

# What Do Speech Foundation Models Not Learn About Speech?

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## Abstract

Understanding how speech foundation models capture non-verbal cues is crucial for improving their interpretability and adaptability across diverse tasks. In our work, we analyze several prominent models—Whisper, Seamless, Wav2Vec, HuBERT, and Qwen2-Audio—focusing on their learned representations in both paralinguistic and non-paralinguistic tasks from the Dynamic-SUPERB benchmark. Our study addresses three key questions: (i) what non-verbal cues (e.g., speaker intent, emotion, environmental context) are captured? (ii) how are these cues represented across different layers of the models? and (iii) to what extent can these representations be effectively adapted to downstream tasks? To answer these questions, we first evaluate the models in a zero-shot setting, followed by fine-tuning on layer-wise features extracted from these models. Our results provide insights into the models’ capacity for generalization, the characteristics of their layer-wise representations, and the degree of transformation required for downstream task adaptation. Our findings suggest that some of these models perform well on various tasks in zero-shot settings, despite not being explicitly trained for those tasks. We also observe that zero-shot performance correlates with better-learned representations. The analysis of layer-wise features demonstrates that some models exhibit a convex relationship between the separability of the learned representations and model depth, with different layers capturing task-specific features.

## 1 Introduction

The rise of large language models (LLMs) using unsupervised pre-training has revolutionized natural language processing (NLP) (Bubeck et al., 2023; Minaee et al., 2024; Liu et al., 2024b; Kaddour et al., 2023). This paradigm shift has spurred an in-

creased focus on understanding the inner workings and capabilities of these models (Ju et al., 2024; Jin et al., 2024; van Aken, 2023; Prakash and Lee, 2023). While initially developed for text-based tasks, transformer-based architectures (Vaswani et al., 2023) have since been adapted for speech processing tasks, such as automatic speech recognition (ASR), text-to-speech (TTS), and speech synthesis (Wang et al., 2019; Baevski et al., 2020a).

Despite considerable research exploring the knowledge captured within text-based models (Ferrando et al., 2024; Mosbach et al., 2024; Hassanin and Moustafa, 2024; Rogers et al., 2020; Luo and Specia, 2024; Räuker et al., 2023; Sindhu et al., 2024; Raiaan et al., 2024; Jawahar et al., 2019a), our understanding of speech foundation models<sup>1</sup> remains limited. Although these models have demonstrated remarkable performance across a variety of tasks, including ASR, speaker identification, and emotion detection, there has been little investigation into what these models actually learn and how their internal representations correspond to various speech-related tasks (Tierney et al., 2020; Wang et al., 2024; Cui et al., 2024).

The black-box nature of these models raises critical questions about whether they capture the rich, nuanced information encoded in human speech—such as paralinguistic features like emotion, stress, or environmental context—or if their impressive results are driven mainly by surface-level patterns. Addressing this gap is crucial not only for improving model interpretability but also for guiding the development of more robust and generalizable speech models. Therefore, it is essential to systematically examine speech foundation models to uncover the representations they learn and better understand how these representations align with a diverse set of speech-related tasks.

<sup>1</sup>A foundation model refers to a large-scale, pre-trained model that serves as a general-purpose model for a wide range of tasks.

In this work, we aim to address this research gap by conducting a comprehensive analysis of several speech foundation models, including Whisper (Radford et al., 2023), Seamless (Barrault et al., 2023a), Wav2Vec (Schneider et al., 2019a), HuBERT (Hsu et al., 2021a), and Qwen2-Audio (Chu et al., 2023). Our investigation focuses on comparing the discriminative characteristics of their learned representations with handcrafted audio features extracted using Librosa (McFee et al., 2015)<sup>2</sup>. Additionally, we explore how well these models generalize to new tasks through zero-shot evaluations, providing insights into their performance on unseen tasks.

More specifically, we select ten tasks from the Dynamic-SUPERB (Huang et al., 2024) benchmark, encompassing both paralinguistic and non-paralinguistic tasks. For each model, we extract features from each layer and train K-Nearest Neighbors (KNN) (Peterson, 2009) and Neural Networks (NN) (Yi et al., 2016) classifiers to evaluate and compare their performance. We also conduct zero-shot evaluations with various prompts to assess the models' generalization capabilities.

Through these experiments, we aim to uncover what these models learn beyond verbal content, focusing on their ability to interpret non-verbal cues. By emphasizing non-content-based tasks, we evaluate how well the models capture paralinguistic features like speaker intent, mood, and context. This helps us assess whether the models grasp the subtleties of human speech, where non-verbal signals are as important as spoken words. Including these tasks provides valuable insights into the models' ability to generalize beyond basic transcription and synthesis, allowing us to measure their understanding of the more nuanced aspects of speech.

We summarize our contributions as follows:

- We conduct a zero-shot evaluation of various speech foundation models across a diverse range of paralinguistic and non-paralinguistic tasks.
- We extract layer-wise features from these models and train classifiers to assess the discriminative capabilities of the learned representations.
- We provide a thorough analysis of our findings, showing that for many tasks and mod-

els, there exists a convex relationship between model performance and specific regions within the model's layers.

**Outline.** The remainder of the paper is organized as follows: In Section 2, we present a review of existing literature. Section 3 discusses preliminaries. In Section 4, we detail the experimental setup, while Section 5 covers the results obtained and offers a discussion of the findings. and we conclude in Section 6. The limitations of our work are outlined in Section 7.

## 2 Related Work

Recent advancement in building speech foundation models (Zhang et al.; Barrault et al., 2023b; Pratap et al., 2023; Zhang et al., 2023; Li et al., 2023; Baevski et al., 2020a) has resulted in massive improvement on downstream tasks such as speech-recognition (Yu et al., 2024) and speech-to-text translation (Zhang et al.). In addition, these models also show the ability to generalize to novel and unseen tasks (Yang et al., 2021). However, their understanding of non-verbal cues in speech remains unexplored (Martín-Raugh et al., 2023), and an analysis of the representations they learn has yet to be investigated (Sanabria et al., 2023).

A number of studies have assessed the transferability of speech model representations for cross-task downstream speech tasks (Chemudupati et al., 2023; Guimarães et al., 2023; Chen et al., 2023; Barrault et al., 2023a). These works aim to interpret the knowledge encoded in extracted features to address the black-box nature of these models (Liu et al., 2021; Belinkov et al., 2020). For this purpose, different methods and frameworks have been developed, including probing classifiers, studies on language modeling behavior (Belinkov, 2022), inference tasks (Liu et al., 2024a), psycholinguistic approaches (Trott, 2024), layerwise analyses (Ju et al., 2024), and other relevant methodologies (Wang et al., 2018; Hewitt and Manning, 2019).

Through probing tasks, researchers found that models tend to encode richer contextual information in the upper layers, expanding from entity-level knowledge in the lower layers (Ju et al., 2024; Chowdhury et al., 2023; Jawahar et al., 2019b; Kashyap et al., 2021). Previous work, such as (Jawahar et al., 2019a), has explored what BERT learns about language structure, revealing that lower layers capture phrase-level information,

<sup>2</sup><https://librosa.org/doc/latest/feature.html>

176 while intermediate layers encode syntactic and semantic features. However, most studies have focused on language models, leaving speech foundation models largely unexplored.

177 Speech models like Whisper (Zhang et al.),  
178 Seamless (Barrault et al., 2023a), Wav2Vec2 (tom  
179 Dieck et al., 2022), HuBERT (Hsu et al., 2021b),  
180 and Qwen2-Audio (Chu et al., 2023) leverage  
181 different architectures and training methods to  
182 improve speech understanding and ASR. While  
183 Whisper has shown potential beyond ASR with  
184 its vast multilingual dataset (Goron et al., 2024),  
185 Wav2Vec2 and HuBERT focus on self-supervised  
186 learning. Despite these advances, little is known  
187 about the specific knowledge encoded in each layer  
188 of these models. Our work fills this gap by eval-  
189 uating layer-wise features across tasks using NN  
190 and KNN classifiers to identify the most effective  
191 layers for task-specific performance.

### 192 3 Preliminaries

193 In this section, we present the two primary ap-  
194 proaches for evaluating speech foundation mod-  
195 els: zero-shot learning with text prompts and  
196 feature-based fine-tuning using k-Nearest Neigh-  
197 bors (KNN) and Neural Networks (NNs).

#### 198 3.1 Zero-Shot Evaluation

200 In the zero-shot setting, we evaluate the mod-  
201 els’ ability to generalize to new tasks by provid-  
202 ing speech input and a text prompt describing the  
203 task, without any task-specific fine-tuning. Let  $\mathcal{M}$   
204 be a speech foundation model trained on a large  
205 dataset  $\mathcal{D} = \{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^N$ , where  $(\mathbf{x}_i, \mathbf{y}_i)$  repre-  
206 sent speech inputs and corresponding labels. For  
207 zero-shot evaluation, we input test speech  $\mathbf{x}_{test}$   
208 along with a task-specific prompt  $\mathbf{p}_{task}$  (e.g., tran-  
209 scription or speaker classification). The model out-  
210 puts the log probabilities for each class.

211 Let  $\mathcal{L}_c$  represent the set of possible classes for  
212 the given task. The model  $\mathcal{M}$  computes the log  
213 probability  $\log P(c|\mathbf{x}_{test}, \mathbf{p}_{task})$  for each class  $c \in$   
214  $\mathcal{L}_c$ . The predicted class  $\hat{\mathbf{y}}_{test}$  is selected as the one  
215 with the highest log probability:

$$216 \hat{\mathbf{y}}_{test} = \arg \max_{c \in \mathcal{L}_c} \log P(c|\mathbf{x}_{test}, \mathbf{p}_{task})$$

217 This approach assesses how well the pre-trained  
218 model generalizes to unseen tasks using its learned  
219 representations. The task-specific knowledge is  
220 embedded in the text prompt, and the model uses

221 its internal representations to infer the most likely  
222 class based on the speech input and task descrip-  
223 tion.

#### 224 3.2 Fine-Tuning on Features

225 In addition to zero-shot evaluation, we analyze  
226 the models by extracting features from each layer  
227 and training classifiers on top of these features. Let  
228  $\mathcal{F}_l(\mathbf{x}_i)$  denote the feature representation extracted  
229 from the  $l$ -th layer of the model  $\mathcal{M}$  for input  $\mathbf{x}_i$ .  
230 We extract layer-wise features from all layers  $l \in$   
231  $\{1, \dots, L\}$ , where  $L$  is the total number of layers  
232 in the model.

233 For KNN, the classifier finds the  $k$  nearest neigh-  
234 bors of the feature representation  $\mathbf{z}_i^l = \mathcal{F}_l(\mathbf{x}_i)$  in  
235 the feature space and assigns a label  $\hat{\mathbf{y}}_i^{KNN}$  based  
236 on majority voting among the neighbors. The pre-  
237 diction for the KNN model is given by:

$$238 \hat{\mathbf{y}}_i^{KNN} = \arg \max_c \sum_{j \in \mathcal{N}_k(\mathbf{z}_i^l)} \mathbb{1}[\mathbf{y}_j = c]$$

239 where  $\mathcal{N}_k(\mathbf{z}_i^l)$  is the set of  $k$  nearest neighbors  
240 of  $\mathbf{z}_i^l$  in the feature space, and  $\mathbb{1}[\mathbf{y}_j = c]$  is an  
241 indicator function that checks whether the label of  
242 neighbor  $j$  matches class  $c$ .

243 For the NN classifier, we define a learnable  
244 function  $\mathcal{G}_\theta(\mathbf{z}_i^l)$  parameterized by  $\theta$ , which maps  
245 the extracted feature vector  $\mathbf{z}_i^l$  to class predictions.  
246 The NN model is trained by minimizing the cross-  
247 entropy loss:

$$248 \mathcal{L}_{DNN} = -\frac{1}{N} \sum_{i=1}^N \sum_{c=1}^C \mathbf{y}_i^c \log \mathcal{G}_\theta(\mathbf{z}_i^l)$$

249 where  $C$  is the number of classes, and  $\mathbf{y}_i^c$  is the  
250 one-hot encoded ground truth label for class  $c$ . The  
251 parameters  $\theta$  are optimized to minimize the loss,  
252 allowing the NN to fine-tune the mapping from the  
253 extracted features to the class labels.

254 Training both KNN and NN classifiers on the  
255 extracted features is crucial for understanding the  
256 quality of the learned representations at different  
257 model layers. KNN, as a non-parametric model, re-  
258 flects the discriminative power of the raw features  
259 without learning any weights, providing insight  
260 into how well the features capture similarities in  
261 an unsupervised manner. NNs, with their learnable  
262 parameters, allow for more complex, task-specific  
263 transformations, improving performance when fea-  
264 tures are not linearly separable.

265 Thus, evaluating both classifiers offers a compre-  
266 hensive view of feature quality—KNN reveals raw

269 feature utility, while NN measures the potential for  
270 further task-specific adaptation.

## 271 4 Experiments

272 We outline our experimental framework de-  
273 signed to evaluate the performance of various foun-  
274 dational speech models across ten distinct audio  
275 classification tasks. Our analysis is structured to  
276 assess the impact of different models, focusing on  
277 their learned representations and performance at  
278 each layer.

### 280 4.1 Dataset

281 We carefully select a subset of tasks from the  
282 Dynamic-SUPERB benchmark (Huang et al.,  
283 2024), which spans a diverse range of tasks re-  
284 lated to speech understanding. While these foun-  
285 dation models have demonstrated strong perfor-  
286 mance on content-based tasks such as speech-to-  
287 text and text-to-speech (Barrault et al., 2023a; Rad-  
288 ford et al., 2023), we limit our evaluation to tasks  
289 that are not content-based, following the cate-  
290 gorization outlined in (Huang et al., 2024; Yang et al.,  
291 2021). This decision is essential because focusing  
292 on non-content-based tasks, such as paralinguistic  
293 and non-paralinguistic tasks, helps us better un-  
294 derstand what these speech foundation models are  
295 learning beyond verbal content—specifically, their  
296 ability to interpret non-verbal cues.

297 Non-verbal cues, such as emotion, speaker iden-  
298 tity, and environmental sounds, are crucial in real-  
299 world communication systems (Dzardanova et al.,  
300 2024). By emphasizing these tasks, we can eval-  
301 uate how effectively the models capture and utilize  
302 paralinguistic features that convey speaker intent,  
303 mood, and context. This understanding is key to as-  
304 sessing whether the models truly comprehend the  
305 subtleties of human communication, where non-  
306 verbal signals often play an equally important role  
307 as linguistic information.

308 We choose ten tasks, broadly categorizing them  
309 into paralinguistic and non-paralinguistic groups.  
310 Each task in Dynamic-SUPERB comes with clearly  
311 defined instructions, facilitating the effective eval-  
312 uation of model performance in previously unseen  
313 contexts. Further details on the tasks used in our  
314 evaluation are provided in Table 1.

### 315 4.2 Models

316 For a more inclusive study, we select three types of  
317 models: encoder-only, decoder-only, and encoder-

Task	Type	nClass
Accent Class.	Paraling	9
Dialogue Act	Semantic	4
Emotion Recog.	Paraling	7
Env. Sound Class.	Audio	10
HowFarAreYou	Paraling	3
Intent Class.	Semantic	6
Multi-Speaker Det.	Speaker	2
Sarcasm Det.	Paraling	2
Spooft Det.	Paraling	2
Stress Det.	Paraling	6

280 Table 1: Table of tasks and their respective categories  
281 in the Dynamic-SUPERB benchmark, along with the  
282 number of target classes (nClass) for each task.

318 decoder. Each model varies in training data, objec-  
319 tives, and architecture, providing unique insights  
320 into how these foundation models process and un-  
321 derstand speech.

322 Encoder-only models (e.g., HuBERT Hsu et al.  
323 (2021b), Wav2Vec Schneider et al. (2019b)) spe-  
324 cialize in extracting acoustic and paralinguistic fea-  
325 tures, making them ideal for tasks like speaker iden-  
326 tification, emotion recognition, and environmental  
327 sound classification.

328 Decoder-only models (e.g., Qwen2-Audio (Chu  
329 et al., 2024)), typically employed for autoregressive  
330 tasks such as speech-to-text, enable us to evaluate  
331 their capability to manage paralinguistic elements  
332 beyond mere sequence generation.

333 Encoder-decoder models (e.g., Whisper Radford  
334 et al. (2023), SeamlessM4T (Barrault et al., 2023a))  
335 combine both feature extraction and sequence gen-  
336 eration, making them versatile for a variety of tasks  
337 that involve both understanding and generating  
338 speech.

339 By selecting models with distinct architectures,  
340 objectives, and training data, we aim explore their  
341 capabilities across a broad range of tasks, assess-  
342 ing performance on both paralinguistic and non-  
343 paralinguistic challenges. Further details about  
344 these models are provided in Table 2.

### 345 4.3 Training and Evaluation

346 **Zero-Shot.** In the zero-shot setting, we evaluate  
347 the ability of models, specifically decoder-only and  
348 encoder-decoder models, to generalize to new tasks  
349 without any task-specific fine-tuning. These mod-  
350 els are capable of generating text from speech in-

Type	Models	Evaluation
Enc	HuBERT, Wav2Vec	FT
Enc-Dec	Whisper, Seamless	ZS, FT
Dec	Qwen2-Audio	ZS, FT

Table 2: Description of the models we used in our evaluation. Abbreviation: Enc - Encoder, Dec - Decoder, ZS - Zero-shot, FT - Finetunning

Name	Prompt
MCQ	{instruction}. Choose the correct answer: {options}. Your answer:
Quiz	{instruction}. Which of the following options is the correct answer? {options}.
Blank	{instruction}. The correct label is _____. Choose from: {options}. Answer:

Table 3: Prompts used for zero-shot evaluation.

put, making them suitable for zero-shot evaluation across various tasks.

For this evaluation, we provide the model with speech input and a text prompt that describes the task (e.g., emotion recognition, speaker classification). Without any prior exposure to the specific task during fine-tuning, the model is expected to infer the correct output based on its pre-trained knowledge. The text prompt helps guide the model’s understanding of the task, while the model leverages its internal representations to process the speech input and produce the corresponding output.

The zero-shot approach allows us to assess how well these models can handle unseen tasks by using the knowledge embedded in their pre-trained representations. Our setup is particularly important for understanding how flexible and adaptable the models are when faced with new, previously unseen scenarios. In our experiments which is also supported by the findings in (Huang et al., 2024), we find that zero-shot models are susceptible to prompt and as result of this we compare three different prompts for zero-shot evaluation. We provide more details about our prompts in Table 3.

**Supervised Finetuning.** We train K-Nearest Neighbors (KNN) and Neural Networks (NN) classifiers on audio feature representations extracted from speech foundation models. Both encoder and decode features from each model were used, eval-

uating classification performance across individual layers as well as mean-pooled features. We standardize the representation using StandardScaler to ensure numerical stability during training. For both KNN and NN, We used 5-fold stratified cross-validation for all tasks. The primary evaluation metric utilized in our experiments was the F1 score, which measures the harmonic mean of precision and recall across all classes for each task. We computed results using k-fold cross-validation, averaging the Macro-F1 scores across folds and reporting standard deviations to quantify the variability and robustness of the results.

#### 4.4 Setup

We utilize Huggingface Transformers (Wolf et al., 2020)<sup>3</sup> to load the pre-trained speech foundation models. Depending on model size, we run our experiments on either 1xA100 GPU or 4xA100 GPUs (for larger models). For each model, we extract layerwise features, which are then used to train Neural Networks (NN) and run K-Nearest Neighbors (KNN) classifiers, as described in 4.3 and in 3.

We provide specific hyperparameters used in our experiments in Appendix 3.1.

## 5 Results and Discussion

We conduct two primary types of experiments. First, we assess various Speech Foundation Models (SFMs) in a zero-shot setting. Next, we extract layer-wise features from all models and train KNN and NN classifiers using these features. This process is applied across all ten tasks in our study. The following sections detail the results of these experiments.

### 5.1 Zero-Shot Results

In our experiments, we evaluate various SFMs in a zero-shot setting. For this, we test each model’s ability to generalize to different tasks without finetuning, as described in 3.1.

Our findings reveal that while some models perform well on several downstream tasks, their zero-shot performance on other tasks can be worse than the random classifier baseline. For instance, Whisper-large-v3 performs better than random classification in many tasks where it was not explicitly trained, demonstrating its ability to generalize to

<sup>3</sup><https://huggingface.co/docs/transformers/en/index>

Task	W-L-v3	D-L-v3	W-M	W-M.en	SM4T-M	SM4T-v2-L	Qwen2	Qwen2-I
AccentClassification	5.30	6.90	6.27	8.02	10.57	1.28	3.95	4.04
DialogueActClassification	18.27	19.74	16.52	17.97	23.27	9.16	26.37	23.98
EmotionRecognition	4.64	1.70	8.15	5.71	7.33	2.59	19.70	11.53
EnvironmentalSoundClassification	4.55	6.74	8.27	15.06	9.93	1.65	28.46	6.86
HowFarAreYou	29.41	33.51	31.12	26.49	28.41	16.66	24.94	26.22
IntentClassification	19.94	16.42	25.95	24.11	35.61	3.95	30.14	23.24
MultiSpeakerDetection	49.40	58.63	35.87	52.71	45.91	33.48	50.22	41.42
SarcasmDetection	36.33	47.09	44.99	49.12	42.86	35.06	35.06	41.65
SpoofDetection	50.17	45.79	47.76	54.82	48.62	34.46	47.60	8.41
StressDetection	14.48	13.40	13.32	10.31	13.84	2.57	9.42	6.25
<b>Average</b>	23.25	24.99	23.82	26.43	26.64	14.09	27.59	19.36

Table 4: F1 score for zero-shot evaluation, averaged across three prompts. Abbreviations: W - Whisper, L - Large, D - DistilWhisper, M - Medium, SM4T - SeamlessM4T, I - Instruct.

new tasks in zero-shot setting. However, for more complex (more classes) tasks like *Stress Detection* and *Emotion Recognition*, even models such as Whisper fall short, highlighting challenges in generalizing across all task types without fine-tuning. We show zero-shot results in Table 4.

We notice that some models are sensitive to prompt type, with performance varying across tasks. For instance, Whisper-large-v2 performs best with MCQ prompts for Dialogue Act and Spoof Detection, while fill-in-the-blank works better for Environmental Sound Classification. Distil-large-v3 shows consistent performance, indicating lower prompt sensitivity. In contrast, Whisper-medium.en is highly sensitive, especially in tasks like Intent Classification and Spoof Detection. Detailed results for each are in Appendix Table 7.

## 5.2 Classification Results on Layer-wise Features

From our experiments, we observe that *Whisper* models show a convergence of performance, with lower-performing tasks like *Stress Detection* and *Intent Classification* gradually improving in deeper layers, while high-performing tasks like *Multi-Speaker Detection* and *Environmental Sound Classification* maintain strong performance. This suggests deeper layers in *Whisper* learn generalized representations that improve complex tasks without negatively affecting simpler ones.

HuBERT and Wav2Vec perform comparably to Whisper, particularly excelling in *MultiSpeaker Detection*. Wav2Vec shows more layer-wise variability, potentially offering opportunities for task-specific layer selection. Both models improve significantly in Intent Classification in deeper layers, highlighting their strength in semantic tasks.

Qwen2-Audio models exhibit stability across layers, performing consistently well, especially in *Environmental Sound Classification*. The Qwen2-Audio-Instruct variant shows improvement in *Intent Classification* early on, likely due to instruction tuning.

Seamless-medium shows a linear F1 score increase across layers, while Seamless-v2-large remains stable but worse. *Accent Classification* trends downwards in both models, indicating a possible trade-off between accent-specific features and general speech representations.

We also experiment with handcrafted audio features from Librosa to provide a lower bound for the representations learned by the model. Our results show that nearly all models capture better audio features than the best Librosa feature (MFCC), as shown in Figure 2. Detailed results for the Librosa features are provided in Appendix 4.2.

## 5.3 Classifier Selection

The distinction between KNN and models with learnable parameters (e.g., NN) highlights key differences in data interpretation. KNN represents classes as concatenations of convex polytopes, limiting its adaptability to complex decision boundaries, while NNs model arbitrary boundaries, allowing for more flexible and nuanced data interpretations. This flexibility explains NN’s better performance across tasks, as deeper layers refine representations by aggregating categories into connected convex clusters, enhancing classification accuracy, particularly in tasks with subtle class distinctions like *MultiSpeaker Detection* and *Emotion Recognition*.

Comparative analysis shows a clear advantage of Neural Networks (NNs) over KNNs when using

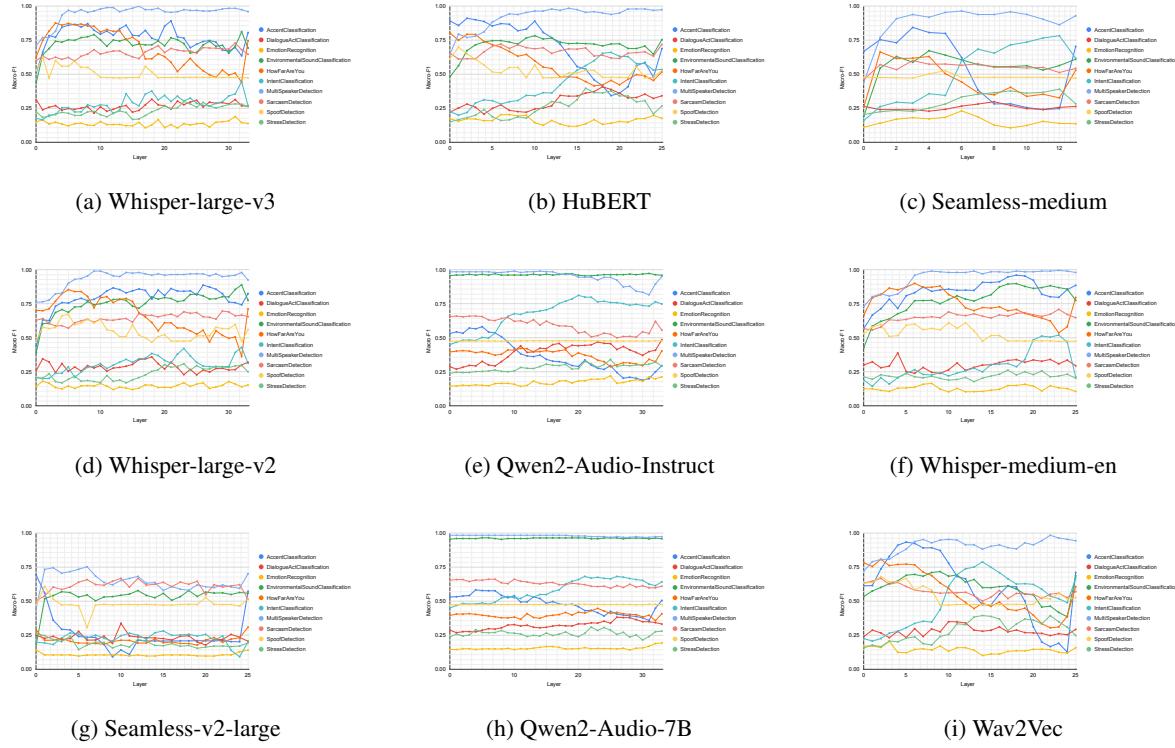


Figure 1: Macro-F1 scores for KNN classifier for different models reported for different layers. We take encoder part of all models except Qwen which is decoder only model.

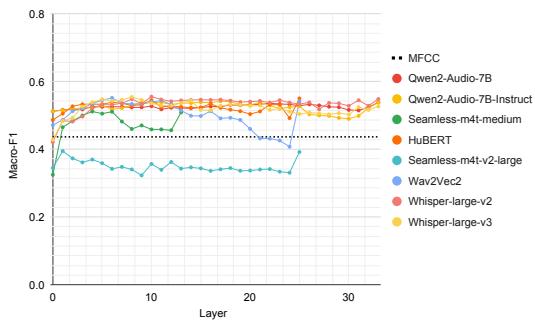


Figure 2: Macro-F1 scores for the KNN classifier, averaged across ten tasks for each layer of all models. The dotted line indicates the Macro-F1 score for MFCC features as a baseline.

features from HuBERT and Wav2Vec, especially in tasks requiring deeper audio understanding, such as *Multi-speaker Detection* and *Intent Classification*. NNs’ hierarchical nature enables them to exploit complex features, leading to superior performance. Following (Jawahar et al., 2019b), we study the features learned by speech foundation models. We quantify the mutual information using Normalized Mutual Information (NMI) and apply t-SNE to visualize the high-dimensional representations. We find that NMI increases in the intermediate layers

of most models, indicating that these layers capture more task-relevant features as shown in 3.

