

End-to-End Framework for Keyword Spotting

Students:

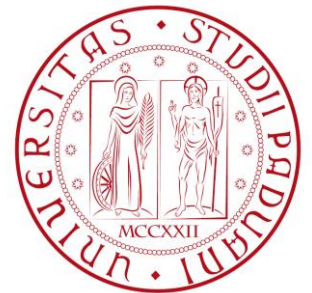
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- The Problem
- The Solution
- What we tried
- Architecture 1: 1DCNN on raw data
- Architecture 2: DSConv
- Architecture 3: Ensemble
- Performance comparisons vs. other papers
- Conclusions

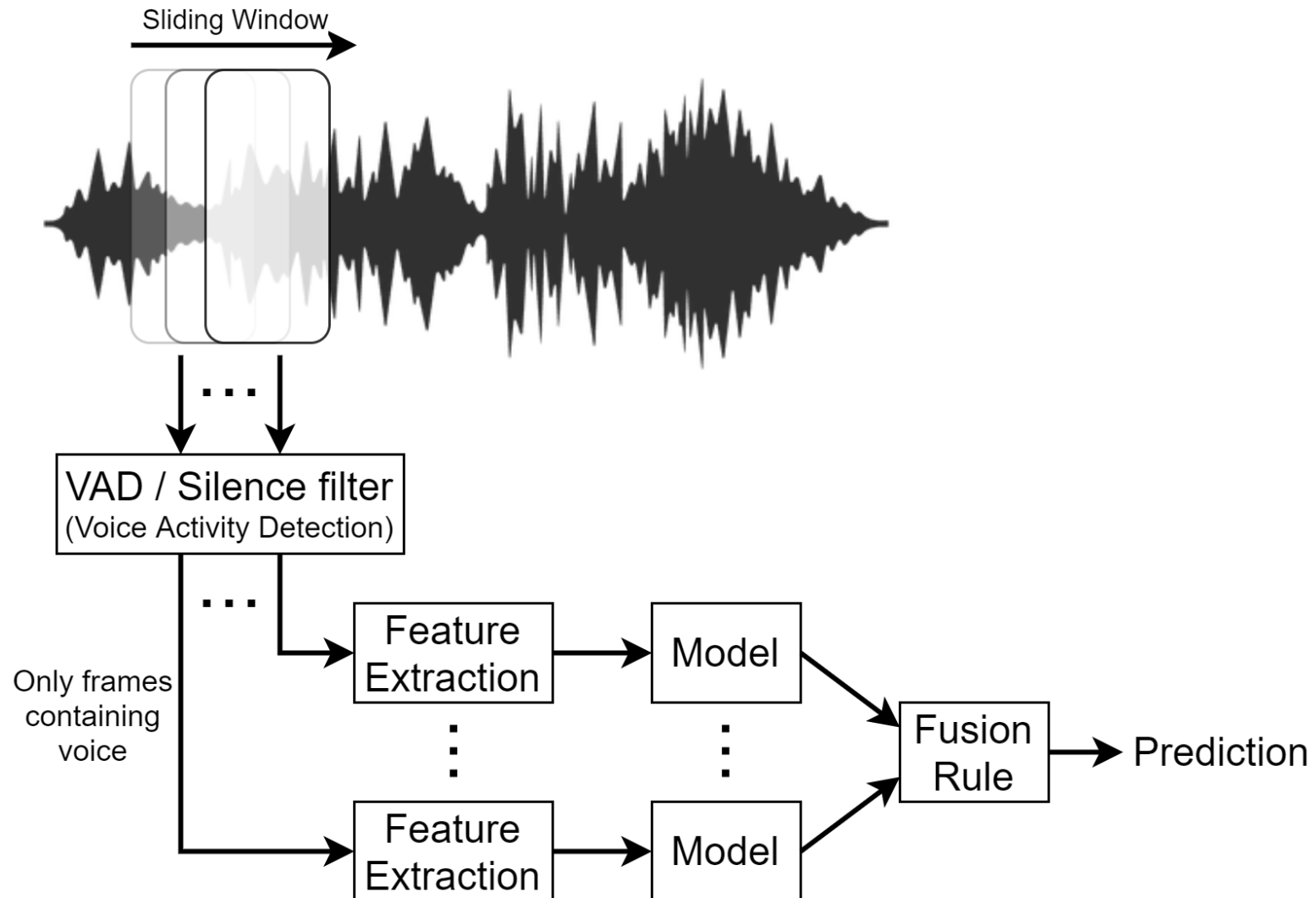
Keyword Spotting

- Detect a relatively small set of predefined keywords (10 or 21) in a stream of user utterances.
- **Application:** Mobile phone, smart home device, consumer and robotics.
- **Constraints:** small footprint and fast (Real Time).

