Looking to listen:
Audio separation and localization with visual clues
Piotr Czarnecki 23.11.2020

Sound Sources Localization by audio only

- Binaural unmasking: mostly important to improve perception if source is from different direction than noise, e.g. coctail party effect.
  - Most important for low frequences
- Localization clues:
  - Azimuth – Inaural time difference: phase delay below 1000Hz/interaural level differences (shadow effect) above 1500Hz also spectral reflections by torso, shoulders, pinnae.
  - Distance – loss of amplitude, loss of high frequencies, ratio of direct to reverberated signal.
- Selective attention
  - Ability to focus on single voice, however able to redirect attention where is urgently required.

Audio-Video background

Human perception

When looking on talking people, human can recognize who the speaker is. Humans, by supplementing hearing with visual clues, can locate more precisely sound source than just by hearing.

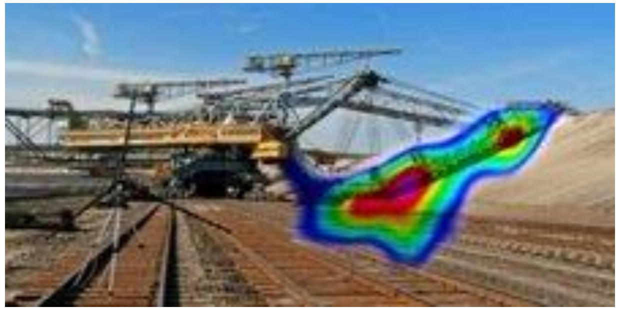
Auditory Illusion

Ventriloquists

audio perception overrided by visual clues. McGurk effect: https://www.youtube.com/watch?v=2k8fHR9jKVM

Audio-only HW

In order to achieve high accuracy in localization sound sources based only on audio, sophisticated microphone arrays are required. That is not feasible to be used for mobiles.



Audio-Video problem

- Wydaje się że dobrze działające przetwarzanie binaural samo w sobie daje bardzo dużo możliwości, więc..

....do czego jeszcze video. -> motywacja jest taka że w wielu apliakcjach nagrania są mono, np.. mowa w nagraniach stereo/również 5.1 zwykle jest mono (w obu kanałach takie samo), lokalizowane są jedynie 'sound efecty'.

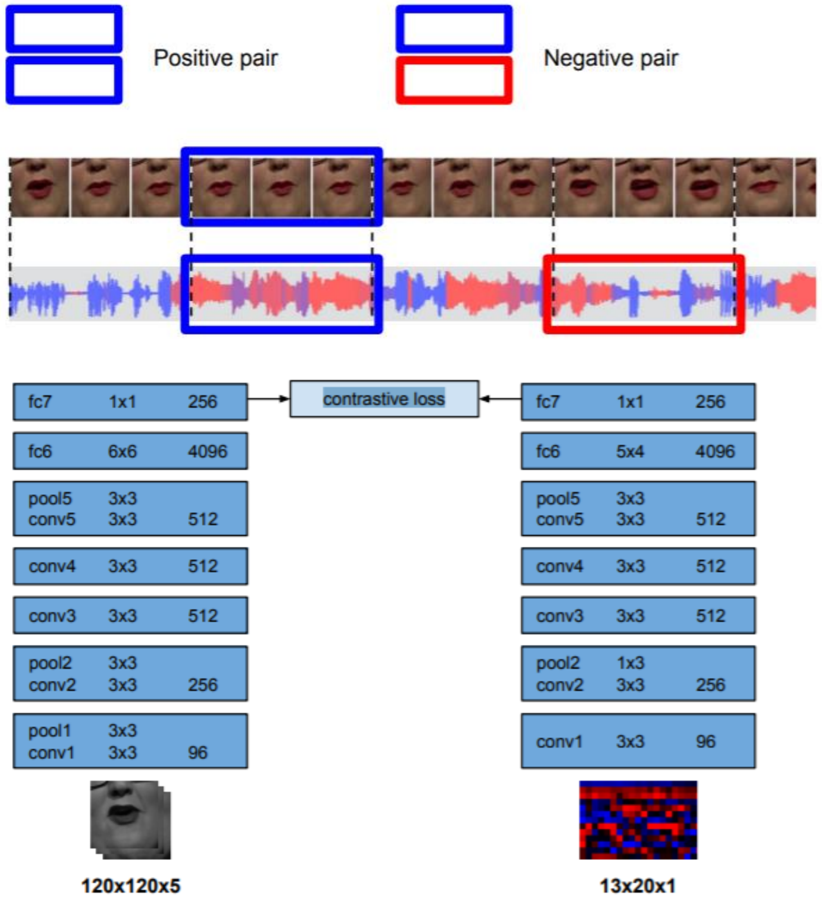
- Generalny problem w technice: jak nagrać dzwięk i jak go zreprodukować żeby podczas odtwarzania był taki jakby człowiek był na miejscu.
- A więc problem to mając mono audio, zlokalizować i odseparować źródła

