深蓝学院
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音频语音与语言处理研究组
SLP
Audio, Speech and Language Processing Group NPU

语音识别：从入门到精通

第六讲：基于DNN-HMM的语音识别系统

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注意

- 本节已假定读者已有一定的深度学习基础知识
- 本节目标
  - 回顾复习基本的深度神经网络知识
  - 重点带读者了解深度神经网络在语音识别中的应用
    - 成功应用的论文和时间
    - 带来了多少错误率的下降
- 所以，本文的重点是一些基本点，基本思想，并不会深入各种神经网络的细节。
- 此外，不是理所当然，本文中所述的每一种神经网络在语音识别中的成功应用，在当时都是里程碑式的贡献。

内容提要

- GMM-HMM语音识别系统(回顾)
- DNN-HMM语音识别系统
- 深度神经网络
  - 前馈神经网络FNN
  - 卷积神经网络CNN
    - CNN
    - TDNN
  - 循环神经网络RNN
    - LSTM
  - 混合神经网络
- 作业

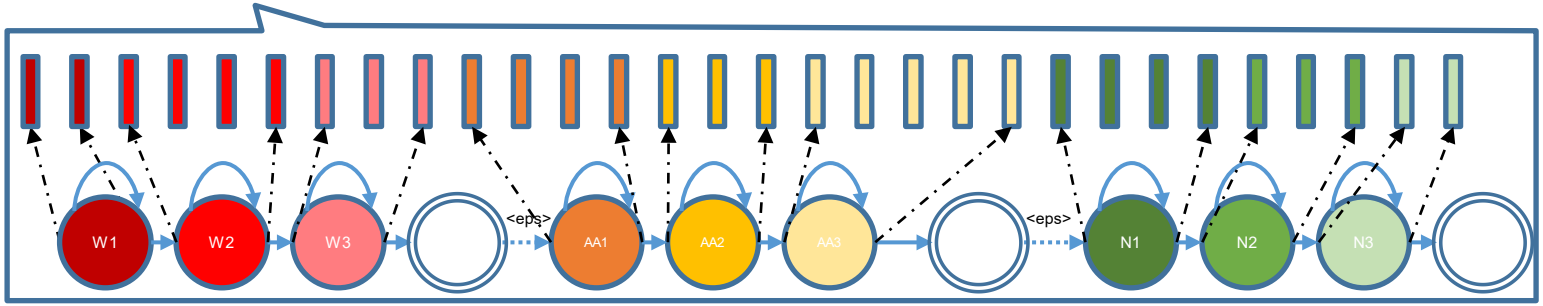
DNN-HMM语音识别系统流程（训练）

数据准备
音素，词典，
训练音频/文本

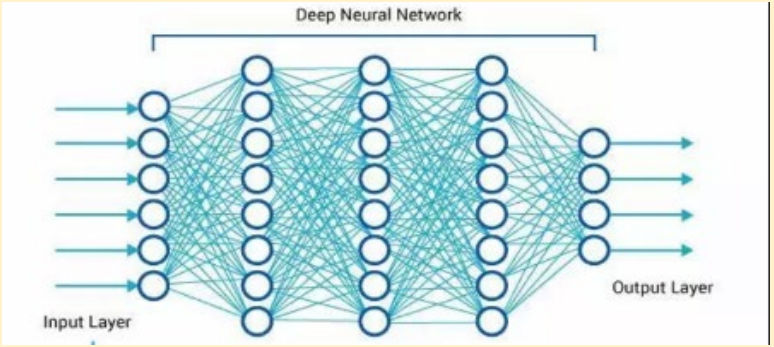
one one one two two two two three three three

