

Background and Motivation

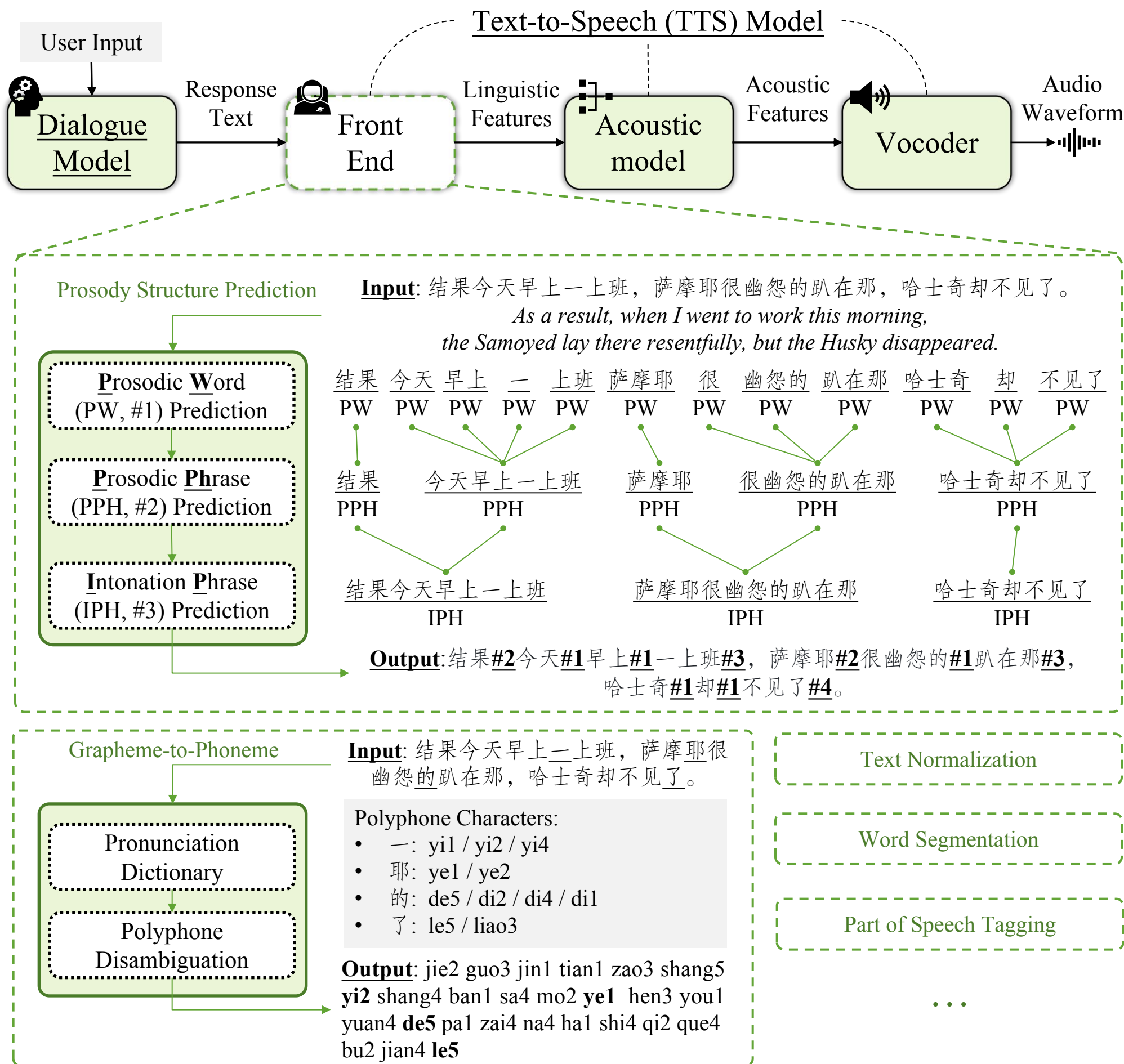


Figure 1: Standard pipeline of current Dialogue-TTS systems (e.g., Apple Siri, Amazon Alexa, XiaoMi XiaoAI, Call Annie). A dialogue model generates response to user input, and the TTS model (front-end→acoustic model→vocoder) convert text to audio subsequently.

The current framework (Fig. 1) works fine, but has the following two limitations:

- Dialogue model and TTS model work independently.** It prohibits the TTS model to obtain the user input and generate speech with proper articulations (emotion, emphasize, etc.) accordingly.
- TTS front-end is based on small language models.** Generation of proper speech articulations requires in-depth understanding of complex dialogue context, which is a difficult task for low-capacity language models.

This study aims to utilize Large Language Models (LLMs) to address this issue. As in Fig. 2, we hope the LLM can “*think how to response*” and “*think how to speak*” at the same time. Moreover, its strong language understanding ability encoded rich world knowledge could enhance its ability to generate improved linguistic features.

