9.0 Speech Recognition Updates

Minimum-Classification-Error (MCE) and Discriminative Training

- **A Primary Problem with the Conventional Training Criterion : Confusing sets**

  find $\lambda^{(i)}$ such that $P(X|\lambda^{(i)})$ is maximum (Maximum Likelihood) if $X \in \boldsymbol{C_i}$

  – This does not always lead to minimum classification error, since it doesn't consider the mutual relationship among competing classes

  – The competing classes may give higher likelihood function for the test data

- **General Objective : find an optimal set of parameters (e.g. for recognition models) to *minimize the expected error of classification***

  – the statistics of test data may be quite different from that of the training data

  – training data is never enough

- **Assume the recognizer is operated with the following classification principles :**

  $\{C_i, i=1,2,...M\}$, M classes

  $\lambda^{(i)}$: statistical model for C_i

  $\Lambda=\{\lambda^{(i)}\}_{i=1......M}$, the set of all models for all classes

  X : observations

  $g_i(X,\Lambda)$: class conditioned likelihood function, for example,

  $$g_i(X,\Lambda) = P(X|\lambda^{(i)})$$

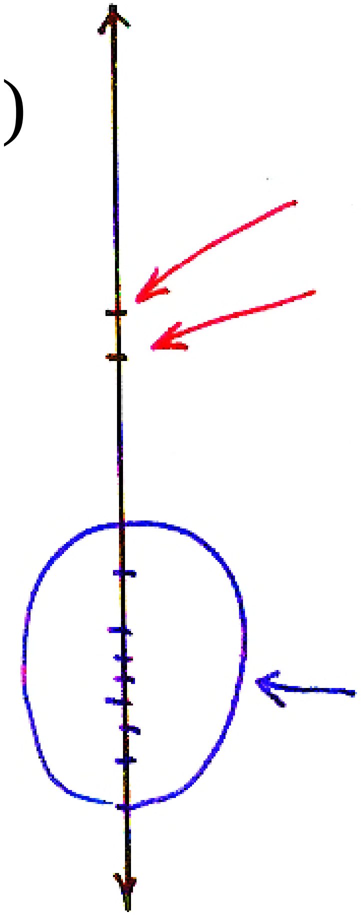
  – $\mathbf{C}(X) = \boldsymbol{C_i}$ if $g_i(X,\Lambda) = \max_j g_j(X,\Lambda)$: classification principles

  an error happens when $P(X|\lambda^{(i)}) = \max$ but $X \notin \boldsymbol{C_i}$

Minimum-Classification-Error (MCE)

$\lambda^{(0)}, \lambda^{(1)}, \lambda^{(2)}, \ldots \lambda^{(9)}$

$P\,(O|\lambda^{(k)})$



$P\,(O|\lambda^{(7)})$: correct

$P\,(O|\lambda^{(1)})$: competing

wrong

Minimum-Classification-Error (MCE) Training

- **One form of the misclassification measure**

$$d_i(X,\Lambda) = -g_i(X,\Lambda) + \left[\frac{1}{M-1}\sum_{j\neq i} g_j(X,\Lambda)^{\alpha}\right]^{\frac{1}{\alpha}} \qquad X \in C_i$$

  - Comparison between the likelihood functions for the correct class and the competing classes

$\alpha = 1$ all other classes included and averaged with equal weights

$\alpha \to \infty$ only the most competing one considered

$d_i(X) \geq 0$ implies a classification error

$d_i(X) < 0$ implies a correct classification

- **A continuous loss function is defined**

$$l_i(X,\Lambda) = l(d_i(X,\Lambda)),\ \mathrm{X} \in \mathrm{C_i}$$

$$l(d) = \frac{1}{1+\exp[-\gamma(d-\theta)]},\ \textit{sigmoid function}$$

  - l(d) →0 when d →-∞
    l(d) →1 when d →∞
    θ: switching from 0 to 1 near θ
    γ: determining the slope at switching point

- **Overall Classification Performance Measure :**

$$L(\Lambda) = E_X[L(X,\Lambda)] = \sum_X [L(X,\Lambda)] = \sum_{i=1}^{M}[\sum_{X\in C_i} l_i\,(X,\Lambda)]$$

Sigmoid Function

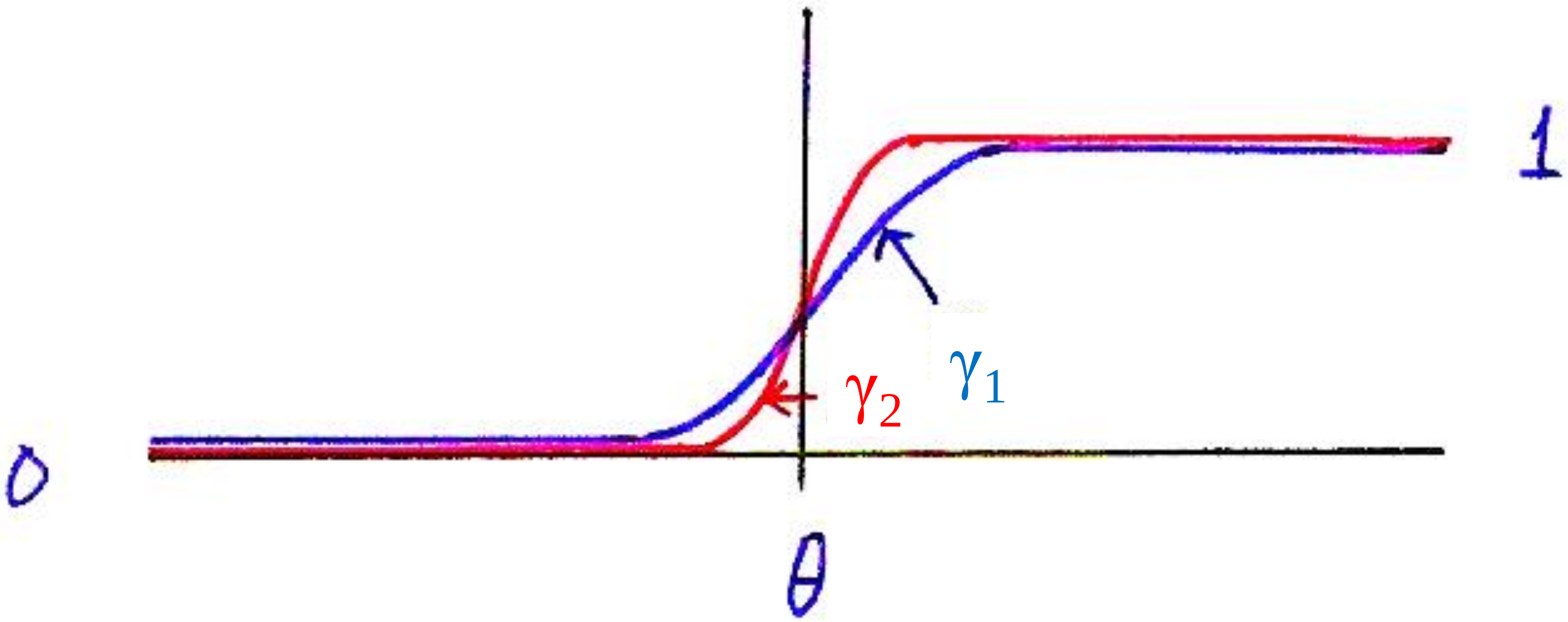
$$1(d) = \frac{1}{1 + exp[-\gamma(d - \theta)]}$$

l(d) →0 when d →-∞

l(d) →1 when d →∞

θ: switching from 0 to 1 near θ

γ: determining the slope at switching point



Minimum-Classification-Error (MCE) Training

- **Find $\hat{\Lambda}$ such that**

$$\hat{\Lambda} = \arg\min_{\Lambda} L(\Lambda) = \arg\min_{\Lambda} E_X \left[L(X, \Lambda) \right]$$

  – the above objective function in general is difficult to minimize directly

  – local minimum can be obtained iteratively using gradient (steepest) descent algorithm

$$\Lambda_{t+1} = \Lambda_t - \varepsilon_t \nabla L(\Lambda_t)$$

∇ : partial differentiation with respect to all different parameters individually

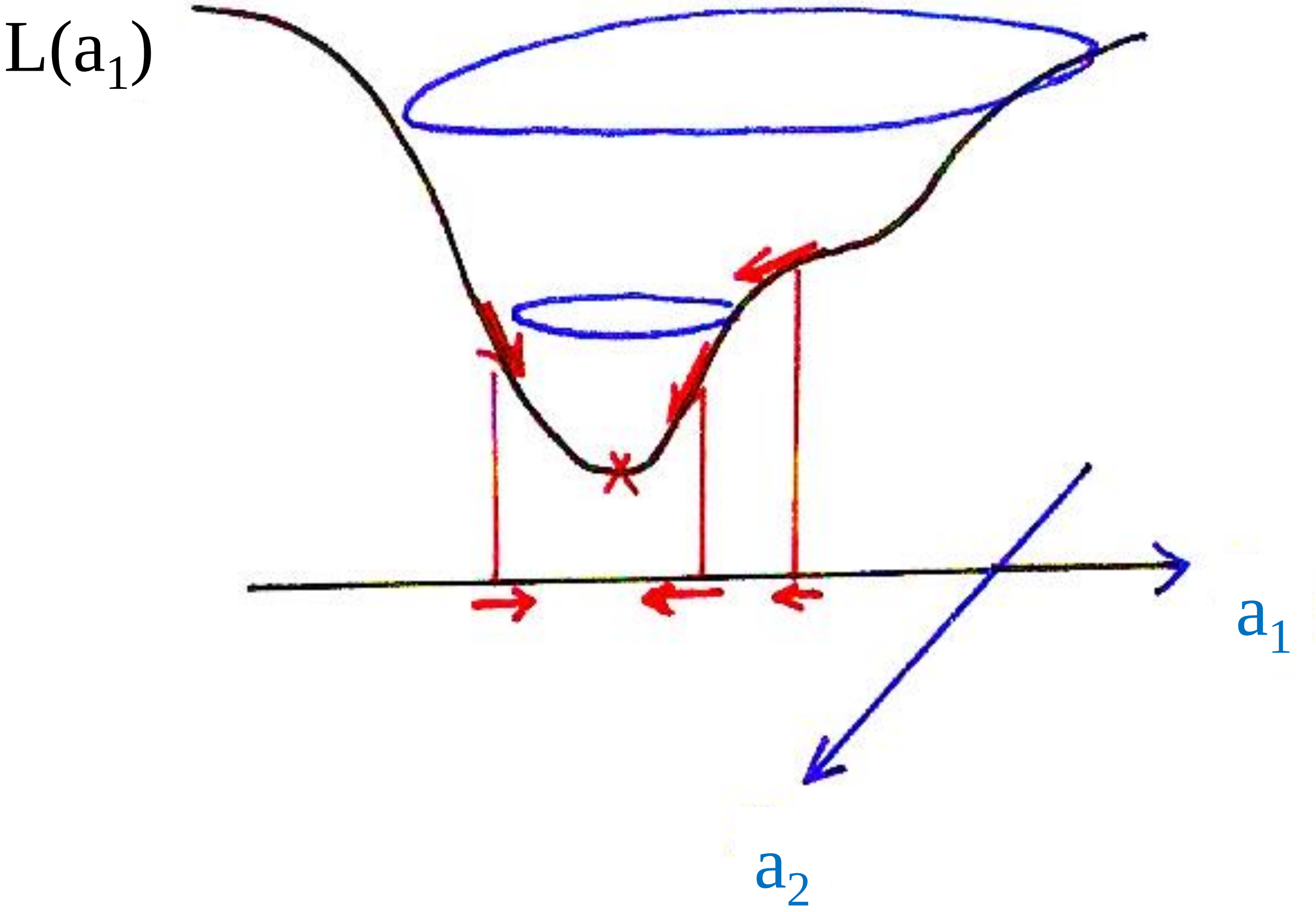
t : the t-th iteration

ε : adjustment step size, should be carefully chosen

$$a_{t+1} = a_t - \varepsilon_t \frac{\partial L(\Lambda)}{\partial a}, a : an\, arbitrary\ parameter of\ \Lambda$$

  – every training observation may change the parameters of ALL models, not the model for its class only

Gradient Descent Algorithm

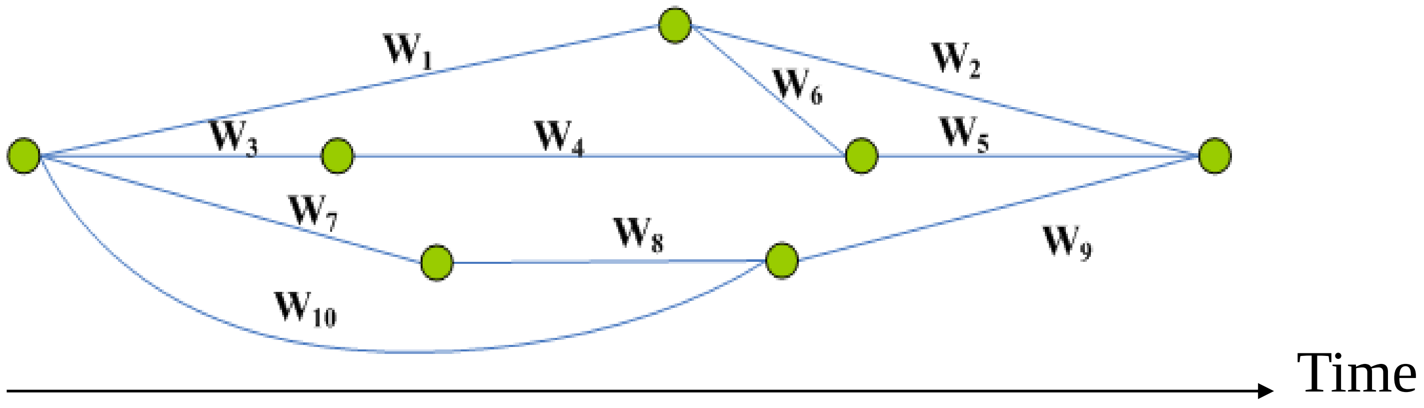


Discriminative Training and Minimum Phone Error Rate (MPE) Training For Large Vocabulary Speech Recognition

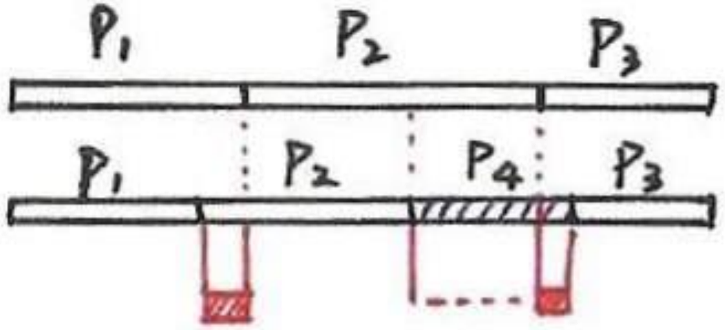
- **Minimum Bayesian Risk (MBR)**
  - $(\Lambda,\Gamma) = \arg\min_{\Lambda',\Gamma'} \sum_r R(s_r \mid O_r)$ adjusting all model parameters to minimize the Bayesian Risk
    - Λ: {λ_i,i=1,2,……N} acoustic models
    - Γ: Language model parameters
    - O_r : r-th training utterance
    - s_r: correct transcription of O_r
  - $R(s_r \mid O_r) = \sum_u P_{\Lambda,\Gamma}(u \mid O_r) L(u, s_r)$ Bayesian Risk
    - u: a possible recognition output found in the lattice
    - *$L(u,s_r)$* : Loss function
    - *$P_{\Lambda,\Gamma}(u|O_r)$* : posteriori probability of *u* given O_r based on Λ,Γ
  - $L(u,s_r) = \begin{cases} 0, u = s_r \\ 1, u \neq s_r \end{cases} \rightarrow MAP$ principle
  - Other definitions of *$L(u,s_r)$* possible
- **Minimum Phone Error Rate (MPE) Training**
  - $(\Lambda,\Gamma) = \arg\max_{\Lambda',\Gamma'} \sum_r \sum_u P(u \mid O_r) Acc(u, s_r)$
    - $Acc(u,s_r)$: phone accuracy
  - Better features obtainable in the same way
    - e.g. $y_t = x_t + Mh_t$ feature-space MPE

Minimum Phone Error (MPE) Rate Training

- **Lattice**



- **Phone Accuracy**



← Reference phone sequence

← Decoded phone sequence for a path in the lattice

References for MCE, MPE and Discriminative Training

- “ Minimum Classification Error Rate Methods for Speech Recognition”, IEEE Trans. Speech and Audio Processing, May 1997

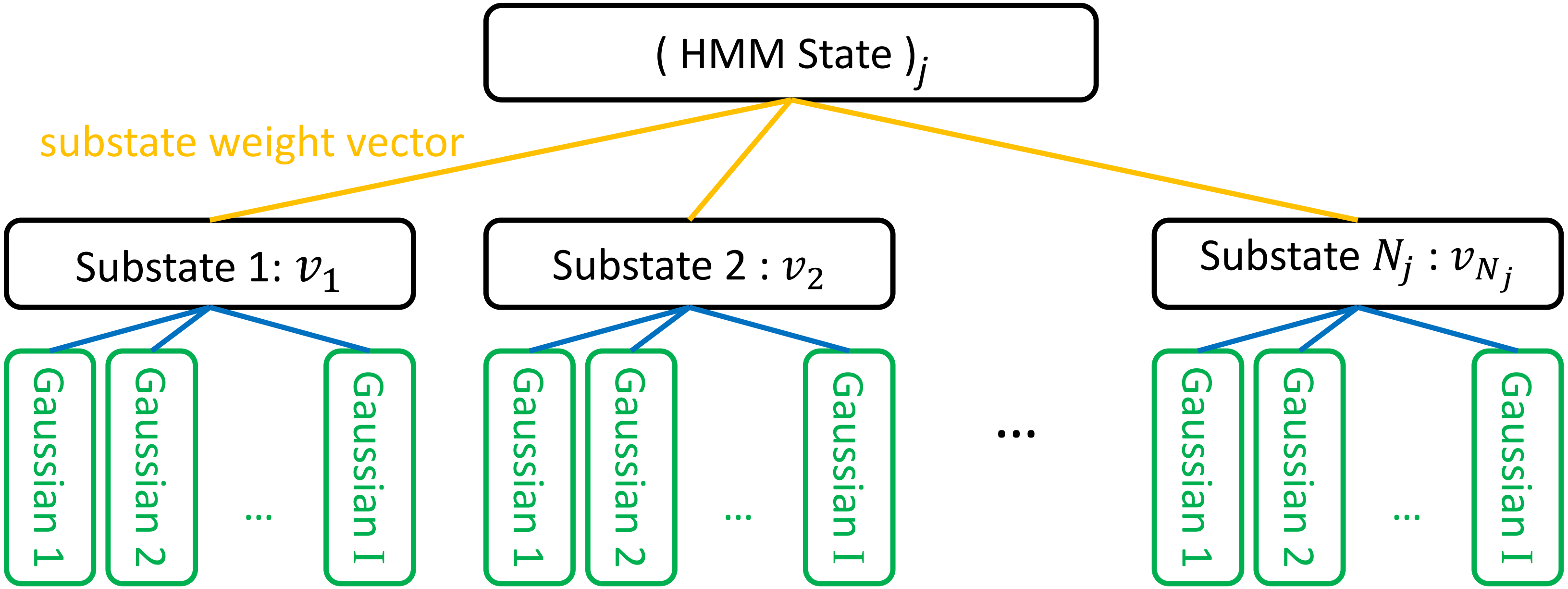
- “Segmental Minimum Bayes-Rick Decoding for Automatic Speech Recognition”, IEEE Trans. Speech and Audio Processing, 2004

- “Minimum Phone Error and I-smoothing for Improved Discriminative Training”, International Conference on Acoustics, Speech and Signal Processing, 2002

- “Discriminative Training for Automatic Speech Recognition”, IEEE Signal Processing Magazine, Nov 2012

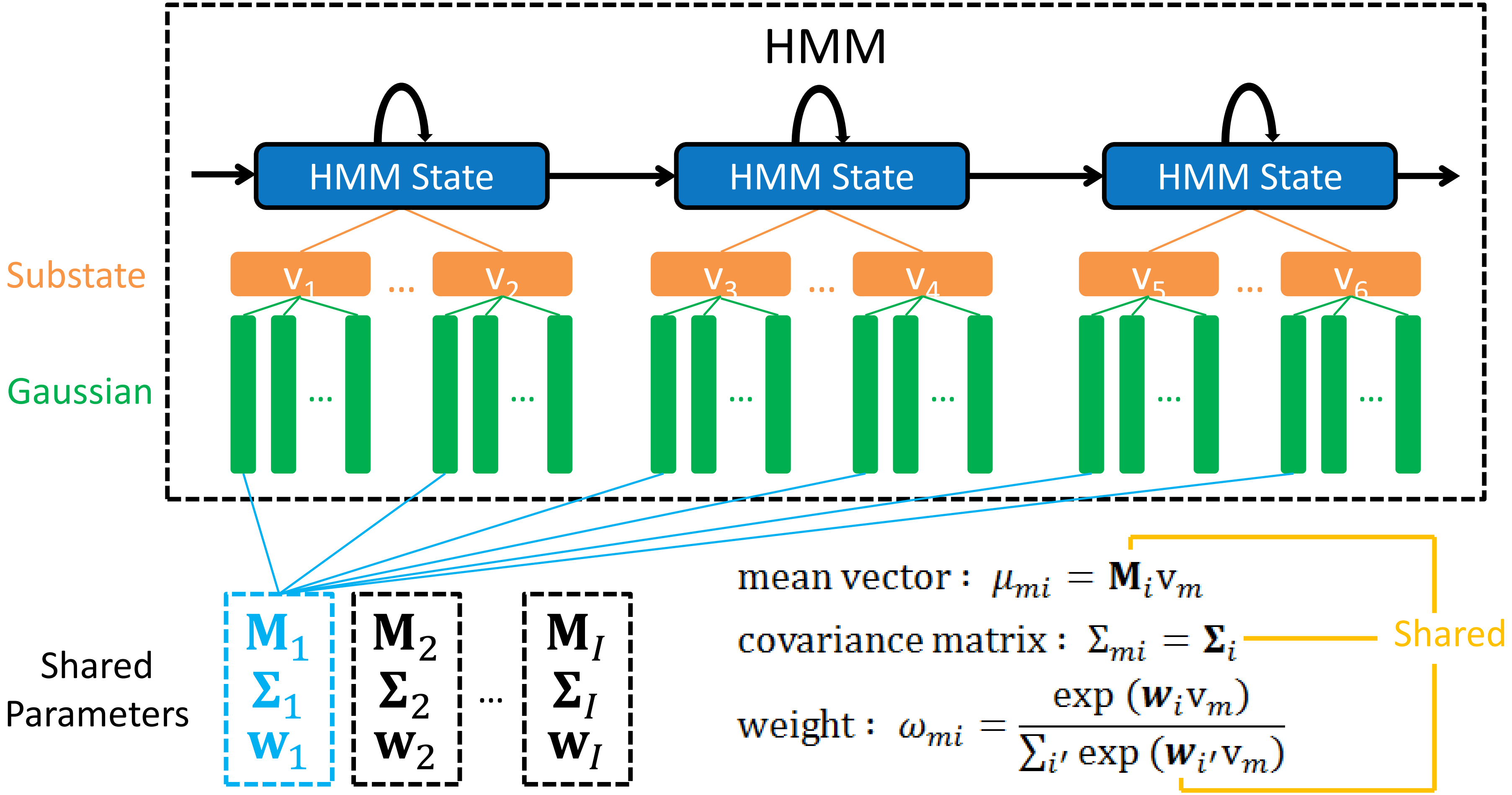
Subspace Gaussian Mixture Model

- **To increase the modeling flexibility while reducing the required free parameters**
  - In a triphone HMM, different states can have different number of substates
  - Fixed number of I Gaussians in each substate, I ≈ 400
  - Similar to many and varying number of Gaussian mixtures in each state in conventional HMM-GMM
  - Each substate specified by a vector v_m of S dimensions only, S ≈ 40, while the parameters of all Gaussians under all different triphones are determined based on a set of shared parameters $\{(M_i,\ \Sigma_i,\ w_i),\ i = 1, 2, \cdots, I\}$



Subspace Gaussian Mixture Model

- **A triphone HMM in Subspace GMM**


HMM
HMM State
HMM State
HMM State
Substate
v_1 … v_2
v_3 … v_4
v_5 … v_6
Gaussian
…
Shared Parameters
$\mathbf{M}_1$ $\boldsymbol{\Sigma}_1$ $\mathbf{w}_1$
$\mathbf{M}_2$ $\boldsymbol{\Sigma}_2$ $\mathbf{w}_2$
…
$\mathbf{M}_I$ $\boldsymbol{\Sigma}_I$ $\mathbf{w}_I$
Shared

mean vector : $\mu_{mi} = \mathbf{M}_i \mathrm{v}_m$

covariance matrix : $\Sigma_{mi} = \boldsymbol{\Sigma}_i$

weight : $\omega_{mi} = \dfrac{\exp\left(\boldsymbol{w}_i \mathrm{v}_m\right)}{\sum_{i'} \exp\left(\boldsymbol{w}_{i'} \mathrm{v}_m\right)}$

I ≈ 400, v_m: S dimensional, S ≈ 40

Subspace Gaussian Mixture Model

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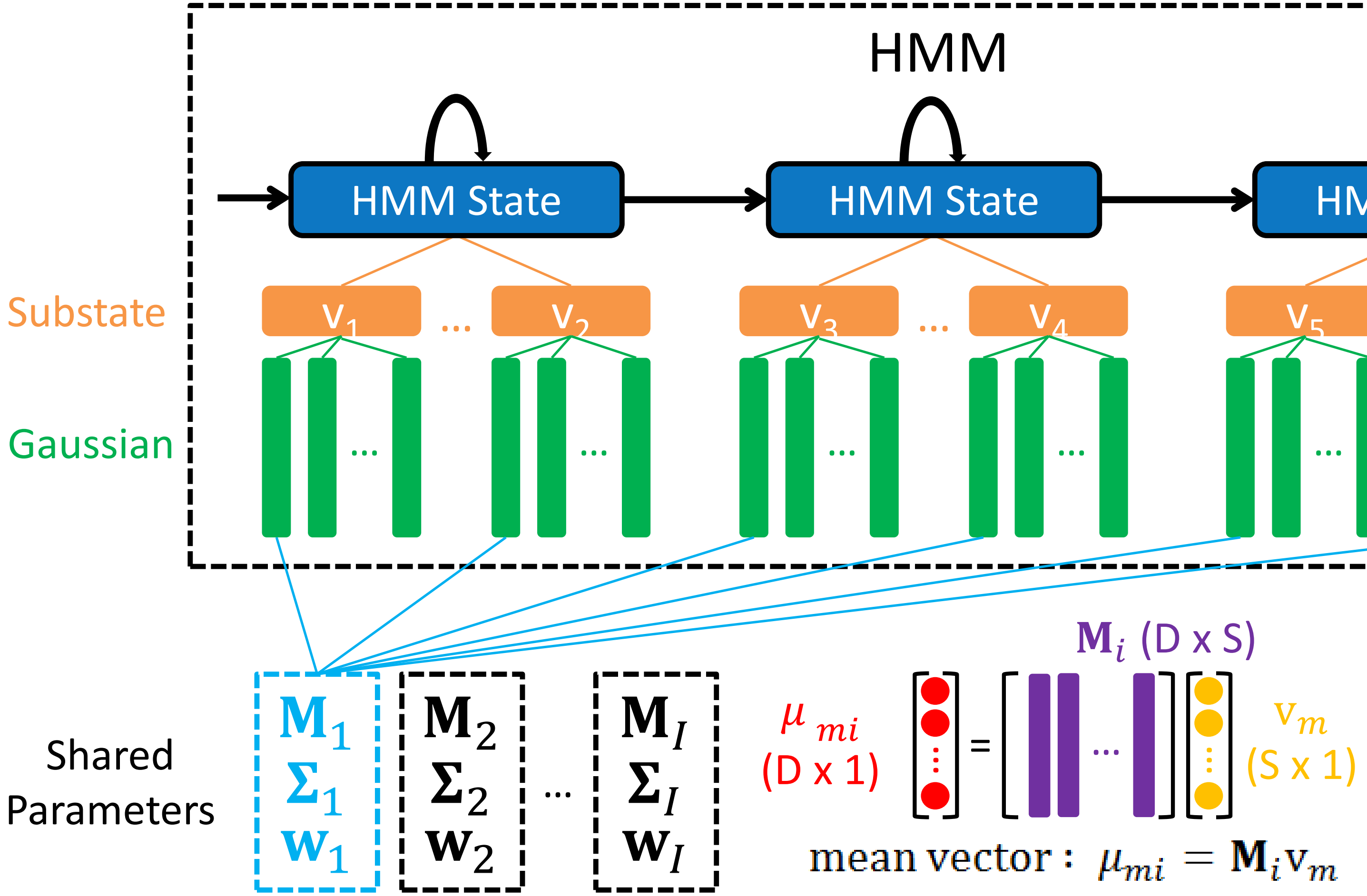