特征提取
MFCC

HMM状态
序列建模

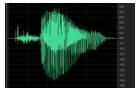


DNN网络

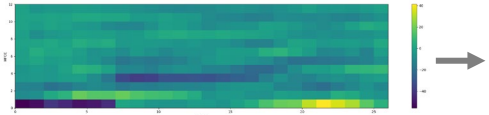


DNN-HMM语音识别系统流程（解码）

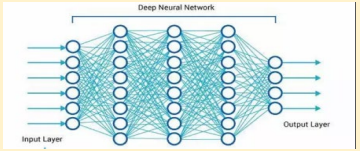
未知wav



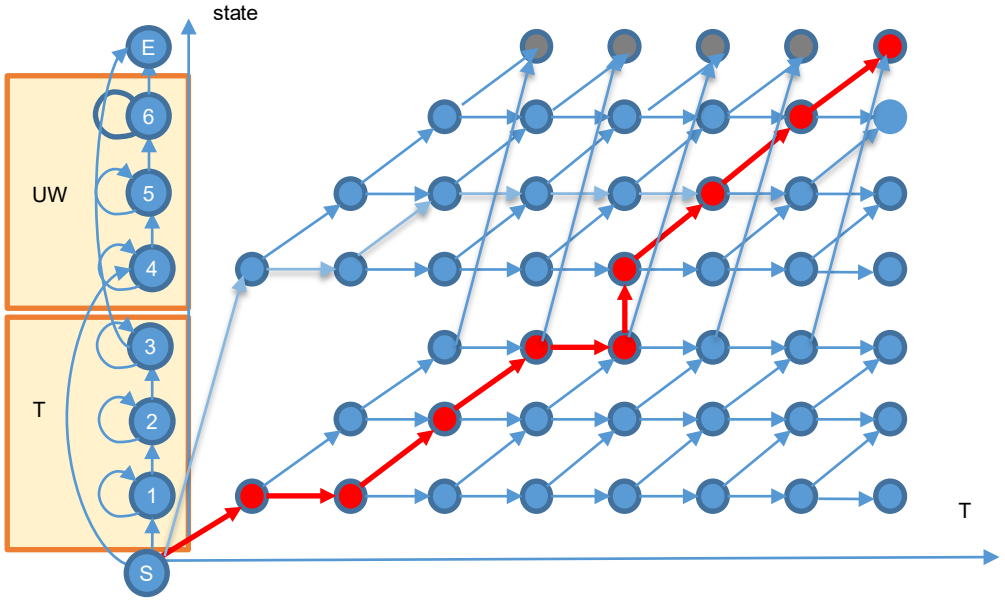
提取特征



DNN模型



Viterbi算法

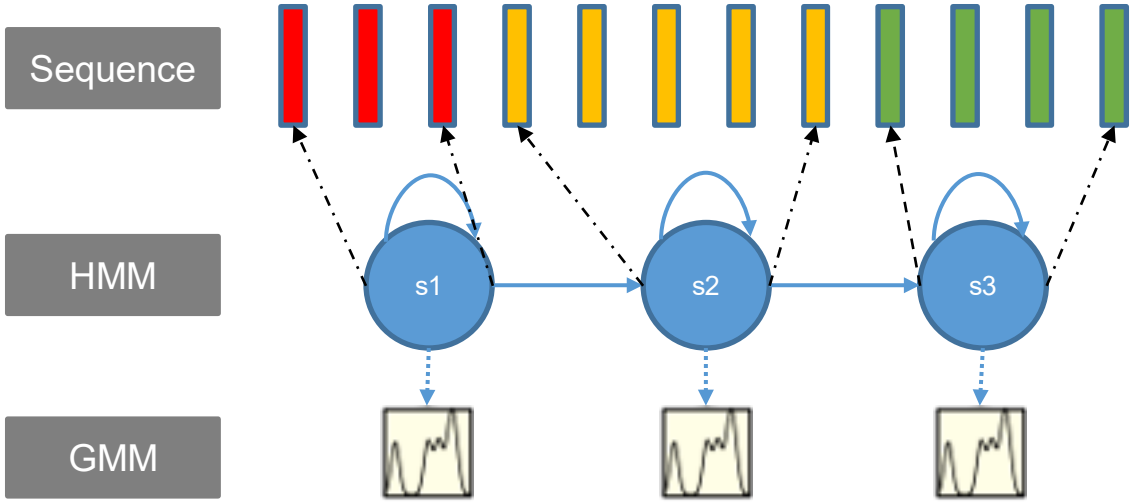


解码结果

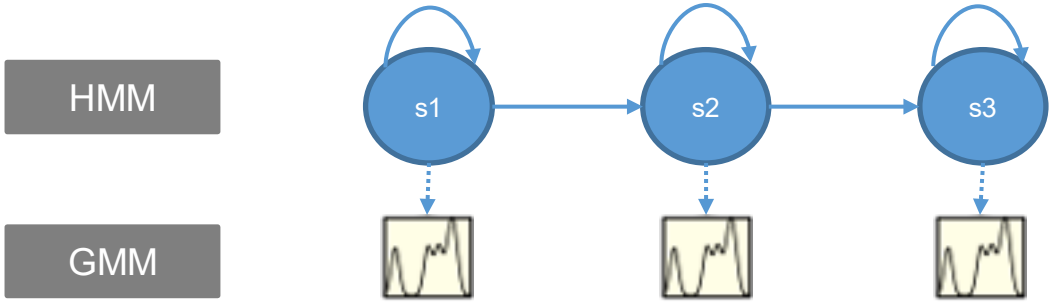
T UW

two

GMM-HMM语音识别系统



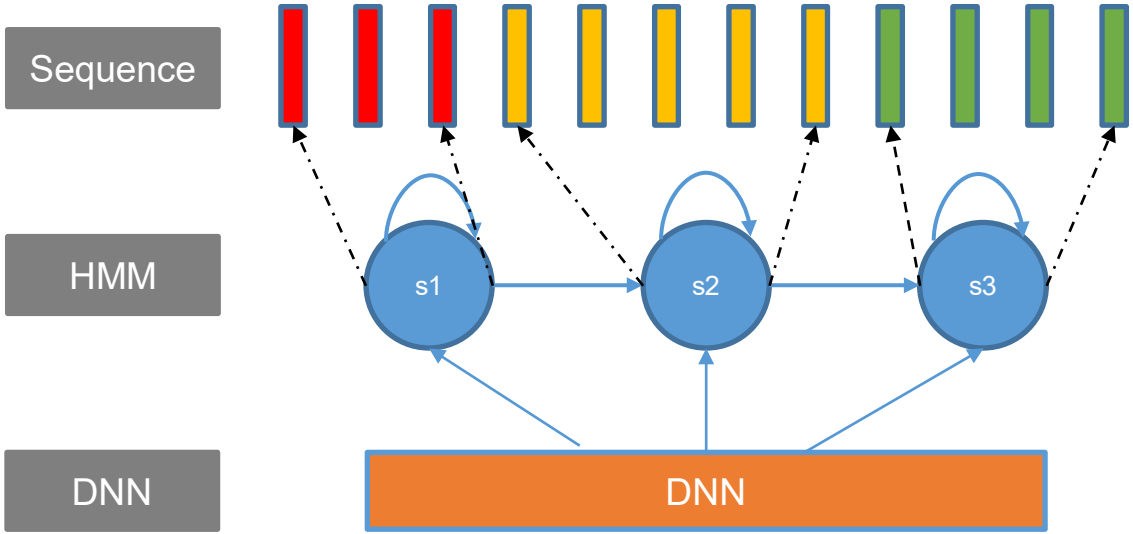
GMM-HMM语音识别系统（解码）



t=1	y_{11}	y_{12}	y_{13}
t=2	y_{21}	y_{22}	y_{23}
t	y_{t1}	y_{t2}	y_{t3}

y_{ts}是在t时刻第s个GMM（状态）上的概率

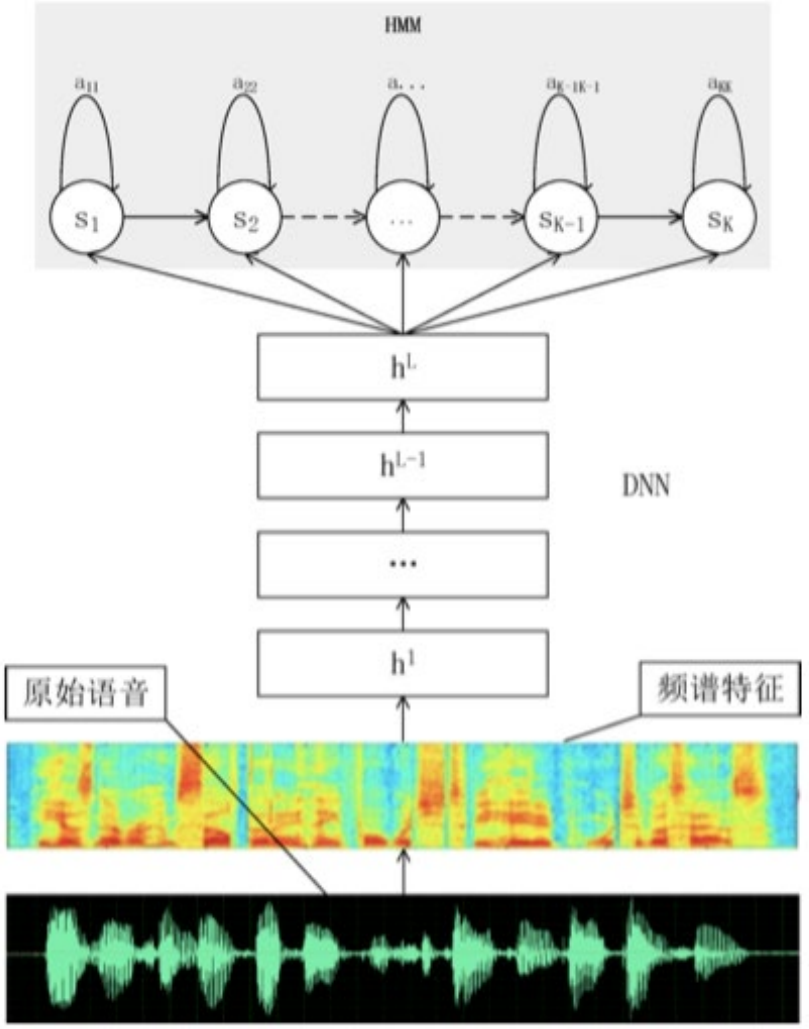
DNN-HMM语音识别系统



