



DEEP LEARNING WORKSHOP

Dublin City University
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Day 2 Lecture 11

Audio & Vision



Eva Mohedano
eva.mohedano@insight-centre.org

Postdoctoral Researcher
Insight Centre for Data Analytics
Dublin City University

Contents

- Feature learning
- Cross-modal retrieval
- Sound source localization
- Sonorization

Contents

- Feature learning
- Cross-modal retrieval
- Sound source localization
- Sonorization

Self-supervised learning

Self-supervised methods **learn features** by training a model to solve a task derived from the **input data itself**, without human labeling

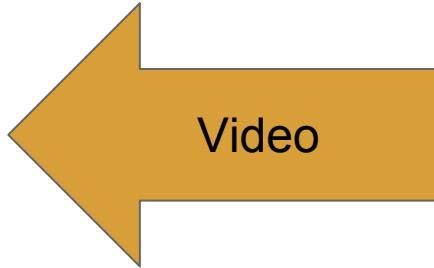


Audio

Visual Feature Learning



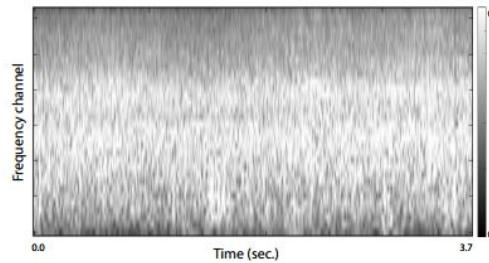
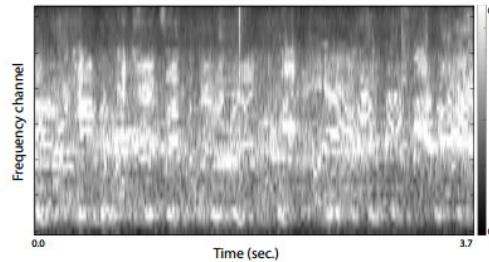
Vision



Audio

Visual Feature Learning

Based on the assumption that ambient sound in video is related to the visual semantics.



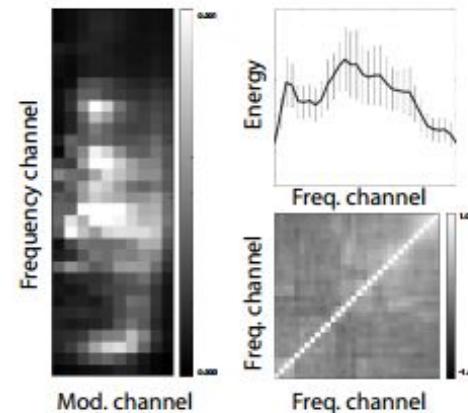
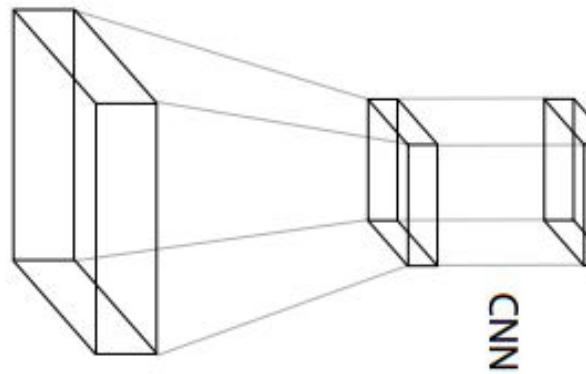
(a) Video frame

(b) Cochleagram

Owens, Andrew, Jiajun Wu, Josh H. McDermott, William T. Freeman, and Antonio Torralba. "[Ambient sound provides supervision for visual learning.](#)" ECCV 2016

Visual Feature Learning

Use videos to train a CNN that predicts the audio statistics of a frame.



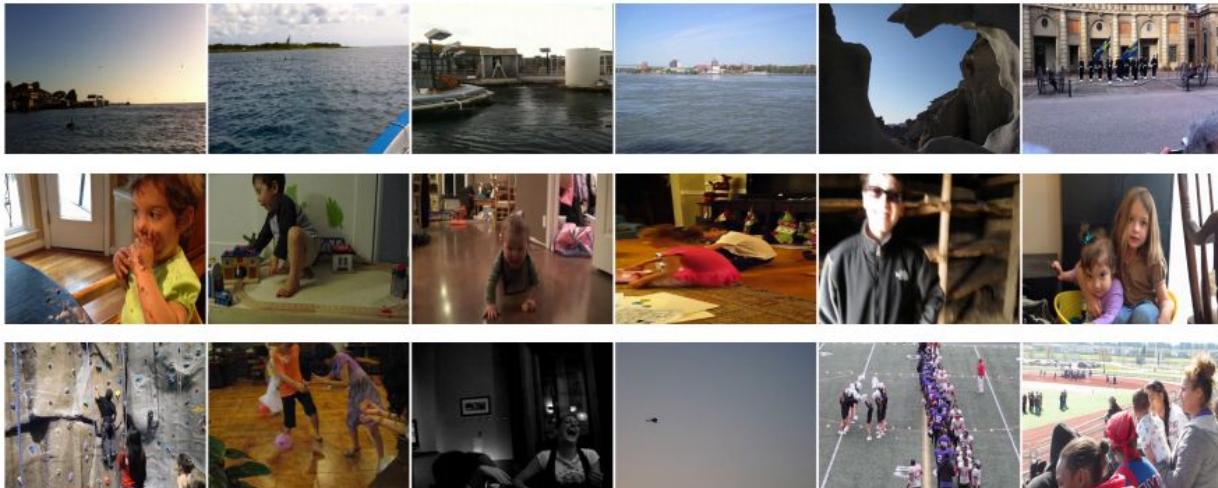
Self-supervised classification problem

Owens, Andrew, Jiajun Wu, Josh H. McDermott, William T. Freeman, and Antonio Torralba. "[Ambient sound provides supervision for visual learning.](#)" ECCV 2016

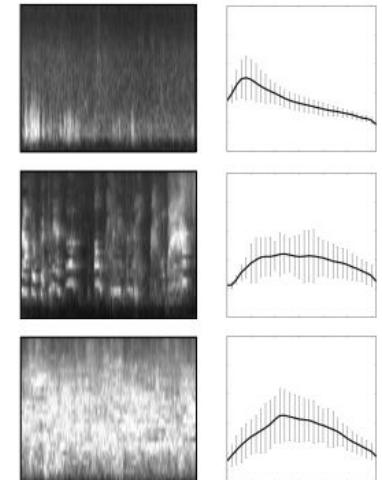
Visual Feature Learning

Task: Use the predicted audio stats to clusters images. Audio clusters built with K-means over training set

Cluster assignments at test time (one row=one cluster)



Average stats



Owens, Andrew, Jiajun Wu, Josh H. McDermott, William T. Freeman, and Antonio Torralba. "[Ambient sound provides supervision for visual learning.](#)" ECCV 2016

Visual Feature Learning

Although the CNN was not trained with class labels, local units with semantic meaning emerge.

baby



grass



person



plant

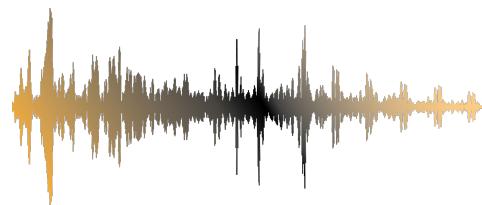
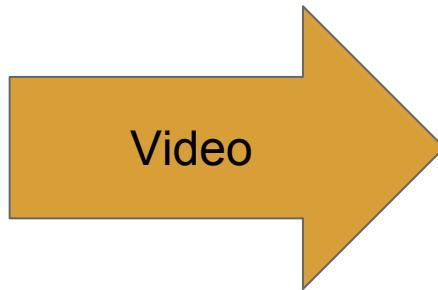


Owens, Andrew, Jiajun Wu, Josh H. McDermott, William T. Freeman, and Antonio Torralba. "[Ambient sound provides supervision for visual learning.](#)" ECCV 2016

