Why DNN Works for Speech and How to Make it More Efficient?

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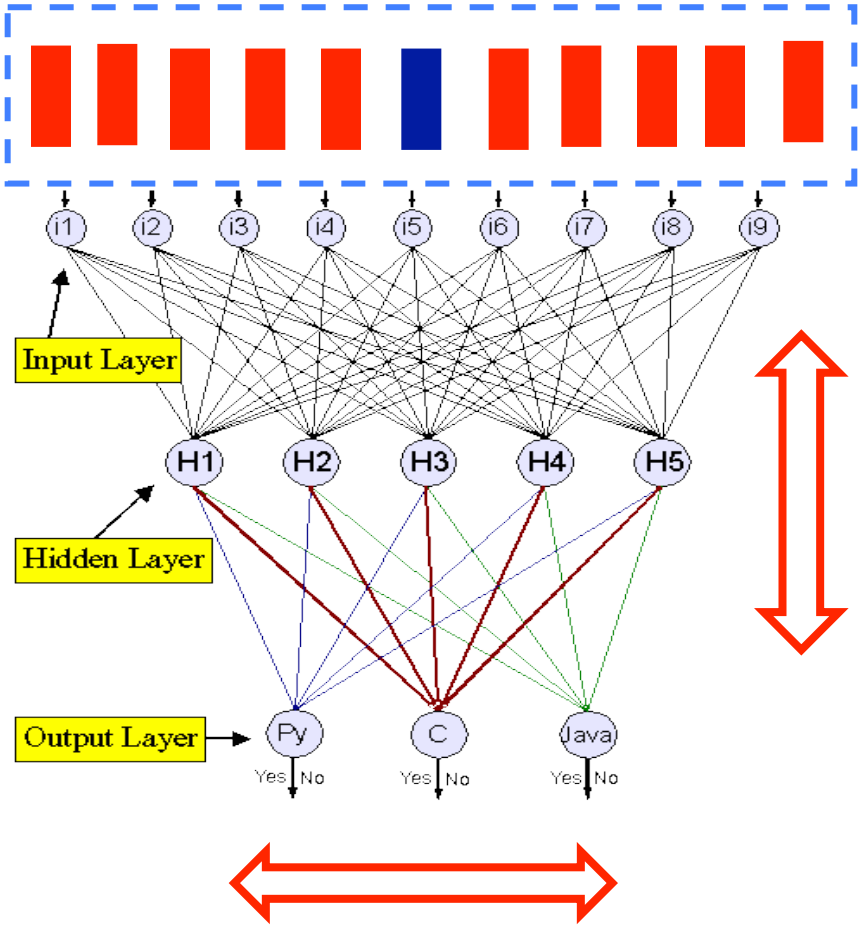
Outline

- Introduction: NN for ASR
- PART I: Why DNN works for ASR
  - DNNs for Bottleneck Features
  - Incoherent Training for DNNs
- PART II: Towards more efficient DNN training
  - DNN with shrinking hidden layers
  - Data-partitioned multi-DNNs
- Summary

Neural Network for ASR

- **1990s: MLP for ASR** *(Bourlard and Morgan, 1994)*
  - **NN/HMM hybrid model (worse than GMM/HMM)**
- **2000s: TANDEM** *(Hermansky, Ellis, et al., 2000)*
  - **Use MLP as Feature Extraction (5-10% rel. gain)**
- **2006: DNN for small tasks** *(Hinton et al., 2006)*
  - **RBM-based pre-training for DNN**
- **2010: DNN for small-scale ASR** *(Mohamed, Yi, et al. 2010)*
- **2011– now: DNN for large-scale ASR**
  - **20-30% rel. gain in Switchboard** *(Seide et al., 2011)*
  - **10-20% rel. gain with sequence training** *(Kingsbury et al., 2012; Su et al., 2013)*
  - **10% rel. gain with CNNs** *(Abdel-Hamid et al., 2012; Sainath et al., 2013)*

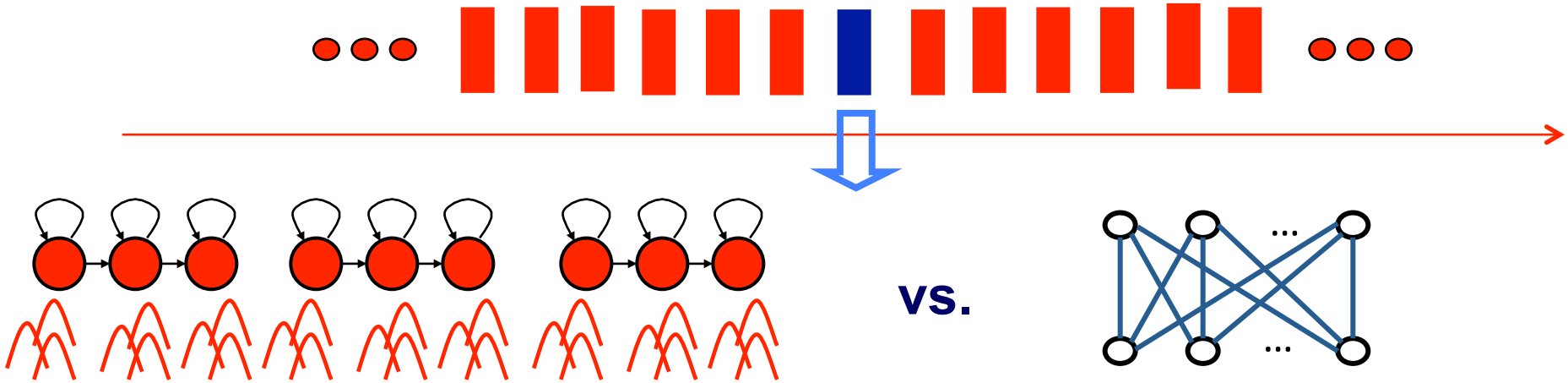
NN for ASR: old and new



- **Deeper network**
  - **more hidden layers**
    - **(1 → 6-7 layers)**
- **Wider network**
  - **more hidden nodes**
  - **more output nodes**
    - **(100 → 5-10 K)**
- **More data**
  - **10-20 hours → 2-10 K hours training data**

GMMs/HMM vs. DNN/HMM

- Different acoustic models
  - GMMs vs. DNN
- Different feature vectors
  - 1 frame vs. concatenated frames (11-15 frames)



Experiment (I): GMMs/HMM vs. DNN/HMM

- In-house 70-hour Mandarin ASR task;
- GMM: 4000 tied HMM states, 30 Gaussians per state
- DNN: pre-trained; 1024 nodes per layer; 1-6 hidden layers

Numbers in word error rates (%)
NN-1: 1 hidden layer; DNN-6: 6 hidden layers
MPE-GMM: discriminatively trained GMM/HMM

Context window	NN-1	DNN-6	MPE-GMM
1	18.0	17.0	16.7
Context window	3	5	7
DNN-6	14.2	13.7	13.5
Context window	9	11	13
DNN-6	13.5	13.4	13.6

Experiment (II): GMMs/HMM vs. DNN/HMM

- 300-hour Switchboard task, Hub5e01 test set
- GMM: 8991 tied HMM states, 40 Gaussian per state
- DNN: pre-trained; 2048 nodes per layer; 1-5 hidden layers

Word error rates (WER) in Hub01 test set (%)
NN-1: 1 hidden layer; DNN-3/5: 3/5 hidden layers
MPE-GMM: discriminatively trained GMM/HMM

context window	MPE GMM	NN-1	DNN-3	DNN-5
1	32.8%	35.4%	34.8%	33.1%
11	n/a	31.4%	25.6%	23.7%

