# A Few Thoughts on How We May Want to Further Study DNN

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# Deep Learning is Amazing!!!

## Tasks for Which Deep Convolutional Nets are the Best

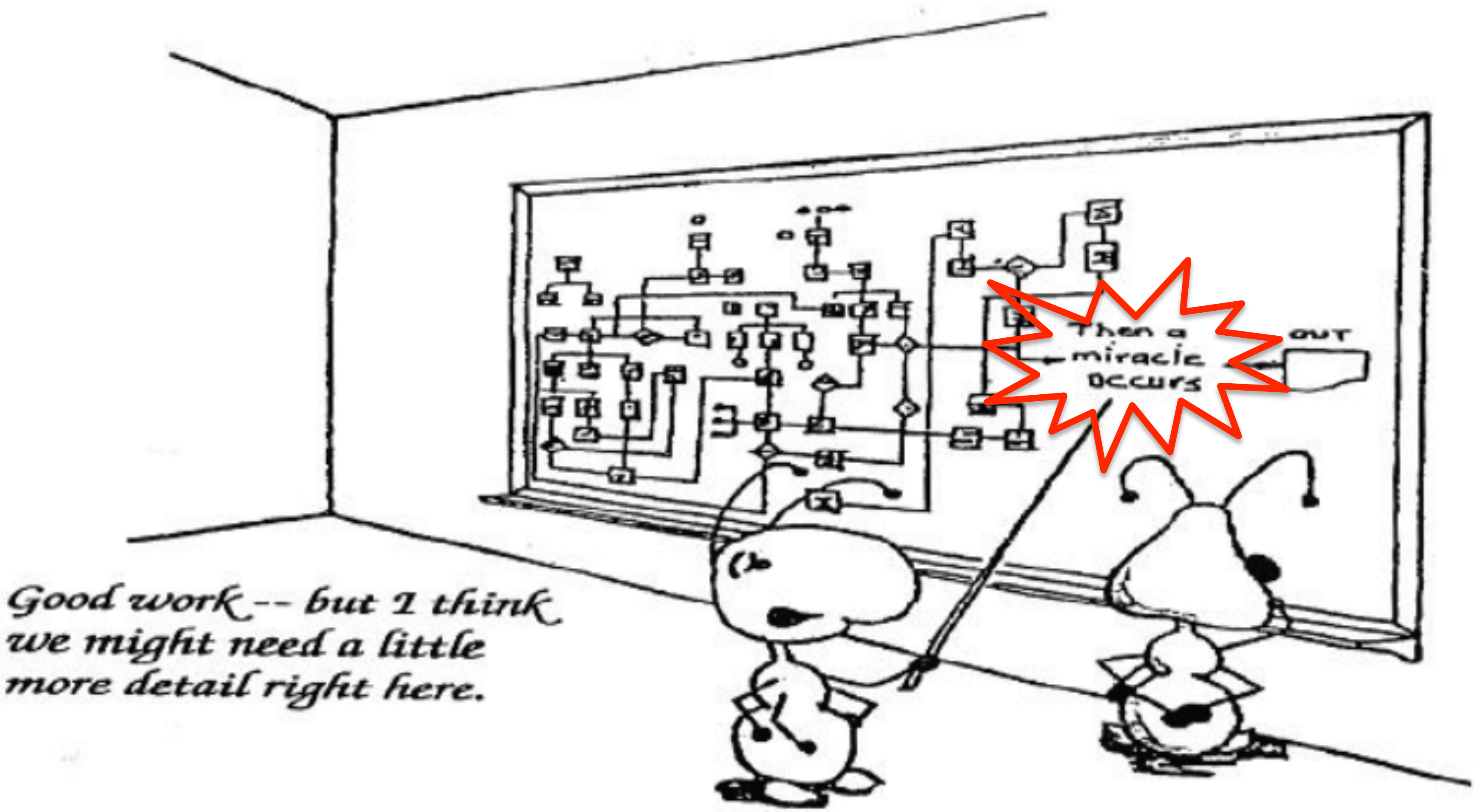
Y LeCun
MA Ranzato

- Handwriting recognition MNIST (many), Arabic HWX (IDSIA)
- OCR in the Wild [2011]: StreetView House Numbers (NYU and others)
- Traffic sign recognition [2011] GTSRB competition (IDSIA, NYU)
- Pedestrian Detection [2013]: INRIA datasets and others (NYU)
- Volumetric brain image segmentation [2009] connectomics (IDSIA, MIT)
- Human Action Recognition [2011] Hollywood II dataset (Stanford)
- Object Recognition [2012] ImageNet competition
- Scene Parsing [2012] Stanford bgd, SiftFlow, Barcelona (NYU)
- Scene parsing from depth images [2013] NYU RGB-D dataset (NYU)
- Speech Recognition [2012] Acoustic modeling (IBM and Google)
- Breast cancer cell mitosis detection [2011] MITOS (IDSIA)

- The list of perceptual tasks for which ConvNets hold the record is growing.
- Most of these tasks (but not all) use purely supervised convnets.

