SpeechWeave: Diverse Multilingual Synthetic Text & Audio Data Generation Pipeline for Training Text to Speech Models

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Abstract

High-quality Text-to-Speech (TTS) model training requires extensive and diverse text and speech data. It is challenging to procure such data from real sources due to issues of domain specificity, licensing, and scalability. Large language models (LLMs) can certainly generate textual data, but they create repetitive text with insufficient variation in the prompt during the generation process. Another important aspect in TTS training data is text normalization. Tools for normalization might occasionally introduce anomalies or overlook valuable patterns, and thus impact data quality. Furthermore, it is also impractical to rely on voice artists for large scale speech recording in commercial TTS systems with standardized voices. To address these challenges, we propose **SpeechWeave**, a synthetic speech data generation pipeline that is capable of automating the generation of multilingual, domain-specific datasets for training TTS models. Our experiments reveal that our pipeline generates data that is **10–48%** more diverse than the baseline across various linguistic and phonetic metrics, along with speaker-standardized speech audio while generating approximately **97%** correctly normalized text. Our approach enables scalable, high-quality data generation for TTS training, improving diversity, normalization, and voice consistency in the generated datasets.

1 Introduction

Text-to-Speech (TTS) systems convert written text to spoken audio and are used in applications such as virtual assistants, accessibility software, navigation systems, and customer service to enable easier and accessible user interaction. TTS systems require massive amounts of training data consisting of text and speech pairs. Most publicly available TTS datasets include book readings or generic passages (Ito and Johnson, 2017), (Panayotov et al., 2015),, (Ardila et al., 2020). However, for domain-specific business data (e.g., Automobile, Healthcare, Retail), one needs to either scrape it from the web or purchase it from data curation companies, which could introduce cost and licensing issues. Additionally, the multilingual nature of such systems complicates the process of obtaining domain-specific data.

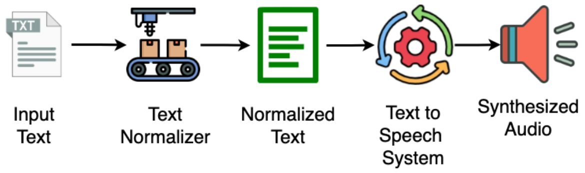

Figure 1: High-level depiction of a TTS system incorporating normalization

1.1 Text Scripts

Text scripts serve as inputs to TTS systems and are essential for adapting these systems to specific business domains. While obtaining domain-specific data from public sources is difficult, it may seem that LLMs can easily generate the necessary data using a simple prompt with the domain as input. However, our experiments with *Mistral-7b-Instruct* (Jiang et al., 2023) show that for short sentences, the generated text remains similar even with high *temperature* and *top_p* values, especially if the input prompt stays unchanged. As shown in Table 1, an LLM, even high temperature values produce almost identical results. Very high values still limit the sub-domain to *Personal Finance* but may also generate unstable, low-quality output. Our analysis in the Diversity Analysis section shows that LLMs, without prompt variation, result in low-diversity datasets, thus making this approach impractical for generating large datasets for training downstream models.

1.2 Normalization

The written and spoken forms of text often differ, primarily in specific entities like addresses, dates,

Temperature	top_p	Output (Generated 3 times with the same settings)
0.7	0.95	1. Maintaining a budget surplus is essential for reducing debt and securing financial stability.
		2. Maintaining a budget surplus can help reduce debt and ensure financial stability.
		3. Maintaining a balanced budget is crucial for achieving financial stability.
1.2	0.95	1. Managing expenses effectively is crucial for maintaining a healthy financial situation.
		2. Making regular investments in a diversified portfolio can help grow your wealth over time.
		3. Maintaining a balanced budget is key to achieving long-term financial stability.
1.2	0.51	1. Maintaining a budget surplus is crucial for reducing debt and ensuring financial stability.
		2. Maintaining a budget helps control your expenses and save for future financial goals.
2.5	0.95	1. A wiser investment would have made twice your savings in a safer market stance. (Implying the reader missed an opportunity for increased returns by prioritizing safeguarded funds)
		2. Exporting Savings: Despite decreased expenses, investments yield higher returns, bolstering my financial security.
		3. A sound financial plan includes creating a budget, building an emergency reserves, saving for retirement, and consistently reducing unnecessary debts. But if you intend a single short sentence it would be- Investing as early and aggressively thanYou Can can enhance long-term returns significantly due toCompainddffects.

Table 1: Generated outputs for different temperature and top-p settings by prompting an LLM directly. Prompt used was "Construct one short sentence in the finance domain".

times, and salutations, known as semiotic classes (Zhang et al., 2019). Table 2 presents examples of text scripts with their normalized forms across languages. A TTS system processes text through a Text Normalization System, such as NeMo's text normalizer (Zhang et al., 2021), before generating speech audio, as depicted in Figure 1. However, normalization systems may have limitations, failing to recognize all semiotic class variations. For example, a date could appear as 03/01/2005, 01-Mar-2005, or March 01, 2005, and some formats may be overlooked. For inference, a pre-processing text normalizer is essential. However, for training data generation, our work demonstrates that normalizing semiotic classes at the time of generation achieves higher accuracy, eliminating the need for a separate text normalizer.

Language	Text Script	Normalized Form
English	The best waffles in Delhi are found in the **10th St., Hauz Khas Vil.** in South Delhi.	The best waffles in Delhi are found in the **tenth street, Hauz Khas Village** in South Delhi.
Spanish	**El Dr.** Johnson se especializa en el manejo de enfermedades relacionadas con el estilo de vida.	**El Doctor** Johnson se especializa en el manejo de enfermedades relacionadas con el estilo de vida.
French	Emily est née le **03/08/1995**.	Emily est née le **trois août mil neuf cent quatre-vingt-quinze.**

Table 2: Examples of text scripts along with their normalized forms across semiotic classes and languages.

1.3 Audio Data

Commercial TTS systems require speaker standardization to allow customers to choose a specific speaker based on their usecase. To achieve this, TTS systems need training data tailored to these specific speakers. Utilizing human voice artists to record speech audio for curating such training data is expensive and therefore not scalable.

To address these challenges, we introduce **SpeechWeave**—*a comprehensive synthetic speech data generation pipeline*. Our key contributions through SpeechWeave include:

- An end-to-end automated pipeline for generating high-quality synthetic data to train Text-to-Speech models.
- Highly diverse text generation—both linguistically and phonetically—with thousands of unique combinations of semiotic classes, normalized at the source with high accuracy.
- High-quality speech audio generation with speaker standardization to ensure consistency in speech characteristics for commercial TTS systems.

2 Related Work

(Holtzman et al., 2020) introduced nucleus sam-

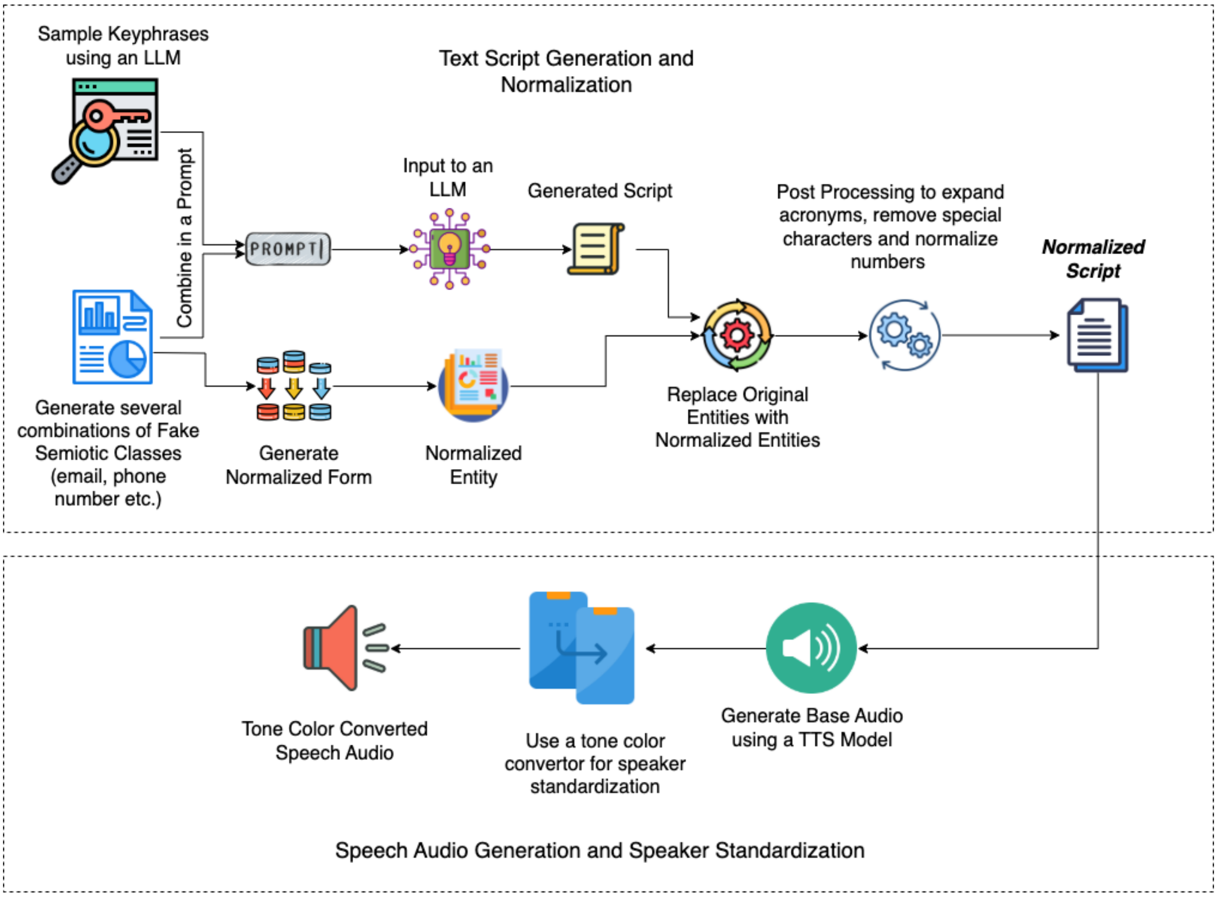
Sample Keyphrases using an LLM
Text Script Generation and Normalization
Combine in a Prompt
PROMPT
Input to an LLM
Generated Script
Post Processing to expand acronyms, remove special characters and normalize numbers
Normalized Script
Generate several combinations of Fake Semiotic Classes (email, phone number etc.)
Generate Normalized Form
Normalized Entity
Replace Original Entities with Normalized Entities
Tone Color Converted Speech Audio
Use a tone color convertor for speaker standardization
Generate Base Audio using a TTS Model
Speech Audio Generation and Speaker Standardization