Metrics

- Accuracy
- Number of parameters
- Prediction speed (milliseconds)

The Solution



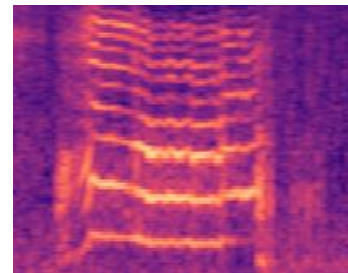
Datasets (Google Speech Dataset V2)

- **10-commands** (“yes”, “no”, “up”, “down”, “left”, “right”, “on”, “off”, “stop”, “go”);
- **21-commands** ([...], “zero”, “one”, “two”, “three”, “four”, “five”, “six”, “seven”, “eight”, “nine”, unknown).

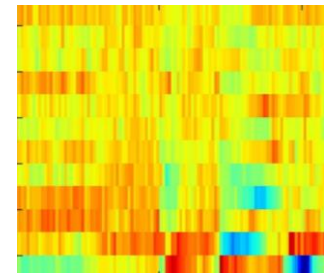
Data Preprocessing techniques

- No preprocessing (Raw Waveform)
- 80 Mel spectrogram
- 40MFCC
- 40MFCC + 40Δ + $40\Delta_s$ (=120)

80 Mels



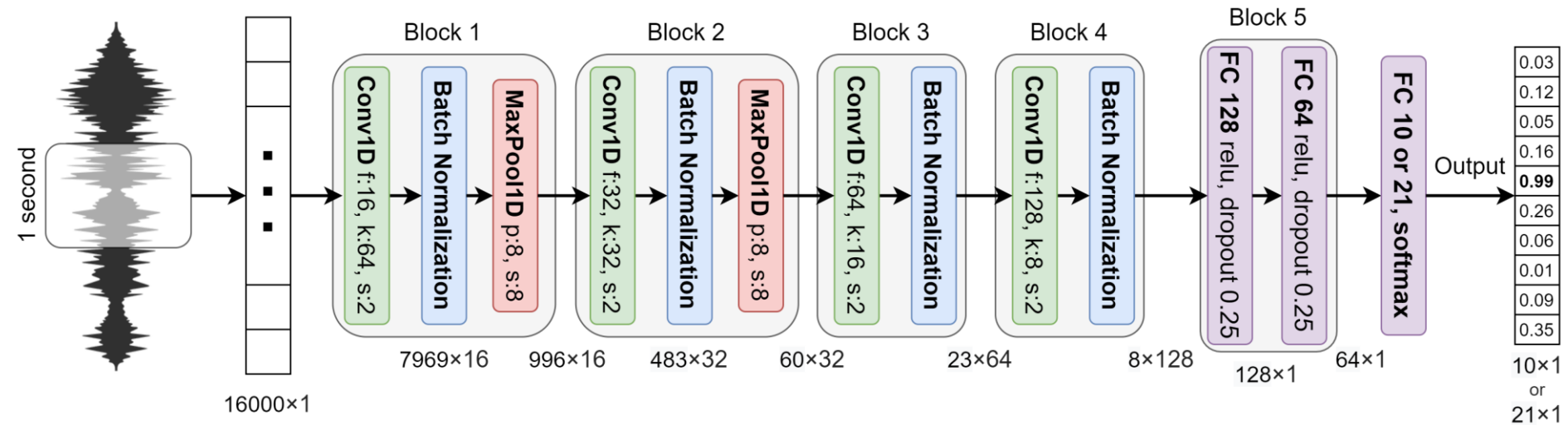
40 MFCC



Learning Architectures

- 1DCNN on raw data
- DSConv (Small - Medium - Large)
- Ensemble (Small - Medium - Large)

1D CNN on raw data



	10-commands (30K – 3K – 3K)	21-commands (84K – 9K – 11K)
Accuracy %	93.0	89.1
# parameters	257,018	257,733
Speed (ms)	28.71	28.25

Separable convolution performs better than regular convolutional layers.

