

1 LOST IN TRANSLATION: TRANSLATING GENERATION
2 ALPHA 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 miscommunication to older generations. This study focuses on Filipino Generation Alpha and their use of internet slang. This study aims to develop a translation tool leveraging Large Language Models (LLMs) to bridge this generational divide. A dataset of Generation Alpha slang sentences and their formal equivalents will be created, followed by the implementation of Low-Rank Adaptation (LoRA) to fine-tune an existing LLM. The model will be trained to translate slang sentences into formal English, and its performance will be evaluated against the baseline model using various performance 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, Miscommunication, LoRA, LLM

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Chapter 1

Introduction

1.1 Overview

Language is how humans communicate and express themselves (Crystal & Robins, 2024). It is dynamic because there are endless structural possibilities, changes in word meanings, and new words created (Libretexts, 2021). 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 social purposes: to identify a group's members, communicate informally, and oppose established authority (McArthur, 2003). Slang is highly contextual and pervasive, even in non-standard English. (Roth-Gordon, 2020) Its figurative nature and how it twists the definitions of the words used in it make it hard for outsiders to understand (Mattiello, 2005).

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 diverse groups online (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 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.

Today, Generation Alpha is the youngest generation. Generation Alpha refers to people born between 2010 and 2025. They were born into an era of rapid technological advancement, where digital devices and the internet are integral to

95 their daily lives (McCrindle & Fell, 2020). Generation Alpha is also called the
96 first true digital natives (Jukić & Škojo, 2021). They are expected to be the most
97 “technologically” skilled and most educated generation as they are the native
98 speakers of the language of the Internet (Prensky, 2001). According to the study
99 *Understanding Generation Alpha*, Generation Alpha is socially driven, which may
100 let them grow up to be creative and unconventional, potentially shaping them to
101 be assets in the future (Jha, 2020).

102 Since Generation Alpha was born with technology, the usage of Internet slang
103 has been prominent in this generation. However, it can create communication
104 barriers between older and younger generations (Venter, 2017 as cited in (Ghazali
105 & Abdullah, 2021)). The communication barriers caused by the usage of Inter-
106 net slang also affect people from the younger generation, especially individuals
107 who are less active on social media and have less exposure to them (Vacalares,
108 Salas, Babac, Cagalawan, & Calimpong, 2023). This gap highlights the need for
109 a tool that can bridge the generational divide, making it easier for individuals
110 to understand the language of Generation Alpha. By fostering a mutual under-
111 standing, such tool can promote more effective and harmonious interactions across
112 generations, enhancing relationships and reducing miscommunication.

113 1.2 Problem Statement

114 Internet slang fosters informal, relatable communication within the younger gen-
115 eration (Ghazali & Abdullah, 2021), especially Generation Alpha, but it presents
116 challenges in understanding for people outside this demographic. The gap in com-
117 prehension with older generations widens as internet slang evolves, often leading
118 to miscommunication affecting social relationships that contribute to the genera-
119 tional divide (Vacalares et al., 2023). A more specific translation tool developed
120 using language models can be used to bridge this divide.

121 1.3 Research Objectives

122 1.3.1 General Objectives

123 This study aims to modify an existing Large Language Model (LLM) for use in
124 the translation of Generation Alpha internet slang used by Filipino children in
125 social media.

126 1.3.2 Specific Objectives

- 127 • To create a dataset of sentences containing Gen Alpha slang and its formal
128 translation
- 129 • To create a Low Rank Adaptation (LoRA) implementation for fine-tuning
130 an existing model
- 131 • To fine-tune an existing LLM to translate sentences containing Gen Alpha
132 slang into formal sentences
- 133 • To evaluate the performance of the trained model and compare it to the
134 based model using several performance metrics

135 1.4 Scope and Limitations of the Research

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

139 1.5 Significance of the Research

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

Chapter 2

Review of Related Literature

2.1 Communication Gap between Generations

Language is dynamic in nature 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* (Ambarsaru, 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 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.

The studies showed that using internet slang improves relationship between those who use it. However, using internet slang for inter-generational communication can be a hindrance to proper and effective communication (Gonzaga, Racal, & Estrada, n.d.).

