MOSCOW INSTITUTE OF PHYSICS AND TECHNOLOGY

Speech Technology 2022

Lecture #5
STFT & Keyword Spotting

@georgygospodinov

Plan

- From Fourier Transform to Short Time Fourier Transform
  - empirical examples
  - windowing
  - scaling
- Keyword Spotting
  - problem formulation
  - challenges
  - metrics
  - architectures
  - benchmarks
- Homework

Why do we need spectrograms?

$$e^{-\frac{(t-T/2)^2}{\beta}} \sin(2\pi\nu t + \alpha t^2)$$

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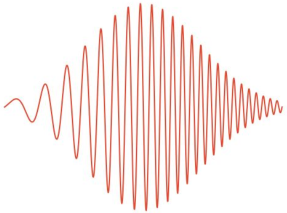

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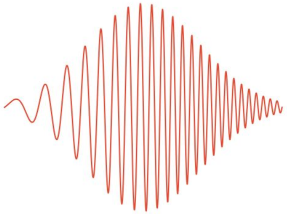

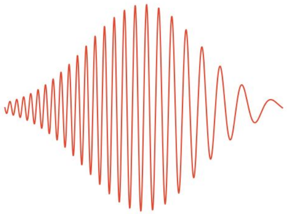

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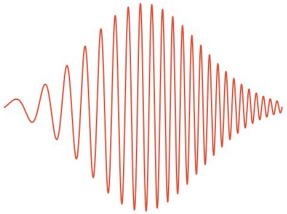

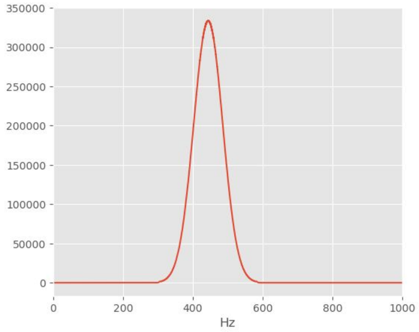

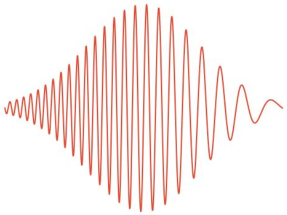

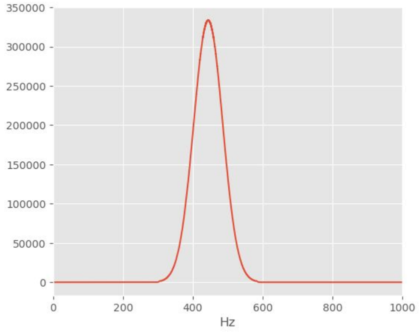

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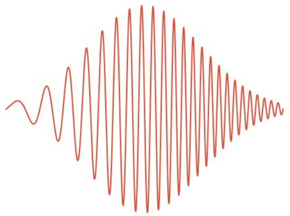
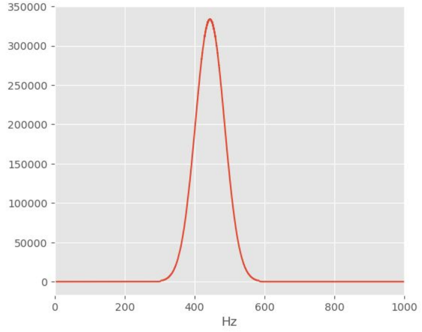
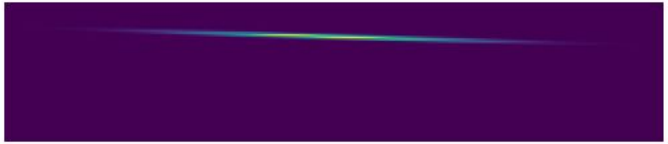
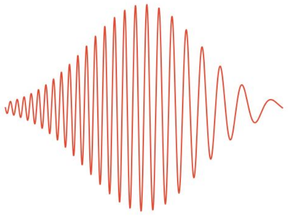
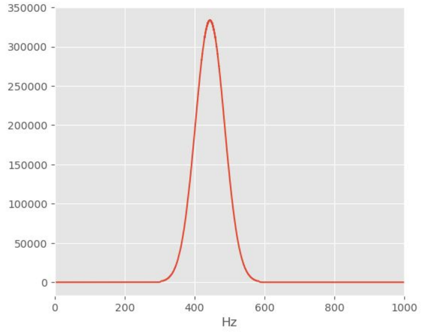


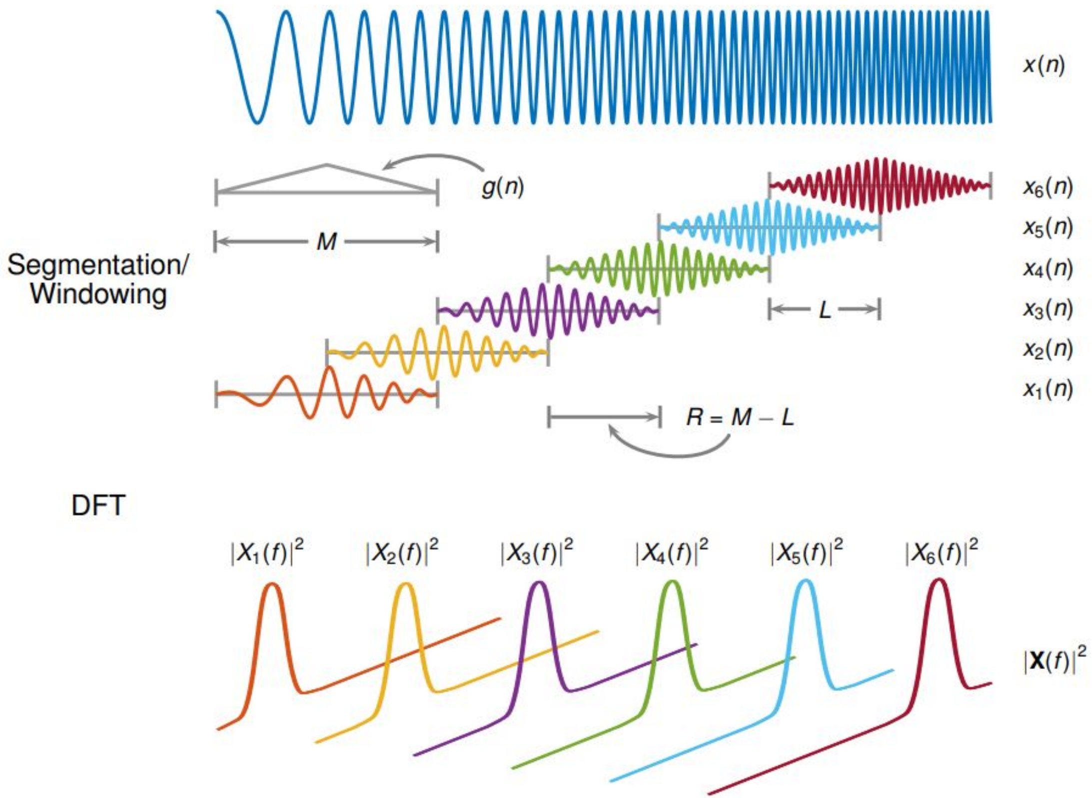






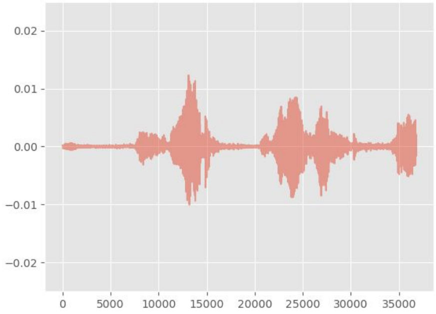


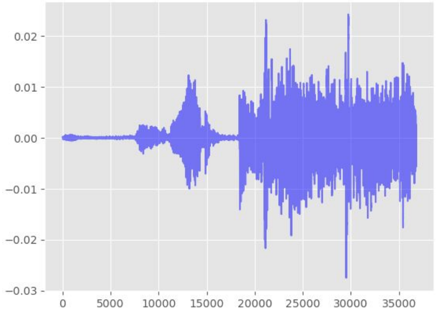
Spectrogram: Short Time Fourier Transform



Why do we need spectrograms?

Time Domain





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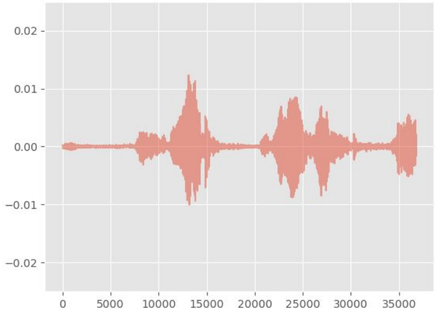
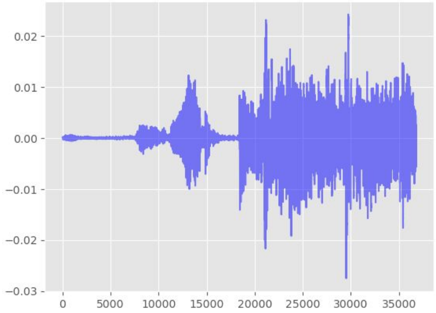
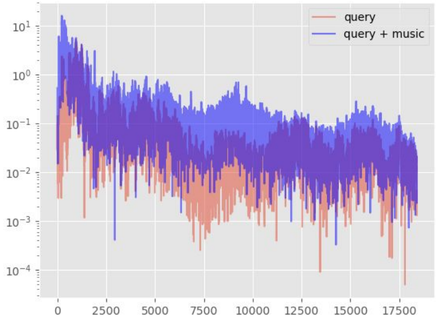




FFT



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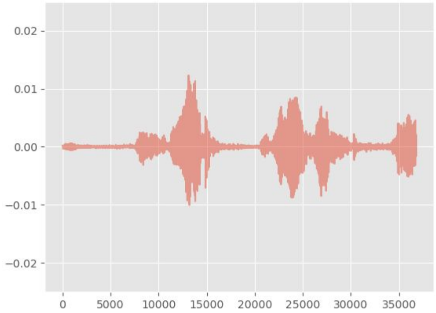

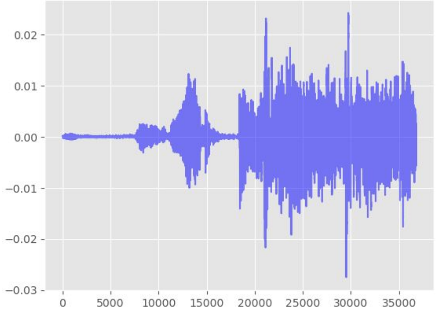

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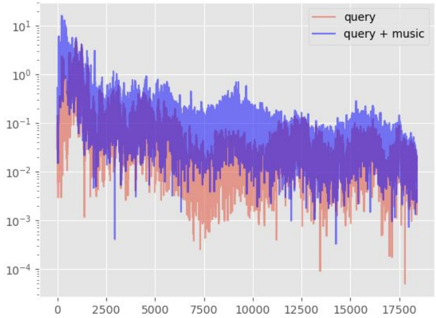
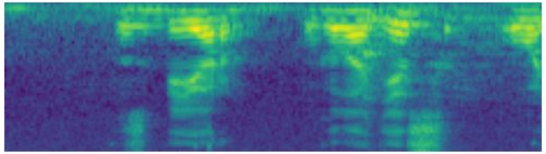
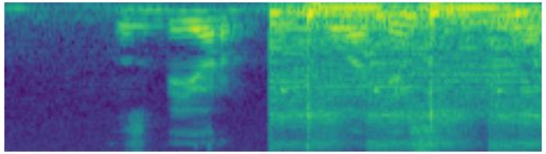
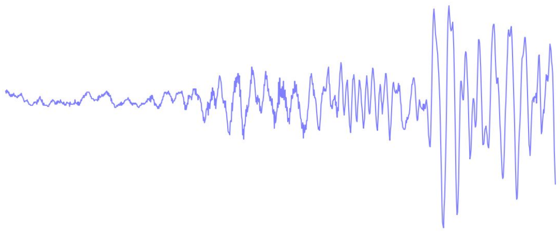


Log Mel STFT





Spectrogram: Windowing



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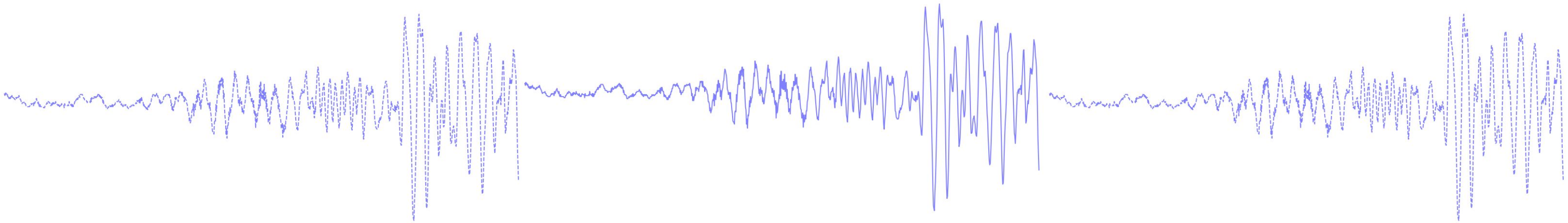

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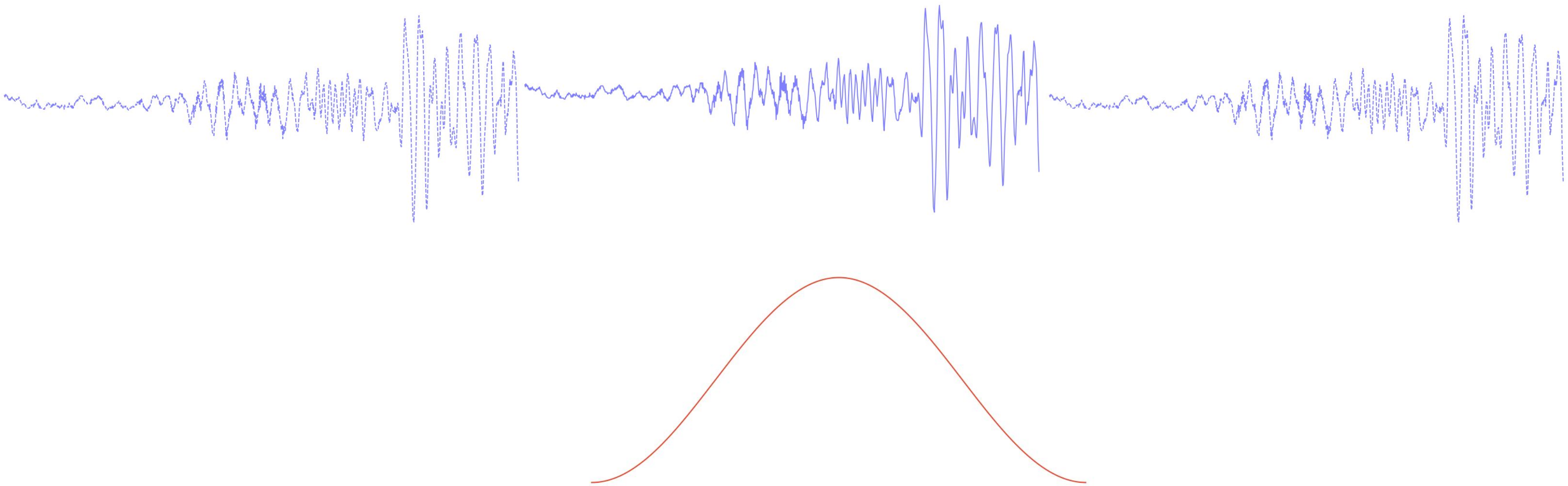

