Lost in Translation: Translating Generation Z Internet Slang using Machine Learning

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Abstract

Internet slang is an informal variation of language that is prominent to the younger generation. The usage of this language brought generational divide between them and the older generations. This study aims to develop a translation tool leveraging Large Language Models (LLMs) to bridge this issue. A dataset of Generation Alpha slang sentences and their formal equivalents will be used to fine-tune an existing LLM. The model will be trained to translate slang sentences into formal English, and will be compared against the baseline model using various evaluation metrics. The study highlights the significance of addressing communication gaps and provides insights into how technology can enhance understanding and reduce miscommunications across generations. This research contributes to the broader discourse on language adaptation and generational communication in the digital age.

Keywords: Internet Slang, Generation Alpha, Generational Divide, LoRA, LLM

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Chapter 1

Introduction

1.1 Overview

Language is how humans communicate and express themselves (Crystal & Robins, 2024). It evolves, adapting to the changing needs of users (Jeresano & Carretero, 2022). New words are borrowed or invented (Mantiri, 2010), and most linguistic changes are initiated by young adults and adolescents (Thump, 2016 as cited in (Jeresano & Carretero, 2022)). This demographic tends to focus on belonging to self-organized groups of peers and friends, forming what can be described as the ”we” generation. Through their interactions, language changes differently, making them remarkably distinct from previous generations.

Slang is a great example of the dynamic nature of language. Slang is an informal language used by people in the same social group (Fernández-Toro, 2016). It serves multiple social purposes: identifying group members, communicating informally, and opposing established authority (McArthur, 2003). Slang is highly contextual and pervasive, even in non-standard English. Its figurative nature and how it twists the definitions of the words used make it difficult for outsiders to understand.

In recent years, the Internet has become a significant medium for the evolution and spread of language, giving rise to ’Internet slang’ (J. Liu, Zhang, & Li, 2023). Internet slang is a collection of everyday language forms used by various online groups (Barseghyan, 2014). Ujang et al. (2018, as cited in (binti Sabri, bin Hamdan, Nadarajan, & Shing, 2020)) state that internet slang is not easily understood by people outside the social group or people who are not fluent in the language where the slang is used. This phenomenon is particularly prominent among the younger generation (Maulidiya, Wijaya, Mauren, Adha, & Pandin, 2021), where they use it to communicate and interact with friends.

Generation Z, individuals born between 1996 and 2009, are regarded as "digital natives" because technology is an integral part of their upbringing (Dua et al., 2024). Even the language of this generation is greatly affected by technology, where newly coined terms and phrases, called Gen Z slang, are tied to the media culture they've grown up with (Jeresano & Carretero, 2022). However, this evolution of language often creates communication barriers with older generations (Venter, 2017 as cited in (Ghazali & Abdullah, 2021)). Furthermore, studies show that even within Generation Z, people with limited exposure to social media may struggle to understand the prevalent slang (Vacalares, Salas, Babac, Cagalawan, & Calimpong, 2023).

These gaps highlight the need for a tool that can bridge the generational divide, making it easier for individuals to understand the language of Generation Z. Multiple studies have tried translating slang into a formal language using machine learning. Khazeni et al. achieved a 81.91% accuracy in translating Persian slang to formal Persian language using deep learning. Another study by Nocon et al. created a translator to translate Filipino colloquialisms into the Filipino language using Tensorflow's sequence-to-sequence model and Moses' phrase-based statistical machine translation. Furthermore, Ibrahim and Sharief developed a slang translator using models from Hugging Face.

building on these studies, this study proposes to create a translation tool specifically to translate Gen Z slang. The tool will utilize Low Rank Adaptation (LoRA) to a selected Large Language Model (LLM). The results will be evaluated using the Recall-Oriented Understudy for Gisting Evaluation (ROUGE).

By fostering mutual understanding, this tool aims to promote more effective and harmonious interactions across age groups, ultimately enhancing relationships and reducing miscommunication.

