

声音技术的未来 大模型带来的音频算法革新

张俊博 小米AI实验室 语音技术专家



讲师简介





小米语音技术专家。

博士毕业于中国科学院声学研究所,多年从事智能语音技术的研究和应用,在语音识别、发音评测、语音合成、音频标记等领域都做过深入的工作,在顶级会议和期刊发表论文 30 余篇,著有出版物《Kaldi 语音识别实战》。

目前在小米负责若干项声学语音新技术的研发。







内容提要

- 对大模型的思考
- 小米的音频大模型探索



对大模型的思考





是"发现",而不是"发明"

```
LlamaModel(
 (embed tokens): Embedding(32000, 256)
(layers): ModuleList(
  (0-7): 8 x LlamaDecoderLayer(
    (self_attn): LlamaAttention(
      (q proj): Linear(in features=256, out features=256, bias=False)
      (k_proj): Linear(in_features=256, out_features=1024, bias=False)
       (v_proj): Linear(in_features=256, out_features=1024, bias=False)
       (o proj): Linear(in features=256, out features=256, bias=False)
      (rotary emb): LlamaRotaryEmbedding()
     (mlp): LlamaMLP(
      (gate_proj): Linear(in_features=256, out_features=11008, bias=False)
      (up proj): Linear(in features=256, out features=11008, bias=False)
       (down_proj): Linear(in_features=11008, out_features=256, bias=False)
       (act fn): SiLUActivation()
     (input layernorm): LlamaRMSNorm()
     (post_attention_layernorm): LlamaRMSNorm()
 (norm): LlamaRMSNorm()
```

Llama2 模型:没有任何模型结构上的创新

原理上是量变,效果上是质变无法解释,只好说"涌现"

大模型的成功,证明了这样的路线是可行的

为 AI 研究指明了方向





为什么大模型具备如此神奇的能力?

不知道

人类对它的原理还远远称不上理解

但大模型研发并没有技术原理上的门槛

虽然不知道麦克斯韦方程组 不妨碍古人发明指南针

虽然暂时未能全面理解大模型 不妨碍我们做出更强的大模型





雨后春笋般的大模型研发



























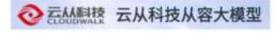








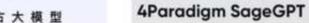


















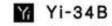






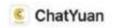


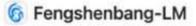










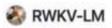


















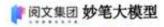






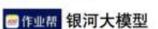


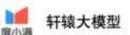


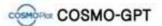






























小米自研大语言模型

本地化、轻量部署

	平均分	STEM	人文学科	社会科学	其他	中国特定主题	
MiLM-1.3B	50.79	40.51	54.82	54.15	53.99	52.26	
Baichuan-13B	54.63	42.04	60.49	59.55	56.6	55.72	
ChatGLM 2-6B	49.95	41.28	52.85	53.37	52.24	50.58	
			CM	IMLU 中文多任领	S语音理解评	估,2023年8月10日数据	

手机端侧大模型部分场景媲美云端



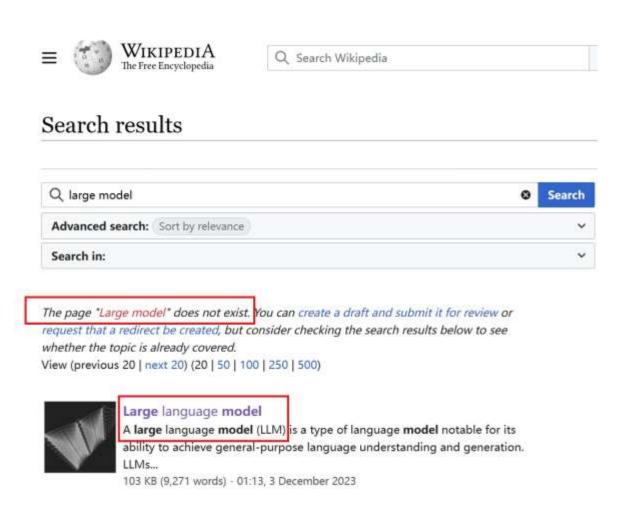


大模型 == 大语言模型?