Figure 2: High-level description of our synthetic text and audio generation pipeline

pling to stabilize text diversity in language models. Studies like (Naik et al., 2024) and (Li et al., 2023a) explored prompt engineering techniques to improve LLM performance. (Meincke et al., 2024) highlighted LLM limitations in generating diverse ideas, showing how strategies like Chain-of-Thought prompting can help. (Hayati et al., 2024) focused on step-by-step recall prompting for diversity.

(Cornell et al., 2024) proposed a pipeline combining LLM-generated text and TTS for ASR data, while Gunduz et al. (Gunduz et al., 2024) introduced an open-source TTS data generation tool that lacked text script generation and normalization, relying on public datasets like the Opus corpus (Tiedemann, 2009) and voice artists for recordings. (chun Hsu et al., 2024) presented a low-resource, self-supervised method for training TTS using unlabeled audio.

Works like (Eldan and Li, 2023) and (Cox et al., 2023) showed how keyphrases can increase text diversity in LLMs. In TTS, (Byambadorj et al., 2021) trained a multi-speaker model for low-resource languages, while (Qin et al., 2024) developed a cross-lingual tone converter for vocal characteristics.

Other studies, like (Zhang et al., 2021), (Mansfield et al., 2019), and (Ro et al., 2022), focused on text normalization systems.

Despite these advancements, no prior work has proposed an integrated pipeline for generating diverse text scripts and their normalized forms and speaker standardized speech audio for TTS training.

3 Our Pipeline and Components

SpeechWeave consists of a **keyphrase sampler**, an **entity sampler with at-source normalizer**, a **postprocessor** and an **audio generation** module.

The pipeline is depicted at a high level in Figure 2. A more detailed representation is available in Figure 6 in Appendix.

3.1 Keyphrase Sampling

As noticed above, if there isn't enough diversity in the inputs to an LLM, the model tends to generate repetitive text. One way to improve the diversity of generated text is through keyphrase infusion in prompts as demonstrated by (Eldan and Li, 2023).

For e.g. instead of prompting the model "Generate a sentence in finance domain", we can prompt, "Generate a sentence in finance domain containing the following keyphrases: Mortgage, Asset Finance". We can prompt the model to generate text with multiple such keyphrase combinations to ensure higher diversity in the generated text.

3.1.1 Multi-Step Prompting

For domain-specific keyphrases, we may prompt an LLM to generate them, but this can lead to repetition. To address this, we use a multi-step prompting approach. As shown by (Hayati et al., 2024), iterative multi-step prompting enhances idea diversity. We begin by generating a list of subdomains within a business domain, such as healthcare. Then we randomly select one from the generated list. The LLM is then prompted to generate a creative paragraph for the chosen subdomain, and then we prompt the LLM to extract relevant keyphrases. To ensure structured output, we use lm-format-enforcer (Gat, 2023) to convert results into a parseable JSON format at each step.

3.1.2 Keyphrase Store and De-Duplication

We utilize an in-memory keyphrase store to store domain and language specific keyphrases. We also utilize fuzzy search based on token sort ratio and Levenshtein distance to ensure that we do not store keyphrases that are very similar to each other. This can also be replaced with a keyphrase embeddings model such as PhraseBERT (Wang et al., 2021), where we find the similarity between the keyphrases by first extracting the keyphrase embeddings, then computing similarity with existing keyphrases in the keyphrase store, and finally deciding whether the keyphrase should be stored. However, we observe that using fuzzy search in the pipeline produces more diverse keyphrases compared to PhraseBERT.

Our keyphrase sampling pipeline is described in Figure 3 and Figure 4 in Appendix.

3.2 Entity Sampler

To address the problem of text normalization, we create an entity generator that not only generates the semiotic classes but also their normalized forms. Our entity sampler can generate complex, real-world variations and combinations of semiotic classes. Since the rules for generating the entities are encoded in the entity sampler, normalization occurs simultaneously with generation. This approach ensures deterministic generation with guaranteed accuracy in normalization, as the entities do not yet exist in the text. For example, we might generate an email address composed of a first name, a last name separated by an underscore, and random characters. This allows us to normalize the email address while these components are being concatenated. Our entity sampler is capable of generating thousands of unique combinations across 9 different entities: *Addresses, Phone Numbers, Email Addresses, URLs, Dates, Times, Percentages, Person Names with Salutations*. Our entity sampler is also locale-sensitive and multilingual. In Appendix, Figure 5 describes the recipes for entity generation and normalization for different semiotic classes, while Table 8 and Table 9 contain different examples of such classes with their normalized forms.

3.3 Text Script Generator

We combine the generated keyphrases with the semiotic classes in a prompt to generate domain-specific text. We use lm-format-enforcer to force the model to generate the text in JSON format, ensuring that only the required text scripts are generated. We also replace the semiotic classes in the text with their normalized forms to generate the normalized script. Using different prompts, we can generate various sentence types for our text scripts. Table 10 in Appendix shows different prompts used for generating text scripts for different sentence types.

3.4 Normalization Post Processing

LLM-generated text may occasionally introduce new semiotic classes. Therefore, we use a basic post-processing algorithm to normalize the text. The algorithm expands the acronyms, converts numbers to their cardinal forms, and removes any hyphens, underscores, and brackets from the normalized script. Our analysis reveals that post-processing steps, such as changing numbers non-contextually to their cardinal forms, may introduce normalization errors. However, given that the scripts we generate are small (upto 50 words) the occurrence of such errors is quite rare, and our overall process still achieves high normalization accuracy (Section 4.2.1).

Language	Dataset	Mean Similarity Score (Grouped)	Max Similarity Score (Grouped)	Mean Similarity Score (Ungrouped)	TTR	MATTR	Diphone Coverage
English	Direct Prompting (Baseline)	0.48	0.70	0.22	0.118	0.761	1442
	English LibriSpeech	-	-	0.36	0.123	0.758	**1792**
	Ours	**0.26**	**0.36**	**0.15**	**0.167**	**0.803**	1694
Spanish	Direct Prompting (Baseline)	0.54	0.77	0.31	0.297	0.966	516
	Spanish LibriSpeech	-	-	0.28	**0.395**	0.962	**651**
	Ours	**0.30**	**0.41**	**0.25**	0.370	**0.979**	565

Table 3: Comparison of similarity scores, lexical diversity (TTR, MATTR), and phoneme coverage (Diphone Coverage) between our method, direct prompting baseline, and public datasets.

3.5 Speech Audio Generation And Cross Lingual Voice Cloning

Once the text and its normalized forms are generated, we feed the normalized text to the Speech Audio Generation Module. The audio generation module takes in the input text, and a reference audio, and generates speech audio with voice cloned as per the reference audio. We first generate a base speech audio using a pretrained TTS model (Zhao et al., 2023). Then, for speaker standardization, we use OpenVoiceV2's (Qin et al., 2024) tone color converter with reference voices taken from proprietary voice artists. The tone color converter is language agnostic i.e. we can use reference audio in English to standardize voices in other languages. This allows us to use standard voice artists across languages for our downstream TTS system.

Data samples generated using SpeechWeave are available in Table 7.