Audio-Video processing

- Video: 30 FPS -> 1 frame every 33.3ms
- Audio: 48 kHz -> 1 video frame takes 1600 samples, processing could be e.g. 16 frames each 200 samples with 100 overlap.
  - Other are: 16kHz (as voice is up to 8kHz. 3 kHz in telecom)
  - STFT/mel features
- Main approaches:
  - Synchronization – regression but usually binary classification
  - Correspondence (coocurence) - binary classification
  - Separation

Main approaches

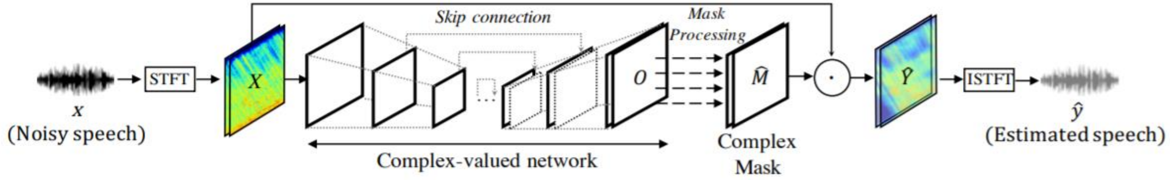
classification



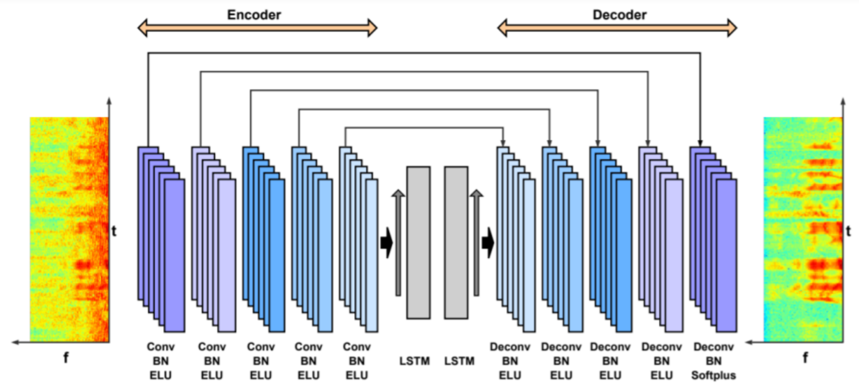
Out of time: automated lip sync in the wild, University of Oxford, ACCV2017

Separation Audio-Only

Deep Complex U-Net



PHASE-AWARE SPEECH ENHANCEMENT WITH DEEP COMPLEX U-NET, Seoul National University, Clova AI Research, NAVER Corp., 2019



A Convolutional RNN for Real-Time Speech Enhancement, The Ohio State University, 2018

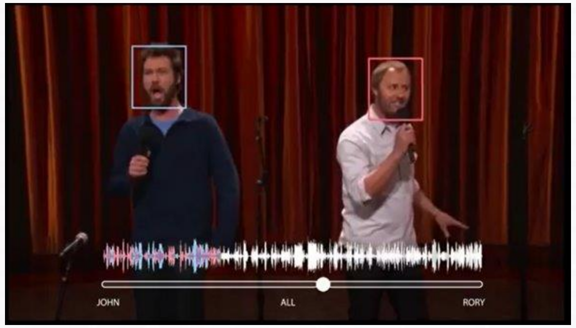
Audio-Video existing solutions

It is feasible to build system that use visual clues (among audio analysis) in order to separate and localize sound sources.

It is feasible to separate voices even if single microphone is used (mono recording).

It is feasible to separate voice of same person (same speech) mixed with delayed copy

