Application of Deep Convolutional Neural Networks to Speech Recognition

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Neural networks in speech recognition

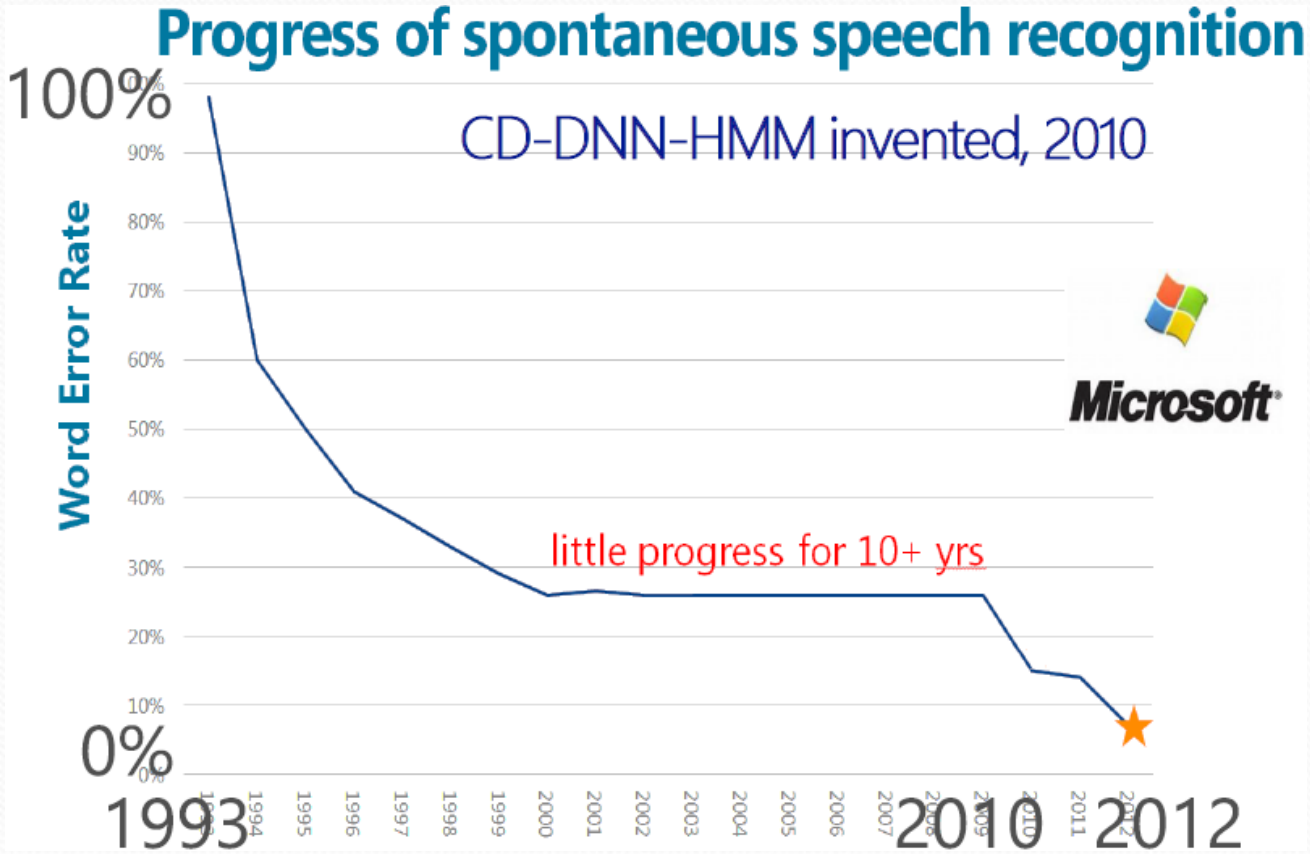
- Hidden Markov modelling (HMM) has been the standard speech recognition technology since the early 80's
- But from the late 80's attempts have been made to use ANNs
- The most successful was the HMM/ANN hybrid model
  - The ANN is responsible for the local labeling (probability estimates)
  - The utterance level combination/search is performed by the HMM
  - Slightly better results than with HMMs, but no breakthrough
- Deep neural networks use the same HMM/ANN scheme
  - The breakthrough is from using DNNs instead of ANNs
  - Although there are approaches to replace the HMM part as well by neural models (end-to-end speech recognition), these are worse yet

The deep learning revolution

- 2006: The first deep learning paper (Science, image data)
- 2009: First application to speech recognition
  - Immediately a new record on the TIMIT dataset
  - It still holds that the new deep learning ideas are first tried on image data
- 2011: Google and Microsoft also applies deep learning
  - They report an error rate decrease of 10-30% in their products
- 2015-16: They already talk about „superhuman performance”
  - „Achieving Human Parity in Conversational Speech Recognition” (Microsoft, 2016)
  - “Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification” (Microsoft, 2015)

The effect of deep learning on ASR

(Slide by Li Deng, ICASSP 2016 keynote talk)



The Sources of this Success

- New learning algorithms and activation functions
  - E.g. RBM-pretraining, ReLU activation
- The availability of enormous data sets
  - The advantages of deep learning do not show up on small data
- The availability or fast hardware
  - The invention of GPUs made deep learning accessible to everyone
- Many of the algorithmic ideas (like the convolutional model) were present decades ago
  - But the lack of hardware and large training datasets did not allow to convincingly prove the advantages of deep models

