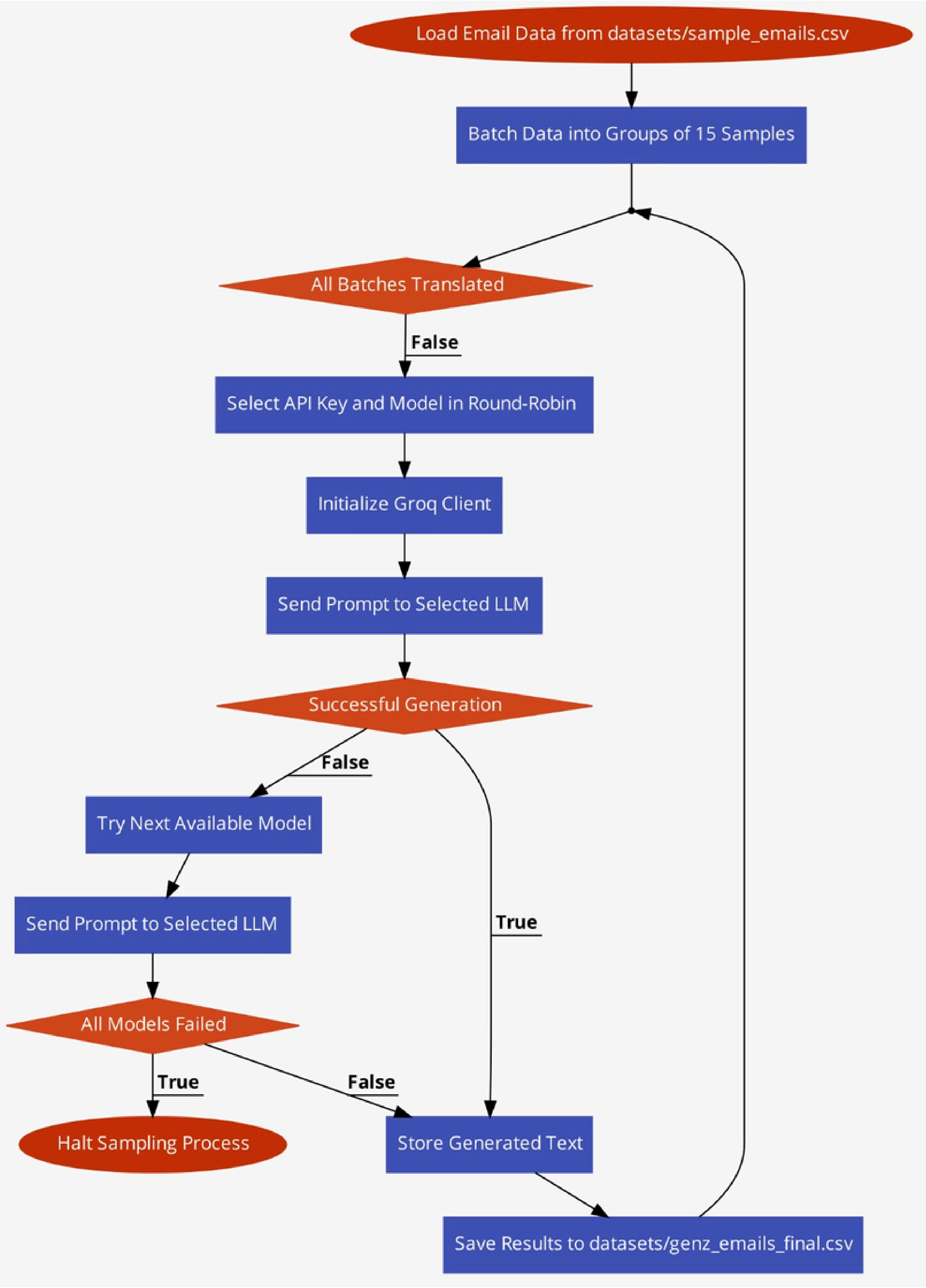
Hierarchical Label : Receiver higher

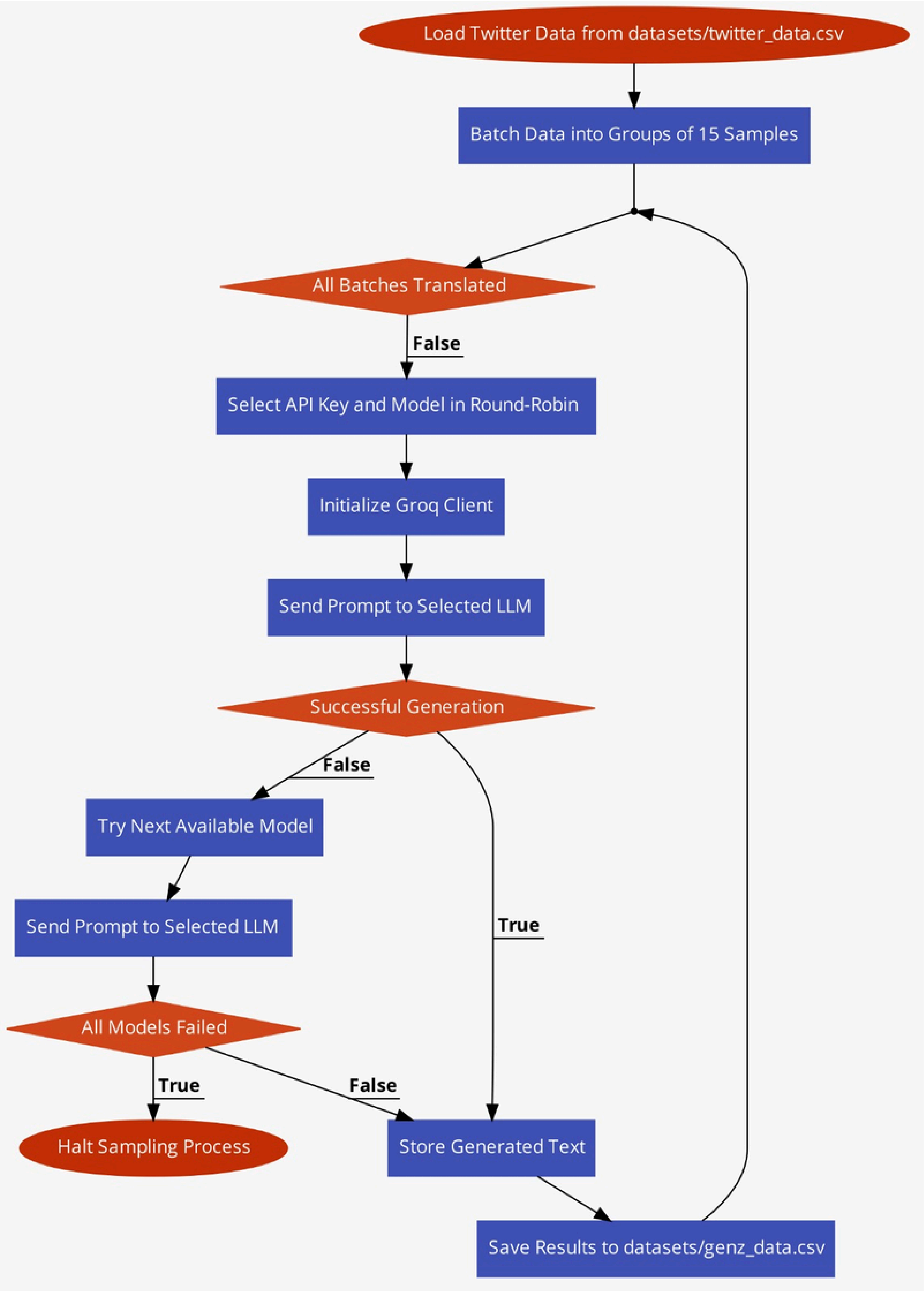
Gen-Z Data Generation & Labeling

Developed a Python-based pipeline to generate Gen Z-style paraphrases of textual data using large language models (LLMs) accessed via the Groq API. We have utilized multiple API keys and a variety of LLMs to automate the process.

Carefully crafted prompts were used to ensure tone consistency, accurate slang translation, and to prevent the addition of emojis or hashtags. The main goal was to convert each sentence into a Gen Z slang version while preserving its original meaning and intent. This approach enabled efficient and controlled slang paraphrasing at scale.