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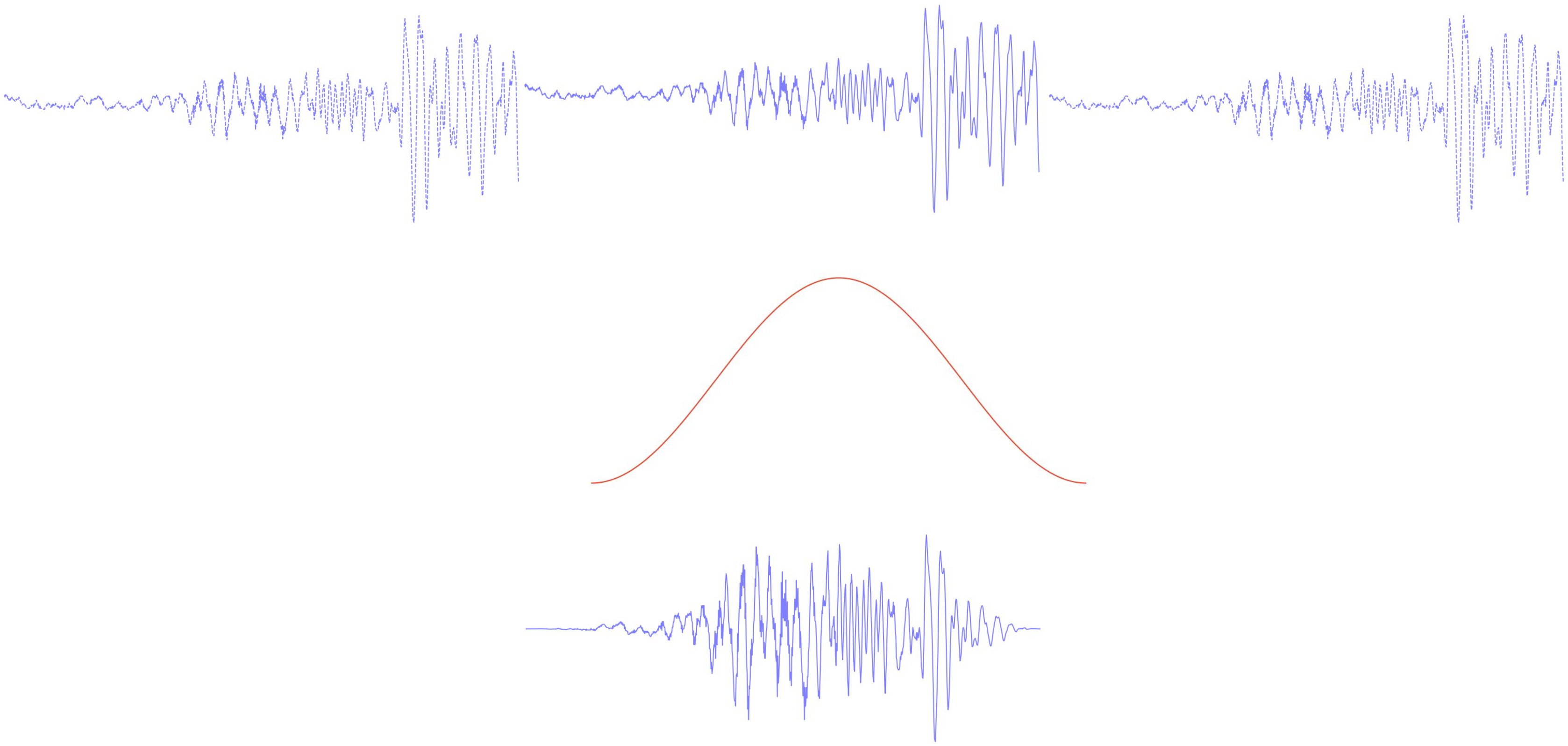

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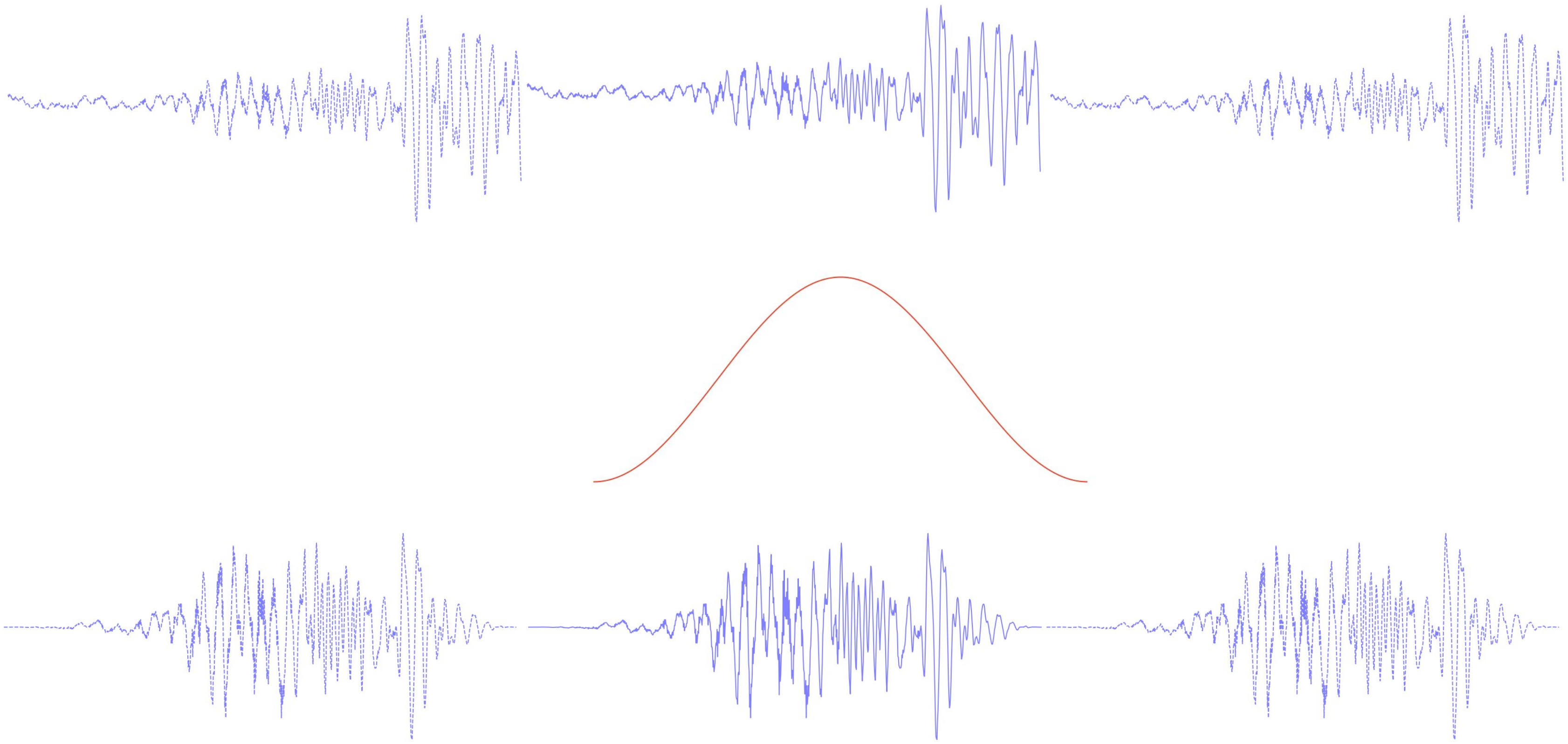
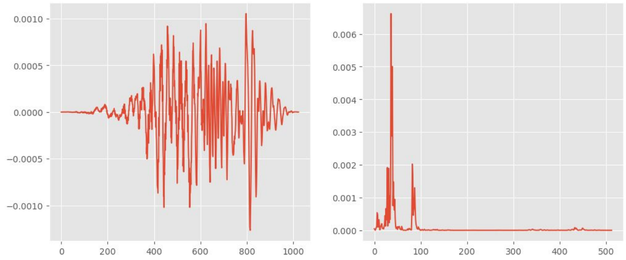


Spectrogram: window length?



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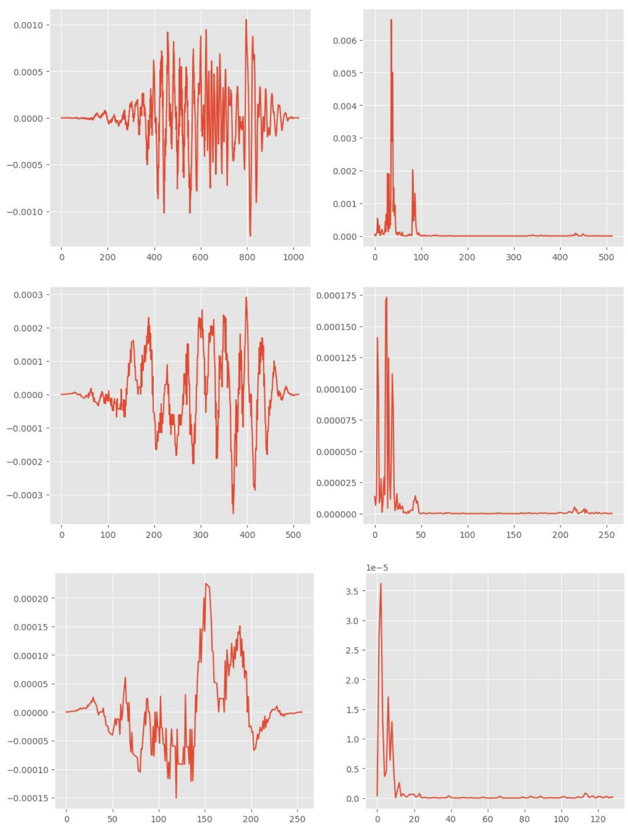

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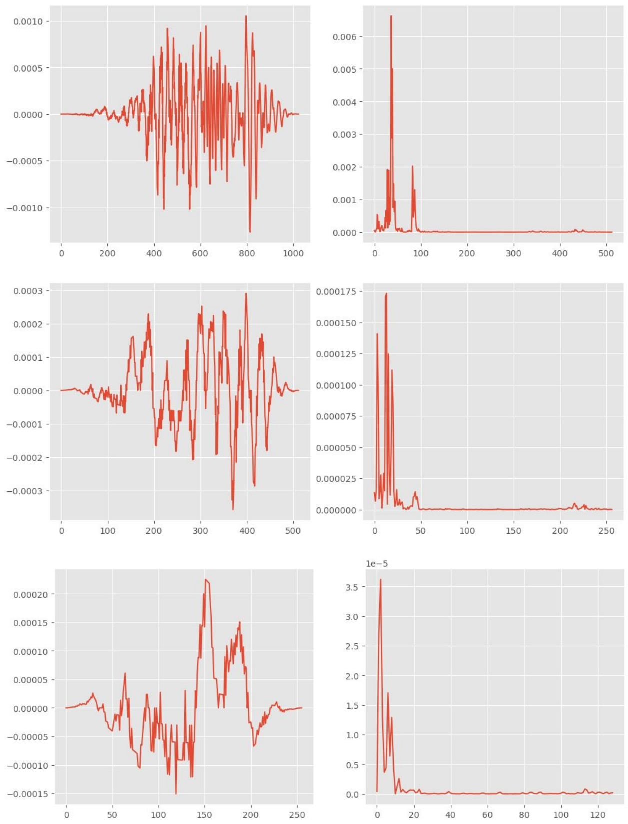
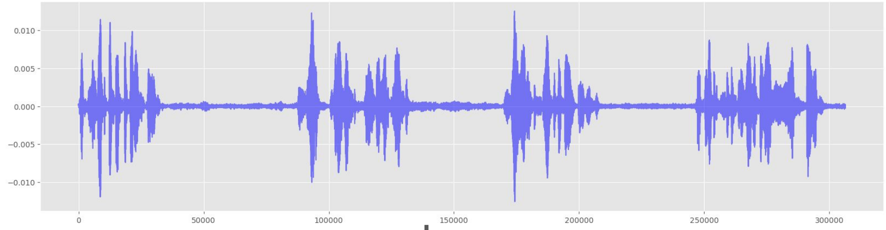
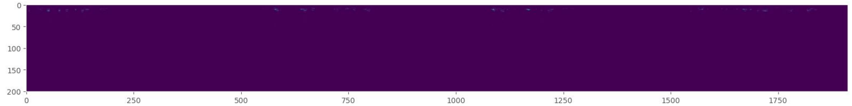


- tradeoff between time-domain and frequency-domain resolution
- typical values:
  - window_length = 25ms
  - hop_length = 10ms

Spectrogram: Logarithmic Scale



torch.stft



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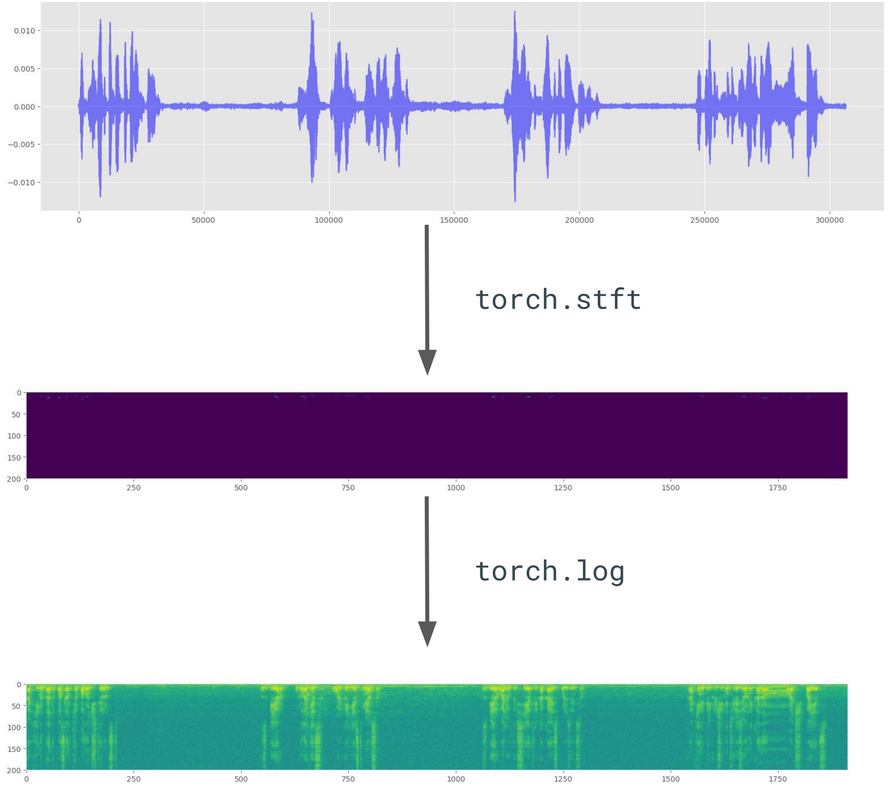


- inspired by human ear sensitivity: we don’t perceive loudness on a linear scale but rather on a logarithmic scale

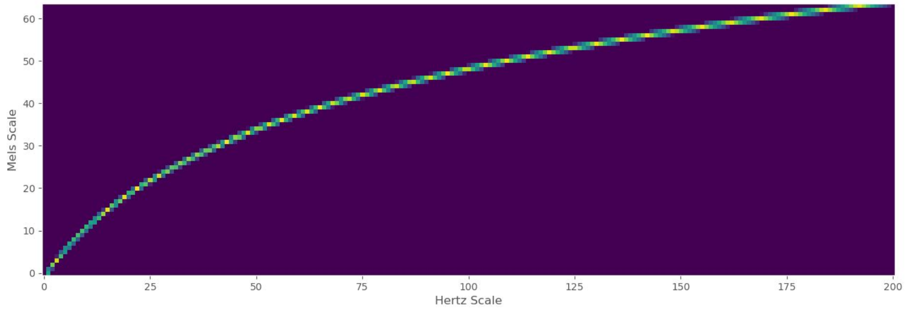
Spectrogram: Mel Scale

$$m[mel] = 1127 \ln(1 + \frac{f[Hz]}{700})$$

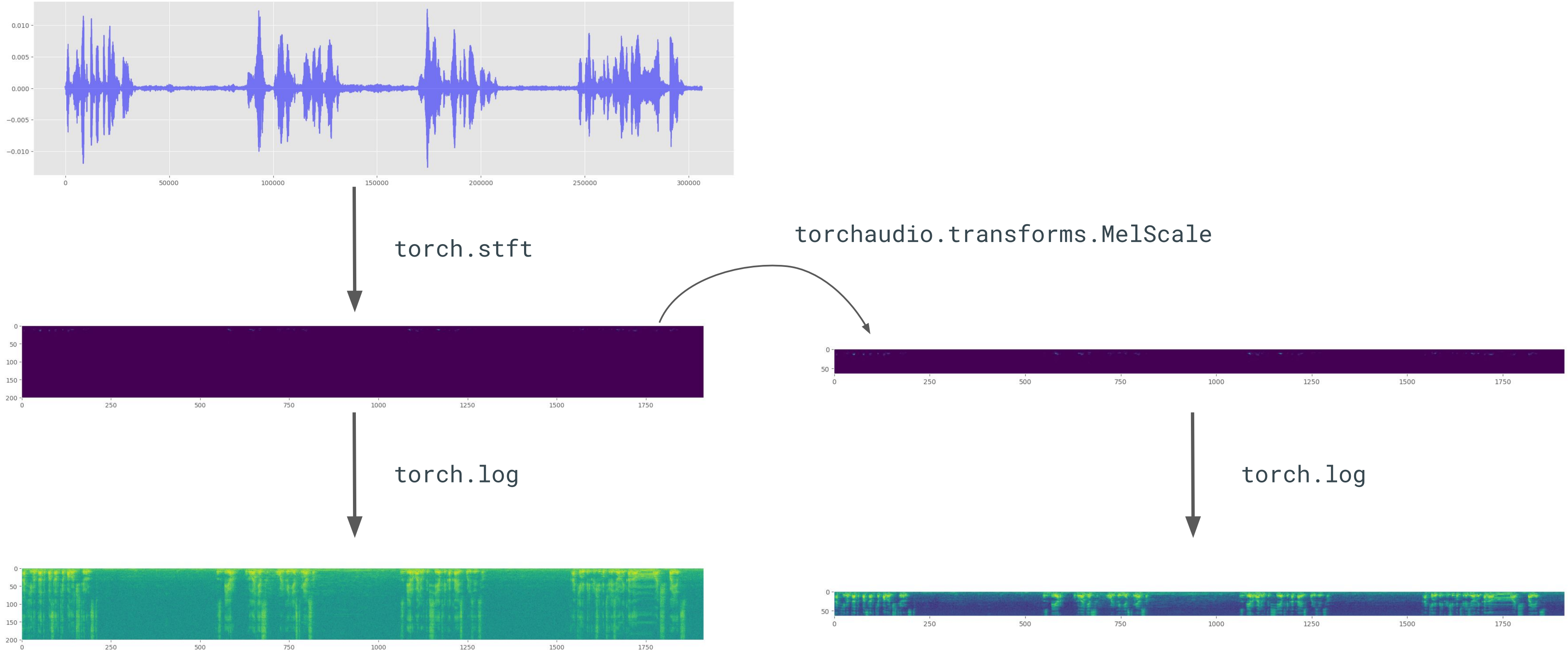
- inspired by human ear sensitivity

```
mel_scaler = torchaudio.transforms.MelScale(
    n_mels=n_mels,
    sample_rate=sr,
    n_stft=n_fft // 2 + 1
)

plt.figure(figsize=(20, 5))
plt.imshow(mel_scaler.fb.T)
plt.xlabel('Hertz Scale')
plt.ylabel('Mels Scale')
plt.grid()
plt.gca().invert_yaxis()
plt.show()
```