Conventional “shallow” ANNs

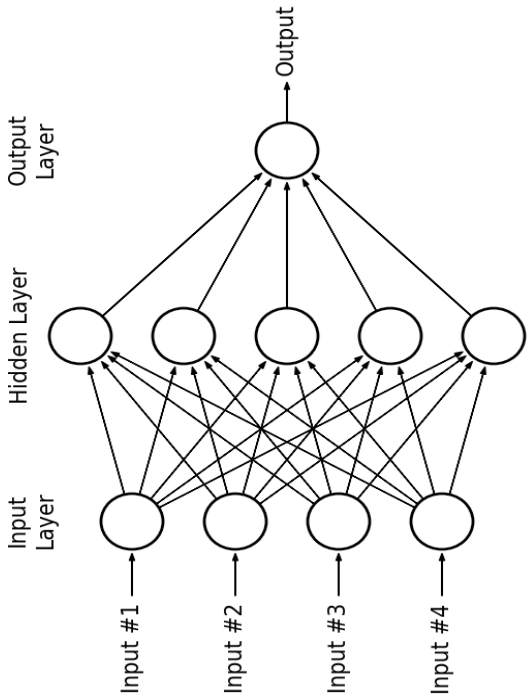
We applied only 1-2 hidden layers

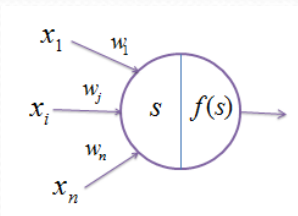
- *Trained by error backpropagation (gradient-based optimization)*

Why only 1-2 hidden layers?

- theoretically, it can achieve arbitrary accuracy by increasing the amount of hidden neurons

- training was already slow





$$s = \sum w \cdot x$$

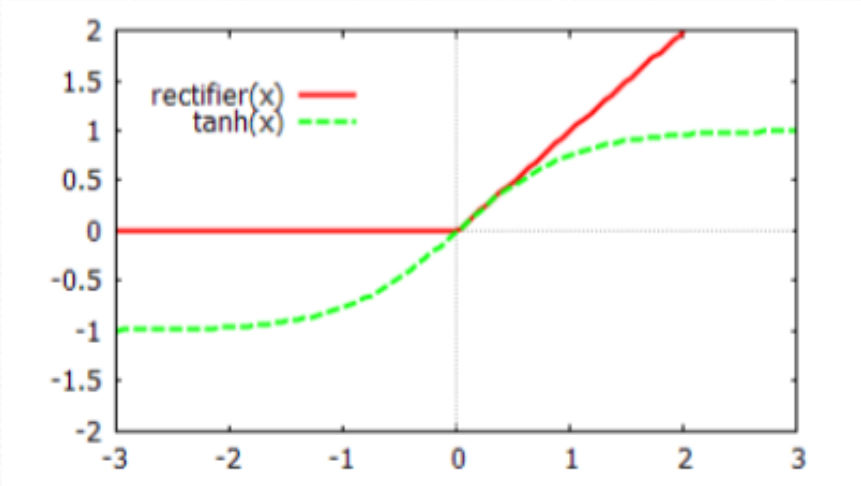
$$f(s) = \frac{1}{1+e^{-s}}$$

Deep networks

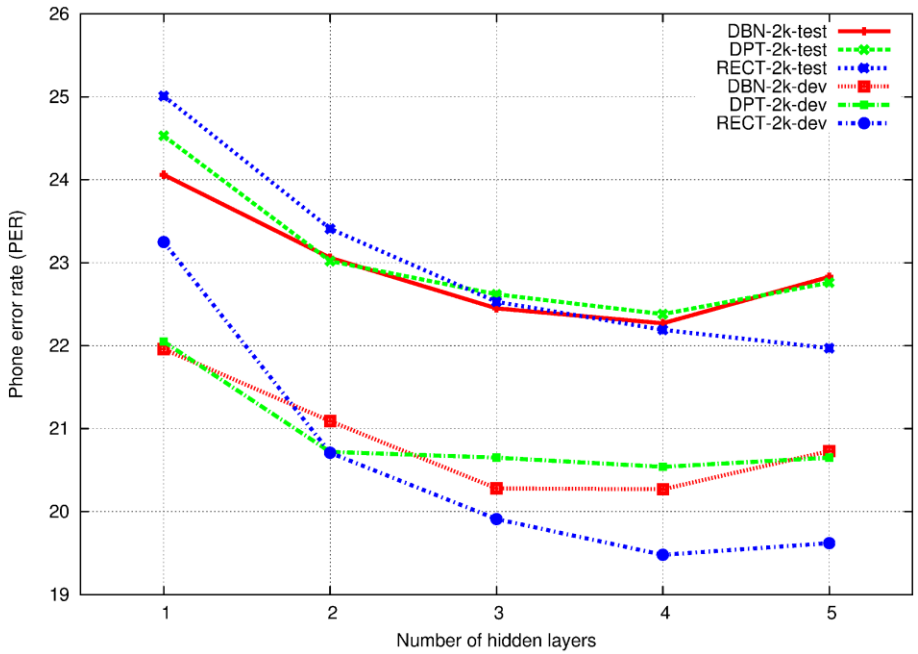
- **Deep network: many (>2) hidden layers**
  - With a *given* number of neurons, arranging them into many layers is more efficient than using only one big hidden layer!
- **The problem of speed**
  - Solved by the invention of GPUs (20-40 times speedup!)
- **The problem of training: backpropagation is not efficient for many hidden layers**
  - Hinton invented the RBM pre-training algorithm in 2006
  - Many new refinements since then (ReLU activation, new intialization schemes, batch normalization…)
  - Current wisdom: pre-training is not necessary if you have enough training data

Rectifier Neural Nets (Glorot, 2011)

- We modify the activations function of the neurons
  - *Replace sigmoid (or tanh) with the max(0,x) function (ReLU)*
- These neurons seem to be more suitable for building deep nets
  - *The activation does not saturate → no "vanishing gradient" effect*
  - *Weight normalization is required to prevent the weights from "blowing up"*