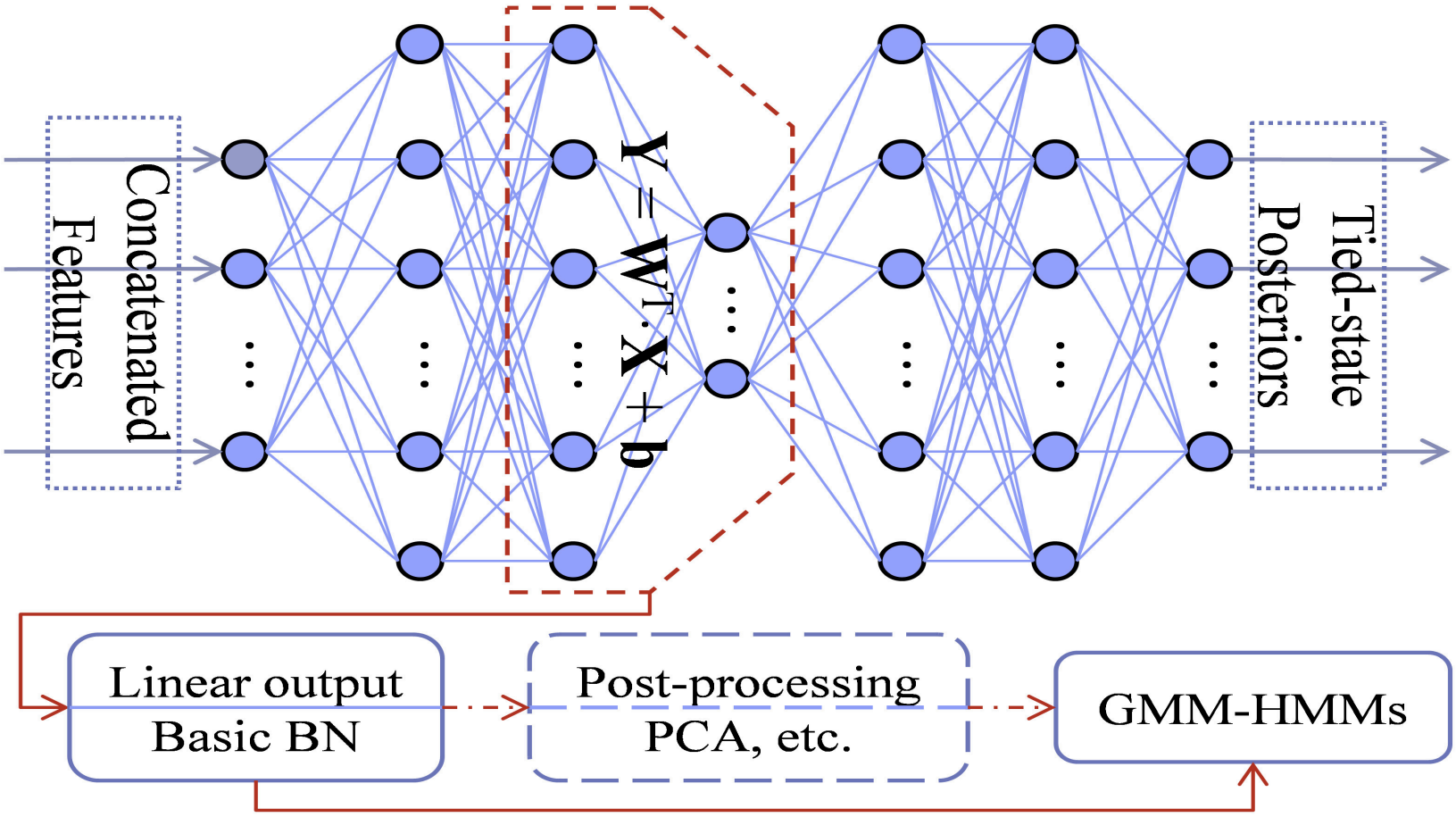
Brief Summary (I)

- The gain of DNN/HMM hybrid is almost entirely attributed to the concatenated frames.
  - The concatenated features contain almost all additional information resulting in the large gain.
  - But they are highly correlated.
- DNN is powerful to leverage highly correlated features.

What's next

- How about GMM/HMM?
- Hard to explore highly correlated features in GMMs.
  - Requires dimensional reduction for de-correlation.
- Linear dimensional reduction (PCA, LDA, KLT, …)
  - Failed to compete with DNN.
- Nonlinear dimensional reduction
  - Using NN/DNN *(Hinton et al.)*, a.k.a. bottleneck features
  - Manifold learning, LLE, MDS, SNE, …?

Bottleneck (BN) Feature



Experiments: BN vs. DNN

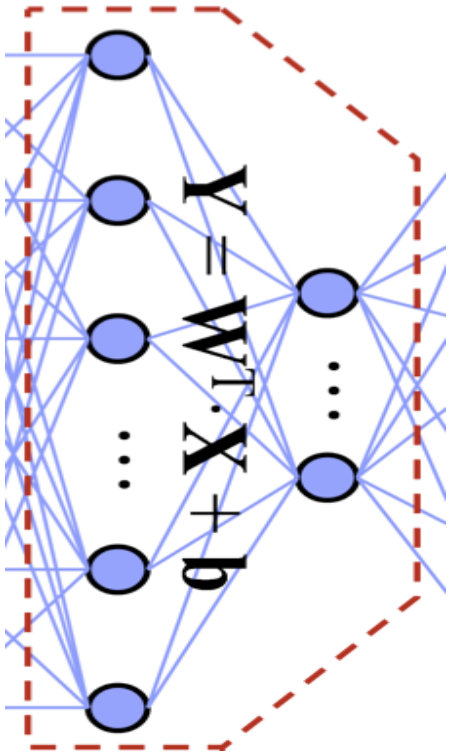
300-hour English Switchboard Task (WER in %)
MLE: maximum likelihood estimation; MPE: discriminative training
ReFA: realigned class labels; DT: sequence training of DNNs
DT+BN: BN features extracted from sequence-trained BN networks

Acoustic models (Features)	Hub5e01		Hub5e00	
	MLE	MPE	MLE	MPE
GMM-HMMs (PLP)	35.4%	32.8%	28.7%	24.7%
GMM-HMMs (BN)	26.0%	23.2%	17.9%	15.9%
DNN (11 PLPs)	23.7%		16.7%	
DNN (ReFA+DT)	--		14.0%	
GMM-HMMs (DT+BN)	--		16.6%	14.6%

Incoherent Training

- Bottleneck (BN) works but:
  - BN hurts DNN performance a little
  - Increasing BN ➔ correlation up

- A “better” Idea: embed de-correlation into back-propagation of DNN training.
  - De-correlation by constraining column vectors of weight matrix *W*
  - How to constrain?