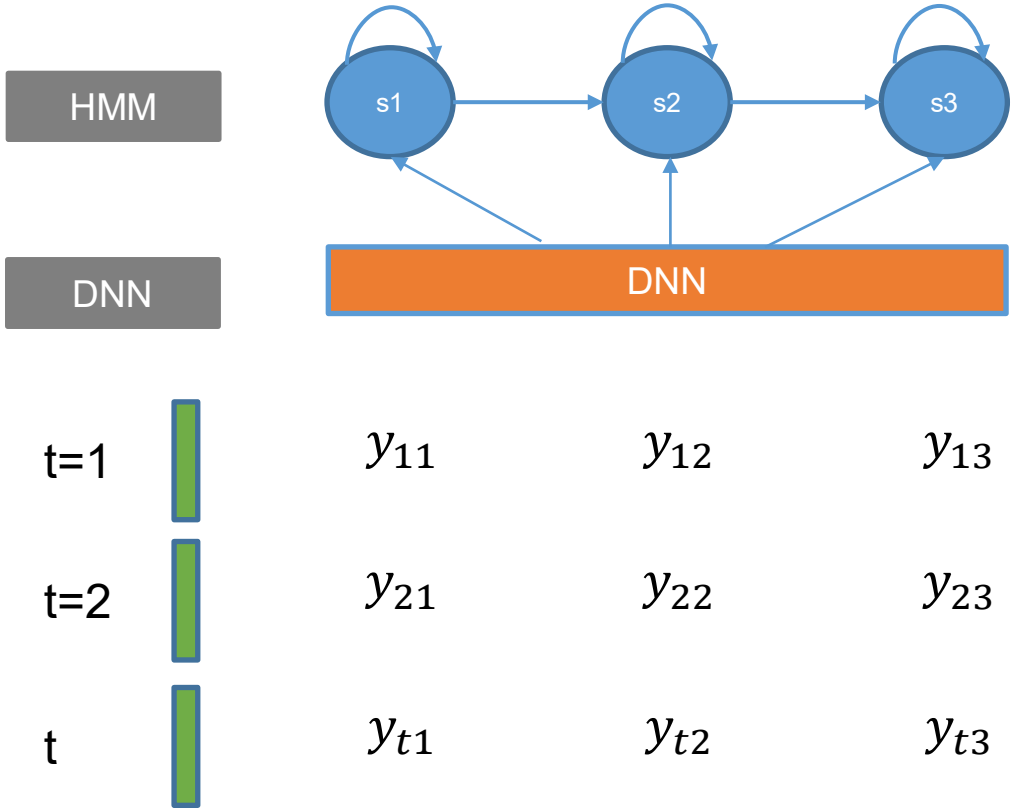
问题：DNN的状态对齐怎么来？

DNN-HMM语音识别系统

- DNN三要素：
  - 输入是什么？
  - 输出是什么？
  - 损失函数是什么（分类问题 Cross Entropy）
- 然后，硬train一发就可以了



DNN-HMM语音识别系统（解码）



y_{ts}是在t时刻第s个DNN输出（状态）上的概率

DNN-HMM语音识别系统流程图

- 都要做哪些数据准备?
- 回想一下单音素训练过程?
- 再回想一下三音素训练过程?

- Kaldi中AISHELL: egs/aishell/s5/run.sh

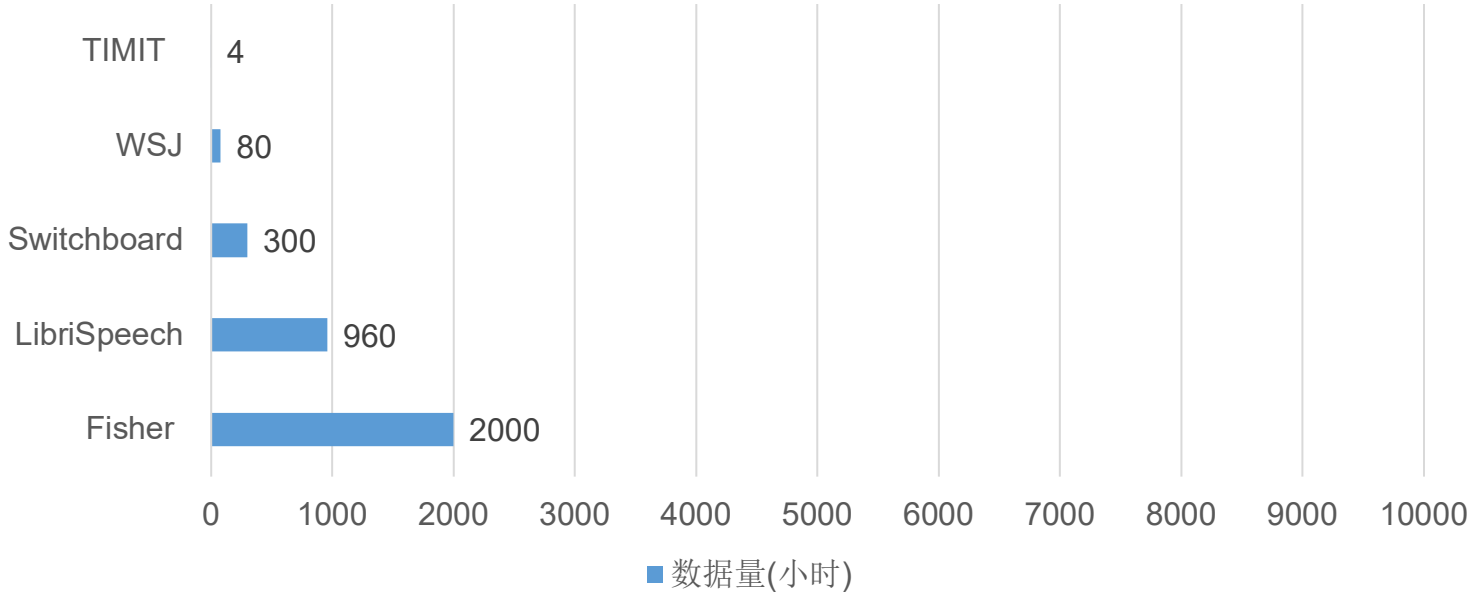
深度神经网络

- 网络类型
- 成功应用的论文和时间
- 错误率下降

语音领域学术会议

- InterSpeech
- ICASSP
- ASRU

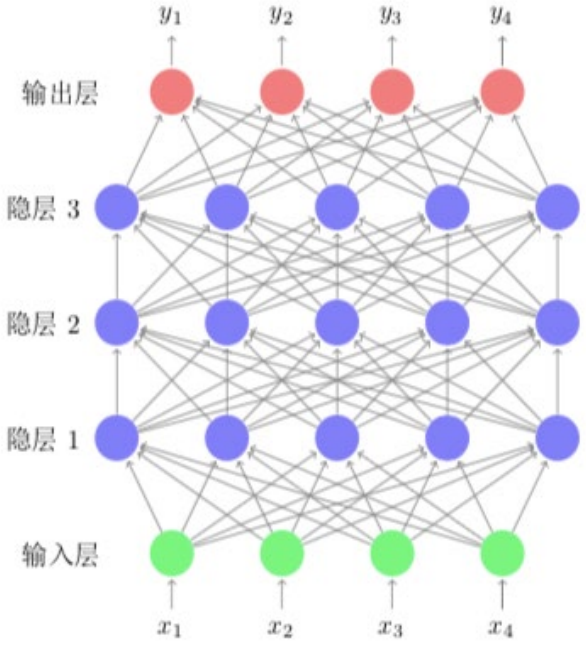
语音识别数据集



- 工业界数据量： 10万+
- 中文Research常用数据集： aishell， 200小时
- 语音开源数据汇总：Open Speech and Language Resources: http://openslr.org/resources.php