Results on TIMIT

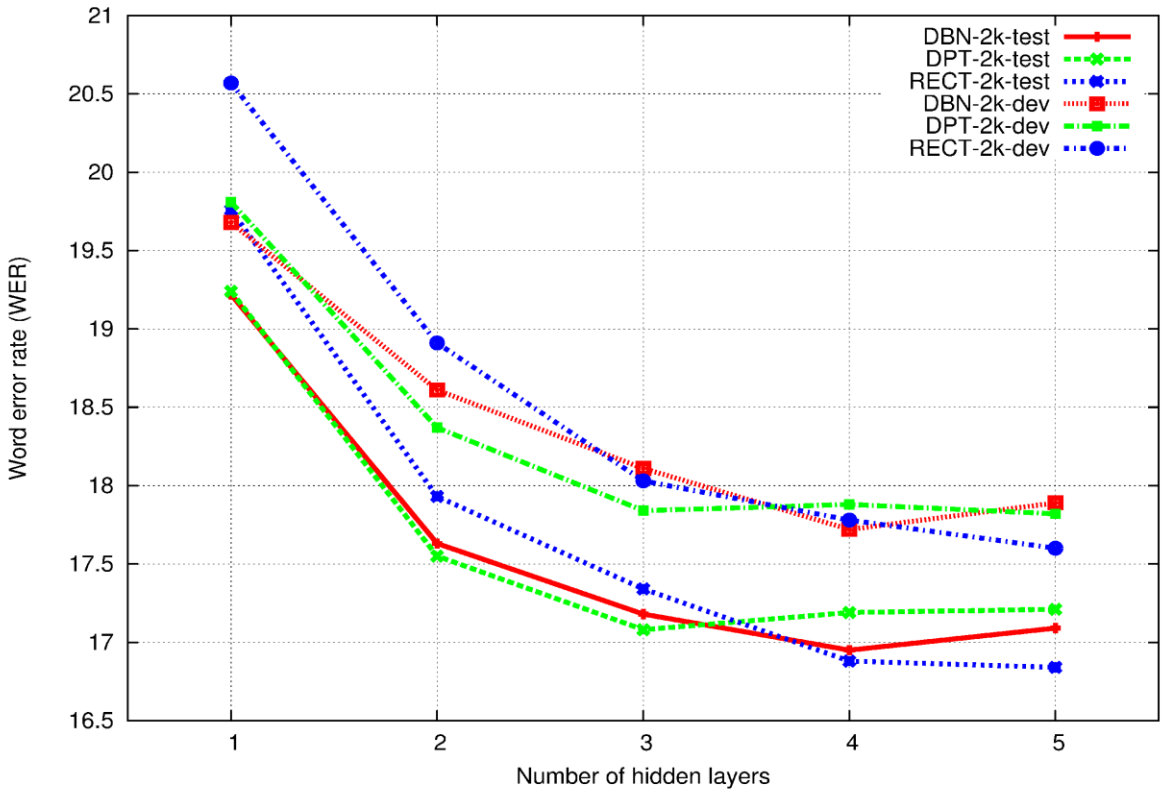


DBN: DBN pre-training

DPT: discriminative pre-training

RECT: rectifier activation (no pre-training)

Results on Broadcast News Data



Comment: HMM: 19.9%

A Comparison of Training Times (Broadcast news dataset)

Method	Pre-training	Backpropagation
DBN pretraining	48 hours	14 hours
DPT pretraining	9 hours	11 hours
ReLU neurons	0 hours	14,5 hours

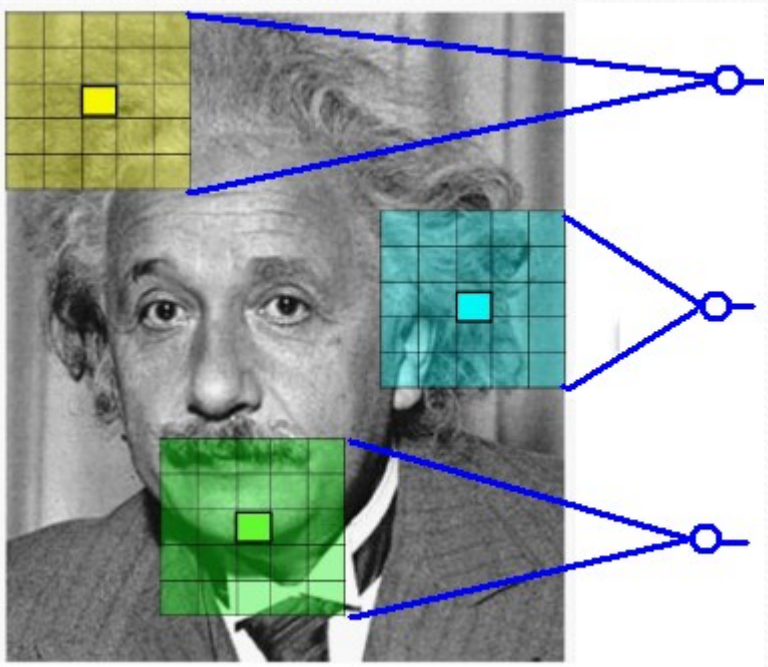
- *We now almost exclusively use only rectifier networks*
- *„the new de-facto standard of deep learning" (Sonoda & Murata)*
- *„the most popular non-linear function is the rectified linear unit (ReLU)" (Hinton et al., Nature 2015)*

Convolutional Neural Nets

- Yet another method taken from image processing
  - The basic concept was already present in the 80's, 90's!
  - But it's only now that we can efficiently train deep structures
  - (A convolutional network is necessarily deep)
- CNNs have a special network structure
  - It assumes that the input builds up hierarchically
  - Lower levels: extraction of local, but detailed information
  - Higher levels: detection of wide-spreading abstract structures
- It was first applied to speech recognition only in 2012
  - (with the exception of TDNN, 1989!)
  - it can be combined with all the previously mentioned techniques

