Structured Deep Learning for Context Awareness in Speech and Language Processing

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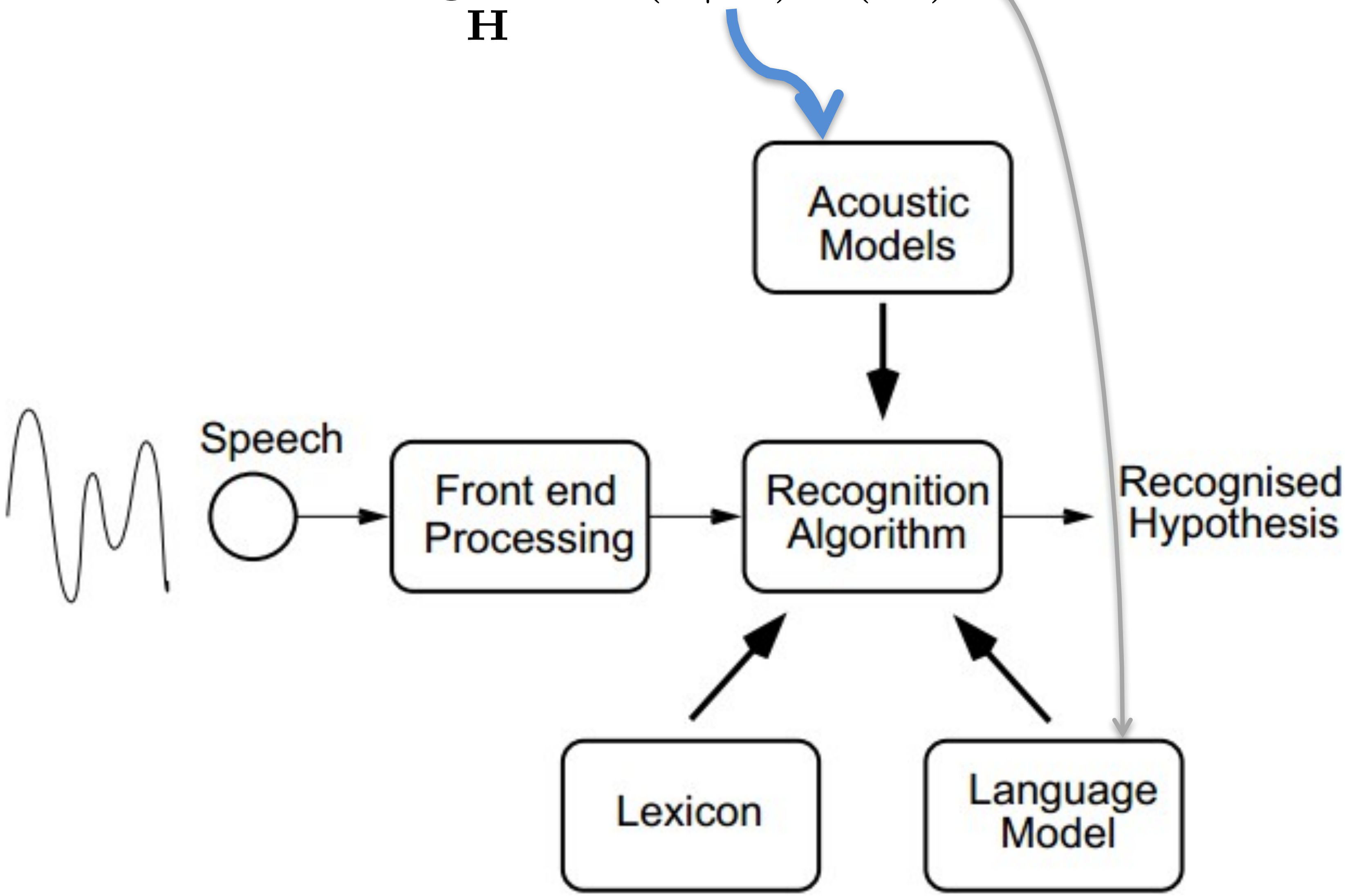
Content

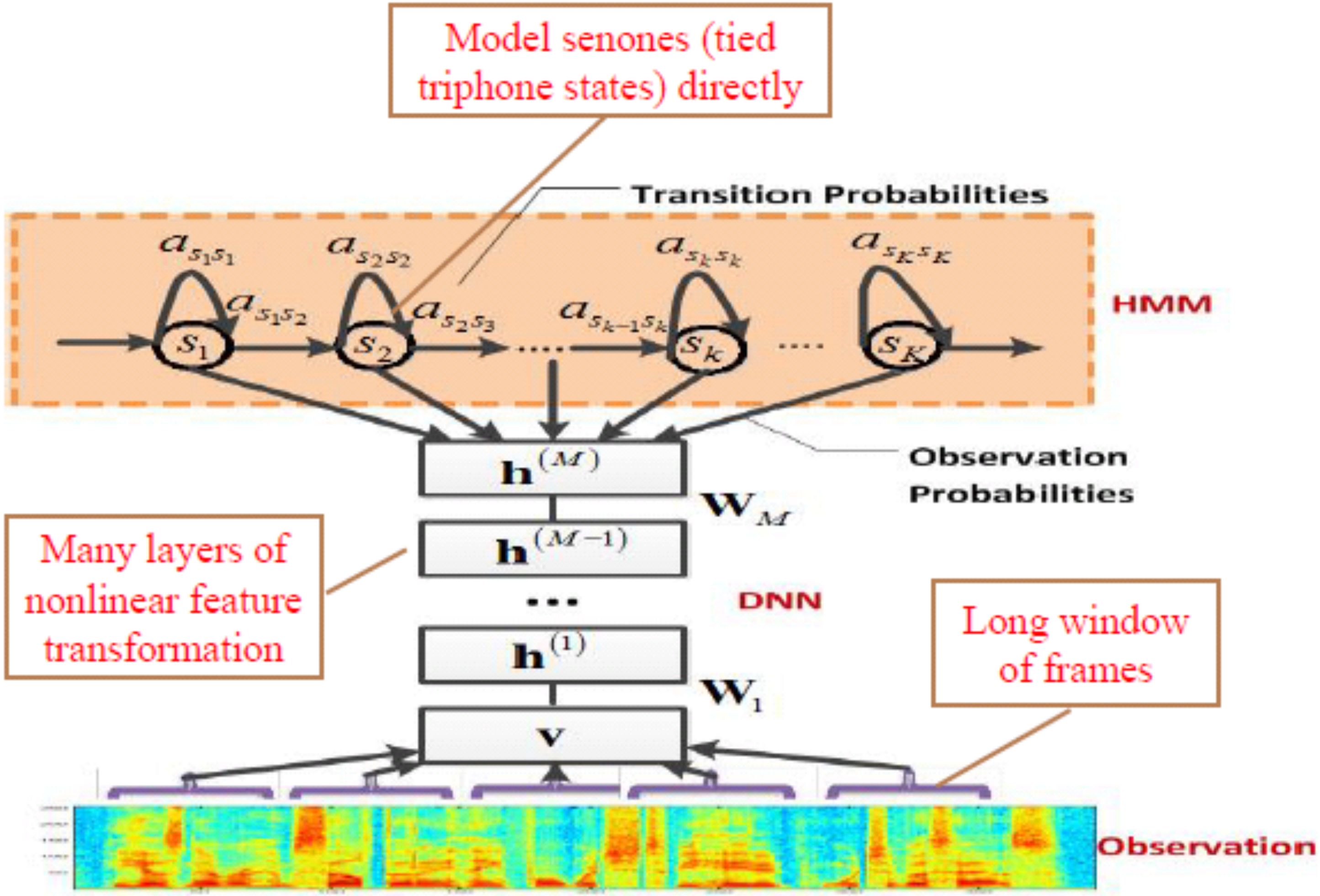
- Part I: Deep learning for Speech Recognition
- Part II: Multi-style and Context-aware Training
- Part III: Structured Deep Learning for Context Awareness

Part I
Deep learning for Speech Recognition

$$\hat{\mathbf{H}} = \arg\max_{\mathbf{H}} p(\mathbf{o}|\mathbf{H})P(\mathbf{H})$$

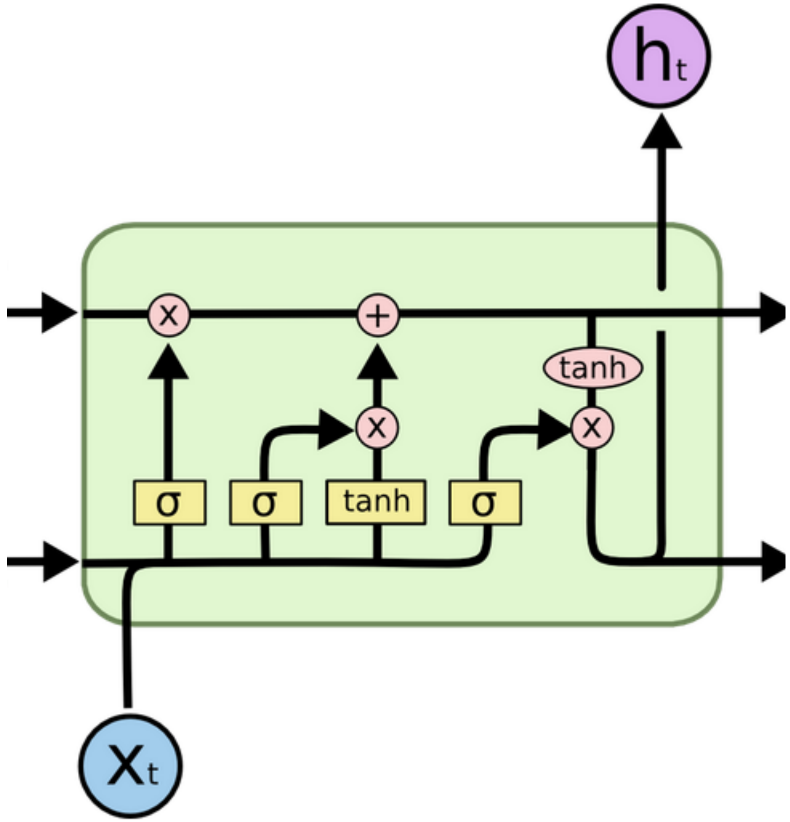


AM: CD-DNN-HMM v.s. GMM-HMM

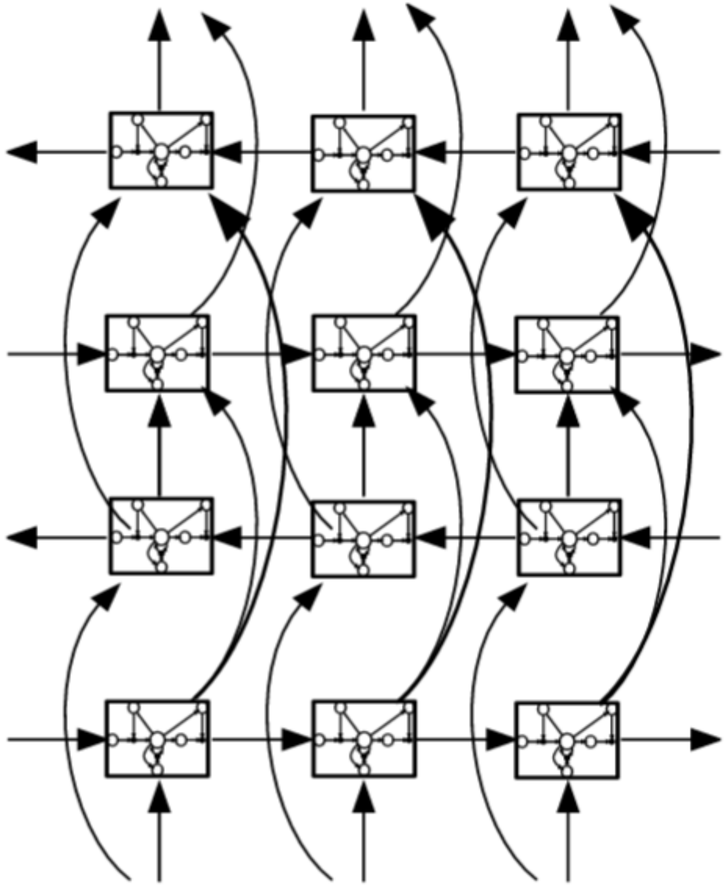


[1]

AM: LSTM



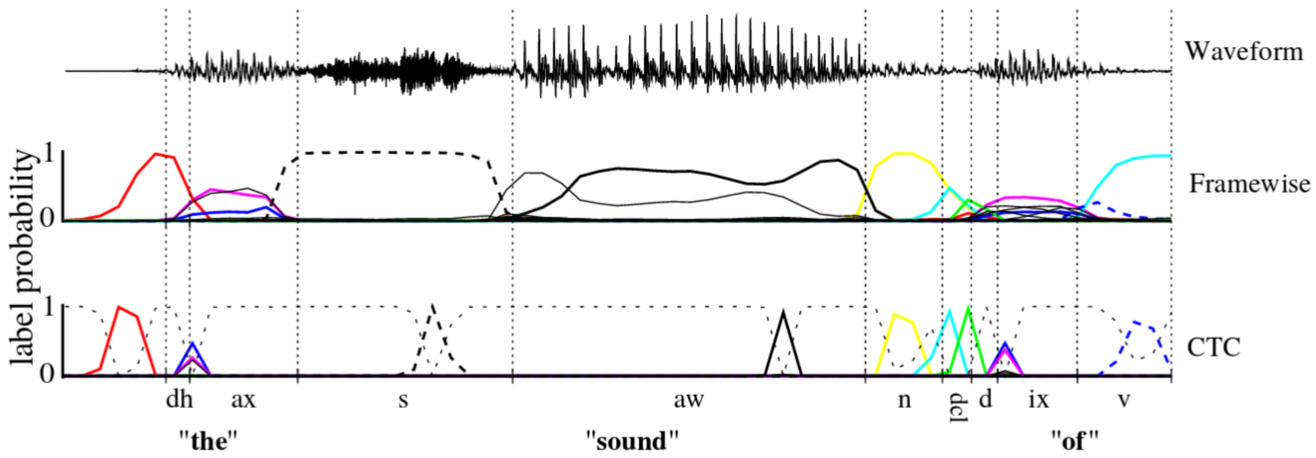
LSTM



[2]

