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Deep Learning for Automatic Speech Recognition

Dong Yu

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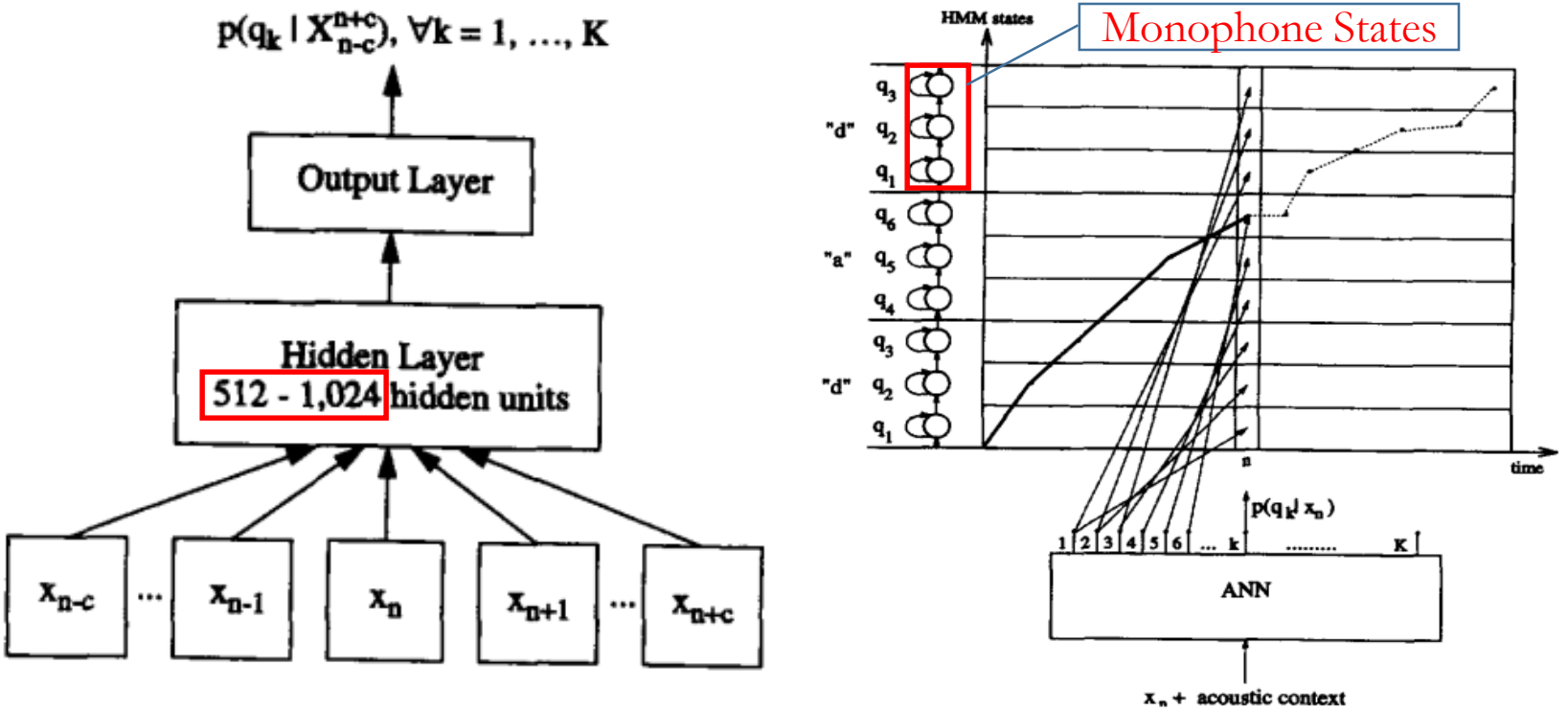
Outline

- **Major Modeling Techniques in ASR**
  - **Deep Neural Networks (DNNs)**
  - Convolutional Neural Networks (CNNs)
  - Long Short-Term Memory (LSTM) RNNs
  - Model Adaptation
- Build Deep ASR Models Using CNTK
  - Computational Networks and CNTK
  - Network Definition Language (NDL)
  - Examples: DNN, LSTM and PAC-RNN
  - Model Editing Language (MEL)
  - Stochastic Gradient Descent (SGD)
- Summary

ANN/HMM Hybrid System

(Morgan and Bourlard 1990, 1995)

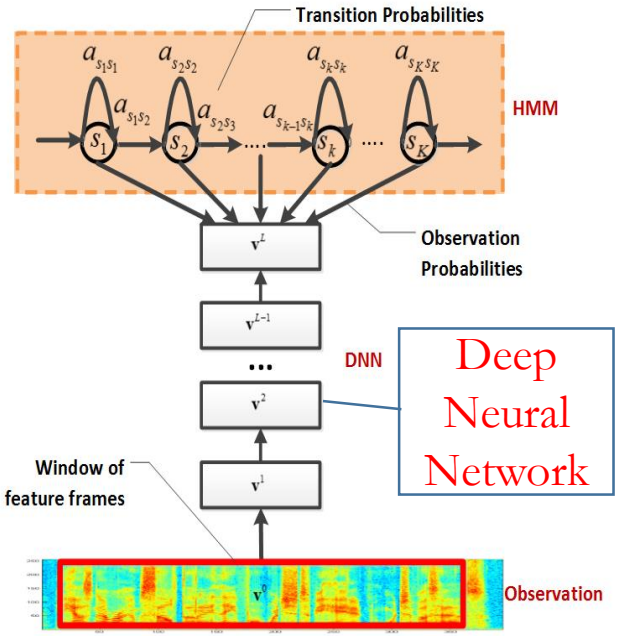


- Used a large context window as inputs
- Models monophone state posterior probability with a neural network
- One-to-two hidden layers. Hidden layer size is comparable with what we use today (but not the output layer size)
- Can easily handle continuous speech due to the integration of HMM

DNN/HMM Hybrid System

(Mohamed, Dahl and Hinton 2009)

- DNN on phoneme recognition
  - TIMIT phone recognition:
    - DNN System: **23.0%** phone error rate (PER)
    - Ref: GMM systems
      - maximum likelihood training (MLT) 25.6%,
      - sequence-discriminative training (SDT) 21.7%
  - **Same architecture as 1990s but deep and pretrained**: models monophone states, frame-discriminative training, MFCC
  - **Observation**: Deep network helps; pretraining helps; has potential



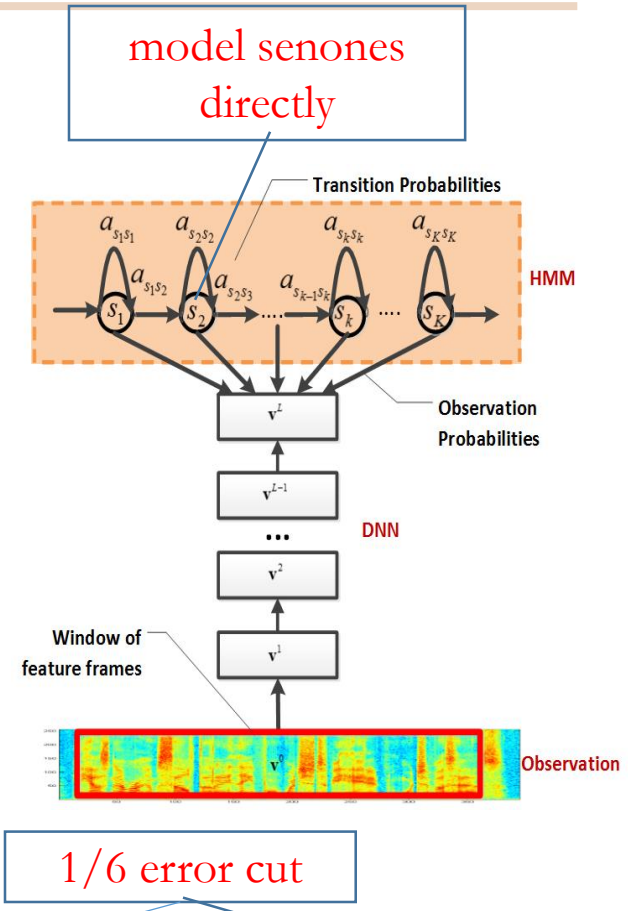
GMM MLT 25.6% → CI-DNN FDT 23.0% → GMM SDT 21.7% → Best GMM 20.0%

better

CD-DNN-HMM

(Yu, Deng & Dahl 2010, Dahl, Yu, Deng & Acero 2011, 2012)

- DNN on large vocabulary ASR
  - **Architectural Difference:** model tied triphone states (senones) directly with DNN
  - On voice search (24 hr) dataset
    - CI-DNN-HMM modeling monophone states, frame-discriminative training (FDT): **37.3%** word error rate (WER)
    - Context-Dependent DNN-HMM (**CD-DNN-HMM**) modeling senones, FDT: **30.1%**
    - Ref: GMM: MLT 39.6%; SDT 36.2%



1/6 error cut

GMM MLT 39.6% → CI-DNN FDT 37.3% → GMM SDT 36.2% → CD-DNN FDT 30.1%

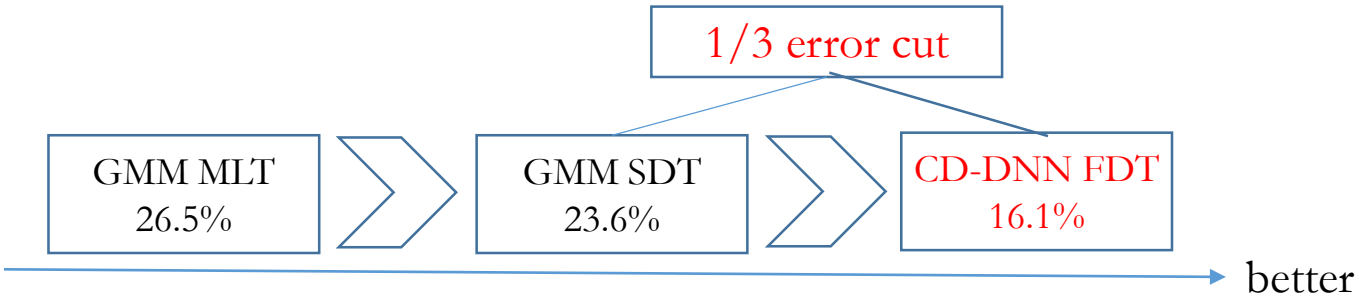
better

CD-DNN-HMM

(Kingsbury 2009)

- CD-DNN-HMM on benchmark task Switchboard (FDT)
  - Scaled to **hundreds of hours of speech** and **thousands of senones**
  - Confirmed the three key elements on larger training set: **modeling senones directly**, using **deep** models, and using a **contextual window** of features as input