Incoherent Training

- **Define coherence of DNN weight matrix *W* as:**

$$G_W = \max_{i,j} g_{ij} = \max_{i,j} \frac{\left| w_i \cdot w_j \right|}{\left\| w_i \right\| \left\| w_j \right\|}$$

- **Intuition: a smaller coherence value indicates all column vectors are more dissimilar.**
- **Approximate coherence using soft-max:**

$$G_W = \log \left(\frac{1}{M} \sum_{i=1}^{N} \sum_{j=i+1}^{N} \exp\{\beta \cdot g_{ij}\} \right)^{\frac{1}{\beta}}$$

Incoherent Training

- All DNN weight matrices are optimized by minimizing a regularized objective function:

$$F^{(new)} = F^{(old)} + \alpha \cdot \max_{W} G_W$$

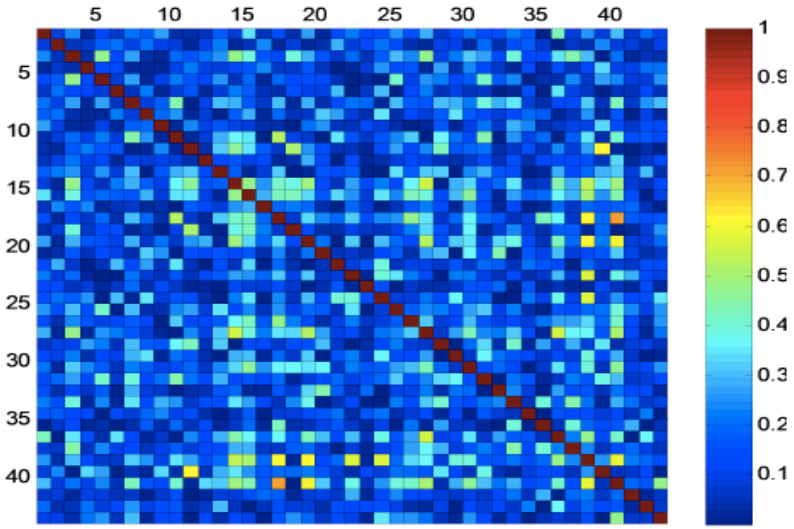
- Derivatives of coherence:

$$\frac{\partial G_W}{\partial w_k} = \sum_{j=1}^{N} \gamma_{kj} g_{kj} \left[\frac{\mathbf{w}_j}{\mathbf{w}_k \cdot \mathbf{w}_j} - \frac{\mathbf{w}_k}{\mathbf{w}_k \cdot \mathbf{w}_k} \right]$$

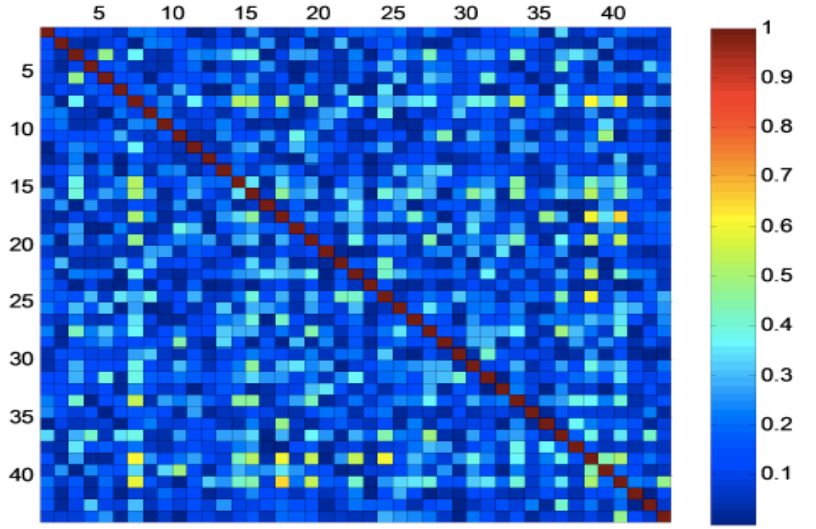
- Back-propagation is still applicable…

Incoherent Training: De-correlation

Applying incoherent training to one weight matrix in BN



(a) Baseline BN



(b) Weight-matrix Incoherent BN

Incoherent Training: Data-driven

- If only applying to one weight matrix *W*: $Y = W^T X + b$

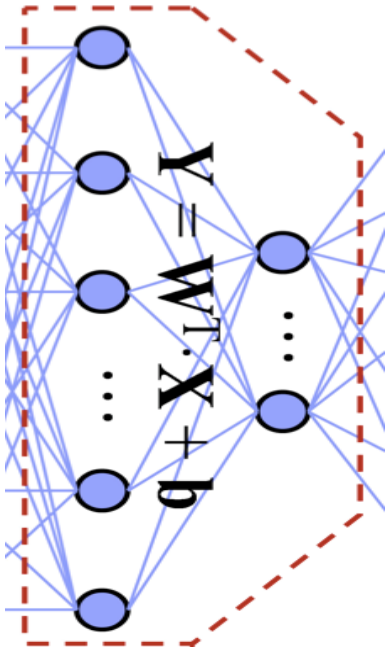
  Covariance matrix of Y: $C_Y = W^T C_X W$

- Directly measure correlation coefficients based on the above covariance matrix:

$$G_W = \max_{i \neq j} g_{ij}$$

with

$$g_{ij} = \frac{\left|(\mathbf{w}_i)^\top \mathbf{C_X} \mathbf{w}_j\right|}{\sqrt{(\mathbf{w}_i)^\top \mathbf{C_X} \mathbf{w}_i} \cdot \sqrt{(\mathbf{w}_j)^\top \mathbf{C_X} \mathbf{w}_j}}$$



C_X is estimated from each mini-batch of data

Incoherent Training: Data-driven

- After *soft-max*, derivatives can be computed as:

$$\frac{\partial G_W}{\partial w_k} = \frac{\sum_{j \neq k}^{N} \left[\exp\{\beta \cdot g_{kj}\} \cdot \frac{\partial g_{kj}}{\partial \mathbf{w}_k} \right]}{\sum_{i=1}^{N} \sum_{j=i+1}^{N} \exp\{\beta \cdot g_{ij}\}}$$

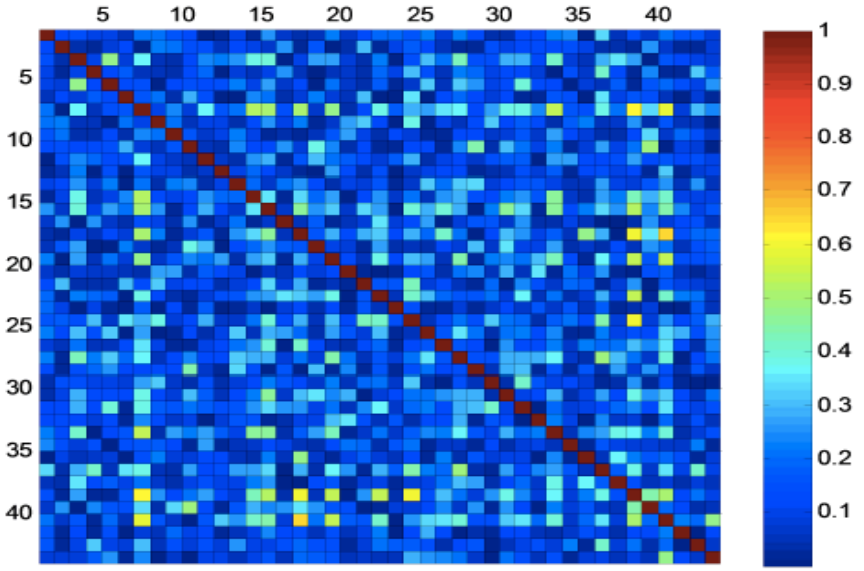
where

$$\frac{\partial g_{kj}}{\partial \mathbf{w}_k} = g_{kj} \left[\frac{\mathbf{C_x w}_j}{(\mathbf{w}_k)^\top \mathbf{C_x w}_j} - \frac{\mathbf{C_x w}_k}{(\mathbf{w}_k)^\top \mathbf{C_x w}_k} \right]$$