BLSTM

AM: LSTM-CTC



[3]

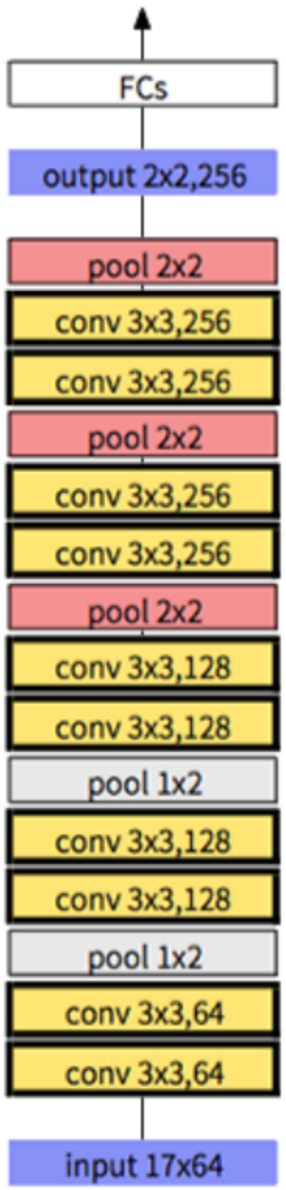
$$\mathcal{L}_{\texttt{ce}} = \sum_{t=1}^{T} \log P(y_t|x_t) \qquad P(\mathbf{y}|\mathbf{x}) = \sum_{\mathbf{a}\in\mathcal{B}^{-1}(\mathbf{y})} P(\mathbf{a}|\mathbf{x})$$

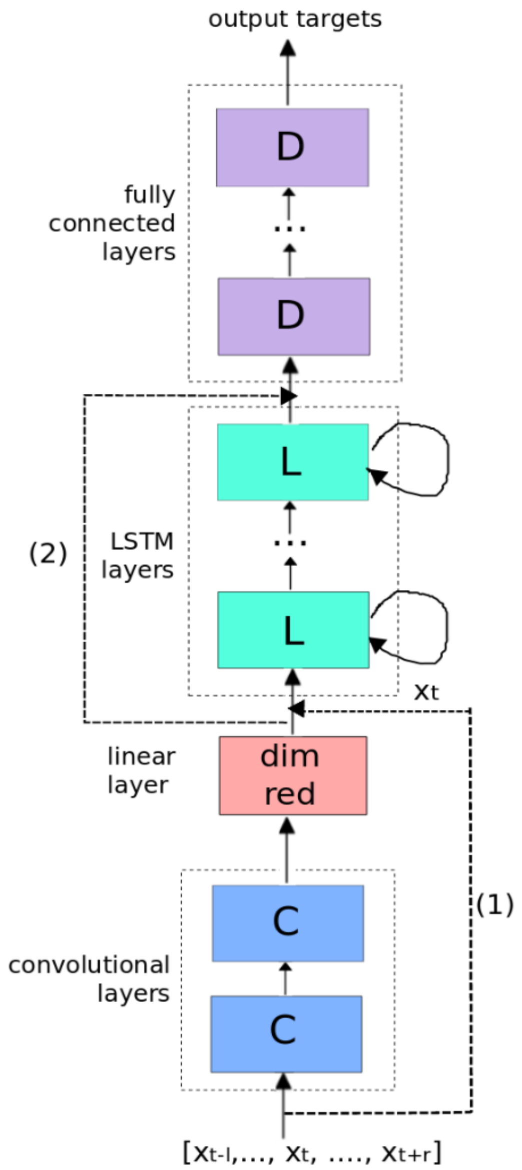
$$\mathcal{L}_{\texttt{ctc}} = \log P(\mathbf{y}|\mathbf{x})$$

$\mathcal{B}$ is an operator that removes first the repeated labels, then the blanks from alignments, for example,

$\mathcal{B}$(a,b,b,b,c,c) = $\mathcal{B}$(a,-,b,-,c,c) = (a,b,c)

AM: Very Deep CNN and CLDNN

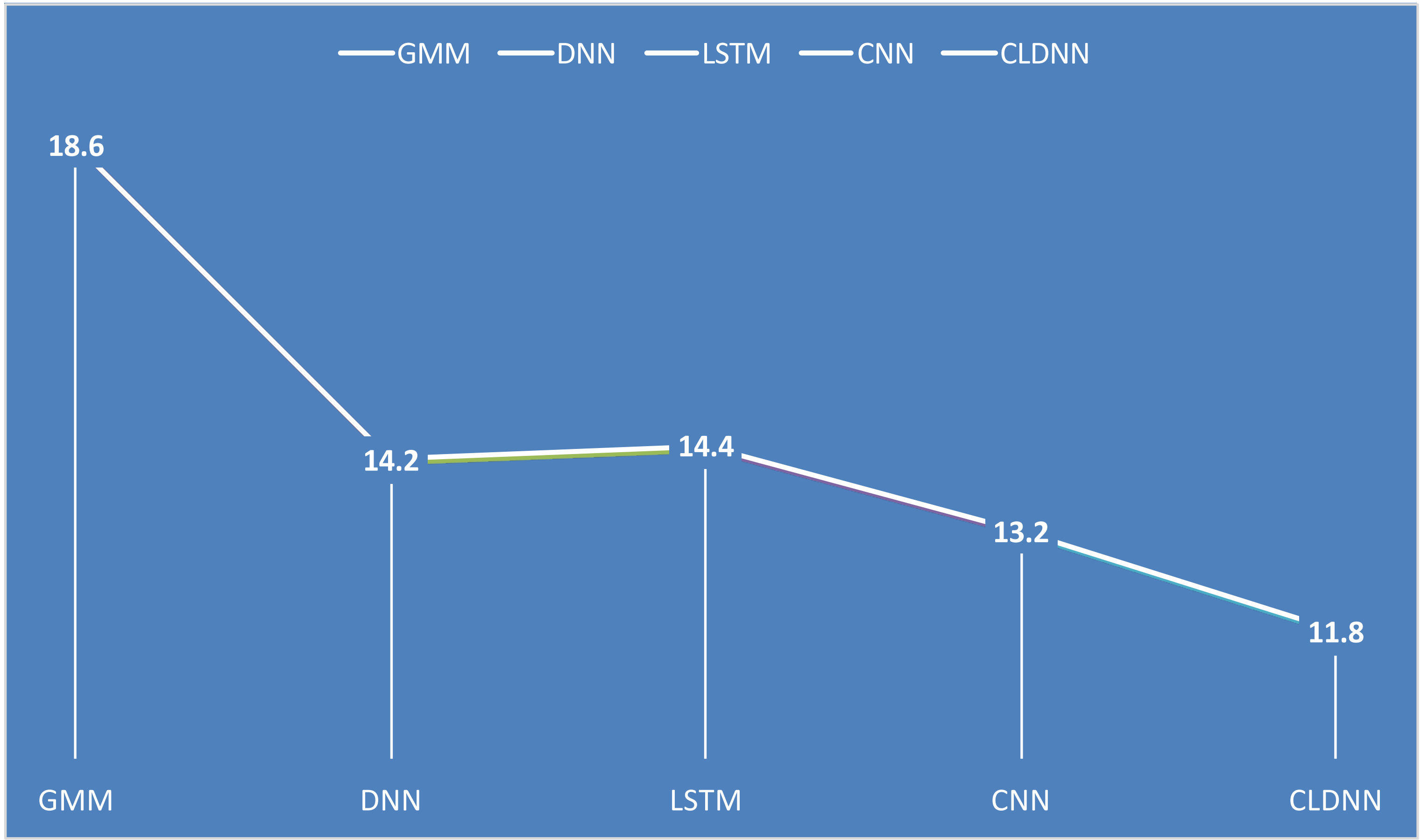




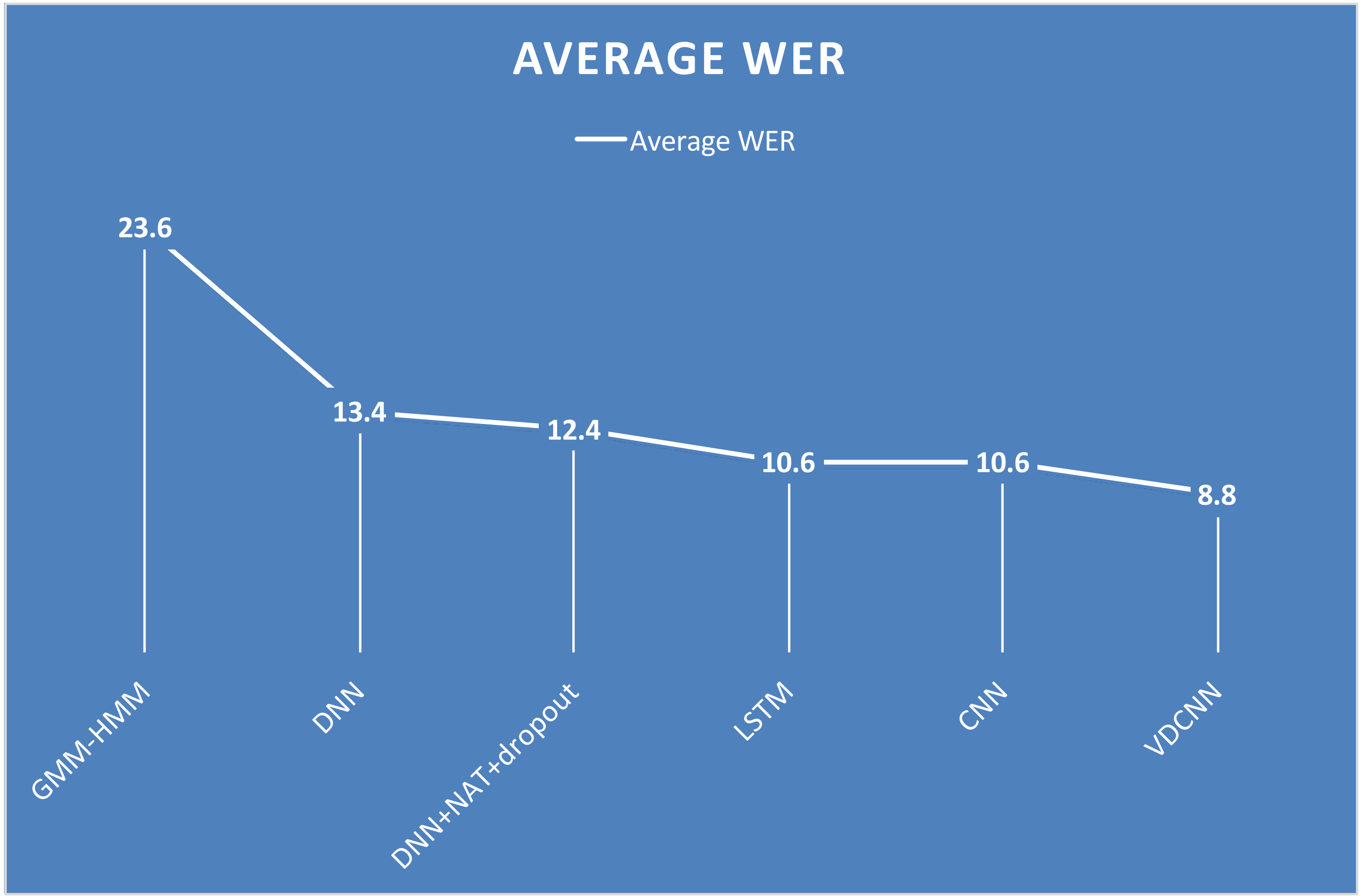
The typical speech inputs, with static, delta and double delta features, can be represented as 3 feature maps and each of them can be viewed as an image-map with a size of #times x #freqs

[4][5]

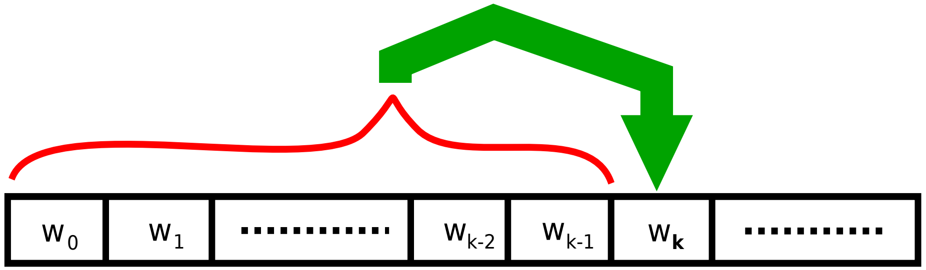
AM: Performance Gain (swbd) [6][7]



AM: Performance Gain (aurora4) [8][9]