4 Evaluation

To evaluate our pipeline, we generate a dataset with 3000 datapoints across 16 business domains, 5 sentence types, 9 semiotic classes, and 2 reference speakers (male and female), each in English and Spanish. Sentences with fewer than 5 or more than 50 words are excluded and regenerated using a different seed. For the baseline (wherever applicable), we prompt a large language model to generate text in the required business domain, as detailed in Table 10 in Appendix. For diversity evaluation, we also compare our results to public datasets — English Librispeech (Panayotov et al., 2015) and Spanish LibriSpeech (Pratap et al., 2020) - sampling 3000 datapoints from each, applying the same filtering criteria. For evaluating the quality of a downstream model trained on our dataset, we use the test splits from the same public datasets. Experiment settings are detailed in Appendix Experimentation Settings.

4.1 Diversity Analysis

For diversity analysis, we examine the variation in both the generated text and speech across different samples produced by the pipeline.

4.1.1 Diphone Coverage

Diphones are adjacent phonemes representing transitions in speech, and diphone coverage indicates how well a corpus captures phoneme combinations. Our results show that relatively, our pipeline's data covers **17.4%** more diphones in English and **9.7%** more in Spanish compared to the baseline. However, the public LibriSpeech datasets cover **5.7%** more in English and **15.2%** more in Spanish than our pipeline's data. The superior coverage in LibriSpeech can largely be attributed to high mean word count compared to our dataset. Experimentation settings and diphone coverage comparisons are provided in Appendix E.2.1 and Figure 7 respectively.

4.1.2 Mean Pairwise Similarity

We evaluated the semantic mean pairwise similarity within sentence groups categorized by business domain and type. Compared to direct prompting, our pipeline generates more diverse text, showing relatively **45.8%** and **44.4%** lower grouped similarity scores for English and Spanish, respectively. Even in the most homogeneous group, our data's similarity scores were relatively **48.5%** and **46.7%** lower for English and Spanish compared to the baseline. Since public speech datasets aren't categorized by business domain, we calculated mean pairwise similarity without grouping for comparison. Our dataset shows greater diversity, with

Language	Technique	Normalization Accuracy
English	NeMo	0.67
	Ours	**0.97**
Spanish	NeMo	0.54
	Ours	**0.94**

Table 4: Comparison of our at-source text normalization accuracy with Nemo's Text Normalizer.

relative mean similarity scores lower by **58.8%** for English and **10.7%** for Spanish. Experimentation settings and some additional analysis are described in Appendix E.2.2

4.1.3 Token Diversity

Token diversity, measured by Type-Token Ratio (TTR) and Moving Average Type-Token Ratio (MATTR), reflects lexical richness. Our results show both TTR and MATTR are higher in our synthesized dataset compared to LLM-generated text and both public datasets - LibriSpeech English and LibriSpeech Spanish.

Table 3 contains a comparison of the datasets on these diversity indicators.

4.2 Quality Analysis

The quality of the data generated by our pipeline is assessed across three key dimensions: Normalization Accuracy, Speech Audio Clarity and Downstream Model Training.

4.2.1 Normalization Accuracy

We evaluate our at-source normalization technique against *Nvidia NeMo's text normalizer* (Zhang et al., 2021). Normalization accuracy is the ratio of correctly normalized sentences to the total evaluated. Our pipeline achieves **0.97** and **0.94** for English and Spanish, while NeMo scores **0.67** and **0.54**, showing superior performance of at-source text normalization for training data generation. NeMo's errors involve mishandling variations of semiotic classes, such as breaking up names, improperly normalizing phone numbers, or missing alternate currencies. Experimentation settings are detailed in Appendix Section E.2.4.

4.2.2 Speech Audio Clarity

We evaluate the acoustic quality of the generated speech to assess the effectiveness of the pretrained model in synthesizing speech from our pipeline's text scripts. Performance is quantified using Mean Signal-to-Noise Ratio (SNR), Automated Mean Opinion Score (MOS), and Word Error Rate (WER).

Language	SNR (dB)	MOS	WER (%)
English	59.82	4.95	9.32
Spanish	53.01	4.87	15.21

Table 5: Speech audio clarity indicators for the data generated by SpeechWeave

Table 5 shows that the synthesized speech achieves high MOS and SNR scores with low WER, demonstrating superior audio quality and strong textual and phonetic accuracy. Experimentation settings available in Appendix E.2.5.

4.2.3 Downstream Model Training

We fine-tuned a *StyleTTS 2* model (Li et al., 2023c) using a *LibriTTS-trained checkpoint* on data generated by our pipeline and evaluated its quality using *WER*. As a baseline, we measured WER on the LibriSpeech test dataset (Panayotov et al., 2015; Pratap et al., 2020) before fine-tuning. Our results show significant WER reductions: **40%** for English and **27%** for Spanish relatively, compared to the baseline, demonstrating the effectiveness of our pipeline in generating high-quality training data for improved speech synthesis.

Model	LibriSpeech English WER (%)	LibriSpeech Spanish WER (%)
LibriTTS Checkpoint (Baseline)	15.37	85.05
Baseline fine-tuned on our data	**9.36**	**48.44**

Table 6: WER before and after fine-tuning StyleTTS 2 with SpeechWeave-generated data

Table 6 summarizes the experimental results with experimentation settings described in Appendix Section E.2.6. It's worth noting that StyleTTS 2 does not have a Spanish-trained checkpoint, which explains the higher overall WER for Spanish. In this context, training on our Spanish data effectively adapts the model to the Spanish language.

5 Conclusion

We introduce **SpeechWeave**, a simple yet effective pipeline for generating diverse, normalized text and speaker standarized speech audio data for training text to speech systems. Our analysis reveals that the data generated by our pipeline is much more diverse than the data generated by directly prompting an LLM, and carries higher normalization accuracy compared to post processing normalizers like NeMo while being speaker-standardized to allow scaling training data. The data is also on par with publicly available speech datasets, while adhering to the required business domains. Given that the data is highly precise in terms of normalization, it can also be used to train text normalization models.

Limitations and Future Work

The accuracy of the normalized text generated by our pipeline is limited by the number of semiotic classes supported by the the entity sampler. Moreover, although our pipeline incorporates *Mistral-7b-Instruct-0.3* and *OpenVoice V2* Stack for data generation, the results may vary depending upon the models chosen for generating the dataset. Our evaluation is also limited to English and Spanish languages and the extent of improvement may vary based on the language for which the data is generated. In the future, we plan to extend the framework to include other morphologically rich languages, with a particular focus on those that are currently underrepresented. Moreover, while, it is fairly straightforward to support a new semiotic class, the post processor may result in occasional normalization errors for unsupported entities. We wish to continue this work by generalizing the framework for semiotic class generation and entity normalization at source. We would also like to extend this work to support styled speech audio generation and speech style standardization.

Ethical Considerations

Our work uses entirely synthetic text and audio data generated through a controlled pipeline, without the involvement of real-world user data or human participants, apart from publicly available speech datasets used solely for evaluation purposes. This design inherently avoids privacy violations and ensures that no personally identifiable information is processed or exposed. As such, our data generation process does not pose significant ethical risks typically associated with data collection, consent, or user harm. By relying on synthetic data, we uphold best practices in privacy-preserving and ethically responsible research.

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Appendices

A Generated Samples

Table 7 contains examples of text scripts generated by our pipeline along with their normalized forms.

B Keyphrase Sampling Pipeline

To generate keyphrases to increase diversity in the generated text scripts, we prompt the LLM in multiple steps. We begin by prompting the LLM to generate subdomains in the required business domain. Then we prompt the LLM to pick one subdomain randomly. Then the LLM is required to write a creative paragraph about the subdomain in the target language. Finally, we prompt the LLM to extract keyphrases from the generated paragraph. Output formats are enforced using lm-format-enforcer (Gat, 2023) and set at different steps in the prompt chain. For each of the generated keyphrases, we determine the similarity score with the rest of the keyphrases generated by the pipeline (grouped by domain and language) using Token Sort Ratio. Any keyphrase that has a token sort ratio of less than 0.8 is then stored in the keyphrase store. The process is repeated unless the required number of keyphrases is available in the store. For the conducted evaluation experiments, we use two keyphrases per text script. Figure 3 describes the keyphrase sampling pipeline, while Figure 4 depicts an example at each step of the prompt chain.

C Entity Sampling

Our entity sampler consists of recipes to generate several forms of semiotic classes along with their normalized forms. The sampler consists of recipes for each language and is extensible to support more languages. In most of the scenarios, the base entities are generated using the Faker library (Faraglia, 2014). For example, for generating an email, person names are generated using Faker library (Panda et al., 2025; Agarwal et al., 2025, 2024). The exact recipes for different entity and their forms are described in Figure 5 and some example of generated entities and their normalized forms are present in Table 8 and Table 9.

D Text Script Generation Pipeline

Entire text script generation pipeline is described in Figure 6.

E Experimentation Settings

E.1 Keyphrases and Text Scripts Generation

The keyphrases and text scripts are generated using Mistral-7b-Instruct-0.3 (Jiang et al., 2023) model with a temperature setting of 1.2, a top_p value of 0.9. The data generated by the baseline technique shares characteristics with the data produced by our pipeline, including the use of the same LLM, dataset size, business domains, sentence types, sampling parameters, and length filtering criteria.

