Computational Networks

A Generalization of Deep Learning Models

A tutorial at ICASSP 2015

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Outline

- Motivation
- Introduction to Deep Learning and Prevailing Deep Learning Models
- Computational Network: A Unified Framework for Models Expressible as Functions
- Computational Network Toolkit: A Generic Toolkit for Building Computational Networks
- Examples: Acoustic Model, Language Model, and Image Classification
- Summary

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Why Are We All Here Today?

- Deep learning and deep neural networks are hot stuff!
    - Big impact in academic & industrial research.
- Why the widespread adoption?
    - Implementing a (deep) neural network is not difficult
        - Many groups were able to quickly adopt this new approach
    - and it works !
- This led to the “era of low hanging fruit”
    - Apply DNN to new tasks, e.g. ASR, TTS, NLP
    - Invent simple extensions, e.g. NAT, SAT
    - Create deep version of other known networks, e.g. RNN
- But, what next?

The Implementation Bottleneck

- It is easy (and fun!) to dream up new architecture variations, topologies, training strategies
  - Recurrence across arbitrary layers
  - RNN across multiple time delays
  - Complicated weight tying strategies
  - Gating
- It is time-consuming to implement these
  - Requires new coding for forward and back propagation
  - CPU + GPU means twice as much coding & debugging!
- Also true if you want to reproduce published research
- This is a big bottleneck to progress

Motivation: Break the Bottleneck

- Our goal: create a tool to try out new ideas quickly.
  - High risk, high reward, fail fast
  - Achieve flexibility without sacrificing efficiency
- Inspiration: Legos
  - Each brick is very simple and performs a specific function
  - Create arbitrary objects by combining many bricks
- CNTK enables the creation of existing and novel models by combining simple functions in arbitrary ways.
- For example, without writing any code you can
  - Create a DNN, RNN, or LSTM
  - Rearrange LSTM's gating structure
  - Add novel recurrence

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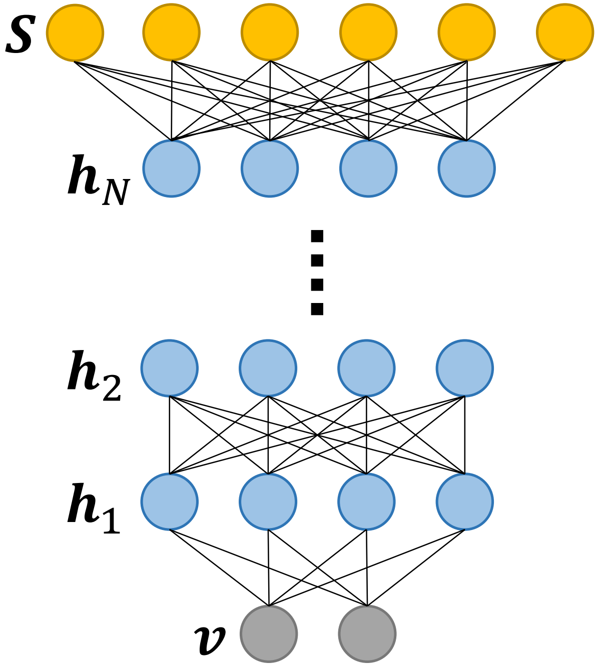
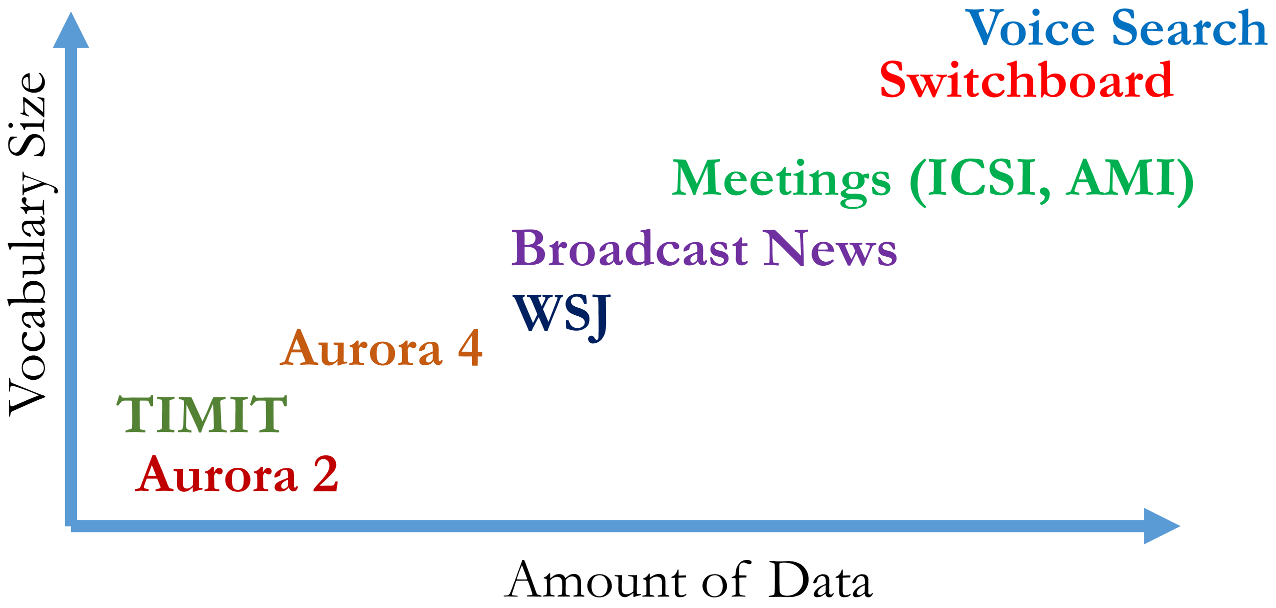
Deep Neural Networks

- Catchy name for multi-layer perceptron (MLP) with "many" hidden layers
  - In: observations (features)
  - Out: prediction (classes or features)
- Training with back propagation to minimize the cross-entropy at the frame or sequence level
- Optimization important & difficult
- Outputs used as is, or in downstream classifier, e.g. hidden Markov model (HMM), support vector machine (SVM)



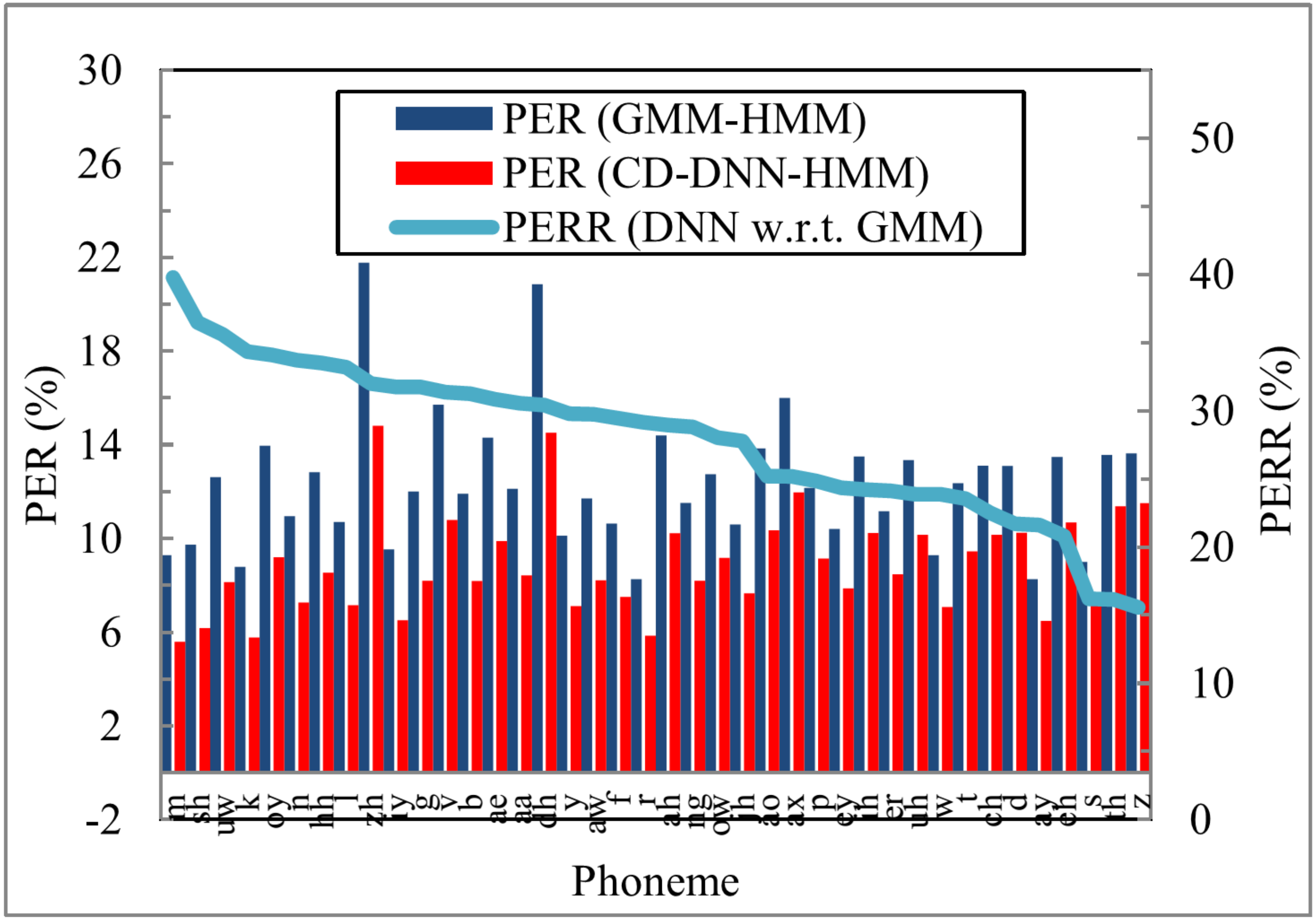
Success Across Many Fields

- Including automatic speech recognition (ASR), image classification, and natural language processing.
- Example: Success in ASR across many tasks



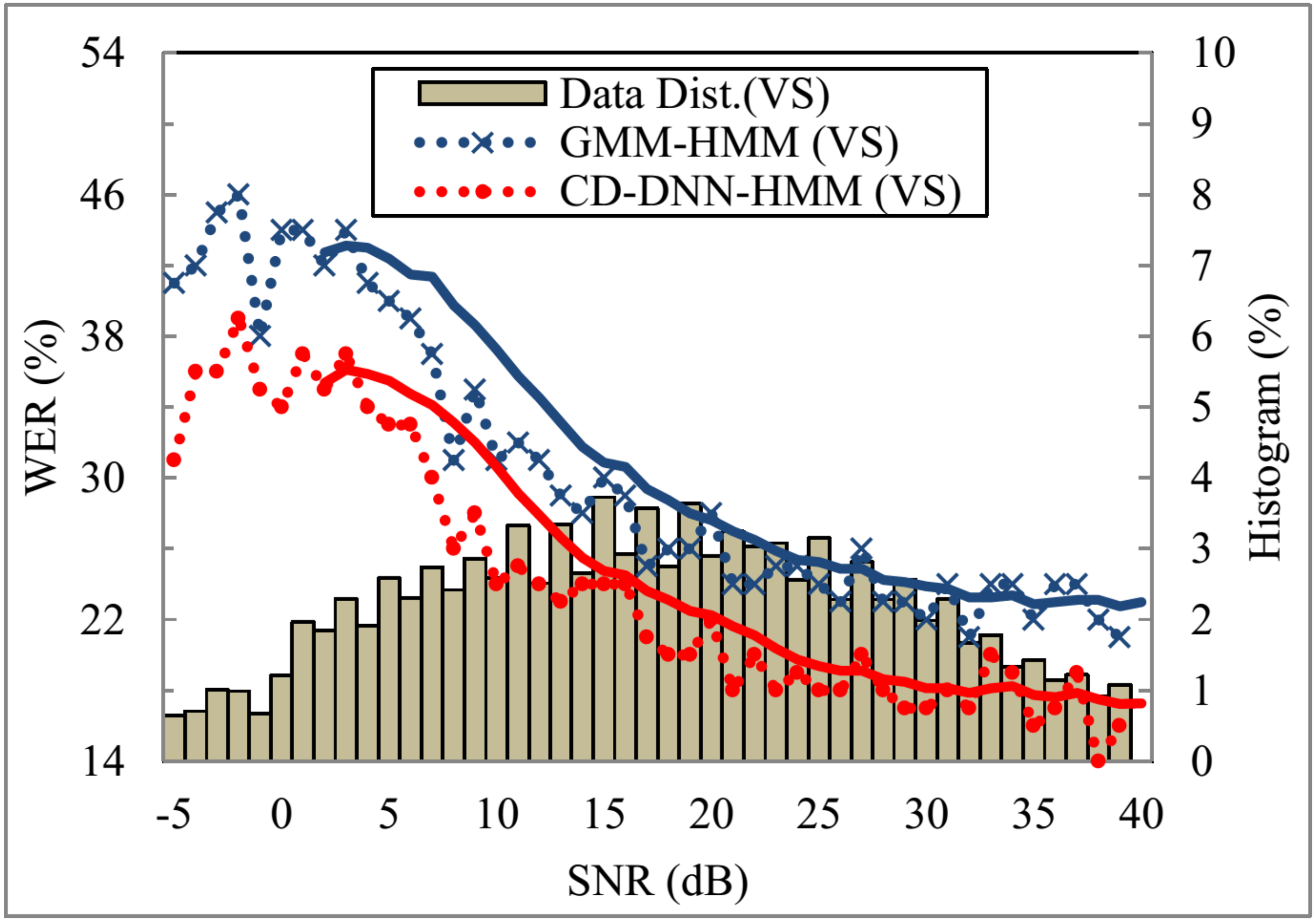
Deep Neural Networks Raise All Boats

- Improve across all phonemes [Huang 2014]



Deep Neural Networks Raise All Boats

- Improve across all signal-to-noise ratios [Huang 2014]



The Power of Depth

- Error rates decrease with depth

# of Layers X # of Neurons	SWBD WER (%) [300hrs]	Aurora 4 WER (%) [10hrs]
1 x 2k	24.2	---
3 x 2k	18.4	14.2
5 x 2k	17.2	13.8
7 x 2k	17.1	13.7
9 x 2k	17.0	13.9

The Power of Depth

- Error rates decrease with depth
- Depth is not just a way to add parameters

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9 x 2k	**17.0**	13.9
1 x 16k	**22.1**	--

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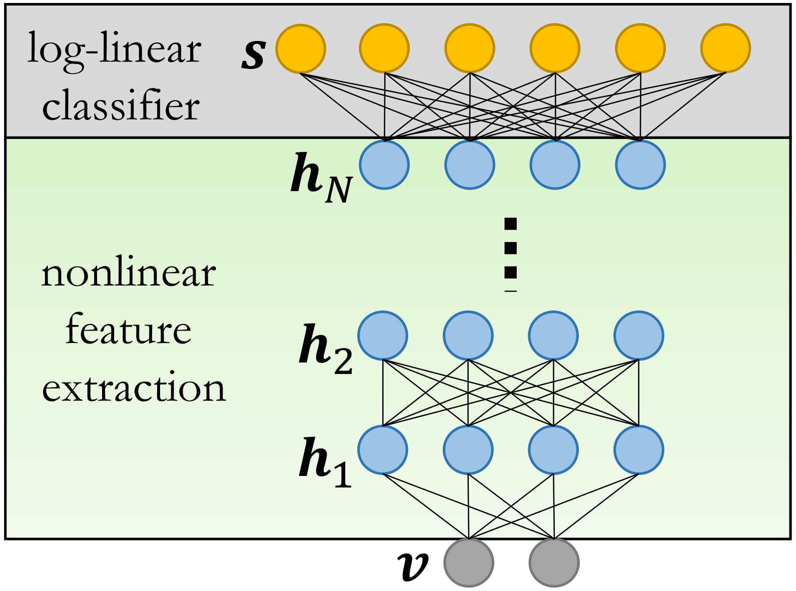
Why DNNs Perform So Well

- It's a combination of nonlinear feature extraction and log-linear classifier
- Many simple nonlinearities combine to form arbitrarily complex nonlinearities for better feature transformation
- Joint feature learning & classifier design
- Lower-layer feature representations are exploited by the higher layer feature detectors
- Features at higher layers more invariant and discriminative than at lower layers

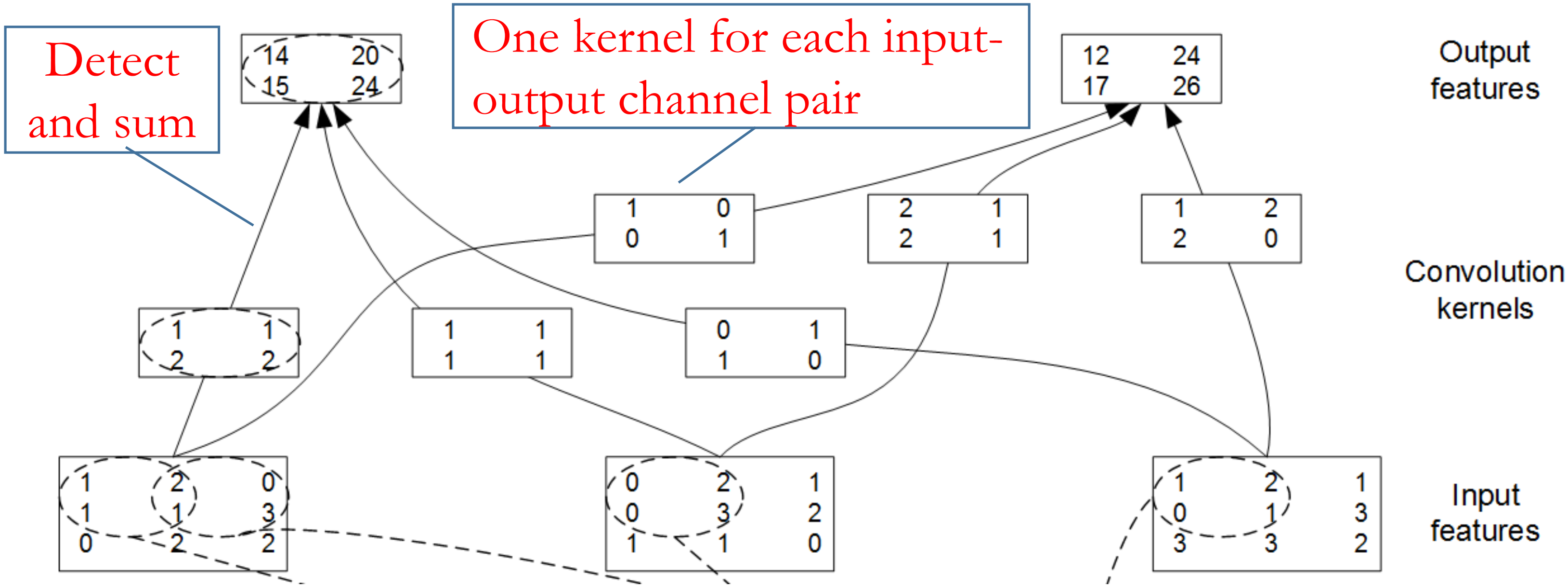


Limitations of DNNs

- We want features that are discriminative and invariant
  - **Discriminative**: transfer the raw feature non-linearly into a higher dimensional space in which things that were non-separable become separable
  - **Invariant**: pool or aggregate features in the new space to introduce invariance
- DNNs achieve this through many layers of non-linear transformations with supervision.
- However,
  - DNNs do not explicitly exploit known structures (e.g., translational variability) in the input data
  - DNNs do not explicitly apply operations that reduces variability (e.g., pooling and aggregation)
- Can we build these properties directly in the neural networks?
  - Yes, e.g., convolutional neural networks (CNNs)

Convolutional Neural Networks

- Explicitly models translational variability and enables shift invariance
  - Shared local filters (weights) tiled across image to detect the same pattern at different locations
  - Sub-sampling through pooling (max, average, or other) to reduce variability

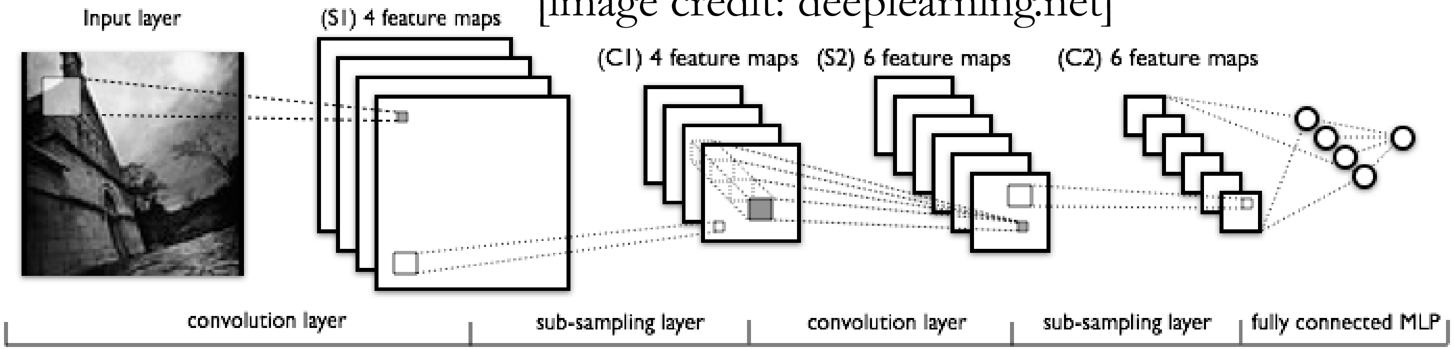


Detect and sum

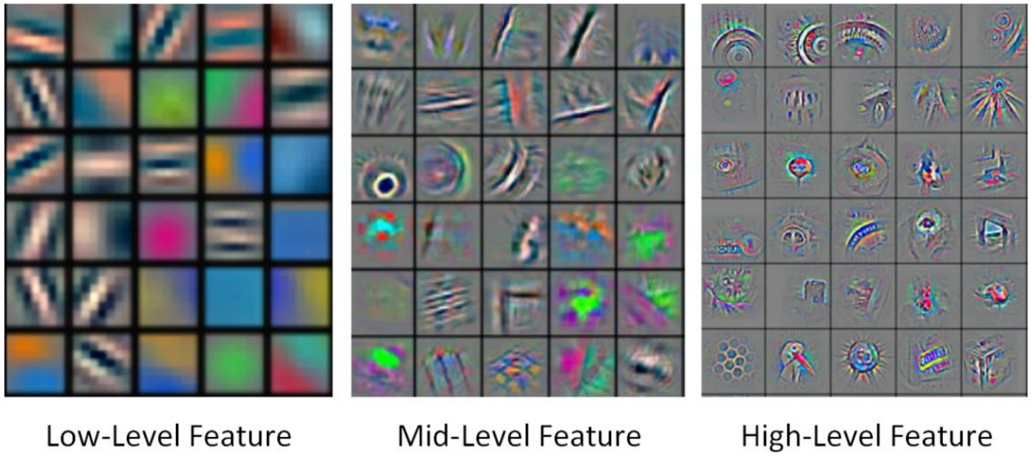
One kernel for each input-output channel pair

Convolutional Neural Networks

- Key to improve image classification accuracy
- Deep CNNs now state of the art for image classification



[image credit: deeplearning.net]



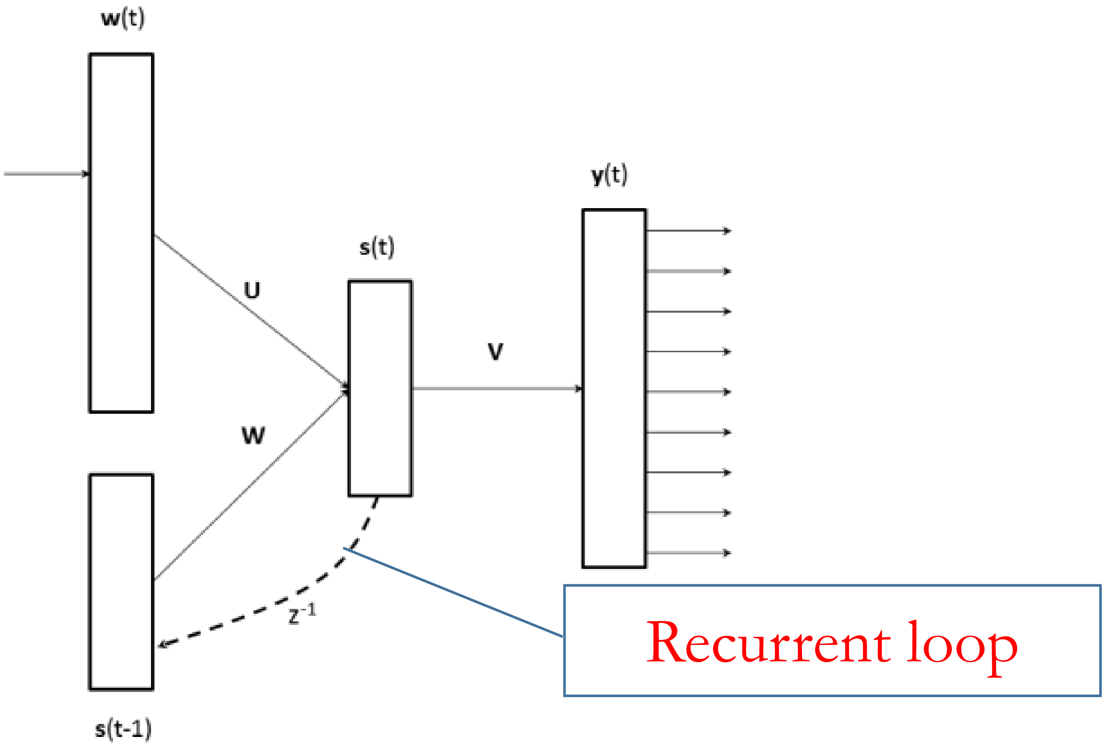
[Zeiler and Fergus, 2013]

