# End-to-End Framework for Key word Spotting

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### Outline



- The Problem
- The Solution
- What we tried
- Architecture 1: 1D CNN on RAW data
- Architecture 2: DSConv
- Architecture 3: Ensemble
- Performances comparison against other papers
- Conclusions

### The Problem



### Key word spotting:

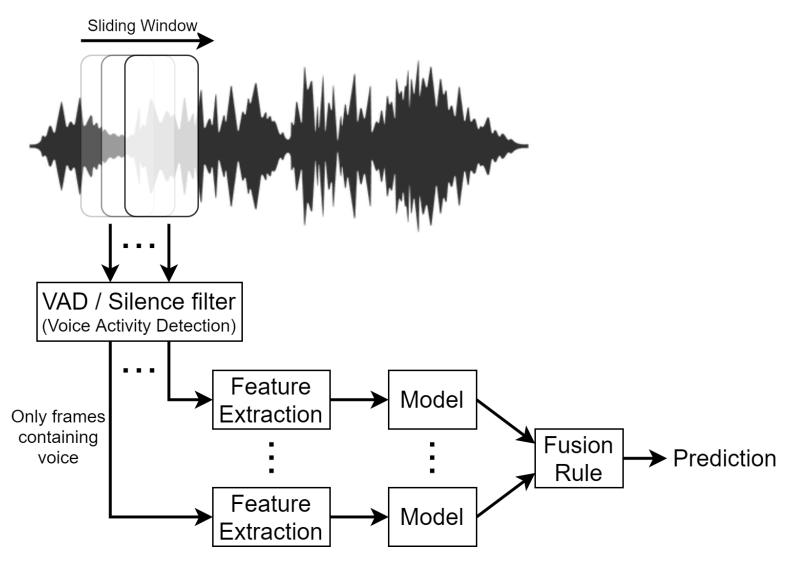
- Detect a relatively small set of predefined keywords (10 or 21) in a stream of user utterances.
- Application: Mobile phone, smart home device, consumer and robotics.
- Constraints: small footprint and fast (Real Time).

#### **Metrics**:

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

### The Solution





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### What we tried



**Datasets:** (Google Speech Dataset V2)

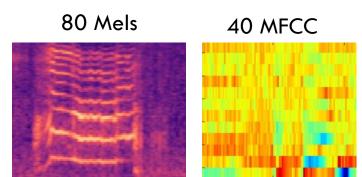
- 10 commands (yes, no, up, down, left, right, on, off, stop, go)
- 21 commands (..., zero, one, two, three, four, five, six, seven, eight, nine, unknown)

### Data Preprocessing techniques:

- No preprocessing (Raw Waveform)
- 80 Mel spectrogram
- 40 MFCC
- 40 MFCC + 40delta + 40deltadelta (=120)

### Learning Architectures:

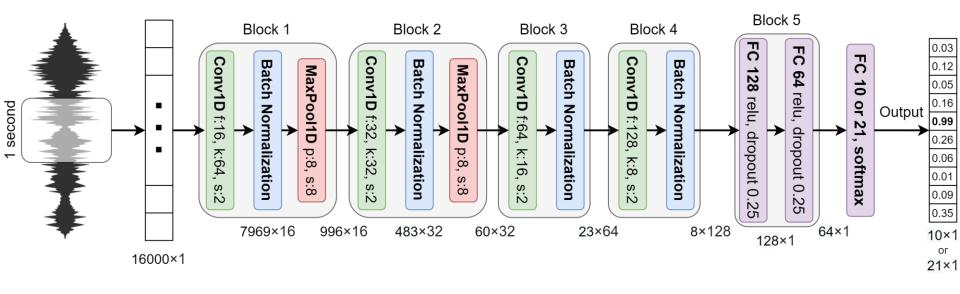
- 1D CNN on RAW data
- DSConv (Small Medium Large)
- Ensemble (Small Medium Large)