E.2 Evaluation

E.2.1 Diphone Coverage

To estimate the diphone coverage in our dataset and compare it with baseline corpora, we begin by extracting all unique phonemes from the text scripts using a phonemizer (Park, 2019; Patel et al., 2025; Bernard and Titeux, 2021). After identifying the phonemes, we compute the diphones by examining each pair of adjacent phonemes. Figure 7 depicts the diphone coverage for different dataset sizes for the three datasets we compared.

E.2.2 Pairwise Similarity

Since the generated text data is domain-specific, we compute mean pairwise similarity (Gong et al., 2019; Thomas et al., 2025) within sentence groups categorized by business domain and sentence type. Specifically, the dataset is first segmented based on these categories, and the mean pairwise similarity is then calculated within each group. A global similarity score (1) is obtained by averaging these group-level similarity scores. The embeddings for calculating this metric are obtained using the LaBSE model (Feng et al., 2022).

$$\text{Grouped Similarity} = \frac{1}{|G|}\sum_{g\in G}\left(\frac{1}{|S_g|(|S_g|-1)}\sum_{i=1}^{|S_g|}\sum_{j=i+1}^{|S_g|}\cos(s_i^g, s_j^g)\right) \tag{1}$$

where $|G|$ is the total number of groups, $|S_g|$ is the number of sentences in group g, and s_i^g and s_j^g are LaBSE embeddings for sentences at indices i and j in group g.

Objectively, our pipeline produces significantly better results than the direct prompting baseline. A quick manual review also reveals that the direct prompting pipeline tends to generate sentences excessively centered around certain phrases. For example: (1) 23% of sentences generated in the Banking domain contain the phrase "savings account," compared to just 1.8% in our pipeline. (2) 14% of all sentences generated in the Finance domain contain the phrase "stock market," compared to just 0.5% in our pipeline.

Non Grouped mean pairwise similarity is calculated as per Equation 2.

$$\text{Non Group Similarity} = \frac{1}{M(M-1)}\sum_{j=1}^{M}\sum_{k=j+1}^{M}\cos(s_j, s_k) \tag{2}$$

where M is the total number of sentences, s_j and s_k are embeddings for sentences at index j and k in the group.

E.2.3 Token Diversity

To compute TTR, MATTR, we first tokenize the text using NLTK's *Punkt* tokenizer (Bird et al., 2009) and SpaCy's *es_core_news_sm* model (Honnibal and Montani, 2017; Pattnayak et al., 2025) for Spanish text processing.

- TTR (Type-Token Ratio): Calculated as the ratio of the number of unique tokens to the total number of tokens in the text.
- MATTR (Moving Average Type-Token Ratio): Calculated as TTR over a sliding window of size 100, and then averaging the values.

E.2.4 Normalization Accuracy

While our pipeline performs at-source text normalization along with some basic post-processing steps, we observe that certain semiotic classes generated by the large language model (which we didn't use in our prompt) may not be correctly normalized. These normalization errors stem from either the absence or incorrect application of normalization to these new semiotic classes. To establish a ground truth for assessing normalization accuracy, we manually evaluate 500 (each for English and Spanish) sentences generated by our pipeline. For any incorrectly normalized sentence, the correct normalization is documented and used as the ground truth.

To further assess the performance of our technique, we apply Nvidia NeMo's WFST text normalizer to the generated sentences. We note that NeMo's text normalizer fails to perform certain fundamental normalization tasks, such as removing hyphens or expanding acronyms, which are handled by our pipeline's postprocessor. To mitigate errors arising from these discrepancies, we apply the same postprocessor to NeMo's output. Additionally, we observe that NeMo follows a different strategy for normalizing phone numbers, specifically regarding the placement of commas, compared to our pipeline. As such, we exclude comma placement from penalties. A sentence is considered penalized if its output does not match the ground truth. We also recognize that NeMo may produce outputs that differ from our normalization process but are still acceptable. To avoid penalizing these differences, we manually review all penalized instances and classify those with acceptable normalization as correct. A couple of examples of such acceptable errors are: (1) Incorrect deduction of locale for normalizing dates. For example, normalizing 02-01-2005 as "February one, twenty twenty five" instead of "January two twenty twenty five" as done by our pipeline. (2) Normalizing large amounts with "and" separator. For example, normalizing $301,000 as "three hundred one thousand" instead of "three hundred and one thousand" as done by our pipeline.

E.2.5 Speech Audio Clarity

- Mean Opinion Score (MOS): We estimated MOS using the NISQA (Neural Speech Quality Assessment) model (Mittag et al., 2021), which predicts speech quality based on perceptual metrics without requiring human evaluation.

- Signal-to-Noise Ratio (SNR): measures the level of speech signal relative to background noise. It is calculated as:

$$SNR = 10\log_{10}\left(\frac{P_{\text{signal}}}{P_{\text{noise}}}\right) \tag{3}$$

  where P_{signal} represents the power of the speech signal, and P_{noise} represents the power of background noise. A higher SNR indicates cleaner audio with less noise interference. Since we lack a reference clean audio, we estimated the noise power from the quietest segments of the audio, assuming that these portions (where no speaker is present) primarily contain background noise.

- Word Error Rate (WER): We utilized WER as a metric to measure how accurately the synthesized audio samples reflect the original normalized text, effectively evaluating the performance of the pipeline generating audio from the normalized text . This is achieved by leveraging an ASR model (NVIDIA, 2025; Harper et al., 2021) to transcribe the synthesized audio samples. We then compute the WER by comparing the transcribed text to the source normalized text.
  It is calculated as:

$$WER = \frac{S + D + I}{N} \times 100 \tag{4}$$

  where:

  - S is the number of substitutions (incorrect words),
  - D is the number of deletions (missing words),
  - I is the number of insertions (extra words), and
  - N is the total number of words in the reference text.

  A lower WER indicates that the synthesized audio samples accurately reflect the input normalized source text.

E.2.6 Downstream Model Training

To evaluate the effectiveness of the synthetic dataset generated by our pipeline for real-world Text-to-Speech synthesis, we conducted downstream model training using the StyleTTS 2 model. We began by using a StyleTTS' LibriTTS checkpoint as our base model.

For the baseline setup, we performed inference on the LibriSpeech test datasets, which are out-of-distribution (OOD) with respect to both our generated dataset and the LibriTTS training data. Test set contains 2618 samples for English and 2385 samples for Spanish. These text inputs were passed through the baseline model to synthesize speech audios.

We then evaluated the synthesized audio using NVIDIA NeMo's automatic speech recognition (ASR) models: stt_en_conformer_ctc_large for English and stt_es_conformer_ctc_large for Spanish (NVIDIA, 2025). These ASR models transcribed the generated audio into text, which was then compared to the reference input using Word Error Rate (WER) as the evaluation metric. To ensure fair and robust evaluation, we used a reference speaker audio that was not present in the training set for both the baseline and fine-tuned models.

For fine-tuning, we trained StyleTTS 2 models using the pipeline-generated datasets for English and Spanish, initializing from the same LibriTTS checkpoint and training for 50 epochs. The training uses PLBERT (Li et al., 2023b) for English and a multilingual variant of the same for Spanish for grapheme predictions.

F Text Script Generation Prompts

Prompts use for generating text scripts using direct prompting and through our pipeline are available in Table 10

G A note on secondary seeds

- Reproducibility is an essential component in any machine learning pipeline. For text generation, we need to ensure that the generated dataset is reproducible.

- We have stochastic components in our pipeline, such as Random Entity Generator, which can cause the entire pipeline to generate different text if not controlled.
- Large Language Models also have stochastic components that cause them to generate different text even when the inputs remain the same.
- One common way to control the stochasticity of both these components is by fixing the random seed. This ensures a component follows the same path when run again and again.
- However, fixing this seed is a limitation for us. There may be situations where we need to generate something in a loop. For example:
  - We may need to generate 5 email addresses. If we fix the seed, we will get the same value repeatedly.
  - When filtering a sentence based on some criteria (e.g., it is too long), generating the sentence using the same seed will keep producing the same sentence.
- To eliminate this, we use a process called secondary seeding.
- We first generate a primary seed and fix it. With the primary seed fixed, we generate a secondary seed anytime we need to run a random generation.
  - For example, if we encounter a generated sentence that is too long and needs to be filtered, we generate a new secondary seed. This generates a new sentence different from the last one.
- Secondary Seeding also ensures reproducibility. Since the secondary seed is generated using the primary seed, the sequence of secondary seed generation remains the same.
- Therefore, if you run the pipeline using the same primary seed again, you will generate the same data.