#### 5.4 Layer-wise Performance Analysis

For most models, performance improves in the initial layers before plateauing or slightly declining in later layers, indicating that earlier layers capture more generalizable features. Models like Whisper-large-v3 maintains consistent performance across layers, suggesting that features learned by these layers are robust. However, performance varies significantly across tasks—Accent Classification and MultiSpeaker Detection perform well, while Emotion and Stress Detection are more challenging for most models.

Models like HuBERT and Seamless-Medium show more fluctuations across layers, indicating uneven distribution of task-relevant features. Qwen2-Audio-Instruct exhibits stable performance across layers, hinting at a more distributed feature representation.

These findings underscore the variability in feature extraction across layers and tasks. Simpler tasks may benefit from earlier layers, while complex tasks often require features from later layers.

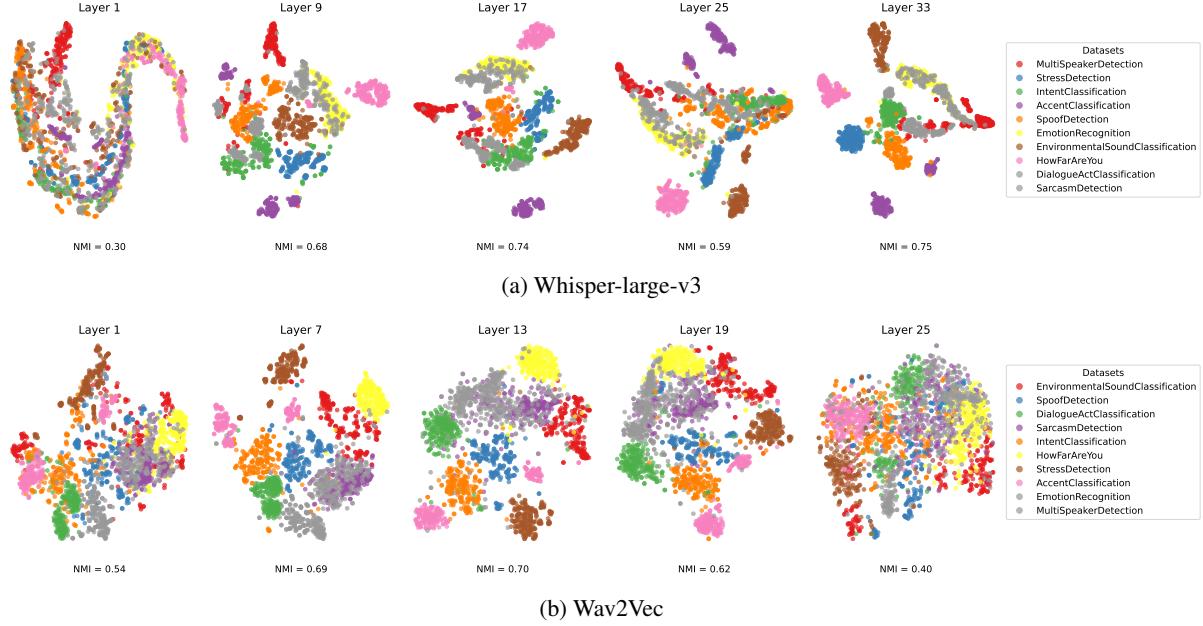


Figure 3: t-SNE embeddings for Wav2Vec and Whisper models.

## 535 5.5 The Role of Model Architecture and 536 Pretraining in Representation Learning

537 The observed patterns across model families emphasize the importance of architecture and  
538 pre-training in capturing task-relevant features. Whisper  
539 models, with their encoder-decoder architecture and large-scale supervised pre-training, show  
540 performance convergence across layers, gradually  
541 improving weaker tasks while maintaining strong  
542 ones.  
543

544 In contrast, self-supervised models like *HuBERT*  
545 and *Wav2Vec* excel in speaker-related tasks due  
546 to their pre-training on unlabeled speech, effectively  
547 capturing fundamental speech characteristics. *Qwen2-Audio*  
548 models exhibit stability across layers, excelling in intent classification, likely due  
549 to their multilingual, multitask pre-training. The  
550 performance difference between *Seamless Medium*  
551 and *Large* models highlights that scaling model  
552 size doesn't always result in uniform improvements  
553 across tasks and layers.  
554

## 556 6 Conclusion

557 We analyzed the feature representations learned  
558 by speech foundation models across various  
559 layers using ten tasks from the Dynamic-SUPERB  
560 benchmark. While models performed well on tasks  
561 like multi-speaker detection and accent classifica-  
562 tion, emotion recognition and stress detection re-  
563 mained challenging, with low F1 scores indicating  
564 difficulty in capturing emotional and contextual

565 subtleties.  
566

567 Our layer-wise analysis showed that earlier layers  
568 capture generalizable features, while mid and  
569 later layers contain more task-specific information.  
570 Models like Whisper and Qwen2-Audio demon-  
571 strated stable performance across layers, while  
572 HuBERT and Wav2Vec showed more variation.  
573 Strong zero-shot performance also correlated with  
574 better representation learning, highlighting the im-  
portance of architecture and pre-training.  
575

## 7 Limitations and Future Works

576 While our study on speech foundation models pro-  
577 vides valuable insights, it has several limitations.  
578 First, the Dynamic-SUPERB tasks selected may  
579 not comprehensively represent all speech-related  
580 challenges, particularly in diverse linguistic and  
581 contextual settings. Additionally, our zero-shot  
582 evaluations occasionally performed worse than ran-  
583 dom, suggesting the need for further investigation  
584 into prompt design and task framing. The choice of  
585 classifiers (K-Nearest Neighbors and Neural Net-  
586 works) and their hyperparameters may have influ-  
587 enced the results, potentially not fully capturing  
588 the models' discriminative capabilities. Moreover,  
589 the real-world applicability of our findings may  
590 be constrained by factors such as data quality and  
591 environmental conditions. Future research should  
592 address these issues to gain a more complete un-  
593 derstanding of model performance across broader  
594 tasks and environments.  
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909		954
910	<b>A Appendix</b>	955
911	<b>B Experiments</b>	956
912		957
913	<b>2.1 Tasks</b>	958
914		959
915	We choose ten tasks, broadly categorizing them into paralinguistic and non-paralinguistic groups. Each task in Dynamic-SUPERB comes with clearly defined instructions, facilitating the effective evaluation of model performance in previously unseen contexts.	960
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921	<b>Dialogue Act Classification.</b> This task involves identifying the primary purpose of an utterance	966
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within its conversational context. Using the DailyTalk Dataset, the goal is to classify utterances into categories such as question, inform, directive, or commissive.

**Accent Classification.** This task focuses on recognizing and classifying different speech accents, utilizing the AccentDB Extended Dataset. Participants aim to accurately identify accents such as American, Australian, Bangla, British, Indian, Malayalam, Odiya, Telugu, or Welsh based on audio samples.

**Emotion Recognition.** The objective here is to classify the emotional category of an utterance, using the Multimodal EmotionLines Dataset. This task can be challenging, as it often requires analyzing not just the linguistic content but also paralinguistic features like pitch and rhythm.

**Stress Detection.** This task involves analyzing stress placement in English words using the MIRSD dataset. The goal is to identify stress patterns, with possible responses ranging from zero to five, which is important for developing nuanced speech models.

**Environmental Sound Classification.** Focusing on recognizing and categorizing environmental sounds, this task employs the ESC50 dataset. Sounds are classified into five categories:

Animals (e.g., dog, cat) Urban Noises (e.g., siren, chainsaw) Human and Non-Speech Sounds (e.g., coughing, laughing) Domestic Sounds (e.g., door knocks, vacuum cleaner) Natural Soundscapes (e.g., rain, thunder)

**HowFarAreYou.** This task assesses the speaker’s distance from a sound source using the 3DSpeaker dataset. Responses indicate distance in meters (e.g., 0.4m, 2.0m), providing insights into audio spatial characteristics critical for auditory scene analysis

**Intent Classification.** This task focuses on identifying the actionable item behind spoken messages, using the FluentSpeechCommands Dataset. The goal is to categorize intents such as activate, deactivate, or change language.

**Sarcasm Detection.** This task aims to identify sarcasm or irony in speech audio, utilizing the MUSTARD dataset. The objective is to determine the presence of sarcasm, with answers being either true or false.

## 2.2 Speech Foundation Models

**Qwen2-Audio (Chu et al., 2024, 2023).** Qwenaudio addresses the challenge of co-training multiple tasks and datasets through a multitask training

framework. The model conditions the decoder output as hierarchical labels, working across more than 30 tasks, eight languages, and various audio types. It mitigates differences in task goals, languages, annotation granularity, and text structure by sharing labels. Qwen-Audio features an audio encoder and the Qwen-7B large language model, a 32-layer Transformer decoder with a hidden size of 4096, totaling 7.7 billion parameters. It employs a unified decoder framework, leveraging self-supervised learning on unlabeled data with task-specific adapters for downstream applications, such as ASR, TTS, voice conversion, and speech translation.

**HuBERT (Hsu et al., 2021b).** HuBERT is pre-trained using 960 hours of data from the LibriSpeech dataset. It is built on the BERT architecture with a multi-layer convolutional feature encoder and a Transformer network for contextualized representations. HuBERT learns discrete speech units iteratively by masking input features to predict hidden units and applying contrastive loss to enhance speech representation learning. The model is primarily used for ASR, speaker identification, emotion recognition, and speech enhancement.

**Wav2Vec (Baevski et al., 2020b).** Wav2Vec is pretrained on 960 hours of LibriSpeech data (base model) and 60,000 hours of Libri-Light data (large model). The model uses a convolutional feature encoder and a Transformer for context representation. It also includes a quantization module to learn discrete units. By masking latent representations and applying contrastive learning, Wav2Vec 2.0 identifies accurate speech representations. The model’s downstream tasks include ASR, speaker identification, language identification, and emotion recognition.

**Seamless (Barrault et al., 2023a).** Seamless is trained on large-scale multilingual speech and text datasets, though specific details are not publicly disclosed. The model uses a modular approach with distinct components for recognition, translation, and synthesis, leveraging Transformer-based architectures. Seamless supports tasks such as speech-to-speech and speech-to-text translation, TTS, and ASR. It integrates these components for end-to-end optimization, sharing representations across modalities to enhance translation quality and naturalness.

**Whisper (Radford et al., 2023).** Whisper is trained on 680,000 hours of multilingual and multitask supervised data sourced from the web. The

1026 model employs an encoder-decoder Transformer  
1027 architecture, with a convolutional layer for process-  
1028 ing raw audio inputs. It uses multi-task training to  
1029 handle a variety of tasks, including ASR, speech  
1030 translation, language identification, and voice ac-  
1031 tivity detection. Whisper processes raw audio with  
1032 a convolutional network, encodes it into contextual-  
1033 ized representations via a Transformer, and decodes  
1034 it into textual outputs using task-specific tokens for  
1035 different languages and tasks.

### 4.3 Classificatin Results on Layer-wise Features

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## C Training

### 3.1 Hyperparameters

Hyperparameter	Value
Neighbors (k)	5
Folds	5
Metric	Macro-F1

Table 5: KNN Hyperparameters

Hyperparameter	Value
Input Size	$\in \mathbb{R}^n$
Hidden Size	128
Layers	2
Activation	ReLU
Optimizer	Adam
Learning Rate	0.001
Loss	Cross-Entropy
Batch Size	16
Epochs	20
Folds	5
Metric	Macro-F1

Table 6: Hyperparameters for neural network classifier.

## D Results

### 4.1 Zero-shot Results

### 4.2 Librosa Features Results

Model	Prompt	Accent	DialAct	Emotion	EnvSound	HowFar	Intent	MSpeaker	Sarcasm	Spoof	Stress
Random		9.66	23.59	11.31	9.86	33.53	15.32	49.76	49.43	39.76	12.55
W-L-v2	MCQ	5.54	27.89	6.70	6.97	34.50	27.51	37.11	43.98	52.99	9.02
	Quiz	9.96	25.68	7.35	10.21	25.39	25.83	33.33	47.87	52.00	11.32
	Blank	9.60	28.10	7.62	10.69	23.76	24.68	34.20	44.61	50.07	11.78
W-L-v3	MCQ	4.60	17.34	4.37	1.18	28.11	22.37	47.05	36.48	48.90	12.17
	Quiz	5.71	20.14	4.71	8.38	32.33	21.01	50.55	36.48	49.34	16.96
	Blank	5.59	17.34	4.85	4.10	27.78	16.45	50.60	36.03	52.28	14.31
W-M.en	MCQ	8.81	21.74	5.33	14.92	25.99	29.29	58.00	51.46	54.40	10.76
	Quiz	7.30	16.16	7.45	10.58	25.14	21.89	51.86	48.30	55.84	10.90
	Blank	7.94	16.01	4.35	19.67	28.33	21.15	48.26	47.59	54.21	9.26
W-M	MCQ	3.84	16.30	8.52	3.57	29.75	29.72	36.77	45.45	50.28	11.33
	Quiz	6.79	15.12	9.97	4.98	33.23	24.65	37.36	45.36	46.67	14.63
	Blank	8.17	18.13	5.97	16.27	30.39	23.49	33.49	44.15	46.32	14.00
SM4T-M	MCQ	10.57	23.27	7.33	9.93	28.41	35.61	45.91	42.86	48.62	13.84
	Quiz	10.57	23.27	7.33	9.93	28.41	35.61	45.91	42.86	48.62	13.84
	Blank	10.57	23.27	7.33	9.93	28.41	35.61	45.91	42.86	48.62	13.84
SM4T-v2-L	MCQ	1.55	4.34	3.83	1.74	16.16	2.18	33.77	35.06	47.78	1.74
	Quiz	1.55	7.26	2.83	1.74	16.54	7.49	32.89	35.06	47.78	1.74
	Blank	0.75	15.87	1.10	1.48	17.28	2.18	33.77	35.06	7.83	4.22
Qwen2	MCQ	2.21	23.33	29.90	30.11	24.60	44.52	32.89	35.06	47.64	10.53
	Quiz	2.11	25.99	2.71	10.19	30.29	16.79	84.01	35.06	47.78	0.34
	Blank	7.51	29.80	26.49	45.07	19.92	29.09	33.77	35.06	47.37	17.38
Qwen2-I	MCQ	4.05	33.15	12.83	3.38	20.23	27.20	32.89	37.71	7.83	0.35
	Quiz	6.40	16.83	10.01	2.23	26.68	23.89	32.89	45.55	9.56	9.55
	Blank	1.68	21.96	11.76	14.98	31.76	18.62	58.50	41.69	7.83	8.86

Table 7: Zero-shot results for different prompts. Abbreviations: W - Whisper, L - Large, D - DistilWhisper, M - Medium, SM4T - SeamlessM4T, I - Instruct.

Feature	Accent	DialAct	Emotion	EnvSound	Distance	Intent	MSpeaker	Sarcasm	Spoof	Stress
MFCC	27.8 <sup>6.1</sup> / 44.2 <sup>6.9</sup>	54.9 <sup>9.1</sup> / 68.0 <sup>13.7</sup>	60.0 <sup>16.3</sup> / 75.3 <sup>10.6</sup>	16.5 <sup>5.6</sup> / 23.3 <sup>4.6</sup>	73.3 <sup>3.6</sup> / 90.0 <sup>2.5</sup>	83.3 <sup>11.1</sup> / 85.3 <sup>7.3</sup>	28.0 <sup>6.6</sup> / 29.6 <sup>5.3</sup>	59.5 <sup>11.8</sup> / 71.6 <sup>3.0</sup>	15.7 <sup>2.2</sup> / 20.8 <sup>0.9</sup>	17.6 <sup>4.2</sup> / 17.5 <sup>3.2</sup>
Mel-Spectrogram	27.8 <sup>7.4</sup> / 40.6 <sup>6.9</sup>	47.5 <sup>0.5</sup> / 47.8 <sup>0.3</sup>	52.9 <sup>4.6</sup> / 63.3 <sup>2.1</sup>	18.0 <sup>2.2</sup> / 27.7 <sup>2.5</sup>	62.4 <sup>7.6</sup> / 57.2 <sup>5.5</sup>	47.0 <sup>6.0</sup> / 65.5 <sup>8.3</sup>	24.1 <sup>6.8</sup> / 27.3 <sup>5.3</sup>	52.1 <sup>9.3</sup> / 61.8 <sup>5.1</sup>	22.0 <sup>0.9</sup> / 23.2 <sup>6.1</sup>	12.6 <sup>3.8</sup> / 14.5 <sup>9.0</sup>
Chroma CENS	23.2 <sup>4.0</sup> / 30.4 <sup>5.7</sup>	51.6 <sup>8.2</sup> / 47.8 <sup>0.3</sup>	54.4 <sup>6.7</sup> / 59.8 <sup>5.2</sup>	11.7 <sup>1.7</sup> / 19.0 <sup>4.5</sup>	49.8 <sup>4.8</sup> / 56.4 <sup>2.5</sup>	43.3 <sup>7.6</sup> / 39.5 <sup>8.9</sup>	21.5 <sup>7.3</sup> / 24.8 <sup>4.8</sup>	39.6 <sup>6.8</sup> / 57.9 <sup>3.8</sup>	26.0 <sup>0.5</sup> / 21.1 <sup>2.8</sup>	15.4 <sup>3.7</sup> / 10.7 <sup>1.1</sup>

Table 8: Performance of KNN / DNN classifiers across tasks using MFCC, Mel Spectrogram, and Chroma CENS features. We report five folds cross-validation scores, with standard deviations shown as superscripts.

