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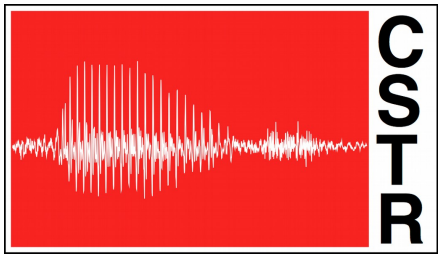
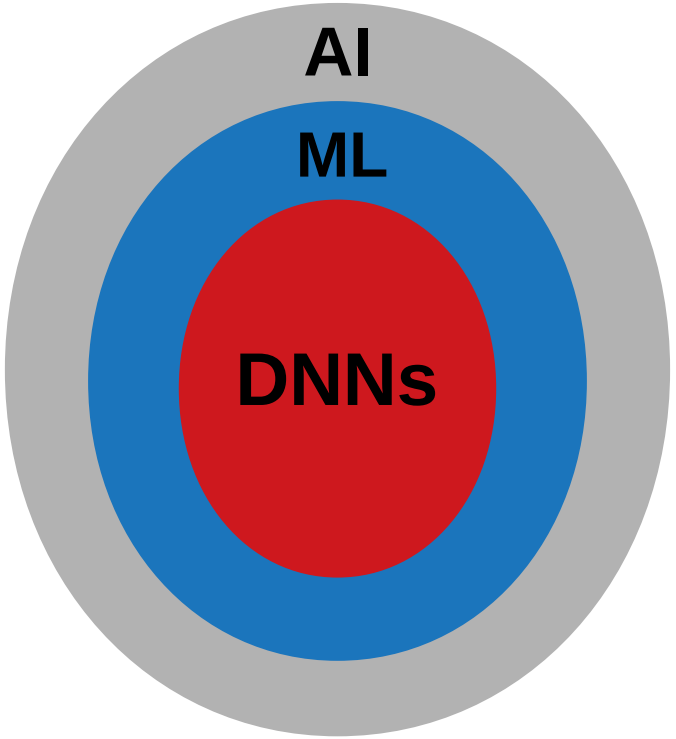


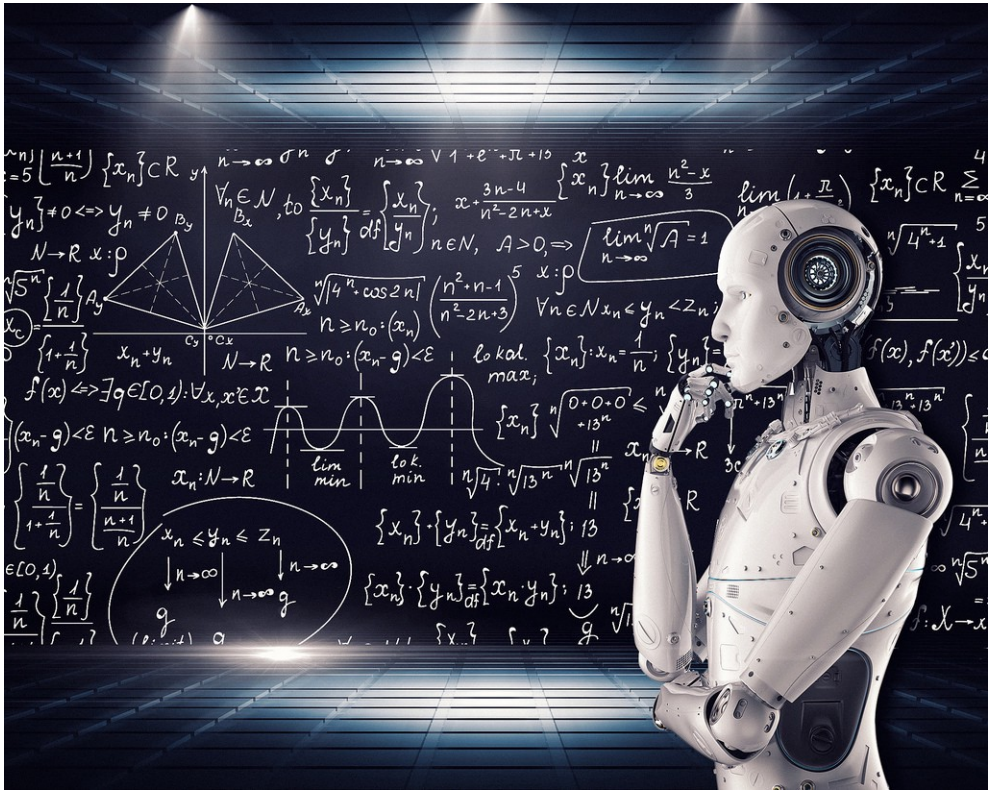
Understanding and Interpreting DNNs for Speech Recognition

Erfan Loweimi, Peter Bell and Steve Renals

Centre for Speech Technology Research (CSTR),
The University of Edinburgh

DNNs are GREAT ...

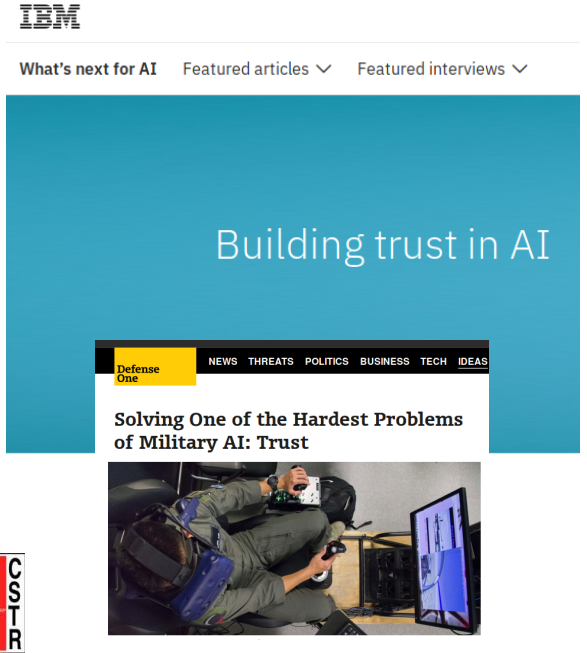


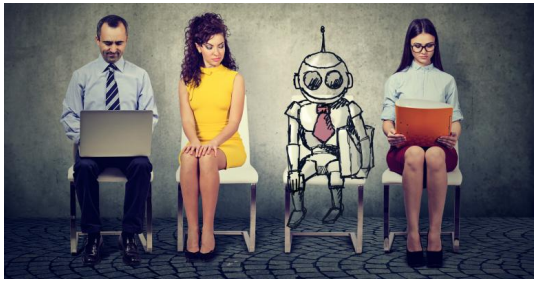


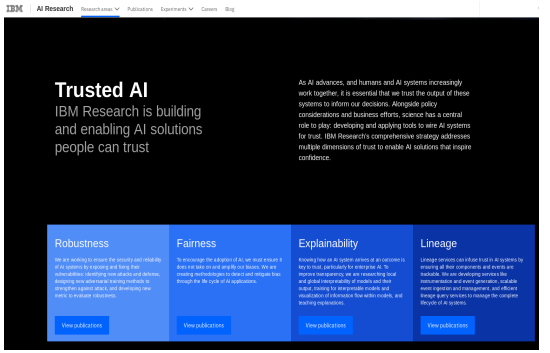
DNNs are GREAT ...
BUT are a **black box**

Importance of Understanding

- Trust







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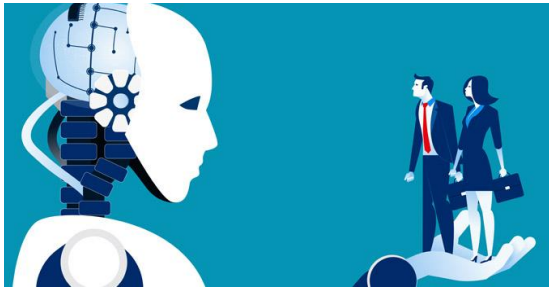
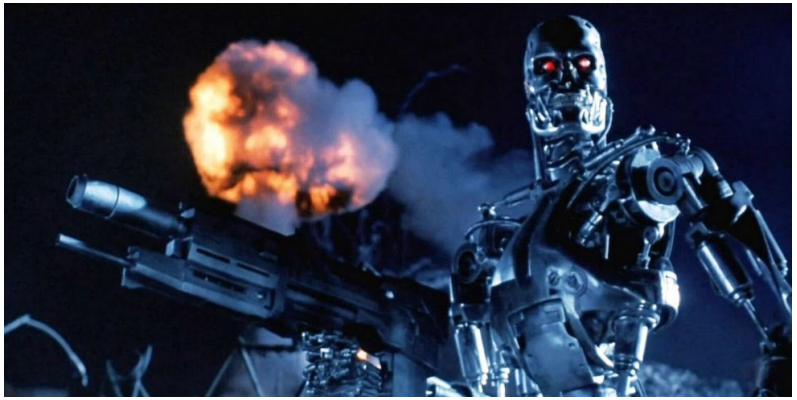
Importance of Understanding

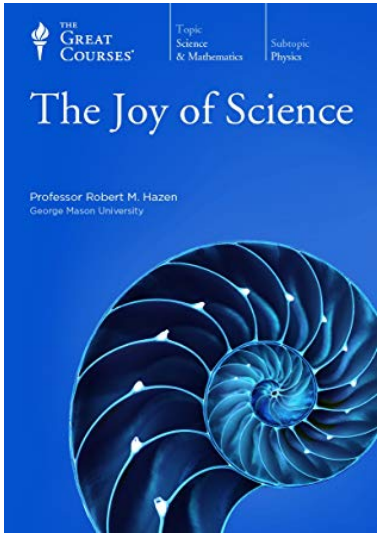
- Control





Importance of Understanding

- The Joy of Science
- Better practice



SpeechWave Project

EPSRC

ICASSP2019

ON THE USEFULNESS OF STATISTICAL NORMALISATION OF BOTTLENECK FEATURES FOR SPEECH RECOGNITION

Erfan Loweimi, Peter Bell and Steve Renals

Centre for Speech Technology Research (CSTR), School of Informatics, The University of Edinburgh
{e.loweimi, peter.bell, s.renals}@ed.ac.uk

Submitted to
INTERSPEECH 2019

On Learning Interpretable CNNs with Parametric Modulated Kernel-based Filters

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Centre for Speech Technology Research (CSTR), School of Informatics, University of Edinburgh
{e.loweimi, peter.bell, s.renals}@ed.ac.uk

Outline

- PART I
  - Interpreting DNN's Activations
    - ICASSP 2019
- PART II
  - Interpreting DNN's Weights
    - Submitted to INTERSPEECH 2019

Outline

- **PART I**
  - Interpreting DNN's Activations
    - ICASSP 2019
- PART II
  - Interpreting DNN's Weights
    - Submitted to INTERSPEECH 2019

"*I have always thought the actions of men the best interpreters of their thoughts.*"

— John Locke

"*I have always thought the activations of NNs the best interpreters of their thoughts.*"

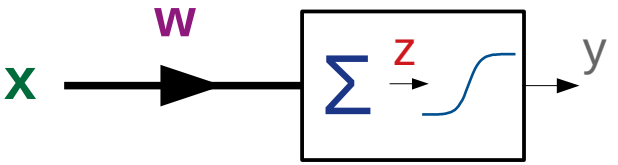
– Unknown :-)

Part I Outline

- Conduct a series of statistical studies on activations
- (Re)-Explaining some observations
- Statistical Normalisation of bottleneck features for ASR

DNNs from Statistical Standpoint

- Effect of the activation function *f*(.) on the density ...
  - **x**: input **w**: weights
  - z: pre-activation y: activation



$$\mathrm{y} = \mathrm{f}(\underbrace{\mathbf{w}^{\mathbf{T}}\mathbf{x}}_{z}) = f(z) \Rightarrow z = f^{-1}(y)$$

DNNs from Statistical Standpoint

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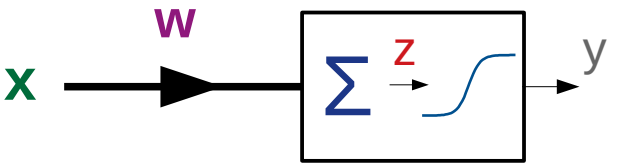

$$\mathrm{y} = \mathrm{f}(\underbrace{\mathbf{w}^{\mathbf{T}}\mathbf{x}}_{z}) = f(z) \Rightarrow z = f^{-1}(y)$$

$$\mathrm{P}_Y(y) = \left|\frac{d}{dy} f^{-1}(y)\right| \; P_Z(f^{-1}(y))$$

DNNs from Statistical Standpoint

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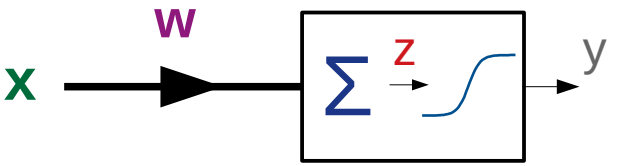

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Derivation of Distribution of Bottleneck Features Analytically – Tanh

$$\mathrm{P}_Y(y) = \left|\frac{d}{dy} f^{-1}(y)\right| P_Z(f^{-1}(y))$$

$$y = f(z) = \tanh(z)$$

Derivation of Distribution of Bottleneck Features Analytically – Tanh

$$\mathrm{P}_Y(y) = \left|\frac{d}{dy} f^{-1}(y)\right| \; P_Z(f^{-1}(y))$$

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$$f^{-1}(y) = \frac{1}{2}\log\frac{1+y}{1-y} \quad , \quad \frac{d}{dy} f^{-1}(y) = \frac{1}{1-y^2}$$

Derivation of Distribution of Bottleneck Features Analytically – Tanh

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$$\Rightarrow P_Y^{\tanh}(y) = \frac{1}{1-y^2} P_Z(\frac{1}{2}\log\frac{1+y}{1-y})$$

Derivation of Distribution of Bottleneck Features Analytically – Tanh

$$\mathrm{P}_Y(y) = \left|\frac{d}{dy} f^{-1}(y)\right| P_Z(f^{-1}(y))$$

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Derivation of Distribution of Bottleneck Features Analytically – Tanh

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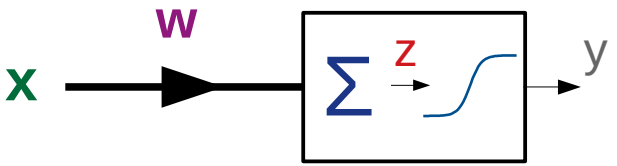
$$P_Y^{\tanh}(y) = \frac{1}{1-y^2} P_Z\left(\frac{1}{2}\log\frac{1+y}{1-y}\right)$$

Distribution of the pre-activation, $P_z(z)$, is required!

Distribution of the Pre-Activation (Z)

- *Pre-activation, Z,* is a weighted sum ...

$$z = \mathbf{w}^T \mathbf{x} = w_1 x_1 + w_2 x_2 + ... + w_N x_N$$

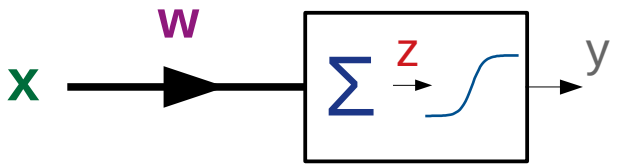


Distribution of the Pre-Activation (Z)

- *Pre-activation, Z,* is a weighted sum
  - *Z* is approximately Gaussian ← CLT*

$$z = \mathbf{w}^T \mathbf{x} = w_1 x_1 + w_2 x_2 + ... + w_N x_N$$

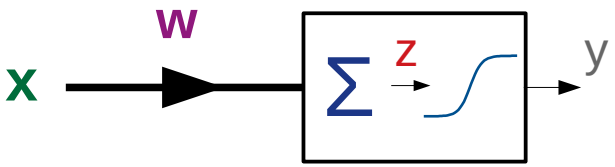
$$z \dot{\sim} \mathcal{N}(z; \mu_z, \sigma_z^2)$$



Distribution of the Pre-Activation (Z)

- *Pre-activation, Z,* is a weighted sum
  - *Z* is approximately Gaussian ← CLT
  - $\mu_z \rightarrow 0$: No preference for positive/negative values

$$z \dot{\sim} \mathcal{N}(z; 0, \sigma_z^2)$$



Distribution of the Activation (y)

- Now we can work out this ...

$$P_Y^{\tanh}(y) = \frac{1}{1-y^2} P_Z\left(\frac{1}{2}\log\frac{1+y}{1-y}\right)$$

$$\mathrm{z} \dot{\sim} \mathcal{N}(z; 0, \sigma_z^2)$$

Distribution of the Activation (y)

- After some algebraic manipulation ...

$$P_Y^{\tanh}(y) = \frac{1}{1-y^2}\,\mathcal{N}\left(\frac{1}{2}\log\frac{1+y}{1-y};0,\sigma_z^2\right)$$

$$= \underbrace{\frac{1}{1-y^2}}_{F_Y^{<1>}(y)}\ \underbrace{\frac{1}{\sqrt{2\pi}\sigma_z}\left(\frac{1+y}{1-y}\right)^{-\frac{1}{8\sigma_z^2}\log\frac{1+y}{1-y}}}_{F_Y^{<2>}(y,\sigma_z)}$$

Distribution of the Activation (y)

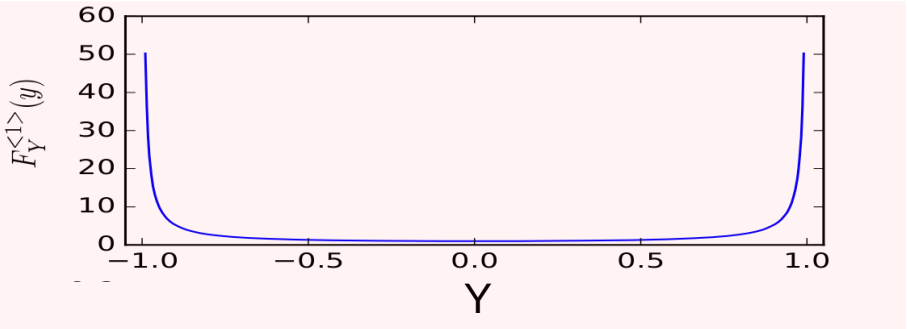
- After some algebraic manipulation ...