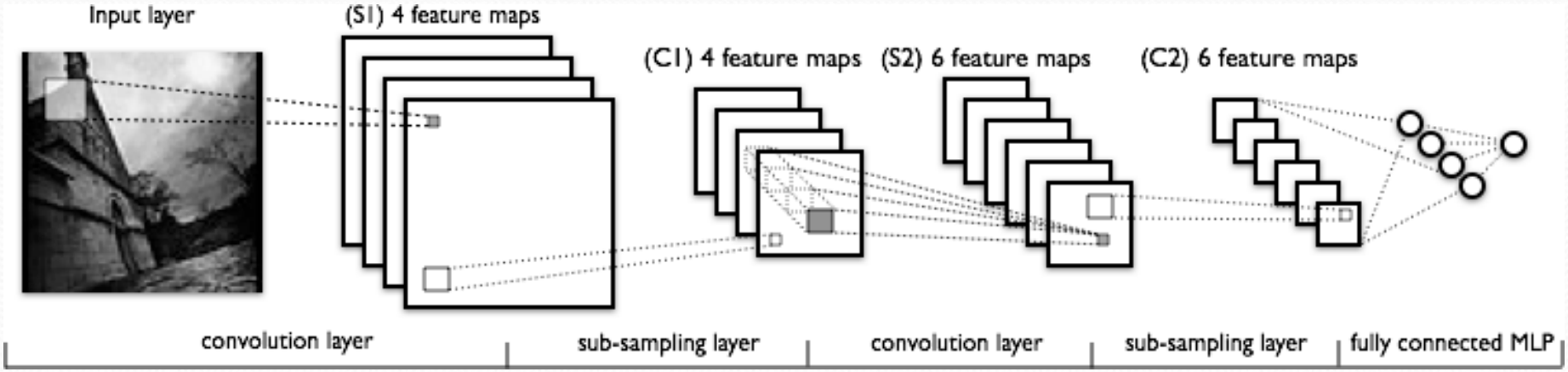
An Example: Face Recognition

- A face is built up hierarchically: lines, circles,… → nose, eye,…→face
- The 3 main features of convolutional processing:
- Locality: each neuron processes only a small part of the picture
- Weight sharing: the same neuron is evaluated at several positions
- Pooling: the resulting values are pooled (eg. taking the max)
- Example: a “nose detector”
- Of course, there may be further, convolutional of fully conntd. layers
- Main advantages:
  - Hierachical processing
  - Shift-invariance



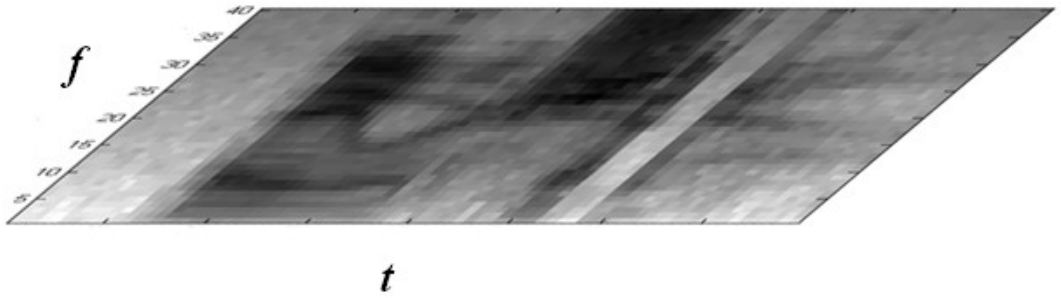
Convolutional Neural Networks

- Image recognition may require a lot of layers
  - Lowest levels: local, high resolution details
  - Higher levels: covering wider and wider areas with lower and lower resolution, detecting more and more abstract components



How to Apply CNNs to Speech?

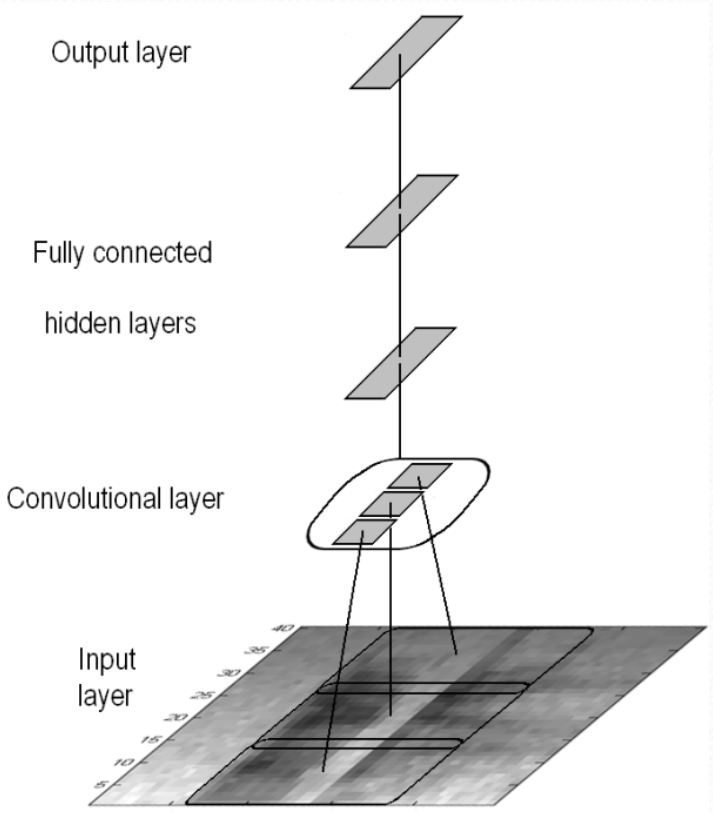
- HMMs: the conventional input is the MFCC representation
  - A short-term spectral representation plus a DCT to decorrelate the features
  - The time context is not taken into consideration (only by the “delta” vectors)
- DNNs:
  - DNNs do not require the decorrelation of features
  - They can efficiently make use of a wider context (9-33 neighboring frames)
- From MFCCs we returned to a spectro-temporal input representation
  - ***f*: 23-40 mel bands**
  - ***t*: 9-33 frames**



- This is an image, so we can apply CNNs!