Layer	Accent	DialAct	Emotion	EnvSound	Distance	Intent	MSpeaker	Sarcasm	Spooft	Stress
En-0	43.5 <sup>5.4</sup> / 86.3 <sup>3.7</sup>	25.9 <sup>8.4</sup> / 37.9 <sup>4.7</sup>	14.3 <sup>4.6</sup> / 18.8 <sup>1.3</sup>	39.1 <sup>1.8</sup> / 69.2 <sup>3.2</sup>	70.2 <sup>6.1</sup> / 90.1 <sup>5.7</sup>	21.0 <sup>6.8</sup> / 32.5 <sup>7.1</sup>	76.2 <sup>9.0</sup> / 85.8 <sup>7.8</sup>	62.8 <sup>13.8</sup> / 74.4 <sup>9.3</sup>	47.6 <sup>0.3</sup> / 79.5 <sup>6.9</sup>	20.5 <sup>5.0</sup> / 25.8 <sup>5.5</sup>
En-1	63.1 <sup>7.5</sup> / 84.8 <sup>5.4</sup>	34.5 <sup>10.2</sup> / 36.4 <sup>4.2</sup>	18.1 <sup>4.1</sup> / 25.7 <sup>6.7</sup>	60.4 <sup>3.6</sup> / 81.5 <sup>3.4</sup>	69.8 <sup>4.5</sup> / 88.6 <sup>9.9</sup>	20.0 <sup>4.6</sup> / 31.9 <sup>1.0</sup>	76.4 <sup>9.2</sup> / 86.4 <sup>8.9</sup>	64.1 <sup>11.7</sup> / 76.1 <sup>11.1</sup>	57.9 <sup>12.9</sup> / 84.3 <sup>9.5</sup>	20.3 <sup>5.0</sup> / 26.9 <sup>6.3</sup>
En-2	62.7 <sup>6.7</sup> / 83.3 <sup>5.3</sup>	32.3 <sup>9.8</sup> / 38.4 <sup>2.2</sup>	16.7 <sup>5.6</sup> / 20.8 <sup>3.7</sup>	60.6 <sup>6.6</sup> / 81.6 <sup>4.3</sup>	71.3 <sup>4.9</sup> / 87.7 <sup>7.7</sup>	20.1 <sup>5.7</sup> / 32.5 <sup>4.7</sup>	77.6 <sup>8.2</sup> / 91.8 <sup>8.2</sup>	60.5 <sup>8.4</sup> / 74.3 <sup>11.6</sup>	56.8 <sup>11.7</sup> / 76.5 <sup>8.6</sup>	23.5 <sup>4.6</sup> / 26.7 <sup>6.9</sup>
En-3	73.2 <sup>6.9</sup> / 85.3 <sup>5.5</sup>	24.4 <sup>6.4</sup> / 39.8 <sup>3.9</sup>	13.4 <sup>1.5</sup> / 20.3 <sup>4.3</sup>	68.6 <sup>7.9</sup> / 85.5 <sup>2.2</sup>	76.9 <sup>4.4</sup> / 89.6 <sup>1.0</sup>	23.9 <sup>4.2</sup> / 35.5 <sup>4.7</sup>	82.3 <sup>9.3</sup> / 92.3 <sup>4.7</sup>	58.7 <sup>13.2</sup> / 71.7 <sup>9.5</sup>	57.6 <sup>13.8</sup> / 79.0 <sup>6.0</sup>	17.8 <sup>3.2</sup> / 30.1 <sup>3.6</sup>
En-4	75.9 <sup>4.3</sup> / 91.2 <sup>3.8</sup>	31.7 <sup>7.3</sup> / 37.5 <sup>3.7</sup>	12.5 <sup>1.9</sup> / 25.2 <sup>10.3</sup>	70.7 <sup>3.8</sup> / 87.7 <sup>2.9</sup>	82.4 <sup>5.6</sup> / 88.2 <sup>2.5</sup>	23.9 <sup>4.8</sup> / 37.2 <sup>1.1</sup>	82.9 <sup>0.0</sup> / 95.4 <sup>4.7</sup>	58.9 <sup>11.8</sup> / 71.6 <sup>12.2</sup>	66.2 <sup>12.0</sup> / 70.7 <sup>12.5</sup>	16.8 <sup>2.4</sup> / 29.7 <sup>3.2</sup>
En-5	75.5 <sup>5.5</sup> / 88.1 <sup>1.9</sup>	25.3 <sup>4.0</sup> / 39.8 <sup>6.3</sup>	14.5 <sup>3.2</sup> / 21.0 <sup>3.5</sup>	68.7 <sup>2.8</sup> / 87.2 <sup>1.5</sup>	85.4 <sup>3.8</sup> / 92.1 <sup>1.0</sup>	28.6 <sup>6.9</sup> / 40.8 <sup>1.5</sup>	90.0 <sup>6.1</sup> / 97.5 <sup>3.2</sup>	57.1 <sup>13.5</sup> / 74.3 <sup>9.6</sup>	67.1 <sup>11.3</sup> / 73.9 <sup>4.0</sup>	19.5 <sup>1.9</sup> / 33.2 <sup>4.5</sup>
En-6	77.7 <sup>6.6</sup> / 89.4 <sup>5.4</sup>	28.5 <sup>2.6</sup> / 34.5 <sup>6.7</sup>	12.8 <sup>3.2</sup> / 20.3 <sup>3.3</sup>	72.6 <sup>5.1</sup> / 86.4 <sup>3.5</sup>	84.0 <sup>4.0</sup> / 92.1 <sup>1.9</sup>	20.9 <sup>3.7</sup> / 41.3 <sup>2.3</sup>	93.0 <sup>2.9</sup> / 99.0 <sup>1.2</sup>	61.0 <sup>16.4</sup> / 70.9 <sup>14.3</sup>	59.6 <sup>15.2</sup> / 72.4 <sup>12.6</sup>	21.8 <sup>4.9</sup> / 30.9 <sup>5.7</sup>
En-7	79.0 <sup>6.5</sup> / 92.9 <sup>4.7</sup>	25.6 <sup>2.2</sup> / 39.2 <sup>7.0</sup>	14.6 <sup>2.6</sup> / 19.2 <sup>1.9</sup>	72.9 <sup>1.1</sup> / 88.3 <sup>2.2</sup>	84.0 <sup>5.7</sup> / 90.7 <sup>3.3</sup>	24.9 <sup>8.5</sup> / 39.6 <sup>2.0</sup>	93.5 <sup>2.5</sup> / 99.0 <sup>1.2</sup>	62.6 <sup>10.8</sup> / 72.7 <sup>14.1</sup>	60.9 <sup>11.2</sup> / 83.1 <sup>5.9</sup>	18.0 <sup>1.9</sup> / 30.1 <sup>8.6</sup>
En-8	77.3 <sup>7.7</sup> / 92.7 <sup>1.1</sup>	29.5 <sup>6.7</sup> / 38.3 <sup>2.1</sup>	14.9 <sup>2.7</sup> / 21.4 <sup>5.3</sup>	76.6 <sup>5.4</sup> / 88.9 <sup>1.0</sup>	80.4 <sup>3.6</sup> / 91.6 <sup>2.0</sup>	28.4 <sup>3.7</sup> / 39.2 <sup>5.1</sup>	95.5 <sup>1.9</sup> / 99.0 <sup>1.2</sup>	63.6 <sup>11.9</sup> / 77.6 <sup>11.7</sup>	63.7 <sup>14.1</sup> / 77.6 <sup>3.8</sup>	18.6 <sup>4.3</sup> / 29.4 <sup>4.7</sup>
En-9	78.2 <sup>10.1</sup> / 89.2 <sup>5.5</sup>	27.8 <sup>6.9</sup> / 35.7 <sup>5.8</sup>	14.5 <sup>2.5</sup> / 19.6 <sup>4.2</sup>	74.3 <sup>1.7</sup> / 87.2 <sup>4.9</sup>	72.0 <sup>5.5</sup> / 90.1 <sup>1.5</sup>	28.9 <sup>2.1</sup> / 42.3 <sup>2.9</sup>	99.0 <sup>1.2</sup> / 99.5 <sup>1.0</sup>	61.4 <sup>12.9</sup> / 76.2 <sup>11.8</sup>	60.9 <sup>11.2</sup> / 75.1 <sup>6.7</sup>	17.9 <sup>4.5</sup> / 27.1 <sup>6.5</sup>
En-10	80.7 <sup>9.0</sup> / 89.6 <sup>5.8</sup>	29.5 <sup>7.2</sup> / 38.5 <sup>5.1</sup>	16.4 <sup>1.8</sup> / 22.3 <sup>5.0</sup>	75.0 <sup>3.3</sup> / 88.6 <sup>4.8</sup>	79.4 <sup>4.3</sup> / 91.0 <sup>0.7</sup>	31.1 <sup>5.3</sup> / 47.7 <sup>1.5</sup>	99.0 <sup>1.2</sup> / 99.5 <sup>1.0</sup>	63.8 <sup>12.0</sup> / 77.1 <sup>0.8</sup>	63.5 <sup>8.5</sup> / 79.8 <sup>6.2</sup>	17.0 <sup>4.7</sup> / 28.7 <sup>6.2</sup>
En-11	84.4 <sup>10.2</sup> / 90.7 <sup>6.7</sup>	25.4 <sup>9.4</sup> / 39.7 <sup>5.4</sup>	14.6 <sup>0.9</sup> / 19.1 <sup>2.1</sup>	76.1 <sup>5.1</sup> / 89.3 <sup>4.1</sup>	80.2 <sup>2.1</sup> / 95.1 <sup>2.4</sup>	27.4 <sup>6.5</sup> / 49.3 <sup>7.3</sup>	97.5 <sup>1.6</sup> / 99.5 <sup>1.0</sup>	63.1 <sup>14.2</sup> / 77.6 <sup>11.5</sup>	56.0 <sup>11.0</sup> / 85.1 <sup>9.2</sup>	22.3 <sup>3.2</sup> / 33.6 <sup>7.7</sup>
En-12	86.7 <sup>8.8</sup> / 89.4 <sup>5.4</sup>	27.7 <sup>6.4</sup> / 45.3 <sup>2.7</sup>	11.9 <sup>2.0</sup> / 22.0 <sup>0.9</sup>	78.1 <sup>2.2</sup> / 92.0 <sup>5.2</sup>	75.9 <sup>7.2</sup> / 89.6 <sup>3.7</sup>	29.9 <sup>7.7</sup> / 47.4 <sup>1.5</sup>	95.5 <sup>3.3</sup> / 99.0 <sup>1.2</sup>	62.9 <sup>13.3</sup> / 77.2 <sup>13.6</sup>	54.9 <sup>9.1</sup> / 85.3 <sup>2.2</sup>	18.0 <sup>7.6</sup> / 29.6 <sup>6.4</sup>
En-13	85.4 <sup>11.9</sup> / 91.9 <sup>5.7</sup>	28.2 <sup>4.6</sup> / 40.1 <sup>5.2</sup>	13.7 <sup>4.1</sup> / 20.4 <sup>5.4</sup>	78.4 <sup>2.4</sup> / 92.6 <sup>3.9</sup>	78.2 <sup>4.4</sup> / 88.7 <sup>2.5</sup>	32.1 <sup>8.2</sup> / 48.9 <sup>3.6</sup>	95.0 <sup>3.5</sup> / 99.0 <sup>1.2</sup>	63.6 <sup>10.1</sup> / 73.2 <sup>11.5</sup>	50.8 <sup>8.6</sup> / 85.7 <sup>10.6</sup>	19.0 <sup>0.0</sup> / 28.8 <sup>5.3</sup>
En-14	83.0 <sup>10.5</sup> / 92.1 <sup>4.0</sup>	29.1 <sup>4.2</sup> / 41.6 <sup>8.7</sup>	13.1 <sup>3.0</sup> / 21.6 <sup>2.9</sup>	77.4 <sup>2.9</sup> / 93.2 <sup>2.6</sup>	78.9 <sup>0.0</sup> / 90.4 <sup>0.8</sup>	34.2 <sup>6.7</sup> / 48.4 <sup>6.9</sup>	98.0 <sup>1.9</sup> / 99.5 <sup>1.0</sup>	64.1 <sup>11.2</sup> / 76.4 <sup>11.6</sup>	51.0 <sup>6.5</sup> / 84.4 <sup>0.7</sup>	16.9 <sup>4.2</sup> / 30.8 <sup>6.3</sup>
En-15	84.5 <sup>12.5</sup> / 92.9 <sup>5.5</sup>	30.4 <sup>3.4</sup> / 43.8 <sup>4.5</sup>	12.0 <sup>2.9</sup> / 19.0 <sup>2.7</sup>	73.2 <sup>4.5</sup> / 88.4 <sup>2.6</sup>	76.7 <sup>5.9</sup> / 85.6 <sup>3.3</sup>	32.0 <sup>3.6</sup> / 53.0 <sup>1.3</sup>	97.5 <sup>1.6</sup> / 99.0 <sup>1.2</sup>	61.5 <sup>10.9</sup> / 75.8 <sup>10.9</sup>	59.6 <sup>10.5</sup> / 79.7 <sup>9.7</sup>	19.1 <sup>3.3</sup> / 33.0 <sup>6.6</sup>
En-16	85.9 <sup>10.7</sup> / 94.7 <sup>3.7</sup>	34.0 <sup>3.8</sup> / 41.9 <sup>3.7</sup>	13.0 <sup>3.5</sup> / 20.4 <sup>1.1</sup>	71.7 <sup>0.7</sup> / 86.2 <sup>4.3</sup>	68.4 <sup>10.4</sup> / 84.2 <sup>4.3</sup>	27.4 <sup>5.9</sup> / 55.3 <sup>8.2</sup>	98.0 <sup>2.5</sup> / 99.5 <sup>1.0</sup>	67.7 <sup>10.9</sup> / 74.7 <sup>11.7</sup>	51.9 <sup>8.4</sup> / 79.0 <sup>0.8</sup>	20.7 <sup>7.3</sup> / 32.7 <sup>6.6</sup>
En-17	84.8 <sup>9.1</sup> / 92.9 <sup>1.4</sup>	34.5 <sup>6.0</sup> / 46.1 <sup>3.5</sup>	15.4 <sup>3.3</sup> / 22.6 <sup>3.0</sup>	75.7 <sup>2.6</sup> / 89.1 <sup>1.3</sup>	65.3 <sup>7.7</sup> / 82.2 <sup>3.0</sup>	35.0 <sup>4.8</sup> / 57.6 <sup>2.0</sup>	97.0 <sup>2.5</sup> / 99.0 <sup>1.2</sup>	66.6 <sup>11.3</sup> / 76.0 <sup>6.9</sup>	50.5 <sup>1.5</sup> / 73.2 <sup>14.2</sup>	22.6 <sup>4.6</sup> / 34.9 <sup>6.0</sup>
En-18	78.4 <sup>5.5</sup> / 93.3 <sup>5.2</sup>	35.9 <sup>7.8</sup> / 41.4 <sup>5.1</sup>	15.2 <sup>4.4</sup> / 20.9 <sup>3.8</sup>	80.0 <sup>5.3</sup> / 91.2 <sup>0.5</sup>	61.2 <sup>5.5</sup> / 78.3 <sup>2.3</sup>	38.5 <sup>8.4</sup> / 58.7 <sup>5.9</sup>	96.0 <sup>3.0</sup> / 99.0 <sup>1.2</sup>	66.5 <sup>11.1</sup> / 72.9 <sup>8.9</sup>	46.8 <sup>1.1</sup> / 73.2 <sup>14.2</sup>	25.3 <sup>2.7</sup> / 37.8 <sup>6.0</sup>
En-19	85.0 <sup>8.0</sup> / 91.8 <sup>5.9</sup>	30.9 <sup>3.2</sup> / 40.7 <sup>6.1</sup>	13.4 <sup>1.7</sup> / 21.9 <sup>4.7</sup>	78.4 <sup>1.7</sup> / 91.6 <sup>3.8</sup>	55.1 <sup>4.4</sup> / 77.4 <sup>5.8</sup>	37.0 <sup>6.3</sup> / 56.7 <sup>8.2</sup>	97.0 <sup>1.9</sup> / 98.5 <sup>2.0</sup>	65.4 <sup>13.2</sup> / 75.3 <sup>11.2</sup>	50.8 <sup>6.6</sup> / 73.2 <sup>14.2</sup>	26.5 <sup>3.2</sup> / 36.4 <sup>6.8</sup>
En-20	81.0 <sup>6.8</sup> / 92.8 <sup>3.4</sup>	27.7 <sup>0.2</sup> / 39.8 <sup>3.6</sup>	13.6 <sup>3.0</sup> / 20.6 <sup>5.5</sup>	79.6 <sup>1.2</sup> / 90.9 <sup>4.8</sup>	61.1 <sup>4.9</sup> / 76.6 <sup>4.2</sup>	33.3 <sup>3.4</sup> / 57.1 <sup>6.8</sup>	96.0 <sup>2.6</sup> / 99.0 <sup>1.2</sup>	66.5 <sup>14.2</sup> / 76.3 <sup>10.4</sup>	52.3 <sup>10.7</sup> / 68.1 <sup>17.4</sup>	30.4 <sup>3.5</sup> / 39.2 <sup>5.9</sup>
En-21	86.2 <sup>8.0</sup> / 94.5 <sup>4.8</sup>	32.0 <sup>5.5</sup> / 46.3 <sup>6.5</sup>	13.4 <sup>2.7</sup> / 21.7 <sup>4.2</sup>	78.9 <sup>5.5</sup> / 92.6 <sup>4.2</sup>	61.0 <sup>10.0</sup> / 76.4 <sup>2.2</sup>	47.0 <sup>2.7</sup> / 72.1 <sup>5.5</sup>	95.5 <sup>7.7</sup> / 99.5 <sup>1.0</sup>	65.1 <sup>9.4</sup> / 77.2 <sup>8.7</sup>	51.5 <sup>8.3</sup> / 70.0 <sup>19.5</sup>	27.0 <sup>7.7</sup> / 41.0 <sup>5.7</sup>
En-22	84.3 <sup>9.2</sup> / 95.6 <sup>3.8</sup>	28.1 <sup>4.9</sup> / 42.8 <sup>7.0</sup>	15.1 <sup>1.5</sup> / 19.9 <sup>6.3</sup>	76.6 <sup>7.6</sup> / 82.8 <sup>3.6</sup>	77.2 <sup>6.6</sup> / 92.8 <sup>3.6</sup>	37.2 <sup>3.8</sup> / 71.2 <sup>1.3</sup>	80.0 <sup>4.6</sup> / 92.5 <sup>1.0</sup>	65.5 <sup>12.1</sup> / 78.7 <sup>1.7</sup>	47.5 <sup>0.5</sup> / 65.0 <sup>4.4</sup>	29.0 <sup>10.0</sup> / 39.5 <sup>4.5</sup>
En-23	84.2 <sup>10.2</sup> / 93.8 <sup>4.7</sup>	22.9 <sup>4.7</sup> / 39.6 <sup>7.7</sup>	16.9 <sup>2.1</sup> / 20.4 <sup>4.1</sup>	77.3 <sup>5.6</sup> / 92.1 <sup>4.6</sup>	57.2 <sup>8.9</sup> / 71.9 <sup>5.5</sup>	42.2 <sup>5.7</sup> / 53.5 <sup>6.1</sup>	96.5 <sup>2.0</sup> / 99.0 <sup>1.2</sup>	69.2 <sup>9.1</sup> / 78.4 <sup>12.0</sup>	47.6 <sup>0.5</sup> / 65.0 <sup>4.4</sup>	30.9 <sup>10.2</sup> / 35.8 <sup>6.7</sup>
En-24	84.5 <sup>8.2</sup> / 91.5 <sup>6.6</sup>	26.7 <sup>4.9</sup> / 40.7 <sup>8.7</sup>	14.3 <sup>2.4</sup> / 21.3 <sup>4.2</sup>	81.8 <sup>1.3</sup> / 92.0 <sup>3.6</sup>	55.1 <sup>2.6</sup> / 92.5 <sup>0.0</sup>	36.7 <sup>4.7</sup> / 52.9 <sup>7.0</sup>	97.0 <sup>1.9</sup> / 99.0 <sup>1.2</sup>	68.0 <sup>11.1</sup> / 76.8 <sup>9.2</sup>	47.6 <sup>0.5</sup> / 67.9 <sup>17.5</sup>	26.2 <sup>8.5</sup> / 32.3 <sup>6.0</sup>
En-25	81.6 <sup>14.5</sup> / 93.2 <sup>5.1</sup>	23.8 <sup>4.2</sup> / 41.6 <sup>7.3</sup>	16.0 <sup>4.0</sup> / 23.4 <sup>3.4</sup>	82.1 <sup>3.7</sup> / 92.2 <sup>4.2</sup>	52.7 <sup>5.3</sup> / 69.0 <sup>4.9</sup>	31.9 <sup>6.0</sup> / 58.2 <sup>7.2</sup>	97.0 <sup>1.9</sup> / 99.5 <sup>1.0</sup>	68.5 <sup>12.3</sup> / 77.6 <sup>9.7</sup>	51.3 <sup>8.3</sup> / 68.1 <sup>17.4</sup>	29.5 <sup>8.7</sup> / 36.2 <sup>8.0</sup>
En-26	88.7 <sup>7.5</sup> / 95.2 <sup>2.5</sup>	26.4 <sup>6.0</sup> / 42.0 <sup>10.4</sup>	16.8 <sup>3.2</sup> / 22.2 <sup>2.9</sup>	80.8 <sup>6.8</sup> / 92.0 <sup>4.4</sup>	55.6 <sup>6.6</sup> / 71.5 <sup>7.4</sup>	29.2 <sup>2.7</sup> / 47.0 <sup>4.5</sup>	97.0 <sup>2.5</sup> / 99.0 <sup>1.2</sup>	65.5 <sup>7.1</sup> / 77.9 <sup>10.0</sup>	51.5 <sup>8.0</sup> / 70.0 <sup>19.5</sup>	27.0 <sup>7.3</sup> / 41.0 <sup>6.9</sup>
En-27	87.3 <sup>9.0</sup> / 94.1 <sup>0.8</sup>	24.9 <sup>4.0</sup> / 47.3 <sup>6.6</sup>	12.8 <sup>2.2</sup> / 22.2 <sup>2.6</sup>	78.5 <sup>6.0</sup> / 90.2 <sup>2.6</sup>	78.5 <sup>6.0</sup> / 90.2 <sup>2.6</sup>	47.8 <sup>4.1</sup> / 72.7 <sup>2.6</sup>	97.0 <sup>1.9</sup> / 99.5 <sup>1.0</sup>	62.9 <sup>2.3</sup> / 77.6 <sup>8.6</sup>	47.5 <sup>0.3</sup> / 67.3 <sup>19.7</sup>	27.0 <sup>7.7</sup> / 41.0 <sup>5.7</sup>
En-28	85.7 <sup>7.2</sup> / 94.0 <sup>1.8</sup>	27.4 <sup>5.5</sup> / 44.6 <sup>8.7</sup>	13.9 <sup>4.9</sup> / 23.4 <sup>1.3</sup>	78.7 <sup>5.7</sup> / 89.5 <sup>7.0</sup>	55.2 <sup>5.5</sup> / 68.6 <sup>8.7</sup>	38.0 <sup>4.6</sup> / 50.5 <sup>4.8</sup>	97.5 <sup>1.2</sup> / 99.5 <sup>1.0</sup>	63.7 <sup>13.3</sup> / 73.5 <sup>7.0</sup>	57.8 <sup>3.0</sup> / 68.5 <sup>18.2</sup>	29.0 <sup>9.4</sup> / 41.8 <sup>7.8</sup>
En-29	82.5 <sup>9.0</sup> / 95.0 <sup>2.3</sup>	27.6 <sup>3.9</sup> / 92.2 <sup>1.6</sup>	15.1 <sup>3.4</sup> / 21.1 <sup>1.6</sup>	80.2 <sup>5.5</sup> / 91.6 <sup>4.0</sup>	51.8 <sup>8.2</sup> / 71.4 <sup>4.5</sup>	28.8 <sup>6.4</sup> / 51.0 <sup>5.6</sup>	94.9 <sup>4.3</sup> / 99.0 <sup>1.2</sup>	69.7 <sup>9.2</sup> / 80.3 <sup>5.4</sup>	56.8 <sup>1.7</sup> / 70.0 <sup>19.5</sup>	28.5 <sup>4.2</sup> / 40.2 <sup>7.7</sup>
En-30	76.3 <sup>3.8</sup> / 92.2 <sup>1.6</sup>	32.3 <sup>8.2</sup> / 52.4 <sup>3.3</sup>	12.7 <sup>5.1</sup> / 20.8 <sup>3.7</sup>	86.8 <sup>4.4</sup> / 94.7 <sup>2.0</sup>	49.6 <sup>7.7</sup> / 66.5 <sup>5.8</sup>	29.0 <sup>5.1</sup> / 55.2 <sup>5.1</sup>	95.4 <sup>4.5</sup> / 99.0 <sup>1.2</sup>	68.0 <sup>9.9</sup> / 79.7 <sup>6.9</sup>	56.6 <sup>11.8</sup> / 67.7 <sup>17.9</sup>	28.2 <sup>4.6</sup> / 41.9 <sup>7.1</sup>
En-31	75.8 <sup>3.6</sup> / 90.1 <sup>5.7</sup>	26.6 <sup>3.4</sup> / 51.2 <sup>3.2</sup>	16.0 <sup>6.0</sup> / 22.7 <sup>6.1</sup>	85.5 <sup>3.7</sup> / 91.7 <sup>8.2</sup>	50.6 <sup>7.5</sup> / 65.1 <sup>1.9</sup>	39.2 <sup>4.7</sup> / 60.2 <sup>3.0</sup>	96.0 <sup>3.5</sup> / 98.5 <sup>2.0</sup>	66.1 <sup>10.8</sup> / 80.4 <sup>6.3</sup>	59.8 <sup>16.9</sup> / 66.3 <sup>16.1</sup>	29.5 <sup>1.1</sup> / 42.4 <sup>7.3</sup>
En-32	74.2 <sup>8.9</sup> / 90.1 <sup>3.6</sup>	30.1 <sup>4.8</sup> / 52								

Layer	Accent	DialAct	Emotion	EnvSound	Distance	Intent	MSpeaker	Sarcasm	Spoof	Stress
En-0	51.2 <sup>7.8</sup> / 84.6 <sup>6.8</sup>	31.3 <sup>9.2</sup> / 35.9 <sup>4.9</sup>	15.1 <sup>2.7</sup> / 20.7 <sup>2.6</sup>	43.8 <sup>5.9</sup> / 66.4 <sup>2.8</sup>	62.8 <sup>9.4</sup> / 88.0 <sup>2.8</sup>	17.6 <sup>2.5</sup> / 31.1 <sup>6.0</sup>	71.1 <sup>10.6</sup> / 87.4 <sup>7.1</sup>	60.1 <sup>6.7</sup> / 72.8 <sup>9.7</sup>	52.8 <sup>10.5</sup> / 76.7 <sup>4.8</sup>	22.4 <sup>7.3</sup> / 24.4 <sup>5.3</sup>
En-1	66.2 <sup>10.3</sup> / 89.0 <sup>4.7</sup>	23.9 <sup>6.5</sup> / 39.1 <sup>6.1</sup>	16.5 <sup>2.4</sup> / 21.3 <sup>4.9</sup>	64.3 <sup>6.1</sup> / 81.8 <sup>3.2</sup>	74.9 <sup>3.9</sup> / 90.1 <sup>5.5</sup>	16.6 <sup>4.3</sup> / 31.8 <sup>5.5</sup>	77.0 <sup>8.2</sup> / 91.9 <sup>5.5</sup>	63.4 <sup>2.6</sup> / 69.6 <sup>15.6</sup>	62.7 <sup>12.6</sup> / 76.7 <sup>4.3</sup>	18.4 <sup>3.6</sup> / 30.0 <sup>8.5</sup>
En-2	78.4 <sup>6.0</sup> / 92.2 <sup>5.0</sup>	25.8 <sup>5.2</sup> / 36.3 <sup>9.0</sup>	13.5 <sup>1.1</sup> / 18.9 <sup>2.9</sup>	68.9 <sup>3.6</sup> / 84.2 <sup>2.4</sup>	81.7 <sup>4.8</sup> / 93.6 <sup>3.3</sup>	20.0 <sup>5.8</sup> / 38.5 <sup>4.2</sup>	77.2 <sup>8.8</sup> / 93.9 <sup>5.4</sup>	61.0 <sup>4.8</sup> / 72.6 <sup>3.4</sup>	47.2 <sup>0.5</sup> / 83.3 <sup>5.8</sup>	19.1 <sup>4.2</sup> / 30.8 <sup>7.9</sup>
En-3	77.2 <sup>4.1</sup> / 93.4 <sup>2.6</sup>	27.0 <sup>5.6</sup> / 33.4 <sup>7.1</sup>	14.8 <sup>3.1</sup> / 18.7 <sup>3.0</sup>	74.3 <sup>5.2</sup> / 85.7 <sup>3.7</sup>	87.7 <sup>2.6</sup> / 95.0 <sup>2.7</sup>	20.4 <sup>2.3</sup> / 37.5 <sup>4.4</sup>	81.6 <sup>6.5</sup> / 94.9 <sup>5.5</sup>	62.5 <sup>4.1</sup> / 73.0 <sup>2.9</sup>	59.9 <sup>9.9</sup> / 80.7 <sup>5.4</sup>	20.8 <sup>0.1</sup> / 31.9 <sup>8.1</sup>
En-4	84.6 <sup>7.6</sup> / 90.9 <sup>5.1</sup>	23.6 <sup>5.5</sup> / 33.3 <sup>5.1</sup>	13.4 <sup>3.1</sup> / 19.4 <sup>3.7</sup>	73.6 <sup>5.8</sup> / 87.4 <sup>4.3</sup>	86.1 <sup>7.0</sup> / 95.5 <sup>2.9</sup>	25.4 <sup>4.7</sup> / 35.9 <sup>5.2</sup>	93.3 <sup>3.8</sup> / 99.5 <sup>1.0</sup>	61.0 <sup>2.4</sup> / 74.8 <sup>1.1</sup>	55.9 <sup>9.9</sup> / 84.9 <sup>3.6</sup>	22.0 <sup>0.1</sup> / 30.3 <sup>9.2</sup>
En-5	86.0 <sup>3.6</sup> / 91.1 <sup>5.5</sup>	24.8 <sup>8.0</sup> / 34.8 <sup>8.3</sup>	12.1 <sup>2.1</sup> / 18.6 <sup>4.0</sup>	75.3 <sup>3.8</sup> / 88.0 <sup>4.2</sup>	87.4 <sup>3.3</sup> / 92.6 <sup>5.5</sup>	25.5 <sup>2.9</sup> / 37.1 <sup>3.6</sup>	97.0 <sup>1.9</sup> / 99.5 <sup>1.0</sup>	62.4 <sup>5.7</sup> / 76.2 <sup>10.1</sup>	55.9 <sup>9.9</sup> / 85.4 <sup>8.8</sup>	21.3 <sup>2.9</sup> / 29.3 <sup>6.8</sup>
En-6	86.7 <sup>9.5</sup> / 97.1 <sup>2.6</sup>	24.2 <sup>6.6</sup> / 36.8 <sup>6.9</sup>	13.7 <sup>1.9</sup> / 17.4 <sup>3.1</sup>	75.0 <sup>8.8</sup> / 89.7 <sup>3.5</sup>	86.4 <sup>3.4</sup> / 90.5 <sup>0.0</sup>	22.3 <sup>3.9</sup> / 39.6 <sup>5.5</sup>	95.5 <sup>2.9</sup> / 99.0 <sup>1.2</sup>	59.7 <sup>13.2</sup> / 75.8 <sup>0.6</sup>	59.6 <sup>10.5</sup> / 80.1 <sup>5.9</sup>	19.7 <sup>2.6</sup> / 32.0 <sup>6.2</sup>
En-7	84.7 <sup>9.4</sup> / 97.3 <sup>3.9</sup>	25.2 <sup>7.6</sup> / 31.5 <sup>5.3</sup>	14.0 <sup>3.3</sup> / 20.7 <sup>3.1</sup>	77.0 <sup>5.6</sup> / 90.6 <sup>1.6</sup>	86.9 <sup>3.1</sup> / 92.5 <sup>2.8</sup>	22.4 <sup>3.4</sup> / 38.6 <sup>5.2</sup>	97.5 <sup>1.6</sup> / 99.5 <sup>1.0</sup>	63.2 <sup>1.2</sup> / 75.0 <sup>4.7</sup>	55.1 <sup>9.0</sup> / 84.3 <sup>10.5</sup>	19.9 <sup>8.8</sup> / 30.9 <sup>8.9</sup>
En-8	87.2 <sup>4.3</sup> / 94.4 <sup>1.1</sup>	26.3 <sup>8.1</sup> / 32.2 <sup>6.6</sup>	12.6 <sup>4.5</sup> / 19.9 <sup>2.3</sup>	77.6 <sup>3.9</sup> / 88.9 <sup>3.0</sup>	85.4 <sup>3.7</sup> / 94.0 <sup>1.2</sup>	27.6 <sup>4.8</sup> / 39.6 <sup>2.8</sup>	95.5 <sup>1.9</sup> / 99.5 <sup>1.0</sup>	64.8 <sup>4.6</sup> / 76.4 <sup>3.8</sup>	55.1 <sup>9.0</sup> / 84.2 <sup>8.8</sup>	22.4 <sup>5.4</sup> / 29.9 <sup>6.8</sup>
En-9	82.4 <sup>6.1</sup> / 93.4 <sup>3.7</sup>	21.5 <sup>5.2</sup> / 34.4 <sup>5.3</sup>	12.4 <sup>4.1</sup> / 19.4 <sup>2.2</sup>	79.2 <sup>5.7</sup> / 90.2 <sup>2.4</sup>	85.4 <sup>3.0</sup> / 93.1 <sup>3.3</sup>	26.0 <sup>3.6</sup> / 42.9 <sup>3.3</sup>	96.5 <sup>1.2</sup> / 99.0 <sup>1.2</sup>	68.1 <sup>14.2</sup> / 74.3 <sup>3.2</sup>	51.8 <sup>8.1</sup> / 89.1 <sup>6.8</sup>	22.7 <sup>4.8</sup> / 31.7 <sup>5.1</sup>
En-10	79.5 <sup>5.8</sup> / 92.7 <sup>2.9</sup>	26.1 <sup>3.5</sup> / 33.6 <sup>5.2</sup>	15.3 <sup>3.9</sup> / 19.2 <sup>0.7</sup>	75.3 <sup>5.9</sup> / 93.5 <sup>4.7</sup>	81.1 <sup>4.6</sup> / 93.5 <sup>4.7</sup>	27.6 <sup>2.9</sup> / 42.4 <sup>4.4</sup>	98.0 <sup>1.0</sup> / 99.0 <sup>1.2</sup>	64.8 <sup>17.7</sup> / 76.3 <sup>3.4</sup>	47.8 <sup>0.3</sup> / 81.8 <sup>5.0</sup>	20.3 <sup>1.2</sup> / 31.8 <sup>6.3</sup>
En-11	81.8 <sup>6.2</sup> / 91.7 <sup>5.5</sup>	22.8 <sup>3.9</sup> / 33.9 <sup>5.0</sup>	13.0 <sup>4.0</sup> / 18.5 <sup>3.7</sup>	70.6 <sup>5.0</sup> / 89.3 <sup>3.0</sup>	82.9 <sup>3.0</sup> / 89.9 <sup>3.7</sup>	21.4 <sup>7.7</sup> / 42.7 <sup>4.0</sup>	99.0 <sup>1.2</sup> / 99.0 <sup>1.2</sup>	66.1 <sup>15.8</sup> / 76.1 <sup>5.8</sup>	47.6 <sup>6.5</sup> / 78.8 <sup>7.5</sup>	18.8 <sup>2.6</sup> / 34.2 <sup>4.6</sup>
En-12	78.7 <sup>3.0</sup> / 91.8 <sup>4.9</sup>	24.3 <sup>5.5</sup> / 38.0 <sup>5.8</sup>	13.0 <sup>2.2</sup> / 18.0 <sup>1.8</sup>	75.2 <sup>6.1</sup> / 91.8 <sup>3.0</sup>	81.5 <sup>3.4</sup> / 91.5 <sup>3.3</sup>	21.2 <sup>3.7</sup> / 38.1 <sup>5.1</sup>	99.0 <sup>1.2</sup> / 99.0 <sup>1.2</sup>	67.0 <sup>11.2</sup> / 73.5 <sup>16.2</sup>	47.5 <sup>0.7</sup> / 82.2 <sup>6.4</sup>	21.4 <sup>7.3</sup> / 31.1 <sup>5.0</sup>
En-13	83.5 <sup>5.5</sup> / 94.0 <sup>3.6</sup>	26.1 <sup>6.6</sup> / 34.3 <sup>3.8</sup>	13.1 <sup>3.6</sup> / 19.4 <sup>4.3</sup>	74.4 <sup>6.2</sup> / 92.3 <sup>3.6</sup>	82.0 <sup>3.6</sup> / 87.7 <sup>1.7</sup>	23.7 <sup>2.2</sup> / 40.7 <sup>3.5</sup>	96.0 <sup>1.2</sup> / 99.5 <sup>1.0</sup>	67.2 <sup>11.5</sup> / 75.6 <sup>15.4</sup>	47.4 <sup>0.6</sup> / 81.0 <sup>6.4</sup>	23.1 <sup>7.5</sup> / 31.0 <sup>7.0</sup>
En-14	86.0 <sup>5.2</sup> / 93.2 <sup>3.1</sup>	21.7 <sup>5.4</sup> / 34.8 <sup>5.3</sup>	12.3 <sup>3.6</sup> / 21.7 <sup>2.8</sup>	75.9 <sup>5.0</sup> / 91.3 <sup>4.6</sup>	75.4 <sup>4.1</sup> / 86.4 <sup>3.6</sup>	35.7 <sup>3.9</sup> / 43.7 <sup>2.7</sup>	97.5 <sup>1.6</sup> / 99.0 <sup>1.2</sup>	64.6 <sup>9.9</sup> / 73.0 <sup>4.0</sup>	47.5 <sup>0.5</sup> / 85.8 <sup>3.3</sup>	21.9 <sup>4.6</sup> / 32.0 <sup>6.6</sup>
En-15	78.7 <sup>10.2</sup> / 92.7 <sup>3.8</sup>	22.1 <sup>4.4</sup> / 35.7 <sup>6.0</sup>	12.1 <sup>2.3</sup> / 21.5 <sup>4.3</sup>	71.0 <sup>7.4</sup> / 88.9 <sup>5.5</sup>	77.2 <sup>3.4</sup> / 87.0 <sup>0.0</sup>	29.2 <sup>5.5</sup> / 38.4 <sup>3.5</sup>	98.5 <sup>1.2</sup> / 99.0 <sup>1.2</sup>	62.8 <sup>9.9</sup> / 77.3 <sup>2.1</sup>	47.6 <sup>0.3</sup> / 76.5 <sup>14.5</sup>	16.8 <sup>8.3</sup> / 30.9 <sup>5.2</sup>
En-16	78.2 <sup>10.5</sup> / 93.7 <sup>5.0</sup>	23.4 <sup>7.7</sup> / 35.9 <sup>8.6</sup>	14.6 <sup>5.0</sup> / 20.8 <sup>3.5</sup>	72.3 <sup>3.8</sup> / 90.9 <sup>3.5</sup>	73.9 <sup>1.8</sup> / 87.9 <sup>3.3</sup>	100.0 <sup>0.0</sup> / 99.5 <sup>1.0</sup>	61.6 <sup>9.4</sup> / 74.8 <sup>1.5</sup>	47.6 <sup>0.3</sup> / 82.8 <sup>9.8</sup>	17.1 <sup>6.0</sup> / 30.4 <sup>6.4</sup>	
En-17	82.3 <sup>7.3</sup> / 98.7 <sup>1.8</sup>	27.5 <sup>4.0</sup> / 38.7 <sup>5.2</sup>	10.6 <sup>2.9</sup> / 19.9 <sup>2.1</sup>	71.6 <sup>3.3</sup> / 90.5 <sup>2.9</sup>	61.3 <sup>1.0</sup> / 80.3 <sup>1.9</sup>	35.4 <sup>1.9</sup> / 51.0 <sup>2.9</sup>	97.5 <sup>1.6</sup> / 99.5 <sup>1.0</sup>	66.5 <sup>1.7</sup> / 74.1 <sup>11.6</sup>	55.8 <sup>10.0</sup> / 80.7 <sup>5.4</sup>	19.7 <sup>3.0</sup> / 30.7 <sup>2.7</sup>
En-18	76.5 <sup>7.8</sup> / 93.8 <sup>5.1</sup>	31.7 <sup>3.9</sup> / 37.1 <sup>7.6</sup>	12.8 <sup>4.5</sup> / 18.9 <sup>3.5</sup>	71.6 <sup>6.4</sup> / 91.5 <sup>4.6</sup>	61.4 <sup>5.4</sup> / 77.4 <sup>2.6</sup>	37.7 <sup>2.0</sup> / 54.3 <sup>3.4</sup>	97.5 <sup>2.2</sup> / 99.5 <sup>1.0</sup>	68.6 <sup>1.0</sup> / 75.3 <sup>11.3</sup>	51.8 <sup>8.1</sup> / 76.3 <sup>15.6</sup>	22.4 <sup>2.1</sup> / 30.1 <sup>8.1</sup>
En-19	74.8 <sup>7.2</sup> / 91.9 <sup>4.4</sup>	27.5 <sup>6.4</sup> / 38.6 <sup>3.8</sup>	16.7 <sup>7.4</sup> / 23.0 <sup>5.8</sup>	74.5 <sup>3.9</sup> / 94.5 <sup>1.9</sup>	65.1 <sup>6.3</sup> / 78.7 <sup>2.8</sup>	31.2 <sup>3.9</sup> / 48.7 <sup>2.8</sup>	98.5 <sup>1.2</sup> / 99.5 <sup>1.0</sup>	71.0 <sup>12.3</sup> / 77.1 <sup>12.2</sup>	47.5 <sup>0.3</sup> / 73.5 <sup>15.6</sup>	24.2 <sup>7.1</sup> / 30.7 <sup>5.5</sup>
En-20	85.4 <sup>9.2</sup> / 95.4 <sup>2.1</sup>	26.9 <sup>6.3</sup> / 38.2 <sup>3.8</sup>	10.8 <sup>3.5</sup> / 22.6 <sup>2.8</sup>	70.9 <sup>2.6</sup> / 92.7 <sup>2.8</sup>	62.0 <sup>5.3</sup> / 76.7 <sup>3.0</sup>	34.5 <sup>5.8</sup> / 58.4 <sup>6.1</sup>	96.0 <sup>2.0</sup> / 99.5 <sup>1.0</sup>	65.9 <sup>5.7</sup> / 77.7 <sup>11.9</sup>	47.6 <sup>0.3</sup> / 62.6 <sup>12.7</sup>	26.9 <sup>8.0</sup> / 32.6 <sup>0.8</sup>
En-21	89.2 <sup>5.7</sup> / 96.3 <sup>2.8</sup>	24.5 <sup>3.8</sup> / 37.1 <sup>5.9</sup>	10.5 <sup>2.2</sup> / 19.6 <sup>5.5</sup>	76.8 <sup>6.6</sup> / 93.0 <sup>4.2</sup>	82.8 <sup>1.2</sup> / 72.7 <sup>2.7</sup>	30.0 <sup>6.5</sup> / 46.8 <sup>7.2</sup>	95.5 <sup>1.2</sup> / 99.0 <sup>1.2</sup>	69.0 <sup>8.3</sup> / 76.3 <sup>6.6</sup>	47.6 <sup>0.3</sup> / 68.8 <sup>11.1</sup>	24.8 <sup>8.2</sup> / 31.6 <sup>3.3</sup>
En-22	77.5 <sup>14.4</sup> / 91.6 <sup>5.0</sup>	30.3 <sup>4.3</sup> / 41.2 <sup>7.9</sup>	10.5 <sup>2.7</sup> / 20.5 <sup>6.4</sup>	75.4 <sup>8.8</sup> / 91.6 <sup>3.4</sup>	52.0 <sup>1.7</sup> / 72.5 <sup>2.9</sup>	34.6 <sup>6.1</sup> / 41.2 <sup>8.0</sup>	96.0 <sup>1.2</sup> / 99.0 <sup>1.2</sup>	67.7 <sup>1.2</sup> / 76.2 <sup>3.9</sup>	47.8 <sup>0.3</sup> / 64.1 <sup>11.7</sup>	25.3 <sup>2.9</sup> / 36.6 <sup>4.4</sup>
En-23	76.6 <sup>9.2</sup> / 92.7 <sup>5.5</sup>	27.6 <sup>3.2</sup> / 39.7 <sup>6.6</sup>	13.7 <sup>2.6</sup> / 21.6 <sup>4.3</sup>	72.6 <sup>6.6</sup> / 90.7 <sup>3.8</sup>	56.9 <sup>7.7</sup> / 73.5 <sup>4.4</sup>	30.3 <sup>6.0</sup> / 51.1 <sup>5.8</sup>	97.5 <sup>2.2</sup> / 99.0 <sup>1.2</sup>	67.1 <sup>6.2</sup> / 79.3 <sup>0.8</sup>	47.6 <sup>0.3</sup> / 66.8 <sup>10.0</sup>	30.1 <sup>1.1</sup> / 31.9 <sup>7.2</sup>
En-24	69.5 <sup>10.9</sup> / 90.2 <sup>4.0</sup>	29.4 <sup>6.9</sup> / 41.2 <sup>7.7</sup>	12.8 <sup>4.0</sup> / 21.0 <sup>5.3</sup>	65.9 <sup>6.9</sup> / 88.7 <sup>4.2</sup>	61.7 <sup>5.1</sup> / 74.6 <sup>2.2</sup>	32.5 <sup>6.9</sup> / 51.4 <sup>4.1</sup>	97.0 <sup>9.2</sup> / 99.5 <sup>1.0</sup>	67.1 <sup>7.6</sup> / 77.3 <sup>11.0</sup>	47.8 <sup>0.3</sup> / 61.9 <sup>12.3</sup>	28.1 <sup>7.0</sup> / 34.6 <sup>6.3</sup>
En-25	72.1 <sup>12.4</sup> / 89.6 <sup>2.2</sup>	30.9 <sup>5.0</sup> / 41.4 <sup>5.6</sup>	13.7 <sup>4.6</sup> / 24.2 <sup>6.2</sup>	66.1 <sup>5.2</sup> / 85.5 <sup>1.1</sup>	56.5 <sup>6.2</sup> / 71.8 <sup>4.0</sup>	28.6 <sup>8.4</sup> / 48.7 <sup>8.5</sup>	97.0 <sup>1.9</sup> / 99.0 <sup>1.2</sup>	65.5 <sup>6.6</sup> / 77.0 <sup>1.1</sup>	47.8 <sup>0.3</sup> / 57.6 <sup>12.3</sup>	25.8 <sup>3.0</sup> / 37.0 <sup>5.2</sup>
En-26	74.1 <sup>12.5</sup> / 86.5 <sup>8.7</sup>	26.0 <sup>6.0</sup> / 45.1 <sup>7.0</sup>	14.0 <sup>2.7</sup> / 23.8 <sup>7.1</sup>	71.5 <sup>9.9</sup> / 87.8 <sup>4.9</sup>	52.6 <sup>7.0</sup> / 69.0 <sup>3.9</sup>	27.2 <sup>7.7</sup> / 49.8 <sup>5.1</sup>	96.5 <sup>2.0</sup> / 98.5 <sup>2.0</sup>	69.6 <sup>9.2</sup> / 76.0 <sup>11.9</sup>	47.8 <sup>0.3</sup> / 55.1 <sup>19.0</sup>	29.3 <sup>4.2</sup> / 38.0 <sup>8.6</sup>
En-27	74.8 <sup>10.5</sup> / 88.4 <sup>4.5</sup>	21.8 <sup>5.6</sup> / 42.3 <sup>7.3</sup>	11.3 <sup>2.8</sup> / 22.9 <sup>2.8</sup>	74.2 <sup>7.7</sup> / 86.7 <sup>3.7</sup>	51.6 <sup>8.3</sup> / 70.7 <sup>2.8</sup>	41.6 <sup>8.8</sup> / 66.0 <sup>6.6</sup>	97.5 <sup>2.2</sup> / 98.5 <sup>2.0</sup>	67.1 <sup>7.9</sup> / 76.2 <sup>4.7</sup>	47.8 <sup>0.3</sup> / 60.7 <sup>17.6</sup>	34.8 <sup>7.9</sup> / 41.9 <sup>5.5</sup>
De-0	1.6 <sup>0.0</sup> / 6.5 <sup>0.1</sup>	4.3 <sup>0.4</sup> / 44.0 <sup>0.6</sup>	9.6 <sup>0.9</sup> / 9.6 <sup>0.9</sup>	2.1 <sup>0.2</sup> / 2.2 <sup>0.9</sup>	17.1 <sup>0.4</sup> / 17.3 <sup>0.3</sup>	6.4 <sup>2.1</sup> / 7.5 <sup>0.2</sup>	32.6 <sup>0.5</sup> / 33.8 <sup>0.5</sup>	31.5 <sup>0.6</sup> / 35.5 <sup>0.5</sup>	7.8 <sup>1.0</sup> / 47.8 <sup>0.3</sup>	11.6 <sup>1.1</sup> / 12.0 <sup>1.1</sup>
De-1	44.6 <sup>5.0</sup> / 80.4 <sup>3.5</sup>	15.3 <sup>3.1</sup> / 22.4 <sup>3.8</sup>	16.5 <sup>4.7</sup> / 28.4 <sup>15.1</sup>	67.4 <sup>4.0</sup> / 89.5 <sup>2.9</sup>	45.7 <sup>1.1</sup> / 59.7 <sup>5.5</sup>	45.5 <sup>3.7</sup> / 63.1 <sup>1.8</sup>	99.0 <sup>1.2</sup> / 98.5 <sup>2.0</sup>	67.7 <sup>13.9</sup> / 76.2 <sup>7.4</sup>	47.8 <sup>0.3</sup> / 60.7 <sup>17.6</sup>	34.8 <sup>7.9</sup> / 41.9 <sup>5.5</sup>
De-2	59.3 <sup>8.1</sup> / 84.5 <sup>8.4</sup>	31.2 <sup>6.6</sup> / 47.4 <sup>5.8</sup>	14.8 <sup>5.5</sup> / 24.3 <sup>5.2</sup>	68.9 <sup>1.7</sup> / 88.7 <sup>4.2</sup>	45.3 <sup>4.6</sup> / 66.9 <sup>9.0</sup>	34.1 <sup>6.4</sup> / 58.8 <sup>3.9</sup>	98.5 <sup>2.0</sup> / 98.5 <sup>2.0</sup>	68.5 <sup>1.8</sup> / 73.5 <sup>11.1</sup>	47.6 <sup>0.5</sup> / 67.0 <sup>16.6</sup>	27.8 <sup>4.3</sup> / 33.9 <sup>5.2</sup>
De-3	49.8 <sup>8.2</sup> / 82.5 <sup>5.2</sup>	32.3 <sup>5.7</sup> / 45.6 <sup>5.5</sup>	12.4 <sup>4.6</sup> / 21.8 <sup>7.4</sup>	71.3 <sup>0.3</sup> / 84.7 <sup>4.9</sup>	44.8 <sup>5.6</sup> / 58.2 <sup>5.5</sup>	44.1 <sup>4.8</sup> / 62.8 <sup>7.7</sup>	97.0 <sup>9.2</sup> / 98.0 <sup>3.0</sup>	63.4 <sup>2.0</sup> / 72.5 <sup>7.1</sup>	47.6 <sup>0.3</sup> / 66.1 <sup>15.5</sup>	28.3 <sup>3.3</sup> / 34.1 <sup>4.2</sup>
De-4	50.0 <sup>8.3</sup> / 82.7 <sup>3.7</sup>	31.6 <sup>5.3</sup> / 48.9 <sup>2.7</sup>	11.1 <sup>4.1</sup> / 24.2 <sup>7.0</sup>	71.4 <sup>0.2</sup> / 86.3 <sup>0.5</sup>	43.2					