Two types of Separable convolution: **Spatial** and **Depthwise**.

Spatial separable convolution divides a kernel into two smaller kernels.

E.g. division of a 3x3 kernel into a 3x1 and 1x3 kernel.

$$\begin{bmatrix} 3 & 6 & 9 \\ 4 & 8 & 12 \\ 5 & 10 & 15 \end{bmatrix} = \begin{bmatrix} 3 \\ 4 \\ 5 \end{bmatrix} \times \begin{bmatrix} 1 & 2 & 3 \end{bmatrix}$$

Problem: not all kernels can be “separated” (mathematically) into two.

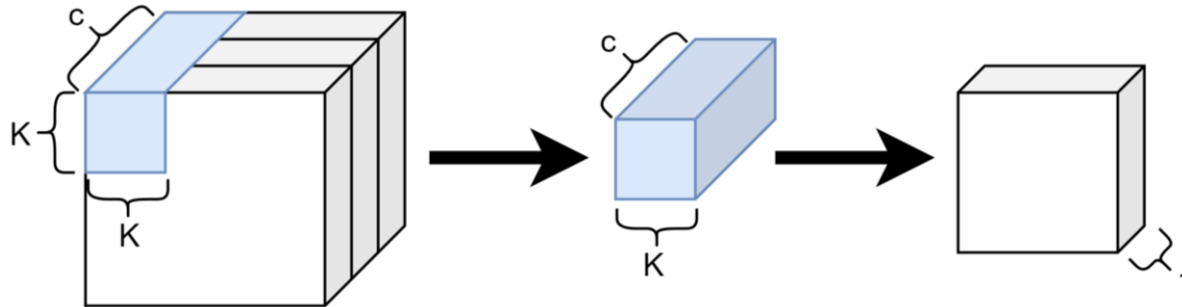
Depthwise Separable convolution uses kernels that cannot be “factored” into two smaller kernels.

It splits a kernel into two separate kernels that do two convolutions:

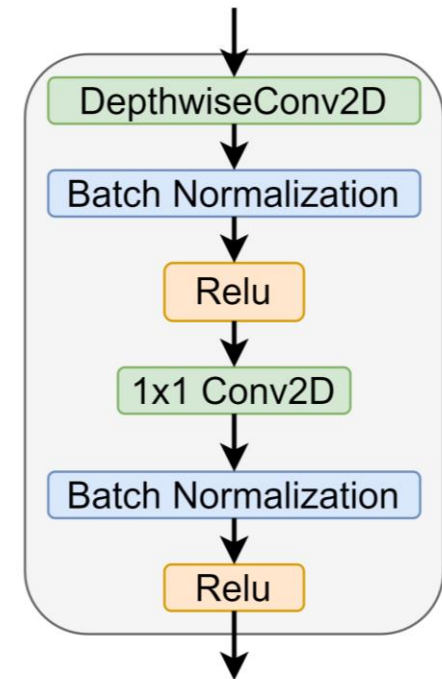
- the **depthwise convolution**;
- the **pointwise (1x1) convolution**.