Spectrogram: Logarithmic Scale



Spectrogram: summary

- STFT + Mel Scaling + Log Scaling
- Parameters:
  - window_length
  - hop_size
  - window_function
  - n_mels
- Example
  - 1 second wav, sr=16kHz
  - window_length=400, hop_size=160, n_mels=64
  - mel-spectrogram 64x101
- Applications:
  - KWS
  - ASR
  - TTS
  - …

Keyword Spotting

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- When user is initiating interaction with device?
- Searching through audio stream by keyword

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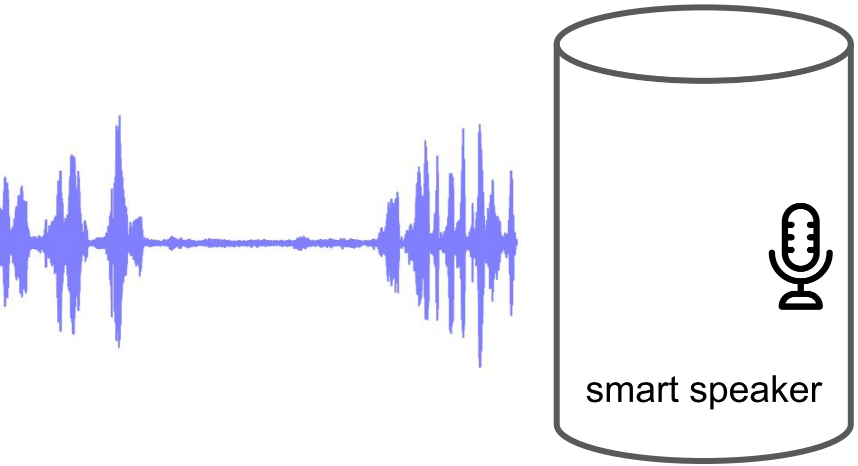
- Searching through audio stream by keyword

- Phrase Spotting
- Wake Word Detection
- Wake-Up Word Detection
- Hotword Detection
- Trigger Word Detection

Keyword Spotting



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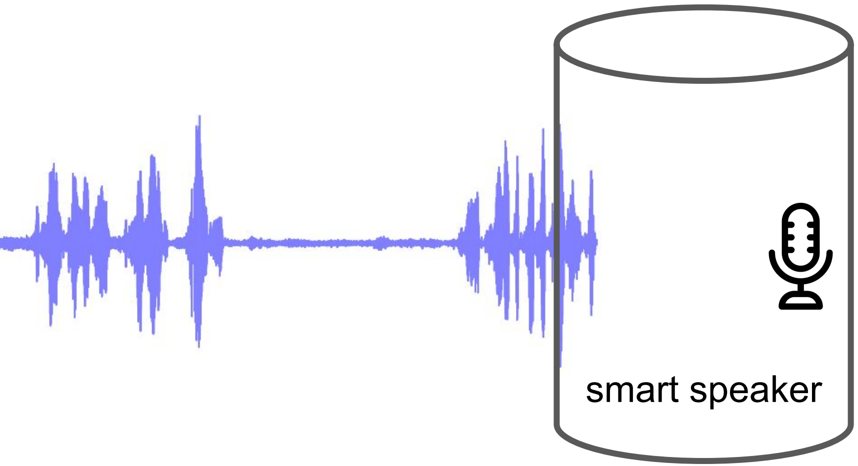

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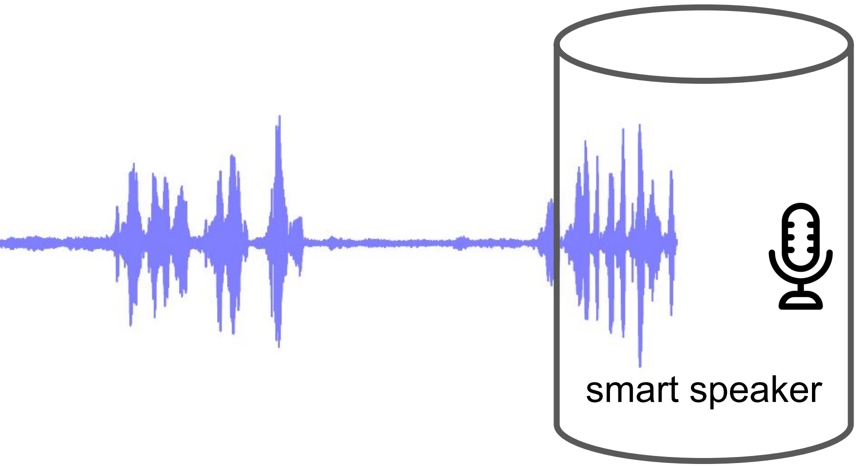

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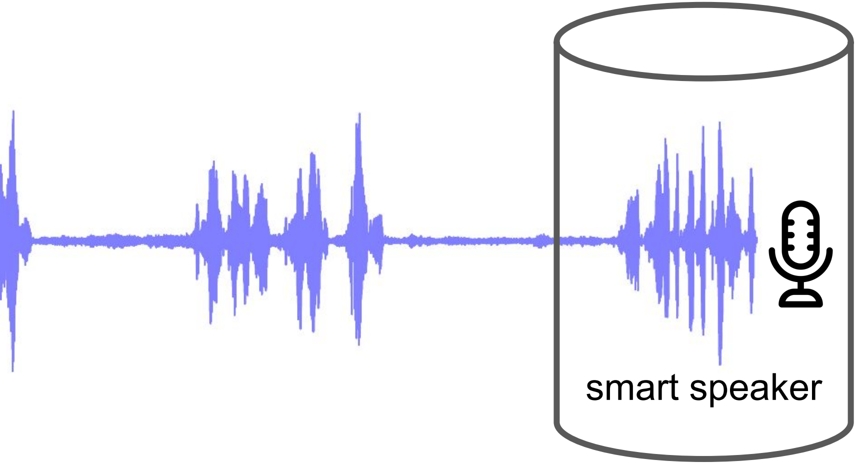
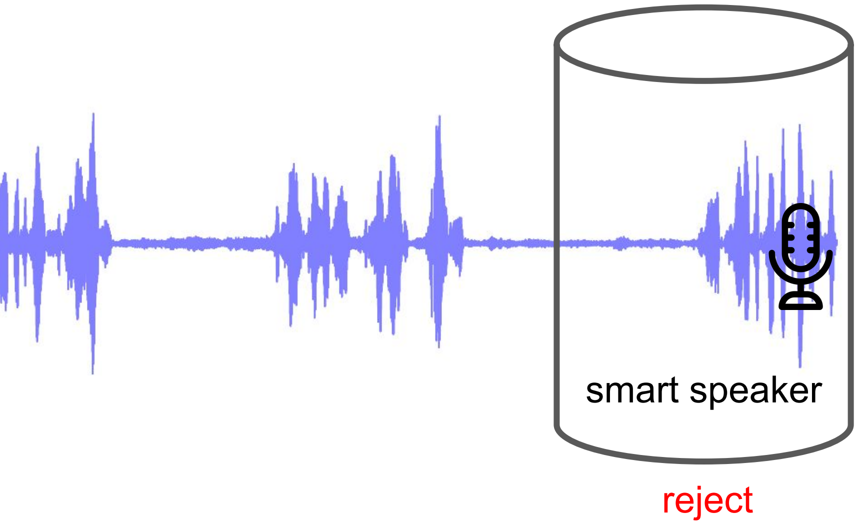


reject

Keyword Spotting



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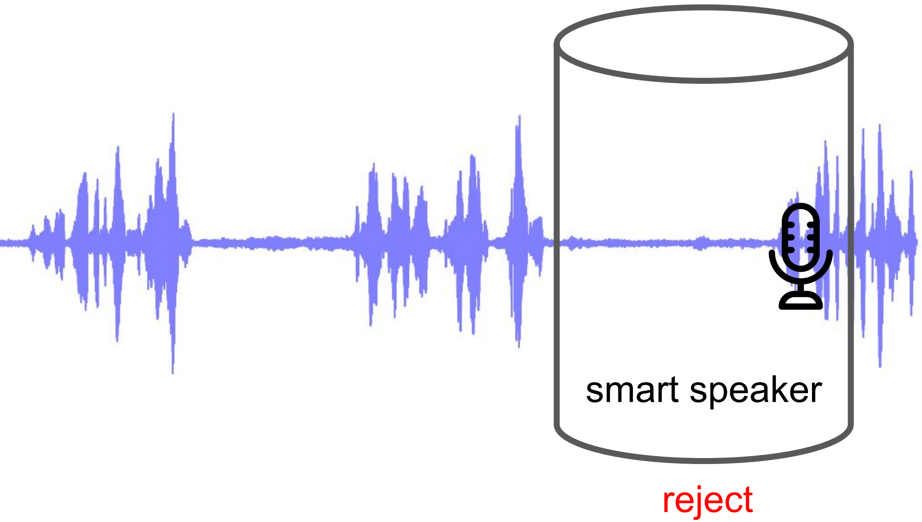

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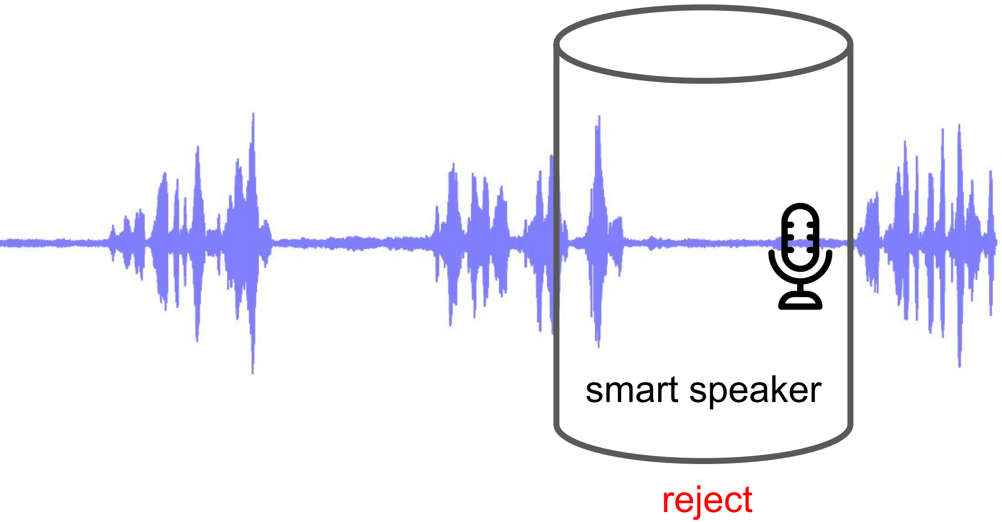

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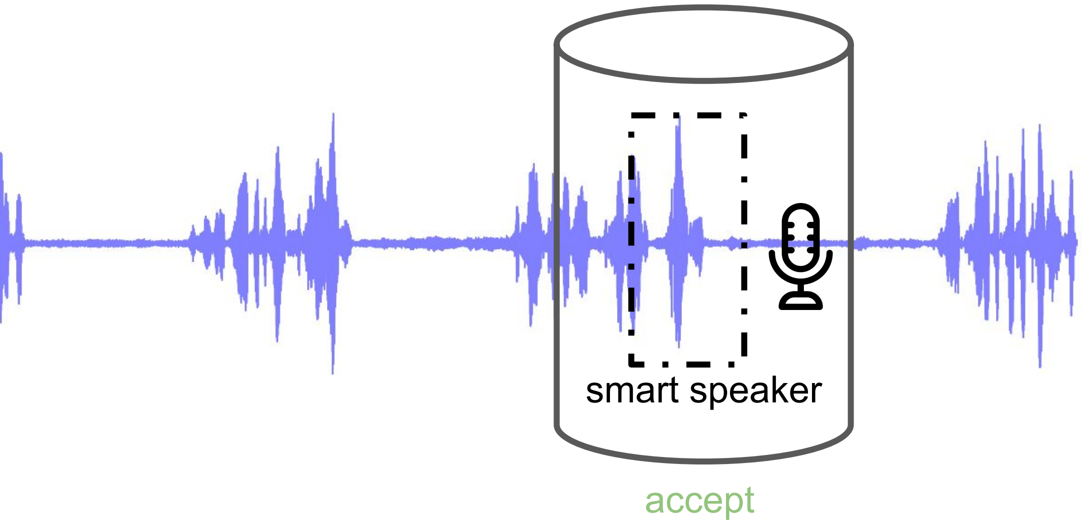

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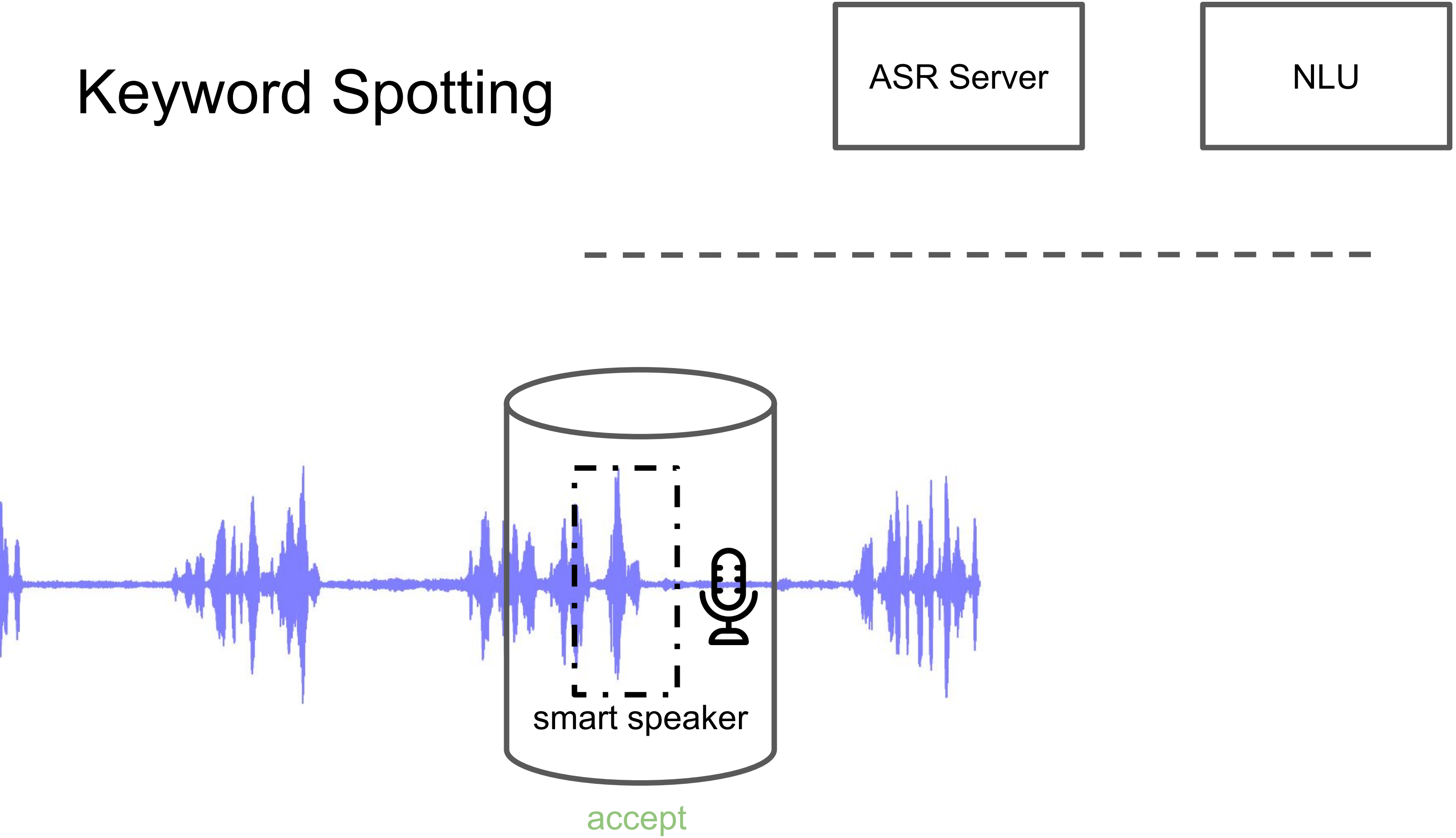

