

DEEP LEARNING FOR SPEECH AND LANGUAGE

Winter School at UPC TelecomBCN Barcelona. 24-30 January 2018.



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<http://bit.ly/dsl2018>



#DLUPC

Day 4 Lecture 3

Audio and Vision



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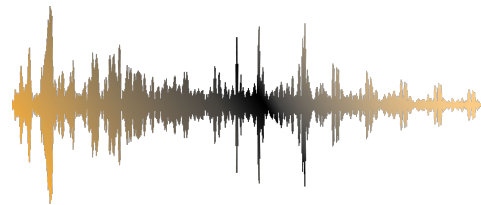
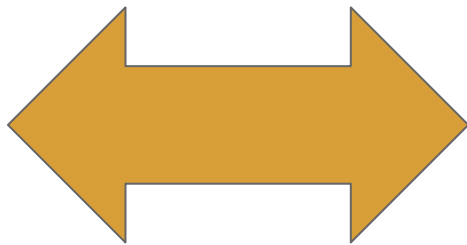
Universitat Politècnica de Catalunya
Technical University of Catalonia



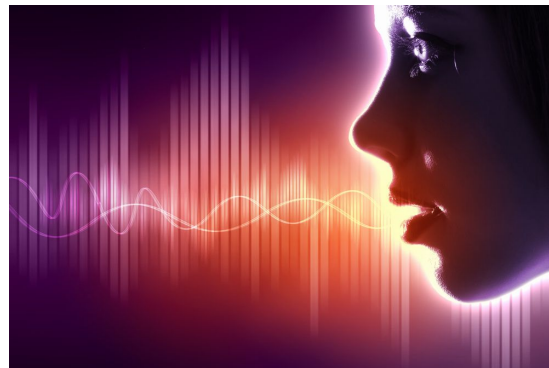
Audio & Vision



Vision



Audio

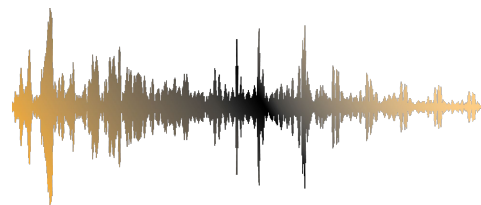
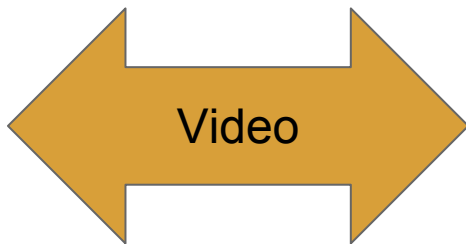


Speech

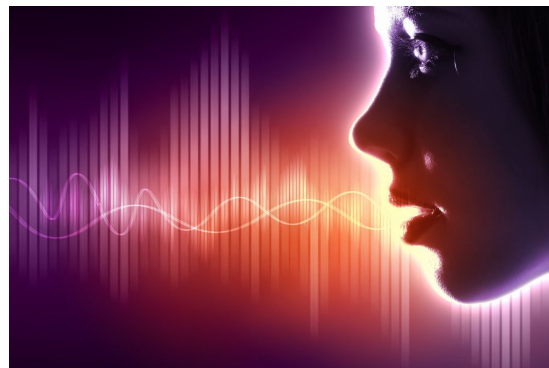
Audio & Vision



Vision



Audio



Speech

Synchronization among modalities captured by **video** is exploited in a self-supervised manner.

Audio & Vision

- Feature Learning
- Cross-modal Retrieval
- Cross-modal Translation

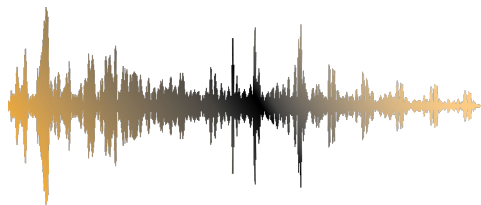
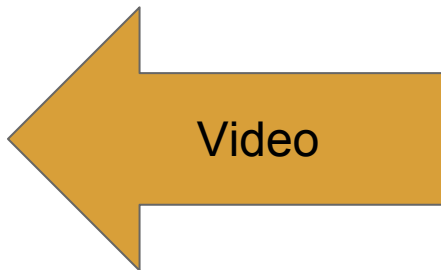
Audio & Vision

- **Feature Learning**
- Cross-modal Retrieval
- Cross-modal Translation

Visual Feature Learning



Vision



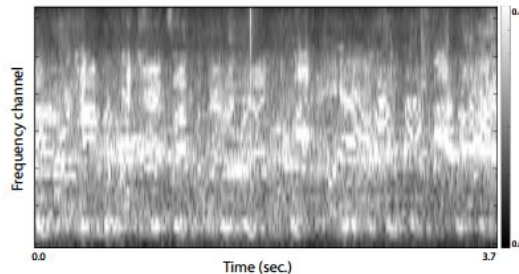
Audio

Visual Feature Learning

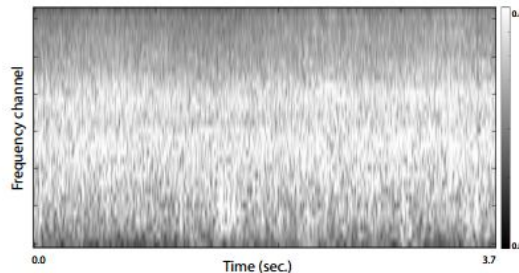
Based on the assumption that ambient sound in video is related to the visual semantics.



(a) Video frame



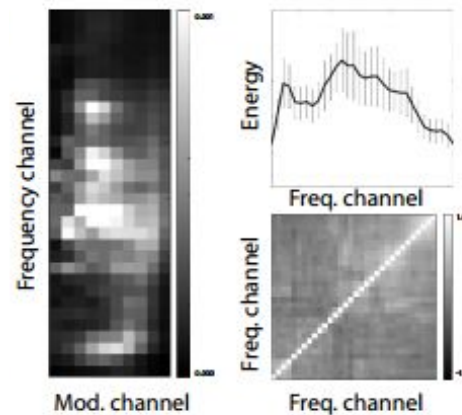
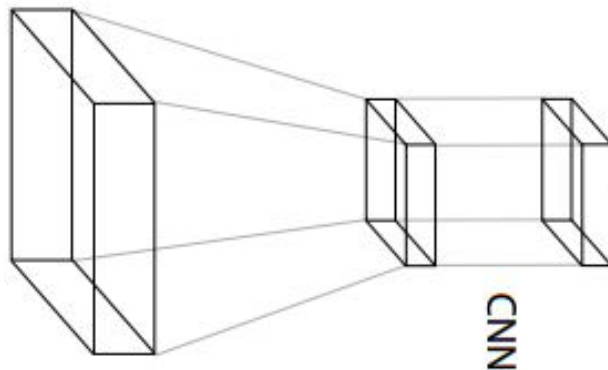
(b) Cochleagram



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.