Audio Feature Learning



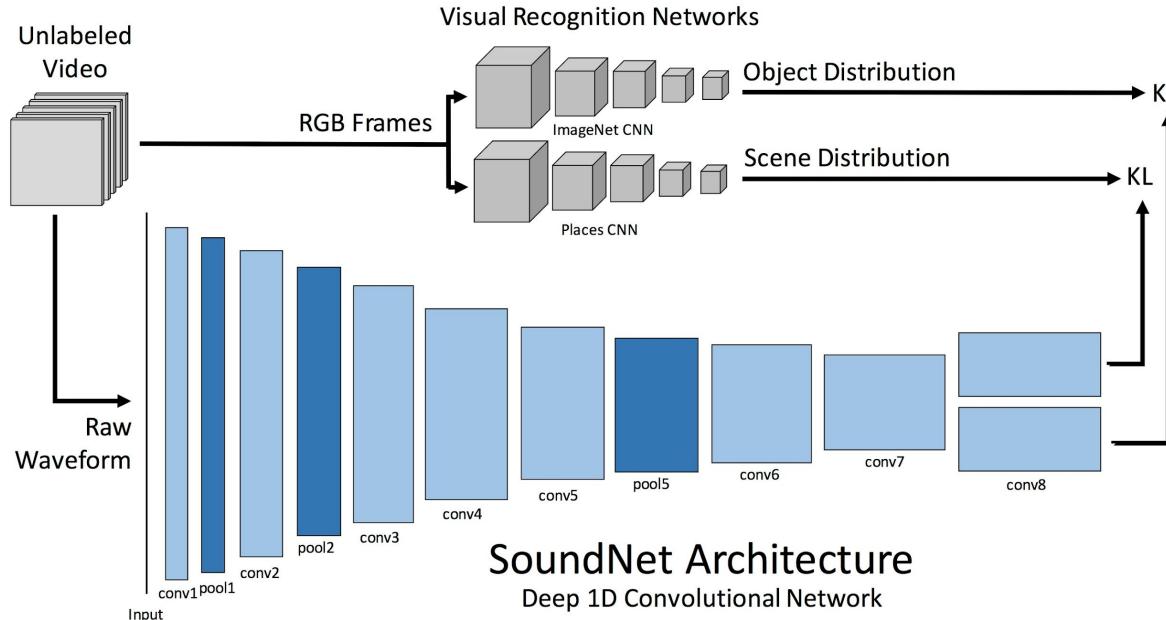
Vision



Audio

Audio Feature Learning

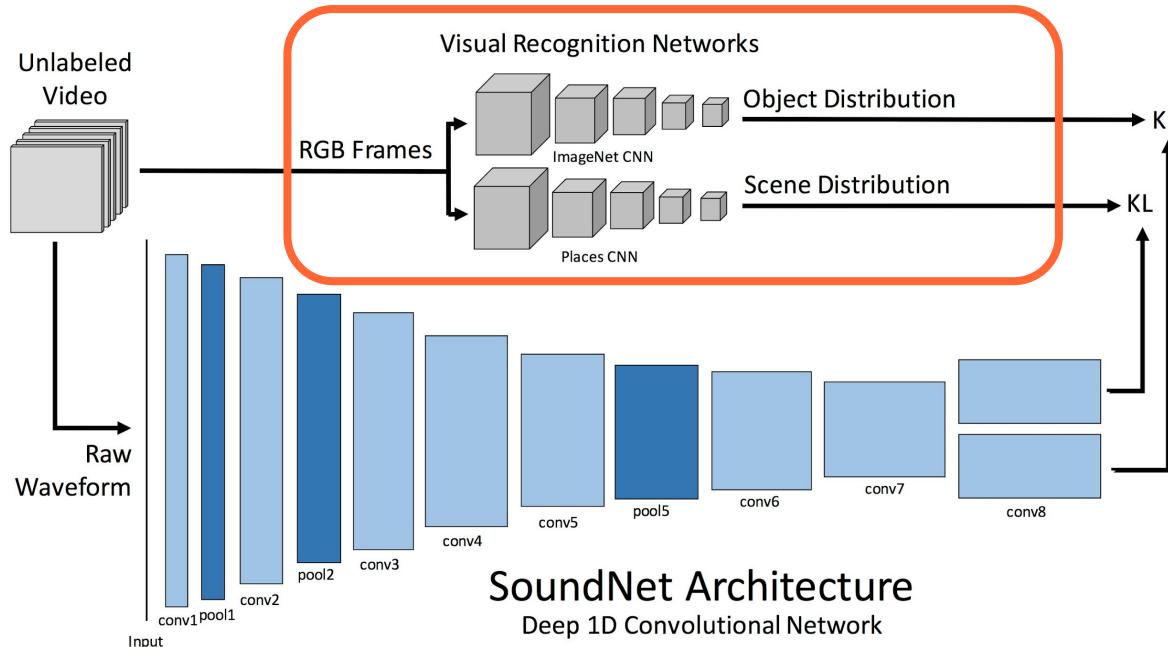
Pretrained visual ConvNets supervise the training of a model for sound representation



Aytar, Yusuf, Carl Vondrick, and Antonio Torralba. "Soundnet: Learning sound representations from unlabeled video." NIPS 2016

Audio Feature Learning

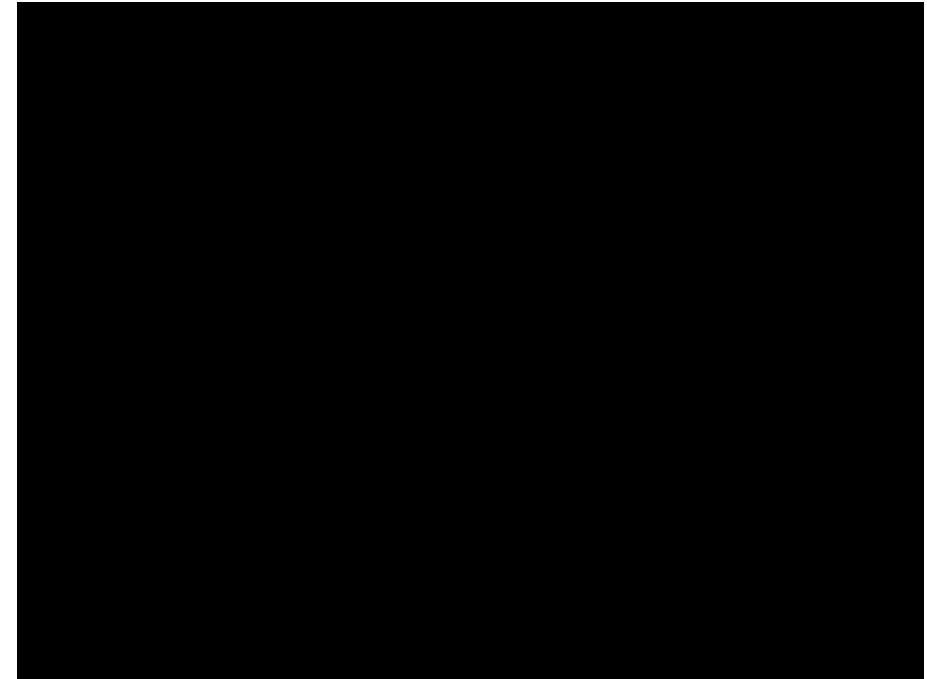
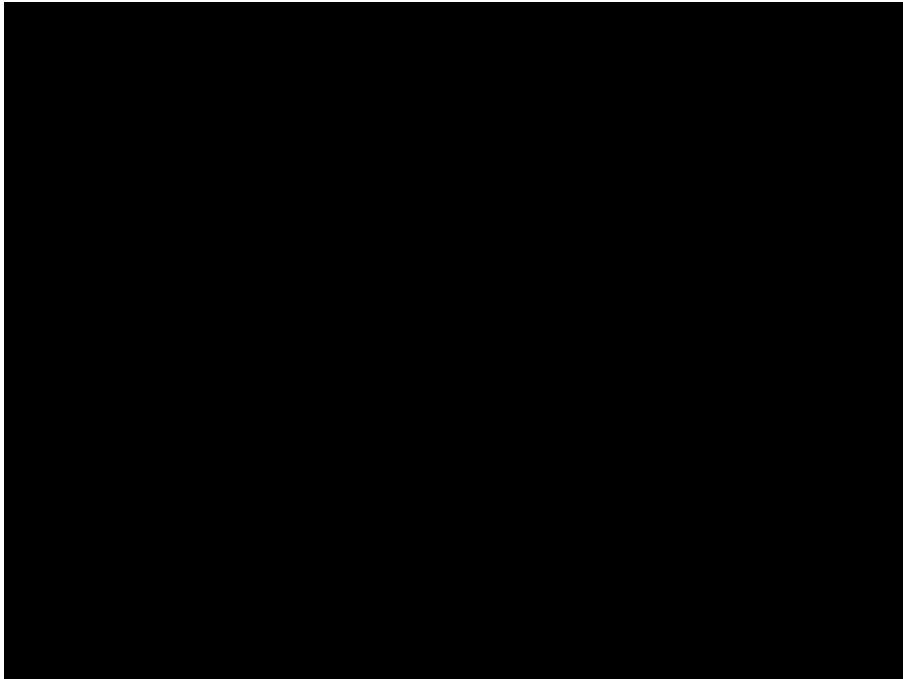
Videos for training are unlabeled. Relies on Convnets trained on labeled images.



Aytar, Yusuf, Carl Vondrick, and Antonio Torralba. "Soundnet: Learning sound representations from unlabeled video." NIPS 2016

Audio Feature Learning

Recognizing Objects and Scenes from Sound



Aytar, Yusuf, Carl Vondrick, and [Antonio Torralba](#). "Soundnet: Learning sound representations from unlabeled video." NIPS 2016

Audio Feature Learning

Hidden layers of Soundnet are used to train a standard SVM classifier that outperforms state of the art.

Method	Accuracy
RG [29]	69%
LTT [21]	72%
RNH [30]	77%
Ensemble [34]	78%
SoundNet	88%

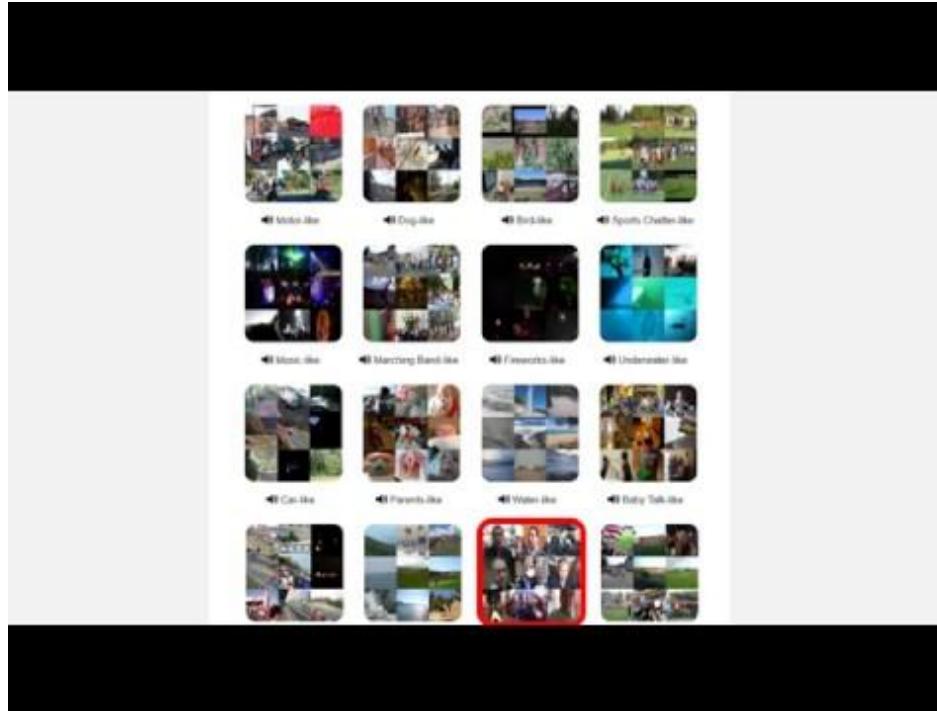
Table 3: Acoustic Scene Classification on DCASE: We evaluate classification accuracy on the DCASE dataset. By leveraging large amounts of unlabeled video, SoundNet generally outperforms hand-crafted features by 10%.