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### 1D CNN on RAW data

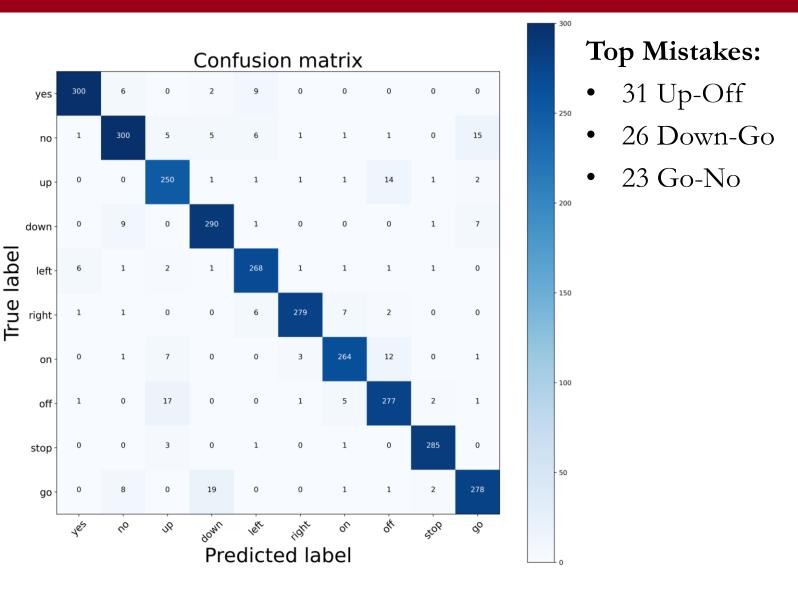




	<b>10 commands</b> (30k - 3k - 3k)	<b>21 commands</b> (84k - 9k - 11k)
Accuracy	93.0	89.1
# parameters	257,018	257,733
Speed (ms)	28.71	28.25

### 1D CNN on RAW data

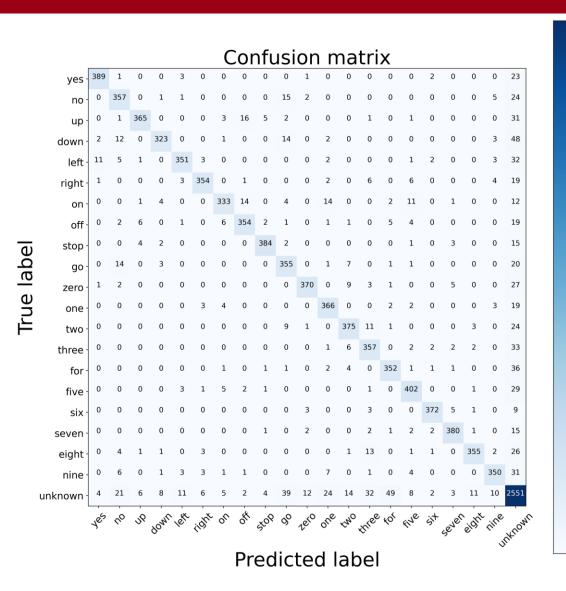




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### 1D CNN on RAW data





### **Top Mistakes:**

- 85 Four-Unknown
- 65 Three-Unknown

Actually it confuses

Four - For

1000

• Three - Tree

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# Separable CONV



**Separable convolution:** uses less parameters, less memory and less computations than regular convolutional layers, and perform better.

There are two types of Separable convolution: Spatial and depthwise

Spatial separable convolution: divides a kernel into two, smaller kernels.

E.g. divide a 3x3 kernel into a 3x1 and 1x3 kernel. So, instead of doing one convolution with 9 multiplications, we do two convolutions with 3 multiplications each (6 in total) to achieve the same effect.

**Problem:** not all kernels can be "separated" (mathematically) into two.

**Depthwise Separable convolution:** uses kernels that cannot be "factored" into two smaller kernels. It deals not just with the spatial dimensions, but also with the depth dimension (number of channels).