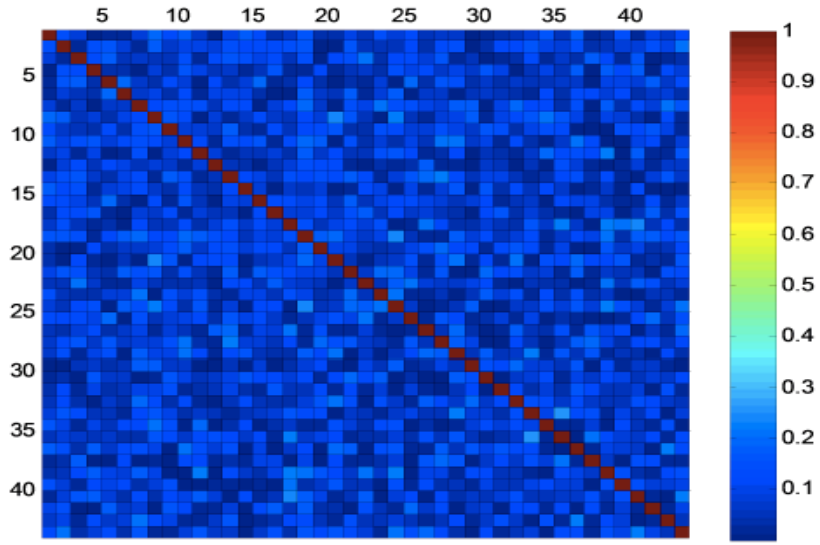
- Back-propagation still applies except Cx is computed from each mini-batch

Incoherent Training: Data-driven De-correlation

When applying Incoherent Training to one weight matrix



(b) Weight-matrix Incoherent BN



(c) Mini-batch-data Incoherent BN

Experiment: Incoherent Training

300-hour English Switchboard Task, WER (%) on Hub5e01
DNN: 6 hidden layers of 2048 nodes
BN: extracted from 5 hidden layers of bottleneck DNN

BN Feature / models	MLE	MPE
DNN	23.7%	
Baseline BN	26.0%	23.2%
Weight-Matrix Incoherent BN	25.7%	--
Mini-batch-data Incoherent BN	25.6%	22.8%

Brief Summary (II)

- Promising to use DNN as feature extractor for the traditional GMM/HMM framework.
- Beneficial to de-correlate BN using the proposed incoherent training.
- Benefits over hybrid DNN/HMM:
  - Slightly better or similar performance
  - Enjoy other ASR techniques (adaptation, …)
  - Faster training process
  - Faster decoding process

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Towards Faster DNN Training

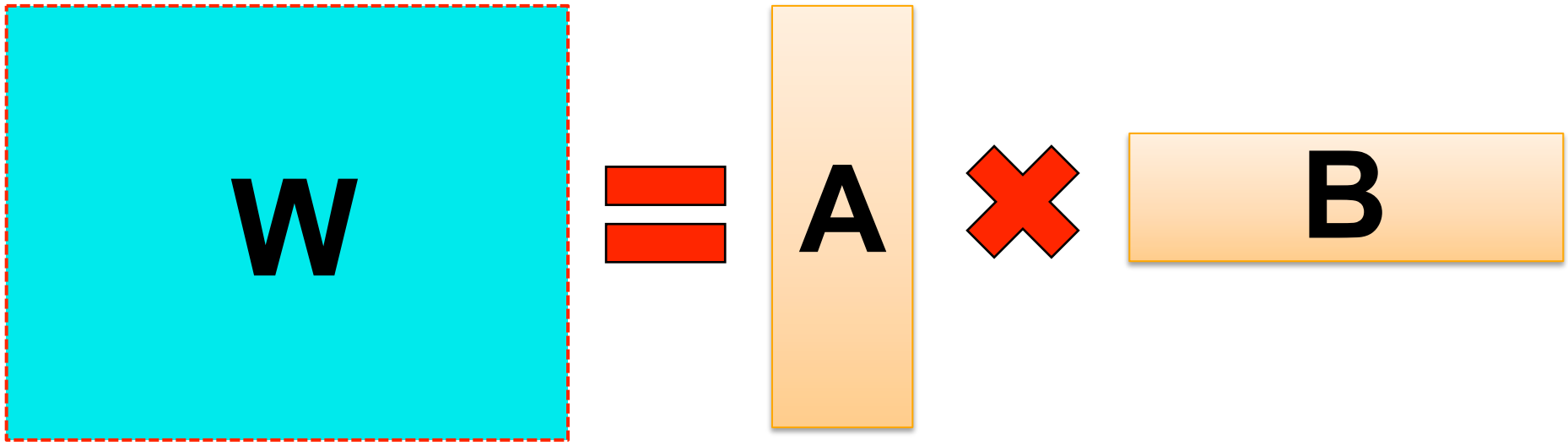
- DNN Training is extremely slow …
  - Taking weeks to months to train large DNNs in ASR
- How to make it more efficient?
  - Simplify DNN model structure …
  - Use training algorithms with faster convergence (than SGD) …
  - Use parallel training methods with many CPUs/GPUs …

Simplify DNN: Exploring Sparseness

- **Sparse DNNs** *(Yu et al, 2012)*: **zeroing 80% of DNN weights leads to no performance loss.**
  - **Smaller model footprint but no gain in speed**

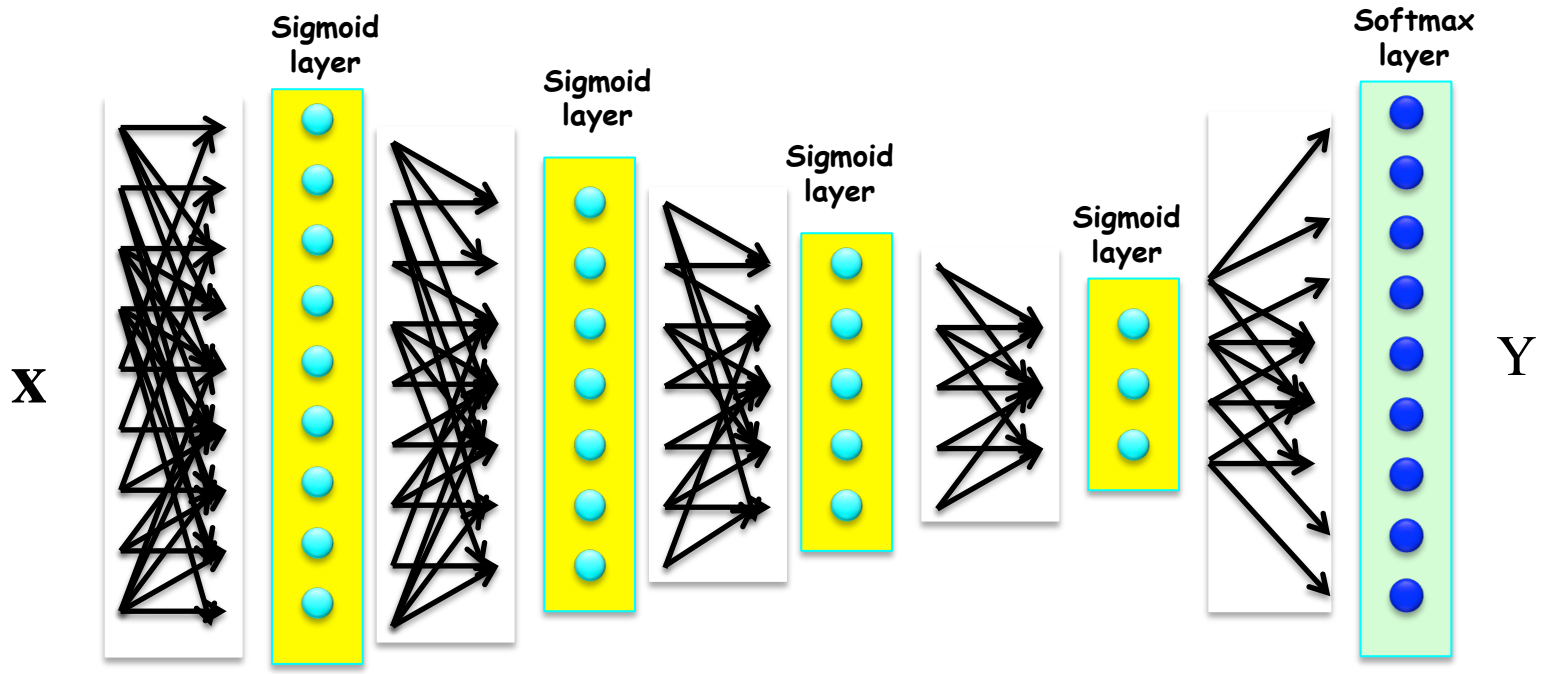
- **How to explore sparseness for speed:**
  - **DNN weight matrix low-rank factorization** *(Sainath et al, 2013 and Xue et al, 2013)*
  - **DNN with shrinking hidden layers** *(to be submitted to ICASSP'14)*