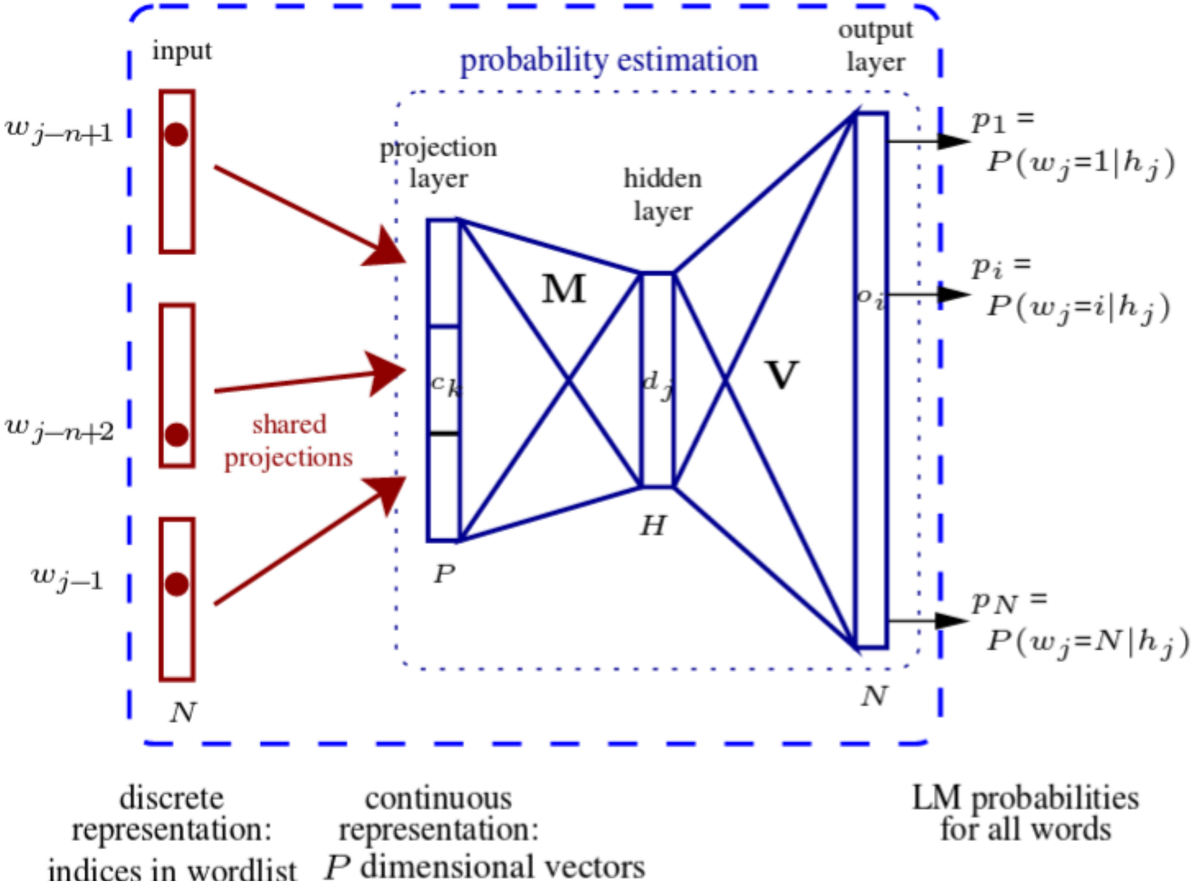


LM: FDNN v.s. N-gram



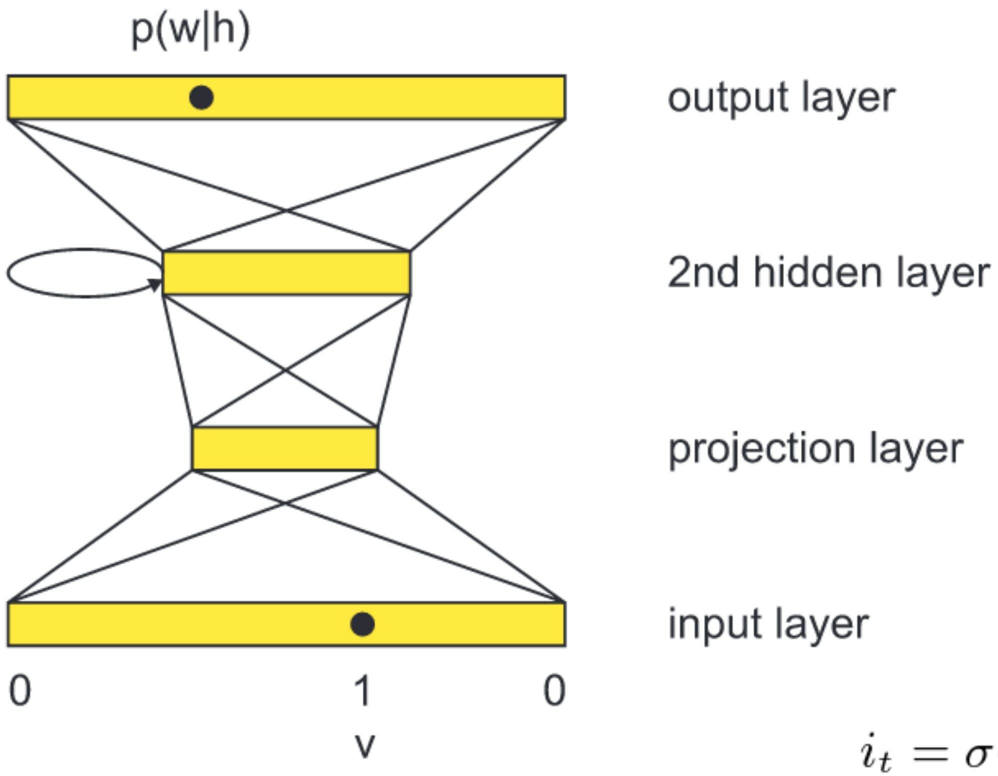
$$P(\mathbf{H}) = \prod_{k=1}^{K+1} P(w_k | w_1, \cdots, w_{k-1})$$

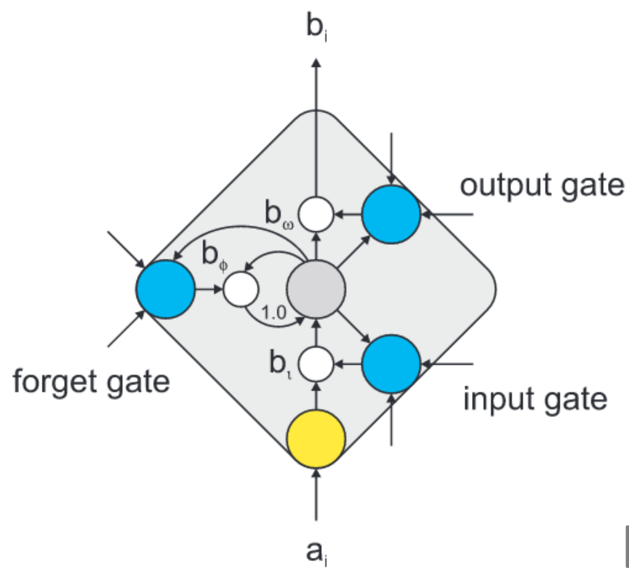
$$P(w_k | w_1, \cdots, w_{k-1}) = P(w_k | w_{k-1}, \cdots, w_{k-n+1})$$



[10]

LM: RNN and LSTM





[11]

$$i_t = \sigma(W_{ix}x_t + W_{im}m_{t-1} + W_{ic}c_{t-1} + b_i)$$
$$f_t = \sigma(W_{fx}x_t + W_{fm}m_{t-1} + W_{fc}c_{t-1} + b_f)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot g(W_{cx}x_t + W_{cm}m_{t-1} + b_c)$$
$$o_t = \sigma(W_{ox}x_t + W_{om}m_{t-1} + W_{oc}c_t + b_o)$$
$$m_t = o_t \odot h(c_t)$$
$$y_t = \phi(W_{ym}m_t + b_y)$$

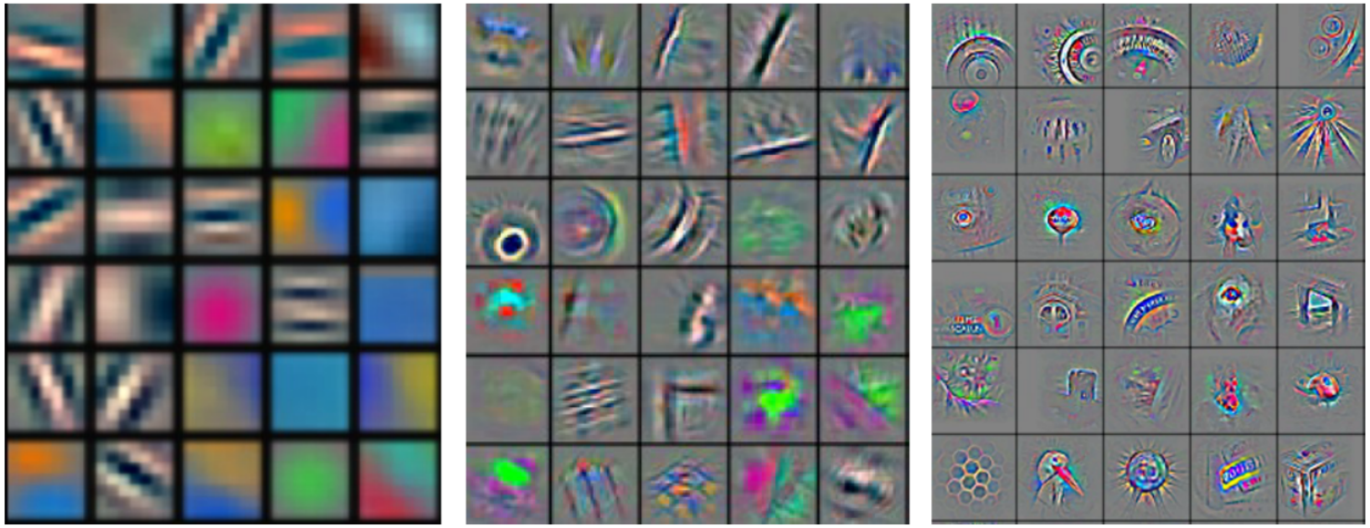
LM: Performance Improvement [12]

Model	Perplexity			Entropy reduction over baseline	
	individual	+KN5	+KN5+cache	KN5	KN5+cache
3-gram, Good-Turing smoothing (GT3)	165.2	-	-	-	-
5-gram, Good-Turing smoothing (GT5)	162.3	-	-	-	-
3-gram, Kneser-Ney smoothing (KN3)	148.3	-	-	-	-
5-gram, Kneser-Ney smoothing (KN5)	**141.2**	-	-	-	-
5-gram, Kneser-Ney smoothing + cache	**125.7**	-	-	-	-
PAQ8o10t	131.1	-	-	-	-
Maximum entropy 5-gram model	142.1	138.7	124.5	0.4%	0.2%
Random clusterings LM	170.1	126.3	115.6	2.3%	1.7%
Random forest LM	131.9	131.3	117.5	1.5%	1.4%
Structured LM	146.1	125.5	114.4	2.4%	1.9%
Within and across sentence boundary LM	116.6	110.0	108.7	5.0%	3.0%
Log-bilinear LM	144.5	115.2	105.8	4.1%	3.6%
Feedforward neural network LM [50]	140.2	116.7	106.6	3.8%	3.4%
Feedforward neural network LM [40]	141.8	114.8	105.2	4.2%	3.7%
Syntactical neural network LM	131.3	110.0	101.5	5.0%	4.4%
Recurrent neural network LM	124.7	105.7	97.5	5.8%	5.3%
Dynamically evaluated RNNLM	123.2	102.7	98.0	6.4%	5.1%
Combination of static RNNLMs	102.1	95.5	**89.4**	7.9%	7.0%
Combination of dynamic RNNLMs	101.0	**92.9**	90.0	8.5%	6.9%

What Issues Have DL Addressed?

- Hierarchical feature representation

Suitable for task



[13]

Low-Level Feature Mid-Level Feature High-Level Feature

Adaptation technique	CD-GMM-HMM (40-mixture)	CD-MLP-HMM (1 × 2,048)	CD-DNN-HMM (7 × 2,048)
Speaker independent	23.6 %	24.2 %	17.1 %
+ VTLN	21.5 % (−9 %)	22.5 % (−7 %)	16.8 % (−2 %)
+ fMLLR/fDLR×4	20.4 % (−5 %)	21.5 % (−4 %)	16.4 % (−2 %)

Deep Learning + Big Data

$\neq$ End_of_SLT_Research

- **Real world data is always non-homogeneous**

Structured Deep Learning

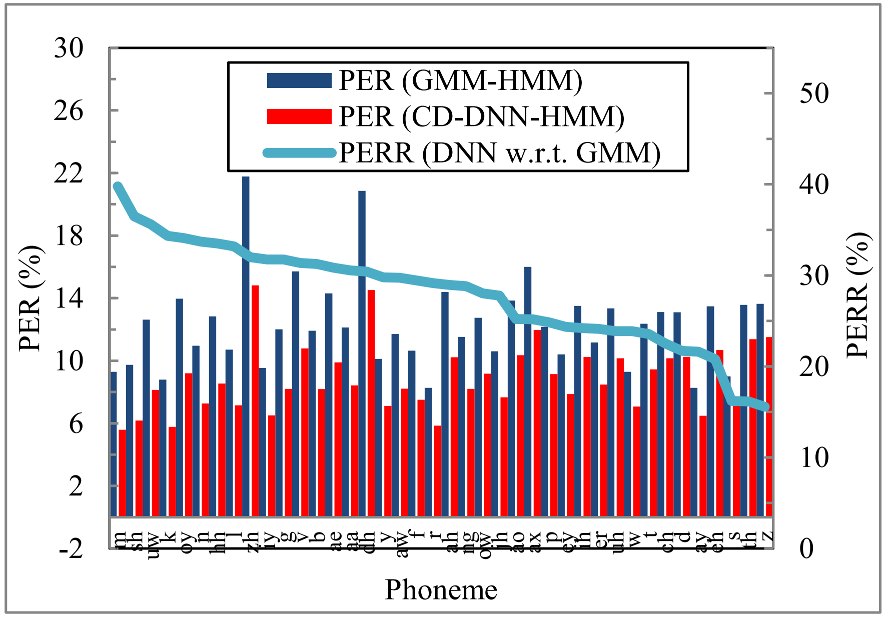
- **From data-driven to data+knowledge driven**

Prior knowledge incorporation

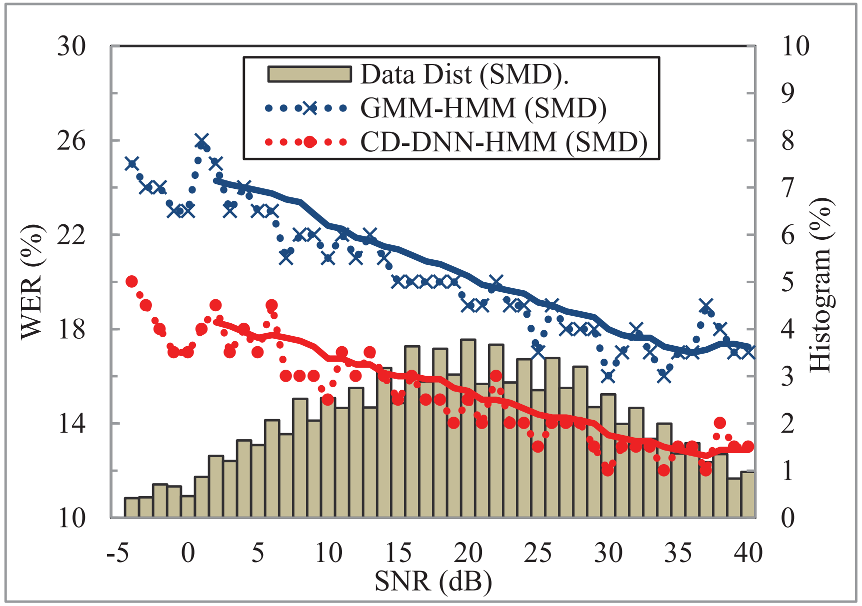
Part II
Multi-style and Context-aware Training

What Issues DL Have Not Addressed?