The main contributions of this study are as follows:

- enhance linguistic understanding between generations through using fine-tuning a LLM to translate Gen Z slang to formal language, leveraging the strengths of advanced NLP techniques
- bridge communication gaps between generations using the proposed model to foster better relationships
- create a scalable framework that can be adapted to translate slang in other languages

1.2 Problem Statement

Internet slang fosters informal, relatable communication within the younger generation (Ghazali & Abdullah, 2021), especially Generation Z, but it presents challenges in understanding for people outside this demographic. The gap in comprehension with older generations widens as internet slang evolves, often leading to miscommunication affecting social relationships that contribute to the generational divide (Vacalares et al., 2023). A more specific translation tool developed using language models can be used to bridge this divide.

By leveraging the ability of LLM to generate a more nuanced and properly constructed answer, a better tool can be made to translate the slangs into proper sentences. It has already been proven by the likes of GPT being modified and tailored for use in several automated chatbots to provide customer service. However, no such tool exists for slang translation of Generation Alpha, which arguably has the most diverse slangs compared to other generations. The creation of this tool will allow translating of such texts into formal sentences and help with bridging the generational divide between them and older people, especially teachers.

1.3 Research Objectives

1.3.1 General Objectives

This study aims to fine-tune the zephyr-7b Large Language Model (LLM) for use in the translation of Generation Z internet slang used by Filipinos in social media.

1.3.2 Specific Objectives

- To create a dataset of sentences containing Generation Z slang used in differing contexts and its formal translation
- To create a Low Rank Adaptation (LoRA) implementation for fine-tuning an existing model
- To fine-tune an existing LLM to translate sentences containing Generation Z slang into formal sentences
- To evaluate the performance of the trained model and compare it to the based model using several performance metrics

1.4 Scope and Limitations of the Research

This study will focus on the usage of internet slang by Filipino Generation Z, with an emphasis on English language since it is widely use on different digital platforms such as social media.

1.5 Significance of the Research

The study contributes to understanding the evolving linguistic landscape shaped by internet slang, especially as used by Generation Z. Insights gained from this study may aid educators, parents, and communication professionals in bridging inter-generational communication gaps and fostering better understanding across age groups.

Chapter 2

Review of Related Literature

2.1 Communication Gap between Generations

Language is dynamic in nature and thus, constantly evolving over time. One example of this behavior is the development of internet slang. Internet slang is a result of language variation and is often regarded as informal (S. Liu, Gui, Zuo, & Dai, 2019). In the study, *The Use of Online Slang for Independent Learning in English Vocabulary* (Ambarsari, Amrullah, & Nawawi, 2020), students used internet slang to express their feelings and emotions, and to align their communication style with their peers.

However, this development has its challenges. It is suggested that younger generation should use slang to communicate with each other instead of older generations because it might cause confusion between them (Jeresano & Carretero, 2022).

This miscommunication is prominent between generations with differences in linguistic familiarity as Suslak (Suslak, 2009) argues that age influences language use, noting that language evolves across generations. Supporting this, a study by Teng and Joo (Teng & Joo, 2023) found that the older a person is, the less likely they are to understand internet language.

Studies have shown that using internet slang improves relationships between those who use it. However, using internet slang for inter-generational communication can be a hindrance to proper and effective communication (?, ?).

2.1.1 Generative AI

Generative AI encompasses machine learning models that create new content, such as text, images, and audio, based on patterns learned from extensive data (Euchner, 2023). These models, including LLMs like those used in ChatGPT and Bing AI, use neural networks to predict the next word or phrase in a sequence, enabling them to generate human-like text (Brynjolfsson, Li, & Raymond, 2023). The ability of generative AI to understand and produce diverse content, ranging from creative writing code, makes it potentially useful for various applications, such as language translation (Fui-Hoon Nah, Zheng, Cai, Siau, & Chen, 2023).

2.2 Existing Studies

Vergho et al.(?, ?) used multiple open source LLMs and compared them with the latest ersion of GPT-3.5 and 4.0 models at that time. They determined zephyr-7b-beta is a viable open-source alternative to these models and is comparable with the latest GPT-4.0 model.

Khazeni et al. (Heydari, Albadvi, & Khazeni, 2024) used deep learning to create a model for translating Persian slang text into formal ones. The researchers explored the challenges of translating Persian slang into English within the context of film subtitling, specifically focusing on the performance of three neural machine translation (NMT) systems, namely Google Translate, Targoman, and Farazin. The primary interest of the paper lies in the understanding of how these NMT systems handle the complexities of slang translation. It was revealed that the NMT systems often struggle to capture the nuances of slang, leading to unnatural and inaccurate translations. Targoman performed best in naturalness, but it fell short of human translation quality. This implies the need for specialized algorithms or training data suitable for slang, and potentially human post-editing, to achieve accurate and culturally appropriate translations in this domain.