Splits a kernel into 2 separate kernels that do two convolutions:

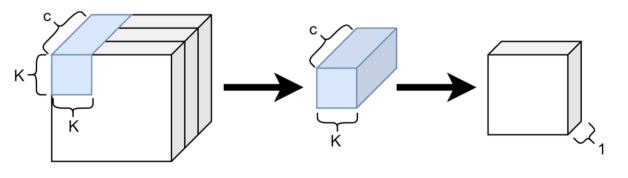
- the depthwise convolution
- the pointwise (1x1) convolution.

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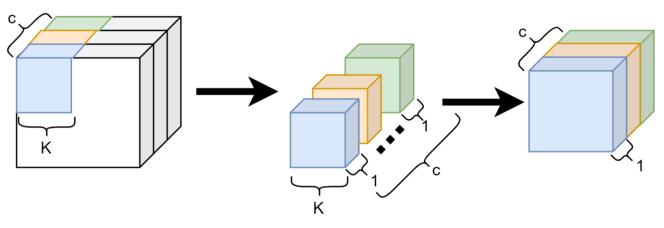
# Depth-wise Sep. CONV



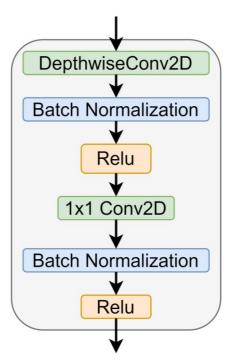
#### 1 Filter Normal Convolution



#### **DepthWise Convolution = 1 filter KxKx1 for each channel**

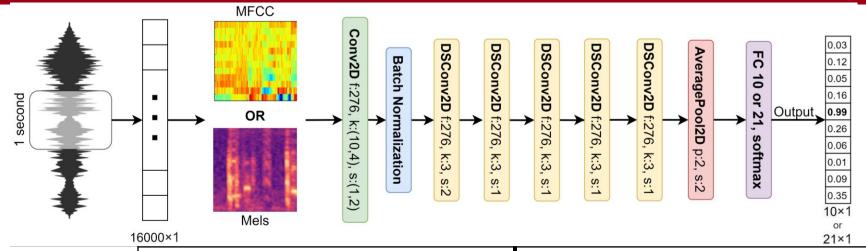


#### **Separaple Depthwise Convolution**



# DSConv Model - Large



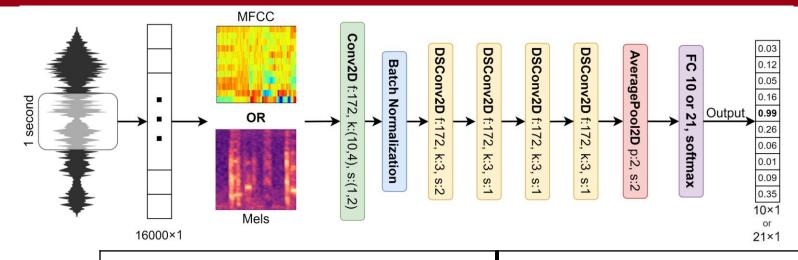


	<b>10 commands</b> (30k - 3k - 3k)		<b>21 commands</b> (84k - 9k - 11k)			
	80 Mels	40 MFCC	$40 + \Delta_s$ MFCC	80 Mels	40 MFCC	$40 + \Delta s$ MFCC
Accuracy	96.0	95.3	95.5	93.4	93.7	92.7
# params	874,930	571,330	1,178,530	1,375,881	738,321	2,013,441
Speed (ms) With FE	33.39 41.44	30.24 45.32	33.42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

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## DSConv Model - Medium = DIPARTIMENTO DI LI DELL'ANTIMENTO DI LI DELL'ANT