Generation Flow Diagram





Genz Style Transformer

Transformer architecture can be used in order to translate the normal style to GenZ style by training it with pairs of normal text and corresponding genz text.

We have generated two sets of Genz data as seen earlier using LLM :

- Genz Enron Emails
- Genz Twitter Text

Transformer Model – 1:

- It is trained only on Enron Email data
- When the samples were generated they weren't satisfactory

Transformer Model - 2:

- It is trained on Enron Email data and Twitter Text
- The samples were much better and genz slangs were used according to the context.

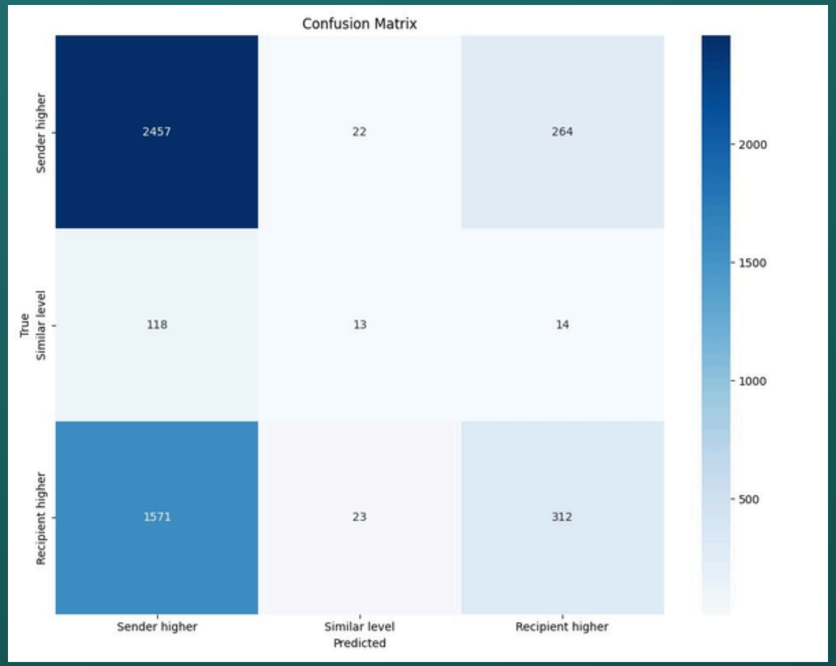
Samples From Model - 1

Original Email	Generated Text
Attached is the revised Committed Reserves Confirm with the language we discussed. Please modify the confirm templates for the Sept. wellhead deals (and those remaining from August) to reflect the revision. Let me know if you have any questions.	the revised Committed Reserves Confirm. Please modify the confirm templates for the Sept. wellhead deals (and those remaining from August) to reflect the revision. Let me know if you have any questions.
Please let me know if this will be problem.	Bitte let me know if this will be problem.
Dad, I was talking with Kathleen this weekend and she had some ideas and suggestions about Enron. I asked her to put them in writing so that I could share them with you.	Dad, I was talking with Kathleen this weekend and she had some ideas and suggestions about Enron.

Samples From Model - 2

Original Email	Generated Text
Attached is the revised Committed Reserves Confirm with the language we discussed. Please modify the confirm templates for the Sept. wellhead deals (and those remaining from August) to reflect the revision. **Let me know if you have any questions.**	attached is the revised Committed Reserves Confirm with the language we discussed. please tweak the confirm templates for the Sept. wellhead deals (and those remaining from August) to reflect the revision. **hit me up if you've got any questions**
Please let me know if this will be problem.	**hit me up 'if this will be sus.**
Dad, I was **talking** with Kathleen this weekend and she had some ideas and suggestions about Enron. I asked her to put them in writing so that I could share them with you.	Dad, I was **vibing** with Kathleen this weekend and she had some ideas and suggestions about Enron. I asked her to put them in writing so that I could share them with you

Models and Metrices



LSTM Classifier:

- Embedding Layer: Vocab size × 128 (for tokens appearing ≥2 times)
- LSTM Layer: 128 hidden units, dropout of 0.3
- Output Layer: Fully connected layer mapping to 3 classes (Sender higher, Similar level, Recipient higher)