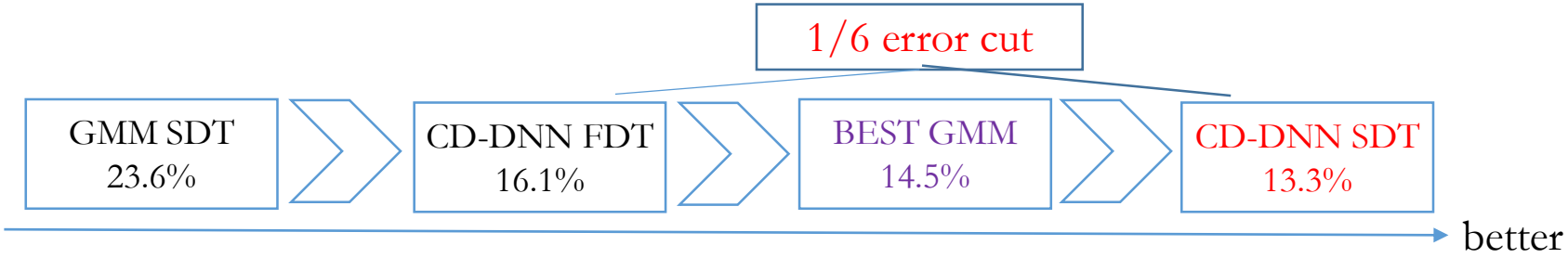
Layers X Neurons	WER (%) [300hrs]
1 x 2k	24.2
3 x 2k	18.4
5 x 2k	17.2
7 x 2k	17.1
9 x 2k	**17.0**
1 x 16k	**22.1**



DNN Sequence Discriminative Training

(Seide, Li & Yu 2011, Mohamed, Yu & Deng 2010, Kingsbury, Sainath & Soltau 2012)

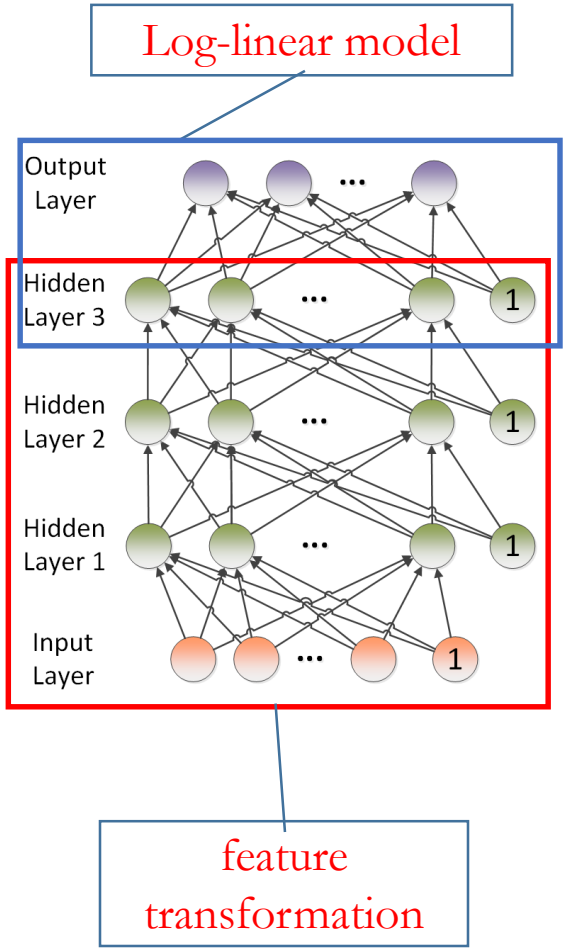
- Sequence Discriminative Training on CD-DNN-HMM
  - **Lattice generation**: generate lattice with your best system (e.g., FDT CD-DNN-HMM instead of MLT CD-GMM-HMM) or generate lattices during SDT using the current best model
  - **Lattice compensation**: handle run-away silence frames, augment lattice with reference transcription, reject bad frames
  - **Over-fit control**: smooth the SDT criterion with the FDT criterion
  - **Learning rate control**: use 1/5-1/10 of the learning rate used in the FDT
  - **Training criterion**: SDT training criterion used does not have huge effect on performance; MMI is simple to implement and thus preferred

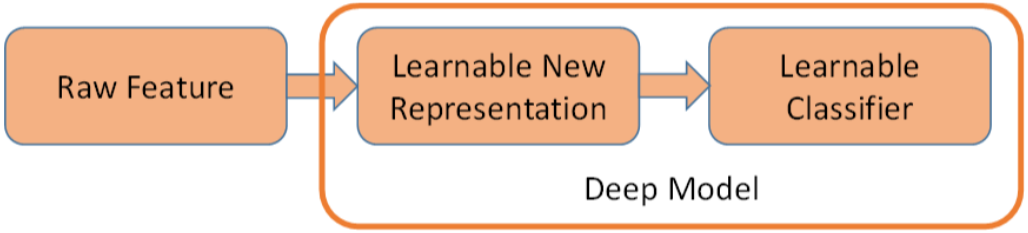


Why DNNs Work

(Seide, Li, Chen & Yu 2011)

- DNN learns the log-linear classifier and the complicated feature transformation jointly
- Many simple nonlinearities combine to form complex nonlinearities for better feature transformation
- DNN is more robust to speaker variations than shallow models
- Feature engineering techniques (e.g., VTLN, fMLLR) help less in deep networks than in shallow models
- Hint: can rewind many feature processing steps usually done in the GMM system, has no assumption on input features





Why DNNs Become Effective Only Now?

- For highly constrained tasks simple solution works
- Lack of training data and computation power limited the potential of some models

Tiger or Cat?

Pictures are from web

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)

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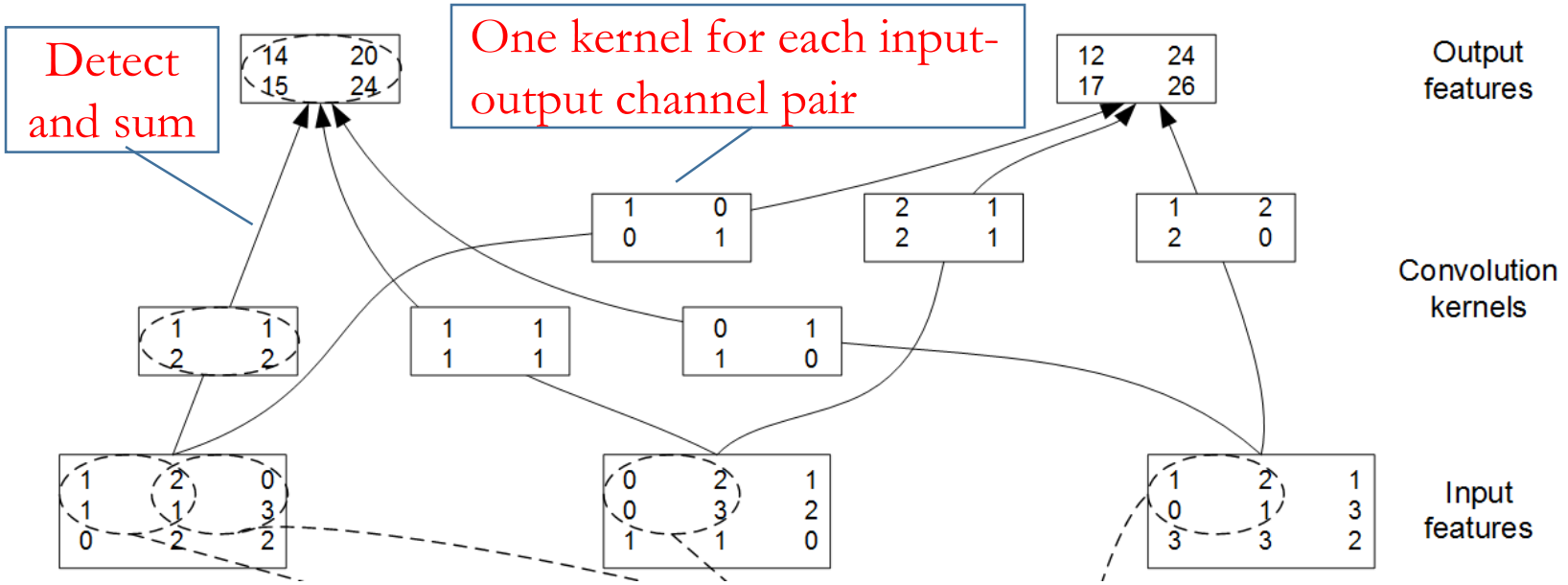
Convolutional Neural Networks

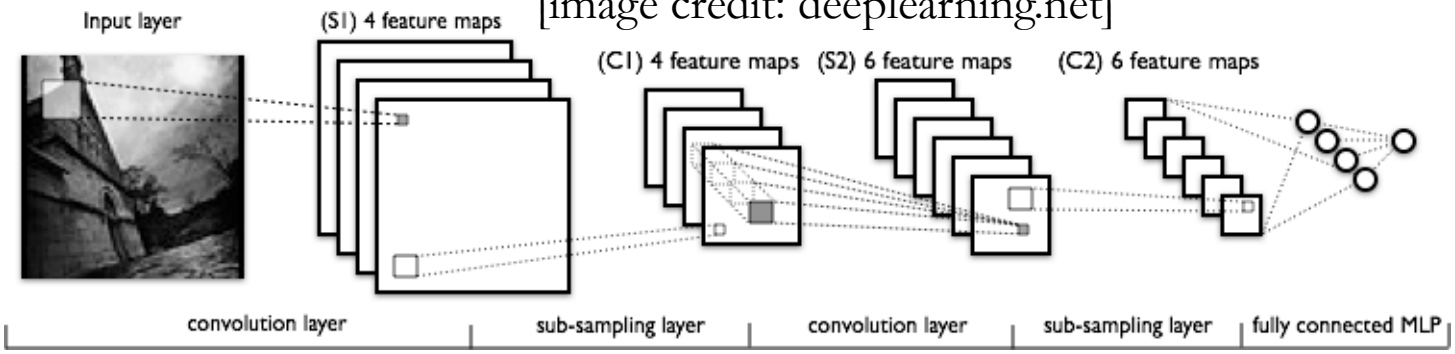
- Explicitly models translational variability and enables shift invariance
  - Shared local filters (weights) tiled across image to detect the same pattern at different locations
  - Sub-sampling through pooling (max, average, or other) to reduce variability

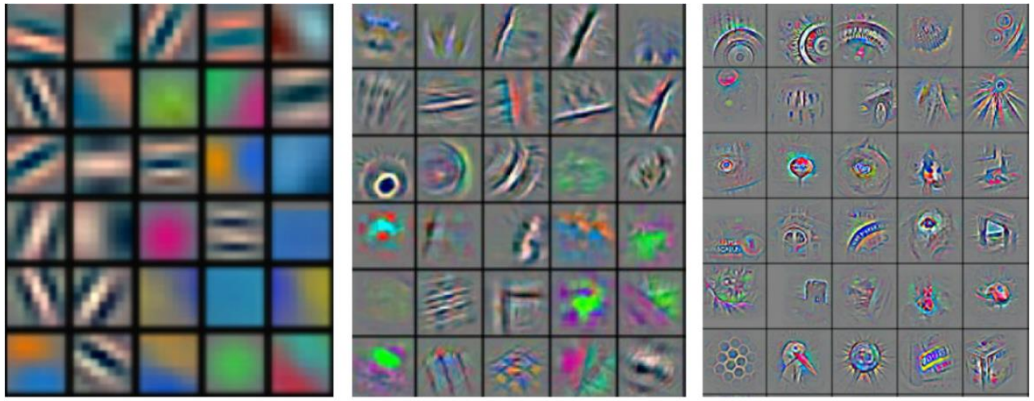


Convolutional Neural Networks

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

[image credit: deeplearning.net]