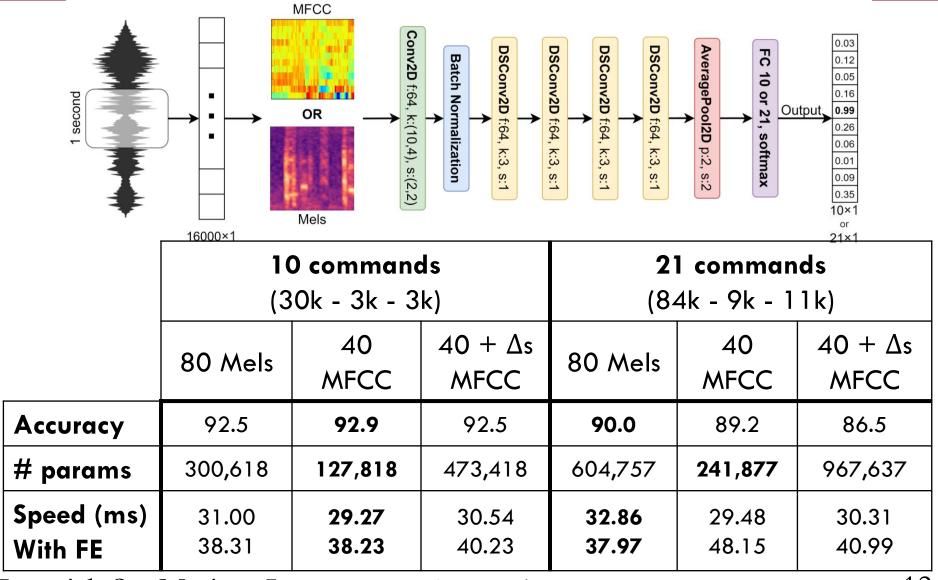


	<b>10 commands</b> (30k - 3k - 3k)		<b>21 commands</b> (84k - 9k - 11k)			
	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		80 Mels	40 MFCC	$40 + \Delta s$ MFCC	
Accuracy	94.3	95.0	94.8	92.7	92.2	91.7
# params	469,398	262,998	675,798	832,673	399,233	1,266,113
Speed (ms) With FE	30.75 38.49	29.55 38.23	30.76 41.82	32.25 39.72	30.01 46.76	33.03 47.08

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### DSConv Model - Small





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### Ensemble 10-cmd



Ensemble between the best models.

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

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# Ensemble 21-cmd



Ensemble between the best models.

	<b>21 commands</b> (84k - 9k - 11k)					
	Large	Large Medium Small				
	DSConv L 80 Mels +	DSConv L 40 MFCC +	DSConv L 40 MFCC +			
	DSConv L 40 MFCC +	DSConv M 80 Mels +	DSConv M 40 MFCC +			
	DSConv L 40 MFCC Δ	DSConv M 40 MFCC	DSConv S 40 MFCC			
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			

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### Performances 10-cmd



	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 1D CNN 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: 1D CNN on raw data

### Performances 21-cmd



	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	<i>7</i> 38,321	39.66
Our DSConvMedium + 80Mels	92,7	832,673	39,72
Our DSConvSmall + 80Mels	90,0	604,757	37,97
Our 1D CNN on Raw data	89,1	257,733	28,25

• **Best**: Ensemble Large

• Smaller: 1D CNN on raw data

• **Fastest**: 1D CNN on raw data

### Conclusions



#### **Conclusions:**

- The tests showed that our model was very good at classify keywords.
- Unfortunately we didn't beat the state-of-the-art models.
- We found that the number of convolutional layers played a key role in detecting high-level concepts
- There is not so much difference between using 80 Mels or 40 MFCCs.
- We presented different model sizes in order to fit different devices.

#### **Future Work:**

- Try different hyper-parameters during training
- Change the **structure** of the **network** using:
  - SincConv
  - GDSConv
- Build a Feature extractor with convolutional autoencoder

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### Thank You



# Thanks for your attention! Any questions?