

TOWARDS LEARNING UNIVERSAL AUDIO REPRESENTATIONS

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ABSTRACT

The ability to learn universal audio representations that can solve diverse speech, music, and environment tasks can spur many applications that require general sound content understanding. In this work, we introduce a holistic audio representation evaluation suite (HARES) spanning 12 downstream tasks across audio domains and provide a thorough empirical study of recent sound representation learning systems on that benchmark. We discover that previous sound event classification or speech models do not generalize outside of their domains. We observe that more robust audio representations can be learned with the SimCLR objective; however, the model’s transferability depends heavily on the model architecture. We find the Slowfast architecture is good at learning rich representations required by different domains, but its performance is affected by the normalization scheme. Based on these findings, we propose a novel normalizer-free Slowfast NFNet and achieve state-of-the-art performance across all domains.

Index Terms— audio representations, representation evaluation, speech, music, acoustic scenes

1. INTRODUCTION

Audio is a ubiquitous form of data that can convey rich information, whether in the form of speech, music, or surrounding environment sounds. An ability to understand all forms of sound in a holistic manner would empower a wide range of diverse applications, from end-to-end audio content understanding to human-computer interactions. Importantly, when used on a new task, such an ability could reduce the amount of labeled data required, thanks to similarities with other domains and synergies with tasks where data is abundant. In this paper, we take a step in this direction by laying the groundwork for learning universal audio representations.

We first turn our attention to evaluation benchmarks, and seek a compact and representative way to measure performance of universal audio representations. In the text domain, GLUE [1] has been effective in driving the progress of unified approaches, and we follow a similar approach here. Meta-benchmarks, such as NOSS [2] and SUPERB [3] have been introduced with similar motivation, but are restricted to the speech domain. The AudioSet benchmark [4] has greatly ac-

celerated progress in sound understanding thanks to its scale and difficulty; but similarly, it provides an incomplete picture on the usefulness of representations. Likewise, MagnaTagATune [5] and NSynth [6] are limited to the music domain. These benchmarks have facilitated model development in each individual domain [7, 8, 9, 10, 11, 12, 13]. A natural question is whether optimizing for performance on these different domains jointly can provide benefits in each domain. The task suites used in [14, 15, 16] constitute early steps in this direction. We build on their proposed benchmark, removing tasks where we noted performance saturation, and including additional challenging tasks, such as AudioSet [4], MagnaTagATune [5], and Fluent Speech Commands [17].

Equipped with this benchmark, we perform thorough empirical studies on recent frameworks and architectures. We first perform an extensive empirical comparison of training objectives and models, especially focusing on the two dominant paradigms of supervised classification [8, 12] and self-supervised contrastive learning [15, 13], and comparing them across a large set of model architectures. We find that models trained with contrastive learning tend to generalize better in the speech and music domain, while performing comparably to supervised pretraining for environment sounds. We also measure the performance of heavily-tuned speech representation systems [18, 9, 10], but we find that their strong performance does not extend to other domains. Motivated by the complementary strengths of Slowfast ResNet50 [19] and NFNet-F0 [20], we combine their design principles and evaluate a novel architecture, Slowfast NFNet-F0, which obtains improved performance across the board. We additionally provide a thorough study on how normalization schemes affect the representations. Putting these all together, we obtain better scores across the speech, music, and environment domain, as measured by our meta benchmark.

To sum up, we make the following contributions: (i) We introduce HARES, an evaluation benchmark designed to drive progress for universal audio representations; (ii) We perform empirical studies on models and learning frameworks. (iii) Based on our findings, we propose a novel architecture, Slowfast NFNet-F0, which significantly improves performance across the board. (iv) Our final model obtains state-of-the-art results, in particular improving by a large margin in the music domain.

Table 1: HARES tasks. HARES unifies existing datasets with the goal of covering the three major audio domains to facilitate the development of models for general auditory content understanding.