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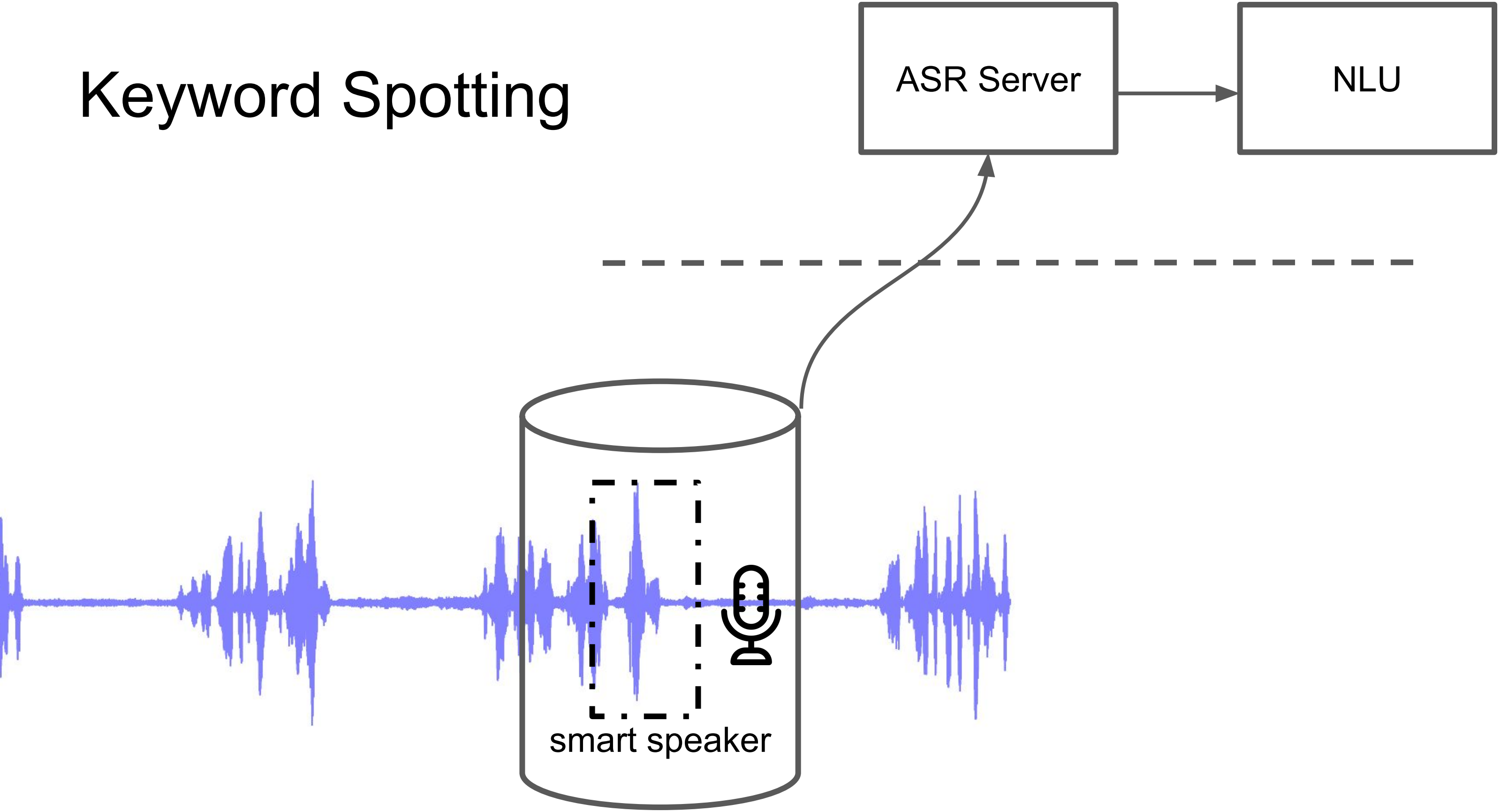

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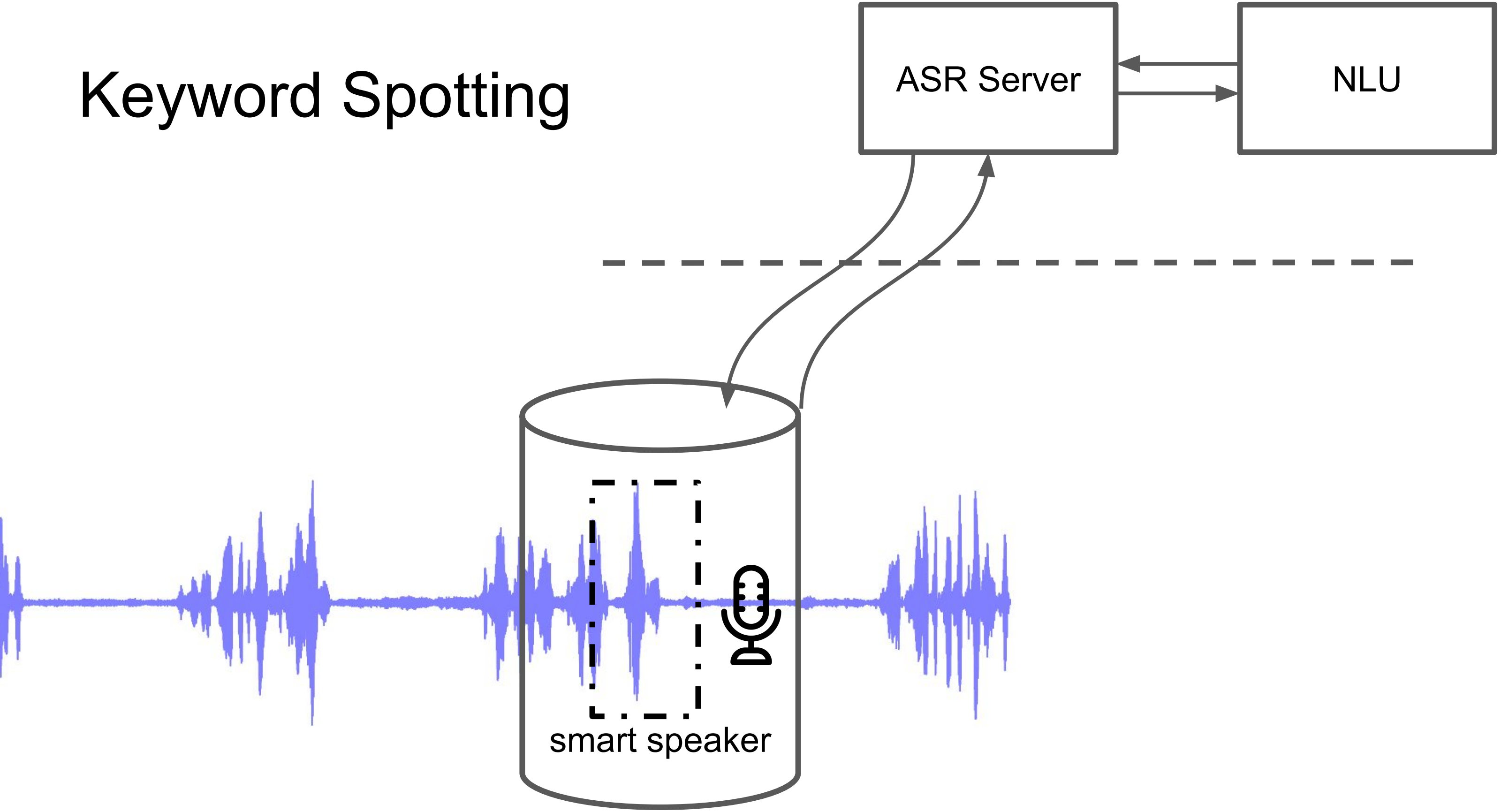

Why on-device?

- Privacy

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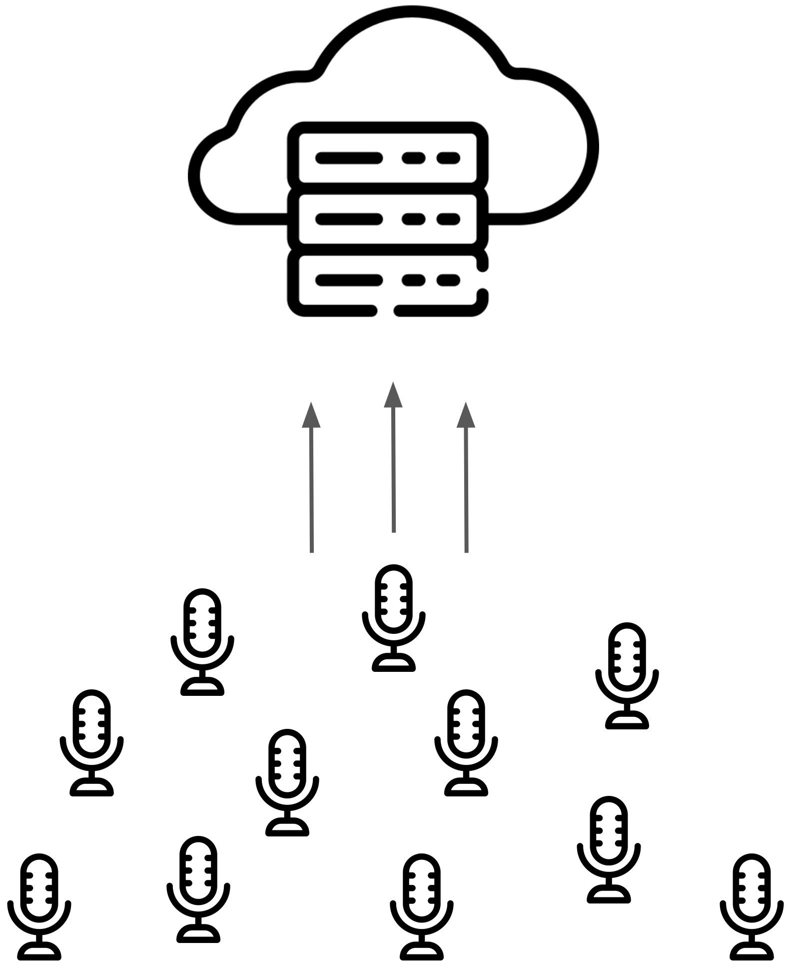
- Computational Costs



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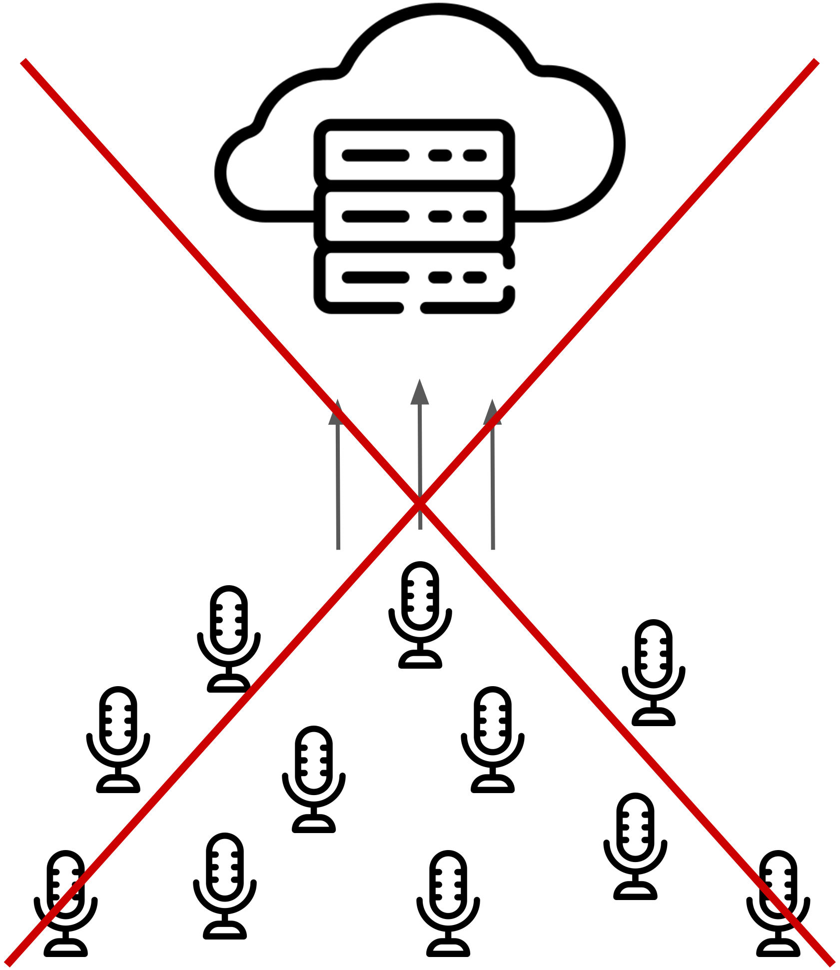
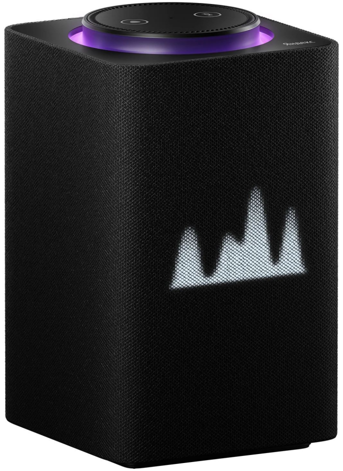
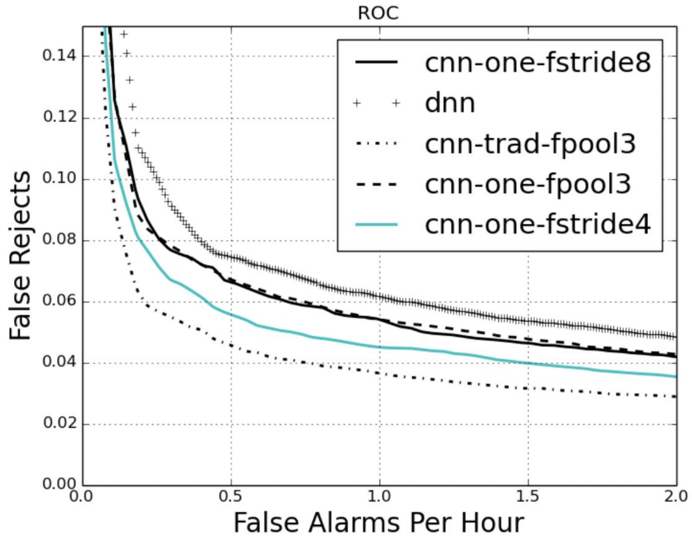


Keyword Spotting: Better, Faster, Smaller



Metrics

- FAR:
  - **F**alse (**A**ccepts / **A**larm / **A**ctivations) **R**ate
  - FAR = FP / (FP + TN)
- FRR
  - **F**alse **R**ejects **R**ate
  - FN / (FN + TP)
- FAh:
  - False Accepts per hour
- lower AUC is better
- model threshold => operation point

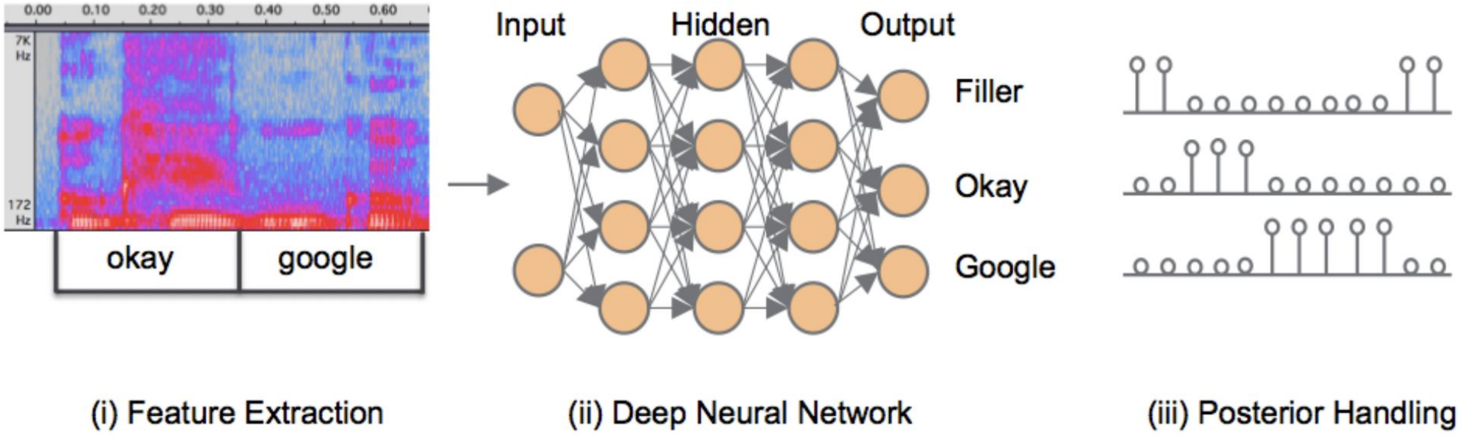


Challenges

- Accuracy: listen continuously, but only trigger at the right moment
  - False Rejects => User Unsatisfaction
  - False Accepts => Privacy
- Latency: Light up immediately
- Robust: low SNR, TV background, music playback, …
- Memory footprint, computational constraints, battery power

SMALL-FOOTPRINT KEYWORD SPOTTING USING DEEP NEURAL NETWORKS

- Google (2014). Cited by 532



[SMALL-FOOTPRINT KEYWORD SPOTTING USING DEEP NEURAL NETWORKS]