Weight Matrix Factorization



- **IBM** *(Sainath et al, 2013)*: **30-50% smaller model size, 30-50% speedup.**
- **Microsoft** *(Xue et al, 2013)*: **80% smaller model size, >50% speedup.**
- **Our investigation shows 50% speedup in training, 40% in testing.**

DNN: Shrinking Hidden Layers



- Significantly reduce number of weights, particularly the output layer.
- Lead to faster matrix multiplication.

Experiments: Shrinking DNNs

- Switchboard task: 300-hour training data, Hub5e00 test set
- Cross-entropy training (10 epochs of BP; minibatch 1024)

Baseline DNN (6 hidden layer): 429-2048*6-8991

Shrinking DNN I (sDNN-I): 429-2048*2+1024*2+512*2-8991

Shrinking DNN II (sDNN-II): 429-2048-1792-1536-1280-1024-768-8991

	WER	DNN Size	Training time* (speedup)
DNN	16.3%	41M	10h
DNN (+pre-train)	16.1%	41M	≈ 20h (x0.5)
sDNN-I	16.7%	13M (32%)	4.5h (x2.2)
sDNN-II	16.5%	19M (48%)	5.5h (x1.8)

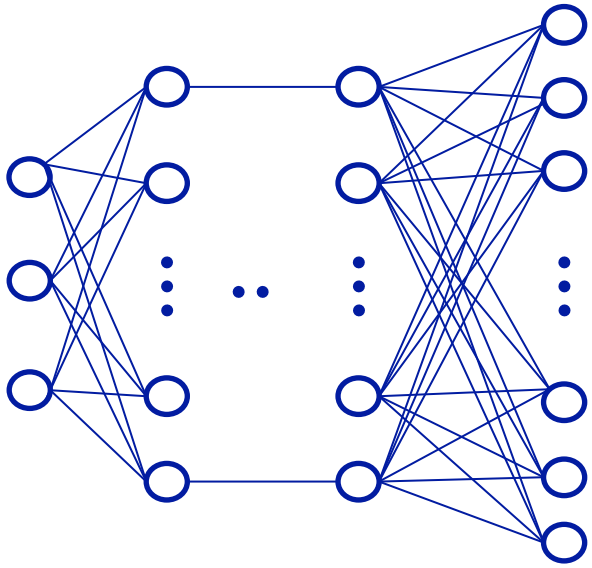
* Average training time (plus pre-training) per epoch using one GTX670

Parallel Training of DNNs

- **If can't make training even faster, why not parallelize it?**
- **Stochastic gradient descent (SGD) is hard to parallelize while second-order optimization (HF) is much higher in complexity.**
- **GPU helps but still not enough: taking weeks to run SGD to train large DNNs for ASR.**
- **GOAL: Parallel Training of DNN using multiple GPUs**
  - **Parallelized (or asynchronous) SGD not optimal for GPUs.**
  - **Pipelined BP** *(Chen et al, 2012)***: data traffic among GPUs.**