HMM
HMM State
HMM State
HMM State
Substate
v_1 … v_2
v_3 … v_4
v_5 … v_6
Gaussian
…
Shared Parameters
$\mathbf{M}_1$ $\boldsymbol{\Sigma}_1$ $\mathbf{w}_1$
$\mathbf{M}_2$ $\boldsymbol{\Sigma}_2$ $\mathbf{w}_2$
…
$\mathbf{M}_I$ $\boldsymbol{\Sigma}_I$ $\mathbf{w}_I$
μ_{mi} (D x 1)
=
$\mathbf{M}_i$ (D x S)
v_m (S x 1)

mean vector : $\mu_{mi} = \mathbf{M}_i \mathrm{v}_m$

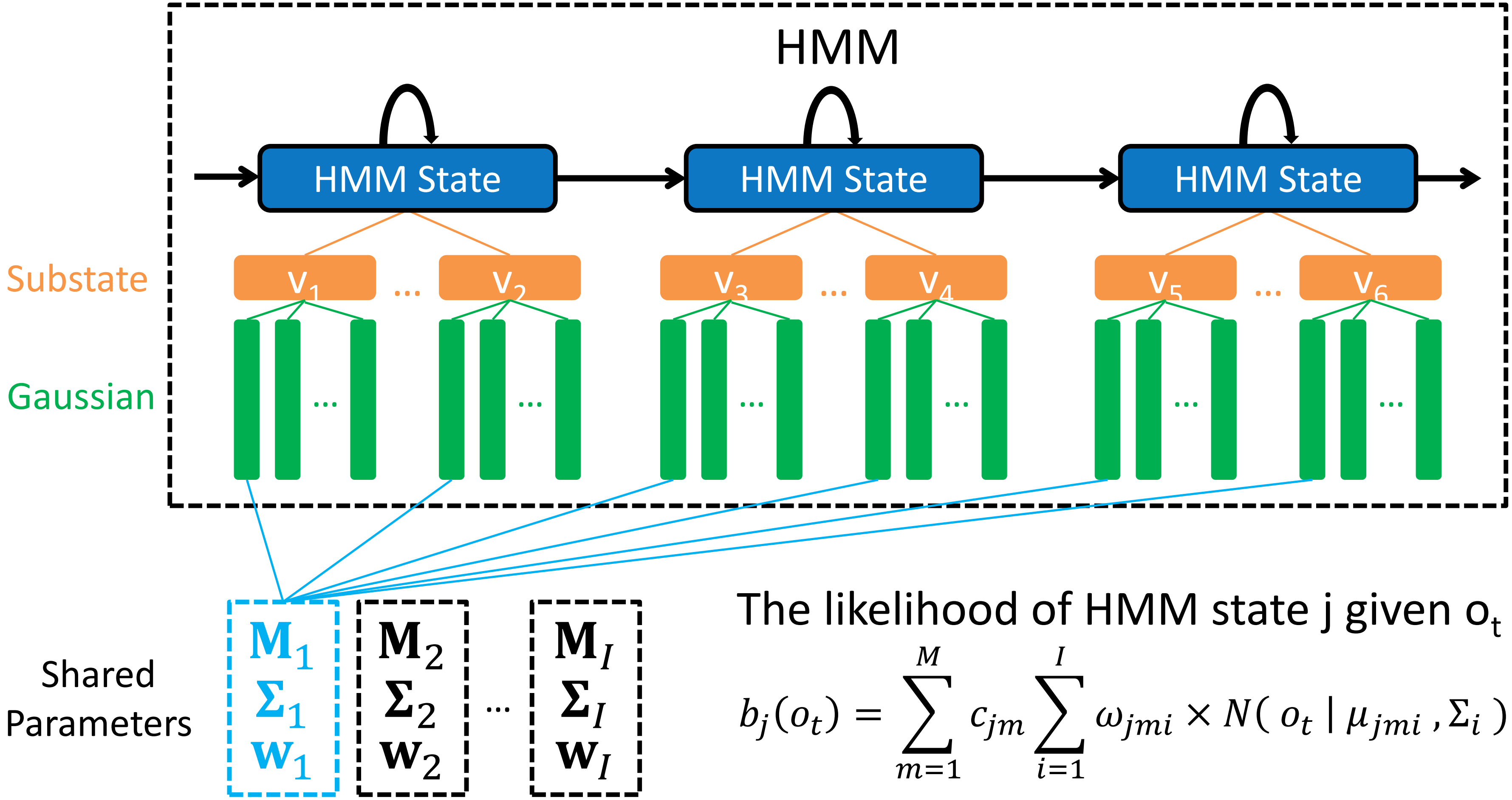
$I \approx 400$

$D \approx 39 \quad S \approx 40$

M$_i$ is the basis set spanning a subspace of mean (columns of **M**$_i$ not necessarily orthogonal)

Subspace Gaussian Mixture Model

- **A triphone HMM in Subspace GMM**


HMM
HMM State
HMM State
HMM State
Substate
v_1
…
v_2
v_3
…
v_4
v_5
…
v_6
Gaussian
…
Shared Parameters
$\mathbf{M}_1$ $\mathbf{\Sigma}_1$ $\mathbf{w}_1$
$\mathbf{M}_2$ $\mathbf{\Sigma}_2$ $\mathbf{w}_2$
…
$\mathbf{M}_I$ $\mathbf{\Sigma}_I$ $\mathbf{w}_I$

The likelihood of HMM state j given o_t

$$b_j(o_t) = \sum_{m=1}^{M} c_{jm} \sum_{i=1}^{I} \omega_{jmi} \times N(\, o_t \mid \mu_{jmi} \,, \Sigma_i \,)$$

j: state, m:substate, i: Gaussian

References for Subspace Gaussian Mixture Model

- **"The Subspace Gaussian Mixture Model– a Structured Model for Speech Recognition"**, D. Povey, Lukas Burget et. al Computer Speech and Language, 2011

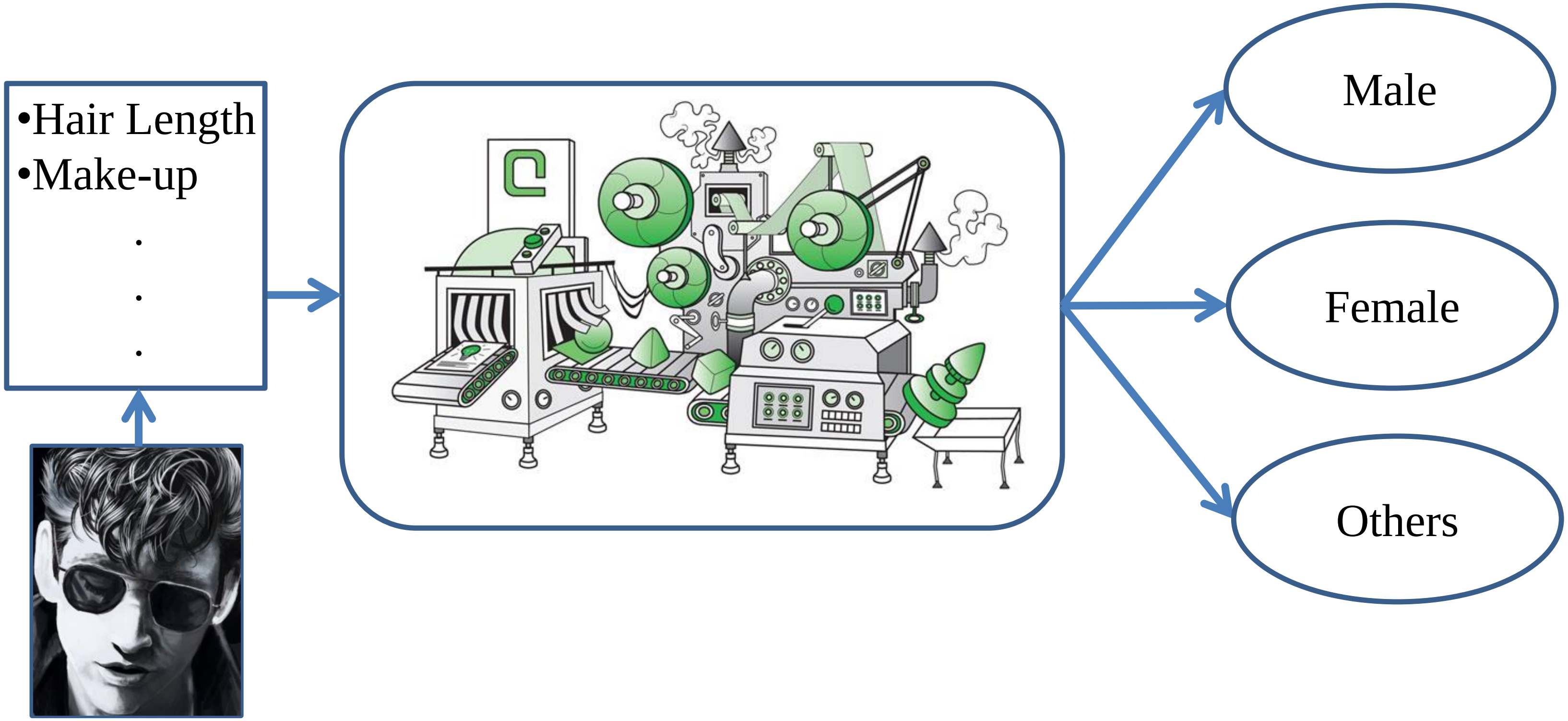
- **"A Symmetrization of the Subspace Gaussian Mixture Model"**, Daniel Povey, Martin Karafiat, Arnab Ghoshal, Petr Schwarz, ICASSP 2011

- **"Subspace Gaussian Mixture Models for Speech Recognition"**, D. Povey, Lukas Burget et al., ICASSP 2010

- **"A Tutorial-Style Introduction To Subspace Gaussian Mixture Models For Speech Recognition"**, Microsoft Research technical report MSR-TR-2009-111

Neural Network — Classification Task

Features **Classifier** **Classes**



- Hair Length
- Make-up

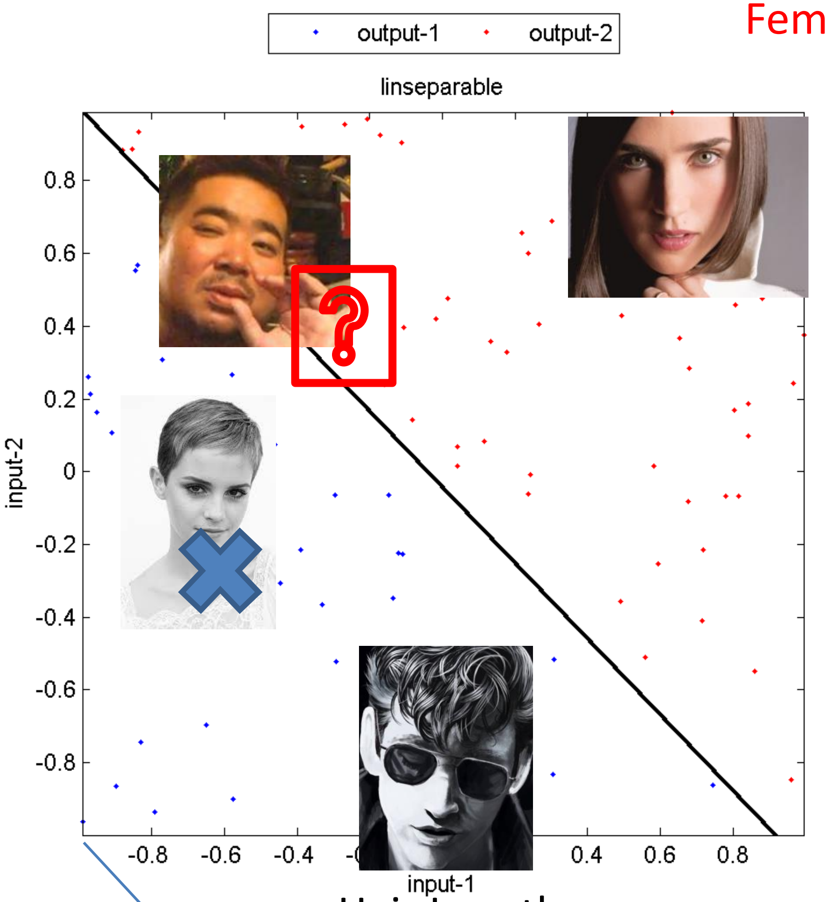
.
.
.

Male

Female

Others

Neural Network — 2D Feature Space



Female

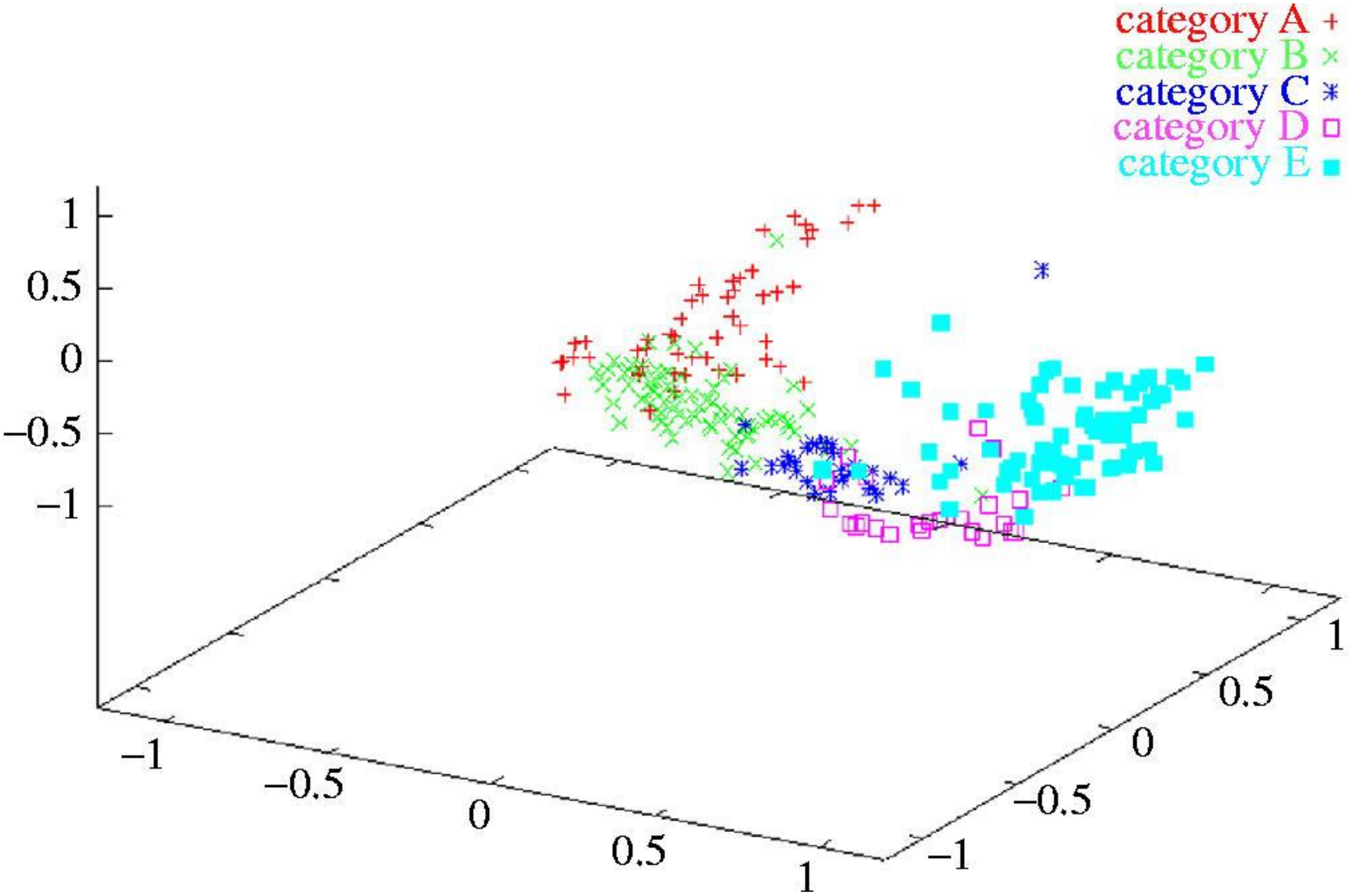
Make-Up

Male

Hair Length

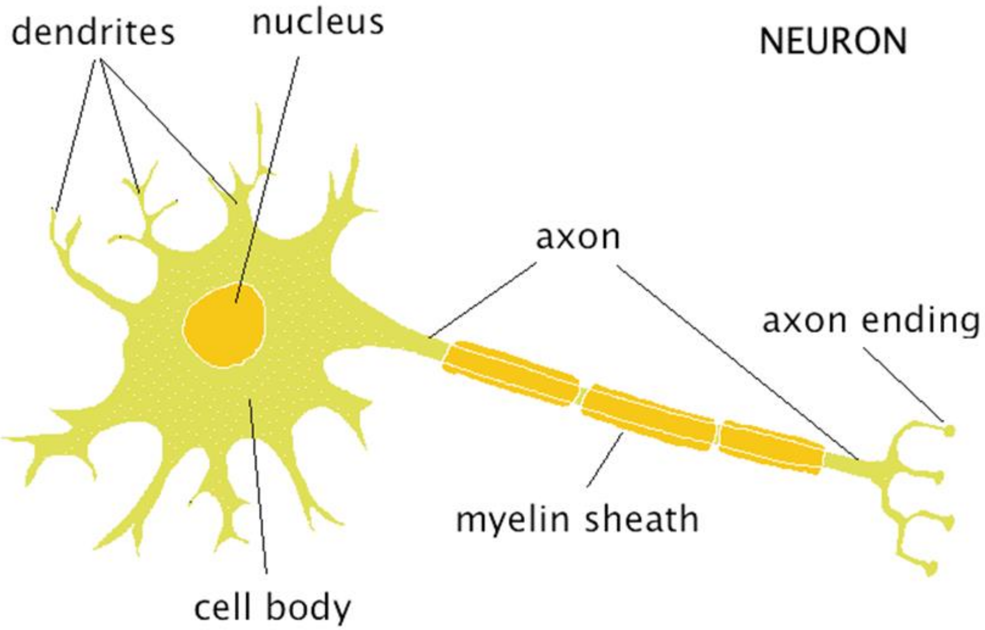
Voice pitch

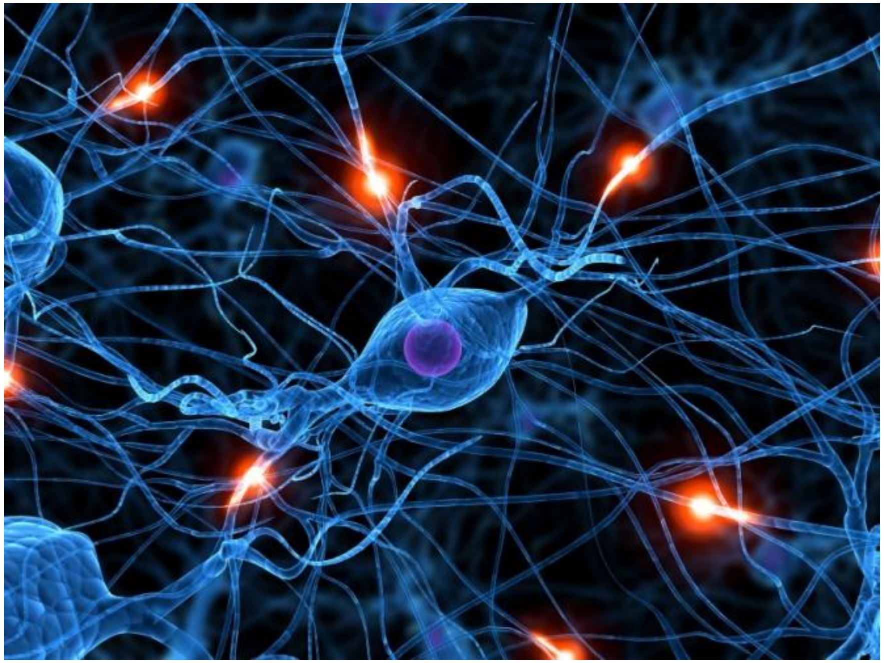
Neural Network – Multi-Dimensional Feature Space



- **We need some type of non-linear function!**

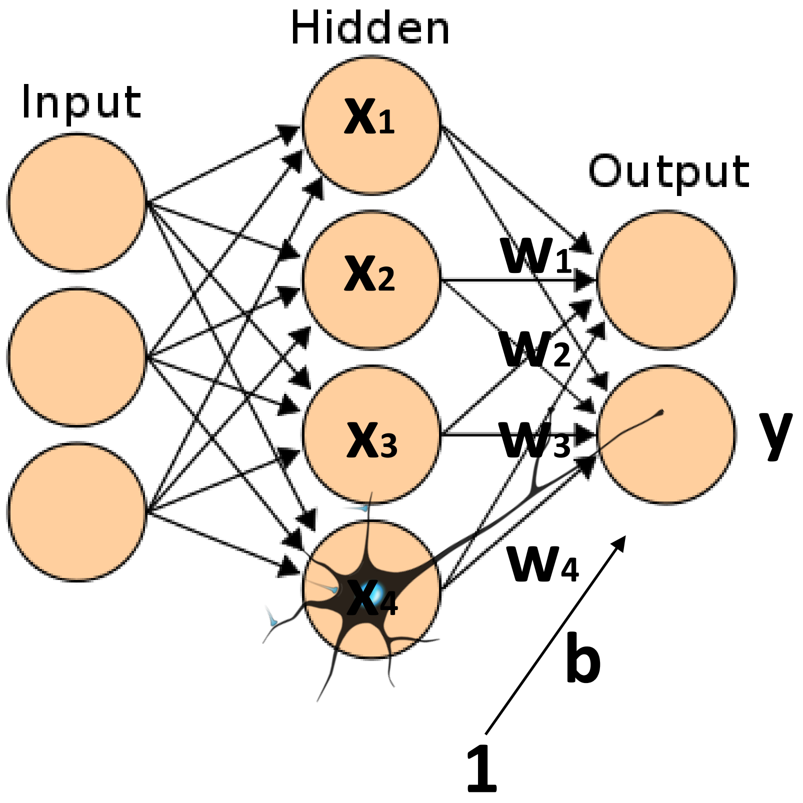
Neural Network — Neurons





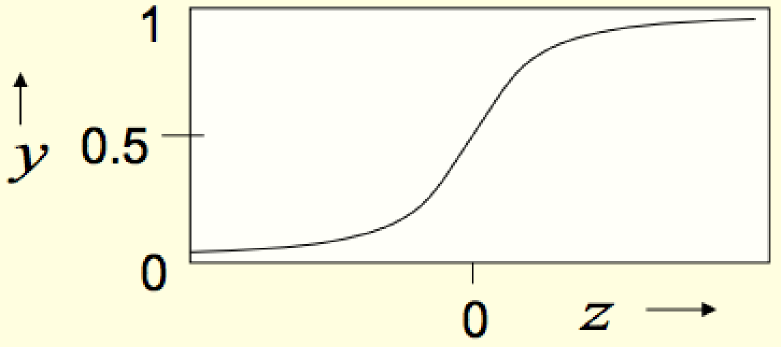
- Each neuron receives inputs from other neurons
- The effect of each input on the neuron is adjustable (weighted)
- The weights adapt so that the whole network learns to perform useful tasks

Neural Network



$$y_k = f(b_k + \sum_i x_i w_{ik})$$

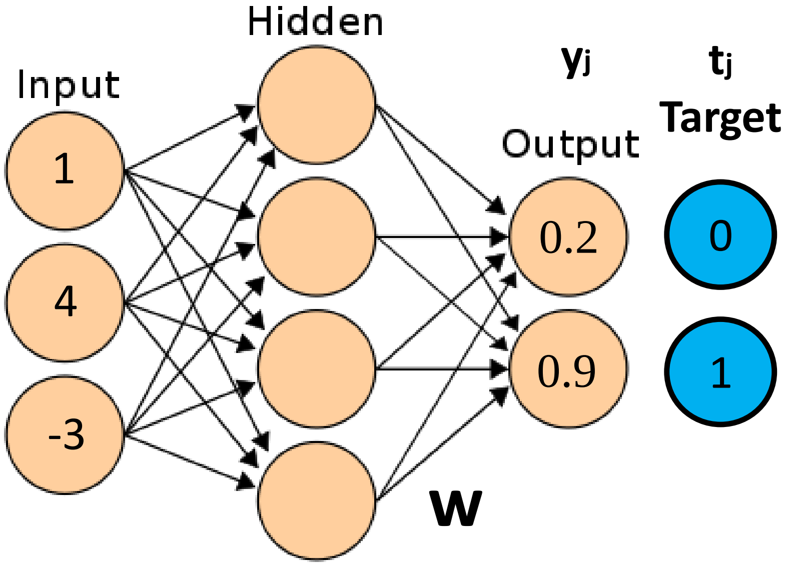
$$z = b + \sum_i x_i w_i \qquad y = \frac{1}{1 + e^{-z}}$$