Limitations of CNNs

- CNNs mainly deal with translational variability
- There are more types of variability in image classification
    - horizontal reflections
    - color intensity differences
    - scaling
- Techniques such as data synthesis and augmentation, and local response normalization are needed to deal with these additional variability
- CNNs cannot take advantage dependencies and correlations between samples (and labels) in a sequence
- Recurrent neural networks (RNNs) are designed for this

Recurrent Neural Networks

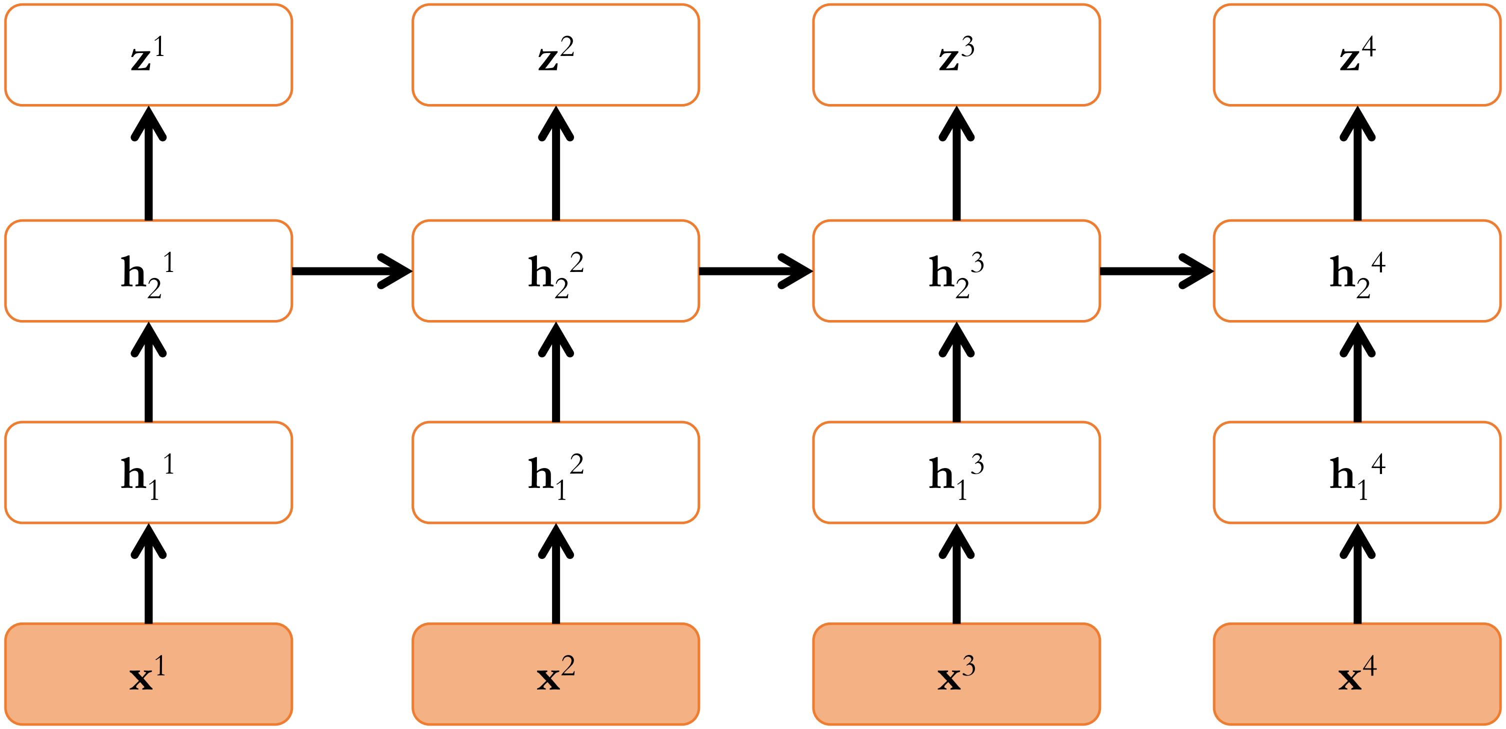
- Models dependencies and correlations between samples (and labels) in a sequence
- Information may be fed back from hidden and output layers in the previous time steps



Recurrent loop

Deep Recurrent Neural Networks

- Combine deep neural networks with recurrent neural networks
- Trained with backpropagation through time (BPTT) and truncated BPTT

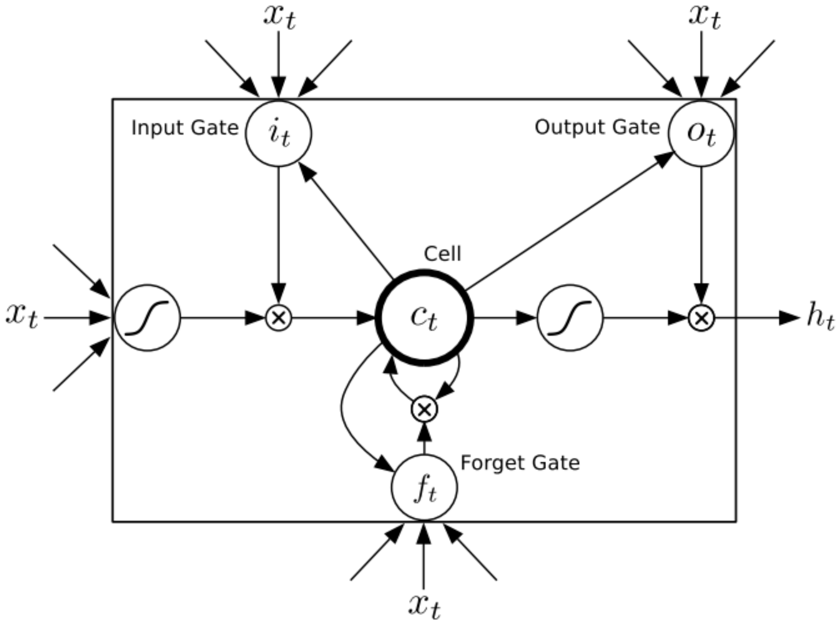


Limitations of Simple RNNs

- Simple RNNs are difficult to train due to diminishing and explosion of gradients over time
  - Can be partially alleviated with gradient thresholding
- Simple RNNs have difficulty modeling long-range dependencies
  - The effect of information from past samples decreases exponentially
- Is it possible to solve the gradient diminishing problem so that we can model long-range dependencies
- Yes, with carefully designed recurrent structures such as long short-term memory (LSTM) RNNs.

Long Short-Term Memory RNNs

- An extension of RNN that addresses vanishing gradient problem
  - Memory cell is linearly time-recurrent
  - Use gates to control and keep long-range information



[image credit: Graves 2013]

Long Short-Term Memory RNNs

- State-of-the-art performance for many sequential recognition problems:
  - ASR
  - hand written character recognition
- Is a generic model
- May not be optimal for the specific problems at hand which requires designing customized models

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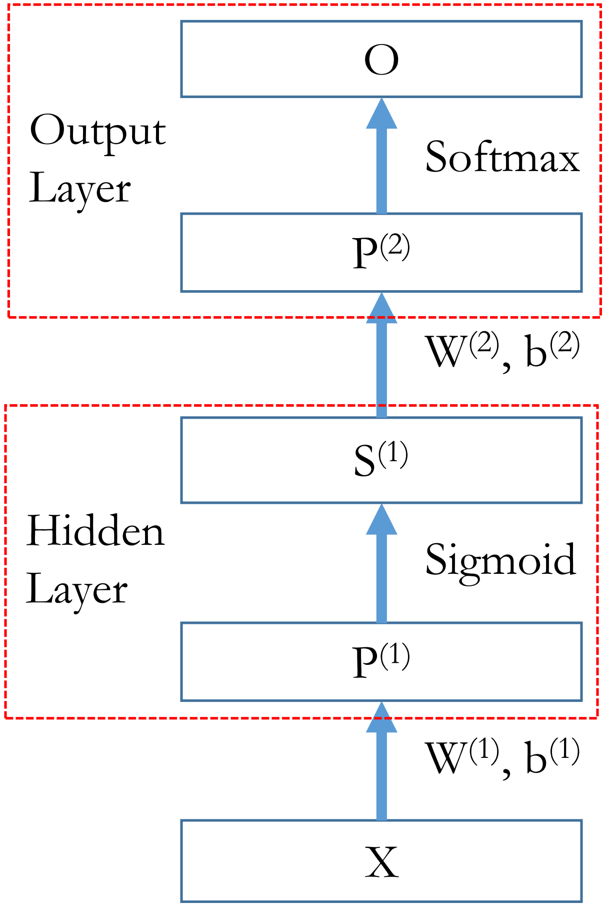
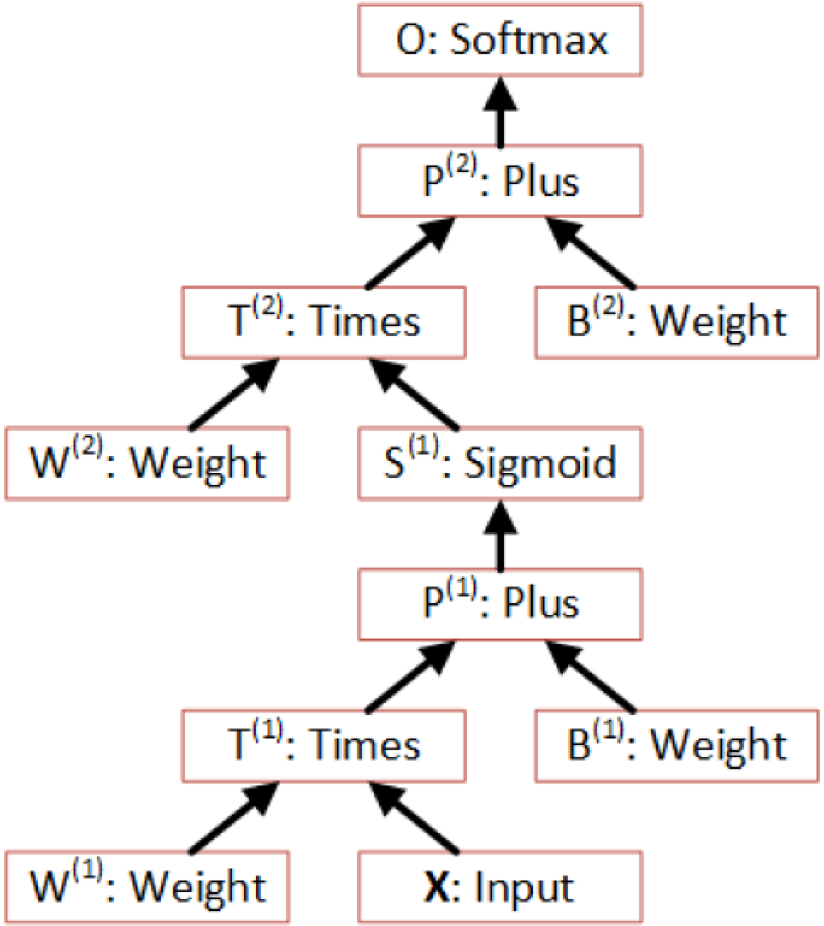
Generalization of Deep Learning Models

- Consider the models we just described…
    - Deep Neural Networks (DNNs)
    - Convolutional Neural Networks (CNNs)
    - Recurrent Neural Networks (RNNs)
    - Long Short-Term Memory (LSTM) RNNs
- …and some other common machine learning models
    - Gaussian Mixture Models (GMMs)
    - Logistic Regression Models (LRMs)
    - Log-Linear Models (LLMs)
- Common property:
    - Can be described as a series of computational steps

Example: One Hidden Layer NN





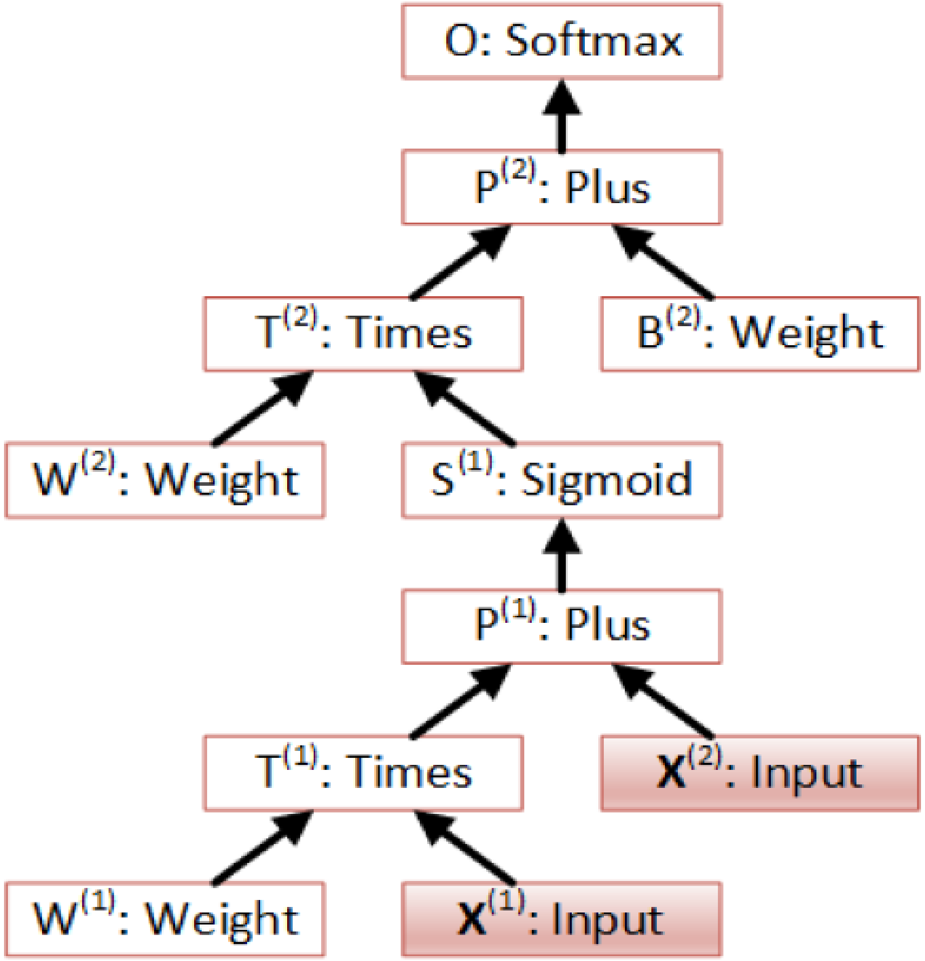
Computational Networks

- A generalization of machine learning models that can be described as a series of computational steps.
- Representation:
  - A list of computational nodes denoted as

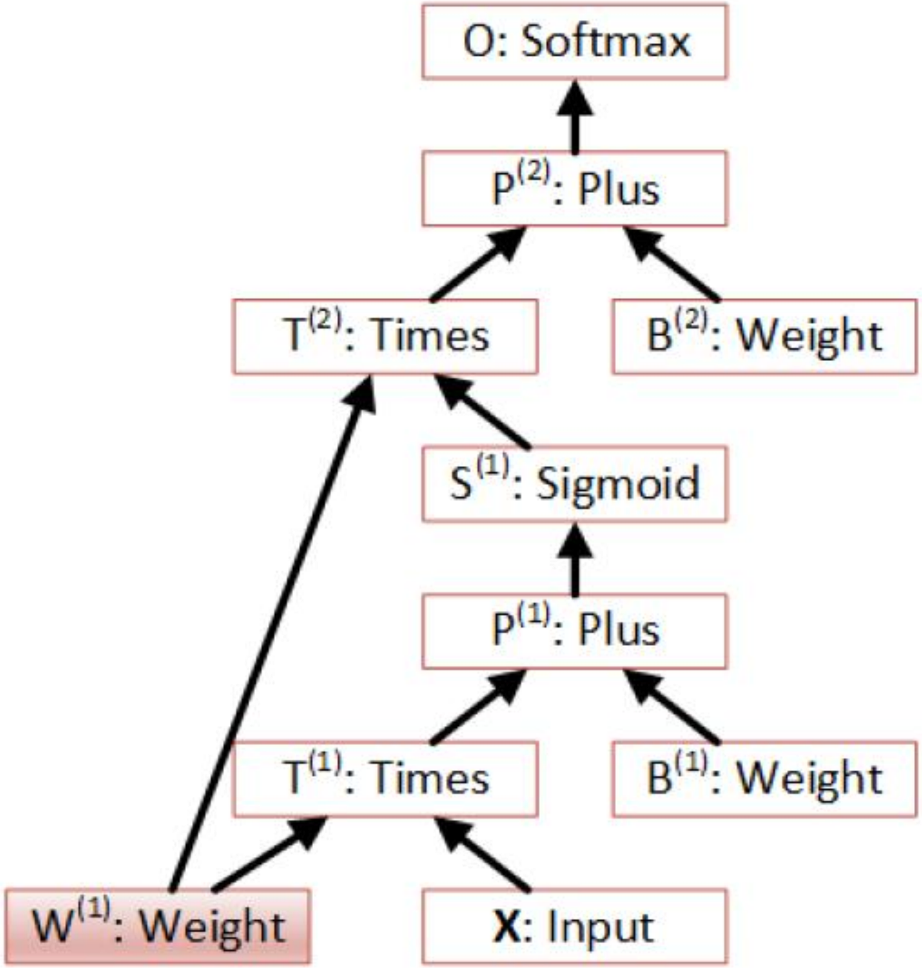
    $n = \{\text{node name} : \text{operation name}\}$
  - The parent-children relationship describing the operands

    $\{n : c_1, \cdots, c_{Kn}\}$
    - Kn is the number of children of node n. For leaf nodes Kn = 0.
    - Order of the children matters: e.g., XY is different from YX
  - Given the inputs (operands) the value of the node can be computed.
- Can describe models that are far more complicated than simple conventional neural networks.

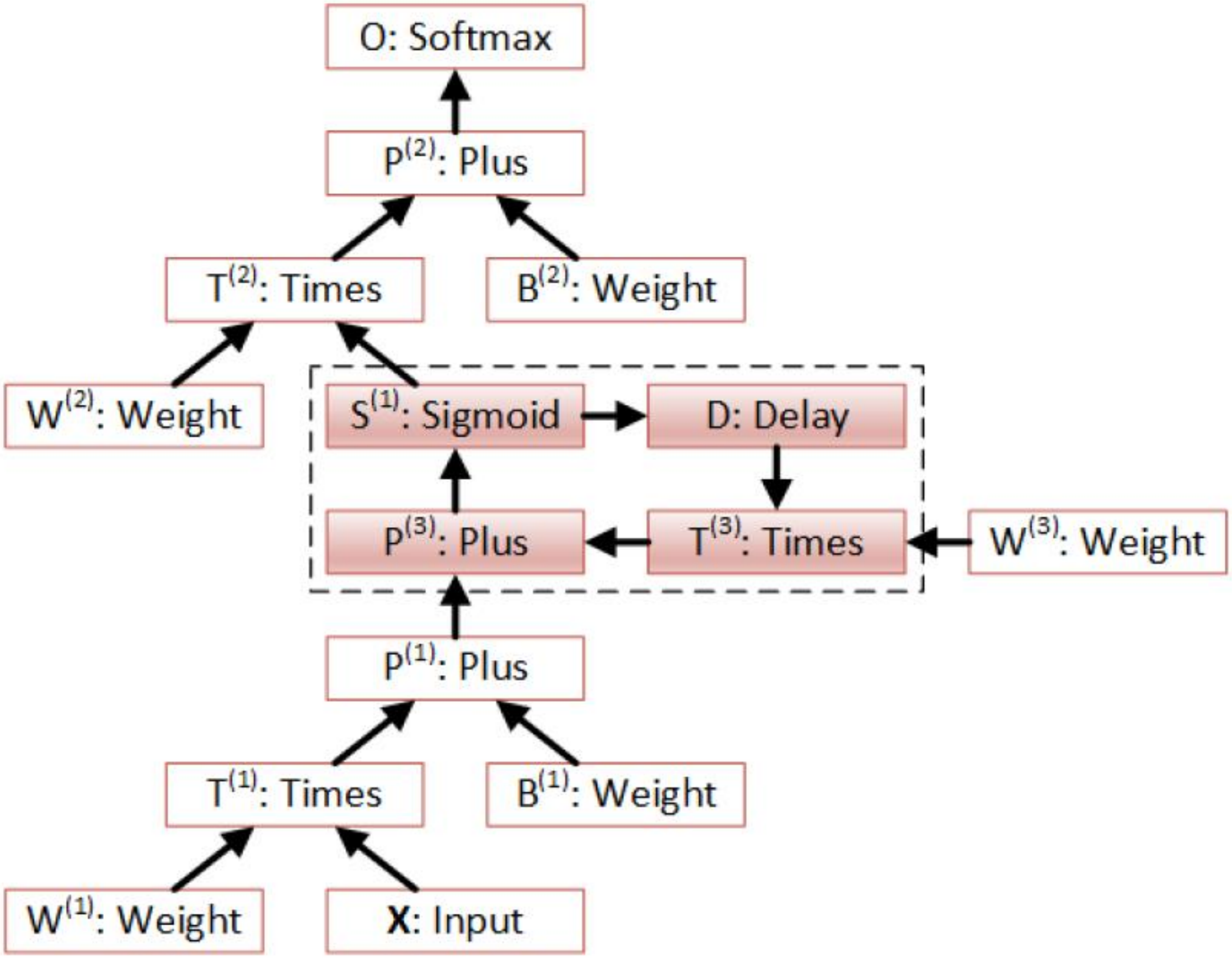
Example: CN with Multiple Inputs



Example: CN with Shared Parameters

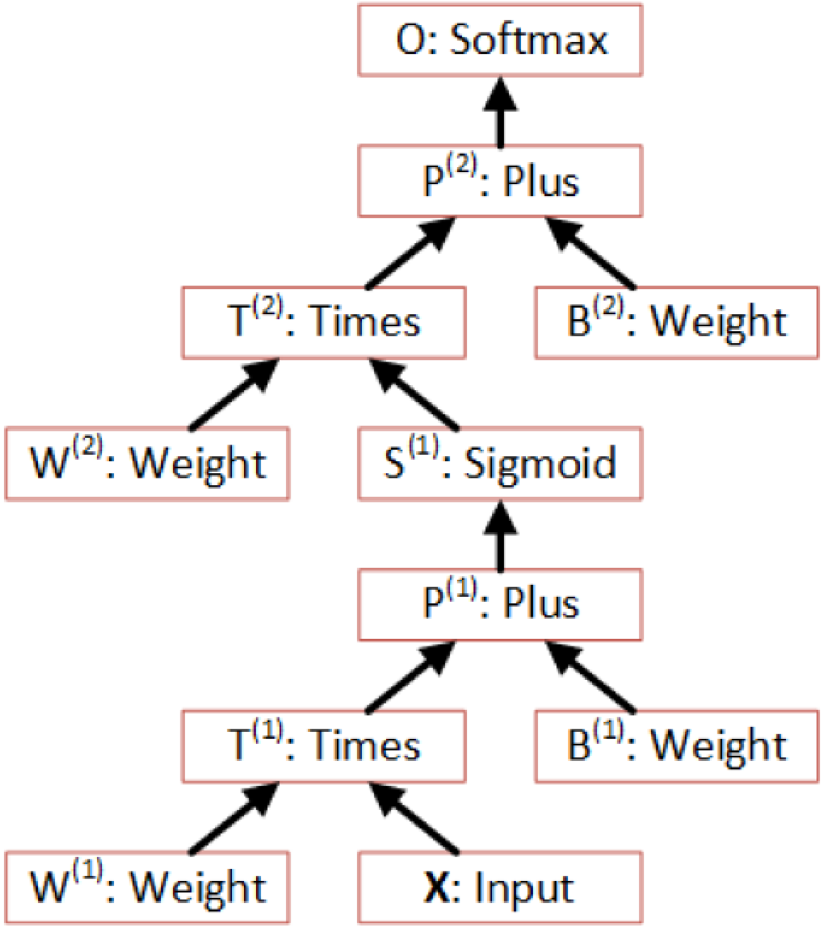


Example: CN with Recurrence



Forward Computation – No Loop

- Given the root node, the computation order can be determined by a depth-first traverse of the directed acyclic graph (DAG).
- Only need to run it once and cache the order