Wow! ☺

# What makes it work? Why?



# An MLer's View of the World

**Loss functions**
(likelihood, reconstruction, margin, …)

**Structures**
(Graphical, group, chain, tree, iid, …)

**Constraints**
(normality, sparsity, label, prior, KL, sum, …)

**Algorithms**
MC (MCMC, Importance), Opt (gradient, IP), …

**Stopping criteria**
Change in objective, change in update …

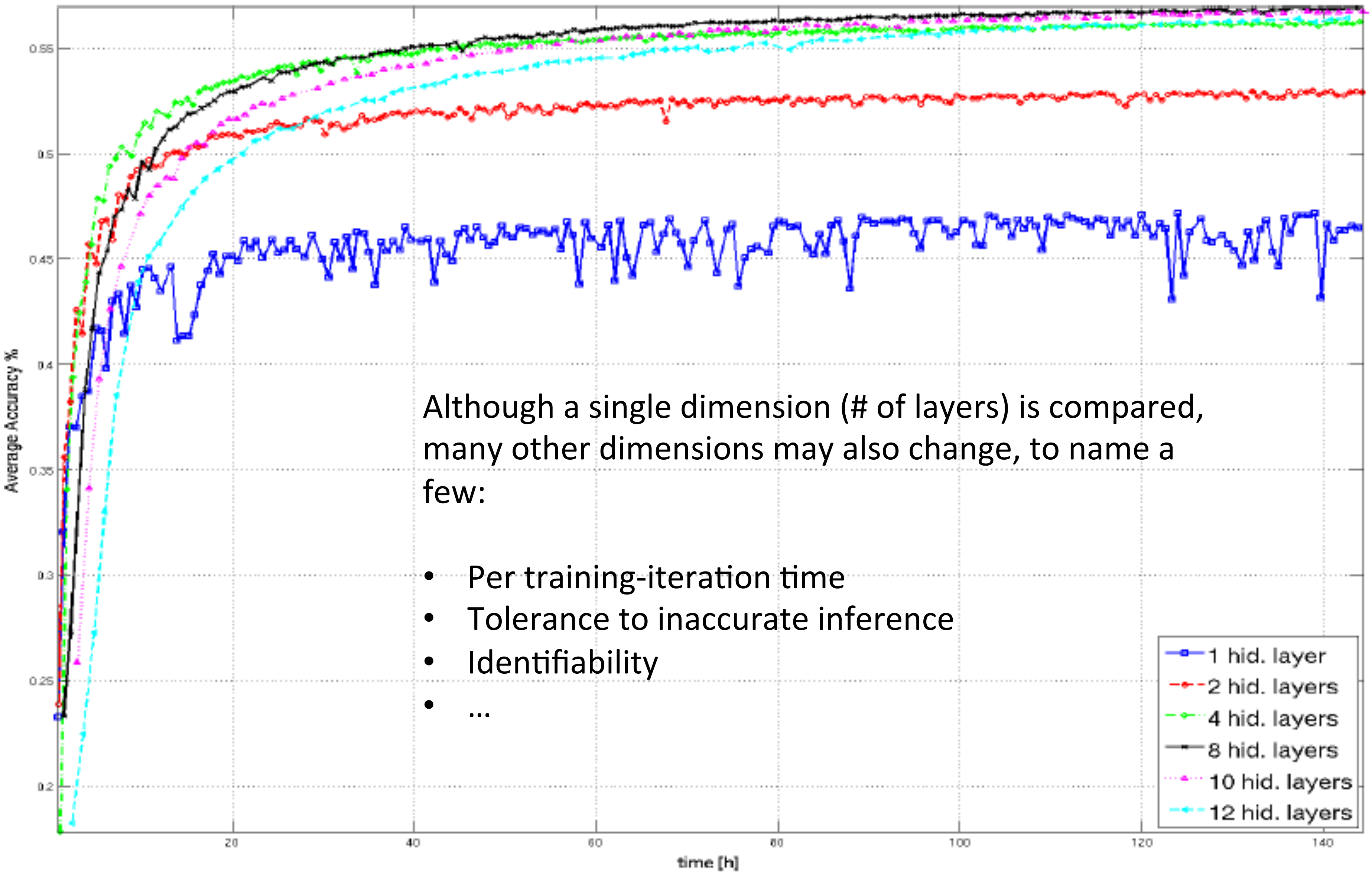
Empirical Performances?

| | DL | $\leq$ ? ML (e.g., GM) |
|---|---|---|
| Empirical goal: | e.g., classification, feature learning | e.g., transfer learning, latent variable inference |
| Structure: | Graphical | Graphical |
| Objective: | Something aggregated from local functions | Something aggregated from local functions |
| | | |
| Vocabulary: | Neuron, activation/gate function … | Variables, potential function |
| Algorithm: | A single, unchallenged, inference algorithm -- BP | A major focus of open research, many algorithms, and more to come |
| Evaluation: | On a black-box score -- end performance | On almost every intermediate quantity |
| Implementation: | Many untold-tricks | More or less standardized |
| Experiments: | Massive, real data (GT unknown) | Modest, often simulated data (GT known) |

# A slippery slope to mythology?

- How to conclusively determine what an improve in performance could come from:
  - Better model (architecture, activation, loss, size)?
  - Better algorithm (more accurate, faster convergence)?
  - Better training data?
- Current research in DL seem to get everything above mixed by evaluating on a black-box “performance score” that is not directly reflecting
  - Correctness of inference
  - Achievability/usefulness of model
  - Variance due to stochasticity

# An Example




Although a single dimension (# of layers) is compared, many other dimensions may also change, to name a few:

- Per training-iteration time
- Tolerance to inaccurate inference
- Identifiability
- …

# Inference quality

- Training error is the old concept of a classifier with no hidden states, no **inference** is involved, and thus inference accuracy is not an issue
- But a DNN is not just a classifier, some DNNs are not even fully supervised, there are MANY **hidden states**, why their inference quality is not taken seriously?