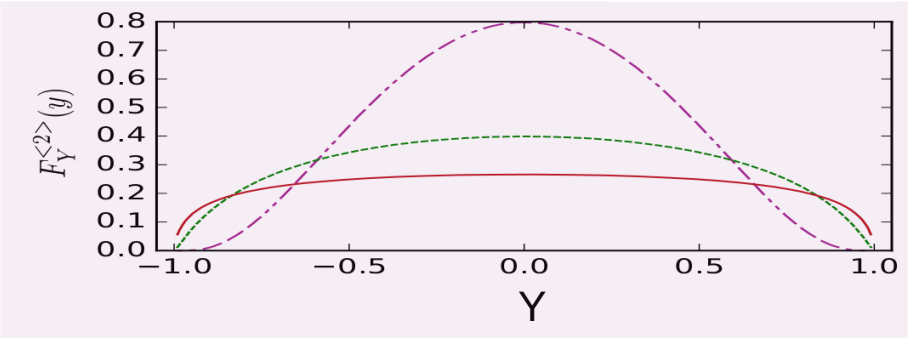
$$P_Y^{\tanh}(y) = \underbrace{\frac{1}{1-y^2}}_{F_Y^{<1>}(y)} \underbrace{\mathcal{N}(\frac{1}{2}\log\frac{1+y}{1-y}; 0, \sigma_z^2)}_{F_Y^{<2>}(y,\sigma_z)}$$

Factor 1 | Factor 2 → function of σ_z

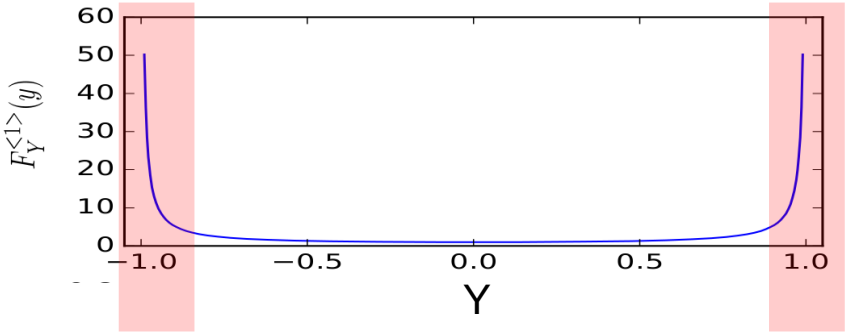
Activation Distribution Factors – Tanh

$$P_Y^{\tanh}(y) = \underbrace{\frac{1}{1-y^2}}_{F_Y^{<1>}(y)} \underbrace{\mathcal{N}(\frac{1}{2}\log\frac{1+y}{1-y}; 0, \sigma_z^2)}_{F_Y^{<2>}(y,\sigma_z)}$$

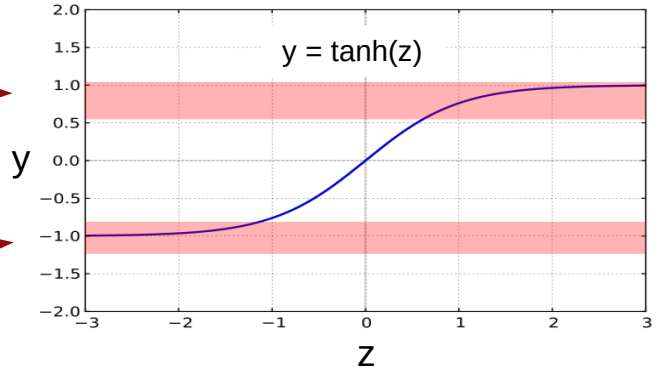




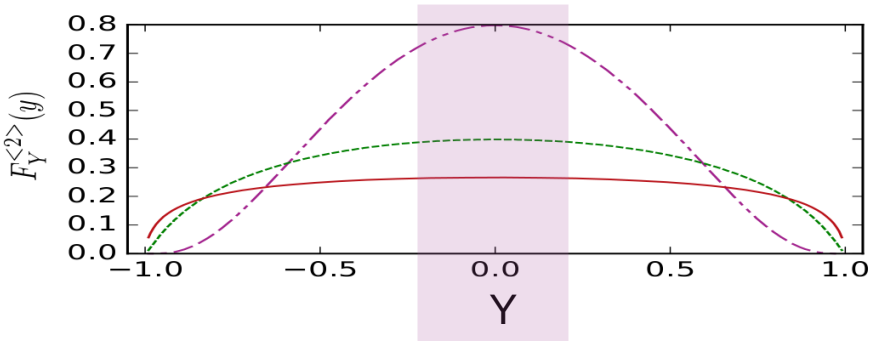
Statistical Interpretation (1)

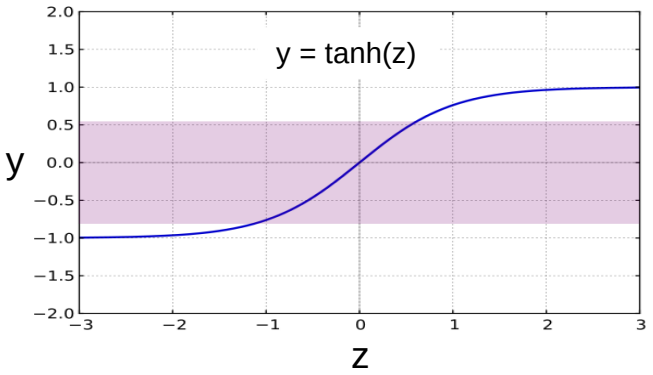


$F^{<1>}$ dominant



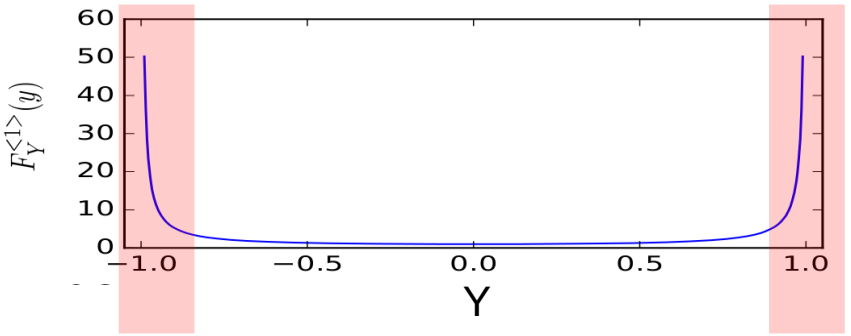
Statistical Interpretation (1)

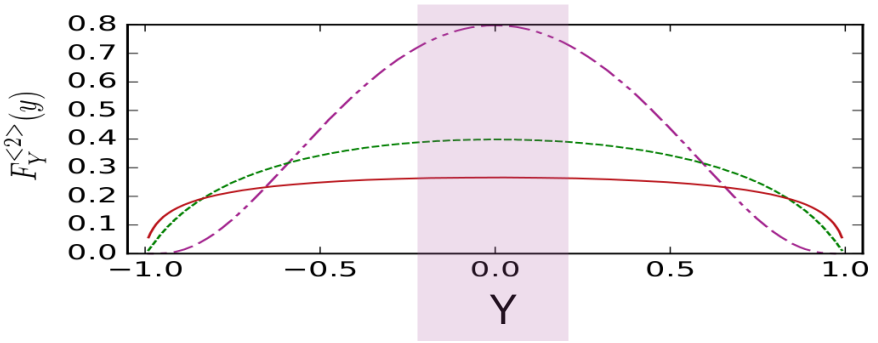




$F^{<2>}$ dominant

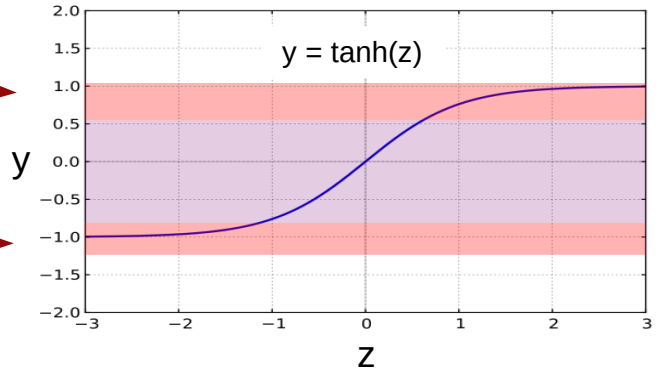
Statistical Interpretation (1)





$F^{<1>}$ dominant

Non-linear region



$F^{<2>}$ dominant

Linear region

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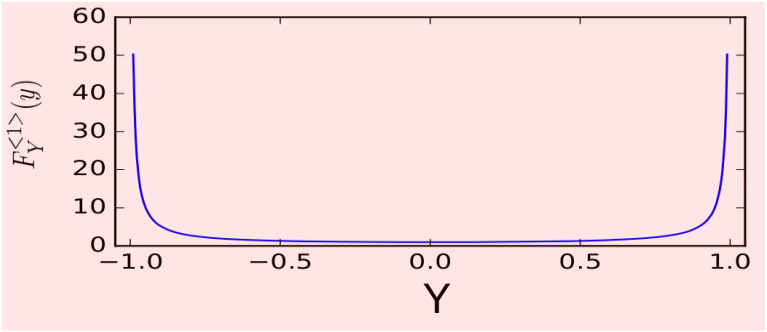
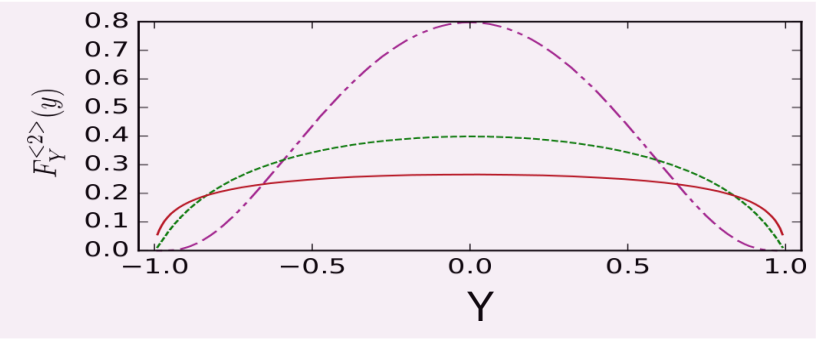
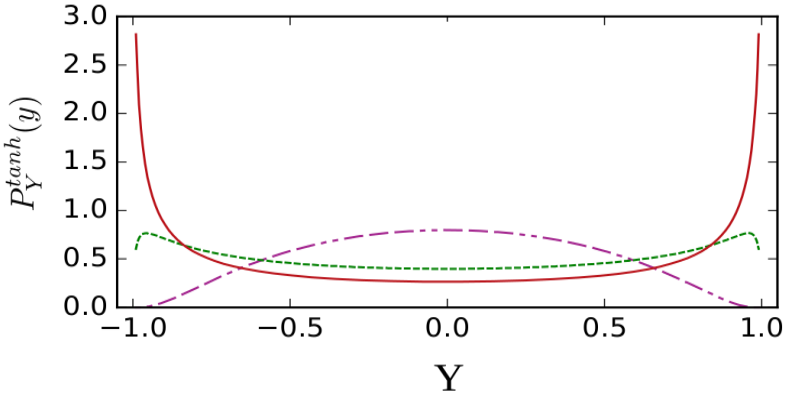
Statistical Interpretation (2) – Product







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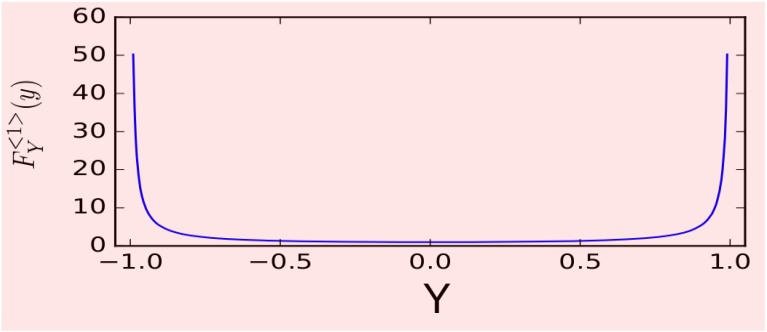
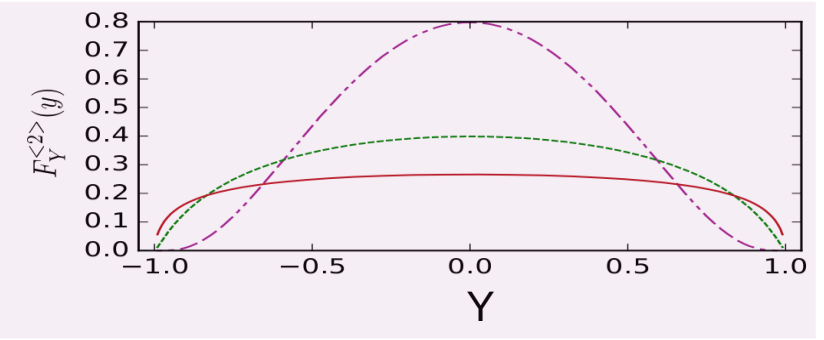
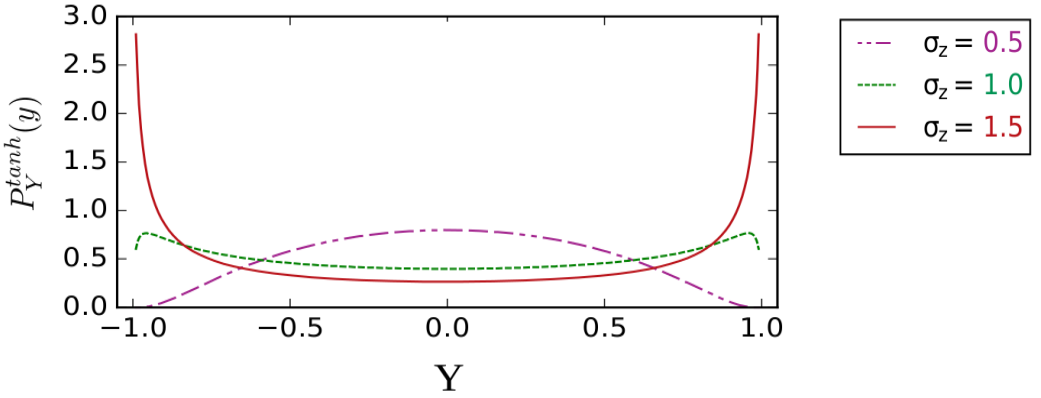




σ_z is a *shape* parameter



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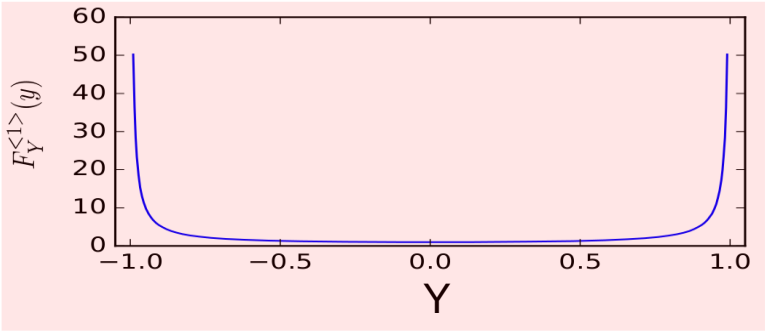
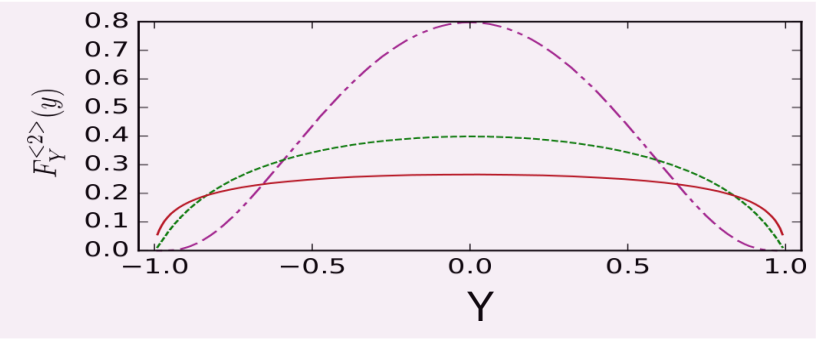
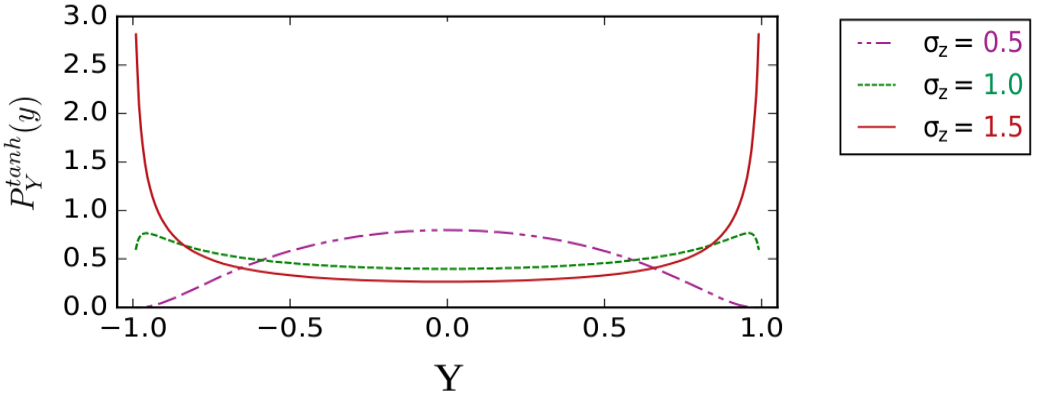


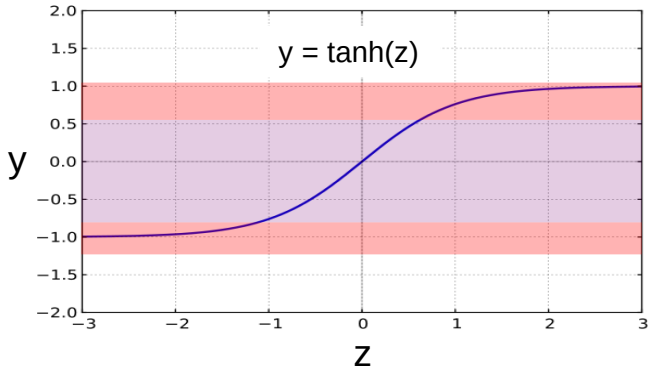


$\sigma_z > 1 \Rightarrow F^{<1>}$ is dominant

$\sigma_z < 1 \Rightarrow F^{<2>}$ is dominant



Statistical Interpretation (2) – Product



Non-linear

$\sigma_z > 1 \Rightarrow F^{<1>}$ is dominant

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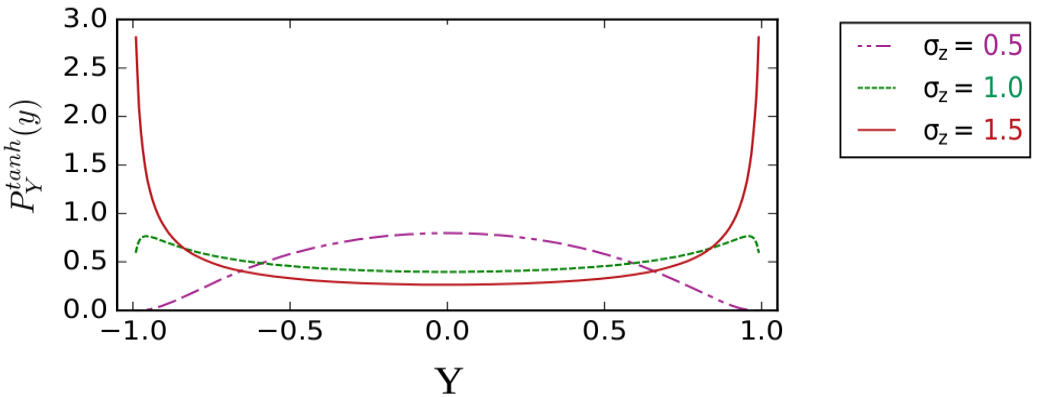
Linear