Posterior Handling

$$p'_{ij} = \frac{1}{j - h_{smooth} + 1} \sum_{k=h_{smooth}}^{j} p_{ik}$$

SMALL-FOOTPRINT KEYWORD SPOTTING USING DEEP NEURAL NETWORKS

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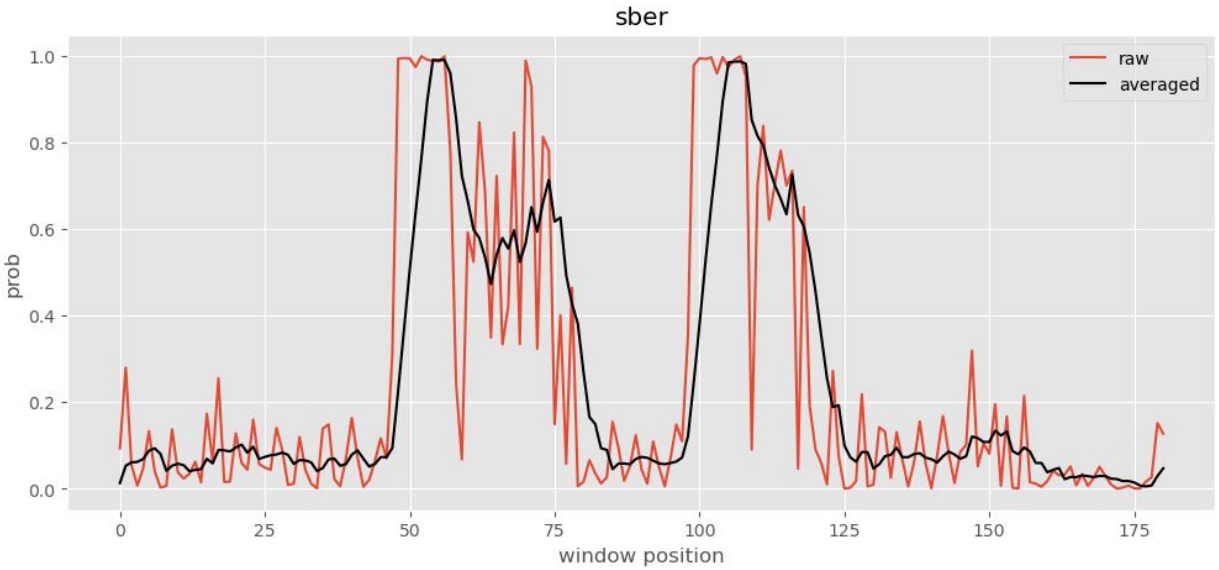
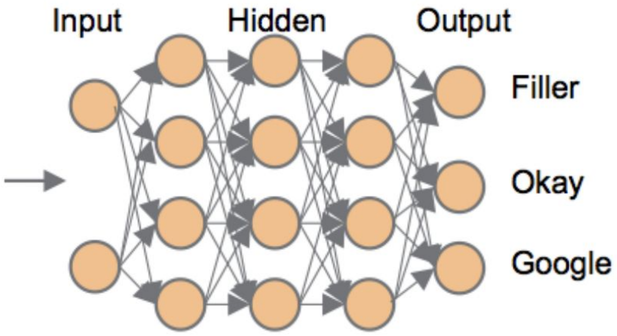


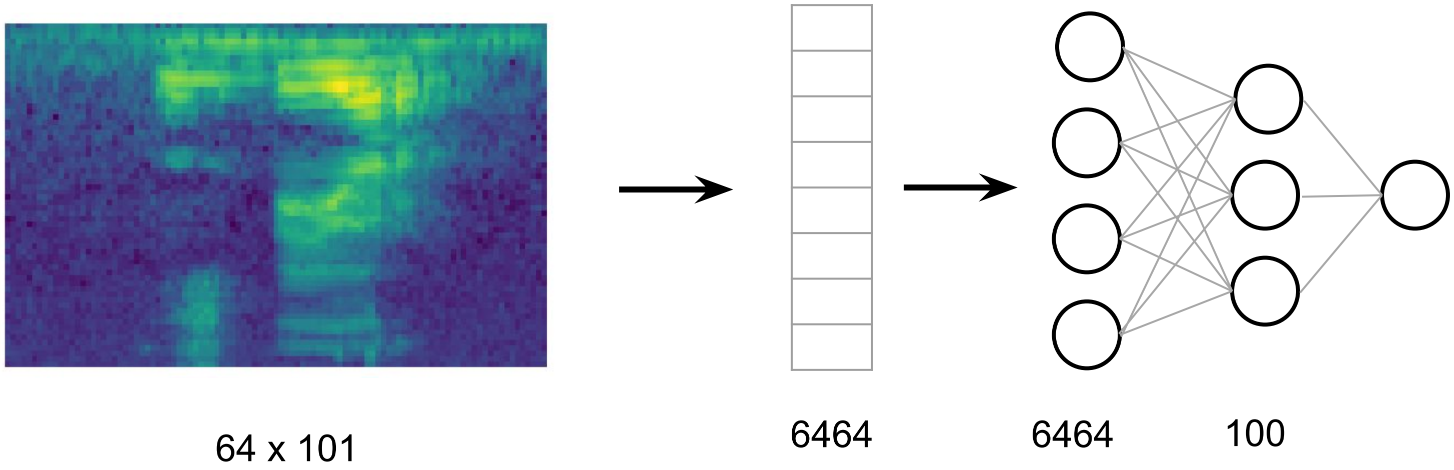
SMALL-FOOTPRINT KEYWORD SPOTTING USING DEEP NEURAL NETWORKS

- Google (2014)
- Problems?

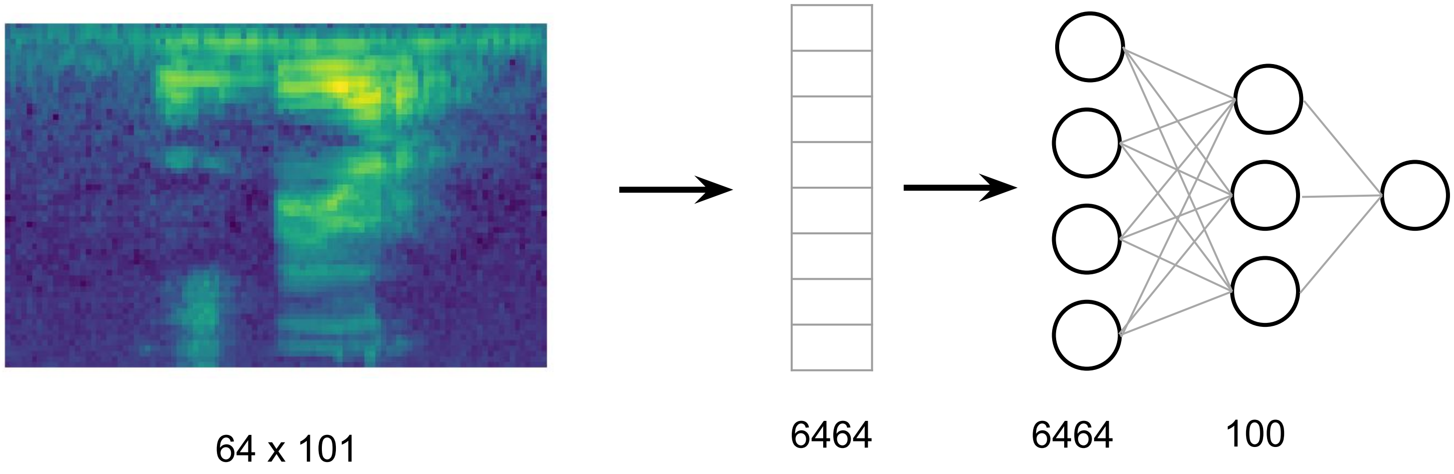


(ii) Deep Neural Network

DNN Problems



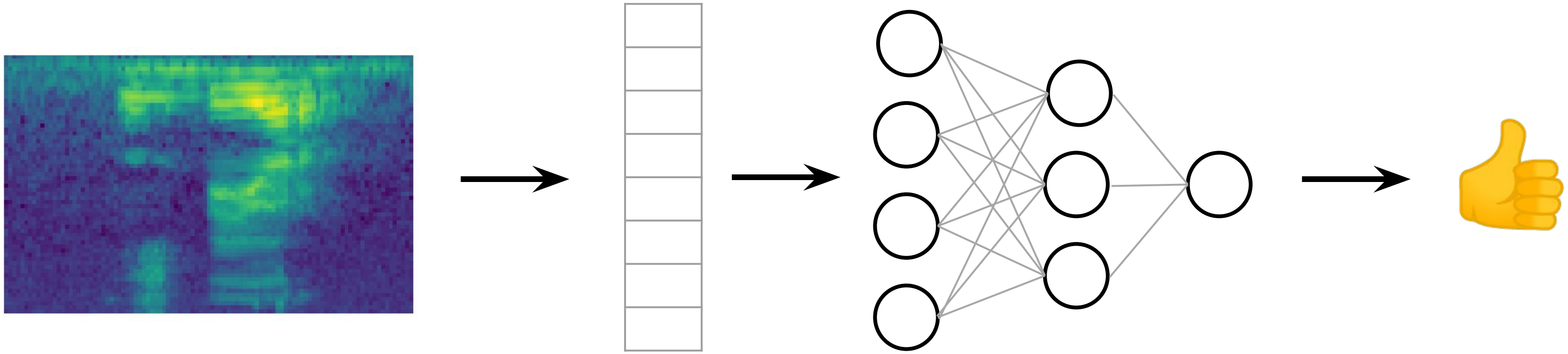
DNN Problems




```
>>> import torch
>>> sum(p.numel() for p in torch.nn.Linear(6464, 100).parameters())
646500
```

DNN Problems

Train



DNN Problems

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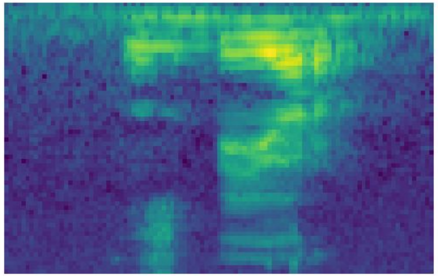
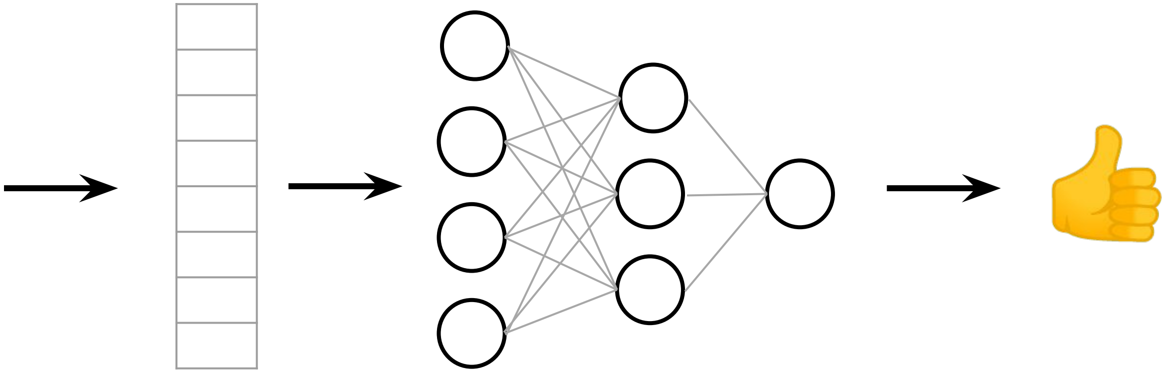
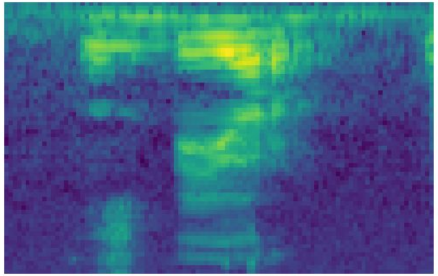
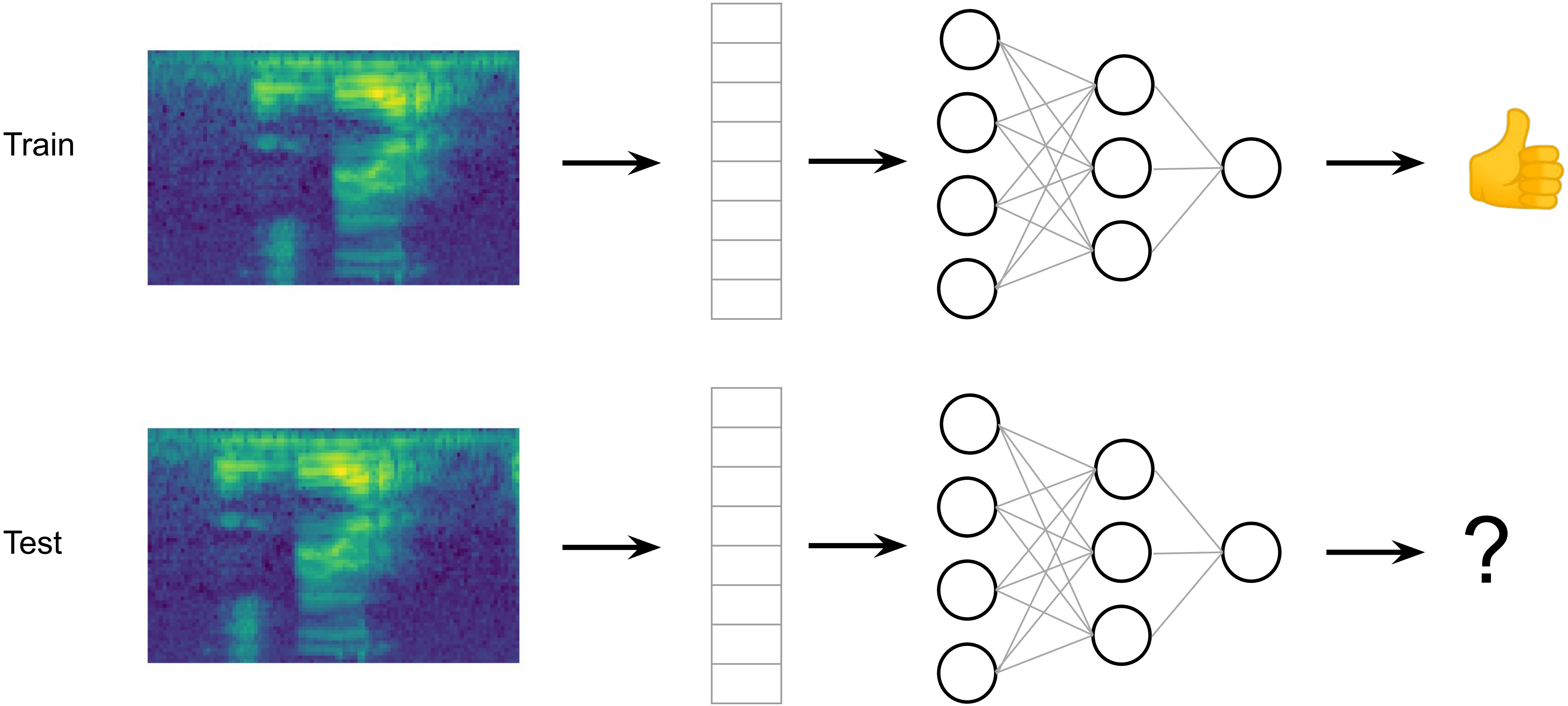