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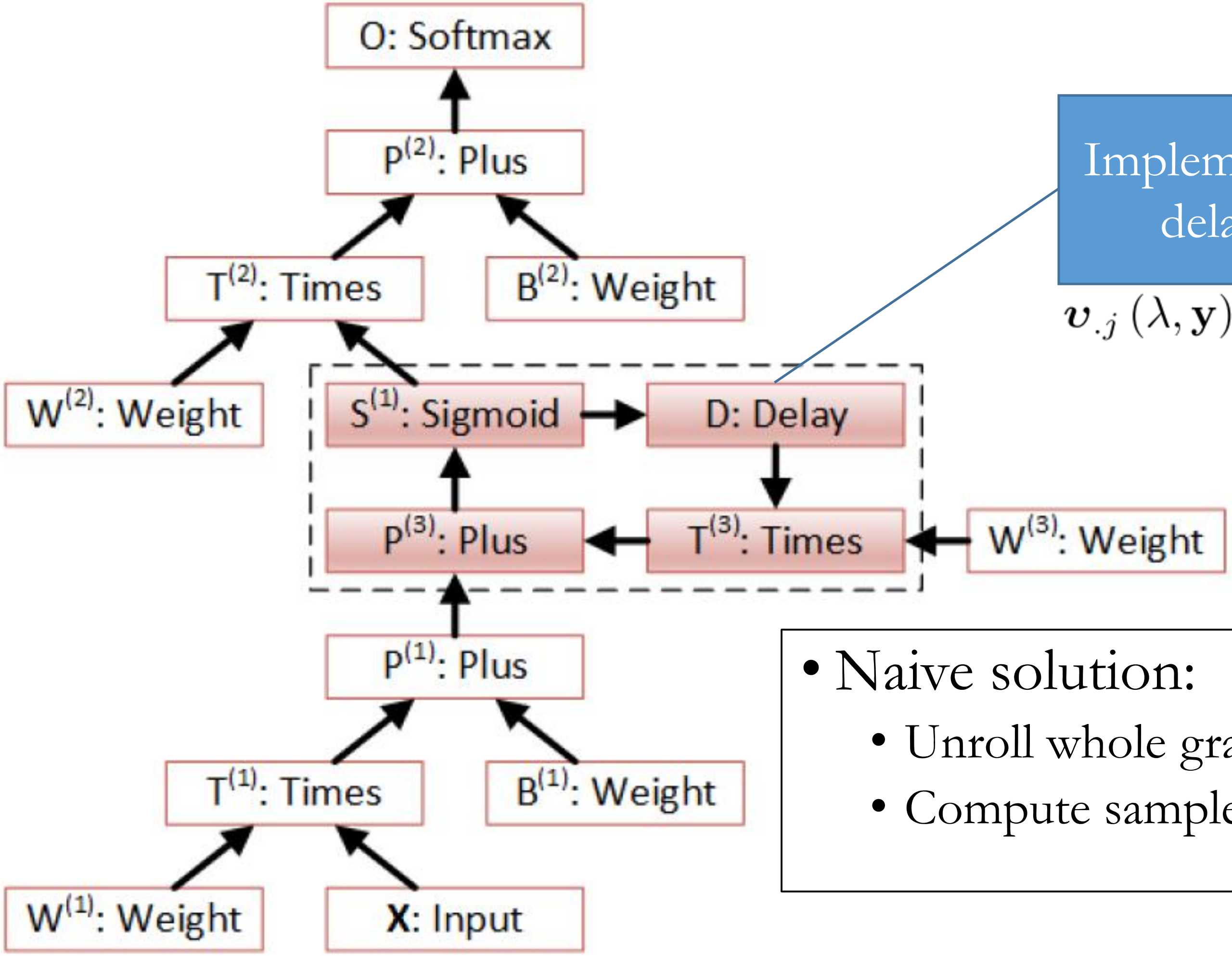
Forward Computation – With Loop

- Very important in many interesting models



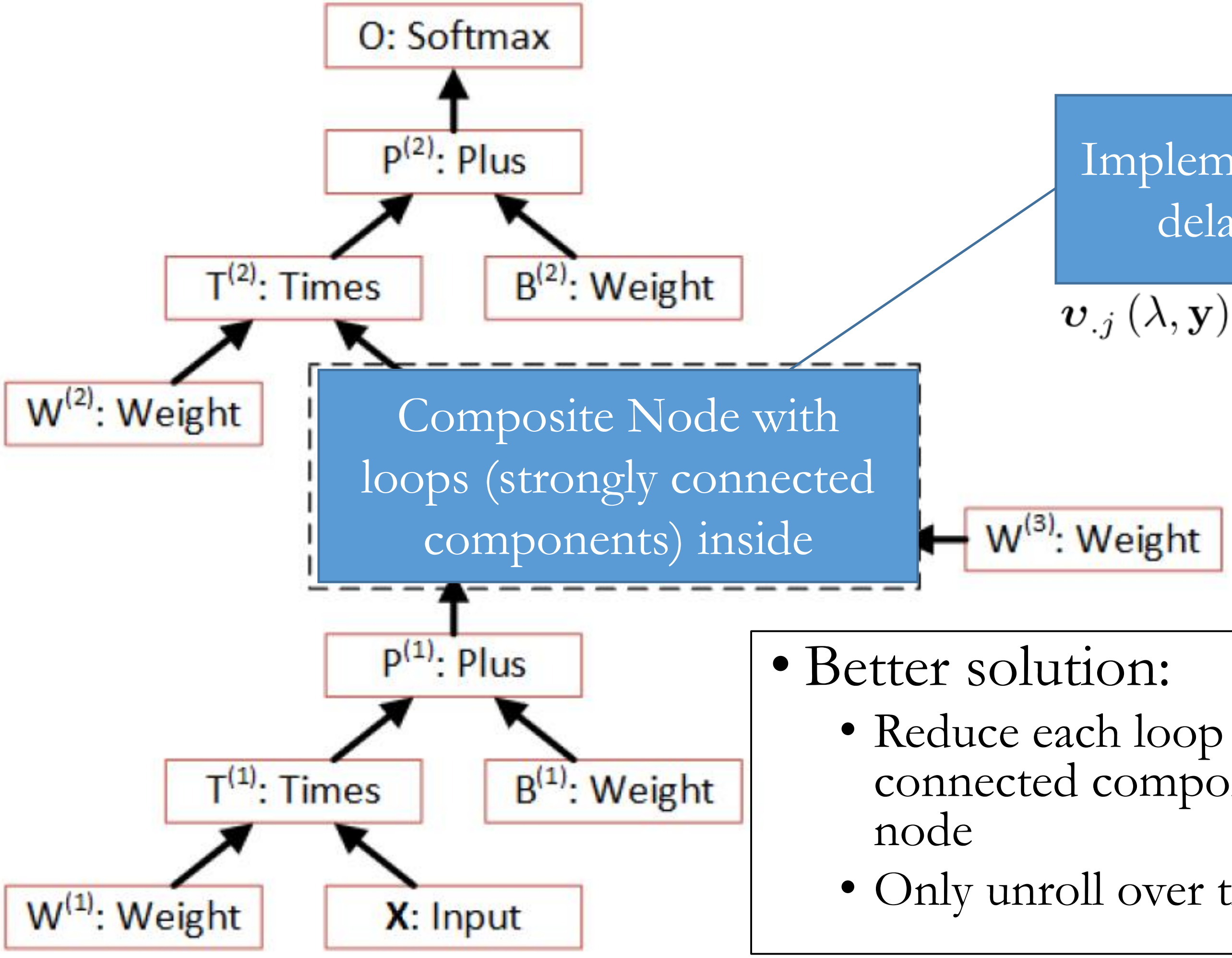
Implemented with delay node

$$\boldsymbol{v}_{.j}\left(\lambda, \mathbf{y}\right) = \mathbf{y}_{.(j-\lambda)}$$

- Naive solution:
  - Unroll whole graph over time
  - Compute sample by sample

Forward Computation – With Loop

- Very important in many interesting models



O: Softmax

$P^{(2)}$: Plus

$T^{(2)}$: Times

$B^{(2)}$: Weight

$W^{(2)}$: Weight

Composite Node with loops (strongly connected components) inside

$W^{(3)}$: Weight

$P^{(1)}$: Plus

$T^{(1)}$: Times

$B^{(1)}$: Weight

$W^{(1)}$: Weight

X: Input

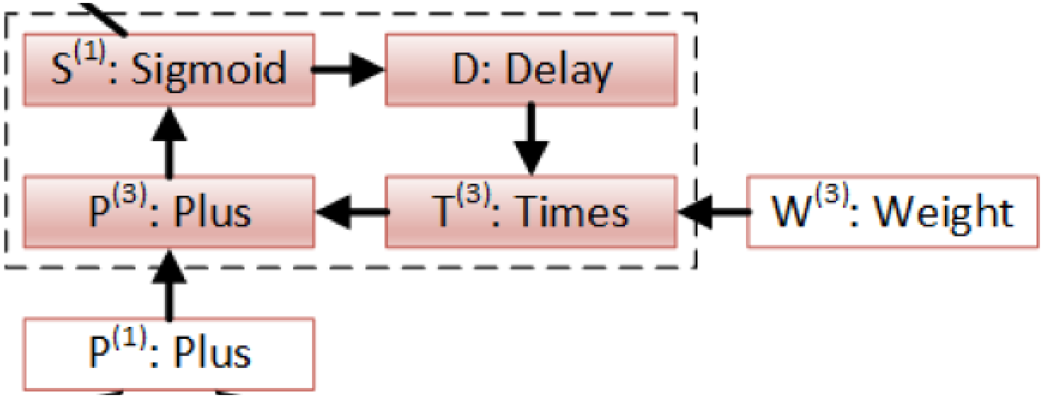
Implemented with delay node

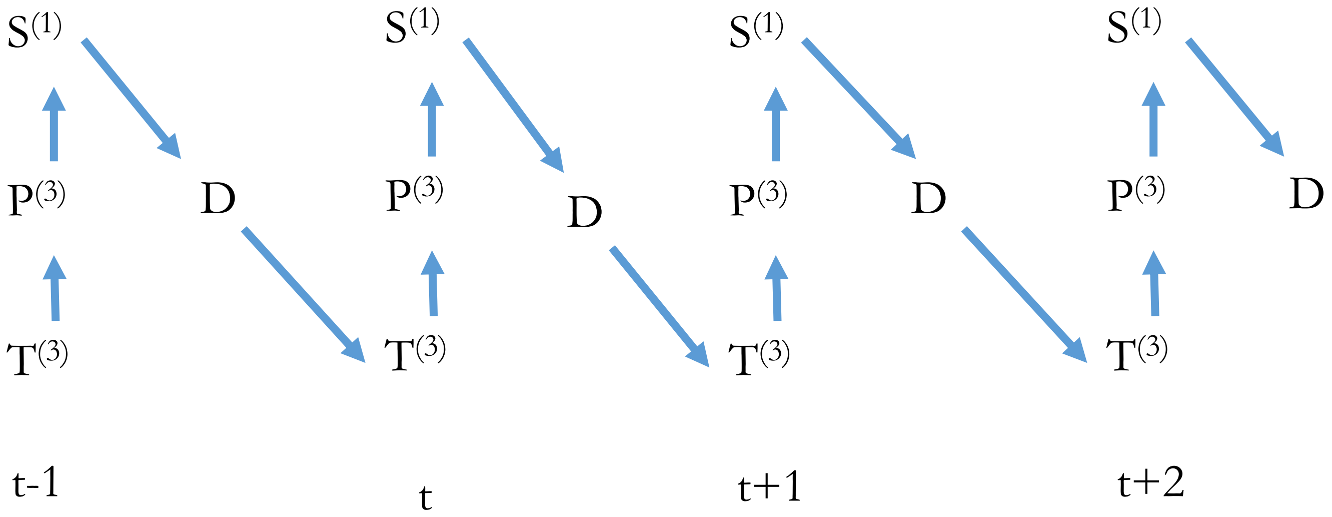
$$\boldsymbol{v}_{.j}\left(\lambda, \mathbf{y}\right) = \mathbf{y}_{.(j-\lambda)}$$

- Better solution:
  - Reduce each loop (strongly connected component) into a single node
  - Only unroll over time inside loops

Forward Computation – With Loop

- Nodes inside the loops need to be computed sample by sample unrolled over time





Forward Computation – With Loop

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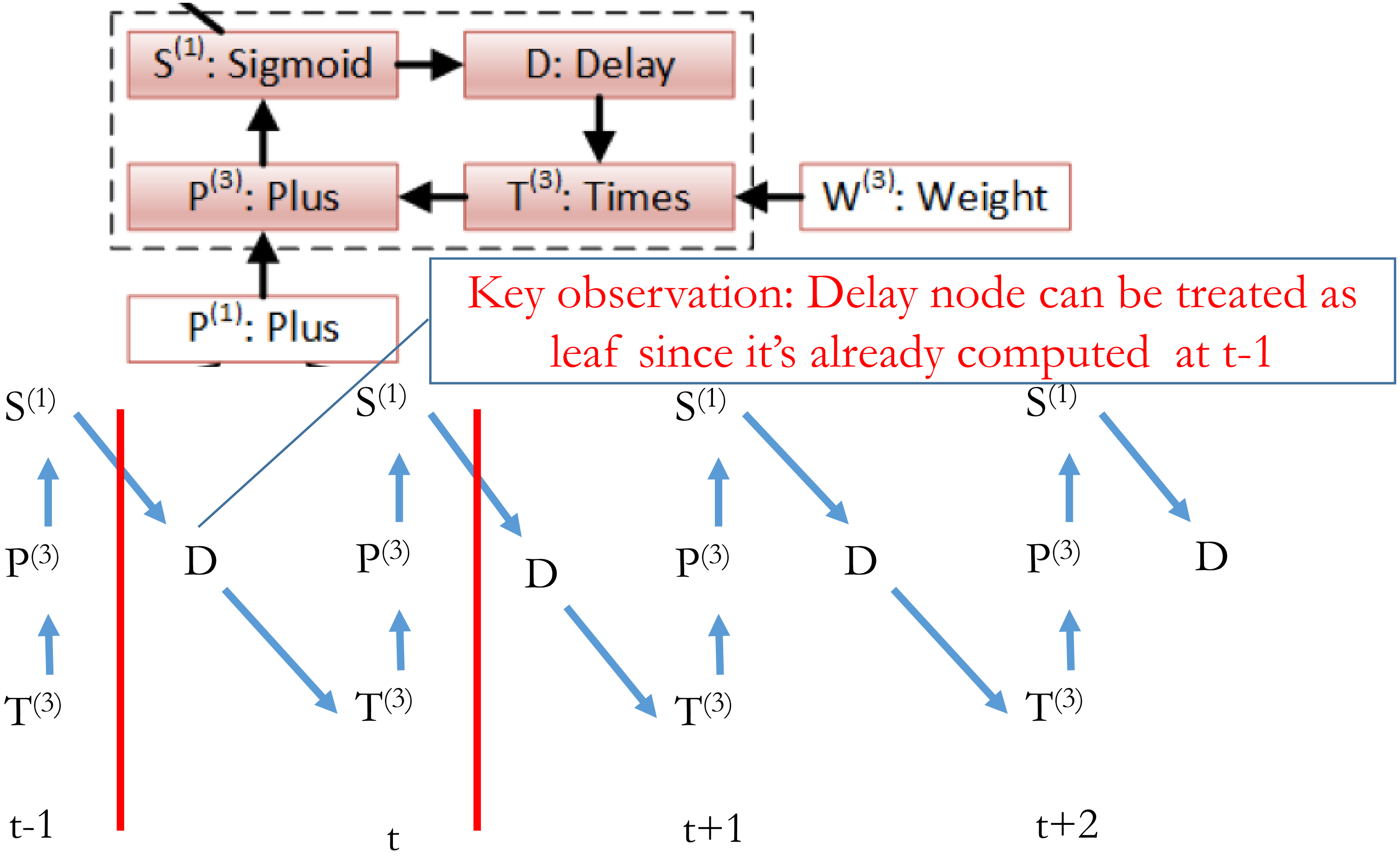
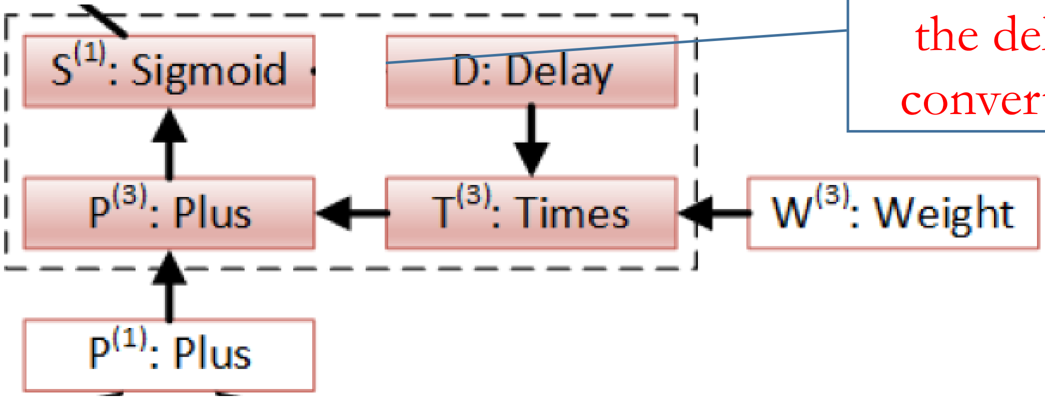


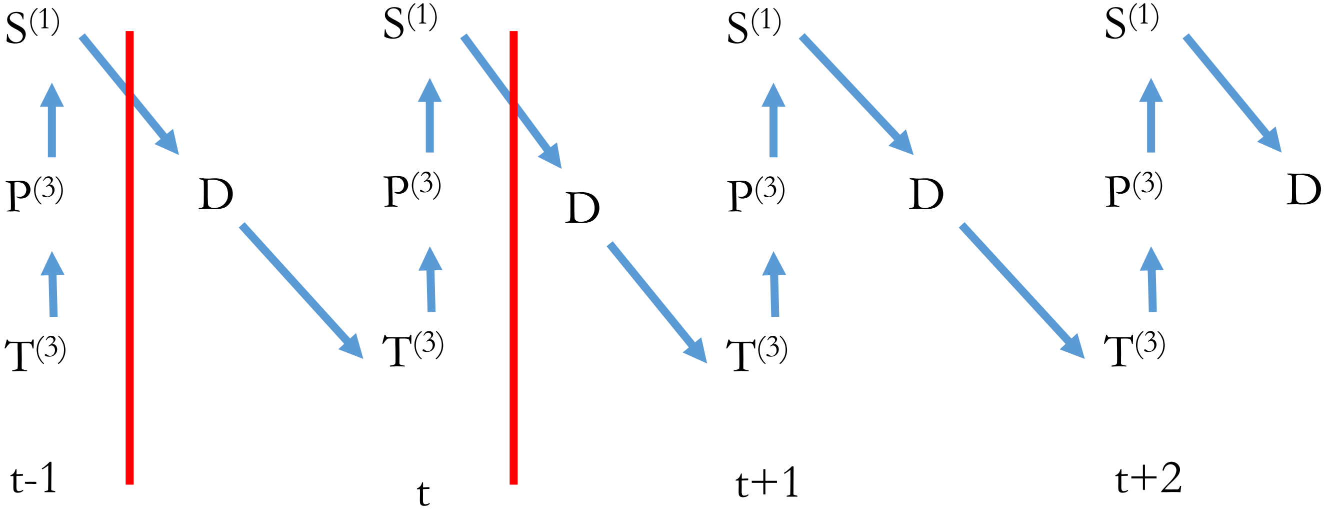
Key observation: Delay node can be treated as leaf since it's already computed at t-1

Forward Computation – With Loop

- Nodes inside the loops need to be computed sample by sample unrolled over time

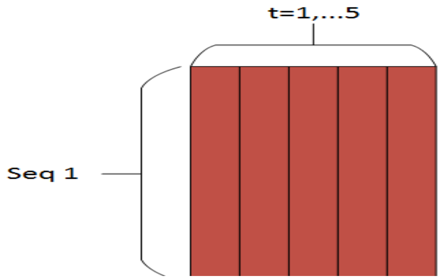
Remove the arrows to the delay node and convert it to a DAG





Forward Computation – With Loop

- May still be slow inside the loops, esp. if loop is long
- Solution: process multiple sequences in a batch



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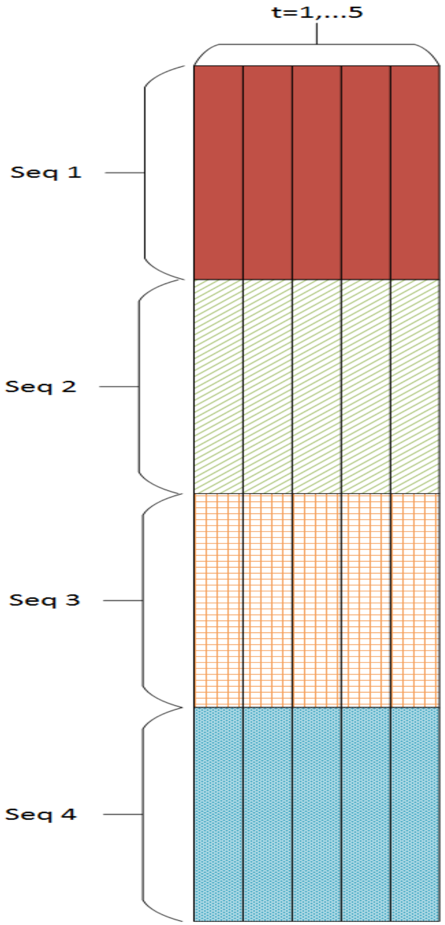

Forward Computation – With Loop

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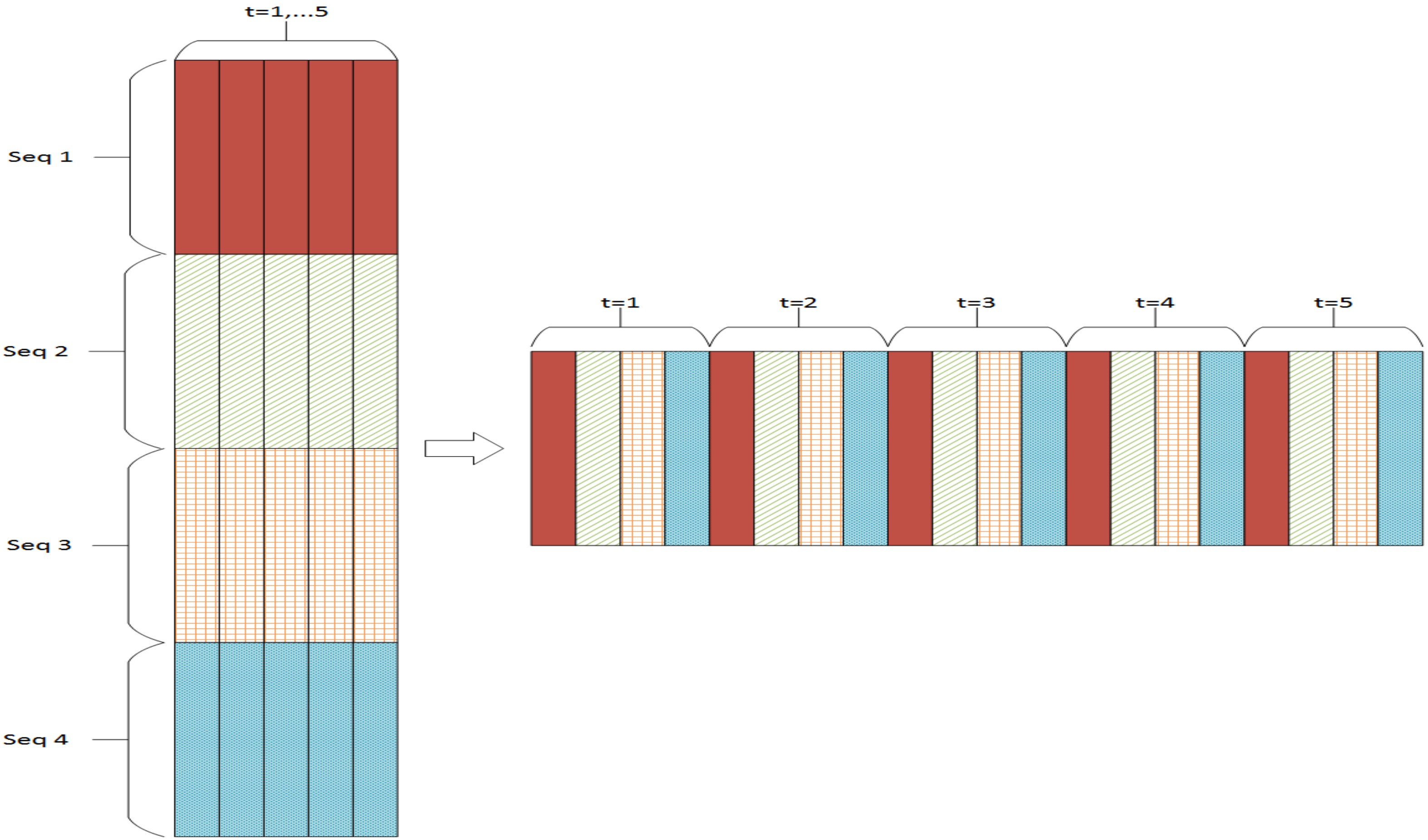
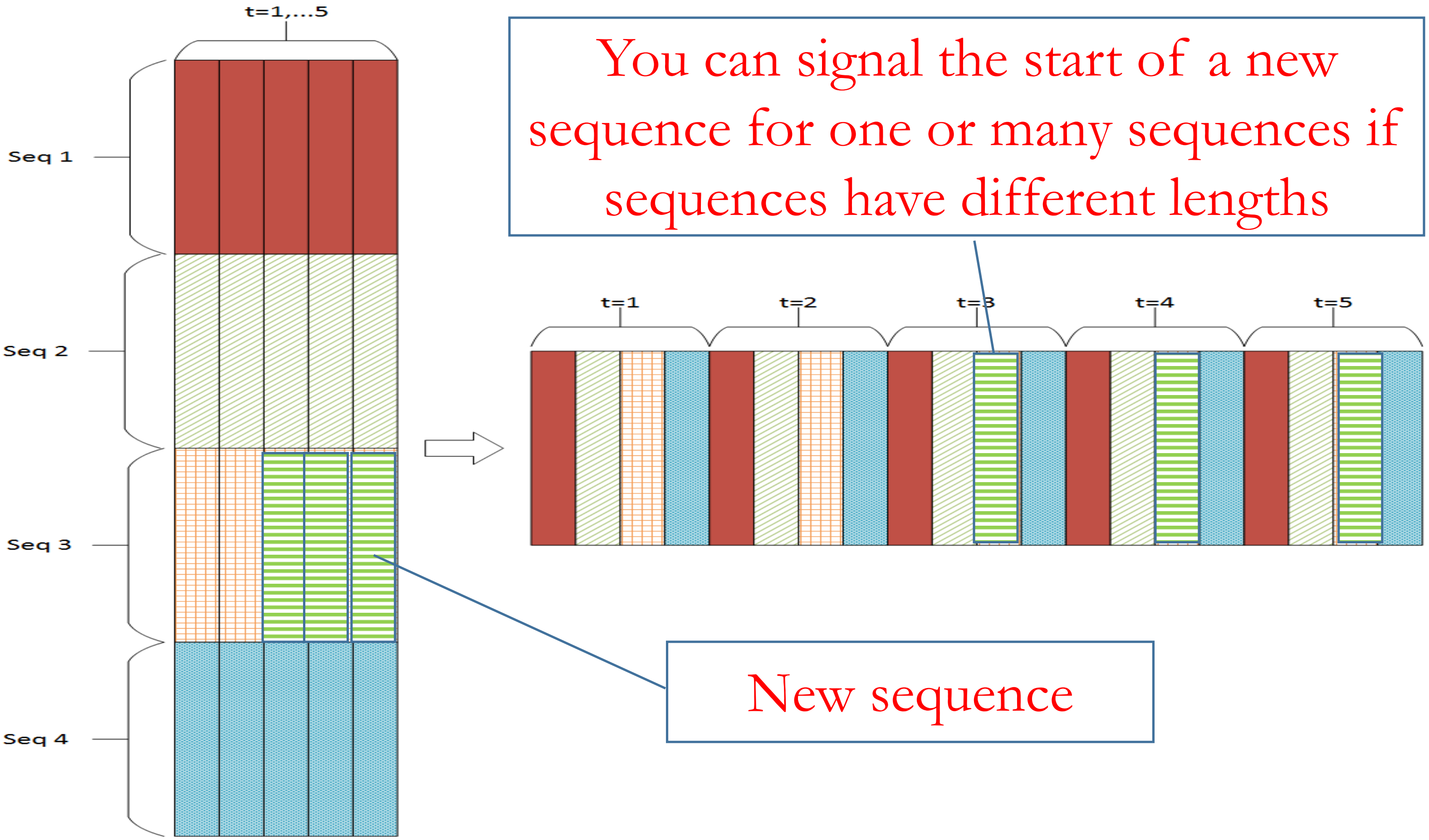