- In DNN, inference accuracy = visualizing features
  - Study of inference accuracy is badly discouraged
  - Loss/accuracy is not monitored

# Inference/Learning Algorithm, and their evaluation

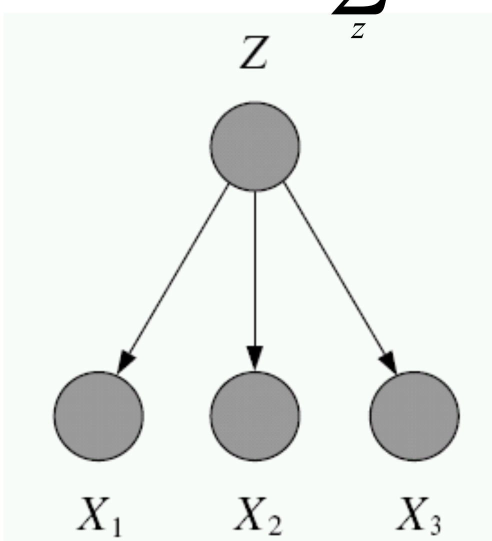
# Learning a GM with Hidden Variables – the thought process

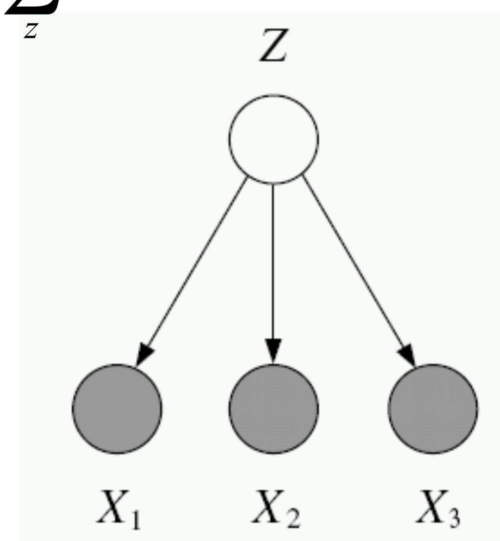
- In fully observed iid settings, the log likelihood decomposes into a sum of local terms (at least for directed models).

$$\ell_c(\theta; D) = \log p(x, z \mid \theta) = \log p(z \mid \theta_z) + \log p(x \mid z, \theta_x)$$

- With latent variables, all the parameters become coupled together via marginalization

$$\ell_c(\theta; D) = \log \sum_z p(x, z \mid \theta) = \log \sum_z p(z \mid \theta_z) p(x \mid z, \theta_x)$$



# Gradient Learning for mixture models

- We can learn mixture densities using gradient descent on the log likelihood. The gradients are quite interesting:

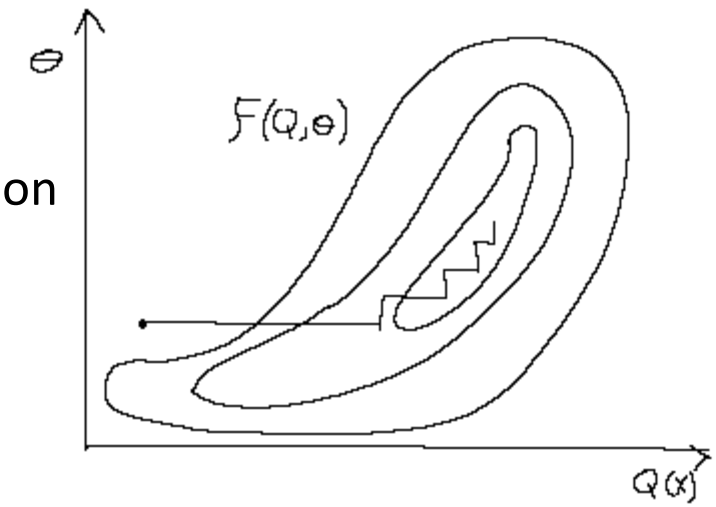
$$l(\theta) = \log p(\mathrm{x} \mid \theta) = \log \sum_k \pi_k p_k(\mathrm{x} | \theta_k)$$

$$\begin{aligned}
\frac{\partial l}{\partial \theta_k} &= \frac{1}{p(\mathrm{x} \mid \theta)} \sum_k \pi_k \frac{\partial p_k(\mathrm{x} | \theta_k)}{\partial \theta_k} \\
&= \sum_k \frac{\pi_k}{p(\mathrm{x} \mid \theta)} p_k(\mathrm{x} | \theta_k) \frac{\partial \log p_k(\mathrm{x} | \theta_k)}{\partial \theta_k} \\
&= \sum_k \pi_k \frac{p_k(\mathrm{x} | \theta_k)}{p(\mathrm{x} \mid \theta)} \frac{\partial \log p_k(\mathrm{x} | \theta_k)}{\partial \theta_k} = \sum_k r_k \frac{\partial l_k}{\partial \theta_k}
\end{aligned}$$

- In other words, the gradient is aggregated from many other intermediate states
  - Implication: costly iteration, heavy coupling between parameters
- Other issues: imposing constraints, identifiability …

# Then Alternative Approaches Were Proposed

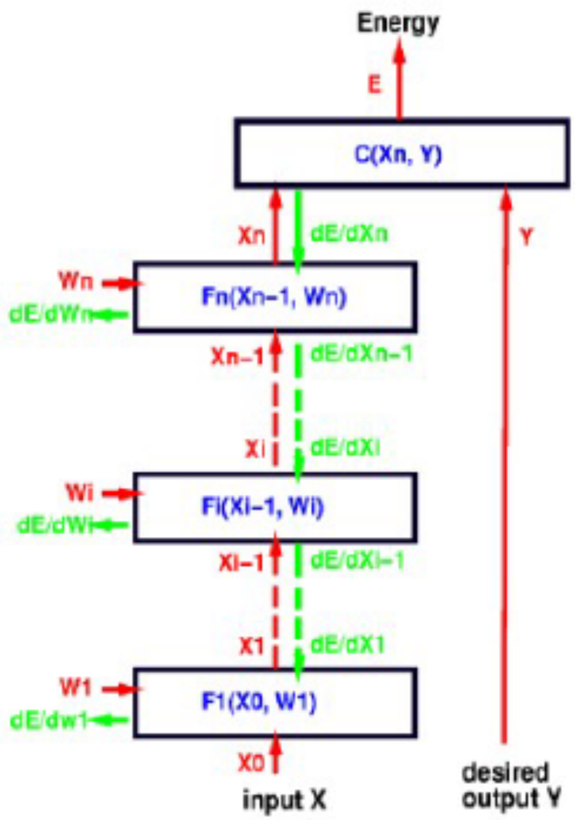
- The EM algorithm
  - M: a convex problem
  - E: approximate constrained optimization
    - Mean field
    - BP/LBP
    - Marginal polytope