Layer	Accent	DialAct	Emotion	EnvSound	Distance	Intent	MSpeaker	Sarcasm	Spoo	Stress
En-0	59.3 <sup>8.0</sup> / 87.4 <sup>3.1</sup>	29.4 <sup>7.2</sup> / 35.1 <sup>5.0</sup>	14.9 <sup>3.0</sup> / 20.9 <sup>2.6</sup>	43.7 <sup>1.5</sup> / 72.5 <sup>4.6</sup>	69.8 <sup>4.8</sup> / 91.6 <sup>4.0</sup>	17.1 <sup>6.3</sup> / 32.2 <sup>5.6</sup>	75.6 <sup>12.7</sup> / 86.8 <sup>5.5</sup>	59.8 <sup>8.7</sup> / 72.4 <sup>10.2</sup>	51.6 <sup>8.2</sup> / 73.9 <sup>14.0</sup>	21.3 <sup>3.6</sup> / 26.5 <sup>6.3</sup>
En-1	68.4 <sup>10.5</sup> / 86.6 <sup>8.0</sup>	28.8 <sup>4.4</sup> / 40.4 <sup>6.3</sup>	14.4 <sup>9.3</sup> / 18.8 <sup>6.5</sup>	59.1 <sup>7.9</sup> / 79.4 <sup>4.0</sup>	79.5 <sup>2.8</sup> / 89.0 <sup>1.2</sup>	21.8 <sup>3.2</sup> / 30.7 <sup>4.5</sup>	77.4 <sup>6.2</sup> / 93.9 <sup>3.9</sup>	60.6 <sup>11.3</sup> / 67.2 <sup>12.1</sup>	47.6 <sup>0.3</sup> / 81.3 <sup>9.3</sup>	24.4 <sup>3.6</sup> / 28.2 <sup>5.7</sup>
En-2	76.0 <sup>11.2</sup> / 91.3 <sup>6.8</sup>	29.1 <sup>3.7</sup> / 44.3 <sup>5.4</sup>	10.1 <sup>2.1</sup> / 20.8 <sup>3.4</sup>	66.1 <sup>3.5</sup> / 84.2 <sup>4.0</sup>	86.2 <sup>2.4</sup> / 90.6 <sup>4.7</sup>	23.6 <sup>9.4</sup> / 33.4 <sup>5.2</sup>	78.6 <sup>9.5</sup> / 96.5 <sup>2.6</sup>	60.3 <sup>11.7</sup> / 68.9 <sup>12.3</sup>	51.1 <sup>6.4</sup> / 72.8 <sup>14.2</sup>	20.2 <sup>0</sup> / 30.4 <sup>4.2</sup>
En-3	87.4 <sup>7.5</sup> / 91.3 <sup>6.6</sup>	27.5 <sup>3.9</sup> / 42.9 <sup>3.2</sup>	11.8 <sup>6.6</sup> / 19.1 <sup>2.1</sup>	77.5 <sup>1.2</sup> / 86.5 <sup>5.5</sup>	87.0 <sup>1.1</sup> / 94.5 <sup>2.5</sup>	24.1 <sup>8.2</sup> / 36.1 <sup>5.5</sup>	82.7 <sup>7.6</sup> / 95.8 <sup>7.2</sup>	57.8 <sup>15.4</sup> / 67.6 <sup>10.9</sup>	51.9 <sup>8.1</sup> / 81.8 <sup>5.0</sup>	20.4 <sup>4.0</sup> / 28.3 <sup>6.3</sup>
En-4	87.6 <sup>9.0</sup> / 94.4 <sup>5.6</sup>	31.4 <sup>2.2</sup> / 36.7 <sup>6.7</sup>	12.3 <sup>2.7</sup> / 18.6 <sup>2.7</sup>	79.8 <sup>8.3</sup> / 88.9 <sup>4.1</sup>	84.7 <sup>3.5</sup> / 91.1 <sup>2.5</sup>	30.1 <sup>2.9</sup> / 35.9 <sup>0.9</sup>	91.9 <sup>5.3</sup> / 98.0 <sup>0.9</sup>	60.2 <sup>11.9</sup> / 72.2 <sup>13.1</sup>	58.0 <sup>12.8</sup> / 84.8 <sup>8.6</sup>	21.9 <sup>2.9</sup> / 27.5 <sup>5.8</sup>
En-5	86.1 <sup>11.7</sup> / 94.1 <sup>5.9</sup>	30.9 <sup>6.4</sup> / 36.4 <sup>7.7</sup>	14.4 <sup>5.7</sup> / 18.7 <sup>3.1</sup>	80.0 <sup>9.9</sup> / 90.4 <sup>5.0</sup>	85.0 <sup>3.2</sup> / 92.0 <sup>3.0</sup>	28.1 <sup>5.4</sup> / 41.1 <sup>5.1</sup>	96.5 <sup>4.7</sup> / 98.5 <sup>2.0</sup>	59.1 <sup>15.6</sup> / 73.1 <sup>13.1</sup>	61.0 <sup>11.1</sup> / 81.3 <sup>9.5</sup>	23.1 <sup>3.6</sup> / 27.5 <sup>4.3</sup>
En-6	89.8 <sup>10.6</sup> / 95.2 <sup>3.7</sup>	31.5 <sup>8.8</sup> / 42.4 <sup>4.0</sup>	12.6 <sup>1.7</sup> / 19.9 <sup>2.0</sup>	86.1 <sup>5.3</sup> / 91.6 <sup>4.1</sup>	85.2 <sup>5.4</sup> / 93.1 <sup>2.5</sup>	28.7 <sup>4.4</sup> / 39.5 <sup>5.9</sup>	97.5 <sup>2.8</sup> / 99.0 <sup>1.2</sup>	61.4 <sup>15.7</sup> / 73.3 <sup>13.7</sup>	62.2 <sup>12.0</sup> / 84.9 <sup>3.6</sup>	19.4 <sup>2.3</sup> / 29.5 <sup>7.7</sup>
En-7	88.5 <sup>12.5</sup> / 95.3 <sup>4.2</sup>	28.6 <sup>4.8</sup> / 37.1 <sup>3.6</sup>	15.1 <sup>4.6</sup> / 19.3 <sup>3.8</sup>	86.9 <sup>4.0</sup> / 90.7 <sup>4.7</sup>	84.1 <sup>1.3</sup> / 93.1 <sup>2.9</sup>	33.4 <sup>4.2</sup> / 41.3 <sup>5.5</sup>	98.5 <sup>1.2</sup> / 99.0 <sup>1.2</sup>	63.7 <sup>10.6</sup> / 77.5 <sup>12.7</sup>	61.0 <sup>11.1</sup> / 83.8 <sup>6.5</sup>	19.6 <sup>3.4</sup> / 31.7 <sup>6.6</sup>
En-8	81.5 <sup>10.6</sup> / 93.8 <sup>3.8</sup>	30.0 <sup>0.1</sup> / 35.1 <sup>5.8</sup>	8.4 <sup>1.2</sup> / 15.3 <sup>2.0</sup>	76.5 <sup>5.1</sup> / 92.6 <sup>3.2</sup>	71.2 <sup>5.3</sup> / 87.2 <sup>1.8</sup>	26.0 <sup>3.8</sup> / 43.1 <sup>7.7</sup>	98.0 <sup>1.9</sup> / 99.1 <sup>2.2</sup>	70.5 <sup>12.8</sup> / 76.3 <sup>11.3</sup>	60.9 <sup>11.2</sup> / 81.8 <sup>5.0</sup>	18.7 <sup>0</sup> / 31.3 <sup>8.2</sup>
En-9	87.5 <sup>11.6</sup> / 94.1 <sup>4.8</sup>	31.2 <sup>4.6</sup> / 38.1 <sup>7.8</sup>	10.3 <sup>2.0</sup> / 20.1 <sup>5.1</sup>	79.8 <sup>3.9</sup> / 90.5 <sup>2.5</sup>	69.4 <sup>5.5</sup> / 81.4 <sup>4.3</sup>	28.8 <sup>5.9</sup> / 44.0 <sup>3.7</sup>	99.0 <sup>1.2</sup> / 99.5 <sup>1.0</sup>	68.7 <sup>11.4</sup> / 77.5 <sup>5.9</sup>	61.2 <sup>11.9</sup> / 79.8 <sup>6.2</sup>	18.3 <sup>3.4</sup> / 32.3 <sup>8.3</sup>
En-10	83.9 <sup>9.4</sup> / 93.3 <sup>5.4</sup>	29.5 <sup>4.0</sup> / 41.8 <sup>6.5</sup>	9.8 <sup>2.0</sup> / 21.5 <sup>4.4</sup>	78.5 <sup>4.3</sup> / 91.5 <sup>3.6</sup>	67.5 <sup>5.5</sup> / 79.5 <sup>5.3</sup>	26.5 <sup>4.0</sup> / 46.0 <sup>5.5</sup>	98.5 <sup>2.0</sup> / 99.5 <sup>1.0</sup>	68.3 <sup>13.9</sup> / 78.6 <sup>7.8</sup>	56.1 <sup>10.9</sup> / 78.8 <sup>16.9</sup>	19.5 <sup>4.1</sup> / 33.0 <sup>10.0</sup>
En-11	83.4 <sup>9.2</sup> / 98.0 <sup>3.3</sup>	26.9 <sup>4.5</sup> / 41.7 <sup>6.7</sup>	11.0 <sup>1.9</sup> / 21.1 <sup>4.2</sup>	80.5 <sup>6.6</sup> / 90.7 <sup>1.4</sup>	62.9 <sup>2.9</sup> / 78.8 <sup>4.4</sup>	33.1 <sup>5.4</sup> / 65.7 <sup>8.6</sup>	96.5 <sup>2.0</sup> / 99.5 <sup>1.0</sup>	67.5 <sup>12.5</sup> / 78.7 <sup>9.7</sup>	56.1 <sup>10.9</sup> / 76.0 <sup>19.0</sup>	16.7 <sup>4.6</sup> / 33.7 <sup>8.0</sup>
En-12	85.1 <sup>4.9</sup> / 94.9 <sup>1.0</sup>	35.2 <sup>5.2</sup> / 43.6 <sup>1.1</sup>	10.8 <sup>1.7</sup> / 18.1 <sup>3.1</sup>	80.3 <sup>2.3</sup> / 91.7 <sup>3.1</sup>	62.3 <sup>2.9</sup> / 74.6 <sup>4.7</sup>	38.0 <sup>4.4</sup> / 57.7 <sup>6.6</sup>	96.5 <sup>2.5</sup> / 99.0 <sup>1.2</sup>	66.2 <sup>11.2</sup> / 80.8 <sup>6.6</sup>	51.0 <sup>5.5</sup> / 64.9 <sup>16.4</sup>	23.1 <sup>2.6</sup> / 38.0 <sup>7.4</sup>
En-13	87.8 <sup>5.9</sup> / 96.9 <sup>2.8</sup>	33.6 <sup>5.8</sup> / 41.8 <sup>10.0</sup>	10.8 <sup>2.9</sup> / 21.9 <sup>3.9</sup>	79.8 <sup>3.9</sup> / 90.2 <sup>2.2</sup>	55.8 <sup>8.4</sup> / 76.0 <sup>8.8</sup>	37.3 <sup>3.0</sup> / 55.6 <sup>6.2</sup>	95.5 <sup>2.9</sup> / 99.0 <sup>1.2</sup>	66.8 <sup>11.0</sup> / 79.8 <sup>10.0</sup>	51.6 <sup>8.2</sup> / 54.7 <sup>13.6</sup>	19.9 <sup>2.2</sup> / 34.5 <sup>5.7</sup>
En-14	89.2 <sup>5.4</sup> / 98.3 <sup>7.7</sup>	33.1 <sup>4.8</sup> / 41.8 <sup>8.8</sup>	9.8 <sup>2.2</sup> / 23.6 <sup>4.4</sup>	75.2 <sup>5.0</sup> / 90.6 <sup>2.8</sup>	52.8 <sup>8.7</sup> / 75.9 <sup>4.2</sup>	37.3 <sup>6.0</sup> / 51.1 <sup>4.4</sup>	96.5 <sup>2.0</sup> / 99.1 <sup>2.2</sup>	65.8 <sup>8.6</sup> / 81.3 <sup>7.4</sup>	51.8 <sup>8.1</sup> / 58.6 <sup>13.5</sup>	21.7 <sup>4.0</sup> / 35.5 <sup>5.5</sup>
En-15	87.7 <sup>9.2</sup> / 98.1 <sup>8.8</sup>	30.7 <sup>5.1</sup> / 39.0 <sup>9.1</sup>	11.0 <sup>2.3</sup> / 19.0 <sup>4.9</sup>	79.1 <sup>2.4</sup> / 91.4 <sup>3.0</sup>	50.5 <sup>12.3</sup> / 67.9 <sup>3.3</sup>	37.7 <sup>5.5</sup> / 59.0 <sup>1.1</sup>	97.0 <sup>1.2</sup> / 99.5 <sup>1.0</sup>	70.6 <sup>9.3</sup> / 77.9 <sup>7.5</sup>	51.9 <sup>8.1</sup> / 63.8 <sup>13.9</sup>	21.9 <sup>4.7</sup> / 35.9 <sup>6.4</sup>
En-16	87.6 <sup>9.2</sup> / 99.4 <sup>1.2</sup>	28.8 <sup>5.4</sup> / 41.0 <sup>7.8</sup>	11.8 <sup>2.1</sup> / 21.3 <sup>3.2</sup>	79.3 <sup>3.0</sup> / 91.5 <sup>3.2</sup>	48.9 <sup>1.7</sup> / 67.7 <sup>6.6</sup>	34.5 <sup>8.6</sup> / 55.7 <sup>5.6</sup>	98.0 <sup>1.0</sup> / 99.0 <sup>1.2</sup>	73.6 <sup>8.8</sup> / 81.3 <sup>8.4</sup>	51.9 <sup>8.1</sup> / 62.7 <sup>12.6</sup>	23.3 <sup>3.3</sup> / 34.5 <sup>8.0</sup>
En-17	85.9 <sup>8.9</sup> / 97.0 <sup>2.6</sup>	27.4 <sup>2.3</sup> / 38.1 <sup>6.8</sup>	11.9 <sup>3.6</sup> / 18.3 <sup>5.5</sup>	79.2 <sup>3.5</sup> / 92.1 <sup>3.6</sup>	49.8 <sup>1.2</sup> / 65.7 <sup>5.5</sup>	31.8 <sup>8.8</sup> / 54.6 <sup>10.2</sup>	98.0 <sup>1.0</sup> / 99.0 <sup>1.2</sup>	74.6 <sup>4.4</sup> / 79.8 <sup>9.3</sup>	51.1 <sup>6.4</sup> / 60.8 <sup>11.4</sup>	22.6 <sup>5.3</sup> / 34.4 <sup>7.5</sup>
En-18	84.5 <sup>8.6</sup> / 97.3 <sup>2.3</sup>	31.5 <sup>5.6</sup> / 38.8 <sup>5.5</sup>	10.4 <sup>3.2</sup> / 19.6 <sup>4.8</sup>	77.5 <sup>8.9</sup> / 92.9 <sup>1.8</sup>	51.6 <sup>5.0</sup> / 66.4 <sup>5.5</sup>	49.7 <sup>5.1</sup> / 98.5 <sup>2.0</sup>	76.6 <sup>4.1</sup> / 79.3 <sup>9.6</sup>	51.1 <sup>6.4</sup> / 63.8 <sup>13.9</sup>	23.2 <sup>3.3</sup> / 38.3 <sup>8.0</sup>	
En-19	84.9 <sup>10.2</sup> / 97.6 <sup>2.2</sup>	34.3 <sup>3.2</sup> / 40.1 <sup>5.4</sup>	9.8 <sup>2.4</sup> / 20.0 <sup>1.6</sup>	79.8 <sup>3.9</sup> / 90.6 <sup>2.5</sup>	46.9 <sup>0.2</sup> / 67.9 <sup>7.5</sup>	49.7 <sup>0.9</sup> / 99.0 <sup>1.2</sup>	71.7 <sup>4.7</sup> / 79.3 <sup>9.2</sup>	56.2 <sup>0.7</sup> / 63.8 <sup>13.3</sup>	24.0 <sup>0.6</sup> / 36.2 <sup>8.4</sup>	
En-20	89.2 <sup>6.8</sup> / 98.1 <sup>2.4</sup>	36.0 <sup>1.0</sup> / 44.7 <sup>2.3</sup>	10.4 <sup>3.0</sup> / 20.1 <sup>5.1</sup>	82.7 <sup>5.5</sup> / 90.5 <sup>3.1</sup>	49.1 <sup>0.9</sup> / 67.2 <sup>2.0</sup>	33.7 <sup>13.9</sup> / 55.0 <sup>1.3</sup>	97.0 <sup>2.5</sup> / 99.0 <sup>1.2</sup>	72.7 <sup>6.6</sup> / 77.1 <sup>11.0</sup>	51.1 <sup>5.4</sup> / 66.1 <sup>17.2</sup>	26.8 <sup>3.4</sup> / 32.0 <sup>6.4</sup>
En-21	84.6 <sup>8.7</sup> / 97.3 <sup>2.3</sup>	32.7 <sup>6.5</sup> / 46.9 <sup>6.5</sup>	11.8 <sup>1.6</sup> / 20.5 <sup>4.5</sup>	79.9 <sup>4.8</sup> / 92.3 <sup>3.2</sup>	53.2 <sup>7.7</sup> / 62.1 <sup>2.8</sup>	40.2 <sup>4.3</sup> / 59.6 <sup>3.1</sup>	98.0 <sup>1.9</sup> / 99.0 <sup>1.2</sup>	70.9 <sup>7.3</sup> / 77.7 <sup>10.2</sup>	51.1 <sup>6.4</sup> / 65.0 <sup>16.3</sup>	22.8 <sup>8.5</sup> / 34.0 <sup>7.1</sup>
En-22	77.7 <sup>8.8</sup> / 95.4 <sup>1.9</sup>	34.6 <sup>4.2</sup> / 52.3 <sup>7.6</sup>	11.5 <sup>2.9</sup> / 20.6 <sup>4.6</sup>	80.7 <sup>2.8</sup> / 92.4 <sup>2.6</sup>	52.6 <sup>5.5</sup> / 61.3 <sup>4.0</sup>	38.6 <sup>1.1</sup> / 60.1 <sup>7.1</sup>	98.0 <sup>1.9</sup> / 98.0 <sup>3.0</sup>	70.6 <sup>7.5</sup> / 79.3 <sup>7.0</sup>	51.0 <sup>6.5</sup> / 65.8 <sup>16.3</sup>	19.3 <sup>4.5</sup> / 32.0 <sup>7.6</sup>
En-23	77.4 <sup>5.1</sup> / 95.5 <sup>3.0</sup>	34.6 <sup>3.0</sup> / 53.1 <sup>10.0</sup>	11.4 <sup>1.2</sup> / 25.6 <sup>9.0</sup>	81.4 <sup>3.4</sup> / 93.4 <sup>2.5</sup>	48.1 <sup>10.5</sup> / 61.0 <sup>1.8</sup>	37.9 <sup>7.0</sup> / 62.3 <sup>6.9</sup>	97.5 <sup>2.2</sup> / 99.0 <sup>1.2</sup>	70.9 <sup>8.8</sup> / 78.6 <sup>9.3</sup>	50.8 <sup>6.6</sup> / 71.0 <sup>13.7</sup>	22.1 <sup>5.0</sup> / 31.9 <sup>7.4</sup>
En-24	76.6 <sup>8.0</sup> / 94.4 <sup>3.0</sup>	38.4 <sup>6.0</sup> / 50.6 <sup>4.9</sup>	12.1 <sup>5.2</sup> / 20.6 <sup>4.7</sup>	84.4 <sup>1.8</sup> / 93.8 <sup>2.0</sup>	48.8 <sup>7.8</sup> / 62.8 <sup>8.8</sup>	37.8 <sup>10.3</sup> / 60.8 <sup>5.5</sup>	97.5 <sup>2.8</sup> / 98.5 <sup>2.0</sup>	66.0 <sup>9.4</sup> / 76.2 <sup>10.7</sup>	54.3 <sup>13.9</sup> / 66.2 <sup>10.1</sup>	19.1 <sup>2.0</sup> / 37.7 <sup>6.6</sup>
En-25	91.6 <sup>3.7</sup> / 98.9 <sup>1.5</sup>	32.4 <sup>3.0</sup> / 39.7 <sup>5.4</sup>	11.1 <sup>2.2</sup> / 20.5 <sup>3.4</sup>	75.3 <sup>7.7</sup> / 91.6 <sup>5.0</sup>	61.8 <sup>7.6</sup> / 79.6 <sup>1.9</sup>	28.1 <sup>6.0</sup> / 52.8 <sup>2.1</sup>	96.6 <sup>0.3</sup> / 99.5 <sup>1.0</sup>	70.2 <sup>10.4</sup> / 79.7 <sup>10.3</sup>	50.1 <sup>5.4</sup> / 67.6 <sup>16.9</sup>	25.3 <sup>8.9</sup> / 33.6 <sup>6.1</sup>
De-0	1.6 <sup>0.0</sup> / 65.5 <sup>1.0</sup>	4.3 <sup>0.4</sup> / 15.9 <sup>3.7</sup>	9.6 <sup>0.9</sup> / 9.6 <sup>0.9</sup>	2.1 <sup>0.2</sup> / 2.2 <sup>0.9</sup>	17.1 <sup>0.4</sup> / 17.3 <sup>0.3</sup>	6.4 <sup>2.1</sup> / 7.5 <sup>0.5</sup>	32.9 <sup>0.5</sup> / 33.8 <sup>0.5</sup>	31.5 <sup>0.6</sup> / 35.3 <sup>0.5</sup>	7.8 <sup>1.0</sup> / 47.8 <sup>8.3</sup>	11.6 <sup>1.1</sup> / 12.0 <sup>1.1</sup>
De-1	54.1 <sup>9.5</sup> / 85.3 <sup>3.7</sup>	24.3 <sup>4.8</sup> / 43.0 <sup>4.4</sup>	15.9 <sup>2.8</sup> / 25.4 <sup>6.9</sup>	72.2 <sup>7.5</sup> / 89.4 <sup>2.5</sup>	34.6 <sup>6.6</sup> / 52.5 <sup>5.1</sup>	24.1 <sup>12.3</sup> / 48.8 <sup>5.7</sup>	92.0 <sup>4.9</sup> / 98.5 <sup>2.0</sup>	62.3 <sup>10.6</sup> / 75.5 <sup>8.1</sup>	47.8 <sup>0.3</sup> / 62.7 <sup>13.7</sup>	22.1 <sup>3.5</sup> / 37.8 <sup>6.6</sup>
De-2	52.9 <sup>7.6</sup> / 83.6 <sup>9.7</sup>	26.4 <sup>4.1</sup> / 52.6 <sup>8.0</sup>	13.2 <sup>2.6</sup> / 24.6 <sup>8.4</sup>	73.1 <sup>1.1</sup> / 89.2 <sup>4.3</sup>	36.4 <sup>5.6</sup> / 61.3 <sup>4.0</sup>	32.9 <sup>7.5</sup> / 50.5 <sup>5.8</sup>	95.0 <sup>2.2</sup> / 98.0 <sup>3.0</sup>	62.8 <sup>11.3</sup> / 74.0 <sup>4.5</sup>	52.9 <sup>10.4</sup> / 63.7 <sup>14.1</sup>	21.4 <sup>1.1</sup> / 34.7 <sup>3.7</sup>
De-3	49.2 <sup>6.7</sup> / 74.4 <sup>5.5</sup>	35.2 <sup>6.6</sup> / 42.9 <sup>3.9</sup>	14.8 <sup>5.2</sup> / 32.2 <sup>1.3</sup>	76.0 <sup>1.9</sup> / 91.8 <sup>4.5</sup>	34.8 <sup>8.4</sup> / 52.7 <sup>8.6</sup>	49.9 <sup>5.6</sup> / 63.5 <sup>3.2</sup>	91.0 <sup>3.4</sup> / 95.5 <sup>4.4</sup>	63.6 <sup>3.3</sup> / 70.2 <sup>5.9</sup>	47.8 <sup>0.3</sup> / 62.0 <sup>21.1</sup>	25.1 <sup>4.2</sup> / 37.1 <sup>2.1</sup>
De-4	42.8 <sup>10.2</sup> / 74.0 <sup>7.6</sup>	36.5 <sup>3.6</sup> / 48.5 <sup>1.9</sup>	16.1 <sup>6.1</sup> / 26.9 <sup>1.4</sup>	68.9 <sup>3.6</sup> / 90.6 <sup>3.7</sup>	36.4 <sup>8.8</sup> / 52.4 <sup>6.6</sup>	46.7 <sup>9.0</sup> / 61.5 <sup>3.2</sup>	88.9 <sup>7.3</sup> / 95.5 <sup>4.9</sup>	64.4 <sup>7.5</sup> / 70.7 <sup>5.2</sup>	47.8 <sup>0.3</sup> / 59.9 <sup>9.9</sup>	19.1 <sup>2.8</sup> / 37.4 <sup>5.9</sup>
De-5	66.6 <sup>13.5</sup> / 83.0 <sup>1.3</sup>	31.9 <sup>5.9</sup> / 46.1 <sup>6.2</sup>	13.9 <sup>2.2</sup> / 23.3 <sup>4.0</sup>	70.1 <sup>4.1</sup> / 89.2 <sup>6.2</sup>	47.9 <sup>7.6</sup> / 61.4 <sup>4.8</sup>	46.5 <sup>9.1</sup> / 56.4 <sup>2.6</sup>	91.0 <sup>5.2</sup> / 96.0 <sup>3.8</sup>	64.5 <sup>8.9</sup> / 71.3 <sup>9.8</sup>	47.8 <sup>0.3</sup> / 62.5 <sup>13.4</sup>	22.0 <sup>2.2</sup> / 34.7 <sup>4.0</sup>
De-6	65.5 <sup>8.1</sup> / 86.5 <sup>5.2</sup>	33.4 <sup>6.7</sup> / 50.6 <sup>5.1</sup>	13.3 <sup>0.9</sup> / 23.1 <sup>3.7</sup>	68.7 <sup>4.3</sup> / 88.7 <sup>5.9</sup>	44.9 <sup>3</sup>					