The study by Nocon et al. (Nocon, Kho, & Arroyo, 2018) explores translating Filipino colloquialisms, such as Conyo and Datkilab, into standardized Filipino, addressing comprehension barriers for non-familiar speakers. Two machine translation (MT) approaches were evaluated: Tensorflow's Sequence-to-Sequence model using Recurrent Neural Networks (RNNs) and Moses' Phrase-based Statistical MT. Moses outperformed Tensorflow on test data due to its handling of phrase combinations and unfamiliar words, while Tensorflow excelled on training data, indicating potential with refinement and more training data. The research underscores the need for robust datasets and highlights the strengths of phrase-based statistical MT in tackling slang translation challenges.

Ibrahim and Mustafa (Ibrahim & Sharief, 2023) developed a system to translate slang into formal language, addressing challenges posed by slang's informality and variability. Using updated datasets of slang words, formal equivalents, and contextual sentences, they fine-tuned pre-trained models from Hugging Face's Transformer library. While the T5-base model showed promise during training, it performed poorly in testing. In contrast, the "facebook/bart-base" model excelled, demonstrating high accuracy and low loss values. The study highlights the importance of fine-tuning and updating datasets for effective slang translation and emphasizes the potential of transformer models like "facebook/bart-base" in bridging informal and formal language gaps.

2.3 LoRA for Fine Tuning

Low Rank Adaptation, or LoRA, is an efficient Parameter Efficient Fine Tuning (PEFT) method proposed by Hu et al (Hu et al., 2021). This can significantly decrease the required storage for training while producing comparable results and in some cases even outperforming other adaptation methods. In addition, it has minimal chance of catastrophic forgetting as the original weights are not being tampered with, unlike other fine-tuning methods. These factors make it a suitable option for slang translation as a quick yet accurate solution. In a study conducted by Zhao et al. (Zhao et al., 2024), they determined that some LLMs using LoRA for fine tuning can outperform GPT-4, one of the most advanced LLM models currently. A study by Nguyen et al. (Nguyen, Wilson, & Dalins, 2023) used LoRA in fine tuning a pre-trained Llama 2 7B model for text classification of a dataset that contains slang. They were able to create a more accurate model compared to models by existing studies at that time.

2.4 Chapter Summary

This chapter shows how generational differences create communication gaps, especially due to internet slang. Younger people tend to use slang to express emotions and connect with friends, but this can confuse older generations who aren't as familiar with these terms. Research shows that as language changes over time, older people are generally less likely to understand the newest internet language. To bridge this gap, some recent studies have utilized machine learning to translate slang into more standard language. For instance, Khazeni et al. (Heydari et al.,

2024) used deep learning to translate Persian slang, while Nocon et al. (Nocon et al., 2018) created a Filipino slang translator using statistical models. Moreover, Ibrahim and Mustafa (?, ?) fine-tuned pre-trained models to learn slang meanings. One promising technique for this is Low Rank Adaptation (LoRA), which is a fine-tuning method that keeps the original model stable while using less storage. Studies by Zhao et al. (Zhao et al., 2024) and Nguyen et al. (Nguyen et al., 2023) show that LoRA models are not only efficient but can even outperform advanced models like GPT-4 when it comes to slang translation and text classification.

Table 2.1: Summary of Existing Studies

Author	Focus	Gaps	Problem Solved
Nocon et al.	Developing machine translators for Filipino colloquialisms using sequence-to-sequence models and statistical machine translation (Moses).	Tensorflow models had issues with unknown tokens and repetitions, and limited ability to generalize to unseen data.	Demonstrated the feasibility of machine translation for Filipino colloquialisms, with Moses as a viable solution.
Ibrahim et.al	Developing an intelligent system to transform English slang words into formal words.	The study noted that more powerful processors could improve the training and testing, and that previous datasets were outdated and needed updating.	Demonstrated an effective model for translating English slang to formal English and highlighted the importance of fine-tuning pre-trained models.
Khazeni et al.	Persian slang text conversion to formal and deep learning of Persian short texts on social media	The BERT models used did not align well with the informal data used in the sentiment analysis.	Created a tool to convert Persian slang to formal text and improved sentiment analysis of short texts using deep learning.