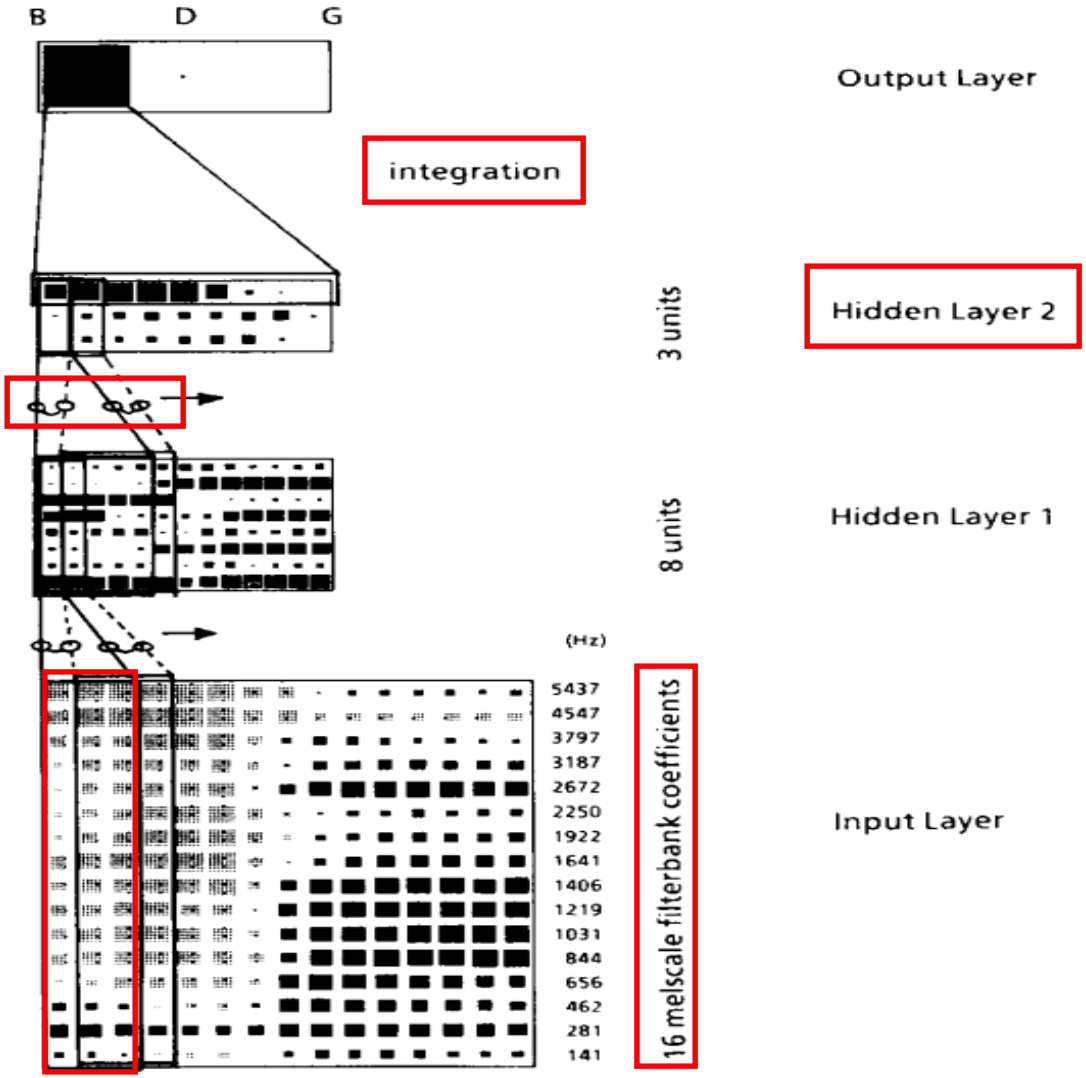


[Zeiler and Fergus, 2013]

TDNN

(Waibel et al. 1989)

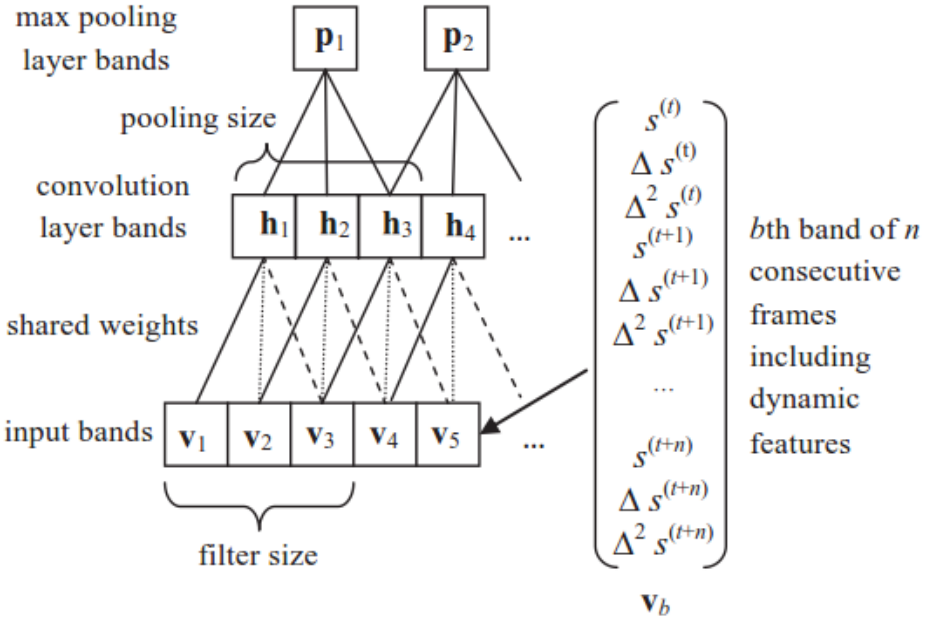
- Convolution over time
- Top layer integration allows for handling variable-length inputs
- Used melscale filterbank coefficient as the inputs.
- Used two hidden layers
- Difficult to handle large vocabulary continuous speech recognition



CNN-HMM

(Abdel-Hamid, et al. 2012, 2013, Sainath et al 2013, Soltau, et al. 2014)

- On TIMIT phone recognition task:
  - CNN with log filter-bank (LFB) features: **20.0%** PER
  - Ref: DNN with LFB features 20.7%
- **Key technique**: Use CNN at the frequency axis to **normalize the speaker differences**. Only feasible with LFB features



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CNN-HMM

(Abdel-Hamid, Deng, Yu 2013, Sainath et al 2013, Soltau, Saon, Sainath 2014)

- On LVCSR
  - Voice search (18 hr training) FDT: **33.4%** WER with CNN vs 35.4% with DNN
  - Switchboard (309 hr training) SDT: **11.8%** WER with CNN vs 12.2% with DNN
- Combine CNN and DNN (IBM)
  - Switchboard (309 hr) CNN+DNN+Adaptation+SDT **10.4%**
  - Switchboard (2000 hr) CNN+DNN+Adaptation+SDT+ Stronger LM **8.0%**
  - Ref: best number with all tricks and adaptation techniques using GMM is 14.5%

Limitations of CNNs

- CNNs mainly deal with translational variability
- It cannot handle variations such as
  - 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
- More importantly, CNNs cannot take advantage dependencies and correlations between samples (and labels) in a sequence
- Recurrent neural networks (RNNs) are designed for this

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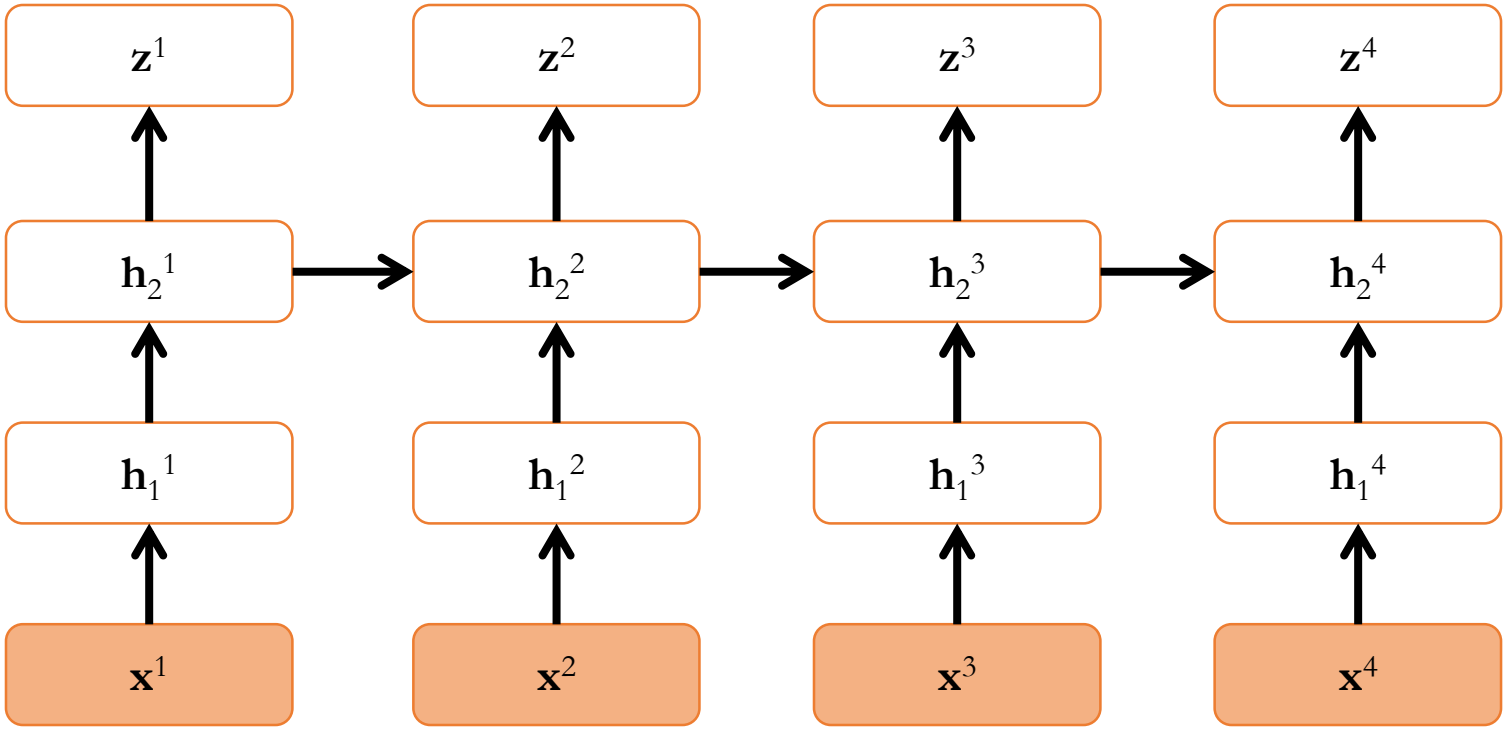
Recurrent Neural Networks

- Models dependencies and correlations between samples (and labels) in a sequence
- Trained with backpropagation through time (BPTT) and truncated BPTT