Method	Accuracy on	
	ESC-50	ESC-10
SVM-MFCC [28]	39.6%	67.5%
Convolutional Autoencoder	39.9%	74.3%
Random Forest [28]	44.3%	72.7%
Piczak ConvNet [27]	64.5%	81.0%
SoundNet	74.2%	92.2%
Human Performance [28]	81.3%	95.7%

Table 4: Acoustic Scene Classification on ESC-50 and ESC-10: We evaluate classification accuracy on the ESC datasets. Results suggest that deep convolutional sound networks trained with visual supervision on unlabeled data outperforms baselines.

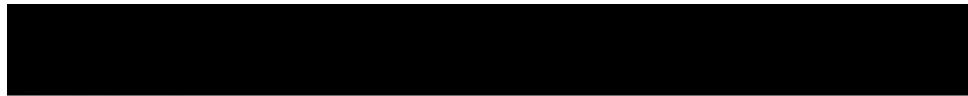
Audio Feature Learning

Hearing sounds that most activate a neuron in the sound network (conv7)



Audio Feature Learning

Hearing sounds that most activate a neuron in the sound network (conv5)



Visualizing conv5

We can also visualize middle layers in the network. Interestingly, detectors for mid-level concepts automatically emerge in conv5.



Visualizing conv1

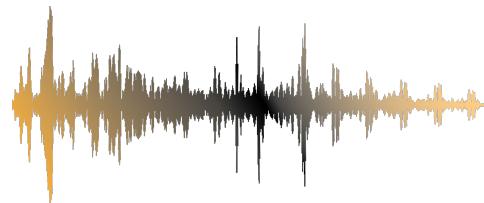
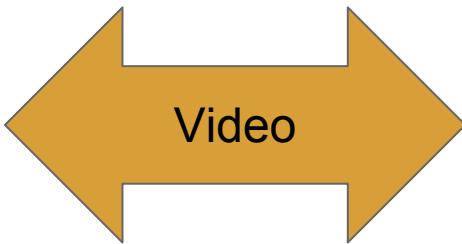
We visualize the first layer of the network by looking at the learned weights of conv1, which you can see below. The network operates on raw waveforms, so the filters are in the time-domain.



Audio & Visual feature learning



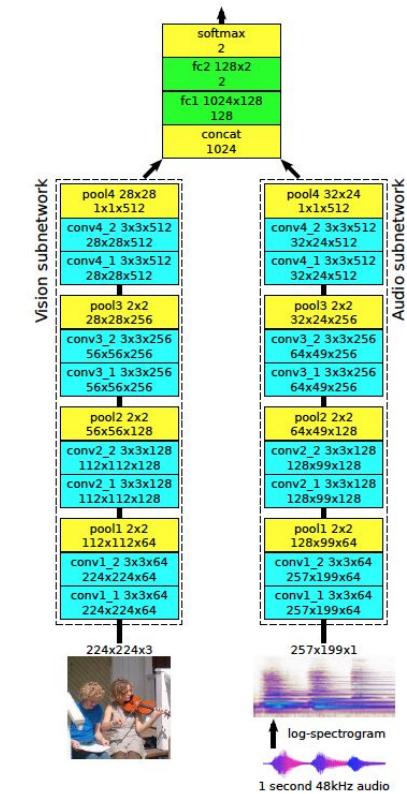
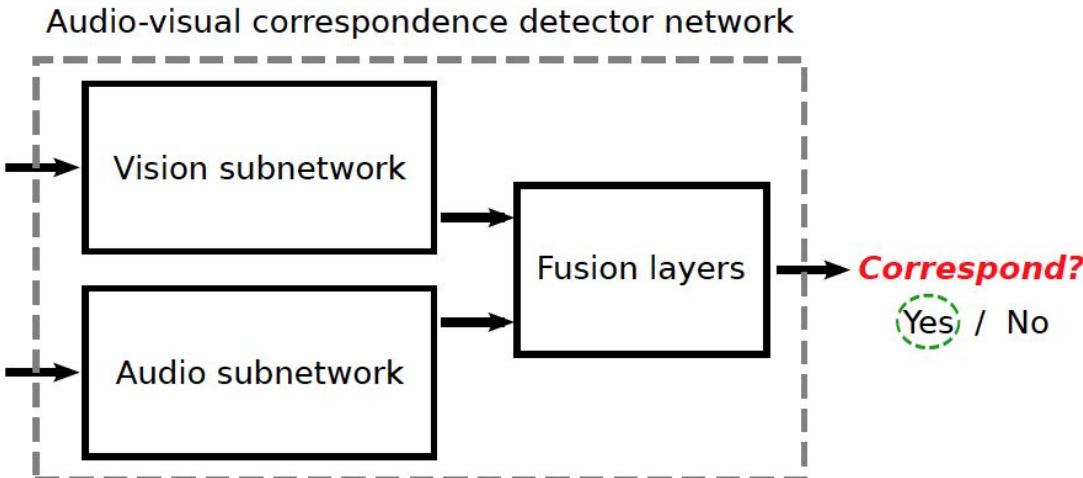
Vision



Audio

Audio & Visual feature learning

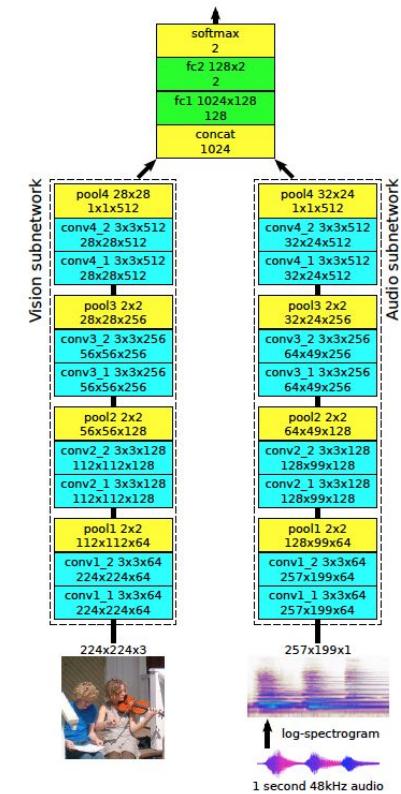
Audio and visual features learned by assessing correspondence.



Audio & Visual feature learning

Audio and visual features learned by assessing correspondence.

- Large collection of **unlabelled videos**
- [Flickr-SoundNet](#) → Subset of 500k videos
- Kinetics-Sound → Subset of 19k videos from the [Kinetics](#) dataset
- 10s length videos
- 1 second of audio as input.
- A visual frame happening within that second is a match



Audio & Visual feature learning

Most activated unit in *pool4* layer of the **visual network**

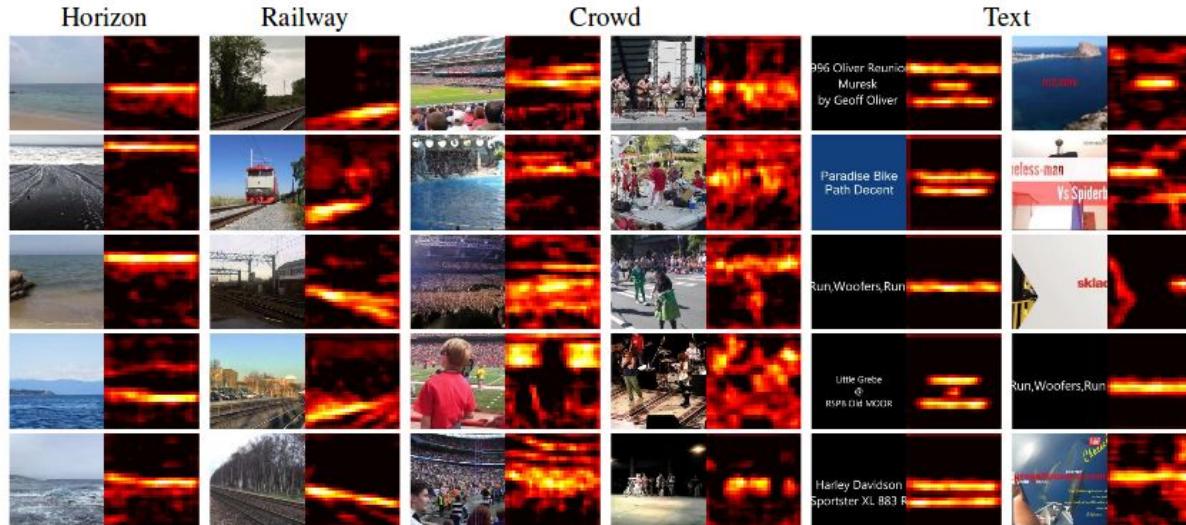
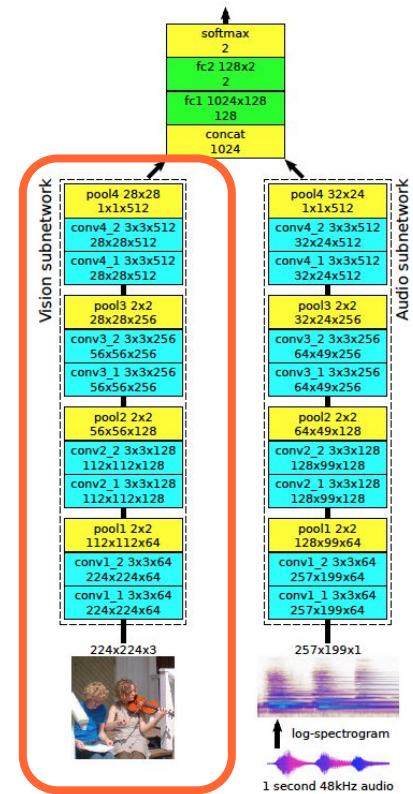