Forward Computation – With Loop

- What if sequences have different lengths
- Randomly select a new sequence and fill it in

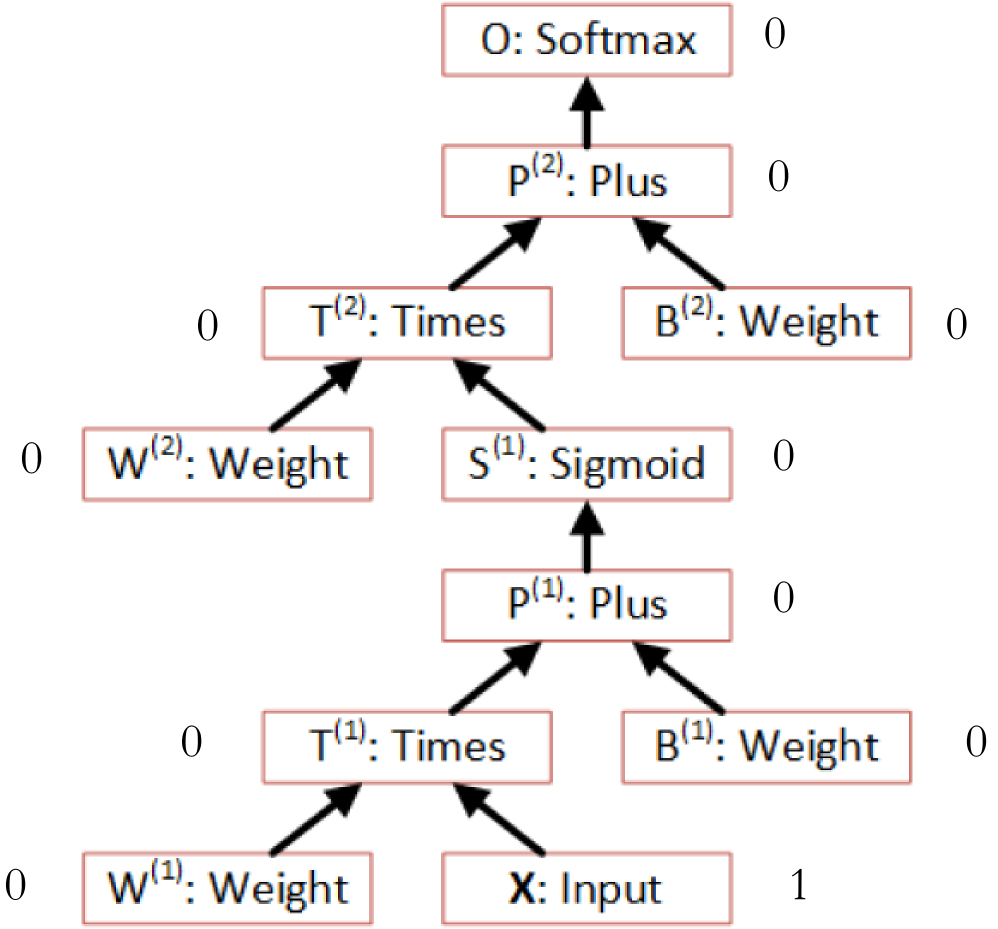


You can signal the start of a new sequence for one or many sequences if sequences have different lengths

New sequence

Forward Computation Efficiency

- Add time stamps to reduce duplicate computation



Forward Computation Efficiency

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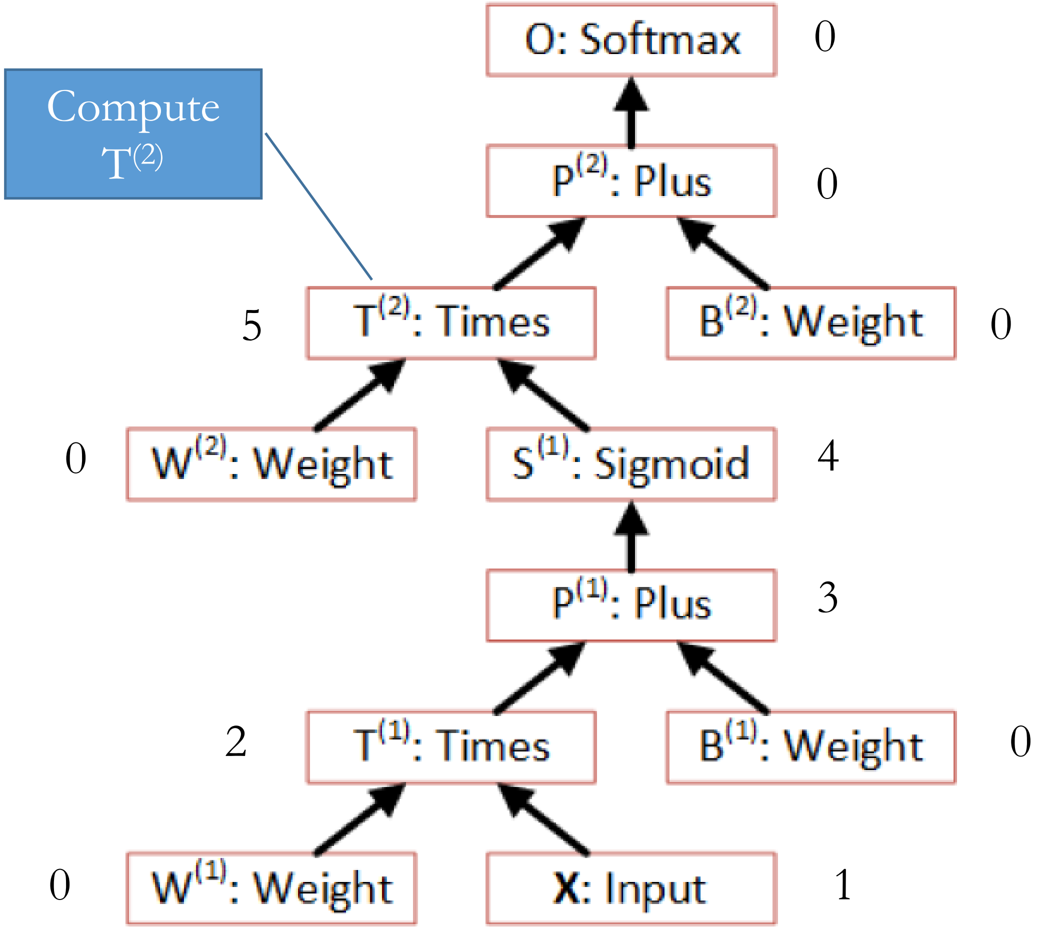

Forward Computation Efficiency

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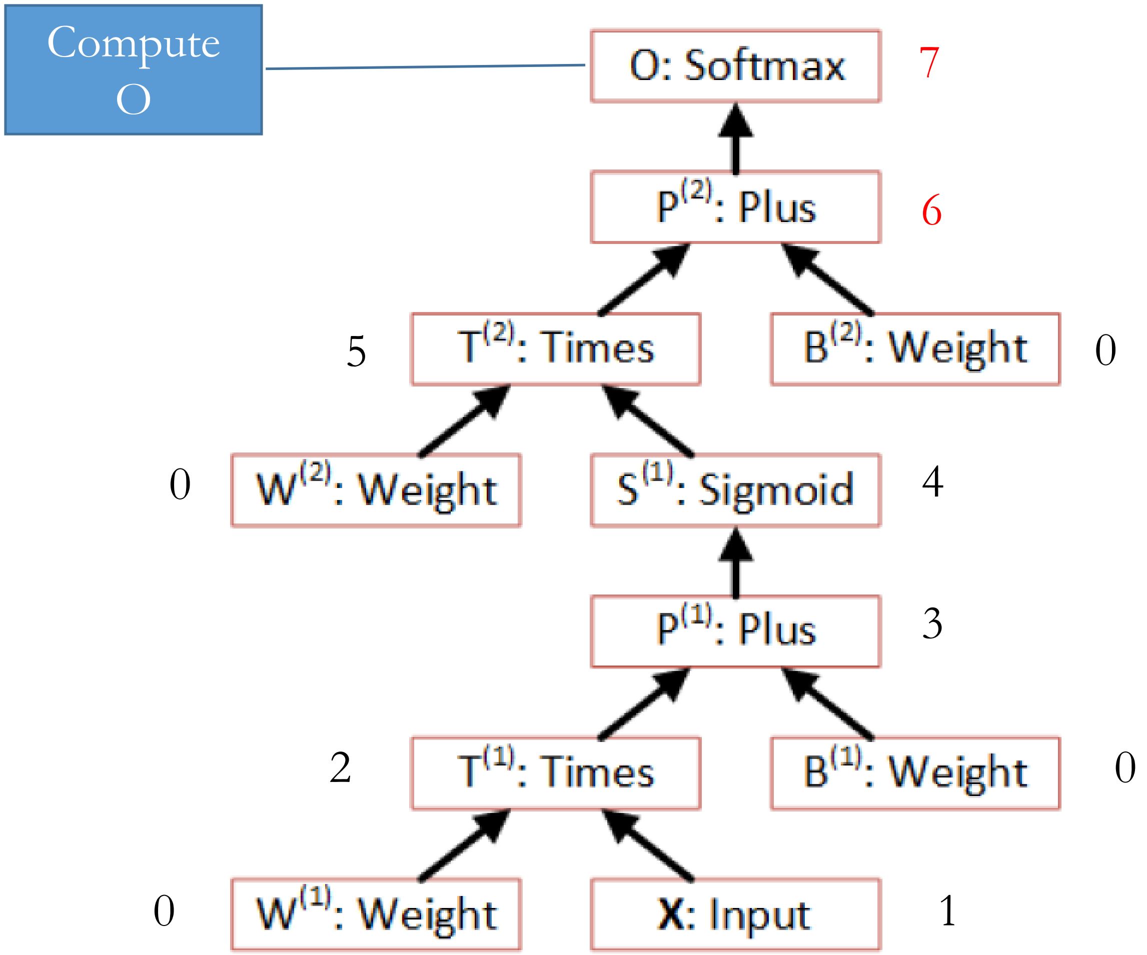
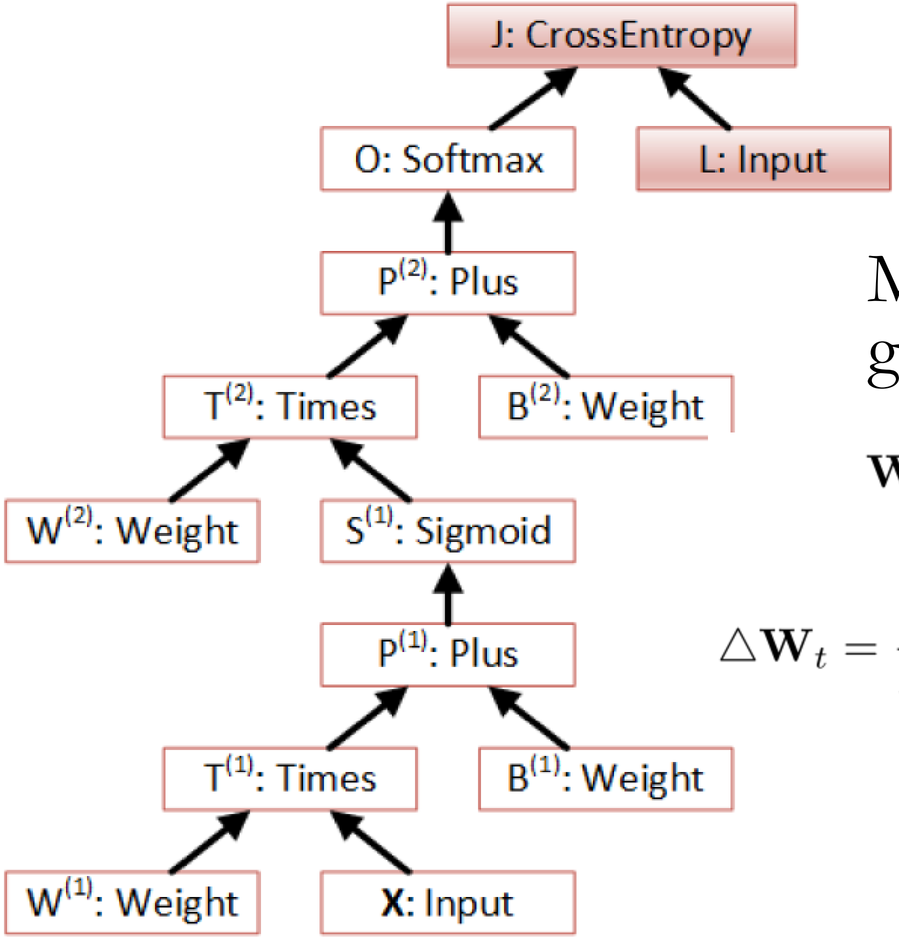


Training

- Decide training criterion and add corresponding computation nodes



Model update with gradient descent

$$\mathbf{W}_{t+1} \leftarrow \mathbf{W}_{\mathrm{t}} - \varepsilon \triangle \mathbf{W}_t,$$

$$\triangle \mathbf{W}_t = \frac{1}{M_b} \sum_{m=1}^{M_b} \nabla_{\mathbf{W}_t} J\left(\mathbf{W}; \mathbf{x}^m, \mathbf{y}^m\right)$$

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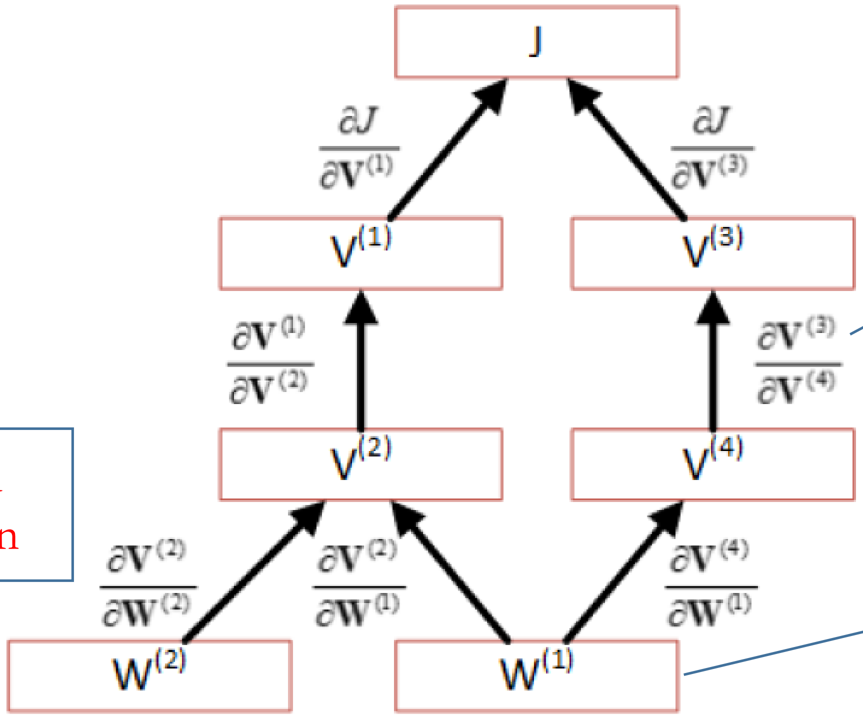
Automatic Gradient Computation

- Naive solution: compute and keep gradients at edges


J
$\frac{\partial J}{\partial \mathbf{V}^{(1)}}$
$\frac{\partial J}{\partial \mathbf{V}^{(3)}}$
$V^{(1)}$
$V^{(3)}$
$\frac{\partial \mathbf{V}^{(1)}}{\partial \mathbf{V}^{(2)}}$
$\frac{\partial \mathbf{V}^{(3)}}{\partial \mathbf{V}^{(4)}}$
$V^{(2)}$
$V^{(4)}$
$\frac{\partial \mathbf{V}^{(2)}}{\partial \mathbf{W}^{(2)}}$
$\frac{\partial \mathbf{V}^{(2)}}{\partial \mathbf{W}^{(1)}}$
$\frac{\partial \mathbf{V}^{(4)}}{\partial \mathbf{W}^{(1)}}$
$W^{(2)}$
$W^{(1)}$

Huge

Duplicated computation

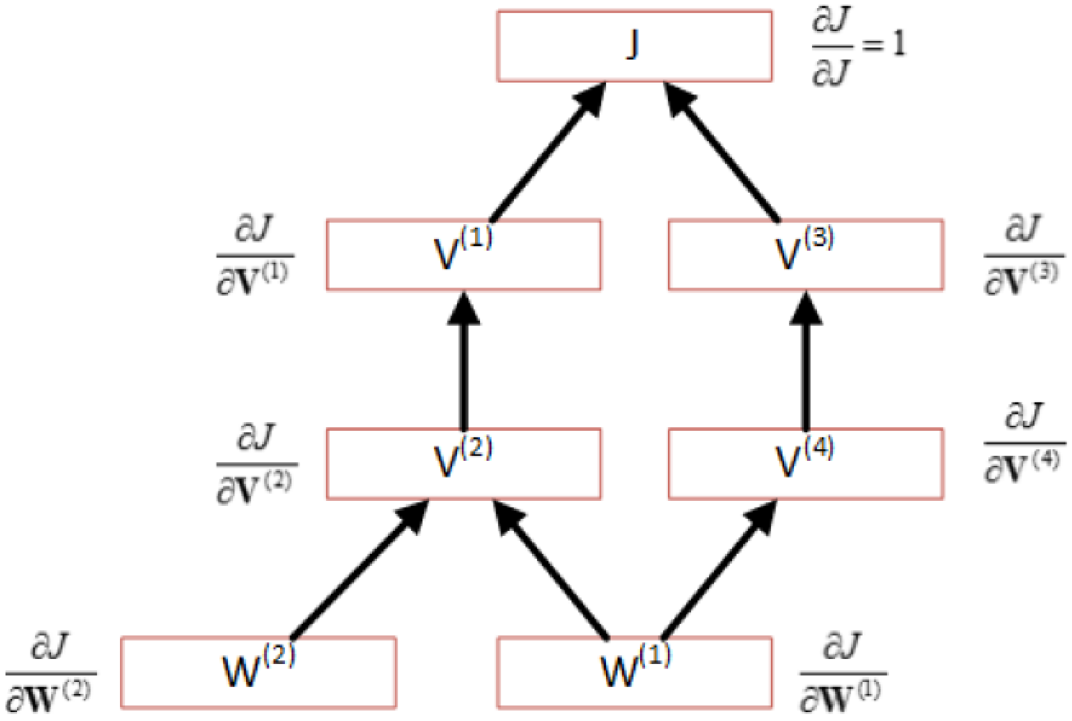
Shared by multiple parents

$$\nabla^{J}_{\mathbf{W}^{(1)}} = \boxed{\frac{\partial J}{\partial \mathbf{V}^{(1)}} \frac{\partial \mathbf{V}^{(1)}}{\partial \mathbf{V}^{(2)}}} \frac{\partial \mathbf{V}^{(2)}}{\partial \mathbf{W}^{(1)}} + \frac{\partial J}{\partial \mathbf{V}^{(3)}} \frac{\partial \mathbf{V}^{(3)}}{\partial \mathbf{V}^{(4)}} \frac{\partial \mathbf{V}^{(4)}}{\partial \mathbf{W}^{(1)}}$$

$$\nabla^{J}_{\mathbf{W}^{(2)}} = \boxed{\frac{\partial J}{\partial \mathbf{V}^{(1)}} \frac{\partial \mathbf{V}^{(1)}}{\partial \mathbf{V}^{(2)}}} \frac{\partial \mathbf{V}^{(2)}}{\partial \mathbf{W}^{(2)}}.$$

Automatic Gradient Computation

- Better solution: compute and keep gradients at nodes


J
$\frac{\partial J}{\partial J}=1$
$\frac{\partial J}{\partial \mathbf{V}^{(1)}}$
$V^{(1)}$
$V^{(3)}$
$\frac{\partial J}{\partial \mathbf{V}^{(3)}}$
$\frac{\partial J}{\partial \mathbf{V}^{(2)}}$
$V^{(2)}$
$V^{(4)}$
$\frac{\partial J}{\partial \mathbf{V}^{(4)}}$
$\frac{\partial J}{\partial \mathbf{W}^{(2)}}$
$W^{(2)}$
$W^{(1)}$
$\frac{\partial J}{\partial \mathbf{W}^{(1)}}$

- Small footprint
- Factorize computation: node sums over all paths
- Isolated the gradient computation to each node

Gradient Computation at Node

- Each node has a ComputeInputPartial function to compute partial derivatives with regard to its children
- Basic rule:

$$\frac{\partial J}{\partial x_{ij}} = \sum_{m,n} \frac{\partial J}{\partial v_{mn}} \frac{\partial v_{mn}}{\partial x_{ij}}$$

child

Current node

- *Sigmoid*: since

$$\frac{\partial v_{mn}}{\partial x_{ij}} = \begin{cases} v_{ij}\left(1 - v_{ij}\right) & m = i \wedge n = j \\ 0 & else \end{cases}$$

we have

$$\frac{\partial J}{\partial x_{ij}} = \sum_{m,n} \frac{\partial J}{\partial v_{mn}} \frac{\partial v_{mn}}{\partial x_{ij}} = \frac{\partial J}{\partial v_{ij}} v_{ij}\left(1 - v_{ij}\right)$$

and

$$\nabla^{J}_{\mathbf{x}} \leftarrow \nabla^{J}_{\mathbf{x}} + \nabla^{J}_{\mathbf{n}} \bullet \left[\boldsymbol{v} \bullet (1 - \boldsymbol{v})\right]$$