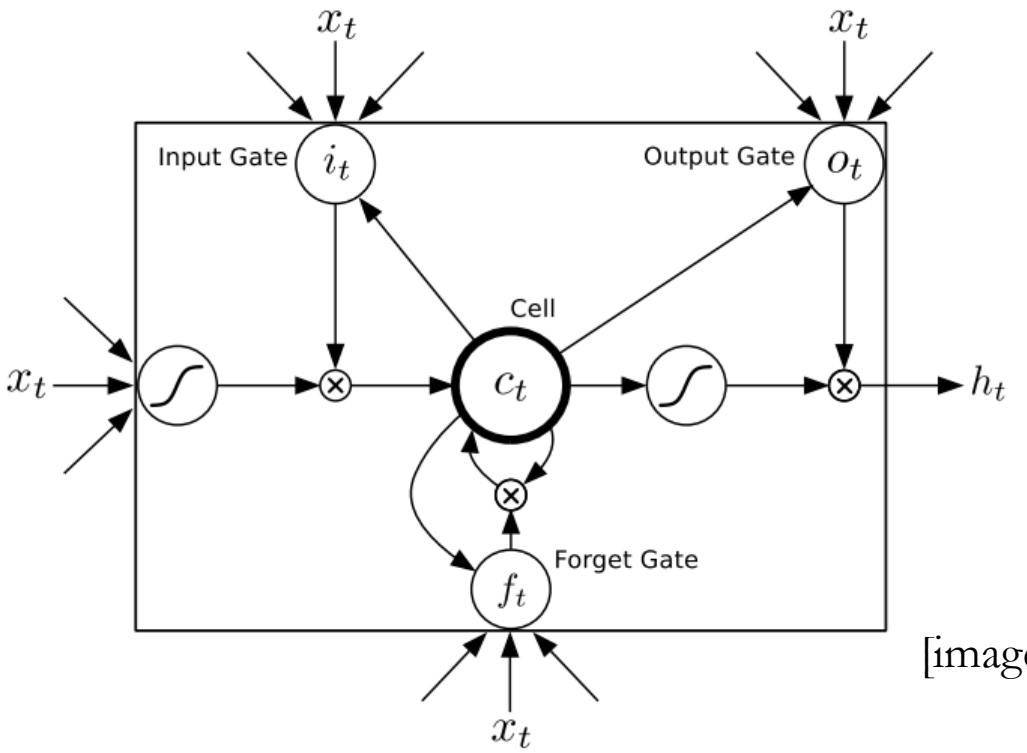


Limitations of Simple RNNs

- 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 (LSTM)

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

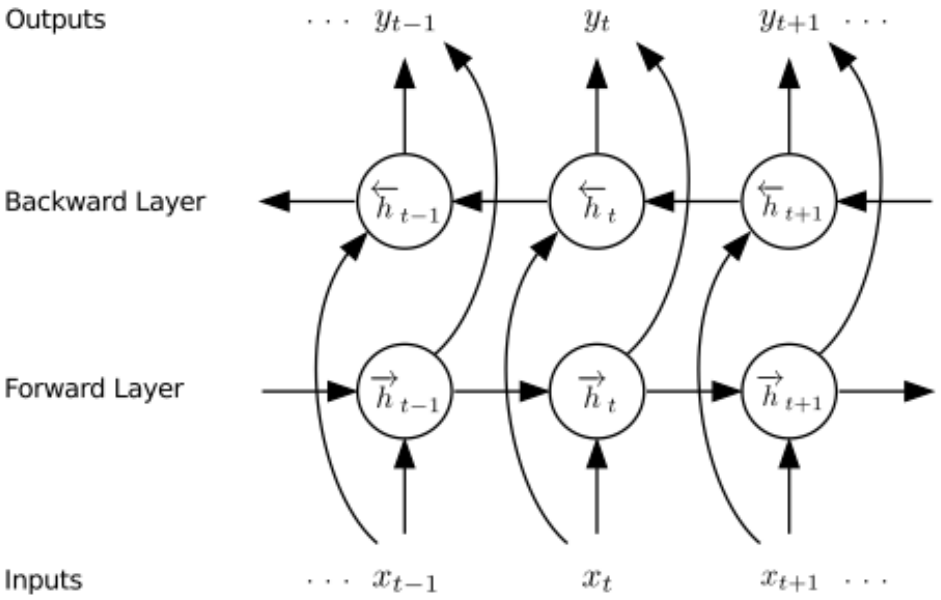


[image credit: Graves 2013]

Long Short-Term Memory (LSTM)

(Graves, Mahamed, Hinton 2013, Graves, Jaitly, Mahamed 2013)

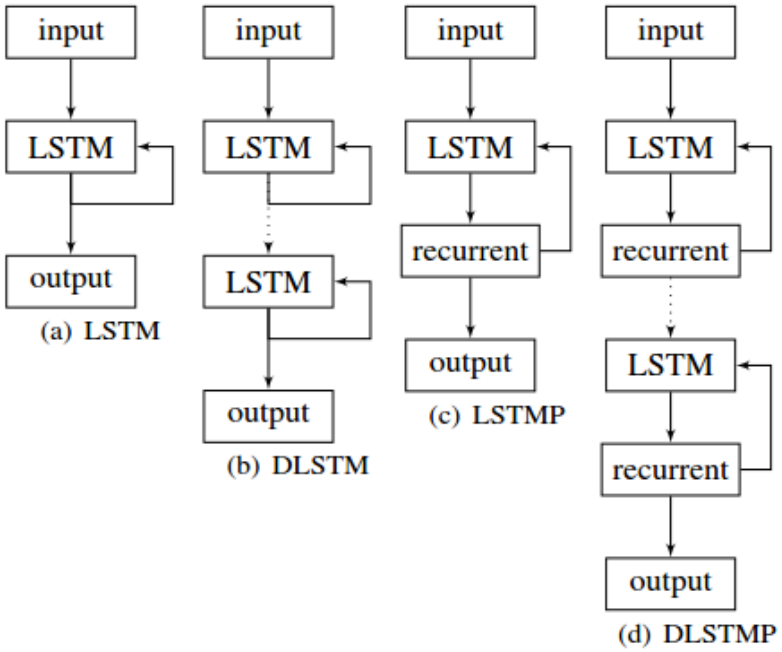
- LSTM for phone recognition
  - **Key techniques**: Bidirectional LSTM, Connectionist Temporal Classification (CTC)
  - TIMIT phone recognition: **18.4%** PER (with same LM)
    - Ref: CNN-HMM 20.0%
- LSTM-HMM for LVSR
  - LSTM-HMM FDT: WSJ **11.7%** WER
  - Ref: CD-DNN-HMM 12.3%

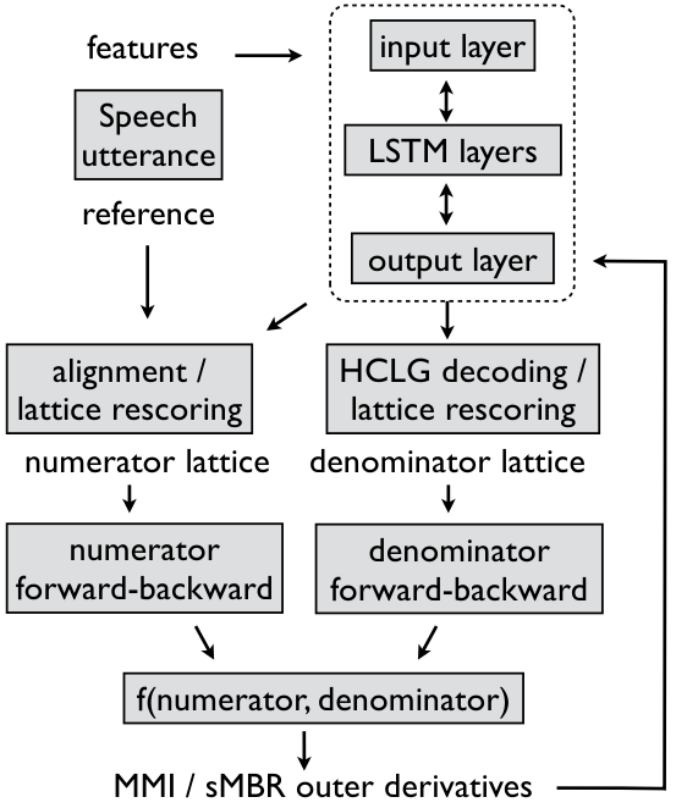


LSTM-HMM

(Sak, Senior, Beaufays 2014, Sak et al. 2014)

- Long-Short Term Memory
  - Key techniques: LSTM-HMM with a projection layer, delay output label by 5 frames, single-frame input, SDT
  - 9.8% WER on VS
    - Ref: 10.4% WER using DNN





LSTM Direct Model on LVCSR

(Sak et al. 2015)

- Use connectionist temporal classification (CTC)
  - Introduce a blank symbol to indicate "uncertain to emit a phone": blank blank a = a
  - Allow repetition of symbols: a a a = a
  - Optimize the sum of log probability of all valid state sequences - no alignment is needed: abc → blank blank a a b blank blank c c c blank
  - Initialize CTC model with CE trained model. Replace the existing softmax layer with a new random softmax layer – can be considered as a pretraining step.
  - Need to clip both the gradient and activation of the memory cell to make training stable.
  - Apply sequence discriminative training on top of CTC
- A bidirectional LSTM RNN CTC model using phone units perform as well as an LSTM RNN model using HMM state alignments

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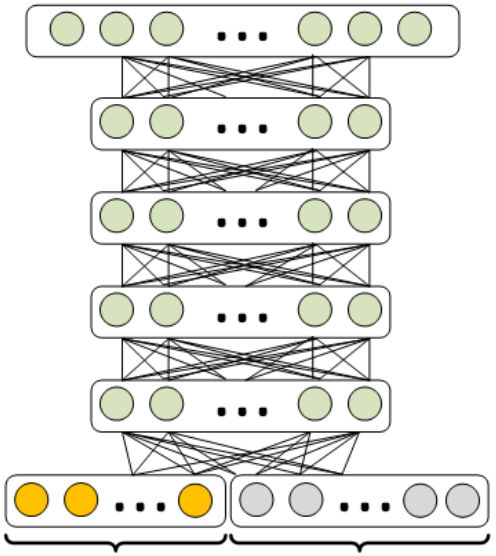
DNN Adaptation (Auxiliary Info)