Figure 5. Learnt visual concepts and semantic heatmaps (Flickr-SoundNet). Each mini-column shows five images that most activate a particular unit of the 512 in *pool4* of the vision subnetwork, and the corresponding heatmap (for more details see Figures 3 and 4). Column titles are a subjective names of concepts the units respond to.

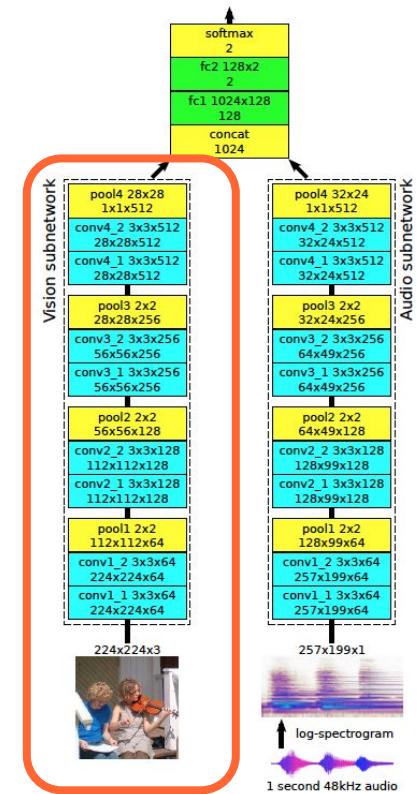


Audio & Visual feature learning

Audio and visual features learned by assessing correspondence.

Method	Top 1 accuracy
Random	18.3%
Pathak <i>et al.</i> [24]	22.3%
Krähenbühl <i>et al.</i> [16]	24.5%
Donahue <i>et al.</i> [7]	31.0%
Doersch <i>et al.</i> [6]	31.7%
Zhang <i>et al.</i> [36] (init: [16])	32.6%
Noroozi and Favaro [21]	34.7%
Ours random	12.9%
Ours	32.3%

Table 3. **Visual classification on ImageNet.** Following [36], our features are evaluated by training a linear classifier on the ImageNet training set and measuring the classification accuracy on the validation set. For more details and discussions see Section 3.4. All performance numbers apart from ours are provided by authors of [36], showing only the best performance for each method over all parameter choices (*e.g.* Donahue *et al.* [7] achieve 27.1% instead of 31.0% when taking features from pool5 instead of conv3).



Audio & Visual feature learning

Most activated unit in *pool4* layer of the **audio network**

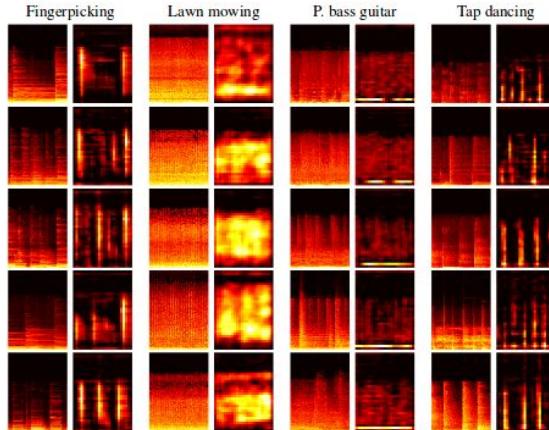
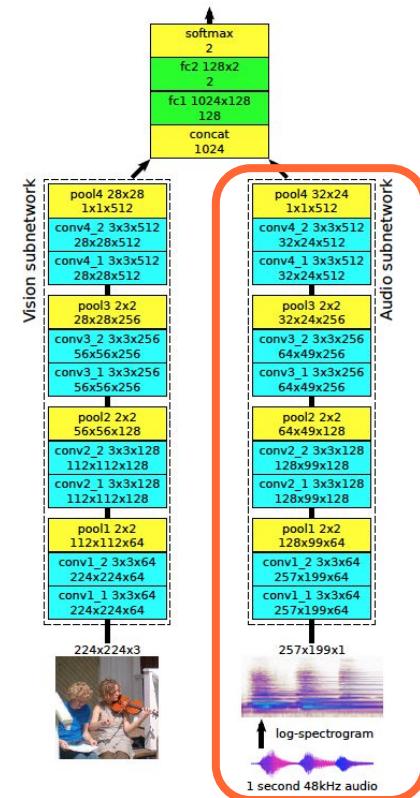


Figure 9. **Audio semantic heatmaps (Kinetics-Sounds).** Each pair of columns shows a single action class (top, “P.” stands for “playing”), five log-spectrograms (left) and spectrogram semantic heatmaps (right) for the class. Horizontal and vertical axes correspond to the time and frequency dimensions, respectively. A semantic heatmap is obtained as a slice of activations of the unit from `conv4_2` of the audio subnetwork which shows preference for the considered class.

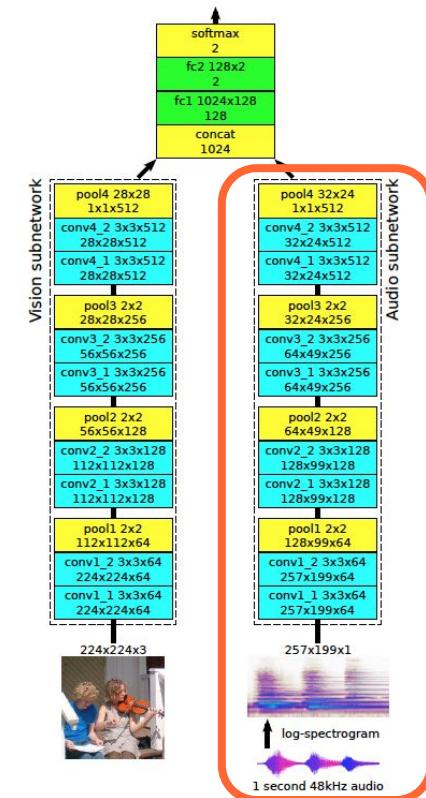


Audio & Visual feature learning

Audio and visual features learned by assessing correspondence.

(a) ESC-50		(b) DCASE	
Method	Accuracy	Method	Accuracy
SVM-MFCC [26]	39.6%	RG [27]	69%
Autoencoder [2]	39.9%	LTT [19]	72%
Random Forest [26]	44.3%	RNH [28]	77%
Piczak ConvNet [25]	64.5%	Ensemble [32]	78%
SoundNet [2]	74.2%	SoundNet [2]	88%
Ours random	62.5%	Ours random	85%
Ours	79.3%	Ours	93%
<i>Human perf. [26]</i>	81.3%		

Table 2. **Sound classification.** “Ours random” is an additional baseline which shows the performance of our network without L^3 -training. Our L^3 -training sets the new state-of-the-art by a large margin on both benchmarks.



Contents

- Feature learning
- **Cross-modal retrieval**
- Sound source localization
- Sonorization

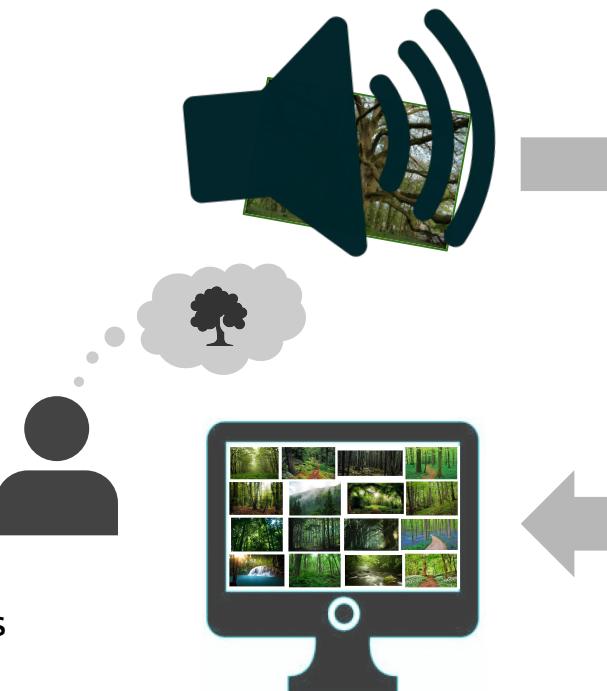
The problem: query by example

Given:

- An example query image that illustrates the user's information need
- A very large dataset of images

Task:

- Rank all images in the dataset according to how likely they are to fulfil the user's information need