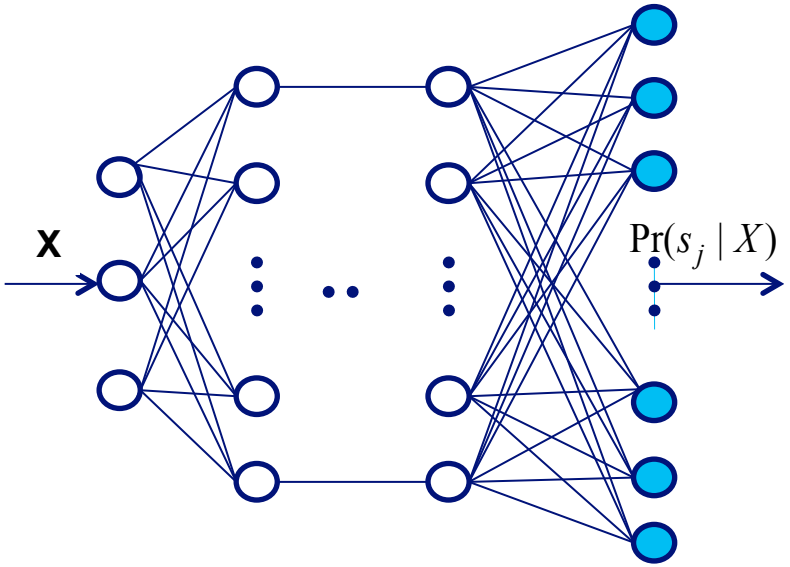
Data-Partitioned Multi-DNNs

Traditional DNN

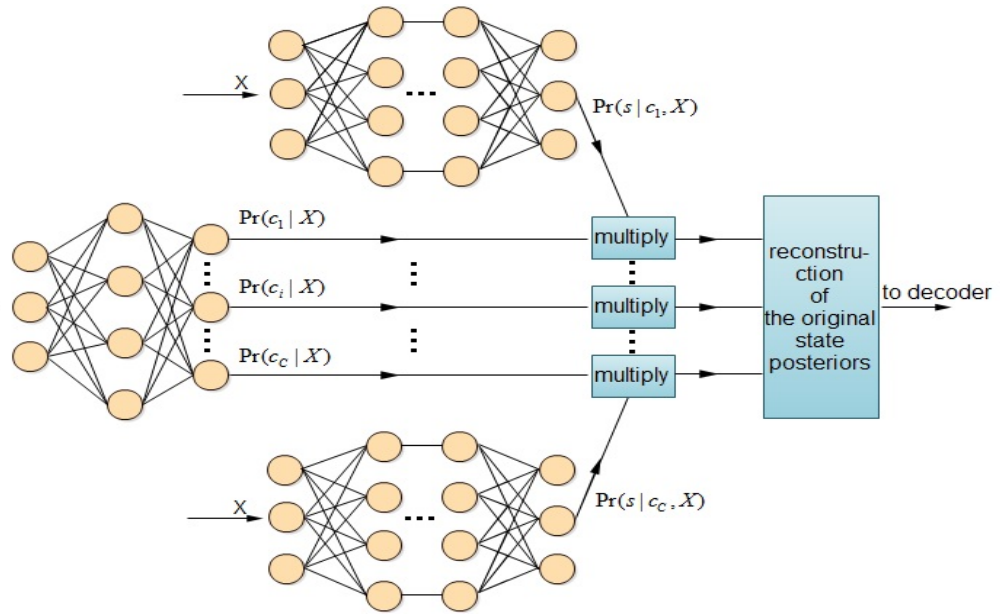


Data-Partitioned Multi-DNNs

Traditional DNN



Multi-DNNs



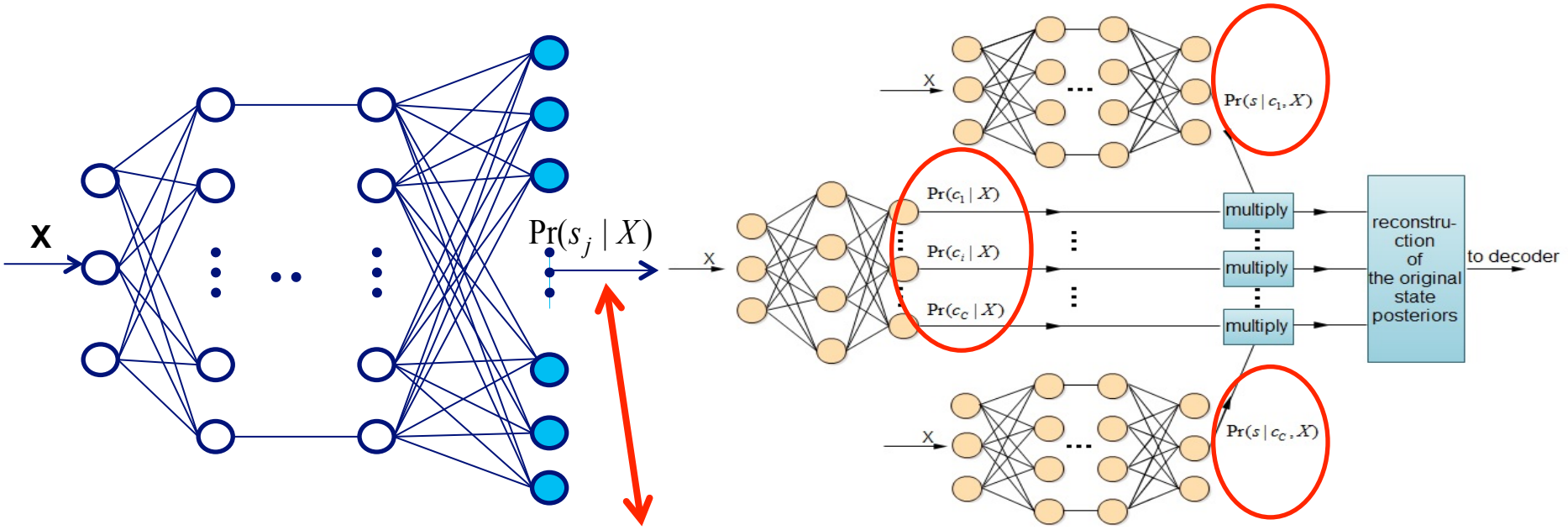
Data Partition

- Unsupervisedly cluster training data into several subsets that have disjoint class labels
- Train DNN on each subset to distinguish labels within each cluster
- Train another top-level DNN to distinguish different clusters

Multi-DNNs: Merging Probabilities

Traditional DNN

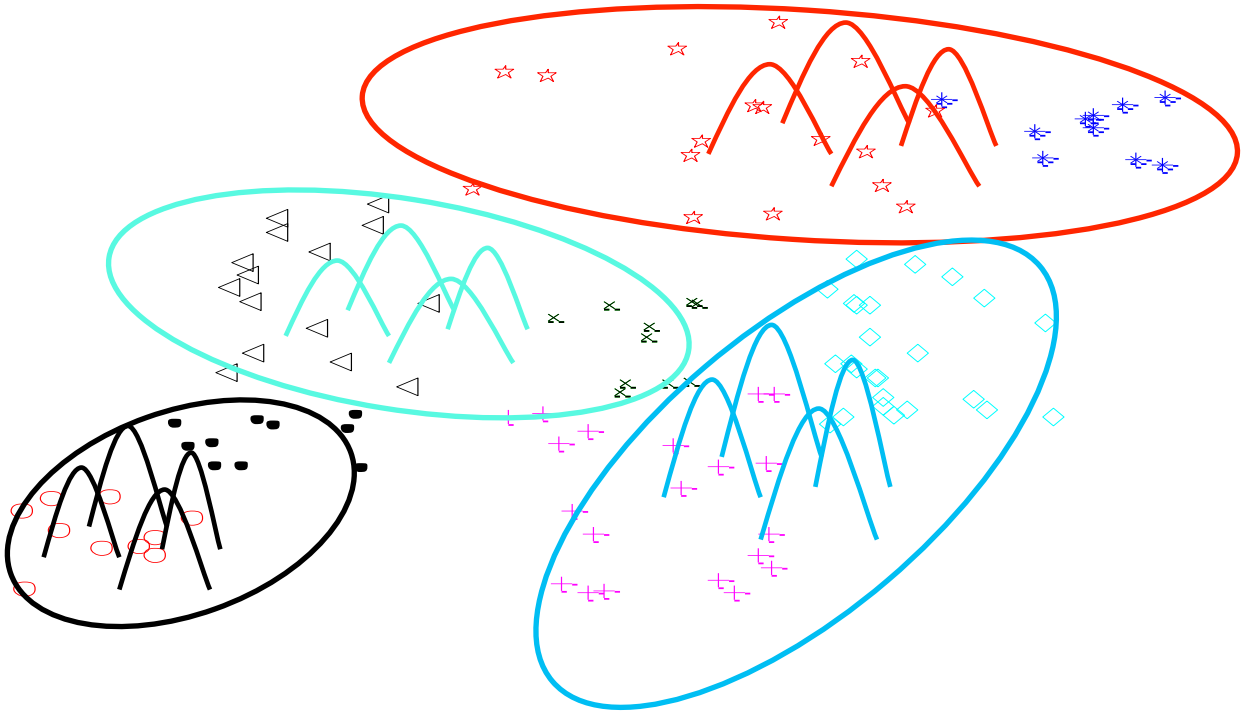
Multi-DNNs



$$\Pr(s_j \mid X) = \Pr(c_i \mid X) \Pr(s_j \mid c_i, X) \quad (with\ s_j \in c_i).$$

Data-driven Clustering

- Iterative GMM based bottom-up clustering of data from all classes (like normal speaker clustering):