Dataset	Task	#Samples	#Classes	Used in
<i>Environment</i>				
AudioSet	Audio tagging	1.9m	527	[7, 8, 12]
Birdsong	Animal sound	36k	2	[14, 15]
TUT18	Acoustic Scenes	8.6k	10	[14, 15]
ESC-50	Acoustic Scenes	2.0k	50	[8, 13]
<i>Speech</i>				
Speech Comm. v1	Keyword	90k	12	[2, 15, 3, 16]
Speech Comm. v2	Keyword	96k	35	[14, 15, 16]
Fluent Speech Comm.	Intention	27k	31	[3]
VoxForge	Language id	145k	6	[2, 15, 16]
VoxCeleb	Speaker id	147k	1251	[2, 15, 3, 16]
<i>Music</i>				
NSynth Instrument	Instrument id	293k	11	[14, 15, 16]
NSynth Pitch	Pitch estimation	293k	128	-
MagnaTagATune	Music tagging	26k	50	[21]

2. METHOD

2.1. Holistic Audio Representation Evaluation Suite

Intuitively, sound can be categorized into three domains: speech, music, and environment (sound of things, animal, nature, etc). Previous evaluation benchmarks either contain saturated tasks and lack coverage in the music and environment domain [14, 15], or focus entirely on the speech domain [2, 3]. We introduce a new evaluation meta-benchmark, named the Holistic Audio Representation Evaluation Suite (HARES) that contains 12 tasks spanning all three domains.¹ We build on top of tasks previously used in [14, 15]. We exclude tasks where performance is saturated (LibriSpeech-speaker-id and MUSAN), and add widely used and challenging tasks, including AudioSet [4], ESC-50 [22], Fluent Speech Commands [17], NSynth-pitch [6], and MagnaTagATune [5]. We summarize all task characteristics (description, relevant statistics and occurrences in related work) in Table 1. Each of these benchmarks has been effective in driving model development, and we propose to jointly optimize performance across domains to obtain universal representations. HARES shares 4 tasks with the SUPERB speech benchmark [3]. We exclude speech and phoneme recognition tasks because the labels are temporally structured and they require sequence-to-sequence modeling. The models need to output representations with a high temporal resolution and it restricts the types of model that can be evaluated.

We evaluate by training a *linear* layer on the *frozen* pre-trained model for all tasks, except for AudioSet where we follow the common 1-hidden-layer MLP protocol [7, 13, 23]. Global average pooling is applied to the representations from the last layer before the fine-tune module. We report the

¹More details about HARES tasks and the Slowfast NFNet-F0 model can be found at https://github.com/deepmind/deepmind-research/tree/master/slowfast_nfnet.

mean average precision (mAP) on AudioSet and MagnaTagATune due to their multi-class nature, and accuracy on all other datasets. Note that although there is an overlap in the tasks, our results on speech tasks are not directly comparable to the SUPERB benchmark [3], where the authors use weighted-sum of hidden representations from different layers and an additional linear projection layer for the downstream evaluation. Our choice follows [14, 15] and keeps homogeneity with the rest.

2.2. Training Frameworks and Architectures

We perform an extensive empirical comparison of training objectives and models. We use AudioSet [4] as the training dataset, due to its combined advantages of size and availability of labels for the supervised setting.

First, we focus our study on two dominant paradigms for pretraining: supervised classification [8, 12] and self-supervised contrastive learning (SimCLR) [15, 13, 23, 21]. We compare the two training objectives across a large set of models used recently for audio representation learning, listed in Table 2. Note that most models are adopted from the vision domain; they treat spectrograms as images and do not distinguish time and frequency dimensions. We use example mixing to augment spectrograms, whose effectiveness has been demonstrated in both settings [8, 13]. Also, for sound classification, techniques including class-balanced data loading and model ensembles can boost the performance on the AudioSet benchmark [8, 12], and pretraining on large image datasets can also significantly improve the performance of methods like ViT [12]. For the sake of simplicity, we leave the exploration of such orthogonal directions for future work.