- Spectrum algorithm:
  - redefine intermediate states, convexify the original problem

# Learning a DNN

To compute all the derivatives, we use a backward sweep called the **back-propagation algorithm** that uses the recurrence equation for $\frac{\partial E}{\partial X_i}$




- $\frac{\partial E}{\partial X_n} = \frac{\partial C(X_n,Y)}{\partial X_n}$
- $\frac{\partial E}{\partial X_{n-1}} = \frac{\partial E}{\partial X_n} \frac{\partial F_n(X_{n-1},W_n)}{\partial X_{n-1}}$
- $\frac{\partial E}{\partial W_n} = \frac{\partial E}{\partial X_n} \frac{\partial F_n(X_{n-1},W_n)}{\partial W_n}$
- $\frac{\partial E}{\partial X_{n-2}} = \frac{\partial E}{\partial X_{n-1}} \frac{\partial F_{n-1}(X_{n-2},W_{n-1})}{\partial X_{n-2}}$
- $\frac{\partial E}{\partial W_{n-1}} = \frac{\partial E}{\partial X_{n-1}} \frac{\partial F_{n-1}(X_{n-2},W_{n-1})}{\partial W_{n-1}}$
- ....etc, until we reach the first module.
- we now have all the $\frac{\partial E}{\partial W_i}$ for $i \in [1, n]$.

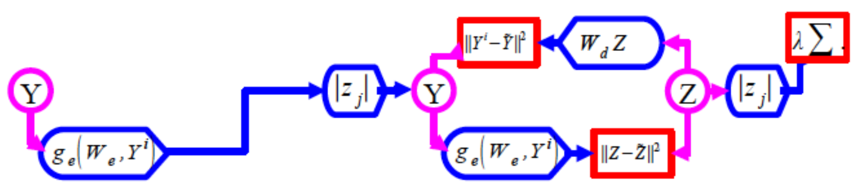
# Learning a DNN

- In a nutshell, sequentially, and recursively apply:

$$w_{j,i}^{t+1} = w_{j,i}^{t} - \eta_t \delta_j z_i$$

$$\delta_i = h^{'}(a_i) \sum_j \delta_j w_{j,i}$$

- Things can getting hairy when locally defined losses are introduced, e.g., auto-encoder, which breaks a loss-driven global optimization formulation




- Depending on starting point, BP converge or diverge with probability 1
  - A serious problem in Large-Scale DNN

# Backprop in Practice

Y LeCun
MA Ranzato

- Use ReLU non-linearities (tanh and logistic are falling out of favor)
- Use cross-entropy loss for classification
- Use Stochastic Gradient Descent on minibatches
- Shuffle the training samples
- Normalize the input variables (zero mean, unit variance)
- Schedule to decrease the learning rate
- Use a bit of L1 or L2 regularization on the weights (or a combination)
  - But it's best to turn it on after a couple of epochs
- Use "dropout" for regularization
  - Hinton et al 2012 http://arxiv.org/abs/1207.0580
- Lots more in [LeCun et al. "Efficient Backprop" 1998]
- Lots, lots more in "Neural Networks, Tricks of the Trade" (2012 edition) edited by G. Montavon, G. B. Orr, and K-R Müller (Springer)

**DL**

## Utility of the network

- A vehicle to conceptually synthesize complex decision hypothesis
  - stage-wise projection and aggregation
- A vehicle for organizing computing operations
  - stage-wise update of latent states
- A vehicle for designing processing steps/computing modules
  - Layer-wise parallization
- No obvious utility in evaluating DL algorithms

## Utility of the Loss Function

- Global loss? Well it is non-convex anyway, why bother ?

**GM**

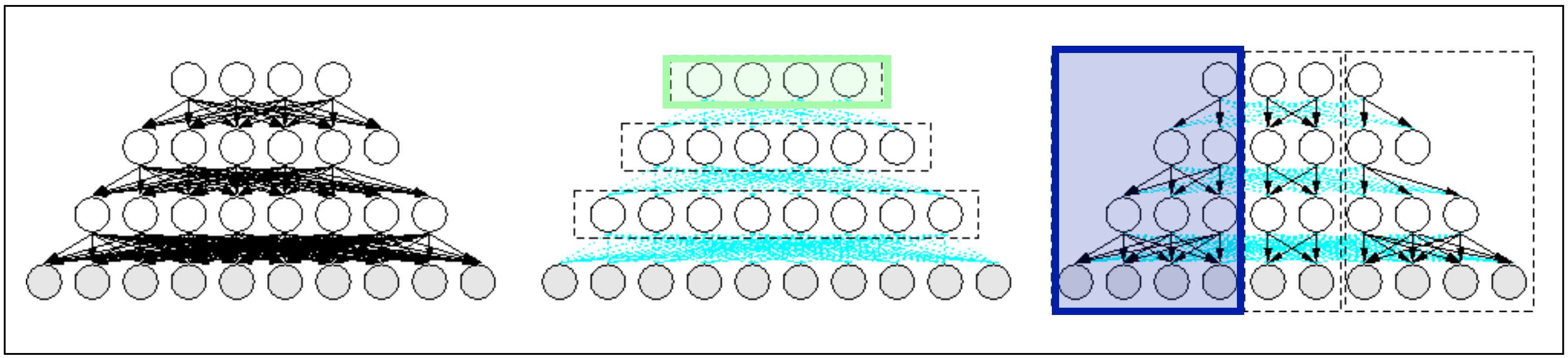
- A vehicle for synthesizing a global loss function from local structure
  - potential function, feature function
- A vehicle for designing sound and efficient inference algorithms
  - Sum-product, mean-field
- A vehicle to inspire approximation and penalization
  - Structured MF, Tree-approx
- A vehicle for monitoring theoretical and empirical behavior and accuracy of inference