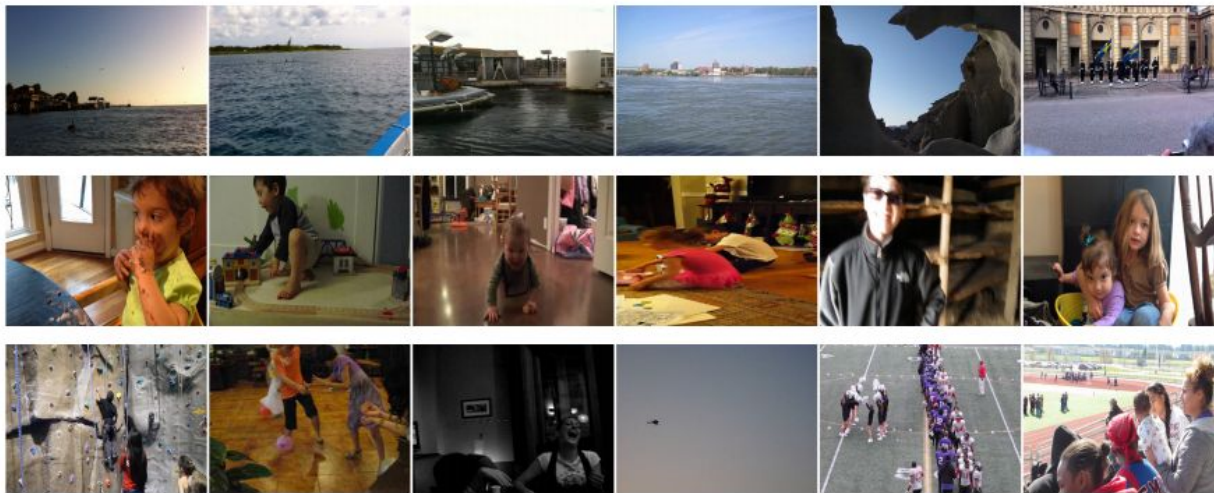


Owens, Andrew, Jiajun Wu, Josh H. McDermott, William T. Freeman, and Antonio Torralba. ["Ambient sound provides supervision for visual learning."](#) ECCV 2016

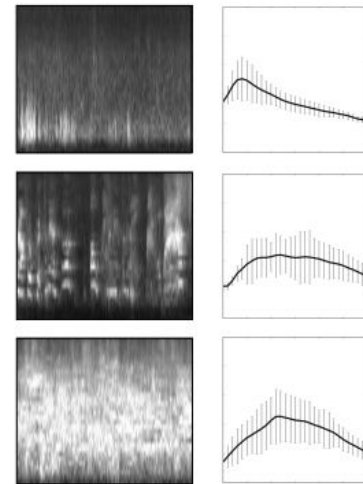
Visual Feature Learning

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

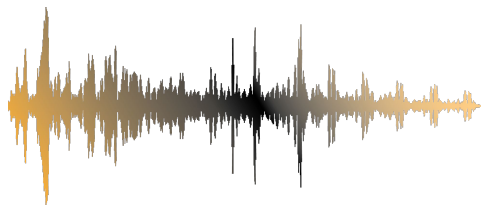
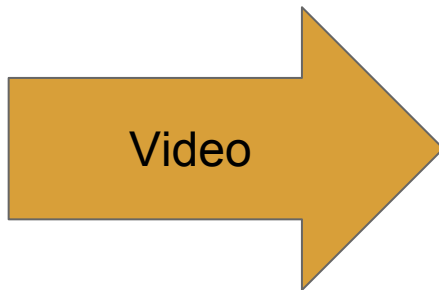


Owens, Andrew, Jiajun Wu, Josh H. McDermott, William T. Freeman, and Antonio Torralba. ["Ambient sound provides supervision for visual learning."](#) ECCV 2016

Audio Feature Learning



Vision



Audio

Predicted Objects and Scenes from Sound Only

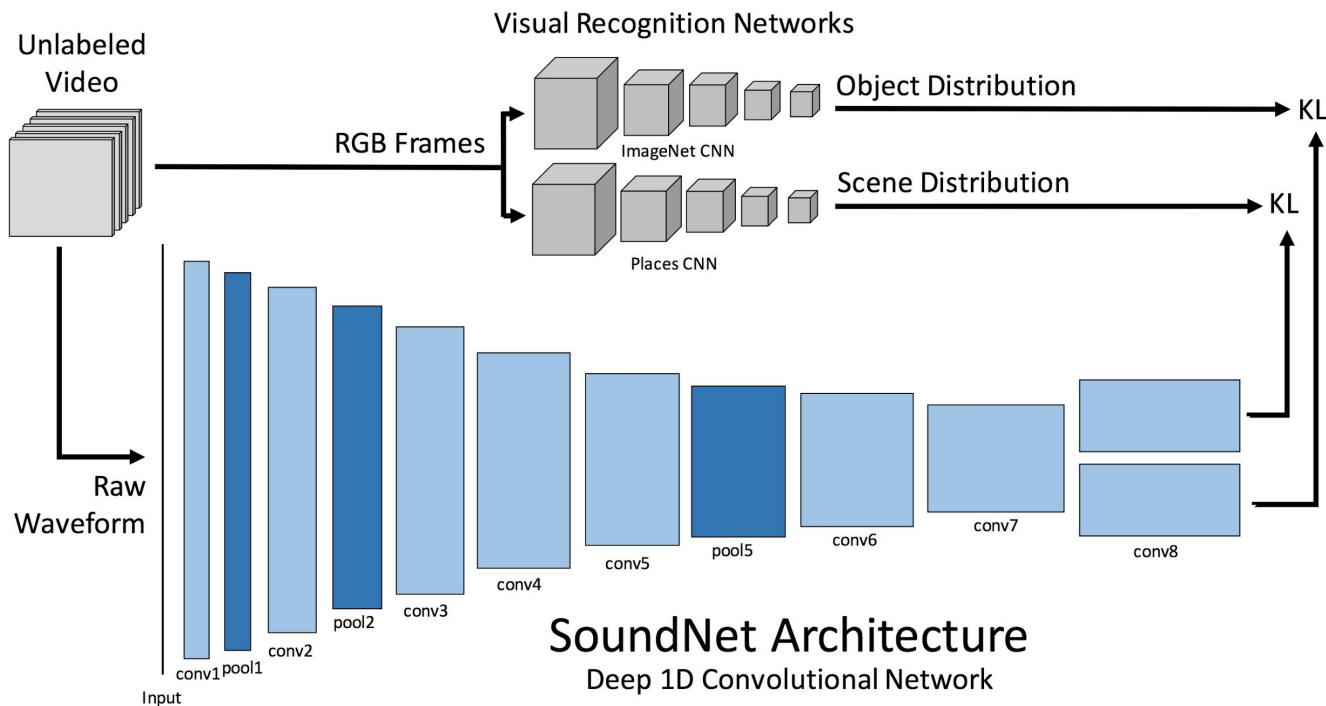


(Videos are blurred so you can try to recognize yourself!)