文本形式训练数据相对更易获取和处理 大模型首先以文本模态出现

但人类更倾向于使用视觉和声音交互







GPT4-V(ision)





User

What is unusual about this image?

GPT-4

The unusual thing about this image is that a man is ironing clothes on an ironing board attached to the roof of a moving taxi.

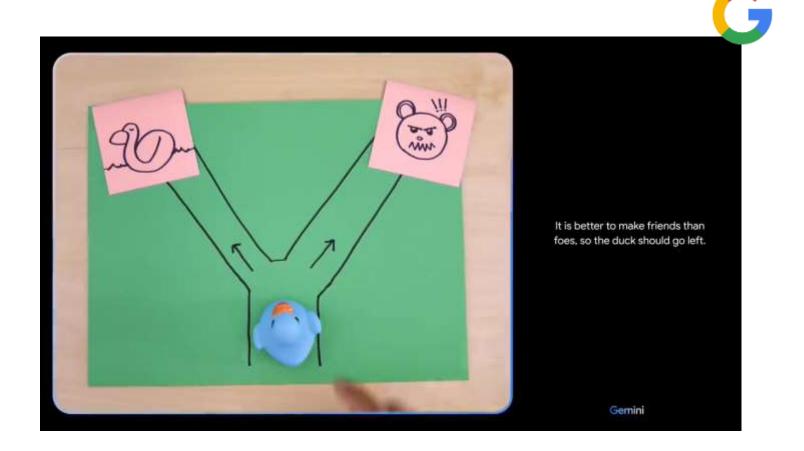






令人震惊的多模态能力强人工智能已实现?