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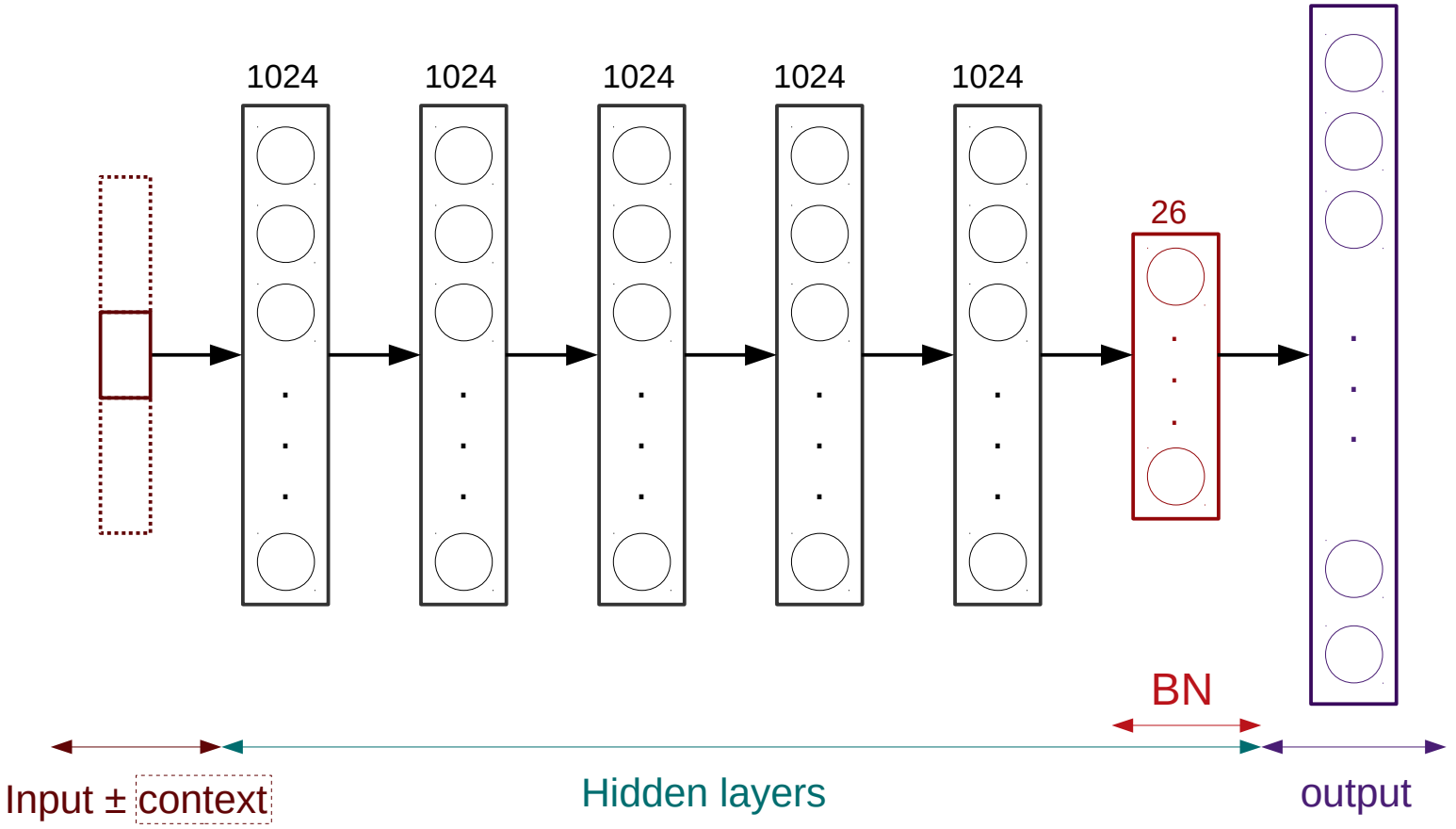
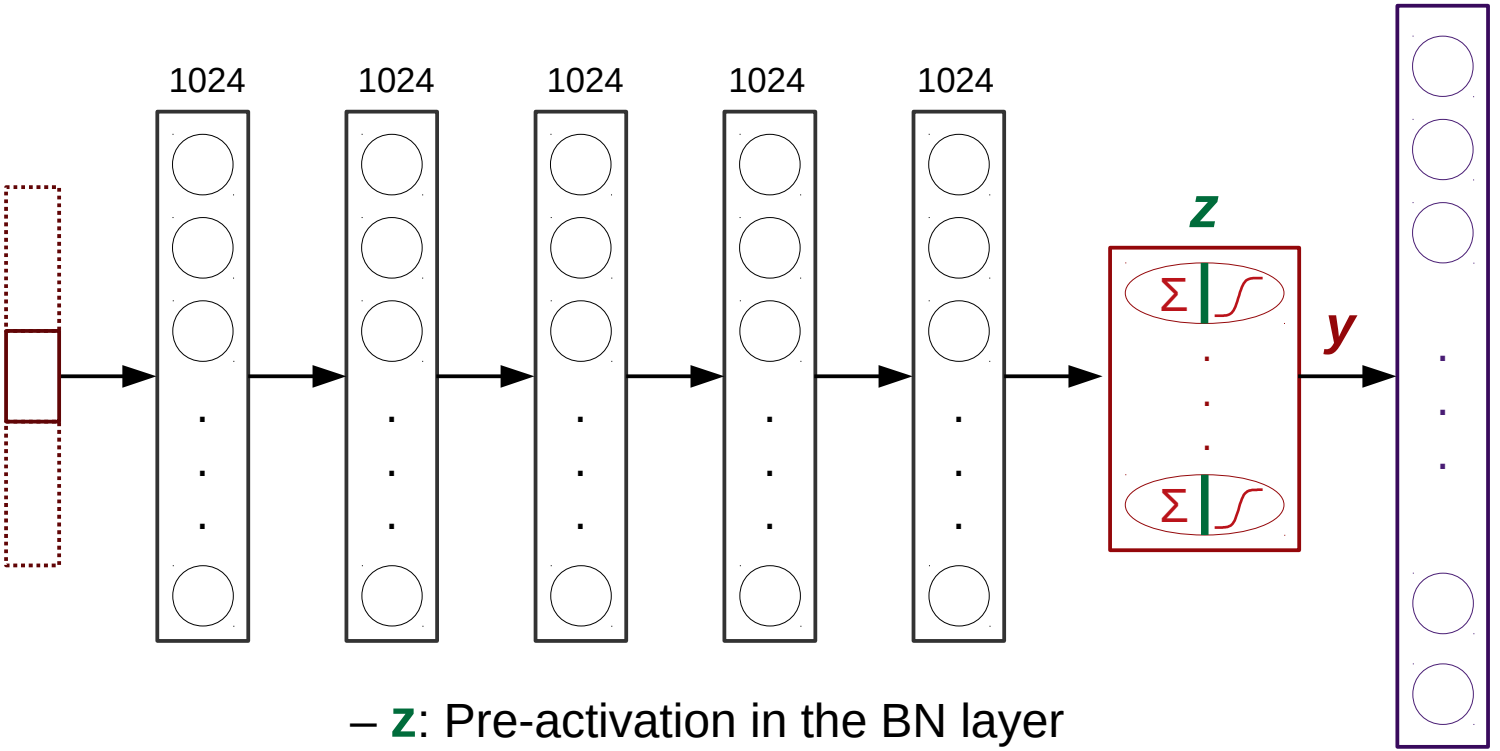
Empirical Studies

- Database: WSJ-5k (SI-84)
- Bottleneck (BN) features extracted using Kaldi
- DNN: TDNN (nnet3), 7 layers: 5x1024 → BN(26D) → output
- Features: log-Filterbank, mean-var normalised, ±5 frames
- #Frames: 5.4 M

DNN Architecture



DNN Architecture



– **z**: Pre-activation in the BN layer

– **y**: Activations of the BN layer

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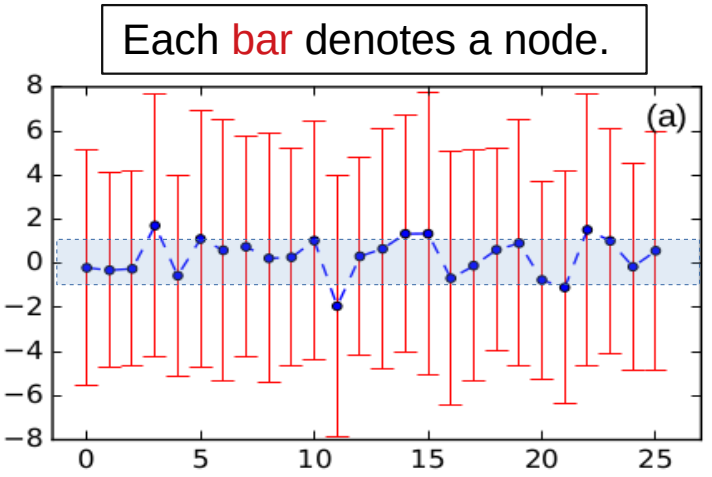
Mean/Std of Pre-activation Z – Error-bar

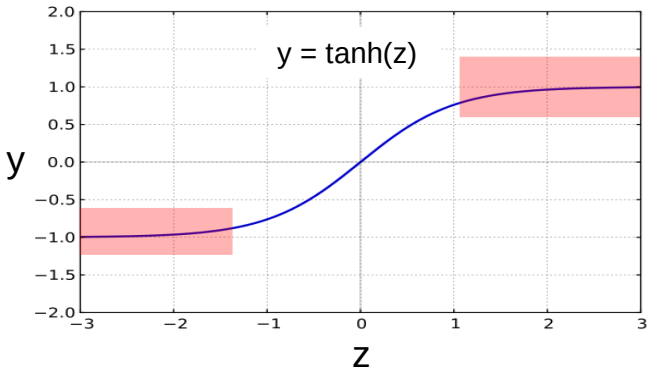
- $\mu_z \rightarrow 0$ approximation is reasonable ...

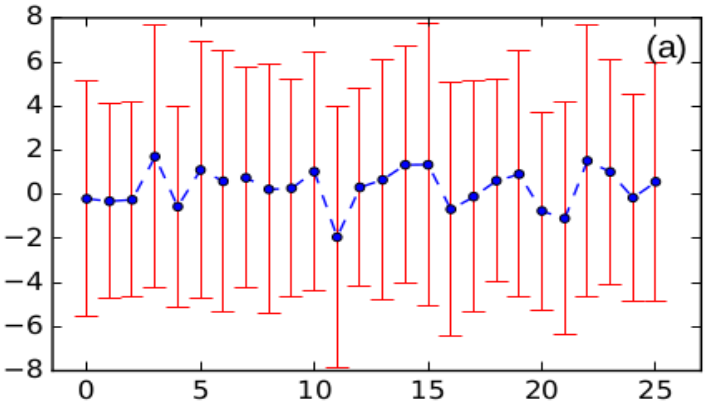
$$z \doteq \mathcal{N}(z; 0, \sigma_z^2)$$



Mean/Std of Pre-activation Z – Error-bar

- $\mu_z \rightarrow 0$ approximation is reasonable ...
- $\sigma_z > 1$ ==>> DNN operates in the *non-linear mode*



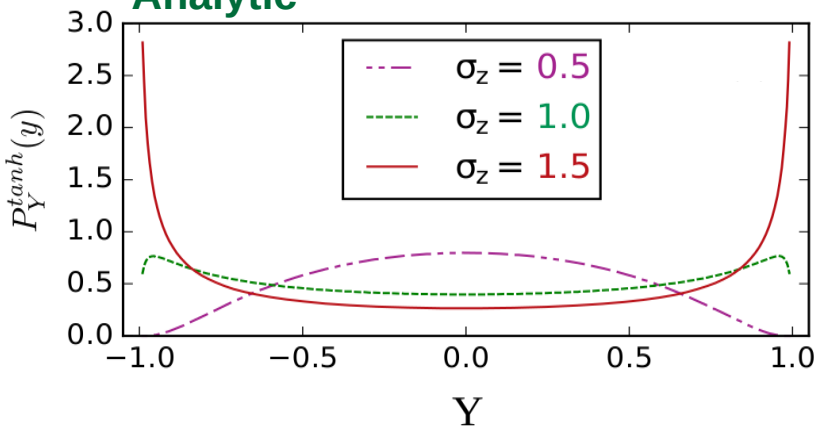


Properties of Z and Y – Empirical Study

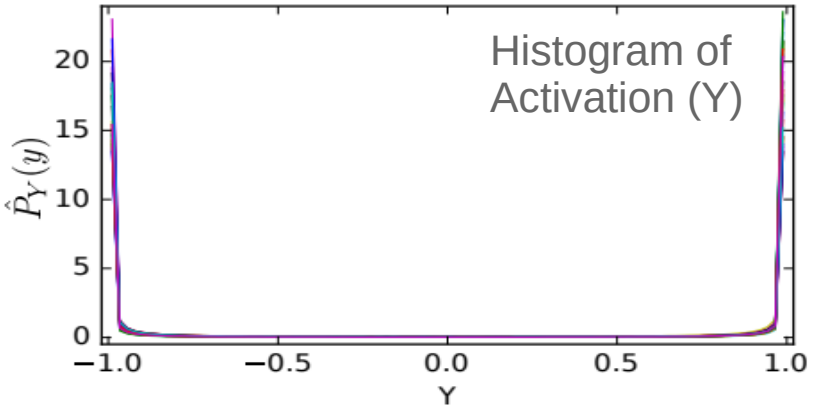
- Distribution of Y matches the derived equation ($\sigma_z > 1$)

$$P_Y^{\tanh}(y) = \frac{1}{1-y^2}\,\mathcal{N}\left(\frac{1}{2}\log\frac{1+y}{1-y}; 0, \sigma_z^2\right)$$

Analytic



Empirical



Explaining Two Side Observations

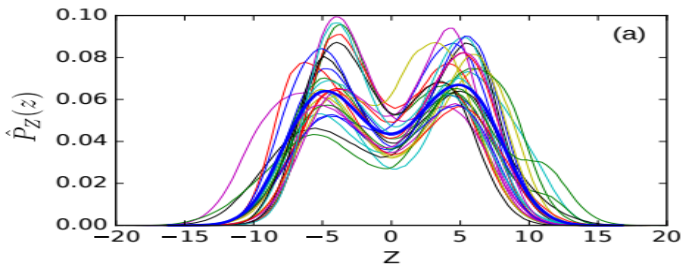
- As bottleneck (BN) features for ASR ...
  - Pre-activation (Z) or activation (Y)?

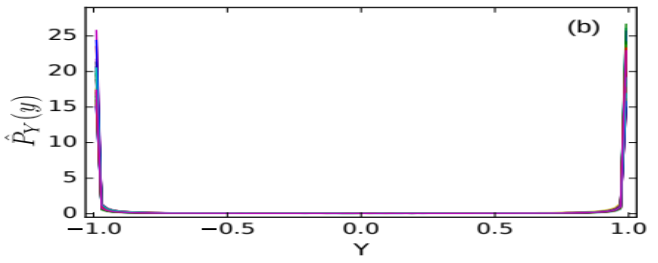
- Sparsity of ReLU; Why and how?

As BN Features, Pre-activation or Activation?

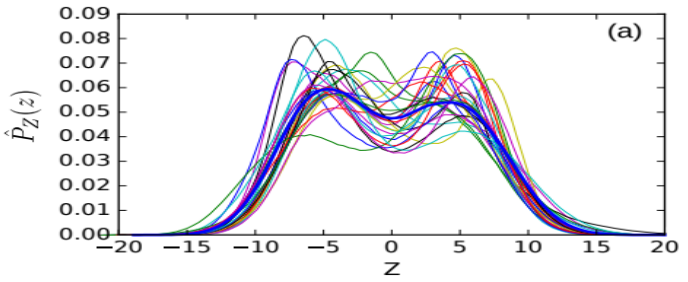
Pre-activation (Z) | Activation (Y)

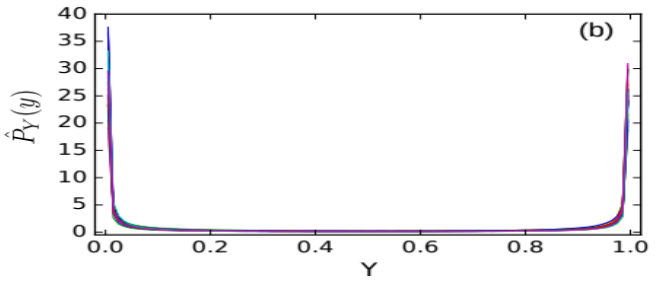
Tanh



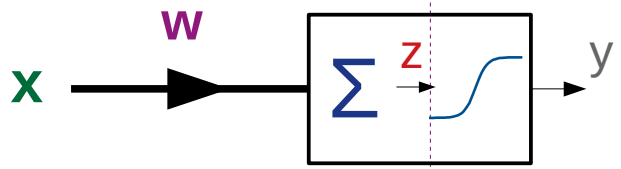


Sigmoid





Each colour denotes a node.



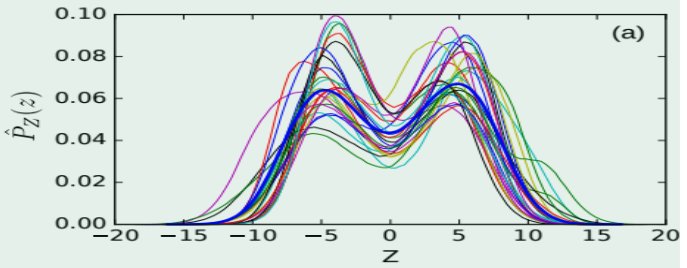
Loweimi et al

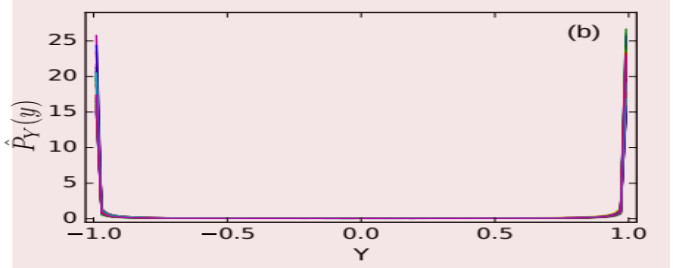
As BN Features, Pre-activation or Activation?

Pre-activation (Z)

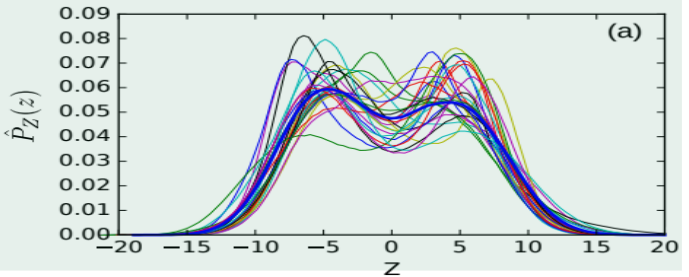
Activation (Y)

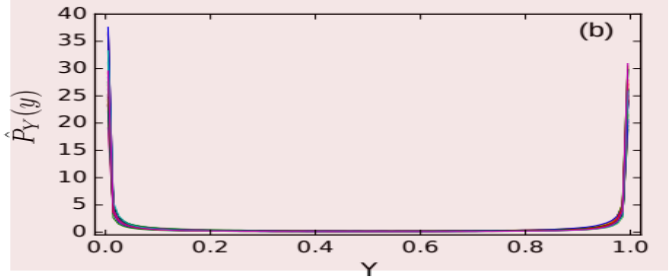
Tanh

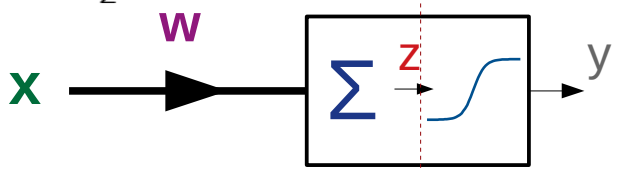




Sigmoid

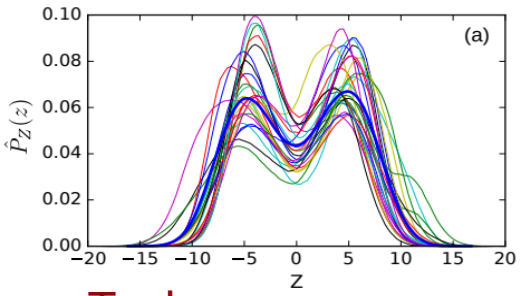




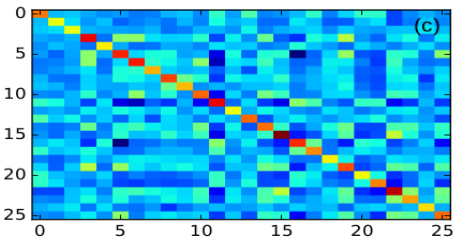


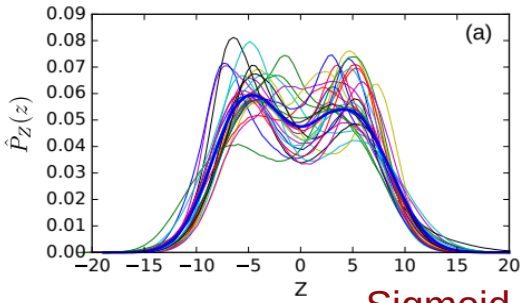
Loweimi et al

As BN Features, Pre-activation or Activation?

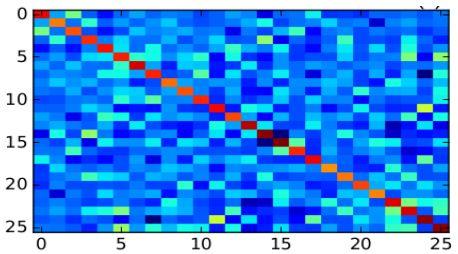


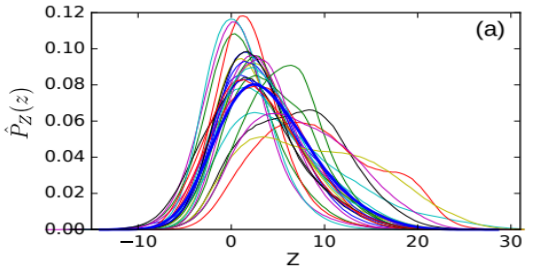
Tanh



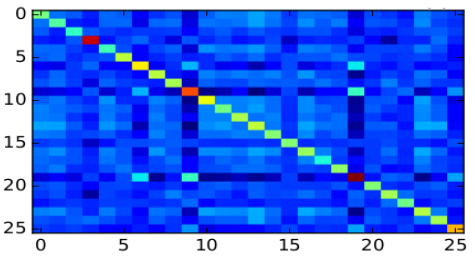


Sigmoid



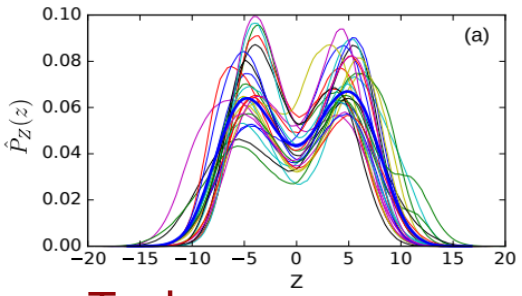


ReLU

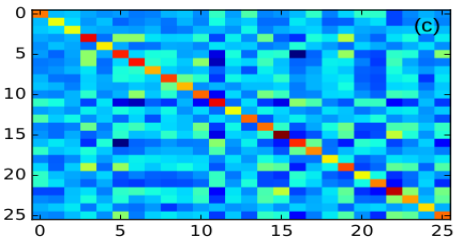


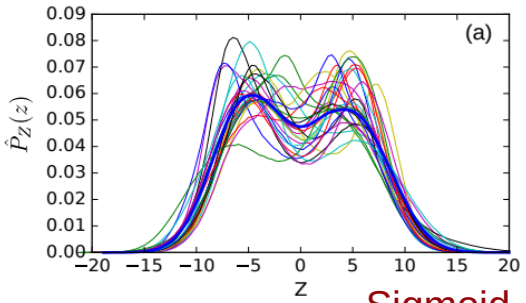
Covariance matrix of Z ...