FNN(Feedforward Neural Network)

$$\boldsymbol{y_l} = f(\boldsymbol{W_l x} + \boldsymbol{b_l})$$



激活函数

- sigmoid

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

- tanh

$$\tanh(z) = \frac{e^{z} - e^{-z}}{e^{z} + e^{-z}}$$

- ReLU(Rectified Linear Unit)

$$\mathrm{Re}LU(z) = \max(0, z)$$

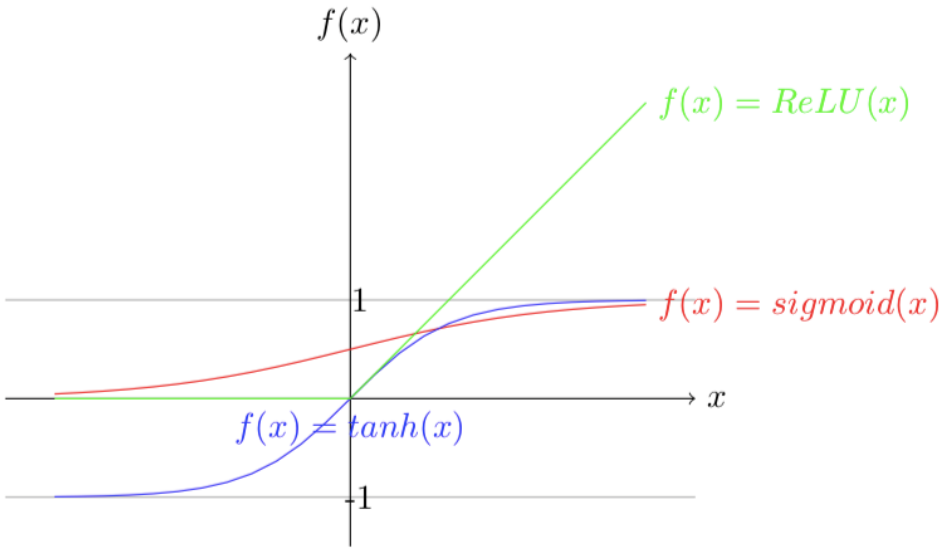


图 3-3 激活函数 *sigmoid*、*tanh* 和 *ReLU* 对比

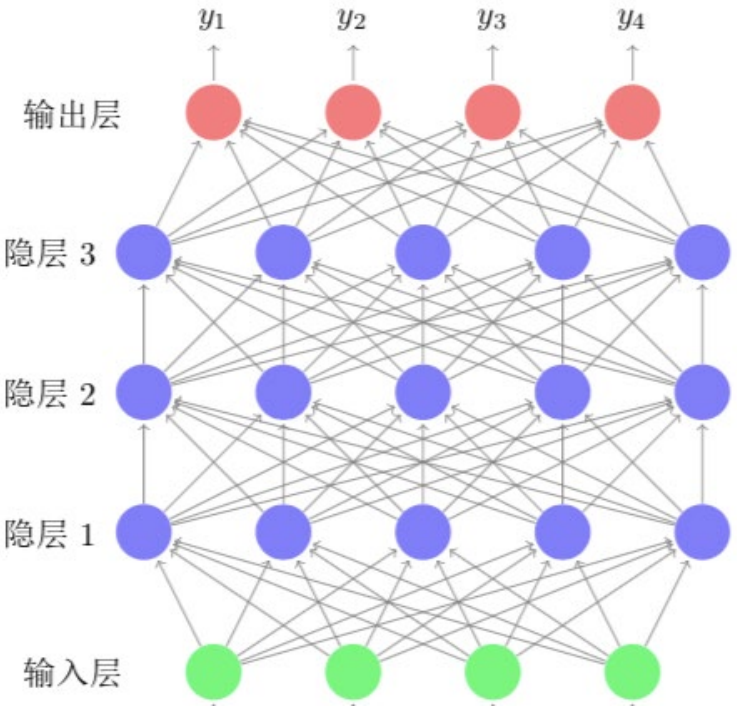
NN分类问题损失函数

- Softmax概率归一化

$$y_k = \frac{\exp(a_k)}{\sum_{j=1}^{K} \exp(a_j)}$$

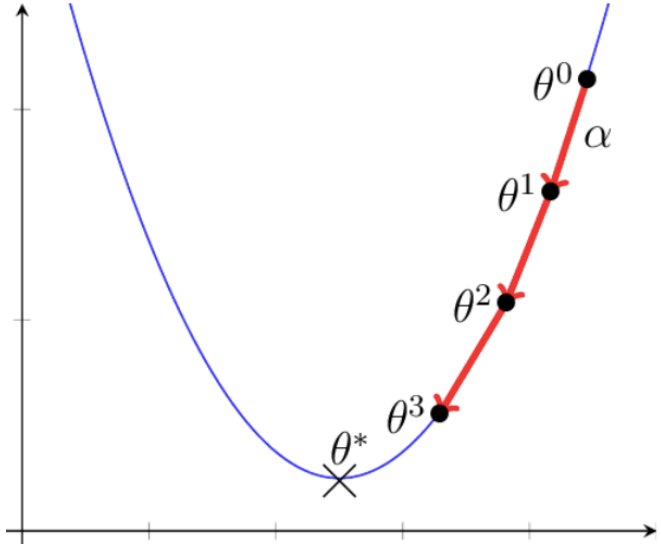
- 交叉熵CE(Cross Entropy)损失函数

$$L = -\sum_{n=1}^{N}\sum_{k=1}^{K} t_{nk} \ln(y_{nk})$$



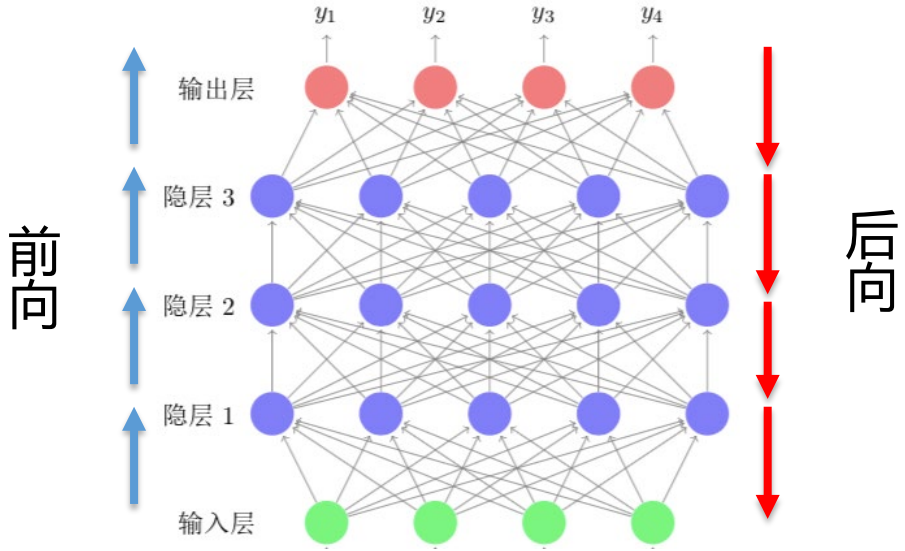
梯度下降（Gradient Descent）

- $\theta^* = \arg\min_{\theta} L(\theta)$ L: 损失函数， θ: NN参数
- $\theta^* = \theta - \alpha \frac{\partial L}{\partial \theta}$, α: 学习率