小米的音频大模型探索





AL 时代的小米

视觉 | 声学语音 | NLP | 知识图谱 | 机器学习 | 大模型 | 多模态

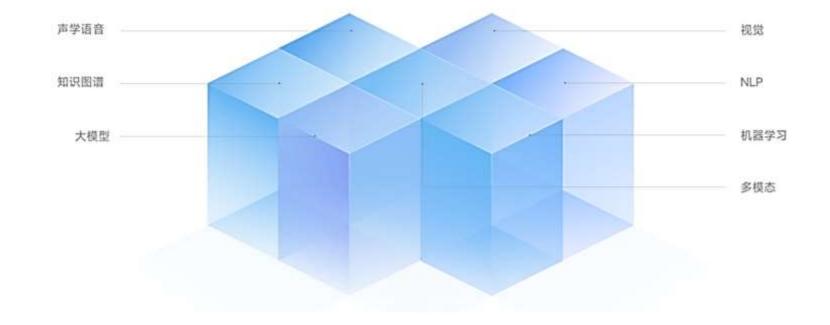
全球最大消费级 IoT 平台

6.99亿

IoT 平台已连接设备数

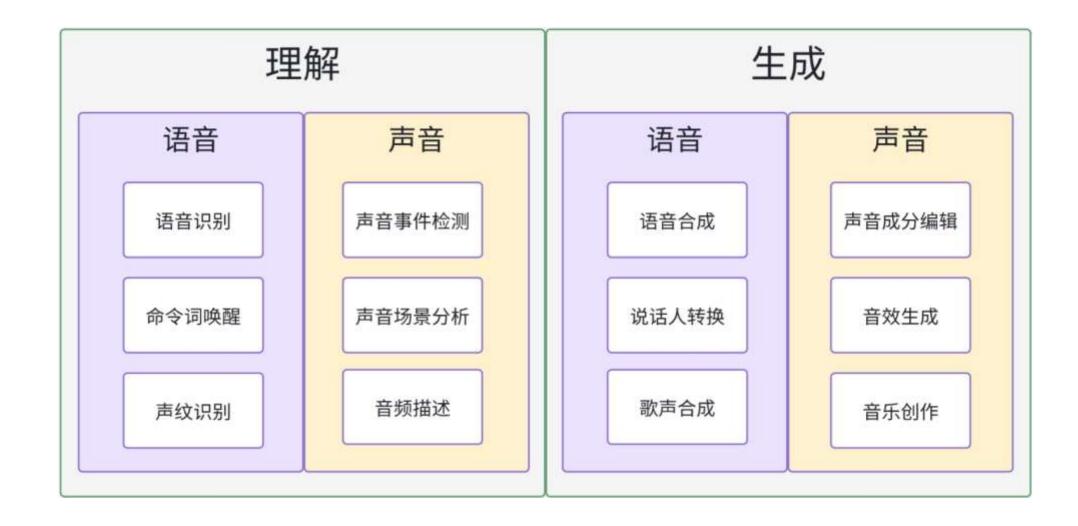
1370万

拥有 5 个及以上小米 IoT 设备的用户数





小米声学语音技术





小爱同学背后的语音识别技术框架

在手机和 IoT 设备上针对垂域的识别率极高,且已经探索出成熟的迭代优化流程



但是! 这不是大模型时代的方案

技术革新势在必行





Whisper: 大模型语音识别



Whisper examples:

Speed talking ~

Whisper examples:

French



This is the Micro Machine Man presenting the most midget miniature motorcade of Micro Machines. Each one has dramatic details, terrific trim, precision paint jobs, plus incredible Micro Machine Pocket Play Sets. There's a police station, fire station, restaurant, service station, and more. Perfect pocket portables to take any place. And there are many miniature play sets to play with, and each one comes with its own special edition Micro Machine vehicle and fun, fantastic features that miraculously move. Raise the boatlift at the airport marina. Man the gun turret at the army base. Clean your car at the car wash. Raise the toll bridge. And these play sets fit together to form a Micro Machine world. Micro Machine Pocket Play Sets, so tremendously tiny, so perfectly precise, so dazzlingly detailed, you'll want to pocket them all. Micro Machines are Micro Machine Pocket Play Sets sold separately from Galoob. The smaller they are, the better they are.

•

Whisper is an automatic speech recognition system based on 680,000 hours of multilingual and multitasking data collected on the Internet. We establish that the use of such a number of data is such a diversity and the reason why our system is able to understand many accents, regardless of the background noise, to understand technical vocabulary and to successfully translate from various languages into English. We distribute as a free software the source code for our models and for the inference, so that it can serve as a starting point to build useful applications and to help progress research in speech processing.

Whisper examples:

K-Pop

Whisper examples:

Accent



While darkness was my everything I ran so hard that I ran out of breath Never say time's up Like the end of the boundary Because my end is not the end •

One of the most famous landmarks on the Borders, it's three hills and the myth is that Merlin, the magician, split one hill into three and left the two hills at the back of us which you can see. The weather's never good though, we stay on the Borders with the mists on the Yildens, we never get the good weather and as you can see today there's no sunshine, it's a typical Scottish Borders day.





Whisper 原理有何不同?

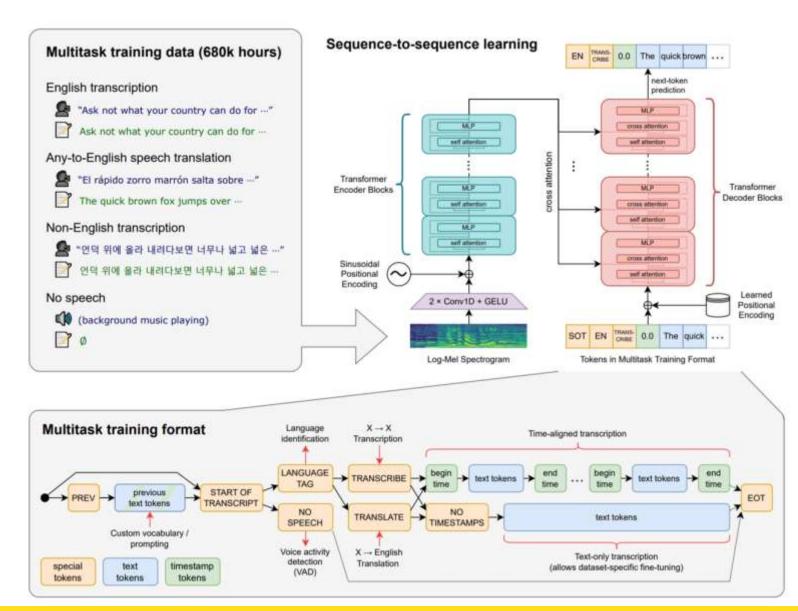
更先进的模型结构? No

模型结构并无不同

多语种训练数据

带有多任务标签

680,000 hours of multilingual and multitask supervised data collected from the web