Layer	Accent	DialAct	Emotion	EnvSound	Distance	Intent	MSpeaker	Sarcasm	Spoof	Stress
En-0	56.9 <sup>9</sup> / 90.0 <sup>2</sup>	30.1 <sup>6</sup> / 36.7 <sup>4</sup>	12.5 <sup>2</sup> / 21.2 <sup>2</sup>	42.9 <sup>5</sup> / 69.7 <sup>3</sup>	66.7 <sup>5</sup> / 89.1 <sup>2</sup>	18.9 <sup>7</sup> / 33.3 <sup>7</sup>	73.1 <sup>10</sup> / 88.2 <sup>4</sup>	56.6 <sup>8</sup> / 72.4 <sup>10</sup>	52.9 <sup>10</sup> / 79.9 <sup>6</sup>	21.2 <sup>4</sup> / 27.0 <sup>6</sup>
En-1	66.7 <sup>9</sup> / 86.1 <sup>12</sup>	32.3 <sup>0</sup> / 38.1 <sup>8</sup>	12.5 <sup>0</sup> / 22.4 <sup>3</sup>	58.6 <sup>5</sup> / 75.1 <sup>4</sup>	79.4 <sup>1</sup> / 89.1 <sup>3</sup>	14.3 <sup>3</sup> / 31.4 <sup>3</sup>	80.2 <sup>7</sup> / 90.8 <sup>4</sup>	55.7 <sup>12</sup> / 69.8 <sup>13</sup>	58.0 <sup>12</sup> / 80.3 <sup>17</sup>	19.5 <sup>6</sup> / 29.8 <sup>0</sup>
En-2	71.4 <sup>10</sup> / 89.3 <sup>11</sup>	28.0 <sup>0</sup> / 36.7 <sup>4</sup>	11.3 <sup>2</sup> / 22.2 <sup>3</sup>	62.1 <sup>5</sup> / 78.0 <sup>2</sup>	81.7 <sup>8</sup> / 92.6 <sup>1</sup>	20.6 <sup>1</sup> / 33.5 <sup>1</sup>	82.3 <sup>6</sup> / 94.9 <sup>1</sup>	57.9 <sup>6</sup> / 67.0 <sup>13</sup>	59.7 <sup>16</sup> / 79.5 <sup>5</sup>	22.8 <sup>7</sup> / 31.4 <sup>7</sup>
En-3	78.4 <sup>12</sup> / 92.0 <sup>7</sup>	29.2 <sup>5</sup> / 39.6 <sup>2</sup>	10.6 <sup>3</sup> / 18.6 <sup>2</sup>	63.9 <sup>4</sup> / 81.0 <sup>5</sup>	86.5 <sup>0</sup> / 95.6 <sup>3</sup>	16.0 <sup>2</sup> / 32.1 <sup>3</sup>	80.6 <sup>8</sup> / 95.3 <sup>7</sup>	63.2 <sup>13</sup> / 70.5 <sup>13</sup>	51.0 <sup>5</sup> / 77.5 <sup>15</sup>	21.7 <sup>6</sup> / 30.4 <sup>6</sup>
En-4	71.6 <sup>8</sup> / 89.4 <sup>5</sup>	38.8 <sup>6</sup> / 37.4 <sup>6</sup>	13.0 <sup>2</sup> / 18.4 <sup>2</sup>	67.7 <sup>3</sup> / 82.5 <sup>4</sup>	85.2 <sup>6</sup> / 94.0 <sup>7</sup>	20.6 <sup>3</sup> / 29.8 <sup>5</sup>	82.2 <sup>9</sup> / 95.9 <sup>3</sup>	62.8 <sup>15</sup> / 71.4 <sup>11</sup>	51.6 <sup>8</sup> / 80.7 <sup>16</sup>	20.8 <sup>7</sup> / 27.3 <sup>8</sup>
En-5	80.9 <sup>2</sup> / 96.5 <sup>9</sup>	25.2 <sup>8</sup> / 35.7 <sup>5</sup>	13.2 <sup>9</sup> / 18.3 <sup>2</sup>	70.2 <sup>2</sup> / 86.8 <sup>1</sup>	87.2 <sup>3</sup> / 94.5 <sup>0</sup>	24.0 <sup>8</sup> / 36.6 <sup>1</sup>	87.4 <sup>7</sup> / 97.5 <sup>0</sup>	63.4 <sup>11</sup> / 74.6 <sup>9</sup>	59.2 <sup>9</sup> / 79.7 <sup>16</sup>	23.7 <sup>6</sup> / 30.3 <sup>5</sup>
En-6	83.2 <sup>9</sup> / 97.5 <sup>4</sup>	23.9 <sup>3</sup> / 39.4 <sup>0</sup>	13.7 <sup>5</sup> / 19.9 <sup>3</sup>	77.3 <sup>4</sup> / 86.7 <sup>5</sup>	90.0 <sup>2</sup> / 95.1 <sup>1</sup>	26.6 <sup>1</sup> / 37.7 <sup>5</sup>	95.9 <sup>0</sup> / 98.5 <sup>2</sup>	65.1 <sup>11</sup> / 76.1 <sup>8</sup>	60.0 <sup>9</sup> / 87.8 <sup>5</sup>	21.4 <sup>2</sup> / 29.7 <sup>9</sup>
En-7	87.4 <sup>5</sup> / 97.7 <sup>3</sup>	28.2 <sup>0</sup> / 40.4 <sup>1</sup>	15.8 <sup>0</sup> / 19.4 <sup>1</sup>	77.3 <sup>1</sup> / 87.4 <sup>2</sup>	87.0 <sup>1</sup> / 97.0 <sup>2</sup>	23.1 <sup>3</sup> / 38.6 <sup>5</sup>	98.0 <sup>3</sup> / 99.5 <sup>1</sup>	64.8 <sup>12</sup> / 74.6 <sup>12</sup>	55.9 <sup>9</sup> / 82.6 <sup>5</sup>	20.6 <sup>8</sup> / 29.2 <sup>6</sup>
En-8	84.1 <sup>8</sup> / 95.1 <sup>8</sup>	24.6 <sup>4</sup> / 40.4 <sup>7</sup>	16.5 <sup>4</sup> / 20.2 <sup>6</sup>	77.6 <sup>4</sup> / 91.2 <sup>9</sup>	87.1 <sup>2</sup> / 95.5 <sup>2</sup>	22.7 <sup>5</sup> / 40.6 <sup>2</sup>	99.0 <sup>1</sup> / 99.5 <sup>1</sup>	65.5 <sup>15</sup> / 75.2 <sup>13</sup>	56.9 <sup>11</sup> / 77.5 <sup>15</sup>	21.5 <sup>7</sup> / 29.8 <sup>4</sup>
En-9	85.2 <sup>8</sup> / 94.4 <sup>3</sup>	23.9 <sup>4</sup> / 37.6 <sup>9</sup>	12.3 <sup>6</sup> / 22.2 <sup>5</sup>	75.0 <sup>7</sup> / 89.9 <sup>2</sup>	88.1 <sup>4</sup> / 94.5 <sup>3</sup>	24.3 <sup>1</sup> / 36.3 <sup>6</sup>	98.5 <sup>2</sup> / 99.5 <sup>1</sup>	64.7 <sup>12</sup> / 78.9 <sup>3</sup>	55.8 <sup>10</sup> / 84.1 <sup>6</sup>	20.2 <sup>7</sup> / 31.8 <sup>5</sup>
En-10	85.7 <sup>6</sup> / 92.7 <sup>2</sup>	26.5 <sup>3</sup> / 37.5 <sup>2</sup>	10.2 <sup>1</sup> / 18.4 <sup>7</sup>	78.1 <sup>8</sup> / 87.4 <sup>1</sup>	81.7 <sup>5</sup> / 92.1 <sup>9</sup>	22.0 <sup>2</sup> / 32.5 <sup>1</sup>	98.0 <sup>1</sup> / 99.5 <sup>1</sup>	69.0 <sup>14</sup> / 77.9 <sup>6</sup>	61.0 <sup>11</sup> / 78.7 <sup>15</sup>	18.9 <sup>5</sup> / 30.8 <sup>5</sup>
En-11	84.9 <sup>7</sup> / 95.4 <sup>2</sup>	31.5 <sup>1</sup> / 39.1 <sup>6</sup>	12.8 <sup>4</sup> / 22.4 <sup>3</sup>	80.8 <sup>3</sup> / 89.5 <sup>4</sup>	78.8 <sup>5</sup> / 91.0 <sup>2</sup>	24.0 <sup>5</sup> / 36.8 <sup>3</sup>	98.0 <sup>1</sup> / 99.5 <sup>1</sup>	67.0 <sup>13</sup> / 75.8 <sup>8</sup>	57.0 <sup>11</sup> / 87.0 <sup>4</sup>	19.4 <sup>5</sup> / 26.9 <sup>6</sup>
En-12	85.0 <sup>7</sup> / 98.6 <sup>2</sup>	26.1 <sup>1</sup> / 36.5 <sup>7</sup>	10.3 <sup>9</sup> / 22.2 <sup>9</sup>	78.5 <sup>6</sup> / 89.6 <sup>1</sup>	72.0 <sup>7</sup> / 86.0 <sup>6</sup>	25.8 <sup>1</sup> / 39.8 <sup>2</sup>	98.0 <sup>1</sup> / 99.5 <sup>1</sup>	66.2 <sup>14</sup> / 78.1 <sup>7</sup>	61.0 <sup>11</sup> / 87.0 <sup>4</sup>	20.9 <sup>5</sup> / 30.2 <sup>4</sup>
En-13	84.8 <sup>7</sup> / 96.5 <sup>2</sup>	28.2 <sup>8</sup> / 37.4 <sup>9</sup>	10.4 <sup>5</sup> / 23.5 <sup>9</sup>	77.0 <sup>5</sup> / 93.1 <sup>8</sup>	70.0 <sup>8</sup> / 85.5 <sup>3</sup>	27.1 <sup>6</sup> / 42.9 <sup>4</sup>	99.0 <sup>1</sup> / 99.5 <sup>1</sup>	67.6 <sup>15</sup> / 75.3 <sup>12</sup>	55.1 <sup>9</sup> / 84.2 <sup>8</sup>	17.8 <sup>9</sup> / 32.4 <sup>3</sup>
En-14	90.8 <sup>6</sup> / 97.5 <sup>1</sup>	30.5 <sup>3</sup> / 40.1 <sup>5</sup>	10.6 <sup>3</sup> / 22.1 <sup>9</sup>	79.5 <sup>6</sup> / 91.2 <sup>9</sup>	72.2 <sup>8</sup> / 85.3 <sup>5</sup>	25.0 <sup>3</sup> / 43.6 <sup>9</sup>	97.0 <sup>1</sup> / 99.0 <sup>2</sup>	65.9 <sup>15</sup> / 75.0 <sup>7</sup>	47.5 <sup>0</sup> / 86.4 <sup>3</sup>	20.3 <sup>7</sup> / 30.5 <sup>6</sup>
En-15	90.6 <sup>7</sup> / 97.4 <sup>1</sup>	30.2 <sup>2</sup> / 40.6 <sup>3</sup>	11.5 <sup>3</sup> / 22.2 <sup>1</sup>	81.6 <sup>7</sup> / 93.9 <sup>2</sup>	71.8 <sup>7</sup> / 86.1 <sup>2</sup>	30.6 <sup>4</sup> / 49.0 <sup>3</sup>	98.5 <sup>2</sup> / 99.0 <sup>1</sup>	64.5 <sup>14</sup> / 76.0 <sup>10</sup>	51.6 <sup>8</sup> / 80.5 <sup>5</sup>	21.9 <sup>6</sup> / 31.9 <sup>4</sup>
En-16	91.2 <sup>5</sup> / 97.4 <sup>3</sup>	31.8 <sup>4</sup> / 41.2 <sup>1</sup>	12.1 <sup>4</sup> / 21.7 <sup>2</sup>	87.4 <sup>9</sup> / 93.7 <sup>4</sup>	72.8 <sup>3</sup> / 88.0 <sup>2</sup>	30.6 <sup>2</sup> / 46.7 <sup>0</sup>	98.5 <sup>2</sup> / 99.5 <sup>1</sup>	66.8 <sup>14</sup> / 74.8 <sup>10</sup>	51.6 <sup>8</sup> / 81.8 <sup>5</sup>	23.2 <sup>6</sup> / 33.4 <sup>2</sup>
En-17	94.7 <sup>4</sup> / 96.9 <sup>2</sup>	33.4 <sup>7</sup> / 38.9 <sup>4</sup>	14.9 <sup>5</sup> / 21.5 <sup>8</sup>	89.5 <sup>4</sup> / 95.3 <sup>5</sup>	69.8 <sup>4</sup> / 86.1 <sup>7</sup>	31.1 <sup>7</sup> / 53.8 <sup>6</sup>	98.0 <sup>1</sup> / 99.5 <sup>1</sup>	65.9 <sup>15</sup> / 77.9 <sup>11</sup>	47.6 <sup>3</sup> / 73.2 <sup>4</sup>	26.2 <sup>5</sup> / 33.5 <sup>2</sup>
En-18	96.0 <sup>4</sup> / 97.8 <sup>2</sup>	34.0 <sup>4</sup> / 38.4 <sup>1</sup>	15.0 <sup>9</sup> / 20.9 <sup>3</sup>	89.8 <sup>6</sup> / 94.9 <sup>7</sup>	70.8 <sup>6</sup> / 84.6 <sup>3</sup>	28.8 <sup>4</sup> / 50.4 <sup>5</sup>	99.0 <sup>1</sup> / 99.0 <sup>2</sup>	68.0 <sup>18</sup> / 80.3 <sup>6</sup>	47.8 <sup>0</sup> / 71.2 <sup>19</sup>	22.7 <sup>4</sup> / 33.6 <sup>2</sup>
En-19	95.4 <sup>5</sup> / 98.1 <sup>9</sup>	32.0 <sup>5</sup> / 39.5 <sup>7</sup>	15.8 <sup>2</sup> / 23.5 <sup>6</sup>	87.8 <sup>9</sup> / 95.4 <sup>3</sup>	67.9 <sup>2</sup> / 84.5 <sup>1</sup>	34.0 <sup>2</sup> / 49.7 <sup>3</sup>	98.5 <sup>1</sup> / 99.0 <sup>2</sup>	68.4 <sup>14</sup> / 77.3 <sup>11</sup>	47.6 <sup>3</sup> / 67.1 <sup>17</sup>	25.1 <sup>8</sup> / 37.0 <sup>5</sup>
En-20	92.3 <sup>4</sup> / 99.2 <sup>1</sup>	33.7 <sup>9</sup> / 43.2 <sup>3</sup>	14.5 <sup>2</sup> / 23.6 <sup>0</sup>	86.3 <sup>9</sup> / 96.6 <sup>3</sup>	66.1 <sup>5</sup> / 79.3 <sup>8</sup>	48.5 <sup>3</sup> / 65.1 <sup>5</sup>	98.5 <sup>2</sup> / 99.0 <sup>1</sup>	67.0 <sup>17</sup> / 76.1 <sup>11</sup>	47.6 <sup>3</sup> / 68.1 <sup>17</sup>	22.9 <sup>6</sup> / 31.7 <sup>5</sup>
En-21	82.0 <sup>7</sup> / 95.9 <sup>6</sup>	32.8 <sup>3</sup> / 42.8 <sup>1</sup>	11.0 <sup>5</sup> / 24.6 <sup>6</sup>	86.9 <sup>2</sup> / 92.6 <sup>3</sup>	64.4 <sup>5</sup> / 81.4 <sup>3</sup>	51.3 <sup>8</sup> / 67.5 <sup>9</sup>	99.0 <sup>1</sup> / 99.5 <sup>1</sup>	65.7 <sup>15</sup> / 74.1 <sup>9</sup>	47.8 <sup>0</sup> / 67.0 <sup>16</sup>	25.7 <sup>4</sup> / 32.5 <sup>6</sup>
En-22	80.1 <sup>9</sup> / 94.0 <sup>6</sup>	34.1 <sup>7</sup> / 41.9 <sup>3</sup>	14.8 <sup>3</sup> / 20.4 <sup>4</sup>	88.3 <sup>0</sup> / 94.1 <sup>8</sup>	62.4 <sup>9</sup> / 75.3 <sup>10</sup>	50.5 <sup>0</sup> / 64.7 <sup>9</sup>	99.0 <sup>1</sup> / 99.0 <sup>2</sup>	67.1 <sup>14</sup> / 77.7 <sup>9</sup>	47.8 <sup>0</sup> / 60.2 <sup>16</sup>	21.3 <sup>3</sup> / 37.2 <sup>5</sup>
En-23	79.7 <sup>4</sup> / 95.1 <sup>8</sup>	30.8 <sup>5</sup> / 43.4 <sup>2</sup>	13.2 <sup>9</sup> / 22.1 <sup>5</sup>	86.9 <sup>2</sup> / 94.5 <sup>3</sup>	53.6 <sup>5</sup> / 75.2 <sup>3</sup>	52.0 <sup>5</sup> / 66.7 <sup>5</sup>	99.5 <sup>10</sup> / 99.0 <sup>1</sup>	70.9 <sup>11</sup> / 75.2 <sup>10</sup>	47.4 <sup>4</sup> / 67.0 <sup>8</sup>	21.9 <sup>2</sup> / 30.4 <sup>3</sup>
En-24	85.4 <sup>7</sup> / 93.8 <sup>5</sup>	33.6 <sup>6</sup> / 47.4 <sup>3</sup>	12.7 <sup>3</sup> / 23.6 <sup>1</sup>	85.8 <sup>1</sup> / 95.4 <sup>3</sup>	58.1 <sup>7</sup> / 71.7 <sup>9</sup>	46.9 <sup>1</sup> / 59.4 <sup>8</sup>	99.0 <sup>1</sup> / 99.0 <sup>2</sup>	67.2 <sup>9</sup> / 74.1 <sup>3</sup>	47.5 <sup>0</sup> / 59.8 <sup>4</sup>	23.5 <sup>0</sup> / 32.4 <sup>2</sup>
En-25	88.5 <sup>8</sup> / 96.5 <sup>3</sup>	29.4 <sup>3</sup> / 38.0 <sup>7</sup>	10.6 <sup>2</sup> / 20.3 <sup>5</sup>	77.5 <sup>4</sup> / 91.9 <sup>4</sup>	79.6 <sup>2</sup> / 92.6 <sup>3</sup>	21.2 <sup>6</sup> / 49.7 <sup>3</sup>	98.0 <sup>1</sup> / 99.0 <sup>2</sup>	64.8 <sup>17</sup> / 76.2 <sup>11</sup>	47.5 <sup>0</sup> / 78.7 <sup>1</sup>	20.3 <sup>7</sup> / 32.9 <sup>6</sup>
De-0	1.6 <sup>0</sup> / 6.5 <sup>0</sup>	4.3 <sup>0</sup> / 15.9 <sup>5</sup>	9.6 <sup>9</sup> / 9.6 <sup>9</sup>	2.1 <sup>2</sup> / 2.2 <sup>0</sup>	17.1 <sup>4</sup> / 17.3 <sup>0</sup>	6.4 <sup>2</sup> / 17.5 <sup>0</sup>	32.9 <sup>0</sup> / 33.8 <sup>5</sup>	31.5 <sup>0</sup> / 35.1 <sup>0</sup>	7.8 <sup>1</sup> / 47.8 <sup>3</sup>	11.6 <sup>1</sup> / 12.0 <sup>1</sup>
De-1	41.4 <sup>8</sup> / 69.7 <sup>3</sup>	37.9 <sup>7</sup> / 44.7 <sup>3</sup>	15.4 <sup>2</sup> / 22.0 <sup>3</sup>	81.4 <sup>6</sup> / 93.2 <sup>2</sup>	44.6 <sup>3</sup> / 72.0 <sup>2</sup>	44.7 <sup>3</sup> / 67.8 <sup>2</sup>	98.5 <sup>1</sup> / 99.0 <sup>2</sup>	68.5 <sup>1</sup> / 72.6 <sup>3</sup>	47.8 <sup>0</sup> / 56.0 <sup>7</sup>	30.4 <sup>9</sup> / 35.9 <sup>7</sup>
De-2	57.5 <sup>11</sup> / 82.8 <sup>5</sup>	31.9 <sup>4</sup> / 41.4 <sup>3</sup>	11.0 <sup>1</sup> / 20.5 <sup>2</sup>	88.3 <sup>0</sup> / 93.7 <sup>1</sup>	51.2 <sup>1</sup> / 73.8 <sup>7</sup>	41.6 <sup>5</sup> / 67.2 <sup>0</sup>	97.5 <sup>2</sup> / 99.5 <sup>1</sup>	65.2 <sup>10</sup> / 74.1 <sup>11</sup>	47.5 <sup>7</sup> / 56.9 <sup>15</sup>	19.5 <sup>1</sup> / 29.6 <sup>4</sup>
De-3	46.1 <sup>11</sup> / 82.9 <sup>4</sup>	36.8 <sup>8</sup> / 41.2 <sup>4</sup>	14.6 <sup>2</sup> / 21.5 <sup>6</sup>	82.8 <sup>6</sup> / 92.3 <sup>3</sup>	43.1 <sup>5</sup> / 72.0 <sup>4</sup>	46.7 <sup>0</sup> / 64.7 <sup>2</sup>	96.5 <sup>3</sup> / 98.5 <sup>2</sup>	64.5 <sup>13</sup> / 72.9 <sup>10</sup>	47.8 <sup>0</sup> / 60.0 <sup>6</sup>	28.0 <sup>8</sup> / 36.3 <sup>6</sup>
De-4	52.6 <sup>12</sup> / 83.5 <sup>7</sup>	30.2 <sup>5</sup> / 39.8 <sup>7</sup>	15.2 <sup>9</sup> / 21.0 <sup>7</sup>	81.3 <sup>1</sup> / 91.4 <sup>2</sup>	44.5 <sup>0</sup> / 72.7 <sup>3</sup>	50.3 <sup>8</sup> / 62.7 <sup>2</sup>	96.0 <sup>3</sup> / 99.0 <sup>2</sup>	64.4 <sup>14</sup> / 74.3 <sup>8</sup>	47.8 <sup>0</sup> / 55.8 <sup>10</sup>	25.8 <sup>9</sup> / 35.4 <sup>6</sup>
De-5	43.2 <sup>6</sup> / 74.6 <sup>8</sup>	31.9 <sup>4</sup> / 44.9 <sup>7</sup>	14.9 <sup>1</sup> / 18.3 <sup>8</sup>	75.0 <sup>4</sup> / 92.0 <sup>3</sup>	42.6 <sup>7</sup> / 66.1 <sup>2</sup>	45.1 <sup>3</sup> / 60.3 <sup>6</sup>	97.0 <sup>1</sup> / 99.0 <sup>2</sup>	65.7 <sup>7</sup> / 70.8 <sup>11</sup>	47.5 <sup>5</sup> / 57.8 <sup>13</sup>	21.6 <sup>6</sup> / 38.7 <sup>10</sup>
De-6	50.7 <sup>12</sup> / 81.8 <sup>3</sup>	29.8 <sup>7</sup> / 42.6 <sup>4</sup>	15.2 <sup>6</sup> / 24.9 <sup>4</sup>	64.5 <sup>4</sup> / 90.0 <sup>2</sup>	37.5 <sup>3</sup> / 68.8 <sup>1</sup>	34.7 <sup>10</sup> / 55.4 <sup>6</sup>	97.5 <sup>3</sup> / 99.0 <sup>2</sup>	66.5 <sup>6</sup> / 74.2 <sup>10</sup>	47.8 <sup>0</sup> / 53.8 <sup>1</sup>	20.9 <sup>8</sup> / 33.4 <sup>5</sup>
De-7	56.6 <sup>6</sup> / 85.1 <sup>8</sup>	31.0 <sup>8</sup> / 44.4 <sup>5</sup>	13.9 <sup>7</sup> / 21.4 <sup>5</sup>	62.8 <sup>5</sup> / 87.0 <sup>6</sup>	47.6 <sup>9</sup> / 65.2 <sup>2</sup>	39.4 <sup>2</sup> / 56.8 <sup>3</sup>	93.0 <sup>3</sup> / 98.0 <sup>1</sup>	64.6 <sup>11</sup> / 73.6 <sup>12</sup>	47.8 <sup>0</sup> / 51.9 <sup>8</sup>	18.4 <sup>7</sup> / 30.2 <sup>4</sup>
De-8	60.1 <sup>7</sup> / 83.0 <sup>8</sup>	35.9 <sup>6</sup> / 38.7 <sup>5</sup>	16.5 <sup>6</sup> / 23.7 <sup>6</sup>	63.5 <sup>6</sup> / 87.0 <sup>7</sup>	48.9 <sup>4</sup> / 67.9 <sup>3</sup>	35.0 <sup>7</sup> / 54.2 <sup>7</sup>	93.0 <sup>2</sup> / 97.5 <sup>3</sup>	63.7 <sup>13</sup> / 74.1 <sup>10</sup>	47.8 <sup>0</sup> / 60.9 <sup>13</sup>	20.8 <sup>9</sup> / 27.7 <sup>5</sup>
De-9	64.3 <sup>7</sup> / 83.4 <sup>9</sup>	36.0 <sup>5</sup> / 39.3 <sup>4</sup>	14.7 <sup>5</sup> / 20.5 <sup>4</sup>	46.8 <sup>5</sup> / 85.4 <sup>1</sup>	46.3 <sup>7</sup> / 71.2 <sup>5</sup>	43.0 <sup>7</sup> / 60.7 <sup>4</sup>	98.0 <sup>1</sup> / 99.0 <sup>2</sup>	63.2 <sup>12</sup> / 75.1 <sup>11</sup>	47.8 <sup>0</sup> / 52.8 <sup>10</sup>	22.5 <sup>3</sup> / 29.8 <sup>4</sup>
De-10	66.7 <sup>8</sup> / 86.6 <sup>9</sup>	36.8 <sup>5</sup> / 40.7 <sup>3</sup>	16.3 <sup>0</sup> / 22.2 <sup>4</sup>	63.5 <sup>4</sup> / 87.4 <sup>5</sup>	43.0 <sup>5</sup> / 70.8 <sup>4</sup>	34.6 <sup>6</sup> / 66.7 <sup>5</sup>	96.5 <sup>2</sup> / 98.5 <sup>1</sup>	65.7 <sup>12</sup> / 74.1 <sup>12</sup>	47.8 <sup>0</sup> / 63.7 <sup>13</sup>	23.4 <sup>0</sup> / 31.1 <sup>3</sup>
De-11	57.5 <sup>9</sup> / 88.9 <sup>5</sup>	31.8 <sup>3</sup> / 42.1 <sup>2</sup>	15.1 <sup>9</sup> / 22.8 <sup>3</sup>	54.5 <sup>2</sup> / 88.4 <sup>0</sup>	53.6 <sup>5</sup> / 73.1 <sup>0</sup>	37.6 <sup>5</sup> / 53.2 <sup>5</sup>	96.0 <sup>2</sup> / 98.5 <sup>1</sup>	65.8 <sup>10</sup> / 75.8 <sup>12</sup>	47.8 <sup>0</sup> / 52.9 <sup>10</sup>	20.5<