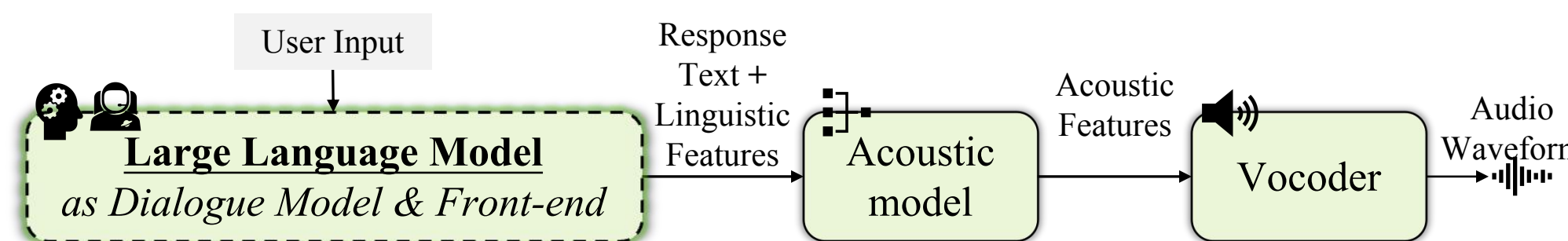


Figure 2: The proposed framework of this study.

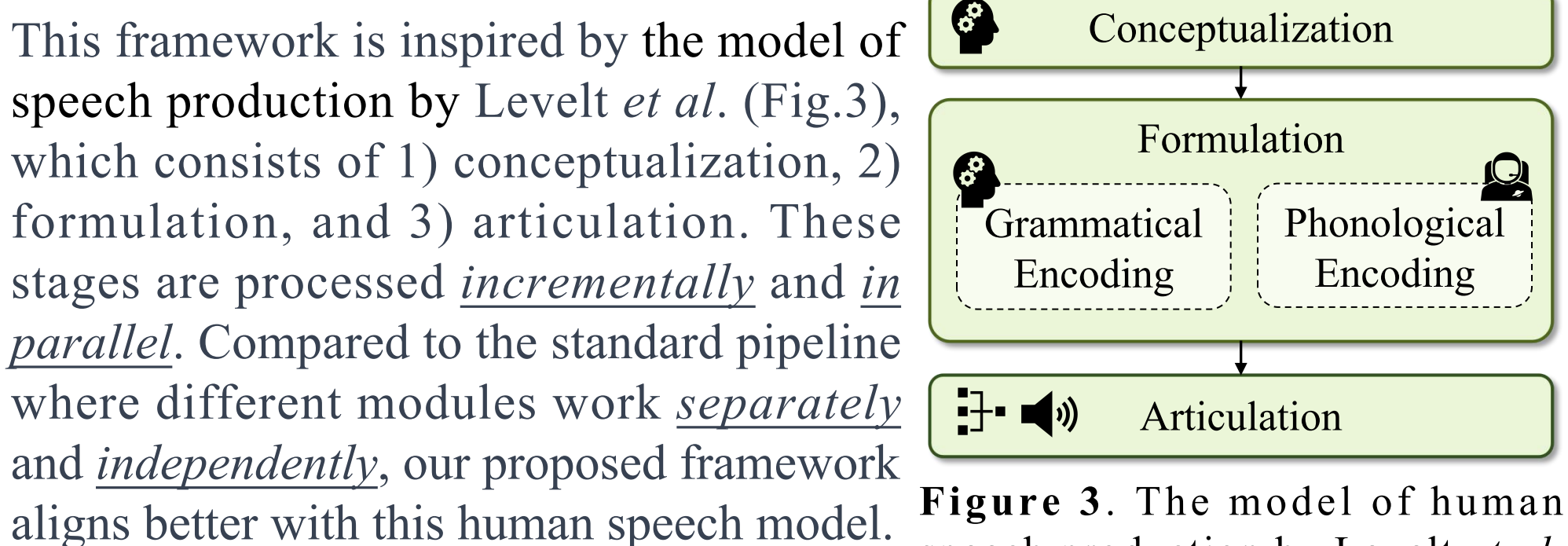


Figure 3. The model of human speech production by Levelt *et al.* (1989) [1].

Speech Data

This project utilized DataBaker  open-source Chinese Standard Mandarin Speech Corpus, which contains:

- Speech Recording**
 - Total duration: about 12 hours (10000 sentences);
 - Average sentence length: about 16 words per sentence;
 - Speaker: one Chinese female;
 - Domain: news, novels, technology, entertainment, etc.
- Linguistic Annotations**
 - Character, pinyin and prosody hierarchy;
 - Phoneme interval and boundary.

