

Syntactic Evolution in Language Usage

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Abstract—This research aims to investigate the dynamic nature of linguistic style throughout various stages of life, from post teenage to old age. By employing linguistic analysis tools and methodologies, the study will delve into the intricacies of how individuals adapt and modify their language use over time. The research uses a data set of blogs from blogger.com from 2004 and focuses on English for syntactic analysis. The findings of this research can have implications for linguistics, psychology, and communication studies, shedding light on the intricate relationship between age and language.

Index Terms—language evolution, linguistic attributes

I. INTRODUCTION

Language is one of the most ancient knowledge that humans have evolved. From the time of homo-sapiens when there might have been no or little words with voice, a gift that would have been naturally acquired, seems to date back about 300,000 years as per the research. However, other civil development took way longer and only dates back to 40,000 years. [10] What I intend to do here is to study a much shorter duration and see if languages do change their shape and texture within a lifespan and a language. Hence for this study, I have majorly focussed on English, across a lifespan of three broad categories of age groups Young (18-34 years old), middle-aged (35-41 years old), and Old (42 years and older) to evenly balance the dataset used for the analysis after pre-processing.

The dataset that I have used comes from the publically available source of blogger.com which was one of the few social media platforms available from the 1990s to the early 2000s. [11] This dataset dates back between 2002-04 and contains text information with the author's age when the blog text and the comment were written. I have derived the age group based on that so that the evolution can be broadly studied. There are about 450,000 rows of text in the dataset, which were finally reduced to about 52,000 rows after pre-processing to balance data. While the demographic details of these users (such as geographic location, and interests) were not explicitly available, it is reasonable to infer that they likely represent a tech-savvy, internet-engaged demographic, potentially skewing towards younger age groups who were more inclined to participate in online blogging at that time.

The following example sentences from the dataset, share different age groups and different complexities

Young: "Love pictures, baby!"

Middle-Aged: "Love those pictures of Tim Peretti."

Old: "I actually love to teach about the first Apostles, espe-

cially since my mother gave me a set of paintings done by an artist, a woman, who wanted to paint what she beleived the Apostles would have looked like."

In principle, the hypothesis is that with time language learning becomes more evolved and we learn to use and understand more complex language structures. Hence the study will involve syntactic feature analysis of the different age groups and also will attempt to forecast a group based on text to see if the study can be used in the future for the cases where communication may need modulation based on the age group of the person, like education.

II. RESEARCH DESIGN

Design of experiment

The overall design of the experiment involved multiple steps which can be briefly illustrated in the following diagram and the description that follows.(fig. 1) High-level Steps:

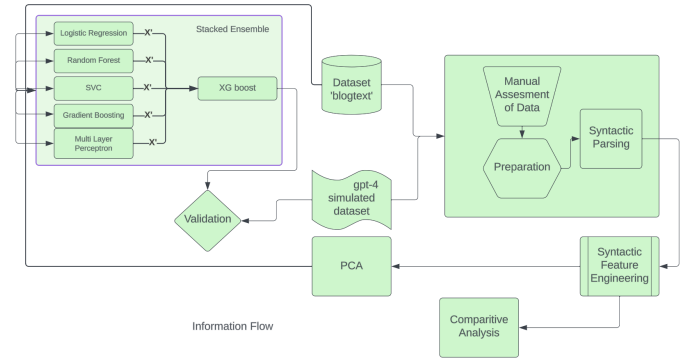


Fig. 1. Information Flow Diagram

1. Performing raw data analysis, manual and WordCloud
2. Preprocessing the data (removal of <18yr) and balancing dataset for forecasting
3. Feature engineering using syntactic parsing
4. Syntactic feature comparison of real user data from bloggers.com with GPT4 output text, using openai API
5. Forecasting age_group using 5-component PCA on syntactic features and 2-layered multi-model stacked ensemble [12] [13]

Syntactic Parsing

Word Cloud Analysis:

Before immersing myself in syntactic analysis, let us see a word cloud to illustrate high-frequency words in different age

and balanced datasets and full datasets for the syntactic parsing table respectively. This comparison gives an encouraging push to the hypothesis where we claim that the experience in language knowledge gives the users confidence in writing complex sentences, being reflected in metrics such as Yngve depth, which is based on dependency parsing. [9]