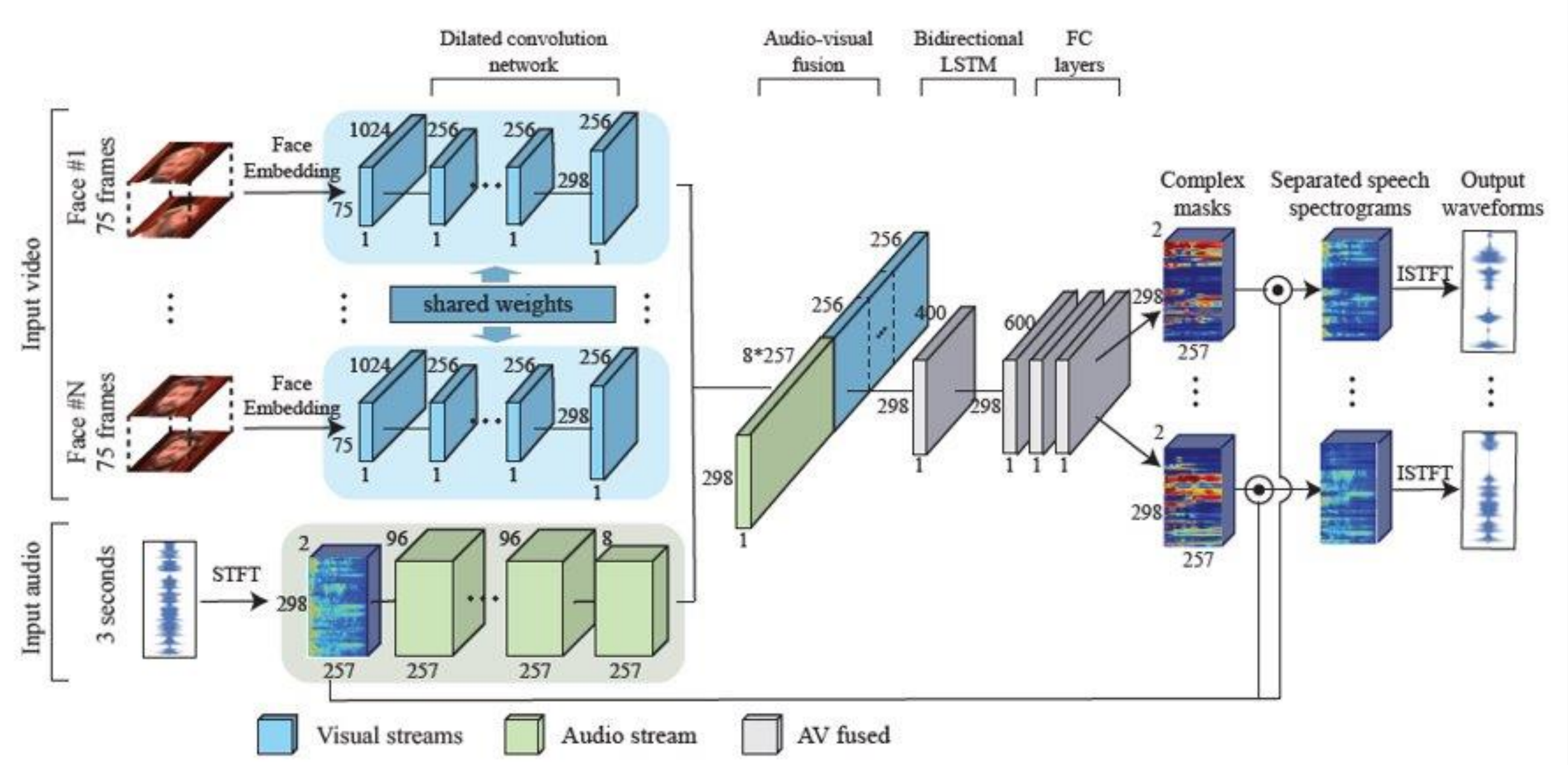
All above is feasible, however not robust and real-time, also difficult to compare solutions as no standard benchmark (no pretrainied models, no exact testset)



https://www.youtube.com/watch?v=rVQVAPiJWKU

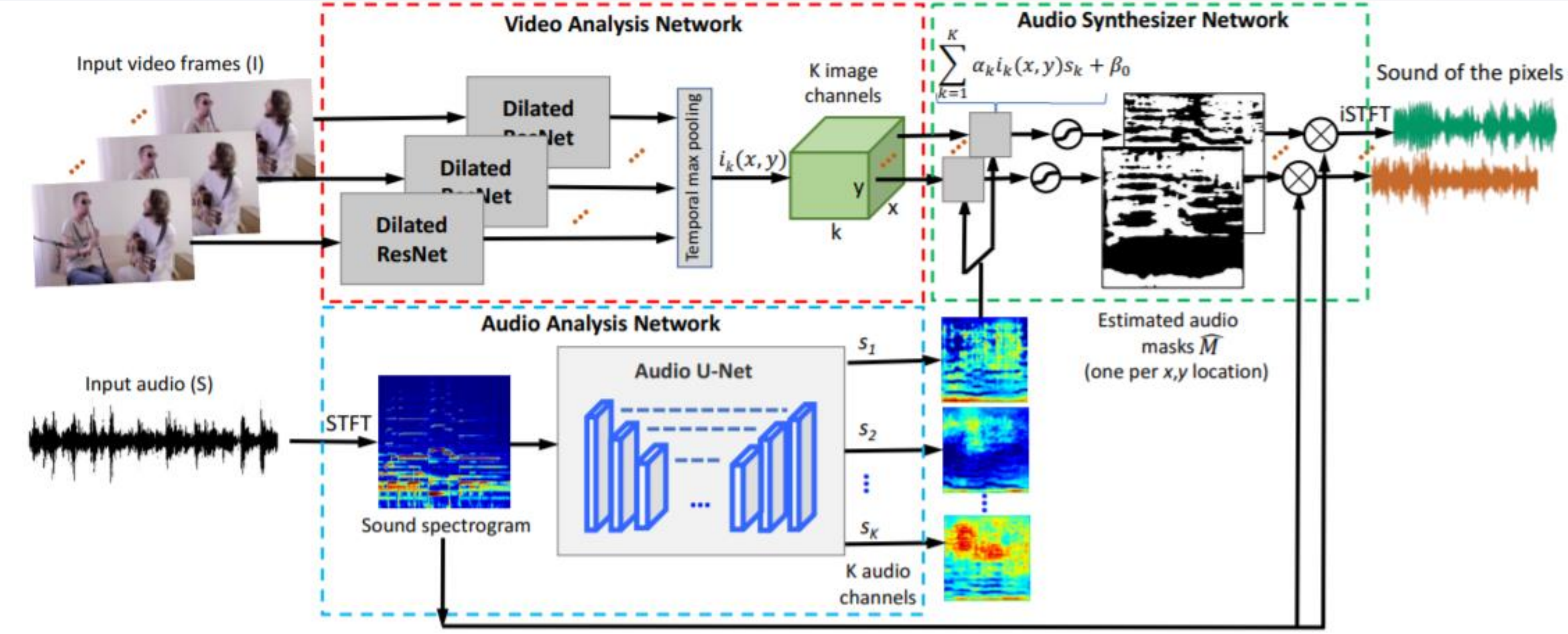
http://www.robots.ox.ac.uk/~vgg/demo/theconversation/