- A major measure of quality of algorithm and model

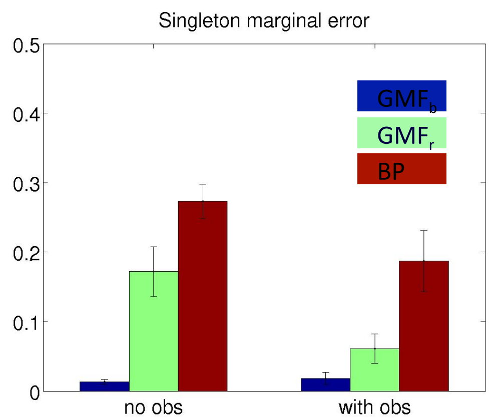
# An Old Study of DL as GM Learning

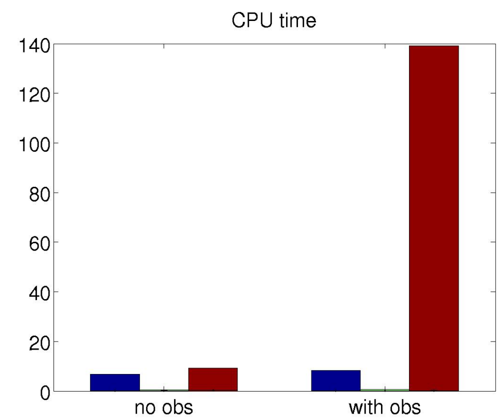
[Xing, Russell, Jordan, UAI 2003]

**A sigmoid belief network at a GM, and mean-field partitions**



**Study focused on only inference/learning accuracy, speed, and partition**



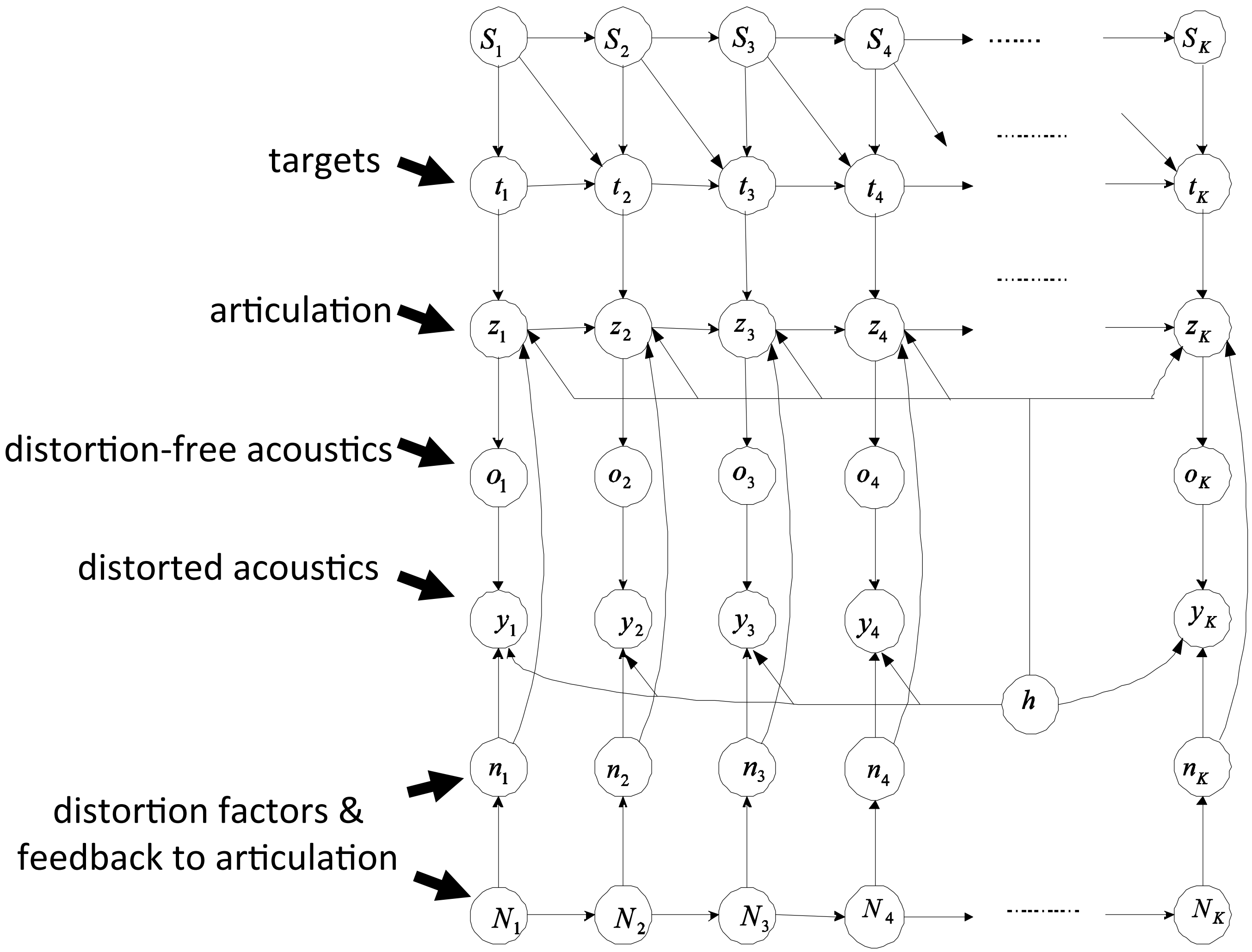




**Now we can ask, with a correctly learned DN, is it doing will on the desired task?**

# Why A Graphical Model formulation of DL might be fruitful

- **Modular design**: easy to incorporate knowledge and interpret, easy to integrate feature learning with high level tasks, easy to built on existing (partial) solutions
- Defines an **explicit and natural objective**
- Guilds strategies for **systematic study** of inference, parallelization, evaluation, and theoretical analysis
- A clear path to further **upgrade**:
  - structured prediction
  - Integration of multiple data modality
  - Modeling complex: time series, missing data, online data …
- Big DL on **distributed architectures**, where things can get messy everywhere due to incorrect parallel computations