Secondary seeding is described in Figure 8

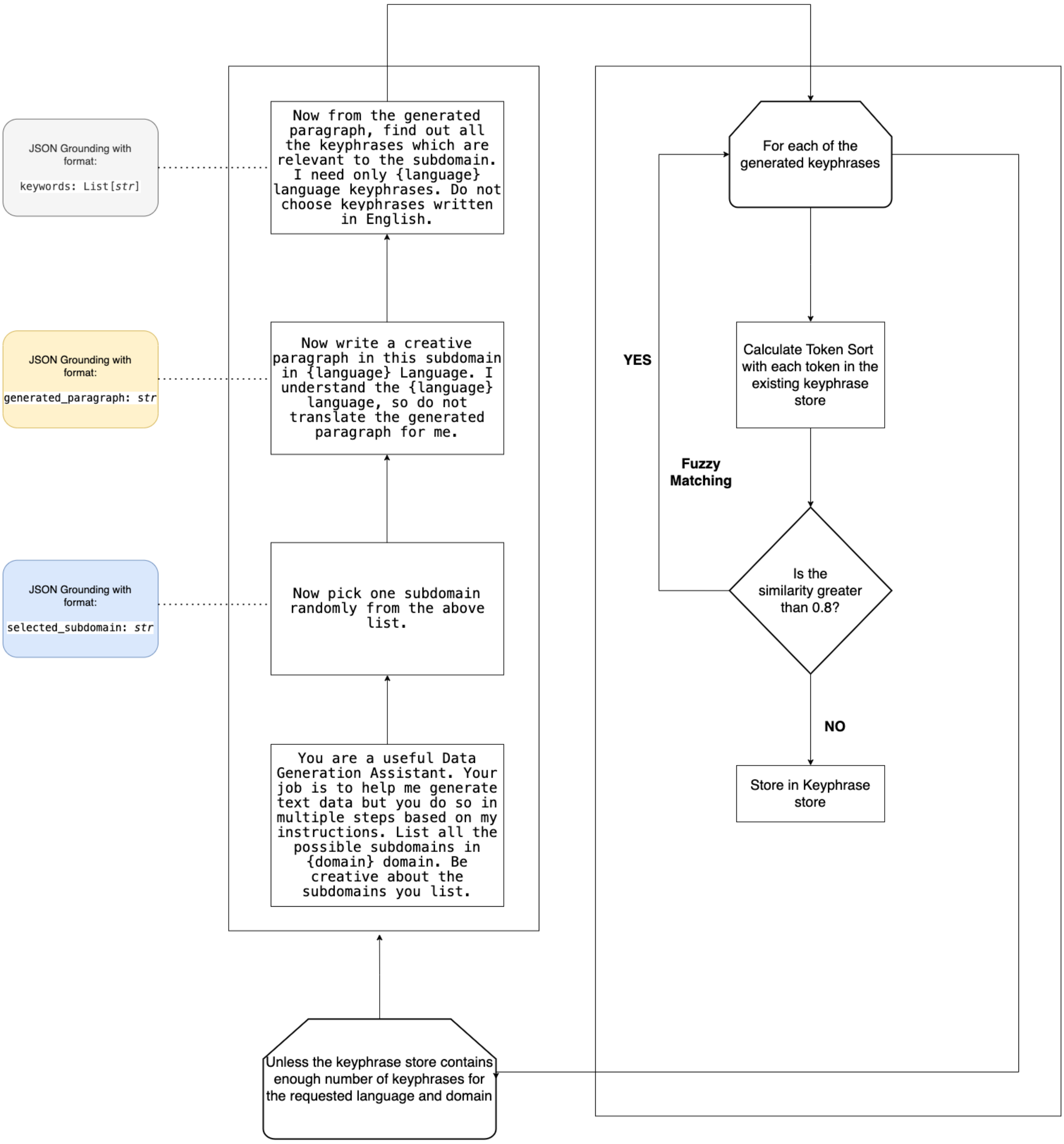
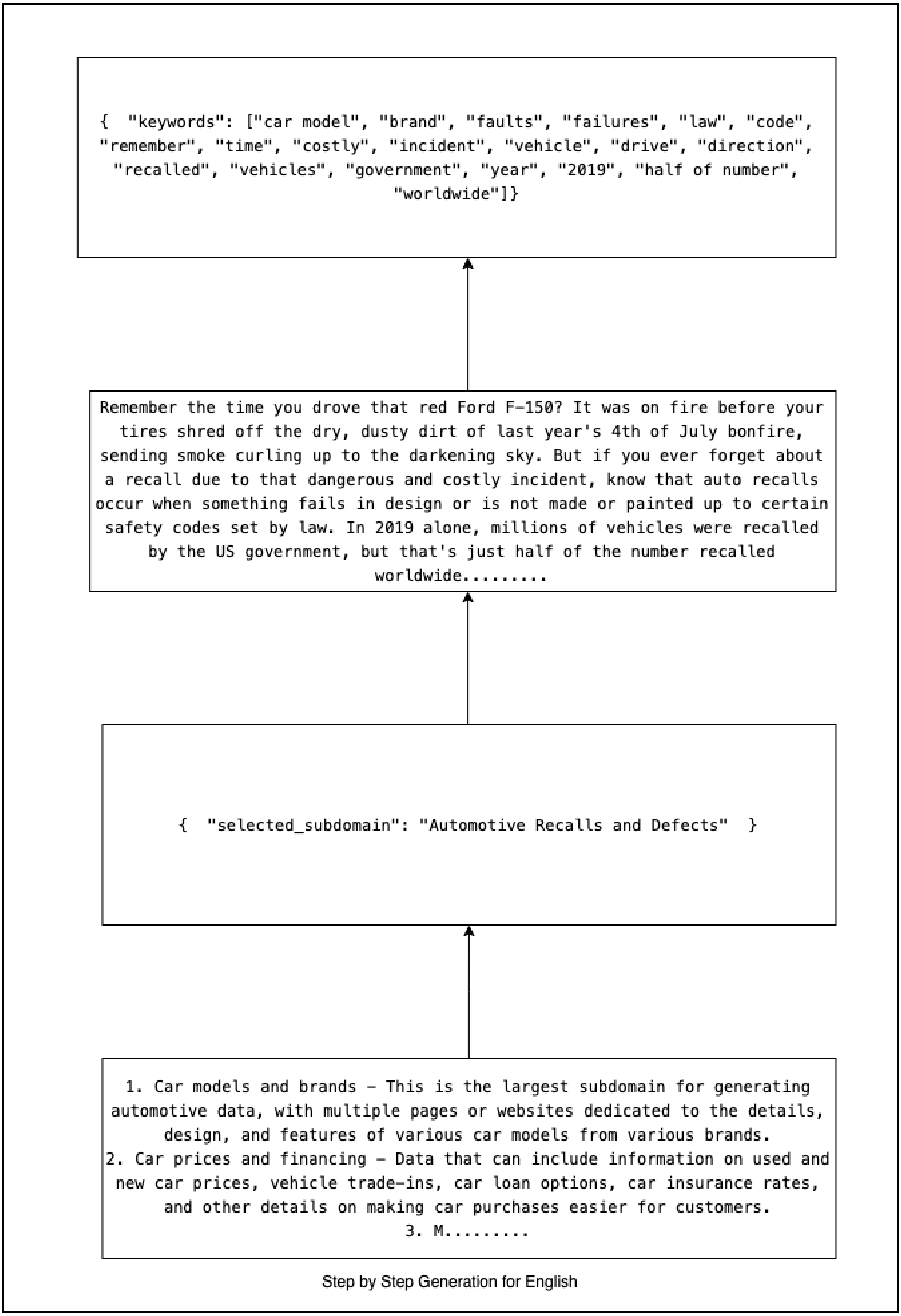

JSON Grounding with format:
keywords: List[str]
JSON Grounding with format:
generated_paragraph: str
JSON Grounding with format:
selected_subdomain: str
Now from the generated paragraph, find out all the keyphrases which are relevant to the subdomain. I need only {language} language keyphrases. Do not choose keyphrases written in English.
Now write a creative paragraph in this subdomain in {language} Language. I understand the {language} language, so do not translate the generated paragraph for me.
Now pick one subdomain randomly from the above list.
You are a useful Data Generation Assistant. Your job is to help me generate text data but you do so in multiple steps based on my instructions. List all the possible subdomains in {domain} domain. Be creative about the subdomains you list.
Unless the keyphrase store contains enough number of keyphrases for the requested language and domain
For each of the generated keyphrases
Calculate Token Sort with each token in the existing keyphrase store
YES
Fuzzy Matching
Is the similarity greater than 0.8?
NO
Store in Keyphrase store

Figure 3: Multistep Keyphrase Sampling Pipeline with De-duplication and Keyphrase Store



```
{  "keywords": ["car model", "brand", "faults", "failures", "law", "code",
"remember", "time", "costly", "incident", "vehicle", "drive", "direction",
"recalled", "vehicles", "government", "year", "2019", "half of number",
"worldwide"]}
```

Remember the time you drove that red Ford F-150? It was on fire before your tires shred off the dry, dusty dirt of last year's 4th of July bonfire, sending smoke curling up to the darkening sky. But if you ever forget about a recall due to that dangerous and costly incident, know that auto recalls occur when something fails in design or is not made or painted up to certain safety codes set by law. In 2019 alone, millions of vehicles were recalled by the US government, but that's just half of the number recalled worldwide.........

```
{  "selected_subdomain": "Automotive Recalls and Defects"  }
```

1. Car models and brands - This is the largest subdomain for generating automotive data, with multiple pages or websites dedicated to the details, design, and features of various car models from various brands.
2. Car prices and financing - Data that can include information on used and new car prices, vehicle trade-ins, car loan options, car insurance rates, and other details on making car purchases easier for customers.
3. M........