Second, we extend our study to other strongly performing approaches that explicitly model the time dimension, namely BYOL-A [16], CPC [18, 9, 11] and masked prediction using Wav2Vec2.0 [10]. We reproduce these methods to evaluate them on our benchmark.

2.3. Slowfast NFNets

Due to its strong performance, we build on the Slowfast network architecture [19], and seek to further improve its performance in the audio domain. It uses separable convolutions to model the time and frequency dimension independently, and two pathways to capture both slow and fast features in the spectrogram. Due to space limitations, we refer the reader to [19] for details.

From our study on various architectures, we notice that the NFNet architecture [20], which is normalizer-free, performs very well. Motivated by this finding, we perform a thorough study on various normalization schemes for Slowfast networks. We compare Batch Norm [24], Layer Norm [25], Instance Norm [26] as well as not using any normalizer. Finally, we combine the design principles of NFNet with

Table 2: Evaluating frameworks and architectures on HARES. We compare the impact of architecture choice under the classification and SimCLR objective. We also show the performance of several other recent strongly performing frameworks. Average scores are reported for tasks in each domain separately, and all three combined. All models are trained on AudioSet except for bidirectional CPC and Wav2Vec2.0, for which we also show results when they are trained on LibriSpeech (LS).

Architecture	#Params	Input format	Used in	Env.	Speech	Music	HARES	AudioSet (mAP)
<i>Classification/SimCLR</i>								
BYOL-A CNN	5.3m	Spectrogram	[16]	69.8/69.9	61.4/69.8	57.6/63.1	63.3/68.2	33.8/32.2
EfficientNet-B0	4.0m	Spectrogram	[15]	70.5/63.8	43.5/40.7	48.0/44.0	53.6/49.2	32.1/26.2
PANNs-CNN14	71m	Spectrogram	[8, 13]	74.8/66.4	56.0/37.3	56.4/44.8	62.4/48.9	38.9/28.8
ViT-Base	86m	Spectrogram	[12]	73.5/74.6	50.4/56.5	60.3/64.2	60.6/64.5	37.6/36.8
ResNet50	23m	Spectrogram	[7]	75.1/74.4	51.7/65.0	59.6/63.7	61.4/67.8	39.4/36.2
SF ResNet50	26m	Spectrogram	[19]	74.3/74.3	56.9/73.4	59.6/65.2	63.4/71.7	38.2/36.6
NFNet-F0	68m	Spectrogram	Ours	76.2/76.0	59.0/65.9	61.8/65.5	65.5/69.2	39.6/37.6
SF NFNet-F0	63m	Spectrogram	Ours	75.4/75.8	65.6/77.2	64.5/68.6	68.6/74.6	38.7/37.8
Bidir-CPC	38m	Waveform	[11]	69.1	72.4	57.6	67.6	28.7
Bidir-CPC (LS)	38m	Waveform	[11]	59.9	75.3	51.5	64.2	21.3
Wav2Vec2.0	95m	Waveform	[10]	48.3	41.2	35.4	42.1	14.8
Wav2Vec2.0 (LS)	95m	Waveform	[10]	48.5	<u>75.6</u>	35.5	56.6	14.8
BYOL-A	5.3m	Spectrogram	[16]	65.4	66.9	60.7	64.9	26.1

those of the Slowfast network, to propose a novel architecture, denoted Slowfast NFNet-F0. It is free from the side effects of normalizers [27] and is optimized for training speed on recent hardware accelerators [20].

3. EMPIRICAL STUDY

We perform thorough empirical studies using the proposed HARES benchmark. Unless further noted, we train classification models with batch size 1024 for 100k steps, as these models converge fast and can overfit easily. We train SimCLR models with batch size 4096 for 200k steps. All models are trained on AudioSet [4] with Adam [28] and an initial learning rate of 2×10^{-4} on a Cloud TPU v3 Pod slice with 32 cores. For classification and SimCLR, we randomly crop 3-second windows for training. We extract log-mel spectrograms with 80 features using a window size of 25 ms and a stride of 10 ms from a waveform sampled at 16kHz. The projector for the SimCLR loss is a MLP with 3 hidden layers of size 4096.