As BN Features, Pre-activation or Activation?

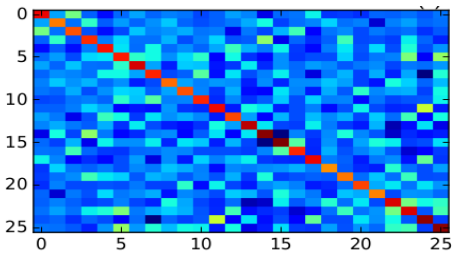


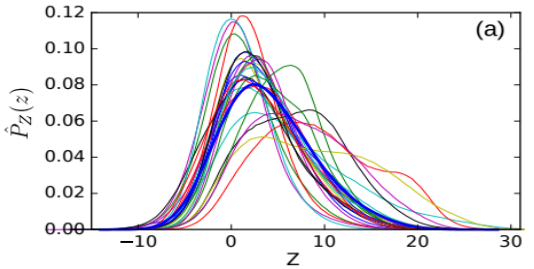
Tanh



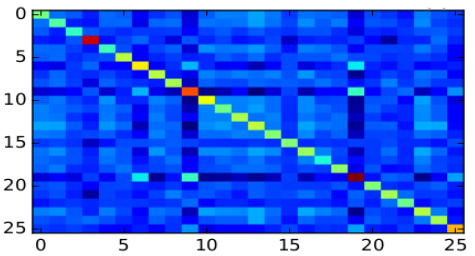


Sigmoid





ReLU



Z Distribution is easily fitted with *diagonal GMMs.*

Sparsity of ReLU

- **ReLU Advantages ...**
  - **Sparse activations**
    - Biologically plausible
    - Info disentanglement
  - Gradient propagation
  - Efficient computation

Deep Sparse Rectifier Neural Networks

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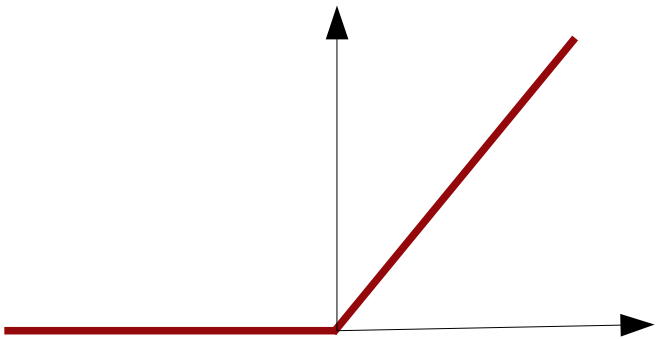
AISTATS 2011

Sparsity of ReLU; Why?

- Glorot et al., "*Deep Sparse Rectifier Neural Networks*", AISTATS 2011
  - Assuming the probability of positive and negative pre-activations is equal, half of the activations (50%) will be zero ...

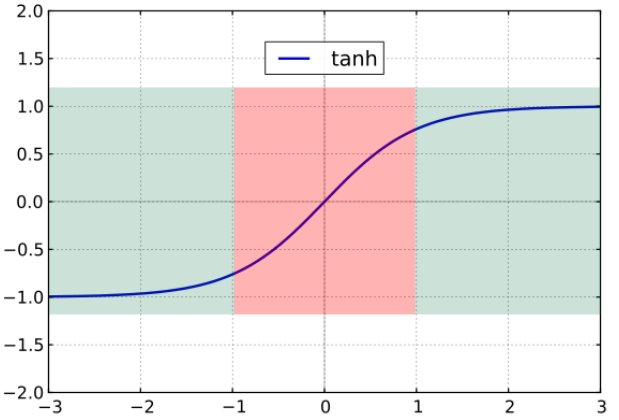


Sparsity of ReLU; Why?

- **Our argument ...**
  - Remember Tanh, linear and non-linear zones ...

Non-linear mode

Linear mode



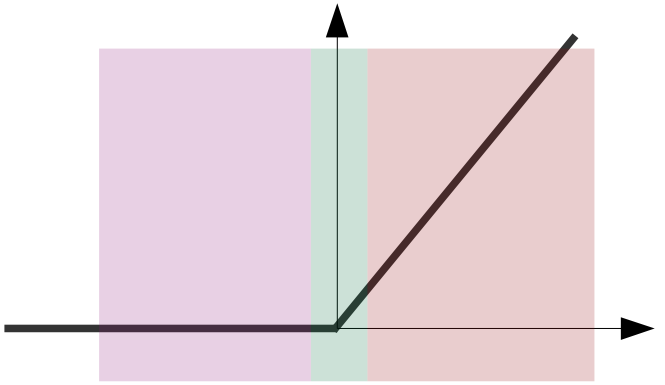
Sparsity of ReLU; Why?

- **Our argument ...**
  - To operate in the non-linear mode, activations must be around **0^+**

⊗ Blocks information

✓ Non-linear mode (switch)

⊗ Linear mode



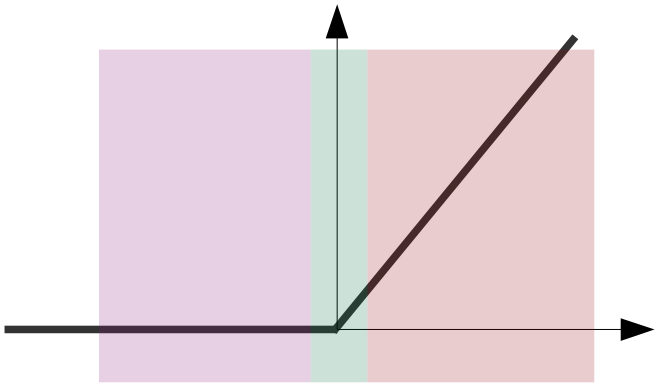
Sparsity of ReLU; Why?

- **Coincidence** of non-linear operating zone with **0^+**

Blocks information

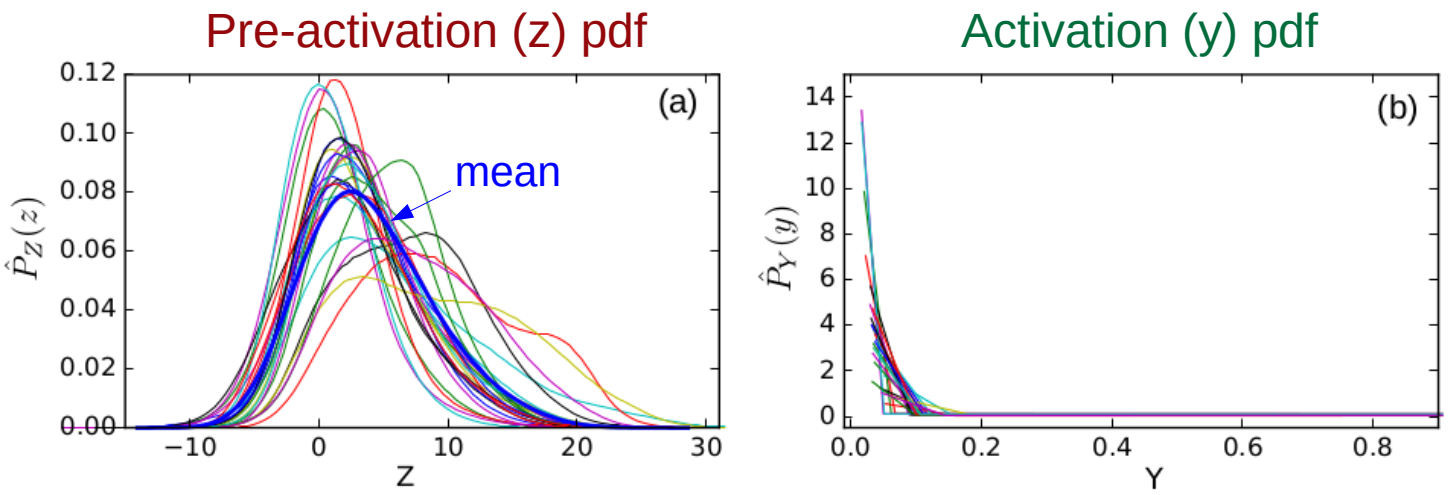
Non-linear mode (switch)

Linear mode



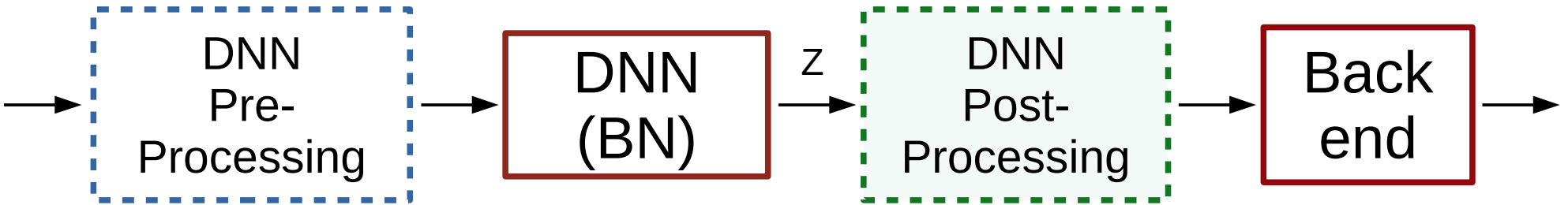
Sparsity of ReLU -- Empirical Results

- Distribution of the pre-activation (z) and activation (y) for ReLU ...



Each colour denotes a node.

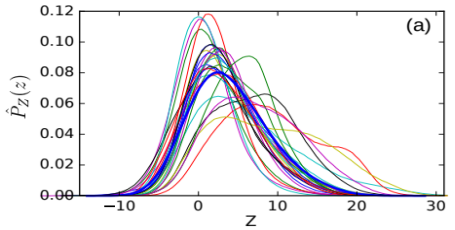
Feature Normalisation for DNNs



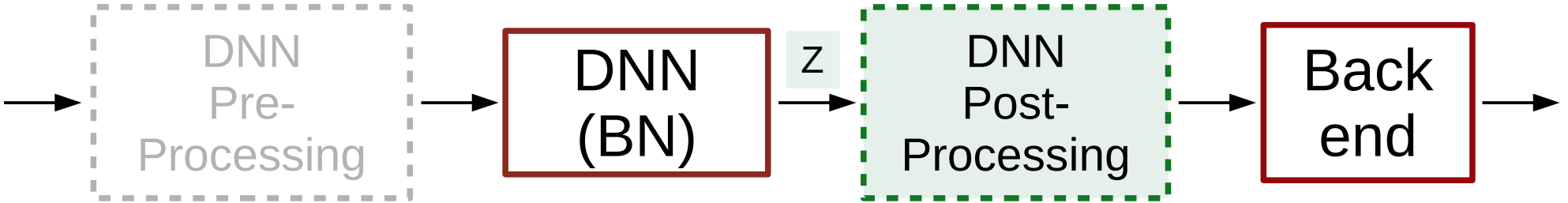
Loweimi et al., ICASSP 2018
(gVTS → DNN)

ICASSP 2019

Feature Normalisation for DNNs



Z is amenable to statistical normalisation



Loweimi et al., ICASSP 2018
(gVTS → DNN)

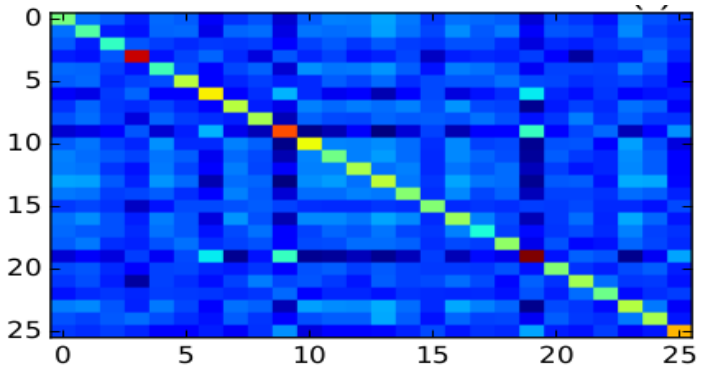
ICASSP 2019

Feature Post-processing for ASR

- Minimise test/train mismatch
  - mean(-variance) normalisation, Gaussianisation

Feature Post-processing for ASR

- Minimise test/train mismatch
  - mean(-variance) normalisation, Gaussianisation
- Orthogonalisation or Decorrelation
  - PCA or DCT



Feature Post-processing for ASR

- Minimise test/train mismatch
  - mean(-variance) normalisation, Gaussianisation
- Orthogonalisation or Decorrelation
  - PCA or DCT
- Feature Enhancement (Noise Robustness)
  - Cannot do (g)VTS → Environment model is not available!
  - Histogram Equalisation (HEQ)

ASR Experiments – Aurora-4 Noisy Training Set (only Additive)

Aurora-4 Train Set:
- – Clean+Additive noise

Aurora-4 Test Sets:
- – A: Clean (match)
- – B: Additive noise (match)
- – C: Channel (mismatch)
- – D: Additive+Channel (match)

- – MN: Mean normalised
- – MVN: Mean-variance normalised
- – Gauss: Gaussianisation
- – HEQ: Histogram Equalisation

Table 1: *WER for Aurora-4 (Kaldi-LDA-MLLT).*

Feature	A	B	C	D	*Ave4*
BN (baseline)	3.87	7.96	21.80	32.72	16.58
BN+MN	3.64	7.66	21.02	32.20	16.13
BN+MVN	4.07	8.31	20.34	33.04	16.44
BN+Gauss	4.15	8.12	20.18	32.67	16.28
BN+HEQ	3.96	7.43	19.76	30.87	15.50
BN+PCA	3.75	7.88	21.56	32.46	16.41
BN+DCT	3.77	7.77	21.76	32.49	16.44

ASR Experiments – Aurora-4
Noisy Training Set (only Additive)

BN post-processing is helpful.

MN is consistently useful.

HEQ → highest WER reduction
– Testset C: 2% WER reduction

Decorrelation has no effect.

Table 1: *WER for Aurora-4 (Kaldi-LDA-MLLT).*

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BN+PCA	3.75	7.88	21.56	32.46	16.41
BN+DCT	3.77	7.77	21.76	32.49	16.44

– MN: Mean normalised
– MVN: Mean-variance normalised
– Gauss: Gaussianisation
– HEQ: Histogram Equalisation

Wrap-up for Part I

- *Statistical* properties of Z and Y was investigated ...
  - *Analytically & Empirically*
- Re-explanations for ...
  - Pre-activation → easily fitted with *diagonal GMMs*
  - *Sparsity* of ReLU → Non-linearity
- *Post-processing* of BN features was investigated …
  - Up to 2% absolute (9% relative) WER reduction achieved

Outline

- PART I
  - Interpreting DNN's Activations
    - ICASSP 2019
- **PART II**
  - Interpreting DNN's Weights
    - Submitted to INTERSPEECH 2019

Part II Outline

- Acoustic Modelling from Raw Waveform via **SincNet**
- CNNs with Parametric Kernel-based Filters
  - Sinc^{2}Net, GammaNet, GaussNet
- Perceptual/Statistical Studies on Learned Filters

Raw Waveform Modelling via SincNet

SPEECH AND SPEAKER RECOGNITION FROM RAW WAVEFORM WITH SINCNET

*Mirco Ravanelli, Yoshua Bengio**

Mila, Université de Montréal , *CIFAR Fellow

ABSTRACT

Deep neural networks can learn complex and abstract representations, that are progressively obtained by combining simpler ones. A recent trend in speech and speaker recognition consists in discovering these representations starting from raw audio samples directly. Differently from standard hand-crafted features such as MFCCs or FBANK, the raw waveform can potentially help neural networks discover better and more customized representations. The high-dimensional raw inputs, however, can make training significantly more challenging.

This paper summarizes our recent efforts to develop a neural architecture that efficiently processes speech from audio waveforms. In particular, we propose *SincNet*, a novel Convolutional Neural Network (CNN) that encourages the first layer to discover meaningful filters by exploiting parametrized sinc functions. In contrast to standard CNNs, which learn all the elements of each filter, only low and high cutoff frequencies of band-pass filters are directly learned from data. This inductive bias offers a very compact way to derive a customized front-end, that only depends on some parameters with a clear physical meaning.

Our experiments, conducted on both speaker and speech recognition, show that the proposed architecture converges faster, performs better, and is more computationally efficient than standard CNNs.

Index Terms— ASR, CNN, SincNet, Raw samples.

We believe that one of the most critical parts of current waveform-based CNNs is the first convolutional layer. This layer not only deals with high-dimensional inputs, but it is also more affected by vanishing gradient problems, especially when employing very deep architectures. As we will show in this paper, th filters learned by CNNs often take noisy and incongruous m especially when few training samples are availa certainly make some sense for the neural network to human intuition, nor appear to lead to an effe of the speech signal.

To help the CNNs discover more meaningf proposed a novel convolutional architecture, that adds some constraints on the filter shape. CNNs, where the filter-bank characteristics rameters (each element of the filter vector is Net convolves the waveform with a set of tions that implement band-pass filters [18] off frequencies of the filters are the only data. This solution still offers considerab network to focus on high-level tunable p physical meaning.

In [18] we obtained promising res cation and speaker verification tasks. out to outperform standard CNNs fed dard features. Motivated by these extends our recent findings to speec recognition experiments conducted

Interpretable Convolutional Filters with SincNet

Mirco Ravanelli
Mila, Université de Montréal

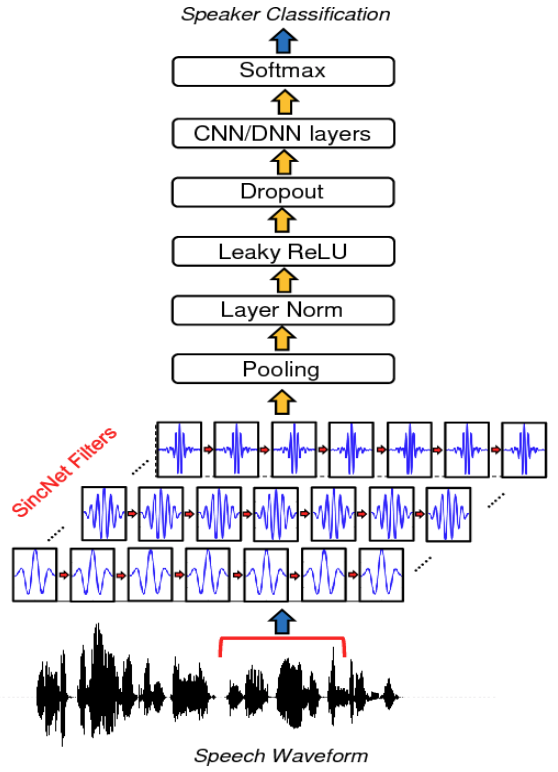
Yoshua Bengio
Mila, Université de Montréal
CIFAR Fellow

Abstract

Deep learning is currently playing a crucial role toward higher levels of artificial intelligence. This paradigm allows neural networks to learn complex and abstract representations, that are progressively obtained by combining simpler ones. Nevertheless, the internal "black-box" representations automatically discovered by current neural architectures often suffer from a lack of interpretability, making of primary interest the study of explainable machine learning techniques.

This paper summarizes our recent efforts to develop a more interpretable neural model for directly processing speech from the raw waveform. In particular, we propose *SincNet*, a novel Convolutional Neural Network (CNN) that encourages the first layer to discover more meaningful filters by exploiting parametrized sinc functions. In contrast to standard CNNs, which learn all the elements of each filter, only low and high cutoff frequencies of band-pass filters are directly learned from data. This inductive bias offers a very compact way to derive a customized filter-bank front-end, that only depends on some parameters with a clear physical meaning. Our experiments, conducted on both speaker and speech recognition, show that the proposed architecture converges faster, performs better, and is more interpretable than standard CNNs.

$$sinc(x) = \frac{\sin(\pi x)}{\pi x}$$



Raw Waveform Modelling via SincNet

SPEECH AND SPEAKER RECOGNITION FROM RAW WAVEFORM WITH SINCNET

*Mirco Ravanelli, Yoshua Bengio**

Mila, Université de Montréal , *CIFAR Fellow

ABSTRACT

Deep neural networks can learn complex and abstract representations, that are progressively obtained by combining simpler ones. A recent trend in speech and speaker recognition consists in discovering these representations starting from raw audio samples directly. Differently from standard hand-crafted features such as MFCCs or FBANK, the raw waveform can potentially help neural networks discover better and more customized representations. The high-dimensional raw inputs, however, can make training significantly more challenging.

This paper summarizes our recent efforts to develop a neural architecture that efficiently processes speech from audio waveforms. In particular, we propose *SincNet*, a novel Convolutional Neural Network (CNN) that encourages the first layer to discover meaningful filters by exploiting parametrized sinc functions. In contrast to standard CNNs, which learn all the elements of each filter, only low and high cutoff frequencies of band-pass filters are directly learned from data. This inductive bias offers a very compact way to derive a customized front-end, that only depends on some parameters with a clear physical meaning.