AudioPaLM: 多语种语音直译



大语言模型作为模型骨架和初始化参数

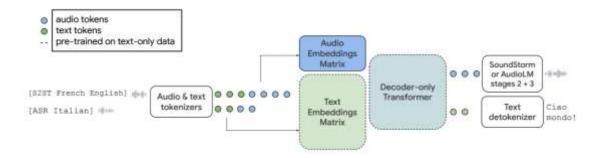
多语种音频和文本数据迭代训练

Mandarin / 中文



Original

我非常开心和你合作



Translation with AudioPaLM

I am very happy to work with you

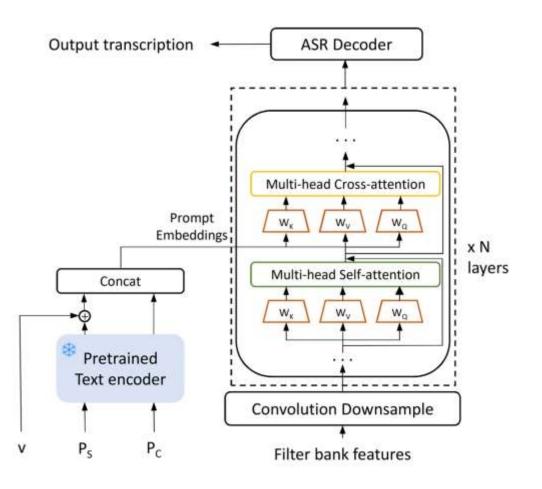


小米 Prompt-ASR

用 prompt 约束语音识别领域,提升识别率

把大语言模型输出通过 cross-attention 联入 encoder

Style Prompt	WITHOUT CASING OR PUNCTUATION
Content Prompt	Welcome to the UEFA Champions League final!
Reference text	TODAY'S MATCH IS BETWEEN REAL MADRID AND LIVERPOOL
Style Prompt	Mixed-cased English with punctuation
Content Prompt	Welcome to the UEFA Champions League final!
Reference text	Today's match is between Real Madrid and Liverpool.





基于大模型的语音合成

更加自然



视频来源 https://www.bilibili.com/video/BV1e84y1U7j4

支持 Prompt 定制



Look a little closer while our guide lets the light of his lamp fall upon the black wall at your side.