Gradient Computation at Node

- *Times*: since

$$\frac{\partial \upsilon_{mn}}{\partial x_{ij}} = \begin{cases} y_{jn} & m = i \\ 0 & else \end{cases}$$

we have

$$\frac{\partial J}{\partial x_{ij}} = \sum_{m,n} \frac{\partial J}{\partial \upsilon_{mn}} \frac{\partial \upsilon_{mn}}{\partial x_{ij}} = \sum_{n} \frac{\partial J}{\partial \upsilon_{in}} y_{jn}$$

or

$$\nabla_{\mathbf{x}}^{J} \leftarrow \nabla_{\mathbf{x}}^{J} + \nabla_{\mathbf{n}}^{J} \mathbf{y}^{T}$$

since

$$\frac{\partial \upsilon_{mn}}{\partial y_{ij}} = \begin{cases} x_{mi} & n = j \\ 0 & else \end{cases}$$

we have

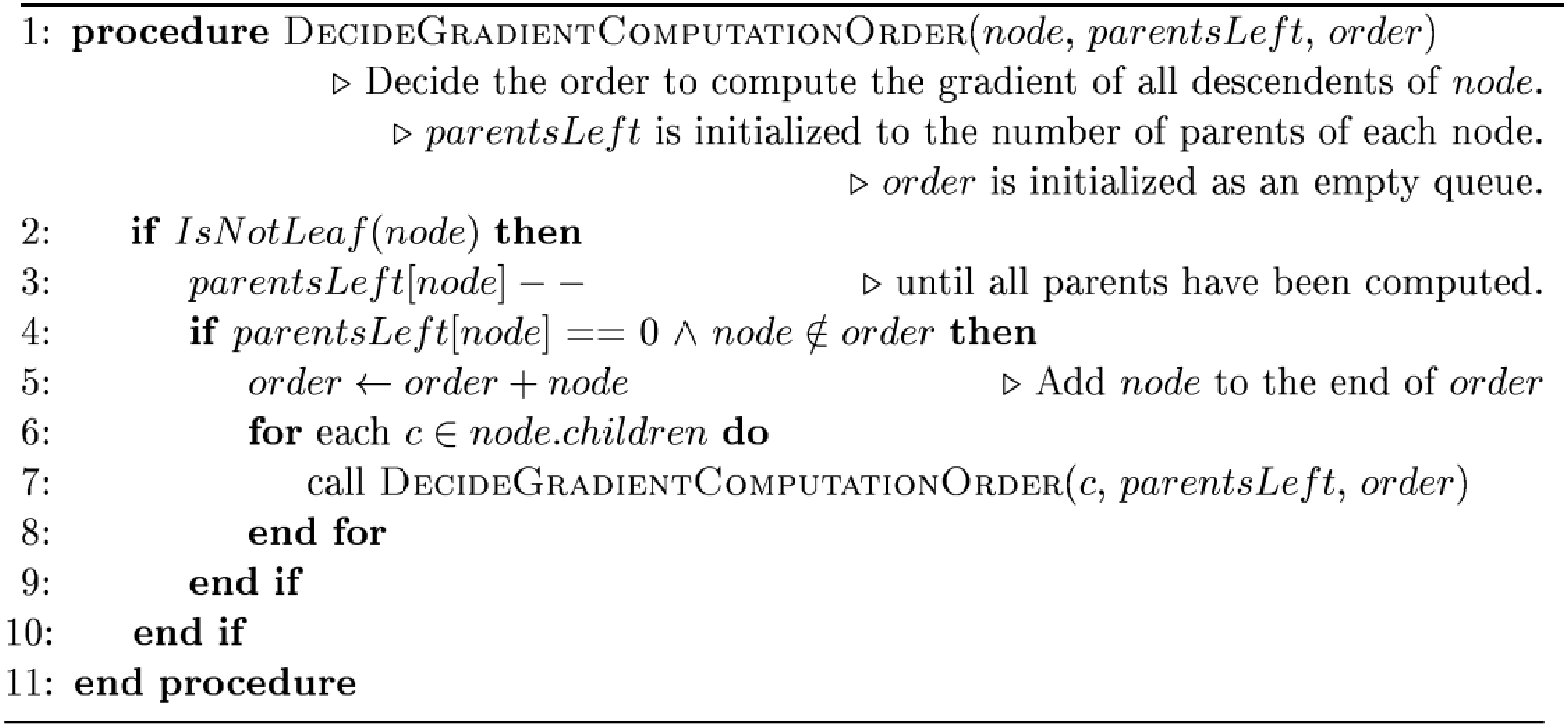
$$\frac{\partial J}{\partial y_{ij}} = \sum_{m,n} \frac{\partial J}{\partial \upsilon_{mn}} \frac{\partial \upsilon_{mn}}{\partial y_{ij}} = \sum_{m} \frac{\partial J}{\partial \upsilon_{mj}} x_{mi}$$

or

$$\nabla_{\mathbf{y}}^{J} \leftarrow \nabla_{\mathbf{y}}^{J} + \mathbf{x}^{T} \nabla_{\mathbf{n}}^{J}$$

Gradient Computation of CN

- Reverse automatic differentiation: call each node's ComputeInputPartial function following the order below

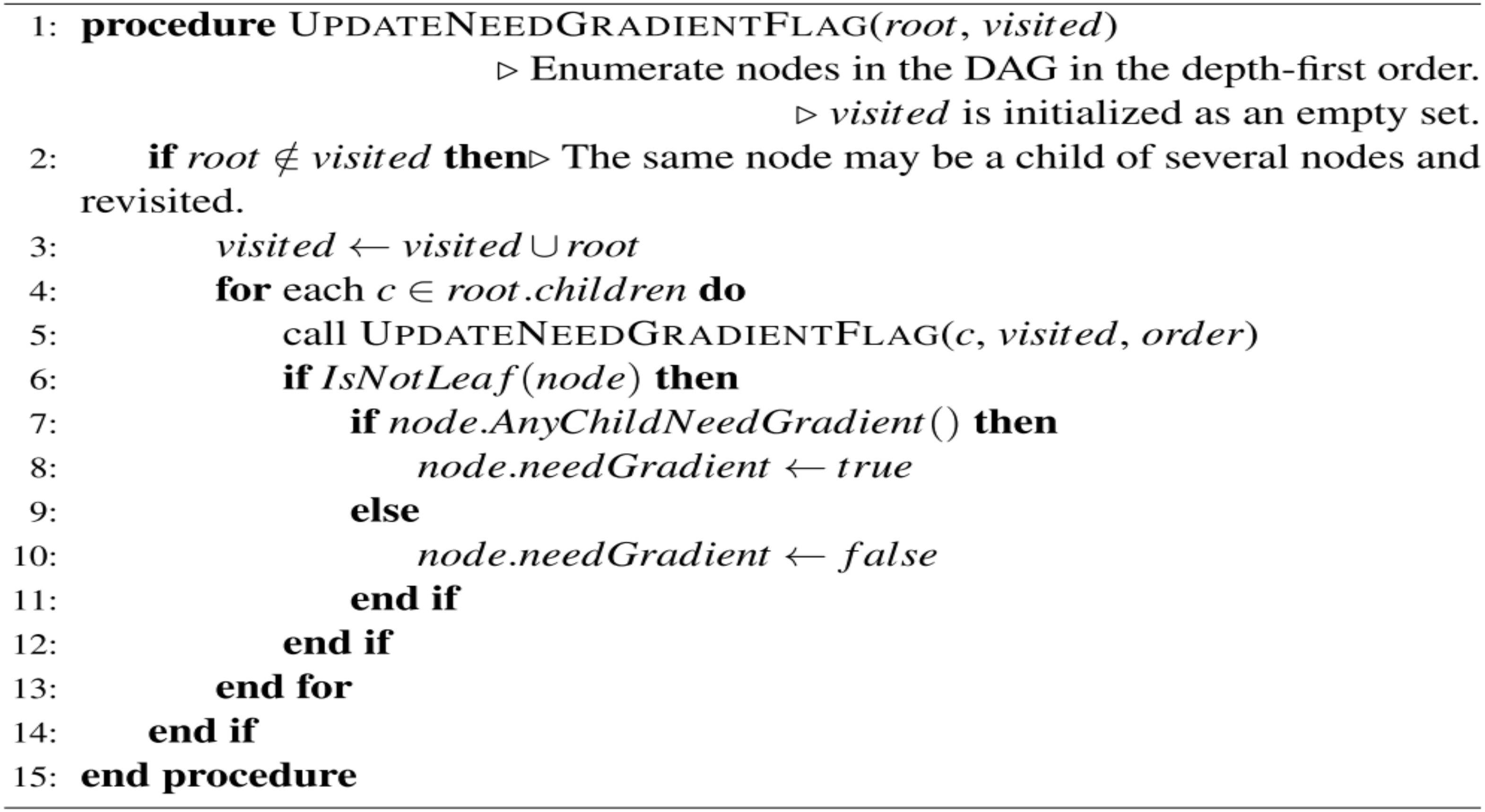


```
procedure DecideGradientComputationOrder($node$, $parentsLeft$, $order$)
                    ▷ Decide the order to compute the gradient of all descendents of $node$.
                    ▷ $parentsLeft$ is initialized to the number of parents of each node.
                    ▷ $order$ is initialized as an empty queue.
    if $IsNotLeaf(node)$ then
        $parentsLeft[node]--$                  ▷ until all parents have been computed.
        if $parentsLeft[node] == 0 \wedge node \notin order$ then
            $order \leftarrow order + node$    ▷ Add $node$ to the end of $order$
            for each $c \in node.children$ do
                call DecideGradientComputationOrder($c$, $parentsLeft$, $order$)
            end for
        end if
    end if
end procedure
```

- Result is another computation graph that can be optimized (e.g., remove trivial computation, cache duplicate computation) or computed asynchronously

Gradient Computation Efficiency

- Gradient computation is not needed for some nodes.
  - Set NeedGradient=false for constant leaf nodes.
  - Propagate the flag up the graph using the depth-first traversal.
  - Only compute the gradient when NeedGradient=true.



```
procedure UpdateNeedGradientFlag($root$, $visited$)
                              ▷ Enumerate nodes in the DAG in the depth-first order.
                                          ▷ $visited$ is initialized as an empty set.
    if $root \notin visited$ then ▷ The same node may be a child of several nodes and revisited.
        $visited \leftarrow visited \cup root$
        for each $c \in root.children$ do
            call UpdateNeedGradientFlag($c$, $visited$, $order$)
            if $IsNotLeaf(node)$ then
                if $node.AnyChildNeedGradient()$ then
                    $node.needGradient \leftarrow true$
                else
                    $node.needGradient \leftarrow false$
                end if
            end if
        end for
    end if
end procedure
```

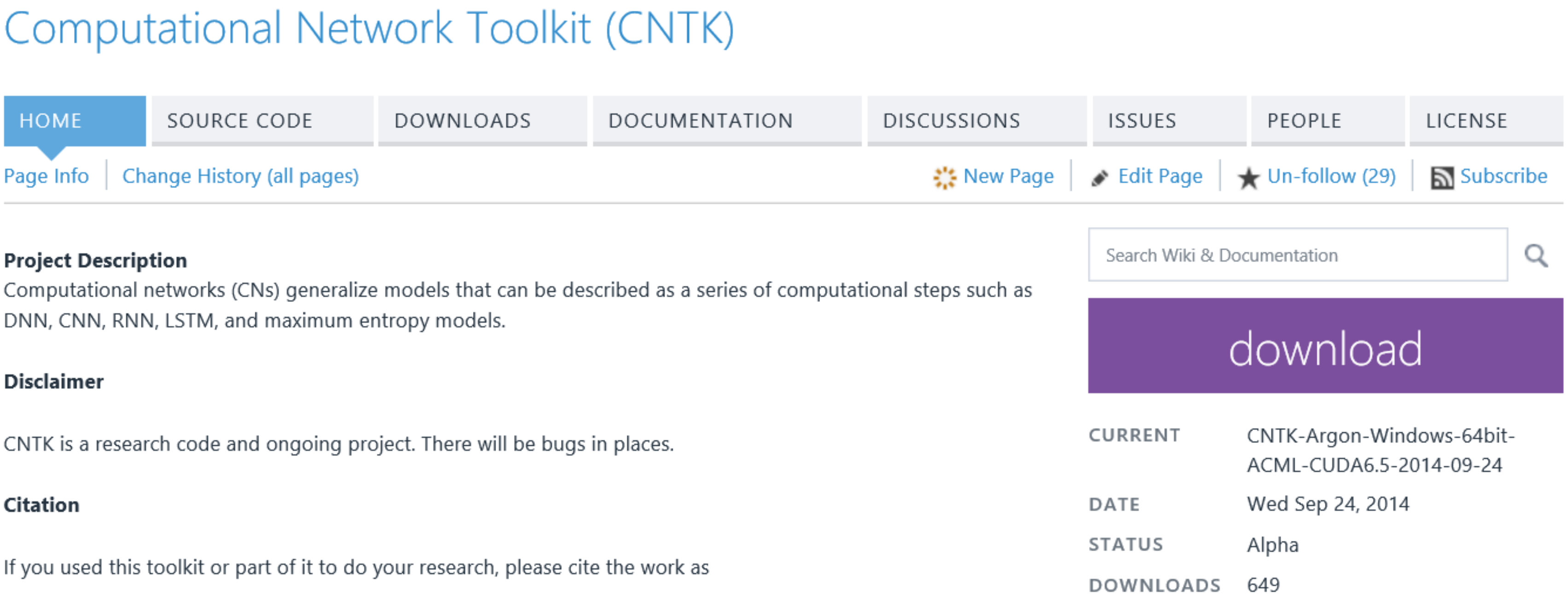
Outline

- Introduction to Deep Learning and Prevailing Deep Learning Models
- Computational Network: A Unified Framework for Models Expressible as Functions
- **Computational Network Toolkit: A Generic Toolkit for Building Computational Networks**
- Examples: Acoustic Model, Language Model, and Image Classification
- Summary

Design Goals of CNTK

- Expression: models and algorithms are descriptions
  - Network definition language (NDL) via plain text
  - Build network via compositions in source code (Simple Network Builder)
- Modularity: to extend to new tasks and new models
  - Abstraction of computation nodes
  - Task-specific readers
- Speed: for state-of-the-art models trained on large data
  - Data parallelism

CNTK: Open Source Toolkit



Computational Network Toolkit (CNTK)

Project Description
Computational networks (CNs) generalize models that can be described as a series of computational steps such as DNN, CNN, RNN, LSTM, and maximum entropy models.

Disclaimer

CNTK is a research code and ongoing project. There will be bugs in places.

Citation

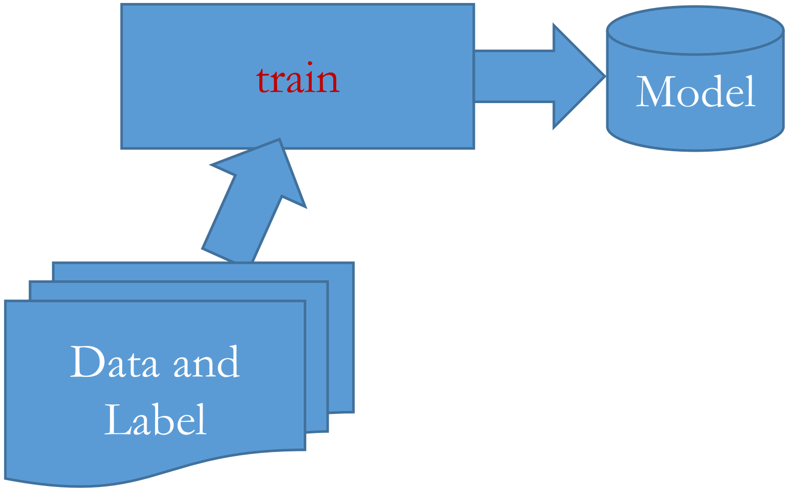
If you used this toolkit or part of it to do your research, please cite the work as

CURRENT	CNTK-Argon-Windows-64bit-ACML-CUDA6.5-2014-09-24
DATE	Wed Sep 24, 2014
STATUS	Alpha
DOWNLOADS	649

- Source code and documents are available at http://cntk.codeplex.com
- Uses GIT for version control
- Supports Windows and Linux

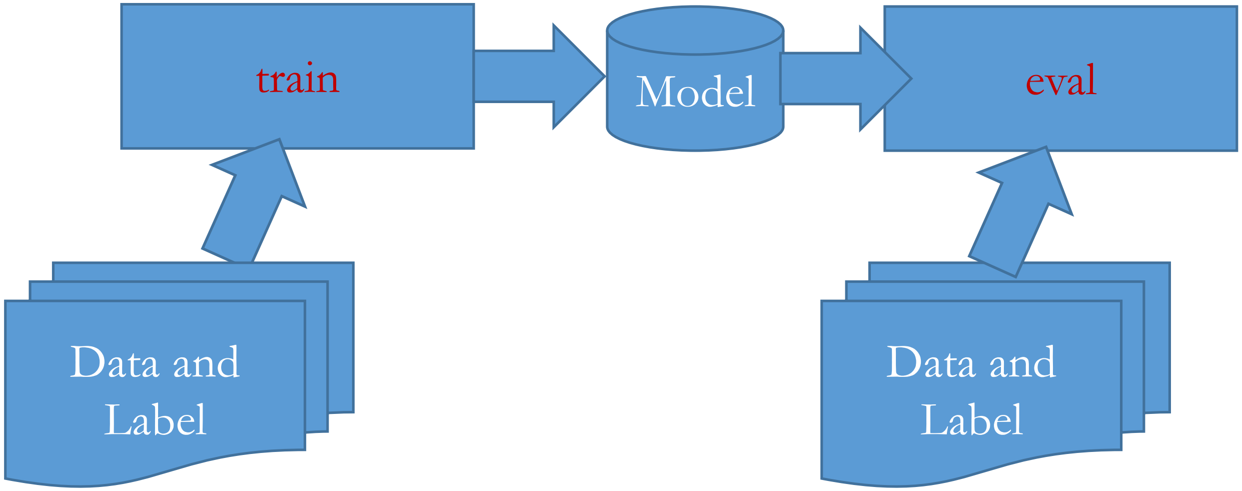
A Typical Workflow of Using CNTK : train

- Train models use `train` command



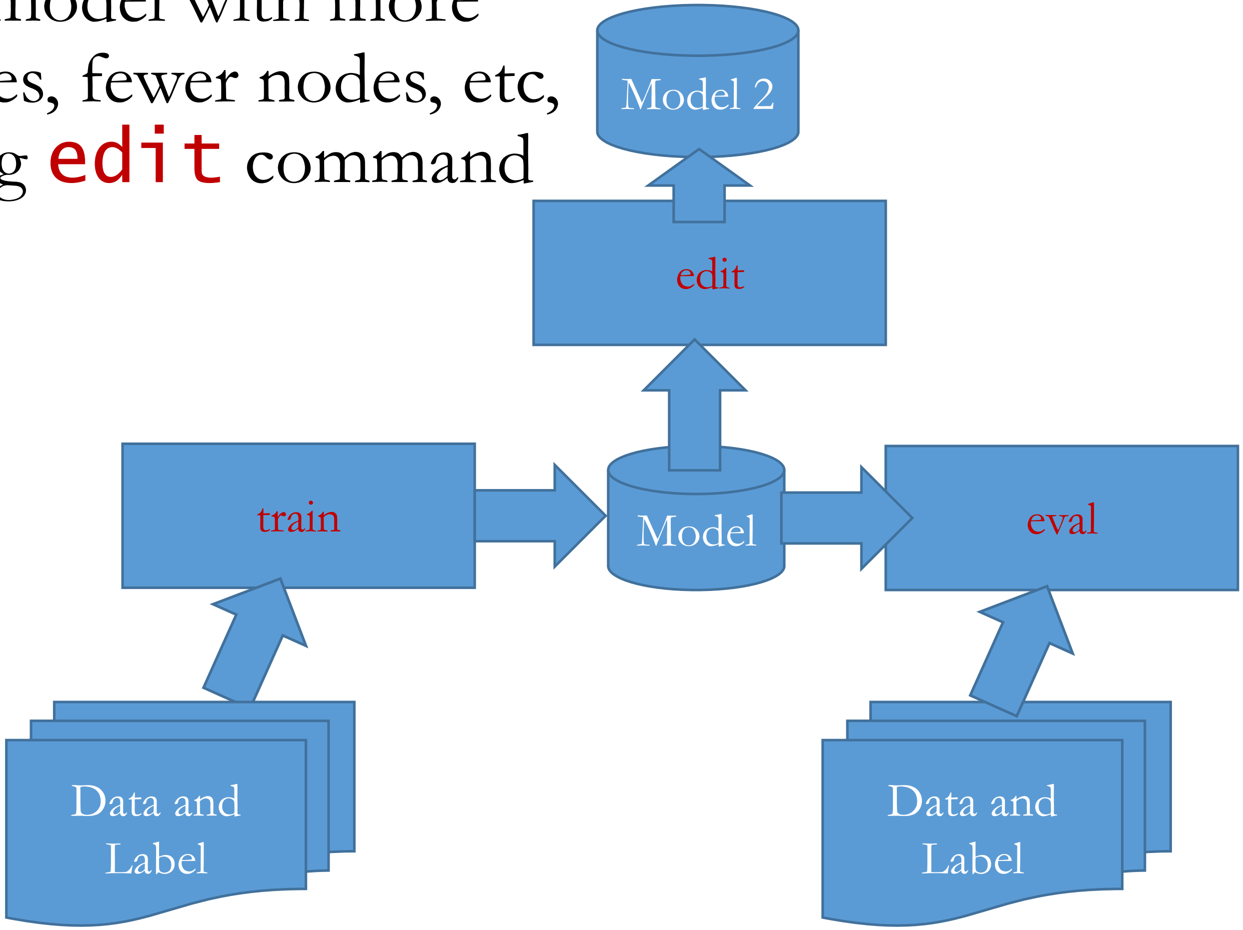
A Typical Workflow of Using CNTK: eval

- Evaluate models using `eval` command



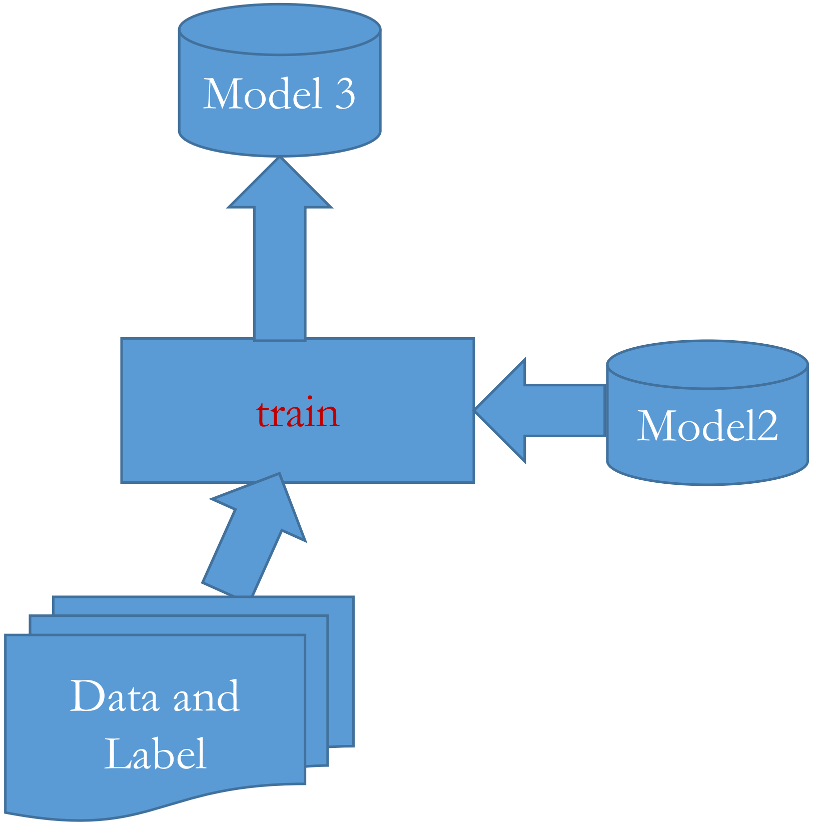
A Typical Workflow of Using CNTK: edit

- Edit models to expand the model with more nodes, fewer nodes, etc, using `edit` command



A Typical Workflow of Using CNTK: update

- Update the newly edited model using `train` command



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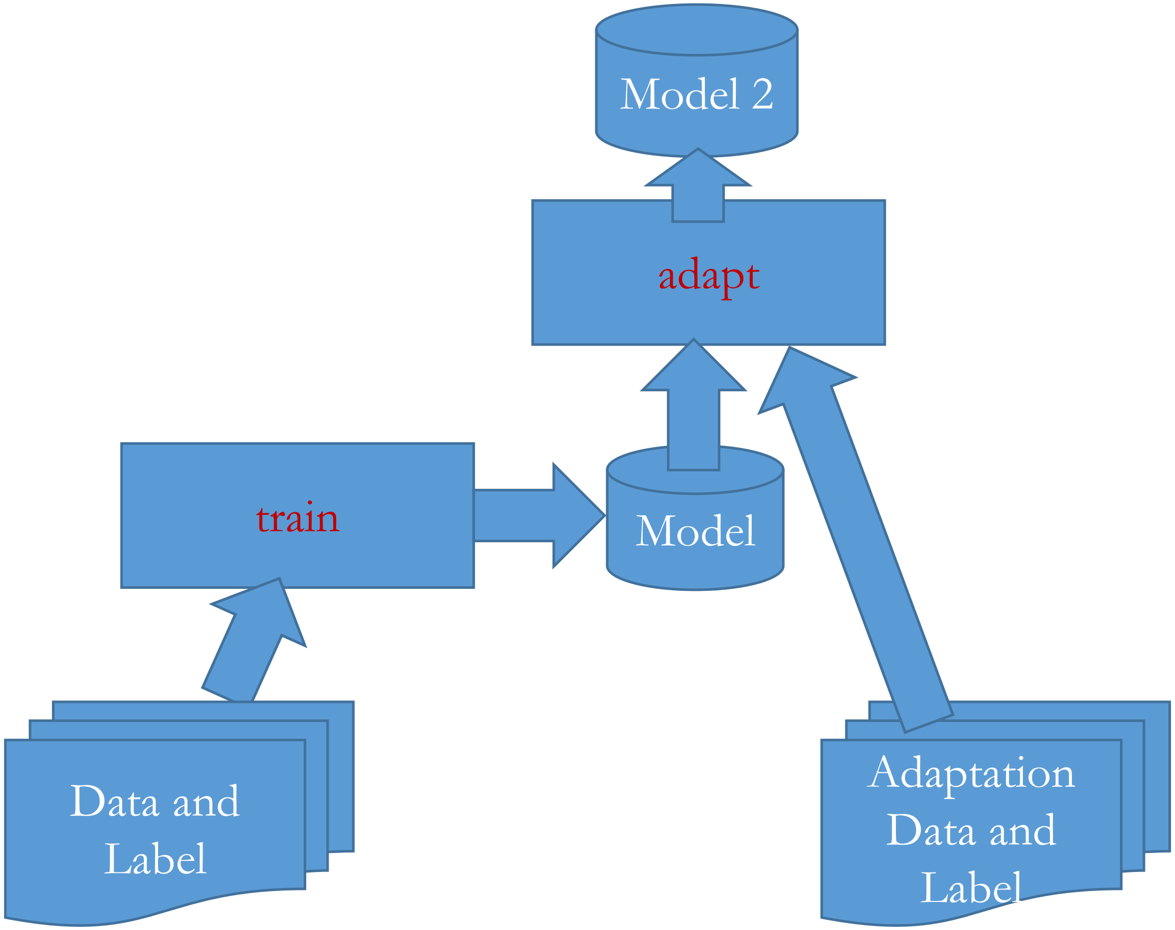
A Typical Workflow of Using CNTK: adapt

