Evaluation of Deep Audio Representations for Semantic Sound Similarity

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- Audio-sharing platforms, such as Freesound, offer sound similarity functions (query-by-example) for content-based retrieval.
  - They typically use manually-engineered audio representations that:
    - Do not capture audio semantics
    - Do not leverage recent developments in deep representation learning.
- **Our goal** is to identify the best deep audio representation for semantic sound similarity and deploy it within the Freesound platform.
- GitHub repository: https://github.com/raraz15/semantic-sound-similarity

Deep representation learning models which use **audio and language** modalities together perform **significantly better** in the **semantic sound similarity** task.

Modality	Model	Pre-training Objective	Param.	Data	Dim.	MAP@N ↑ N=15	MAP@N ↑ N=150	MR1 ↓
A	Freesound	-	-	-	846	0.09	0.03	43
A	VGGish	Classification	62M	80M	128	0.20	0.11	27
	YAMNet	Classification	4M	2M	1024	0.27	0.15	25
	FSD-SINet	Classification	5M	51K	512	0.33	0.19	18
	BEATs	Classification	90M	1.8M	768	0.37	0.20	13
A & I	OpenL3	Audiovisual correspondence	5M	296K	512	0.15	0.06	31
	CAV-MAE	Audiovisual correspondence	85M	1.8M	768	0.33	0.18	15
A & L	CLAP2022	Contrastive alignment	81M	128K	1024	0.38	0.25	20
	LAION-CLAP	Contrastive alignment	31M	2.5M	512	**0.53**	**0.37**	**8**
	CLAP2023	Contrastive alignment	31M	4.6M	1024	0.50	0.34	10
	Pengi	Question-answering	31M	3.4M	1024	0.49	0.35	12
A & I & L	AudioCLIP	Contrastive alignment	30M	1.8M	1024	0.06	0.02	56
	Wav2CLIP	Contrastive alignment	12M	200K	512	0.12	0.04	36
A & I & L & O	ImageBind	Contrastive alignment	85M	1.8M	1024	0.29	0.17	22

Model performances on the semantic sound similarity task

Methodology

Data: FSD50K evaluation set - 10,231 audio clips with 200 sound class labels from 7 sound families.

Task: Evaluate the audio representations of Freesound and 13 neural networks. For each representation, optimize:
- Embedding processing parameters,
- Similarity search functions.

Evaluation:
- **Objective :** MAP@15, MAP@150, and MR1. On,
  - Class-wise (e.g., birds, bells, motor.)
  - Family-wise
  - Macro-averaged
- **Subjective:** Using our web interface (see our GitHub repo)

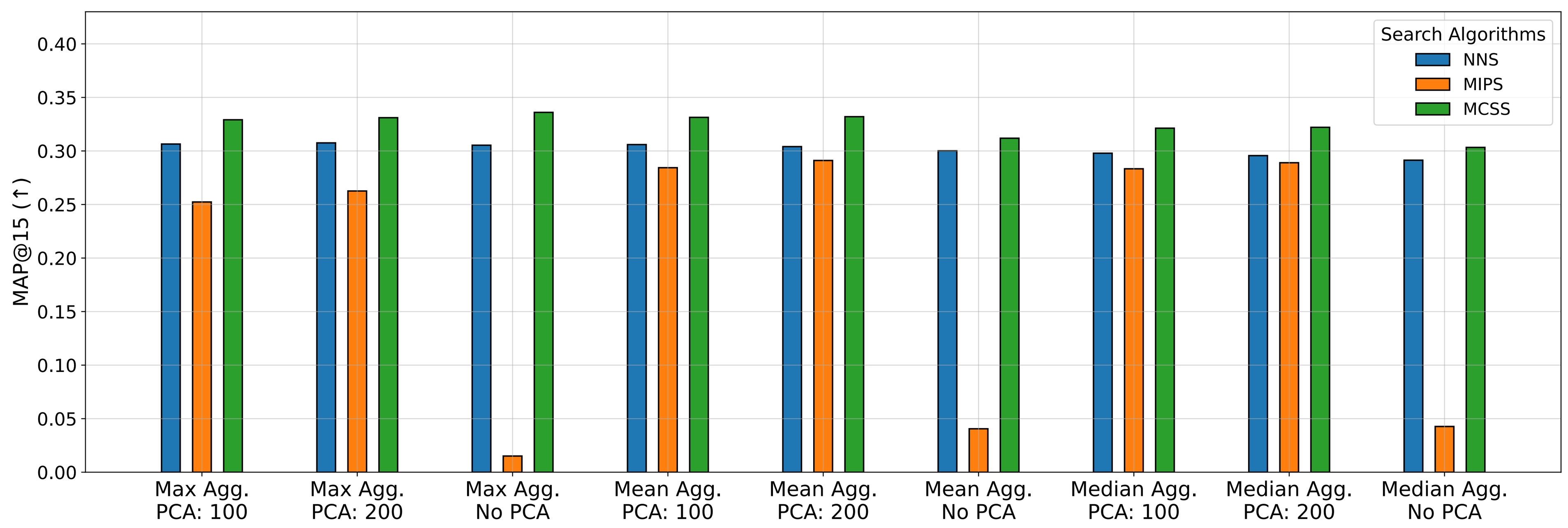
Conclusion

Learning paradigm
- Input modalities are crucial for retrieval performance
  - Audio & language > audio > audio & image
- LAION-CLAP works the best across all families.
- Models that outperform others in the sound event classification task underperform in the semantic sound similarity task.

Embedding processing
- Dimensionality can be greatly reduced by as much as 90%, while increasing performance slightly.

Similarity search
- Maximum Cosine Similarity Search (MCSS) works the best for all.

Results



Macro-averaged MAP@15 scores of QbE systems that use FSD-SINet VGG42-tlpf

	Animal	Human Sounds	Music	Natural Sounds	Sounds Of Things	Source Ambiguous Sounds
Freesound	0.047	0.085	0.194	0.117	0.062	0.053
VGGish	0.192	0.170	0.378	0.222	0.156	0.099
YAMNet	0.374	0.262	0.410	0.336	0.208	0.127
FSD-SINet	0.382	0.304	0.500	0.336	0.290	0.217
BEATs	0.421	0.339	0.491	0.472	0.343	0.225
OpenL3	0.119	0.141	0.296	0.174	0.104	0.072
CAV-MAE	0.410	0.298	0.493	0.368	0.286	0.172
CLAP2022	0.470	0.370	0.502	0.391	0.340	0.230
LAION-CLAP	0.613	0.483	0.676	0.526	0.507	0.376
CLAP2023	0.572	0.440	0.627	0.534	0.482	0.344
Pengi	0.592	0.411	0.605	0.525	0.480	0.289
AudioCLIP	0.070	0.068	0.138	0.063	0.036	0.018
Wav2CLIP	0.081	0.108	0.245	0.095	0.083	0.061
ImageBind	0.387	0.206	0.449	0.373	0.274	0.123

Family-wise MAP@15 scores

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Scan the QR code to access the project's GitHub repository! with the **code, full paper,** and **additional material**.