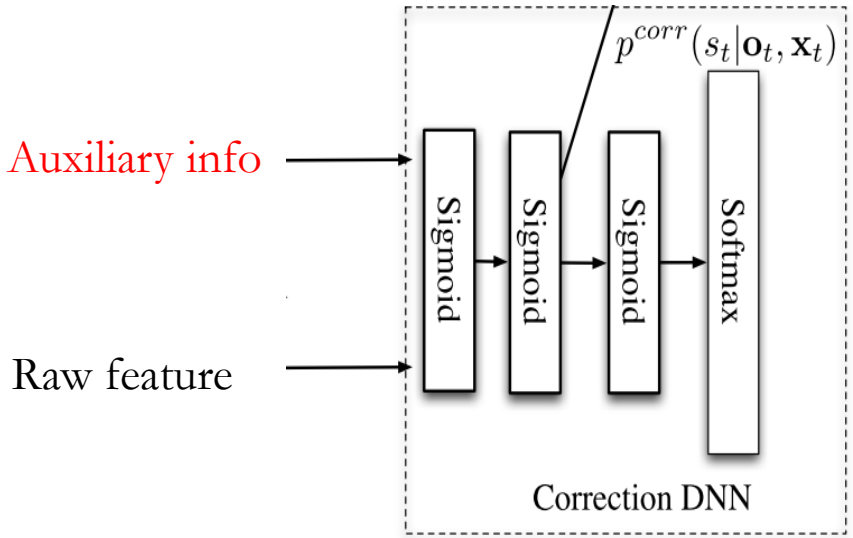
(Seltzer, Yu, Wang 2013, Abdel-Hamid, Jiang 2013, Saon et al. 2013)

- Noise (or speaker)-aware training
  - Key technique: estimate noise (or speaker, e.g., i-vector and speaker code) and use it as part of the input to the DNN
  - Effectively used a different (adaptive) bias for different noise condition
- DNN FDT on Aurora4 13.4% WER, + noise-aware training **12.4%**
  - Ref: GMM: SDT 22.5%; +adaptive training 15.3%, +VAT+Joint compensation 13.4%
- DNN SDT on SWB 14.1%; + SaT: **12.4%** WER → 12% error cut



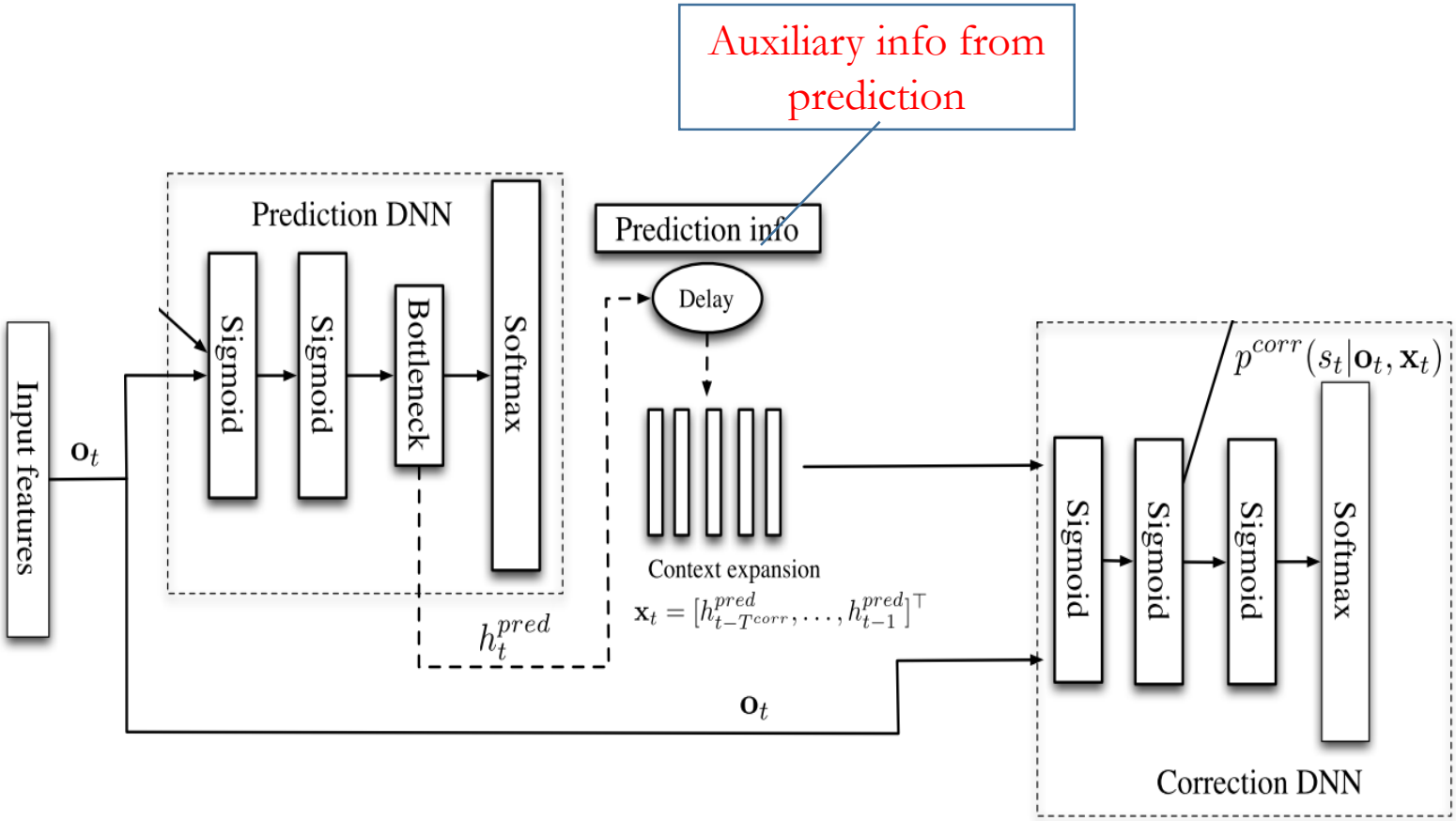
DNN with Auxiliary Information

- Augment the raw feature with auxiliary information
- Auxiliary information needs to be provided separately



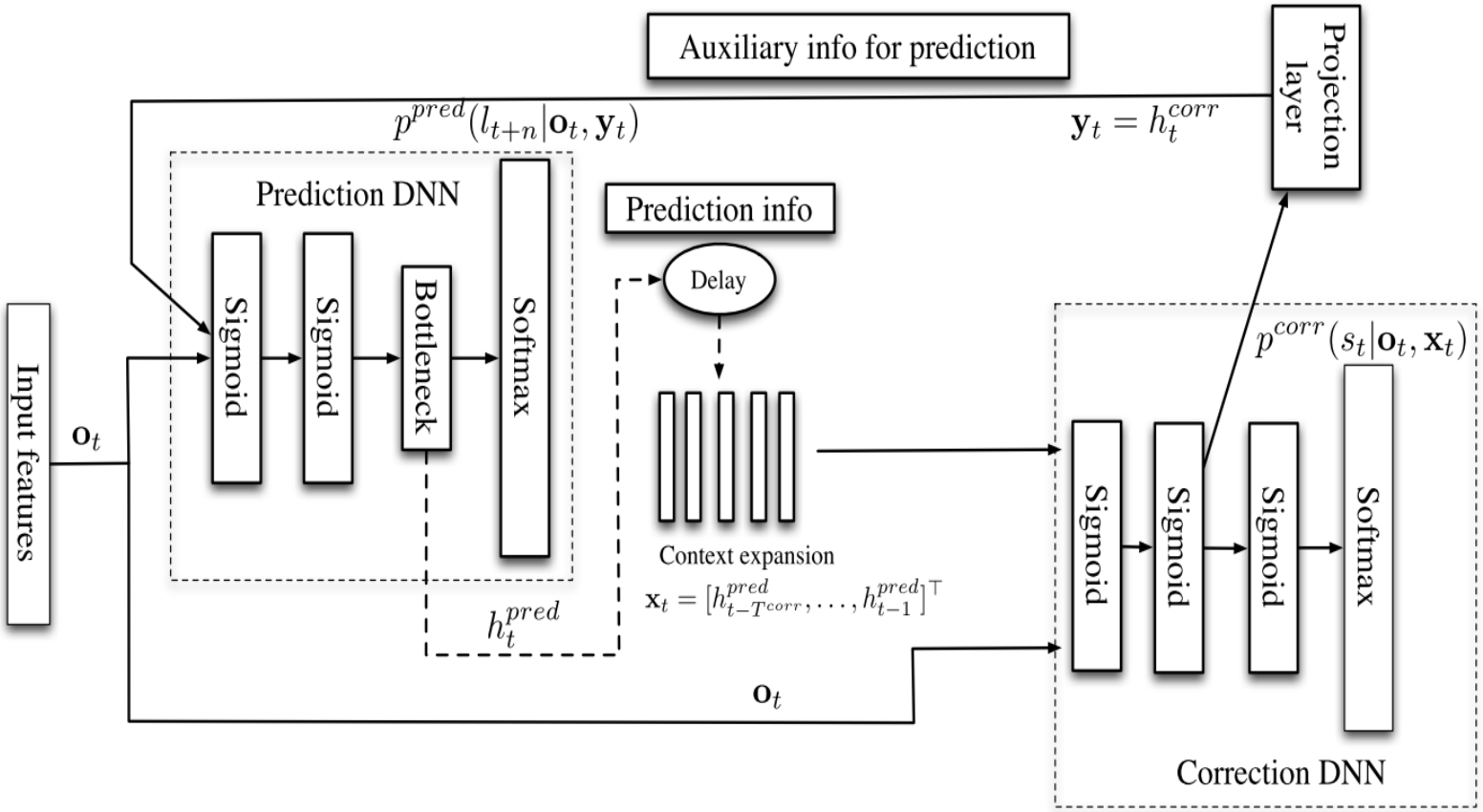
PAC-RNN: Predict Auxiliary Info

- Predict the auxiliary information
- Both components are jointly trained



PAC-RNN: Feedback

- Forms a recurrent network
- Both components are adaptive and trained jointly
- Better than LSTM and DNN on both TIMIT phone recognition and babel evaluation



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New Models

- To further improve the accuracy new models are needed
- This requires new tools