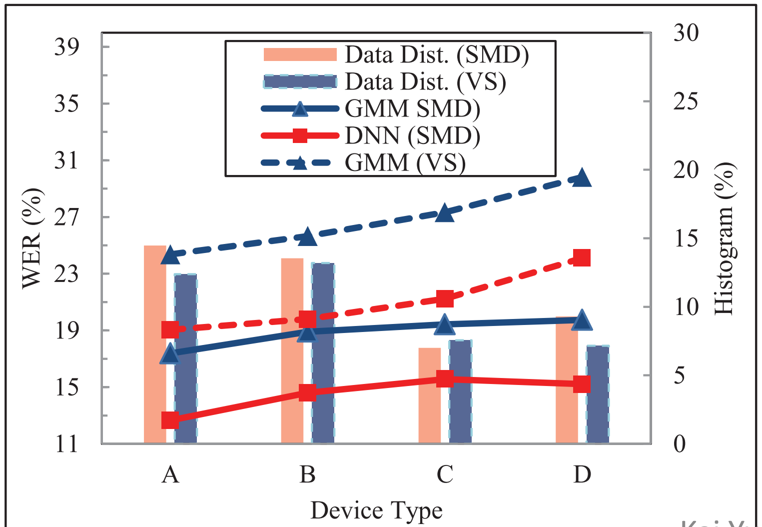
Phone Discrimination



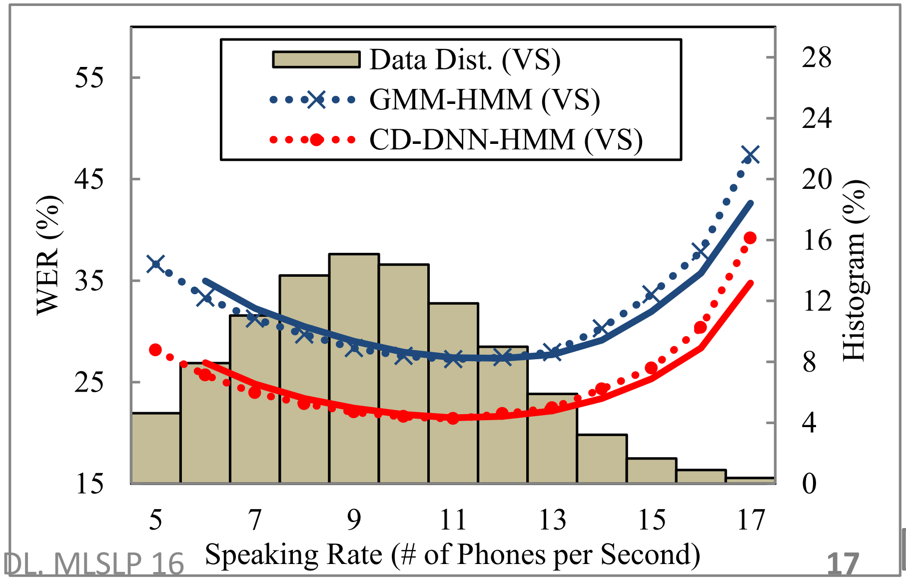
Noise Robustness



Channel Mismatch



Speaking Rate



[14]

Acoustic Variabilities for AM

- **Speech** variability – **desired**
  – Inherent variability related to what a speaker says

- **Acoustic context** variability – **unwanted**
  – Speaker: male/female, accent, speaking rate, etc.
  – Emotion: happy, fear, neutral, etc.
  – Spontaneity: read, natural, spontaneous, etc.
  – Environment: office, car, street, airport, etc.
  – Channel: mobile, microphone, bluetooth, etc.

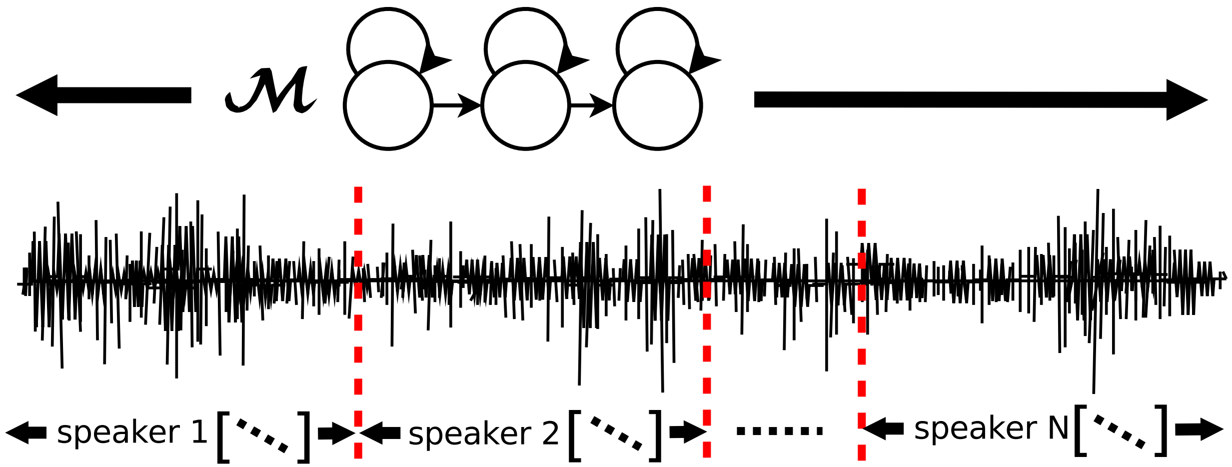
Linguistic Variabilities for LM

- **Word** variability – **desired**
  - Inherent variability related to what a speaker says
- **Linguistic context** variability – **unwanted**
  - Domain: news, science, novel, etc.
  - Topic: politics, sports, family, technology, etc.
  - Speaker role: child, parents, professional, etc.
  - Emotion: sad, happy, disgust, etc.
  - Dialogue: conversation history, search record, etc.

Context and Homogeneity

- **Effect**
  - Non-Targeted but Influential factors
- **Granularity**
  - Different from the primary variability
  - Usually beyond local estimation
- **Prior knowledge is a special kind of context**
  - E.g. telephone number constraint, etc.
- **Context is also structured**
  - E.g. environment, speaker, channel have intersection

Context and **Homogeneity**

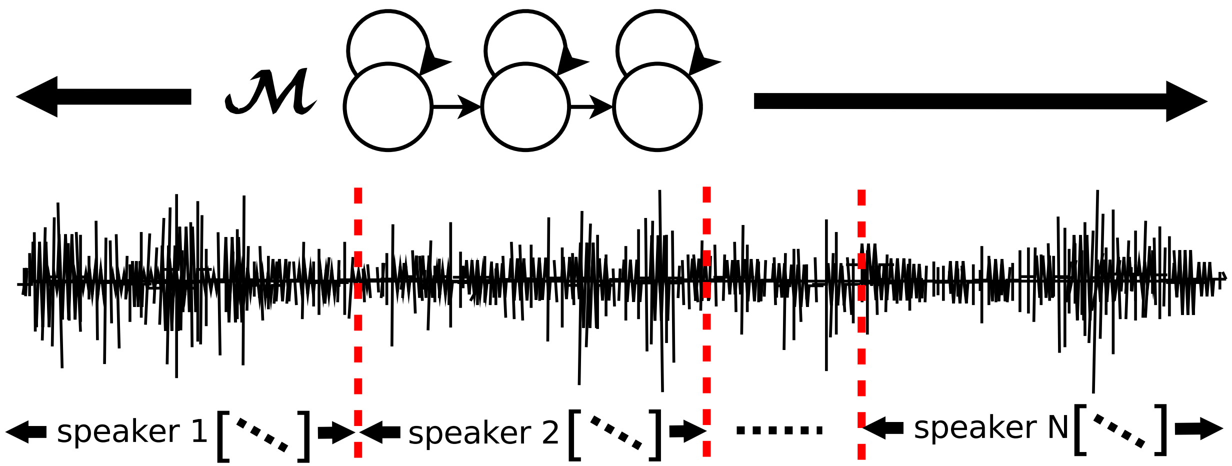


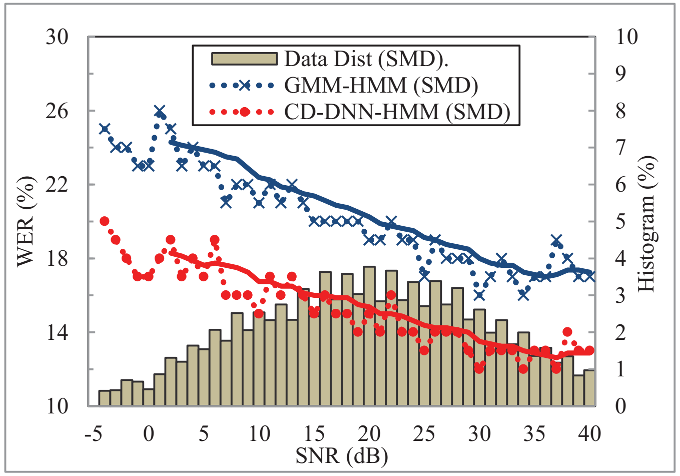
$$\mathcal{O} = \{\mathbf{O}^{(1)}, \cdots, \mathbf{O}^{(S)}\}$$

- Data within a homogeneous block share the same context (concrete specific statistical property)
- Homogeneous block is dependent on context
- **How to deal with non-homogeneity?**
  – Deep learning + big data?

Multi-style Training with Big Data

Multi-style training



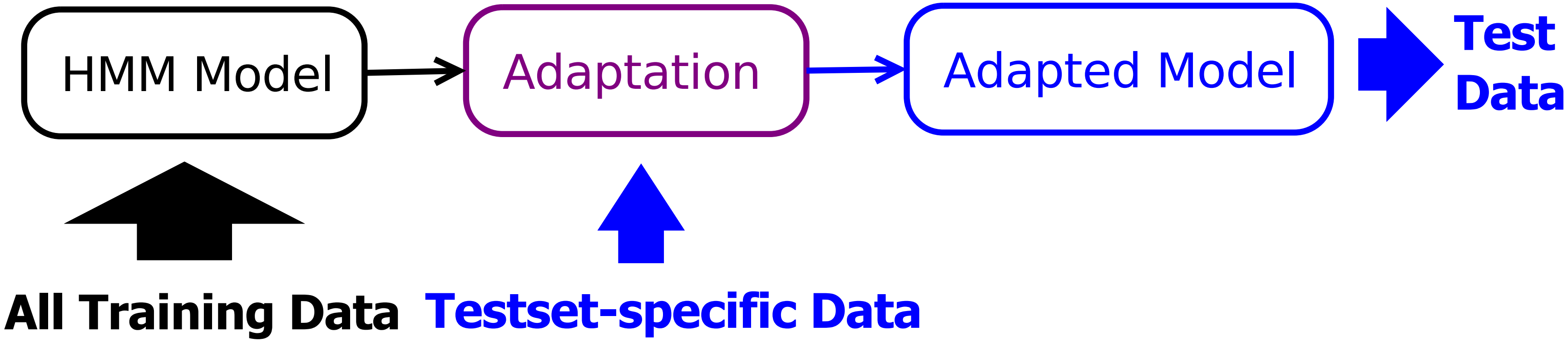


[14]

- Train models on data with large variability as if they are “homogeneous”, i.e. ignore mismatch inside training data
- Rely on good model and big data coverage
- **Big data ≠ rich context**
- **Implicit context modelling has limitation**
- **Explicit modelling: adaptation and adaptive training**

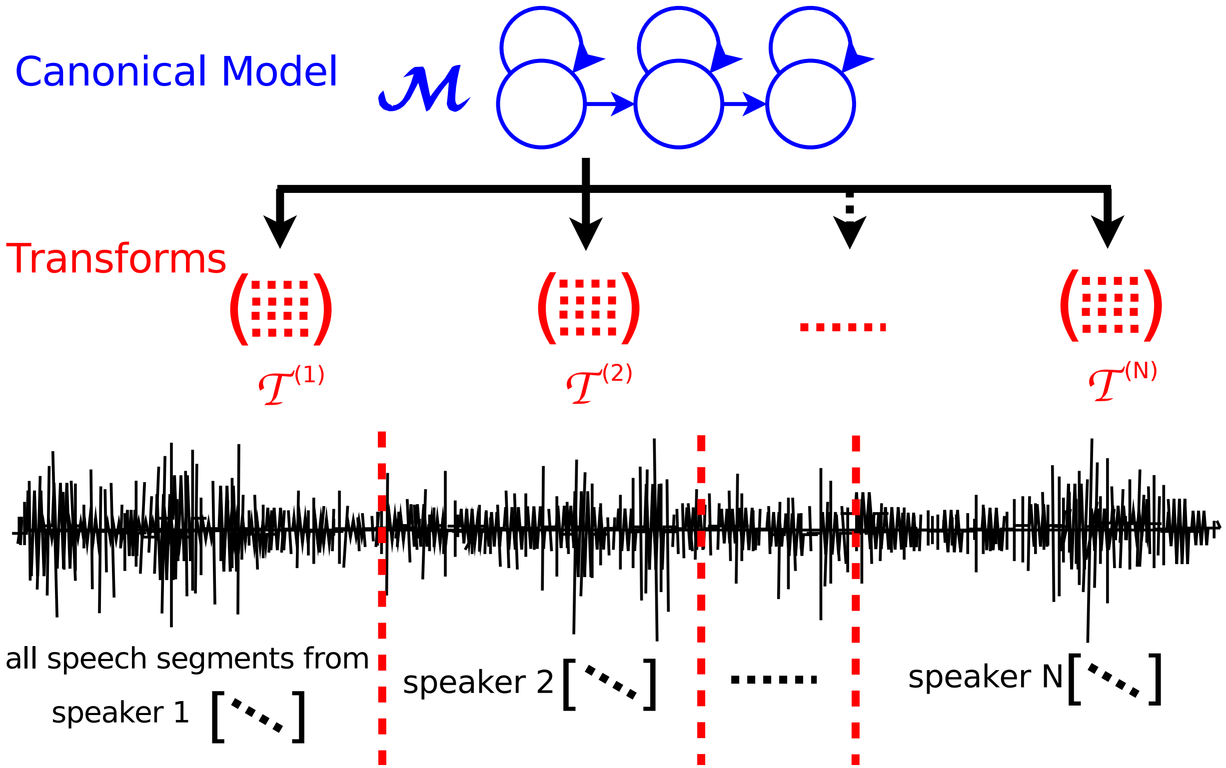
Adaptation – No Change in Training

- Well-built model already exists



- Mode
  - Supervised: annotations are available
  - Unsupervised: only raw data is available