167 2.2 Existing Studies

168 Khazeni et al. used deep learning to create a model for translating Persian slang
169 text into formal ones (Heydari, Albadvi, & Khazeni, 2024). They were able to
170 create a model to convert texts from social media into sentiments for classification.
171 Nocon et al. (Nocon, Kho, & Arroyo, 2018) created a Filipino colloquialism trans-
172 lator using Tensorflow’s sequence-to-sequence model and Moses’ phrase-based sta-
173 tistical machine translation. They found that the Moses model was able to create
174 a natural sounding translation, while the Tensorflow model often produced bad
175 sentences.

176 A slang translation system developed by Ibrahim and Mustafa (Abdulstar Ibrahim
177 & Shareef Mustafa, 2023) used models obtained from Hugging Face, a repository
178 of pre-trained models, and retrained it using a dataset containing slang and their
179 corresponding definition and example. They determined that these models can
180 be tweaked into learning the relationship between the slang and its meaning.

181 2.3 LoRA for Fine Tuning

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

195 2.4 Chapter Summary

196 This chapter shows how generational differences create communication gaps, espe-
197 cially due to internet slang. Younger people tend to use slang to express emotions

198 and connect with friends, but this can confuse older generations who aren't as
199 familiar with these terms. Research shows that as language changes over time,
200 older people are generally less likely to understand the newest internet language.
201 To bridge this gap, some recent studies have utilized machine learning to translate
202 slang into more standard language. For instance, Khazeni et al. (Heydari et al.,
203 2024) used deep learning to translate Persian slang, while Nocon et al. (Nocon et
204 al., 2018) created a Filipino slang translator using statistical models. Moreover,
205 Ibrahim and Mustafa (Abdulstar Ibrahim & Shareef Mustafa, 2023) fine-tuned
206 pre-trained models to learn slang meanings. One of the promising techniques for
207 this is Low Rank Adaptation (LoRA), which is a fine-tuning method that keeps
208 the original model stable while using less storage. Studies by Zhao et al. (Zhao
209 et al., 2024) and Nguyen et al. (Nguyen et al., 2023) show that LoRA models are
210 not only efficient but can even outperform advanced models like GPT-4 when it
211 comes to slang translation and text classification.

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 Alpha slangs and its formal translation or an approximation of will be created. This will involve data scraping, use of existing datasets, or any other suitable methods of obtaining data. This dataset will be used for the training and evaluation of the model. To ensure it is a high quality dataset, it will be manually checked for accuracy and grammatically correctness. It will also be checked for any potential biases that may exist in the dataset or the data collection process.

3.1.2 Identification of potential LLM to be used

The researchers will be reading upon existing LLM comparison studies to identify potential LLMs to be used for this study. They will be primarily using studies that used dataset containing slangs as they are the most similar to the required dataset.

231 **3.1.3 Lookup on available GPU on demand services**

232 Available computing power rental services will be looked up for this study. As
233 LLM training are a resource-intensive process, it is important to ensure that the
234 necessary computing power is available. However, this computing power requires
235 expensive equipment that might not see usage after the project is completed.
236 Thus, it has been decided that it is better to rent the computing power for the
237 duration of the project. A report on available GPU on demand services will be
238 created using market research and price to computing power ratio.

239 **3.1.4 Study on LoRA implementation for LLM**

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

247 **3.1.5 Preprocessing of data**

248 The dataset used for the fine-tuning of the model will be cleaned up. This will
249 require removal of non essential information such as email addresses, URLs, etc.
250 This is to ensure that the model can focus on learning the patterns between the
251 slang and its formal translation without being affected by noise.

252 **3.1.6 Prototype implementation of LoRA**

253 A prototype implementation of LoRA will be created using a less demanding
254 model. This is to avoid incurring costs from constantly retraining the model due
255 to bugs in the code. It will be also developed on the same platform as the final
256 implementation to avoid any issues with the code running on different platforms.
257 As it is a prototype, it will be used to create a foundation for the complete
258 implementation of LoRA. It will ensure that during the final implementation,
259 there will be no issues with the code and the model can be fairly evaluated.

260 **3.1.7 Implementation of LoRA on selected model**

261 A full implementation of LoRA will be done using the previously created prototype
262 as a basis. Since it has been proven to work, this step will mostly involve fine-
263 tuning the selected model and fixing any hidden bugs.

264 **3.1.8 Implementation on LLM Evaluation Metrics**

265 A set of evaluation metrics will be used to determine if the fine-tuned model will
266 perform better than the base model. These metrics will be taken from existing
267 studies on LoRA finetuning and slang translation. It will serve as the primary
268 measure in which LLMs are compared with from each other.