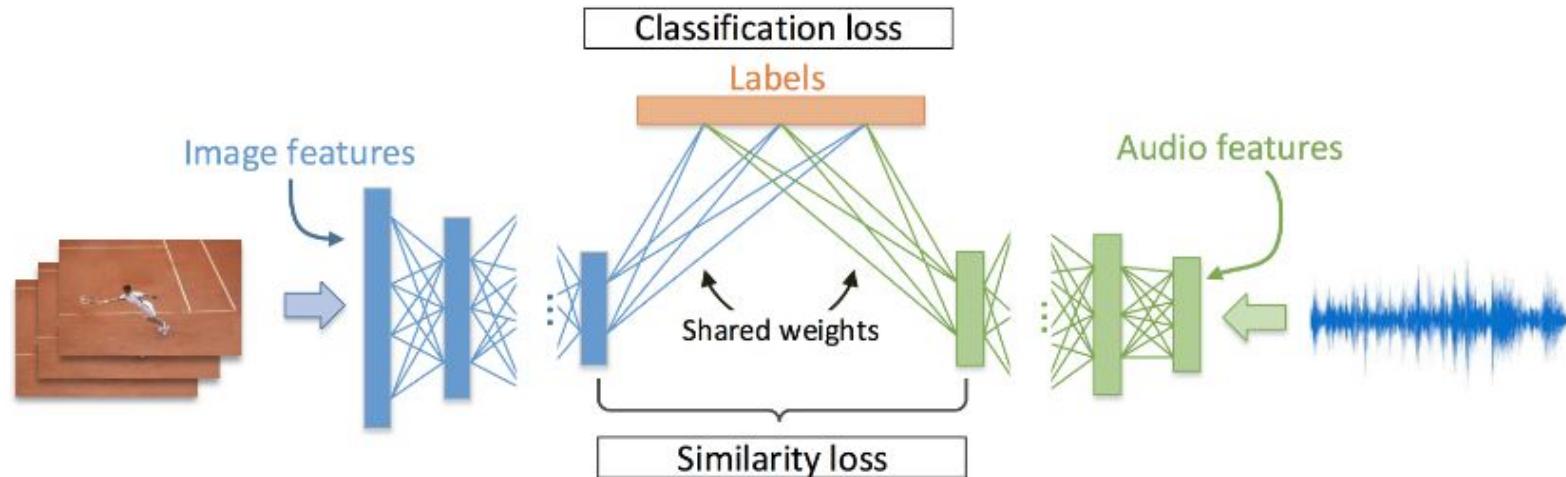


How to make audio and visual features comparable?

Cross-modal retrieval



Video-level features



Surís, Didac, Amanda Duarte, Amaia Salvador, Jordi Torres, and Xavier Giró-i-Nieto. "[Cross-modal Embeddings for Video and Audio Retrieval](#)." arXiv preprint arXiv:1801.02200 (2018).

Cross-modal retrieval

$$L = L_{cos} + \lambda L_{class}$$

Similarity loss

$$\text{similarity} = \cos(x, z) = \frac{\sum_{k=1}^N x_k z_k}{\sqrt{\sum_k^N x_k^2} \sqrt{\sum_i^N z_k^2}}$$
$$L_{cos}((\Phi^a, \Phi^i), y) = \begin{cases} 1 - \cos(\Phi^a, \Phi^i), & \text{if } y = 1 \\ \max(0, \cos(\Phi^a, \Phi^i) - \alpha), & \text{if } y = -1 \end{cases}$$

Classification Regularization

$$L_{class}(p^i, p^a, c^i, c^a) = - \sum_k (p_k^i \log(c_k^i) + p_k^a \log(c_k^a))$$

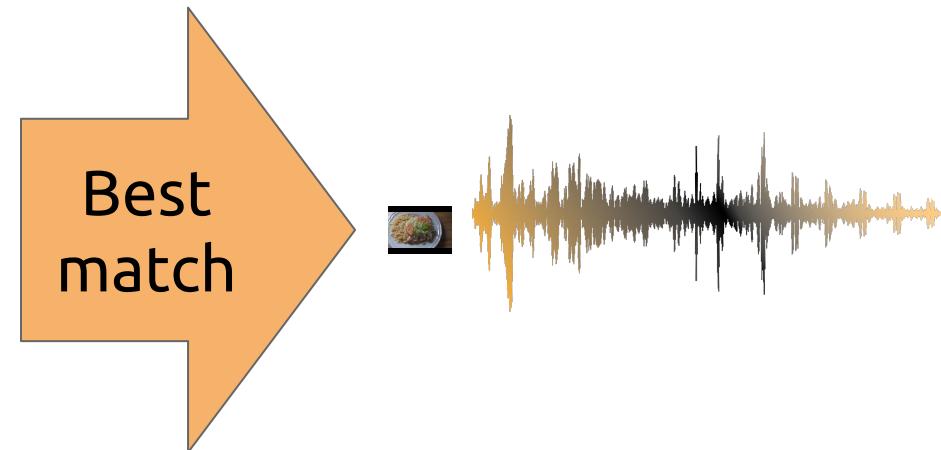
Surís, Didac, Amanda Duarte, Amaia Salvador, Jordi Torres, and Xavier Giró-i-Nieto. "[Cross-modal Embeddings for Video and Audio Retrieval.](#)" arXiv preprint arXiv:1801.02200 (2018).

Cross-modal retrieval

Visual feature



Audio feature



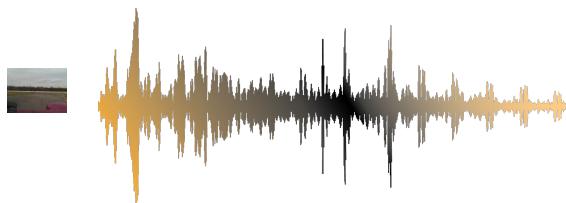
Surís, Didac, Amanda Duarte, Amaia Salvador, Jordi Torres, and Xavier Giró-i-Nieto. "[Cross-modal Embeddings for Video and Audio Retrieval.](#)" arXiv preprint arXiv:1801.02200 (2018).

Cross-modal retrieval

Visual feature

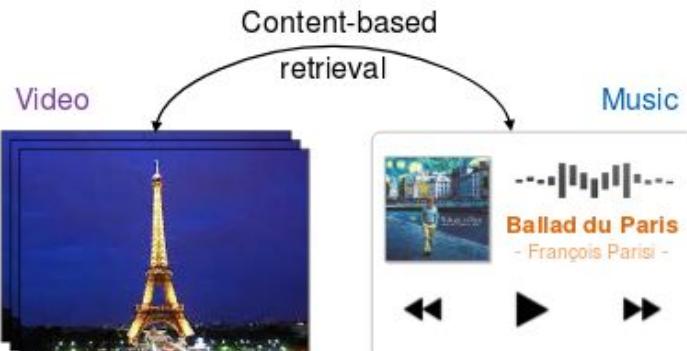


Audio feature

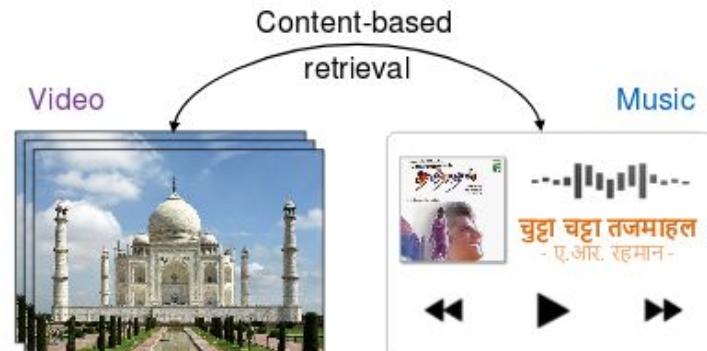


Best
match

Cross-modal retrieval



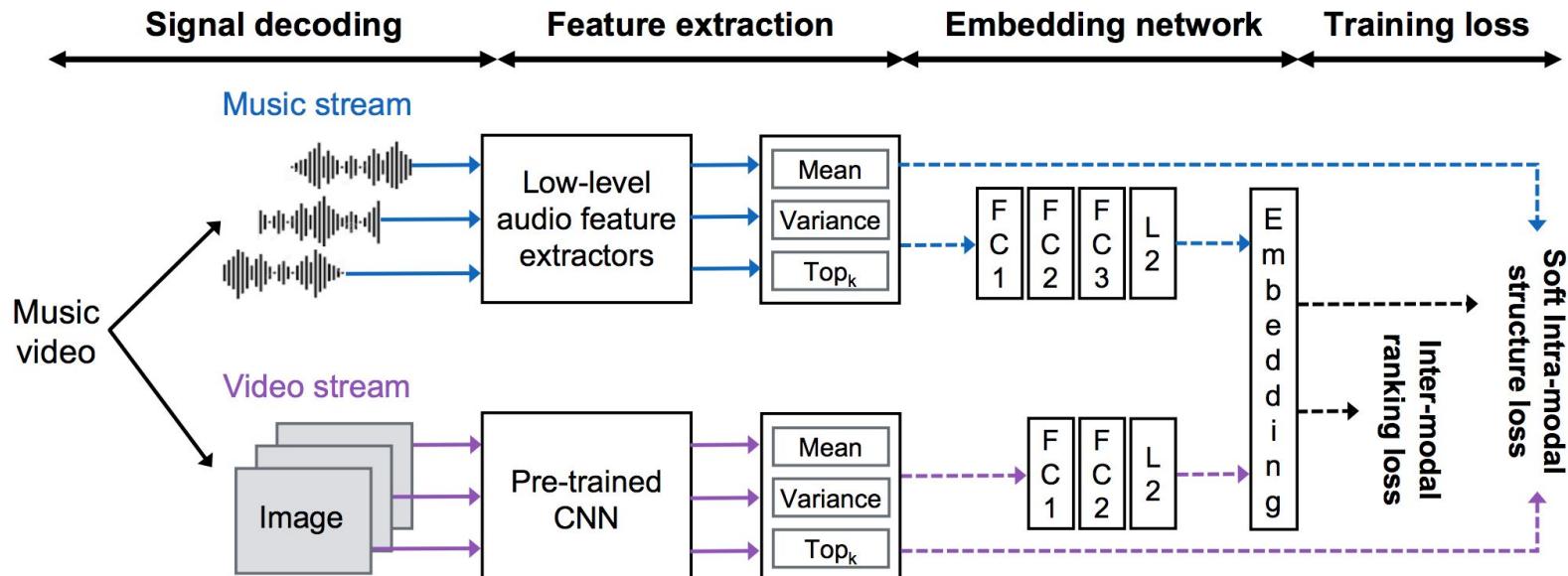
(a) Eiffel Tower scenes \Longleftrightarrow Music based on the Paris night view