Layer	Accent	DialAct	Emotion	EnvSound	Distance	Intent	MSpeaker	Sarcasm	Spoof	Stress
En-0	69.1 <sup>10.6</sup> / 74.4 <sup>7.1</sup>	25.0 <sup>6.3</sup> / 35.4 <sup>6.8</sup>	14.2 <sup>4.4</sup> / 15.3 <sup>2.3</sup>	18.2 <sup>3.2</sup> / 37.0 <sup>6.0</sup>	28.9 <sup>3.4</sup> / 45.7 <sup>7.1</sup>	19.9 <sup>6.5</sup> / 21.7 <sup>6.2</sup>	45.3 <sup>7.1</sup> / 65.4 <sup>6.6</sup>	50.5 <sup>6.3</sup> / 64.1 <sup>5.1</sup>	47.6 <sup>0.3</sup> / 68.5 <sup>10.7</sup>	26.3 <sup>8.1</sup> / 22.3 <sup>6.1</sup>
En-1	56.0 <sup>5.7</sup> / 72.9 <sup>1.8</sup>	22.7 <sup>5.3</sup> / 34.7 <sup>4.9</sup>	10.6 <sup>1.8</sup> / 12.9 <sup>2.7</sup>	51.9 <sup>3.1</sup> / 71.3 <sup>5.7</sup>	21.3 <sup>5.6</sup> / 30.7 <sup>3.2</sup>	19.4 <sup>2.1</sup> / 26.9 <sup>7.2</sup>	73.4 <sup>9.9</sup> / 91.9 <sup>7.5</sup>	53.9 <sup>3.3</sup> / 68.2 <sup>7.4</sup>	60.9 <sup>11.2</sup> / 76.0 <sup>17.5</sup>	24.8 <sup>6.2</sup> / 25.1 <sup>3.4</sup>
En-2	36.1 <sup>7.5</sup> / 52.1 <sup>7.0</sup>	24.2 <sup>4.6</sup> / 38.0 <sup>7.6</sup>	10.5 <sup>1.9</sup> / 12.4 <sup>2.1</sup>	54.2 <sup>3.9</sup> / 74.1 <sup>5.8</sup>	21.4 <sup>3.3</sup> / 28.5 <sup>2.9</sup>	18.2 <sup>3.9</sup> / 28.1 <sup>5.6</sup>	74.6 <sup>10.9</sup> / 83.6 <sup>15.1</sup>	60.4 <sup>5.0</sup> / 73.7 <sup>5.6</sup>	51.6 <sup>8.2</sup> / 72.0 <sup>15.3</sup>	21.9 <sup>0.0</sup> / 26.0 <sup>7.3</sup>
En-3	29.5 <sup>3.5</sup> / 45.6 <sup>11.6</sup>	21.7 <sup>4.7</sup> / 36.2 <sup>2.3</sup>	10.5 <sup>1.9</sup> / 14.7 <sup>2.7</sup>	57.0 <sup>5.6</sup> / 75.6 <sup>0.0</sup>	22.7 <sup>5.0</sup> / 30.3 <sup>2.7</sup>	23.1 <sup>3.9</sup> / 29.8 <sup>4.4</sup>	70.6 <sup>11.4</sup> / 80.5 <sup>14.1</sup>	58.7 <sup>3.7</sup> / 71.1 <sup>6.8</sup>	47.4 <sup>0.6</sup> / 74.6 <sup>10.2</sup>	20.3 <sup>3.3</sup> / 26.4 <sup>0.0</sup>
En-4	28.9 <sup>5.3</sup> / 35.2 <sup>5.7</sup>	22.7 <sup>10.5</sup> / 32.7 <sup>5.1</sup>	10.5 <sup>1.9</sup> / 14.6 <sup>2.0</sup>	56.4 <sup>9.8</sup> / 73.9 <sup>0.4</sup>	20.5 <sup>4.2</sup> / 30.2 <sup>2.8</sup>	26.7 <sup>5.8</sup> / 33.0 <sup>0.3</sup>	71.8 <sup>7.4</sup> / 80.4 <sup>11.6</sup>	60.4 <sup>0.9</sup> / 63.4 <sup>12.6</sup>	47.5 <sup>0.3</sup> / 68.0 <sup>10.3</sup>	24.3 <sup>3.4</sup> / 23.8 <sup>1.2</sup>
En-5	24.1 <sup>5.4</sup> / 36.3 <sup>5.7</sup>	27.9 <sup>8.5</sup> / 38.1 <sup>12.3</sup>	9.7 <sup>1.8</sup> / 14.8 <sup>4.6</sup>	53.1 <sup>7.8</sup> / 72.9 <sup>0.2</sup>	19.3 <sup>3.4</sup> / 35.1 <sup>3.2</sup>	25.9 <sup>6.0</sup> / 32.7 <sup>3.9</sup>	73.5 <sup>9.5</sup> / 80.1 <sup>10.6</sup>	64.0 <sup>8.8</sup> / 67.0 <sup>7.8</sup>	46.6 <sup>0.5</sup> / 51.1 <sup>6.4</sup>	14.5 <sup>4.6</sup> / 23.7 <sup>4.1</sup>
En-6	23.5 <sup>3.3</sup> / 41.8 <sup>7.4</sup>	21.4 <sup>5.1</sup> / 32.9 <sup>9.5</sup>	10.4 <sup>1.8</sup> / 12.6 <sup>3.6</sup>	54.6 <sup>10.5</sup> / 72.3 <sup>4.6</sup>	19.3 <sup>3.4</sup> / 34.6 <sup>3.5</sup>	23.0 <sup>3.9</sup> / 32.0 <sup>0.6</sup>	75.4 <sup>11.2</sup> / 78.9 <sup>11.6</sup>	65.9 <sup>5.3</sup> / 65.7 <sup>6.6</sup>	30.8 <sup>4.4</sup> / 47.6 <sup>0.5</sup>	17.8 <sup>3.3</sup> / 23.1 <sup>4.2</sup>
En-7	23.4 <sup>6.6</sup> / 39.0 <sup>5.0</sup>	21.5 <sup>7.3</sup> / 36.4 <sup>7.6</sup>	10.5 <sup>2.1</sup> / 13.4 <sup>3.2</sup>	50.3 <sup>3.6</sup> / 70.9 <sup>3.5</sup>	19.0 <sup>4.0</sup> / 33.7 <sup>2.7</sup>	25.1 <sup>6.9</sup> / 34.0 <sup>0.0</sup>	68.5 <sup>7.0</sup> / 76.2 <sup>9.7</sup>	62.3 <sup>9.0</sup> / 66.0 <sup>9.5</sup>	47.4 <sup>0.4</sup> / 47.8 <sup>0.3</sup>	19.9 <sup>2.4</sup> / 23.4 <sup>3.8</sup>
En-8	18.2 <sup>7.6</sup> / 26.8 <sup>5.5</sup>	24.3 <sup>8.2</sup> / 32.1 <sup>8.2</sup>	10.5 <sup>1.9</sup> / 12.2 <sup>2.7</sup>	53.2 <sup>9.9</sup> / 72.1 <sup>8.2</sup>	18.4 <sup>2.4</sup> / 40.6 <sup>3.7</sup>	22.8 <sup>1.5</sup> / 34.5 <sup>0.7</sup>	63.8 <sup>6.6</sup> / 77.9 <sup>5.1</sup>	61.8 <sup>8.8</sup> / 64.6 <sup>5.5</sup>	47.8 <sup>0.3</sup> / 47.8 <sup>0.3</sup>	19.8 <sup>8.6</sup> / 24.1 <sup>5.8</sup>
En-9	9.2 <sup>2.2</sup> / 12.4 <sup>4.4</sup>	19.1 <sup>2.5</sup> / 35.8 <sup>7.2</sup>	10.5 <sup>1.9</sup> / 13.3 <sup>2.7</sup>	53.4 <sup>8.6</sup> / 68.8 <sup>2.7</sup>	20.4 <sup>7.7</sup> / 29.8 <sup>4.2</sup>	20.6 <sup>6.8</sup> / 33.1 <sup>0.0</sup>	62.1 <sup>4.4</sup> / 64.2 <sup>15.0</sup>	64.7 <sup>7.5</sup> / 64.2 <sup>15.0</sup>	47.4 <sup>0.6</sup> / 47.8 <sup>0.3</sup>	15.7 <sup>6.6</sup> / 25.3 <sup>4.1</sup>
En-10	14.2 <sup>4.2</sup> / 21.1 <sup>2.3</sup>	33.8 <sup>7.4</sup> / 39.2 <sup>5.7</sup>	10.6 <sup>1.8</sup> / 13.5 <sup>1.2</sup>	54.4 <sup>10.4</sup> / 68.6 <sup>7.6</sup>	21.4 <sup>3.3</sup> / 29.5 <sup>1.1</sup>	24.7 <sup>3.3</sup> / 34.3 <sup>8.4</sup>	65.4 <sup>8.1</sup> / 74.8 <sup>8.5</sup>	66.9 <sup>1.5</sup> / 66.3 <sup>7.3</sup>	47.6 <sup>0.3</sup> / 47.8 <sup>0.3</sup>	17.9 <sup>3.5</sup> / 24.1 <sup>4.1</sup>
En-11	10.9 <sup>3.1</sup> / 14.6 <sup>2.2</sup>	24.5 <sup>6.1</sup> / 34.4 <sup>5.5</sup>	9.8 <sup>2.1</sup> / 12.3 <sup>2.0</sup>	52.5 <sup>10.7</sup> / 66.1 <sup>10.0</sup>	21.3 <sup>3.3</sup> / 28.9 <sup>1.0</sup>	26.6 <sup>6.6</sup> / 32.2 <sup>1.1</sup>	66.8 <sup>6.4</sup> / 71.2 <sup>5.9</sup>	60.4 <sup>11.6</sup> / 64.5 <sup>12.3</sup>	47.6 <sup>0.3</sup> / 47.8 <sup>0.3</sup>	16.4 <sup>2.7</sup> / 25.7 <sup>9.9</sup>
En-12	21.3 <sup>2.8</sup> / 18.6 <sup>3.5</sup>	23.8 <sup>0.9</sup> / 31.2 <sup>9.5</sup>	10.5 <sup>1.9</sup> / 14.5 <sup>2.1</sup>	57.9 <sup>11.6</sup> / 67.3 <sup>3.3</sup>	19.3 <sup>3.4</sup> / 34.9 <sup>4.2</sup>	25.0 <sup>7.1</sup> / 34.4 <sup>8.8</sup>	68.3 <sup>8.3</sup> / 63.3 <sup>10.6</sup>	47.5 <sup>0.5</sup> / 47.8 <sup>0.3</sup>	22.1 <sup>6.4</sup> / 25.4 <sup>5.1</sup>	
En-13	20.8 <sup>2.8</sup> / 18.3 <sup>2.4</sup>	23.5 <sup>0.5</sup> / 33.1 <sup>16.1</sup>	9.8 <sup>1.9</sup> / 12.5 <sup>1.9</sup>	54.3 <sup>8.6</sup> / 66.8 <sup>8.8</sup>	19.3 <sup>3.4</sup> / 39.2 <sup>2.5</sup>	22.5 <sup>2.1</sup> / 33.3 <sup>9.9</sup>	63.2 <sup>3.8</sup> / 73.9 <sup>4.4</sup>	61.9 <sup>8.9</sup> / 64.7 <sup>9.1</sup>	47.8 <sup>0.3</sup> / 47.8 <sup>0.3</sup>	20.5 <sup>7.7</sup> / 23.5 <sup>5.1</sup>
En-14	20.8 <sup>2.8</sup> / 18.4 <sup>2.2</sup>	23.1 <sup>4.0</sup> / 29.9 <sup>4.1</sup>	9.8 <sup>1.9</sup> / 12.5 <sup>0.9</sup>	52.6 <sup>8.3</sup> / 68.5 <sup>5.5</sup>	22.5 <sup>2.1</sup> / 41.5 <sup>4.3</sup>	26.9 <sup>2.7</sup> / 29.7 <sup>8.8</sup>	63.8 <sup>4.0</sup> / 70.3 <sup>1.0</sup>	62.5 <sup>7.6</sup> / 62.7 <sup>13.0</sup>	47.5 <sup>0.5</sup> / 47.8 <sup>0.3</sup>	17.6 <sup>5.0</sup> / 28.1 <sup>6.4</sup>
En-15	20.8 <sup>2.7</sup> / 20.7 <sup>2.6</sup>	22.6 <sup>3.4</sup> / 32.6 <sup>4.4</sup>	10.5 <sup>1.9</sup> / 13.9 <sup>1.5</sup>	55.8 <sup>9.9</sup> / 65.9 <sup>0.0</sup>	19.5 <sup>3.9</sup> / 39.6 <sup>4.1</sup>	28.2 <sup>5.5</sup> / 30.5 <sup>5.2</sup>	57.9 <sup>8.1</sup> / 72.9 <sup>5.2</sup>	63.9 <sup>0.0</sup> / 61.3 <sup>12.8</sup>	47.2 <sup>1.4</sup> / 47.8 <sup>0.3</sup>	17.3 <sup>3.8</sup> / 24.5 <sup>3.1</sup>
En-16	20.8 <sup>2.7</sup> / 21.0 <sup>3.5</sup>	21.6 <sup>6.0</sup> / 31.8 <sup>3.0</sup>	10.5 <sup>1.9</sup> / 14.2 <sup>1.7</sup>	50.7 <sup>6.8</sup> / 68.2 <sup>7.6</sup>	20.0 <sup>4.0</sup> / 36.1 <sup>3.9</sup>	25.0 <sup>3.4</sup> / 32.8 <sup>0.5</sup>	60.8 <sup>7.5</sup> / 71.3 <sup>1.7</sup>	60.7 <sup>7.6</sup> / 60.7 <sup>15.6</sup>	47.2 <sup>0.7</sup> / 47.8 <sup>0.3</sup>	18.9 <sup>4.4</sup> / 24.6 <sup>3.8</sup>
En-17	20.9 <sup>2.8</sup> / 20.1 <sup>2.7</sup>	24.3 <sup>3.1</sup> / 31.1 <sup>3.7</sup>	10.5 <sup>1.9</sup> / 14.5 <sup>2.1</sup>	53.4 <sup>7.1</sup> / 67.4 <sup>0.9</sup>	19.0 <sup>5.3</sup> / 36.8 <sup>0.9</sup>	25.2 <sup>8.1</sup> / 34.5 <sup>0.8</sup>	58.9 <sup>7.7</sup> / 70.8 <sup>0.0</sup>	64.1 <sup>0.9</sup> / 64.0 <sup>10.9</sup>	47.6 <sup>0.3</sup> / 47.8 <sup>0.3</sup>	16.9 <sup>5.1</sup> / 24.1 <sup>3.8</sup>
En-18	20.9 <sup>2.8</sup> / 16.1 <sup>1.9</sup>	24.6 <sup>3.1</sup> / 32.5 <sup>1.1</sup>	9.5 <sup>1.9</sup> / 14.5 <sup>3.3</sup>	57.9 <sup>9.1</sup> / 66.5 <sup>8.3</sup>	19.0 <sup>5.3</sup> / 37.5 <sup>0.9</sup>	25.8 <sup>8.3</sup> / 36.7 <sup>5.8</sup>	62.5 <sup>4.9</sup> / 64.3 <sup>5.9</sup>	47.8 <sup>0.3</sup> / 47.8 <sup>0.3</sup>	17.5 <sup>3.0</sup> / 26.2 <sup>3.6</sup>	
En-19	21.0 <sup>2.7</sup> / 17.9 <sup>5.6</sup>	20.1 <sup>3.2</sup> / 30.4 <sup>1.5</sup>	9.9 <sup>2.1</sup> / 16.2 <sup>1.3</sup>	53.5 <sup>7.8</sup> / 61.4 <sup>0.2</sup>	17.8 <sup>4.6</sup> / 39.6 <sup>4.3</sup>	24.4 <sup>0.5</sup> / 33.1 <sup>8.3</sup>	62.0 <sup>7.2</sup> / 70.6 <sup>1.7</sup>	64.7 <sup>8.8</sup> / 66.4 <sup>4.4</sup>	47.6 <sup>0.3</sup> / 51.1 <sup>6.4</sup>	15.4 <sup>4.1</sup> / 25.3 <sup>4.4</sup>
En-20	21.0 <sup>3.0</sup> / 26.1 <sup>2.2</sup>	17.9 <sup>3.1</sup> / 31.3 <sup>2.7</sup>	9.7 <sup>1.9</sup> / 12.7 <sup>2.4</sup>	56.7 <sup>6.6</sup> / 64.3 <sup>1.2</sup>	21.6 <sup>2.6</sup> / 42.4 <sup>8.8</sup>	25.7 <sup>2.5</sup> / 33.2 <sup>9.3</sup>	60.7 <sup>9.5</sup> / 73.3 <sup>0.0</sup>	78.1 <sup>0.0</sup> / 73.5 <sup>1.0</sup>	52.8 <sup>10.5</sup> / 47.8 <sup>0.3</sup>	16.4 <sup>2.8</sup> / 25.0 <sup>3.0</sup>
En-21	20.9 <sup>2.8</sup> / 20.1 <sup>3.1</sup>	21.8 <sup>1.1</sup> / 31.7 <sup>1.9</sup>	9.7 <sup>1.9</sup> / 14.4 <sup>3.2</sup>	56.1 <sup>5.9</sup> / 63.6 <sup>0.3</sup>	23.4 <sup>3.1</sup> / 38.7 <sup>4.2</sup>	21.4 <sup>7.7</sup> / 34.0 <sup>0.7</sup>	60.1 <sup>4.9</sup> / 70.4 <sup>5.7</sup>	62.2 <sup>1.3</sup> / 61.4 <sup>9.1</sup>	47.8 <sup>0.3</sup> / 47.8 <sup>0.3</sup>	17.0 <sup>6.6</sup> / 23.9 <sup>2.7</sup>
En-22	21.2 <sup>2.7</sup> / 19.2 <sup>1.3</sup>	22.0 <sup>2.4</sup> / 31.8 <sup>4.3</sup>	10.6 <sup>2.0</sup> / 13.1 <sup>2.8</sup>	56.2 <sup>9.6</sup> / 65.0 <sup>10.0</sup>	19.8 <sup>5.5</sup> / 37.4 <sup>4.5</sup>	24.5 <sup>4.8</sup> / 34.2 <sup>2.9</sup>	62.6 <sup>2.2</sup> / 70.1 <sup>0.7</sup>	60.5 <sup>11.0</sup> / 63.0 <sup>15.3</sup>	47.6 <sup>0.3</sup> / 47.8 <sup>0.3</sup>	17.1 <sup>2.5</sup> / 23.7 <sup>2.8</sup>
En-23	20.3 <sup>3.4</sup> / 26.3 <sup>2.6</sup>	25.7 <sup>2.8</sup> / 32.7 <sup>2.4</sup>	55.0 <sup>1.8</sup> / 32.7 <sup>1.8</sup>	50.5 <sup>1.8</sup> / 58.4 <sup>5.2</sup>	22.2 <sup>3.8</sup> / 36.8 <sup>4.2</sup>	22.8 <sup>2.3</sup> / 38.3 <sup>4.6</sup>	60.6 <sup>6.7</sup> / 67.0 <sup>2.2</sup>	60.6 <sup>6.7</sup> / 69.0 <sup>6.2</sup>	61.3 <sup>4.9</sup> / 68.1 <sup>6.8</sup>	47.6 <sup>0.5</sup> / 47.8 <sup>0.3</sup>
En-24	20.3 <sup>3.5</sup> / 27.3 <sup>3.6</sup>	23.5 <sup>3.0</sup> / 31.9 <sup>5.6</sup>	12.6 <sup>5.1</sup> / 16.4 <sup>2.6</sup>	56.5 <sup>13.3</sup> / 61.8 <sup>0.6</sup>	23.2 <sup>3.1</sup> / 34.8 <sup>2.4</sup>	9.2 <sup>0.8</sup> / 20.0 <sup>1.9</sup>	59.5 <sup>6.0</sup> / 68.0 <sup>8.6</sup>	62.2 <sup>14.2</sup> / 61.7 <sup>14.0</sup>	46.5 <sup>0.8</sup> / 47.8 <sup>0.3</sup>	17.1 <sup>7.7</sup> / 23.9 <sup>4.3</sup>
En-25	25.4 <sup>9.3</sup> / 71.6 <sup>2.8</sup>	20.6 <sup>4.4</sup> / 31.6 <sup>3.4</sup>	9.9 <sup>2.1</sup> / 16.2 <sup>1.3</sup>	53.5 <sup>7.8</sup> / 61.4 <sup>0.2</sup>	30.9 <sup>5.5</sup> / 46.3 <sup>3.3</sup>	20.0 <sup>0.1</sup> / 21.6 <sup>6.7</sup>	70.2 <sup>0.2</sup> / 77.8 <sup>10.0</sup>	51.6 <sup>9.9</sup> / 66.2 <sup>2.7</sup>	51.8 <sup>8.1</sup> / 72.0 <sup>15.3</sup>	19.5 <sup>8.8</sup> / 22.7 <sup>1.1</sup>
De-0	1.6 <sup>0.0</sup> / 6.5 <sup>0.1</sup>	4.3 <sup>0.4</sup> / 15.9 <sup>0.3</sup>	9.6 <sup>0.9</sup> / 16.5 <sup>0.3</sup>	2.1 <sup>2.0</sup> / 17.3 <sup>0.9</sup>	17.1 <sup>0.4</sup> / 21.7 <sup>0.9</sup>	6.4 <sup>2.2</sup> / 17.3 <sup>0.9</sup>	6.2 <sup>0.7</sup> / 69.7 <sup>0.7</sup>	32.9 <sup>0.5</sup> / 33.5 <sup>0.5</sup>	31.5 <sup>0.6</sup> / 33.5 <sup>0.5</sup>	11.6 <sup>1.1</sup> / 12.0 <sup>1.1</sup>
De-1	20.3 <sup>3.5</sup> / 27.0 <sup>5.7</sup>	20.8 <sup>6.1</sup> / 32.1 <sup>2.2</sup>	11.2 <sup>2.2</sup> / 15.8 <sup>2.1</sup>	48.5 <sup>1.7</sup> / 58.4 <sup>7.0</sup>	30.3 <sup>6.6</sup> / 38.7 <sup>4.7</sup>	20.5 <sup>7.5</sup> / 25.4 <sup>2.7</sup>	64.6 <sup>8.8</sup> / 68.7 <sup>5.5</sup>	47.6 <sup>0.3</sup> / 47.8 <sup>0.3</sup>	16.6 <sup>8.0</sup> / 24.0 <sup>9.3</sup>	
De-2	20.4 <sup>3.4</sup> / 23.9 <sup>3.8</sup>	26.7 <sup>6.8</sup> / 33.3 <sup>2.6</sup>	10.5 <sup>2.3</sup> / 13.4 <sup>2.1</sup>	54.7 <sup>5.7</sup> / 61.4 <sup>0.7</sup>	30.0 <sup>5.9</sup> / 39.7 <sup>2.7</sup>	17.6 <sup>3.4</sup> / 23.3 <sup>3.4</sup>	61.5 <sup>5.0</sup> / 67.8 <sup>6.1</sup>	62.3 <sup>7.4</sup> / 64.5 <sup>16.9</sup>	47.6 <sup>0.3</sup> / 47.8 <sup>0.3</sup>	16.3 <sup>3.3</sup> / 24.1 <sup>4.5</sup>
De-3	21.2 <sup>2.8</sup> / 26.5 <sup>3.5</sup>	26.8 <sup>7.5</sup> / 36.5 <sup>3.6</sup>	10.6 <sup>2.4</sup> / 15.0 <sup>1.1</sup>	52.9 <sup>8.5</sup> / 65.5 <sup>5.7</sup>	27.3 <sup>6.8</sup> / 39.7 <sup>4.9</sup>	19.7 <sup>3.9</sup> / 22.9 <sup>3.5</sup>	63.0 <sup>4.8</sup> / 67.8 <sup>7.2</sup>	62.4 <sup>7.6</sup> / 65.7 <sup>8.3</sup>	47.6 <sup>0.3</sup> / 47.8 <sup>0.3</sup>	16.2 <sup>8.7</sup> / 24.0 <sup>1.8</sup>
De-4	20.9 <sup>2.8</sup> / 26.0 <sup>7.2</sup>	26.5 <sup>6.6</sup> / 34.7 <sup>5.8</sup>	10.6 <sup>2.4</sup> / 14.7 <sup>2.7</sup>	53.4 <sup>7.9</sup> / 60.2 <sup>0.9</sup>	27.2 <sup>6.8</sup> / 42.2 <sup>4.6</sup>	17.9 <sup>7.7</sup> / 22.3 <sup>3.6</sup>	63.0 <sup>5.3</sup> / 67.0 <sup>8.5</sup>	62.4 <sup>7.6</sup> / 65.7 <sup>8.3</sup>	47.6 <sup>0.3</sup> / 47.8 <sup>0.3</sup>	16.2 <sup>8.7</sup> / 24.6 <sup>5.5</sup>
De-5	20.9 <sup>2.8</sup> / 25.1 <sup>6.6</sup>	28.7 <sup>2.0</sup> / 34.9 <sup>0.9</sup>	10.6 <sup>2.4</sup> / 17.1 <sup>1.7</sup>	52.9 <sup>7.2</sup> / 61.5 <sup>5.2</sup>	30.4 <sup>5.5</sup> / 36.5 <sup>0.0</sup>	18.8 <sup>2.5</sup> / 25.8 <sup>3.0</sup>	65.2 <sup>4.3</sup> / 67.8 <sup>7.6</sup>	62.9 <sup>7.6</sup> / 66.7 <sup>2.7</sup>	47.6 <sup>0.3</sup> / 47.8 <sup>0.3</sup>	16.2 <sup>8.8</sup> / 24.4 <sup>3.2</sup>
De-6	20.9 <sup>2.8</sup> / 26.7 <sup>5.7</sup>	28.0 <sup>7.4</sup> / 34.8 <sup>3.4</sup>	10.6 <sup>2.1</sup> / 15.7 <sup>2.0</sup>	50.4 <sup>0.0</sup> / 62.0 <sup>16.0</sup>	29.1 <sup>0.6</sup> / 38.9 <sup>5.8</sup>	19.8 <sup>7.4</sup> / 24.6 <sup>4.2</sup>	60.6 <sup>7.7</sup> / 66.9 <sup></sup>			