Model – late fusion/face detector (2018)



Looking to Listen at the Cocktail Party: A Speaker-Independent Audio-Visual Model for Speech Separation, Google Research and The Hebrew University of Jerusalem, Israel, SIGGRAPH

Model – no object detector (2018)

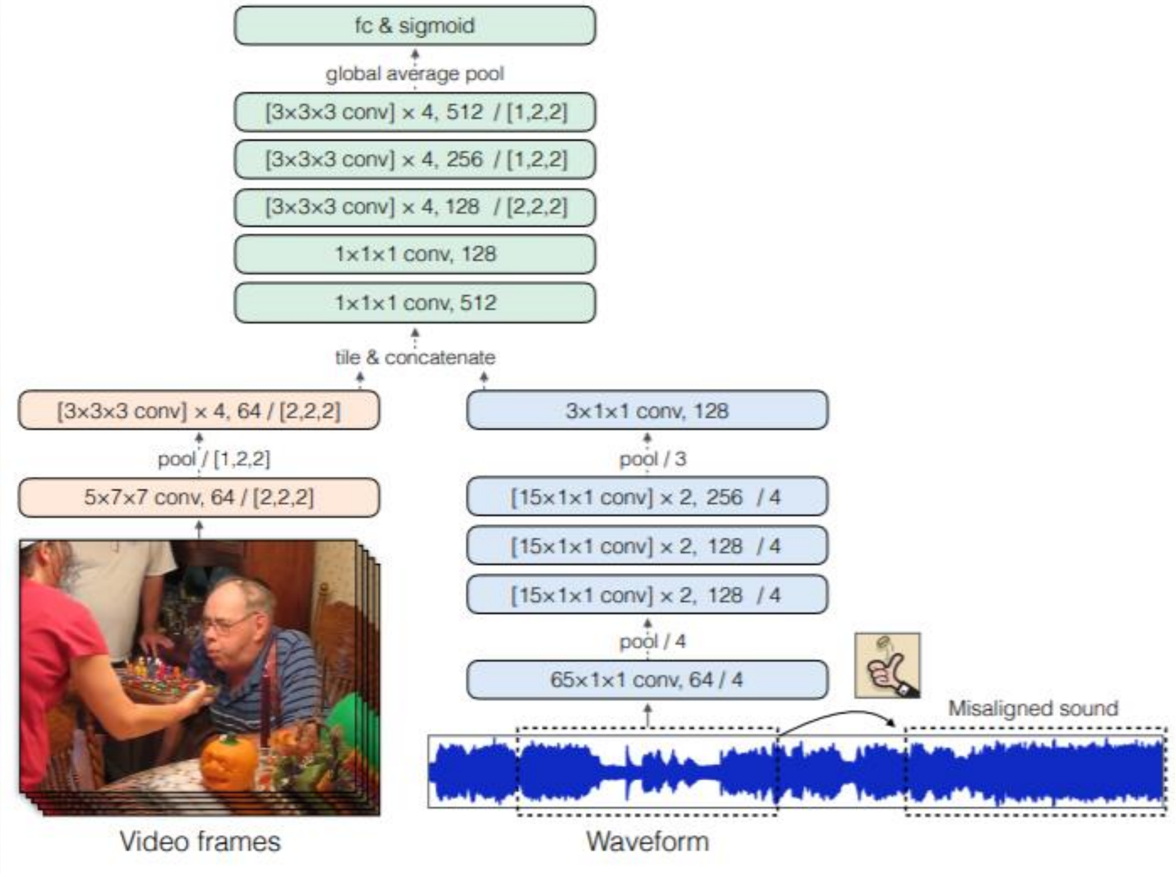


For an input video of size T×H×W×3, the ResNet model extracts per-frame features with size T×(H/16)×(W/16)×K. After temporal pooling and sigmoid activation, we obtain a visual feature ik(x, y) for each pixel with size K.