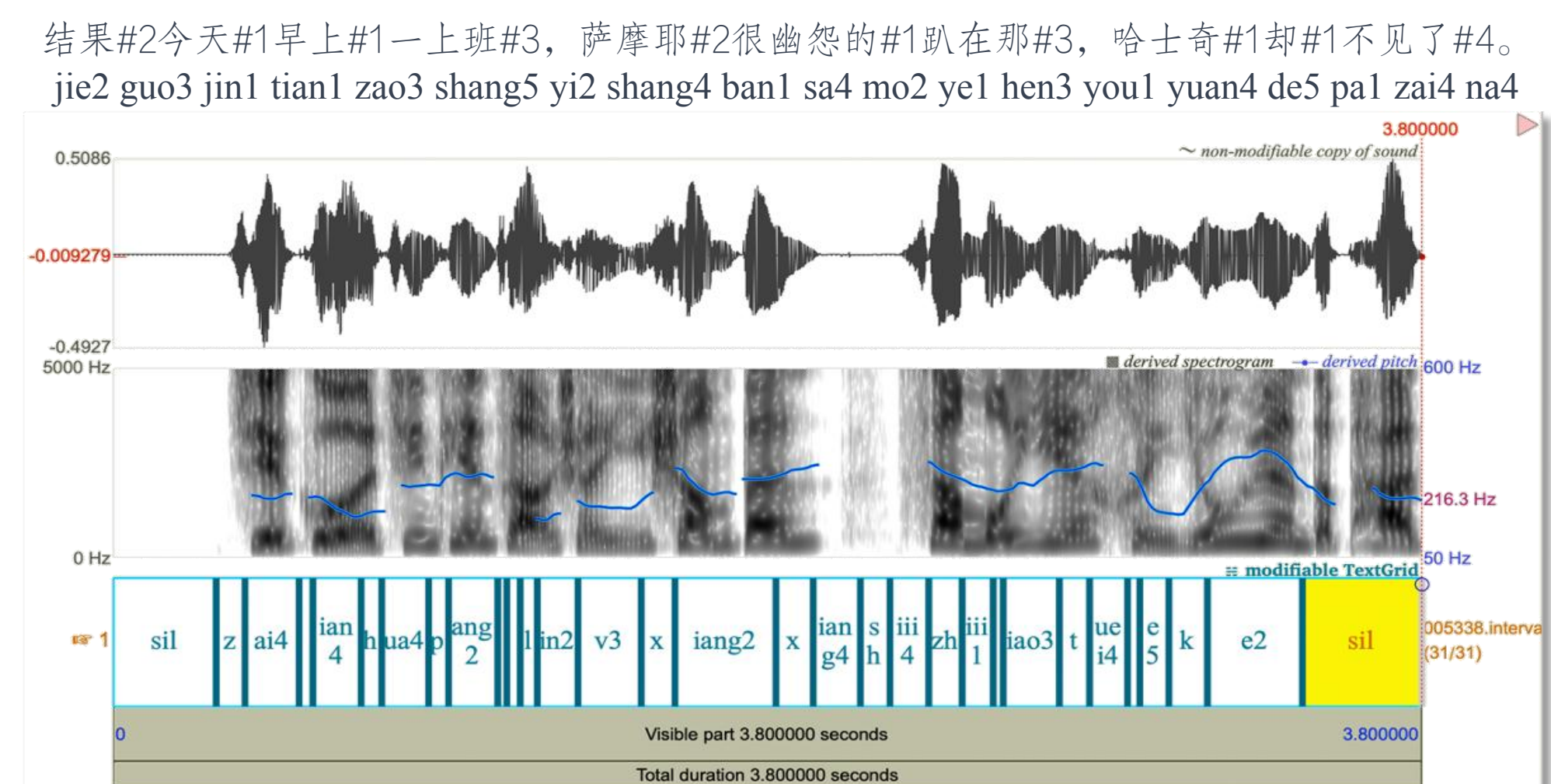


Figure 4. Visualization of audio recording and annotations of one sample in the dataset.

Large Language Model as TTS Front-end: A Case Study of Prosodic Structure Prediction