Test



DNN Problems



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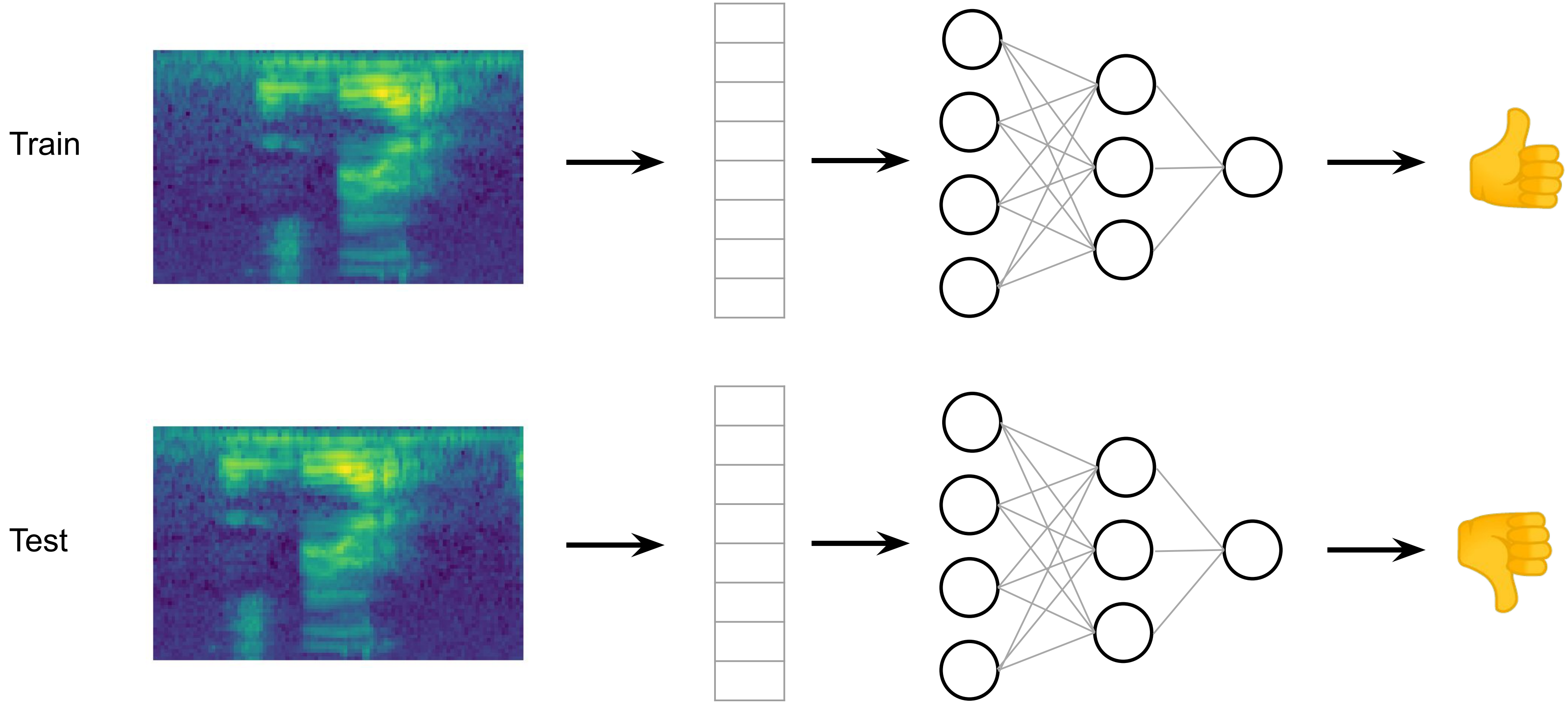
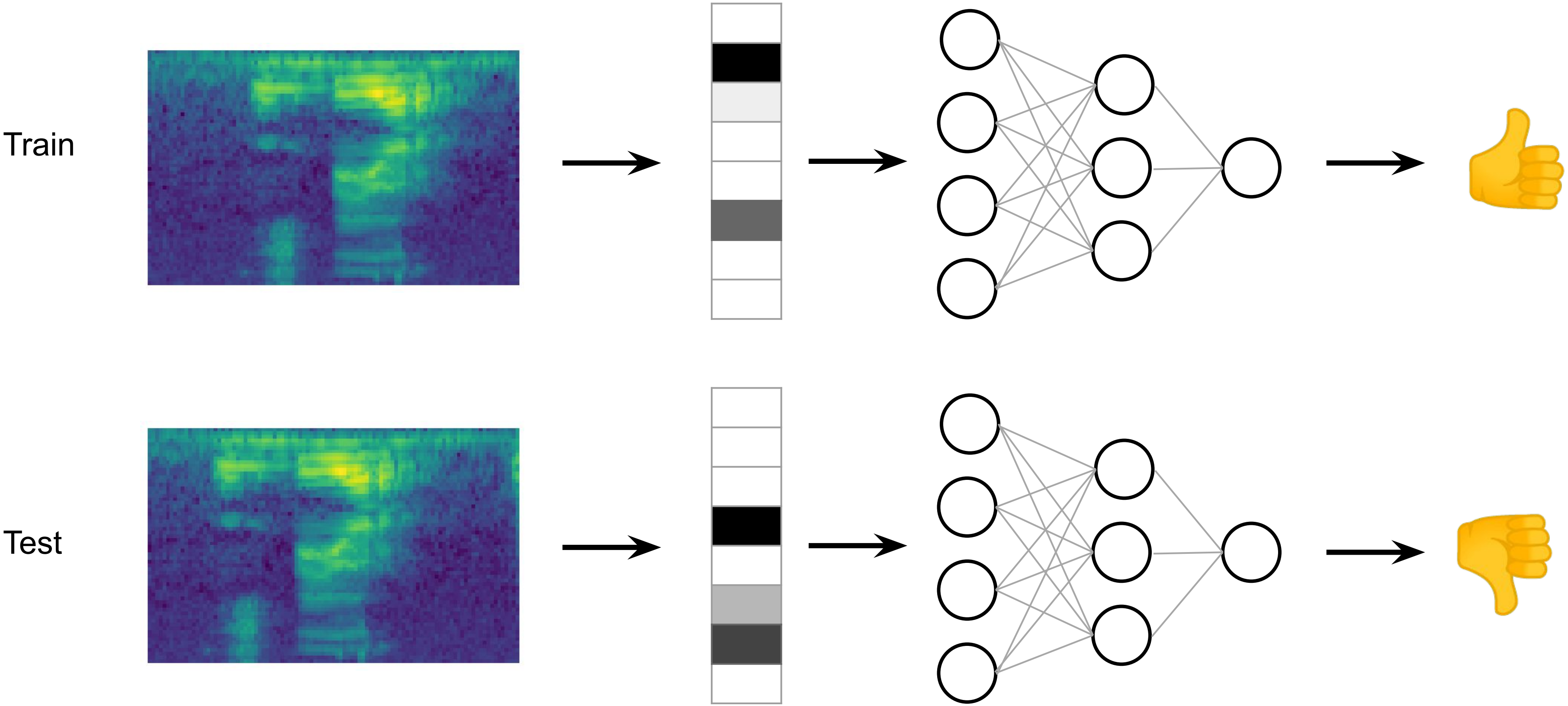


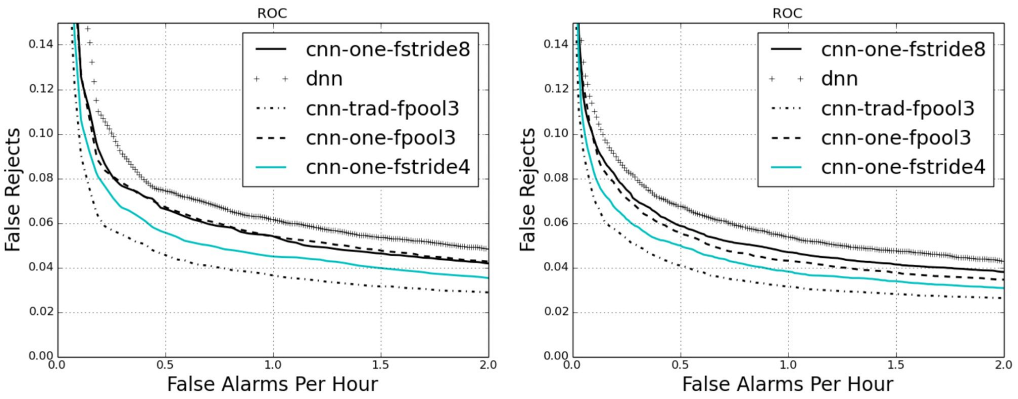
DNN Problems: no translational equivariance



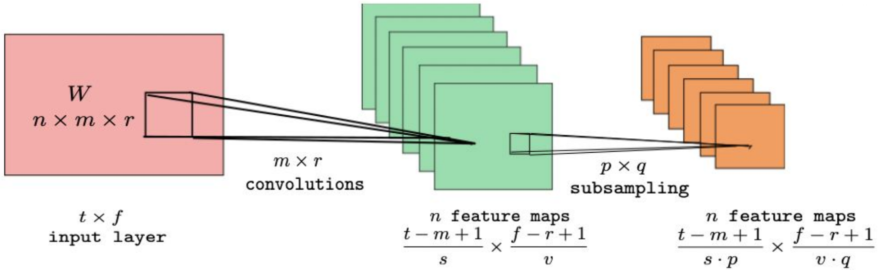
Convolutional Neural Networks for Small-footprint Keyword Spotting

- Google (2015), cited by 522

type	m	r	n	p	q	Params	Mult
conv	32	8	54	1	3	13.8K	456.2K
linear	-	-	32	-	-	19.8K	19.8K
dnn	-	-	128	-	-	4.1K	4.1K
dnn	-	-	128	-	-	16.4K	16.4K
softmax	-	-	4	-	-	0.5K	0.5K
Total	-	-	4	-	-	53.8K	495.6K



(a) Results on Clean (b) Results on Noisy



Convolution

$$(A * w)_{ij} = \sum_{i'=0}^{K-1} \sum_{j'=0}^{K-1} A(i+i', j+j')w(i', j')$$

$A =$

3	1	4
1	5	9
2	6	5

$w =$

1	0
0	-1

$(A * w) =$

Convolution

$$(A * w)_{ij} = \sum_{i'=0}^{K-1} \sum_{j'=0}^{K-1} A(i + i', j + j')w(i', j')$$

$$A = \begin{array}{|c|c|c|} \hline 3 & 1 & 4 \\ \hline 1 & 5 & 9 \\ \hline 2 & 6 & 5 \\ \hline \end{array} \qquad w = \begin{array}{|c|c|} \hline 1 & 0 \\ \hline 0 & -1 \\ \hline \end{array} \qquad (A * w) = \begin{array}{|c|c|} \hline \boxed{-2} & \\ \hline & \\ \hline \end{array}$$

Convolution

$$(A * w)_{ij} = \sum_{i'=0}^{K-1} \sum_{j'=0}^{K-1} A(i+i', j+j')w(i', j')$$

$A =$

3	1	4
1	5	9
2	6	5

$w =$

1	0
0	-1

$(A * w) =$

-2	-8

Convolution

$$(A * w)_{ij} = \sum_{i'=0}^{K-1} \sum_{j'=0}^{K-1} A(i+i', j+j')w(i', j')$$

$$A = \begin{bmatrix} 3 & 1 & 4 \\ 1 & 5 & 9 \\ 2 & 6 & 5 \end{bmatrix} \quad w = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \quad (A * w) = \begin{bmatrix} -2 & -8 \\ \boxed{-1} & \end{bmatrix}$$

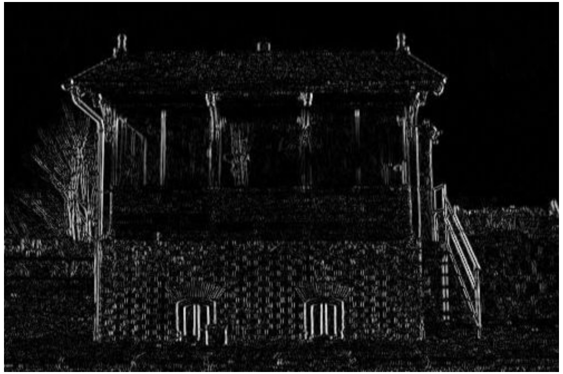
Convolution

$$(A * w)_{ij} = \sum_{i'=0}^{K-1} \sum_{j'=0}^{K-1} A(i+i', j+j') w(i', j')$$

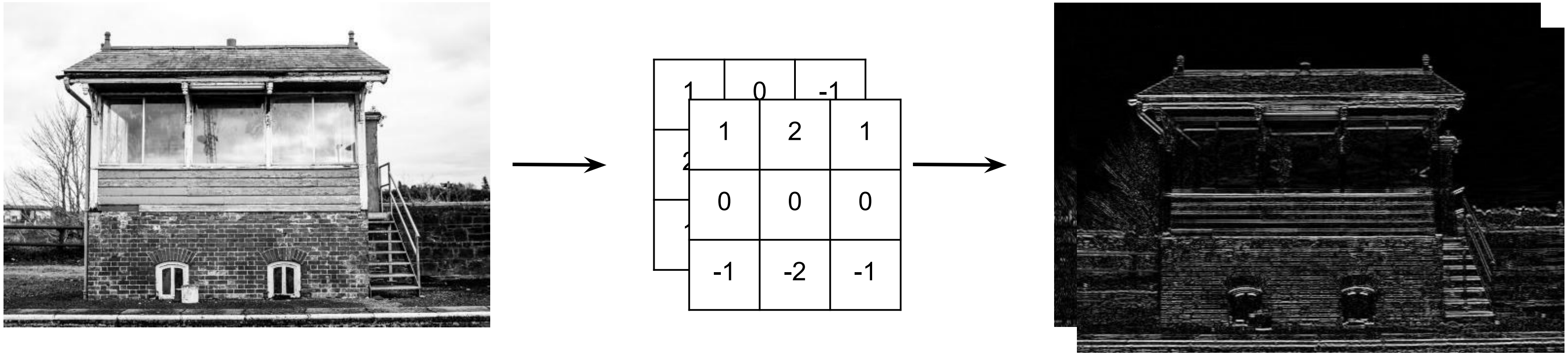
$$A = \begin{bmatrix} 3 & 1 & 4 \\ 1 & 5 & 9 \\ 2 & 6 & 5 \end{bmatrix} \quad w = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \quad (A * w) = \begin{bmatrix} -2 & -8 \\ -1 & \boxed{0} \end{bmatrix}$$