Convolution along the frequency axis

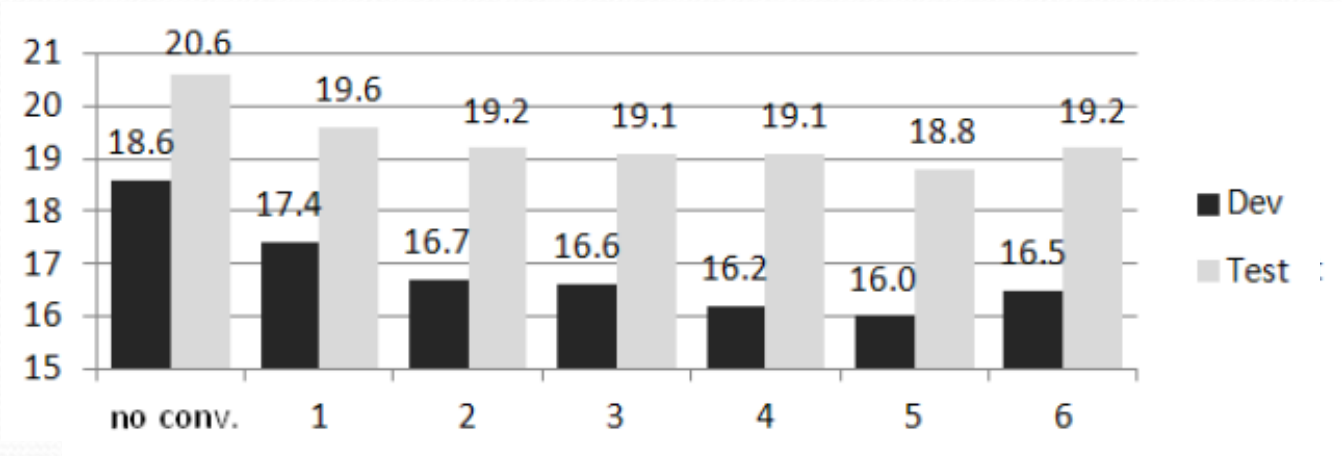
- Basic idea: Abdel-Hamid (2012), Sainath (2013)
- How to exploit the shift invariance of CNNs?
- The frequency axis is divided into wider bands (the optimum was at 7 bands)
- We allow small shifts along the freq. axis
- The output of the convolutional layers is processed by further fully connected layers
- Why convolution (shift invariance) helps: decreases the speaker and speaking-style variance (e.g. tolerates small differences in the formant positions)



Convolution along the time axis

Results (TIMIT)

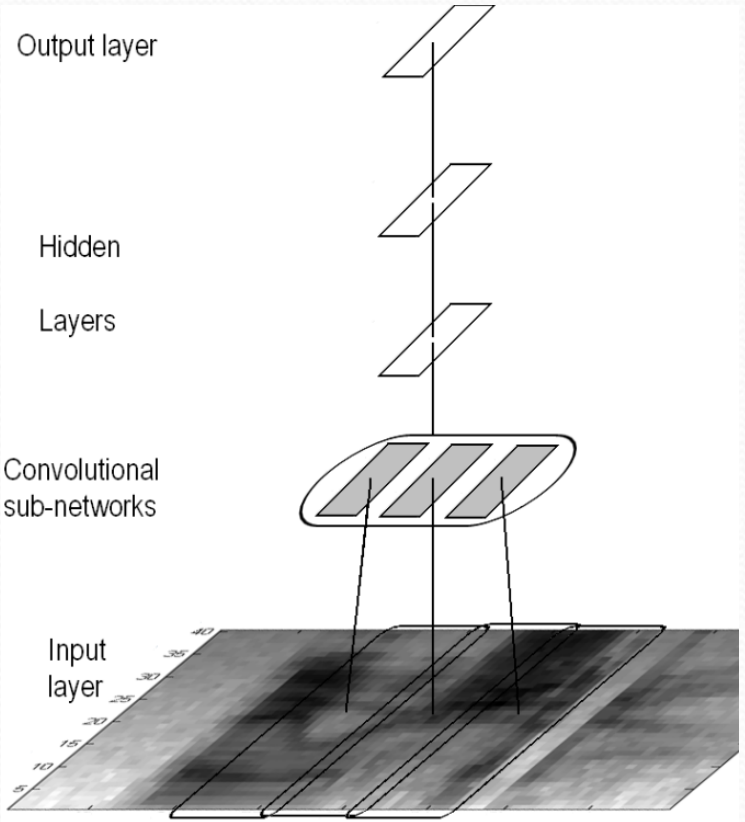
Phone error rate as a function of the pooling size



- The optimal size for „pooling” (shifting) is 4-5 mel-channels
- Convolution reduces the error rate by about 9% relative
- There is error reduction already at pooling size = 1
(there is no pooling, just a local processing of spectral parts!)