Prompting LLM for Prosodic Structure Prediction

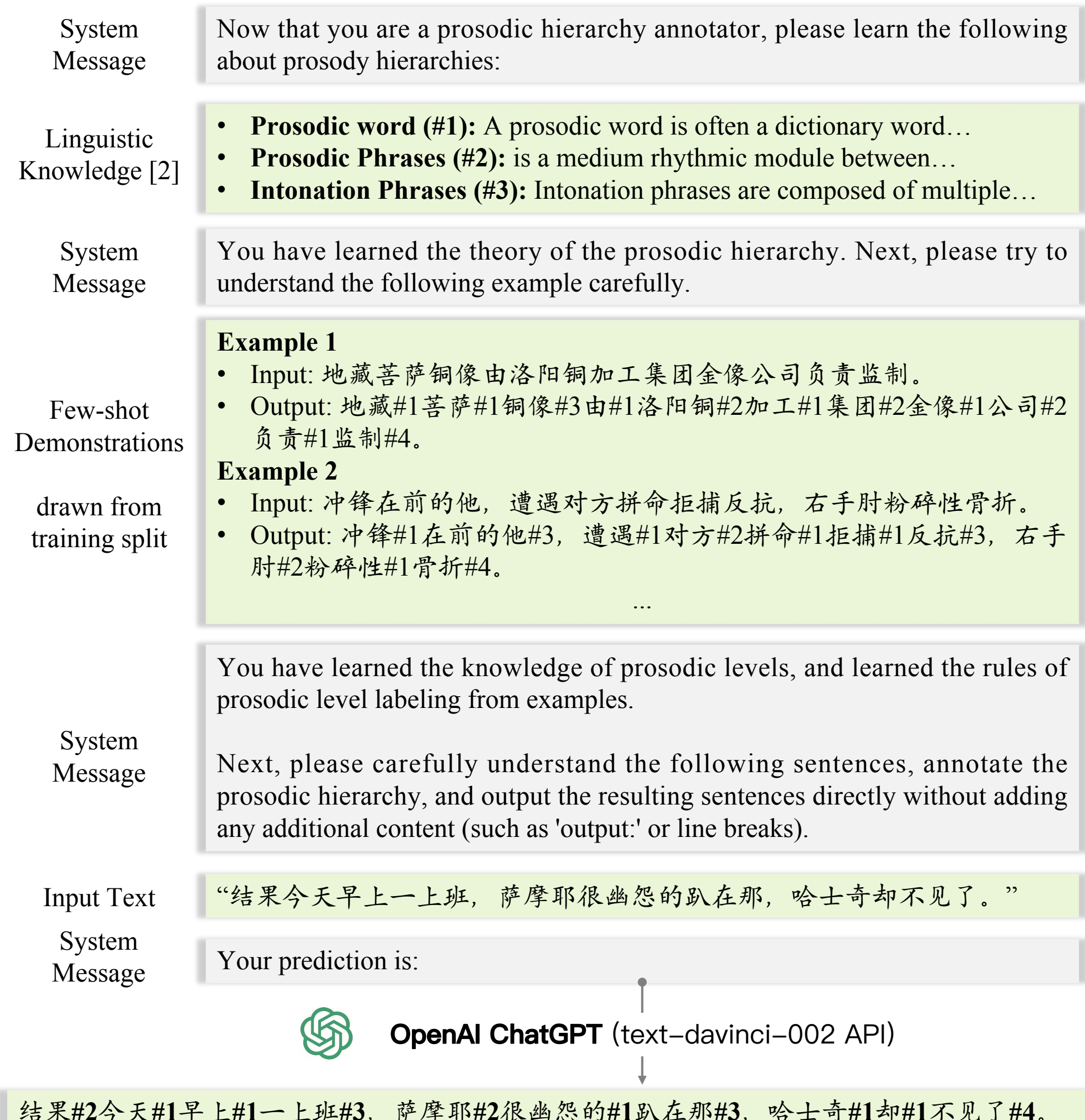


Figure 5: Prompt design of LLM (ChatGPT)-based zero-shot instructed prosody structure prediction.

Ablation Study

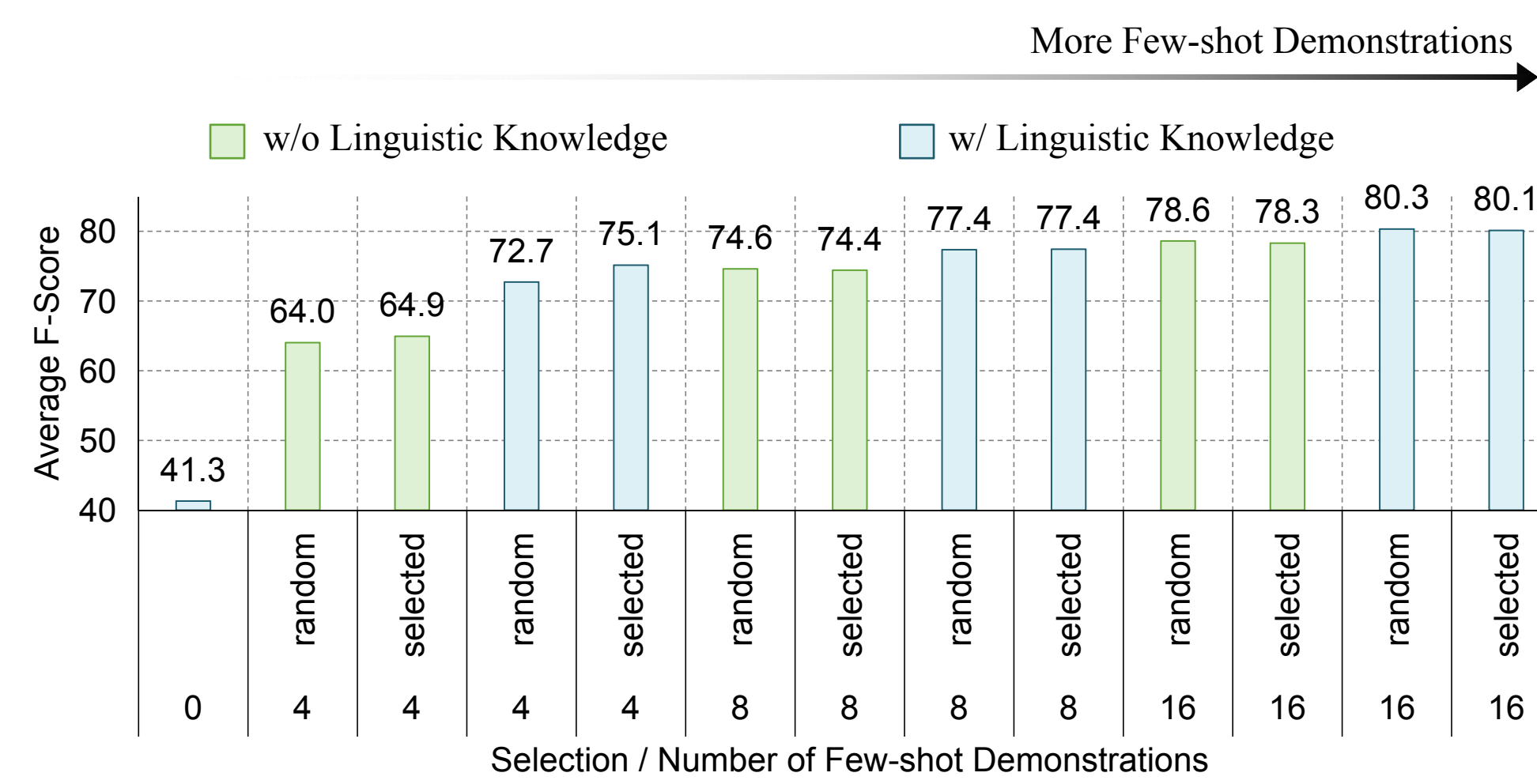


Figure 6. Ablation study of selection & number of shots, linguistic knowledge for ChatGPT-based prosody structure prediction.