Adaptive Training – Explicit Modelling of Context



Acoustic Modelling as an Example

Training data is split *homogeneous* blocks

$$\mathcal{O} = \left\{ \mathbf{O}^{(1)}, \cdots, \mathbf{O}^{(S)} \right\}$$

- Speech and non-speech variability separately modelled

GMM-HMM Adaptive Training Techniques

- Feature Normalization
  – Cepstral Mean and Variance Normalization
  – Gaussianization
  – Vocal Tract Length Normalization
- Model Adaptation
  – Linear transform based (MLLR, CMLLR etc.)
  – Cluster adaptive training

[15,16,17,18,19,20,21]

Feature Normalization [15][16]

- Simplest form: CMN/CVN

$$\hat{\mathbf{o}}_t^{\texttt{CMN}(s)} = \mathbf{o}_t^{(s)} - \bar{\mathbf{o}}^{(s)} = \mathbf{o}_t^{(s)} - \frac{1}{T}\sum_{i=1}^{T} \mathbf{o}_i^{(s)} \qquad \hat{o}_{t,d}^{\texttt{CVN}(s)} = \hat{o}_{t,d}^{\texttt{CMN}(s)} / \sqrt{\sigma_{dd}^{(s)}}$$

  - Homogeneous block varies from utterance to speaker or corpus
- Comparison to global CMN/CVN
  - Each homogeneous block has ***different*** feature transforms
  - Normalize training and test data ***separately***

Part III
Structured Deep Learning for Context Awareness

Context-aware Deep Learning

- **Re-training under context** – **Implicit** modelling

Basic Idea: Let the updated model be close to the original well-trained model

  – Additional Regularization
    - Conservative training [22]
    - KL-divergence regularization [23]
  – Selective update
    - Only update input/output layer [24]
    - Update weights connected to maximum variance nodes [25]

- **Structured deep learning** – **Explicit** modelling
  – **Multi-view** input with context representation
  – **Multi-task** output with context target or constraint
  – **Structured model** parameter to reflect context

Structured Input – Multi-view Techniques

- External context embedding as input

Basic Idea: Estimate context representation using an external model and augment feature with the context representation

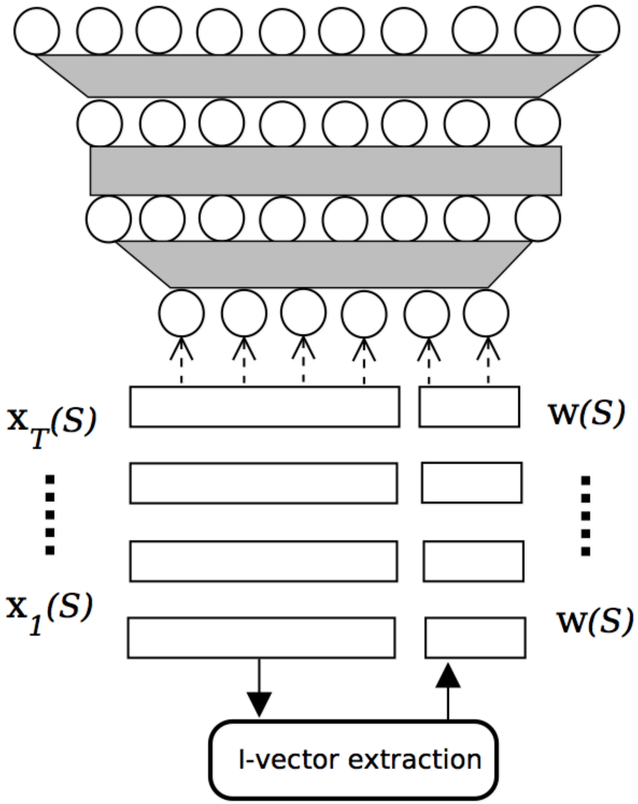
  - Speaker feature: i-vector [26], i-vector for LSTM [31]
  - Environment-feature or combined:noise-energy [27], combined [28]
  - Structured VAD [32]

- Internal trainable context embedding

Basic Idea: Context representation is estimated using the same model for speech recognition

  - Speaker-code [29]
  - Paragraph-vector [30]

i-Vector-based DNN Adaptation[26,33]

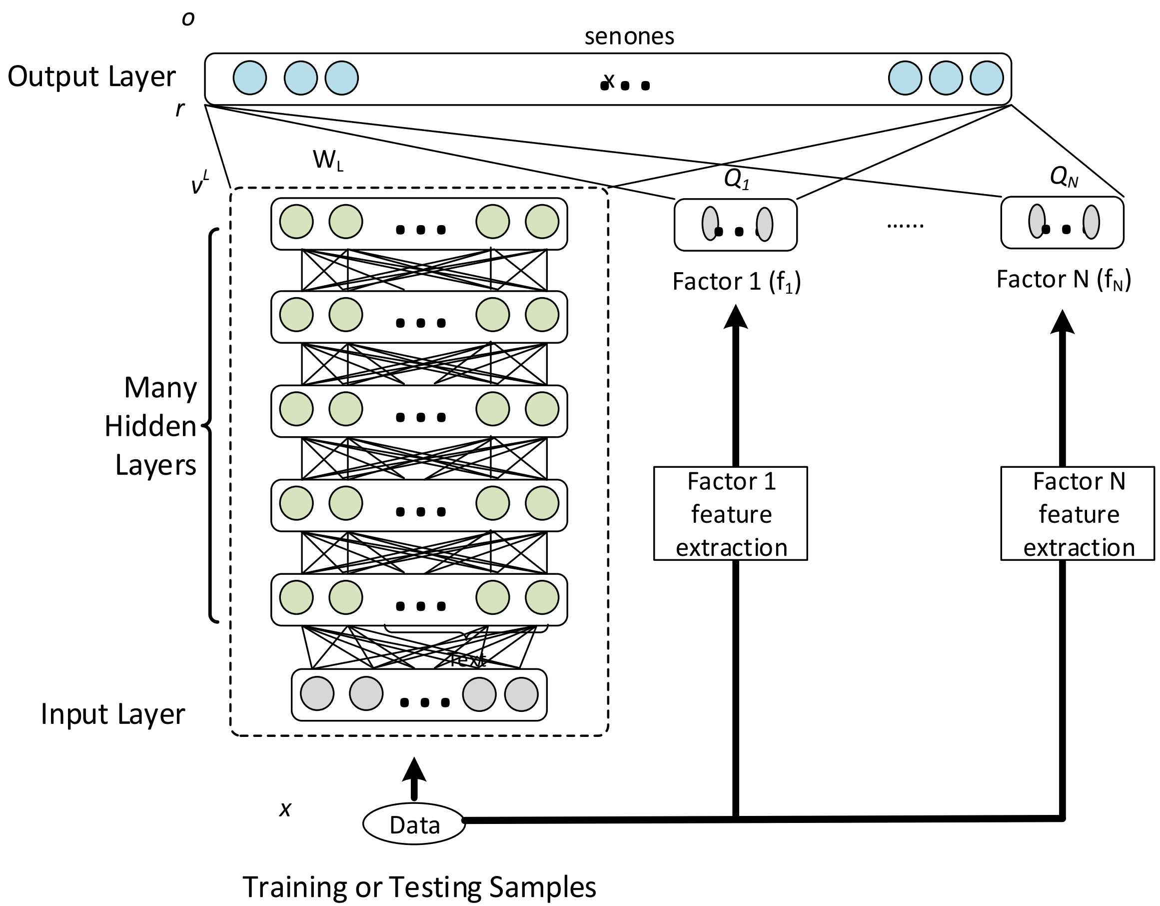


Crit.	Sys	Hub5	RT03-Fsh	RT-03-Swb
CE	DNN	16.1	18.9	29.0
	+iVec	**13.9**	**16.7**	**25.8**
Sequence	DNN	14.1	16.9	26.5
	+iVec	**12.4**	**15.0**	**24.0**

Conversational Telephone Speech (English)

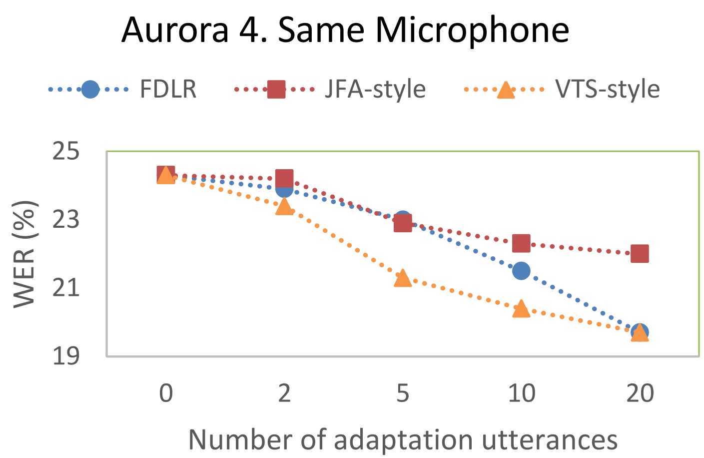
- i-Vector encapsulates all relevant information about a speaker's identity in a low-dimensional vector
- i-Vector extraction is independent of DNN training
- Speaker-level i-Vector is fed into DNN together with frame-level features as augmented input features
- Noise-vector (energy) can also be used in the framework [27]

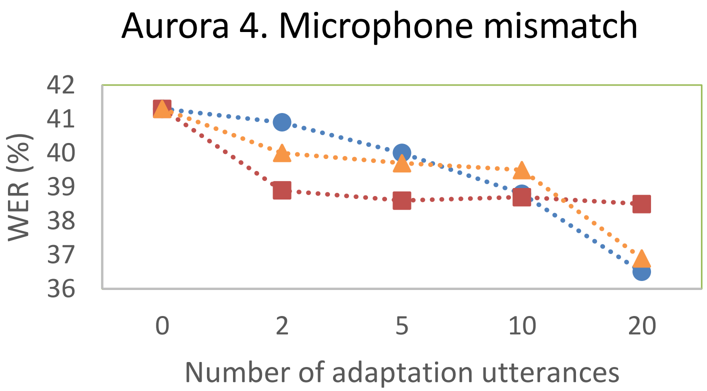
Factored DNN Adaptation [28]



Factor vector estimation

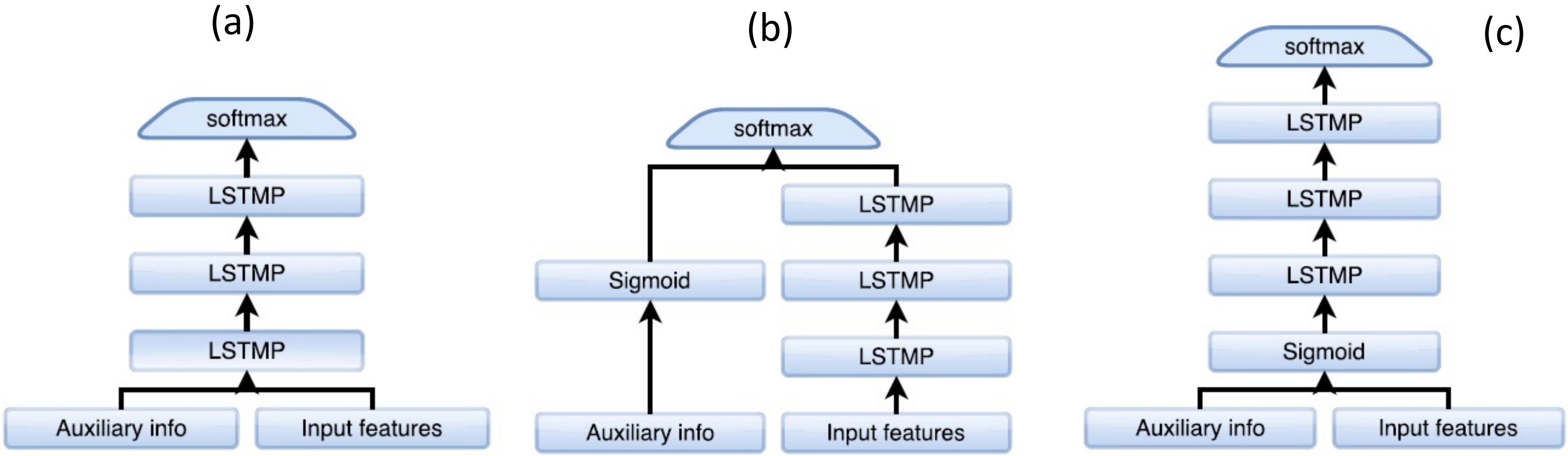
- Joint factor analysis (JFA) [34]
- Vector Taylor Series (VTS) [35,36]





- Factors are estimated separately from DNN
- Factor vectors fed to the softmax output layer
- Loading matrix (weights connected to acoustic factor vectors) need to be estimated using standard BP

Speaker-aware training on LSTM-RNNs [31]