Convolution along the time axis

- Basic idea: Vesely (2011)
- We divide the input along the time axis
- Why convolution helps:
  - Allowing shifts is not important (the HMM handles time shifts)
  - It allows the hierarchical processing of a wider input with fewer neurons
- Very similar to the Time-Delay Neural Network of Waibel et al from 1989!
- As by "convolutional" people mean convolution by frequency, I prefer calling it the hierarchical model
- The Kaldi implementation of TDNN consists of several such layers



Convolution along the frequency axis

Results (TIMIT)

Fully connected ReLU network	20.6%
Convolutional network (along time)	18,6%

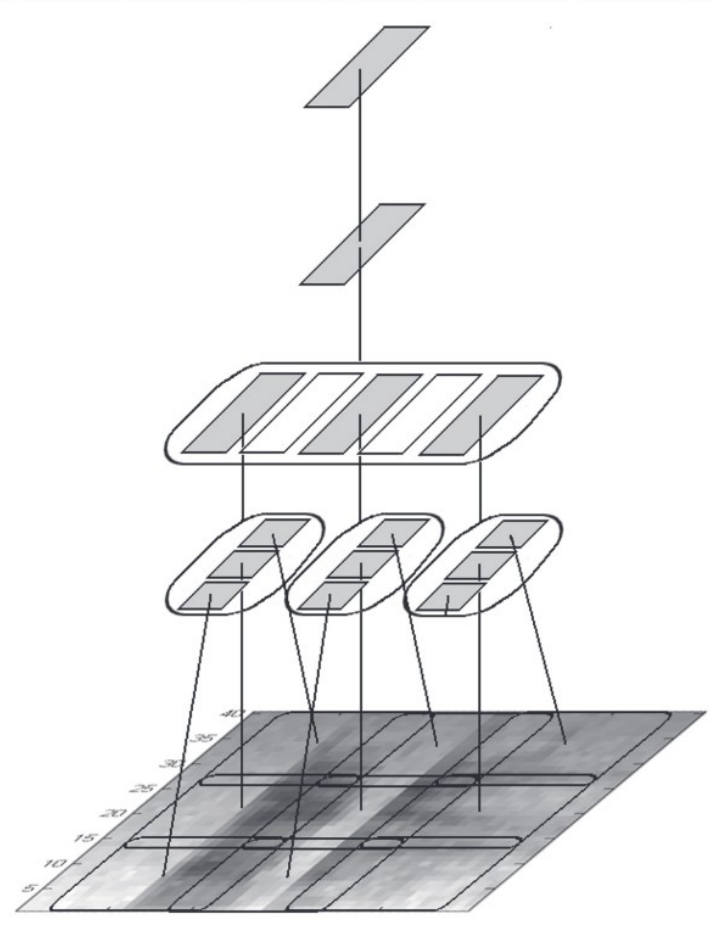
•Convolution along time brings an error rate reduction of about 9%

Convolution along both axes

- **The two concepts of convolution (time domain – Vesely vs. freq. domain – Abdel Hamid) are totally different, but can be easily combined**
  - **and this combination results in a significant reduction of the recognition error rates.**

Convolution along both axes

- The input is divided along both time and frequency
- The lowest layer perform the convolution along frequency
- A higher layer performs the fusion along time
- The are several further, fully connected layers



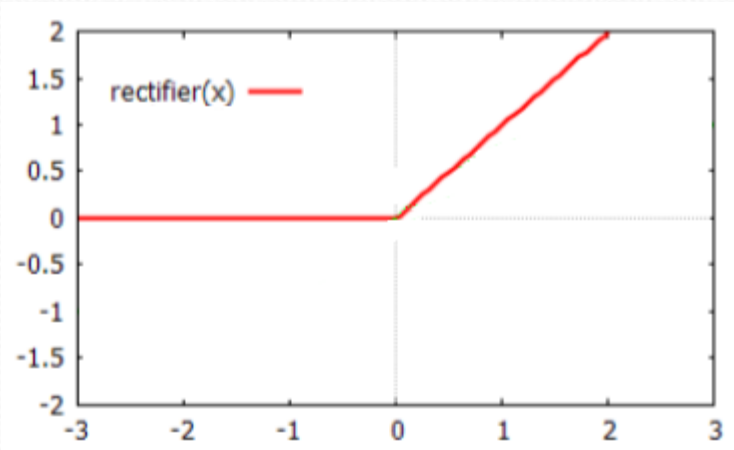
Error rates (TIMIT)

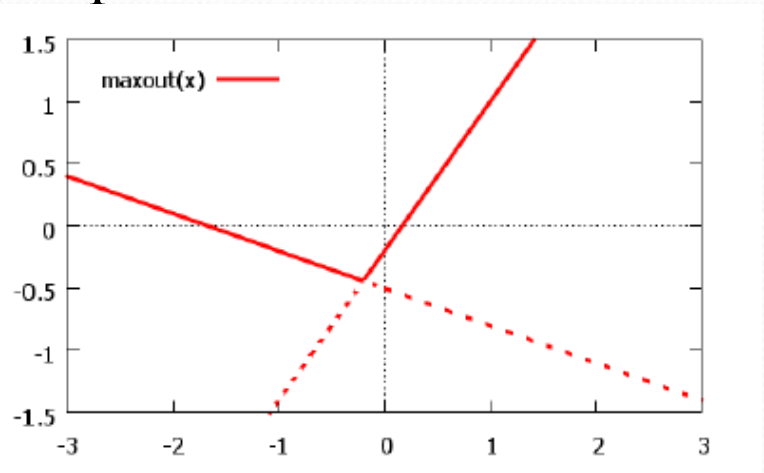
Convolution only along the freq. axis	18.8%
Convolution only along the time axis	18.6%
Convolution along both axes	17.6%

• Compared to the previous best result, by combining the two convolution methods we obtained a further error rate reduction of 6% relative