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

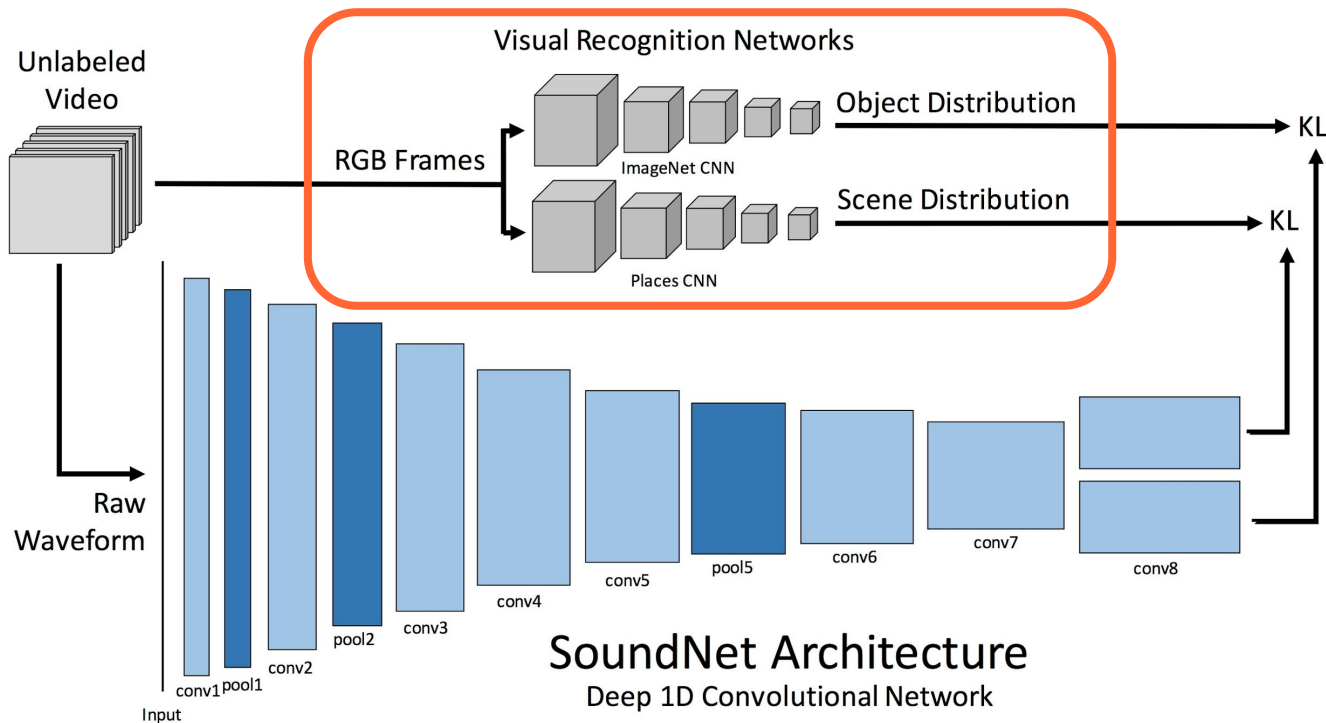
Audio Feature Learning: SoundNet

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



Audio Feature Learning: SoundNet

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



Audio Feature Learning: SoundNet

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%

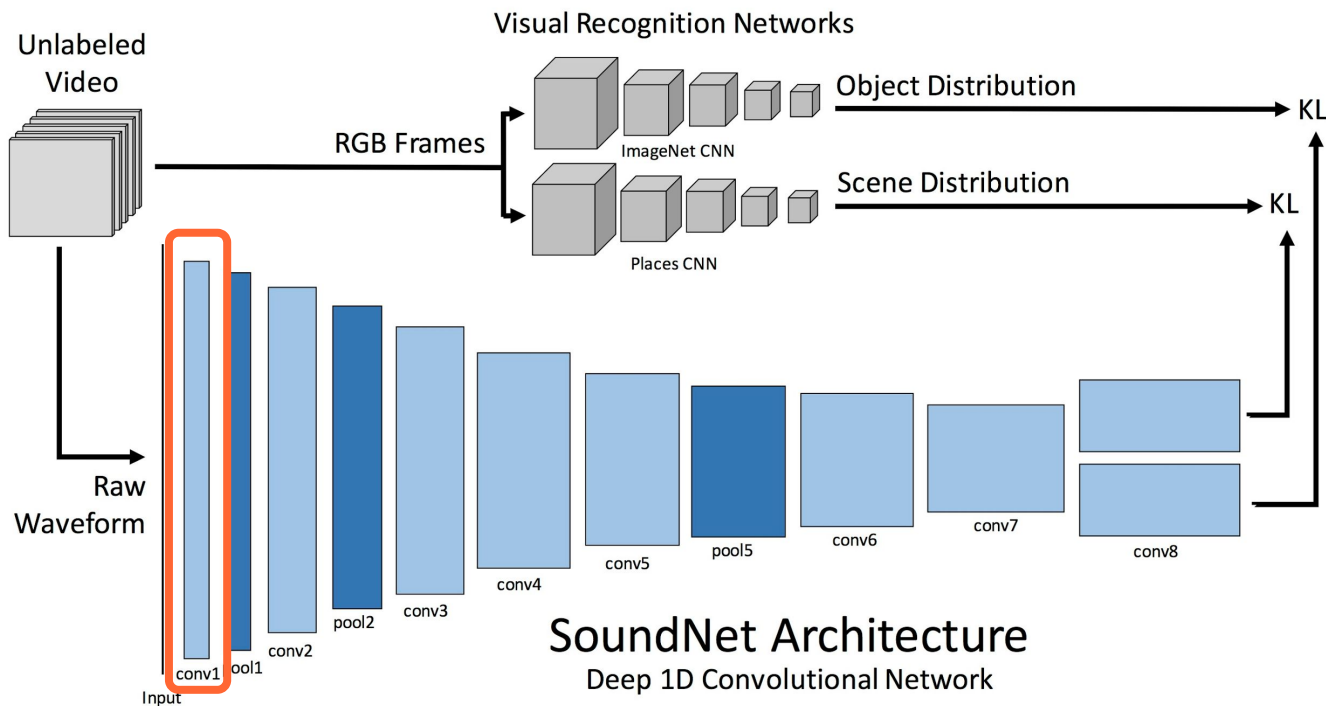
Table 3: Acoustic Scene Classification on DCASE: We evaluate classification accuracy on the DCASE dataset. By leveraging large amounts of unlabeled video, SoundNet generally outperforms hand-crafted features by 10%.

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.

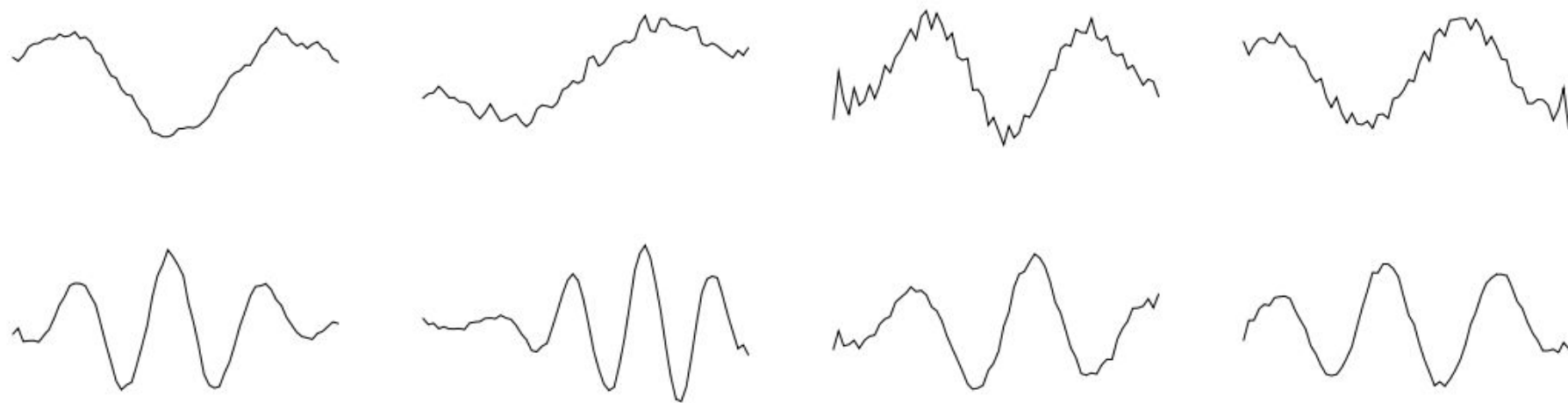
Audio Feature Learning: SoundNet

Visualization of the 1D filters over raw audio in conv1.