269 **3.1.9 Model Evaluation and Analysis of Results**

270 The model obtained from previous steps will be evaluated using the evaluation
271 metrics determined from the previous step. To do this, the testing set split of the
272 dataset will be used as the basis of evaluation. In addition, descriptive information
273 such as loss function per epoch, accuracy, precision, recall, and F1 score will be
274 determined. This information will be used as supplement to evaluation metrics to
275 determine if the fine-tuned model will perform better than the base model.

276 **3.1.10 Documentation**

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

282 **3.2 Calendar of Activities**

283 Table 3.1 shows a Gantt chart of the activities. Each bullet represents approxi-
284 mately one week worth of activity.

Table 3.1: Timetable of Activities

Activities (2024-2025)	Nov	Dec	Jan	Feb	Mar	Apr	May
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 on 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.

References

- Abdulstar Ibrahim, A., & Shareef Mustafa, B. (2023, Oct). Intelligent system to transformer slang words into formal words. *NTU Journal of Engineering and Technology*, 2(2). doi: 10.56286/ntujet.v2i2.689
- Ambarsaru, S., Amrullah, A., & Nawawi, N. (2020, Aug). The use of online slang for independent learning in english vocabulary. *Proceedings of the 1st Annual Conference on Education and Social Sciences (ACCESS 2019)*, 465, 295–297. doi: 10.2991/assehr.k.200827.074
- Barseghyan, L. (2014). *On some aspects of internet slang*. Retrieved from <https://api.semanticscholar.org/CorpusID:51730779>
- binti Sabri, N. A., bin Hamdan, S., Nadarajan, N.-T. M., & Shing, S. R. (2020, Jun). The usage of english internet slang among malaysians in social media. *Selangor Humaniora Review*, 4(1), 16-17.
- Crystal, D., & Robins, R. H. (2024, Oct). *Language*. Encyclopædia Britannica, inc. Retrieved from <https://www.britannica.com/topic/language>
- Fernández-Toro, M. (2016, Jun). *Exploring languages and cultures*. Retrieved from <https://www.open.edu/openlearn/languages/exploring-languages-and-cultures/content-section-3.2>
- Ghazali, N. M., & Abdullah, N. N. (2021, Dec). Slang language use in social media among malaysian youths: A sociolinguistic perspective. *International Young Scholars Journal of Languages*, 4(2), 69. Retrieved from https://www.iium.edu.my/media/77652/Slang%20Language%20Use%20in%20Social%20Media%20Among%20Malaysian%20Youths_A%20Sociolinguistic%20Perspective.pdf
- Gonzaga, L. M. T., Racal, J. T. Q., & Estrada, K. O. (n.d.). “forda convo ang ferson”: Analysis of gen z slang in the lens of batstateu faculty members.
- Heydari, M., Albadvi, A., & Khazeni, M. (2024). Persian slang text conversion to formal and deep learning of persian short texts on social media for sentiment classification. *Journal of Electrical and Computer Engineering Innovations (JECEI)*. Retrieved from https://jecei.sru.ac.ir/article_2172.html doi: 10.22061/jecei.2024.10745.731
- Hu, E. J., Shen, Y., Wallis, P., Allen-Zhu, Z., Li, Y., Wang, S., ... Chen, W.

(2021). *Lora: Low-rank adaptation of large language models*. Retrieved from <https://arxiv.org/abs/2106.09685>

Jeresano, E., & Carretero, M. (2022, Feb). Digital culture and social media slang of gen z. *United International Journal for Research Technology*, 3(4), 11–25. doi: <http://dx.doi.org/10.1314/RG.2.2.36361.93285>

Jha, A. (2020, Jun). *Understanding generation alpha*. doi: 10.31219/osf.io/d2e8g

Jukić, R., & Škojo, T. (2021). The educational needs of the alpha generation. In *2021 44th international convention on information, communication and electronic technology (mipro)* (p. 564-569). doi: 10.23919/MIPRO52101.2021.9597106