baseline



中文说话人



合成效果

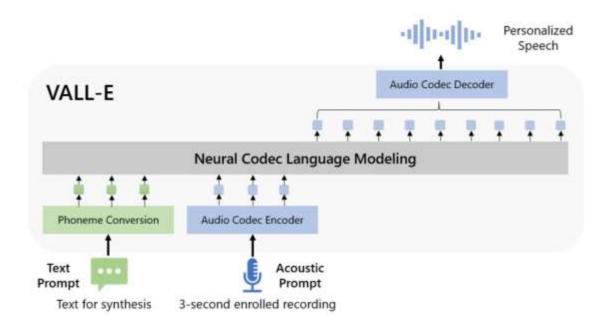


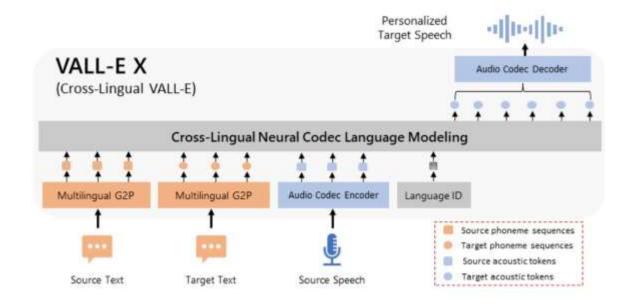




VALL-E (X) 算法框架

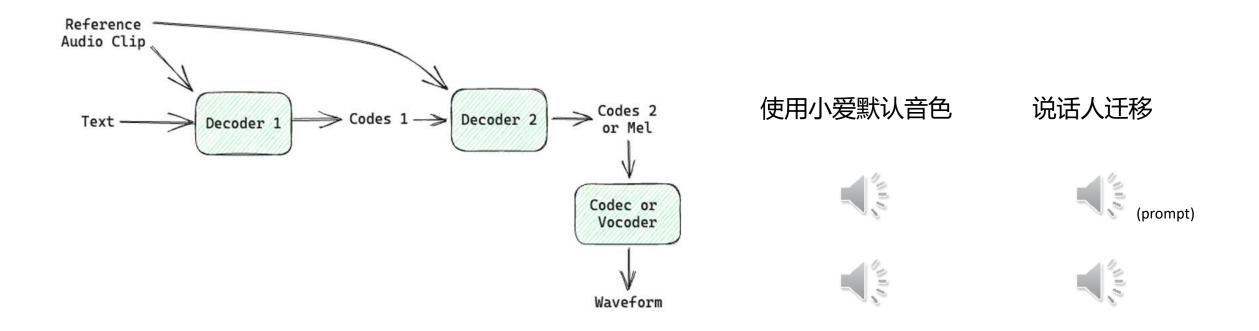






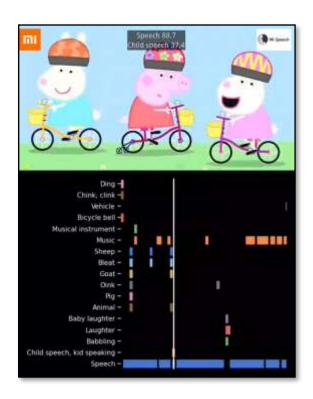


基于大模型的小米自然语音 TTS





小米声音识别技术



目前支持 85 种声音事件









大模型时代的声音理解



► 0:00 / 0:06 **-----** • :

请描述这段声音的主要内容?

► 0:00 / 0:04 **—** •

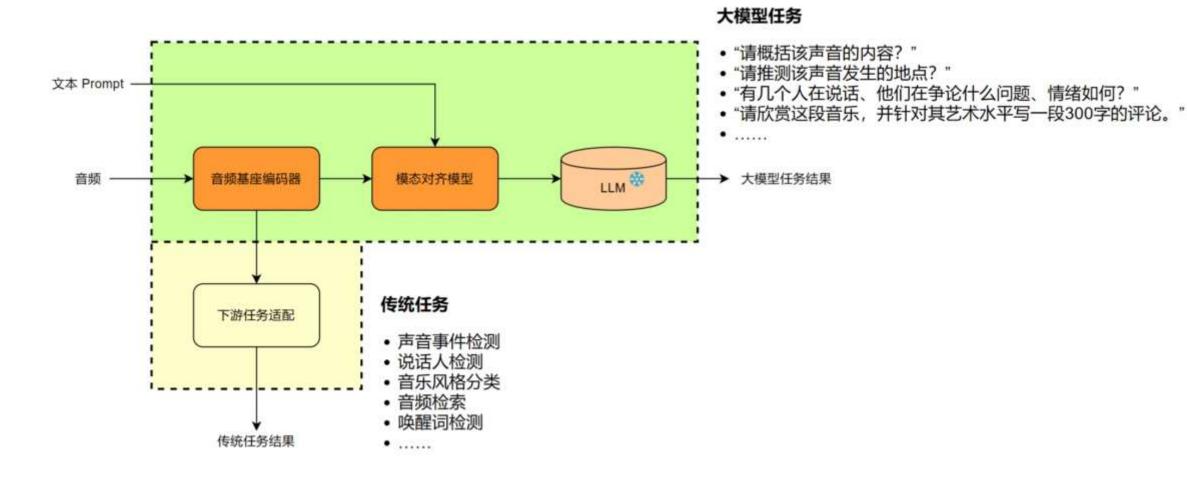
他们在讨论什么问题?结论是什么?

► 0:00 / 0:05 **→**

现场的气氛怎样?