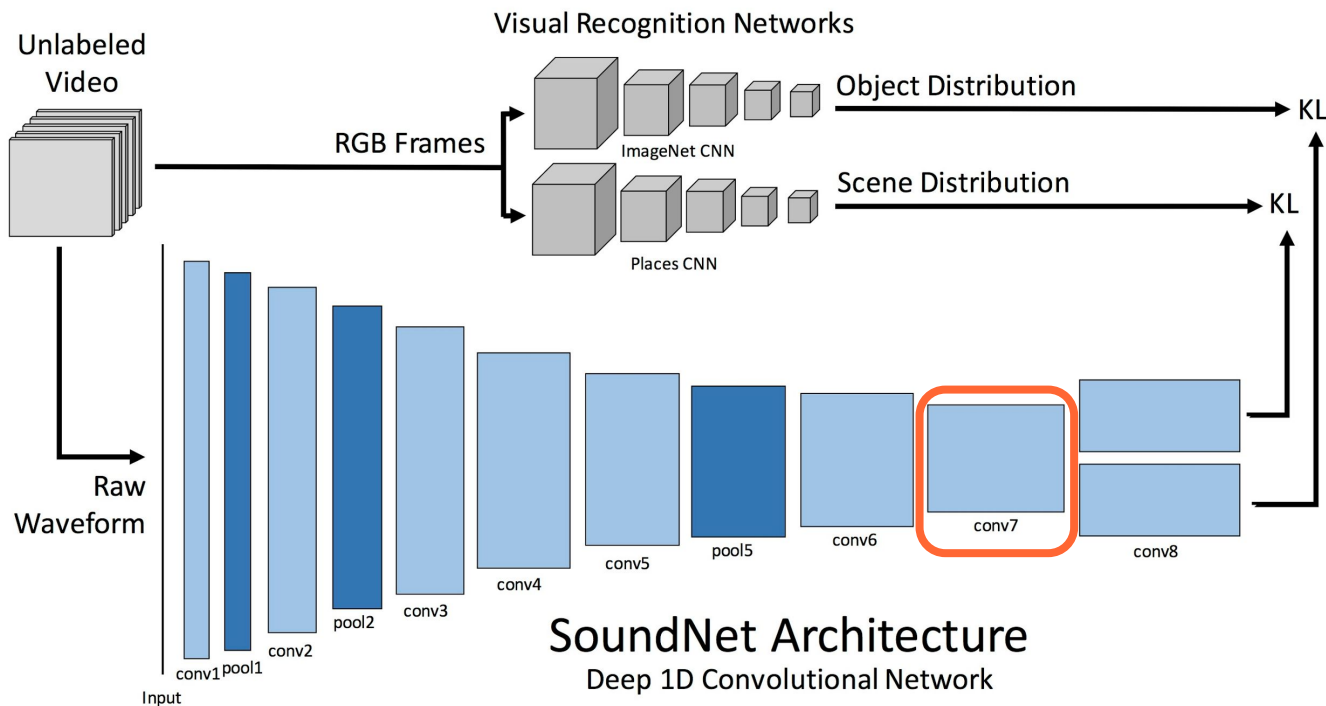
Audio Feature Learning: SoundNet

Visualization of the 1D filters over raw audio in conv1.



Audio Feature Learning: SoundNet

Visualize samples that mostly activate a neuron in a late layer (conv7)



Audio Feature Learning: SoundNet

Visualization of the video frames associated to the sounds that activate some of the last hidden units (conv7):



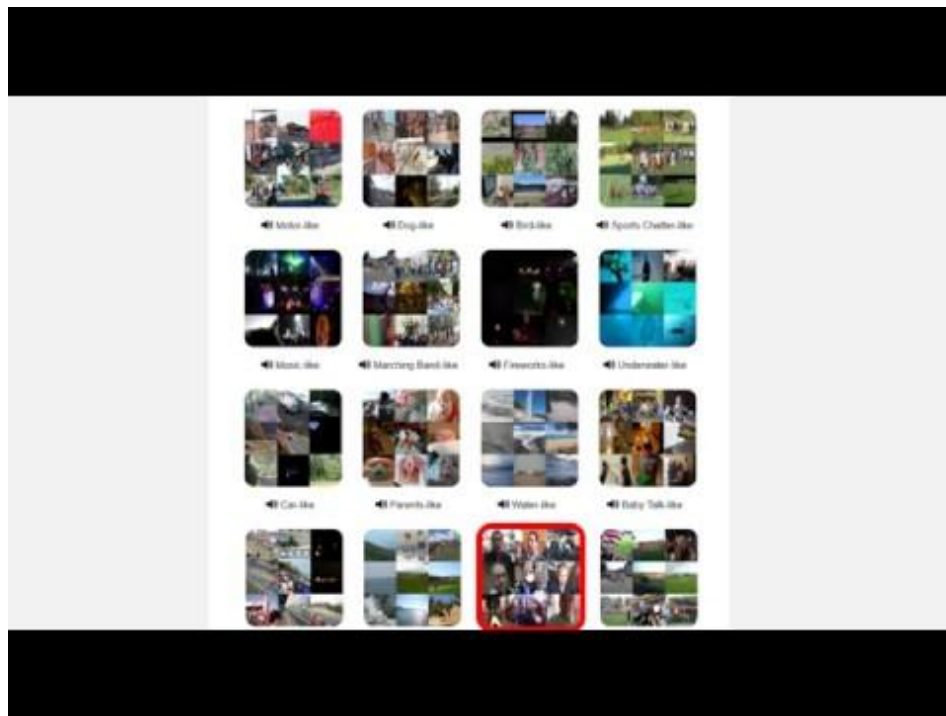
Baby Talk



Bubbles

Audio Feature Learning: SoundNet

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



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

Audio Feature Learning: SoundNet

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

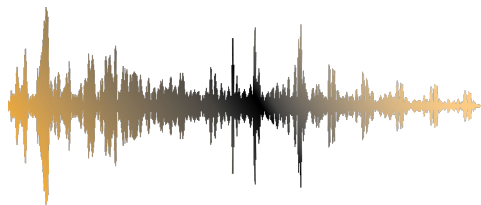
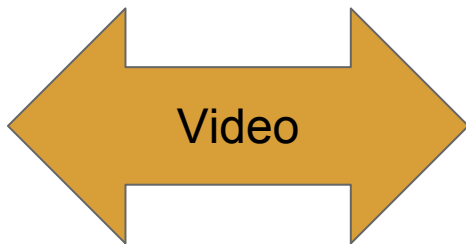
We visualize the first layer of the network by looking at the learned weights of conv1, which you can see below. The network operates on raw waveforms, so the filters are in the time-domain.



Audio & Visual Feature Learning



Vision

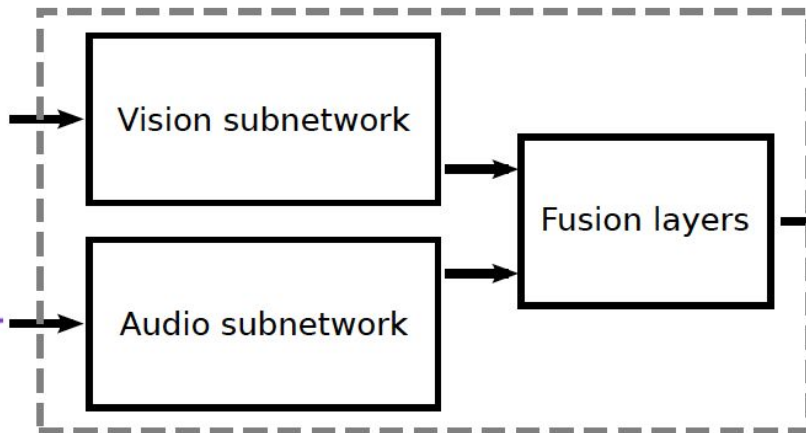


Audio

Audio & Visual Feature Learning

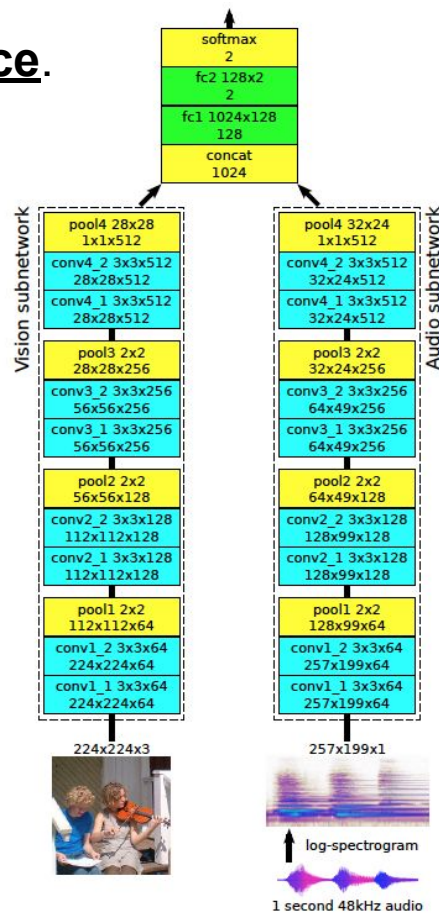
Audio and visual features learned by assessing correspondence.

Audio-visual correspondence detector network



Correspond?