The Maxout Activation Function

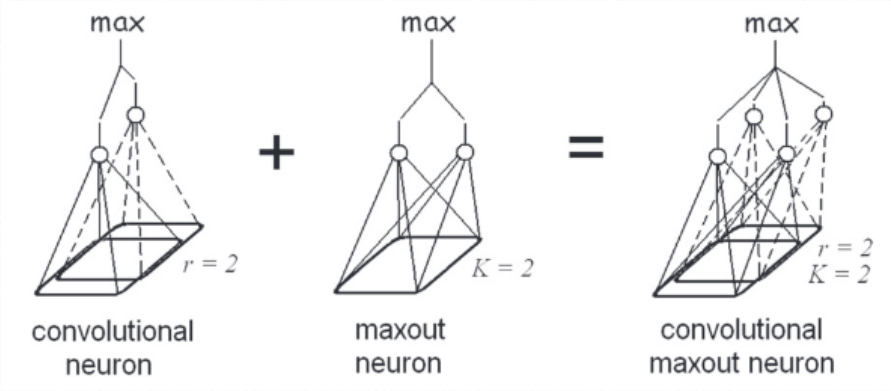
- "Maxout" can be interpreted as a generalization of the rectifier activation function
- The neurons are divided into groups (eg. 2 neurons/groups)
- There is one output pre group, defined as the maximum of the linear activations within the group





Convolutional Maxout Neurons

- The convolutional step can be easily combined with the maxout activation:
  - Convolution: The „pooling” step fuses the outputs of the same neuron obtained at different positions
  - Maxout: The „pooling” step fuses the outputs of different neurons on the same input
  - The two pooling operations can be executed in one step



Results (TIMIT)

Network type	PhER (%)
Conv. ReLU	17,6%
Conv. Maxout	17,0%

- Other authors have found that Maxout outperforms ReLU most importantly in low-resource conditions (<30h) (Miao et al, 2013)
- Since then, newer variants of the ReLU activation have been proposed, but these are not convincingly better.
- Currently, ReLU is the most popular activation function for DNNs

The „Dropout” Method (Hinton et al, 2012)

- During training, a group of randomly selected neurons (10-50%) are discarded (their output is replaced by zeros)
  - Effect: the neurons within the same layer are forced to rely less on each other
  - Result: decreases the risk of overfitting
  - It can be combined with all the previous network types
  - The only drawback is that training takes 3-5 time longer
- Results (TIMIT):

Network type	PhER (%)	PhER with dropout (%)
Conv. ReLU	17,6%	16,7%
Conv. Maxout	17,0%	16.5%

Current trends #1: Recognition from Raw Waveforms

- Goal: get rid of hand-crafted features (MFCC, PLP,…)
  - They might be suboptimal
  - They require expert knowledge
- Long-term Goal: “End-to-end” speech recognition
  - No separate modules, jut one big network
  - Input: raw sound file, output: text
- It would be a very big theoretical achievement
  - However, a lot of experts are very skeptic if it’s possible

Recognition from Raw Waveforms

- The first step of current feature extraction methods is to process the signal by a filter bank (e.g mel-filters)
  - The operation of a filter is very similar to the operation of a neuron
  - This gives the idea to learn the filter parameters by a special convolutional network structure

[PDF] Acoustic modeling with deep neural networks using **raw** time signal for LVCSR.
Z **Tüske**, P Golik, R Schlüter, H Ney - INTERSPEECH, 2014 - 193.6.4.39

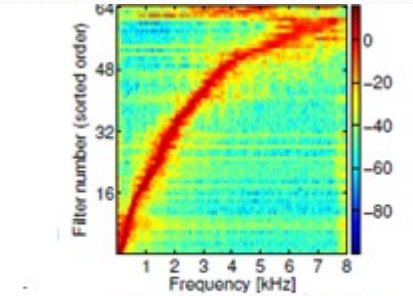
[PDF] Convolutional neural networks for acoustic modeling of **raw** time signal in lvcsr
P Golik, Z **Tüske**, R Schlüter... - ... **Speech** ..., 2015 - www-i6.informatik.rwth-aachen.de

[PDF] Analysis of cnn-based **speech recognition** system using **raw speech** as input
D Palaz, R Collobert - Proceedings of Interspeech, 2015 - infoscience.epfl.ch

[PDF] Learning the **speech** front-end with **raw** waveform cldnns
TN Sainath, RJ Weiss, A Senior, KW Wilson... - Proc. ..., 2015 - ee.columbia.edu

Learning Filter Banks- Results

- Tüske et al (Interspeech 2014):

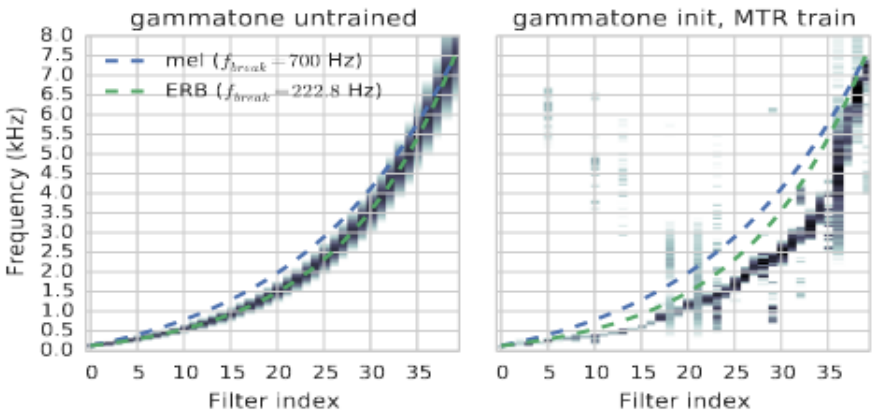


magnitude spectrum of the weights learned by a convolutional layer.