我们的算法框架

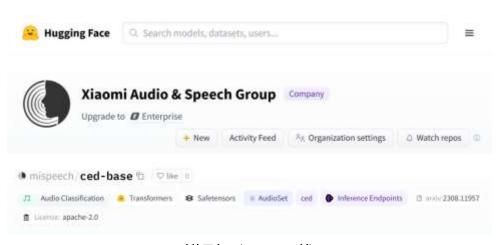


基座音频编码器

训练数据时长超过30年

参数量超过10亿 正在探索百亿参数量的模型

独创的一致性集成蒸馏技术 论文已被 ICASSP 2024 接收



模型开源可下载

CED: CONSISTENT ENSEMBLE DISTILLATION FOR AUDIO TAGGING

Heinrich Dinkel. Yangqing Wang. Zhiyong Yan. Junbo Zhang, Yajun Wang

Xiuomi Corporation, Beijing, China

ABSTRACT

2023

00

GS

1957v2

arXiv:2308.1

Augmentation and knowledge distillation (KD) are wellestablished techniques employed in audio classification tasks, aimed at enhancing performance and reducing model sixes on the walety recognized Audioset (AS) benchmark. Although both techniques are effective individually, their combined use. called consistent southing, been't been explored before. This paper proposes CED, a simple inaming framework that distils student models from large teacher ensembles with consistent teaching. To achieve this, CED officiently atoms logits as well. as the augmentation methods on disk, making it scalable so large-scale datasets. Central to CED's efficacy is its label-free nature, meaning that only the stored logits are used for the optimiration of a student model only requiring 0.3% additional disk space for AS. The study trains rurious transformer-based models, including a 10M parameter model achieving a 49.0 mean average precision (mAP) on AS. Fretuined models and ende are evallable entire.

Index Toron- audio tagging, audio classification, efficient data storage, teacher student, knowledge distillation.

1. INTRODUCTION

Audio tagging (AT) is a task that categorizes sounds into a fised set of event classes, e.g., a buby crying or water running. Applications of AT systems include aid for the hearing impaired, general monitoring of sounds [1, 2] as well as additional targets for keyword spotting [3, 4]. Enhancing performance and minuresing the size of AT systems is vital for practical deployment. We target performance and size inhancement through common methods: data augmentation and knowledge distillation (KD).

In KD, a large teacher model generates soft labels (logits) for a smaller student model to fours from. Typically, the objective of KD involves optimizing both the original hard labels and the logits together. Yet, recent research [7] found that using only logits as training targets can significantly improve performance compared to the usual method. By combining KD and data argmentation, also known as consistent teaching [12], it has been suggested that performance can be further boosted. Surprisingly, no previous research has applied this approach to AT. We believe that the limited exploration of this

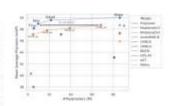


Fig. 1. Our achievest performance in comparison to other works on Audioun (AS-2M). We reference results from the works in 15. 6. 7. 8. 9. 10. 111.

Practically, these are two main ways to implement KD: 1. Online KD infers each soft label during training by forwarding. a cample jointly through the teacher as well as the enders. 2 Offine KD stores sugmented samples as well as the teacher's soft labels on disk and roads them during student training. Both these methods have prox and cons, detailed in Figure 2. Online KD is handicapped by its slow training speed because samples need to be sequentially forwarded through student and teacher, while offline KD can "parallelize" this process by first creating the teacher's data/logits. Conversely, offline KD struggles when handling substantial augmented data due to the storage demand of augmented samples. Thus, in practice, only logits from non-augmented training data are stored on disk. Missower, the performance of offline KD drops when (incomintent) data augmentation techniques are used on the studenc's imput, as demonstrated in previous studies [7, 13]. Our research shows (Section 4.1) that consistent augmentation for both tracker and student inputs is eneral to improve

We would like highlight key distinctions between our research two comparable works. Efficient-AT [13] and PSL [7] works. Efficient-AT (13) has utilized standard offline KD to achieve state-of-the-ert (SOEA) performance on Audioset [14] (AS), but due to the same of offline KD, could not apply consistent tracking. Further, work in [7] showed that label-time coding KD in figuritie for AT, yet could only approach is due to challenges in efficiently implementing KD use simple seather residels (MobileNetV2), since larger mod