反向传播（Back Propagation）

- $\theta = \{W_1, b_1, W_2, b_2, \ldots, W_N, b_N\}$
- $\theta^* = \theta - \alpha \frac{\partial L}{\partial \theta}$, α: 学习率
- 链式求导法则：$y = f(x)$, $z = g(y)$, 则 $\frac{dz}{dx} = \frac{dz}{dy}\frac{dy}{dx}$



训练流程(python pseudo code)

```
# model: NN model, such as DNN
# theta: NN parameters
# lr: learning rate
init_model_with_parameter_theta(model, theta)
for epoch in range(max_epoch):
    for minibatch in data:
        # Get minibatch data, include input feature and label
        input, label = minibatch
        output = model.forward(input)
         loss = compute_loss(output, label)
         delta = model.backward(loss)
         theta = theta - lr * delta
```

其他NN必备知识

- Optimizer(SGD/Momentum/Adam …)
- Dropout
- Regularization
- Residual Connection
- Batch Normalization
- 详请参考李宏毅老师的深度学习课程：https://www.bilibili.com/video/BV1JE411g7XF?p=1

FNN在语音识别中的应用

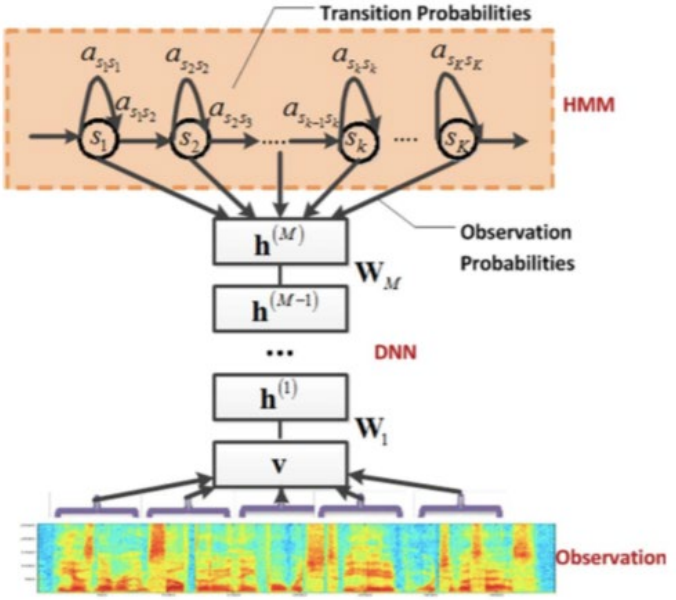


Fig. 1. Diagram of our hybrid architecture employing a deep neural network. The HMM models the sequential property of the speech signal, and the DNN models the scaled observation likelihood of all the senones (tied tri-phone states). The same DNN is replicated over different points in time.

TABLE II
CD-GMM-HMM BASELINE RESULTS

Criterion	Dev Accuracy	Test Accuracy
ML	62.9%	60.4%
MMI	65.1%	62.8%
MPE	65.5%	63.8%

TABLE VI
EFFECTS OF ALIGNMENT AND TRANSITION PROBABILITY TUNING ON BEST DNN ARCHITECTURE

Alignment	Tune Trans.	Dev Acc	Test Acc
from CD-GMM-HMM ML	no	70.3%	68.4%
from CD-GMM-HMM MPE	no	70.7%	68.8%
from CD-GMM-HMM MPE	yes	71.0%	69.0%
from CD-DNN-HMM	no	71.7%	69.6%
from CD-DNN-HMM	yes	71.8%	69.6%

- 错误率GMM->DNN
  - Dev: 37.1% -> 28.1%
  - Test: 39.6% -> 31.4%
- 错误率下降 20%

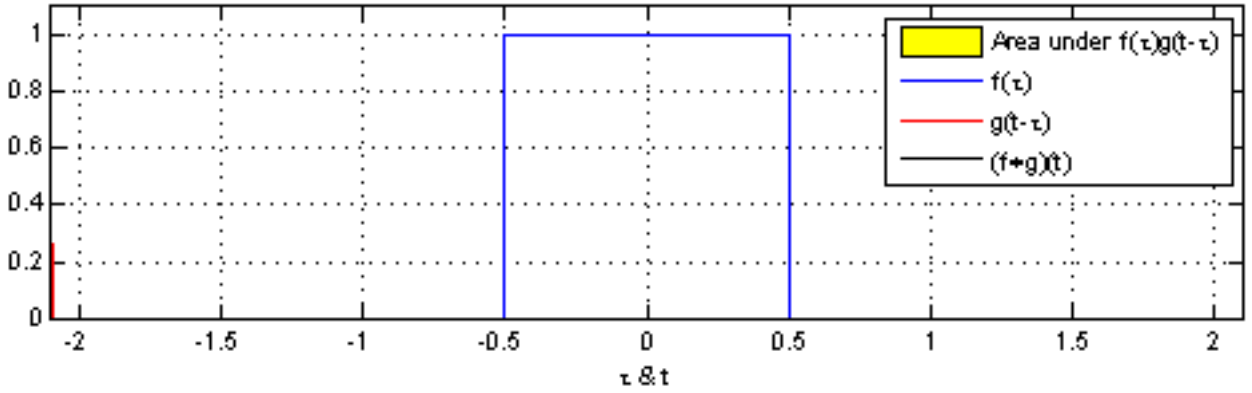
2012 - Dahl et al. - Context-Dependent Pre-Trained Deep Neural Networks for Large-Vocabulary Speech Recognition

CNN(Convolution Neural Network)

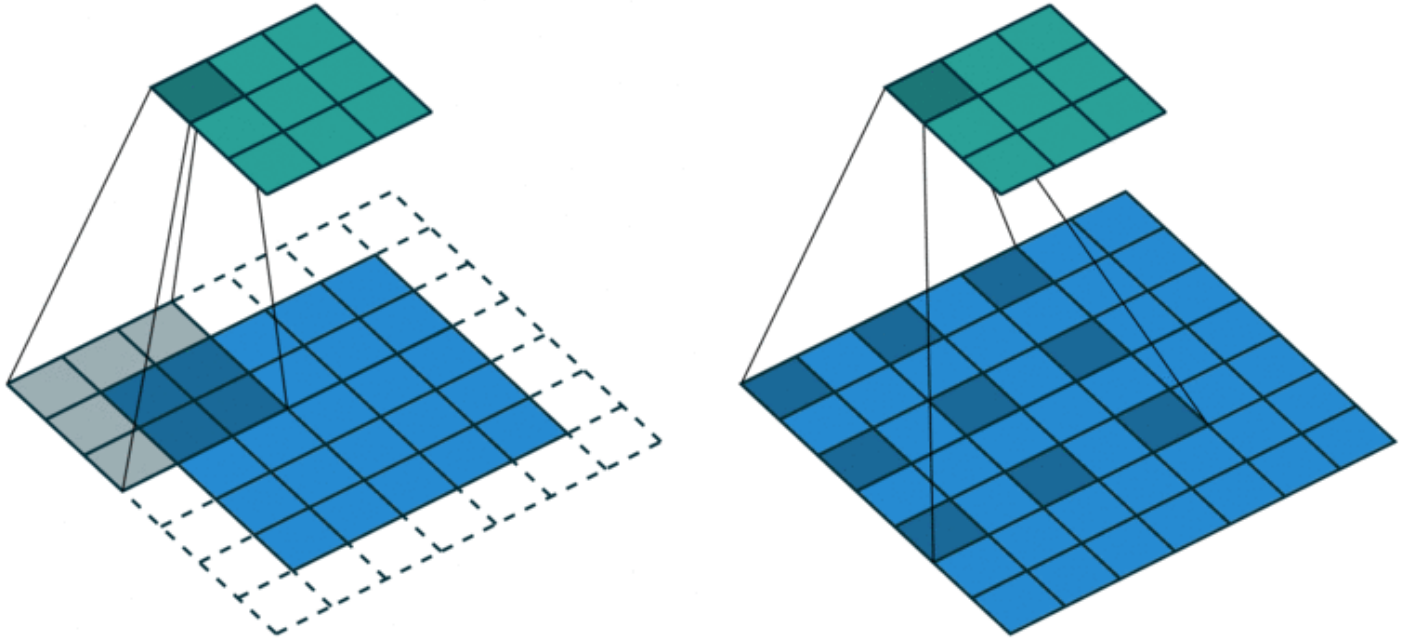
- Convolution(卷积，信号处理)