(b) Taj Mahal scenes \Longleftrightarrow Traditional Indian music

Hung-IM Music-Video: Large-scale video-music pair dataset 200k video-music pairs
Based on all videos tagged with “music video” in Y8M

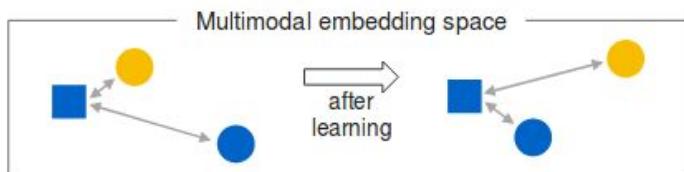
Cross-modal retrieval



Cross-modal retrieval

Inter-modal ranking constraint

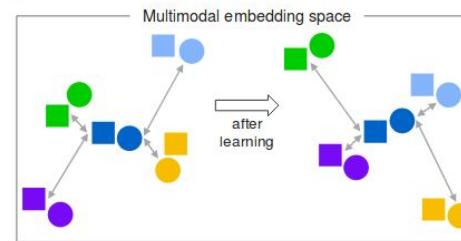
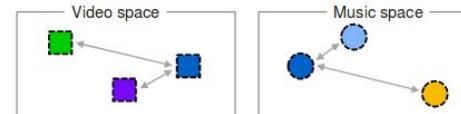
$$d(v_i, m_i) + e < d(v_i, m_j)$$



Soft intra-modal structure constraint

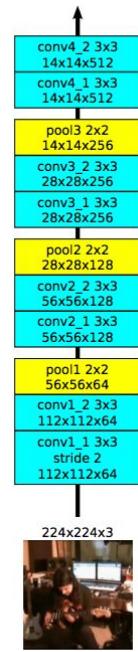
$$d(v_i, v_j) < d(v_i, v_k) \quad \text{if } d(\tilde{v}_i, \tilde{v}_j) < d(\tilde{v}_i, \tilde{v}_k)$$

$$d(m_i, m_j) < d(m_i, m_k) \quad \text{if } d(\tilde{m}_i, \tilde{m}_j) < d(\tilde{m}_i, \tilde{m}_k)$$



Cross-modal retrieval

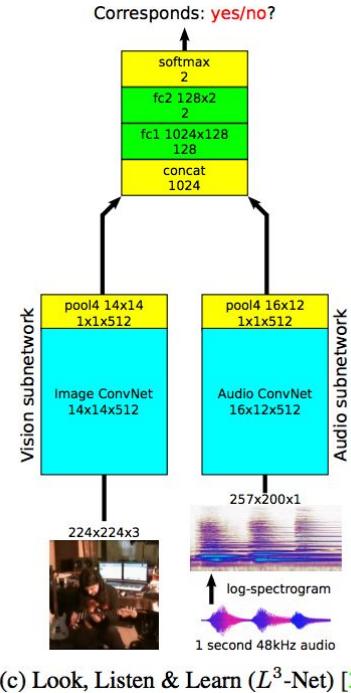
Unsupervised feature learning



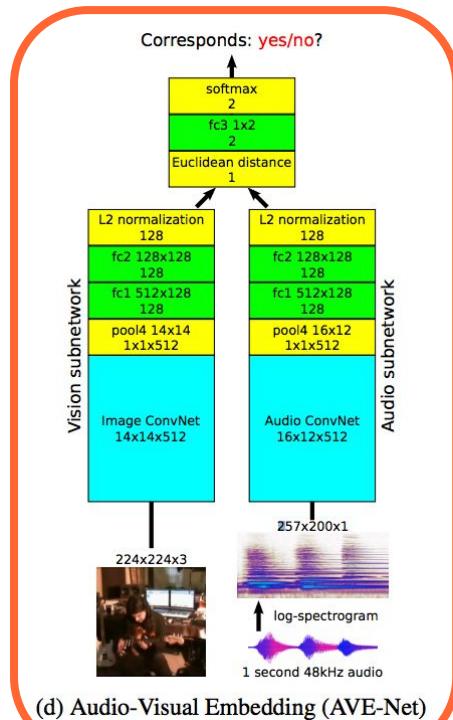
(a) Vision ConvNet



(b) Audio ConvNet



(c) Look, Listen & Learn (L^3 -Net) [3]



(d) Audio-Visual Embedding (AVE-Net)

Cross-modal retrieval

Method	im-im	im-aud	aud-im	aud-aud
Random chance	.407	.407	.407	.407
L^3 -Net [3]	.567	.418	.385	.653
L^3 -Net with CCA	.578	.531	.560	.649
VGG16-ImageNet [29]	.600	—	—	—
VGG16-ImageNet + L^3 -Audio CCA	.493	.458	.464	.618
AVE-Net	.604	.561	.587	.665

Table 1: **Cross-modal and intra-modal retrieval.** Comparison of our method with unsupervised and supervised baselines in terms of the average nDCG@30 on the AudioSet-Instruments test set. The columns headers denote the modalities of the query and the database, respectively, where *im* stands for *image* and *aud* for *audio*. Our AVE-Net beats all baselines convincingly.

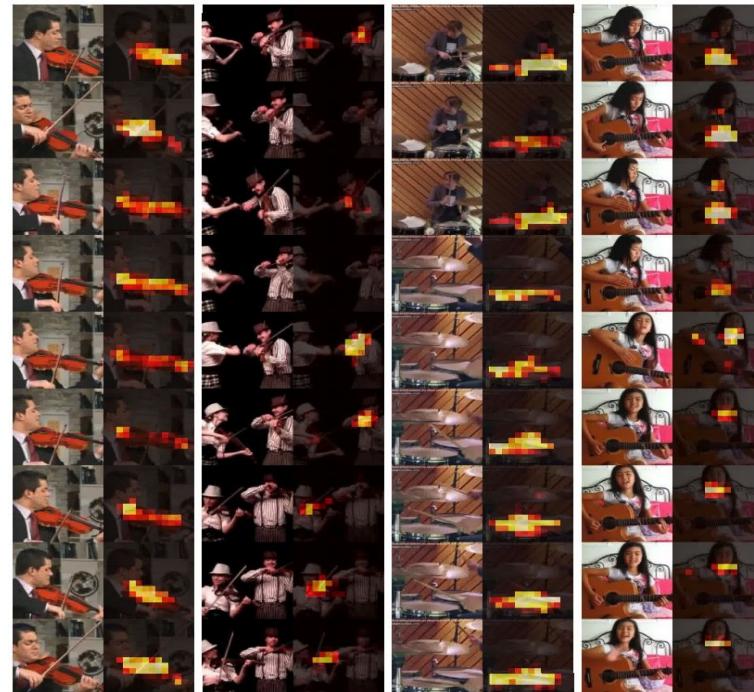
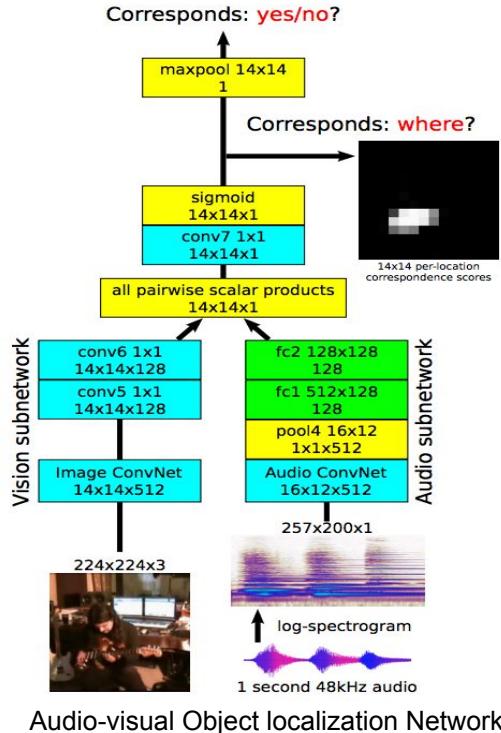


Contents

- Feature learning
- Cross-modal retrieval
- **Sound source localization**
- Speech generation