Mean Pivot: representing per blog information

	Young_blogtext	Middle Aged_blogtext	Old_blogtext	Young_chatGPT	Middle Aged_chatGPT	Old_chatGPT
parameters						
Content Density	6.34	6.28	6.70	4.27	6.22	5.37
Max Yngve Depth	7.42	7.51	8.07	4.89	4.68	4.70
Mean Yngve Depth	2.40	2.45	2.57	2.17	2.23	2.14
Total Yngve Depth	669.48	736.01	907.55	39.07	35.83	39.44
Noun Phrase Rate	5.12	4.91	6.62	3.69	3.69	4.40
Noun-Verb Ratio	1.70	1.84	1.91	1.37	2.00	2.11
Proportion of Nouns with Adjectives	0.01	0.01	0.01	0.00	0.00	0.00

Fig. 4. Syntactic Feature Comparison: GPT-4 vs BlogText on the balanced dataset (about 51k rows). Represented as heatmap at row level

Mean Pivot: representing per blog information

	Young_blogtext	Middle Aged_blogtext	Old_blogtext	Young_chatGPT	Middle Aged_chatGPT	Old_chatGPT
parameters						
Content Density	6.29	6.26	6.67	4.27	6.22	5.37
Max Yngve Depth	7.37	7.45	8.04	4.89	4.68	4.70
Mean Yngve Depth	2.37	2.43	2.58	2.17	2.23	2.14
Total Yngve Depth	671.81	705.27	892.84	39.07	35.83	39.44
Noun Phrase Rate	5.15	4.84	6.69	3.69	3.69	4.40
Noun-Verb Ratio	1.67	1.82	1.93	1.37	2.00	2.11
Proportion of Nouns with Adjectives	0.01	0.01	0.01	0.00	0.00	0.00

Fig. 5. Syntactic Feature Comparison: GPT-4 vs BlogText on the full dataset (about 450k rows)

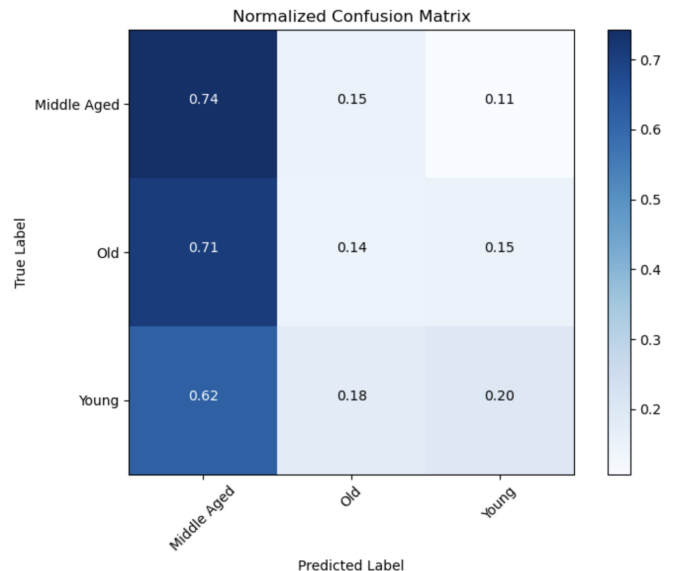
B. Forecasting accuracy on new text generated by GPT-4

Observing the forecasting bit was not so encouraging as when the dataset was trained, the accuracy of the model was low, but when tested on new text from GPT-4, it went down further low. Suggesting either the model in GPT-4 might not be trained on the language evolution of humans, or the dataset from blogger.com is not conclusive enough. (fig.6)

One probable cause of the forecasting inaccuracy seems to be coming from the variance in metrics used as a feature to forecast, due to non-standard writing in blogs by users. Fig. 7 plots the variance over the bar graph in one of the metrics observed, Yngve depth, where the height of the variance is clearly over 60-70% of the height of the bar graph itself indicating a high variance. Hence, even though the overall aggregated metrics show a clear trend, forecasting would still be a challenge considering the range of variance. Hence, this also calls for different datasets for training for forecasting the age group based on text, although the difference is majorly known at a higher level based on parsing results.