Yes / No



Audio & Vision

- Feature Learning
- **Cross-modal retrieval**
- Cross-modal Translation



Visually Indicated Sounds

Andrew Owens

Phillip Isola

Josh McDermott

Antonio Torralba

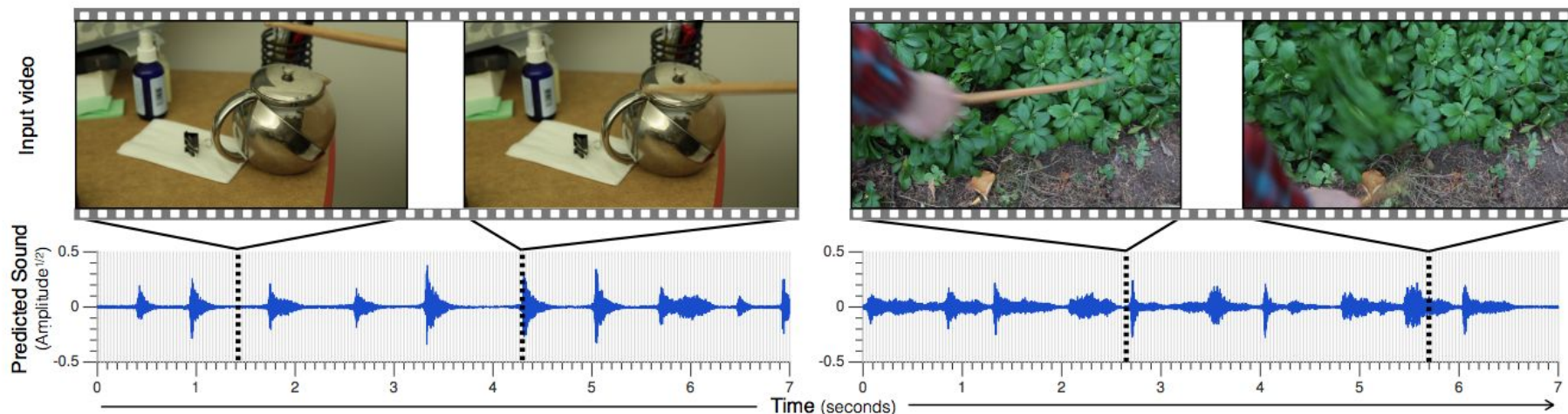
Edward Adelson

William Freeman

Owens, Andrew, Phillip Isola, Josh McDermott, Antonio Torralba, Edward H. Adelson, and William T. Freeman. "Visually indicated sounds." CVPR 2016.

Cross-modal Retrieval

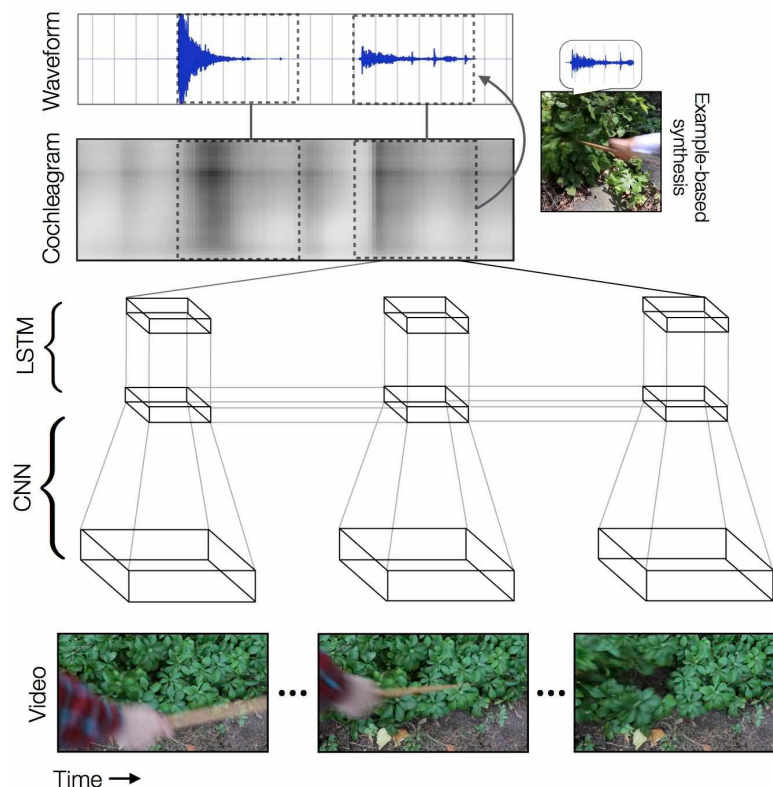
Learn synthesized sounds from videos of people hitting objects with a drumstick.



Owens, Andrew, Phillip Isola, Josh McDermott, Antonio Torralba, Edward H. Adelson, and William T. Freeman. ["Visually indicated sounds."](#) CVPR 2016.

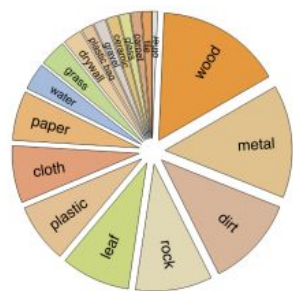
Cross-modal Retrieval

Not end-to-end

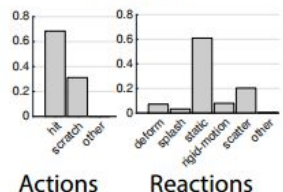


Cross-modal Retrieval

The Greatest Hits Dataset



Materials



Actions

Reactions



Carpet



Ceramic



Cloth



Dirt



Glass



Scattering



Grass



Gravel



Leaf



Metal



Paper



Deformation



Plastic



Plastic bag



Rock



Water



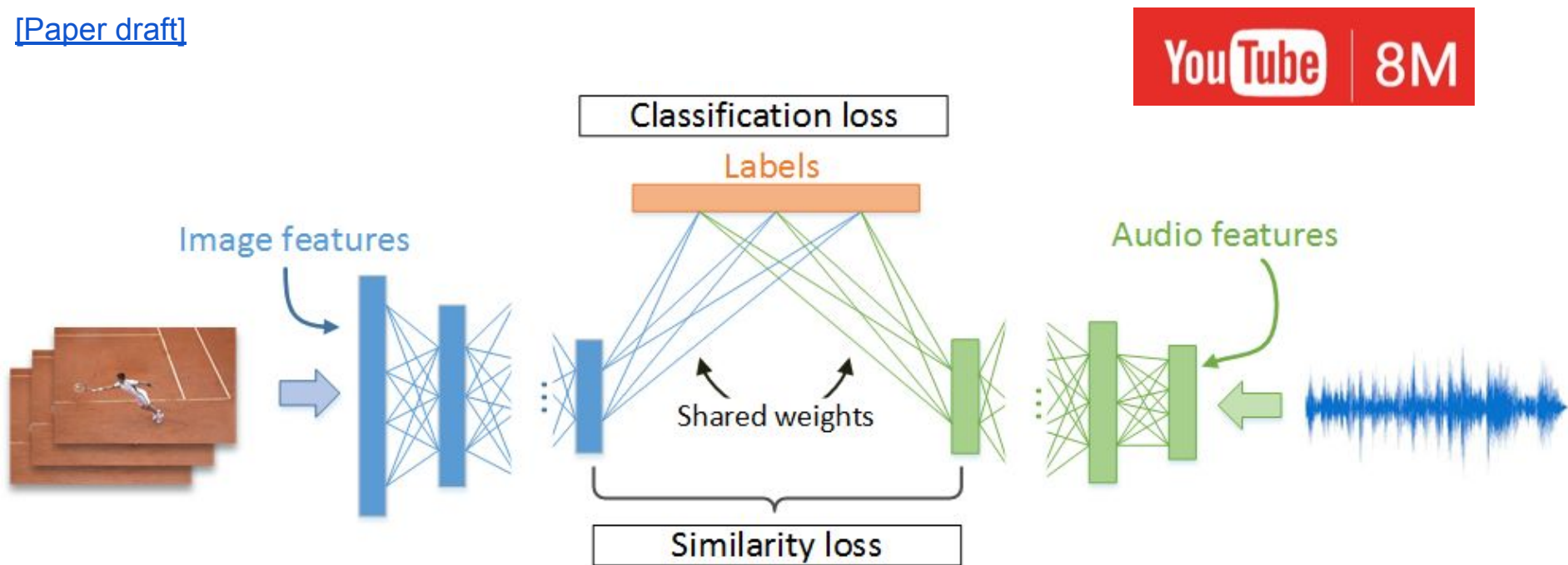
Wood



Splash

Cross-modal Retrieval

[Paper draft]