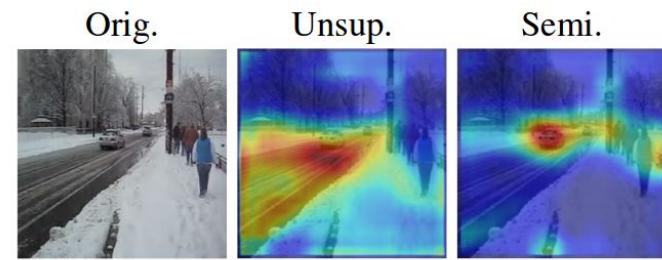
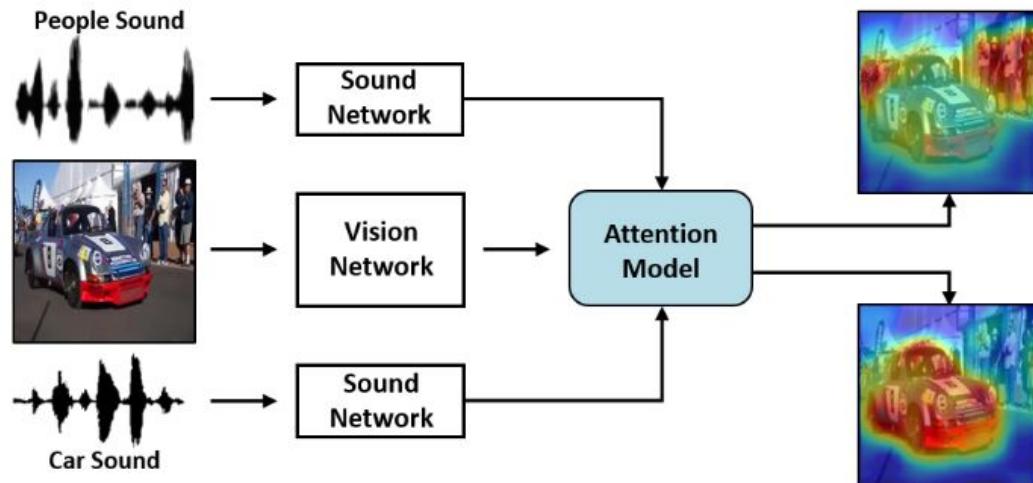
Sound source localization

Unsupervised feature learning



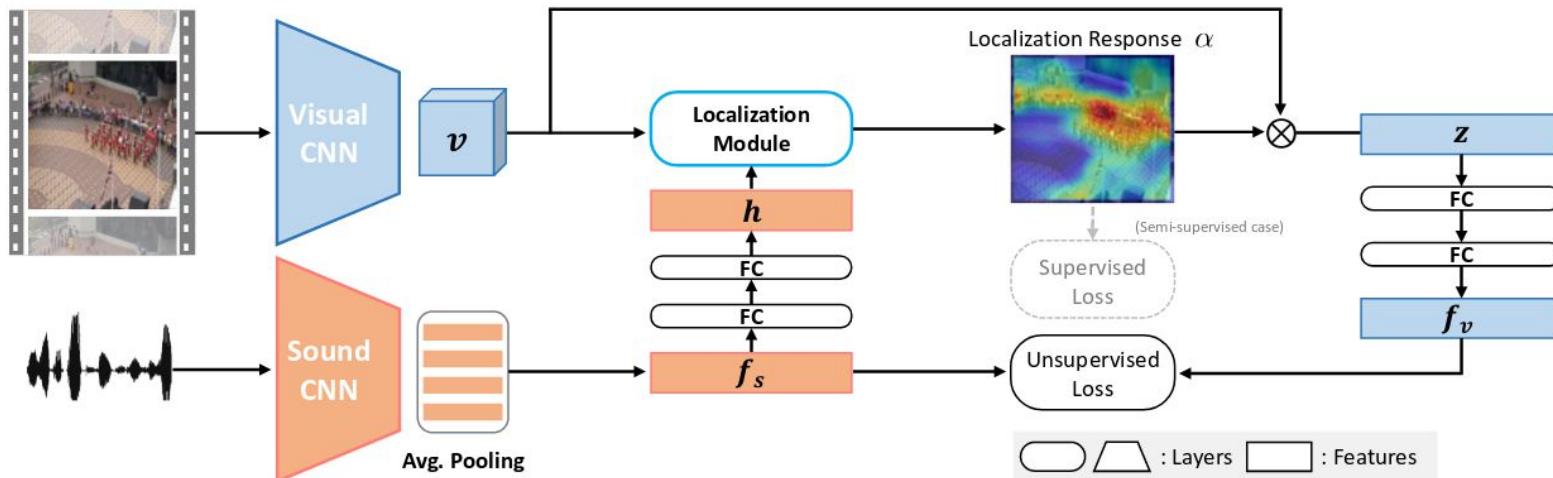
Sound source localization

Semi-supervised feature learning



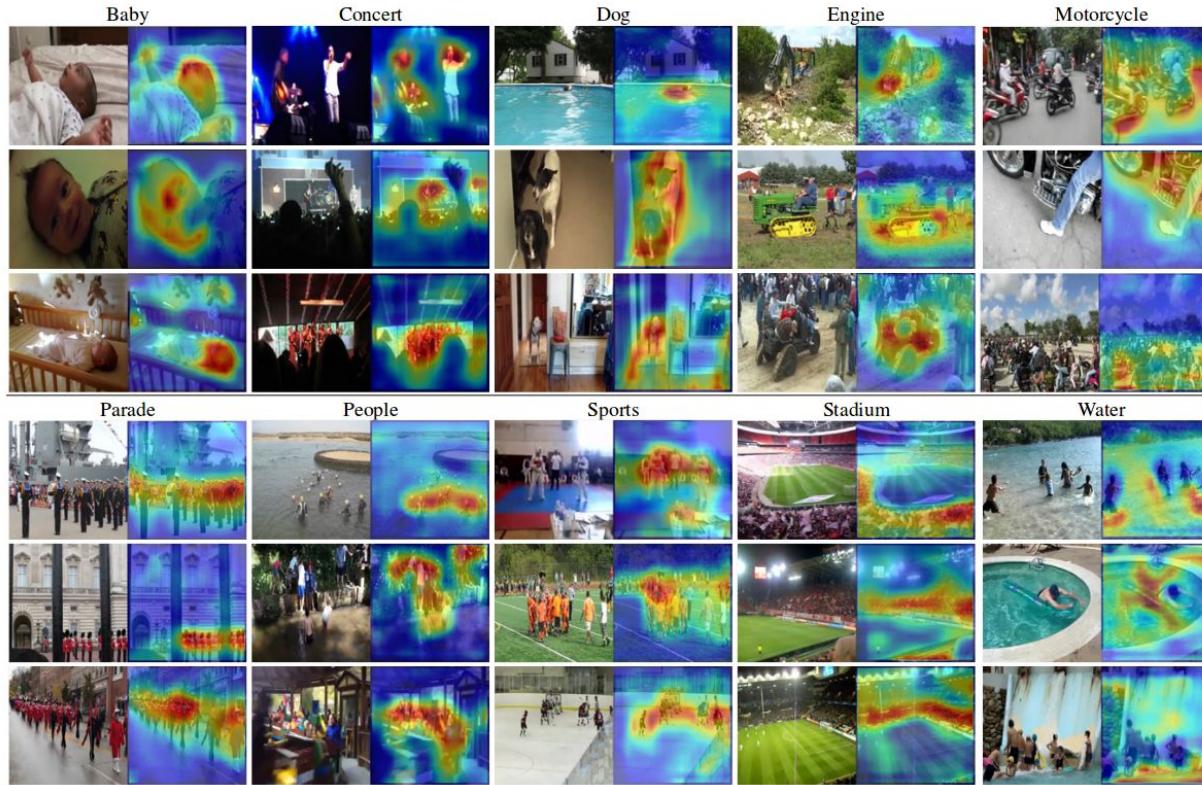
Sound source localization

Semi-supervised feature learning



- Flickr-SoundNet subset of 144k frame pairs for training
- New dataset from Flickr with manual localization annotations (2.5k frames)
 - Manually annotate those frame with non-matching audio (edited or not present object)

Sound source localization

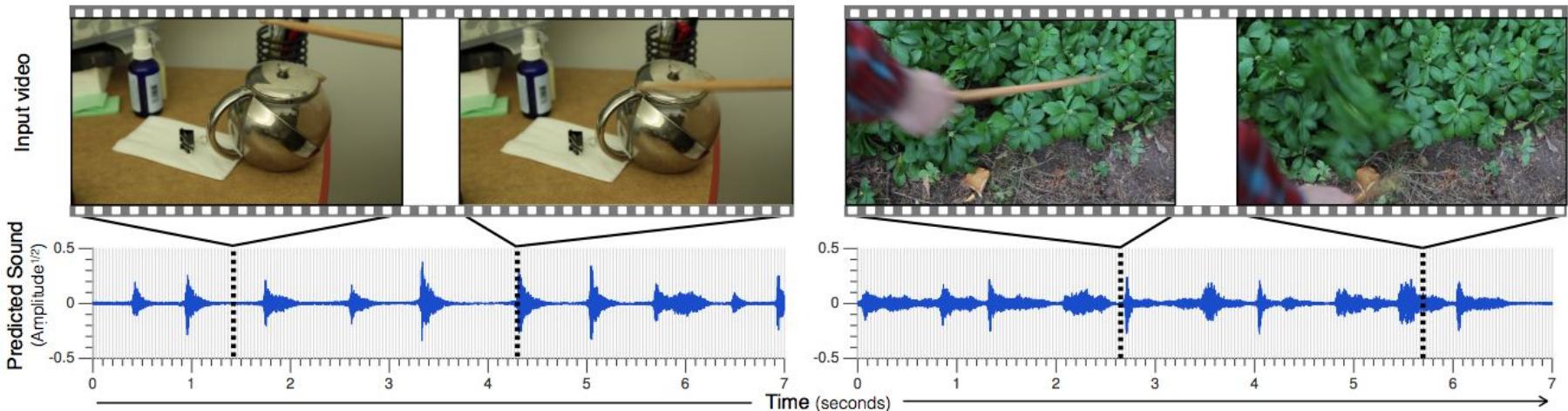


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Sonorization

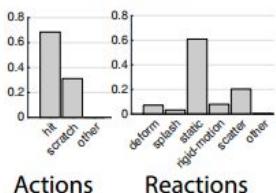
Learn synthesized sounds from videos of people hitting objects with a drumstick.