BERT Classifier:

- Tokenizer: bert-base-uncased from HuggingFace (lowercase, truncate/pad to 128 tokens)
- Model Architecture:
  - Pre-trained BERT encoder
  - Classification head on [CLS] token
  - Final layer outputs 3 hierarchy classes

Performance Metrics Used:

- Accuracy
- Precision
- Recall
- F1-Score
- Confusion Matrix

Results

LSTM

Normal English data:

Accuracy: 84.3

F-score:

- Sender Higher: 0.87
- Recipient Higher: 0.81
- Similar Level: 0.75

GenZ Slang data:

Accuracy: 78.2

F-score:

- Sender Higher: 0.81
- Recipient Higher: 0.73
- Similar Level: 0.91

BERT

On Normal English data:

Accuracy: 93.21%

Class	Precision	Recall	F1-Score	Support
Recipient higher	0.9328	0.9121	0.9224	1081
Sender higher	0.9272	0.9464	0.9367	1306
Similar level	0.9823	0.9569	0.9694	116
Accuracy			**0.9321**	2503
Macro Avg	0.9475	0.9385	0.9428	2503
Weighted Avg	0.9322	0.9321	0.9320	2503

On Gen-Z Slang Data:

Accuracy: 85.30%

Class	Precision	Recall	F1-Score	Support
Recipient higher	0.8571	0.7993	0.8272	1081
Sender higher	0.8401	0.8974	0.8678	1306
Similar level	0.9900	0.8534	0.9167	116
Accuracy			**0.8530**	2503
Macro Avg	0.8958	0.8500	0.8706	2503
Weighted Avg	0.8544	0.8530	0.8525	2503