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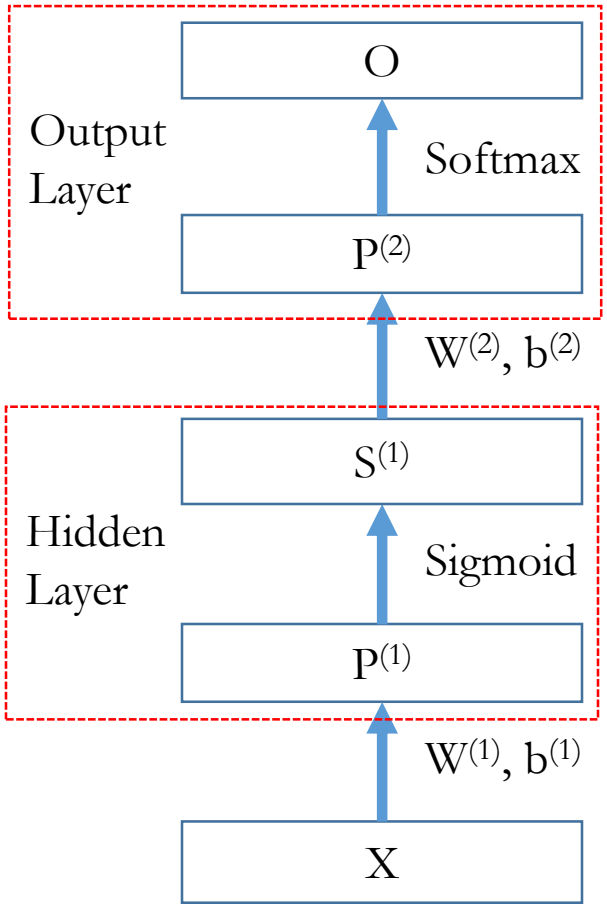
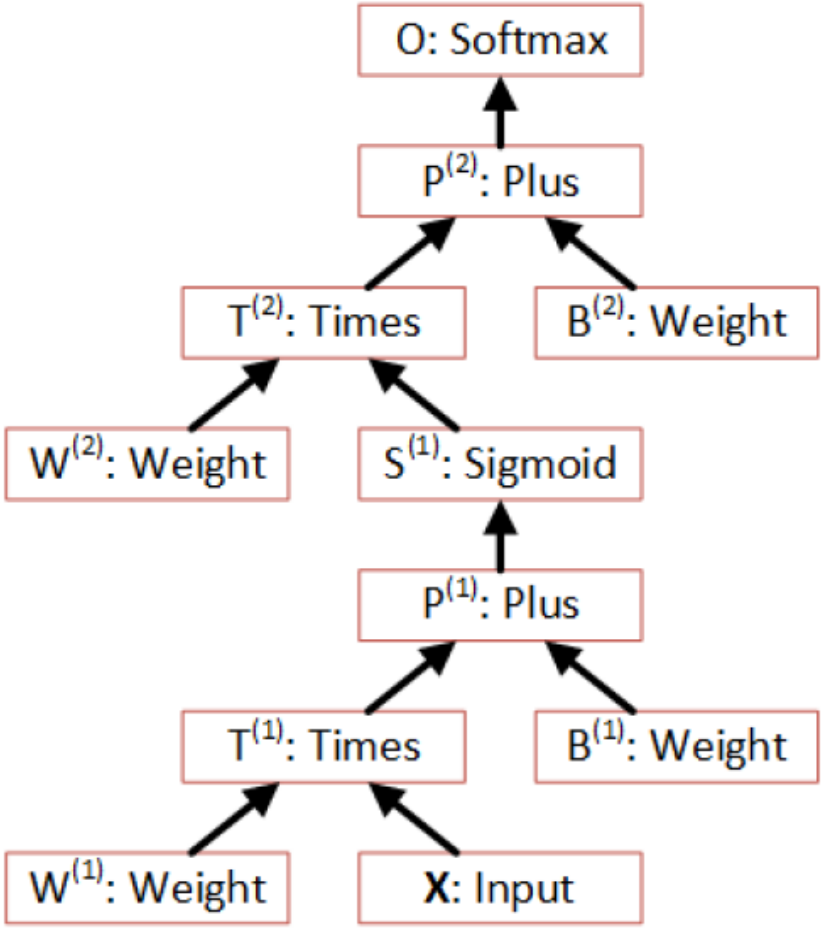
Computational Networks

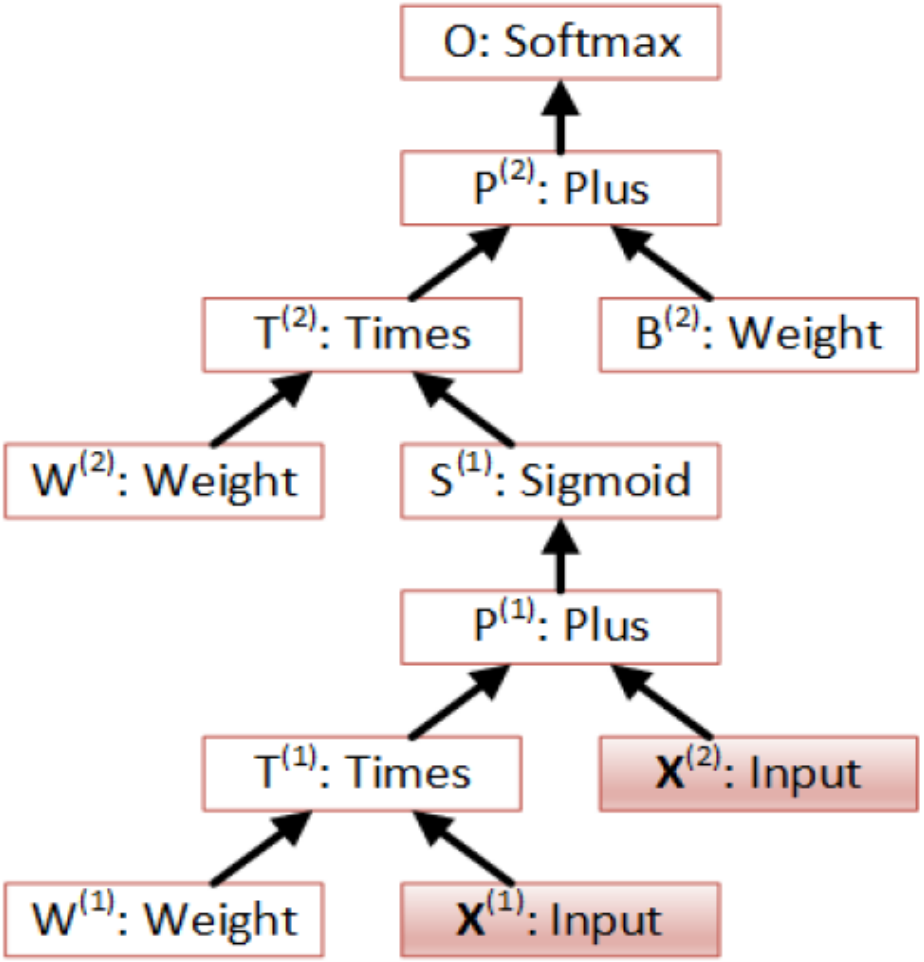
- A generalization of machine learning models that can be described as a series of computational steps.
- Examples of computational networks
  - Deep Neural Networks (DNNs)
  - Convolutional Neural Networks (CNNs)
  - Recurrent Neural Networks (RNNs)
  - Long Short-Term Memory (LSTM) RNNs
  - PAC-RNN
- …and some other common machine learning models
  - Gaussian Mixture Models (GMMs)
  - Logistic Regression Models (LRMs)
  - Log-Linear Models (LLMs)

Example: One Hidden Layer NN

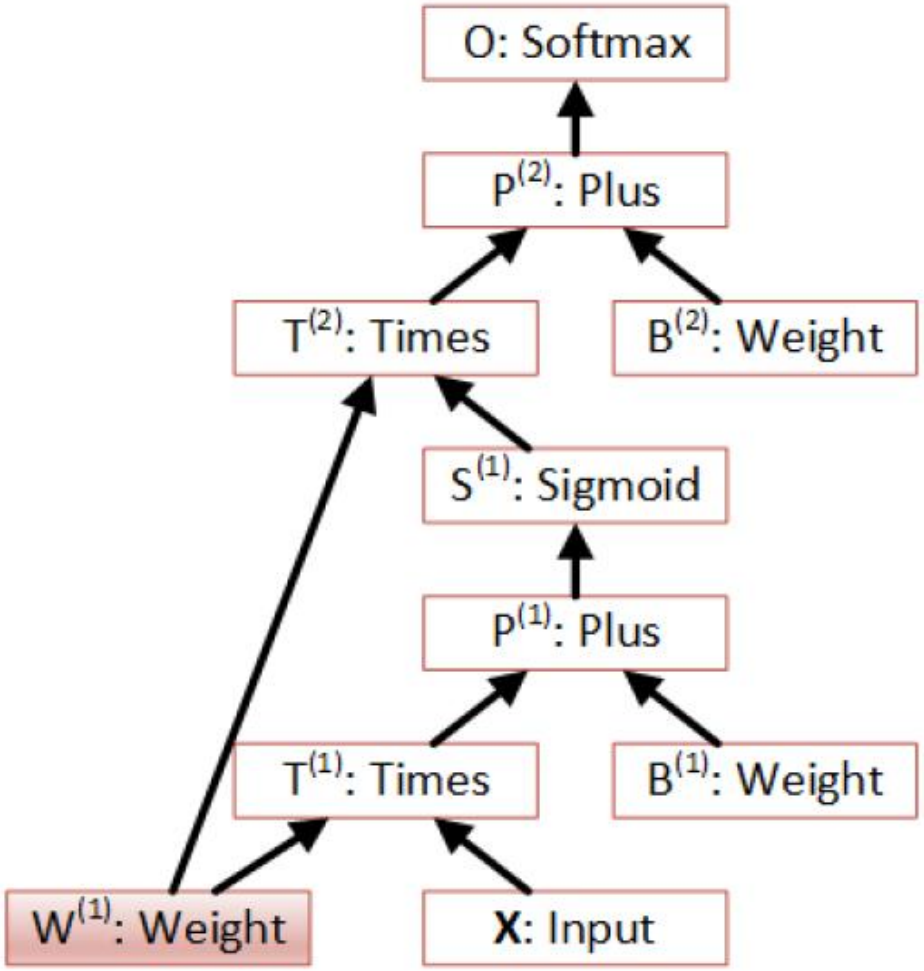




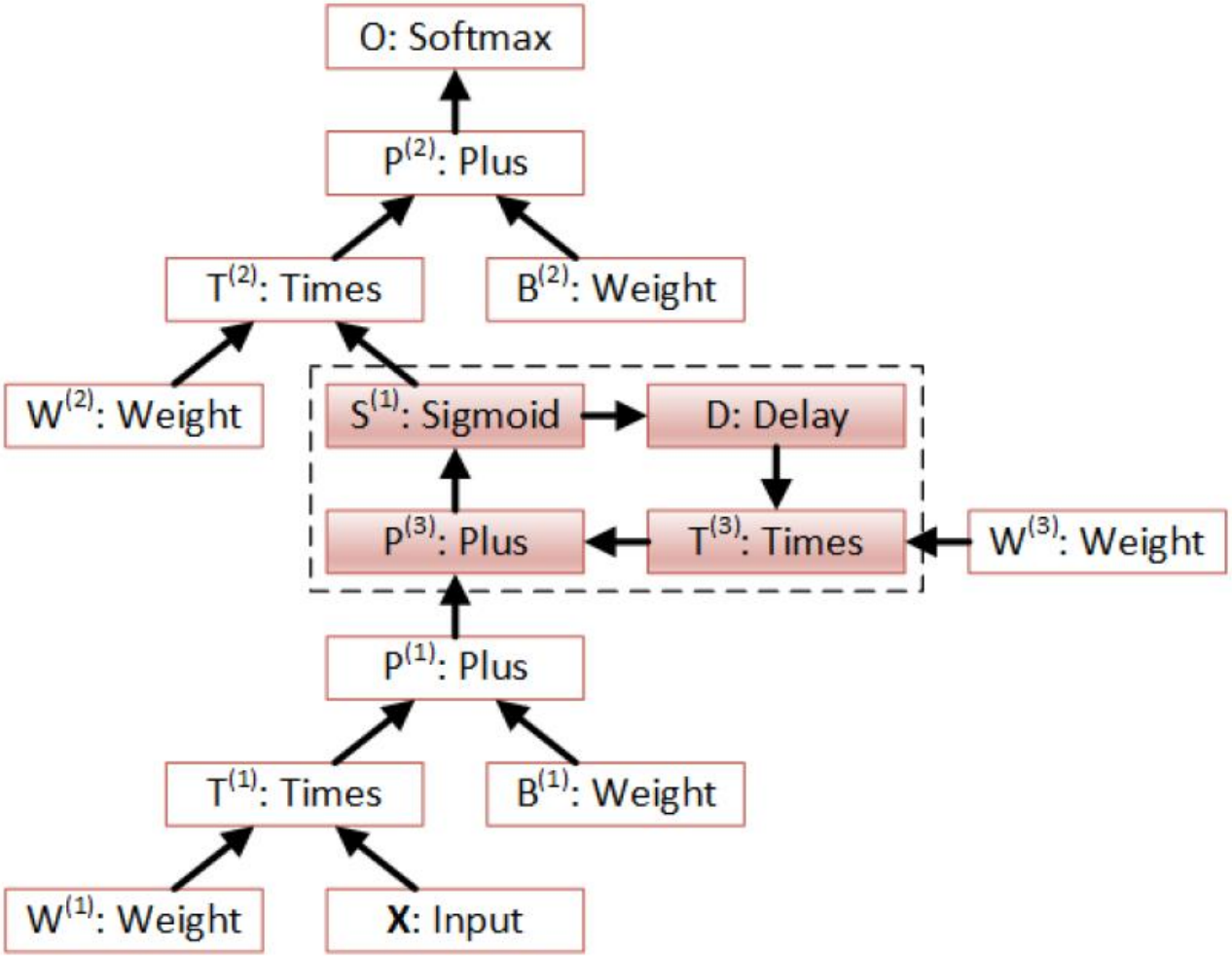
Example: CN with Multiple Inputs



Example: CN with Shared Parameters



Example: CN with Recurrence



CNTK: Implementation of CN

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Computational Network Toolkit (CNTK)

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Page Info | Change History (all pages)

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.