Convolution: Feature Transformation

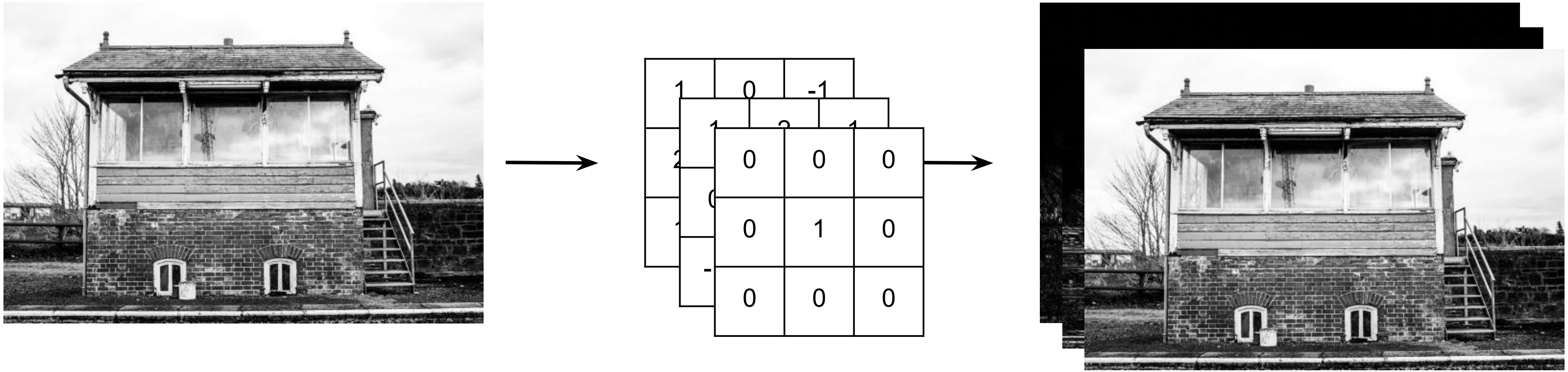
1	0	-1
2	0	-2
1	0	-1



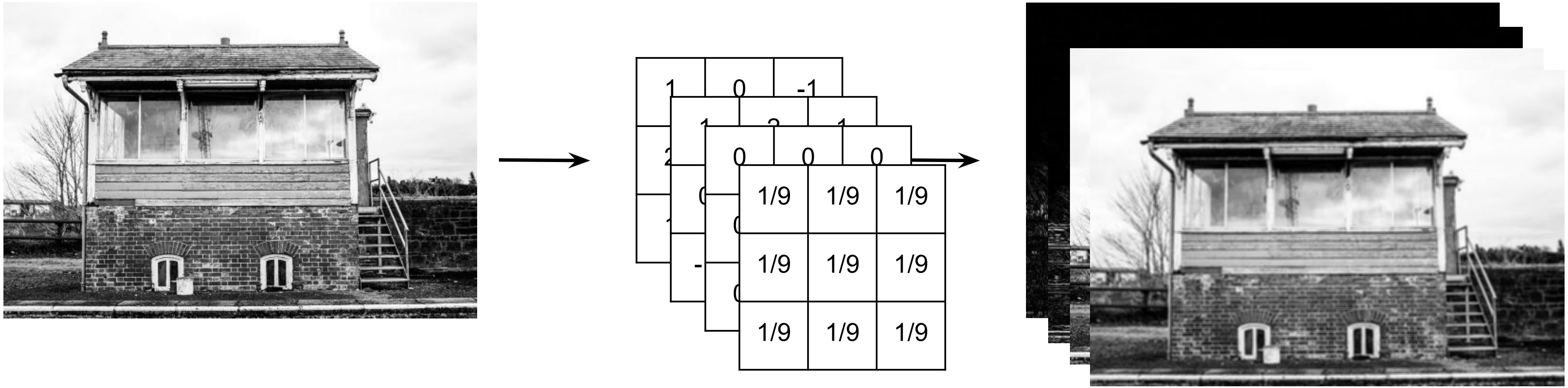
Convolution: Feature Transformation



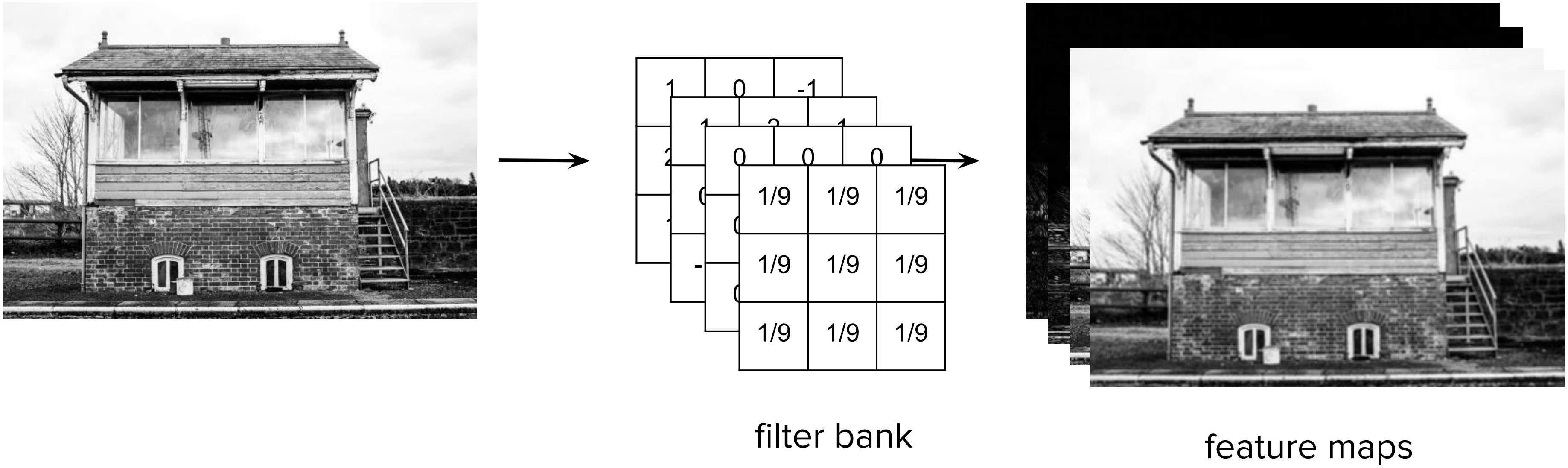
Convolution: Feature Transformation



Convolution: Feature Transformation



Convolution: Feature Transformation



Convolution: Pattern Finding

$$(A * w)_{ij} = \sum_{i'=0}^{K-1} \sum_{j'=0}^{K-1} A(i+i', j+j')\, w(i', j')$$

$A =$

1	2	-1	0	1
-1	1	3	4	4
2	-3	4	3	-4
-3	2	0	-1	0
5	2	-4	0	1

$w =$

1	0
0	-1

$(A * w) =$

0	-1	-5	-4
2	-3	0	8
0	-3	5	3
-5	6	0	-1

Convolution: Pattern Finding

$$(A * w)_{ij} = \sum_{i'=0}^{K-1} \sum_{j'=0}^{K-1} A(i+i', j+j') w(i', j')$$

$$A = \begin{array}{|c|c|c|c|c|} \hline 1 & 2 & -1 & 0 & 1 \\ \hline -1 & 1 & 3 & 4 & 4 \\ \hline 2 & -3 & 4 & 3 & -4 \\ \hline -3 & 2 & 0 & -1 & 0 \\ \hline 5 & 2 & -4 & 0 & 1 \\ \hline \end{array} \qquad w = \begin{array}{|c|c|} \hline 1 & 0 \\ \hline 0 & -1 \\ \hline \end{array} \qquad (A * w) = \begin{array}{|c|c|c|c|} \hline 0 & -1 & -5 & -4 \\ \hline 2 & -3 & 0 & \boxed{8} \\ \hline 0 & -3 & 5 & 3 \\ \hline -5 & \boxed{6} & 0 & -1 \\ \hline \end{array}$$

Convolution: Pattern Finding

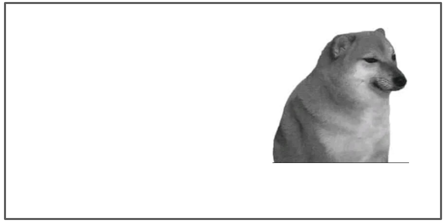
0	1	0
0	1	0
0	1	0

0	0	0
1	1	1
0	0	0

Convolution: summary

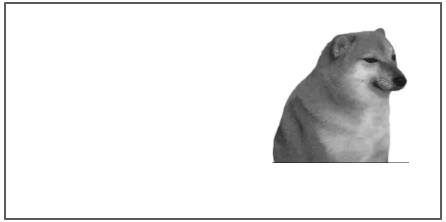
- weights sharing
- pattern finder
- feature transformation
- translational equivariance

Convolution: images vs log mel-spectrograms

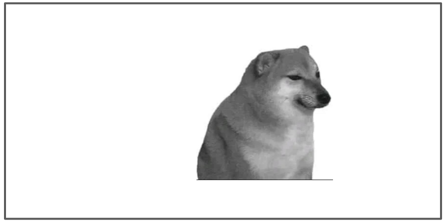


dog

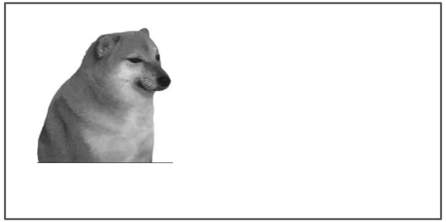
Convolution: images vs log mel-spectrograms



dog

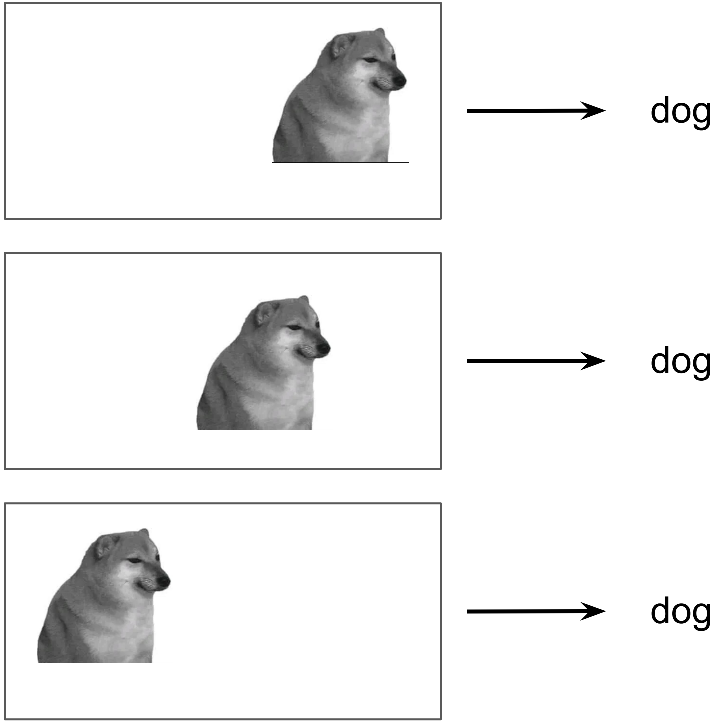


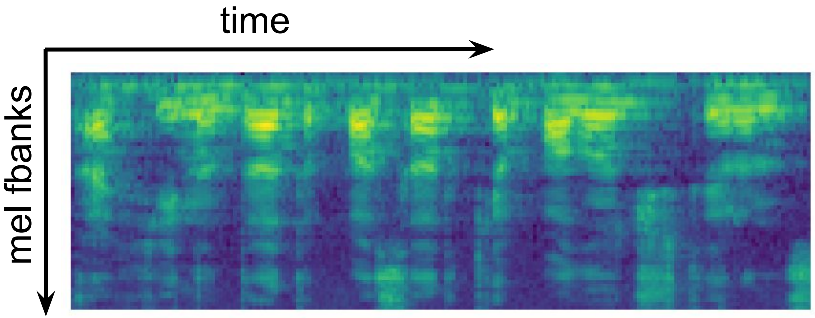
dog



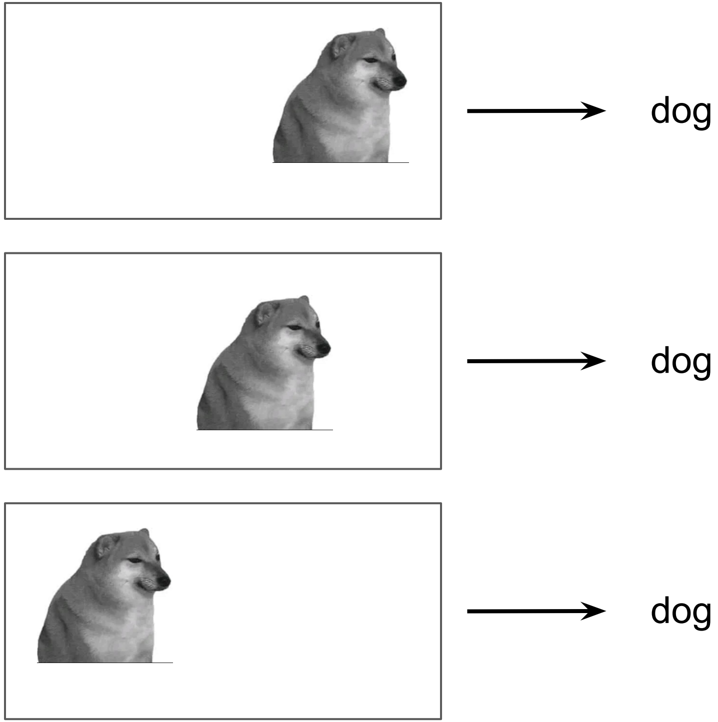
dog

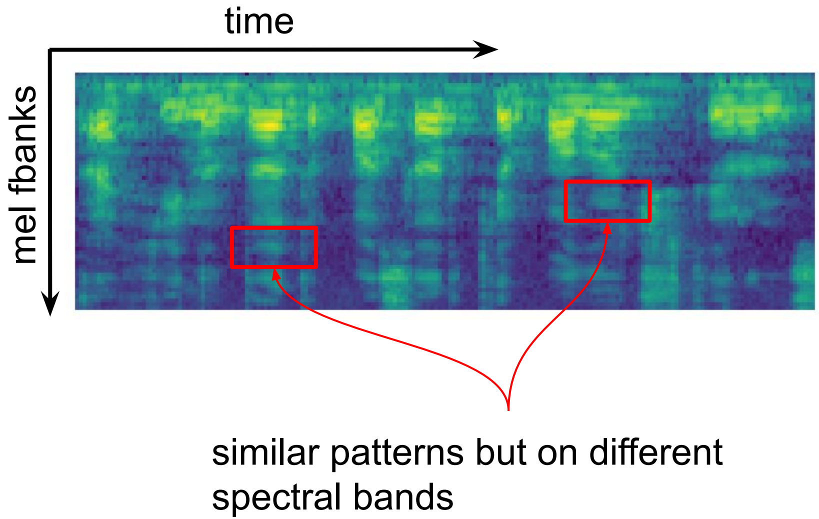
Convolution: images vs log mel-spectrograms



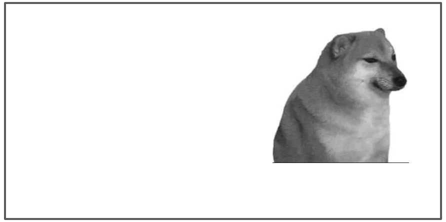


Convolution: images vs log mel-spectrograms

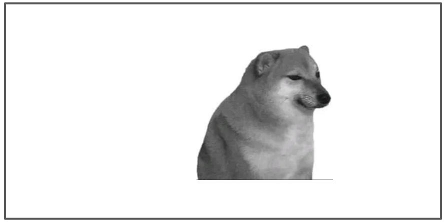




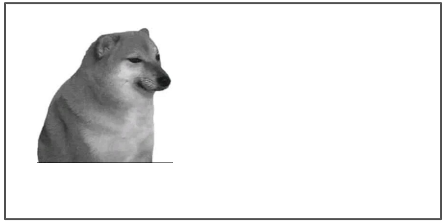
Convolution: images vs log mel-spectrograms



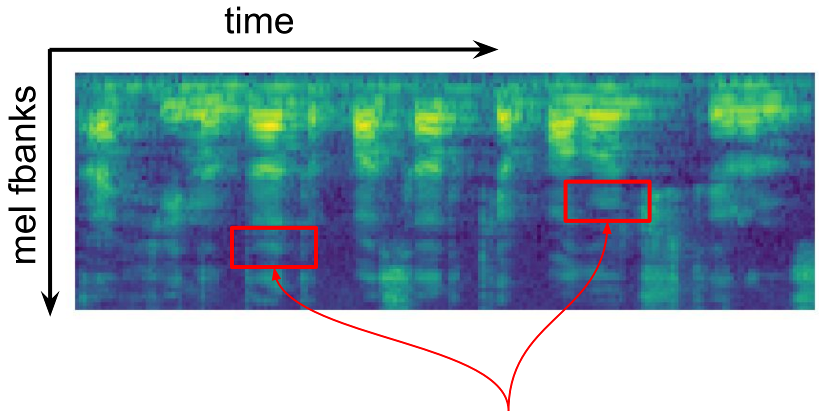
dog



dog



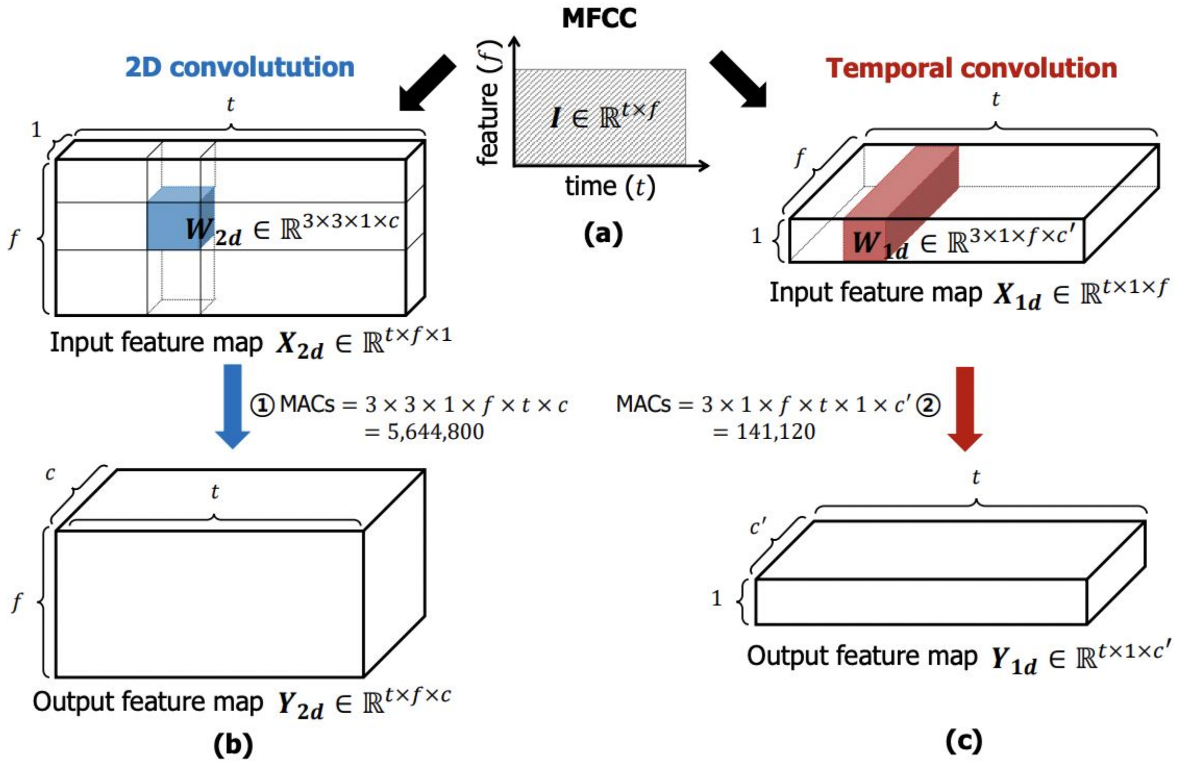
dog



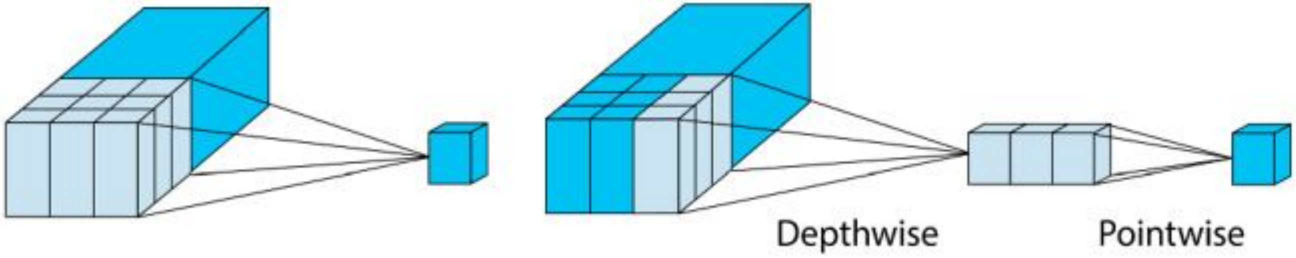
similar patterns but on different spectral bands

do we really need translational equivariance along the frequency axis ?