Our experiments, conducted on both speaker and speech recognition, show that the proposed architecture converges faster, performs better, and is more computationally efficient than standard CNNs.

***Index Terms*—** ASR, CNN, SincNet, Raw samples.

We believe that one of the most critical parts of current waveform-based CNNs is the first convolutional layer. This layer not only deals with high-dimensional inputs, but it is also more affected by vanishing gradient problems, especially when employing very deep architectures. As we will show in this paper, th- filters learned by CNNs often take noisy and incongruous m- especially when few training samples are availa- certainly make some sense for the neural network to human intuition, nor appear to lead to an effi- of the speech signal.

To help the CNNs discover more meaningf- proposed a novel convolutional architecture, that adds some constraints on the filter shape. CNNs, where the filter-bank characteristics rameters (each element of the filter vector is Net convolves the waveform with a set of tions that implement band-pass filters [18] off frequencies of the filters are the only data. This solution still offers considerab network to focus on high-level tunable p physical meaning.

In [18] we obtained promising res- cation and speaker verification tasks. out to outperform standard CNNs fed dard features. Motivated by these e extends our recent findings to speec recognition experiments conducted

Interpretable Convolutional Filters with SincNet

Mirco Ravanelli
Mila, Université de Montréal

Yoshua Bengio
Mila, Université de Montréal
CIFAR Fellow

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Deep learning is currently playing a crucial role toward higher levels of artificial intelligence. This paradigm allows neural networks to learn complex and abstract representations, that are progressively obtained by combining simpler ones. Nevertheless, the internal "black-box" representations automatically discovered by current neural architectures often suffer from a lack of interpretability, making of primary interest the study of explainable machine learning techniques.

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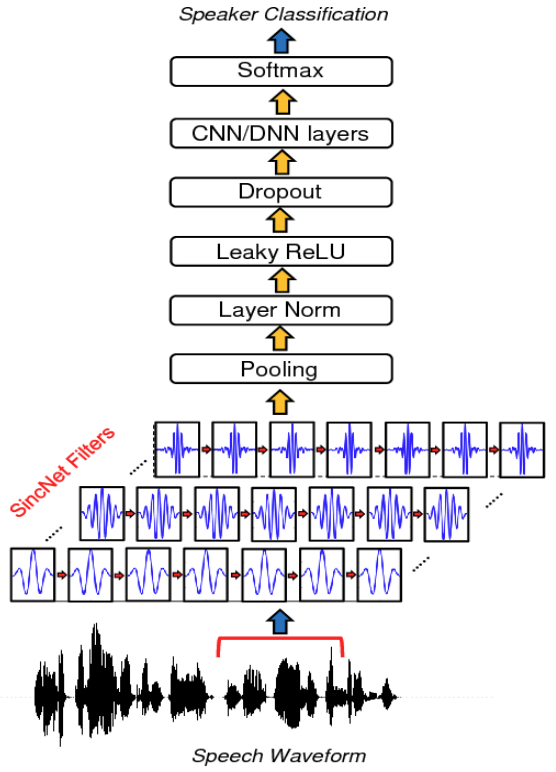
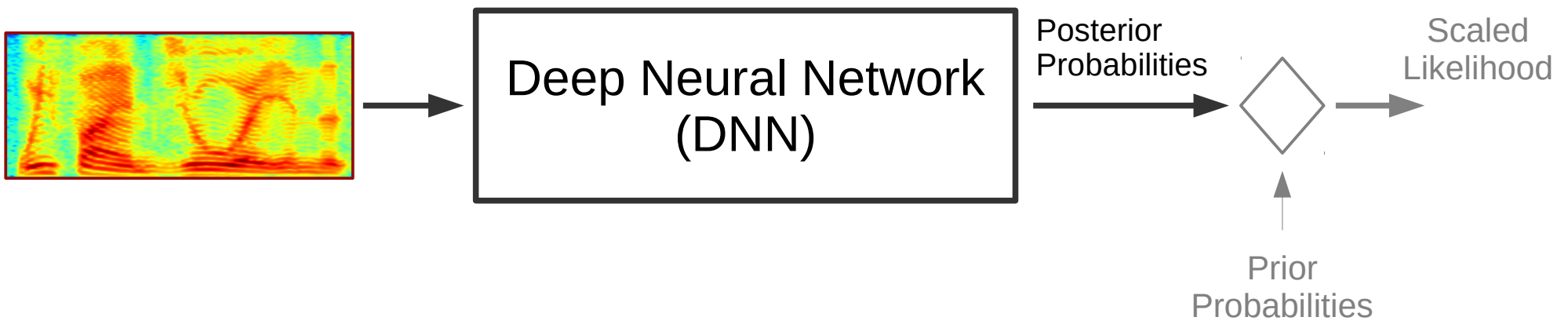


Acoustic Modelling from Conventional Features

- Conventional Features ↔ Fourier magnitude-based



Acoustic Modelling from Raw Waveform

- Advantages w.r.t. Fourier-based features

Acoustic Modelling from Raw Waveform

- Advantages w.r.t. Fourier-based features
  - Learned vs handcrafted pipeline
    - Task-oriented → optimal for the given tasks/labels
    - Employ all signal info → including *all-pass* and *phase* spec.
    - Learning basis functions → instead of Fourier's *complex exp.*

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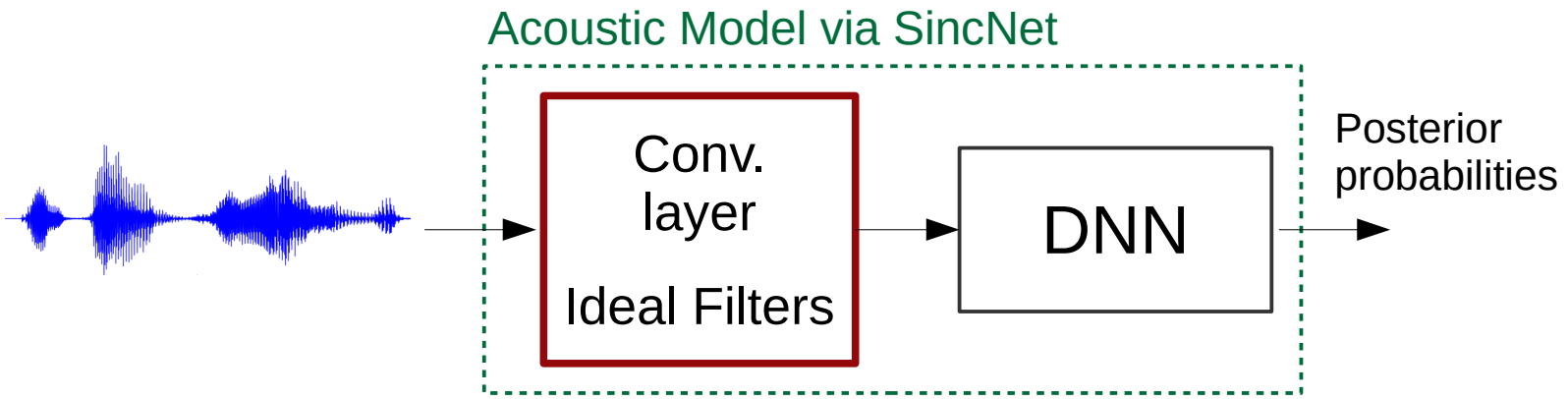
E. Loweimi, "**Robust Phase-based Speech Signal Processing; From Source-filter Separation to Model-based Robust ASR**," Ph.D. dissertation, University of Sheffield, Sheffield, UK, Feb 2018. [Online]. Available: http://etheses.whiterose.ac.uk/19409/

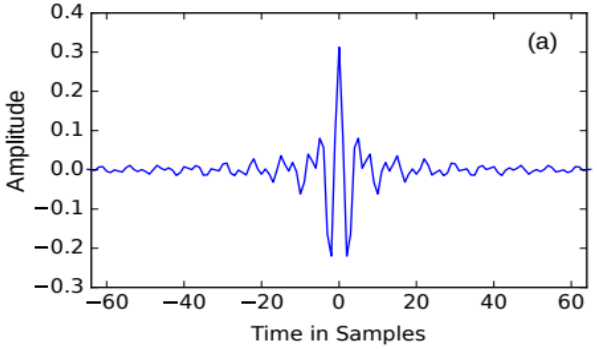
SincNet – Definition

- Convolutional layer with ideal bandpass filters
  - Impulse response ← Sinc



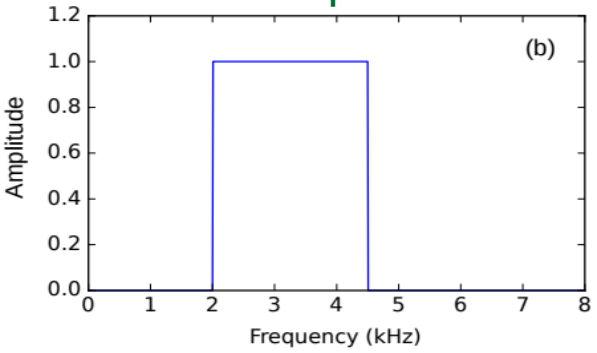
SincNet – Filters

- Impulse & Frequency Responses



Impulse response

Ideal bandpass filters



Frequency response

SincNet – Filters

- Filters' mathematical definition ...

$$h(t;\theta^{(i)}) = 2f_2^{(i)} sinc(2f_2^{(i)}t) - 2f_1^{(i)} sinc(2f_1^{(i)}t)$$

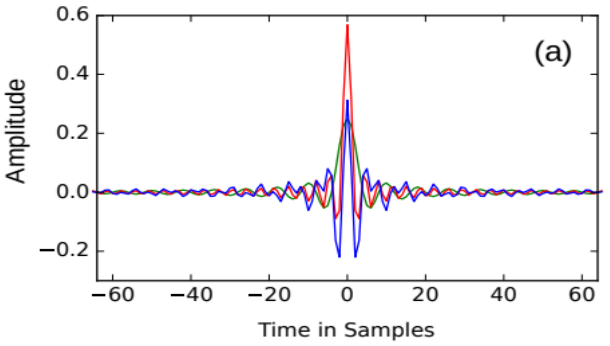
$$H(f;\theta^{(i)}) = \Pi(\frac{f}{2f_2^{(i)}}) - \Pi(\frac{f}{2f_1^{(i)}})$$

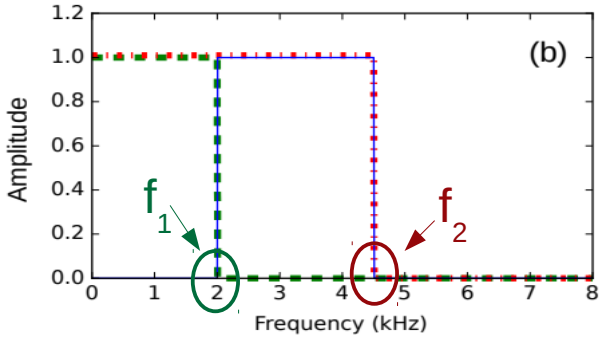
i: filter index in the filterbank

SincNet – Filters Shape

$$h(t;\theta^{(i)}) = 2f_2^{(i)} sinc(2f_2^{(i)}t) - 2f_1^{(i)} sinc(2f_1^{(i)}t)$$

$$H(f;\theta^{(i)}) = \Pi(\frac{f}{2f_2^{(i)}}) - \Pi(\frac{f}{2f_1^{(i)}})$$





SincNet – Parameters

- Parameter Set (Θ) → cut-off frequencies: f_1 & f_2

$$h(t;\theta^{(i)}) = 2f_2^{(i)} sinc(2f_2^{(i)}t) - 2f_1^{(i)} sinc(2f_1^{(i)}t)$$

$$H(f;\theta^{(i)}) = \Pi(\frac{f}{2f_2^{(i)}}) - \Pi(\frac{f}{2f_1^{(i)}})$$

$$\Theta = \{\theta^{(i)}\} = \{f_1^{(i)}, f_2^{(i)}\}$$

Backprop ←

Advantages of SincNet

SincNet vs CNN -- Advantages

- Parametric vs Non-parametric

SincNet vs CNN -- Advantages

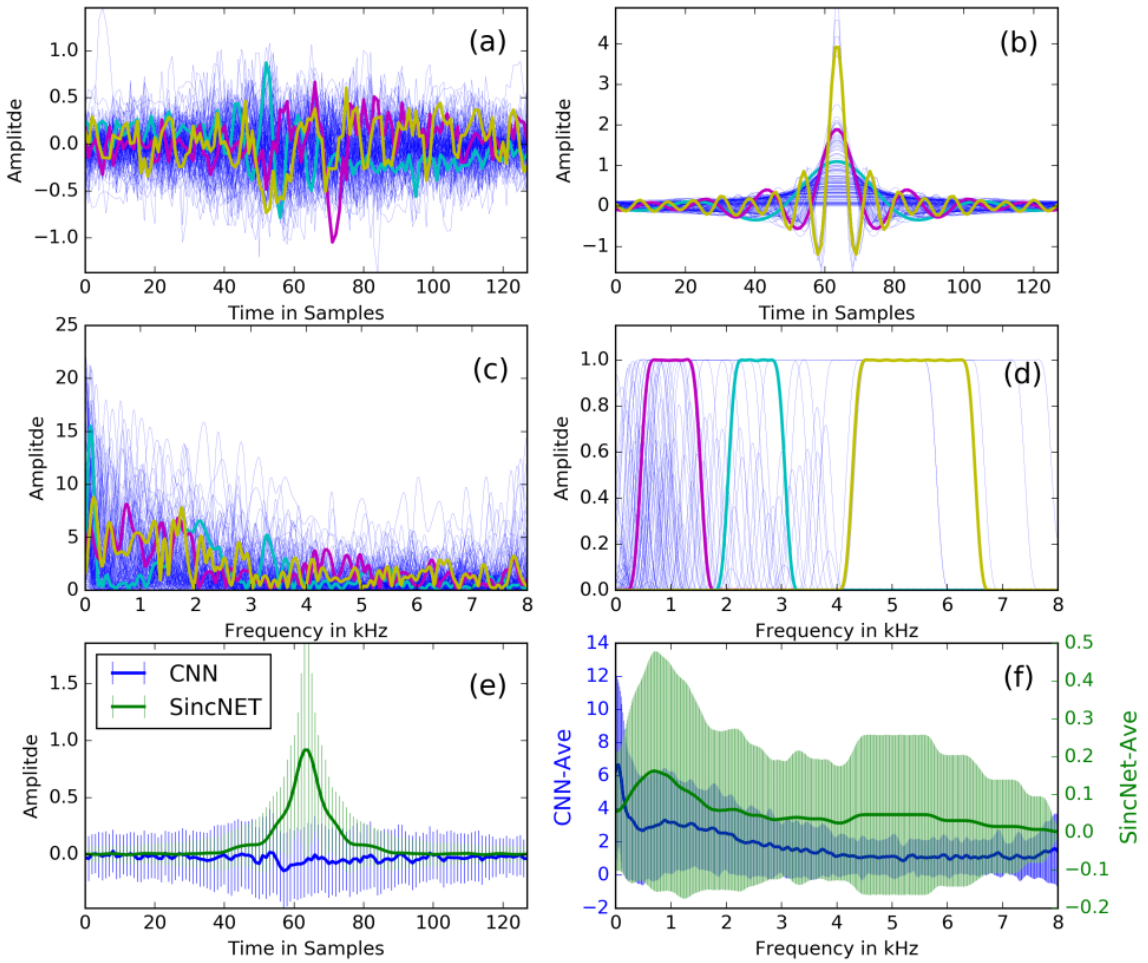
- **Parametric** vs Non-parametric
  - More Interpretable

CNN vs SincNet

CNN
impulse responses

CNN
Frequency responses

Average
impulse responses



SincNet
impulse responses

SincNet
Frequency responses

Average
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SincNet vs CNN -- Advantages

- **Parametric** vs Non-parametric
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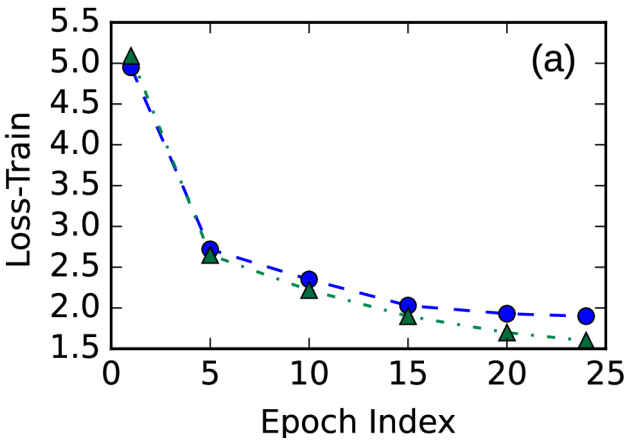
  - Constraint on hypothesis space
    - Regularisation → better generalisation

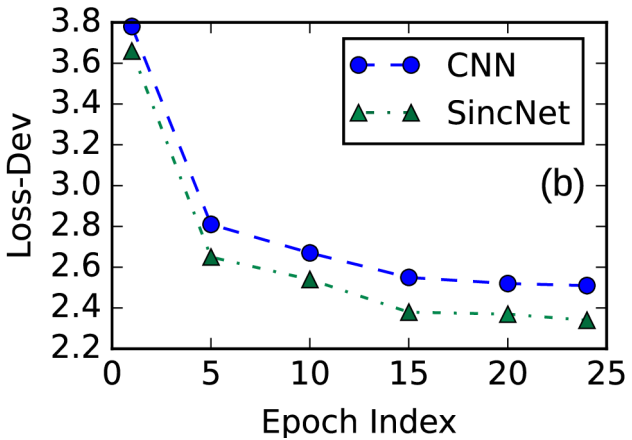
SincNet vs CNN -- Advantages

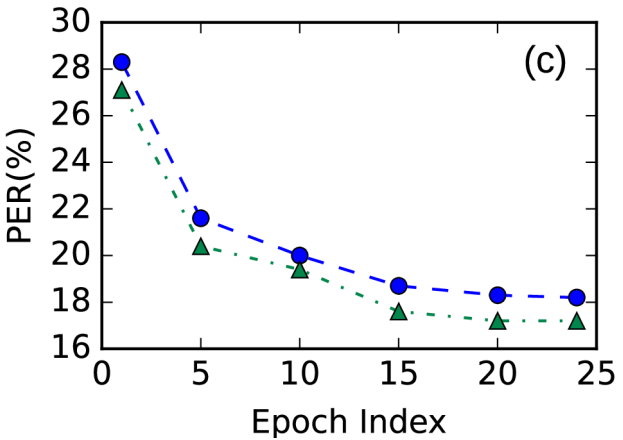
- **Parametric** vs Non-parametric
  - More interpretable
  - Constraint on hypothesis space
    - Regularisation → better generalisation
  - Fewer parameters
    - Less training data required
    - Faster learning/convergence

SincNet vs CNN -- Advantages

- Parametric vs Non-parametric
- Better performance on TIMIT ...
  - Lower loss and phone error rate (PER)



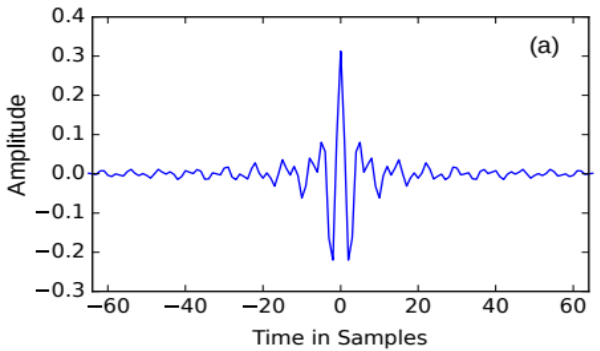


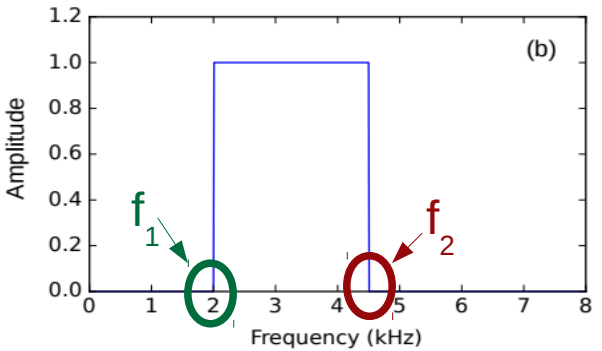


General Formulation for Interpretable Kernel-based CNNs

Interpretable Kernel-based CNNs

$$h(t;\theta^{(i)}) = 2f_2^{(i)} sinc(2f_2^{(i)}t) - 2f_1^{(i)} sinc(2f_1^{(i)}t)$$