3.1. Architectures and Losses

We report the results of our comparison between supervised classification and SimCLR loss in Table 2. In general, we observe that the widely used AudioSet benchmark [4] does not correlate with our HARES benchmark - it aligns with the overall score on the environment sub-suite. On the speech and music benchmarks SimCLR leads to better generalization across architectures, and they perform similarly on the environment benchmark, with the exception of EfficientNet-B0 and CNN14. We think this is because labels presented in supervised pretraining bias the network towards extracting more overall and slow features than local traits. Architectures from the vision domain show strong performance on environment tasks but get relatively low scores on speech tasks. This is

Table 3: Impact of normalizer on Slowfast networks trained with the SimCLR objective. We consider Batch Norm (BN), Layer Norm (LN), Instance Norm (IN), and Normalizer-Free (NF) architectures. Latencies are given as the time required for a full training step on TPU.

Architectures	Env.	Speech	Music	HARES	TPUv3 Train
SF ResNet50 (no BN)	74.1	74.1	65.6	71.9	131.1 ms
SF ResNet50	74.3	73.4	65.2	71.7	188.0 ms
SF ResNet50-LN	74.0	76.0	<u>67.1</u>	73.1	203.7 ms
SF ResNet50-IN	73.7	77.7	66.0	<u>73.5</u>	207.9 ms
SF NF-ResNet50	<u>74.0</u>	75.7	66.6	72.9	158.0 ms
SF NFNet-F0	75.8	<u>77.2</u>	68.6	74.6	280.9 ms

possibly because they treat the time-frequency spectrograms as images with two equal spatial dimensions, which may ignore local features present in the audio. This hypothesis is supported by the fact that approaches that handle the two dimensions differently tend to perform better on speech tasks: Slowfast networks thank to the use of separable convolutions, and BYOL-A CNN thanks to its fully connected layers only operating on the frequency and channel dimension.

Next, we replicate and evaluate the bidirectional version of CPC/Wav2Vec [11], Wav2Vec2.0 [10], and BYOL-A [16]. All three models show competitive performance on speech tasks, but they do not transfer well on the other two domains. CPC and Wav2Vec2.0 directly operate on raw audio sequences and use the contrastive objective over time steps: this procedure preserves the temporal structure of the data by design. Interestingly, we find Wav2Vec2.0 does not perform well when trained with AudioSet. This is possibly because the complexity of the data is beyond the capability of the masked prediction objective, which works the best on clean speech datasets such as LibriSpeech [29]. BYOL-A [16] uses a Siamese framework but takes only one temporal crop at random and augments it with random resize cropping: this effectively biases the model towards local semantics.

Table 4: Comparisons to the state-of-the-art on HARES. Both Slowfast networks are trained with the SimCLR loss. Wav2Vec2.0 is trained on LibriSpeech (LS) because it does not perform well when trained on AudioSet. CLMR is trained on MagnaTagATune and Million Songs. All other models are trained on AudioSet. *No class-balanced dataloader.