The Sound of Pixels, Massachusetts Institute of Technology, MIT-IBM Watson AI Lab, Columbia University, CVPR

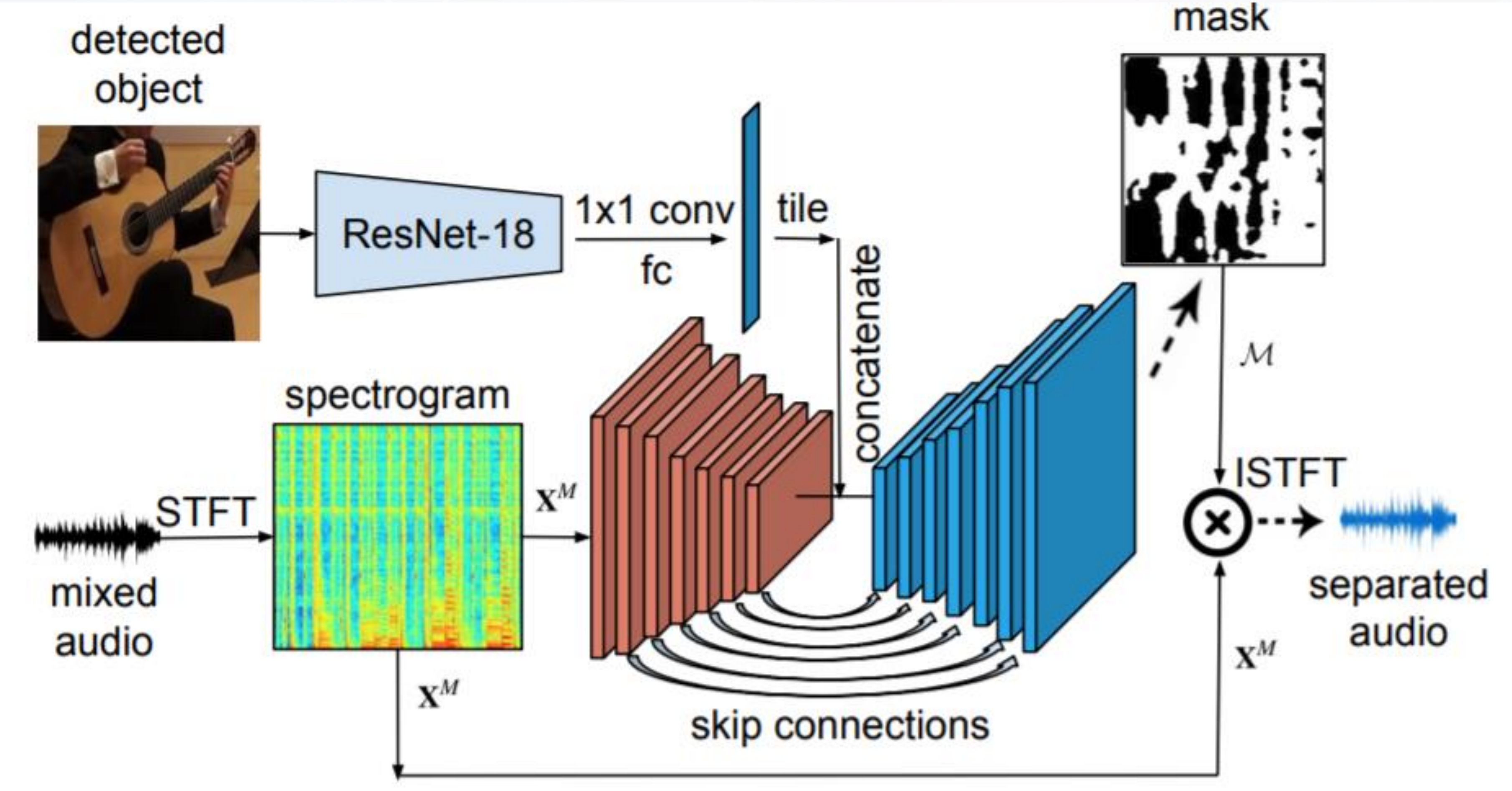
Model – early fusion, no detector (2018)

On/off-screen audio-visual source separation



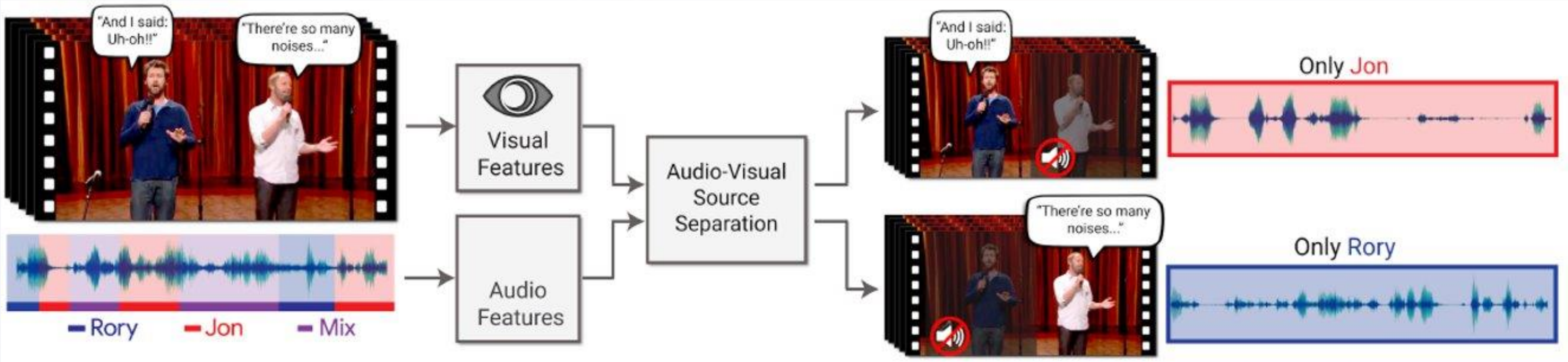
Audio-Visual Scene Analysis with Self-Supervised Multisensory Features, UC Berkeley, CVPR