Depth-wise Sep. CONV

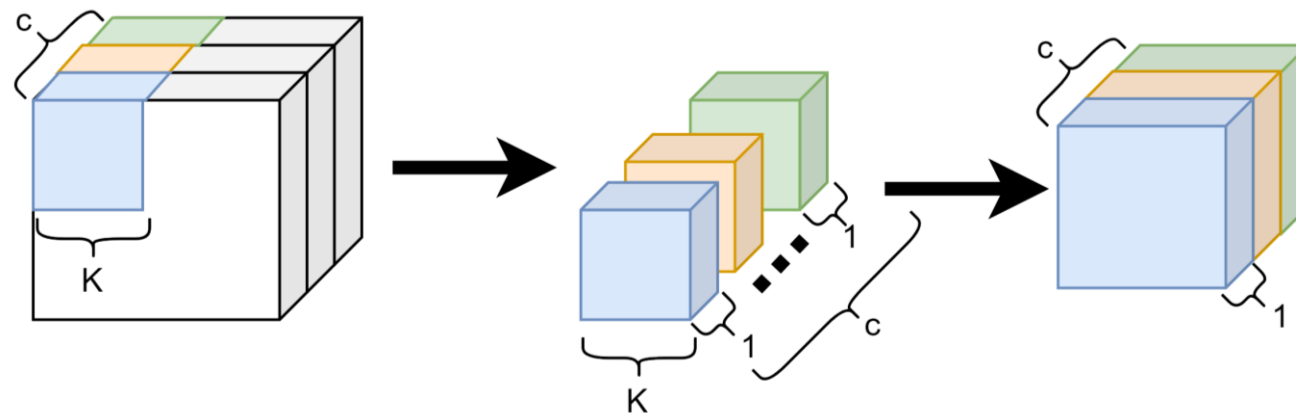
1 Filter Normal Convolution



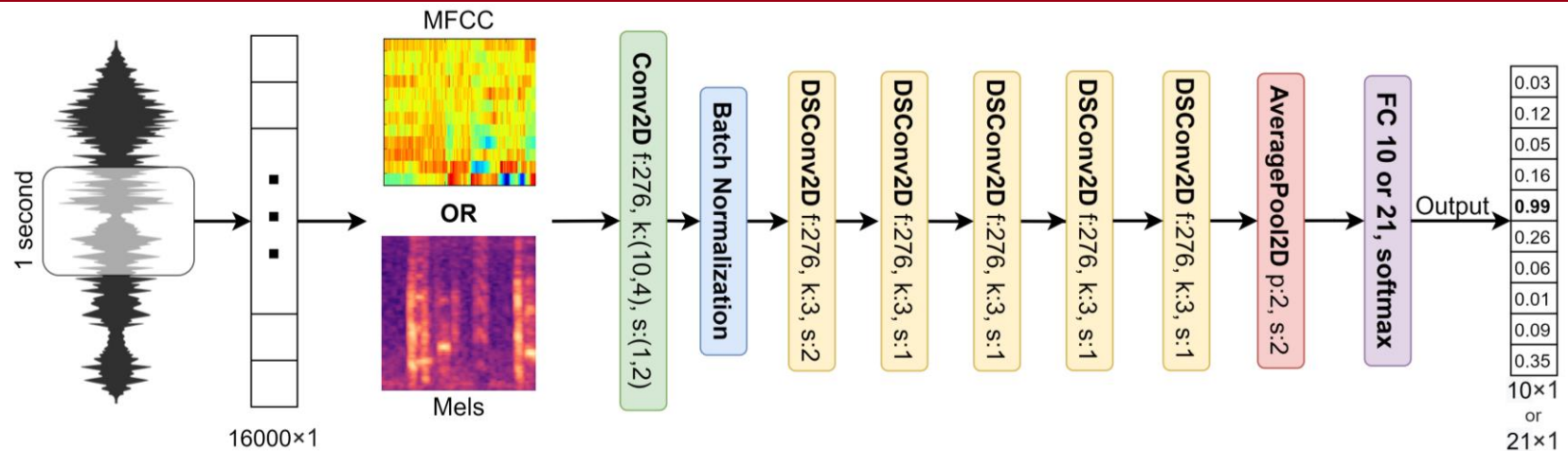
Separable Depthwise Convolution



DepthWise Convolution = 1 filter $K \times K \times 1$ for each channel

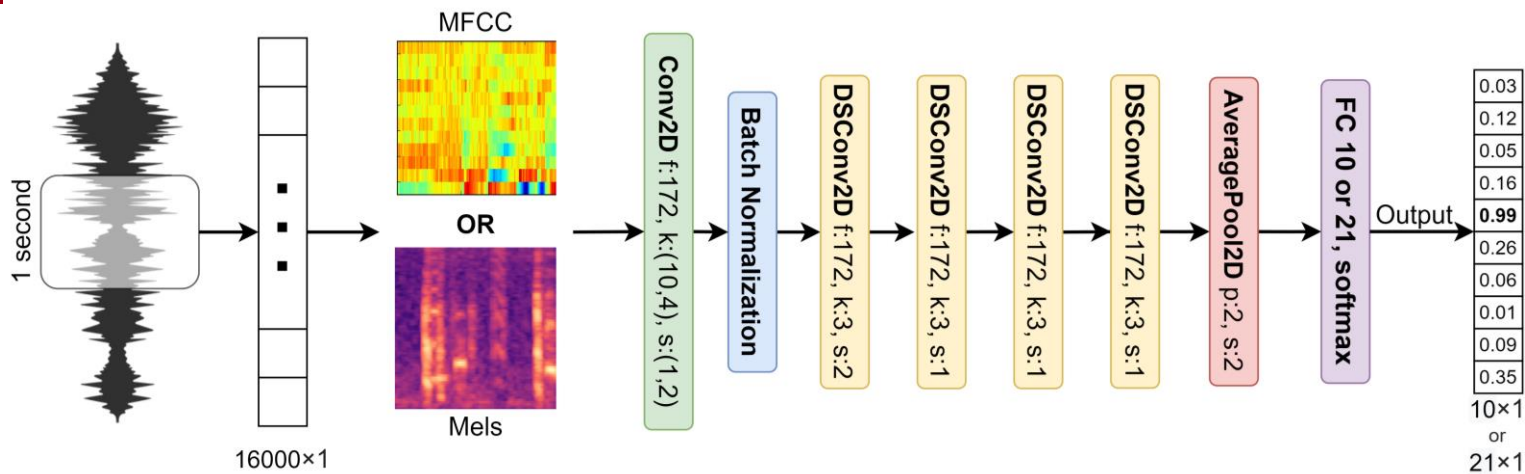


DSCConv Model - Large