conv2d vs conv1d

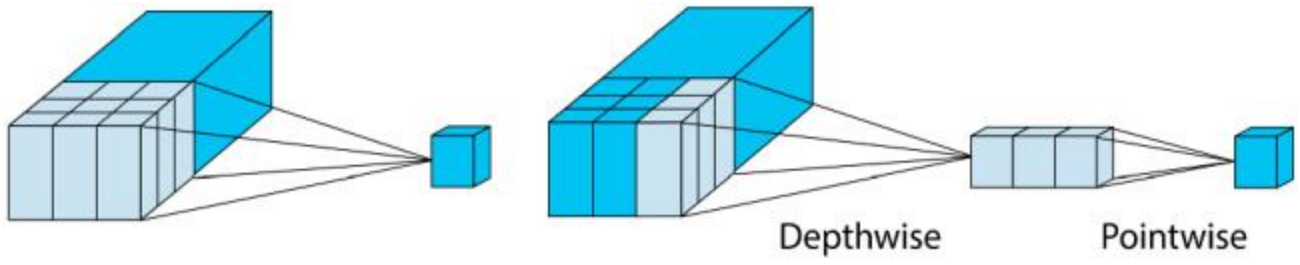


Depthwise Separable Convolutions



(a) Standard 1-D Convolution (b) Depth wise separable 1-D Convolution

Depthwise Separable Convolutions



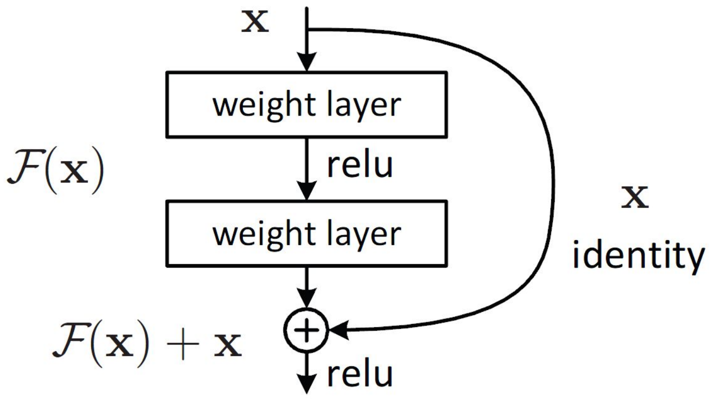
(a) Standard 1-D Convolution (b) Depth wise separable 1-D Convolution

- Standard Convolution:
    - ch_in x kernel_size x ch_out
- Depthwise Separable Convolution
    - ch_in x kernel_size + ch_in x ch_out

Depthwise Separable Convolutions

```
>>> import torch
>>> import thop
>>> conv1d = torch.nn.Sequential(
...     torch.nn.Conv1d(in_channels=64, out_channels=32, kernel_size=3)
... )
>>> depth_wise_conv1d = torch.nn.Sequential(
...     torch.nn.Conv1d(in_channels=64, out_channels=64, kernel_size=3, groups=64),
...     torch.nn.ReLU(),
...     torch.nn.Conv1d(in_channels=64, out_channels=32, kernel_size=1)
... )
>>> inputs = (torch.randn((1, 64, 101)),)
>>> thop.profile(conv1d, inputs=inputs)
[INFO] Register count_convNd() for <class 'torch.nn.modules.conv.Conv1d'>.
[INFO] Register zero_ops() for <class 'torch.nn.modules.container.Sequential'>.
(608256.0, 6176.0)
>>> thop.profile(depth_wise_conv1d, inputs=inputs)
[INFO] Register count_convNd() for <class 'torch.nn.modules.conv.Conv1d'>.
[INFO] Register zero_ops() for <class 'torch.nn.modules.activation.ReLU'>.
[INFO] Register zero_ops() for <class 'torch.nn.modules.container.Sequential'>.
(221760.0, 2336.0)
>>>
```

Residual Block (Skip Connections)



[Deep Residual Learning for Image Recognition](2015)

[DEEP RESIDUAL LEARNING FOR SMALL-FOOTPRINT KEYWORD SPOTTING] (2018)

[MatchboxNet: 1D Time-Channel Separable Convolutional Neural Network Architecture for Speech Commands Recognition]

- NVIDIA, 2020

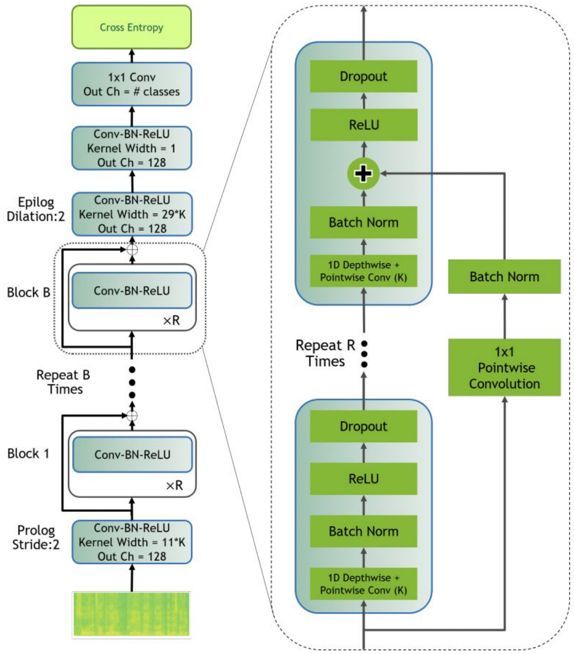
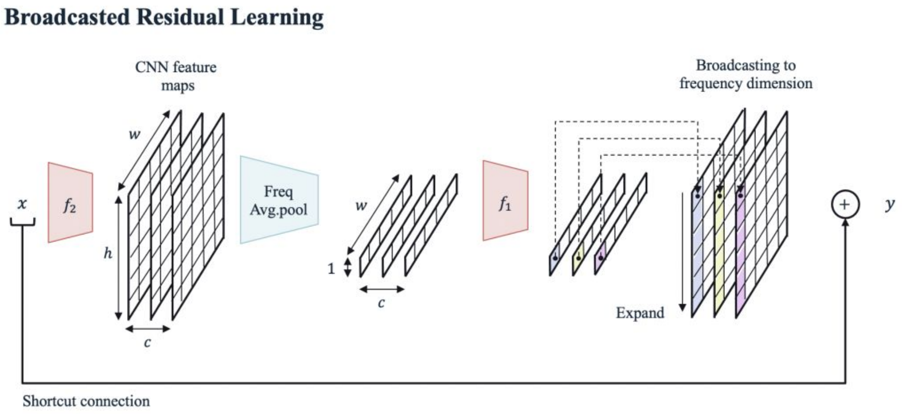
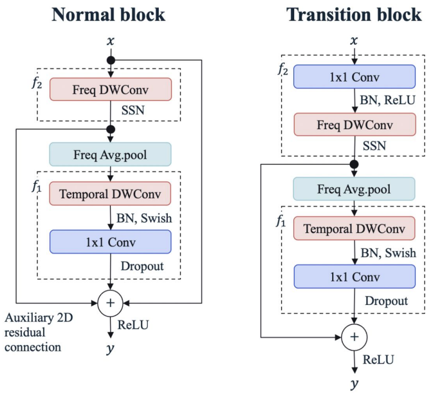


Figure 1: *MatchboxNet BxRxC model: B - number of blocks, R - number of sub-blocks, C - the number of channels.*

Broadcasted Residual Learning for Efficient Keyword Spotting

- Qualcomm AI Research, 2021

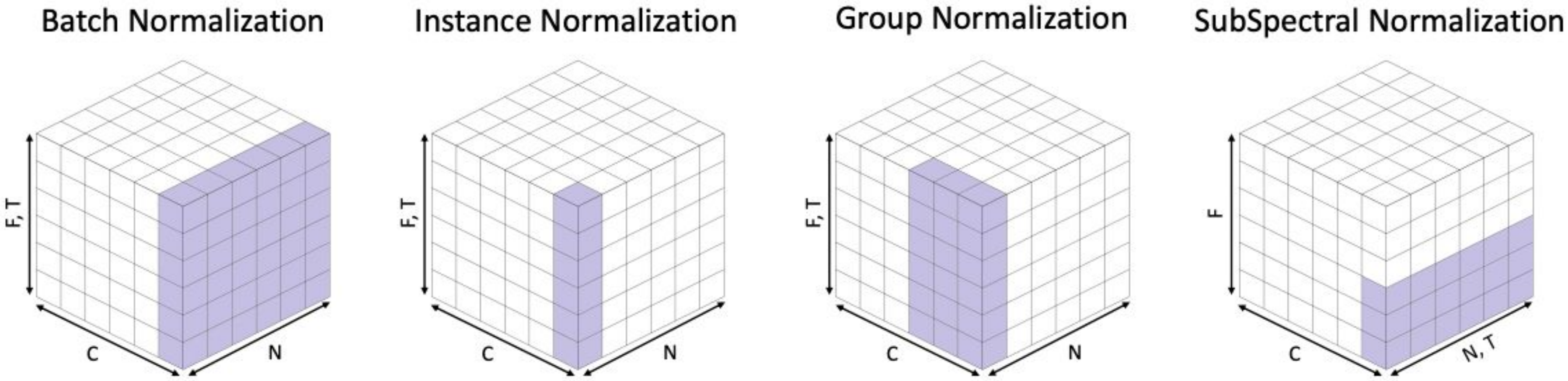




Input	Operator	n	c	s	d
$1 \times 40 \times W$	conv2d 5x5	-	16	(2,1)	1
$16 \times 20 \times W$	BC-ResBlock	2	8	1	1
$8 \times 20 \times W$	BC-ResBlock	2	12	(2,1)	(1,2)
$12 \times 10 \times W$	BC-ResBlock	4	16	(2,1)	(1,4)
$16 \times 5 \times W$	BC-ResBlock	4	20	1	(1,8)
$20 \times 5 \times W$	DWconv 5x5	-	20	1	1
$20 \times 1 \times W$	conv2d 1x1	-	32	1	1
$32 \times 1 \times W$	avgpool	-	-	-	-
$32 \times 1 \times 1$	conv2d 1x1	-	12	-	-

Broadcasted Residual Learning for Efficient Keyword Spotting
SubSpectral Normalization

- Qualcomm AI Research, 2021



Broadcasted Residual Learning for Efficient Keyword Spotting

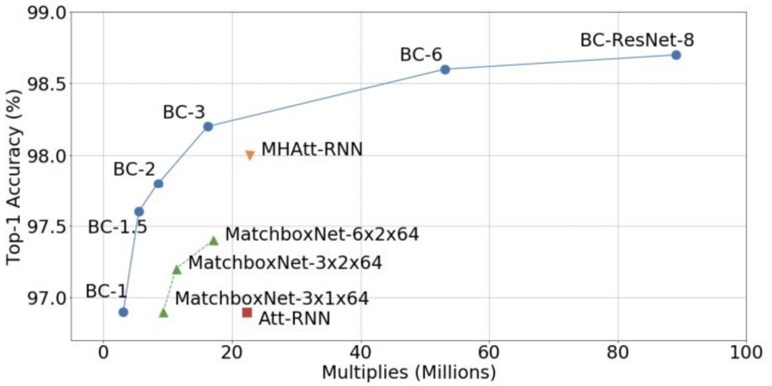


Figure 3: ***MACs vs. Google speech command dataset v2 Accuracy.*** *Details are in Table 3.*

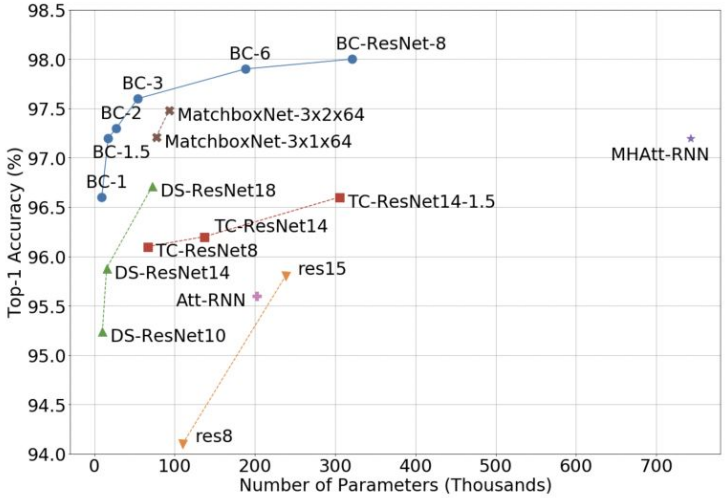
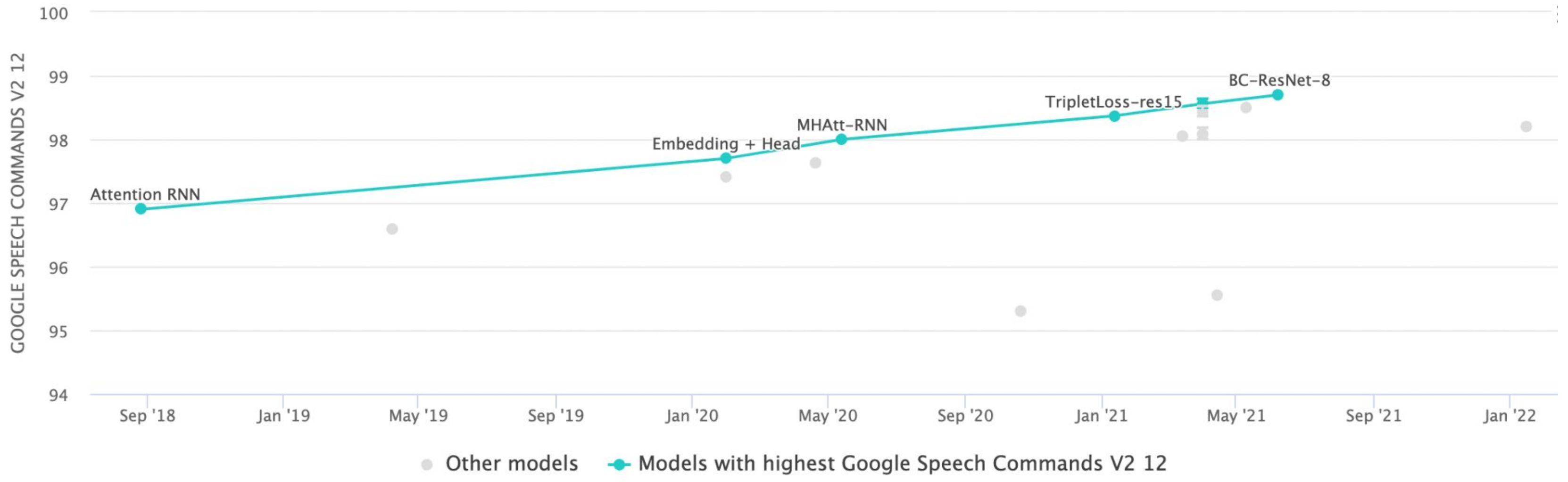


Figure 1: ***Model Size vs. Google speech command dataset v1 Test Accuracy.*** *The proposed BC-ResNets significantly outperform other KWS approaches. The smallest BC-ResNet-1 achieves 96.6% accruacy with less than 10k parameters. We scale the BC-ResNet-1 by channel width with a factor of 8, and BC-ResNet-8 achieves the state-of-the-art 98.0%. The details are in Table 3.*

KWS Benchmark

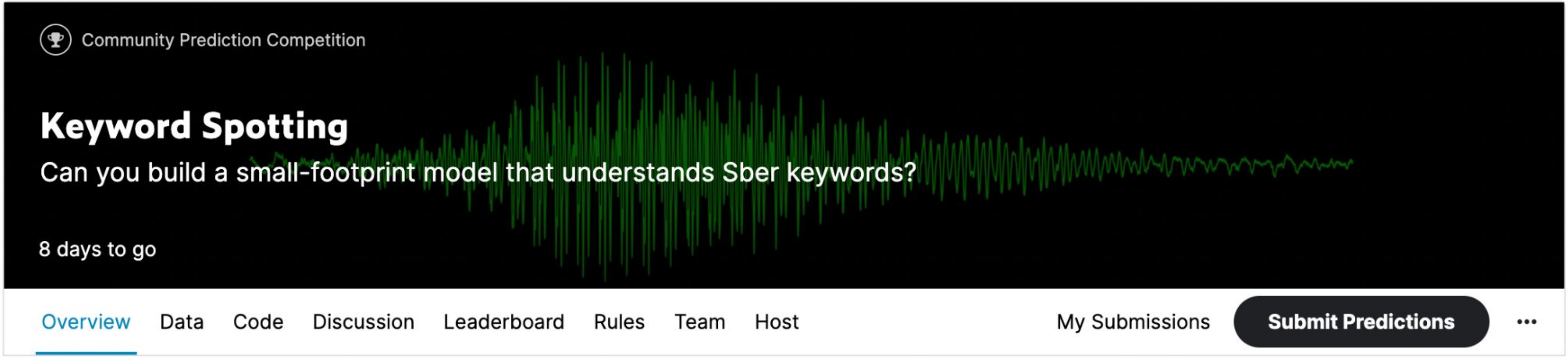
- [Google Speech Commands]
    - v1: 65,000 one-second long utterances of 30 short words, by thousands of different people
    - v2: 105,829 utterances of 35 words



Homework

Keyword Spotting

- Kaggle In-Class Competition
- 100k train, 2k test
- model: <= **1e4** params, <= **1e6** MACs
- report + model-checkpoint + leaderboard submits
- deadline: 2022-10-11 17:59



Thank you for your attention!

@georgygospodinov