$$(f * g)[t] = \sum_{\tau} f(\tau) g(t - \tau)$$

- 平移
- 点乘
- 求和

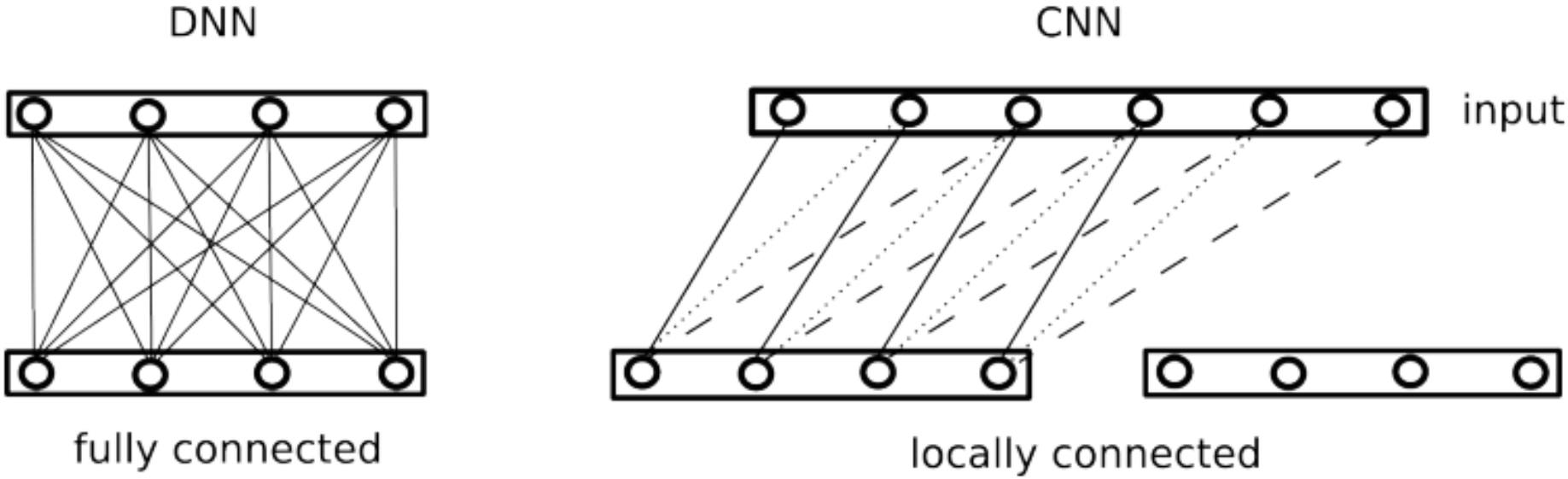


CNN



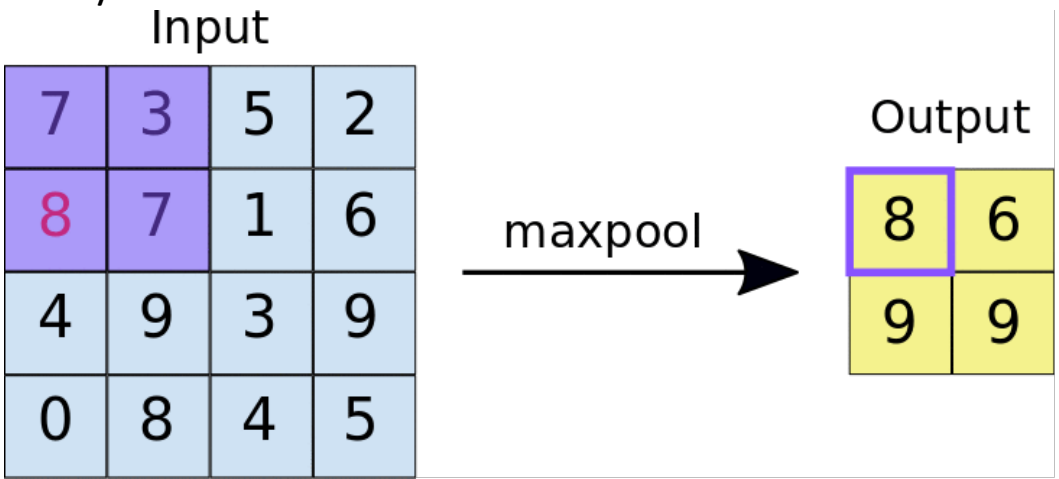
$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

CNN/DNN



Pooling

- 类型
  - Max Pooling
  - Average Pooling
- 作用
  - Dimension Reduction
  - Invariance/Robust



CNN在语音识别中的应用-CNN

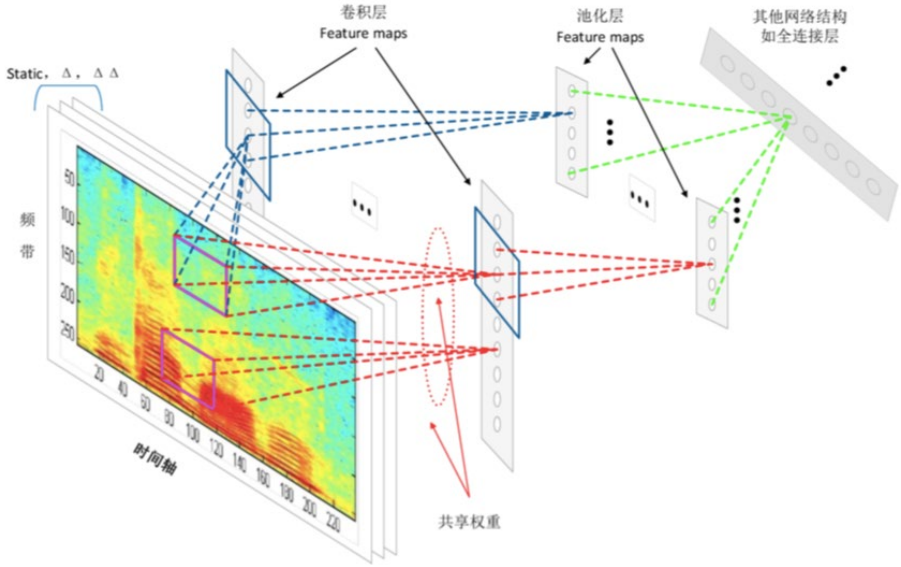


图 3-5 基于 CNN 的声学模型

Table 1: *Comparisons of TIMIT phone recognition accuracy among different CNN architectures. LWS: limited weight sharing; FWS: full weight sharing; K: # of feature maps; PS: pooling size; FS: filter size; B: # of bands.*