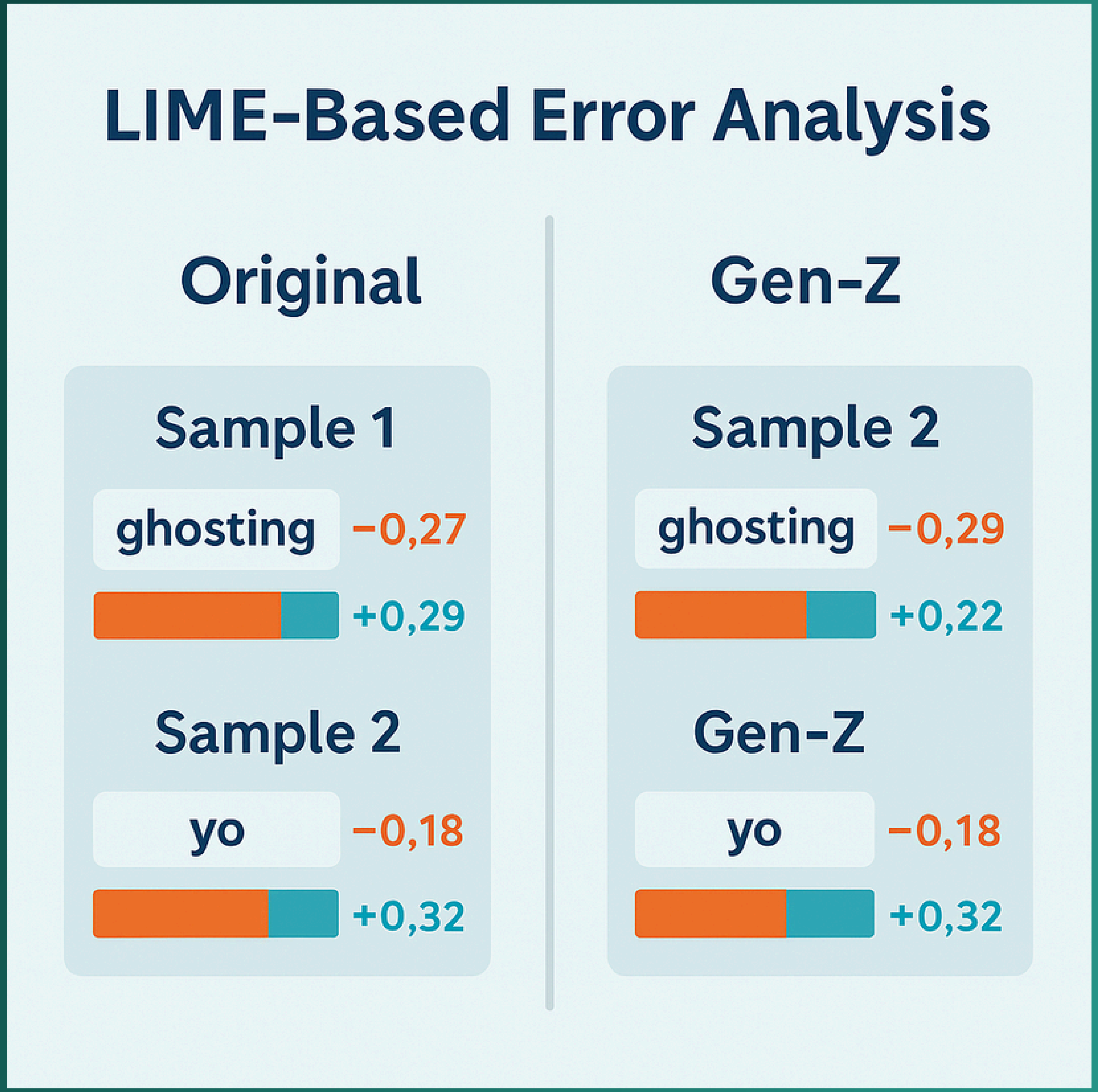
Analysis

Stable Predictions, Shifting Attributions

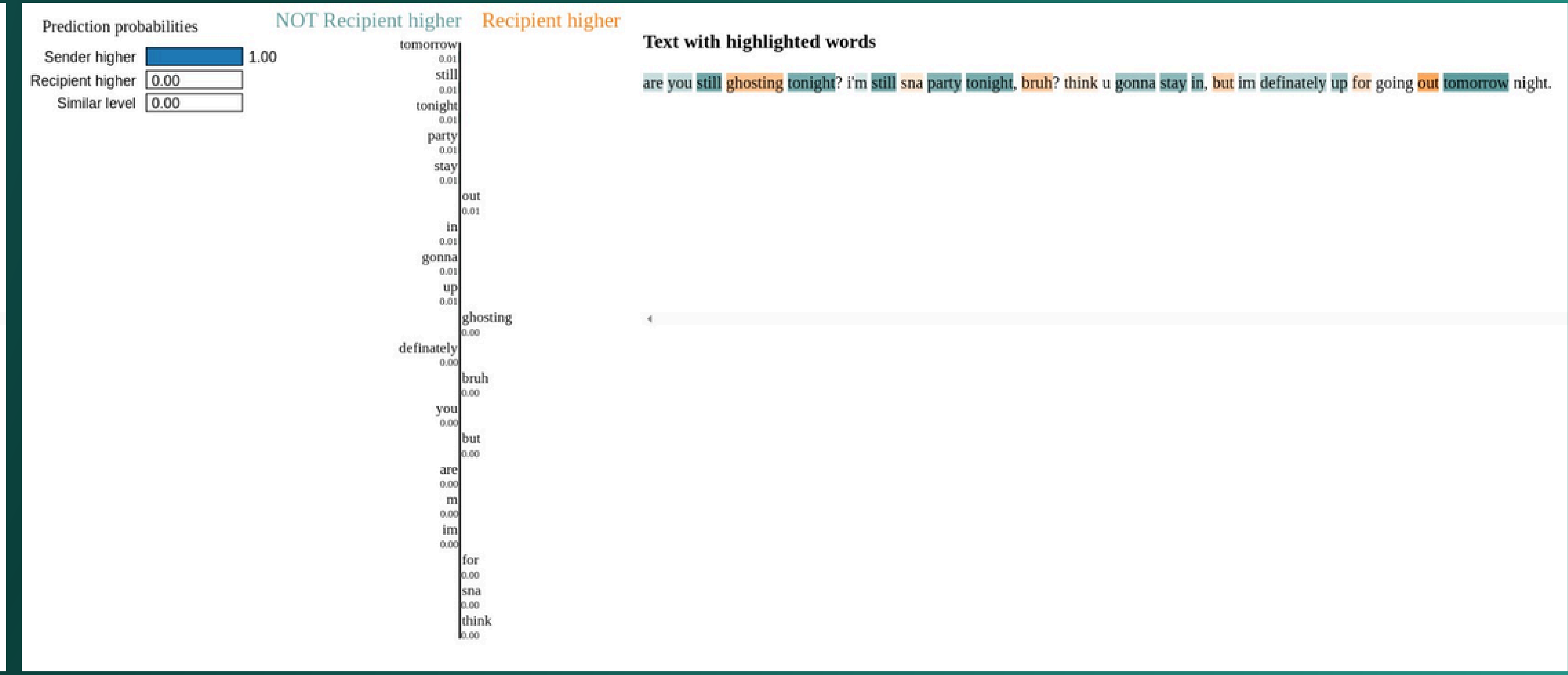
While the classifier's top-level decisions remain unchanged on both original and Gen-Z texts, LIME reveals that slang terms like "ghosting" and "yo" receive significant weights—sometimes flipping their contributions toward opposing classes and subtly altering the model's rationale.