C. Issues Encountered

The research journey brought forth several challenges, contributing to a nuanced understanding of the complexities inherent in the study. The primary hurdle emerged in the accessibility of key referenced research papers, which were archived with restricted access. Consequently, reliance on publicly available data became a formidable challenge.



Classification Report:

	precision	recall	f1-score	support
0	0.24	0.74	0.36	225
1	0.51	0.14	0.22	545
2	0.30	0.20	0.24	230
accuracy			0.29	1000
macro avg	0.35	0.36	0.28	1000
weighted avg	0.40	0.29	0.26	1000

Fig. 6. Running Model on GPT-4 data

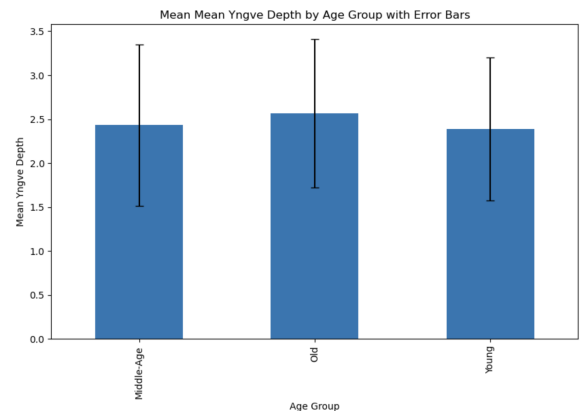


Fig. 7. Variance over Bar Graph for Mean Yngve Depth

- Extraction of data revealed the inclusion of authors under 18 years, necessitating their removal to ensure ethical analysis.
- Notably, the data exhibited skewness toward the young age group, introducing a potential bias in the findings.
- The language model, GPT-4, demonstrated limitations in handling age or maturity-driven linguistic changes, impeding the generation of nuanced and contextually appropriate comparisons. [5]
- Forecasting is not encouraging, as despite deploying a multi-model ensemble (which is a well-known technique

in multiclass scenarios [14] [15] [16]) with 5 models stacked in 1st layer and 1 ensemble in the second (logistic regression, random_forest, svc, gradient_boosting, mlp_classifier and over that ran XGboost taking model outputs as features), accuracy achieved was only about 40%, while on new text from GPT-4 it reduced to about 30%, with best recall of 74% in middle-aged class.

D. Notes for Future Work

The encountered challenges served as valuable lessons, providing insights that can inform and refine future research endeavors.

- Guided by the analysis, patterns, and trends can be identified that may warrant further investigation or hypothesis testing. For instance, exploration could be undertaken to discern whether certain syntactic features correlate with specific topics or sentiments within each age group.
- To address the temporal gap in the data, a recommendation for future work involves training the model on the latest data, incorporating age_group and text variables.
- The imperative of sourcing diverse validation data from multiple channels is emphasized, ensuring a comprehensive and representative dataset.
- Exploring advanced methodologies, such as an ensemble of artificial neural networks or alternative machine learning techniques, is suggested to enhance the model's accuracy.
- Beyond the immediate scope, the envisioned future applications of this model extend to the creation of user-focused content in education and fields that demand psychologically inspired communication. This potential highlights the broader societal impact of refining and advancing the current research paradigm. The practical application of the model would still need a further detailed discussion, while the findings show a clear trend.

E. Conclusion

In this study, our analysis of blogger.com data revealed how writing styles vary with age. This insight is valuable for understanding digital communication in linguistics. It shows how the language used online can change depending on the user's age, which is important for researchers studying language evolution in the digital era.

For communication, these findings help professionals like marketers and content creators. They can use this knowledge to better connect with different age groups online, making their messages more effective.

However, another finding is that AI models like GPT-4 aren't yet very good at matching language styles to specific age groups, specifically complexity across age groups. It often made mistakes when trying to mimic how different ages write as it did not resemble consistently the data from real users. This suggests that more work is needed to improve AI in understanding and replicating human language styles evolved with demographics.

Overall, while our study focuses on a specific set of data, it offers broader insights. It helps us understand language use in the digital world and points out where AI can improve. This can guide future research in linguistics, communication, and AI development.

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