- A lot of simple non-linearity → complex non-linearity

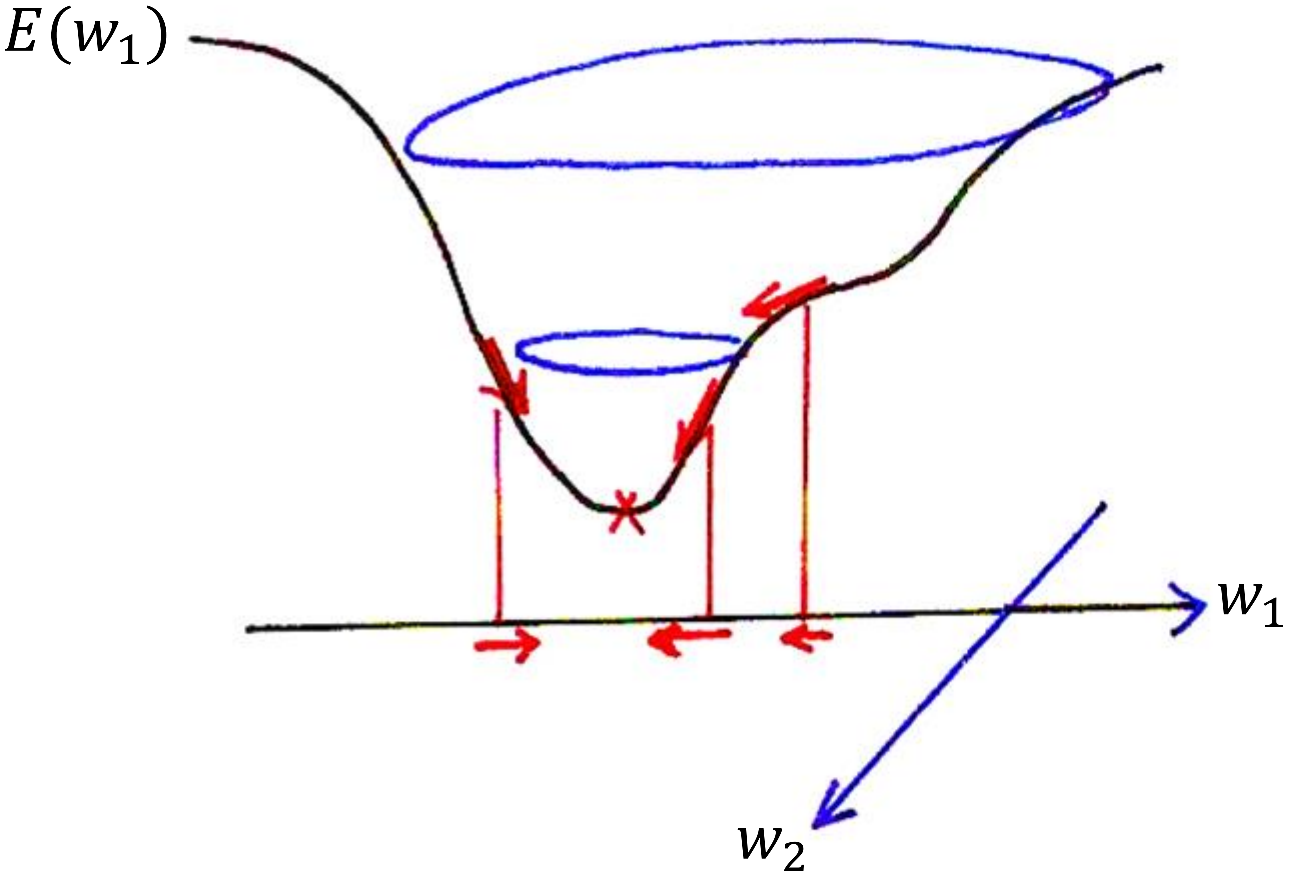
Neural Network Training – Back Propagation

- **Start with random weights**
- **Compare the outputs of the net to the targets**
- **Try to adjust the weights to minimize the error**

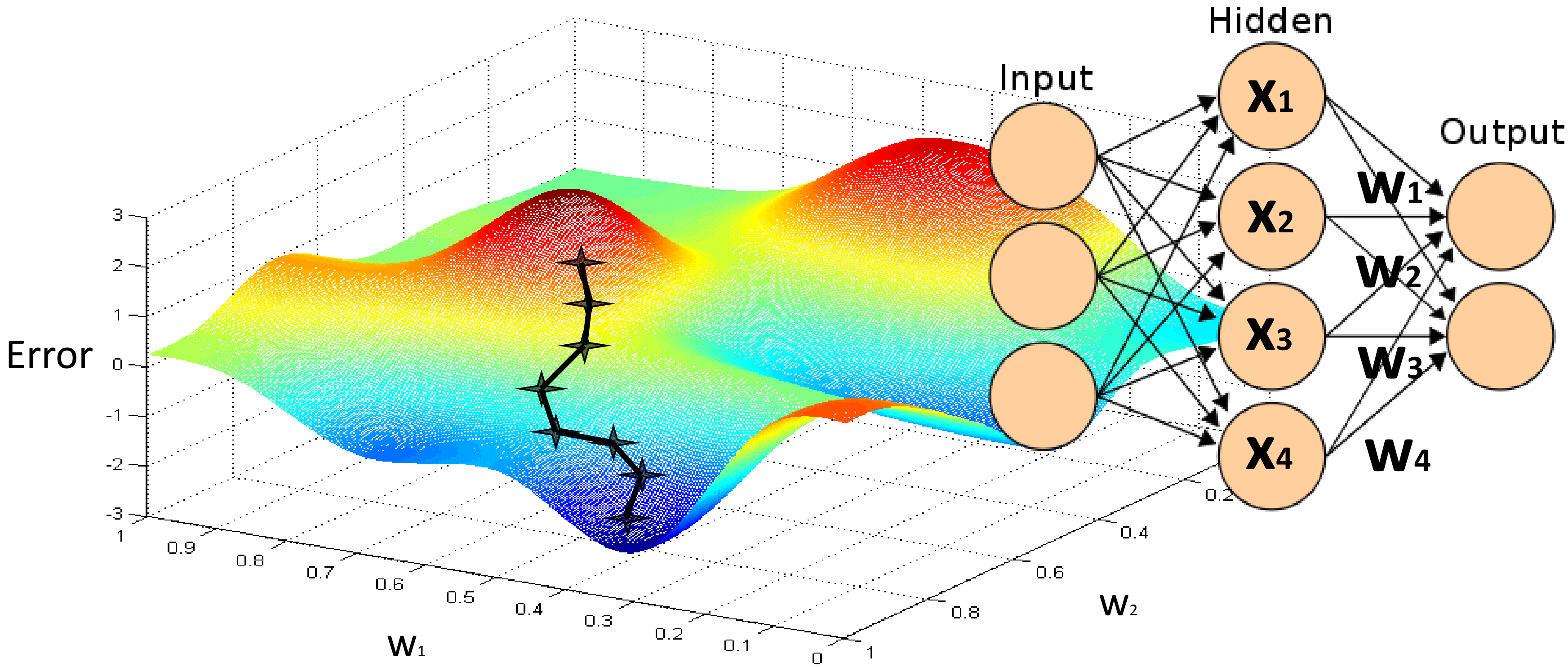


$$E = \tfrac{1}{2} \sum_{j \in output} (t_j - y_j)^2$$

Gradient Descent Algorithm



Gradient Descent Algorithm



$$w_{t+1} = w_t - \alpha \frac{\partial E}{\partial w}$$

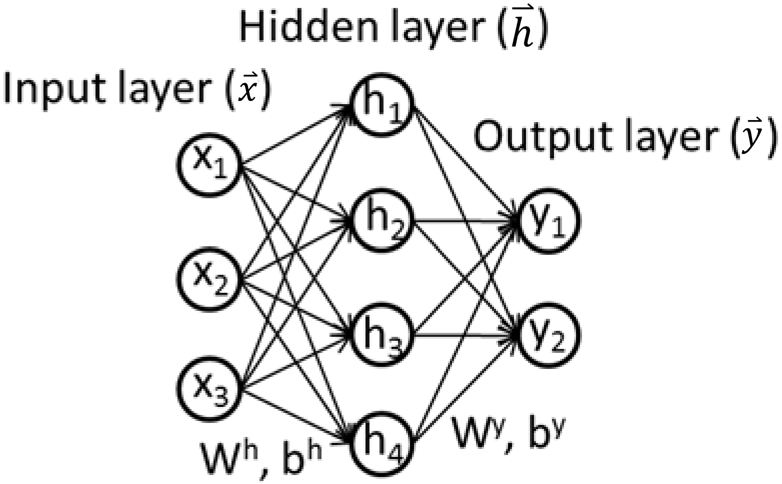
Updated weights

Learning rate

Weight at t-th iteration

Neural Network — Formal Formulation

- **Neural Network (Multi-Layer Perceptron):**
  - a non-linear statistical modeling tool
  - architecture: input layer $\vec{x}$, hidden layer $\vec{h}$, and output layer $\vec{y}$



$$\vec{h} = f(W^h\vec{x} + b^h)$$
$$\vec{y} = g(W^y\vec{h} + b^y)$$

f,g: non-linear functions

e.g. $f(z) = \frac{1}{1+e^{-z}}$ (sigmoid)

$\mathrm{g}(z_m) = \frac{e^{z_m}}{\sum_k e^{z_k}}$ (softmax)

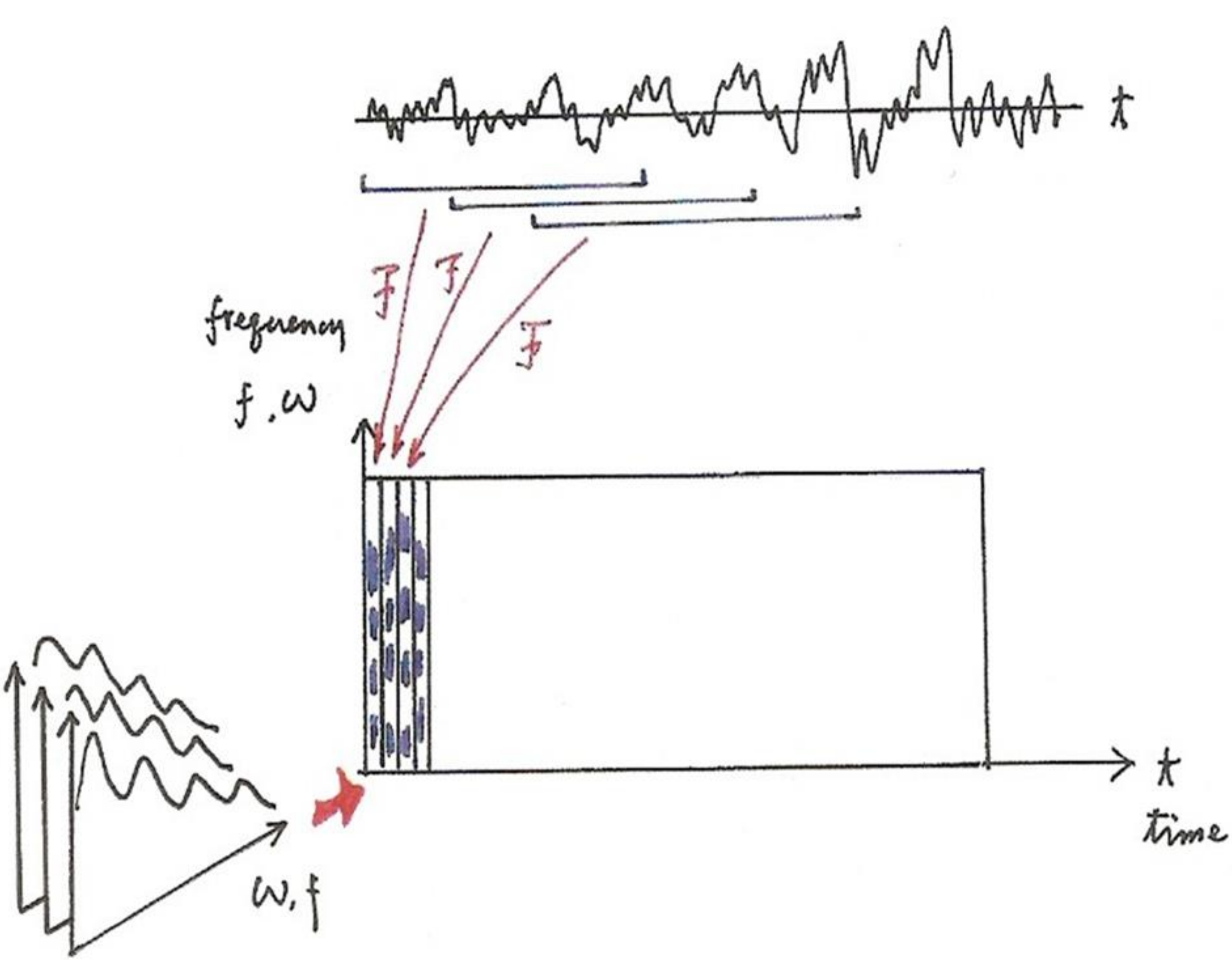
  - W^h, W^y: weight matrix; b^h, b^y: bias vector

- **Neural Network Training:**
  - with training examples $(\vec{x}^{(i)}, l^{(i)})$ ($l^{(i)}$: labels)
  - minimize the error function: $E(W^h, W^y, b^h, b^y) = \sum_i ||y^{(i)} - l^{(i)}||^2$
  - back propagation: minimizing the error function by adjusting the parameters applied beforehand

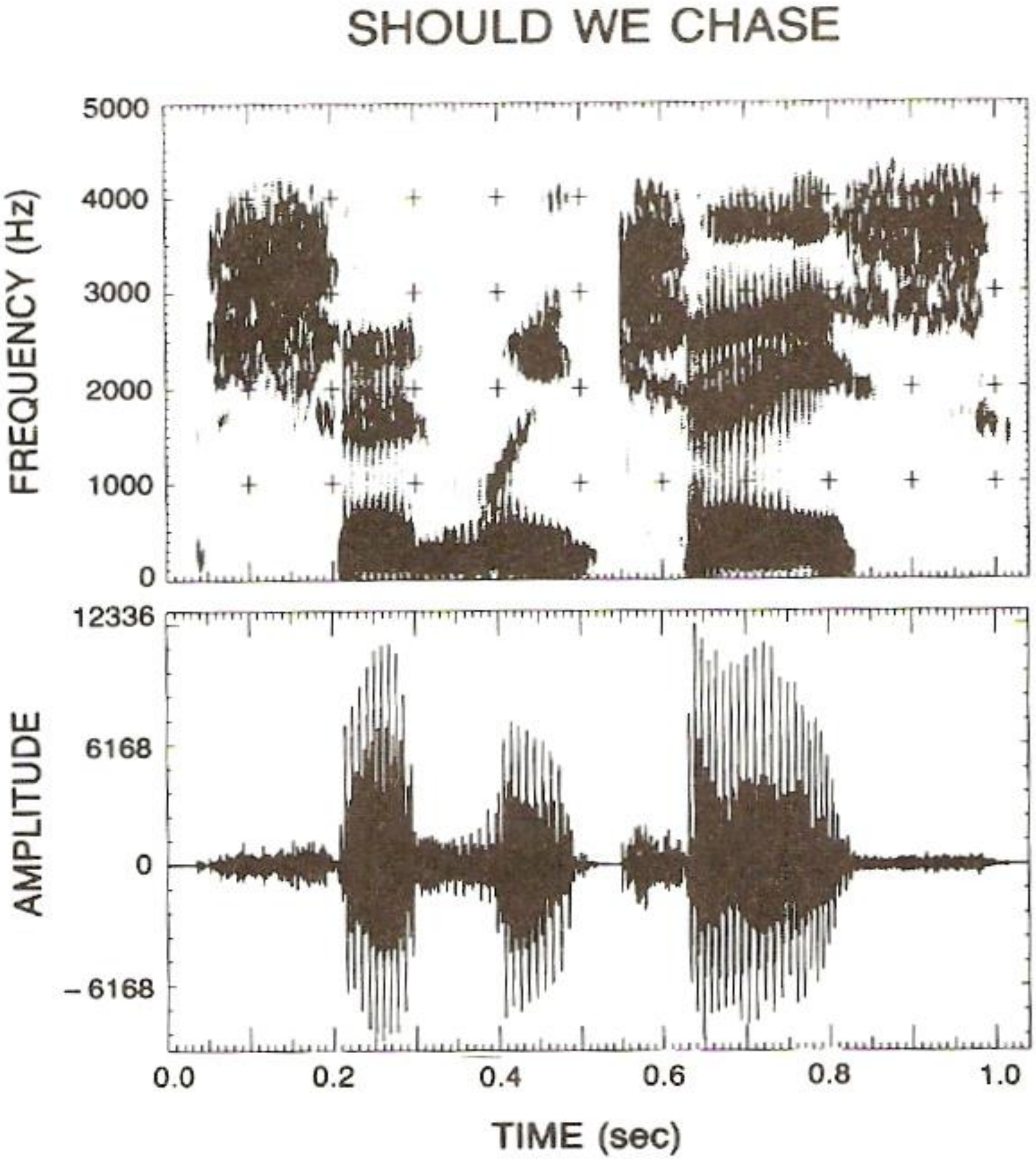
References for Neural Network

- Rumelhart, David E.; Hinton, Geoffrey E., Williams, Ronald J. "Learning representations by back-propagating errors". Nature, 1986.
- Alpaydın, Ethem. Introduction to machine learning (2nd ed.), MIT Press, 2010.
- Albert Nigrin, Neural Networks for Pattern Recognition(1st ed.). A Bradford Book, 1993.
- Reference: Neural Networks for Machine Learning course by Geoffrey Hinton, Coursera

Spectrogram



Spectrogram

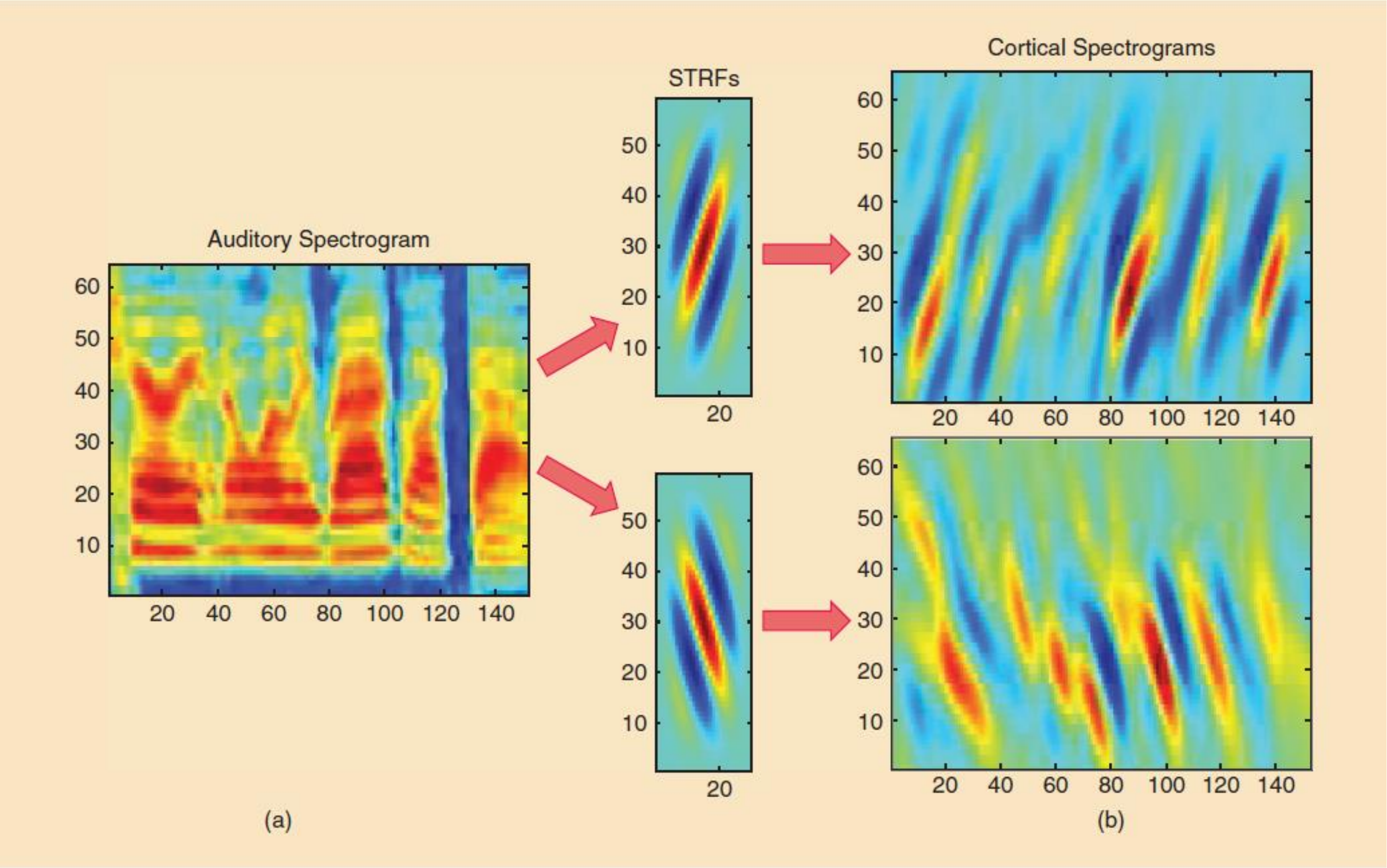


Gabor Features (1/2)

$$G(t,f) = \frac{1}{2\pi\sigma_f\sigma_t} exp\left[\frac{-(f-f_0)^2}{2\sigma_f^2} + \frac{-(t-t_0)^2}{2\sigma_t^2}\right] exp\left[iw_f(f-f_0) + iw_t(t-t_0)\right]$$

- **2-dim Gabor filters**
  - 2-dim Gaussian multiplied by 2-dim sine waves
  - 2-dim convolution with the 2-dim (mel-) spectrogram
- **Gabor Features**
  - a whole set of features defined by $(f_0, t_0, \sigma_f^2, \sigma_t^2, w_f, w_t)$
  - some of them simulating human perception to some degree
  - spectrogram can be read by human expert in the past
  - how these features are related to sounds represented by speech signals can be learned by machine

Gabor Features (2/2)

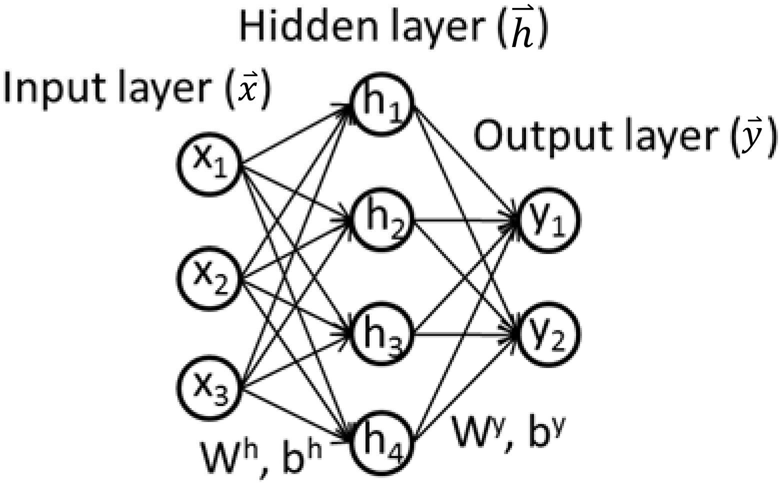


Integrating HMM with Neural Networks

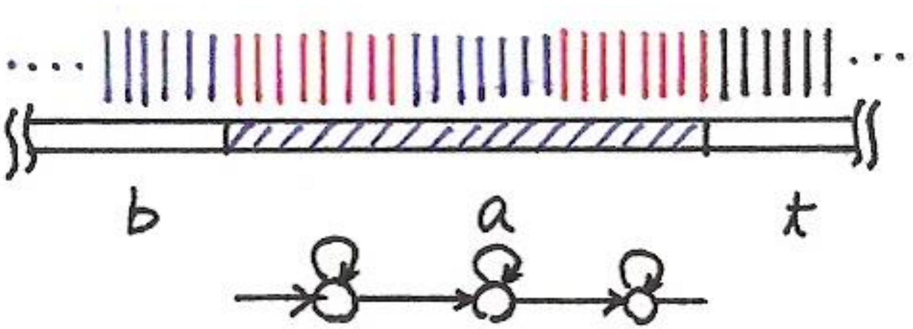
- **Tandem System**
  - Multi-layer Perceptron (MLP, or Neural Network) offers phoneme posterior vectors (posterior probability for each phoneme)
  - MLP trained with known phonemes for MFCC (or plus Gabor) vectors for one or several consecutive frames as target
  - phoneme posteriors concatenated with MFCC as a new set of features for HMM
  - phoneme posterior probabilities may need further processing to be better modeled by Gaussians
- **Hybrid System**
  - Gaussian probabilities in each triphone HMM state replaced by state posteriors for phonemes from MLP trained by feature vectors with known state segmentation

Phoneme Posteriors and State Posteriors

- **Neural Network Training**

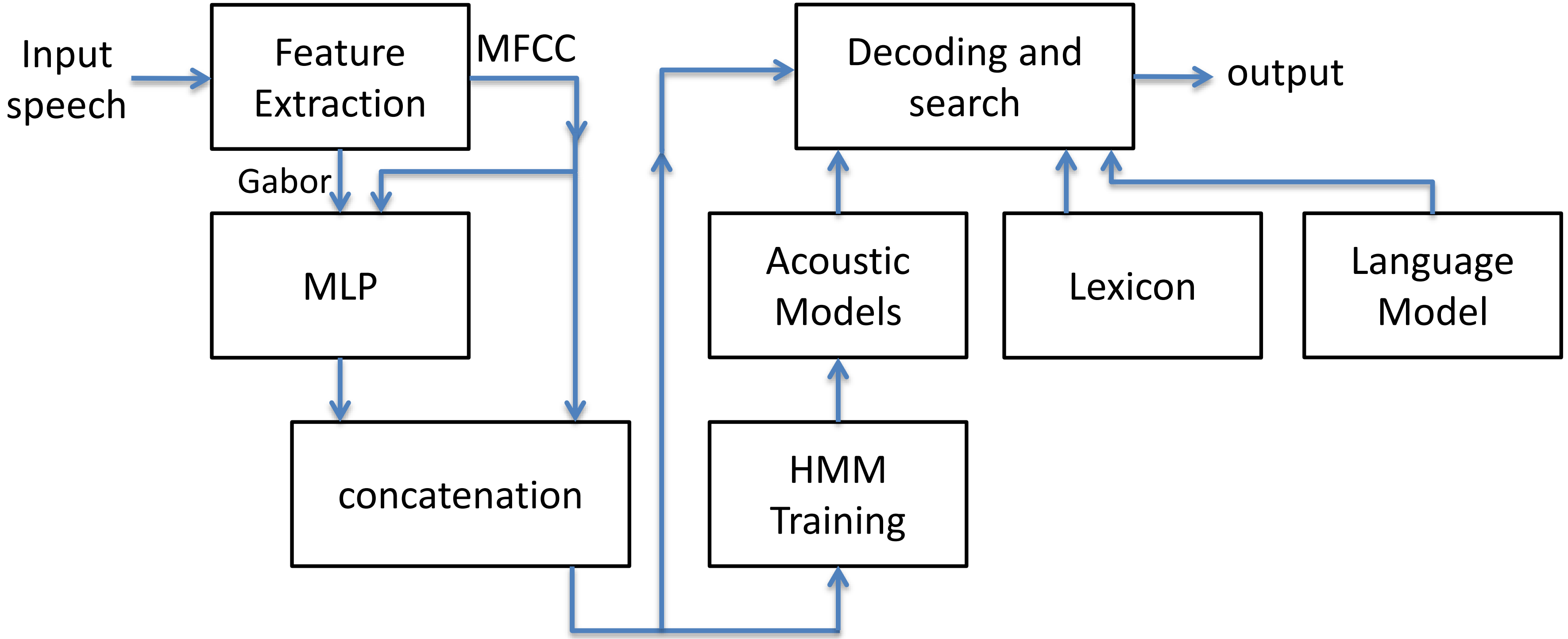


Phone Posterior	State Posterior
$P(a\|x)$	$P(b\text{–}\,a(1)\text{–}\,t\|x)$
$P(b\|x)$	$P(b\text{–}\,a(2)\text{–}\,t\|x)$
⋮	⋮



Integrating HMM with Neural Networks

- **Tandem System**
  - phoneme posterior vectors from MLP concatenated with MFCC as a new set of features for HMM



Integrating HMM with Neural Networks

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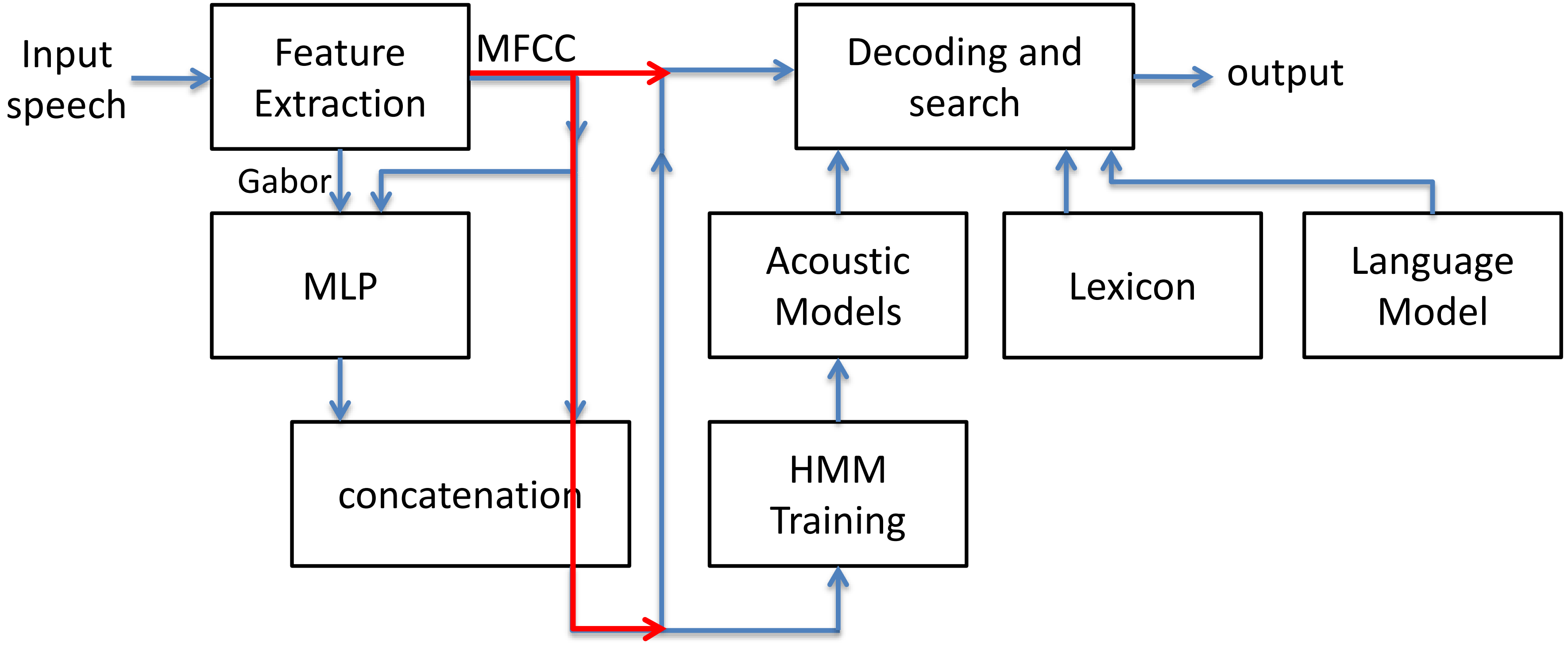
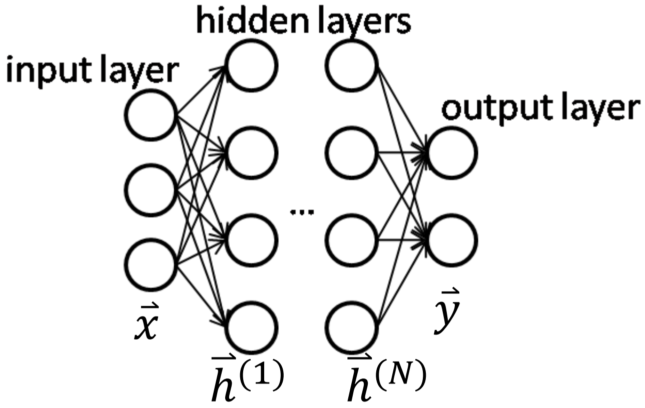


References

- **References for Gabor Features and Tandem System**
  - Richard M. Stern & Nelson Morgan, “Hearing Is Believing”, IEEE SIGNAL PROCESSING MAGAZINE, NOVEMBER 2012
  - Hermansky, H., Ellis, D.P.W., Sharma, S., “Tandem Connectionist Feature Extraction For Conventional Hmm Systems”, in Proc. ICASSP 2000.
  - Ellis, D.P.W. and Singh, R. and Sivadas, S., “Tandem acoustic modeling in large-vocabulary recognition”, in Proc. ICASSP 2001.
  - “Improved Tonal Language Speech Recognition by Integrating Spectro-Temporal Evidence and Pitch Information with Properly Chosen Tonal Acoustic Units”, Interspeech, Florence, Italy, Aug 2011, pp. 2293-2296.