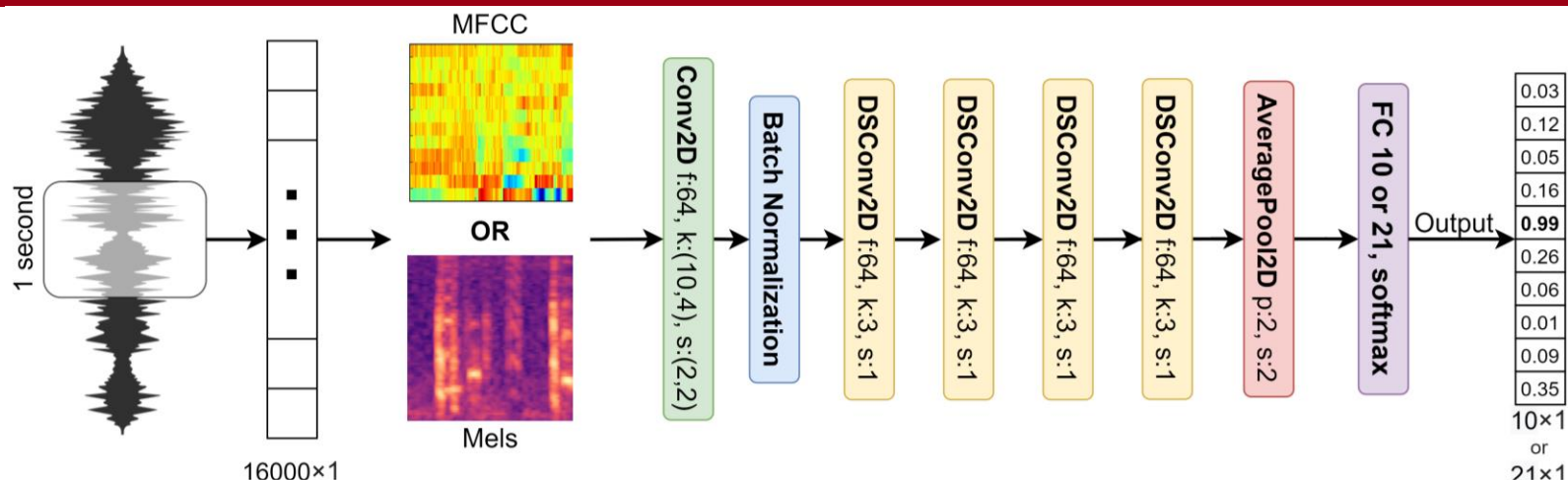
	10-commands (30K-3K-3K)			21-commands (84K-9K-11K)		
	80 Mels	40MFCC	40 + Δ_s MFCC	80 Mels	40MFCC	40 + Δ_s MFCC
Accuracy	96.0	95.3	95.5	93.4	93.7	92.7
# params	874,930	571,330	1,178,530	1,375,881	738,321	2,013,441
Speed (ms)	33.39	30.24	33.42	33.79	30.87	33.13
With FE	41.44	45.32	44.25	41.62	39.66	44.62