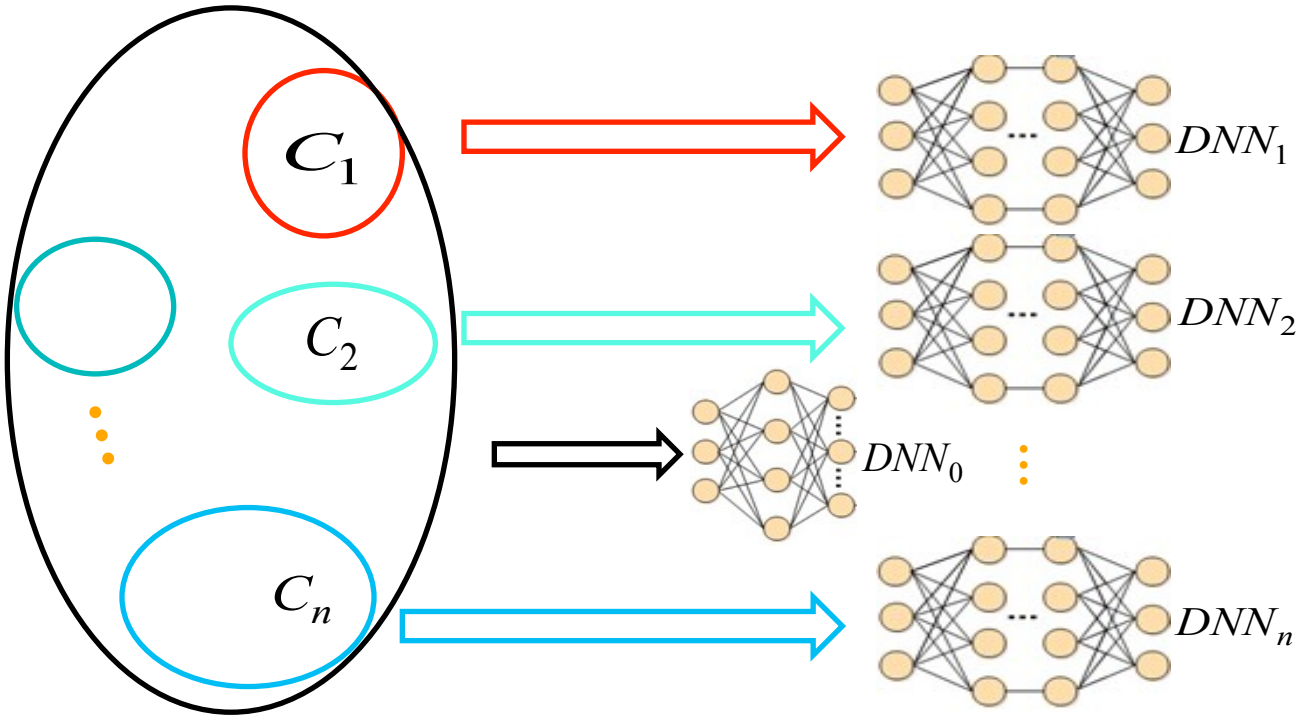
Model Parallelization

- **Advantage of Multi-DNNs:**
  - **Easy to parallelize**

$$e_k = \frac{\partial E^n}{\partial y_K}\frac{\partial y_K}{\partial a_k} = \begin{cases} 0, & k \notin C \\ y_m - t_m, & k \in C \end{cases}$$

  - **Each DNN is learned only from one subset**

Parallel Training Scheme



ZERO communication data across GPUs

Experiment: Multi-DNNs

- Switchboard training data (300 hour, 8991 classes)
- Test sets：Hub01 and Hub00
- GMM-based bottom-up clustering method to group training data into 4 subsets to train 4 DNNs in parallel

	C1	C2	C3	C4
Num. of states	2450	3661	20	2860
Data %	45.0%	25.3%	9.3%	20.4%

Experiments: Multi-DNNs

Baseline DNN: 4-6 hidden layers of 2048 nodes
Multi-DNNs: DNN1-4 has 6 hidden layers of 2048 nodes
DNN0 has 3 hidden layers of 2048 nodes

	Hidden layer	4	5	6
baseline DNN	WER	24.4%	23.7%	23.6%
	Time (hr)	13.0h	13.5h	15.1h
Multi-DNNs (3 GPUs)	WER	24.5%	24.2%	23.8%
	Time (hr)	3.7h	4.3h	4.9h
	Speed-up	x3.5	x3.1	x3.1

Switchboard ASR: WER (in %) on Hub5e01 set and training time per epoch using 3 GPUs

Experiments: Multi-DNNs

Baseline DNN: 4-6 hidden layers of 2048 nodes
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Multi-DNNs (3 GPUs)	WER	17.0%	16.9%	16.7%
	Time (hr)	3.7	4.3	4.9
	Speed-up	x3.5	x3.1	x3.1

Switchboard ASR: WER (in %) on Hub5e00 set and training time per epoch using 3 GPUs

Experiments: Smaller Multi-DNNs

Baseline DNN: 4-6 hidden layers of 2048 nodes
Multi-DNNs: DNN1-4 has 6 hidden layers of 1024 nodes
DNN0 has 3 hidden layers of 1024 nodes

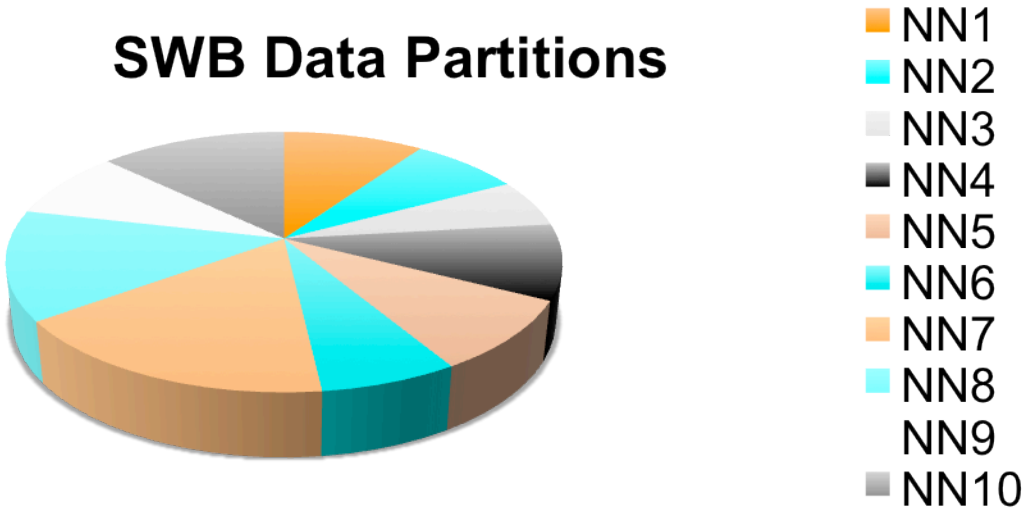
	Hidden layer	4	5	6	ReFA
baseline DNN	WER	17.0%	16.7%	16.2%	15.9%
	Time (hr)	13.0h	13.5h	15.1h	
Multi-DNNs (3 GPUs)	WER	17.8%	17.6%	17.4%	16.4%
	Time (hr)	1.8h	2.1h	2.3h	
	Speed-up	x7.0	x6.6	x6.5	

Switchboard ASR: WER (in %) on Hub5e00 set and training time per epoch using 3 GPUs

More Clusters for better Speedup

- Clustering SWB training data (300-hr, 8991 classes) to 10 clusters

	NN0	DNN1	DNN2	DNN3	DNN4	DNN5	DNN6	DNN7	DNN8	DNN9	DNN10
%	100%	9.7%	7.6%	5.9%	9.3%	8.9%	6.8%	16.8%	13.6%	8.5%	12.9%
class	10	1258	1162	993	1232	1042	1127	40	357	926	854



More Clusters for Faster Speed

- Baseline: single DNN with 2048 nodes per hidden layer
- Multi-DNNs: 1200 hidden nodes per layer for DNN1-10; NN0 is 4*2048

Hidden Layers		3	4	5	6
Baseline	WER	17.8%	17.0%	16.9%	16.2%
	Time (h)	11.0 h	13.0 h	13.5 h	15.0h
Multi-DNN (10 GPUs)	WER	17.7%	17.7%	17.4%	17.4%
	Time (h)	0.6h	0.7h	0.8h	0.9h
	speedup	x18.5	x18.9	x16.6	x16.3

Switchboard ASR: WER (in %) on Hub5e00 set
and training time per epoch using 10 GPUs