Deep Neural Network (DNN)

- **Deep Neural Network (DNN):**
  - Neural network with multiple hidden layers
  - architecture: with input $\vec{x}$, N hidden layers and output $\vec{y}$



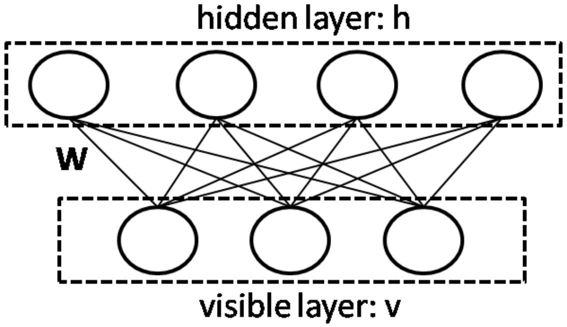
$$\vec{h}^{(1)} = f(W_{0,1}\vec{x} + b_{0,1})$$
$$\vec{h}^{(n)} = f(W_{n-1,n}\vec{h}^{(n-1)} + b_{n-1,n})$$
$$\vec{y} = g(W_{N,N+1}\vec{h}^{(N)} + b_{N,N+1})$$

- **Property:**
  - able to deal with huge and complicated structure of data

- **Difficulties:**
  - large quantities of labelled data needed for training
  - very long training time needed
  - solution: Restricted Boltzmann Machine for initialization

Restricted Boltzmann Machine

- **Restricted Boltzmann Machine (RBM):**
  - a generative model for probability of visible examples (p(v))
  - with a hidden layer of random variables (h)
  - topology: undirected bipartite graph



$$p(\mathrm{v},\mathrm{h}) = \frac{1}{Z} e^{-E(\mathrm{v},\mathrm{h})}$$

$$E(\mathrm{v},\mathrm{h}) = -a^T\mathrm{v} - b^T\mathrm{h} - \mathrm{v}^T W \mathrm{h}$$

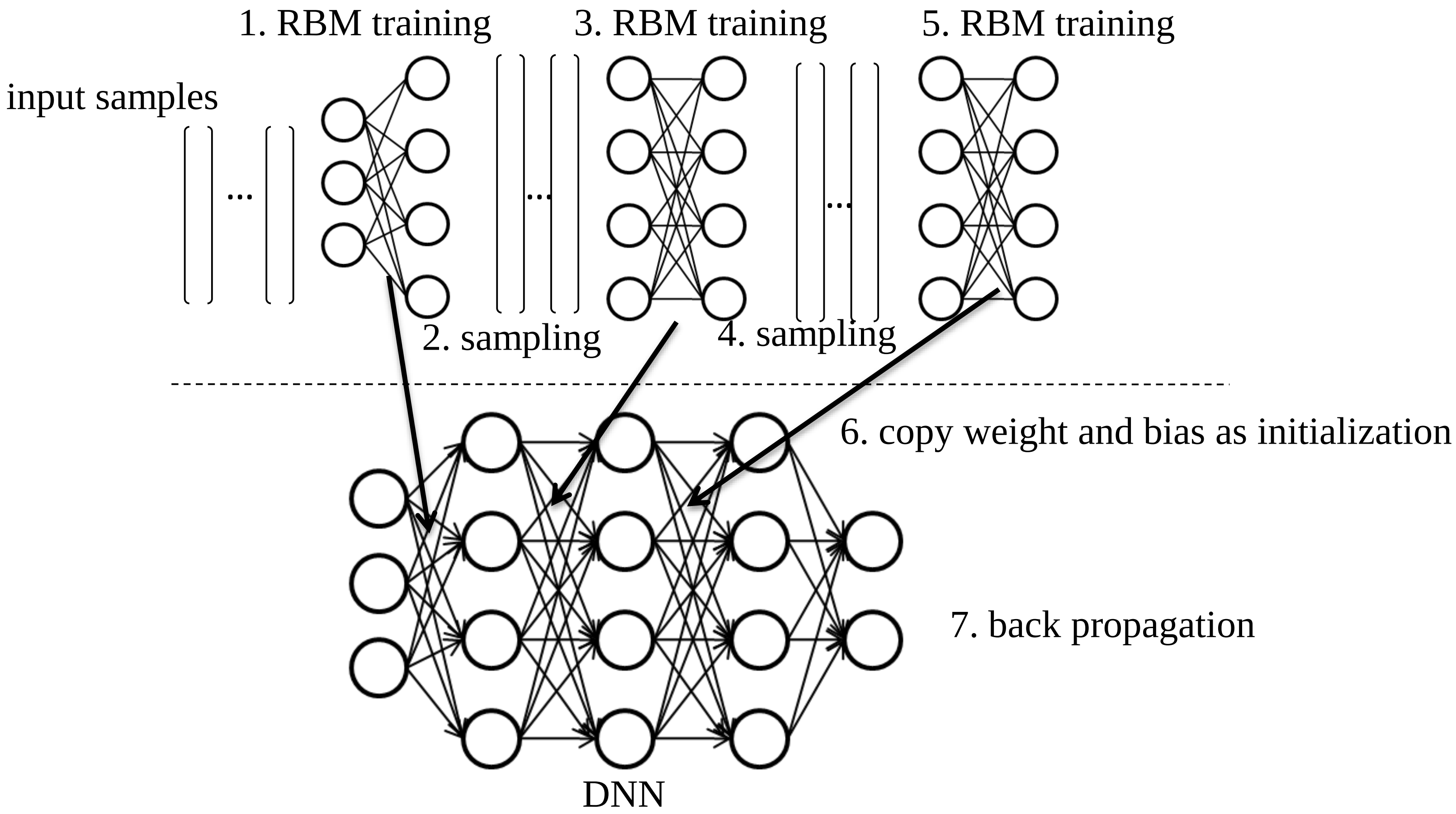
$$p(\mathrm{v}) = \frac{1}{Z}\sum_{\mathrm{h}} e^{-E(\mathrm{v},\mathrm{h})}$$

  - W: weight matrix, describing correlation between visible and hidden layers
  - a, b: bias vectors for visible and hidden layers
  - E: energy function for a (v,h) pair
  - RBM training: adjusting W, a, and b to maximize p(v)

- **Property:**
  - finding a good representation (h) for v in unsupervised manner
  - Using large quantities of unlabelled data

RBM Initialization for DNN Training

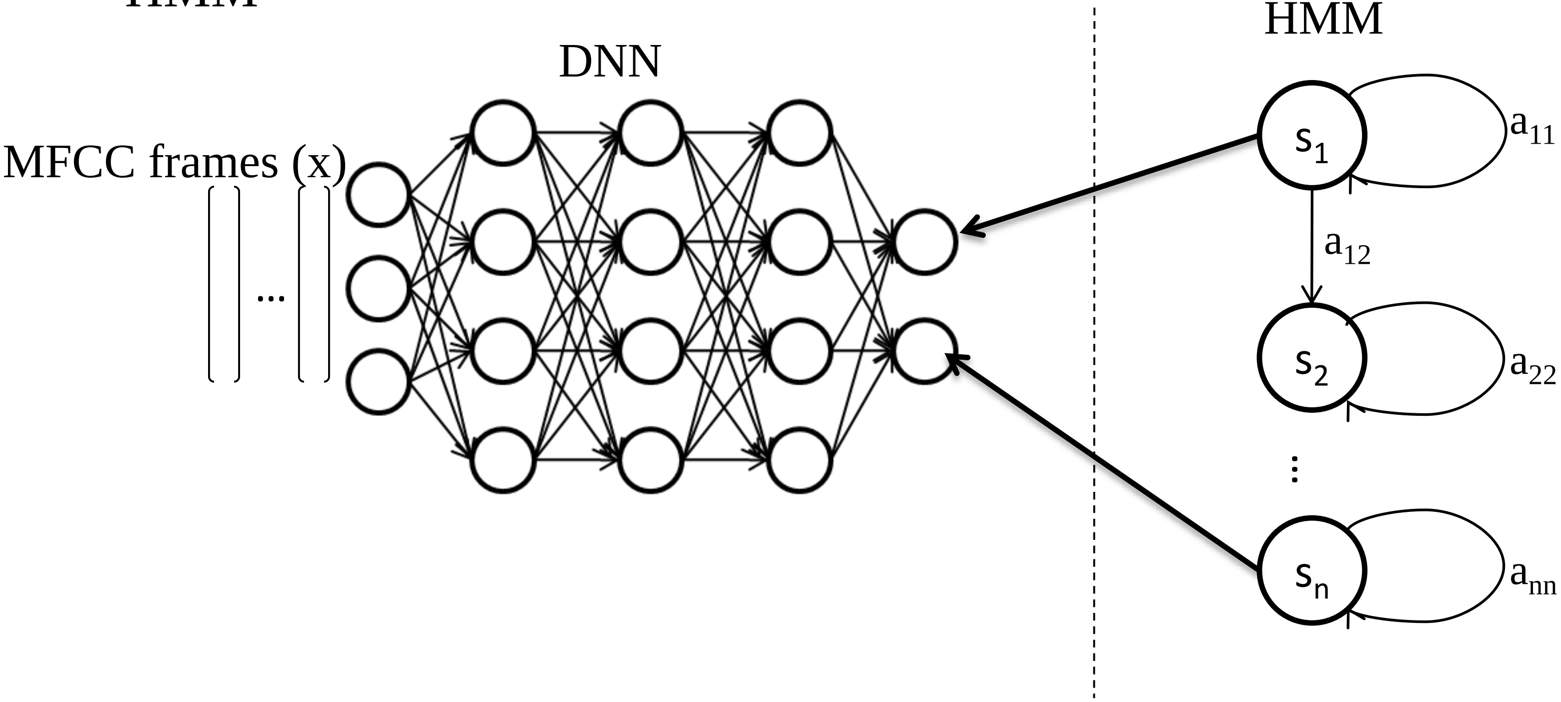
- **RBM Initialization**
  - weight matrices of DNN initialized by weight matrixes of RBMs
  - after training an RBM, generate samples in hidden layer used for next layer of RBM
  - steps of initialization (e.g. 3 hidden layers)



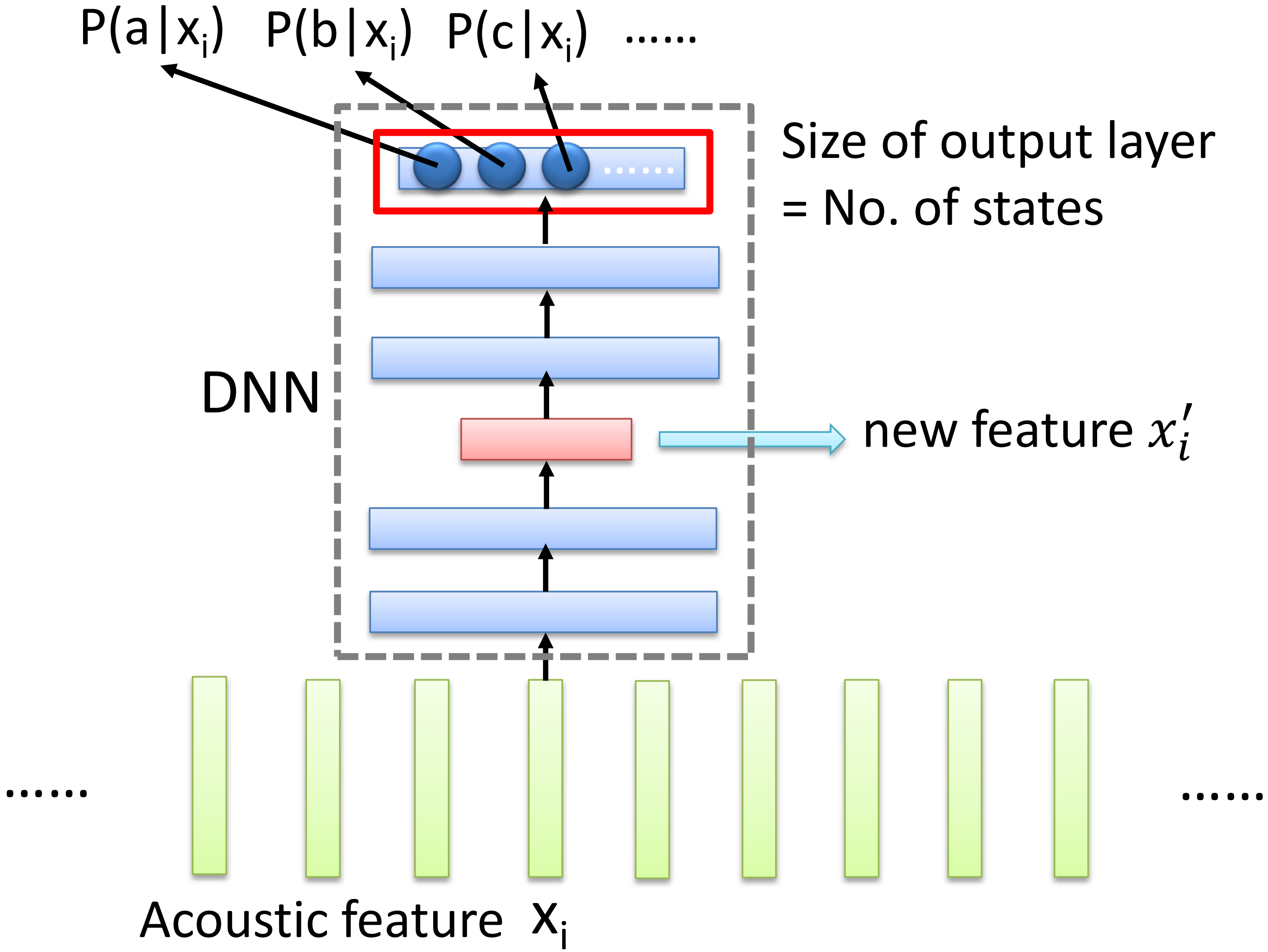
Deep Neural Network for Acoustic Modeling

- **DNN as triphone state classifier**
  - input: acoustic features, e.g. MFCC
  - output layer of DNN representing triphone states
  - fine tuning the DNN by back propagation using labelled data

- **Hybrid System**
  - normalized output of DNN as posterior of states p(s|x)
  - state transition remaining unchanged, modeled by transition probabilities of HMM



Bottleneck Features from DNN



References for DNN

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  - IEEE Trans. on Audio, Speech and Language Processing, Jan, 2012
- **A fast learning algorithm for deep belief**
  - Hinton, G. E., Osindero, S. and Teh, Y
  - Neural Computation, 18, pp 1527-1554, 2006
- **Deep Neural Networks for Acoustic Modeling in Speech Recognition**
  - G. Hinton, L. Deng, D. Yu, G. Dahl, A.Mohamed, N. Jaitly, A. Senior, V. Vanhoucke, P. Nguyen, T. Sainath, and B. Kingsbury
  - IEEE Signal Processing Magazine, 29, November 2012
- **Deep Learning and Its Applications to Signal and Information Processing**
  - IEEE Signal Processing Magazine, Jan 2011
- **Improved Bottleneck Features Using Pretrained Deep Neural Networks**
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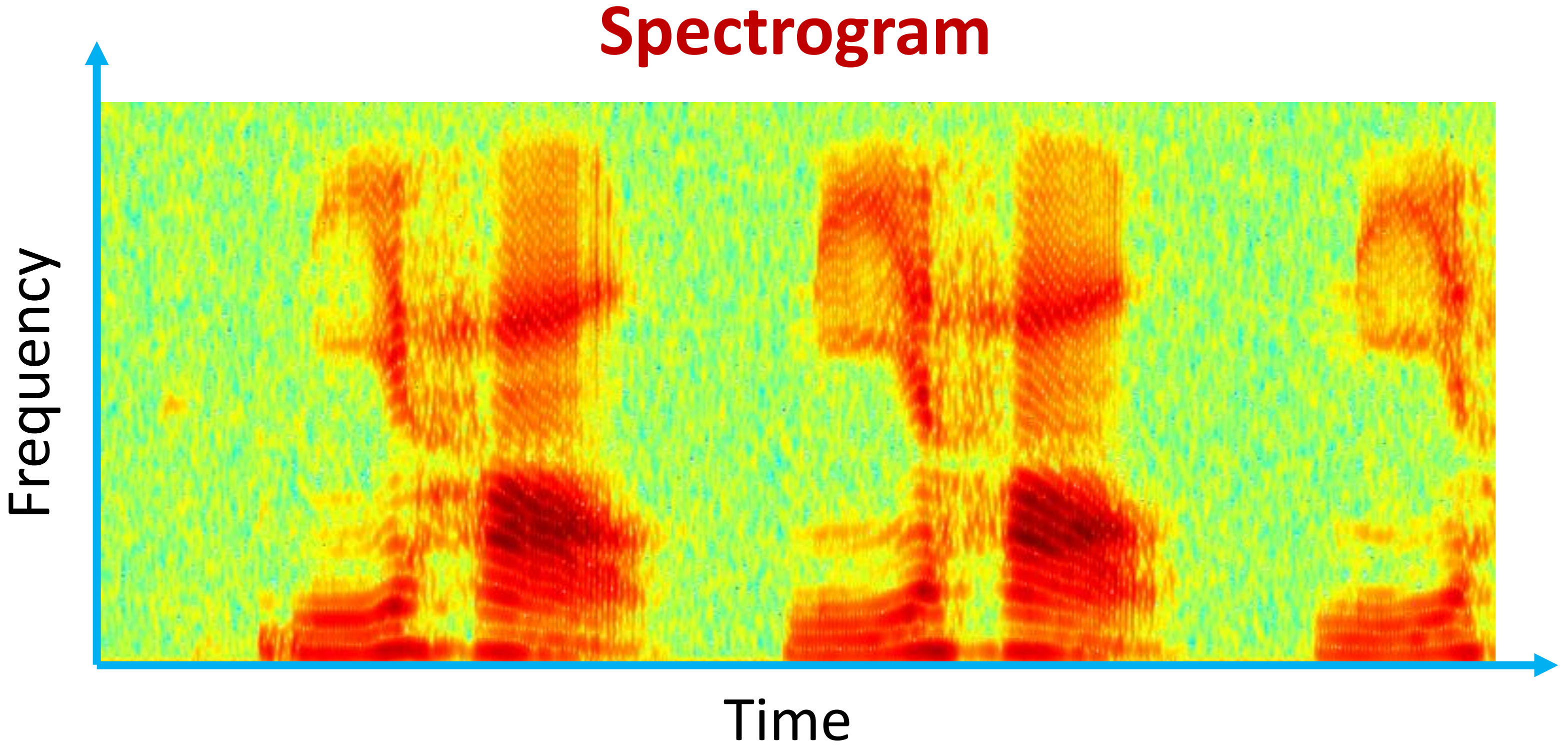
  - Gehring, Jonas, et al.
  - ICASSP 2013

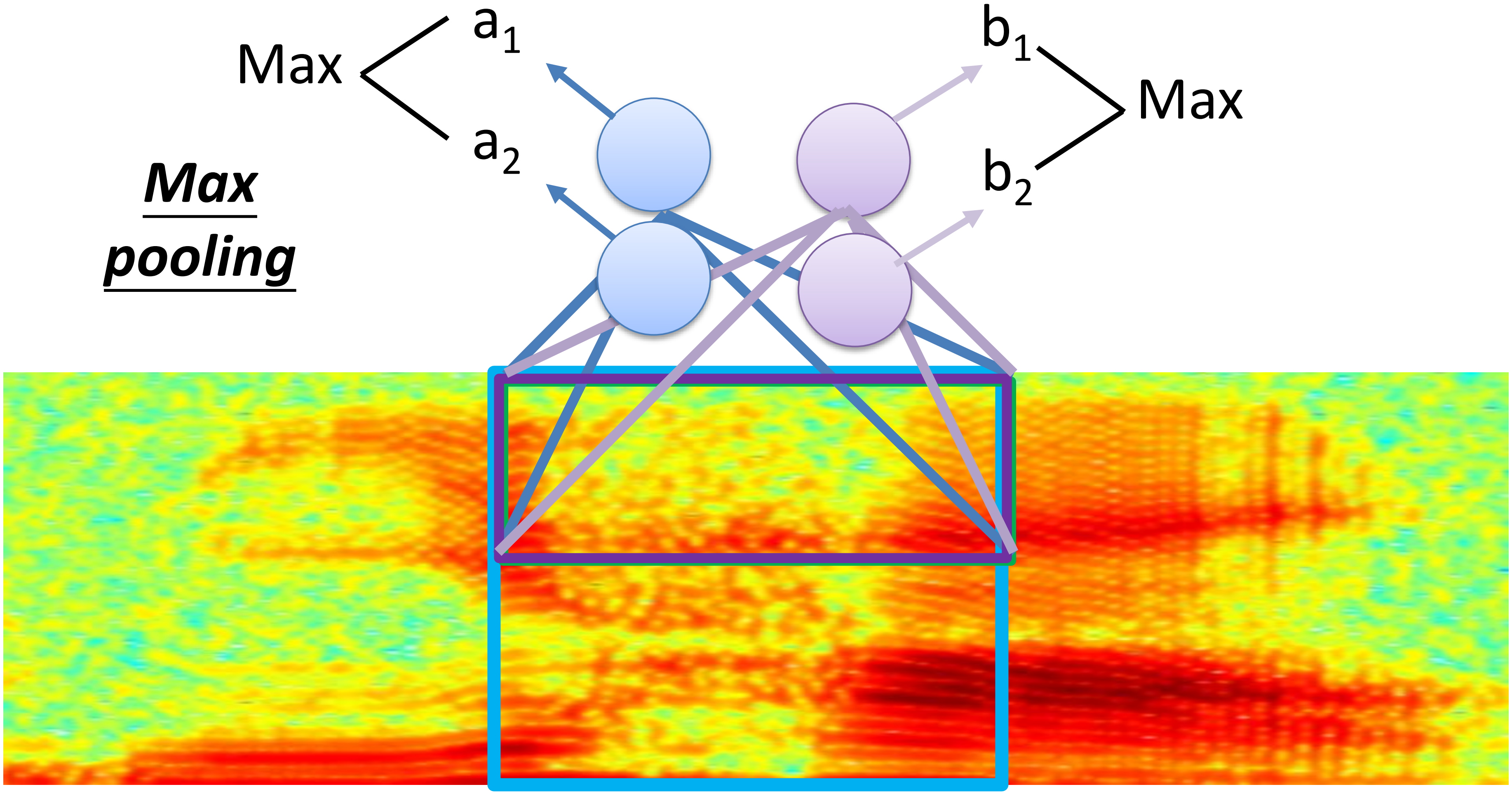
Convolutional Neural Network (CNN)