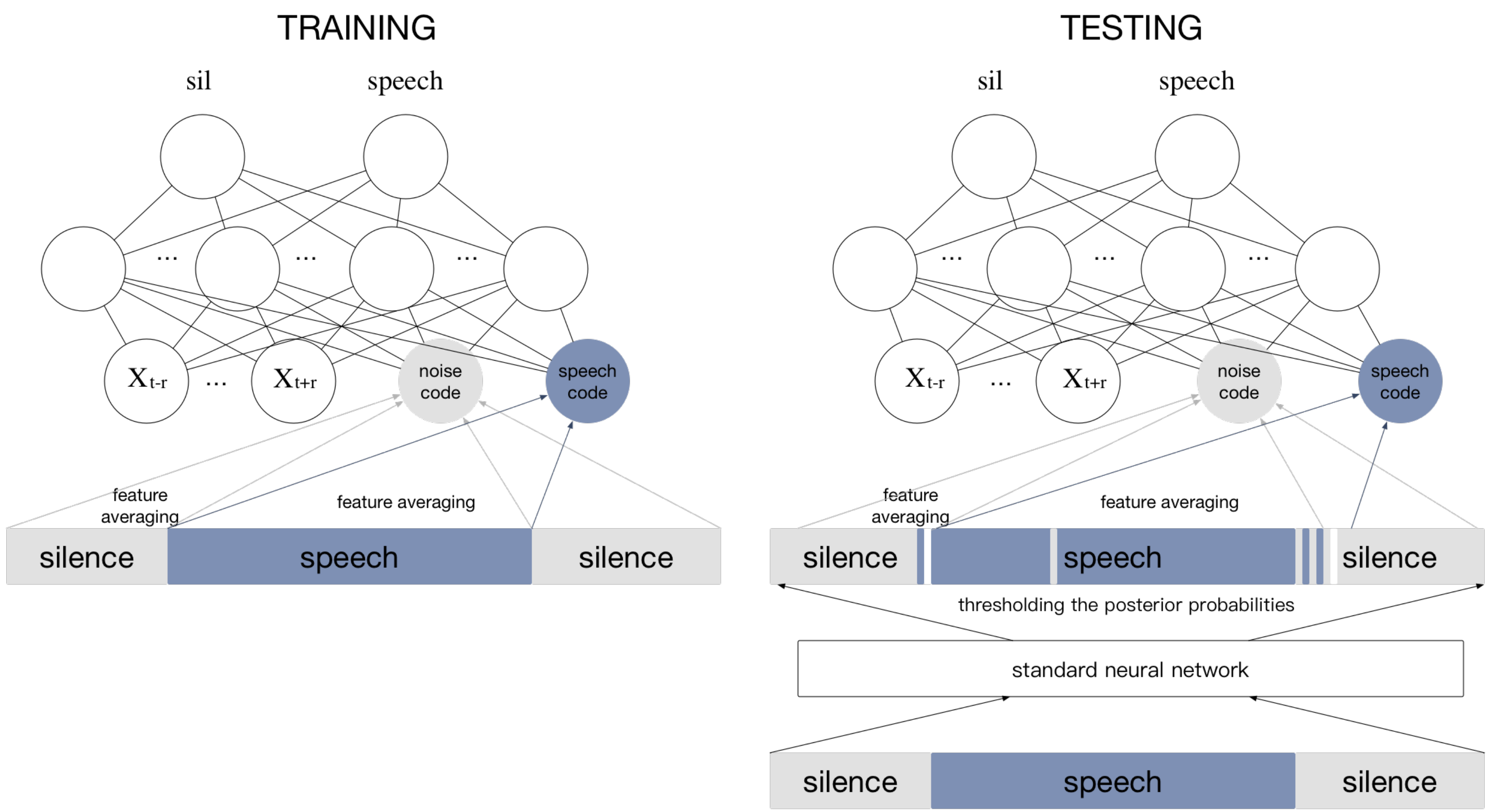
AMI ihm subset

Model	Structure	WER
LSTMP	-	32.4
+ i-vector	(a)	**31.1**
	(b)	33.2
	(c)	34.5

AMI ihm full set

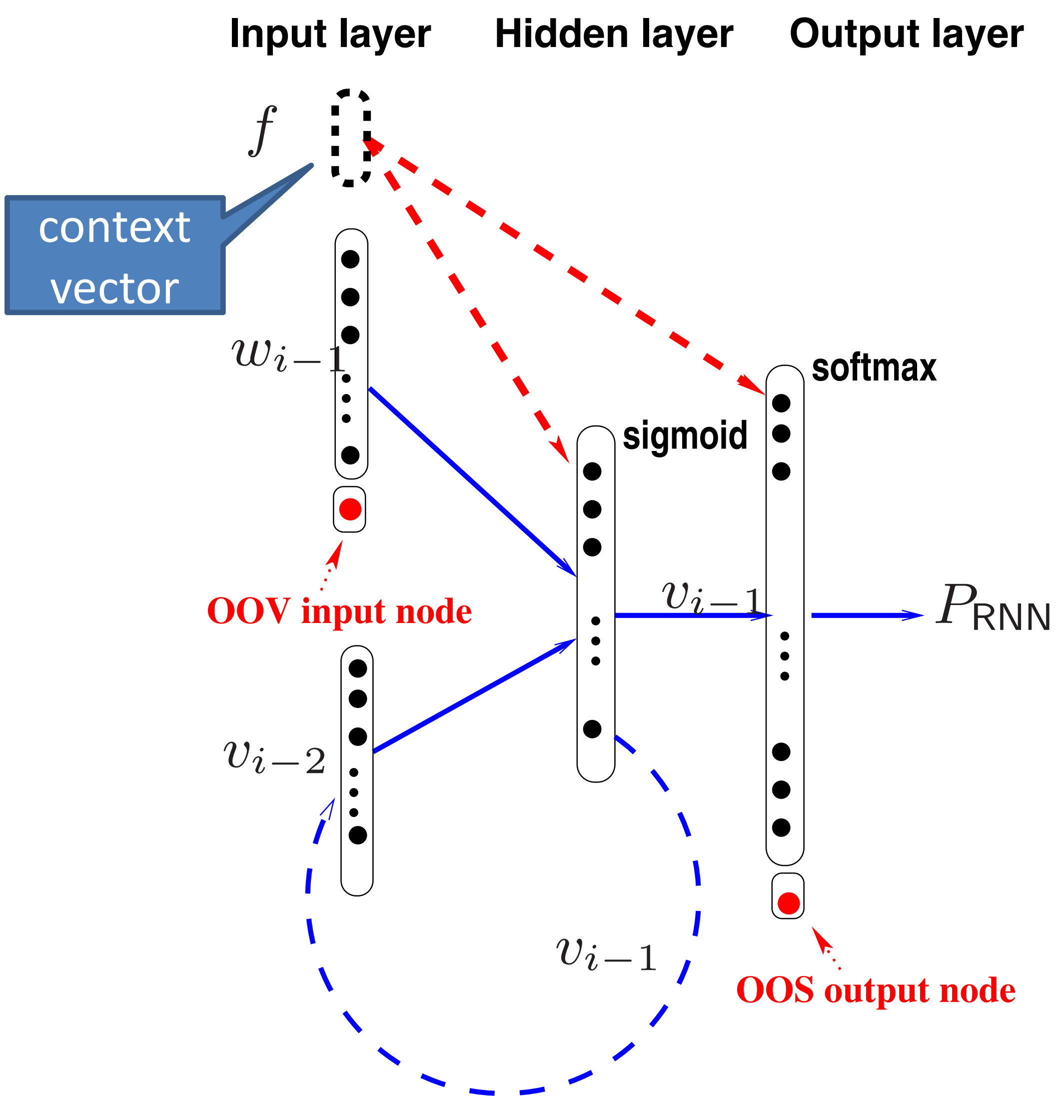
Feature	WER
FMLLR	26.0
+ i-vector + BSV + speaking rate	**24.3** 25.0 25.7

Noise-aware VAD [32]



TEST SET	NAT-DNN	NAT-LSTM	NAT-CNN
SEEN NOISE	(3.52)->3.14	(3.15)->2.82	(5.05)->3.30
UNSEEN NOISE	(11.19)->8.58	(9.24)->6.72	(9.76)->7.14

RNN Language Model Adaptation[37]

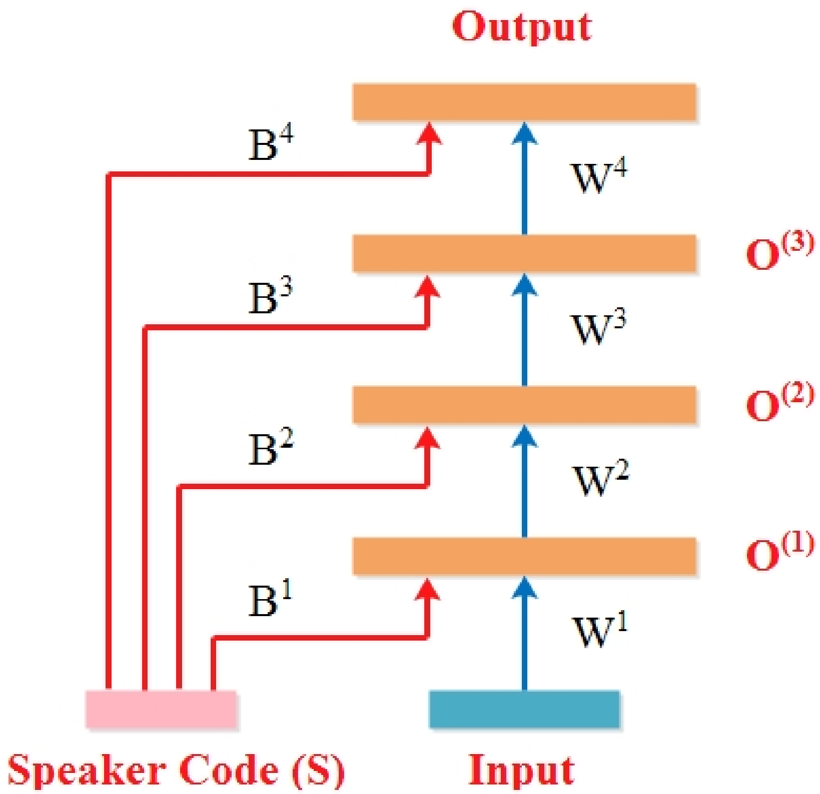


Unsupervised Topic *f* extraction:

- **LDA**
- **PLSA**
- **HDP**

Topic M	Sup	PPL		WER
		RNN	+4g	
-	-	152.5	113.5	31.38
PLSA	hyp	137.8	106.3	31.16
	ref	137.3	105.1	31.08
LDA	hyp	133.7	105.0	31.14
	ref	134.1	104.2	31.07
HDP	hyp	138.9	106.6	31.19
	ref	138.0	105.2	31.10

Speaker Code for DNN Adaptation [29]



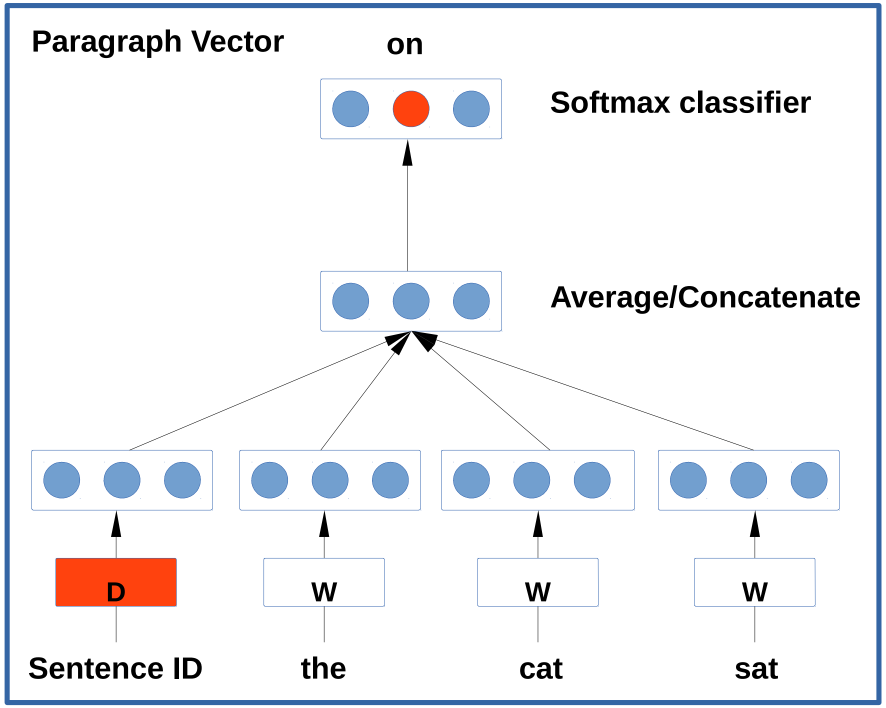
Use 10 adaptation utterances for speaker code estimation

Crit.	Additional Training Data for Speaker Code Connection	WER
CE	0	16.2
	10%	15.8
	100%	15.2
Sequence	0	14.0
	10%	13.7
	100%	13.4

- Speaker code is a vector embedding speaker identity using DNN
- Speaker code and connection weights are randomly intialized and updated using standard BP during training
- Smaller set of training data may be used to train B
- During adaptation, only the speaker code is updated on adaptation data and re-decoding is then performed

Paragraph Vector [30]

Distributed Memory Model



Model	Error rate (Positive/ Negative)	Error rate (Fine-grained)
Naïve Bayes (Socher et al., 2013b)	18.2 %	59.0%
SVMs (Socher et al., 2013b)	20.6%	59.3%
Bigram Naïve Bayes (Socher et al., 2013b)	16.9%	58.1%
Word Vector Averaging (Socher et al., 2013b)	19.9%	67.3%
Recursive Neural Network (Socher et al., 2013b)	17.6%	56.8%
Matrix Vector-RNN (Socher et al., 2013b)	17.1%	55.6%
Recursive Neural Tensor Network (Socher et al., 2013b)	14.6%	54.3%
Paragraph Vector	**12.2%**	**51.3%**

- Paragraph matrix is shared for all words within the paragraph
- Standard BP training can be used to estimate paragraph vector
- Not used for language model adaptation yet.