# Easy to incorporate knowledge and interpret




Slides Courtesy:
Li Deng

# Easy to integrate feature learning with high level tasks

Hidden Markov Model
+
Gaussian Mixture Model

Jointly trained, but shallow

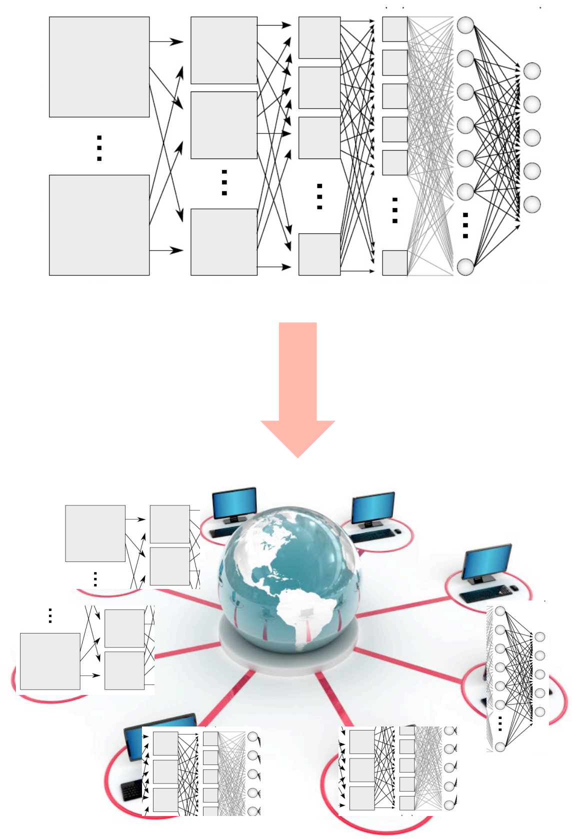
Hidden Markov Model
+
Deep Neural Network

Deep, but separately trained

Hidden Markov Model
+
Deep Graphical Models

Jointly trained and deep

# Distributed DL



# Mathematics 101 for ML

$$\underset{\vec{\theta}}{\arg\max} \equiv \mathcal{L}(\{\mathbf{x}_i, \mathbf{y}i\}_{i=1}^{N} \; ; \; \vec{\theta}) + \Omega(\vec{\theta})$$

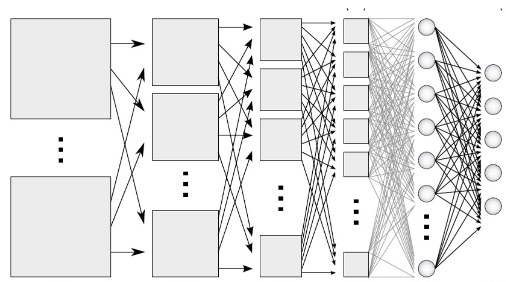
Model Data Parameter

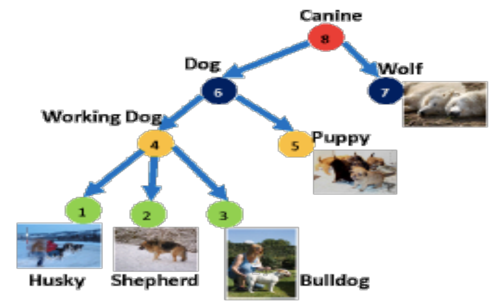
$$\vec{\theta}^{t+1} = \vec{\theta}^{t} + \underline{\Delta_f \vec{\theta}(\mathcal{D})}$$

This computation needs to be parallelized!