Tasks	SF NFNet-F0 (ours)	SF ResNet50 [19] (ours)	Wav2Vec2.0 [10] (ours, LS)	Bidir-CPC [11] (ours)	BYOL-A [16] (ours)	PANNs-CNN14 [8] (ours)	COLA [15]	BYOL-A [16]	PANNs-CNN14 [8]	CLMR [21]
<i>Environment</i>										
AudioSet	37.8	36.6	14.8	28.7	26.1	38.9	-	-	37.5*	-
Birdsong	77.6	77.9	60.9	77.6	77.1	78.0	77.0	-	-	-
TUT18	96.8	92.3	49.3	90.9	76.3	88.9	94.0	-	-	-
ESC-50	91.1	90.5	69.2	79.2	82.3	93.6	-	-	90.8	-
Avg.	75.8	74.3	48.5	69.1	65.4	74.8	-	-	-	-
<i>Speech</i>										
Speech Comm. v1	91.7	88.8	95.1	92.0	90.1	71.4	71.7	91.0	-	-
Speech Comm. v2	93.0	91.5	94.8	92.4	89.7	76.4	62.4	92.2	-	-
VoxForge	90.4	89.2	91.2	89.1	83.9	78.5	71.3	90.2	-	-
VoxCeleb	64.9	59.4	41.6	40.7	39.5	30.9	29.9	40.1	-	-
Fluent Comm.	46.1	38.3	55.3	47.9	31.3	22.8	-	-	-	-
Avg.	77.2	73.4	75.6	72.4	66.9	56.0	-	-	-	-
<i>Music</i>										
NSynth-Pitch	88.0	83.2	34.6	78.1	71.4	58.4	-	-	-	-
NSynth-Instrument	78.2	73.5	40.2	58.4	73.6	71.4	63.4	74.1	-	-
MagnaTagATune	39.5	38.8	31.7	36.3	37.1	39.4	-	-	-	36.0
Avg.	68.6	65.2	35.5	57.6	60.7	56.4	-	-	-	-
HARES	74.6	71.7	56.6	67.6	64.9	62.4	-	-	-	-

Notably, we find that with the same CNN architecture, our SimCLR-based framework obtains much better performance than the original BYOL framework proposed in [16]. We note that this could be in part due to the more extensive study we perform under the former setting. An in-depth comparison between SimCLR and BYOL for audio is beyond the scope of this work.

Overall, NFNet-F0 performs remarkably on the environment sub-suite. When comparing the Slowfast networks with their vanilla counterparts, we find that they are comparable on environment tasks, but better on the speech and music tasks. This shows the effectiveness of the Slowfast architecture.

3.2. Normalizers Matter For Slowfast Networks

We find that the choice of normalizer affects transferability. The original Slowfast ResNet50 [19] for audio makes use of Batch Norm. In Table 3, we observe that using Layer Norm or Instance Norm, which do not break the independence between training examples in the batch, improves the scores in all domains. We adapt the NF ResNet50 [27] and NFNet-F0 [20] to the Slowfast setting. The latter is better optimized for performance on recent hardware accelerators. Even in the absence of any normalizer, Slowfast NF ResNet50 performs similarly to when layer or instance normalization is used instead. Furthermore, our Slowfast NFNet-F0 outperforms all other models.

3.3. Comparison to the State-of-the-Art

We compare our best models to previous works in Table 4. Our Slowfast NFNet-F0 trained with the SimCLR objective outperforms all previous frameworks on the overall HARES

benchmark as well as in each domain, including COLA [15] and BYOL-A [16] previously developed for general-purpose audio understanding. It outperforms the previously proposed Slowfast ResNet50 [19] on almost all tasks. In addition, it also outperforms strongly performing frameworks developed in different audio domains. It has a slight edge over the supervised PANNs-CNN14 sound classification model on environment tasks. It performs slightly worse on semantic speech tasks than Wav2Vec2.0 (trained on LibriSpeech), but there is a substantial improvement on the VoxCeleb speaker identification task. Meanwhile, it shows strong performance on the music sub-suite. It achieves an audio-only state-of-the-art on the MagnaTagATune task with an mAP of 39.5, outperforming CLMR trained on a music corpus at 36.0 [21].

4. CONCLUSION

In this paper, we devised a task suite called HARES for holistic evaluation of audio representations. We study several recent pre-training frameworks, focusing in particular on supervised classification and self-supervised contrastive learning with many different models. We find that models trained with contrastive learning and Slowfast networks tend to generalize better across different domains. We also perform a thorough study of different normalization schemes, building on the Slowfast network architecture, and obtain significant performance improvements using a new Slowfast NFNet-F0. Our final model significantly outperforms previous general-purpose audio representation models. We hope the HARES benchmark and the findings presented in this paper can spur future research towards further improving universal audio representations.

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