- Successful in processing images
- Speech can be treated as images



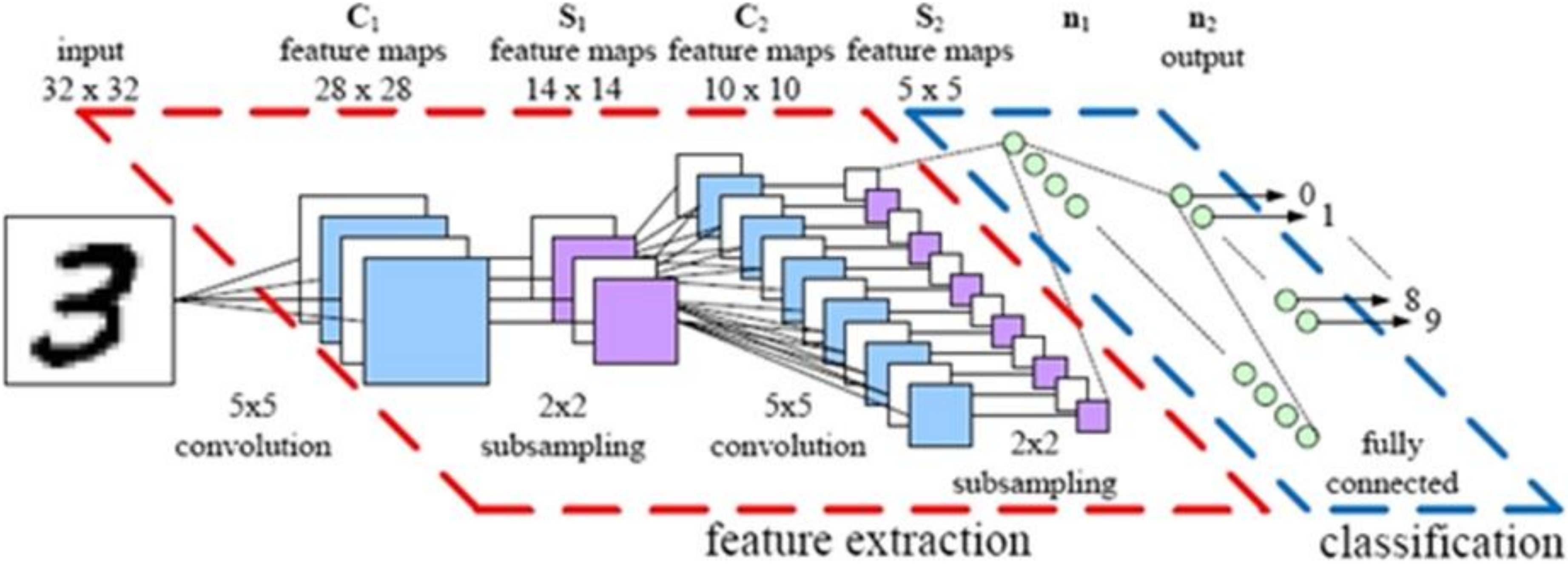
Convolutional Neural Network (CNN)

- An example



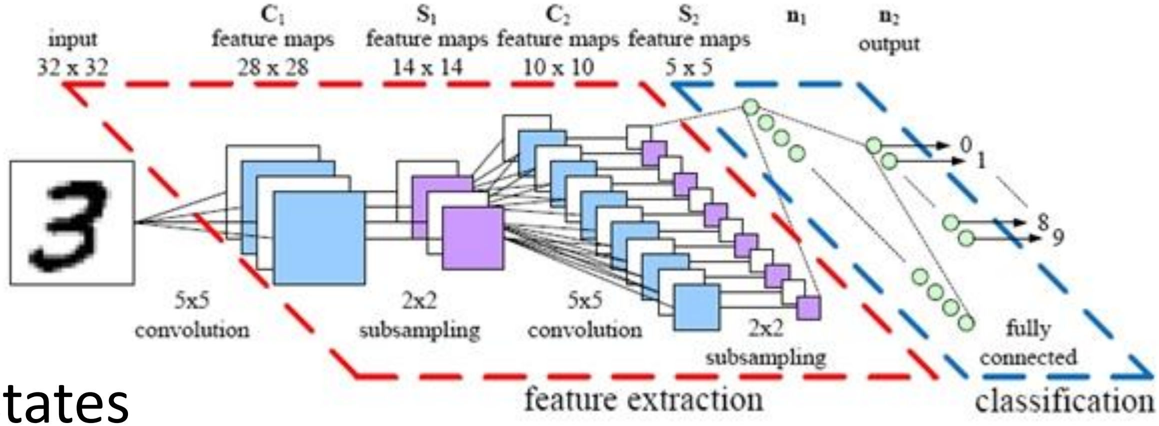
Convolutional Neural Network (CNN)

- An example

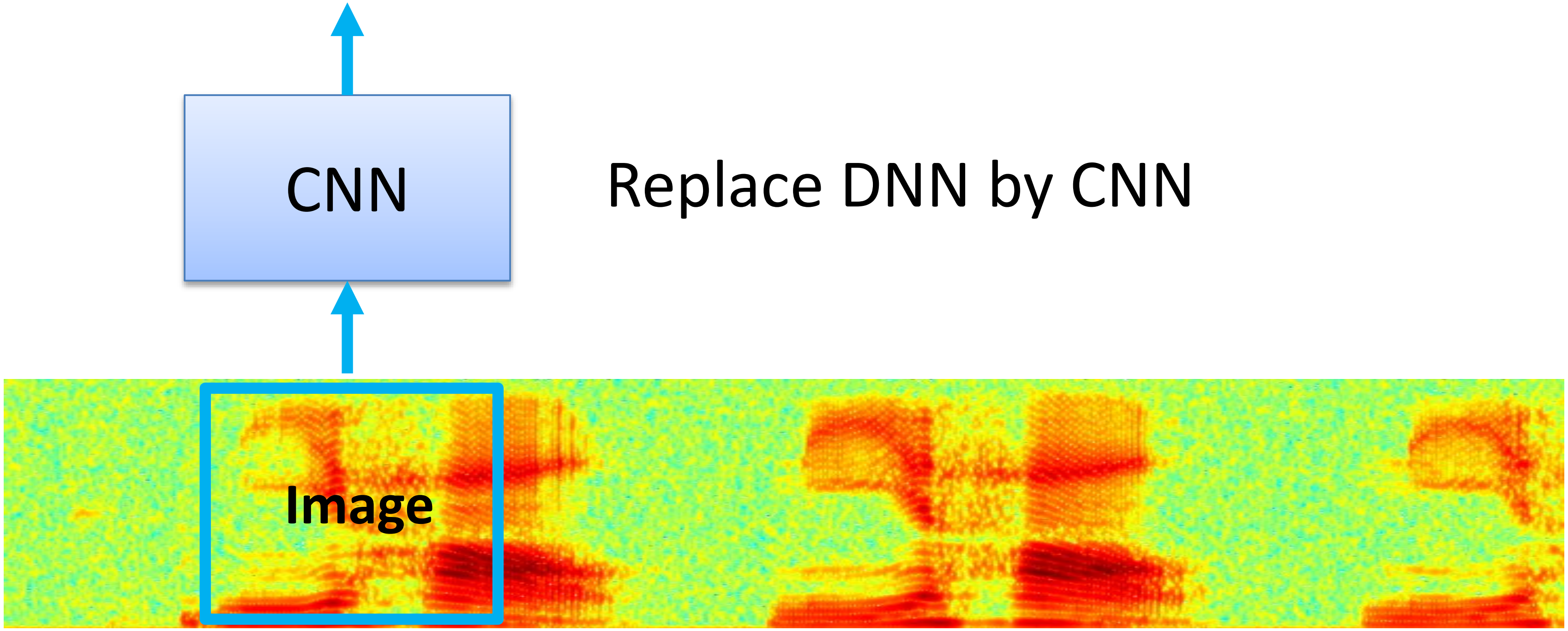


Convolutional Neural Network (CNN)

- An example

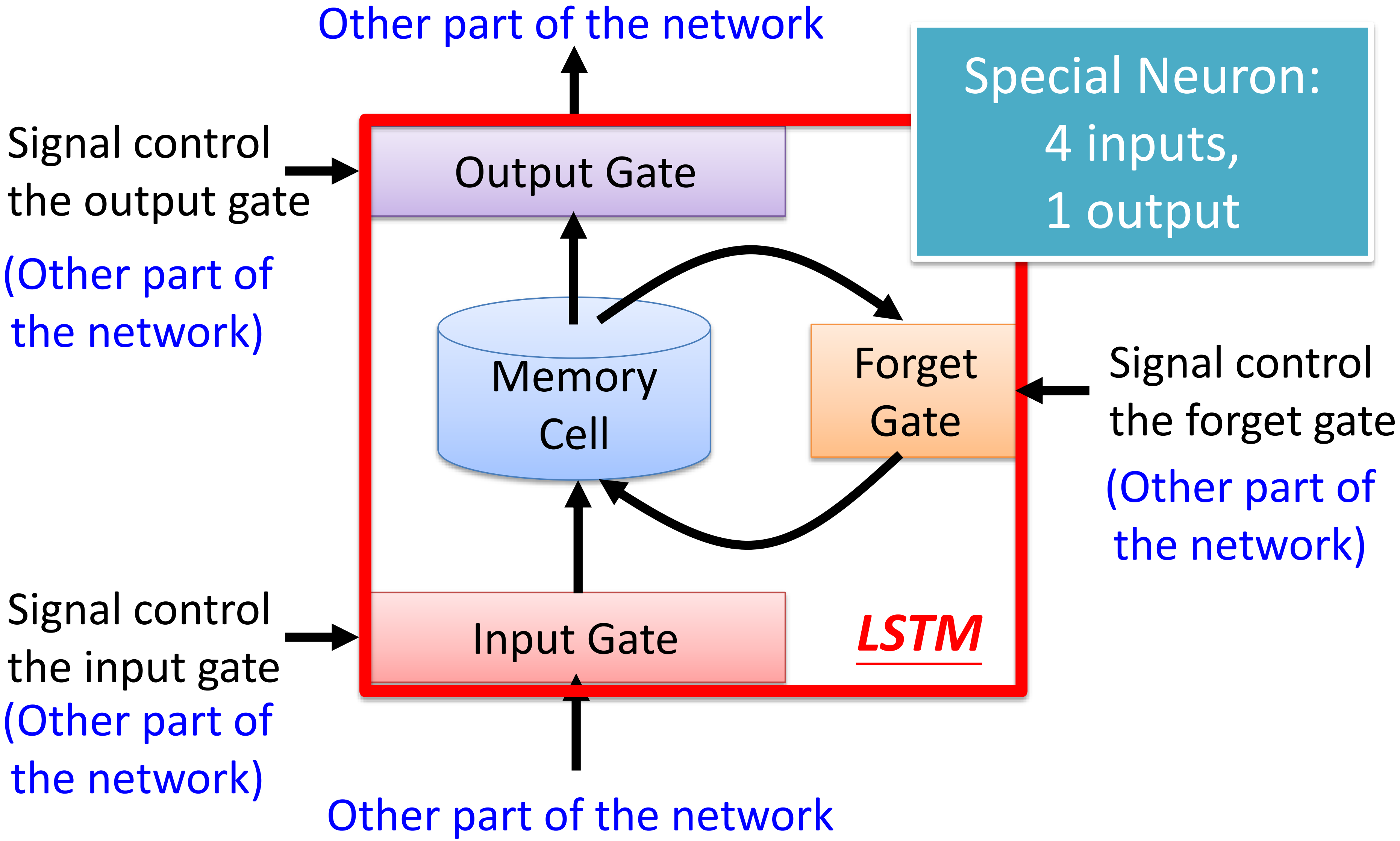


Probabilities of states



Replace DNN by CNN

Long Short-term Memory (LSTM)



Other part of the network

Special Neuron:
4 inputs,
1 output

Signal control the output gate

(Other part of the network)

Output Gate

Memory Cell

Forget Gate

Signal control the forget gate

(Other part of the network)

Signal control the input gate

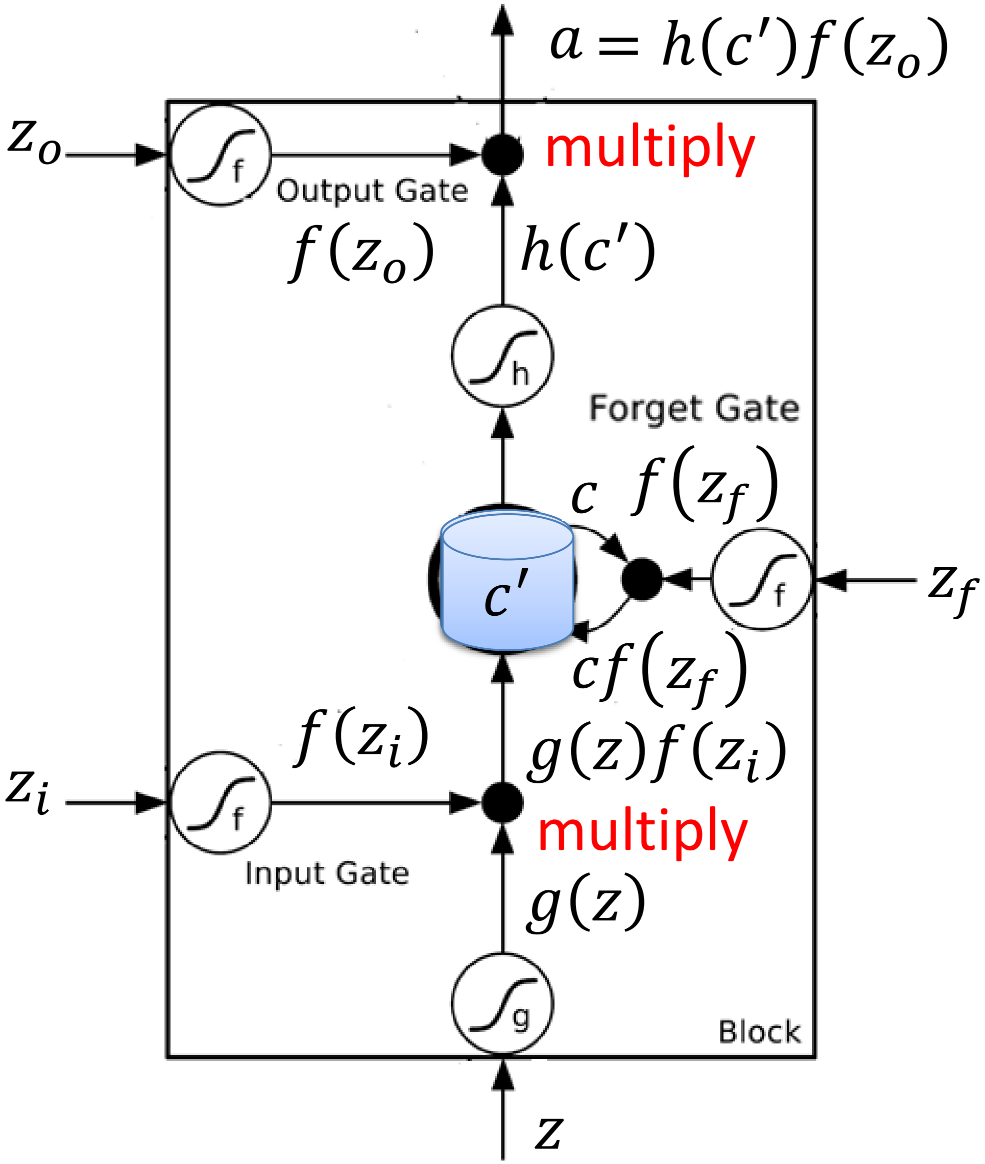
(Other part of the network)

Input Gate

LSTM

Other part of the network

Long Short-term Memory (LSTM)



Activation function f(·) is usually a sigmoid function

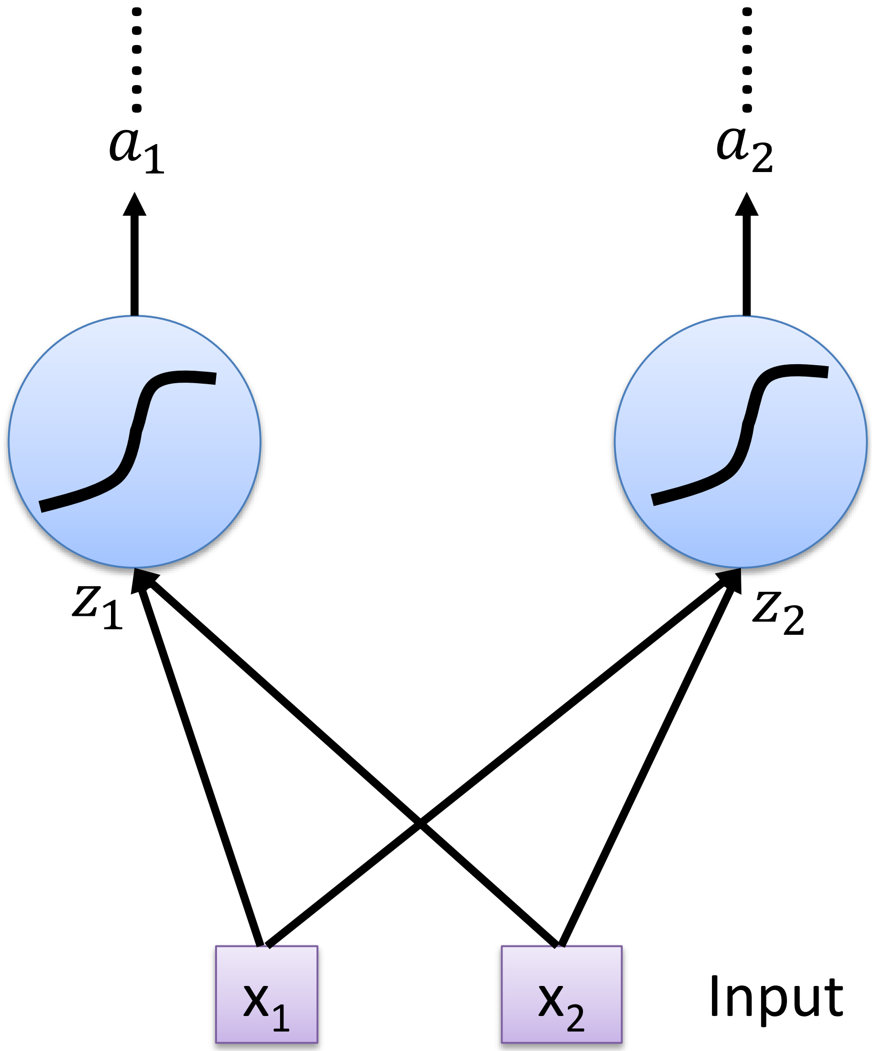
between 0 and 1 for

opening and closing the gate

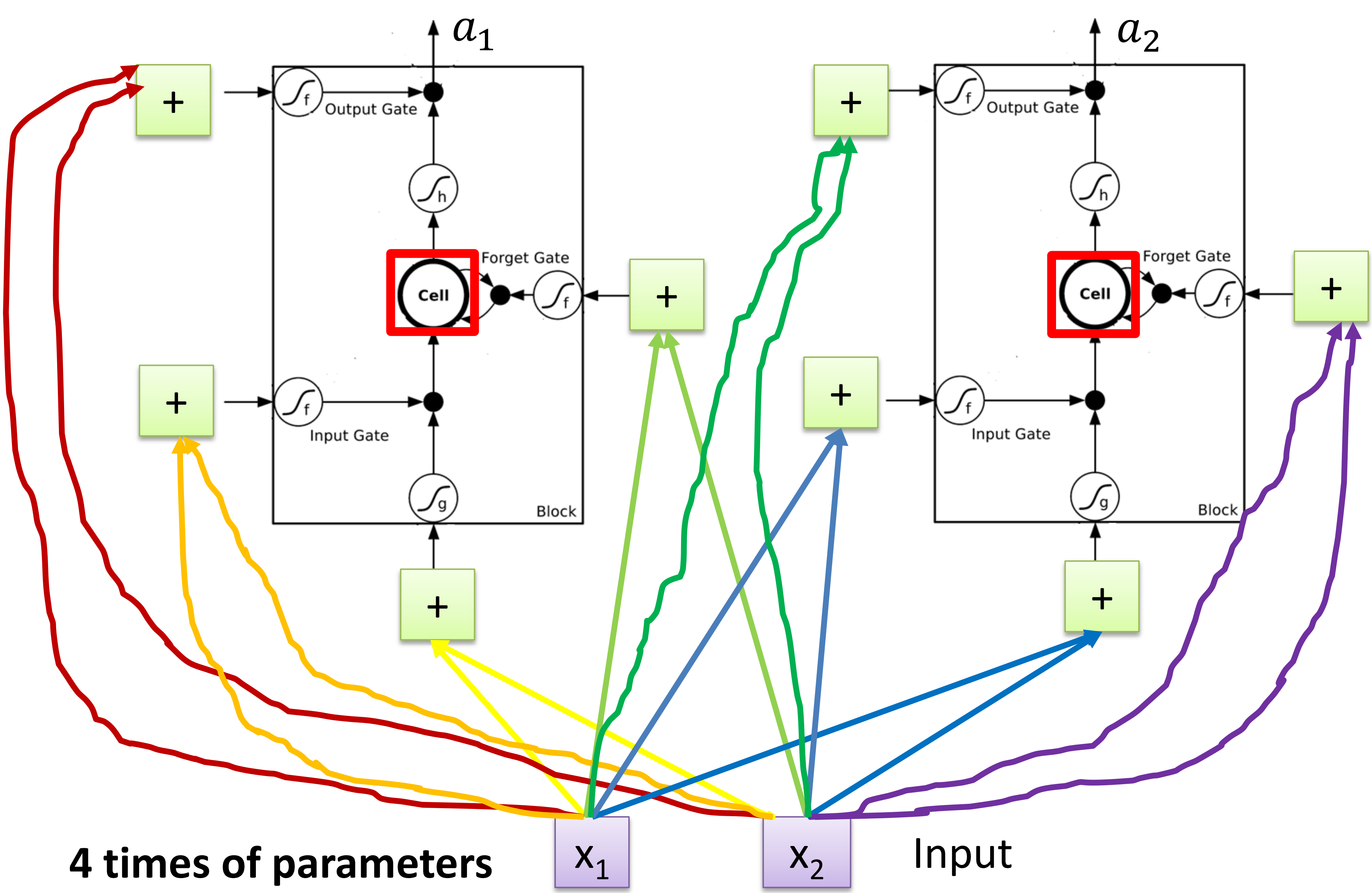
$$c' = g(z)f(z_i) + cf(z_f)$$

Long Short-term Memory (LSTM)

- **Simply replacing the neurons with LSTM**
  - original network



Long Short-term Memory (LSTM)



4 times of parameters

References

Convolutional Neural Network (CNN)

- Convolutional Neural Network for Image processing
  - Zeiler, M. D., & Fergus, R. (2014). “Visualizing and understanding convolutional networks.” In Computer Vision–ECCV 2014
- Convolutional Neural Network for speech processing
  - Tóth, László. "Convolutional deep maxout networks for phone recognition." Proc. Interspeech. 2014.
- Convolutional Neural Network for text processing
  - Shen, Yelong, et al. "A latent semantic model with convolutional-pooling structure for information retrieval." Proceedings of the 23rd ACM International Conference on Conference on Information and Knowledge Management. ACM, 2014.

Long Short-term Memory (LSTM)

- Graves, N. Jaitly, A. Mohamed. “Hybrid Speech Recognition with Deep Bidirectional LSTM”, ASRU 2013.
- Graves, Alex, and Navdeep Jaitly. "Towards end-to-end speech recognition with recurrent neural networks." Proceedings of the 31st International Conference on Machine Learning (ICML-14). 2014.

Neural Network Language Modeling

- **Input words represented by 1-of-N encoding**

$$\underbrace{[\;0\;0\;0\cdots0\;1\;0\;0\cdots0\;]}_{\text{vocabulary size}}$$

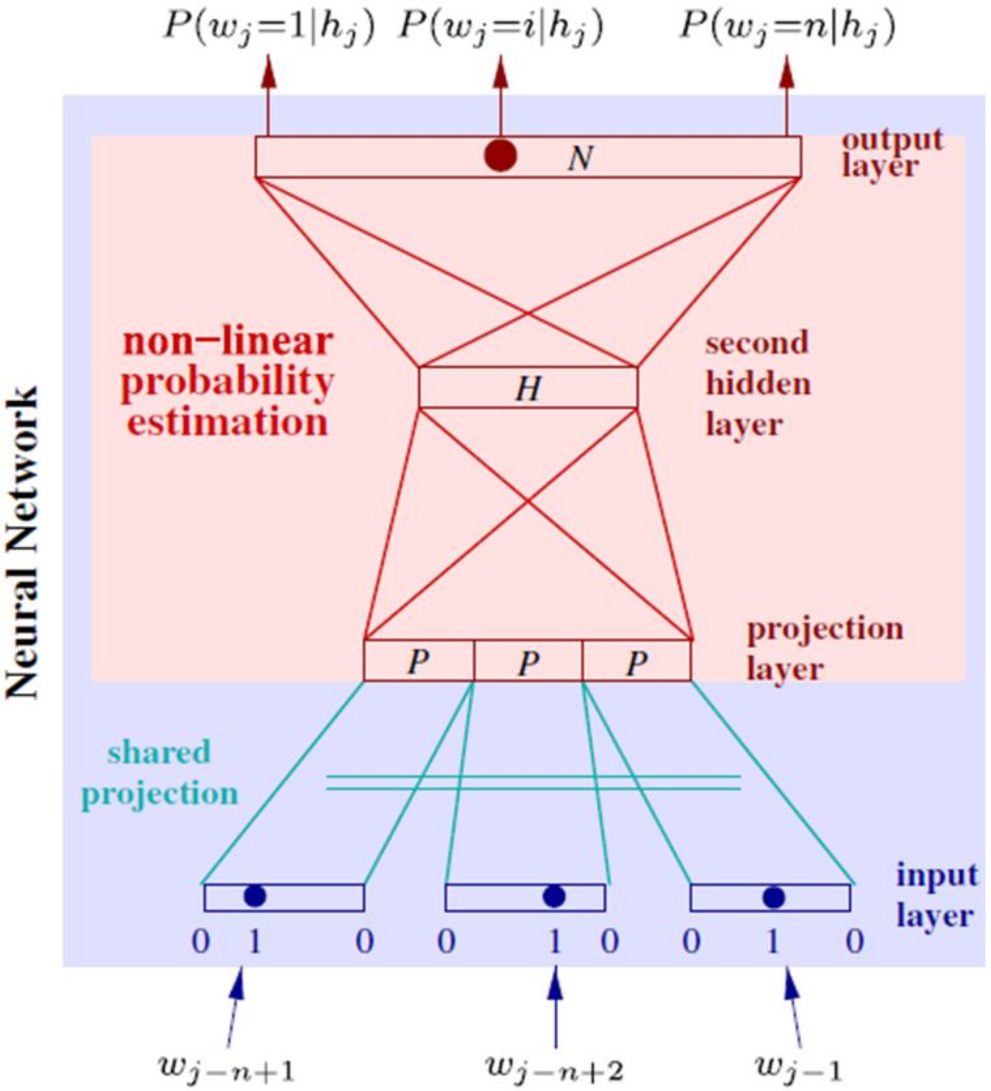
- **Output layer gives the probabilities of words given the history**

$$\text{Prob}\left[\,w_j = i \,\middle|\, h_j\,\right]$$

- **Example:**

P=120, H=800

- **Continuous space language modeling**



Recurrent Neural Network Language Modeling(RNNLM)

Probability distribution of next word, vocabulary size.

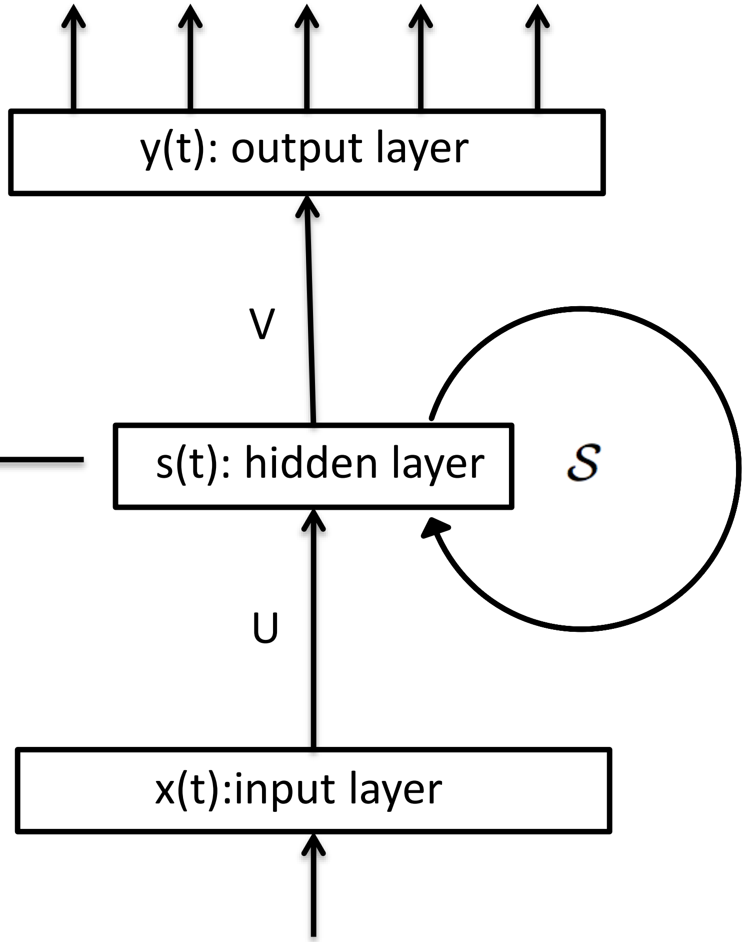
using softmax: $g(z_k) = \frac{e^{z_k}}{\sum_k e^{z_k}}$

Recursive structure preserves long-term historical context.