Figure 4: Example output from keyphrase sampling pipeline at each step of the prompt chain

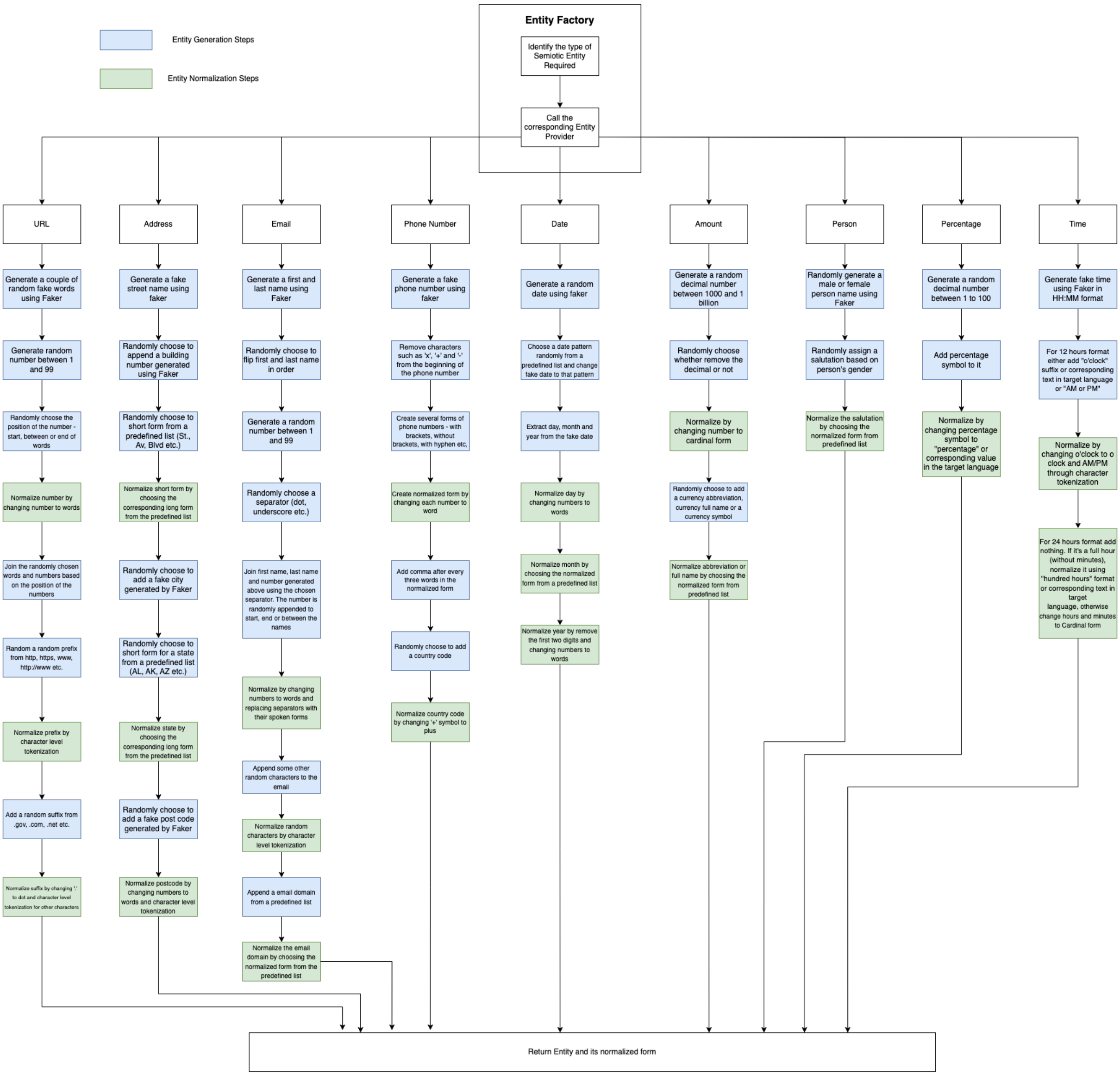

Entity Generation Steps
Entity Normalization Steps
Entity Factory
Identify the type of Semiotic Entity Required
Call the corresponding Entity Provider
URL
Generate a couple of random fake words using Faker
Generate random number between 1 and 99
Randomly choose the position of the number - start, between or end of words
Normalize number by changing number to words
Join the randomly chosen words and numbers based on the position of the numbers
Random a random prefix from http, https, www, http://www etc.
Normalize prefix by character level tokenization
Add a random suffix from .gov, .com, .net etc.
Normalize suffix by changing '.' to dot and character level tokenization for other characters
Address
Generate a fake street name using faker
Randomly choose to append a building number generated using Faker
Randomly choose to short form from a predefined list (St., Av, Blvd etc.)
Normalize short form by choosing the corresponding long form from the predefined list
Randomly choose to add a fake city generated by Faker
Randomly choose to short form for a state from a predefined list (AL, AK, AZ etc.)
Normalize state by choosing the corresponding long form from the predefined list
Randomly choose to add a fake post code generated by Faker
Normalize postcode by changing numbers to words and character level tokenization
Email
Generate a first and last name using Faker
Randomly choose to flip first and last name in order
Generate a random number between 1 and 99
Randomly choose a separator (dot, underscore etc.)
Join first name, last name and number generated above using the chosen separator. The number is randomly appended to start, end or between the names
Normalize by changing numbers to words and replacing separators with their spoken forms
Append some other random characters to the email
Normalize random characters by character level tokenization
Append a email domain from a predefined list
Normalize the email domain by choosing the normalized form from the predefined list
Phone Number
Generate a fake phone number using faker
Remove characters such as 'x', '+' and '-' from the beginning of the phone number
Create several forms of phone numbers - with brackets, without brackets, with hyphen etc,
Create normalized form by changing each number to word
Add comma after every three words in the normalized form
Randomly choose to add a country code
Normalize country code by changing '+' symbol to plus
Date
Generate a random date using faker
Choose a date pattern randomly from a predefined list and change fake date to that pattern
Extract day, month and year from the fake date
Normalize day by changing numbers to words
Normalize month by choosing the normalized form from a predefined list
Normalize year by remove the first two digits and changing numbers to words
Amount
Generate a random decimal number between 1000 and 1 billion
Randomly choose whether remove the decimal or not
Normalize by changing number to cardinal form
Randomly choose to add a currency abbreviation, currency full name or a currency symbol
Normalize abbreviation or full name by choosing the normalized form from predefined list
Person
Randomly generate a male or female person name using Faker
Randomly assign a salutation based on person's gender
Normalize the salutation by choosing the normalized form from predefined list
Percentage
Generate a random decimal number between 1 to 100
Add percentage symbol to it
Normalize by changing percentage symbol to "percentage" or corresponding value in the target language
Time
Generate fake time using Faker in HH:MM format
For 12 hours format either add "o'clock" suffix or corresponding text in target language or "AM or PM"
Normalize by changing o'clock to o clock and AM/PM through character tokenization
For 24 hours format add nothing. If it's a full hour (without minutes), normalize it using "hundred hours" format or corresponding text in target language, otherwise change hours and minutes to Cardinal form
Return Entity and its normalized form

Figure 5: Recipes for generating different semiotic classes and their normalized forms

Text Script	Normalized Form
Mrs. Julie Young was blown away by the sheer size of the aircraft and the luxurious amenities offered by the airline!	Missis Julie Young was blown away by the sheer size of the aircraft and the luxurious amenities offered by the airline!
I'll be reaching out to Abigail Walker at 5.abigail.walker@yandex.com to discuss this further.	I'll be reaching out to Abigail Walker at five dot abigail dot walker at yandex dot com to discuss this further.
With 87% of repair manuals available online in step-by-step instructions, maintenance and repairs on automobiles have become more accessible and efficient.	With eighty seven percent of repair manuals available online in step by step instructions, maintenance and repairs on automobiles have become more accessible and efficient.
Dr. Angel Roberts has made it easier for customers to make major purchases by simplifying the process and reducing the necessary steps.	Doctor Angel Roberts has made it easier for customers to make major purchases by simplifying the process and reducing the necessary steps.
The city council is working on delivering a new £273 million scheme to improve the built environment for its residents.	The city council is working on delivering a new two hundred and seventy three million pounds scheme to improve the built environment for its residents.
El 02-01-1997 fue la fecha en la que Desmarca abrió su tienda, con un fuerte énfasis en la personalización de los productos.	El dos de enero de mil novecientos noventa y siete fue la fecha en la que Desmarca abrió su tienda, con un fuerte énfasis en la personalización de los productos.
El sistema de control de vuelo utiliza una señal de posición con un 93,45% de precisión para determinar la ubicación de la aeronave sobre la Tierra.	El sistema de control de vuelo utiliza una señal de posición con un noventa y tres coma cuarenta y cinco por ciento de precisión para determinar la ubicación de la aeronave sobre la Tierra.
¿Has realizado un análisis financiero de los instrumentos financieros que están disponibles para invertir CA$572?	¿Has realizado un análisis financiero de los instrumentos financieros que están disponibles para invertir quinientos setenta y dos dólares canadienses?
El informe sobre la corrupción en el gobierno se puede consultar en 86corrupti.net.	El informe sobre la corrupción en el gobierno se puede consultar en ocho seis corrupti punto net.