Table 1. Ablations of removing each level of knowledge.

Knowledge Ablation	PW #1 F-Score	PPH #2 F-Score	IPH #3 F-Score	Average F-Score
w/o #1	88.54	64.66	78.30	77.17
w/o #2	87.57	61.63	79.09	76.10
w/o #3	87.72	64.69	78.14	76.85
Default (all)	88.14	65.03	79.52	77.56

Observations

- Linguistic knowledge helps, especially for PPH and IPH.
- Carefully selection of demonstrations yields improvements in low-shot settings.
- More shots lead to better performance but longer (near maximum) context length.

Fine-tuning Smaller LLMs

In respond to observation 3, we tried to fine-tune the ChatGLM2-6B model, which is an open-source bilingual (English & Chinese) LLM. It is much smaller than ChatGPT (6B vs. 175B parameters) thus can be efficiently trained on local machine.

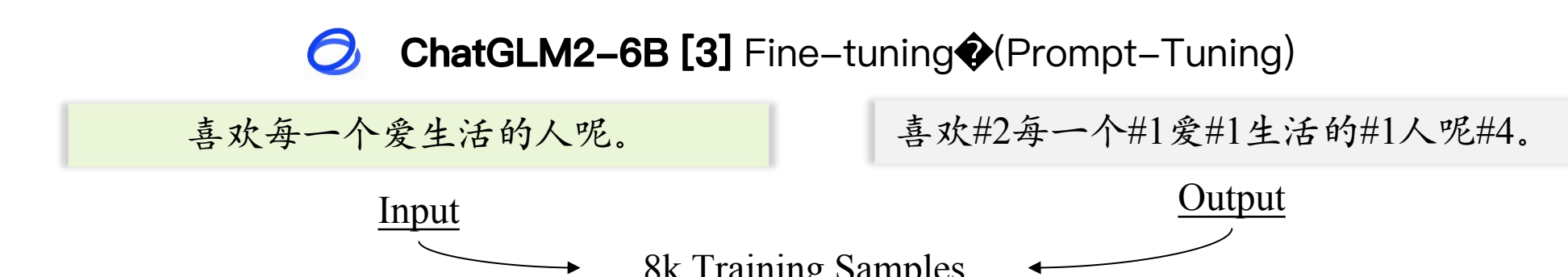


Figure 7: Illustration of fine-tuning LLM (ChatGLM2-6B) for prosody prediction.

Performance Comparison

Table 2. Benchmarking results of traditional BERT-based method and prompting or fine-tuning LLM based methods. Carefully crafted linguistic knowledge and selected examples enable ChatGPT to outperform traditional method SpanPSP, but such strategy failed (N/A) at smaller open-source LLM (ChatGLM) due to its limited capacity. However, we proved that fine-tuning smaller LLM can outperform prompting larger LLM, as it can access more training samples (8k training set vs maximum 16 in-context examples)

Model	Params (Billion)	Variation	PW #1 F-Score	PPH #2 F-Score	IPH #3 F-Score	Average F-Score
SpanPSP [2] (BERT-based)	0.3	Databaker Pretrained	96.35	69.34	65.64	77.11
		PeopleDaily Pretrained	89.20	71.08	79.12	79.80
ChatGPT (text-davinci-002)	175	Knowledge Only	61.87	27.27	34.78	41.31
		16 Random Examples	88.51	69.40	77.91	78.61
		Knowledge + 16 Selected Demo	90.12	69.40	80.85	80.12
ChatGLM-6B	6	Knowledge + 16 Selected Demo	N/A	N/A	N/A	N/A
		Fine-tuned	93.86	73.28	80.00	82.38

Joint Prediction of Dialogue Response and Linguistic Features via LLM

Data Preparation

We want to verify the possibility of building a unified model that learns to generate *both* proper dialogue response to user query *and* various fine-grained linguistic features for TTS (Fig. 2).

However, the available data only contains recordings of independent sentences. Inspired by LongForm [4], we prompt ChatGPT to predict the dialogue context and convert it into a single-turn dialogue dataset (Fig. 8).