Structured Output – Multi-task Training

- Multi-task training

Basic Idea: Jointly estimate the target-of-interest and context-related task, expecting context is embedded during deep feature extraction

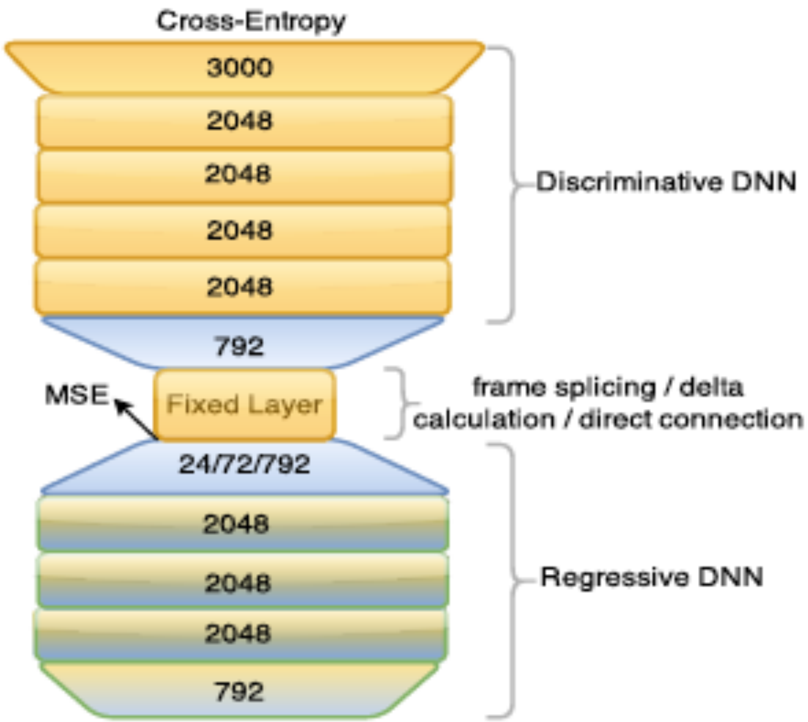
  – Multi-task training for text-dependent speaker verification
  – Multi-task joint training for robust ASR

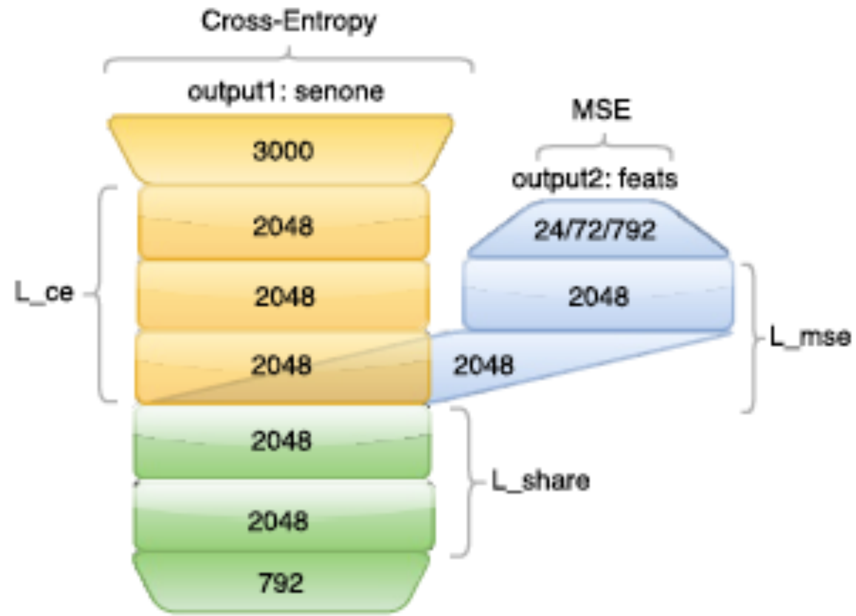
- Multi-view and multi-task combination

Basic Idea: Reinforce context modelling by combining both input and output context representation

  – Multi-factor training for robust ASR

Multi-task Joint Learning for Robust ASR [40]



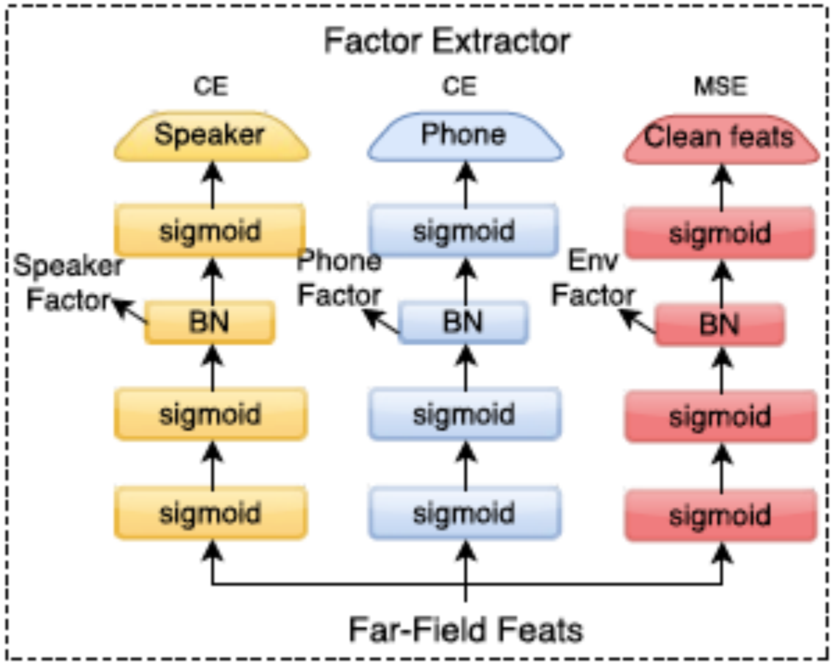


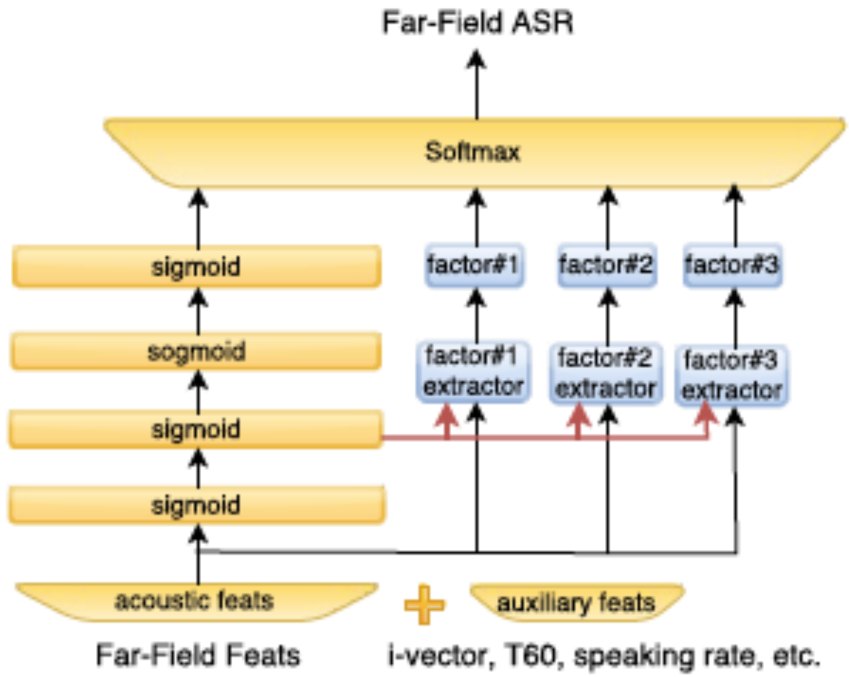
Aurora 4 Result

System	A	B	C	D	AVG
Baseline	4.6	8.2	8.8	18.5	12.4
MT Joint Learning	3.9	6.7	6.3	15.4	10.2
+ NAT	3.8	6.5	6.0	14.5	9.7

System	A	B	C	D	AVG
Best GMM-HMM [9]	5.6	11.0	8.8	17.8	13.4
DNN NAT DP [10]	5.4	8.3	7.6	18.5	12.4
DNN PP [15]	4.5	7.5	7.4	19.3	12.3
Spectral Mask [27]	4.5	7.9	7.5	17.7	11.4
JNAT [14]	4.5	7.4	8.1	16.5	11.1
TVWR Adap [6]	4.4	7.5	7.1	15.6	10.7
Joint FE BE [18]	4.4	6.8	6.4	15.4	10.3
AD OSN LRF [19]	4.0	7.2	6.4	14.5	10.0
MT Joint-learning	3.8	6.5	6.0	14.5	9.7

Multi-factor Joint Training [41]





System	Factor	Integration	WER(%)
DNN	—	—	65.2
MF-DNN	Speaker	Output	61.6
		+X-connection	**61.0**
	Phone	Output	61.4
		+X-connection	**60.8**
	Env	Output	61.2
		+X-connection	**60.7**
	Spk+Phn+Env	Output	60.4
		+X-connection	**60.1**

AMI Far-field Dataset

System	Sub Set	Full Set
DNN	65.2	55.9
DNN+i-vector	62.5	52.0
MF-DNN	60.1	53.5
MF-DNN+i-vector	**57.1**	**50.0**

Structured Model – Context-Specific Structure

- Context-specific linear transform

Basic Idea: Apply speaker-specific linear transform to normalize hierarchical deep features

  - Input/output feature transform [42][43][46][47][49]
  - Hidden layer feature transform [44][45]

- Explicit context-specific structure

Basic Idea: Construct context specific subspace within deep learning models

  - Context-dependent layer [48]
  - Additional or factorized structures [49][50][51][52][38]

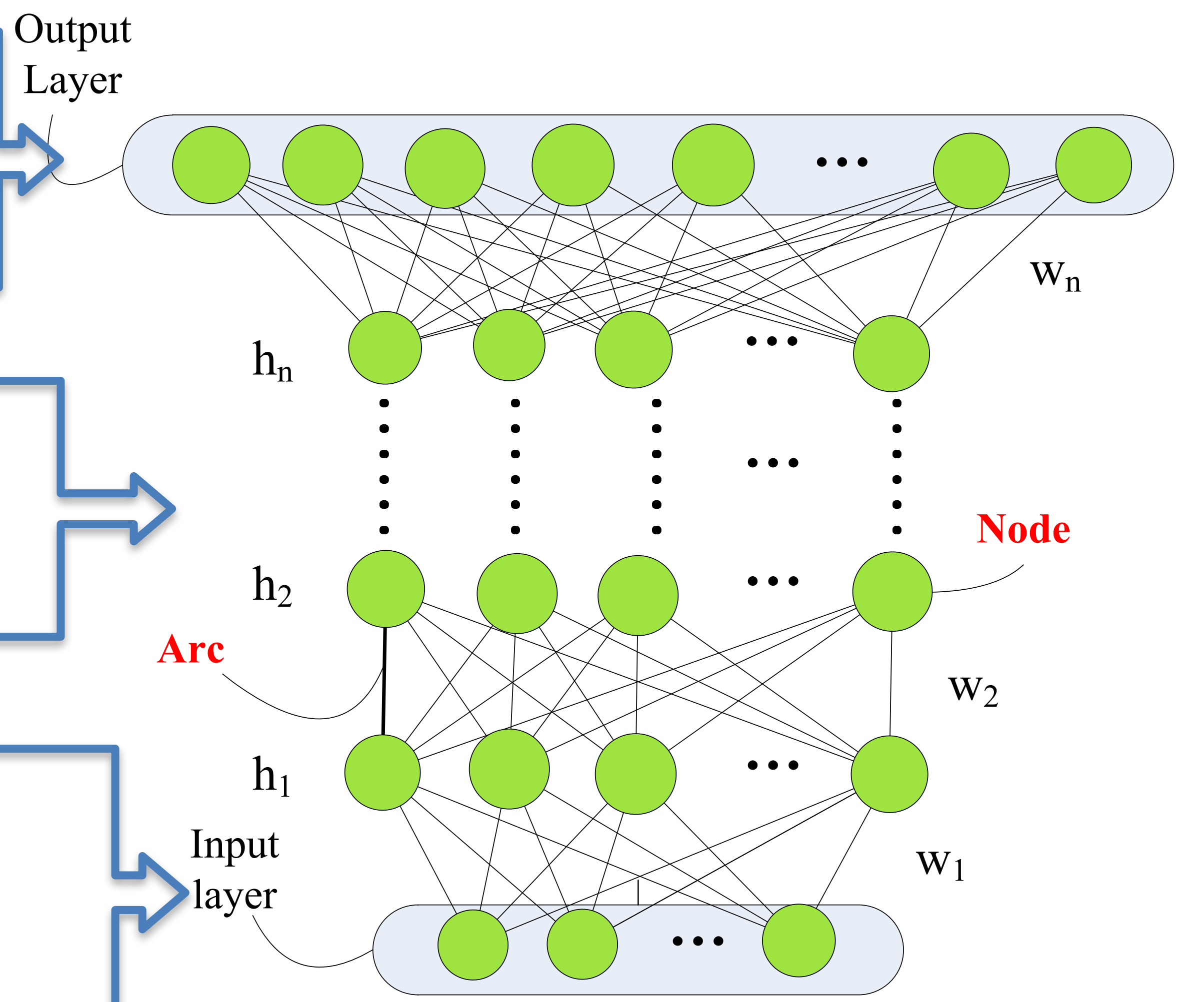
Transfer Linear Transform Adaptation to DNN

Basic Idea: Apply context-specific linear transform to normalize features of DNN

- Output feature discriminative linear transform (oDLR) [42]
- Linear output network (LON) [43]