Table 7: Examples of generated text scripts and their normalized forms.

Type	Generated Entity	Normalized Form
Amount	863k Canadian Dollars	Eight Hundred and Sixty Three Thousand Canadian Dollars
	29 USD	Twenty Nine U S Dollars
	£723m	Seven Hundred and Twenty Three Million Pounds
Date	10-04-2023	October fourth twenty twent three
	10/21/1997	October twenty first ninet seven
	06/Jan/10	January sixth ten
Person	Dr. Yvette Nelson	Doctor Yvette Nelson
	Mr. Cameron Carter	Mister Cameron Carter
	Mrs. Julia Thomas	Missis Julia Thomas
Email	cbrwthomaswalker29@hotmail.com	c b r w thomas walker two nine at hot mail dot com
	l51sonyasanders@mail.com	l five one sonya sanders at mail dot com
Phone Number	7854017402	seven eight five, four zero one, seven four zero two
	+1-47859964121	plus one, four seven eight five, nine nine six, four one two one
Percentage	39.29%	thirty nine point two nine percent
URL	*http://though15.eu*	h t t p colon slash slash though one five dot e u
Address	Johnson Trail Plz KY 45287	Johnson Trail Plaza Kentucky four five two eight seven
	Chen Inlet North Dakota 34101	Chen Inlet North Dakota three four one zero one
Time	13:59	Thirteen fifty nine
	17:00	Seventeen hundred hours
	02:34 PM	Two thirty four P M
	11 o'clock	Eleven o clock

Table 8: Examples of generated entities and their normalized forms across various semiotic classes in English.

Type	Generated Entity	Normalized Form
Amount	CA$572	quinientos setenta y dos dólares canadienses
	A$485,986,561.71	cuatrocientos ochenta y cinco millones novecientos ochenta y seis mil quinientos sesenta y uno con setenta y un centavos dólares australianos
	£723m	setecientos veintitrés millones de libras
Date	05/22/93	veintidós de mayo de mil novecientos noventa y tres
	02-Oct-1988	dos de octubre de mil novecientos ochenta y ocho
	08-04-2000	ocho de abril de dos mil
Person	Prof. Edgardo Aragón Trujillo	El Profesor Edgardo Aragón Trujillo
	Dr. Bernabé Quintanilla Cerezo	El Doctor Bernabé Quintanilla Cerezo
	Sr. Rodolfo del Cid	El Señor Rodolfo del Cid
Email	16rosaliaquesada@outlook.com	uno seis rosalia quesada en outlook punto com
	ferreraclara36@outlook.com	ferrera clara tres seis en outlook punto com
Phone Number	4 835600765	cuatro ocho tres, cinco seis cero, cero siete seis cinco
	4807 14 77 34	cuatro ocho cero, siete uno cuatro, siete siete tres cuatro
Percentage	69.76%	sesenta y nueve punto setenta y seis por ciento
	76%	setenta y seis por ciento
URL	73corporis.gov	siete tres corporis punto gov
Address	79 Pasaje de Claudio Jimenez Vlg Tarragona Colorado 11282	siete nueve Pasaje de Claudio Jiménez Aldea Tarragona Colorado uno uno dos ocho dos
	Pasadizo Julián Bosch Louisiana 32198	Pasadizo Julián Bosch Louisiana tres dos uno nueve ocho
Time	09:20	nueve veinte
	07:59 pm	siete cincuenta y nueve p m
	las 2 en punto	las dos en punto

Table 9: Examples of generated entities and their normalized forms across various semiotic classes in Spanish.

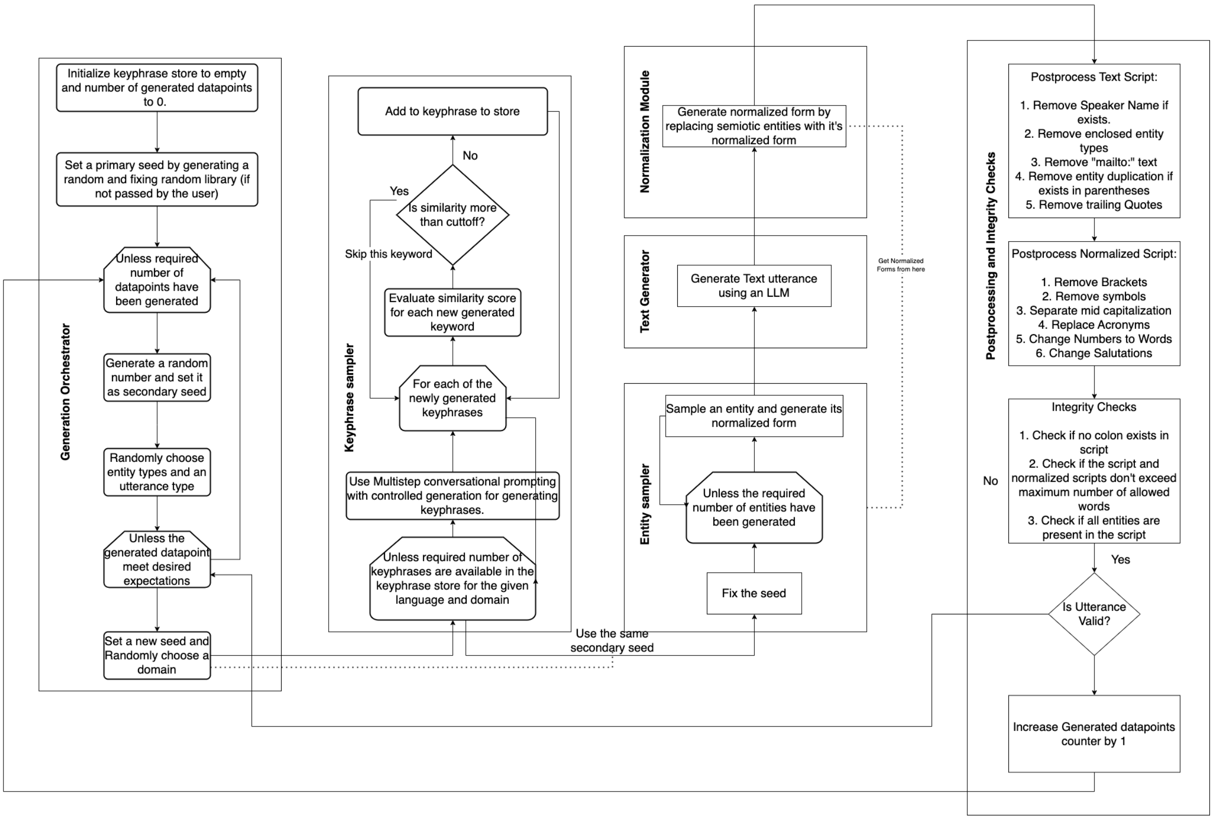

Generation Orchestrator
Initialize keyphrase store to empty and number of generated datapoints to 0.
Set a primary seed by generating a random and fixing random library (if not passed by the user)
Unless required number of datapoints have been generated
Generate a random number and set it as secondary seed
Randomly choose entity types and an utterance type
Unless the generated datapoint meet desired expectations
Set a new seed and Randomly choose a domain
Keyphrase sampler
Add to keyphrase to store
No
Yes
Is similarity more than cuttoff?
Skip this keyword
Evaluate similarity score for each new generated keyword
For each of the newly generated keyphrases
Use Multistep conversational prompting with controlled generation for generating keyphrases.
Unless required number of keyphrases are available in the keyphrase store for the given language and domain
Use the same secondary seed
Normalization Module
Generate normalized form by replacing semiotic entities with it's normalized form
Text Generator
Generate Text utterance using an LLM
Get Normalized Forms from here
Entity sampler
Sample an entity and generate its normalized form
Unless the required number of entities have been generated
Fix the seed
Postprocessing and Integrity Checks
Postprocess Text Script:
1. Remove Speaker Name if exists.
2. Remove enclosed entity types
3. Remove "mailto:" text
4. Remove entity duplication if exists in parentheses
5. Remove trailing Quotes
Postprocess Normalized Script:
1. Remove Brackets
2. Remove symbols
3. Separate mid capitalization
4. Replace Acronyms
5. Change Numbers to Words
6. Change Salutations
Integrity Checks
1. Check if no colon exists in script
2. Check if the script and normalized scripts don't exceed maximum number of allowed words
3. Check if all entities are present in the script
No
Yes
Is Utterance Valid?
Increase Generated datapoints counter by 1

Figure 6: Detailed description of text script generation pipeline

Dataset	Sentence Type	Prompt
Direct Prompting (Baseline)	Statement	Construct one sentence in {language} language in {domain} domain. I am well aware of {language} language, so do not translate it.
	Exclamation	Construct one sentence in {language} language in {domain} domain. The generated sentence should be exclamatory and have a surprising tone. I am well aware of {language} language, so do not translate it.
	Question	Construct one sentence in {language} language in {domain} domain. The generated sentence should be a question. I am well aware of {language} language, so do not translate it.
	Phrase	Construct a short phrase in {language} language in {domain} domain. The phrase should contain about 5 to 7 words. It should be strictly a phrase and not a sentence. I am well aware of {language} language, so do not translate it.
	Utterance	Construct a short arbitrary conversation between two people in {language} language in {domain} domain. I am well aware of {language} language, so do not translate it.
Ours	Statement	Construct one sentence in {language} language in {domain} domain with the following words: {words}. The following entities should also be present in the text: {entities}.
	Exclamation	Construct one sentence in {language} language in {domain} domain with the following words: {words}. The following entities should also be present in the text: {entities}. The generated sentence should be exclamatory and have a surprising tone.
	Question	Construct one sentence in {language} language in {domain} domain with the following words: {words}. The following entities should also be present in the text: {entities}. The generated sentence should be a question.
	Phrase	Construct a short phrase in {language} language in {domain} domain with the following words: {words}. The phrase should contain about 5 to 7 words. The phrase should not have any numbers or dates. It should be strictly a phrase and not a sentence.
	Utterance	Construct a short arbitrary conversation between two people in {language} language in {domain} domain containing the following words: {words}. The following entities should also be present in the text: {entities}.