Cross-modal Retrieval

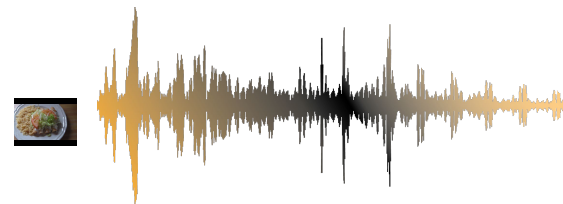
Video sonorization

Visual feature



Best
match

Audio feature

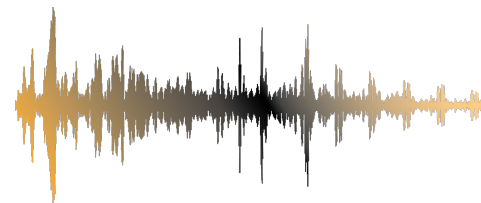
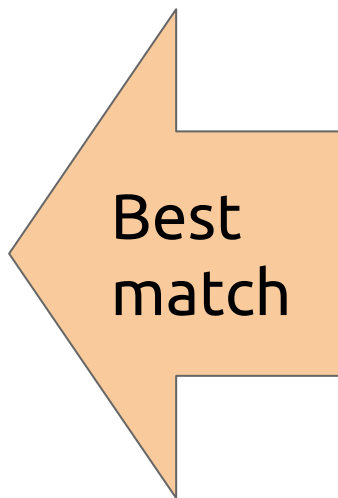


Cross-modal Retrieval

Audio coloring

Visual feature

Audio feature



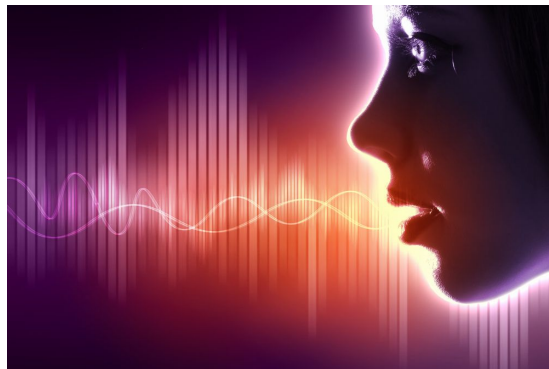
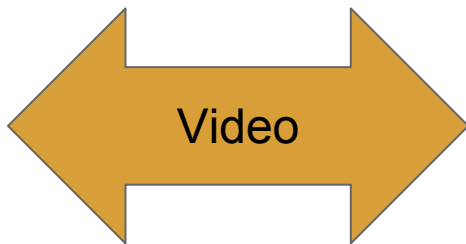
Audio & Vision

- Feature Learning
- Cross-modal retrieval
- **Cross-modal Translation**

Audio & Vision



Vision

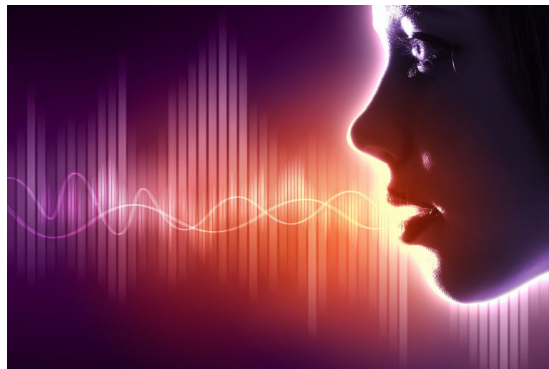
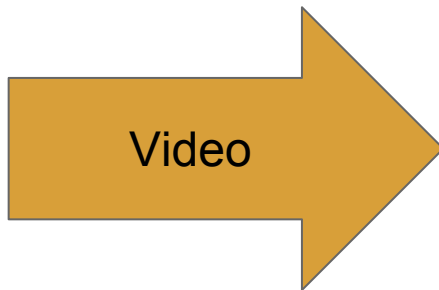


Speech

Audio & Vision



Vision

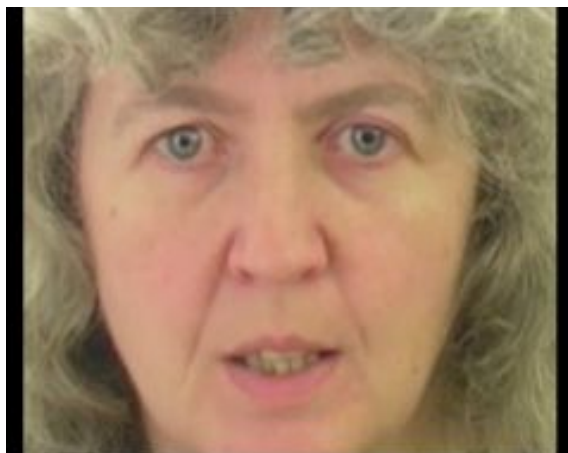


Speech

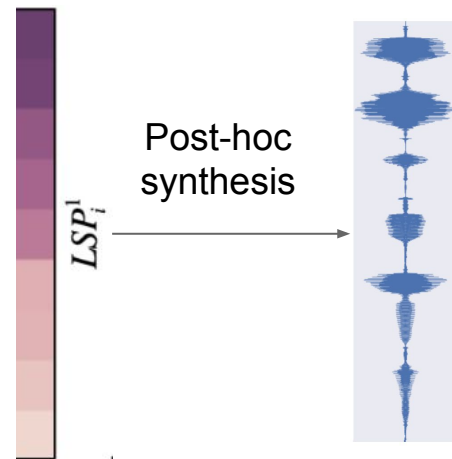
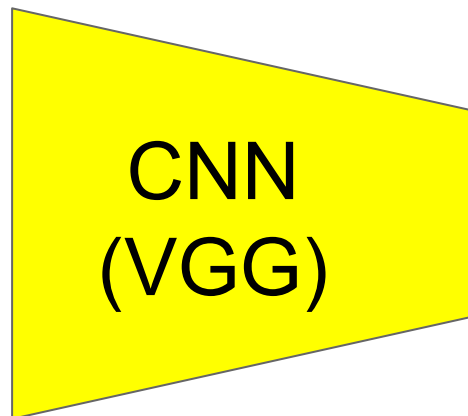


Ephrat, Ariel, Tavi Halperin, and Shmuel Peleg. "Improved speech reconstruction from silent video." In ICCV 2017 Workshop on Computer Vision for Audio-Visual Media. 2017.

Speech Generation from Video

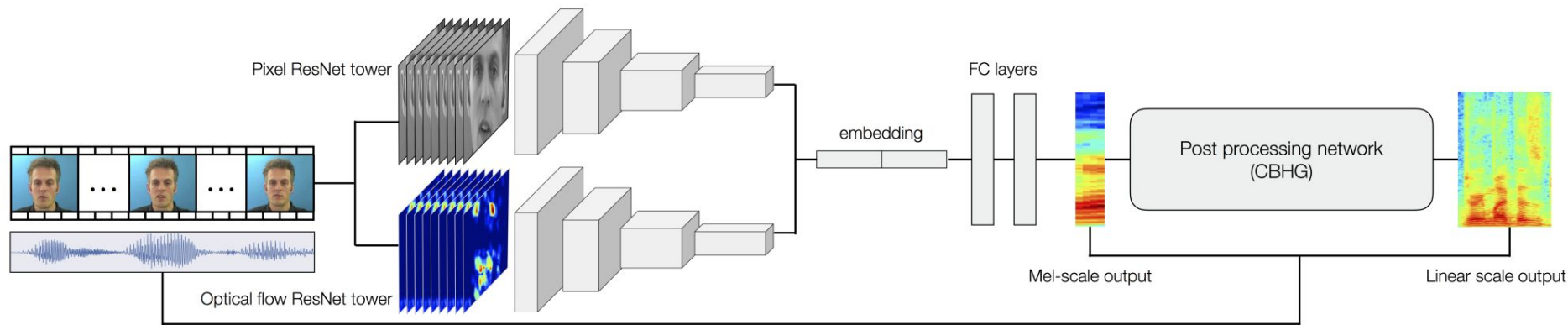


Frame from a
silent video



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.