Convolution architecture	PER
No convolution	22.9 %
Freq FWS (K:200, PS:6, FS:8, B:20)	21.6%
Freq LWS (K:84, PS:6, FS:8, B:20)	20.5%
Time FWS (K:400, PS:2, FS:8, B:7)	22.5%
2D Multi-layers (K:40, PS:2,2, FS:3,3, B:20,7), (K:200, PS:3,1, FS:5,7, B:18,1)	21.5%

- 5~10%错误率下降
- 2D CNN在当时没有取得比较好的效果

2013 - Abdel-Hamid, Deng, Yu - Exploring Convolutional Neural Network Structures and Optimization Techniques for Speech Recognition

CNN在语音识别中的应用-TDNN

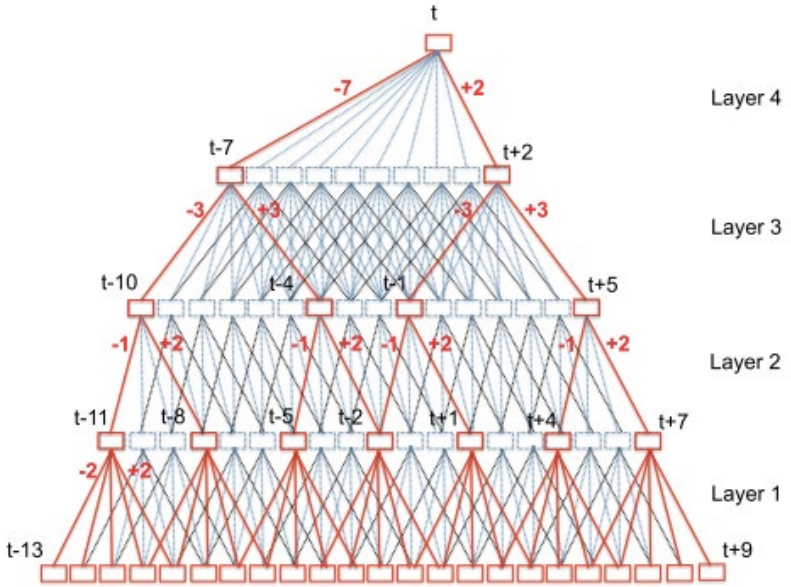


Figure 1: Computation in TDNN with sub-sampling (red) and without sub-sampling (blue+red)

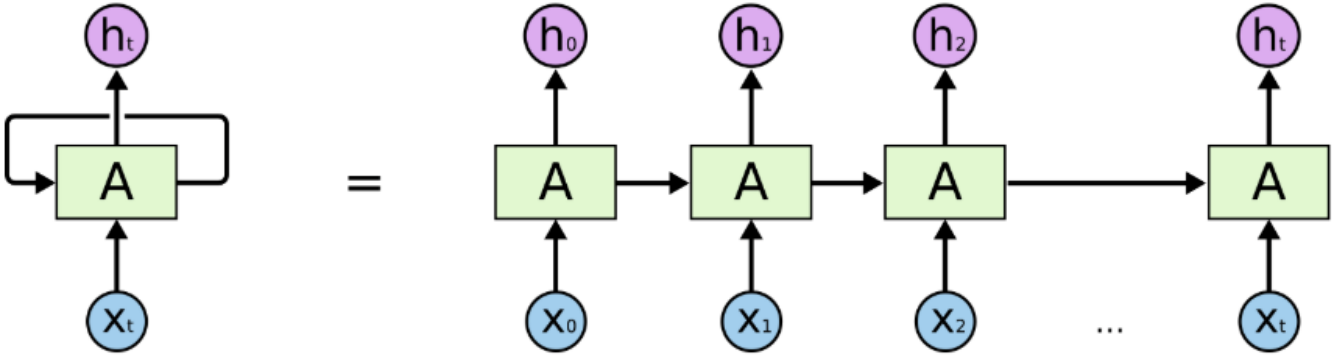
Table 4: Baseline vs TDNN on various LVCSR tasks with different amount of training data

Database	Size	WER		Rel.
		DNN	TDNN	Change
Res. Management	3h hrs	2.27	2.30	-1.3
Wall Street Journal	80 hrs	6.57	6.22	5.3
Tedlium	118 hrs	19.3	17.9	7.2
Switchboard	300 hrs	15.5	14.0	9.6
Librispeech	960 hrs	5.19	4.83	6.9
Fisher English	1800 hrs	22.24	21.03	5.4

- TDNN(Time Delay Neural Network)和扩张卷积的想法是一致的
- 仅时域卷积，没有pooling
- 5~10%错误率下降

2015 - Peddinti, Povey, Khudanpur - A time delay neural network architecture for efficient modeling of long temporal contexts

RNN(Recurrent Neural Network)

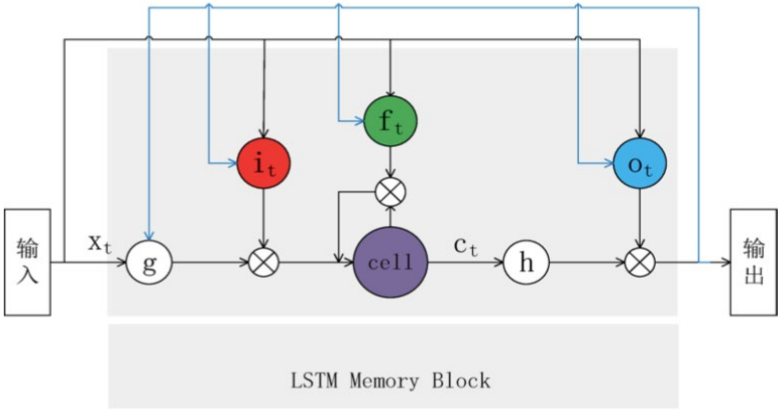


An unrolled recurrent neural network.

$$\mathbf{h}_t = f(\mathbf{W}_{xh}\mathbf{x}_t + \mathbf{W}_{hh}\mathbf{h}_{t-1})$$

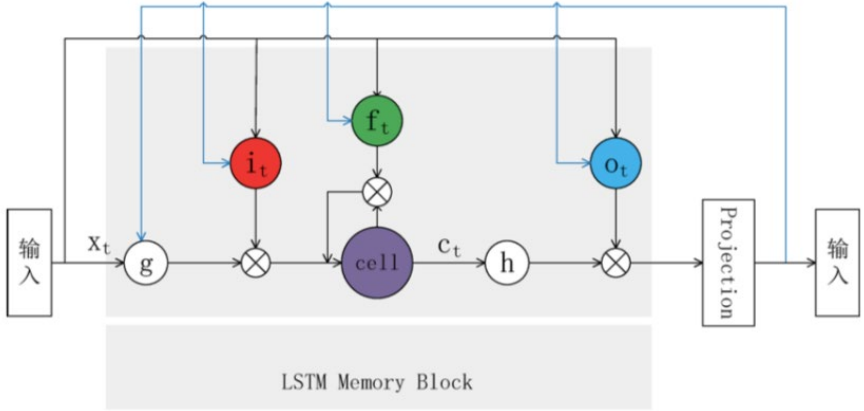
其中 $f(.)$ 表示激活函数, $\mathbf{W}_{xh}$ 是 $N \times M$ 的连接前一层的权值矩阵， $\mathbf{W}_{hh}$ 是 $N \times N$ 的连接 $t-1$ 时刻该循环层输出 $\mathbf{h}_{t-1}$ 的权值矩阵， $\mathbf{h}_{t-1}$ 即是 RNN 的内部状态。