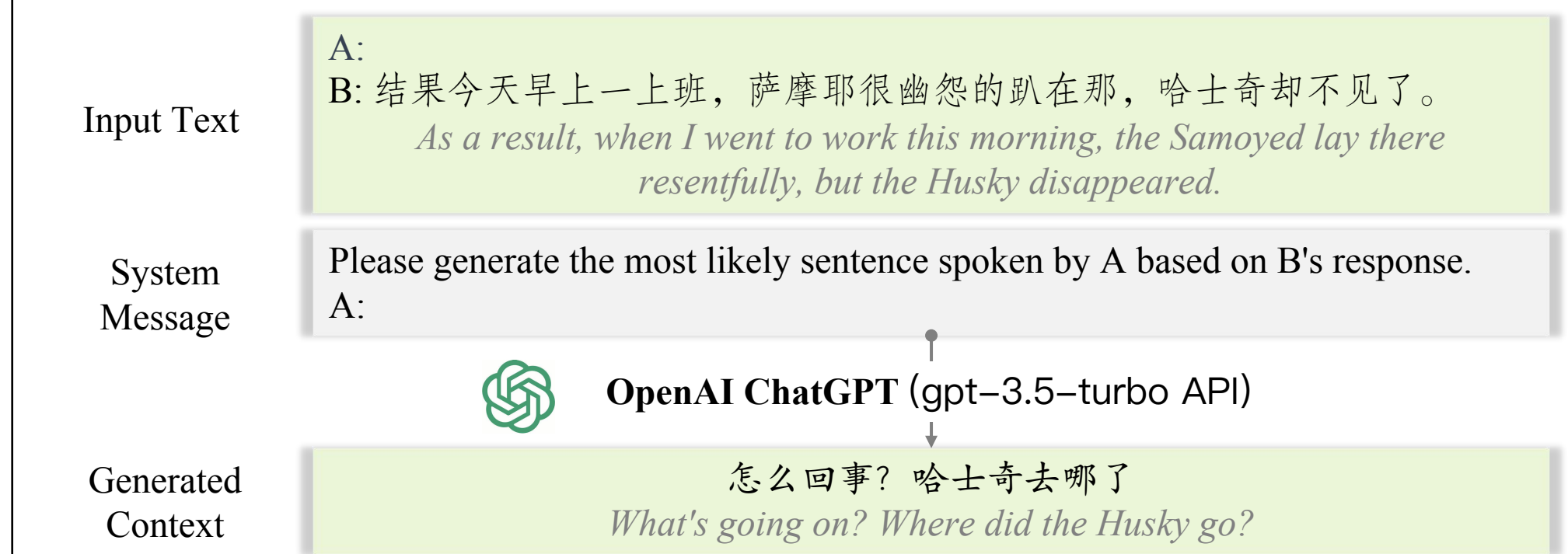


Figure 8: Prompt structure for automated context generation. ChatGPT infers possible user utterance based on the given response sentence.

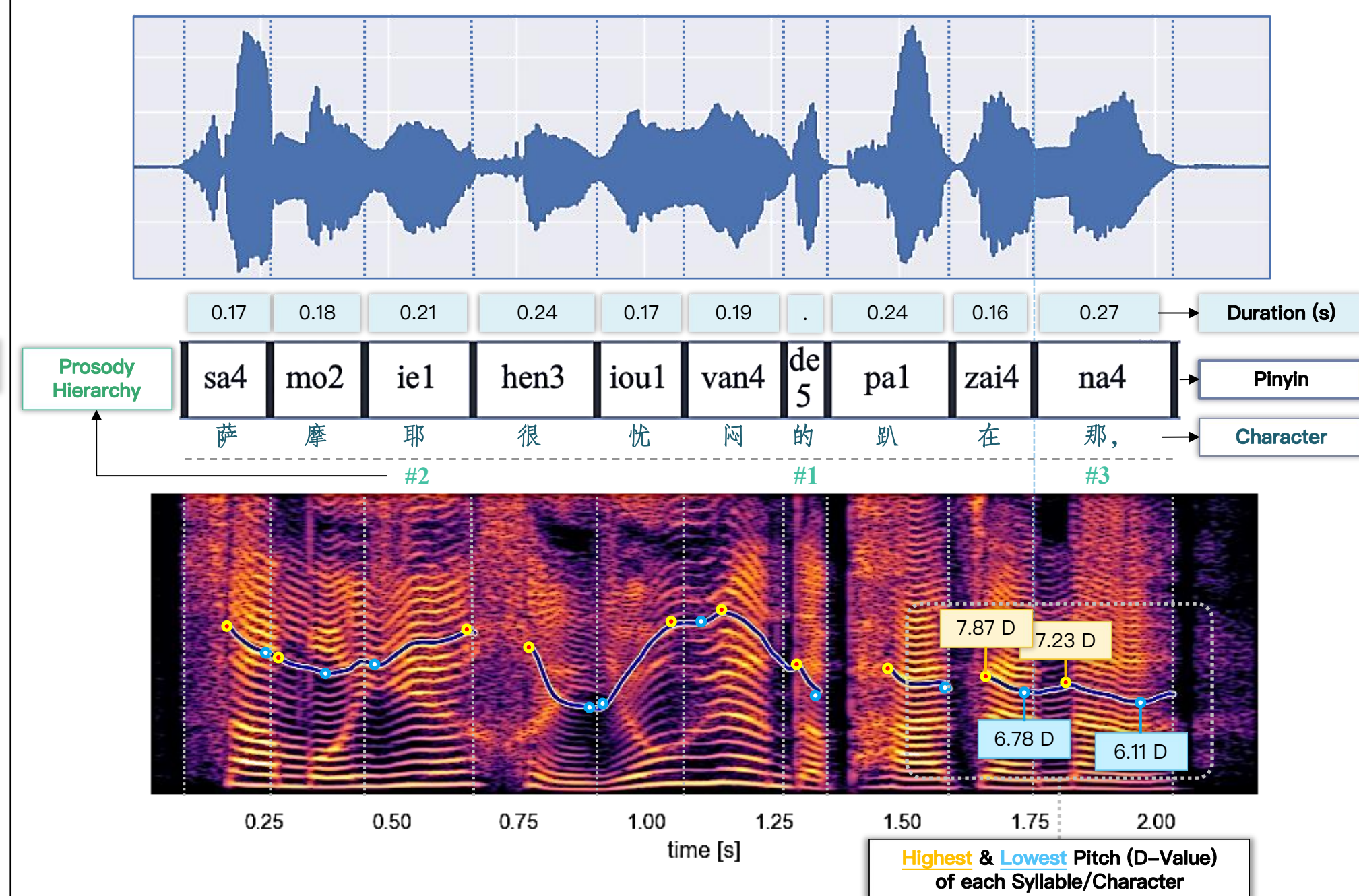
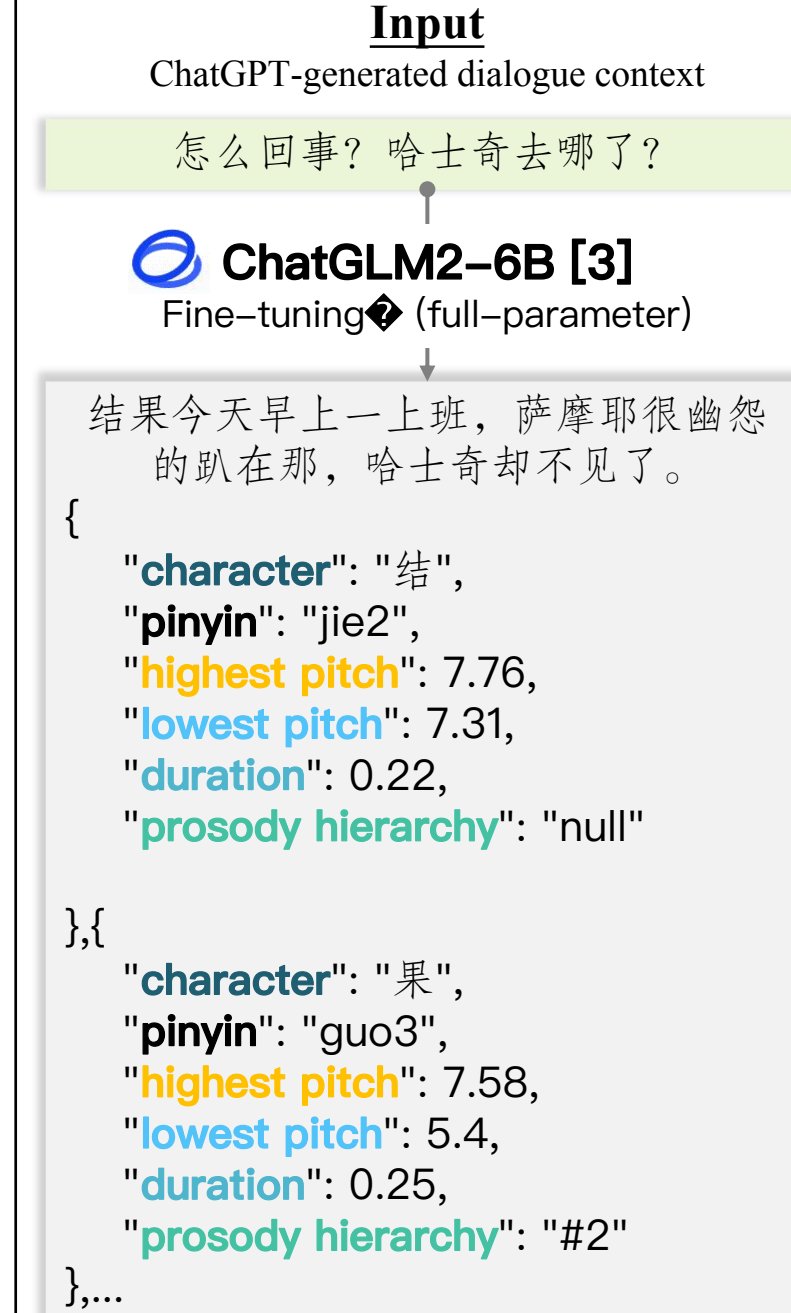