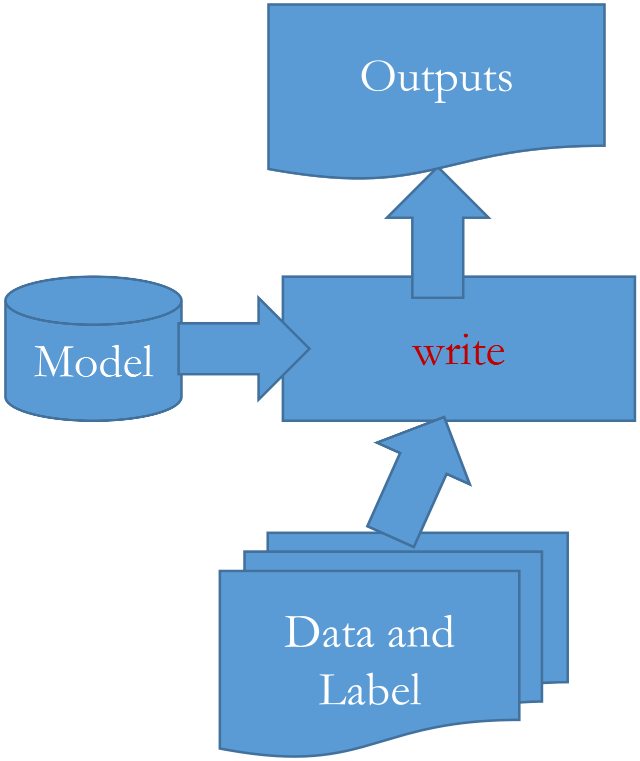
- Adapt models on new data using `adapt` command



A Typical Workflow of Using CNTK: write

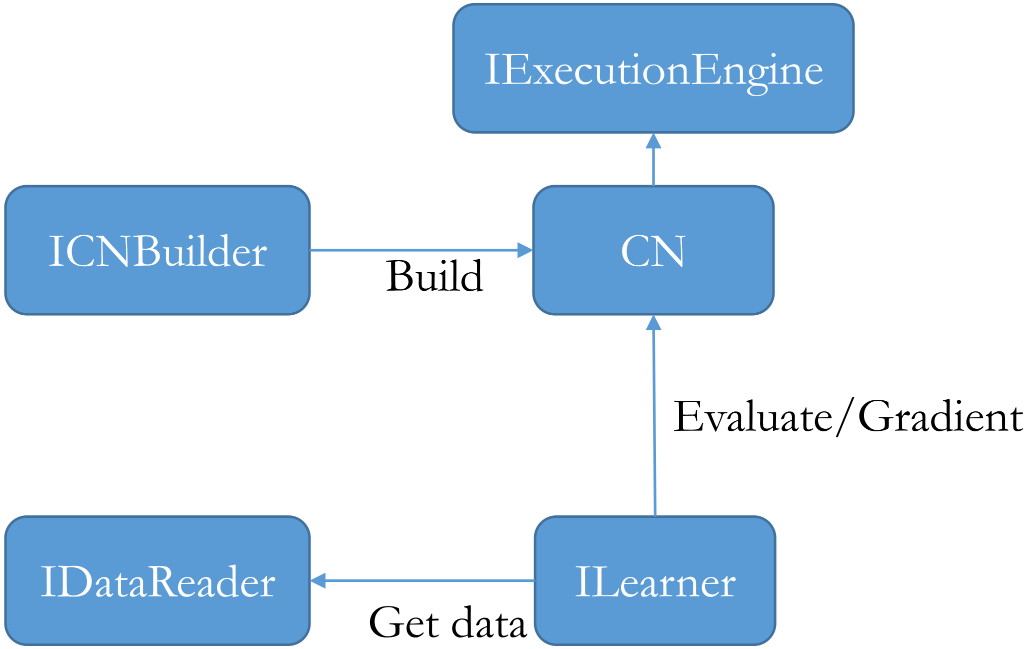
- Write outputs from a node in the trained model using `write` command

- A node can be designed to output
  - Activity, e.g., used for training bottleneck features
  - Decoding results, e.g., used for output semantic tags in SLU example



CNTK Architecture

- Abstraction



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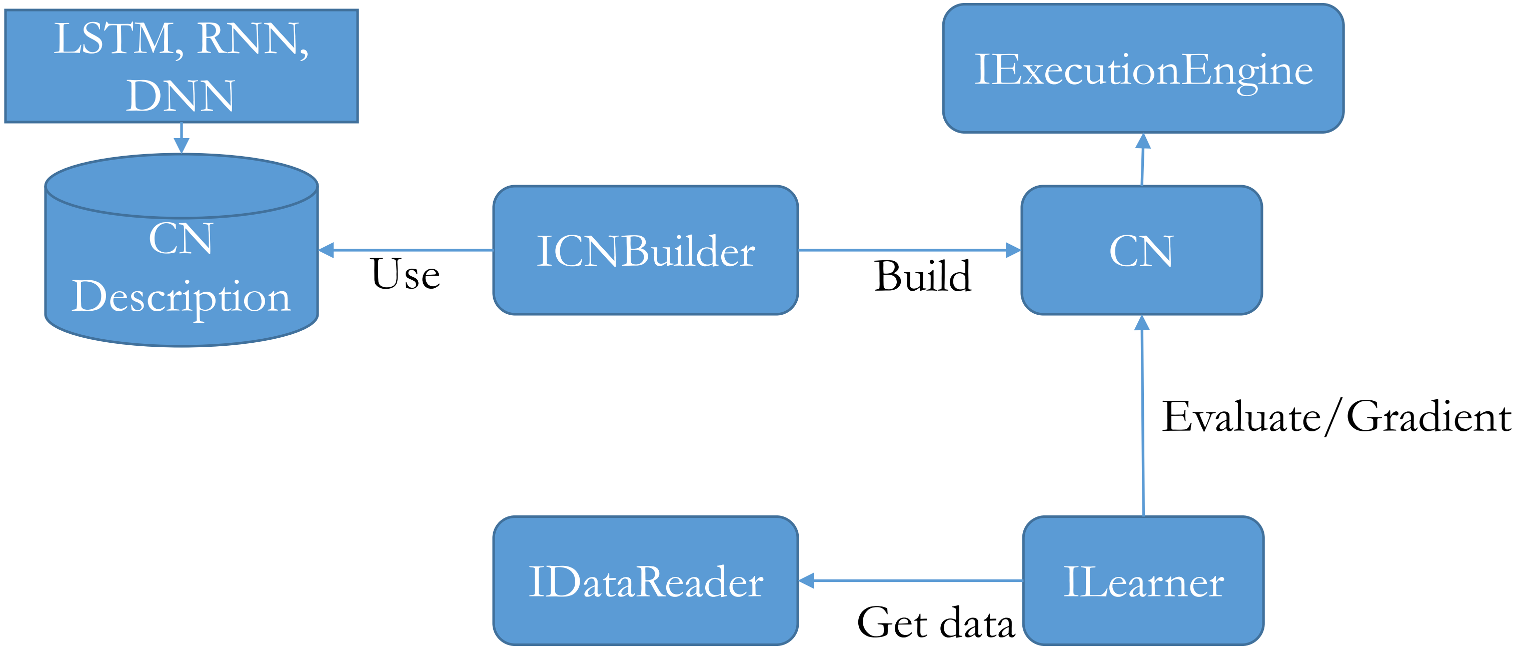
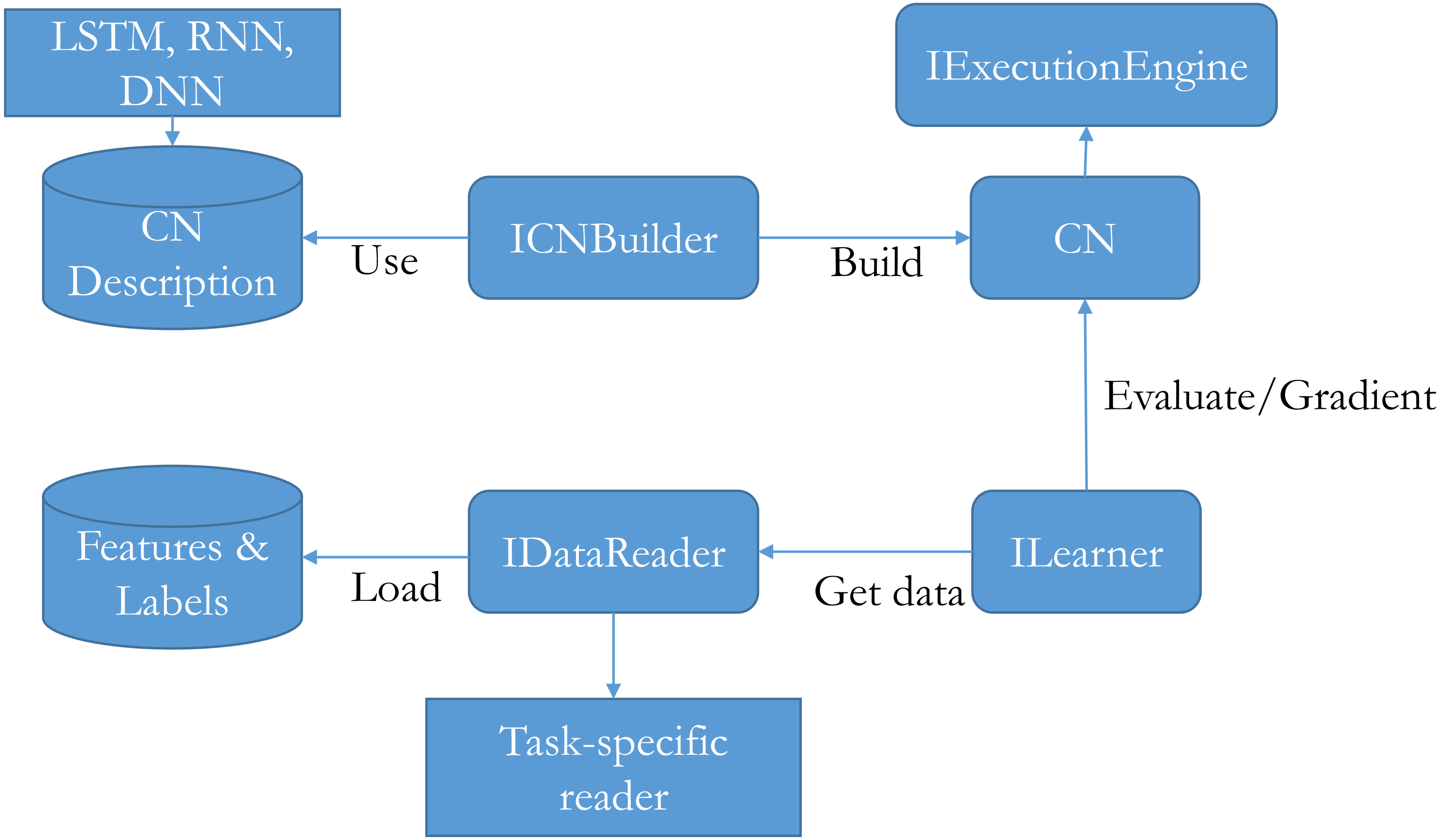
CNTK Architecture

- Network description



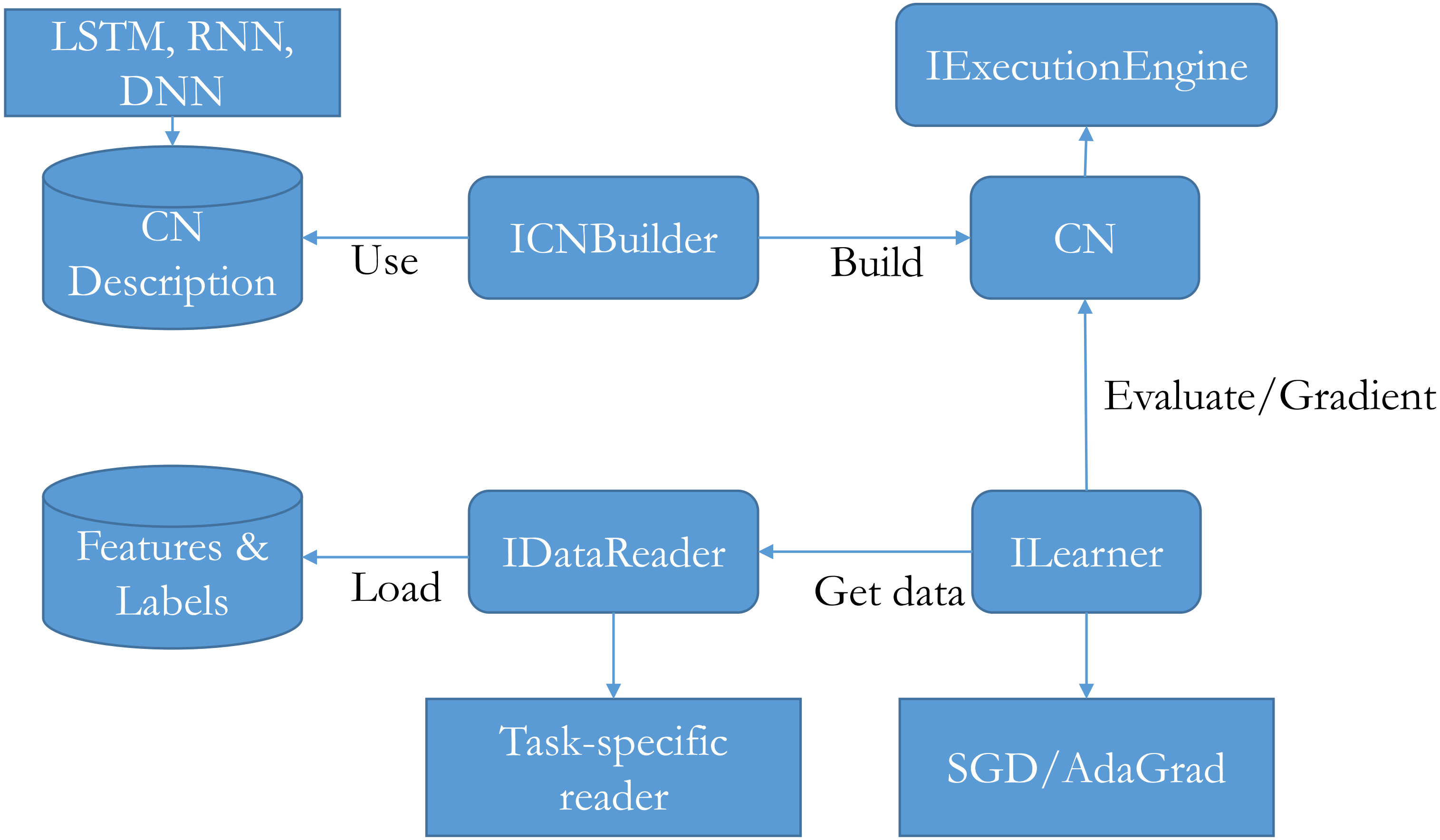
CNTK Architecture

- Task-specific readers



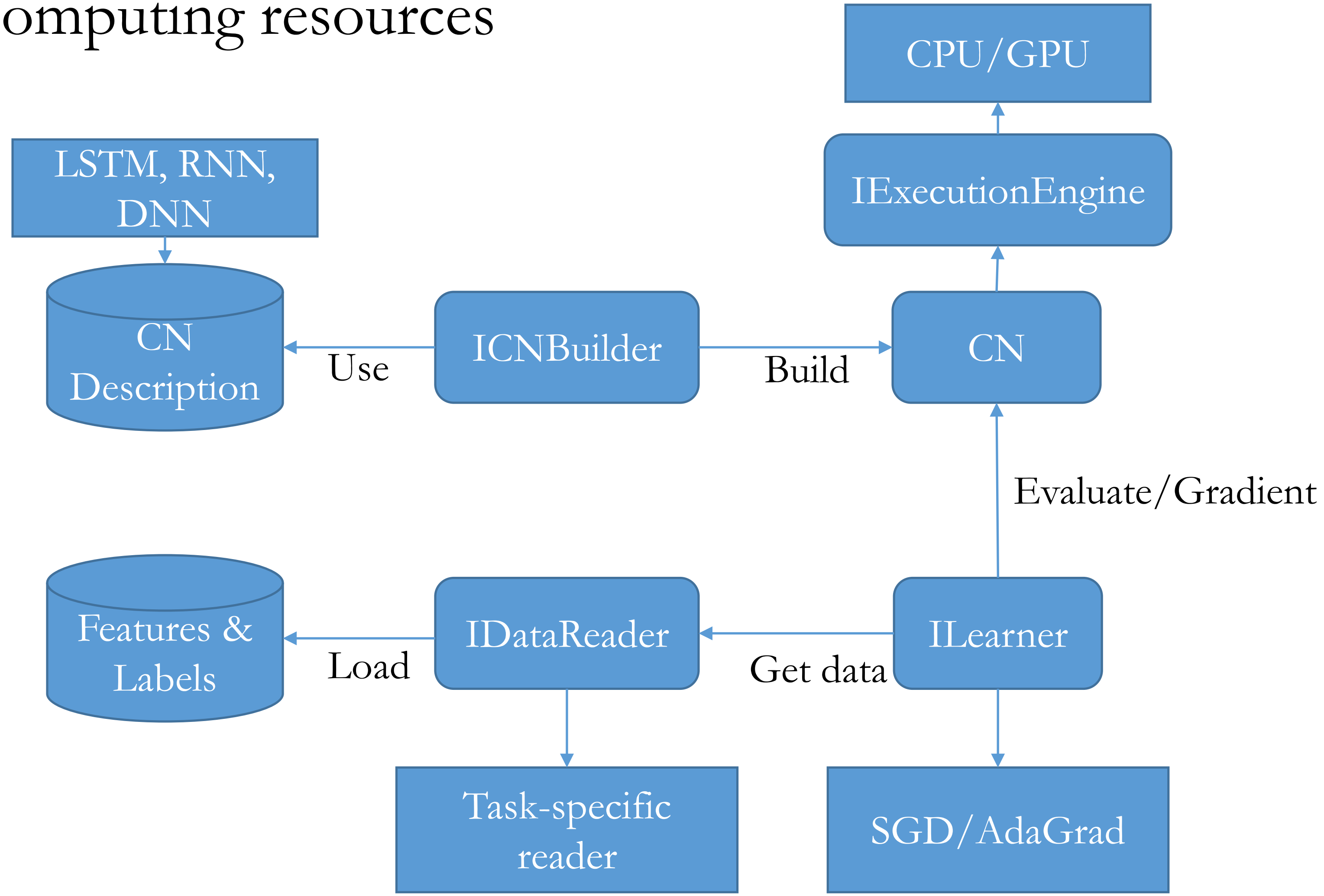
CNTK Architecture

- Learning algorithms



CNTK Architecture

- Computing resources

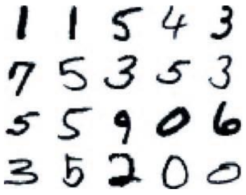


Implemented Nodes

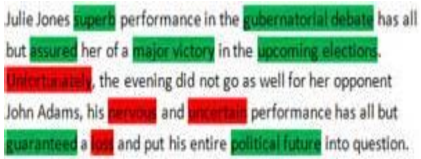
- Inputs
  - Input, ImageInput, LookupTable
- One operand
  - ReLU, Sigmoid, Tanh, Log, Cos, Dropout, Negate, Softmax, LogSoftmax
- Matrices and Vectors
  - SumElements, RowSlice, Scale, Times, DiagTimes, Plus, Minus, ElementTimes
- Training criterion
  - SquareError, CrossEntropyWithSoftmax, ClassificationError, ClassBasedCrossEntropyWithSoftMax, GMMLogLikelihood
- Sequence-level training
  - CRF
- Parameters
  - Parameter, Constant
- Tensor
  - KhatriRaoProduct,
- Regularization
  - MatrixL1Reg, MatrixL2Reg,
- Normalization
  - Mean, InvStdDev, PerDimMVNorm
- CNN related
  - Convolution, MaxPooling, AveragePooling
- RNN related
  - Delay
- Bi-directional models related
  - TimeReverse

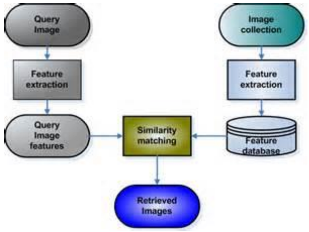
CNTK Task-specific Readers

- **UCIFastReader**
  - Space deliminated file formats
  - uses BinaryReader to cache and speed up
- **HTKMLFReader**
  - Speech feature and labels in HTK format
- **KaldiReader**
  - Speech feature and labels in Kaldi format
- **LMSequenceReader**
  - Text file sequence reader for language model
- **LUSequenceReader**
  - Text file sequence reader for language understanding
- **DSSMReader**
  - For training and evaluating DSSM model for query and document pairs



times gone by.
– ORIGIN C16: fr
language ● n.
either spoken
in a structured
expression or


Julie Jones superb performance in the gubernatorial debate has all but assured her of a major victory in the upcoming elections. Unfortunately, the evening did not go as well for her opponent John Adams, his nervous and uncertain performance has all but guaranteed a loss and put his entire political future into question.



TIMIT Example

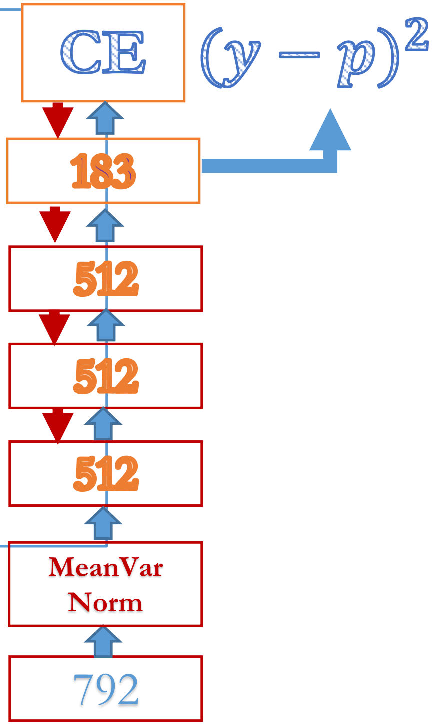
- cn.exe configFile=yourConfigFile.config DeviceNumber=1

```
command=TIMIT_TrainNDL

TIMIT_TrainNDL=[
    action=train
    deviceId=$DeviceNumber$
    modelPath=$your_model_path$

    SimpleNetworkBuilder=[…]
    SGD=[…]
    reader=[…]
]
```

CPU: -1 or CPU
GPU: >=0

TIMIT DNN Network

```
SimpleNetworkBuilder=[
    layerSizes=792:512*3:183

    applyMeanVarNorm=true
    trainingCriterion=CrossEntropyWithSoftmax

    evalCriterion=ErrorPrediction
]
```



TIMIT SGD

$$g_t = m\, g_{t-1} - \alpha \Delta L(\theta_t)$$
$$\theta_t = \theta_{t-1} + g_t$$

```
SGD=[
    minibatchSize=256:1024
    learningRatesPerMB=0.8:3.2*14:0.08
    momentumPerMB=0.9
]
```

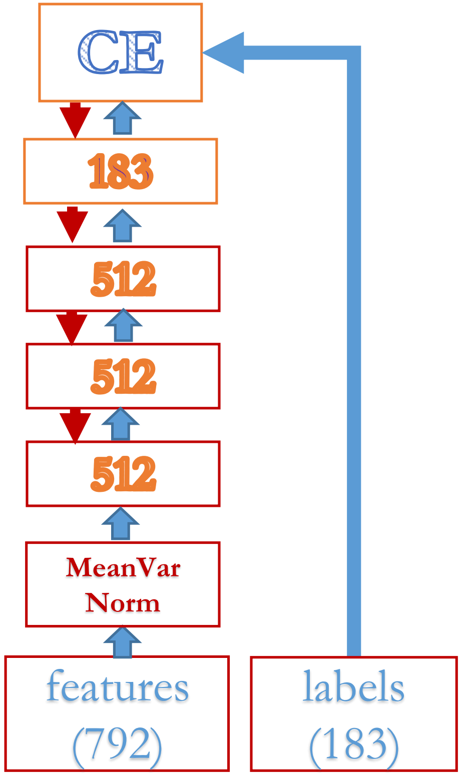
Epoch 1: minibatch size=256, learning rate= 0.8