- Supports Windows and Linux
- Documentation: D. Yu, A. Eversole, M. Seltzer, K. Yao, Z. Huang, B. Guenter, O. Kuchaiev, Y. Zhang, F. Seide, H. Wang, J. Droppo, G. Zweig, C. Rossbach, J. Currey, J. Gao, A. May, B. Peng, A. Stolcke, M. Slaney, "**An Introduction to Computational Networks and the Computational Network Toolkit**", Microsoft Technical Report MSR-TR-2014-112, 2014.

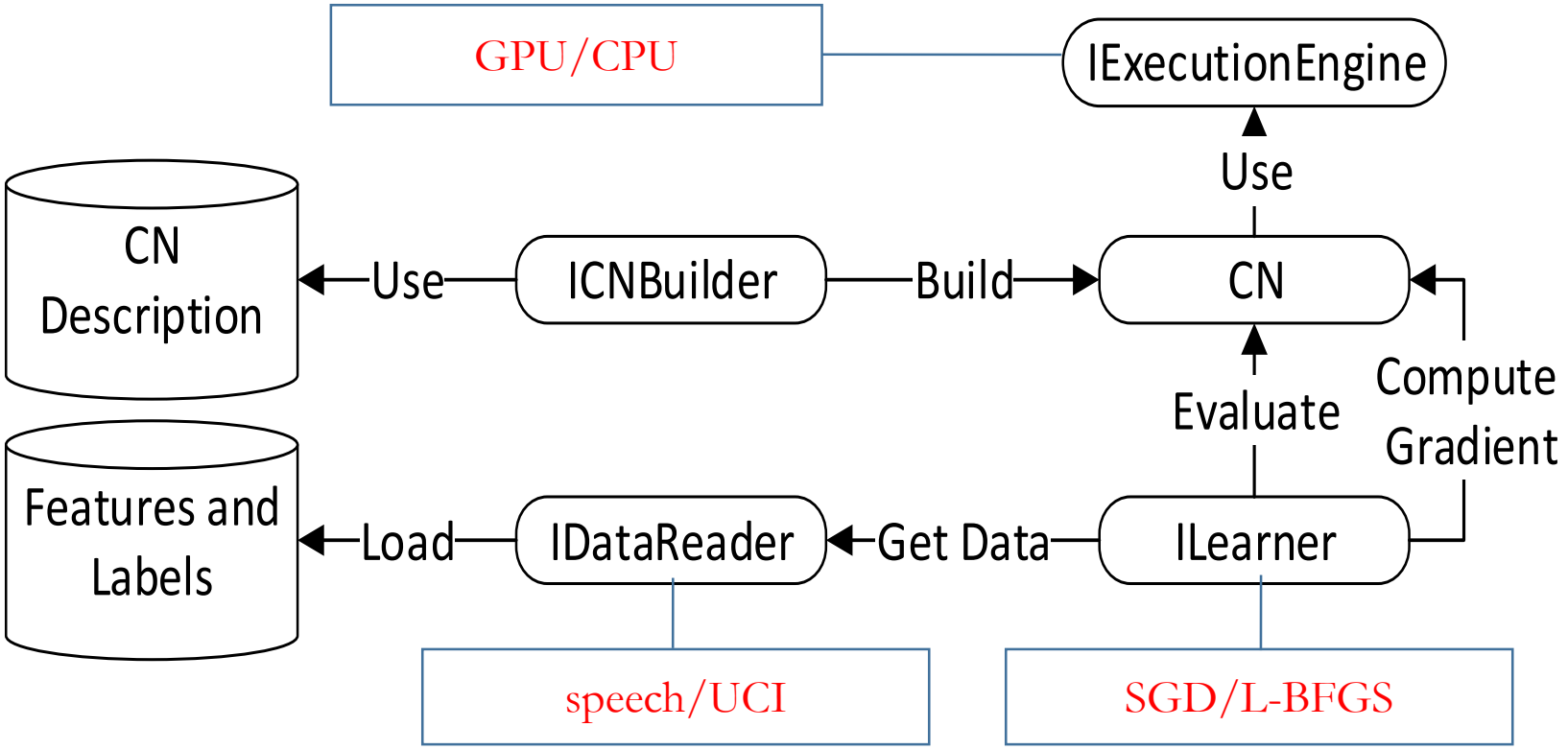
Source Code Enlist

- Source code repository
  - http://cntk.codeplex.com
- Enlist instruction:
  - https://cntk.codeplex.com/documentation
- Uses git for source version control management
  - Suggest to read git introduction and manual
  - Suggest to install git-extension for visual studio http://code.google.com/p/gitextensions/
  - Much better than the Git manager integrated in VS 2013.
- Clone the source code
  - git clone https://git01.codeplex.com/cntk (on Windows)
  - git clone https://git.codeplex.com/cntk and then git checkout linux-gcc (on Linux to check out the Linux branch)

Prerequisites to Build CNTK

- Compilers:
  - Windows: Visual Studio 2013 or above (since project and solution files are in VS 2013 format)
  - Linux: g++ 4.8.3 (or above)
- CPU BLAS library (do one of the followings)
  - Install the ifort64 variant (e.g., acml5.3.1-ifort64.exe) of ACML 5.3.1 or above from http://developer.amd.com/tools/cpu-development/amd-core-math-library-acml/acml-downloads-resources/ (free). Set the system environment variable ACML_PATH to C:\AMD\acml5.3.1\ifort64_mp or the folder you installed ACML
  - Install Intel MKL library from https://software.intel.com/en-us/intel-math-kernel-library-evaluation-options and define USE_MKL in the CNTKMath project (requires license)
- GPU library
  - Install CUDA 7.0 from https://developer.nvidia.com/cuda-downloads
  - If you don't want to install CUDA (e.g., no disk space or don't care GPU), define CPUONLY in the CNTKMath project
- MPI library
  - To use model averaging based data parallelization, define MPI_SUPPORT
  - Install Microsoft MS-MPI package, e.g., http://www.microsoft.com/en-us/download/details.aspx?id=41634, add lib msmpi.lib

CNTK Architecture



- Provides flexibility and freedom to enhance and tailor for different purposes

Functionality

- Supports automatic differentiation
- Supports SGD (BP, BPTT, and truncated BPTT, Adagrad, and rmsprop)
- Supports arbitrary valid computational networks
  - Building DNN, CNN, RNN, LSTM, GMM, MDN is as simple as describing the operations of the networks.
- Supports both dense and sparse inputs
- Supports multiple inputs/outputs, and multi-objective training
- Efficient computation
  - Remove duplicated computations in both forward and backward computations
  - Use minimal memory and don't reallocate memory if possible
  - Optimized CPU and GPU computation
  - Do batch computation whenever possible

To Run CNTK: TIMIT Example

- cntk configFile=yourConfigFile.config DeviceNumber=1 ExpDir=xyz
- Inside the config file

```
stderr=$ExpDir$\TrainNDLNetwork\log\log
command=TIMIT_TrainNDL
precision=float

TIMIT_TrainNDL=[
    action=train
    deviceId=$DeviceNumber$  #Stringize Variables
    modelPath=$ExpDir$\TrainNDLNetwork\model\cntkSpeech.dnn

    traceLevel=1

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

CPU: -1 or CPU
GPU: >=0
Auto: Auto

To Run CNTK: TIMIT Example

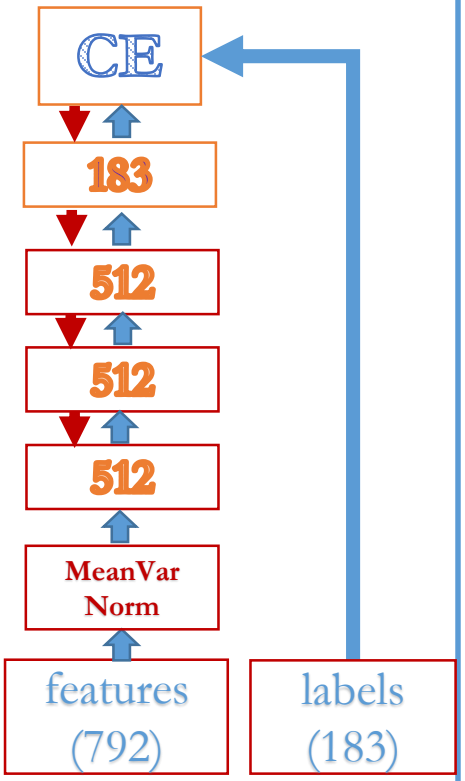
- cntk configFile=yourConfigFile.config DeviceNumber=1 ExpDir=xyz
- Inside the config file

Log file

```
stderr=$ExpDir$\TrainNDLNetwork\log\log
command=TIMIT_TrainNDL
precision=float