Model – object detector, U-Net (2019)



Co-Separating Sounds of Visual Objects, UT Austin and Facebook AI Research, ICCV

Dataset - AVSpeech

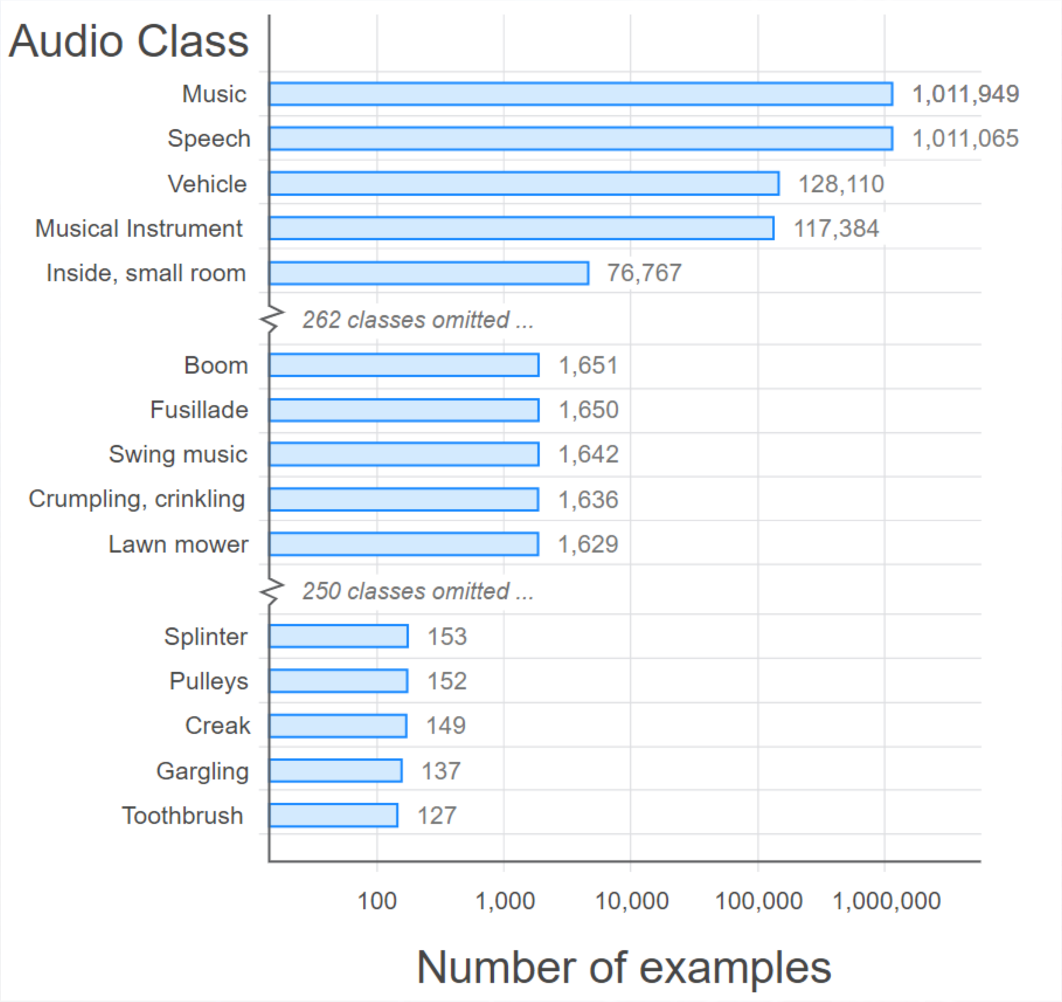


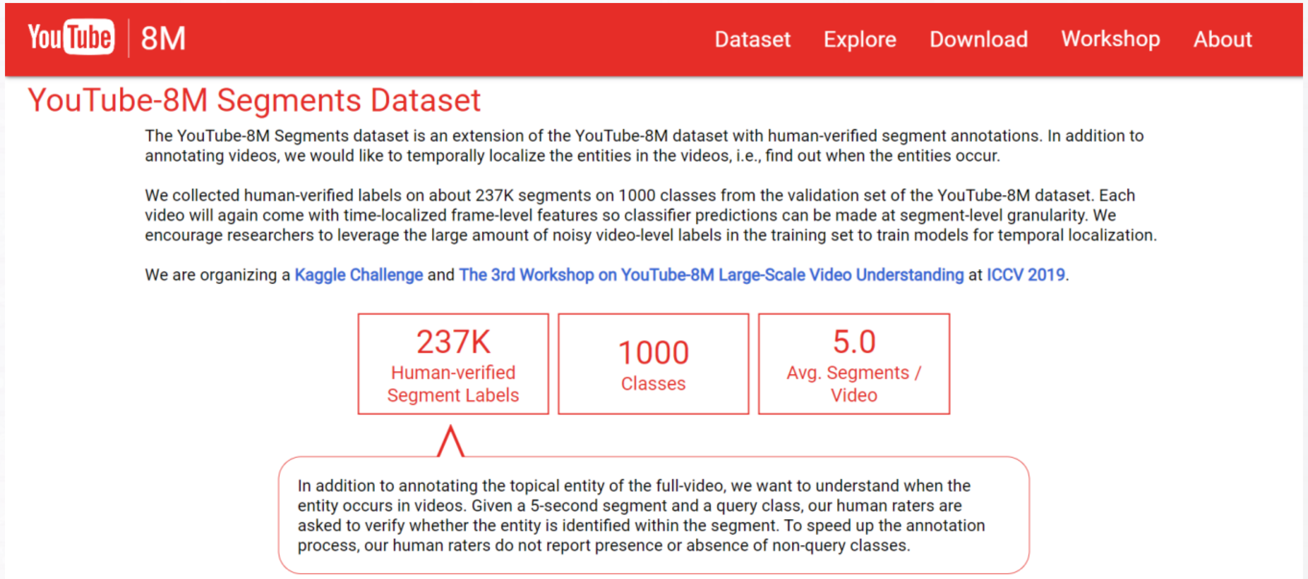
AVSpeech YouTube

150k distinct speakers, 4700 hours of video segments (~6.5 months of speech), from a total of 290k YouTube videos, clean speech (one user) segments for training. Web demo on https://www.youtube.com/watch?v=rVQVAPiJWKU. During training, series of feces (not whole