Chapter 3

Research Methodology

This chapter lists and discusses the specific steps and activities that will be performed to accomplish the project. The discussion covers the activities from pre-proposal to Final SP Writing.

3.1 Research Activities

3.1.1 Creation of the dataset

A dataset of sentences containing Generation Z slang and its formal translation or an approximation of will be created. This will involve data scraping of social media posts, use of existing datasets, or any other suitable methods of obtaining data.

For data scraping, we will be using Facebook as the main platform from which data will be collected. This will involve the use of web scraping scripts using the Facebook API obtained from publicly available scripts on GitHub to search for public posts of people with a birth date between 1997 and 2012. The scraped data will then be manually cleaned up and formatted by the researchers.

A complete dataset of sentences containing Generation Z slang is expected at the end of this task.

3.1.2 Identification of potential LLM to be used

We will be reading upon existing LLM comparison studies to identify potential LLMs to be used for this study. We will be primarily using studies that used datasets containing slang as they are the most similar to our required dataset but we will still take a look at general translation work using LLMs.

A good potential model is zephyr-7b-beta due to its popularity, more open license, and number of parameters. Having 7B parameters allows the training of models on a 16GB GPU with a 4-bit quantization. In addition, zephyr-7b-beta has been proven to be better compared to other LLMs (?, ?) (Zhao et al., 2024). These studies have proven that the model is superior to well known models on generative tasks based on automatic and human evaluation.

The model to use should be determined at the end of this task.

3.1.3 Lookup for available GPU on demand services

Available computing power rental services will be looked up for this study. As LLM training is a resource-intensive process, it is important to ensure that the necessary computing power is available. However, this computing power requires expensive equipment that might not see usage after the project is completed. Thus, it has been decided that it is better to rent the computing power for the duration of the project.

For this project, the computer that will be used for the training must have a minimum of 16GB of vram to load the entire model after quantization and still allow for fine-tuning activities. The computing power is not as important as it only dictates the length of the training but a faster machine is preferrable to expedite the speed of testing and debugging.

A report on available GPU on demand services will be created using market research and price to computing power ratio.

3.1.4 Study on LoRA implementation for LLM

A thorough study on the implementation of LoRA for fine-tuning will be done. This includes learning the necessary steps, logic behind the idea, and other necessary information necessary for implementation. For this step, reading upon guide materials regarding fine-tuning and LoRA as well as existing studies will be done. We will be primarily using the guide provided by HuggingFace as it is one of the largest repositories for prebuilt LLMs. In addition, they also provide guides for fine-tuning models for specific purposes and have model specific guides.

3.1.5 Preprocessing of data

The dataset used for the fine-tuning of the model will be preprocessed to ensure optimal performance of the model. Data cleaning will be performed to remove errors, inconsistencies, and irrelevant information in the dataset. This will require removal of non-essential information such as email addresses, URLs, duplicates, etc. Removal of punctuation and stop words will be performed as these do not contribute to the meaning of the sentence. The dataset will be checked manually for grammar and accuracy and any errors found will be fixed. This is to ensure that the model can focus on learning the patterns between the slang and its formal translation without being affected by noise.

The transformer library by HuggingFace provides a Tokenizer class to automatically convert the cleaned dataset into input for the model. The model we will be using, which is zephyr-7b-beta model, is a fine-tuned Mistral 7B LLM according to their documentation and is supported by the library. The train-test-validation ratio that we will be using is 80-10-10 to ensure no overfitting while still allowing the model to adapt to the pattern of slang.

3.1.6 Prototype implementation of LoRA

A prototype implementation of LoRA will be created using a less demanding model. This is to avoid incurring costs from constantly retraining the model due to bugs in the code. The test will also be developed in the same language as the final implementation to avoid any issues with the code translation. As it is a prototype, it will be used to create a foundation for the complete implementation of LoRA. This will ensure that during the final implementation, there will be no issues with the code and the model can be fairly evaluated.