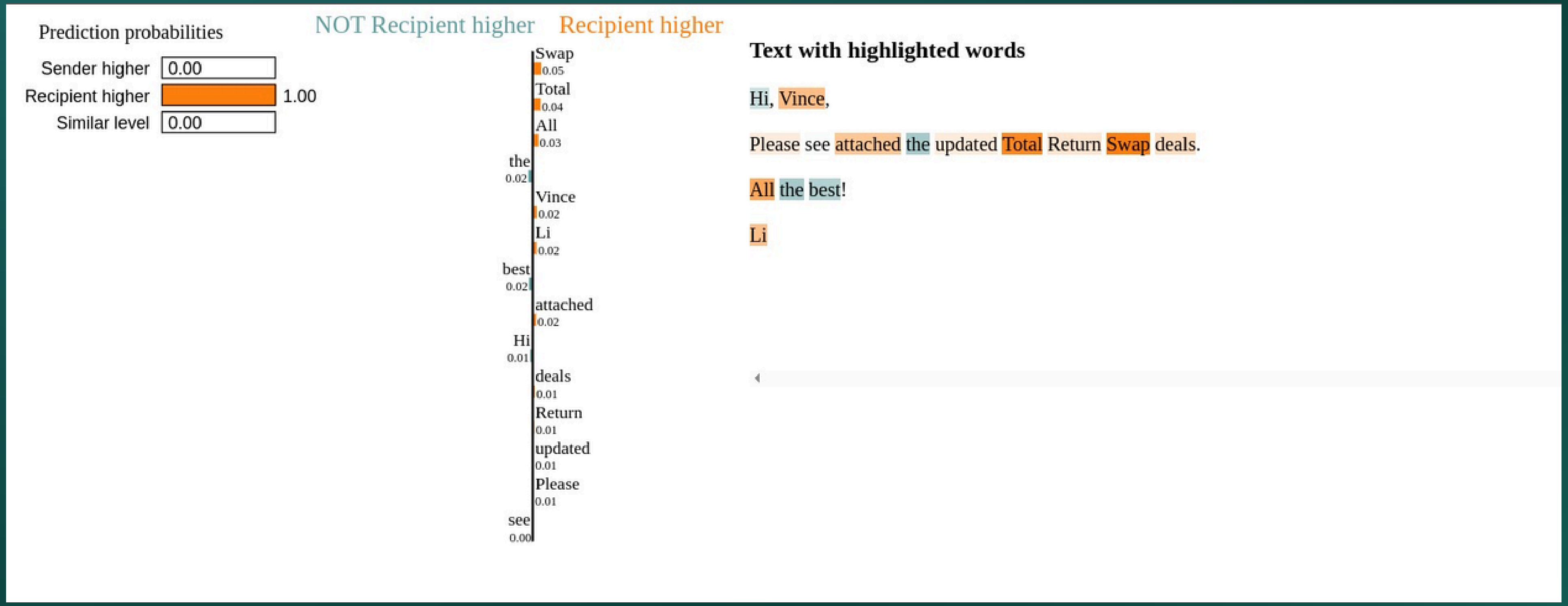
Slang-Induced Interpretability Drift

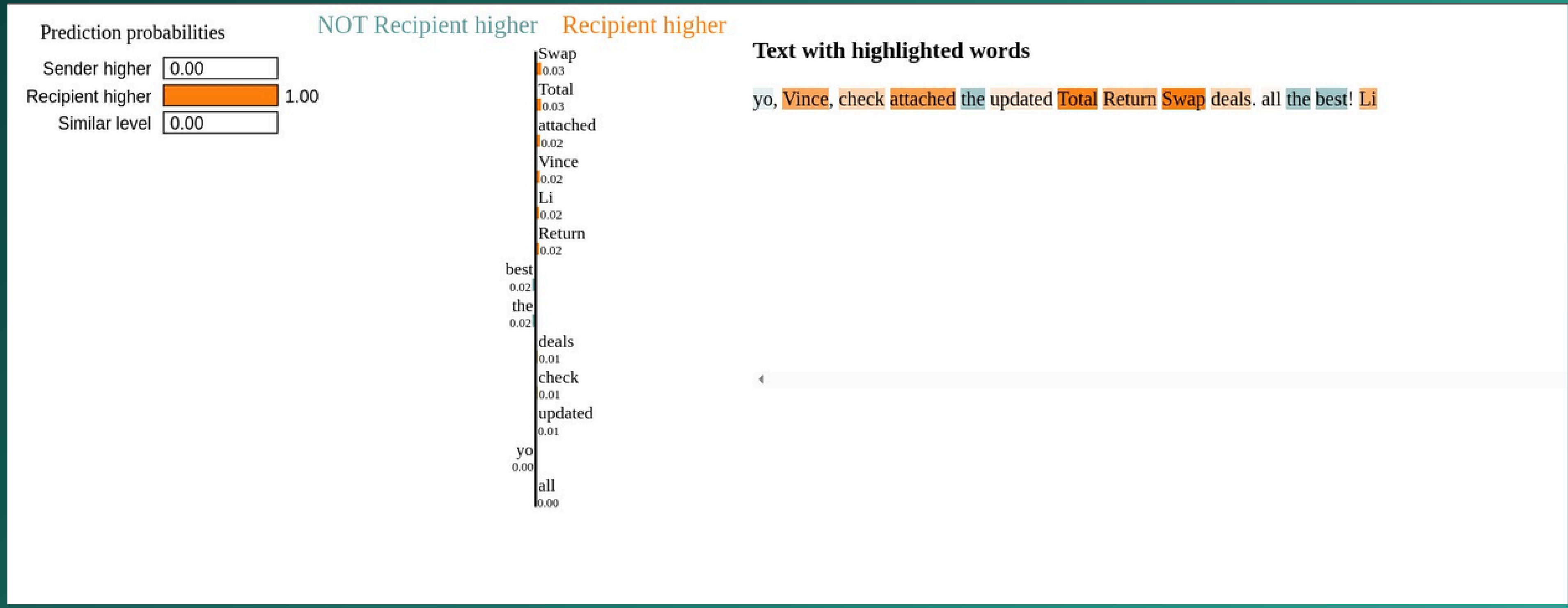
Key Gen-Z tokens introduce new influential features: e.g., "ghosting" in Sample 1 boosts the Receiver Higher score, and "yo" in Sample 2 pulls against Sender Higher, demonstrating that informal language can reshape the model's explanation even without changing its final label.



LIME Anaysis







Conclusion

- Our findings indicate that standard-trained language models struggle with Gen Z slang due to a combination of domain shift, semantic ambiguity, and stylistic divergence.
  - Many slang terms (e.g., idk, sus) are absent from training data, leading to vocabulary mismatch.
  - Additionally, figurative expressions like ”He ghosted me” or ”That’s a big W” often defy literal interpretation, posing challenges for models not fine-tuned on such language.

- Through our experiments, we observed some differences in the types of phrases used in Gen Z emails compared to standard or professional emails. These differences significantly affect the overall style and tone of the text.
  - Gen Z messages often include informal expressions, abbreviations, and culturally specific slang, which create a more casual and conversational tone.
  - In contrast, standard emails tend to use formal, structured language

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Reference

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