Are features learned when training for sound prediction useful to identify the object's material?

Sonorization

The Greatest Hits Dataset



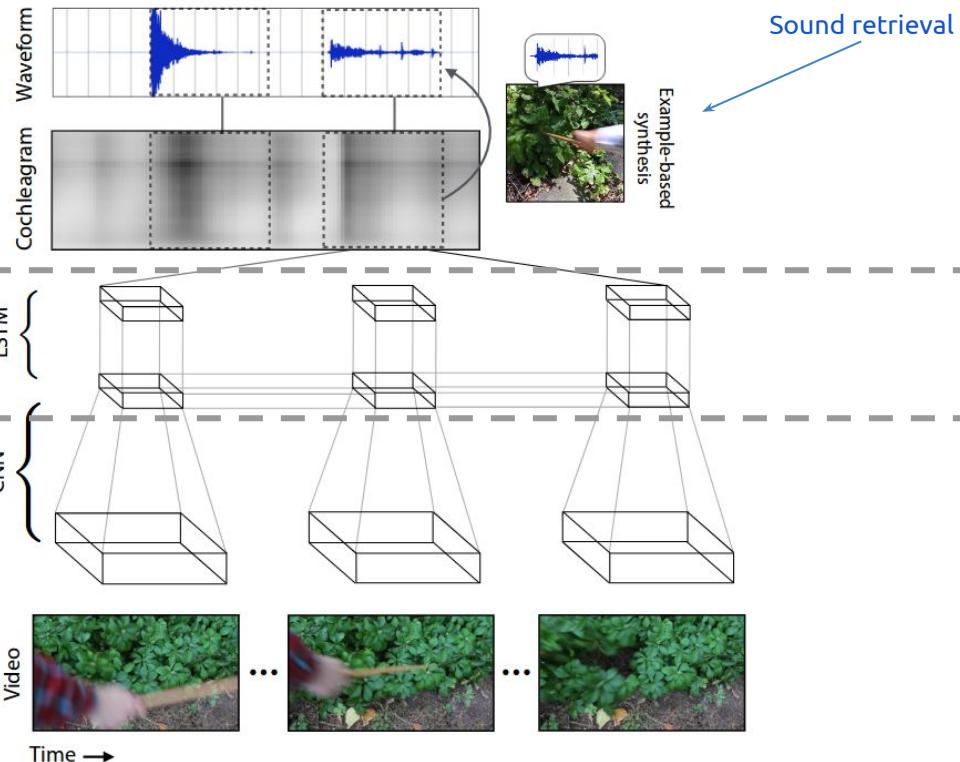
Sonorization

The Greatest Hits Dataset



Sonorization

Sound Generation



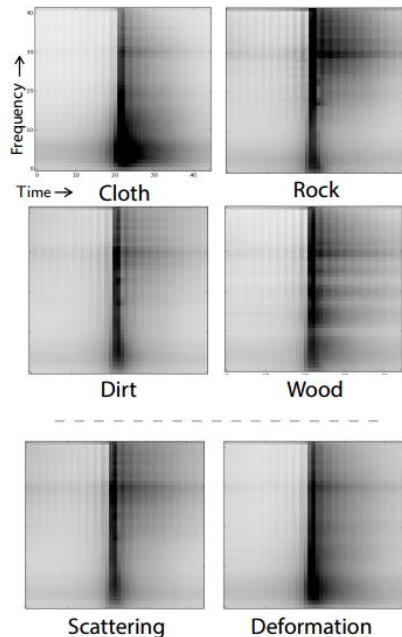
Two stream CNN

At each time step, RGB frame (one stream) and
3-spatiotemporal image (current, prev and following)

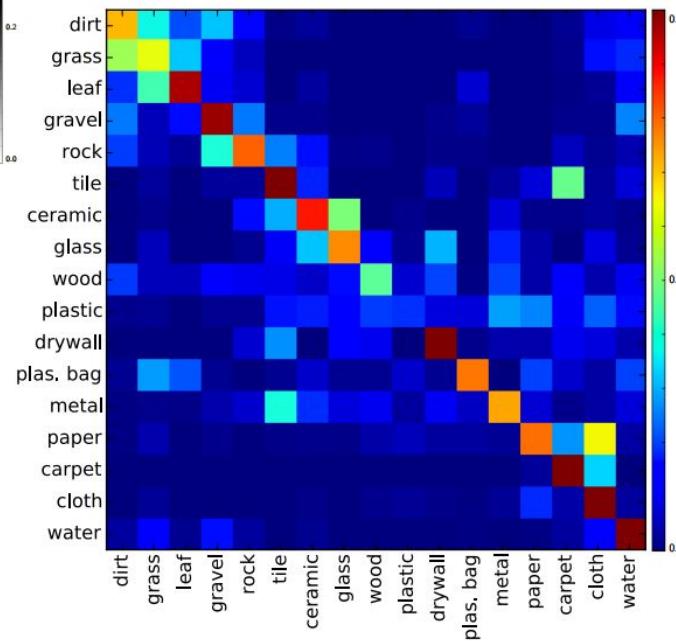
Sonorization



Sonorization



(a) Mean cochleograms



(b) Sound confusion matrix

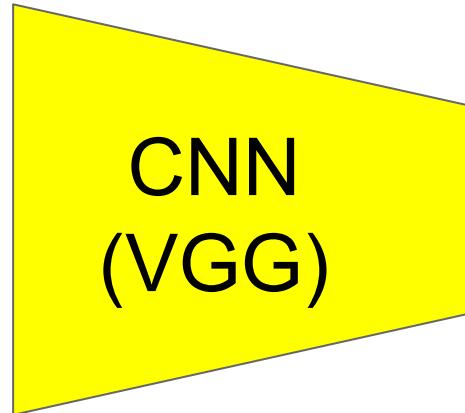


Ephrat, Ariel, Tavi Halperin, and Shmuel Peleg. "Improved speech reconstruction from silent video." In ICCV 2017 Workshop on Computer Vision for Audio-Visual Media. 2017.

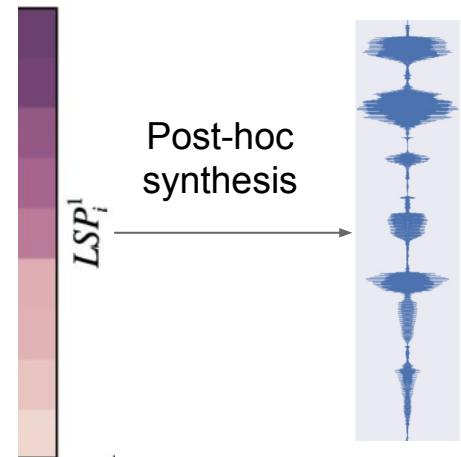
Speech generation from video



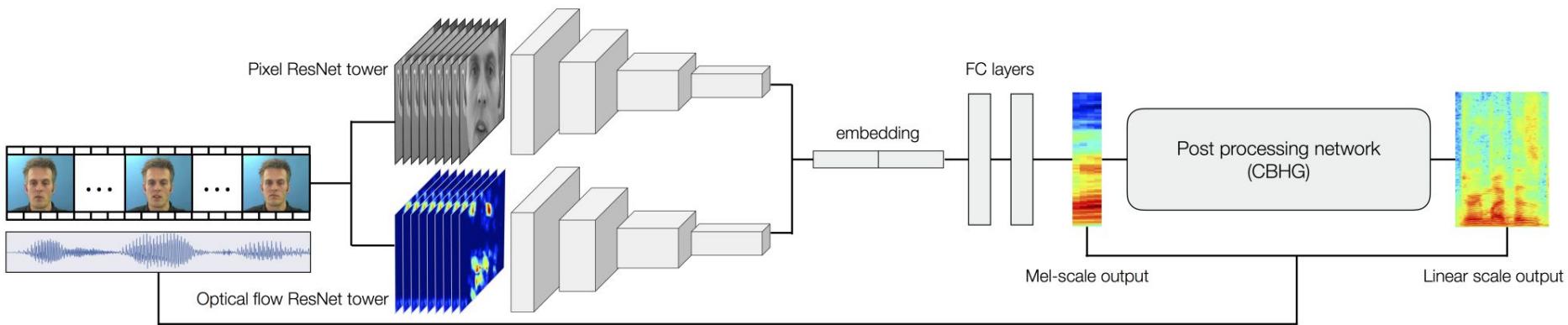
Frame from a
silent video



Audio feature



Speech generation from video



Ephrat, Ariel, Tavi Halperin, and Shmuel Peleg. "[Improved speech reconstruction from silent video.](#)" In ICCV 2017 Workshop on Computer Vision for Audio-Visual Media. 2017.

Visual to Sound

Model trained to **directly predict raw signal**

Inputs RGB + Optical flow

LSTM

SampleRNN for sound generation

Dataset:

[Visually Engaged and Grounded AudioSet \(VEGAS\)](#)



Zhou, Y., Wang, Z., Fang, C., Bui, T. and Berg, T.L., 2017. [Visual to Sound: Generating Natural Sound for Videos in the Wild](#). *arXiv 2017*

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Thank you!