For this task, Google Colab will be used as a platform of choice due to the free cloud computing resource, the use of Jupyter notebook, and a computing power-on-demand service. The platform allows us to debug the code for model fine-tuning for free and have the full training by paying for additional resources. In addition, Python will be used as the language of choice due to the abundance of available libraries for training LLMs. The transformers library provided by HuggingFace will be used. This was chosen because of its ease of use with its API, as well as support for popular pretrained models such as LLaMA, BERT, and Mistral. It is also made by the same company as the zephyr-7b model itself and has even published a guide on fine-tuning the model.

3.1.7 Implementation of LoRA on selected model

A full implementation of LoRA will be done using the previously created prototype as a basis. We will also be using the entirety of the dataset to train the selected model. This step will mostly involve tweaking the parameters used to train the selected model and fixing any hidden bugs in the generated results.

3.1.8 Implementation of LLM Evaluation Metrics

A set of automatic evaluation metrics will be used to determine if the fine-tuned model will perform better than the base model. These metrics will be taken from existing studies on LoRA finetuning and slang translation. This will serve as the primary measure by which LLMs are compared with each other. For this purpose, Recall-Oriented Understudy for Gisting Evaluation (ROUGE) will be used to score the generated output compared to ground truth. Using the LLM as a judge with might also be considered to directly compare the results of the fine-tuned and the base model. We will be using the Prometheus-eval application from GitHub to assess the model's response using both Prometheus and GPT 4 as judges. This allows it to mimic human evaluation at a relatively low expense while having reproducible results.

Manual evaluation metrics will also be used to validate the quality of the translation. This will involve the use of surveys to compare the generated texts between the base model and the fine-tuned model. This allows for insights that cannot be easily detected by automatic metrics such as sentence quality, coherence, etc.

3.1.9 Model Evaluation and Analysis of Results

The model obtained from previous steps will be evaluated using the evaluation metrics determined from the previous step. To do this, the testing set split of the dataset will be used as the basis of evaluation. In addition, descriptive information such as loss function per epoch and perplexity, or the measurement of how well the model predicts text, will be determined. This information will be used as a supplement to the selected evaluation metrics to determine if the fine-tuned model performed better than the base model.

3.1.10 Documentation

All members are tasked to provide accurate and detailed logs of their activities. This includes steps on the task they are working on, the status of the work being done, and the time spent on the task. It will serve both as documentation and as a progress tracker to determine how far the project is from being done. This will be done every week at the member's leisure.

3.2 Calendar of Activities

Table 3.1 shows a Gantt chart of the activities. Each bullet represents approximately one week's worth of activity.

Table 3.1: Timetable of Activities

Activities (2024-2025)	Dec	Jan	Feb	Mar	Apr	May	Jun
Creation of the dataset	•						
Identification of potential LLM to be used	•						
Lookup on available GPU on demand services	•						
Study on LoRA implementation for LLM	•						
Preprocessing of data	•••						
Prototype implementation of LoRA	•	••••					
Implementation of LoRA on selected model			••				
Implementation of LLM Evaluation Metrics			••				
Model Evaluation and Analysis of Results				••••			
Documentation	••	••••	••••	••••	••••		

Chapter 4

Preliminary Results/System Prototype

A prototype LoRA implementation was created on Google Colab. This uses zephyr-7b-beta model as the base model for finetuning and a part of the ultrachat dataset as the training dataset. The zephyr-7b-beta model was chosen as it is one of the best performing model after LoRA finetuning (Zhao et al., 2024).

This snippet is based on the fine-tuning guides available on HuggingFace and the PEFT guides on several websites. This prototype only uses 100 iterations to train the model based on the ultrachat dataset. Most of the parameters used in this prototype is the same with the examples but it establishes a proof of concept on the usage of Google Colab as a potential training platform and the ability of LoRA to improve generative results.