video) from two videos was put as input with mixed audio from both videos on audio input. Model was trained to separate each speaker on its output (ground true was known as dataset is based on clean speech segments). Much effort was put to create clear speech of single speaker dataset (AVSpeech).

Similar technology developed by other team http://www.robots.ox.ac.uk/~vgg/demo/theconversation/.

Dataset - Audioset/YouTube-8M



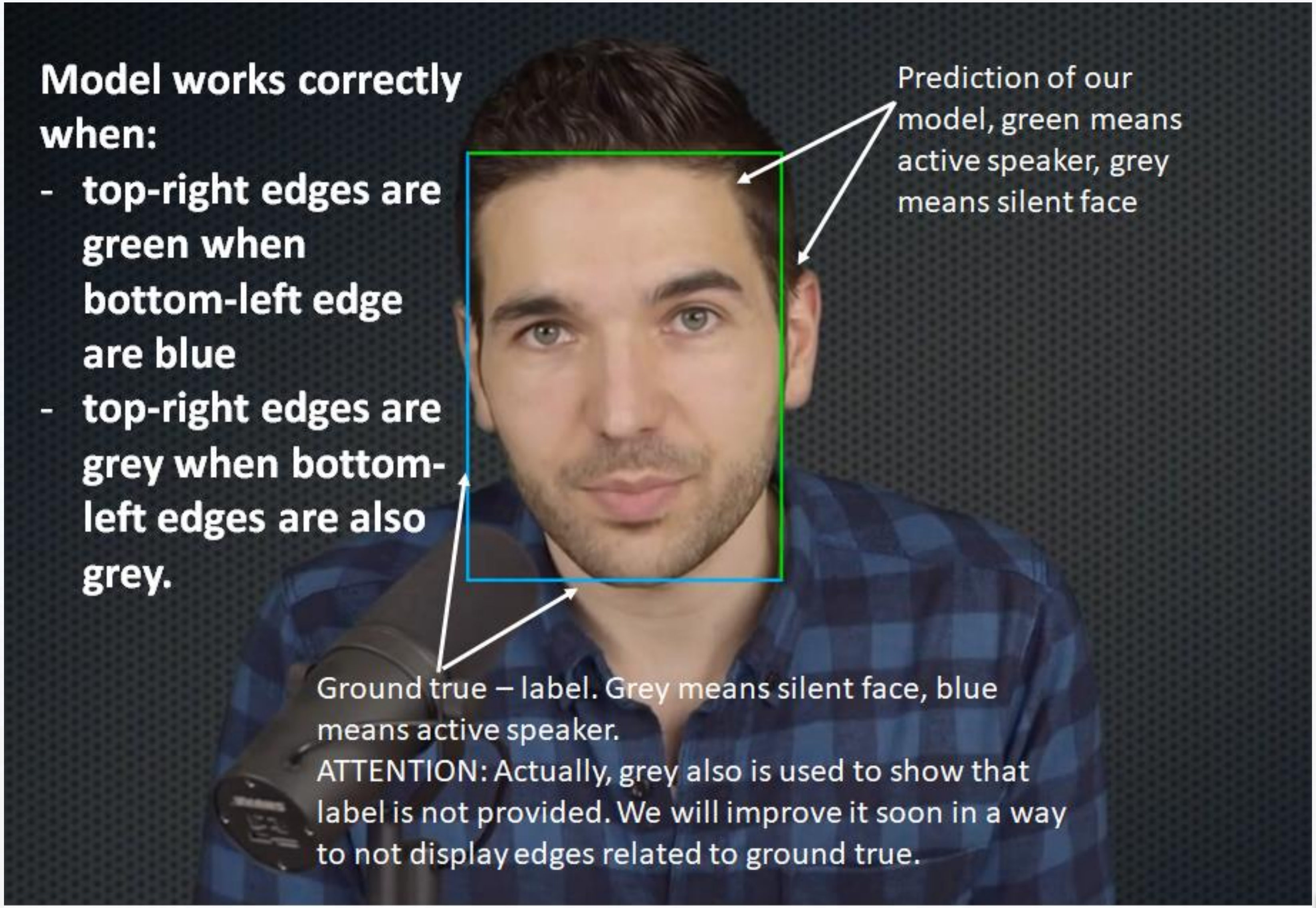


(embeddings only, no raw A-V)