Figure 9: Extraction of linguistic feature, including [character](#), [pinyin](#), [prosody hierarchy](#), [highest pitch](#) and [lowest pitch](#) (D-Value). The use of D-Value is inspired by Shen Jiong's theory [6]: the D-value is a logarithmic scale used to describe pitch and quantifies the relationship between a pitch (F) in Hertz and a reference frequency (F0). It is defined as $D = 5 \times \log_2 (F/F_0)$. It provides a measure of pitch variation, which is especially useful for observing pitch contours in speech.

Model Training and Evaluation



As shown in Fig. 10, we format extracted linguistic features (Fig. 9) into string of Json-style dictionary, and concatenate it with the response text, together serving as the learning target. Instruction tuning on such dataset enables LLM to jointly predict dialogue response and speech features.

During testing (Table 3 and Fig.11), we use the ground truth response as generation prefix, and try to parse the generated dictionary and compare them with ground truth linguistic features.

	Parasable Samples	Matched Characters	Matched Pinyin
Train Split	95.90%	86.88%	98.79%
Test Split	89.70%	69.26%	86.29%

Table 3. On unseen testing samples, the model successfully generated Json-style linguistic features with a 89.70% success rate. However, due to the limited capacity of small LLM, missing characters are frequently observed, and only 69.29% characters in ground truth can be found in generation results.