Layer	Accent	DialAct	Emotion	EnvSound	Distance	Intent	MSpeaker	Sarcasm	Spof	Stress
En-0	89.1 <sup>10.0</sup> / 92.5 <sup>0.0</sup>	22.2 <sup>1.1</sup> / 37.9 <sup>1.7</sup>	17.3 <sup>5.7</sup> / 18.6 <sup>4.2</sup>	48.3 <sup>4.6</sup> / 67.8 <sup>6.9</sup>	80.3 <sup>1.5</sup> / 89.5 <sup>3.7</sup>	22.5 <sup>5.7</sup> / 31.4 <sup>2.7</sup>	65.0 <sup>12.0</sup> / 91.3 <sup>5.5</sup>	65.4 <sup>12.0</sup> / 73.1 <sup>5.6</sup>	61.6 <sup>11.8</sup> / 88.0 <sup>0.2</sup>	15.0 <sup>3.5</sup> / 17.3 <sup>4.2</sup>
En-1	85.9 <sup>7.4</sup> / 96.1 <sup>4.0</sup>	25.2 <sup>5.2</sup> / 38.6 <sup>5.8</sup>	15.5 <sup>9.1</sup> / 20.7 <sup>3.0</sup>	56.3 <sup>4.4</sup> / 74.3 <sup>1.3</sup>	75.0 <sup>3.5</sup> / 89.0 <sup>1.5</sup>	20.0 <sup>8</sup> / 35.7 <sup>6.0</sup>	79.6 <sup>4.4</sup> / 95.4 <sup>8</sup>	61.2 <sup>8.4</sup> / 77.8 <sup>4.8</sup>	70.0 <sup>4.1</sup> / 88.4 <sup>3.4</sup>	16.7 <sup>7.4</sup> / 24.3 <sup>2.4</sup>
En-2	91.2 <sup>7.7</sup> / 96.6 <sup>3.3</sup>	28.1 <sup>7.6</sup> / 43.0 <sup>5.0</sup>	17.3 <sup>6.5</sup> / 22.2 <sup>4.7</sup>	67.4 <sup>6.2</sup> / 83.2 <sup>5.3</sup>	79.4 <sup>4.0</sup> / 89.5 <sup>5.9</sup>	21.9 <sup>6.9</sup> / 38.1 <sup>4.5</sup>	77.0 <sup>5.5</sup> / 95.4 <sup>0</sup>	61.4 <sup>14.1</sup> / 76.8 <sup>7.7</sup>	65.0 <sup>9.1</sup> / 88.5 <sup>6.6</sup>	18.2 <sup>1.9</sup> / 25.0 <sup>4.4</sup>
En-3	90.1 <sup>7.5</sup> / 96.1 <sup>4.3</sup>	25.8 <sup>8.1</sup> / 35.4 <sup>4.9</sup>	17.1 <sup>3.7</sup> / 21.2 <sup>3.9</sup>	71.6 <sup>6.9</sup> / 85.5 <sup>6.7</sup>	79.3 <sup>3.3</sup> / 87.6 <sup>5.7</sup>	29.0 <sup>6.6</sup> / 38.6 <sup>6.2</sup>	78.0 <sup>7.9</sup> / 97.0 <sup>3.8</sup>	61.3 <sup>13.7</sup> / 73.2 <sup>7.8</sup>	61.0 <sup>1.1</sup> / 83.3 <sup>5.8</sup>	19.9 <sup>4.1</sup> / 25.4 <sup>4.2</sup>
En-4	88.8 <sup>5.4</sup> / 95.8 <sup>4.2</sup>	20.7 <sup>7.4</sup> / 38.3 <sup>5.5</sup>	15.9 <sup>5.0</sup> / 19.8 <sup>4.8</sup>	73.8 <sup>3.8</sup> / 85.8 <sup>3.8</sup>	74.1 <sup>6.2</sup> / 89.4 <sup>7.2</sup>	31.2 <sup>5.5</sup> / 42.1 <sup>5.4</sup>	81.1 <sup>5.3</sup> / 97.5 <sup>4.0</sup>	66.5 <sup>9.1</sup> / 75.7 <sup>6.5</sup>	56.9 <sup>11.5</sup> / 85.3 <sup>6.7</sup>	24.1 <sup>4.8</sup> / 28.8 <sup>5.0</sup>
En-5	85.5 <sup>8.1</sup> / 96.9 <sup>3.9</sup>	24.9 <sup>9.3</sup> / 42.2 <sup>5.1</sup>	15.9 <sup>3.0</sup> / 23.8 <sup>7.5</sup>	74.7 <sup>5.8</sup> / 86.8 <sup>5.0</sup>	71.8 <sup>4.6</sup> / 86.5 <sup>5.8</sup>	30.6 <sup>9</sup> / 39.5 <sup>3.7</sup>	88.4 <sup>5.5</sup> / 96.9 <sup>0.7</sup>	70.6 <sup>10.6</sup> / 77.8 <sup>8.5</sup>	51.8 <sup>8.1</sup> / 77.3 <sup>18.2</sup>	18.8 <sup>3.1</sup> / 24.6 <sup>2.9</sup>
En-6	87.3 <sup>8.9</sup> / 96.6 <sup>2.9</sup>	27.6 <sup>6.1</sup> / 40.8 <sup>5.6</sup>	20.3 <sup>4.3</sup> / 18.2 <sup>2.3</sup>	74.8 <sup>6.0</sup> / 89.2 <sup>0.7</sup>	69.8 <sup>6.6</sup> / 84.7 <sup>7.2</sup>	28.1 <sup>4.8</sup> / 44.2 <sup>3.5</sup>	91.9 <sup>5.5</sup> / 98.0 <sup>0.0</sup>	72.2 <sup>8.8</sup> / 76.1 <sup>9.7</sup>	51.0 <sup>5.5</sup> / 85.3 <sup>6.7</sup>	16.0 <sup>2.2</sup> / 26.5 <sup>2.0</sup>
En-7	86.8 <sup>6.2</sup> / 97.8 <sup>3.9</sup>	23.5 <sup>3.8</sup> / 40.3 <sup>6.1</sup>	20.3 <sup>3.6</sup> / 22.6 <sup>5.8</sup>	73.7 <sup>4.2</sup> / 88.7 <sup>5.5</sup>	66.7 <sup>3.5</sup> / 85.2 <sup>7.8</sup>	29.9 <sup>4.0</sup> / 46.6 <sup>7.7</sup>	94.4 <sup>5.6</sup> / 98.5 <sup>2.0</sup>	69.0 <sup>13.2</sup> / 79.2 <sup>9.1</sup>	55.1 <sup>9.0</sup> / 82.1 <sup>7.8</sup>	16.5 <sup>2.2</sup> / 24.6 <sup>3.9</sup>
En-8	82.0 <sup>5.2</sup> / 97.0 <sup>3.9</sup>	22.6 <sup>1.9</sup> / 37.3 <sup>2.9</sup>	19.4 <sup>5.2</sup> / 24.3 <sup>4.6</sup>	72.2 <sup>5.9</sup> / 89.6 <sup>5.4</sup>	63.3 <sup>6.9</sup> / 84.1 <sup>7.6</sup>	30.7 <sup>7.2</sup> / 51.5 <sup>5.2</sup>	93.9 <sup>1.2</sup> / 97.5 <sup>4.0</sup>	71.7 <sup>7.3</sup> / 78.2 <sup>10.3</sup>	55.1 <sup>9.0</sup> / 73.9 <sup>6.6</sup>	18.7 <sup>5.8</sup> / 30.9 <sup>5.7</sup>
En-9	83.2 <sup>3.5</sup> / 96.5 <sup>3.3</sup>	22.1 <sup>4.4</sup> / 42.6 <sup>3.8</sup>	19.9 <sup>8.1</sup> / 24.6 <sup>5.4</sup>	76.7 <sup>3.2</sup> / 89.0 <sup>5.0</sup>	64.6 <sup>6.6</sup> / 82.5 <sup>7.2</sup>	34.5 <sup>10.4</sup> / 57.3 <sup>10.6</sup>	95.4 <sup>1.5</sup> / 98.5 <sup>2.0</sup>	69.6 <sup>9.0</sup> / 76.8 <sup>9.6</sup>	47.6 <sup>0.3</sup> / 75.3 <sup>15.7</sup>	17.8 <sup>3.7</sup> / 27.0 <sup>6.5</sup>
En-10	89.1 <sup>7.2</sup> / 96.2 <sup>3.3</sup>	24.5 <sup>8.6</sup> / 40.8 <sup>5.9</sup>	14.5 <sup>6.8</sup> / 21.5 <sup>6.3</sup>	78.3 <sup>3.8</sup> / 89.2 <sup>4.8</sup>	59.9 <sup>6.4</sup> / 75.1 <sup>10.3</sup>	34.2 <sup>5.5</sup> / 58.6 <sup>9.3</sup>	96.5 <sup>4.7</sup> / 98.5 <sup>2.0</sup>	68.8 <sup>9.7</sup> / 74.7 <sup>8.7</sup>	56.9 <sup>11.5</sup> / 75.2 <sup>16.0</sup>	22.4 <sup>3.6</sup> / 29.0 <sup>5.7</sup>
En-11	80.7 <sup>7.9</sup> / 94.7 <sup>3.5</sup>	25.2 <sup>2.7</sup> / 43.1 <sup>5.5</sup>	12.5 <sup>3.2</sup> / 22.6 <sup>6.9</sup>	75.9 <sup>6.7</sup> / 88.7 <sup>3.2</sup>	55.2 <sup>2.4</sup> / 73.6 <sup>1.9</sup>	56.5 <sup>5.8</sup> / 77.9 <sup>0.2</sup>	69.5 <sup>9.3</sup> / 99.0 <sup>1.2</sup>	47.5 <sup>0.3</sup> / 67.8 <sup>17.7</sup>	25.9 <sup>8.4</sup> / 31.1 <sup>9.0</sup>	
En-12	76.9 <sup>6.8</sup> / 94.6 <sup>1.6</sup>	26.8 <sup>3.8</sup> / 45.2 <sup>5.5</sup>	16.1 <sup>5.9</sup> / 21.5 <sup>7.1</sup>	76.6 <sup>6.2</sup> / 88.9 <sup>5.2</sup>	54.3 <sup>2.8</sup> / 69.4 <sup>5.6</sup>	36.3 <sup>0.0</sup> / 64.6 <sup>6.3</sup>	98.0 <sup>3.0</sup> / 98.5 <sup>2.0</sup>	65.3 <sup>10.0</sup> / 75.5 <sup>9.5</sup>	47.5 <sup>0.3</sup> / 70.8 <sup>14.8</sup>	30.0 <sup>6.3</sup> / 34.6 <sup>4.1</sup>
En-13	72.1 <sup>3.4</sup> / 89.8 <sup>4.5</sup>	34.5 <sup>7.0</sup> / 46.6 <sup>3.2</sup>	13.4 <sup>3.4</sup> / 22.4 <sup>4.7</sup>	73.6 <sup>6.0</sup> / 86.0 <sup>1.0</sup>	47.9 <sup>7.8</sup> / 69.2 <sup>7.6</sup>	42.3 <sup>7.5</sup> / 64.7 <sup>4.2</sup>	97.0 <sup>7.7</sup> / 98.5 <sup>2.0</sup>	67.4 <sup>8.4</sup> / 73.1 <sup>7.9</sup>	47.6 <sup>0.3</sup> / 66.5 <sup>15.9</sup>	29.3 <sup>4.4</sup> / 37.4 <sup>3.9</sup>
En-14	63.9 <sup>6.0</sup> / 90.0 <sup>4.9</sup>	33.9 <sup>6.1</sup> / 46.7 <sup>3.3</sup>	11.8 <sup>3.3</sup> / 23.4 <sup>5.2</sup>	72.5 <sup>5.2</sup> / 86.5 <sup>1.7</sup>	48.2 <sup>11.1</sup> / 69.6 <sup>6.7</sup>	58.5 <sup>2.0</sup> / 99.0 <sup>1.2</sup>	68.7 <sup>11.3</sup> / 72.6 <sup>8.8</sup>	51.0 <sup>5.5</sup> / 67.8 <sup>17.7</sup>	26.5 <sup>7.5</sup> / 40.5 <sup>6.9</sup>	
En-15	55.6 <sup>1.8</sup> / 87.6 <sup>1.0</sup>	34.0 <sup>3.5</sup> / 48.8 <sup>5.4</sup>	11.9 <sup>2.6</sup> / 22.8 <sup>3.5</sup>	72.8 <sup>4.2</sup> / 87.1 <sup>2.5</sup>	47.7 <sup>6.2</sup> / 64.2 <sup>5.0</sup>	53.0 <sup>7</sup> / 77.1 <sup>6.6</sup>	97.5 <sup>3.2</sup> / 98.5 <sup>2.0</sup>	68.5 <sup>12.3</sup> / 72.0 <sup>6.7</sup>	51.0 <sup>5.5</sup> / 59.8 <sup>14.9</sup>	31.4 <sup>8.4</sup> / 38.4 <sup>11.3</sup>
En-16	53.7 <sup>6.6</sup> / 79.2 <sup>2.8</sup>	36.2 <sup>5.6</sup> / 47.3 <sup>5.8</sup>	13.5 <sup>4.0</sup> / 25.0 <sup>4.8</sup>	72.5 <sup>5.3</sup> / 86.6 <sup>1.3</sup>	44.6 <sup>1.8</sup> / 57.1 <sup>5.9</sup>	56.4 <sup>5.2</sup> / 75.6 <sup>5.2</sup>	95.5 <sup>3.7</sup> / 99.0 <sup>1.2</sup>	69.4 <sup>13.8</sup> / 71.0 <sup>9.3</sup>	52.9 <sup>0.4</sup> / 64.8 <sup>14.6</sup>	39.7 <sup>10.4</sup> / 40.8 <sup>10.4</sup>
En-17	46.0 <sup>8.4</sup> / 76.6 <sup>2.5</sup>	37.3 <sup>2.7</sup> / 48.9 <sup>1.6</sup>	16.7 <sup>5.6</sup> / 28.4 <sup>5.7</sup>	72.2 <sup>4.8</sup> / 85.1 <sup>2.9</sup>	41.5 <sup>8.7</sup> / 61.8 <sup>3.3</sup>	60.0 <sup>8</sup> / 78.8 <sup>7.1</sup>	96.0 <sup>3.0</sup> / 99.0 <sup>1.2</sup>	63.4 <sup>11.7</sup> / 69.5 <sup>9.3</sup>	52.9 <sup>0.4</sup> / 59.8 <sup>1.9</sup>	36.5 <sup>2.3</sup> / 39.5 <sup>6.6</sup>
En-18	41.4 <sup>9.1</sup> / 73.6 <sup>3.4</sup>	40.8 <sup>9.1</sup> / 49.3 <sup>5.1</sup>	13.2 <sup>6.3</sup> / 24.9 <sup>7.1</sup>	70.8 <sup>8.5</sup> / 86.0 <sup>1.7</sup>	42.2 <sup>5.8</sup> / 63.5 <sup>8.9</sup>	65.5 <sup>5.3</sup> / 77.6 <sup>5.7</sup>	95.0 <sup>4.2</sup> / 99.0 <sup>1.2</sup>	64.0 <sup>11.7</sup> / 71.3 <sup>10.3</sup>	47.8 <sup>0.3</sup> / 59.7 <sup>15.0</sup>	36.3 <sup>5.7</sup> / 42.6 <sup>5.5</sup>
En-19	34.7 <sup>7.0</sup> / 62.6 <sup>0.7</sup>	38.9 <sup>7.7</sup> / 53.4 <sup>3.6</sup>	14.1 <sup>3.0</sup> / 22.7 <sup>7.0</sup>	72.3 <sup>8.4</sup> / 85.2 <sup>1.9</sup>	45.5 <sup>8.4</sup> / 59.6 <sup>6.4</sup>	66.1 <sup>9.2</sup> / 78.4 <sup>6.2</sup>	94.0 <sup>4.4</sup> / 99.0 <sup>1.2</sup>	62.0 <sup>10.0</sup> / 71.0 <sup>9.4</sup>	47.8 <sup>0.3</sup> / 56.5 <sup>11.5</sup>	37.8 <sup>8.6</sup> / 42.2 <sup>9.0</sup>
En-20	36.1 <sup>8.7</sup> / 67.3 <sup>7.5</sup>	36.1 <sup>10.7</sup> / 53.5 <sup>6.5</sup>	15.5 <sup>6.4</sup> / 24.2 <sup>6.2</sup>	72.4 <sup>6.9</sup> / 84.7 <sup>5.3</sup>	42.3 <sup>8.9</sup> / 61.0 <sup>6.0</sup>	63.2 <sup>0.0</sup> / 80.2 <sup>6.6</sup>	95.0 <sup>5.5</sup> / 98.5 <sup>2.0</sup>	61.7 <sup>9.5</sup> / 70.9 <sup>9.6</sup>	47.8 <sup>0.3</sup> / 58.6 <sup>14.1</sup>	34.1 <sup>8.9</sup> / 46.2 <sup>12.7</sup>
En-21	40.9 <sup>6.3</sup> / 70.2 <sup>2.9</sup>	32.6 <sup>8.1</sup> / 52.2 <sup>5.1</sup>	14.8 <sup>6.6</sup> / 22.1 <sup>8.0</sup>	69.0 <sup>5.3</sup> / 86.7 <sup>1.8</sup>	46.3 <sup>6.8</sup> / 61.3 <sup>4.9</sup>	63.0 <sup>0.0</sup> / 78.5 <sup>5.5</sup>	98.0 <sup>1.9</sup> / 99.0 <sup>1.2</sup>	65.5 <sup>11.2</sup> / 73.5 <sup>10.1</sup>	47.6 <sup>0.5</sup> / 61.9 <sup>13.8</sup>	34.1 <sup>4.8</sup> / 42.3 <sup>5.3</sup>
En-22	56.3 <sup>4.9</sup> / 81.2 <sup>2.8</sup>	32.9 <sup>6.6</sup> / 46.5 <sup>3.4</sup>	17.3 <sup>10.1</sup> / 23.5 <sup>4.5</sup>	68.9 <sup>6.2</sup> / 83.3 <sup>3.8</sup>	49.8 <sup>9.0</sup> / 64.3 <sup>2.1</sup>	57.8 <sup>1.8</sup> / 75.8 <sup>8.0</sup>	98.0 <sup>2.9</sup> / 98.0 <sup>0.0</sup>	66.0 <sup>8.4</sup> / 73.7 <sup>8.7</sup>	55.8 <sup>0.0</sup> / 64.7 <sup>14.7</sup>	29.7 <sup>8.0</sup> / 40.3 <sup>6.7</sup>
En-23	58.8 <sup>7.8</sup> / 81.9 <sup>5.0</sup>	35.4 <sup>11.3</sup> / 48.3 <sup>5.8</sup>	17.4 <sup>8.8</sup> / 23.1 <sup>6.9</sup>	60.7 <sup>7.4</sup> / 80.5 <sup>2.0</sup>	48.7 <sup>11.0</sup> / 68.5 <sup>3.8</sup>	58.0 <sup>5.5</sup> / 76.8 <sup>1.1</sup>	98.0 <sup>1.9</sup> / 98.0 <sup>0.9</sup>	66.5 <sup>11.5</sup> / 72.6 <sup>11.8</sup>	47.4 <sup>0.8</sup> / 63.7 <sup>14.1</sup>	30.6 <sup>5.5</sup> / 42.3 <sup>8.9</sup>
En-24	47.8 <sup>6.6</sup> / 73.6 <sup>8.6</sup>	32.2 <sup>7.2</sup> / 47.4 <sup>8.8</sup>	19.8 <sup>6.5</sup> / 21.4 <sup>5.5</sup>	64.8 <sup>6.5</sup> / 83.3 <sup>2.9</sup>	45.4 <sup>9.7</sup> / 65.0 <sup>5.5</sup>	53.1 <sup>4.0</sup> / 74.0 <sup>7.6</sup>	97.0 <sup>2.9</sup> / 98.5 <sup>2.0</sup>	63.3 <sup>6.0</sup> / 73.2 <sup>10.8</sup>	47.8 <sup>0.3</sup> / 63.8 <sup>13.9</sup>	20.9 <sup>5.6</sup> / 33.0 <sup>8.0</sup>
En-25	68.8 <sup>7.0</sup> / 95.1 <sup>2.3</sup>	34.2 <sup>1.4</sup> / 48.1 <sup>3.2</sup>	17.6 <sup>7.3</sup> / 25.1 <sup>9.4</sup>	75.4 <sup>6.1</sup> / 87.6 <sup>3.8</sup>	51.8 <sup>7.6</sup> / 71.9 <sup>4.7</sup>	53.6 <sup>3.5</sup> / 72.7 <sup>4.1</sup>	97.5 <sup>2.8</sup> / 99.0 <sup>1.2</sup>	71.9 <sup>11.4</sup> / 74.7 <sup>9.6</sup>	52.8 <sup>10.5</sup> / 78.5 <sup>10.7</sup>	26.6 <sup>6.3</sup> / 37.3 <sup>6.0</sup>