trend

- Model
  - U-Net
  - RNN (GRU/LSTM/bi-LSTM)
  - transformer (2020 CVPR: Listen to Look: Action Recognition by Previewing Audio, The University of Texas at Austin, Facebook AI Research)
  - Wavenet (Generative Model for Raw Audio, 2016, 2018, 2019)
- Dataset
  - AVSpeech
  - Audioset
  - Youtube8M (embeddings only)

Our implementation demo run



Our implementation demo run

https://slack-files.com/T5BNTD7V4-F01FARWEAQJ-499aaac40d

https://slack-files.com/T5BNTD7V4-F01FAFCEF5G-1f19a014df

Dataset improvements

As is: 1 or 2 speaking faces, with different level of noise.

To be:
- 2 and more simultaneous speakers
- not speaking faces (i.e. no lips movement)
- Inaudible faces (removed corresponding voice, add voice of different speaker)
- Speaking face but audio out of synch.
- Speaking face but audio replaced to be looks like in synch e.g. https://www.youtube.com/user/BadLipReading

Training dataset improvement by increase cases diversity

As is: 145 clips covering only talk-shows, NEWS

To be: Continuous real 48h TV stream with 5 channels (containing TV shows, TV series, NEWS, ads, etc.) – no annotations yet.

Test dataset improvement by record real TV stream

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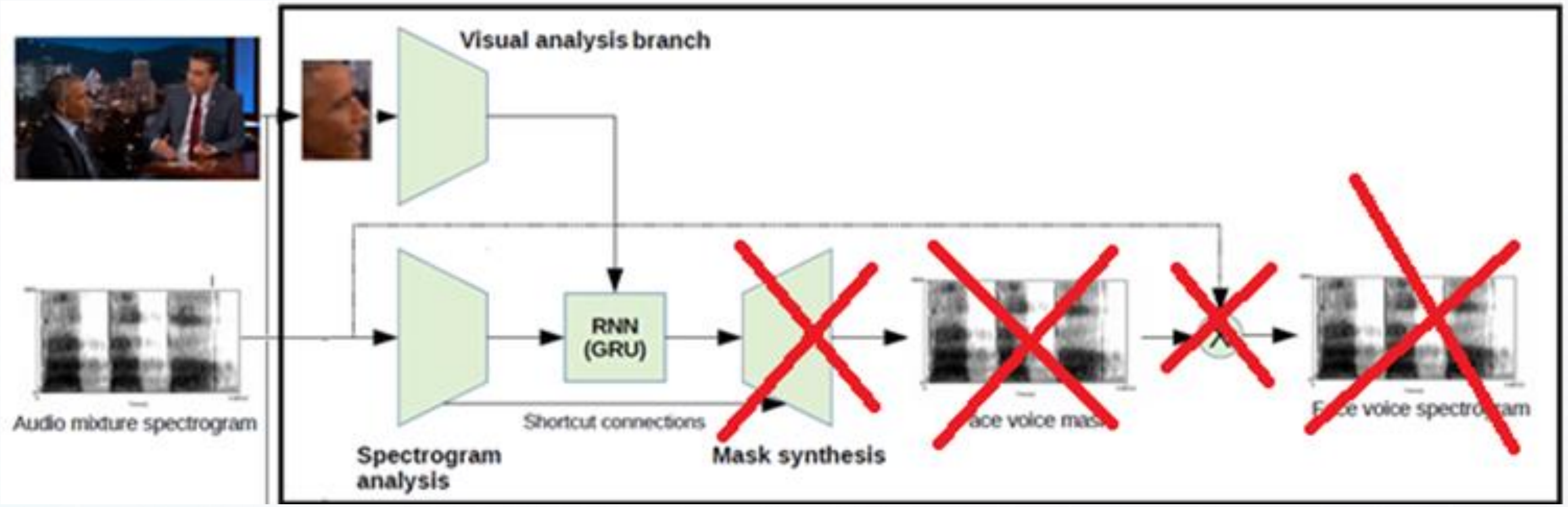
Active Speaker classification verification



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Research in progress

Voice localization and separation

- Pending patent application (hope soon published, submitted 2019…)
- Benchmark with existing solutions (https://paperswithcode.com)
- Training dataset improvement by increase cases diversity
- Test dataset improvement by record real TV stream
- Replace model to lightweight (etc. depth wise separable convolutions)
- Improve model architecture

- Publication of result for A-V speaker separation, also A-V Active Speaker Detector

Dziękuję za uwagę!