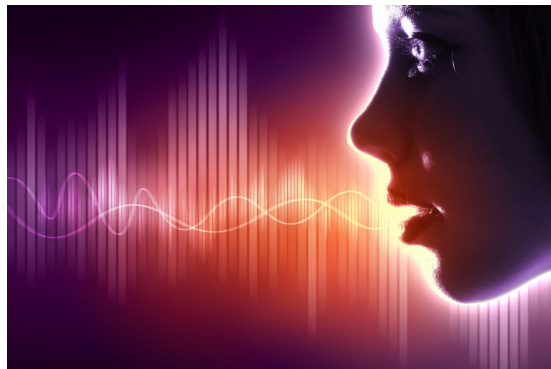
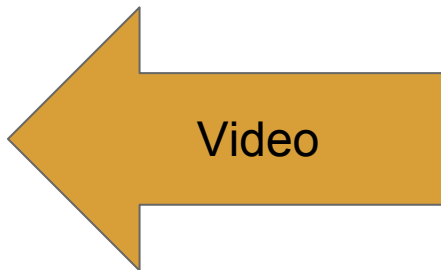


Chung, Joon Son, Amir Jamaludin, and Andrew Zisserman. "You said that?." BMVC 2017.

Audio & Vision



Vision



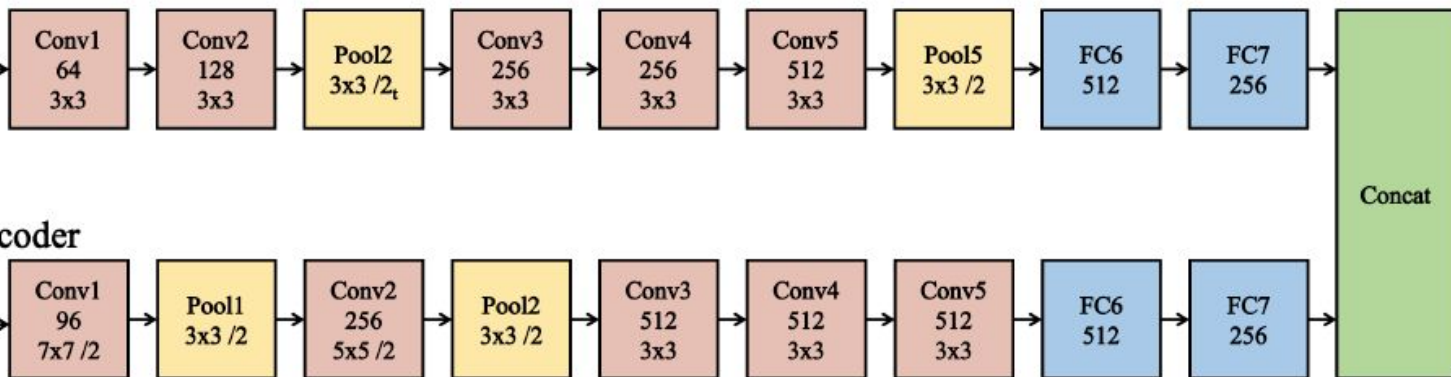
Speech

Speech to Video Synthesis (mouth)

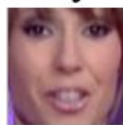
Audio Encoder



12x35x1



Identity Encoder



112x112x3

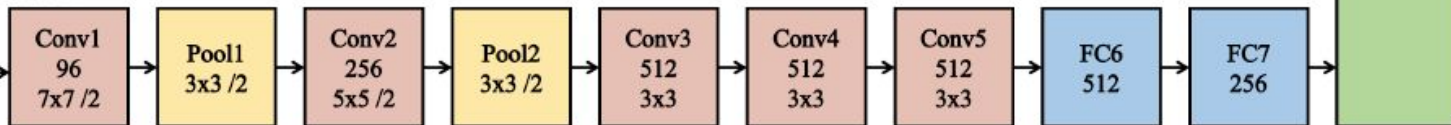
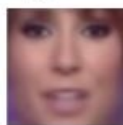
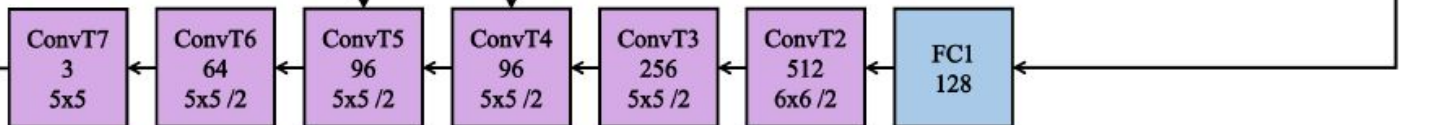


Image Decoder



109x109x3





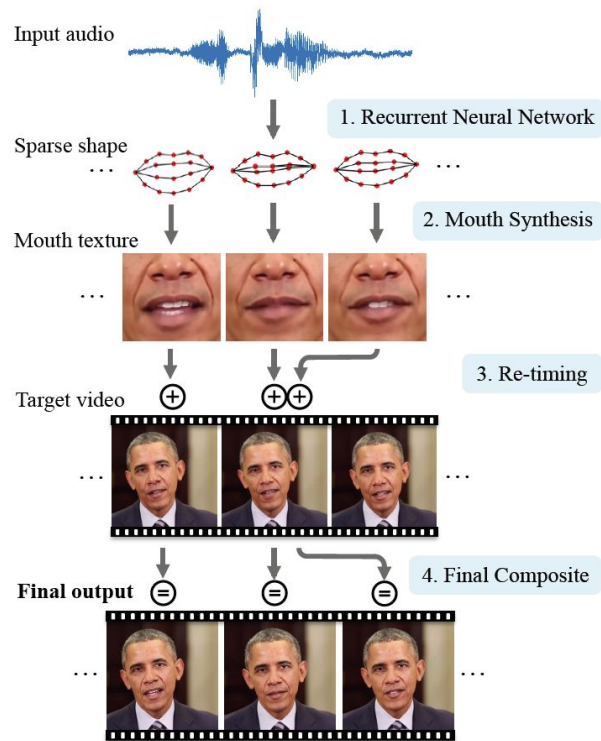
Without Re-timing



With Re-timing
(Our Result)

Karras, Tero, Timo Aila, Samuli Laine, Antti Herva, and Jaakko Lehtinen. "Audio-driven facial animation by joint end-to-end learning of pose and emotion." SIGGRAPH 2017

Speech to Video Synthesis (mouth)