Table 1: *Baseline results. WER in %.*

Features	model	# hidden layers	dev	eval
MFCC	GMM	-	24.4	31.6
	DNN	9	16.9	22.1
time signal	DNN	9	20.7	26.3
	DNN	12	20.3	25.5

- Google (Interspeech 2015):



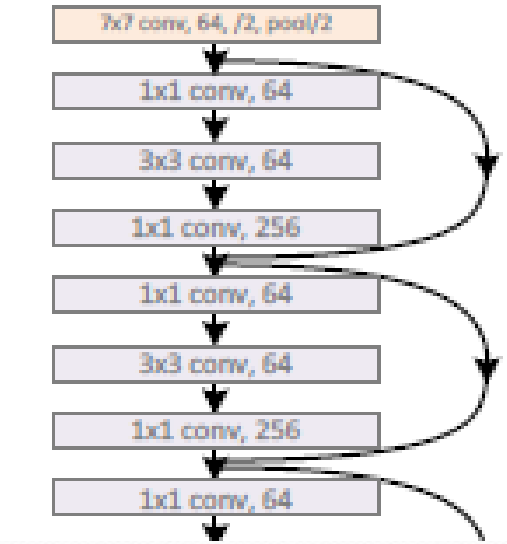
Filter Size (N (ms))	Window Size (M (ms))	Init	WER
400 (25ms)	400 (25ms)	random	19.9
400 (25ms)	560 (35ms)	random	16.4
400 (25ms)	560 (35ms)	gammatone	**16.2**
400 (25ms)	560 (35ms)	gammatone untrained	16.4

Current Trends #2: Very Deep CNNs

- DNNs:
  - We did not obtain significant improvements above 5-6 layers
  - Most people in the literature do not go beyond 5-9 layers
- CNNs:
  - We applied only 1+1 convolutional layer (along freq+time)
  - "Early" literature: 2 conv. layers is slightly better than 1, no further improvements with 3 (Sainath et al., 2013)
  - But nowadays, in image processing, people experiment with CNNs of 50-150 layers!
- The training of these very deep networks require special solutions

Current Trends #2: Very Deep CNNs

- Methods to efficiently backpropagate the error to lower layers:
  - „linear pass-through” or „jump” connections
  - „Highway networks”
  - „Linearly augmented” layers
  - „Residual network”
- These all operate quite similarly:
  - They introduce direct connections between layers farther away
  - This allows the direct propagation of the error to deeper layers, thus alleviates the “vanishing gradient” problem



Example #1: Linearly Augmented Layers

- One layer of a normal net (V is an extra linear transformation):

$$f_i(x) = V_i\phi(U_i x + b_i)$$

- In comparison, a linearly augmented layer:

$$f_i(x) = V_i\phi(U_i x + b_i) + T_i x$$

  - T is not necessarily a full transformation matrix, good results were obtained using a diagonal matrix, or a fixed (non-trainable) unity matrix

Num of H.Layers	Layers Size	# Params	PER %
3	1024X256	2.9M	**22.39**
12	512X256	3.8M	21.8
48	256X128	3.4M	**21.7**

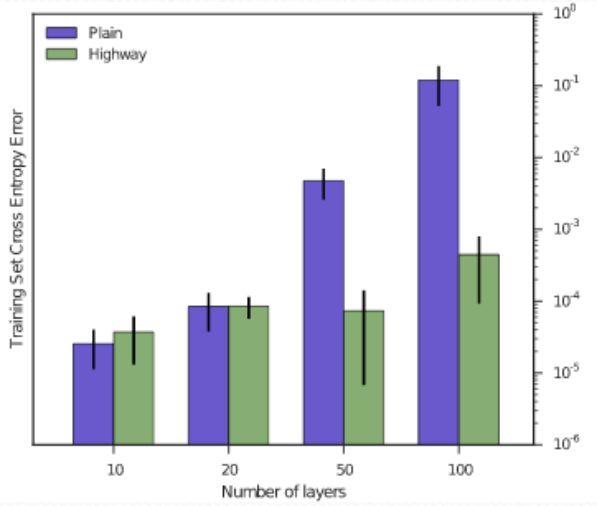
(Results on TIMIT, taken from Droppo et al, ICASSP 2016)

Example #2: Highway Networks

- The networks has „highway” connections which allow the information to flow without transformation
  - Layer of a conventional net $\mathbf{y} = H(\mathbf{x}, \mathbf{W_H})$
  - Layer of a highway net: $\mathbf{y} = H(\mathbf{x}, \mathbf{W_H}) \cdot T(\mathbf{x}, \mathbf{W_T}) + \mathbf{x} \cdot (1 - T(\mathbf{x}, \mathbf{W_T}))$
    - Where T is a „transfer gate”: $T(\mathbf{x}) = \sigma(\mathbf{W_T}^T \mathbf{x} + \mathbf{b_T})$
    - T can take values between 0 and 1
    - The output in the cases of T=0 or T=1:

$$\mathbf{y} = \begin{cases} \mathbf{x}, & \text{if } T(\mathbf{x}, \mathbf{W_T}) = \mathbf{0}, \\ H(\mathbf{x}, \mathbf{W_H}), & \text{if } T(\mathbf{x}, \mathbf{W_T}) = \mathbf{1}. \end{cases}$$

    - That is, T controls the ratio of how much is let through from the non-transformed x and the transformed H(x)



Current trends #3: Combination with Recurrent Networks

- Currently, the fastest developing trend in speech recognition is the application of Recurrent Neural Networks (RNNs)
  - While images have no “directions”, speech is a left-to-right process, which is definitely a very important factor
  - Currently, very good results are achieved by RNNs, or its more refined variants (LSTM, GRU, …)
- Right now, in speech recognition RNNs seems to be more promising for future improvements than CNNs
  - But the two may be combined, eg. using convolution in the deeper layers and recurrent layers at higher levels!

Thank you for your attention!