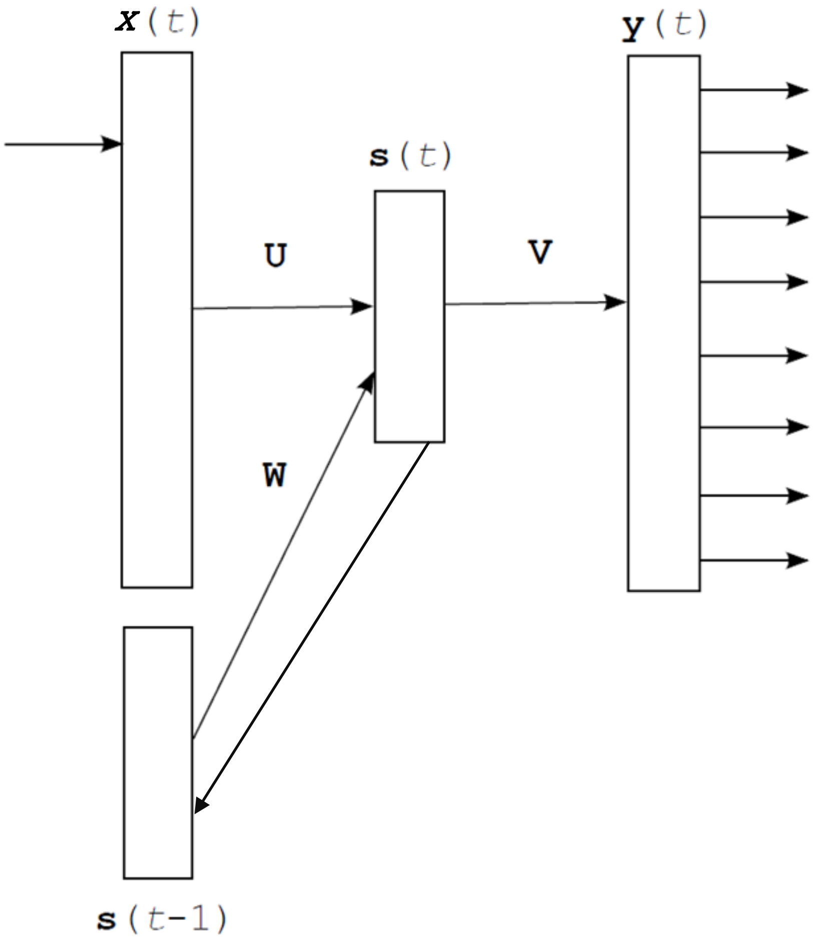
using logic unit: $f(z) = \frac{1}{1+e^{-z}}$

Previous word, using 1-of-N encoding

$$\underbrace{[\;0\;0\;0 \ldots\ldots\ldots 0\;0\;1\;0\;0\;0 \ldots\;]}_{\text{Vocab. size}}$$



RNNLM Structure



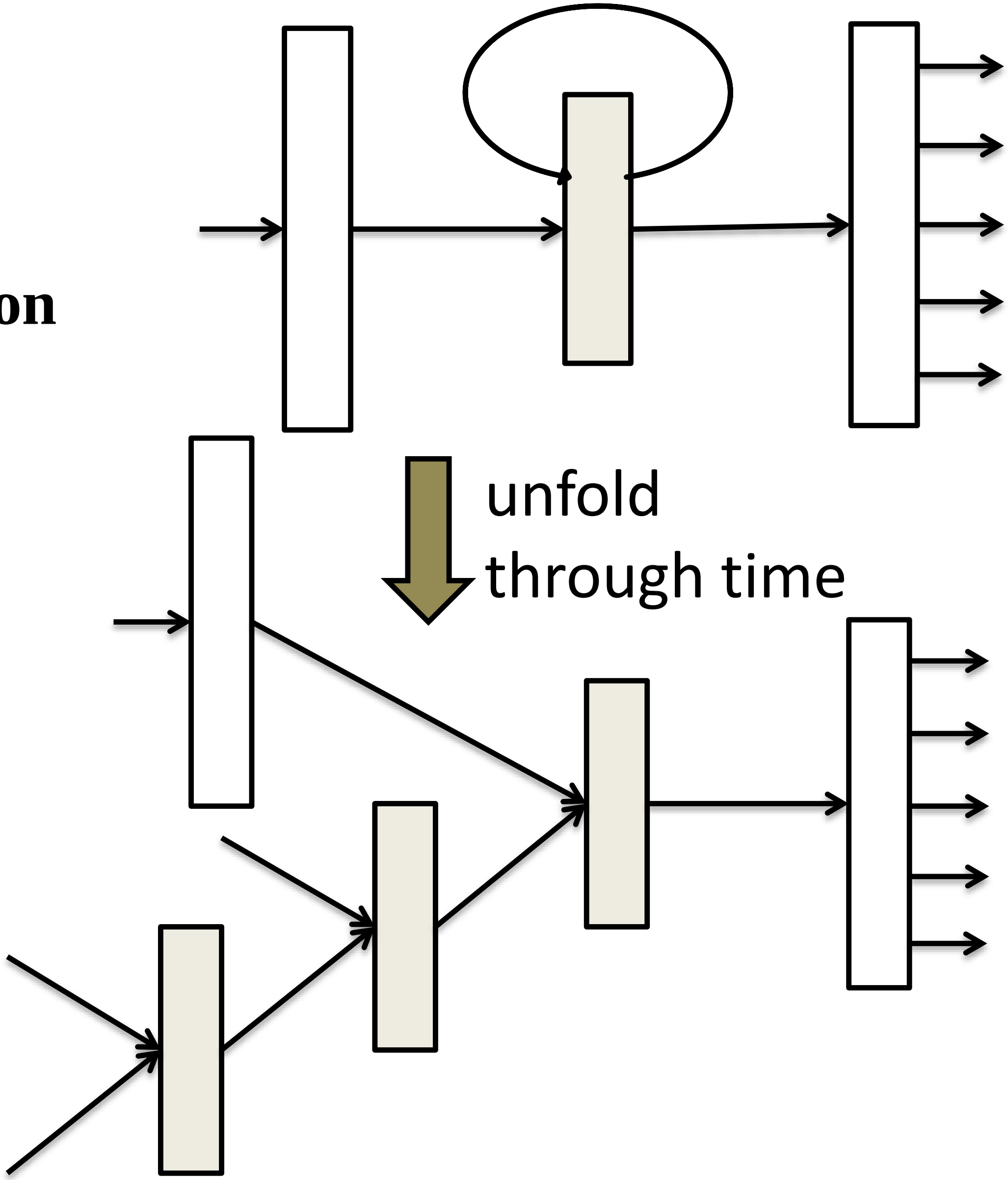
$$s_j(t) = f\left(\sum_i x_i(t)\, u_{ji} + \sum_l s_l(t-1)\, w_{jl}\right)$$

$$y_k(t) = g\left(\sum_j s_j(t)\, v_{kj}\right)$$

$$f(z) = \frac{1}{1+e^{-z}}, \quad g(z_m) = \frac{e^{z_m}}{\sum_k e^{z_k}}$$

Back propagation for RNNLM

1. Unfold recurrent structure
2. Input one word at a time
3. Do normal back propagation



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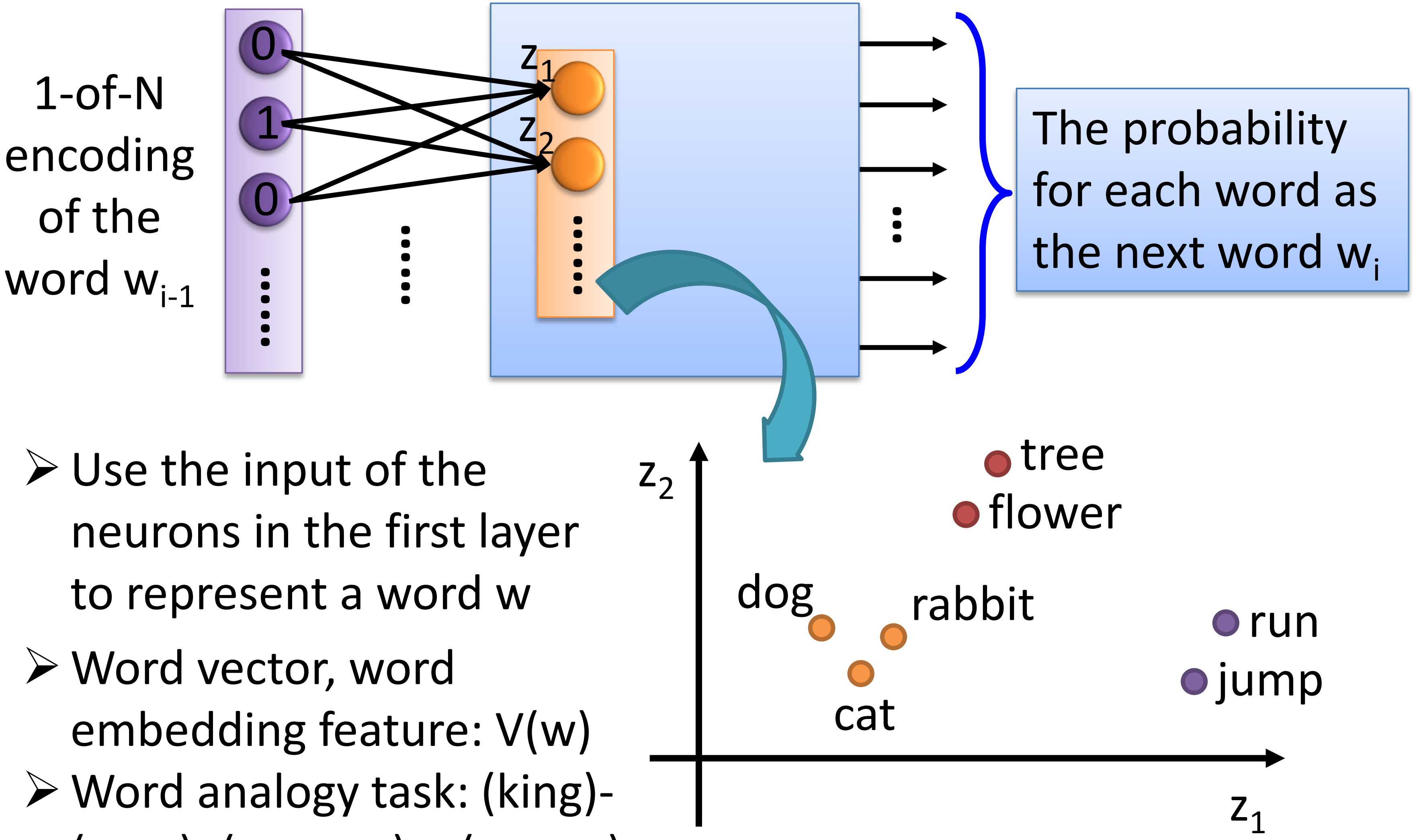
- Yoshua Bengio, Rejean Ducharme and Pascal Vincent. "**A neural probabilistic language model**," *Journal of Machine Learning Research*, 3:1137–1155, 2003
- Holger Schwenk. "**Continuous space language models**," *Computer Speech and Language*, vol. 21, pp. 492–518, 2007
- Tomáš Mikolov, Martin Karafiát, Lukáš Burget, Jan Černocký and Sanjeev Khudanpur. "**Recurrent neural network based language model**," in *Interspeech 2010*
- Mikolov Tomáš et al, "Extensions of Recurrent Neural Network Language Model", ICASSP 2011.
- Mikolov Tomáš et al, "Context Dependent Recurrent Neural Network Language Model", IEEE SLT 2012.

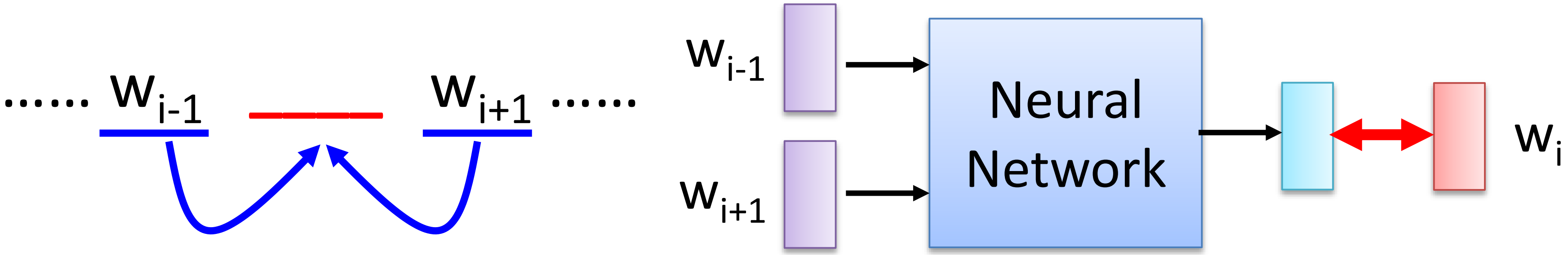
Word Vector Representations (Word Embedding)


1-of-N encoding of the word w_{i-1}
0
1
0
z_1
z_2
The probability for each word as the next word w_i
z_2
tree
flower
dog
rabbit
cat
run
jump
z_1

- ➢ Use the input of the neurons in the first layer to represent a word w
- ➢ Word vector, word embedding feature: V(w)
- ➢ Word analogy task: (king)-(man)+(woman)→(queen)

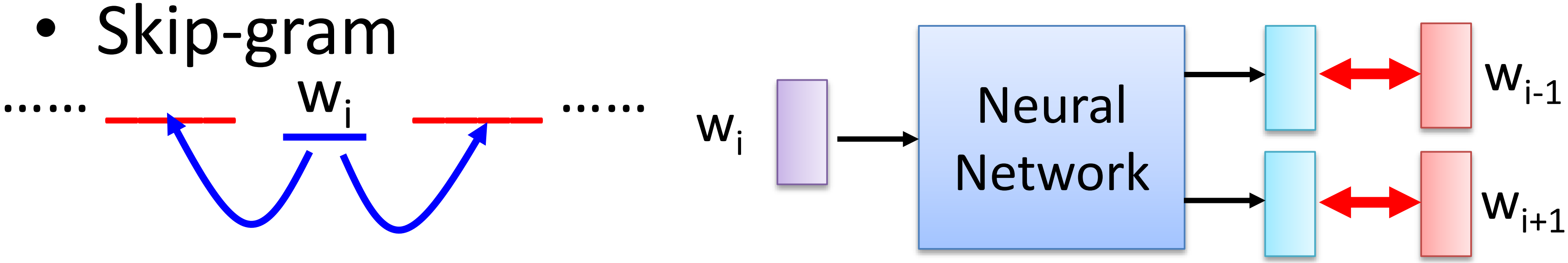
Word Vector Representations – Various Architectures

- Continuous bag of word (CBOW) model



predicting the word given its context

- Skip-gram



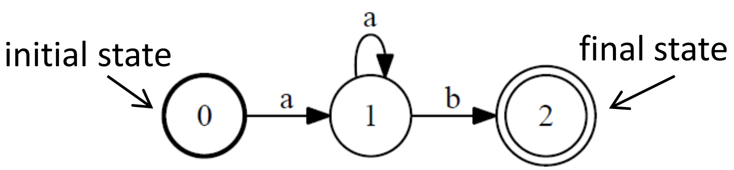
predicting the context given a word

References for Word Vector Representations

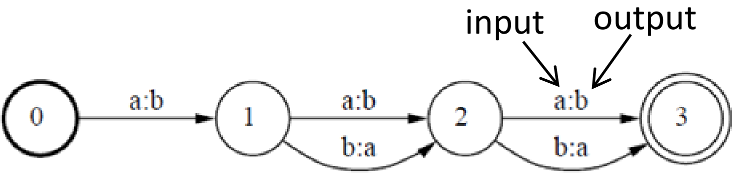
- Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. ”Efficient Estimation of Word Representations in Vector Space.” In Proceedings of Workshop at ICLR, 2013.
- Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg Corrado, and Jeffrey Dean. ”Distributed Representations of Words and Phrases and their Compositionality.” In Proceedings of NIPS, 2013.
- Tomas Mikolov, Wen-tau Yih, and Geoffrey Zweig. ”Linguistic Regularities in Continuous Space Word Representations.” In Proceedings of NAACL HLT, 2013.

Weighted Finite State Transducer(WFST)

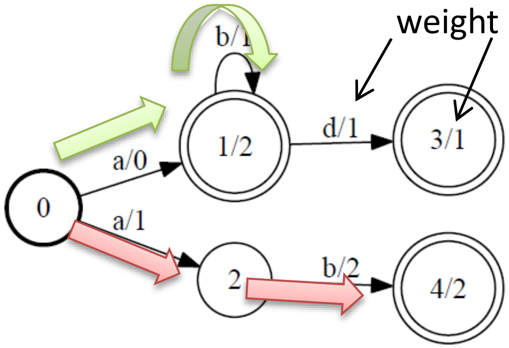
- **Finite State Machine**
  - A mathematical model with theories and algorithms used to design computer programs and digital logic circuits, which is also called “Finite Automaton”.
  - The common automata are used as acceptors, which can recognize its legal input strings.
- **Acceptor**
  - Accept any legal string, or reject it
  - EX: {ab, aab, aaab, . . .} = aa*b



- **Transducer**
  - A finite state transducer (FST) is an extension to an acceptor
  - Transduce any legal input string to another output string, or reject it
  - EX: {aaa, aab, aba, abb} -> {bbb, bba, bab, baa}

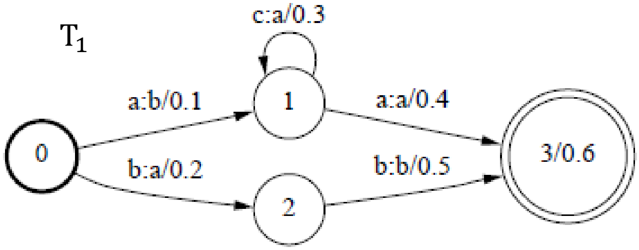


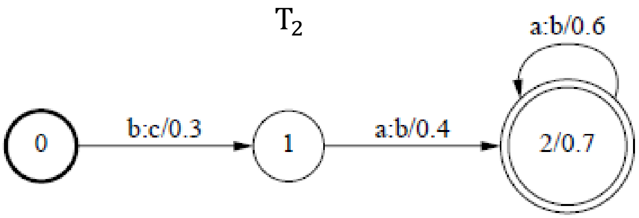
- **Weighted Finite State Machine**
  - FSM with weighted transition
  - Two paths for “ab”
    - Through states (0, 1, 1); cost is (0+1+2) = 3
    - Through states (0, 2, 4); cost is (1+2+2) = 5

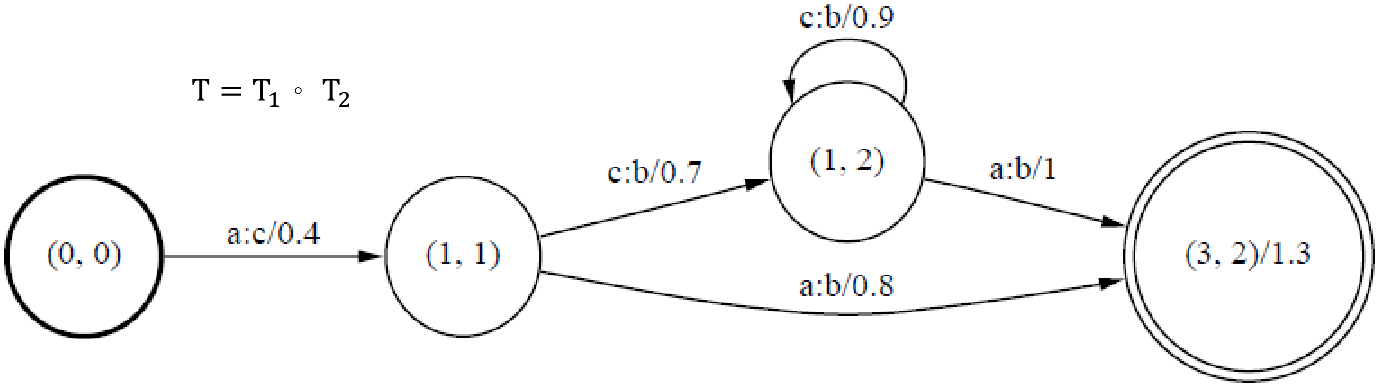


WFST Operations (1/2)

- **Composition**
  - Combining different levels of representation
  - T is the composition of T_1 and T_2 $\Rightarrow T \equiv T_1 \circ T_2$
  - The fact that T mapping u to w, implying T_1 mapping u to v, and T_2 mapping v to w.





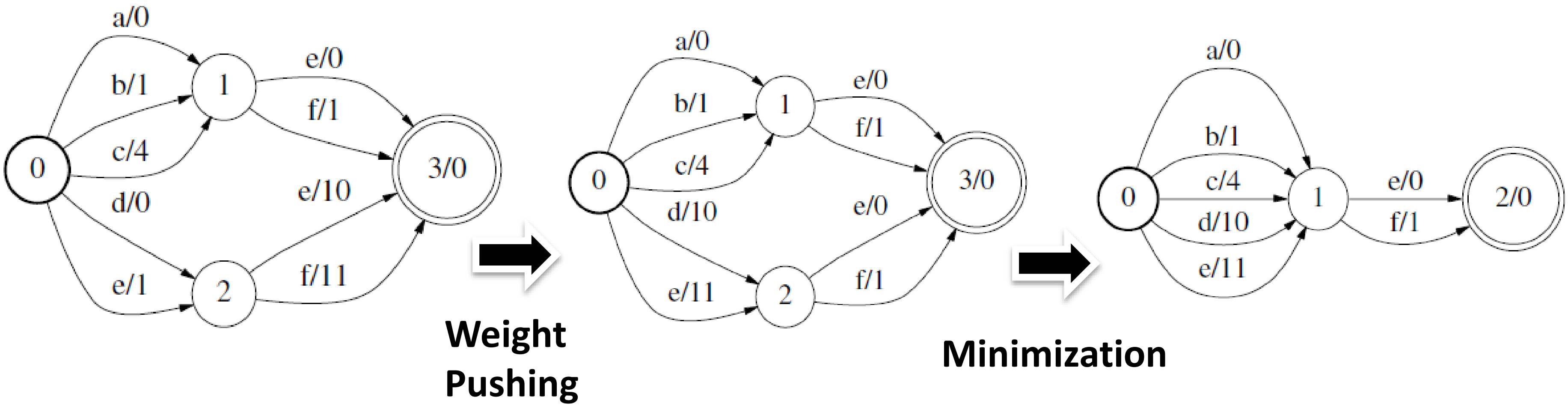


$$\{aa\} \rightarrow \{ba\} : 1.1$$
$$\{ba\} \rightarrow \{cb\} : 1.4$$

⇨ $\{aa\} \rightarrow \{cb\} : 2.5$

WFST Operations (2/2)

- **Minimization**
  - The equivalent automaton with least number of states and least transitions
- **Weight pushing**
  - Re-distributing weight among transitions while kept equivalent to improve search(future developments known earlier, *etc*.), especially pruned search



Weight Pushing

Minimization

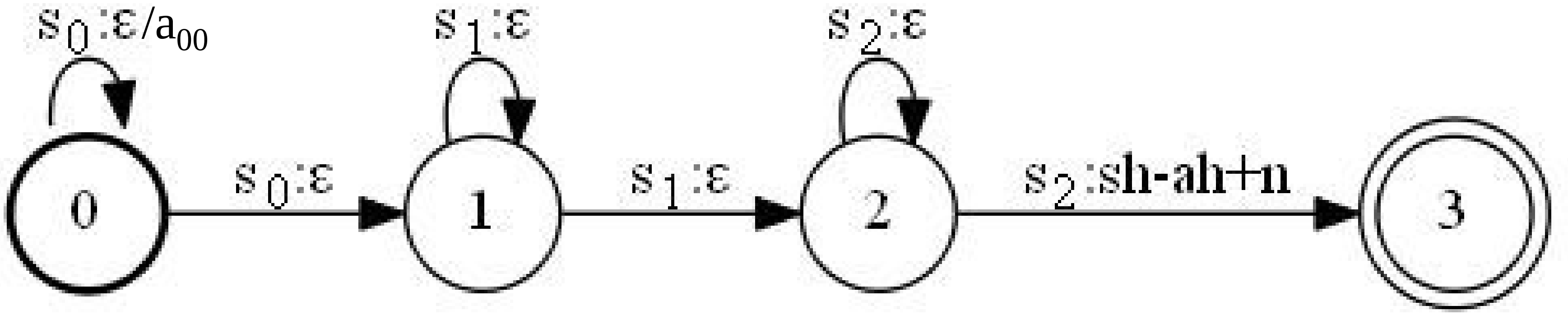
WFST for ASR (1/6)

- **HCLG ≡ H ∘ C ∘ L ∘ G is the recognition graph**
  - G is the grammar or LM (an acceptor)
  - L is the lexicon
  - C adds phonetic context-dependency
  - H specifies the HMM structure of context-dependent phones

	Input	Output
H	HMM state sequence	triphone
C	triphone	phoneme
L	Phoneme sequence	word
G	word	word

WFST for ASR (2/6)

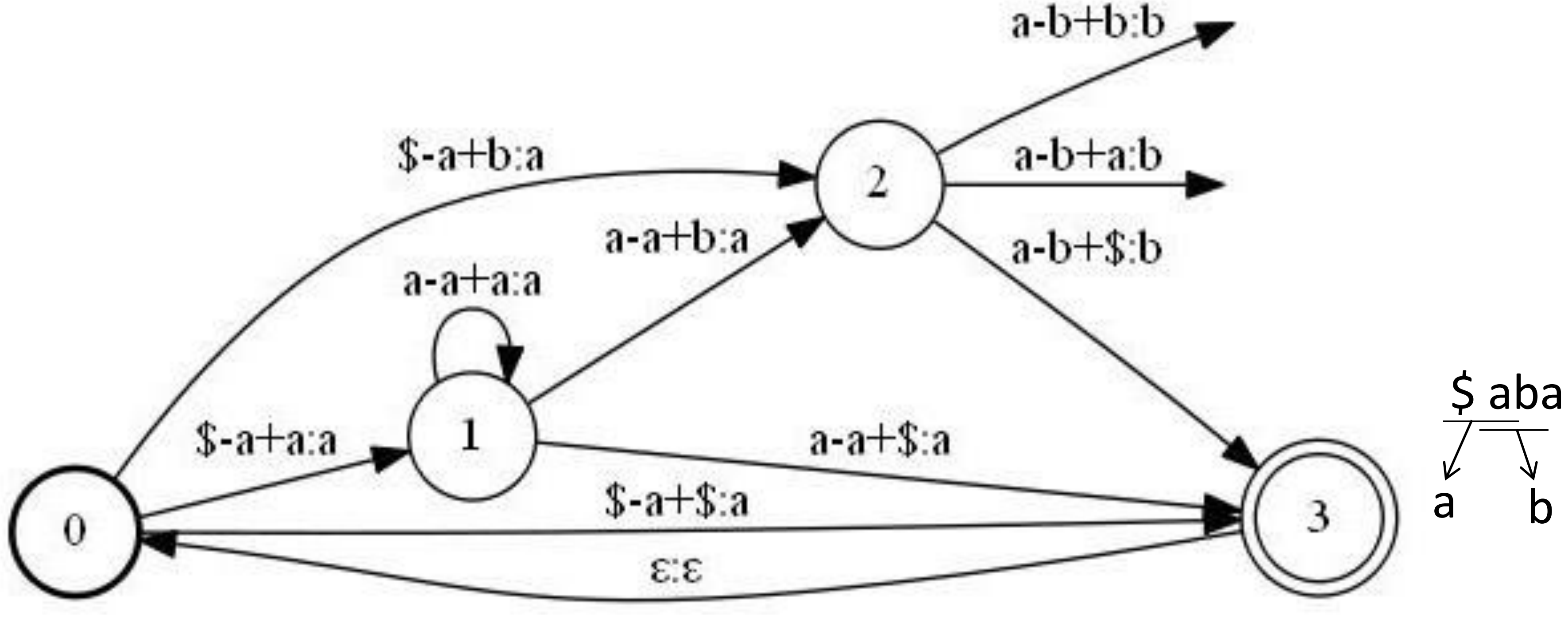
- **Transducer H: HMM topology**
  - Input: HMM state sequence
  - Output: context-dependent phoneme (e.g., triphone)
  - Weight: HMM transition probability



$$\{s_0\ s_0\ s_0\ s_1\ s_1\ s_2\ s_2\ s_2\} \rightarrow \{sh - ah + n\} : a_{00}a_{00}\ a_{01} \cdots$$