LSTM (Long Short Term Memory)



a) LSTM

$$i_t = \sigma(W_{ix}x_t + W_{ih}h_{t-1} + b_i)$$
$$f_t = \sigma(W_{fx}x_t + W_{fh}h_{t-1} + b_f)$$
$$o_t = \sigma(W_{ox}x_t + W_{oh}h_{t-1} + b_o)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_{cx}x_t + W_{ch}h_{t-1} + b_c)$$
$$h_t = o_t \odot \tanh(c_t)$$



b) LSTMP

$$i_t = \sigma(W_{ix}x_t + W_{ih}h_{t-1} + b_i)$$
$$f_t = \sigma(W_{fx}x_t + W_{fh}h_{t-1} + b_f)$$
$$o_t = \sigma(W_{ox}x_t + W_{oh}h_{t-1} + b_o)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_{cx}x_t + W_{ch}h_{t-1} + b_c)$$
$$m_t = o_t \odot \tanh(c_t)$$
$$h_t = W_m m_t$$

LSTM在语音识别中的应用

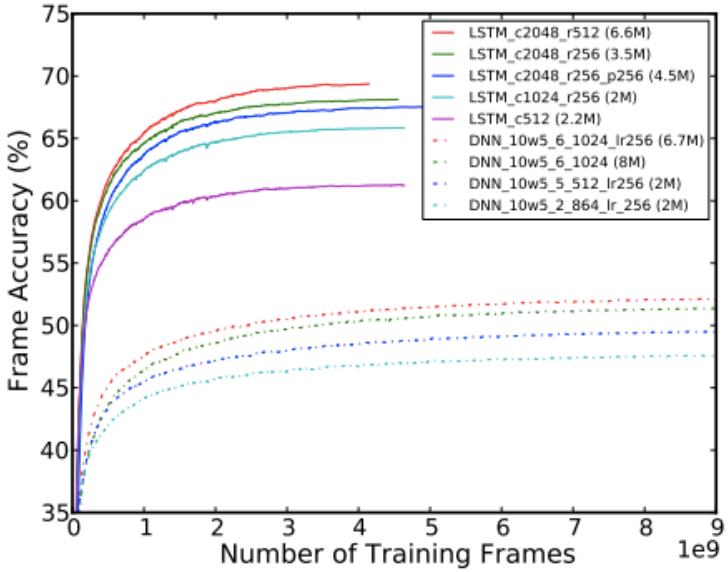


Fig. 3. 2000 context dependent phone HMM states.

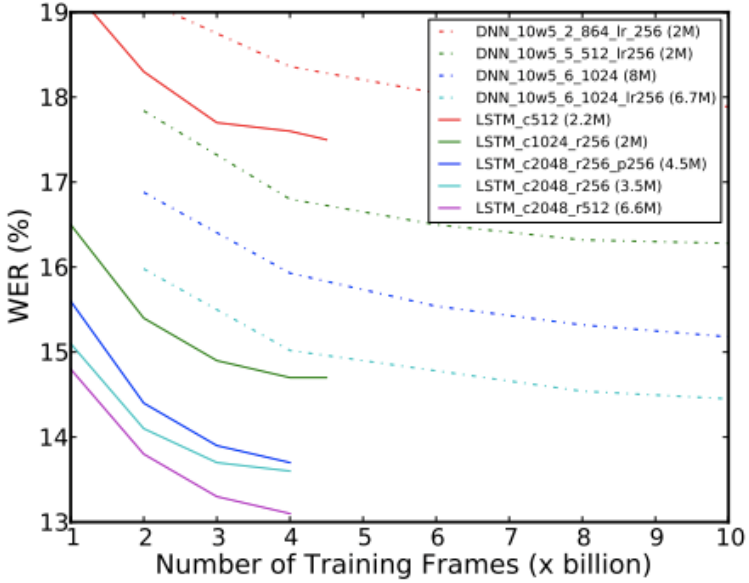


Fig. 6. 2000 context dependent phone HMM states.

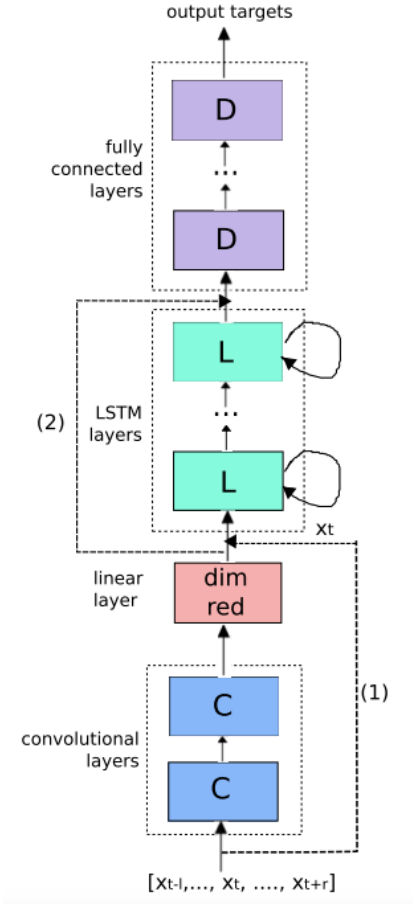
- 训练帧正确率高很多
- 5~10%错误率下降

2014 - Sak, Senior, Beaufays - Long Short-Term Memory Based Recurrent Neural Network Architectures for Large Vocabulary Speech Recognition

混合神经网络

- FNN
  - 全局特征抽取
- CNN
  - 局部特征抽取
  - Invariance
  - 有限时序建模能力
- RNN
  - 记忆
  - 时序建模能力
- 复杂网络基本是以上三种网络的组合

CLDNN



Method	WER-CE	WER-Seq
LSTM	20.3	18.8
CLDNN	19.4	**17.4**
multi-scale CLDNN	**19.2**	**17.4**

Table 9. WER, Models Trained on 2,000 hours, Noisy

2015 - Sainath et al. - Convolutional, Long Short-Term Memory, fully connected Deep Neural Networks

本章总结

- GMM-HMM语音识别系统（回顾）
- DNN-HMM语音识别系统
- 深度神经网络
  - 前馈神经网络FNN
  - 卷积神经网络CNN
    - CNN
    - TDNN
  - 循环神经网络RNN
    - LSTM
  - 混合神经网络
- 作业

作业

- 作业地址 https://github.com/nwpuaslp/ASR_Course/tree/master/06-DNN-HMM
- 作业1：完善DNN代码，并基于该DNN实现11个数字识别
  - 基本实验：拓展ReLU和FullyConnect的前向后向算法
  - 拓展1: 超参数如学习率、隐层数、隐层节点数
  - 拓展2: 基于该框架实现神经网络的一些基本算法，如
    - sigmoid和tanh激活函数
    - dropout
    - L2 regularization
    - optimizer(momentum/adam)
- 作业2：基于Kaldi和THCHS30理解梳理基于DNN-HMM的语音识别系统。
  - 基本流程步骤
  - 每一步骤的输入、输出
  - 步骤间的依赖关系

感谢各位聆听！