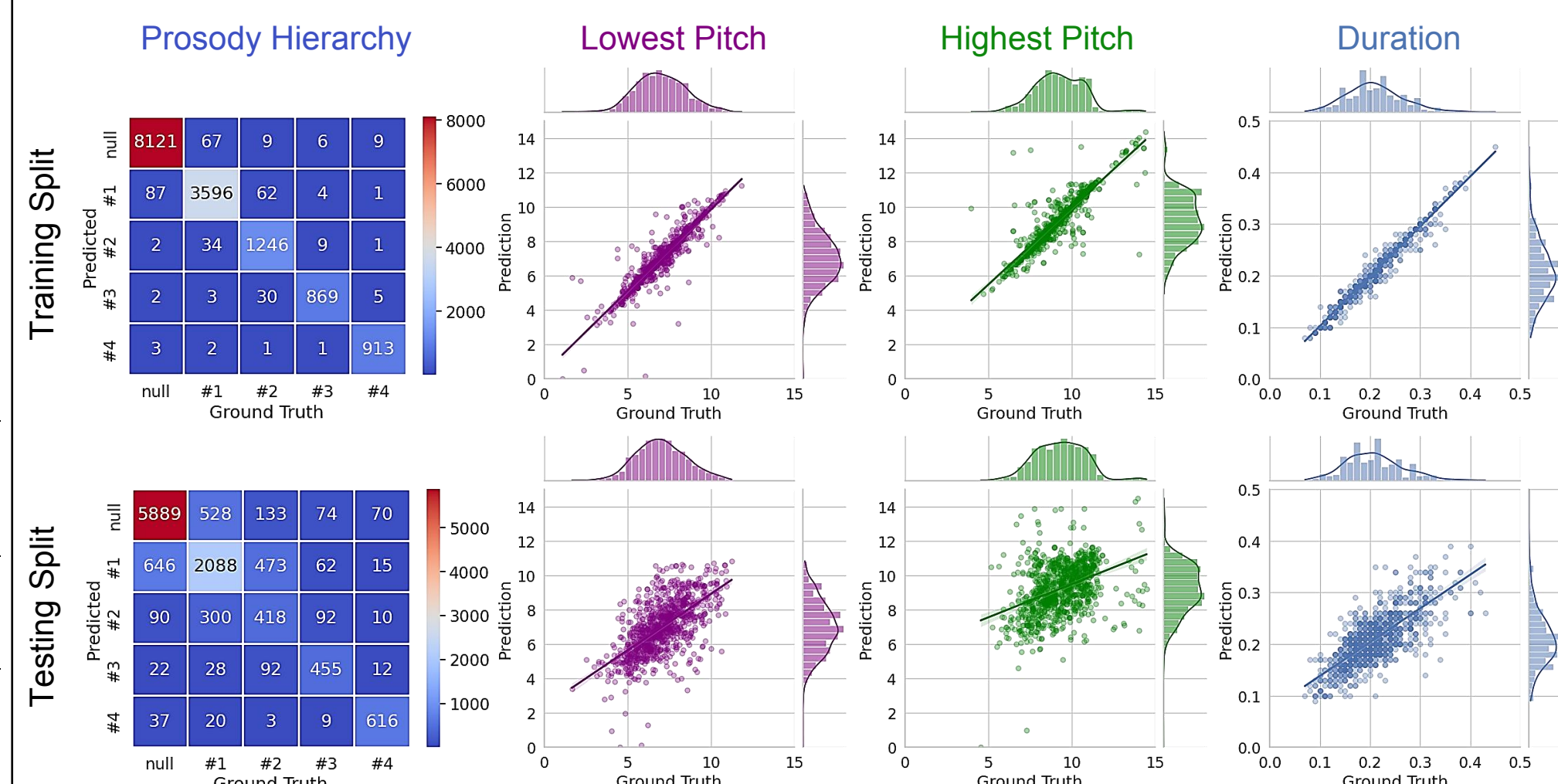


Figure 11: Evaluation results show that the model have fit the training set quite well and demonstrated certain generalization abilities.

Limitations and Future Work

- Model Perspective**
 - Training Cost is High.** Fine-tuning ChatGLM2-6B for 10,000 steps consumes 12 hours on a single NVIDIA A100 machine, which is considerably expensive. By contrast, fine-tuning for prosody structure prediction (as depicted in Fig.7) takes approximately 1 hour.
 - Inference is Time-consuming.** The auto-regressive decoding of Json-style linguistic features lacks parallelization, resulting in time-consuming inference. Processing a single sentence can take up to at least 15 seconds. More efficient methods for encoding linguistic features are imperative to address this challenge.
- Data Perspective**
 - Data Scale is Insufficient.** The training dataset consisting of only 8,000 samples is inadequate for training a large language model. Consequently, significant overfitting occurs as depicted Table 3 and Fig. 11.
 - Speech Style is Limited.** The existing dataset is sourced from a solitary female speaker, encompassing solely formal speech recordings. However, these recordings tend to sound more like reading rather than natural speech, thereby lacking the distinctive nuances inherent in communication through voice. Therefore, we plan to use a bigger conversation speech dataset with multiple speakers in different scenarios.
- TTS Perspective**
 - Finer-grained Speech Annotations.** We plan to adopt an annotation paradigm inspired by interactional linguistics and conversation analysis which emphasis on suprasegmental elements as well as voice quality, breath patterns, repair, pause and other resources
 - No Acoustic Models and Vocoder.** The subsequent acoustic models and vocoders are not included in this project.

References

- [1] Levelt, W. J., & JM, W. *Speaking: From intention to articulation* - A bradford book. MIT Press, 1989.
- [2]曹剑芬. 基于语法信息的汉语韵律结构预测. 中文信息学报 2003. (Cao Jianfen. *Prediction of Prosodic Organization Based on Grammatical Information*. *Journal of Chinese Information Processing* 2003.)
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- [4] THUDM Group, Tsinghua University. ChatGLM2-6B: An Open Bilingual Chat LLM. Url: <https://github.com/THUDM/ChatGLM2-6B>. 2023.
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