Figure 4.1: Code snippet of the prototype

```
from transformers import TrainingArguments

YOUR_HF_USERNAME = "chichiboo"

output_dir = f"{YOUR_HF_USERNAME}/zephyr-7b-qlora-ultrachat"
per_device_train_batch_size = 4
gradient_accumulation_steps = 4
optim = "paged_adamw_32bit"
save_steps = 10
logging_steps = 10
learning_rate = 2e-4
max_grad_norm = 0.3
max_steps = 100
warmup_ratio = 0.03
lr_scheduler_type = "constant"

training_arguments = TrainingArguments(
    output_dir=output_dir,
    per_device_train_batch_size=per_device_train_batch_size,
    gradient_accumulation_steps=gradient_accumulation_steps,
    optim=optim,
    save_steps=save_steps,
    logging_steps=logging_steps,
    learning_rate=learning_rate,
    max_grad_norm=max_grad_norm,
    max_steps=max_steps,
    warmup_ratio=warmup_ratio,
    lr_scheduler_type=lr_scheduler_type,
```

Table 4.1: Difference between Generated Answers of the Base and LoRA Fine-Tuned Model

Before LoRA:	
USER:	Can you explain contrastive learning in machine learning in simple terms for someone new to the field of ML?
ASSISTANT:	Contrastive learning is a machine learning technique that involves training a model to learn from data that is similar to the target data. The model is trained to identify patterns in the data that are similar to the target data, and to use those patterns to make predictions about new data.
After LoRA:	
USER:	Can you explain contrastive learning in machine learning in simple terms for someone new to the field of ML?
ASSISTANT:	Contrastive learning is a technique in machine learning that uses a technique called contrastive loss to train a model. The idea is to train a model to distinguish between similar and dissimilar data. In contrastive learning, a model is trained to distinguish between a pair of similar data, such as a pair of images, and a pair of dissimilar data, such as a pair of different images. The model is trained to minimize the loss, which is the difference between the similarity and dissimilarity of the data. In contrast, traditional machine learning techniques, such as supervised learning, are trained to distinguish between different types of data, such as a classification or regression task. In summary, contrastive learning is a technique in machine learning that uses a technique called contrastive loss to train a model to distinguish between similar and dissimilar data, which is different from traditional machine learning techniques, such as supervised learning.

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Appendix A

Figures and Tables

Figure A.1: Code snippet of the prototype

```
from transformers import TrainingArguments

YOUR_HF_USERNAME = "chichiboo"

output_dir = f"{YOUR_HF_USERNAME}/zephyr-7b-qlora-ultrachat"
per_device_train_batch_size = 4
gradient_accumulation_steps = 4
optim = "paged_adamw_32bit"
save_steps = 10
logging_steps = 10
learning_rate = 2e-4
max_grad_norm = 0.3
max_steps = 100
warmup_ratio = 0.03
lr_scheduler_type = "constant"

training_arguments = TrainingArguments(
    output_dir=output_dir,
    per_device_train_batch_size=per_device_train_batch_size,
    gradient_accumulation_steps=gradient_accumulation_steps,
    optim=optim,
    save_steps=save_steps,
    logging_steps=logging_steps,
    learning_rate=learning_rate,
    max_grad_norm=max_grad_norm,
    max_steps=max_steps,
    warmup_ratio=warmup_ratio,
    lr_scheduler_type=lr_scheduler_type,
```

Table A.1: Difference between Generated Answers of the Base and LoRA Fine-Tuned Model

Before LoRA:	
USER:	Can you explain contrastive learning in machine learning in simple terms for someone new to the field of ML?
ASSISTANT:	Contrastive learning is a machine learning technique that involves training a model to learn from data that is similar to the target data. The model is trained to identify patterns in the data that are similar to the target data, and to use those patterns to make predictions about new data.
After LoRA:	
USER:	Can you explain contrastive learning in machine learning in simple terms for someone new to the field of ML?
ASSISTANT:	Contrastive learning is a technique in machine learning that uses a technique called contrastive loss to train a model. The idea is to train a model to distinguish between similar and dissimilar data. In contrastive learning, a model is trained to distinguish between a pair of similar data, such as a pair of images, and a pair of dissimilar data, such as a pair of different images. The model is trained to minimize the loss, which is the difference between the similarity and dissimilarity of the data. In contrast, traditional machine learning techniques, such as supervised learning, are trained to distinguish between different types of data, such as a classification or regression task. In summary, contrastive learning is a technique in machine learning that uses a technique called contrastive loss to train a model to distinguish between similar and dissimilar data, which is different from traditional machine learning techniques, such as supervised learning.