DSCConv Model - Medium



	10-commands (30K-3K-3K)			21-commands (84K-9K-11K)		
	80 Mels	40MFCC	40 + Δ_s MFCC	80 Mels	40MFCC	40 + Δ_s MFCC
Accuracy	94.3	95.0	94.8	92.7	92.2	91.7
# params	469,398	262,998	675,798	832,673	399,233	1,266,113
Speed (ms)	30.75	29.55	30.76	32.25	30.01	33.03
With FE	38.49	38.23	41.82	39.72	46.76	47.08

DSCConv Model - *Small*



	10-commands (30K-3K-3K)			21-commands (84K-9K-11K)		
	80 Mels	40MFCC	40 + Δ_s MFCC	80 Mels	40MFCC	40 + Δ_s MFCC
Accuracy	92.5	92.9	92.5	90.0	89.2	86.5
# params	300,618	127,818	473,418	604,757	241,877	967,637
Speed (ms)	31.00	29.27	30.54	32.86	29.48	30.31
With FE	38.31	38.23	40.23	37.97	48.15	40.99

Ensemble: 10-commands

Ensemble between the best models.

	10-commands (30K-3K-3K)		
	Large	Medium	Small
	<i>DSCnv L 80 Mels</i> + <i>DSCnv L 40 MFCC</i> + <i>DSCnv L 40 MFCC Δ</i>	<i>DSCnv L 40 MFCC</i> + <i>DSCnv M 80 Mels</i> + <i>DSCnv M 40 MFCC Δ</i>	<i>DSCnv M 40 MFCC</i> + <i>DSCnv S 80 Mels</i> + <i>DSCnv S 40 MFCC</i>
Accuracy	96.8	96.4	95.6
# params	2,624,790	1,303,726	691,463
Speed (ms)	131.01	122.04	106.09

Ensemble: 21-commands

Ensemble between the best models.

	21-commands (84K-9K-11K)		
	Large	Medium	Small
	<i>DSCnv L 80 Mels</i> + <i>DSCnv L 40 MFCC</i> + <i>DSCnv L 40 MFCC Δ</i>	<i>DSCnv L 40 MFCC</i> + <i>DSCnv M 80 Mels</i> + <i>DSCnv M 40 MFCC</i>	<i>DSCnv L 40 MFCC</i> + <i>DSCnv M 40 MFCC</i> + <i>DSCnv S 40 MFCC</i>
Accuracy	95.2	95.0	94.2
# params	2,498,019	1,970,227	1,379,431
Speed (ms)	125.9	114.21	109.03

Performances: 10-commands

	Accuracy %	# Parameters	Speed (ms)
SincConv [Mittermaier et al.]	97.4	162K	40.35
Our Ensemble Large	96.8	2,624,790	131.01
Our Ensemble Medium	96.4	1,303,726	122.04
Our DSConvLarge + 80Mels	96.0	874,930	41,44
Our Ensemble Small	95.6	691,463	106.09
Our DSConvMedium + 40MFCC	95.0	262,998	38,23
Our 1DCNN on raw data	93,0	257,018	28,71
Our DSConvSmall + 40MFCC	92,9	127,818	38,23

- **Best:** Ensemble Large
- **Smaller:** DSConvSmall + 40MFCC
- **Fastest:** 1DCNN on raw data

Performances: 21-commands

	Accuracy %	# Parameters	Speed (ms)
SincConv [Mittermaier et al.]	97.4	162K	40.35
Our Ensemble Large	95.2	2,498,019	125.9
Our Ensemble Medium	95.0	1,970,227	114.21
Our Ensemble Small	94.2	1,379,431	109.03
Our DSConvLarge + 40MFCC	93.7	738,321	39.66
Our DSConvMedium + 80Mels	92,7	832,673	39,72
Our DSConvSmall + 80Mels	90,0	604,757	37,97
Our 1DCNN on raw data	89,1	257,733	28,25

- **Best:** Ensemble Large
- **Smaller:** 1DCNN on raw data
- **Fastest:** 1DCNN on raw data

Conclusions

- Tests: our models are **very good at classifying keywords**;
- We did not beat the state-of-the-art models;
- We found that the number of convolutional layers played a key role in detecting high-level concepts;
- No difference between 80 Mels or 40 MFCCs;
- Different model sizes in order to fit different devices.

Future Work

- Try different hyperparameters during training;
- Change the **structure** of the **network** using:
 - SincConv;
 - GDSCov.
 - Attention model