Table 16: HuBERT

Layer	Accent	DialAct	Emotion	EnvSound	Distance	Intent	MSpeaker	Sarcasm	Spof	Stress
De-0	53.2 <sup>4.7</sup> / 78.3 <sup>6.5</sup>	28.7 <sup>4.2</sup> / 51.5 <sup>6.1</sup>	14.6 <sup>2.4</sup> / 23.5 <sup>4.6</sup>	95.6 <sup>3.2</sup> / 96.6 <sup>2.7</sup>	39.6 <sup>5.1</sup> / 58.7 <sup>2.7</sup>	45.1 <sup>8.9</sup> / 74.3 <sup>3.4</sup>	98.5 <sup>1.2</sup> / 98.5 <sup>2.0</sup>	65.5 <sup>9.5</sup> / 76.1 <sup>10.1</sup>	47.5 <sup>0.8</sup> / 59.1 <sup>9.4</sup>	23.8 <sup>3.9</sup> / 35.9 <sup>6.6</sup>
De-1	53.3 <sup>4.7</sup> / 74.6 <sup>11.6</sup>	26.6 <sup>9.5</sup> / 47.9 <sup>6.2</sup>	14.5 <sup>2.4</sup> / 23.8 <sup>2.1</sup>	96.1 <sup>3.3</sup> / 95.6 <sup>3.7</sup>	40.7 <sup>5.0</sup> / 59.0 <sup>0.8</sup>	47.0 <sup>10.3</sup> / 75.9 <sup>5.1</sup>	98.5 <sup>1.2</sup> / 99.0 <sup>1.2</sup>	66.0 <sup>0.0</sup> / 75.2 <sup>10.2</sup>	47.5 <sup>0.8</sup> / 63.6 <sup>8.8</sup>	25.9 <sup>9.2</sup> / 37.0 <sup>5.1</sup>
De-2	53.9 <sup>4.5</sup> / 78.3 <sup>8.1</sup>	27.7 <sup>5.1</sup> / 50.5 <sup>5.1</sup>	15.1 <sup>3.0</sup> / 24.0 <sup>3.3</sup>	96.1 <sup>3.3</sup> / 98.1 <sup>1.7</sup>	40.6 <sup>8.8</sup> / 60.2 <sup>3.4</sup>	48.4 <sup>8.8</sup> / 74.1 <sup>6.8</sup>	98.5 <sup>1.2</sup> / 99.5 <sup>1.0</sup>	66.0 <sup>0.0</sup> / 75.1 <sup>8.9</sup>	47.6 <sup>0.5</sup> / 55.6 <sup>10.2</sup>	24.5 <sup>3.5</sup> / 38.1 <sup>5.3</sup>
De-3	54.2 <sup>1.8</sup> / 78.6 <sup>10.6</sup>	27.7 <sup>4.8</sup> / 50.4 <sup>4.4</sup>	15.1 <sup>2.0</sup> / 23.3 <sup>4.0</sup>	96.1 <sup>3.3</sup> / 97.5 <sup>1.8</sup>	40.9 <sup>6.5</sup> / 60.1 <sup>6.3</sup>	47.9 <sup>8.1</sup> / 75.6 <sup>6.8</sup>	98.5 <sup>1.2</sup> / 99.0 <sup>1.2</sup>	64.5 <sup>7.9</sup> / 73.6 <sup>7.7</sup>	47.6 <sup>0.5</sup> / 51.8 <sup>8.1</sup>	25.2 <sup>4.5</sup> / 38.3 <sup>3.3</sup>
De-4	58.4 <sup>4.1</sup> / 76.7 <sup>3.9</sup>	27.5 <sup>3.5</sup> / 51.1 <sup>6.0</sup>	14.6 <sup>1.7</sup> / 22.2 <sup>4.6</sup>	96.0 <sup>2.5</sup> / 97.5 <sup>2.3</sup>	40.4 <sup>6.6</sup> / 57.1 <sup>4.7</sup>	48.1 <sup>9.8</sup> / 78.6 <sup>5.6</sup>	98.5 <sup>1.2</sup> / 99.5 <sup>1.0</sup>	65.6 <sup>7.4</sup> / 76.2 <sup>10.8</sup>	47.6 <sup>0.5</sup> / 55.5 <sup>10.2</sup>	29.1 <sup>8.0</sup> / 37.8 <sup>5.9</sup>
De-5	57.9 <sup>5.6</sup> / 77.6 <sup>10.4</sup>	28.7 <sup>3.8</sup> / 51.0								

Layer	Accent	DialAct	Emotion	EnvSound	Distance	Intent	MSpeaker	Sarcasm	Spoof	Stress
De-0	53.2 <sup>4.7</sup> / 78.6 <sup>9.9</sup>	28.7 <sup>4.2</sup> / 50.7 <sup>3.8</sup>	14.6 <sup>2.4</sup> / 24.5 <sup>5.5</sup>	95.6 <sup>3.2</sup> / 97.0 <sup>2.5</sup>	39.6 <sup>5.1</sup> / 57.4 <sup>3.2</sup>	45.1 <sup>8.9</sup> / 78.5 <sup>3.3</sup>	98.51 <sup>1.2</sup> / 99.5 <sup>1.0</sup>	65.5 <sup>9.5</sup> / 73.3 <sup>10.9</sup>	47.5 <sup>0.8</sup> / 51.6 <sup>8.6</sup>	23.8 <sup>3.9</sup> / 36.1 <sup>3.5</sup>
De-1	54.4 <sup>4.2</sup> / 77.2 <sup>8.4</sup>	26.9 <sup>4.5</sup> / 51.5 <sup>6.1</sup>	14.5 <sup>2.4</sup> / 23.5 <sup>2.7</sup>	96.1 <sup>3.3</sup> / 97.0 <sup>1.9</sup>	40.2 <sup>5.6</sup> / 58.0 <sup>6.6</sup>	46.7 <sup>9.5</sup> / 76.3 <sup>3.3</sup>	98.51 <sup>1.2</sup> / 99.0 <sup>1.2</sup>	66.0 <sup>0.9</sup> / 75.8 <sup>10.1</sup>	47.5 <sup>0.8</sup> / 52.6 <sup>1.0</sup>	24.6 <sup>3.6</sup> / 35.1 <sup>6.2</sup>
De-2	53.3 <sup>4.7</sup> / 75.3 <sup>8.6</sup>	28.3 <sup>4.5</sup> / 49.2 <sup>7.9</sup>	15.1 <sup>3.0</sup> / 23.9 <sup>7.7</sup>	96.1 <sup>3.3</sup> / 97.9 <sup>2.1</sup>	40.6 <sup>6.8</sup> / 57.6 <sup>4.1</sup>	48.2 <sup>8.6</sup> / 76.0 <sup>4.1</sup>	98.51 <sup>1.2</sup> / 99.0 <sup>1.2</sup>	65.4 <sup>8.6</sup> / 75.0 <sup>9.0</sup>	47.6 <sup>0.5</sup> / 51.0 <sup>6.5</sup>	24.5 <sup>3.5</sup> / 38.4 <sup>5.0</sup>
De-3	57.2 <sup>5.1</sup> / 77.9 <sup>10.4</sup>	29.7 <sup>5.3</sup> / 49.2 <sup>5.8</sup>	14.8 <sup>1.9</sup> / 23.6 <sup>2.8</sup>	96.7 <sup>2.4</sup> / 97.0 <sup>2.0</sup>	40.2 <sup>5.8</sup> / 57.0 <sup>5.4</sup>	48.3 <sup>9.0</sup> / 75.0 <sup>6.7</sup>	98.51 <sup>1.2</sup> / 99.5 <sup>1.0</sup>	66.0 <sup>7.6</sup> / 73.0 <sup>8.7</sup>	47.5 <sup>0.8</sup> / 57.2 <sup>7.9</sup>	24.5 <sup>3.6</sup> / 35.5 <sup>3.7</sup>
De-4	56.6 <sup>5.0</sup> / 77.3 <sup>8.8</sup>	29.3 <sup>4.9</sup> / 49.5 <sup>5.5</sup>	15.4 <sup>2.4</sup> / 25.0 <sup>2.7</sup>	96.0 <sup>2.5</sup> / 97.6 <sup>2.5</sup>	39.1 <sup>6.1</sup> / 56.5 <sup>5.8</sup>	48.0 <sup>10.0</sup> / 77.3 <sup>7.6</sup>	98.51 <sup>1.2</sup> / 99.0 <sup>1.2</sup>	66.0 <sup>8.4</sup> / 72.7 <sup>11.1</sup>	47.6 <sup>0.5</sup> / 58.8 <sup>8.8</sup>	25.2 <sup>3.0</sup> / 36.3 <sup>5.0</sup>
De-5	58.1 <sup>6.4</sup> / 74.0 <sup>9.9</sup>	32.6 <sup>5.5</sup> / 49.0 <sup>5.5</sup>	15.1 <sup>2.6</sup> / 24.7 <sup>2.2</sup>	96.7 <sup>2.4</sup> / 96.9 <sup>1.9</sup>	39.8 <sup>8.0</sup> / 58.7 <sup>5.1</sup>	50.2 <sup>9.6</sup> / 79.2 <sup>5.7</sup>	98.51 <sup>1.2</sup> / 99.5 <sup>1.0</sup>	65.6 <sup>8.8</sup> / 72.8 <sup>9.5</sup>	47.6 <sup>0.5</sup> / 54.9 <sup>9.1</sup>	25.3 <sup>4.4</sup> / 37.0 <sup>3.0</sup>
De-6	54.2 <sup>3.2</sup> / 77.5 <sup>9.2</sup>	30.4 <sup>4.5</sup> / 51.0 <sup>5.6</sup>	14.7 <sup>2.2</sup> / 22.5 <sup>3.1</sup>	96.0 <sup>2.5</sup> / 97.0 <sup>2.5</sup>	38.7 <sup>9.5</sup> / 59.5 <sup>2.4</sup>	49.8 <sup>8.9</sup> / 78.2 <sup>7.7</sup>	98.51 <sup>1.2</sup> / 98.5 <sup>2.0</sup>	63.1 <sup>8.8</sup> / 75.3 <sup>9.2</sup>	47.6 <sup>0.5</sup> / 51.8 <sup>8.1</sup>	25.6 <sup>4.1</sup> / 36.0 <sup>5.6</sup>
De-7	53.6 <sup>6.9</sup> / 76.3 <sup>8.9</sup>	29.3 <sup>5.8</sup> / 53.6 <sup>1.8</sup>	16.4 <sup>2.9</sup> / 24.8 <sup>3.0</sup>	97.1 <sup>2.3</sup> / 97.0 <sup>2.0</sup>	37.3 <sup>11.5</sup> / 60.2 <sup>5.7</sup>	53.4 <sup>8.5</sup> / 80.5 <sup>4.8</sup>	98.0 <sup>1.9</sup> / 99.0 <sup>1.2</sup>	62.6 <sup>9.3</sup> / 73.6 <sup>9.4</sup>	47.6 <sup>0.5</sup> / 62.6 <sup>2.7</sup>	26.4 <sup>4.1</sup> / 40.9 <sup>4.2</sup>
De-8	50.8 <sup>9.4</sup> / 72.4 <sup>10.3</sup>	32.5 <sup>4.0</sup> / 55.5 <sup>3.3</sup>	16.5 <sup>2.5</sup> / 24.4 <sup>4.6</sup>	96.0 <sup>2.5</sup> / 97.5 <sup>1.6</sup>	37.9 <sup>9.5</sup> / 58.6 <sup>4.1</sup>	61.3 <sup>4.4</sup> / 87.8 <sup>3.2</sup>	98.0 <sup>1.9</sup> / 98.5 <sup>2.0</sup>	64.2 <sup>9.8</sup> / 73.1 <sup>13.5</sup>	47.5 <sup>0.8</sup> / 61.0 <sup>8.9</sup>	25.3 <sup>5.0</sup> / 40.0 <sup>4.5</sup>
De-9	46.9 <sup>9.3</sup> / 73.2 <sup>8.8</sup>	35.9 <sup>2.7</sup> / 57.6 <sup>5.2</sup>	16.5 <sup>3.0</sup> / 25.7 <sup>4.6</sup>	96.1 <sup>3.3</sup> / 97.5 <sup>3.2</sup>	41.1 <sup>9.6</sup> / 54.8 <sup>8.8</sup>	65.8 <sup>4.7</sup> / 89.7 <sup>5.3</sup>	98.51 <sup>1.2</sup> / 99.0 <sup>1.2</sup>	65.0 <sup>11.1</sup> / 72.0 <sup>12.7</sup>	47.6 <sup>0.5</sup> / 54.0 <sup>8.8</sup>	25.1 <sup>4.1</sup> / 38.7 <sup>6.5</sup>
De-10	42.4 <sup>10.9</sup> / 64.5 <sup>12.2</sup>	40.1 <sup>5.4</sup> / 58.8 <sup>2.4</sup>	15.8 <sup>1.8</sup> / 26.7 <sup>5.5</sup>	96.1 <sup>3.3</sup> / 96.1 <sup>12.8</sup>	40.9 <sup>11.2</sup> / 59.4 <sup>4.4</sup>	67.7 <sup>7.7</sup> / 93.2 <sup>8.8</sup>	99.0 <sup>1.2</sup> / 99.0 <sup>1.2</sup>	62.1 <sup>10.5</sup> / 72.0 <sup>13.0</sup>	47.6 <sup>0.5</sup> / 54.8 <sup>9.2</sup>	25.6 <sup>2.9</sup> / 40.1 <sup>4.7</sup>
De-11	38.2 <sup>11.6</sup> / 65.1 <sup>16.9</sup>	44.0 <sup>3.2</sup> / 60.1 <sup>6.8</sup>	14.2 <sup>1.4</sup> / 26.5 <sup>6.1</sup>	96.1 <sup>3.3</sup> / 98.0 <sup>2.5</sup>	42.2 <sup>11.8</sup> / 56.6 <sup>5.3</sup>	67.2 <sup>8.0</sup> / 92.7 <sup>3.2</sup>	98.0 <sup>1.9</sup> / 98.5 <sup>2.0</sup>	62.5 <sup>12.0</sup> / 70.5 <sup>14.0</sup>	47.8 <sup>0.3</sup> / 60.4 <sup>15.5</sup>	28.6 <sup>6.0</sup> / 39.4 <sup>7.8</sup>
De-12	36.7 <sup>13.3</sup> / 60.6 <sup>7.1</sup>	39.2 <sup>3.8</sup> / 60.6 <sup>4.9</sup>	15.0 <sup>2.8</sup> / 27.1 <sup>17.2</sup>	96.1 <sup>3.3</sup> / 98.6 <sup>1.1</sup>	42.0 <sup>8.9</sup> / 55.8 <sup>1.9</sup>	68.8 <sup>5.7</sup> / 93.2 <sup>1.7</sup>	98.51 <sup>1.2</sup> / 99.0 <sup>1.2</sup>	60.9 <sup>10.0</sup> / 72.1 <sup>10.5</sup>	47.8 <sup>0.3</sup> / 62.2 <sup>12.0</sup>	27.6 <sup>5.5</sup> / 42.3 <sup>3.6</sup>
De-13	36.2 <sup>11.3</sup> / 59.0 <sup>10.0</sup>	39.7 <sup>4.7</sup> / 61.5 <sup>5.8</sup>	18.1 <sup>2.5</sup> / 26.4 <sup>5.9</sup>	96.7 <sup>2.3</sup> / 98.6 <sup>1.1</sup>	39.7 <sup>5.4</sup> / 53.3 <sup>1.8</sup>	69.0 <sup>0.1</sup> / 95.1 <sup>3.4</sup>	98.51 <sup>1.2</sup> / 98.5 <sup>2.0</sup>	63.3 <sup>8.9</sup> / 71.5 <sup>15.7</sup>	47.8 <sup>0.3</sup> / 60.9 <sup>1.2</sup>	27.4 <sup>4.0</sup> / 39.7 <sup>4.5</sup>
De-14	37.3 <sup>8.0</sup> / 55.8 <sup>7.4</sup>	42.3 <sup>4.0</sup> / 62.8 <sup>6.5</sup>	16.4 <sup>2.9</sup> / 26.8 <sup>6.5</sup>	96.1 <sup>2.4</sup> / 99.1 <sup>1.2</sup>	39.8 <sup>3.8</sup> / 52.5 <sup>1.9</sup>	69.7 <sup>7.2</sup> / 95.7 <sup>2.7</sup>	99.0 <sup>1.2</sup> / 99.0 <sup>1.2</sup>	59.3 <sup>7.0</sup> / 72.0 <sup>14.6</sup>	47.8 <sup>0.3</sup> / 58.5 <sup>9.2</sup>	28.9 <sup>3.0</sup> / 40.4 <sup>2.9</sup>
De-15	34.2 <sup>8.9</sup> / 55.8 <sup>12.7</sup>	42.0 <sup>3.8</sup> / 59.0 <sup>5.5</sup>	15.9 <sup>2.7</sup> / 30.2 <sup>10.3</sup>	96.7 <sup>2.3</sup> / 96.0 <sup>2.5</sup>	40.6 <sup>4.6</sup> / 56.1 <sup>3.1</sup>	70.6 <sup>5.5</sup> / 94.8 <sup>3.6</sup>	98.51 <sup>1.2</sup> / 99.0 <sup>1.2</sup>	62.2 <sup>7.7</sup> / 70.6 <sup>12.1</sup>	47.8 <sup>0.3</sup> / 54.9 <sup>9.1</sup>	30.6 <sup>3.6</sup> / 41.7 <sup>2.9</sup>
De-16	32.8 <sup>9.8</sup> / 50.2 <sup>7.7</sup>	45.0 <sup>5.1</sup> / 59.3 <sup>4.0</sup>	15.8 <sup>3.2</sup> / 31.4 <sup>9.0</sup>	96.1 <sup>2.4</sup> / 98.6 <sup>1.2</sup>	39.6 <sup>5.7</sup> / 54.1 <sup>6.3</sup>	72.2 <sup>5.3</sup> / 95.7 <sup>2.9</sup>	98.51 <sup>2.2</sup> / 99.5 <sup>1.0</sup>	60.6 <sup>9.3</sup> / 69.7 <sup>12.5</sup>	47.8 <sup>0.3</sup> / 55.1 <sup>9.0</sup>	29.8 <sup>4.4</sup> / 40.7 <sup>5.9</sup>
De-17	32.4 <sup>9.9</sup> / 55.4 <sup>7.5</sup>	45.8 <sup>3.4</sup> / 59.5 <sup>3.9</sup>	18.3 <sup>3.9</sup> / 31.9 <sup>8.9</sup>	96.5 <sup>5.2</sup> / 97.7 <sup>1.4</sup>	40.5 <sup>5.3</sup> / 54.3 <sup>3.5</sup>	75.3 <sup>5.1</sup> / 95.0 <sup>2.7</sup>	97.0 <sup>1.9</sup> / 98.5 <sup>2.0</sup>	58.7 <sup>12.4</sup> / 69.0 <sup>11.1</sup>	47.8 <sup>0.3</sup> / 55.8 <sup>0.0</sup>	29.6 <sup>6.6</sup> / 36.9 <sup>4.6</sup>
De-18	31.6 <sup>8.3</sup> / 49.2 <sup>2.9</sup>	42.1 <sup>3.7</sup> / 62.5 <sup>5.7</sup>	18.5 <sup>3.7</sup> / 33.0 <sup>9.6</sup>	97.0 <sup>1.9</sup> / 97.5 <sup>1.5</sup>	41.2 <sup>5.4</sup> / 53.5 <sup>2.0</sup>	76.8 <sup>4.1</sup> / 93.9 <sup>2.8</sup>	96.51 <sup>1.2</sup> / 99.0 <sup>1.2</sup>	58.6 <sup>11.3</sup> / 67.4 <sup>12.0</sup>	47.8 <sup>0.3</sup> / 61.9 <sup>3.8</sup>	30.4 <sup>4.7</sup> / 40.8 <sup>4.1</sup>
De-19	29.6 <sup>8.9</sup> / 44.3 <sup>9.4</sup>	44.5 <sup>7.1</sup> / 63.0 <sup>9.3</sup>	16.8 <sup>4.8</sup> / 27.0 <sup>5.4</sup>	97.0 <sup>1.9</sup> / 97.5 <sup>2.3</sup>	36.4 <sup>4.5</sup> / 51.7 <sup>1.8</sup>	78.5 <sup>4.9</sup> / 95.1 <sup>1.6</sup>	96.51 <sup>1.2</sup> / 99.0 <sup>1.2</sup>	58.2 <sup>11.0</sup> / 67.5 <sup>11.6</sup>	47.8 <sup>0.3</sup> / 55.8 <sup>10.0</sup>	27.0 <sup>4.5</sup> / 39.0 <sup>5.5</sup>
De-20	28.9 <sup>8.1</sup> / 44.4 <sup>8.5</sup>	44.1 <sup>5.4</sup> / 62.8 <sup>5.3</sup>	18.3 <sup>4.2</sup> / 28.2 <sup>2.9</sup>	96.0 <sup>2.5</sup> / 97.6 <sup>2.5</sup>	38.0 <sup>9.4</sup> / 52.4 <sup>3.2</sup>	81.2 <sup>5.6</sup> / 94.6 <sup>3.1</sup>	94.51 <sup>9.9</sup> / 99.0 <sup>1.2</sup>	53.5 <sup>10.9</sup> / 65.6 <sup>12.9</sup>	47.8 <sup>0.3</sup> / 54.9 <sup>9.1</sup>	27.3 <sup>6.2</sup> / 39.0 <sup>4.6</sup>
De-21	33.7 <sup>9.3</sup> / 43.2 <sup>9.0</sup>	44.4 <sup>6.5</sup> / 60.5 <sup>3.9</sup>	18.5 <sup>4.8</sup> / 33.9 <sup>11.1</sup>	95.5 <sup>2.4</sup> / 97.0 <sup>3.6</sup>	37.2 <sup>4.7</sup> / 47.6 <sup>2.1</sup>	79.9 <sup>5.7</sup> / 95.5 <sup>2.7</sup>	94.51 <sup>9.9</sup> / 98.5 <sup>1.2</sup>	54.51 <sup>1.1</sup> / 68.0 <sup>10.2</sup>	47.8 <sup>0.3</sup> / 54.0 <sup>8.1</sup>	32.7 <sup>2.4</sup> / 35.8 <sup>6.6</sup>
De-22	29.9 <sup>6.6</sup> / 40.1 <sup>9.7</sup>	44.8 <sup>4.7</sup> / 59.4 <sup>9.5</sup>	19.5 <sup>9.1</sup> / 31.8 <sup>8.4</sup>	95.5 <sup>2.4</sup> / 99.0 <sup>2.0</sup>	36.3 <sup>9.3</sup> / 53.5 <sup>5.3</sup>	79.8 <sup>4.9</sup> / 95.4 <sup>2.3</sup>	94.51 <sup>0.9</sup> / 98.0 <sup>1.9</sup>	50.7 <sup>12.2</sup> / 68.1 <sup>10.6</sup>	47.8 <sup>0.3</sup> / 58.0 <sup>8.1</sup>	30.9 <sup>9.2</sup> / 41.9 <sup>4.1</sup>
De-23	27.6 <sup>5.7</sup> / 40.9 <sup>8.1</sup>	46.6 <sup>9.0</sup> / 65.0 <sup>6.6</sup>	19.6 <sup>10.3</sup> / 33.6 <sup>1.5</sup>	96.0 <sup>2.1</sup> / 98.0 <sup>1.0</sup>	33.5 <sup>8.4</sup> / 50.6 <sup>4.8</sup>	76.3 <sup>5.5</sup> / 94.2 <sup>4.0</sup>	92.5 <sup>2.3</sup> / 97.5 <sup>1.6</sup>	51.6 <sup>12.1</sup> / 67.5 <sup>13.2</sup>	47.8 <sup>0.3</sup> / 54.0 <sup>8.1</sup>	28.2 <sup>8.9</sup> / 41.3 <sup>7.2</sup>
De-24	26.8 <sup>4.2</sup> / 41.9 <sup>7.7</sup>	45.9 <sup>3.2</sup> / 57.2 <sup>5.8</sup>	19.9 <sup>9.1</sup> / 33.0 <sup>8.6</sup>	96.4 <sup>1.9</sup> / 98.5 <sup>1.2</sup>	32.5 <sup>7.1</sup> / 51.5 <sup>1.5</sup>	76.8 <sup>3.7</sup> / 94.2 <sup>1.4</sup>	94.53 <sup>0.9</sup> / 96.5 <sup>2.1</sup>	53.4 <sup>10.3</sup> / 66.6 <sup>9.3</sup>	47.8 <sup>0.3</sup> / 54.1 <sup>8.0</sup>	30.4 <sup>5.6</sup> / 41.1 <sup>9.2</sup>
De-25	29.5 <sup>5.5</sup> / 36.2 <sup>7.6</sup>	45.7 <sup>4.0</sup> / 63.5 <sup>8.1</sup>	22.0 <sup>8.1</sup> / 28.6 <sup>7.0</sup>	96.4 <sup>2.0</sup> / 98.1 <sup>1.7</sup>	28.7 <sup>6.1</sup> / 45.9 <sup>2.0</sup>	75.9 <sup>3.9</sup> / 93.3 <sup>2.3</sup>	94.4 <sup>4.1</sup> / 96.5 <sup>2.1</sup>	52.6 <sup>12.9</sup> / 66.1 <sup>11.8</sup>	47.6 <sup>0.5</sup> / 57.5 <sup>8.6</sup>	34.1 <sup>9.7</sup> / 36.6 <sup>5.8</sup>
De-26	24.5 <sup>2.8</sup> / 36.0 <sup>8.8</sup>	41.3 <sup>5.7</sup> / 59.1 <sup>6.1</sup>	16.5 <sup>3.3</sup> / 32.2 <sup>6.8</sup>	96.4 <sup>2.0</sup> / 97.6 <sup>2.5</sup>	30.0 <sup>8.3</sup> / 46.7 <sup>3.8</sup>	75.8 <sup>5.0</sup> / 93.1 <sup>3.5</sup>	92.3 <sup>5.5</sup> / 96.0 <sup>1.7</sup>	49.9 <sup>9.4</sup> / 65.4 <sup>8.8</sup>	47.6 <sup>0.5</sup> / 59.0 <sup>7.1</sup>	28.8 <sup>10.2</sup> / 36.4 <sup>5.8</sup>
De-27	20.3 <sup>4.7</sup> / 32.8 <sup>7.1</sup>	43.6 <sup>4.5</sup> / 57.9 <sup>6.7</sup>	17.1 <sup>3.7</sup> / 29.0 <sup>4.4</sup>	96.4 <sup>2.0</sup> / 98.1 <sup>1.7</sup>	31.7 <sup>1.8</sup> / 50.3 <sup>4.4</sup>	75.1 <sup>5.3</sup> / 94.8 <sup>0.8</sup>	87.3 <sup>9.7</sup> / 96.0 <sup>2.1</sup>	50.9 <sup>12.4</sup> / 66.3 <sup>7.8</sup>	47.6 <sup>0.5</sup> / 57.0 <sup>1.4</sup>	30.0 <sup>10.3</sup> / 37.7 <sup>7.9</sup>
De-28	21.0 <sup>3.2</sup> / 32.3 <sup>6.7</sup>	41.1 <sup>4.0</sup> / 59.7 <sup>6.6</sup>	18.2 <sup>4.2</sup> / 28.9 <sup>5.1</sup>	96.8 <sup>2.0</sup> / 97.8 <sup>2.0</sup>	31.5 <sup>11.7</sup> / 49.0 <sup>0.1</sup>	73.9 <sup>6.1</sup> / 93.7 <sup>4.0</sup>	87.9 <sup>3.3</sup> / 95.4 <sup>4.7</sup>	51.1 <sup>12.3</sup> / 67.1 <sup>8.9</sup>	47.6 <sup>0.5</sup> / 57.6 <sup>8.4</sup>	29.4 <sup>13.0</sup> / 36.1 <sup>7.2</sup>
De-29	20.3 <sup>4.1</sup> / 34.2 <sup>11.1</sup>	39.2 <sup>5.9</sup> / 60.8 <sup>4.3</sup>	19.2 <sup>4.4</sup> / 27.9 <sup>5.9</sup>	96.4 <sup>2.0</sup> / 98.5 <sup>1.2</sup>	30.8 <sup>10.5</sup> / 48.3 <sup>4.4</sup>	74.6 <sup>5.1</sup> / 92.2 <sup>2.5</sup>	84.2 <sup>13.6</sup> / 96.0 <sup>4.7</sup>	50.5 <sup>11.8</sup> / 65.2 <sup>6.1</sup>	47.6 <sup>0.5</sup> / 54.5 <sup>8.5</sup>	30.0 <sup>12.3</sup> / 38.7 <sup>7.0</sup>
De-30	18.9 <sup>4.0</sup> / 33.9 <sup>10.2</sup>	37.1 <sup>7.2</sup> / 61.1 <sup>5.5</sup>	18.1 <sup>4.7</sup> / 29.7 <sup>5.6</sup>	96.8 <sup>1.9</sup> / 98.9 <sup>1.4</sup>	29.5 <sup>0.0</sup> / 46.5 <sup>0.5</sup>	73.7 <sup>3.6</sup> / 92.6 <sup>2.3</sup>	83.5 <sup>14.9</sup> / 96.0 <sup>3.5</sup>	54.4 <sup>13.6</sup> / 64.7 <sup>0.5</sup>	47.6 <sup>0.5</sup> / 55.7 <sup>7.1</sup>	30.2 <sup>14.7</sup> / 35.9 <sup>5.4</sup>
De-31	19.9 <sup>3.2</sup> / 37.3 <sup>8.4</sup>	39.9 <sup>5.7</sup> / 58.6 <sup>6.0</sup>	21.6 <sup>6.7</sup> / 27.7 <sup>4.9</sup>	97.3 <sup>1.8</sup> / 97.9 <sup>2.1</sup>	34.2 <sup>8.6</sup> / 47.6 <sup>4.0</sup>	73.2 <sup>4.0</sup> / 93.1 <sup>2.6</sup>	81.6 <sup>16.1</sup> / 97.5 <sup>2.8</sup>	53.1 <sup>14.9</sup> / 66.5 <sup>6.9</sup>	47.6 <sup>0.5</sup> / 50.5 <sup>5.2</sup>	30.6 <sup>11.5</sup> / 34.4 <sup>5.4</sup>
De-32	25.0 <sup>6.4</sup> / 39.1 <sup>11.2</sup>	40.8 <sup>4.4</sup> /								