Libretexts. (2021, Jul). *3.1.2: Functions of language*. Author. Retrieved from [https://socialsci.libretexts.org/Courses/American_River_College/SPEECH_361%3A_The_Communication_Experience_\(Coleman\)/03%3A_Verbal_Codes/3.01%3A_Verbal_Communication/3.1.02%3A_Functions_of_Language](https://socialsci.libretexts.org/Courses/American_River_College/SPEECH_361%3A_The_Communication_Experience_(Coleman)/03%3A_Verbal_Codes/3.01%3A_Verbal_Communication/3.1.02%3A_Functions_of_Language)

Liu, J., Zhang, X., & Li, H. (2023, Aug). Analysis of language phenomena in internet slang: A case study of internet dirty language. *Open Access Library Journal*, 10(08), 1–12. doi: 10.4236/oalib.1110484

Liu, S., Gui, D.-Y., Zuo, Y., & Dai, Y. (2019, Jun). Good slang or bad slang? embedding internet slang in persuasive advertising. *Frontiers in Psychology*, 10. doi: 10.3389/fpsyg.2019.01251

Mattiello, E. (2005). The pervasiveness of slang in standard and non-standard english.. Retrieved from <https://api.semanticscholar.org/CorpusID:140842571>

Maulidiya, R., Wijaya, S. E., Mauren, C., Adha, T. P., & Pandin, M. G. R. (2021, Dec). *Language development of slang in the younger generation in the digital era*. OSF Preprints. Retrieved from osf.io/xs7kd doi: 10.31219/osf.io/xs7kd

McArthur, T. (2003). *Concise oxford companion to the english language* (1st ed.). Oxford University Press.

McCrindle, M., & Fell, A. (2020). *Understanding generation alpha*. McCrindle Research Pty Ltd.

Nguyen, T. T., Wilson, C., & Dalins, J. (2023). *Fine-tuning llama 2 large language models for detecting online sexual predatory chats and abusive texts*. Retrieved from <https://arxiv.org/abs/2308.14683>

Nocon, N., Kho, N. M., & Arroyo, J. (2018, Oct). Building a filipino colloquialism translator using sequence-to-sequence model. *TENCON 2018 - 2018 IEEE Region 10 Conference*, 2199–2204. doi: 10.1109/tencon.2018.8650118

Prensky, M. (2001, Oct). Digital natives, digital immigrants. *On the Horizon*, 9(5). doi: <https://doi.org/10.1108/10748120110424816>

Roth-Gordon, J. (2020). Language and creativity: Slang. In *The international encyclopedia of linguistic anthropology* (p. 1-8). John Wi-

372 ley Sons, Ltd. Retrieved from [https://onlinelibrary.wiley.com/doi/](https://onlinelibrary.wiley.com/doi/abs/10.1002/9781118786093.iela0192)
 373 abs/10.1002/9781118786093.iela0192 doi: [https://doi.org/10.1002/](https://doi.org/10.1002/9781118786093.iela0192)
 374 9781118786093.iela0192
 375 Suslak, D. F. (2009). The sociolinguistic problem of generations. *Language Com-*
 376 *munication*, 29(3), 199-209. Retrieved from [https://www.sciencedirect](https://www.sciencedirect.com/science/article/pii/S0271530909000196)
 377 .com/science/article/pii/S0271530909000196 (Reflecting on language
 378 and culture fieldwork in the early 21st century) doi: [https://doi.org/](https://doi.org/10.1016/j.langcom.2009.02.003)
 379 10.1016/j.langcom.2009.02.003
 380 teng, C. E., & Joo, T. M. (2023). Is internet language a destroyer to communica-
 381 tion? In X.-S. Yang, R. S. Sherratt, N. Dey, & A. Joshi (Eds.), *Proceedings of*
 382 *eighth international congress on information and communication technology*
 383 (pp. 527–536). Singapore: Springer Nature Singapore.
 384 Vacalares, S. T., Salas, A. F. R., Babac, B. J. S., Cagalawan, A. L., & Calimpong,
 385 C. D. (2023, Jun). The intelligibility of internet slangs between millennials
 386 and gen zers: A comparative study. *International Journal of Science and*
 387 *Research Archive*, 9(1), 400–409. doi: 10.30574/ijrsra.2023.9.1.0456
 388 Zhao, J., Wang, T., Abid, W., Angus, G., Garg, A., Kinnison, J., ... Rishi, D.
 389 (2024). *Lora land: 310 fine-tuned llms that rival gpt-4, a technical report*.
 390 Retrieved from <https://arxiv.org/abs/2405.00732>

³⁹¹ **Appendix A**

³⁹² **Appendix Title**