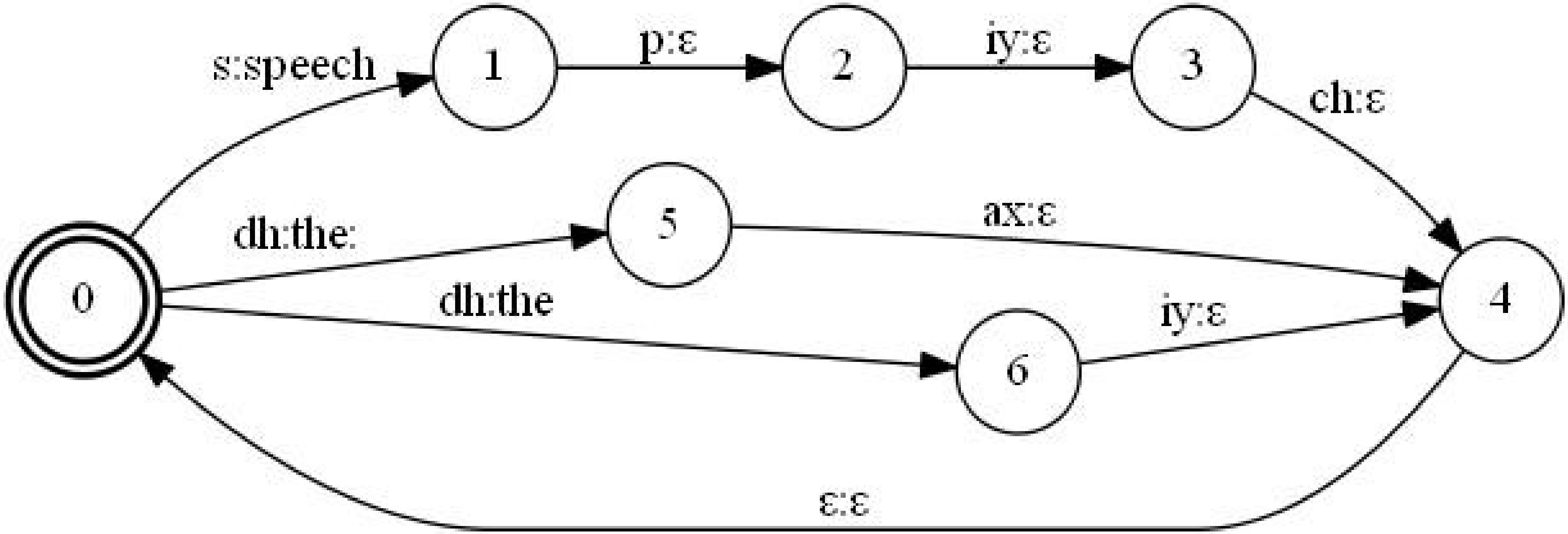
WFST for ASR (3/6)

- **Transducer C: context-dependency**
  - Input: context-dependent phoneme (triphone)
  - Output: context-independent phoneme (phoneme)



WFST for ASR (4/6)

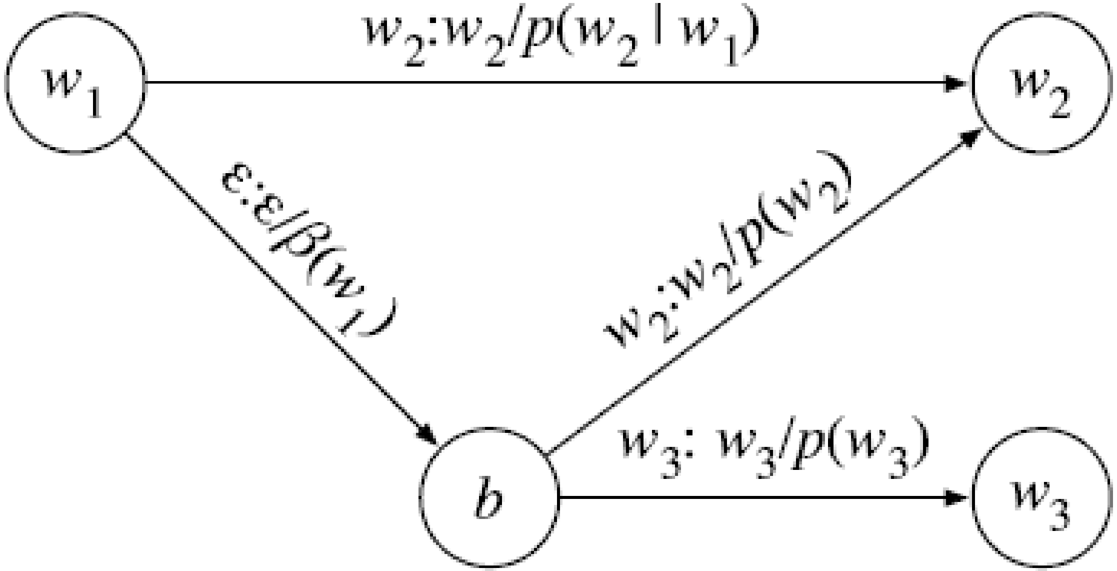
- **Transducer L: lexicon**
  - Input: context-independent phoneme (phoneme) sequence
  - Output: word
  - Weight: pronunciation probability



$\{s, p, iy, ch\}$ → speech
$\{dh, ax\}$ → the

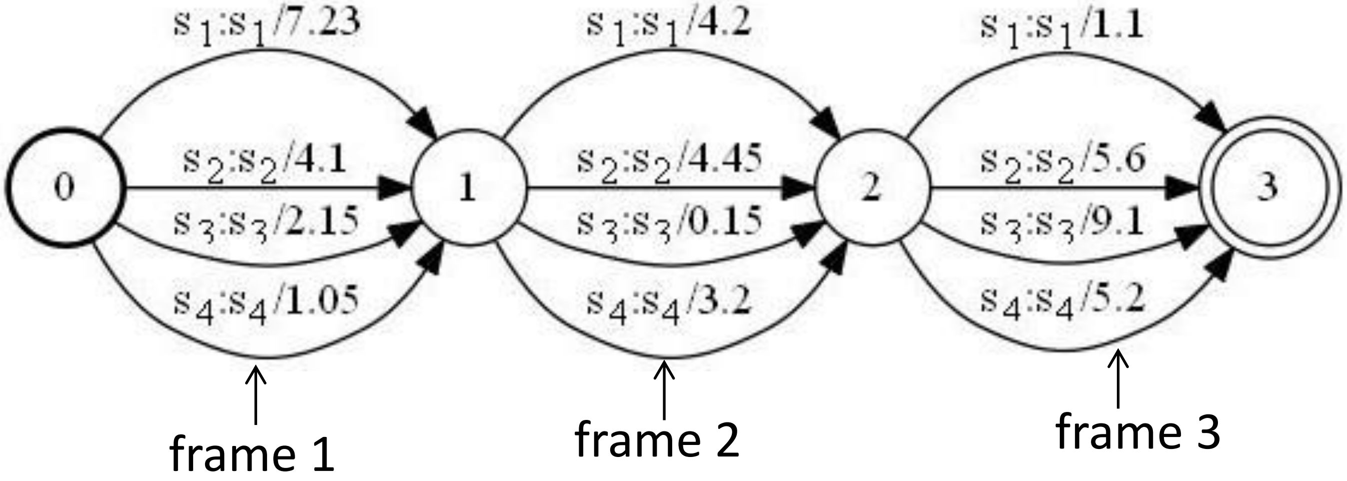
WFST for ASR (5/6)

- **Acceptor G: N-gram models**
- **Bigram**
  - Each word has a state
  - Each bigram w1w2 has a transition w1 to w2
  - Introducing back-off state b for back-off estimation.
  - An unseen w1w3 bigram is represented as two transitions: an ε-transition from w1 to b and a transition from b to w3.


w_1
$w_2{:}w_2/p(w_2 \mid w_1)$
w_2
$\varepsilon{:}\varepsilon/\beta(w_1)$
$w_2{:}w_2/p(w_2)$
$w_3{:}\ w_3/p(w_3)$
b
w_3

WFST for ASR (6/6)

- **Acceptor U: utterance**
  - Transition between the state labeled t-1 and the state labeled t giving the posterior probabilities for all HMM states given frame t



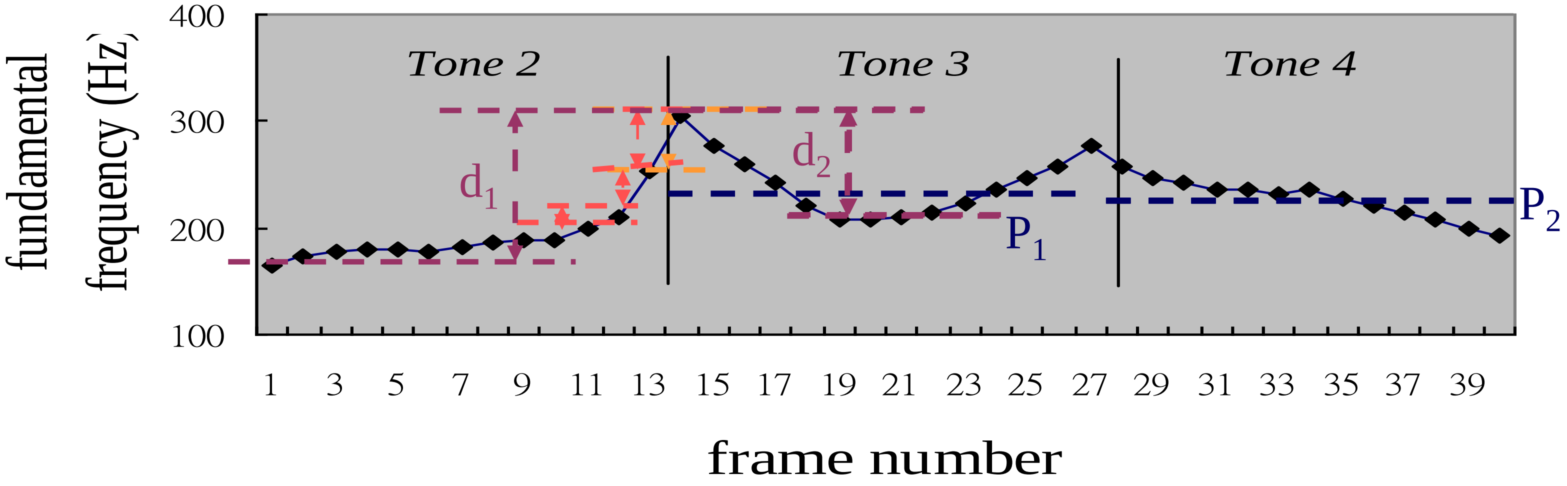
- **Decoding**
  - $w' = argmax_w \, U \circ (H \circ C \circ L \circ G)$
  - $(H \circ C \circ L \circ G)$ replacing the conventional tree structure expanded by lexicon trees, built off-line
  - $U \circ (H \circ C \circ L \circ G)$ constructing a graph given U, over which all constraints or criteria for search can be applied

References

- **WFST**
  - Mehryar Mohri, “Finite-state transducers in language and speech processing,”Comput. Linguist., vol. 23, no. 2, pp. 269–311, 1997.
- **WFST for LVCSR**
  - Mehryar Mohri, Fernando Pereira, and Michael Riley, “Weighted automata in text and speech processing,” in European Conference on Artificial Intelligence. 1996, pp. 46–50, John Wiley and Sons.
  - Mehryar Mohri, Fernando C. Pereira, and Michael Riley, “Speech Recognition with Weighted Finite-State Transducers,” in Springer Handbook of Speech Processing, Jacob Benesty, Mohan M. Sondhi, and Yiteng A. Huang, Eds., pp. 559–584. Springer Berlin Heidelberg, Secaucus, NJ, USA, 2008.

Prosodic Features (Ⅰ)

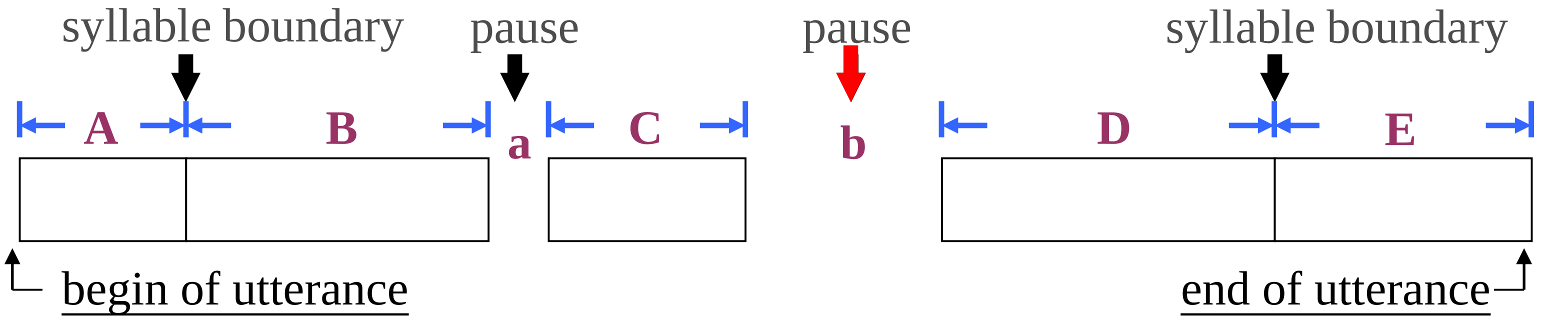
- **Pitch-related Features (examples in Mandarin Chinese)**
  - The average pitch value within the syllable
  - The maximum difference of pitch value within the syllable
  - The average of absolute values of pitch variations within the syllable
  - The magnitude of pitch reset for boundaries
  - The difference of such feature values of adjacent syllable boundaries (P_1-P_2 , d_1-d_2 , etc.)



  - at least 50 pitch-related features

Prosodic Features (Ⅱ)

- **Duration-related Features (examples in Mandarin Chinese)**



□ Pause duration b

□ Average syllable duration

(B+C+D+E)/4 *or* ((D+E)/2 + C)/2

□ Average syllable duration ratio

(D+E)/(B+C) *or* (D+E)/2 /C

□ Combination of pause & syllable features (ratio or product)

C*b , D*b, C/b, D/b

□ Lengthening C / ((A+B)/2)

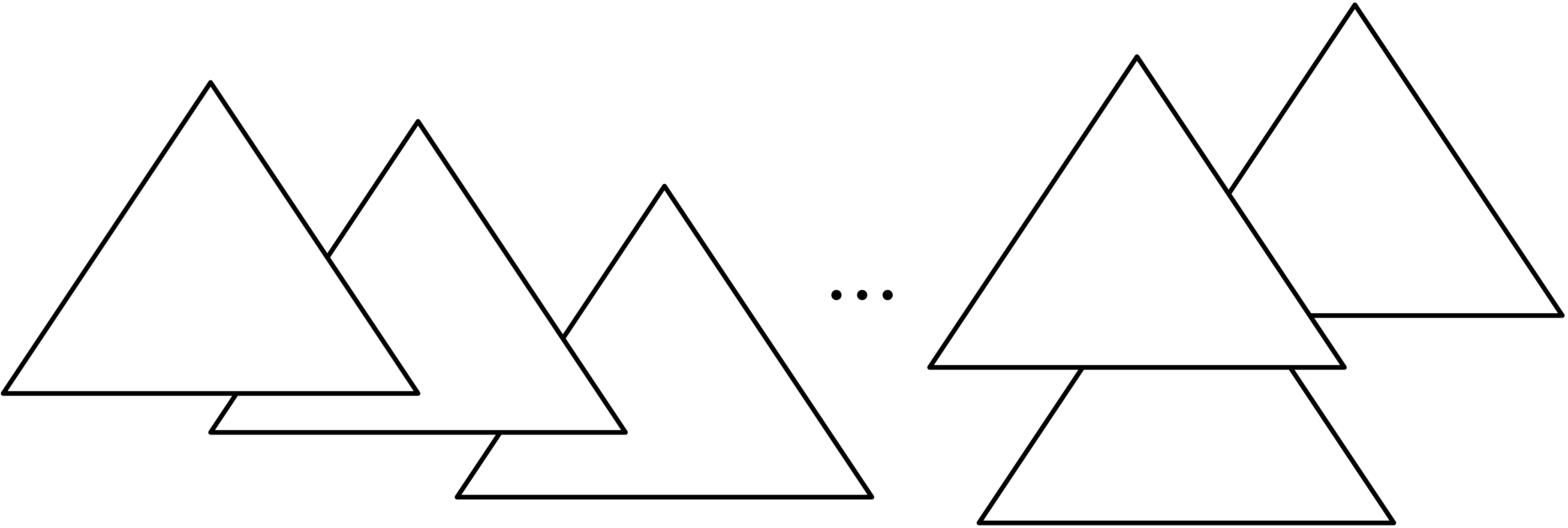
□ Standard deviation of feature values

  - at least 40 duration-related features

- **Energy-related Features**
  - similarly obtained

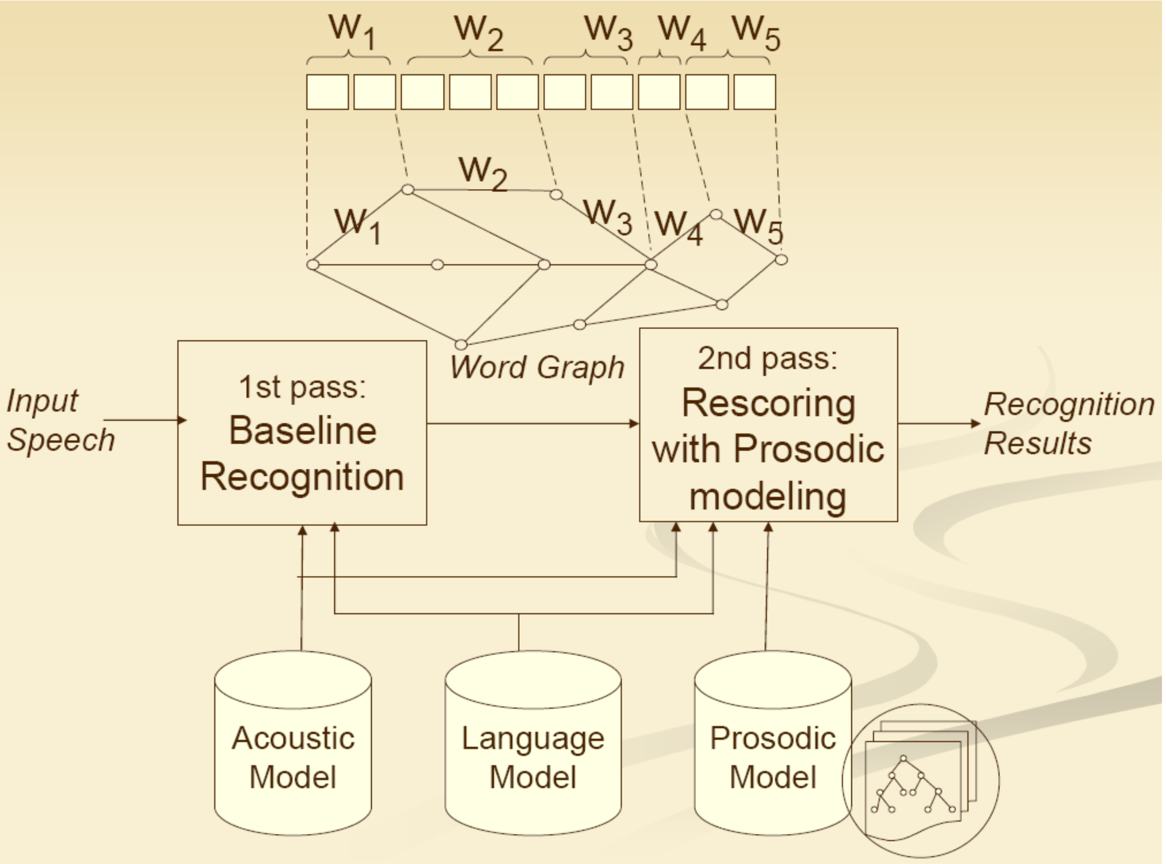
Random Forest for Tone Recognition for Mandarin

- **Random Forest**
  - a large number of decision trees
  - each trained with a randomly selected subset of training data and/or a randomly selected subset of features
  - decision for test data by voting of all trees



Recognition Framework with Prosodic Modeling

- **An example approach: Two-pass Recognition**



- **Rescoring Formula:**

$$S(W) = \log P\left(X \middle| W\right) + \lambda_l \log P\left(W\right) + \lambda_p \log P\left(F \middle| W\right)$$

Prosodic model

λ_l, λ_p: weighting coefficients

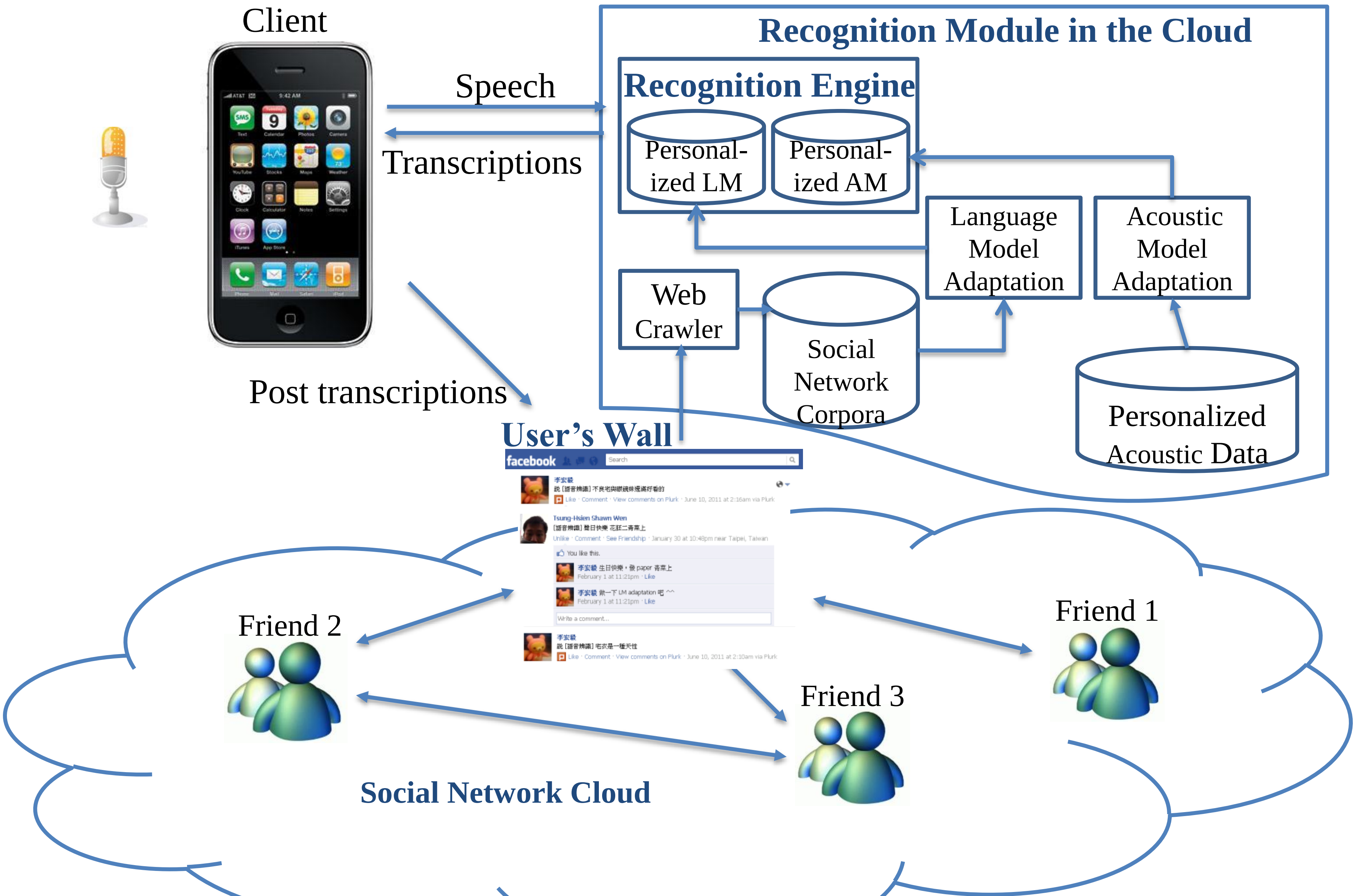
References

- **Prosody**
  - “Improved Large Vocabulary Mandarin Speech Recognition by Selectively Using Tone Information with a Two-stage Prosodic Model”, Interspeech, Brisbane, Australia, Sep 2008, pp. 1137-1140
  - “Latent Prosodic Modeling (LPM) for Speech with Applications in Recognizing Spontaneous Mandarin Speech with Disfluencies”, International Conference on Spoken Language Processing, Pittsburgh, U.S.A., Sep 2006.
  - “Improved Features and Models for Detecting Edit Disfluencies in Transcribing Spontaneous Mandarin Speech”, IEEE Transactions on Audio, Speech and Language Processing, Vol. 17, No. 7, Sep 2009, pp. 1263-1278.
- **Random Forest**
  - http://stat-www.berkeley.edu/users/breiman/RandomForests/cc_home.htm
  - http://stat-www.berkeley.edu/users/breiman/RandomForests/cc_papers.htm

Personalized Recognizer and Social Networks

- **Personalized recognizer is feasible today**
  - Smart phone user is personal
    - each smart phone used by a single user
    - user identification is known once the smart phone is turned on
  - Personal corpus is available
    - Audio data easily collected at server
    - Text data available on social networks

Personalized Recognizer and Social Networks



李宏毅
說 [語音辨識] 不良宅與眼鏡妹還滿好看的
Like · Comment · View comments on Plurk · June 10, 2011 at 2:16am via Plurk

Tsung-Hsien Shawn Wen
[語音辨識] 聲日快樂 花莊二青菜上
Unlike · Comment · See Friendship · January 30 at 10:48pm near Taipei, Taiwan

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李宏毅 生日快樂，發 paper 青菜上
February 1 at 11:21pm · Like