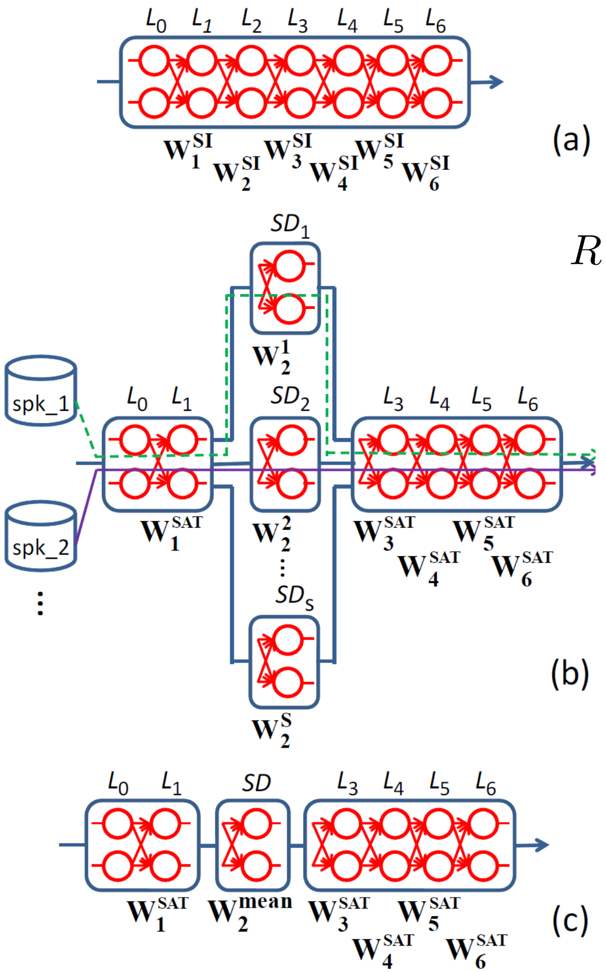
- SVD bottleneck adaptation [44]
- Linear hidden network [45]

- Feature discriminative linear transform (fDLR) [46]
- Linear input network (LIN) [47,49]



Adaptive Training with Context-specific Layer [48]

Basic Idea: Split DNN into context-dependent and context-independent layers and interleavingly update them



- Regularization is required for speaker-dependent layer update

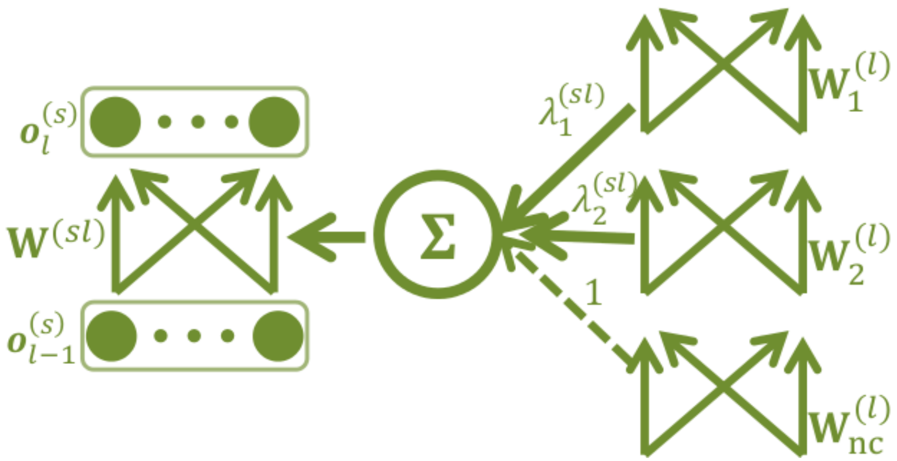
$$R(\Lambda) = \frac{1}{2}\left\|\mathbf{W}_{l_{\text{SD}}}^{t} - \mathbf{W}_{l_{\text{SD}}}^{\texttt{mean}}\right\|_2^2 + \frac{1}{2}\left\|\mathbf{b}_{l_{\text{SD}}}^{t} - \mathbf{b}_{l_{\text{SD}}}^{\texttt{mean}}\right\|_2^2 \quad (t = 1, 2, 3, \cdots, T)$$

- Performance

l_{SD}	SI	Adaptation	SAT
1	26.4	20.0	18.9
2	26.4	19.0	18.2
3	26.4	18.7	18.0
4	26.4	19.0	18.4
5	26.4	19.5	19.0

TED Talks corpus, supervised adaptation

Cluster Adaptive Training [49]



DNN

$$\boldsymbol{y_l} = \boldsymbol{W}^{(l)}\boldsymbol{o_{l-1}} + \boldsymbol{b}^{(l)}$$

$$\boldsymbol{o_l} = \boldsymbol{\sigma}(\boldsymbol{y_l})$$

CAT-DNN

$$\boldsymbol{y}_l^{(s)} = \boldsymbol{W}^{(sl)}\boldsymbol{o}_{l-1}^{(s)} + \boldsymbol{b}^{(l)}$$

$$\boldsymbol{o_l} = \boldsymbol{\sigma}(\boldsymbol{y_l})$$

$$\mathbf{M}^{(l)} = \left[\boldsymbol{W}_1^{(l)} \dots \boldsymbol{W}_P^{(l)}\right]$$

$$\boldsymbol{\lambda}^{(sl)} = \left[\boldsymbol{\lambda}_1^{(sl)} \dots \boldsymbol{\lambda}_P^{(sl)}\right]^{\top}$$

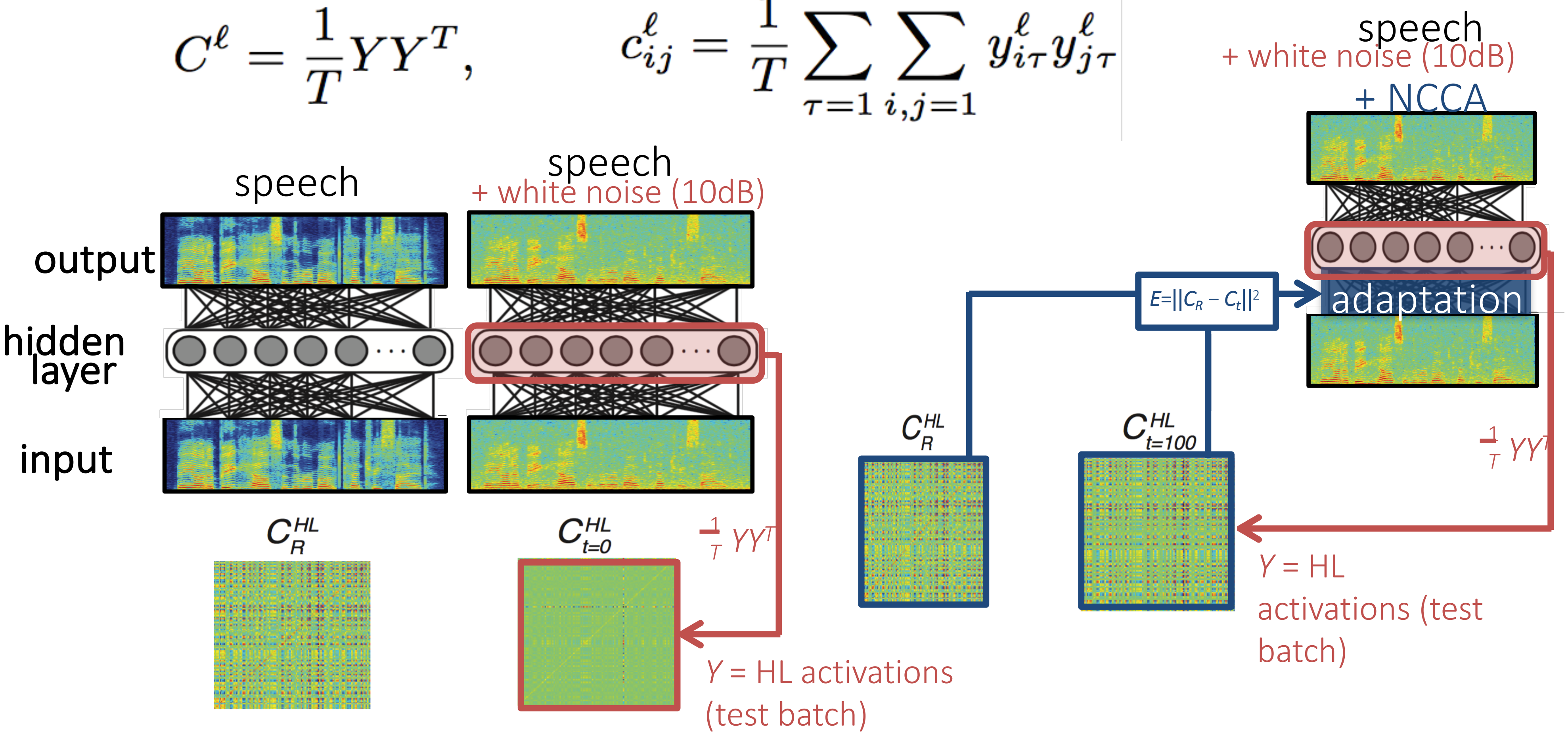
$$\mathbf{W}^{(sl)} = \sum_{c=1}^{P} \lambda_c^{(sl)} \boldsymbol{W}_c^{(l)}$$

System	Cluster	#Adapt Para	swb	fsh
SI	-	0	15.8	19.9
+ i-vector	-	100	14.8	18.3
H1	2	2	15.2	18.8
	5	5	15.0	18.7
	10	10	**14.6**	**17.8**

Unsupervised Adaptation with Node Co-activation Prior [38]

Node co-activation matrix: captures the correlational structure of nodes over time

$$C^{\ell} = \frac{1}{T} Y Y^{T}, \qquad c_{ij}^{\ell} = \frac{1}{T} \sum_{\tau=1}^{T} \sum_{i,j=1}^{N} y_{i\tau}^{\ell} y_{j\tau}^{\ell}$$



Sequence summarizing [50]

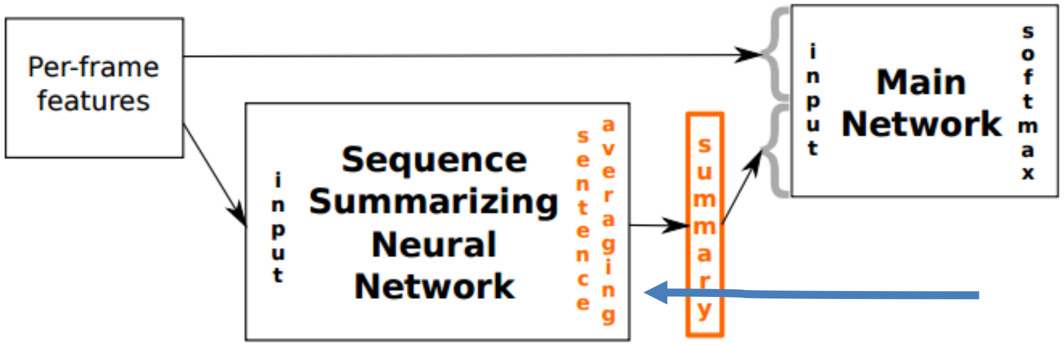
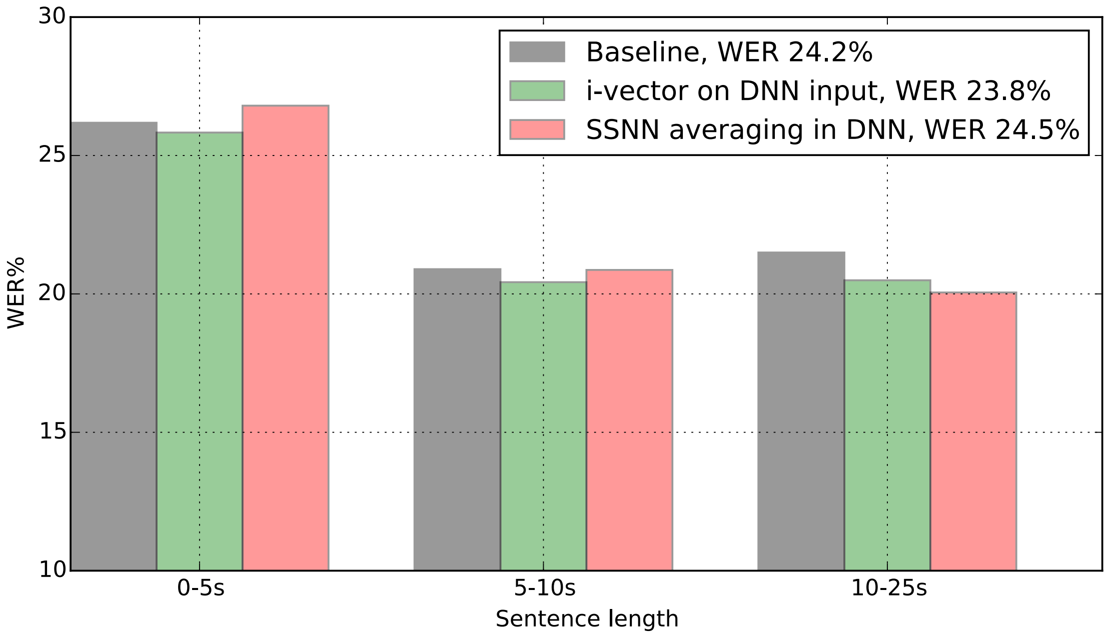


Fig. 1. *Topology of main-network with "sequence summary" input. The summary is computed by Sequence Summarizing Neural Network with sentence-averaging on the output.*

$$\bar{\mathbf{o}}_{u,t} = [\mathbf{o}_{u,t} \quad \mathbf{x}_u]^\top$$

$$\mathbf{x}_u(\mathbf{o}_u;\theta_x) = \frac{1}{T_u}\sum_{t=1}^{T_u}\mathbf{x}_u(\mathbf{o}_u;\theta_x)$$



- Sequence sum network estimates utterance level context representation
- Joint training of summarizing NN and main NN
- Sequence level BP
- Better for long sentence

Context Modelling with Structured Learning

- Information rate modelling
- Easy prior knowledge incorporation
- Explicit structure related to context effect
- Unsupervised on-line context learning
- Text based context modelling

Summary

- Context is the non-targeted but influential factors, which may have different information rates
- Context modelling is an unsolved issue for DL
- **Re-training under context** – **Implicit** modelling
- **Structured deep learning** – **Explicit** modelling

Multi-view input with context representation

Multi-task output with context target or constraint

Structured model parameters to incorporate context

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- Some figures are redrawn based on lecture notes/slides from the web.The original authors are also appreciated.

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