Interpretable Kernel-based CNNs

$$h(t;\theta^{(i)}) = 2f_2^{(i)} sinc(2f_2^{(i)}t) - 2f_1^{(i)} sinc(2f_1^{(i)}t)$$

$$h(t;\theta^{(i)}) = \frac{1}{\pi t}(\sin(2\pi f_2^{(i)}t) - \sin(2\pi f_1^{(i)}t))$$

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$$\sin\alpha - \sin\beta = 2\sin\frac{\alpha-\beta}{2}\cos\frac{\alpha+\beta}{2}$$

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$$h^{(i)}(t) = 2B^{(i)} sinc(B^{(i)}t)\ \cos(2\pi f_c^{(i)}t)$$

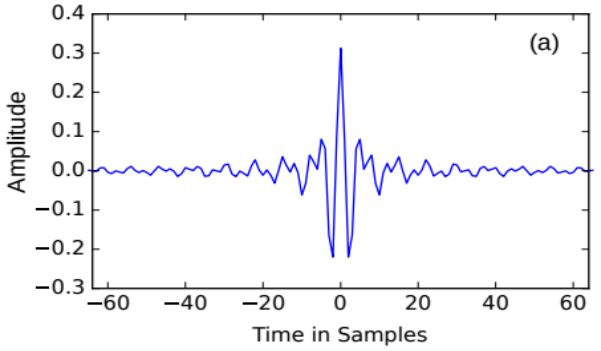
$$B^{(i)} = f_2^{(i)} - f_1^{(i)} \quad , \quad f_c^{(i)} = \frac{f_1^{(i)} + f_2^{(i)}}{2}$$

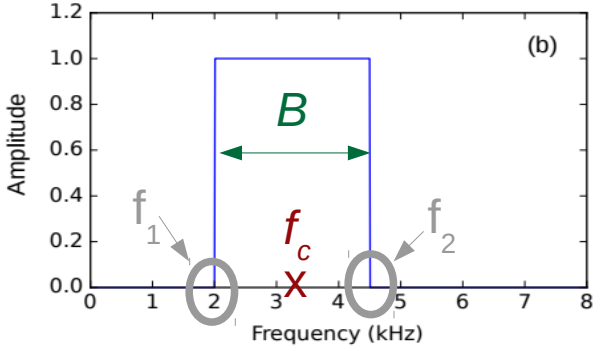
Interpretable Kernel-based CNNs

$$h^{(i)}(t) = 2B^{(i)} sinc(B^{(i)} t) \cos(2\pi f_c^{(i)} t)$$

Baseband filter ≡ Kernel

Carrier





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Baseband filter ≡ Kernel

Carrier

$$h^{(i)}(t; \theta^{(i)}, f_c^{(i)}) = K(t; \theta^{(i)}) \; carrier(t; f_c^{(i)})$$

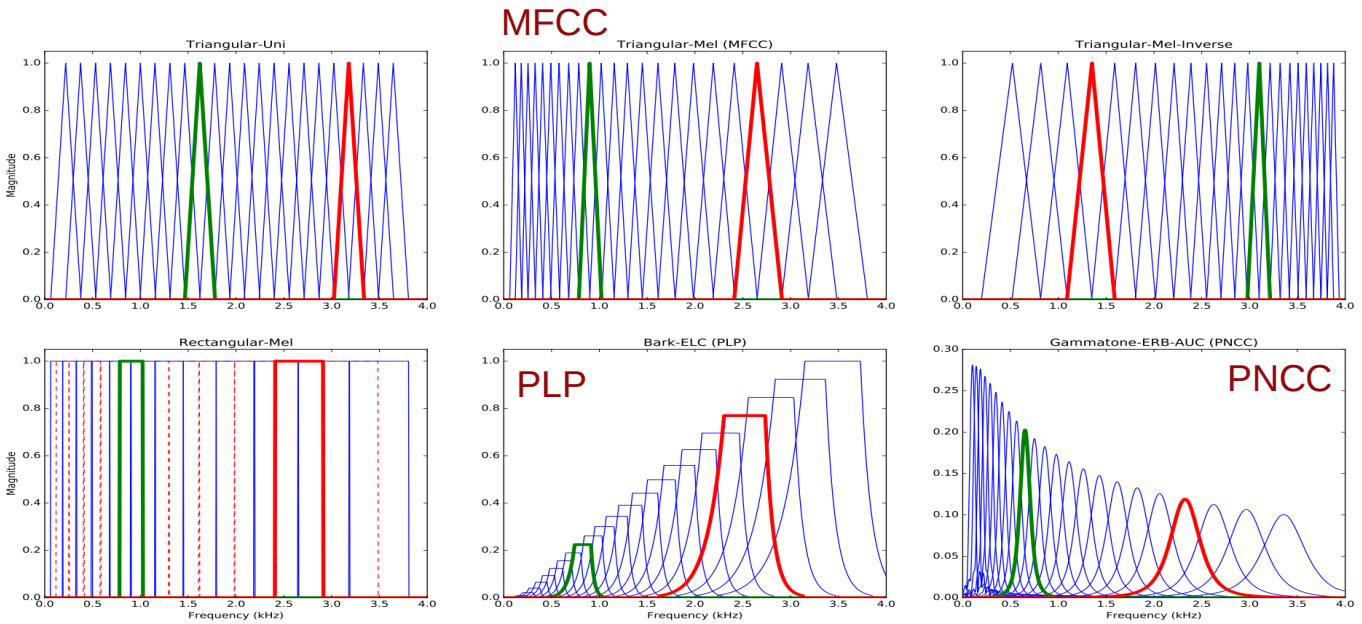
Interpretable Kernel-based CNNs

$$\text{Parameter Set: } \Theta = \{\theta^{(i)}, f_c^{(i)}\}$$

Kernel Carrier

$$h^{(i)}(t; \theta^{(i)}, f_c^{(i)}) = K(t; \theta^{(i)}) \; carrier(t; f_c^{(i)})$$

Learning Kernel-based Filterbanks



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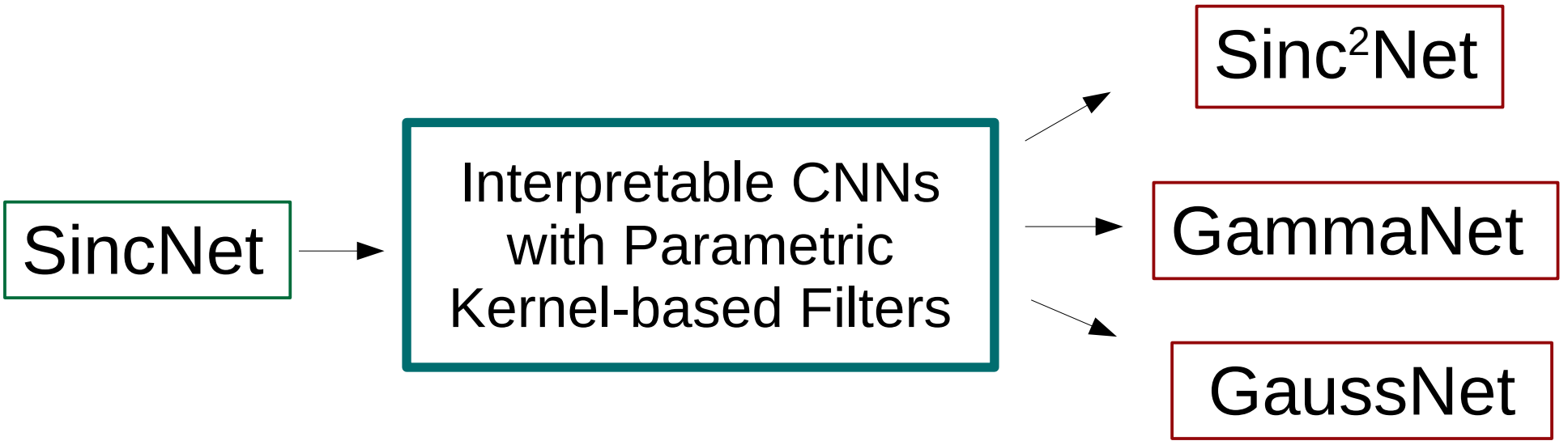
Learning Kernel-based Filterbanks



Sinc²Net: Triangular Filters

- Widely used in Speech processing → MFCC
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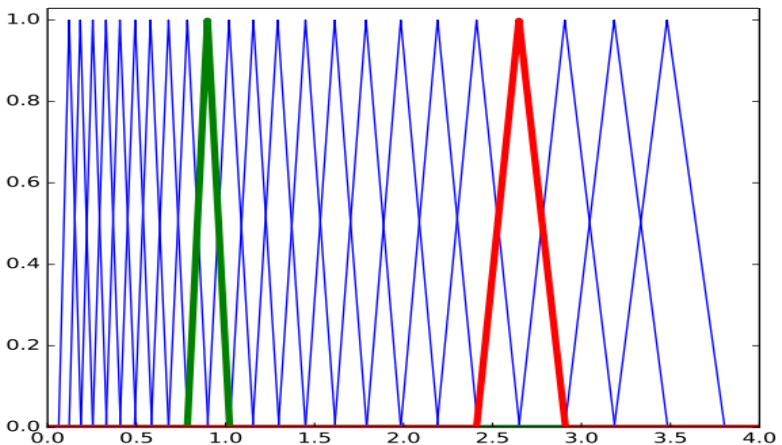
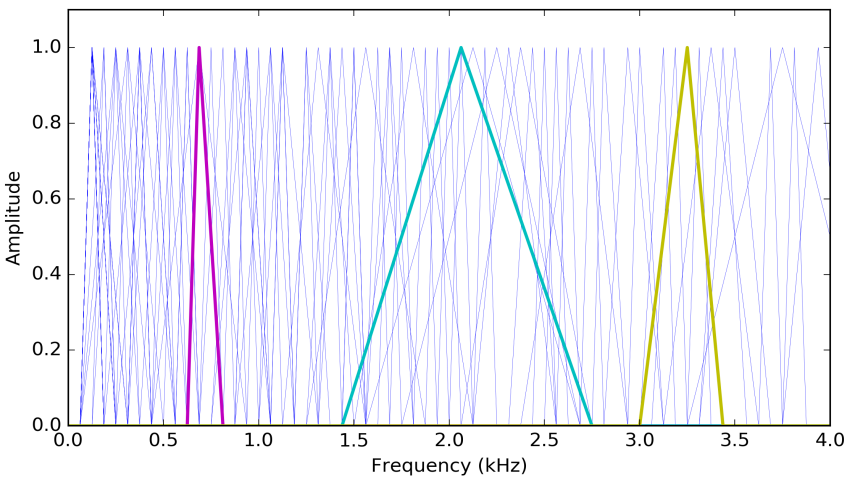
Engineered



Learned



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$$K(t;\theta^{(i)}) = A^{(i)} sinc^2(B^{(i)}t)$$

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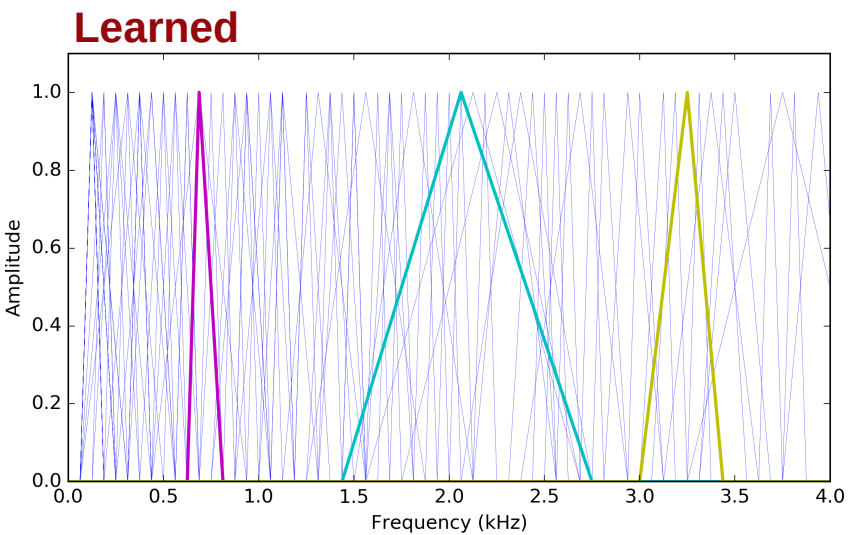

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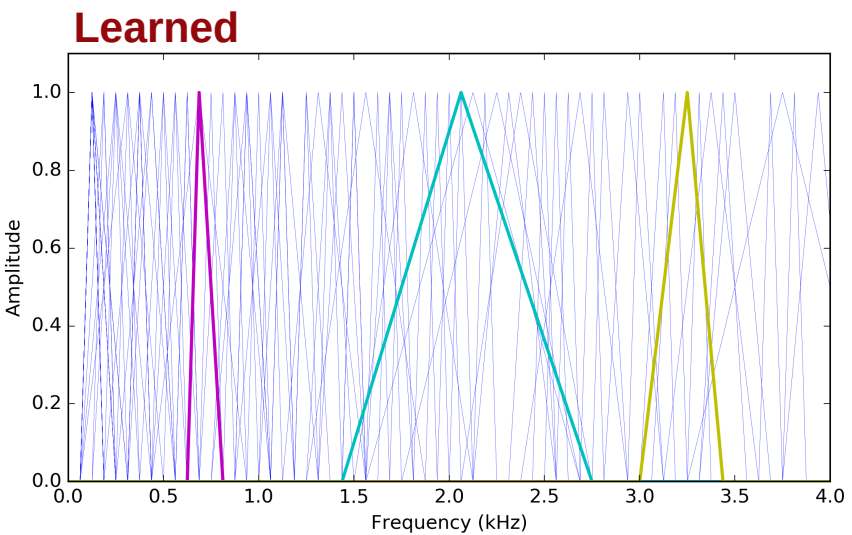
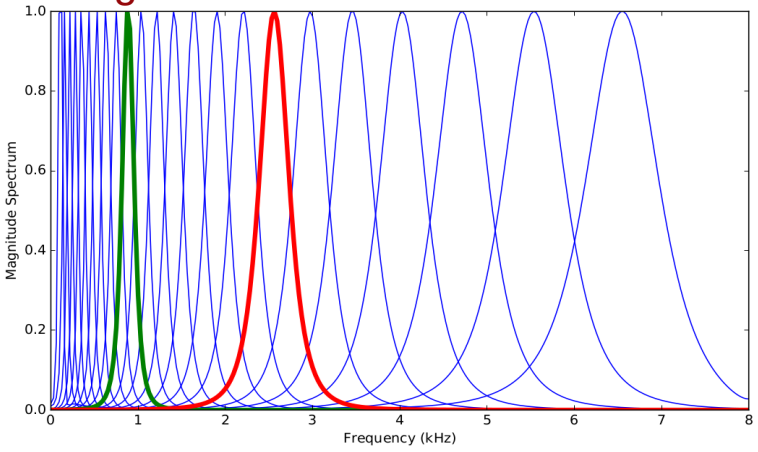
Amplitude Bandwidth



GammaNet: Gammatone Filters

- Even more biologically plausible
  - Describes impulse response of auditory filters in Cochlea

Engineered



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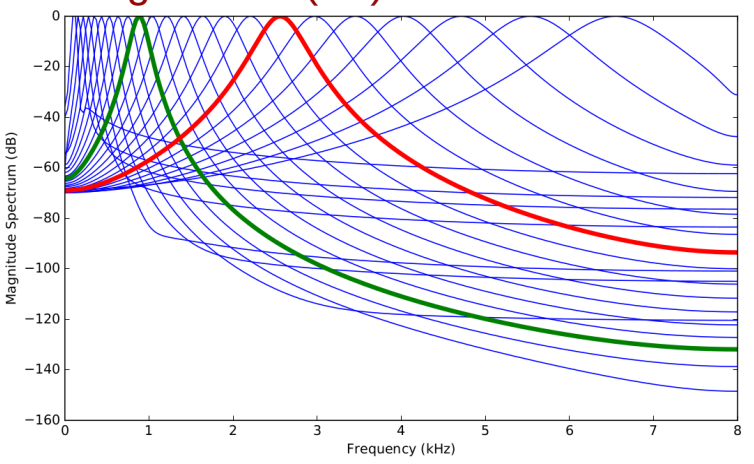

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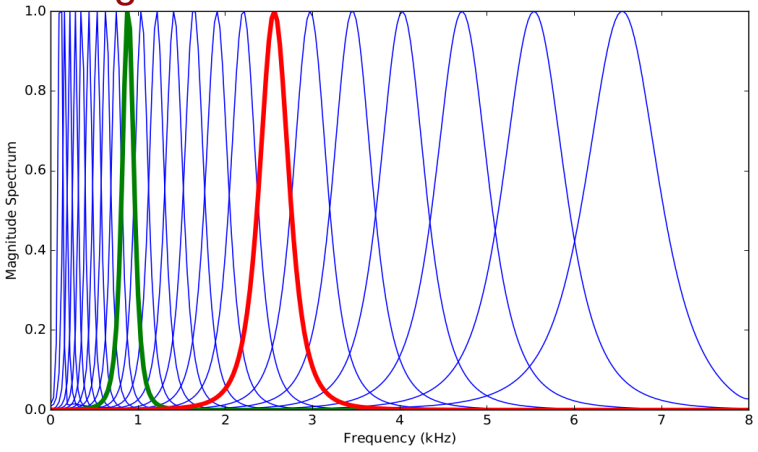
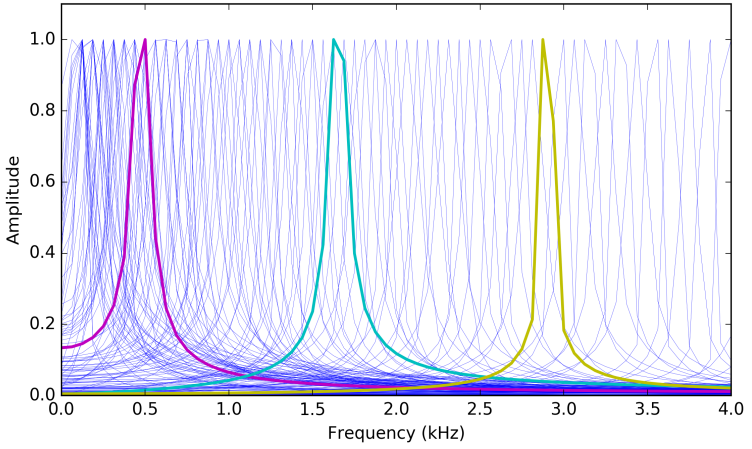


Learned



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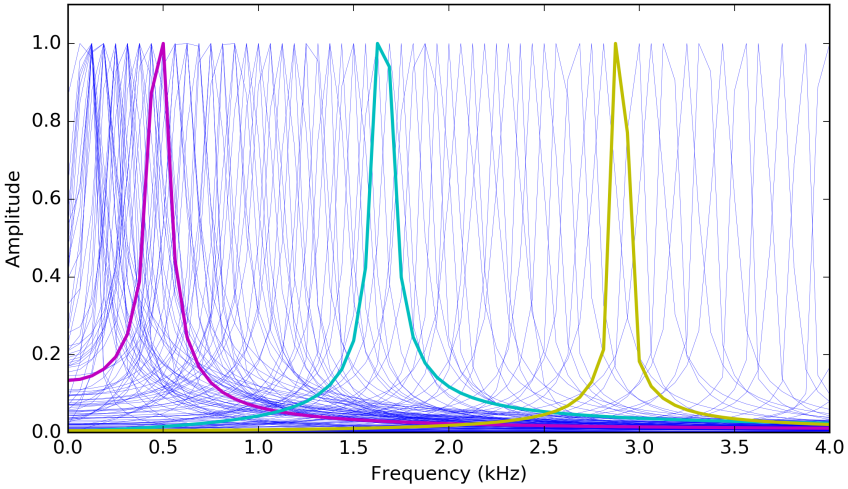
$$K(t;\theta^{(i)}) = A^{(i)} t^{(N^{(i)}-1)} e^{-2\pi B^{(i)} t}$$

$$\theta^{(i)} = \{A^{(i)}, B^{(i)}, N^{(i)}\}$$



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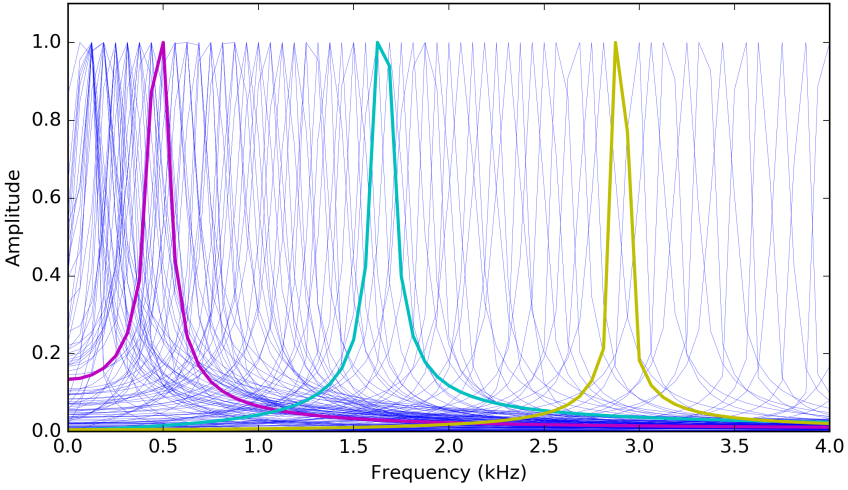
Order