李宏毅 做一下 LM adaptation 吧 ^^
February 1 at 11:21pm · Like

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李宏毅
說 [語音辨識] 宅衣是一種天性
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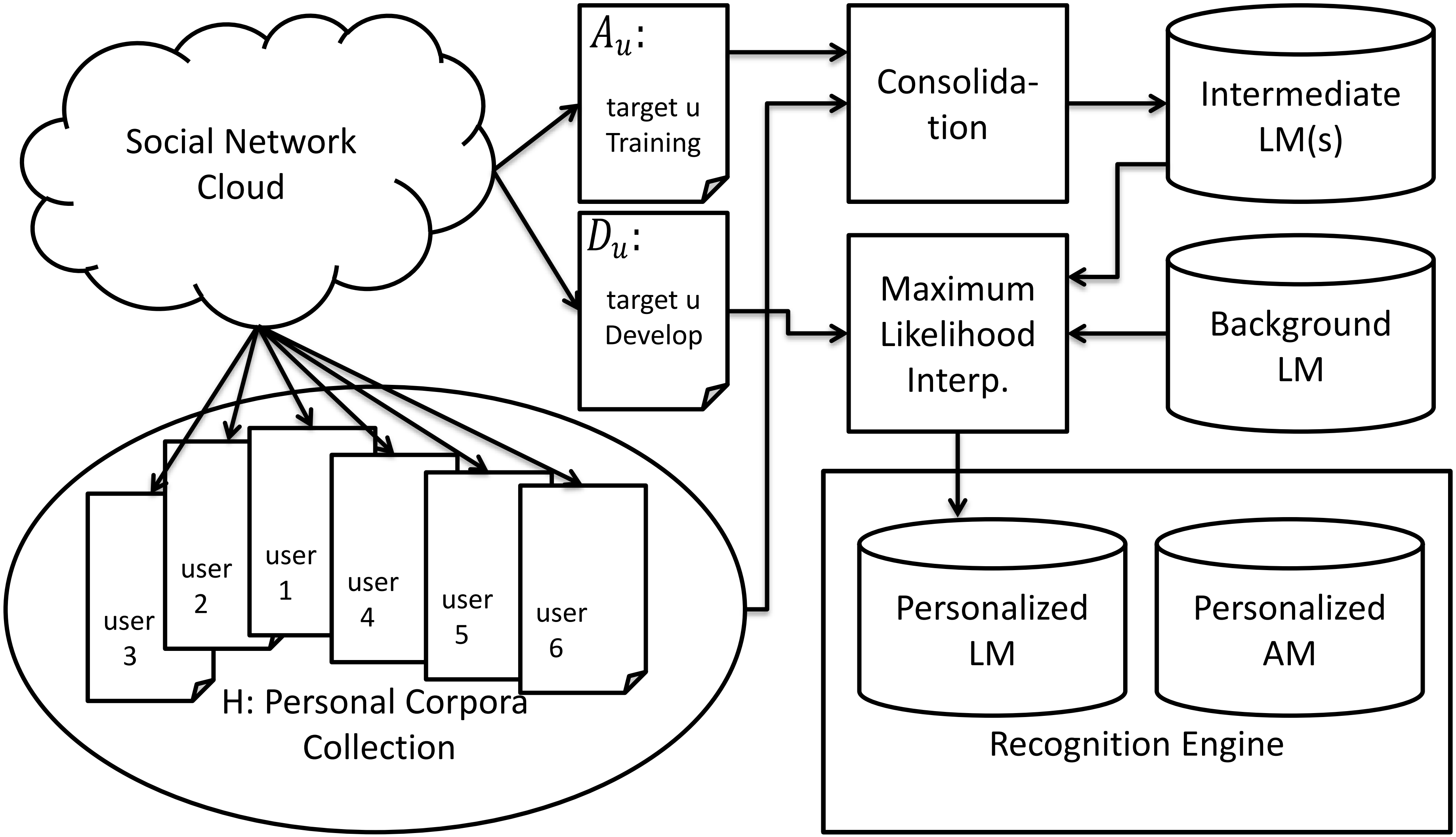
Language Model Adaptation Framework



References for Personalized Recognizer

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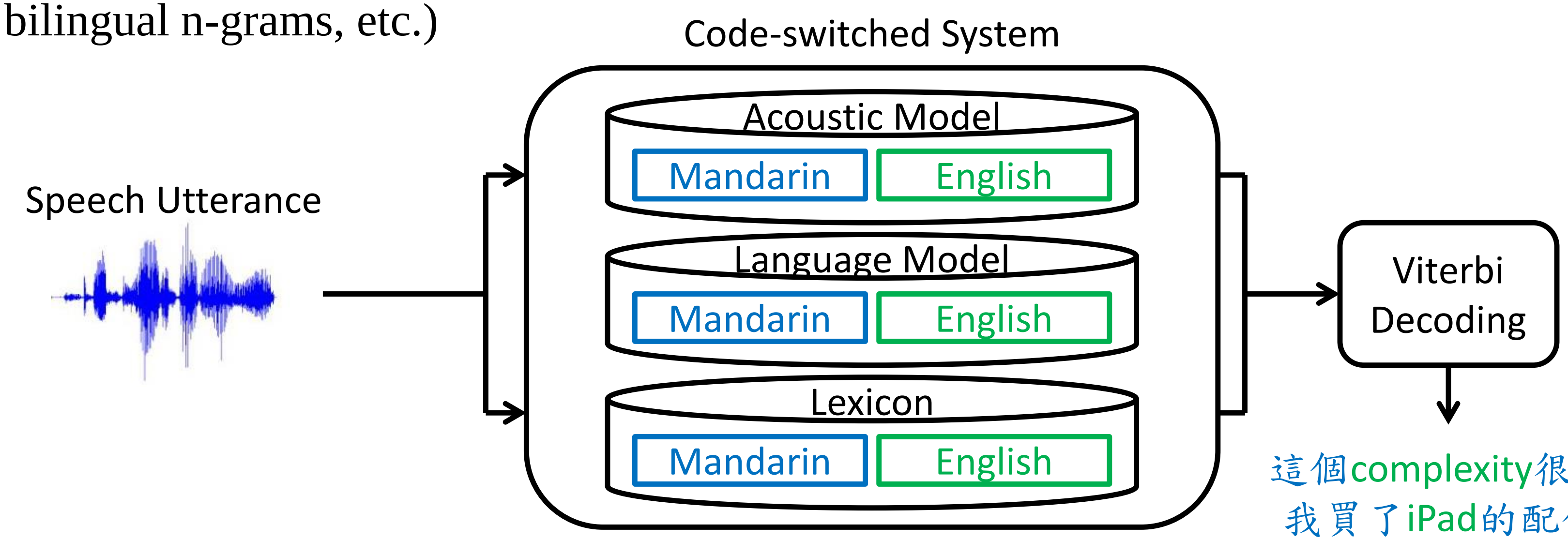
Recognizing Code-switched Speech

- **Definition**
  - Code-switching occurs from word to word in an utterance
  - Example : 當我們要作 Fourier Transform 的時候

    “Host” language　“Guest” language

- **Speech Recognition**
  - Bilingual acoustic models, language model, and lexicon
  - A signal frame may belong to a Mandarin phoneme or an English phoneme, a Mandarin phoneme may be preceded or followed by an English phoneme and vice versa, a Chinese word may be preceded or followed by an English word and vice versa (bilingual triphones, bilingual n-grams, etc.)



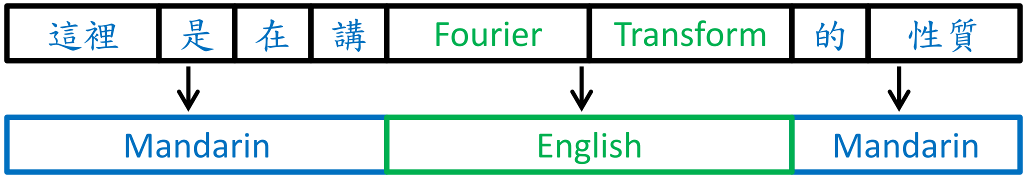
這個complexity很高

我買了iPad的配件

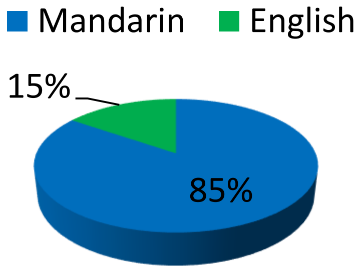
Recognizing Code-switched Speech

- **Code-switching issues**
  - Imbalanced data distribution
    - There are much more data for host language but only very limited for guest language
    - The models for guest language are usually weak, therefore accuracy is low
  - Inter-lingual ambiguity
    - Some phonemes for different languages are very similar but different (*e.g.* ㄅ vs. B), but may be produced very closely by the same speaker
  - Language identification (LID)
    - Units for LID are smaller than an utterance
    - Very limited information is available

Language Identification

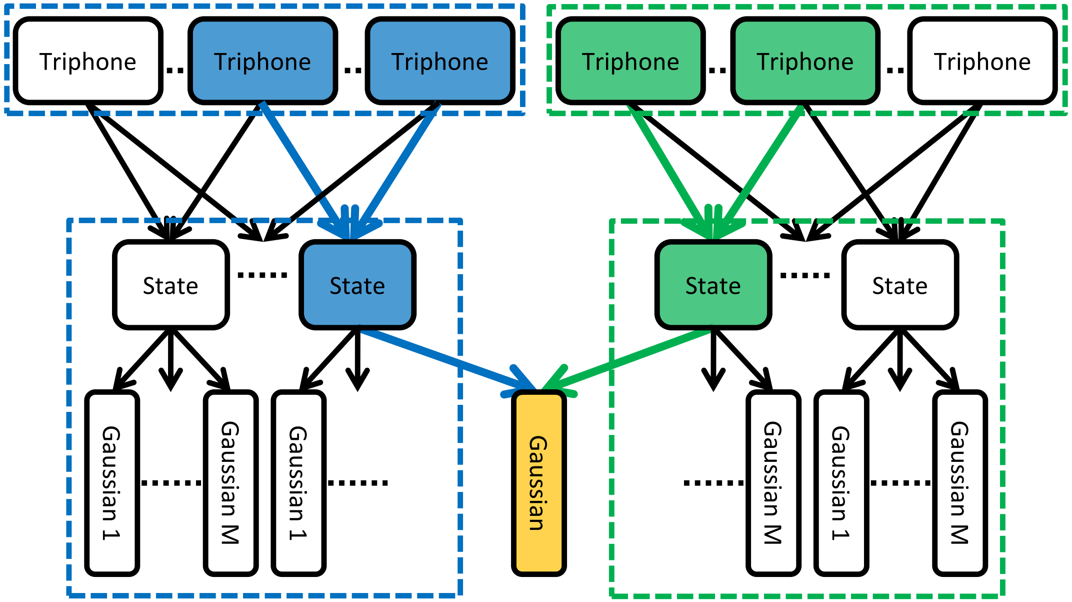


Statistics of DSP 2006 Spring

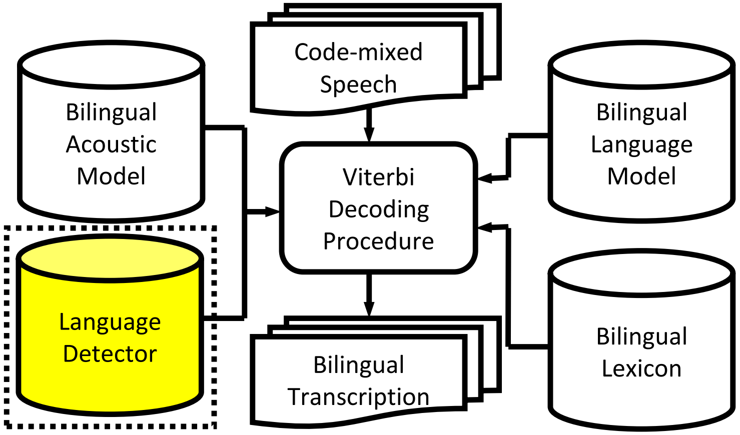


Recognizing Code-switched Speech

- **Some approaches to handle the above problems**
  - Acoustic unit merging and recovery
    - Some acoustic units shared across languages: Gaussian, state, model
    - Shared training data
    - Models recovered with respective data to preserve the language identity
  - Frame-level language identification (LID)
    - LID for each frame
    - Integrated in recognition



Integration of Language Identification and Speech Recognition



References for Recognizing Code-switched Speech

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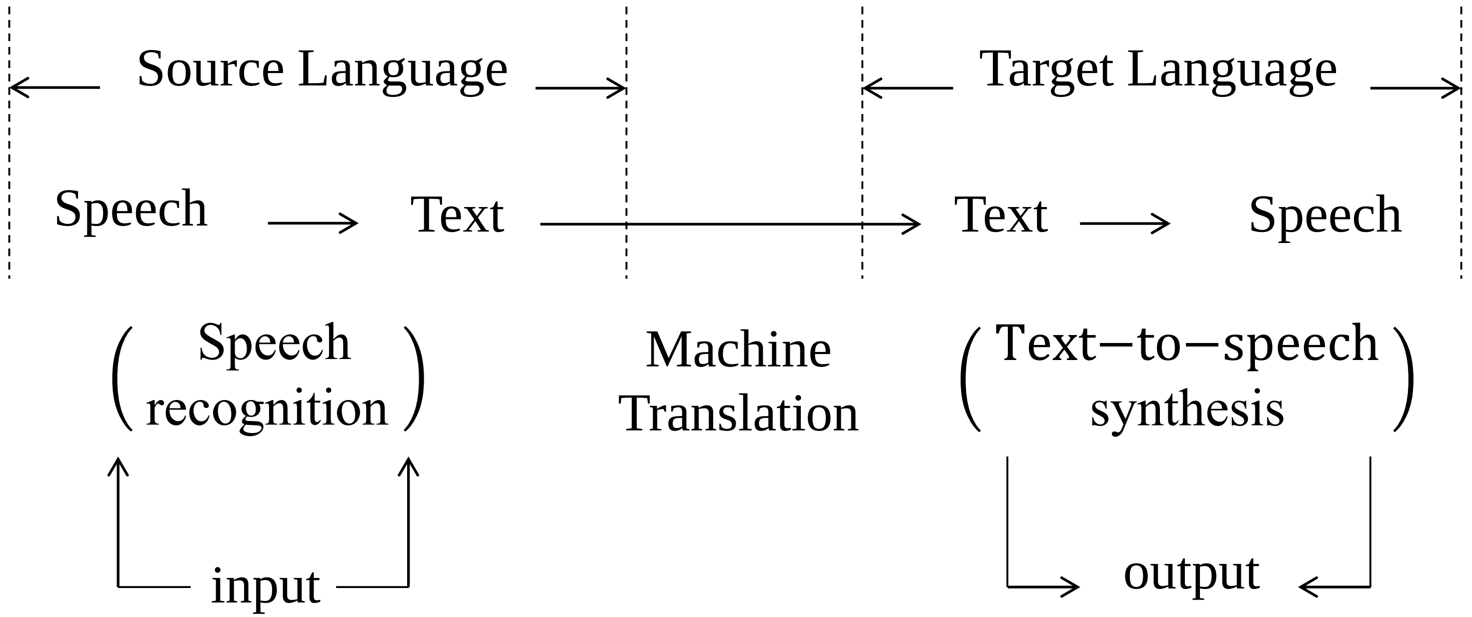
2. **“Recognition Of Highly Imbalanced Code-mixed Bilin-gual Speech With Frame-level Language Detection Based On Blurred Posteriorgram,”** *ICASSP, 2012.*
3. **“Language Independent And Language Adaptive Acoustic Modeling For Speech Recognition,”** Tanja Schultz and Alex Waibel, *Speech Communication, 2001.*
4. **“Learning Methods In Multilingual Speech Recognition,”** Hui Lin, Li Deng, Jasha Droppo, Dong Yu, and Alex Acero, *NIPS, 2008.*

Speech-to-speech Translation



- **Language difference is a major problem in the globalized world**
- **For N languages considered, ~ N^2 pairs of languages for translation**
- **Human revision after machine translation feasible**

Machine Translation — Simplified Formulation

- **Source language (Foreign) f:**
  - word set (dictionary): F
  - a sentence: f = $f_1 f_2 \ldots f_j \ldots f_J$, $f_j \in F$, J: number of words

- **Target language (English) e:**
  - word set (dictionary): E
  - a sentence: e = $e_1 e_2 \ldots e_i \ldots e_I$, $e_i \in E$, I: number of words

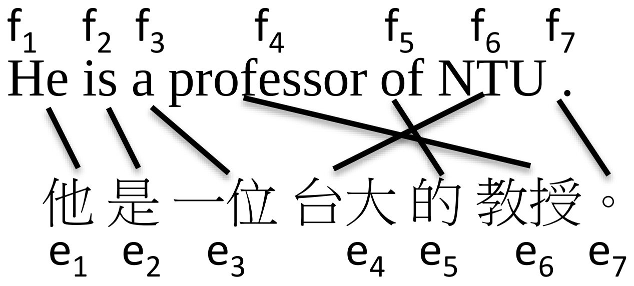
- **Statistical Machine Translation (SMT) task:**
  - model $p(e|f)$
  - given a new source language sentence $f', e' = argmax_e\, p(e|f')$
  - $e' = argmax_{Y(f')}\, p(e|f')$

    $Y(f')$: a smaller set of e considered
  - $p(e|f) = p(f|e)p(e)/p(f) \propto p(f|e)p(e)$ (Bayesian theorem)
  - $p(e)$: language model
  - $p(f|e)$: translation model

Generative Models for SMT

- **Language model (p(e)):**
  - –conventional n-gram model
  - –recurrent neural network
  - –domain adaptation can be applied (corpus collection needed)

- **Translation model (p(f|e)):**
  - –$p(f|e) = \sum_a p(f|e,a)p(a)$, a : alignment
  - –$p(f|e,a)$: unit (word/phrase) translation model
  - –$p(a)$: reordering model
  - –Example for an alignment:



f_1 f_2 f_3 f_4 f_5 f_6 f_7

He is a professor of NTU .

他 是 一位 台大 的 教授。

e_1 e_2 e_3 e_4 e_5 e_6 e_7

For this example alignment a

$p(f|e,a)$= p(He|他)*p(is|是)…

$p(a)$= p(a: He<-->他, is<-->是,….)

All probabilities trained with parallel bilingual corpora aligned or not

Generative Models for SMT

- **Unit translation model p(f|e,a):**
  - Based on unit translation table:
  - Examples:

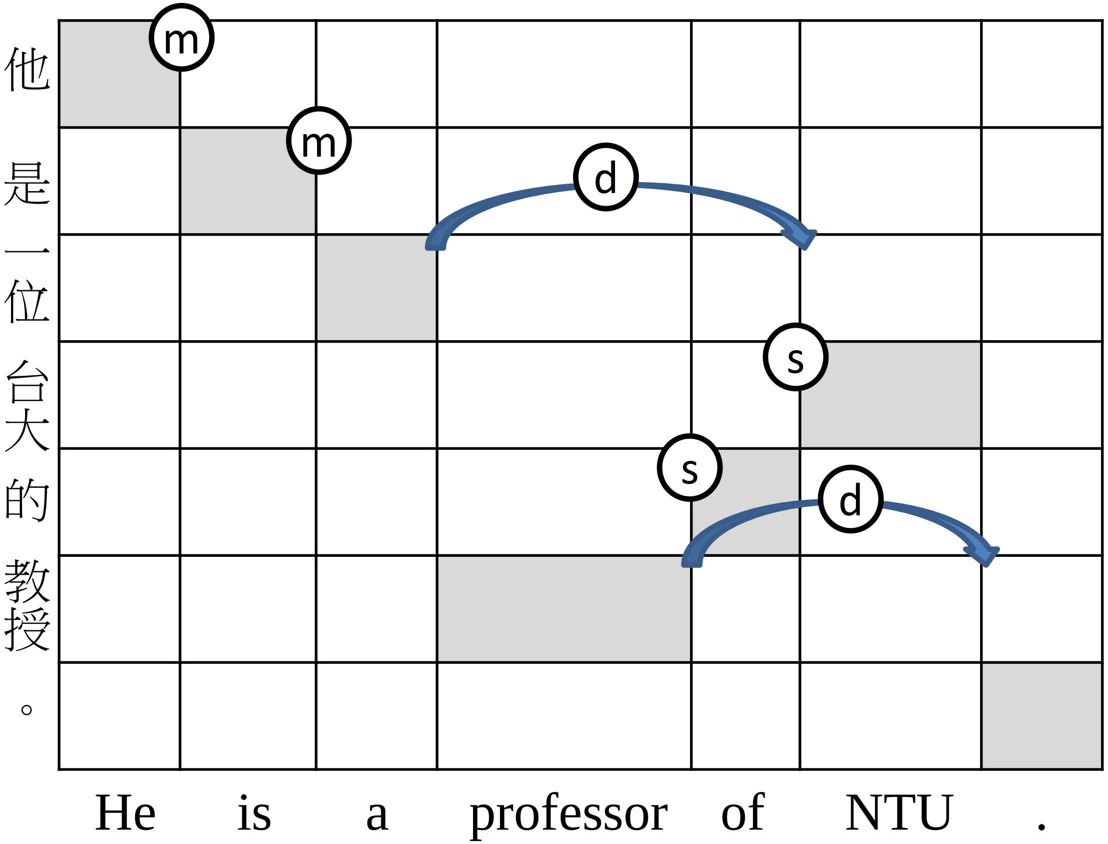
p(book|書)	0.95
p(write|書)	0.05

p(walk|走)	0.8
p(leave|走)	0.2

  - Tables can be accumulated from training data

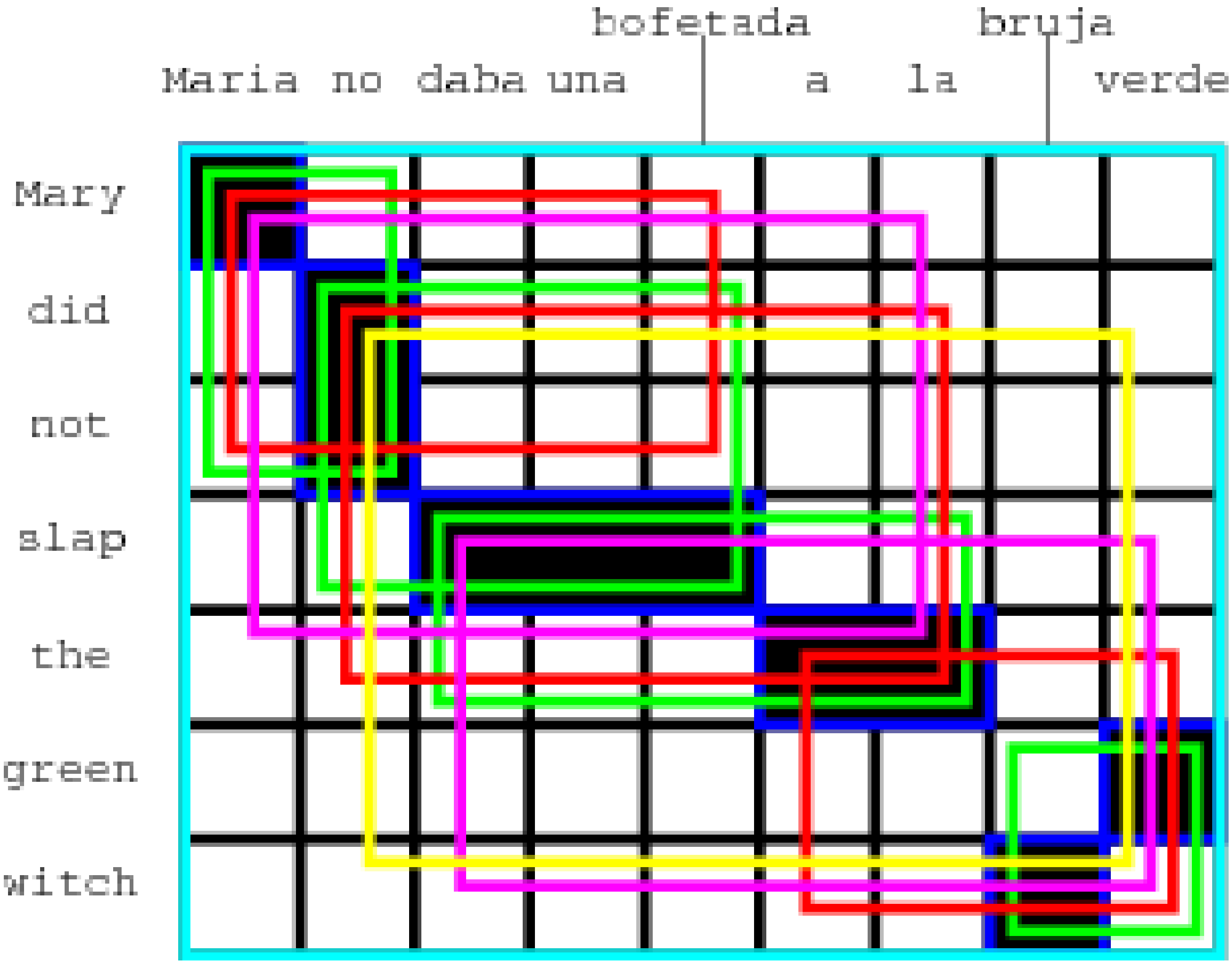
An Example of Reordering Model

- **Lexicalized reordering model:**
  - model the orientation
  - orientation types: monotone(m), swap(s), discontinuous(d)
  - Ex. p(他<-->He,是<-->is…)=p({他,He,(m)}, {是,is,(m)}, {一位,a,(d)}, {台大,NTU,(s)}, {的,of,(s)}, {教授,professor,(d)})



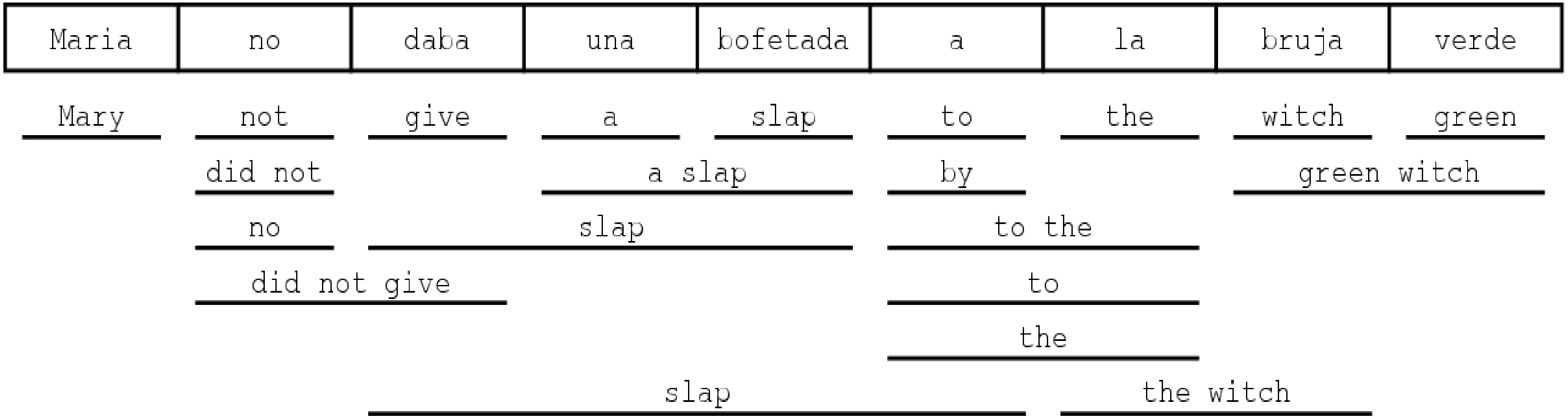
Probabilities trained with parallel bilingual corpora

Modeling the Phrases



Decoding Considering Phrases

- **Phrase-based Translation**
  - – first source word covered
  - – last source word covered
  - – phrase translation considered
  - – phrase translation probabilities trained



Maria	no	daba	una	bofetada	a	la	bruja	verde
Mary	not	give	a	slap	to	the	witch	green
	did not		a slap		by		green witch	
	no	slap			to the			
	did not give				to			
					the			
		slap				the witch		

References for Translation

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- **Statistical Machine Translation**
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