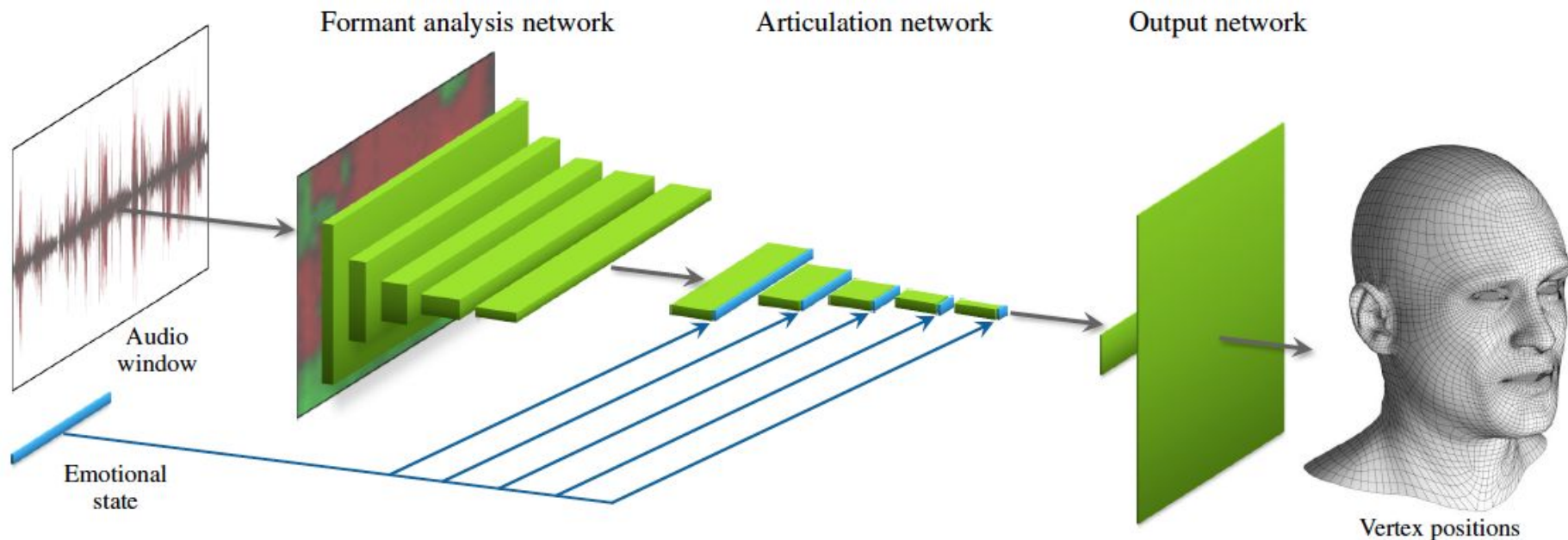


Suwajanakorn, Supasorn, Steven M. Seitz, and Ira Kemelmacher-Shlizerman. ["Synthesizing Obama: learning lip sync from audio."](#) SIGGRAPH 2017.



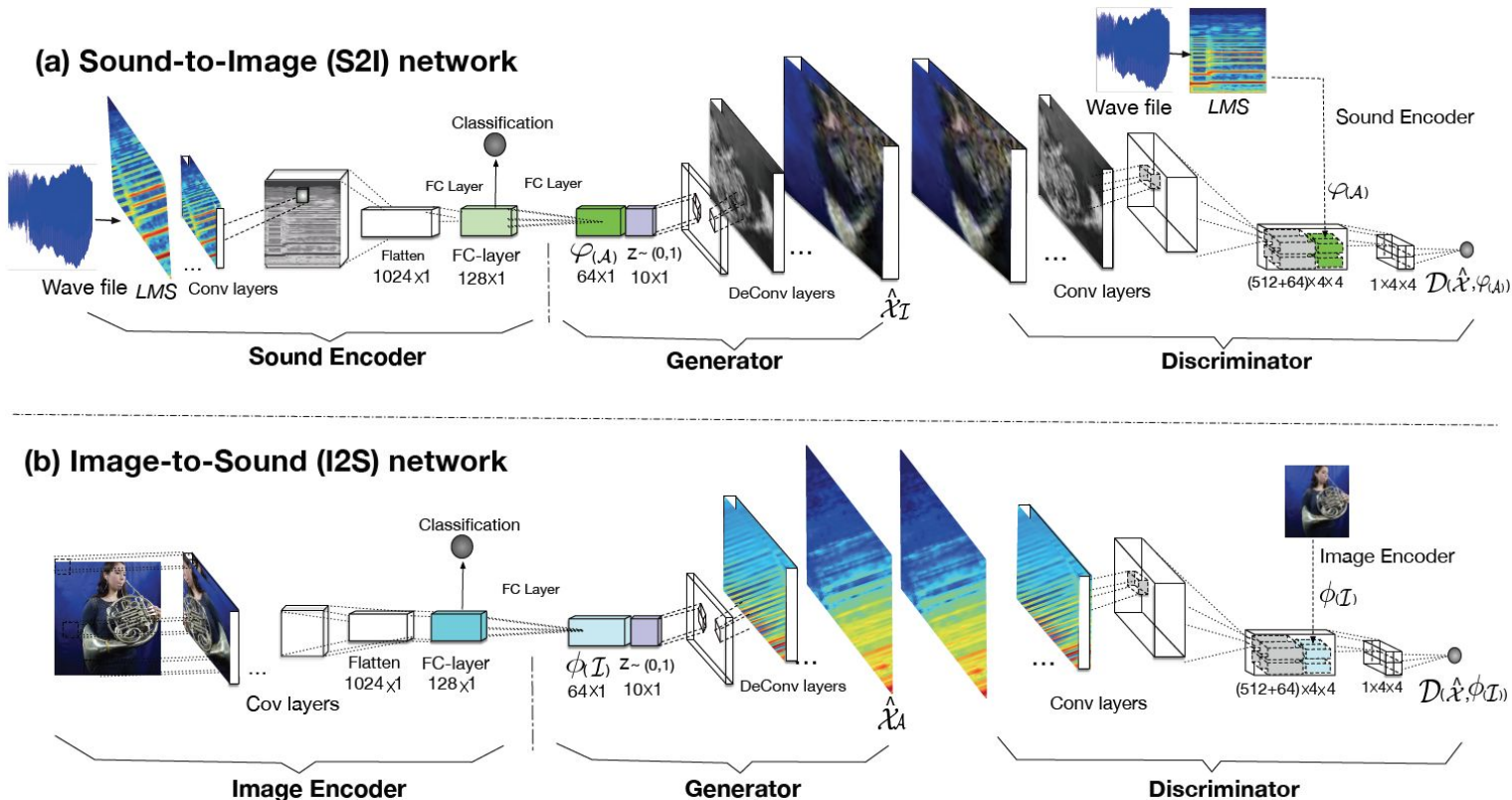
Karras, Tero, Timo Aila, Samuli Laine, Antti Herva, and Jaakko Lehtinen. "Audio-driven facial animation by joint end-to-end learning of pose and emotion." SIGGRAPH 2017

Speech to Video Synthesis (pose & emotion)



Karras, Tero, Timo Aila, Samuli Laine, Antti Herva, and Jaakko Lehtinen. ["Audio-driven facial animation by joint end-to-end learning of pose and emotion."](#) SIGGRAPH 2017

Audio & Visual Generation



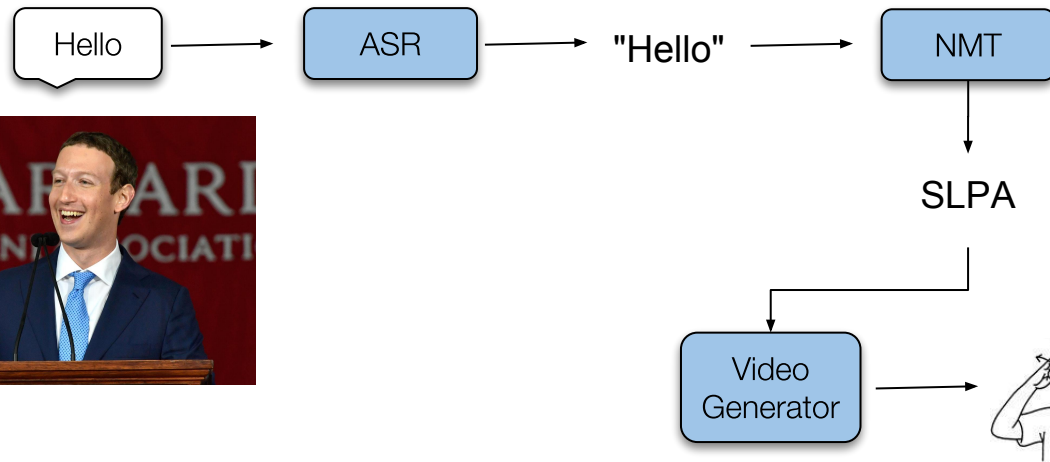
Speech2Signs (under work)



UNIVERSITAT POLITÈCNICA DE CATALUNYA
BARCELONATECH

Department of Signal Theory
and Communications

Image Processing Group



Caffe2

facebook research

Audio & Vision

- Feature Learning
- Cross-modal retrieval
- Cross-modal Translation

Questions ?

Undergradese

What undergrads ask vs. what they're REALLY asking

"Is it going to be an open book exam?"

Translation: "I don't have to actually memorize anything, do I?"

"Hmm, what do you mean by that?"

Translation: "What's the answer so we can all go home."

"Are you going to have office hours today?"

Translation: "Can I do my homework in your office?"

"Can i get an extension?"

Translation: "Can you re-arrange your life around mine?"

"Is this going to be on the test?"

Translation: "Tell us what's going to be on the test."

"Is grading going to be curved?"

Translation: "Can I do a mediocre job and still get an A?"

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