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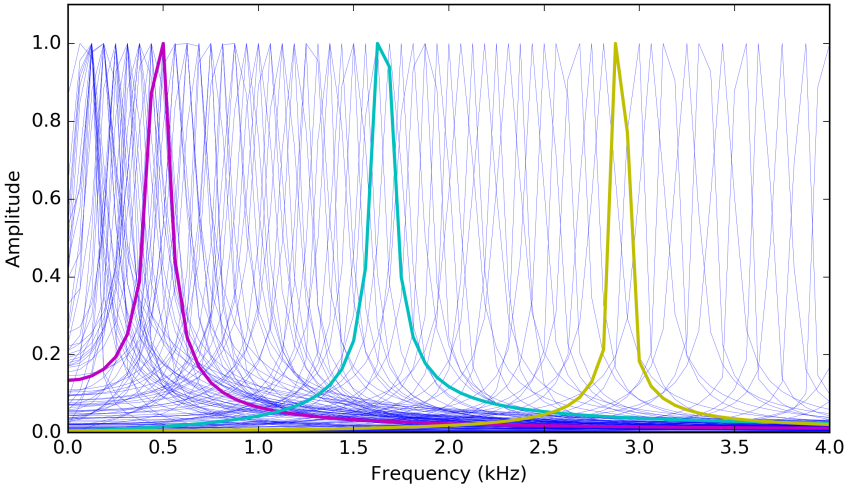
$$\theta^{(i)} = \{A^{(i)}, B^{(i)}, N^{(i)}\}$$

Typical value: 4

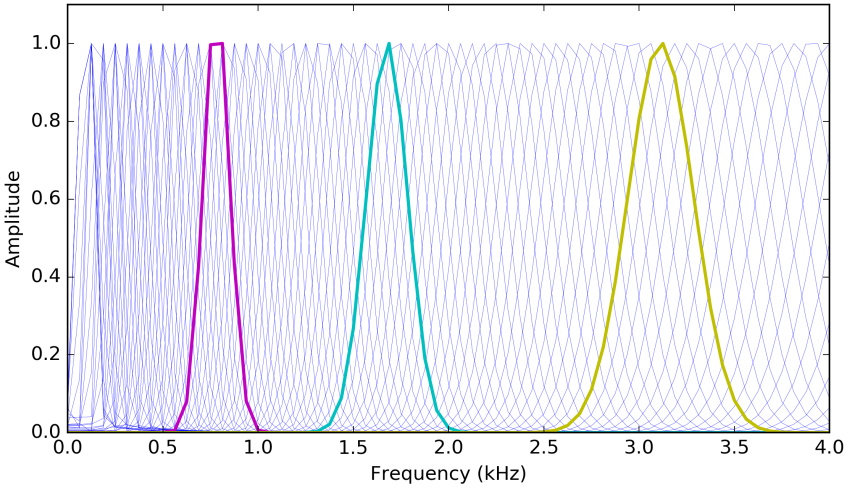


GaussNet: Gaussian Filters

- Bell-shaped Filters

$$K(t;\theta^{(i)}) = A^{(i)} \exp(-t^2/\sigma_i^2)$$

$$\theta^{(i)} = \{A^{(i)}, \sigma^{(i)}\}$$



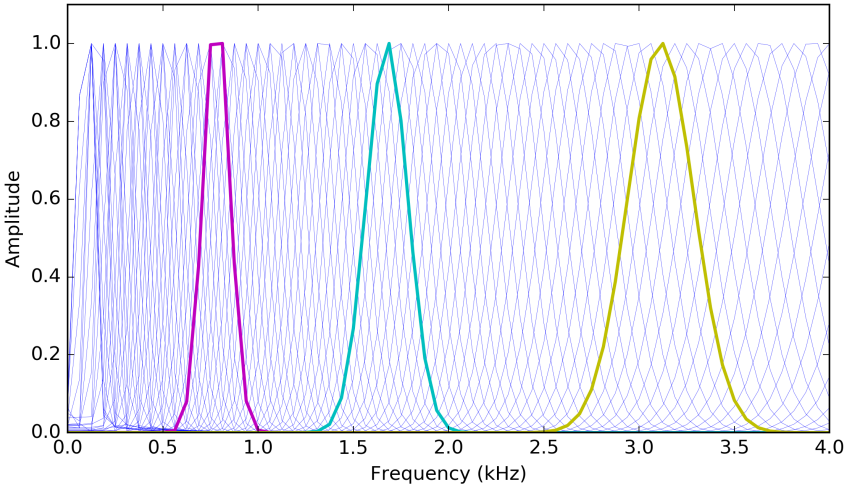
GaussNet: Gaussian Filters

- Bell-shaped Filters

$$K(t;\theta^{(i)}) = A^{(i)} \exp(-t^2/\sigma_i^2)$$

$$\sigma_i = \frac{\sqrt{log2}}{2\pi B_i}$$

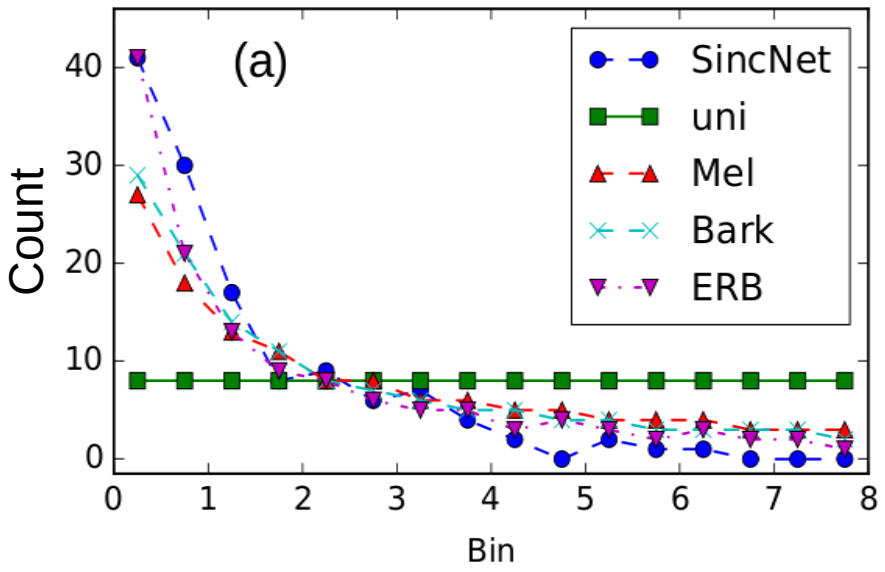
3 dB bandwidth (Hz) of the *i*th filter



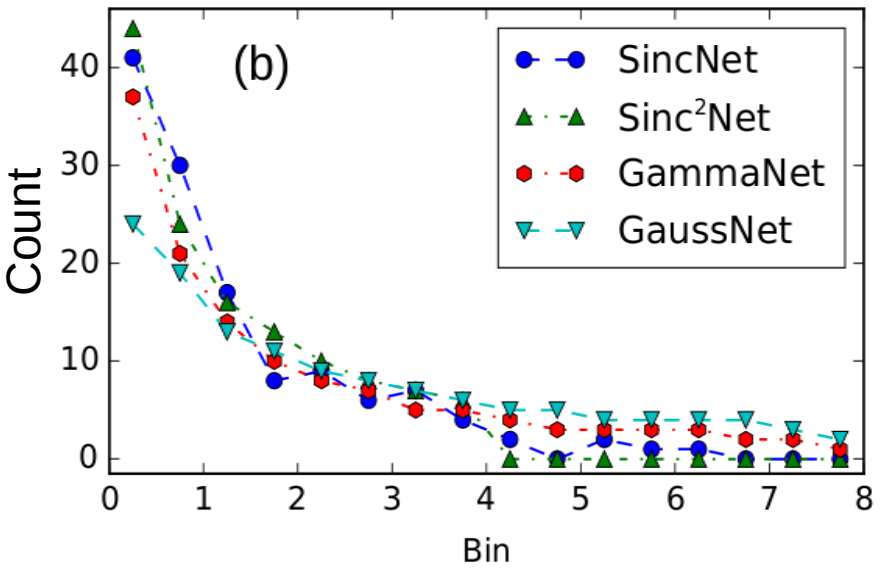
Perceptual and Statistical Studies

Filters' Centre Frequency Distribution

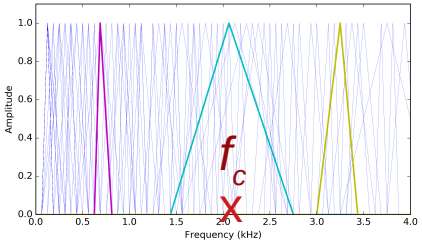
Histograms



Histograms

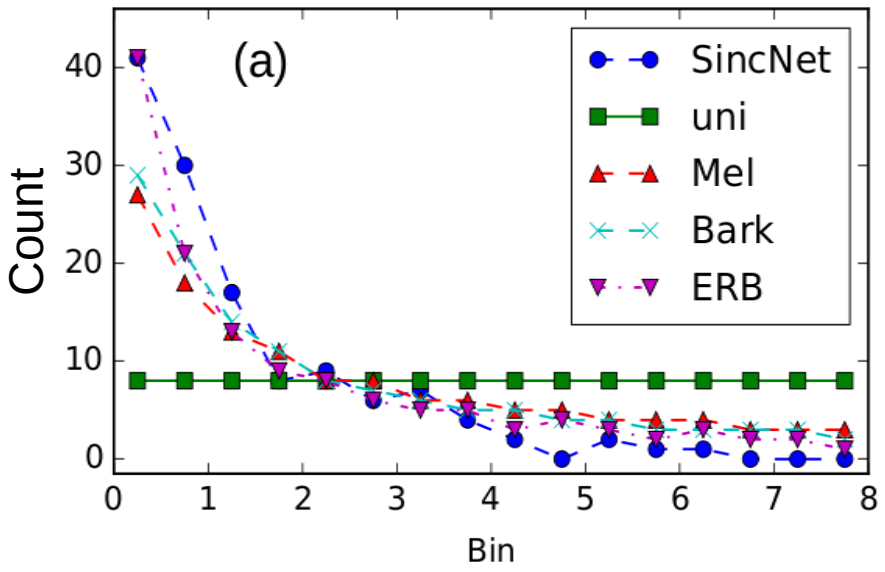


Centre frequency in kHz

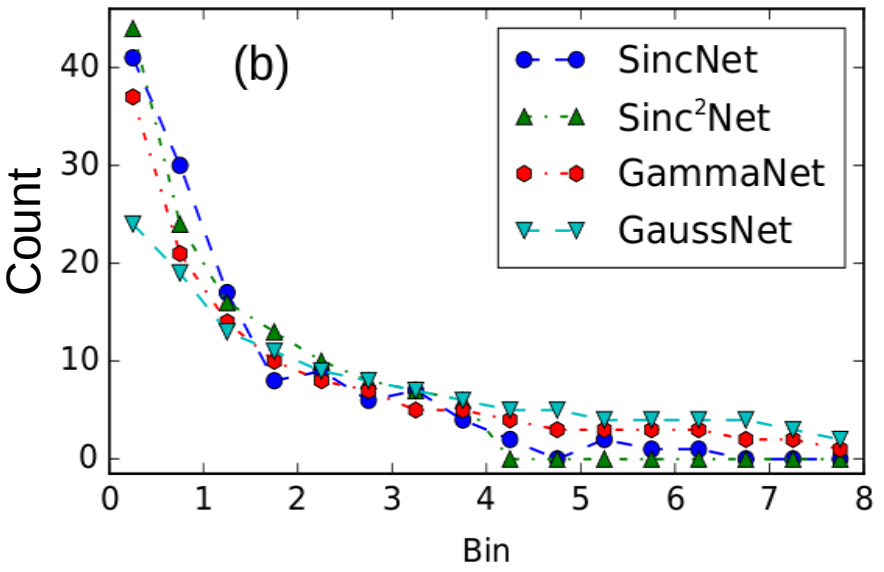


Filters' Centre Frequency Distribution

Histograms



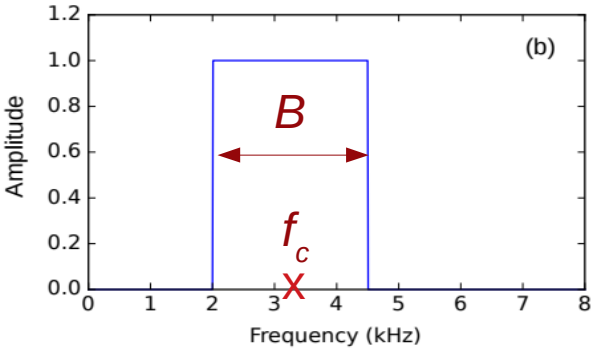
Histograms



Higher filter concentration at low frequencies (< 2 kHz).
==>> More discriminative and selective filtering ...

Quality Factor (Q) of the Filters

$$Q^{(i)} = \frac{f_c^{(i)}}{B^{(i)}}$$



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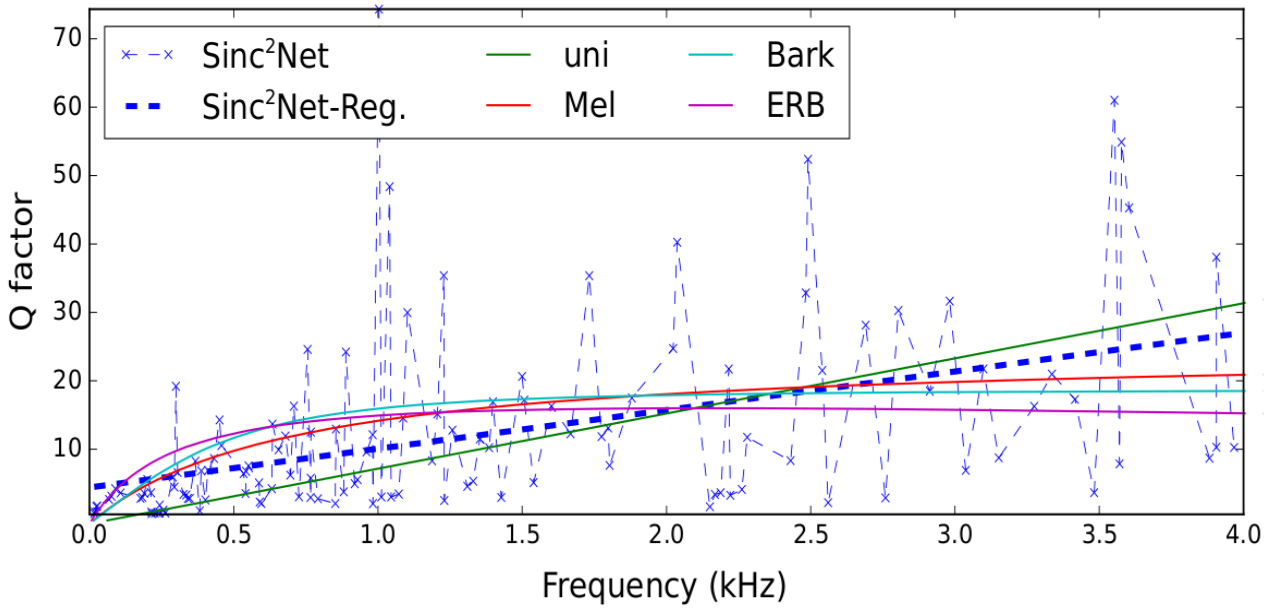
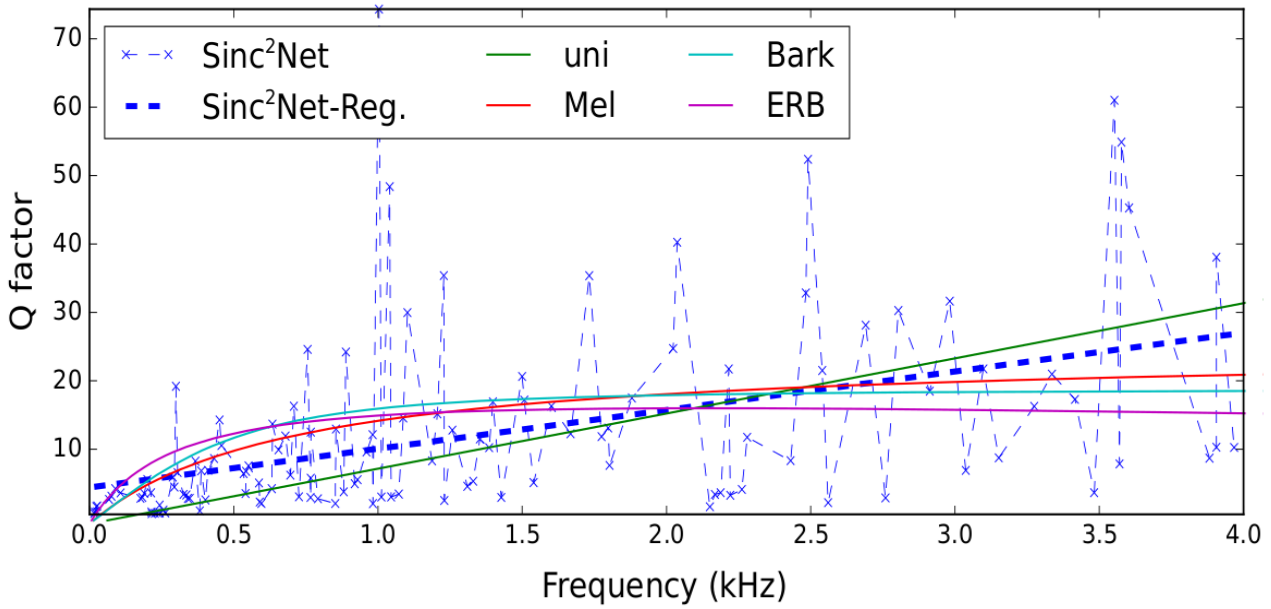
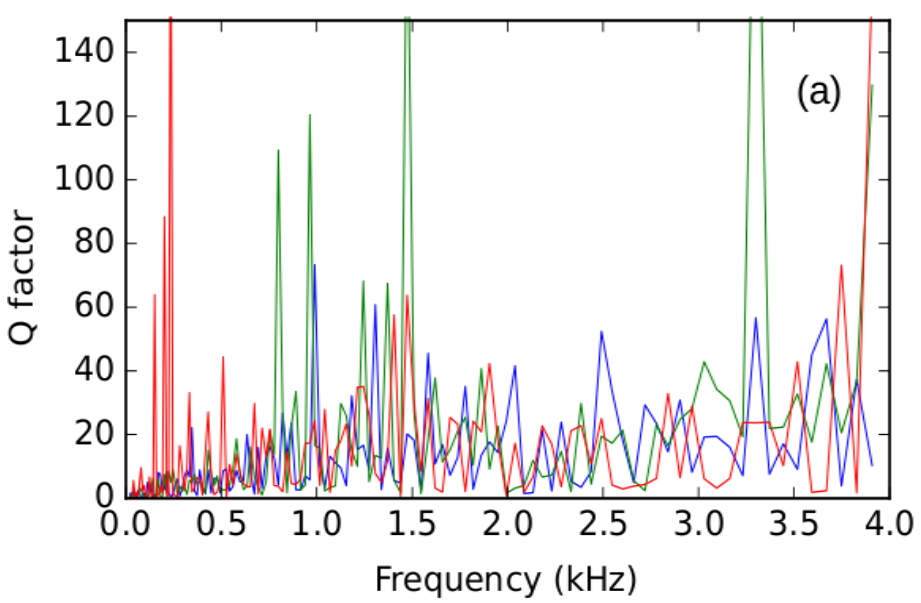


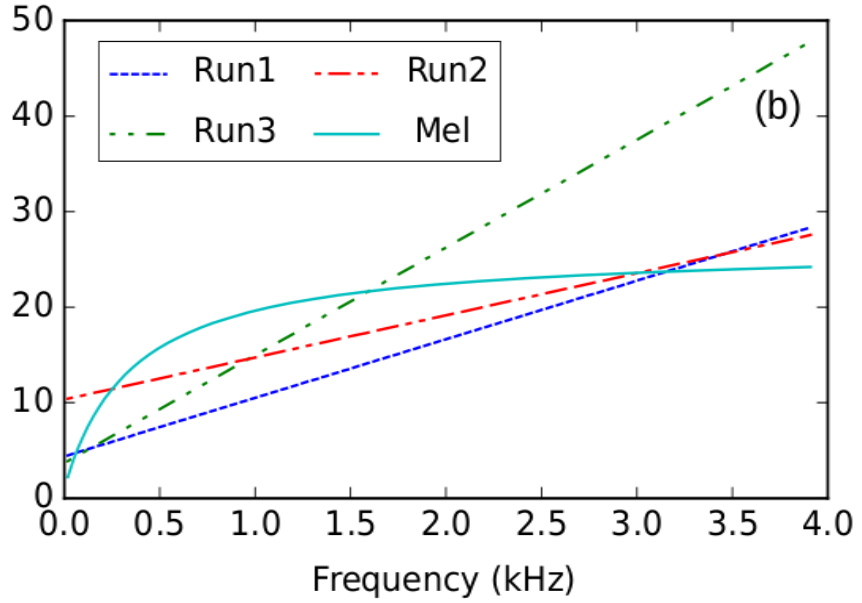
Quality Factor (Q) of the Filters



Similar trend to the perceptual measures.