基座音频编码器的多任务应用



Holistic Endustion of Audio Representations

HEAR Leaderboard

Model	UNL	Submission. Date	Bothive	Betjing Opera	D D	DCASE 2016	88C- 80	PSDMK	GTZAN Genre	OTZAN Music/Speech	Gundot	Libelcount	Maestro 3h	Mridangam Stroke	Mridangam Tonic	NSynth Pitch 50h	Niiymth Pitch 5h	Speech commands 5h	Speech commands	Vocal Instation	VoxLingua107 top 10
RedRice ced_base	137	2023-00-26	0.4835	0.9660	0.0010	0.0219	0.9065	0.6548	0.990	0.9436	0.8929	0.6795	0.1426	0.9743	0.9655	0.8281	0.66(0)	0,9683	0.5067	0.2200	0.3457
GURA Fuse Cut H+w+C	EJ.	HEAR 2027		9,9600	0.7474	0.8290	9.7810	0.4197	0.9000	0.0082	0.9845	0.6872	9.4413	0.9735	0.0285	0.8402	0.6400	0.0003	0.9677	0.1000	0.7203
Redflice cod_small	Of	2023-00-20	0.5170	0.9000	0.6064	0.9163	0.9595	0.0433	0.8950	0.9122	0.0045	0.6550	0.1006	0.0002	0.0004	0.3986	0.6020	0.8092	0.8519	0.2392	0.3853
GURA Fuse Cut H+w+C (time)	D3	HEAR 2021		0.90%	0.7427	0.3280	REST	0.3742	0.7600	0.9436	0.0048	0.6591	9.403	0.9753	0.0043	0.9900	0.0540	0.0000	0.960	0.2153	0.02%
RedRice ced_mini	13	2023-09-26	0.5017	0.9036	0.6520	0.9006	0.9535	0.6388	0.9000	0.9409	0.8601	0.680	0.09289	0.9636	0.0002	0.7520	0.5500	0.2739	0.8196	0.2017	0.3467
Logitech AI SERAB BYOL-S	05*	HEAR 2021	0,5467	0.0033	0.6560	0.6121	плинан	0.3068	0.8270	0.9085	0.8571	0.7853	0.007960	0.9736	0.9965	0.7116	0.3900	0.9137	0,0481	0.1508	9.4078
CP-JKU mn40_ss (s1+1+sH_m)	of.	2023-01-03	0.5027	0.9534	0.6400	0.8130	0.9615	0.0312	0.9000	0.0840	0.0107	0.7253	0.01862	0.0713	0.9047	0.6353	0.3040	0.7767	0.9472	0.2010	0.3179
GURA Fue Hubert	e#	HEAR 2021		0.9493	0.7521	0.8300	8.7485	0.4132	0.7960	0.9000	0.0296	0.6954	0.1657	15,9738	0.0000	0.6002	0.0000	0.0408	0.9571	0.1548	0.7140
GURA Cas H+w+C	c#	HEAR 2021		0.9063	0.6394	0.6808	0.5110	0.3144	H.7290	0.9000	0,9610	0.6390	11.4091	0.9378	0.8591	11,4968	0.8000	0.9270	0.9429	0.(1)4	0.4500
OpenLit	EI	HEAR 2027	0.6040	0.0746	0.5497	0,8329	9.7500	0.4470	0.8790	0.9696	0.9494	0.0414	0.01650	0.9006	0.9000	0.7310	0.5000	0.6796	0.7934	0.07812	0.8413
GURA Pine wor2vec2	cr*	HEAR 2021		0.9410	0.6024	0.7963	0.0050	0.4028	0.7930	0.1032	0.0673	0.6026	0.3130	0.0623	0.8376	0.0059	0.8300	0.0071	0.9697	0.1740	0.7058
GURA Avg H+w+C	137	HEAR 2021		0.9449	0.5473	6,6236	0.1200	0.2636	0.7000	8.8965	0.8571	0.6300	0.4500	0.9544	0.8873	0.0063	0.4620	0.4025	0.8908	0.00415	0.3210
CP-JKU PaSST 2b/1-mel	D)	HEAR 2021		0.9660	0.6104	0.9254	0.9425	0.6400	0,4930	0.9709	0.9405	0.6001		0.9650	0.0194	0.5409	0.2500	0.000	0.0387	0.1820	0.2588
CP-JKU PaiST 20vt	07	HEAR 2021		0.9600	8.6104	0.01302	0.9473	0.6400	0.8830	0.9760	0.0405	0.0001		0.9630	0.8194	0.5400	0.2500	0.0810	0.6167	0.1820	0.2500
GURA Avg Hubert+Crope	m*	BEAR 2021		0.9023	0.5807	0.6104	0.4365	0.2526	0.00%0	0.0405	0.8452	6140234	0.4634	0.0170	0.8000	0.0066	0.8790	0.7472	0.9283	0.07905	0.2902
RedRice EfficientNet-B2	137	HEAR 2021	0.5332	0.9535	0.5746	0.7901	0.9945	0.6873	0.9790	0.9679	0.8780	0.6509	0.0001910	0.34465	0.9432	0.3914	0.1680	6.5734	0.6757	0.1365	0.2551
CP-JKU PaSST base	D [*]	BEAR 2021		0.9600	0.0104	0.7979	0.0475	0.6400	0.6800	0.0700	0,9405	10001		0.9650	0.9194	0.5400	0.2500	0.6010	0.6367	0.1820	0.2500
GURA Cut www2vec2+cnque	tif	HEAR 2021		0.0198	0.430%	0.5855	0.3430	0.2341	0.6810	0.9078	0.8338	0.5694	0.4626	0.8077	0.8226	0.9900	0.800	0.8803	0.9188	0.07640	0.3007
war2vec2	137	HEAR 2021		0.5007	0.0002	0.6630	0.5610	0.3417	0.7900	0.9462	0.8487	0.6921	0.00290	0.9432	0.9263	0.6530	0.4020	0.6062	0.9795	0.09006	0.4029