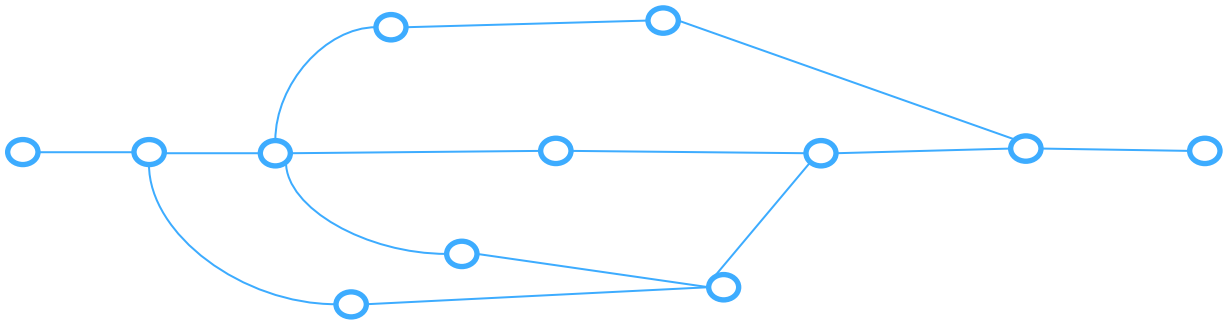
Sequence Training of Multi-DNNs

- SGD-based sequence training of DNNs using GPUs
  - H-Criterion for smoothing MMI *(Su et al., 2013)*
  - Implementing BP/SGD and lattice computation in GPU(s)

- For each mini-batch (utterances and word graphs)
  - ① DNN forward pass (parallel in 1 vs. N GPUs)
  - ② States occupancy for all arcs (parallel in 1 vs. N GPUs)
  - ③ Process lattices for arc posteriori probs (CPU vs. 1 GPU)
  - ④ Sum state statistics for all arcs (parallel in 1 vs. N GPUs)
  - ⑤ DNN back-propagation pass (parallel in 1 vs. N GPUs)

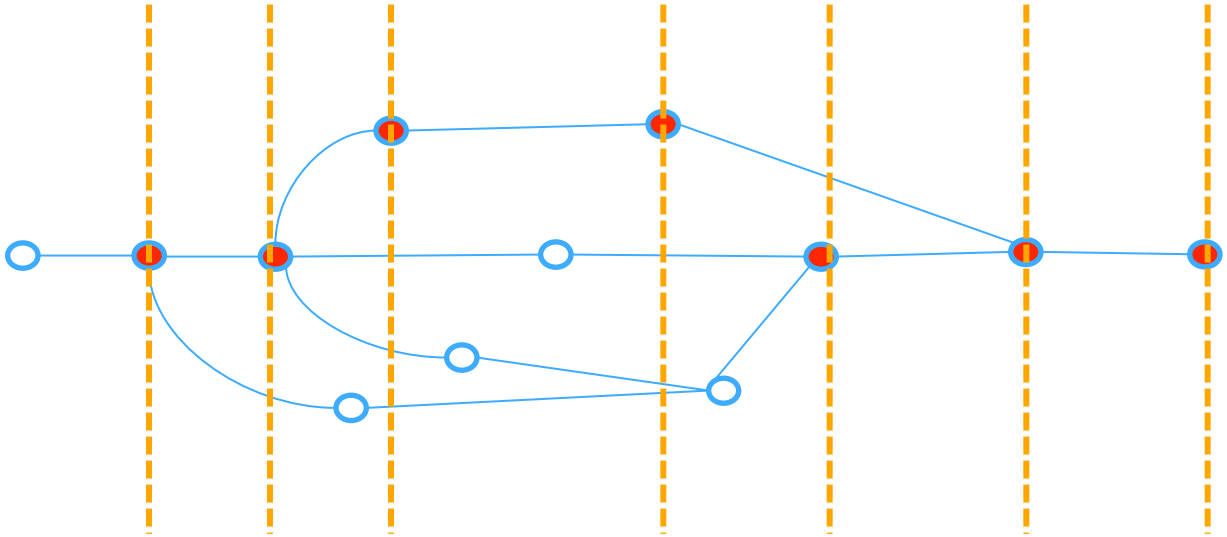
Process word graphs with GPU

- Sort all arcs based on starting time



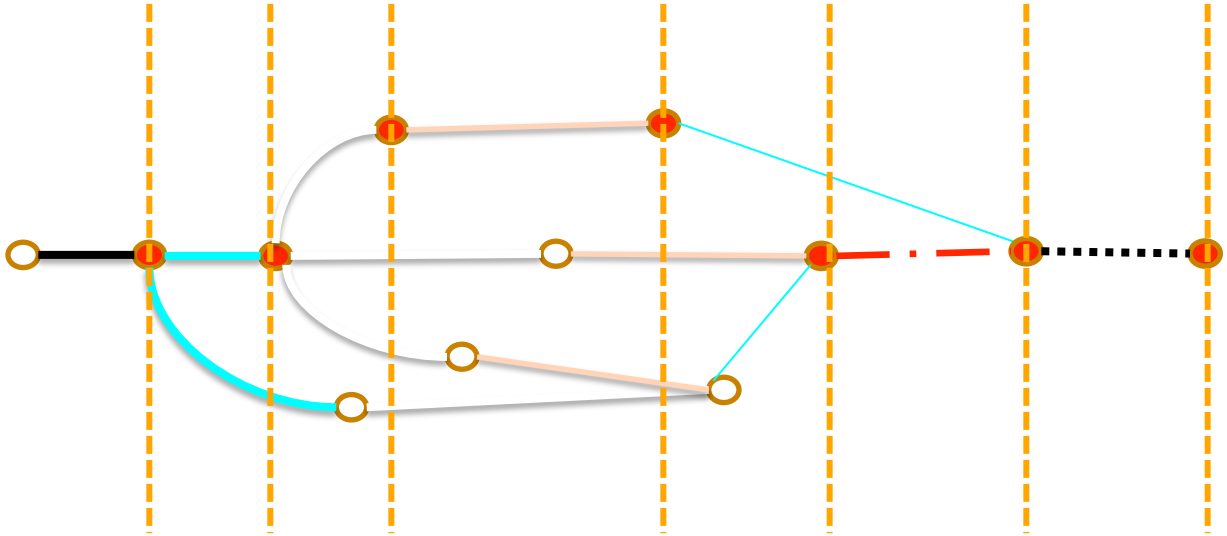
Process word graphs with GPU

- Find splitting nodes in the sorted list based on max starting time and min ending time of arcs.



Process word graphs with GPU

- Split all arcs into subsets for different CUDA launches.
- In each launch, arcs do forward-backward in parallel.



Experiment: Sequence Training of 4-cluster Multi-DNNs

Baseline DNN: 6 hidden layers of 2048 nodes
Multi-DNNs: DNN1-4 has 6 hidden layers of 1024 or 1200 nodes
DNN0 has 3 hidden layers of 1200 nodes

	CE (FA)	DT	Speedup (3 GPUs)
Baseline DNN	15.9%	14.2%	--
Multi-DNNs 6x1024	16.4%	15.4%	x4.1**
Multi-DNNs 6x1200	16.1%	15.2%*	x3.6**

CE (FA): 10 epochs of CE training using realigned labels
DT: CE(FA) plus one iteration of sequence training
* Mismatched lattices; ** based on simulation estimation

Final Remarks

- DNN PAIN: extremely time-consuming to train DNNs.
- Critical to expedite DNN training for big data sets.
- DNN training can be largely accelerated via:
  - Simplify model structure by exploring sparseness
  - Employ parallel training using multiple GPUs