Epoch 2-15: minibatch size = 1024, learning rate = 3.2

Epoch 16+: minibatch size = 1024, learning rate = 0.08

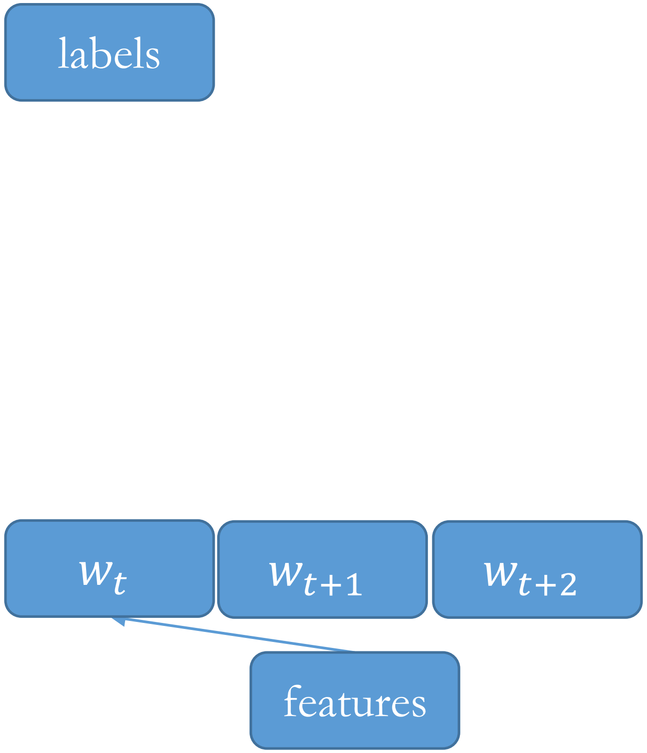
TIMIT Reader

```
reader=[
   readerType=HTKMLFReader

   randomize=Auto

   features=[
      dim=792
      scpFile=$FBankScpShort$
   ]

   labels=[
      mlfFile=$MlfDir$\TIMIT.train.mlf
      labelDim=183

    labelMappingFile=$MlfDir$\TIMIT.statelist
   ]
]
```



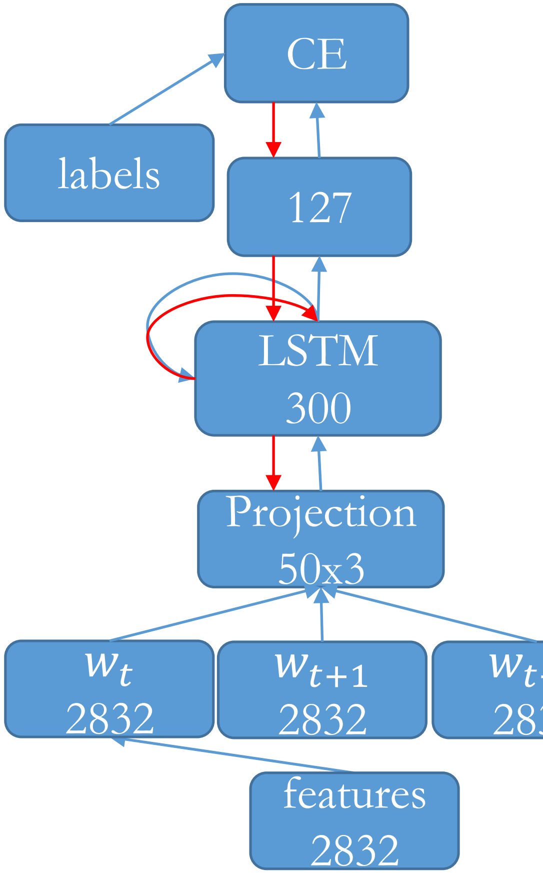
SLU Example : Reader

```
reader=[
   readerType=LUSequenceReader
   features=[
    dim=2832
   ]
   labelIn=[
    token=$DataDir$\input.txt
   ]
   wordContext=0:1:2
   labels=[
    token=$DataDir$\output.txt
   ]
]
```



SLU Example: Network

```
SimpleNetworkBuilder=[
    rnnType=LSTM
    layerSizes=2832:50:300:127
    recurrentLayer=2
    trainingCriterion=CrossEntropyWithSoftmax
    evalCriterion=CrossEntropyWithSoftmax
]
```



Network Definition Language (NDL)

- Non-standard networks can be created using Network Definition Language (NDL)
- Nodes and connections can be specified through a series of atomic or macro operations

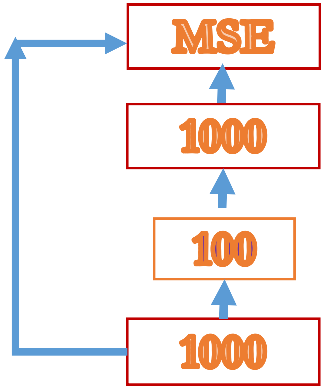
NDL Example: Single layer Auto-encoder

```
featDim=1000
hiddenDim=100

features=Input(featDim, tag=feature)

Wh = Parameter(hiddenDim,featDim)
Th = Times(Wh,features)
Sh = Sigmoid(Th)



Wo = Parameter(featDim,hiddenDim)
Po = Times(Wo,Sh)




MSE = SquareError(features, Po, tag=criteria)
```

Encode: Hidden Layer

Decoder: Output

Training Criterion



Using Macros in NDL

- Macros can be defined to encapsulate a common set of parameters and/or sequence of operations

```
RFF(x1, w1, b1)=RectifiedLinear(Plus(Times(w1,x1),b1))
FF(X1, W1, B1)
   {
        T=Times(W1,X1)
        FF=Plus(T, B1)
   }
```

- Can access internal variables via the dot syntax, e.g.,

```
L1 = FF(X1, W1, B1)
```

L1.T can be used to access the result of Times Op in the macro FF.

Example Macros

```
FF(X1, W1, B1)
{
   T=Times(W1,X1)
   FF=Plus(T, B1)
}
```

Affine transformation

```
BFF(in, rows, cols)
{
   B=Parameter(rows, init=fixedvalue, value=0)
   W=Parameter(rows, cols)
   BFF=FF(in, W, B)
}
```

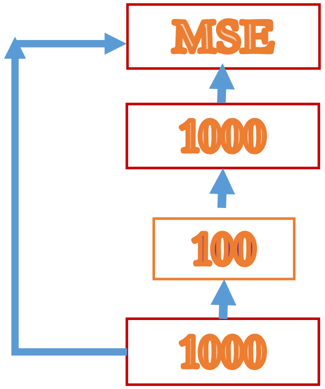
Affine transformation given row and column number

```
SBFF(in, rows, cols)
{
    BFF=BFF(in, rows, cols)
    SBFF=Sigmoid(BFF)
}
```

Sigmoid transformation given row and column number

Macros in Effect: Auto-encoder Example

```
featDim=1000
hiddenDim=100

features=Input(featDim, tag=feature)



L1 = SBFF(features, hiddenDim, featDim)




L2 = BFF(L1, featDim, hiddenDim)




MSE = SquareError(features, L2, tag=criteria)
```



Invoking NDL Networks

- Invoked in the configuration file using **`NDLNetworkBuilder`**
- Each NDL file can contain many network definitions
  - Use `run` command to determine which network to use

```
NDLNetworkBuilder=[
    ndlMacros=$NdlDir$\default_macros.ndl
    AutoEncoderNDL=$NdlDir$\mynetwork.ndl
    run=AutoEncoderNDL
]
```

Stochastic Gradient Descent Learner

- Compute gradient of objective function with respect to model parameters.
    - Gradient descent uses the entire training set.
        - Provable linear convergence.
    - SGD uses a random subset (minibatch) of the training set.
        - Convergence requires decreasing learning rates.
        - Provable sub-linear convergence bound.
        - In practice, convergence only slow as model approaches the optimum.
        - Beneficial when training time is the training bottleneck.
- Parameter update is a function of this gradient.

SGD Learner Configuration

- Gradient Update Options
  - Options for CNTK are: none, adagrad, or rmsprop.
- Learning rate search
- Model Averaging (parallel training)
  - Compile code with USE_MPI defined.
  - At the end of every epoch, all nodes exchange and average their parameters.
- Regularization
  - Gradient Noise
    - Adds Guassian noise to each gradient computation.
  - L2 regularizer
    - Adds a scaled version of the parameters into the gradient, biasing parameter values to zero.
  - L1 regularizer
    - Uses the proximal gradient descent algorithm to shrink the weights

Default Gradient Update

- Conventional SGD is the default
    - Apply learning rate to gradients.
    - Apply momentum to gradients.
    - Subtract result from parameter values.
- Equivalent to setting “Gradient update: none”

Gradient Update: Adagrad

- Scales each dimension by the l_2 norm of all gradients for that dimension up to, and including, the current time.

$$\beta_t[k] = \beta_{t-1}[k] + d_t^2[k],\ \ d_t[k] \leftarrow \frac{d_t[k]}{\sqrt{\beta_t[k]+\epsilon}}$$

- Effective gradient scale factor is non-increasing over time.
- Optional: As a final step, the average multiplier over all features is found, and used to re-scale the gradient.

$$m = \sum_{k=0}^{K-1} \frac{1}{\sqrt{\beta_{t[k]}+\epsilon}},\quad d_t[k] \leftarrow \frac{d_t[k]}{m}$$

- This preserves the absolute scale of the gradient, retaining only the relative scaling of adagrad.

Gradient Update: RMSProp

- Per-dimension scale factor with two components.

$$d_t[k] \leftarrow d_t[k] \frac{r_t[k]}{\sqrt{\beta_t[k] + \epsilon}}$$

  - A smoothed estimate of the l_2 norm of recent gradients for that dimension up to, and including, the current time.

$$\beta_t[k] = \gamma \beta_{t-1}[k] + (1 - \gamma) d_t^2[k]$$

  - An rprop style factor, that increases when the gradient sign matches from one time to the next, and decreases otherwise.

$$r_t[k] \leftarrow \begin{cases} \min(r_{t-1}[k] * w_{inc}, w_{max}) & if\ signs\ match \\ \max(r_{t-1}[k] * w_{dec}, w_{min}) & otherwise \end{cases}$$

- Parameters
  - rms_gamma: Smoothing factor for exponential window variance estimate.
  - rms_wgt_inc, rms_wgt_dec: Factors to multiply each weight by, to increase or decrease its value.
  - rms_wgt_max, rms_wgt_min: Ceiling and floor for the weight factors.
- As in adagrad, the average multiplier over all features is found, and used to re-scale the gradient.

$$m = \sum_{k=0}^{K-1} \frac{r_t[k]}{\sqrt{\beta_{t[k]} + \epsilon}}, \quad d_t[k] \leftarrow \frac{d_t[k]}{m}$$

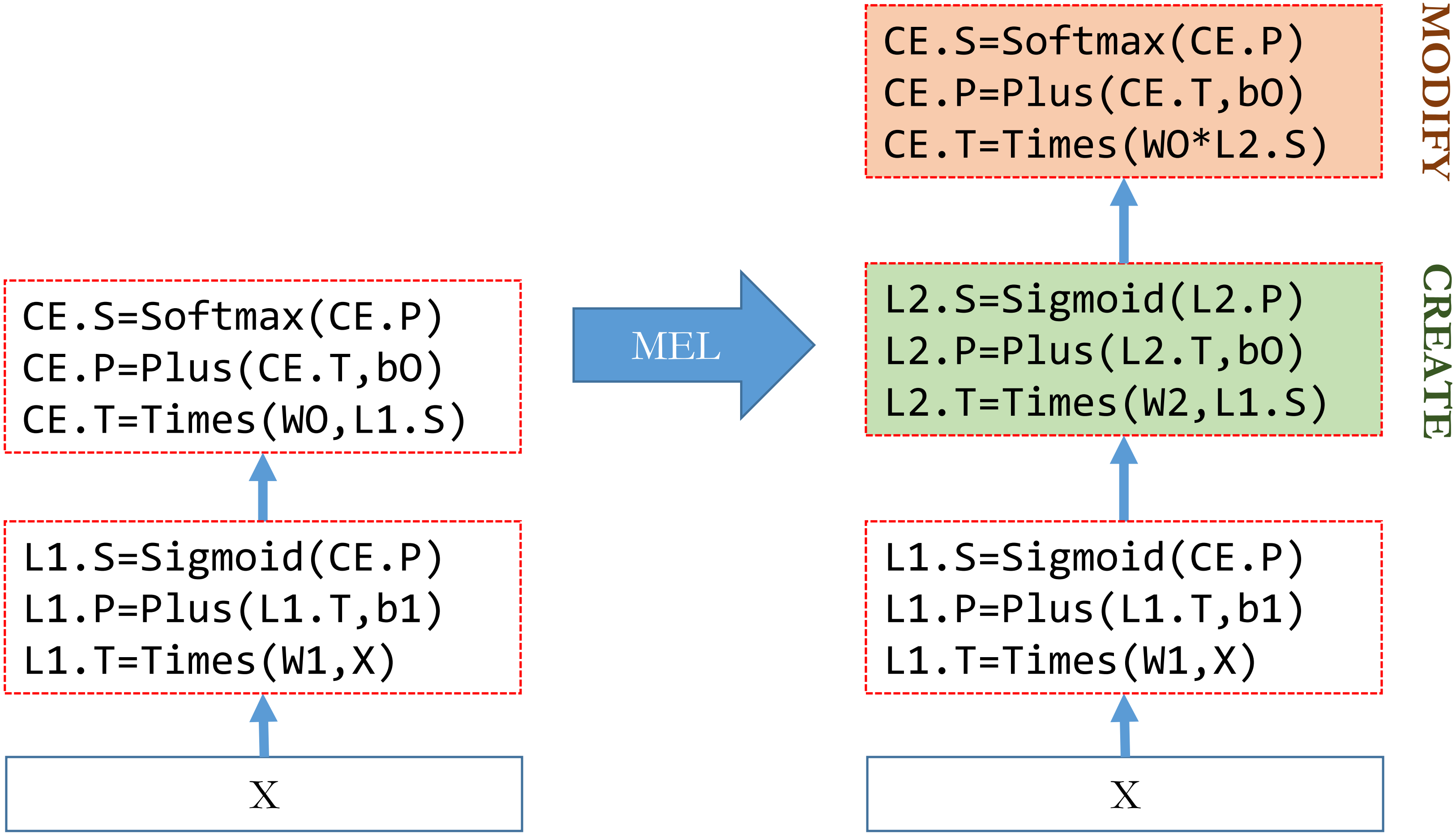
Model Editing Language

- Sometimes it is useful to edit a model
  - Copy parameters from one model or node to another
  - Overwrite parameters
  - Freeze or unfreeze certain parameters during training
- This can be done using CNTK’s Model Editing Language (MEL)
- Examples of MEL functionality:
  - Load multiple CNTK models
  - Copy parameters, a node, or a group of nodes
  - Add new nodes to existing model using “inline” NDL
  - Change node properties, e.g. needGradient or criteria node

MEL example

- MEL can be used to do layer-by-layer discriminative pre-training (DPT)
  - Construct a 1 layer model
  - Train model
  - Use MEL to remove output layer and add a new hidden layer and a new output layer
  - Train new model
  - Repeat until desired depth is reached

MEL Example: DPT



```
CE.S=Softmax(CE.P)
CE.P=Plus(CE.T,bO)
CE.T=Times(WO,L1.S)
```

```
L1.S=Sigmoid(CE.P)
L1.P=Plus(L1.T,b1)
L1.T=Times(W1,X)
```

X

MEL

MODIFY

```
CE.S=Softmax(CE.P)
CE.P=Plus(CE.T,bO)
CE.T=Times(WO*L2.S)
```

CREATE

```
L2.S=Sigmoid(L2.P)
L2.P=Plus(L2.T,bO)
L2.T=Times(W2,L1.S)
```

```
L1.S=Sigmoid(CE.P)
L1.P=Plus(L1.T,b1)
L1.T=Times(W1,X)
```

X

MEL Example: DPT

- Configuration file to perform edit operation:

```
AddLayer2=[
    action=edit
    CurrModel=.\cntkSpeech.dnn
    NewModel=.\cntkSpeech.dnn.0
    editPath=.\ add_layer.mel
]
```

- MEL commands to add a layer to the current model

```
m1=LoadModel($CurrModel$, format=cntk)
SetDefaultModel(m1)
HDim=512
L2=SBFF(L1.S,HDim,HDim)         #CREATE
SetInput(CE.*.T, 1, L2.S)       #MODIFY
SetInput(L2.*.T, 1, L1.S)
SaveModel(m1,$NewModel$, format=cntk)
```

Extending the functionality of CNTK

- You can add a new data reader either to speed up loading time or to support a new data format by implementing the IDataReader interface with two key operations
  - StartMinibatchLoop()
  - GetMinibatch()
- You can add a new node type derived from class ComputationNode by implementing
  - EvaluateThisNode()
  - ComputeInputPartial()

And adding the related instantiation methods to the ComputationNetwork and NetworkDefinitionLanguage classes

Outline

- Motivation
- Introduction to Deep Learning and Prevailing Deep Learning Models
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DNN-HMM AM Example

- Design criteria
  - Frame stacking. Input layer is multiple of feature size.
  - Hidden layer width.
  - Model depth.
- Input data
  - Label files (HTK MLF format)
    - start_frame end_frame label_string label_index
  - Traditional script files pointing to HTK parameters
    - \\path\to\test\dr1\faks0\si1573.fbank_zda
  - Or, HTK archive format script files
    - test-dr1-faks0-si1573.fbank_zda=\\path\to\big\file.fbank_zda[0,494]
    - test-dr1-faks0-si2203.fbank_zda=\\path\to\big\file.fbank_zda[495,843]

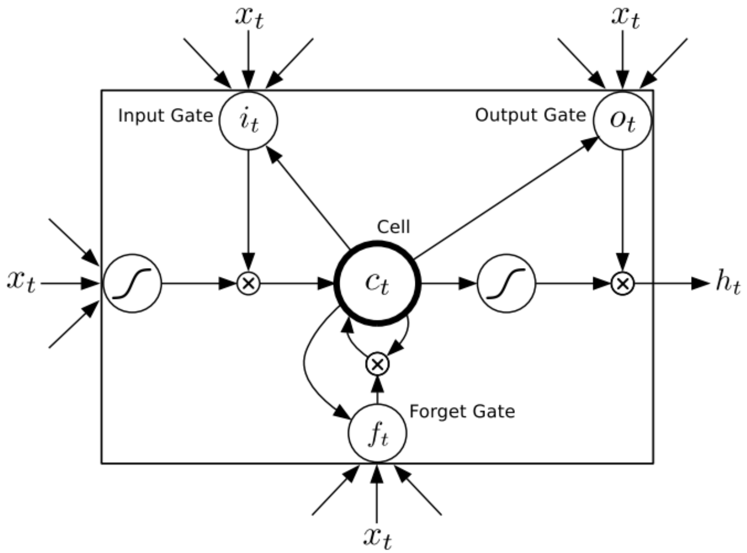
DNN-HMM AM Example

```
TIMIT_TrainSimple =[
  action = train
  modelPath = $ExpDir$\cntkSpeech.dnn
  SimpleNetworkBuilder = [
    layerSizes = 792:512*3:183
    trainingCriterion =
       CrossEntropyWithSoftmax
    evalCriterion = ErrorPrediction
    layerTypes = Sigmoid
    initValueScale = 1.0
    applyMeanVarNorm= true
    uniformInit = true
    needPrior = true
  ]
  SGD=[
    epochSize = 0
    minibatchSize = 256:1024
    learningRatesPerMB =
        0.8:3.2*14:0.08
    momentumPerMB = 0.9
    maxEpochs=25
  ]
```

```
  reader = [
    readerType = HTKMLFReader
    readMethod = rollingWindow
    miniBatchMode = Partial
    randomize = Auto
    verbosity = 1
    features = [
      dim=792
      scpFile =
        $ScpDir$\TIMIT.train.scp
    ]
    labels = [
      mlfFile = $MlfDir$\TIMIT.mlf
      labelDim = 183
      labelMappingFile=
        $MlfDir$\TIMIT.statelist
    ]
  ]
]
```

Microsoft Research

DNN-HMM AM Example: LSTM



$$
\begin{aligned}
\mathbf{i}_t &= \sigma\left(\mathbf{W}^{(xi)}\mathbf{x}_t + \mathbf{W}^{(hi)}\mathbf{h}_{t-1} + \mathbf{W}^{(ci)}\mathbf{c}_{t-1} + \mathbf{b}^{(i)}\right) \\
\mathbf{f}_t &= \sigma\left(\mathbf{W}^{(xf)}\mathbf{x}_t + \mathbf{W}^{(hf)}\mathbf{h}_{t-1} + \mathbf{W}^{(cf)}\mathbf{c}_{t-1} + \mathbf{b}^{(f)}\right) \\
\mathbf{c}_t &= \mathbf{f}_t \bullet \mathbf{c}_{t-1} + \mathbf{i}_t \bullet \tanh\left(\mathbf{W}^{(xc)}\mathbf{x}_t + \mathbf{W}^{(hc)}\mathbf{h}_{t-1} + \mathbf{b}^{(c)}\right) \\
\mathbf{o}_t &= \sigma\left(\mathbf{W}^{(xo)}\mathbf{x}_t + \mathbf{W}^{(ho)}\mathbf{h}_{t-1} + \mathbf{W}^{(co)}\mathbf{c}_t + \mathbf{b}^{(o)}\right) \\
\mathbf{h}_t &= \mathbf{o}_t \bullet \tanh\left(\mathbf{c}_t\right),
\end{aligned}
$$

DNN-HMM AM Example: LSTM

```
 LSTMComponent(inputDim, outputDim, inputVal)
{
    Wxo = Parameter(outputDim, inputDim)
    Wxi = Parameter(outputDim, inputDim)
    Wxf = Parameter(outputDim, inputDim)
    Wxc = Parameter(outputDim, inputDim)

    bo = Parameter(outputDim, init=fixedvalue, value=-1.0)
    bc = Parameter(outputDim, init=fixedvalue, value=0.0)
    bi = Parameter(outputDim, init=fixedvalue, value=-1.0)
    bf = Parameter(outputDim, init=fixedvalue, value=-1.0)

    Whi = Parameter(outputDim, outputDim)
    Wci = Parameter(outputDim)
    Whf = Parameter(outputDim, outputDim)
    Wcf = Parameter(outputDim)
    Who = Parameter(outputDim, outputDim)
    Wco = Parameter(outputDim)
    Whc = Parameter(outputDim, outputDim)
```

parameters

DNN-HMM AM Example: LSTM

```
delayH = Delay(outputDim, output, delayTime=1)
delayC = Delay(outputDim, ct, delayTime=1)
```

Delay node

```
WxiInput = Times(Wxi, inputVal)
WhidelayHI = Times(Whi, delayH)
WcidelayCI = DiagTimes(Wci, delayC)
```

$$\mathbf{i}_t \quad = \quad \sigma\left(\mathbf{W}^{(xi)}\mathbf{x}_t + \mathbf{W}^{(hi)}\mathbf{h}_{t-1} + \mathbf{W}^{(ci)}\mathbf{c}_{t-1} + \mathbf{b}^{(i)}\right)$$

```
it = Sigmoid (Plus ( Plus (Plus (WxiInput, bi), WhidelayHI),
        WcidelayCI))
```

```
WhfdelayHF = Times(Whf, delayH)
WcfdelayCF = DiagTimes(Wcf, delayC)
Wxfinput = Times(Wxf, inputVal)
```

$$\mathbf{f}_t \quad = \quad \sigma\left(\mathbf{W}^{(xf)}\mathbf{x}_t + \mathbf{W}^{(hf)}\mathbf{h}_{t-1} + \mathbf{W}^{(cf)}\mathbf{c}_{t-1} + \mathbf{b}^{(f)}\right)$$

```
ft = Sigmoid( Plus (Plus (Plus(Wxfinput, bf), WhfdelayHF),
        WcfdelayCF))
```

Microsoft Research

DNN-HMM AM Example: LSTM

```
        WxcInput = Times(Wxc, inputVal)
        WhcdelayHC = Times(Whc, delayH)
        bit = ElementTimes(it, Tanh( Plus(WxcInput, Plus(WhcdelayHC, 
bc))))
        bft = ElementTimes(ft, delayC)

        ct = Plus(bft, bit)
```

$$\mathbf{c}_t \quad = \quad \mathbf{f}_t \bullet \mathbf{c}_{t-1} + \mathbf{i}_t \bullet \tanh\left(\mathbf{W}^{(xc)}\mathbf{x}_t + \mathbf{W}^{(hc)}\mathbf{h}_{t-1} + \mathbf{b}\right.$$

```
        Wxoinput = Times(Wxo, inputVal)
        WhodelayHO = Times(Who, delayH)
        Wcoct = DiagTimes(Wco, ct)

        ot = Sigmoid( Plus( Plus( Plus(Wxoinput, bo), WhodelayHO), 
Wcoct))
```

$$\mathbf{o}_t \quad = \quad \sigma\left(\mathbf{W}^{(xo)}\mathbf{x}_t + \mathbf{W}^{(ho)}\mathbf{h}_{t-1} + \mathbf{W}^{(co)}\mathbf{c}_t + \mathbf{b}^{(o)}\right)$$

```
        output = ElementTimes(ot, Tanh(ct))
    }
```

$$\mathbf{h}_t \quad = \quad \mathbf{o}_t \bullet \tanh\left(\mathbf{c}_t\right)$$

DNN-HMM AM Example: LSTM

- Top level command:

```
action=train
```

- Reader changes

```
reader=[
      readerType=HTKMLFReader
      readMethod=blockRandomize

      frameMode=false

      Truncated=true

      nbrUttsInEachRecurrentIter=32
```