Quality Factor (Q) of the Filters





It is not a random effect ...

Gammatone Filters Order -- Perceptual Studies

Page - 7 -

A. A Comparison of Roex and Gammatone Amplitude Spectra

Schofield (1985) has recently demonstrated that a gammatone filter with order 4 provides a good fit to the average auditory filters presented in Patterson (1976).

Schofield, D. (1985). Visualisations of speech based on a model of the peripheral auditory system. NPL Report DITC 62/85.

AN EFFICIENT AUDITORY FILTERBANK BASED ON THE GAMMATONE FUNCTION

Roy Patterson and Ian Nimmo-Smith

MRC Applied Psychology Unit
15 Chaucer Road
Cambridge CB2 2EF

John Holdsworth and Peter Rice

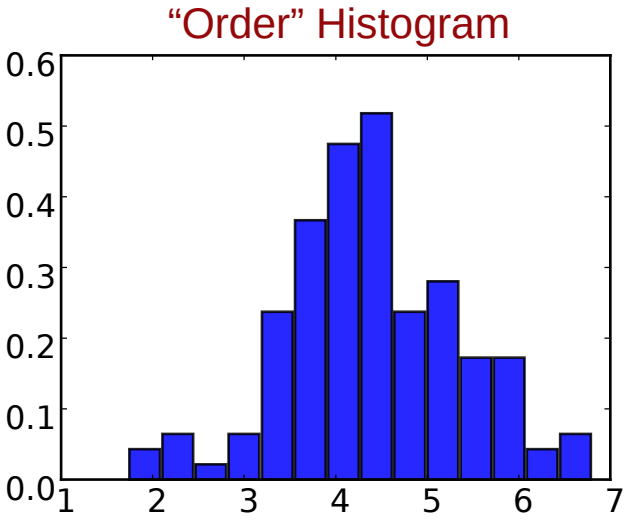
Cambridge Electronic Design
Science Park
Milton Road
Cambridge

December 1987

Gammatone Filters Order Perceptual vs Learned

Table 1: *Statistics of the GammaNet learned filters order.*

	Mean	Median	Std	Min	Max
GammaNet	4.39	4.30	0.97	1.73	6.80



No constraint was imposed on filters order during training.

Gammatone Filters Order Perceptual vs Learned

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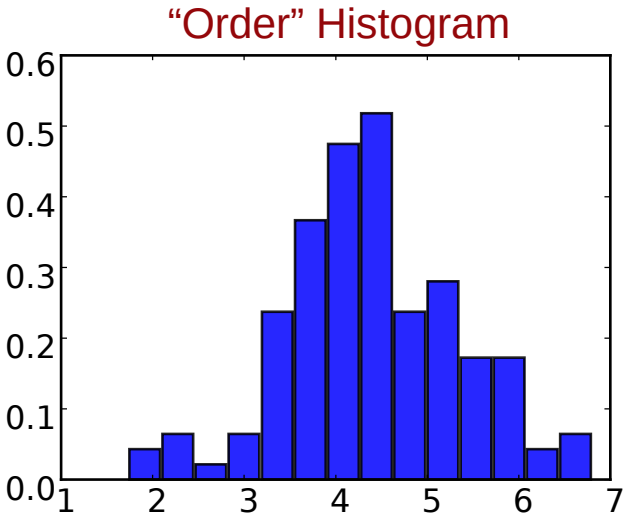
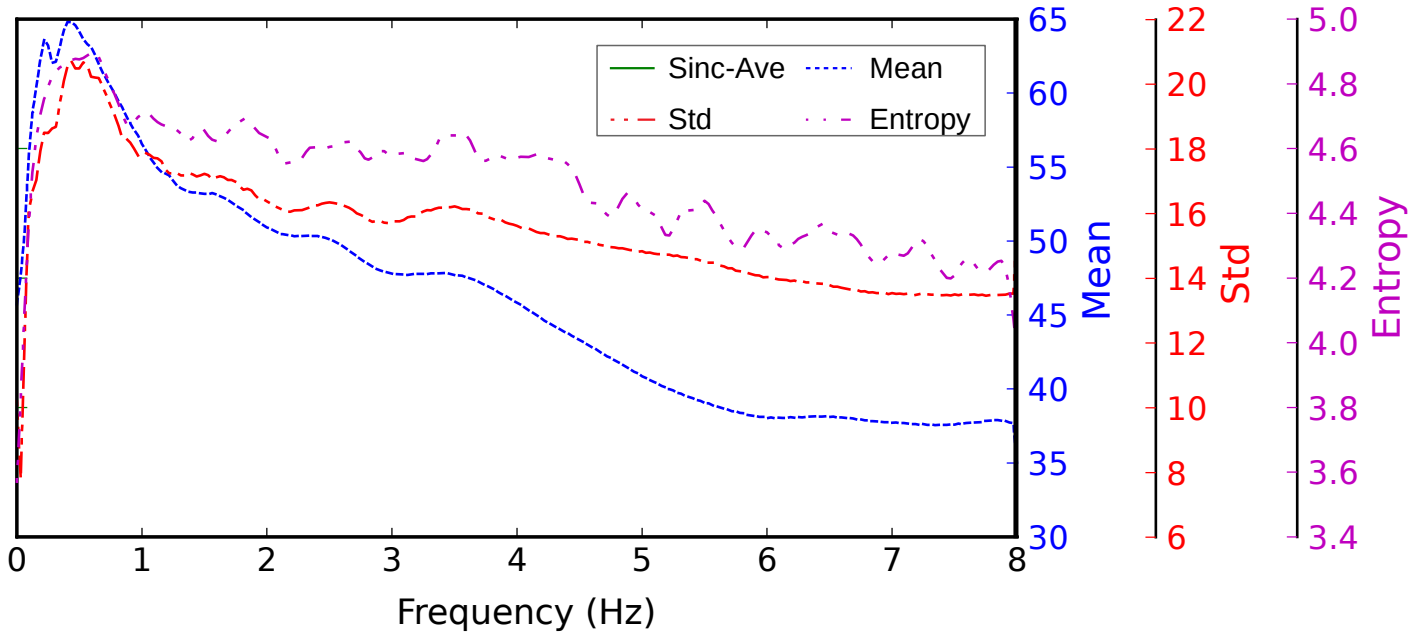


Matches with perceptual studies on human auditory system.

Statistical Properties of the Data and the Learned Filters

Statistical Properties of the Data and the Learned Filters



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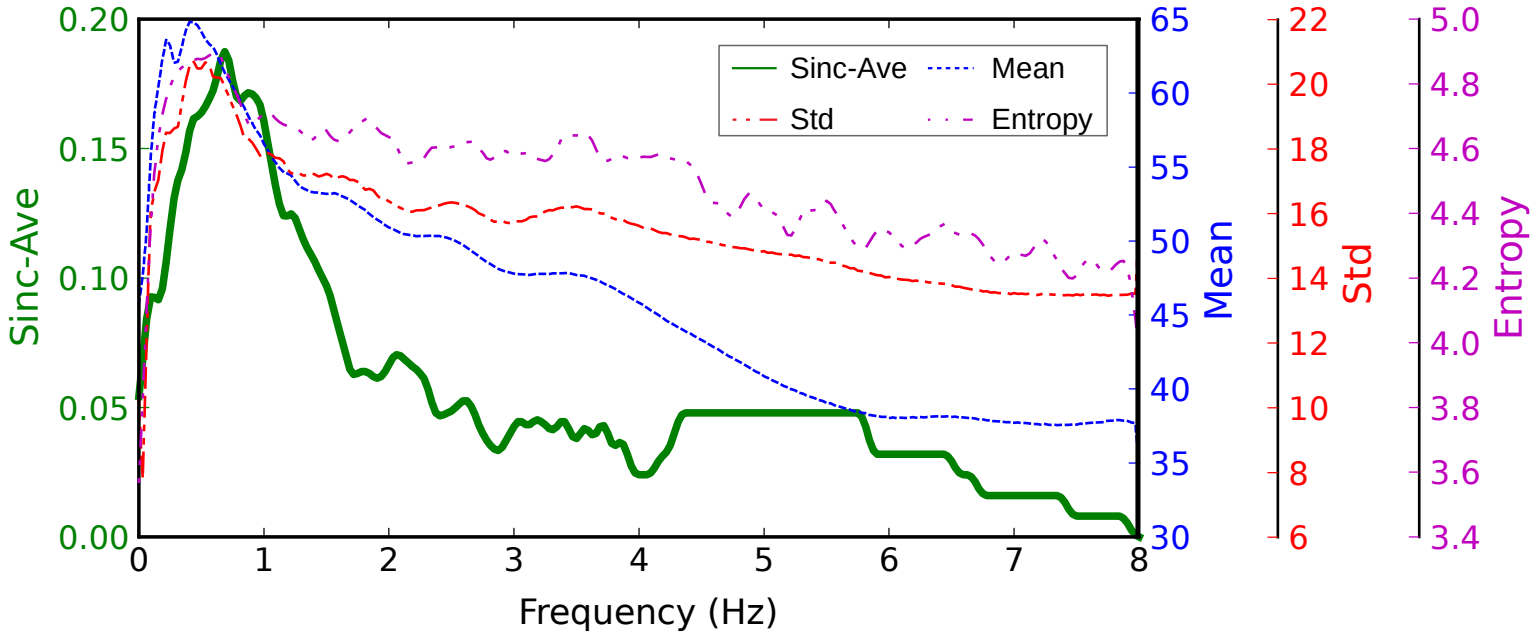
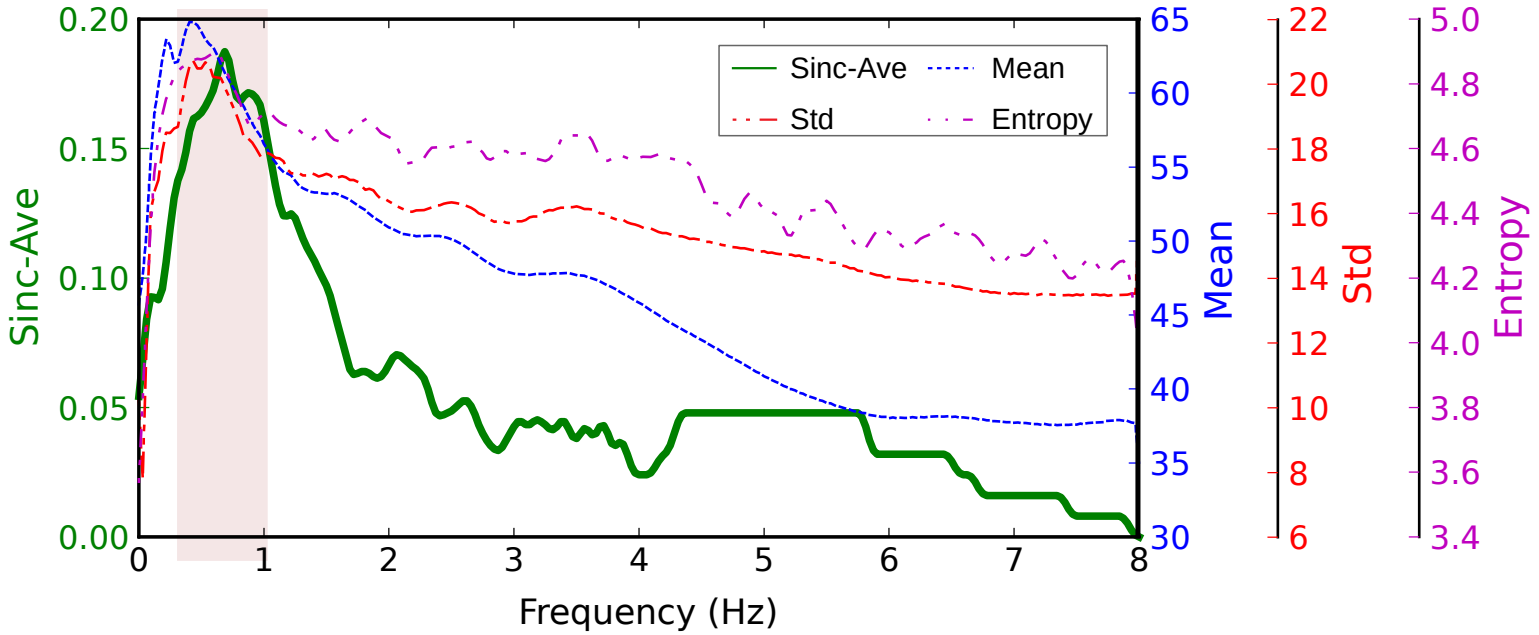


Statistical Properties of the Data and the Learned Filters



Argmax Entropy ≈ Argmax Std ≈ Argmax Ave Filter Mag.

Experimental Results

Experimental Results – Setup

- Task: TIMIT phone recognition
- Tools: Kaldi + PyTorch-Kaldi
- Frame length: 200 ms, frame shift: 10 ms
- Optimisation: 24 Epochs, RMSprop
- Architecture: Convolutional layer + MLP + output layer
  - MLP → 5 hidden layers, 1024 nodes, ReLU

Experimental Results – PER

Table 2: *TIMIT PER for different kernels (200 ms).*

	MLP	CNN	Sinc	Sinc^2	Gamma	Gauss
PER	18.5	18.2	17.6	16.9	17.2	17.0

Experimental Results – PER

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log-Filterbank

Raw Waveform models

Raw waveform models outperform log-Filterbank features.

Experimental Results – PER

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	MLP	CNN	Sinc	Sinc^2	Gamma	Gauss
PER	18.5	18.2	17.6	16.9	17.2	17.0

Non-Parametric ◄——► Parametric

Parametric Nets outperform non-parametric CNN.

Experimental Results – PER

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	MLP	CNN	Sinc	$Sinc^2$	Gamma	Gauss
PER	18.5	18.2	17.6	16.9	17.2	17.0

SincNet

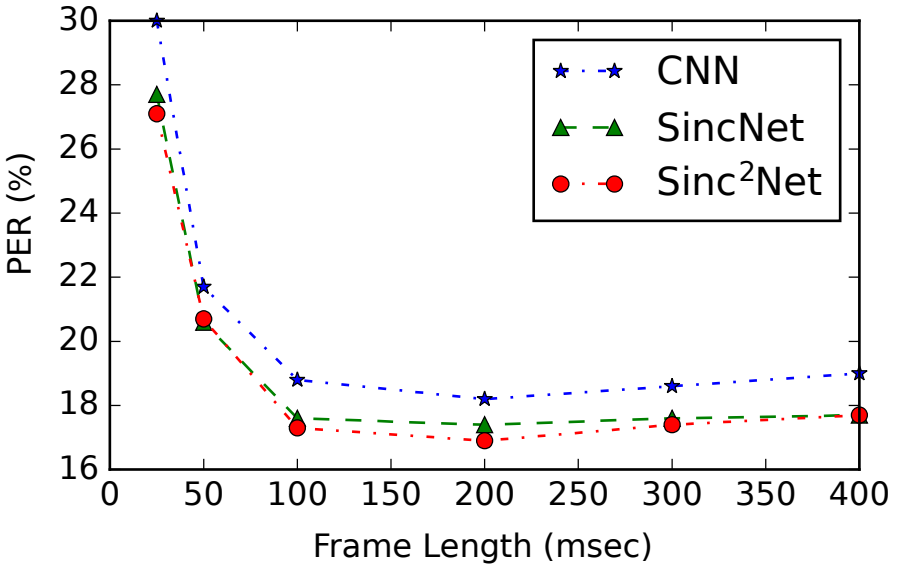
X-Nets

X-Nets outperform SincNet (also are more biologically plausible).

Frame Length Effect Investigation

Table 3: *TIMIT PER for different frame lengths (ms).*

	25	50	100	200	300	400
CNN	30.0	21.7	18.8	18.2	18.6	19.0
SincNet	27.7	20.6	17.6	17.4	17.6	17.7
Sinc^{2}Net	27.1	20.7	17.3	16.9	17.4	17.7



Optimal Frame Length: 200 ms

Table 3: *TIMIT PER for different frame lengths (ms).*

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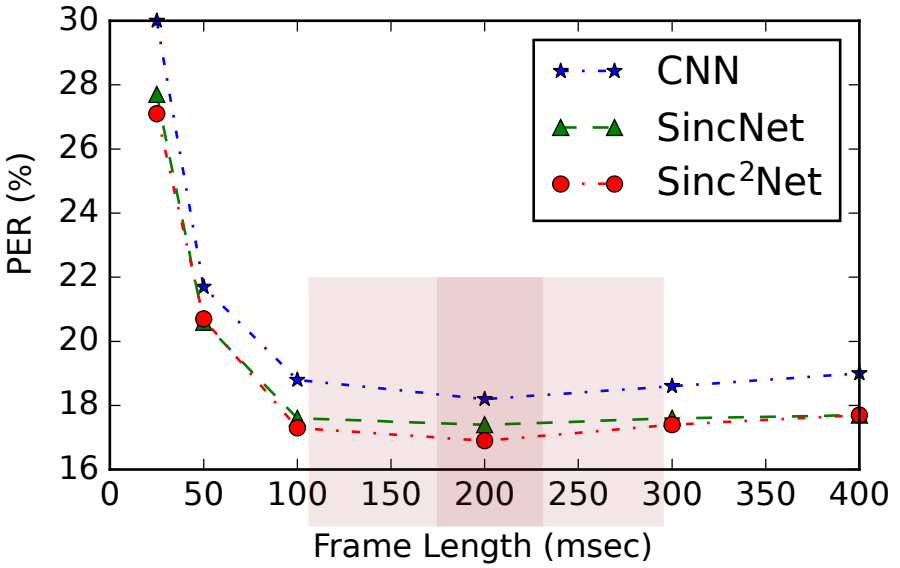

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(1) Pros/Cons?

(2) WHY?

Optimal Frame Length: 200 ms

Pros/Cons

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- Suppressing harmful **mid-term** properties (e.g. speaker-ind. ASR)
- Preserving useful **mid-term** properties (e.g. speaker/emotion ID)
- Higher memory is required

Optimal Frame Length: 200 ms

WHY

Table 3: *TIMIT PER for different frame lengths (ms).*

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Optimal Frame Length: 200 ms

WHY

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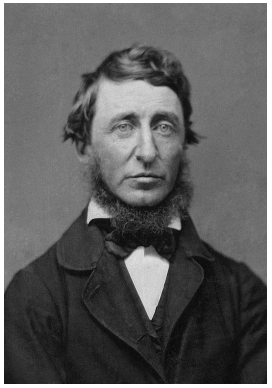
1. Optimal Temporal Masking or Coarticulation Modelling
– Optimal combination of masker and maskee

2. Optimal Syllable Modelling
– Mean syllable length in English is 200 ms (Greenberg et al, 1999)

Wrap-up for Part II

- Waveform acoustic modelling via convolutional layer
- A general formulation for interpretable CNNs with modulated kernel-based filters (X-Net) was derived
- Learned filters were studied statistically/perceptually
- Mid-term (~ 200ms) processing is required for raw waveform modelling through X-Nets



“Not until we are lost do we begin to understand … ”

- Henry David Thoreau

That's It!

- Thanks for Your Attention
- Q/A

- Acknowledgements:
  - Supported by EPSRC Project EP/R012180/1 (*SpeechWave*)
  - Benefited from discussion with Zoran Cvetkovic (KCL)

Appendices

1) SincNet – Practical Considerations

SincNet – Practical Considerations

- Sinc length is finite → Apply a tapered window
- Monitor the cut-off frequencies value
- Amplitude learning is not necessary
- Initialisation of Parameters (cut-off frequencies)
  - Any perceptual scale may be used, e.g. Mel, Bark, ERB
  - Using random initialisation is still fine
    - PyTorch-Kaldi → neural_networks.py → class SincConv(nn.Module) →
      - hz = np.sort(np.random.uniform(low_hz, high_hz, out_channels+1)) / self.sample_rate