$$\vec{\theta}^{t+1} = \vec{\theta}^{t} + \Delta_f \vec{\theta}(\mathcal{D})$$

# Toward Big ML

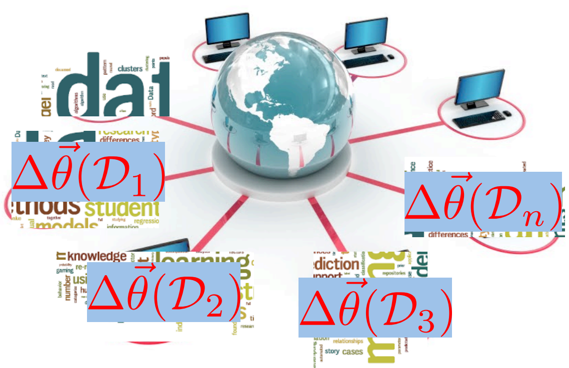



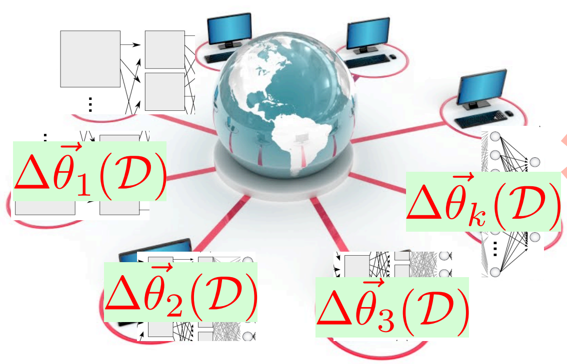


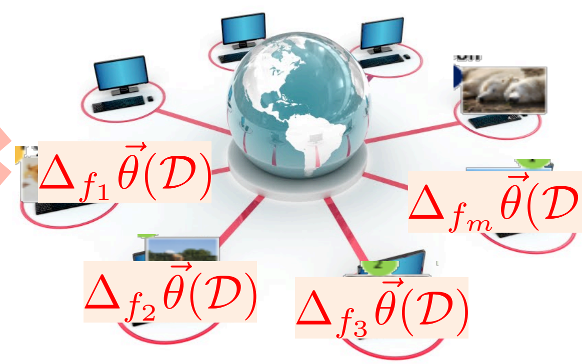

**Data Parallel**

**Model Parallel**

**Task Parallel**



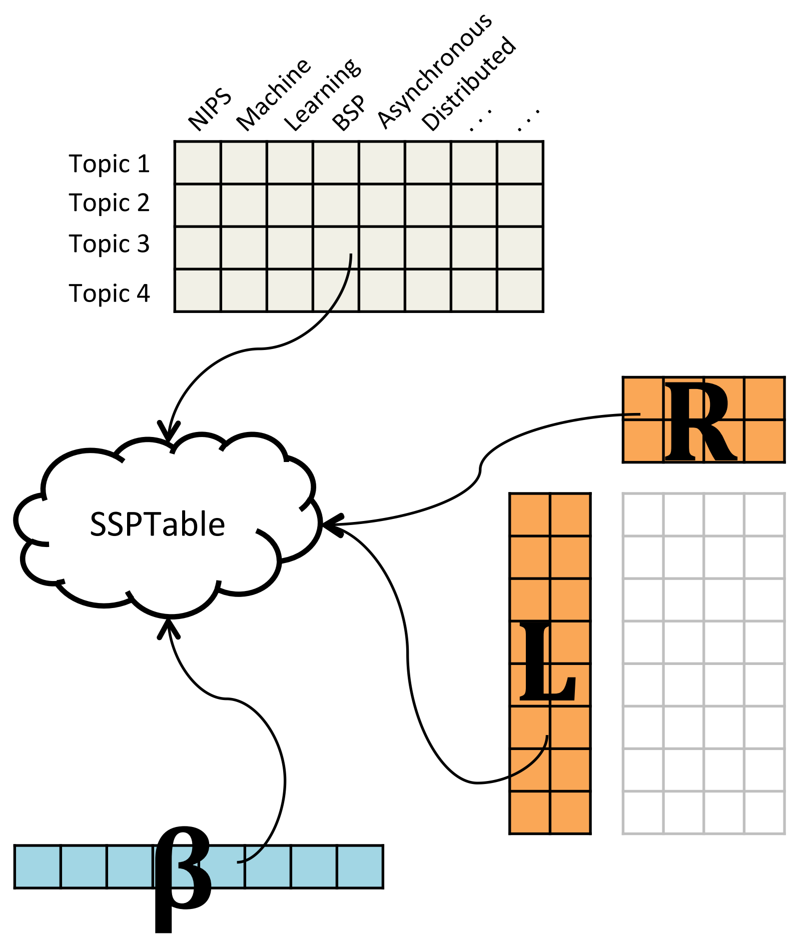

$$\mathcal{D} \equiv \{\mathcal{D}_1, \mathcal{D}_2, \ldots, \mathcal{D}_n\}$$

$$\vec{\theta} \equiv [\vec{\theta}_1^{\,\mathrm{T}}, \vec{\theta}_2^{\,\mathrm{T}}, \ldots, \vec{\theta}_k^{\,\mathrm{T}}\}^{\mathrm{T}}$$

$$f \equiv \{f_1, f_2, \ldots, f_m\}$$

# Data-Parallel DNN using Petuum Parameter Server

- Just put global parameters in SSPTable:
- **DNN (SGD)**
  - **The weight table**
- **Topic Modeling (MCMC)**
  - Topic-word table
- **Matrix Factorization (SGD)**
  - Factor matrices L, R
- **Lasso Regression (CD)**
  - Coefficients β
- SSPTable supports generic classes of algorithms
  - With these models as examples