Table 10: Prompts used for Text Generation through direct prompting (baseline) and our pipeline.

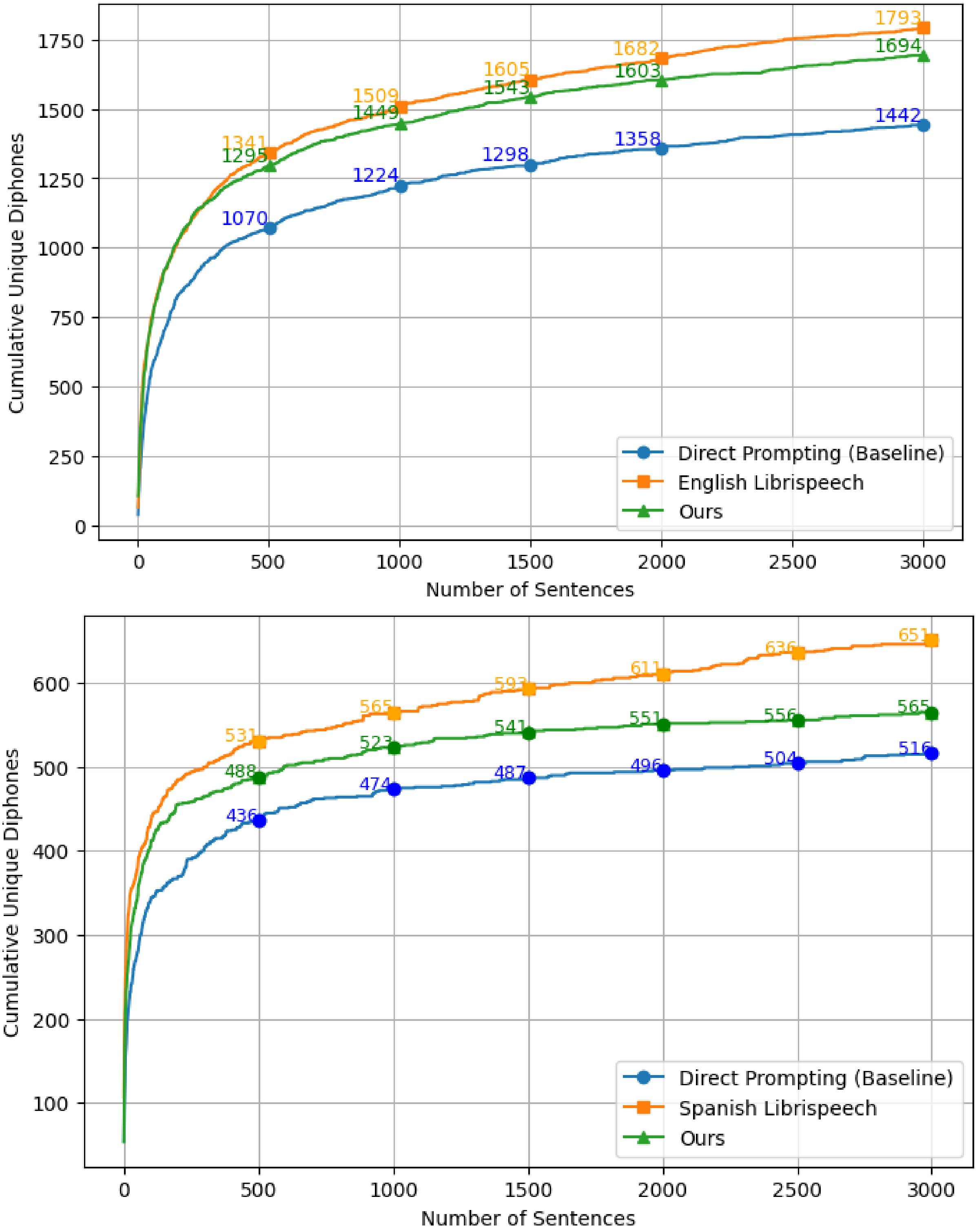


Figure 7: Diphone coverage for different dataset sizes for Baseline, Librispeech and Our Pipeline for English and Spanish text scripts

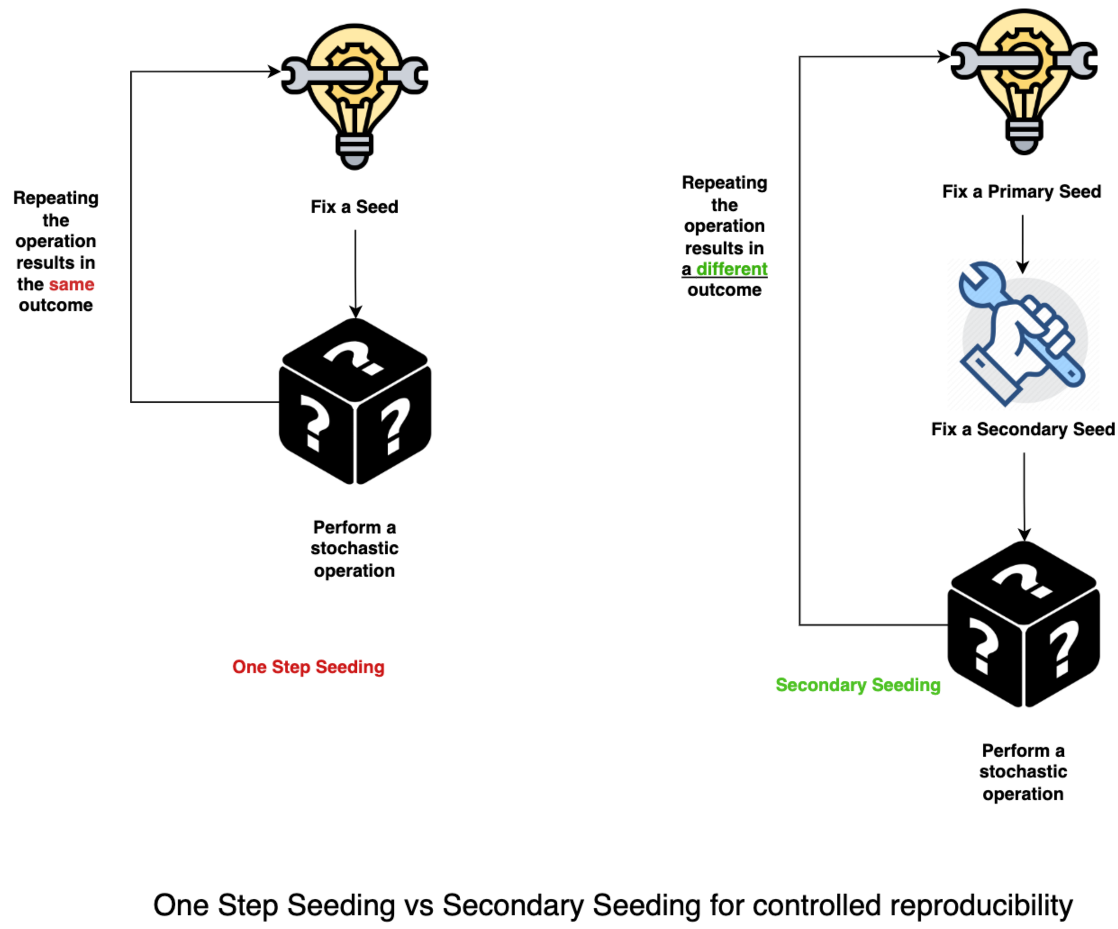

Repeating the operation results in the same outcome
Fix a Seed
Perform a stochastic operation
One Step Seeding
Repeating the operation results in a different outcome
Fix a Primary Seed
Fix a Secondary Seed
Perform a stochastic operation
Secondary Seeding
One Step Seeding vs Secondary Seeding for controlled reproducibility

Figure 8: Detailed description of text script generation pipeline