Sequence mode

Truncated BPTT

Number of utterances in each minibatch

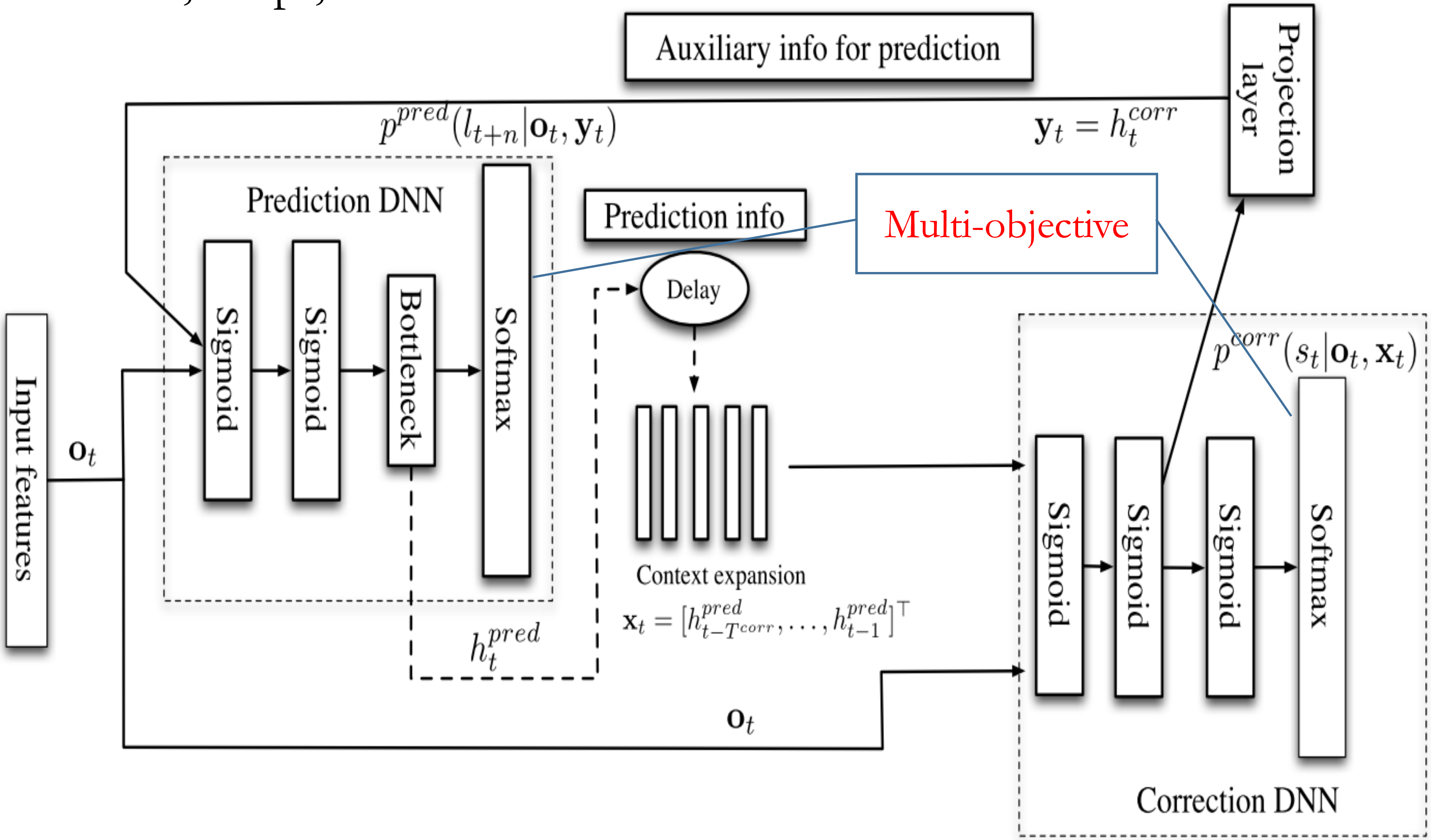
- SGD block meaning change

```
minibatchsize=20
```

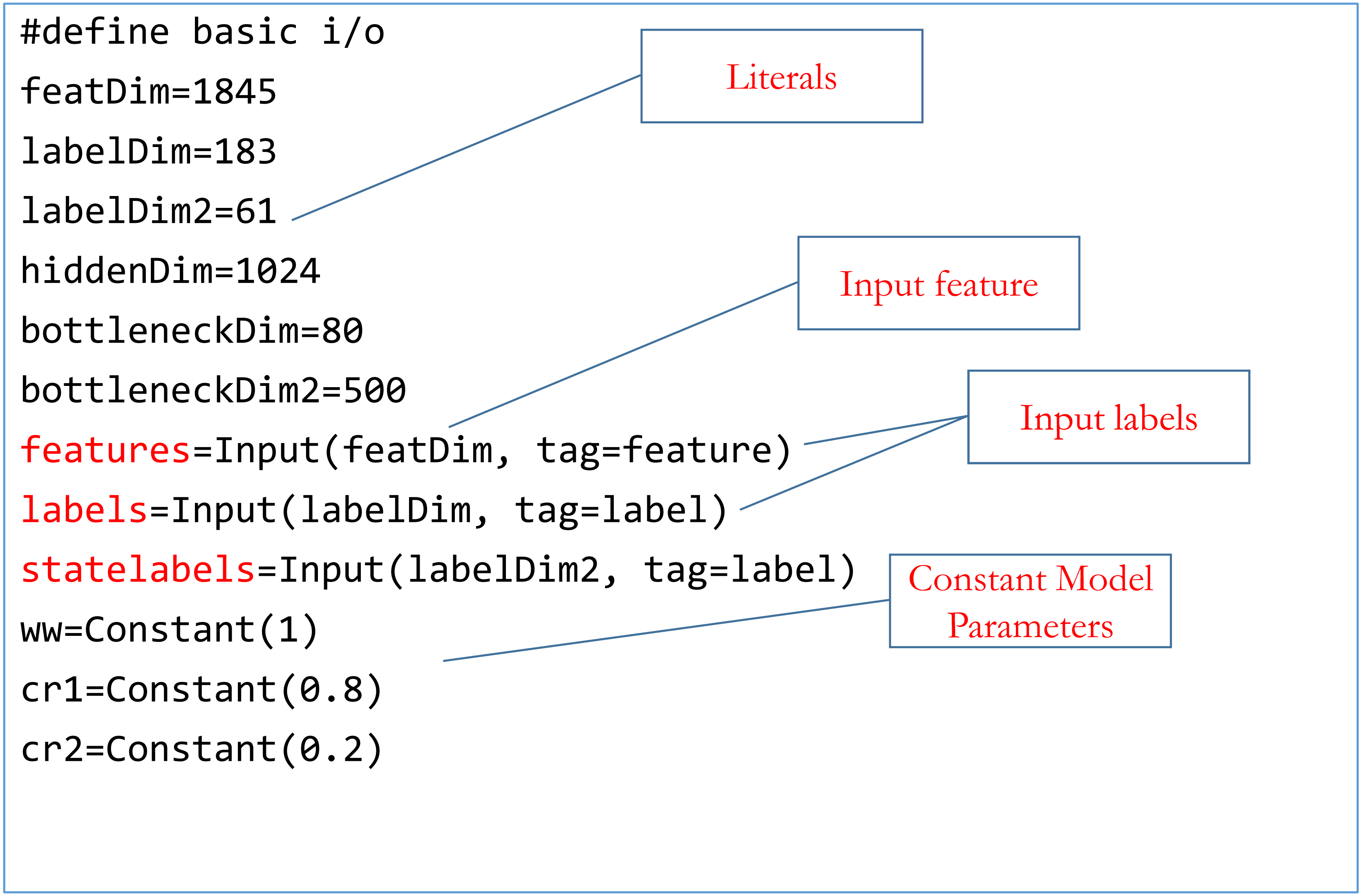
Truncation size

Prediction-Based AM Example

- A recurrent system with two major components
- Predict, adapt, and correct


Auxiliary info for prediction
Projection layer
$p^{pred}(l_{t+n}|\mathbf{o}_t, \mathbf{y}_t)$
$\mathbf{y}_t = h_t^{corr}$
Prediction DNN
Prediction info
Multi-objective
Delay
Sigmoid
Sigmoid
Bottleneck
Softmax
Input features
$\mathbf{o}_t$
$p^{corr}(s_t|\mathbf{o}_t, \mathbf{x}_t)$
Context expansion
$\mathbf{x}_t = [h_{t-T^{corr}}^{pred}, \ldots, h_{t-1}^{pred}]^\top$
h_t^{pred}
Sigmoid
Sigmoid
Sigmoid
Softmax
$\mathbf{o}_t$
Correction DNN

Prediction Based AM Example



```
#define basic i/o
featDim=1845
labelDim=183
labelDim2=61
hiddenDim=1024
bottleneckDim=80
bottleneckDim2=500
features=Input(featDim, tag=feature)
labels=Input(labelDim, tag=label)
statelabels=Input(labelDim2, tag=label)
ww=Constant(1)
cr1=Constant(0.8)
cr2=Constant(0.2)
```

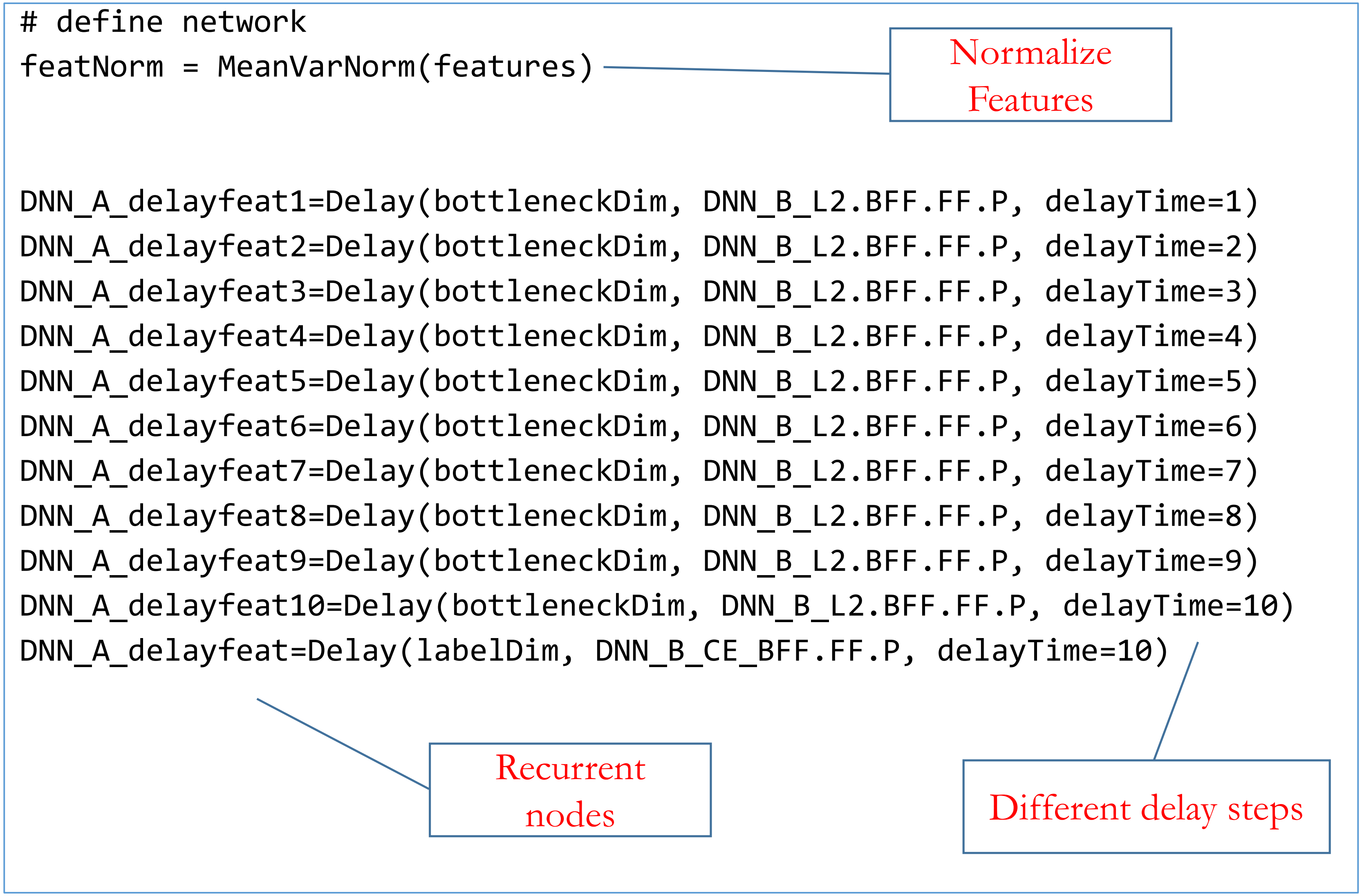
Literals

Input feature

Input labels

Constant Model Parameters

Prediction Based AM Example



```
# define network
featNorm = MeanVarNorm(features)


DNN_A_delayfeat1=Delay(bottleneckDim, DNN_B_L2.BFF.FF.P, delayTime=1)
DNN_A_delayfeat2=Delay(bottleneckDim, DNN_B_L2.BFF.FF.P, delayTime=2)
DNN_A_delayfeat3=Delay(bottleneckDim, DNN_B_L2.BFF.FF.P, delayTime=3)
DNN_A_delayfeat4=Delay(bottleneckDim, DNN_B_L2.BFF.FF.P, delayTime=4)
DNN_A_delayfeat5=Delay(bottleneckDim, DNN_B_L2.BFF.FF.P, delayTime=5)
DNN_A_delayfeat6=Delay(bottleneckDim, DNN_B_L2.BFF.FF.P, delayTime=6)
DNN_A_delayfeat7=Delay(bottleneckDim, DNN_B_L2.BFF.FF.P, delayTime=7)
DNN_A_delayfeat8=Delay(bottleneckDim, DNN_B_L2.BFF.FF.P, delayTime=8)
DNN_A_delayfeat9=Delay(bottleneckDim, DNN_B_L2.BFF.FF.P, delayTime=9)
DNN_A_delayfeat10=Delay(bottleneckDim, DNN_B_L2.BFF.FF.P, delayTime=10)
DNN_A_delayfeat=Delay(labelDim, DNN_B_CE_BFF.FF.P, delayTime=10)
```

Normalize Features

Recurrent nodes

Different delay steps

Prediction Based AM Example

```
DNN_A_L1 = SBFF_multi8(featNorm,DNN_A_delayfeat1,
      DNN_A_delayfeat2, DNN_A_delayfeat3, DNN_A_delayfeat4,
      DNN_A_delayfeat5, DNN_A_delayfeat6, DNN_A_delayfeat7,
      DNN_A_delayfeat8, DNN_A_delayfeat9, DNN_A_delayfeat10,
      hiddenDim, featDim, bottleneckDim)
```

Concatenate information from past

```
DNN_A_L2 = SBFF(DNN_A_L1,hiddenDim,hiddenDim)

DNN_A_L2_B = SBFF(DNN_A_L1,bottleneckDim2,hiddenDim)

DNN_A_CE_BFF = BFF(DNN_A_L2,labelDim,hiddenDim)


DNN_B_L1 = SBFF_multi(featNorm, DNN_A_L2_B.BFF.FF.P,
                      hiddenDim, featDim, bottleneckDim2)

DNN_B_L2 = SBFF(DNN_B_L1, bottleneckDim, hiddenDim)

DNN_B_CE_BFF = BFF(DNN_B_L2, labelDim2, bottleneckDim)
```

Prediction Based AM Example

```
criterion1 = CrossEntropyWithSoftmax(labels,
                                     DNN_A_CE_BFF)
criterion2 = CrossEntropyWithSoftmax(statelabels,
                                     DNN_B_CE_BFF)


criterion = Plus(Scale(cr2,criterion2),
                 Scale(cr1,criterion1),
                 tag=Criteria)


Err = ErrorPrediction(labels, DNN_A_CE_BFF,tag=Eval)


LogPrior = LogPrior(labels)
ScaledLogLikelihood=Minus(DNN_A_CE_BFF, logPrior,
                          tag=Output)
```

Multiple criteria

Combine criteria

Prediction Based AM Example

```
reader=[
    readerType=HTKMLFReader
    readMethod=blockRandomize


    frameMode=false
    Truncated=true


nbruttsineachrecurrentiter=5
    features=[
        dim=1845
        scpFile=$scpFilePath$
    ]
```

Utterance mode for RNN

Truncated BPTT

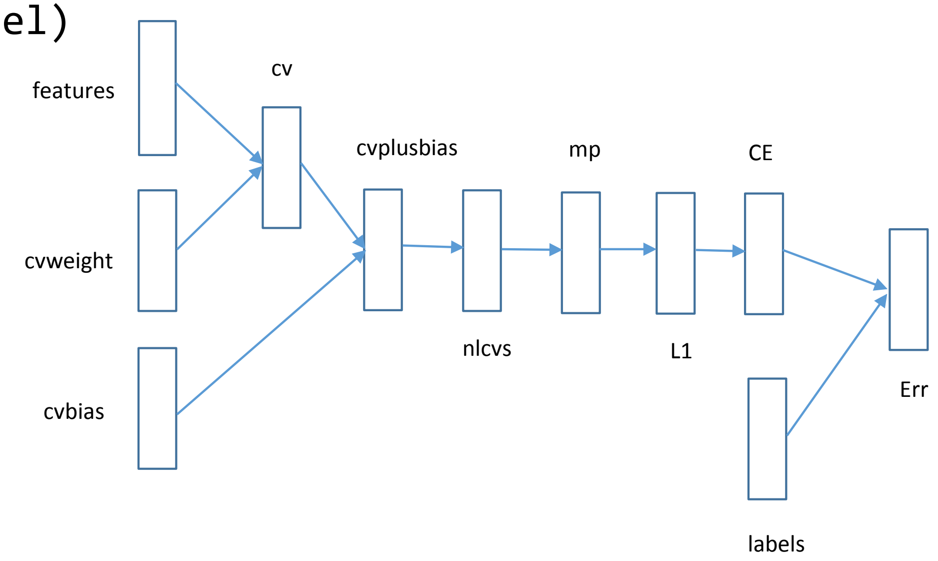
```
  labelDim=183
  labelType=Category

  labels=[

 mlfFile=$normalLabelFilePath$
    ]
    statelabels=[
mlfFile=$predictLableFilePath$
    ]
]
```

Main label

Prediction label

NDL Example: CNN

```
# Sample, Hidden, and Label dimensions
SDim=784
LDim=10

inputWidth=28
inputHeight=28
inputChannels=1

features=ImageInput(inputWidth, inputHeight, inputChannels,
   tag=feature)
labels=Input(LDim, tag=label)

#convolution
kernelWidth=5
kernelHeight=5
outputChannels=24
horizontalSubsample=2
verticalSubsample=2
```



NDL Example: CNN

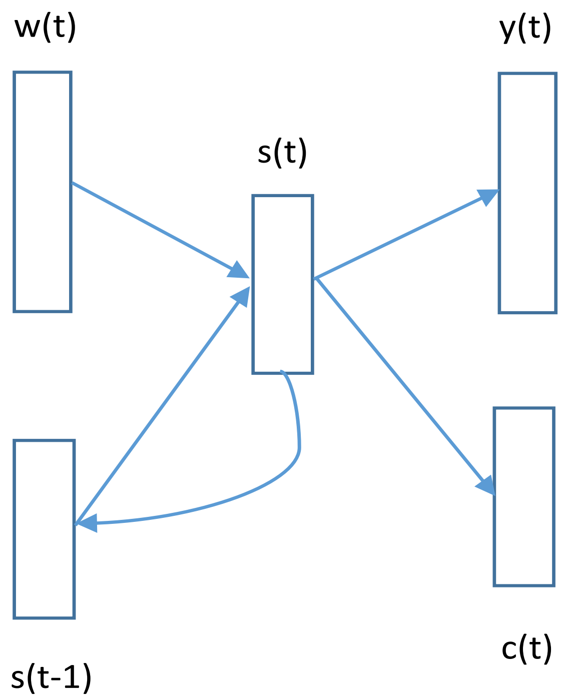
```
# weight[outputChannels, kernelWidth * kernelHeight * inputChannels]
cvweight=Parameter(outputChannels, 25)

cv = Convolution(cvweight, features, kernelWidth, kernelHeight,
                 outputChannels, horizontalSubsample, verticalSubsample,
                 zeroPadding=false)

#one bias per channel
cvbias=Parameter(outputChannels, 1)

cvplusbias=Plus(cv, cvbias);
nlcv=Sigmoid(cvplusbias);

#outputWidth = (m_inputWidth-m_kernelWidth)/m_horizontalSubsample + 1;
outputWidth=12

#outputHeight = (m_inputHeight-m_kernelHeight)/m_verticalSubsample + 1;
outputHeight=12
```

NDL Example: CNN

```
#maxpooling
windowWidth=2
windowHeight=2
stepW=2
stepH=2
mp=MaxPooling(nlcv, windowWidth, windowHeight, stepW, stepH)

#m_outputSizePerSample = m_outputWidth * m_outputHeight * m_channels;
mpoutputSizePerSample=864

# Layer operations
HDim=128
L1 = SBFF(mp, HDim, mpoutputSizePerSample)
CE = SMBFF(L1, LDim, HDim, labels, tag=Criteria)
Err=ErrorPrediction(labels, CE.BFF, tag=Eval)

# rootNodes defined here
OutputNodes=(CE.BFF)
```

Class-based RNN LM Example

- RNN example with additional class info included in output layer



Class-based RNN LM Example

- Top level commands and parameters

```
    action=train
    minibatchSize=10
    deviceId=auto
    defaultHiddenActivity=0.1
```

The initial (default) activity for delay nodes

- Network Definition

```
ndlCreateNetwork=[
    featDim=10000
    labelDim=10000
    hiddenDim=200
    nbrClass=50

    initScale=6

    features=SparseInput(featDim, tag=feature)

    # labels in classbasedCrossEntropy is dense
    # and contain 4 values for each sample
    labels=Input(4, tag=label)
```

Vocabulary Size

Hidden Layer Size

Number of Classes

Enlarge initial weight value ranges by 6 times

Class-based RNN LM Example

```
     WFeat2Hid=Parameter(hiddenDim, featDim, init=uniform, initValueScale=initScale)
    WHid2Hid=Parameter(hiddenDim, hiddenDim, init=uniform, initValueScale=initScale)


    # WHid2Word is special that it is hiddenSize X labelSize
    WHid2Word=Parameter(hiddenDim, labelDim, init=uniform, initValueScale=initScale)
    WHid2Class=Parameter(nbrClass, hiddenDim, init=uniform, initValueScale=initScale)


    PastHid = Delay(hiddenDim, HidAfterSig, delayTime=1, needGradient=true)
    HidFromFeat = Times(WFeat2Hid, features)
    HidFromRecur = Times(WHid2Hid, PastHid)
    HidBeforeSig = Plus(HidFromHeat, HidFromRecur)
    HidAfterSig = Sigmoid(HidBeforeSig)


    Out = Times(WHid2Word, HidAfterSig)  #word part
    ClassProbBeforeSoftmax=Times(WHid2Class, HidAfterSig)


    cr = ClassBasedCrossEntropyWithSoftmax(labels, HidAfterSig, WHid2Word,
                                           ClassProbBeforeSoftmax, tag=Criteria)

    EvalNodes=(Cr)
    OutputNodes=(Cr)
]
```

Customized Initialization

Info from Past Hidden

Special Node for Class Based Classification

Same Node Can be Used for Difference Purposes

Class-based RNN LM Example

- SGD section

```
SGD=[
    learningRatesPerSample=0.1
    momentumPerMB=0
    gradientClippingWithTruncation=true
    clippingThresholdPerSample=15.0
    maxEpochs=40
    gradUpdateType=None

    modelPath=$ExpFolder$\modelRnnCNTK
    loadBestModel=true

    # settings for Auto Adjust Learning Rate
    AutoAdjust=[
       autoAdjustLR=adjustAfterEpoch
       reduceLearnRateIfImproveLessThan=0.001
       continueReduce=true
       learnRateDecreaseFactor=0.5
    ]
]
```

Clip the gradient to prevent exploding

load best model before training next epoch

Adjust learning rate after each epoch

Continue reducing learning rate once it’s reduced

Outline

- Motivation
- Introduction to Deep Learning and Prevailing Deep Learning Models
- Computational Network: A Unified Framework for Models Expressible as Functions
- Computational Network Toolkit: A Generic Toolkit for Building Computational Networks
- Examples: Acoustic Model, Language Model, and Image Classification
- **Summary**

Summary

- Computational networks generalize many existing deep learning models
- You may design new computational networks to attack new problems by exploiting problem-specific structures and domain knowledge
- We described the forward and backward computation algorithms and theories for CNs with and without recurrent loops
- CNTK implements CNs so that you only need to focus on designing the CNs instead of implementing learning algorithms for your specific CN

Summary

- CNTK is a powerful tool that supports CPU/GPU and runs under Windows/Linux
- CNTK is extensible with the low-coupling modular design: adding new readers and new computation nodes is easy
- Network definition language, macros, and model editing language makes network design and modification easy
- We have shown many examples to indicate that CNTK can support DNN, CNN, RNN, class-based LM, LSTM, and PAC-AM and to solve AM, LM, and SLU problems

Additional Resources

- CNTK Reference Book
  - Dong Yu, Adam Eversole, Mike Seltzer, Kaisheng Yao, Zhiheng Huang, Brian Guenter, Oleksii Kuchaiev, Yu Zhang, Frank Seide, Huaming Wang, Jasha Droppo, Geoffrey Zweig, Chris Rossbach, Jon Currey, Jie Gao, Avner May, Baolin Peng, Andreas Stolcke, Malcolm Slaney, "An Introduction to Computational Networks and the Computational Network Toolkit", Microsoft Technical Report MSR-TR-2014-112, 2014.
  - Contains all the information you need to understand and use CNTK
- Codeplex source code site
  - https://cntk.codeplex.com/
  - Contains all the source code and example setups
  - You may understand better how CNTK works by reading the source code
  - New functionalities are added constantly

Please Contribute!

- If you write your own readers or computation nodes we would like them to be checked-in to the main branch
- CNTK becomes more powerful when all computation nodes and readers people want to use are available