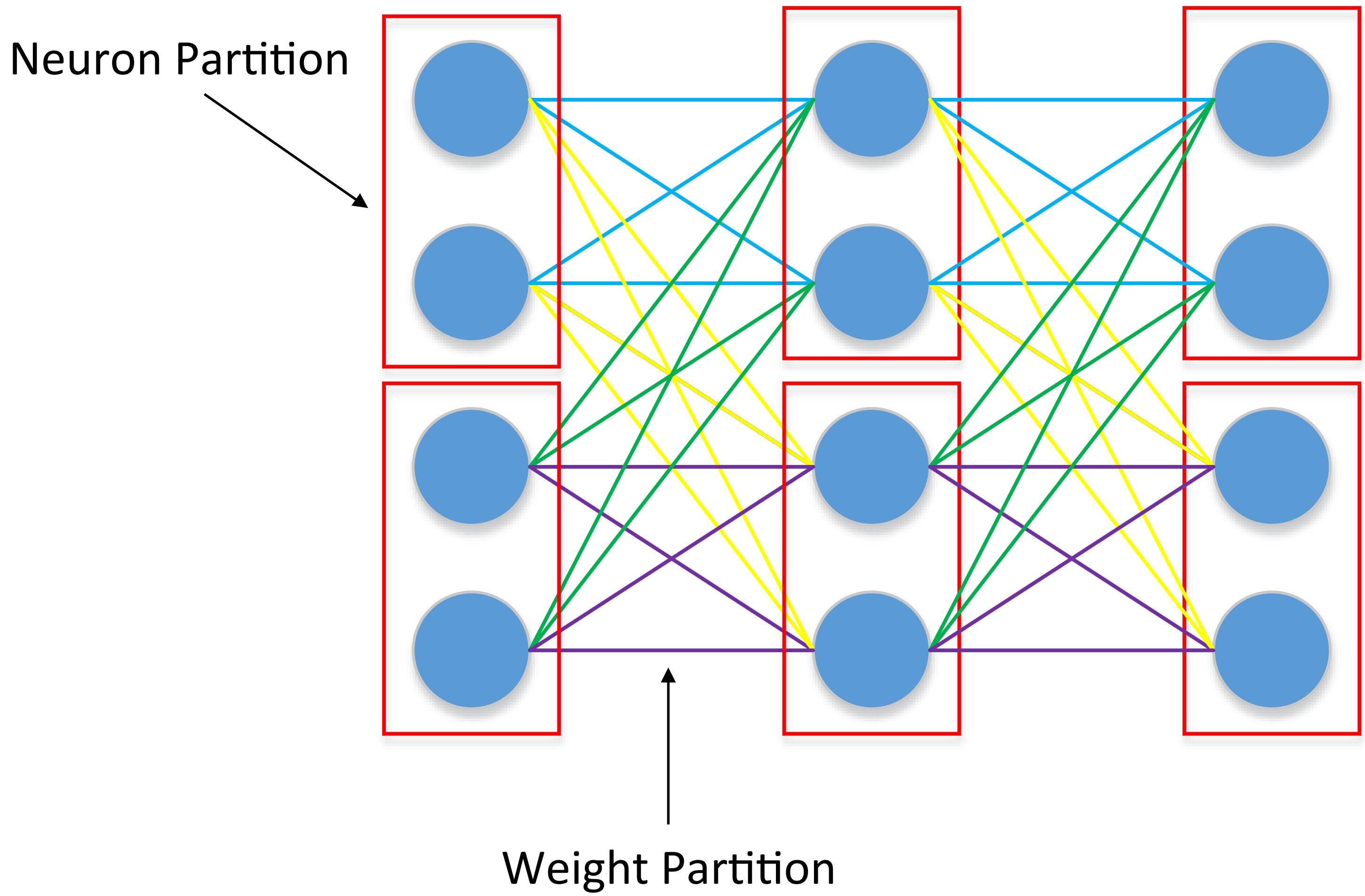


# **Theorem:** Multilayer convergence of SSP based distributed DNNs to optima

- If the undistributed BP updates of a multi-layer DNN lead to weights $w_t$ , and the distributed BP updates under SSP lead to weights $\tilde{w}_t$ , then $\tilde{w}_t$ converges in probability to $w_t$ , i.e . $(\tilde{w}_t \xrightarrow{P} w_t)$

Consequently $(\tilde{w}_t^* \xrightarrow{P} w^*)$

# Model-Parallel DNN using Petuum Scheduler



# **Theorem:** Multilayer convergence of model distributed DNNs to optima

- If the undistributed BP updates of a multi-layer DNN lead to weights $w_t$ and the distributed BP updates in model distributed setting lead to weights $\tilde{w}_t$, then $\tilde{w}_t$ converges in probability to $w_t$, i.e . $(\tilde{w}_t \xrightarrow{P} w_t)$ .Consequently

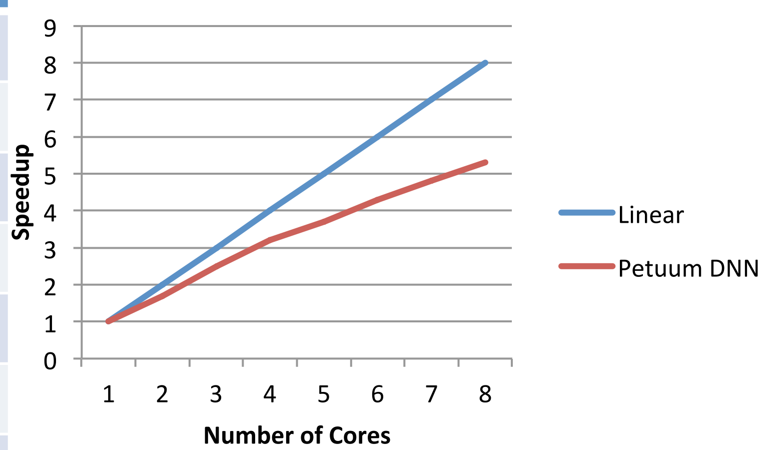
$$(\tilde{w}_t^* \xrightarrow{P} w^*)$$

- In case of model distributed DNN we divided the DNN vertically such that a single layer is distributed across processors

# Distributed DNN: (preliminary)

- Application: phoneme classification in speech recognition.
- Dataset: TIMIT dataset with 1M samples.
- Network configuration: input layer with 440 units, output layer with 1993 units, six hidden layers with 2048 units in each layer

| Methods | PER |
|---|---|
| Conditional Random Field [1] | 34.8% |
| Large-Margin GMM [2] | 33% |
| CD-HMM [3] | 27.3% |
| Recurrent Neural Nets [4] | 26.1% |
| Deep Belief Network [5] | 23.0% |
| Petuum DNN (Data Partition) | 24.95% |
| Petuum DNN (Model Partition) | 25.12% |



# Conclusion

- In GM: lots of efforts are directed to improving inference accuracy and convergence speed
  - An advanced tutorial would survey dozen's of inference algorithms/ theories, but few use cases on empirical tasks
- In DL: most effort is directed to comparing different architectures and gate functions (based on empirical performance on a downstream task)
  - An advanced tutorial typically consist of a list of all designs of nets, many use cases, but a single name of algorithm: back prop of SGD
- The two fields are similar at the beginning (energy, structure, etc.), and soon diverge to their own signature pipelines
- A convergence might be necessary and fruitful