声音增强/编辑/生成

已有成果其实已经具备了部分大模型的能力

需要进一步整合





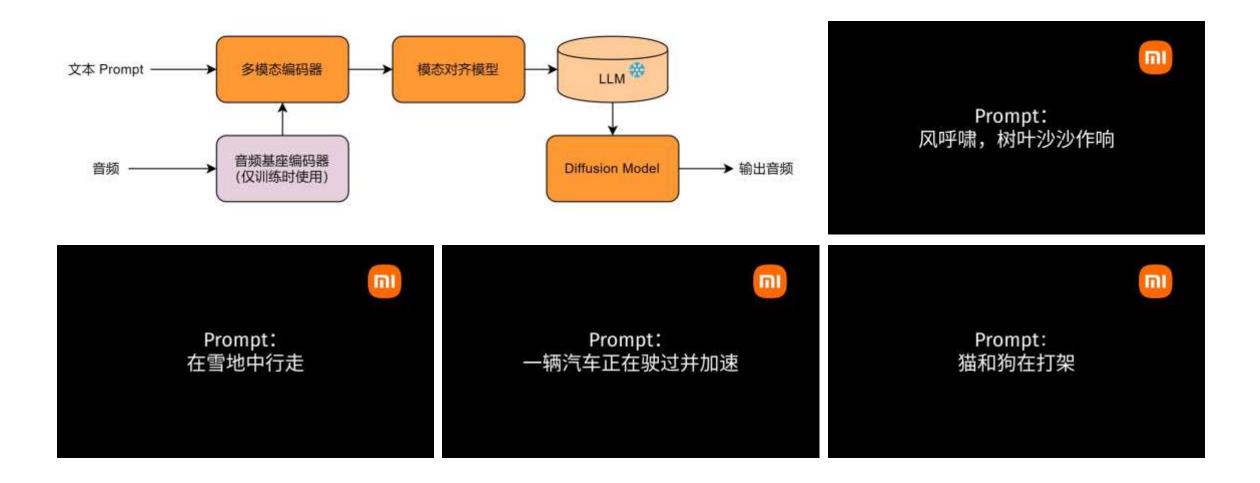








基于 Prompt 的声音生成





结语

- 大模型的成功为 AI 研究指明了方向
- 多任务统一学习可以带来真正的理解能力和强大的任务自推广能力
- 各任务的统一、各模态的统一是大势所趋

inn '

_{主办方} msup[®]



微信官方公众号: 壹佰案例 关注查看更多年度实践案例