TIMIT_TrainNDL=[
    action=train
    deviceId=$DeviceNumber$  #Stringize Variables
    modelPath=$ExpDir$\TrainNDLNetwork\model\cntkSpeech.dnn

    traceLevel=1

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

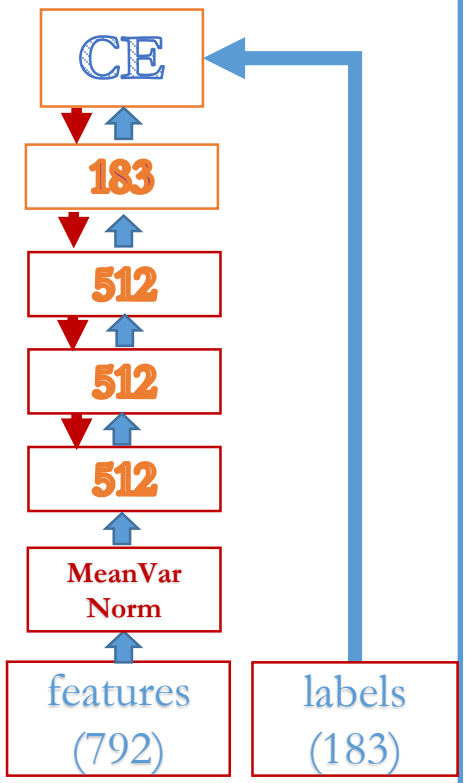
Inside Configuration File

```
TIMIT_TrainNDL=[
        #parameters used by SimpleNetworkBuilder block may be defined here #
        SimpleNetworkBuilder=[
                layerSizes=792:512*3:183
                trainingCriterion=CrossEntropyWithSoftmax
                evalCriterion=ErrorPrediction
                layerTypes=Sigmoid
                applyMeanVarNorm=true
                needPrior=true
            ]
        SGD=[
                epochSize=0
                minibatchSize=256:1024
                learningRatesPerMB=0.8:3.2*14:0.08
                momentumPerMB=0.9
                dropoutRate=0.0
                maxEpochs=$MaxNumEpochs$
            ]
]
```



Insight Config File

```
reader=[
    readerType=HTKMLFReader
    readMethod=rollingWindow
    miniBatchMode=Partial
    randomize=Auto

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

    labels=[
        mlfFile=$MlfDir$\TIMIT.train.align_cistate.mlf.cntk
        labelDim=183
        labelMappingFile=$MlfDir$\TIMIT.statelist
    ]
]
```



Top-Level Action Commands

- **Train** - train a model
- **Adapt** - adapts an already trained model using KL divergence regularization
- **Eval** - evaluate/test a model for accuracy, usually with a test dataset
- **CV** - evaluates a series of models from different epochs on a development (or cross validation) set and displays the information of the best model
- **Write** - writes the value of an output node to a file
- **Edit** - executes a model editing language (MEL) script
- **Dumpnode** - dumps the information of node(s) to an output file. MEL can do the same thing.

Existing Readers

- UCIFast Reader
  - Space deliminated file formats
  - uses BinaryReader to cache and speed up
- HTKMLFReader
  - Speech feature and labels in HTK 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

Outline

- Major Modeling Techniques in ASR
  - Deep Neural Networks (DNNs)
  - Convolutional Neural Networks (CNNs)
  - Long Short-Term Memory (LSTM) RNNs
  - Model Adaptation
- **Build Deep ASR Models Using CNTK**
  - Computational Networks and CNTK
  - **Network Definition Language (NDL)**
  - Examples: DNN, LSTM and PAC-RNN
  - Model Editing Language (MEL)
  - Stochastic Gradient Descent (SGD)
- Summary

Network Definition Language

- Provides a simple yet powerful way to define a network in a code-like fashion.
- **Variables**, e.g., SDim=784
  - Any alphanumeric sequence that starts with a letter
  - Can not use reserved words (e.g., function names)
  - Case-insensitive
  - Immutable – can only assign value once
- **Inputs**, e.g., features=Input(SDim)
  - Represent input data and labels associated with the samples
  - Values note saved in the model
- **Parameters**, e.g., B0=Parameter(HDim)
  - Represent model parameters
  - Values saved as part of the model

Network Definition Language

- **Functions**, e.g., **Times1=Times(W0, features)**
  - Describe computation steps
  - Links different nodes to form a network
- **Special nodes**
  - Specify features, labels, default output nodes, default evaluation nodes and training criteria nodes
  - Can be specified directly or through node tagging
  - Example (direct):
    - **FeatureNodes=(features1, features2)**
    - **LabelNodes=(labels)**
    - **CriteriaNodes=(CE)**
    - **EvalNodes=(ErrPredict)**
    - **OutputNodes=(Plus2)**
  - Example (through tagging):
    - **myFeatures=Input(featDim, tag=feature)**

Functions

- Input, ImageInput
- Parameter, Constant
- ReLU, Sigmoid, Tanh, Log, Exp, Cos, Dropout, Negate, Softmax, LogSoftmax
- SumElements
- RowSlice, RowStack
- Scale, Times, DiagTimes, Plus, Minus, ElementTimes
- KhatriRaoProduct,
- GMMLogLikelihood
- SquareError, CrossEntropy, CrossEntropyWithSoftmax, ClassificationError, ClassCrossEntropyWithSoftmax, Logistic
- CosDistance, CosDistanceWithNegSamples (for DSSM)
- MatrixL1Reg, MatrixL2Reg,
- Mean, InvStdDev, PerDimMVNorm
- Convolution, MaxPooling, AveragePooling
- Delay (for recursion)

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Macros

- Can be defined as a one line function, e.g.,
  RFF(x1, w1, b1)=RectifiedLinear(Plus(Times(w1,x1),b1))
- Or as a block of code, e.g.,

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

- **A macro** may call another macro but not recursively
- Can access internal variables via the dot syntax, e.g.,
  CE = SMBFF(L1, LDim, HDim, labels)
  Err=ErrorPrediction(labels, CE.F)
- **Optional Parameters**
  - **Ordered**: Based on the order of arguments
  - **Named**: Based on the argument name
  - B0=Parameter(HDim, init=zero)
  - W0=Parameter(HDim, SDim, init=uniform)

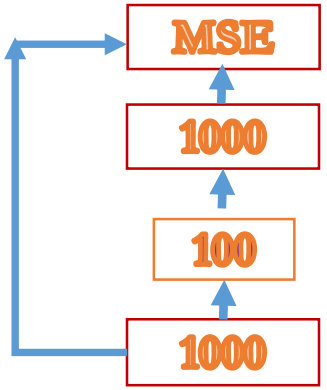
Example Macros

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

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

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

Macros in Effect: Auto-encoder Example

- Without Macros

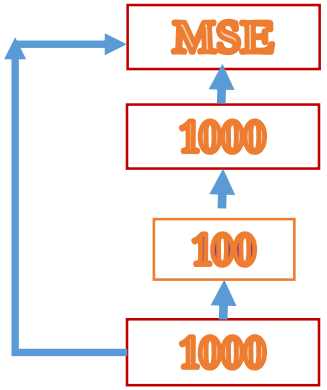
```
featDim=1000
hiddenDim=100

features=Input(featDim, tag=feature)

Wh = Parameter(hiddenDim,featDim)
Bh = Parameter(hiddenDim, init=fixedvalue, value=0)

Th = Times(Wh,features)
Ph = Plus(Th,Bh)
Sh = Sigmoid(Ph)

Wo = Parameter(featDim,hiddenDim)
Bo = Parameter(featDim, init=fixedvalue, value = 0)
To = Times(Wo,Sh)
Po = Plus(To,Bo)

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



Macros in Effect: Auto-encoder Example

- With Macros

```
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)
EvalNodes=(MSE)
```



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- Summary

NDL Example: DNN

```
NDLNetworkBuilder=[
        ndlMacros=$NdlDir$\default_macros.ndl
        networkDescription=$NdlDir$\classify.ndl
    ]
```

```
load=ndlMacroDefine
run=ndlCreateNetwork
ndlMacroDefine=[
    MeanVarNorm(x)
    {
            xMean = Mean(x)
            xStdDev = InvStdDev(x)
            xNorm=PerDimMeanVarNormalization(x,xMean,xStdDev)
    }
    LogPrior(labels)
    {
            Prior=Mean(labels)
            LogPrior=Log(Prior)
    }
]
```

Decide which macro set to use

Decide which block to run

NDL Example: DNN

```
ndlCreateNetwork=[
        featDim=792
        labelDim=183
        hiddenDim=512
        myFeatures=Input(featDim, tag=feature)
        myLabels=Input(labelDim, tag=label)

        # define network
        featNorm = MeanVarNorm(myFeatures)
        L1 = SBFF(featNorm,hiddenDim,featDim)
        L2 = SBFF(L1,hiddenDim,hiddenDim)
        L3 = SBFF(L2,hiddenDim,hiddenDim)
        CE = SMBFF(L3,labelDim,hiddenDim,myLabels,tag=Criteria)
        Err = ErrorPrediction(myLabels,CE.BFF.FF.P,tag=Eval)

        # define output (scaled loglikelihood)
        logPrior = LogPrior(myLabels)
        ScaledLogLikelihood=Minus(CE.BFF.FF.P,logPrior,tag=Output)
]
```

Indicate this is a feature node

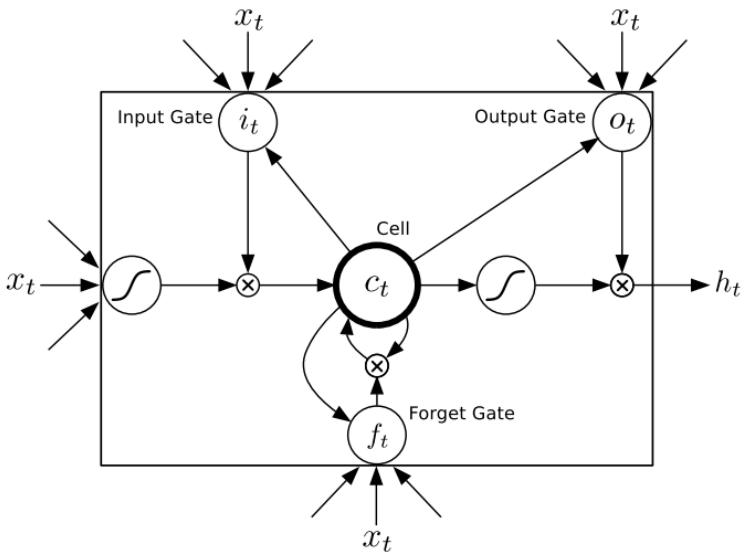
Must match that in the reader

Training criterion

Evaluation criterion

Output of CN

NDL Example: LSTM



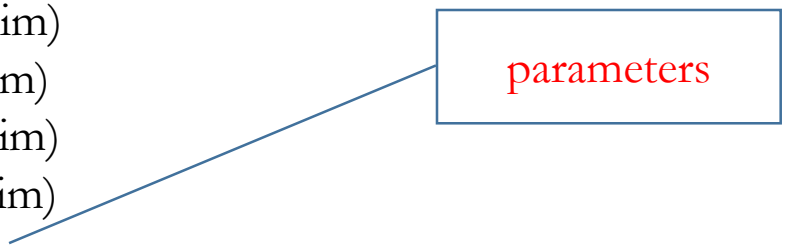
$$
\begin{aligned}
\mathbf{i}_t &= \sigma\left(\mathbf{W}^{(xi)}\mathbf{x}_t + \mathbf{W}^{(hi)}\mathbf{h}_{t-1} + \mathbf{W}^{(ci)}\mathbf{c}_{t-1} + \mathbf{b}^{(i)}\right) \\
\mathbf{f}_t &= \sigma\left(\mathbf{W}^{(xf)}\mathbf{x}_t + \mathbf{W}^{(hf)}\mathbf{h}_{t-1} + \mathbf{W}^{(cf)}\mathbf{c}_{t-1}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

NDL 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)
```



NDL Example: LSTM

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

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

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

Delay node

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

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

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

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

NDL 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)
```

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

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

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

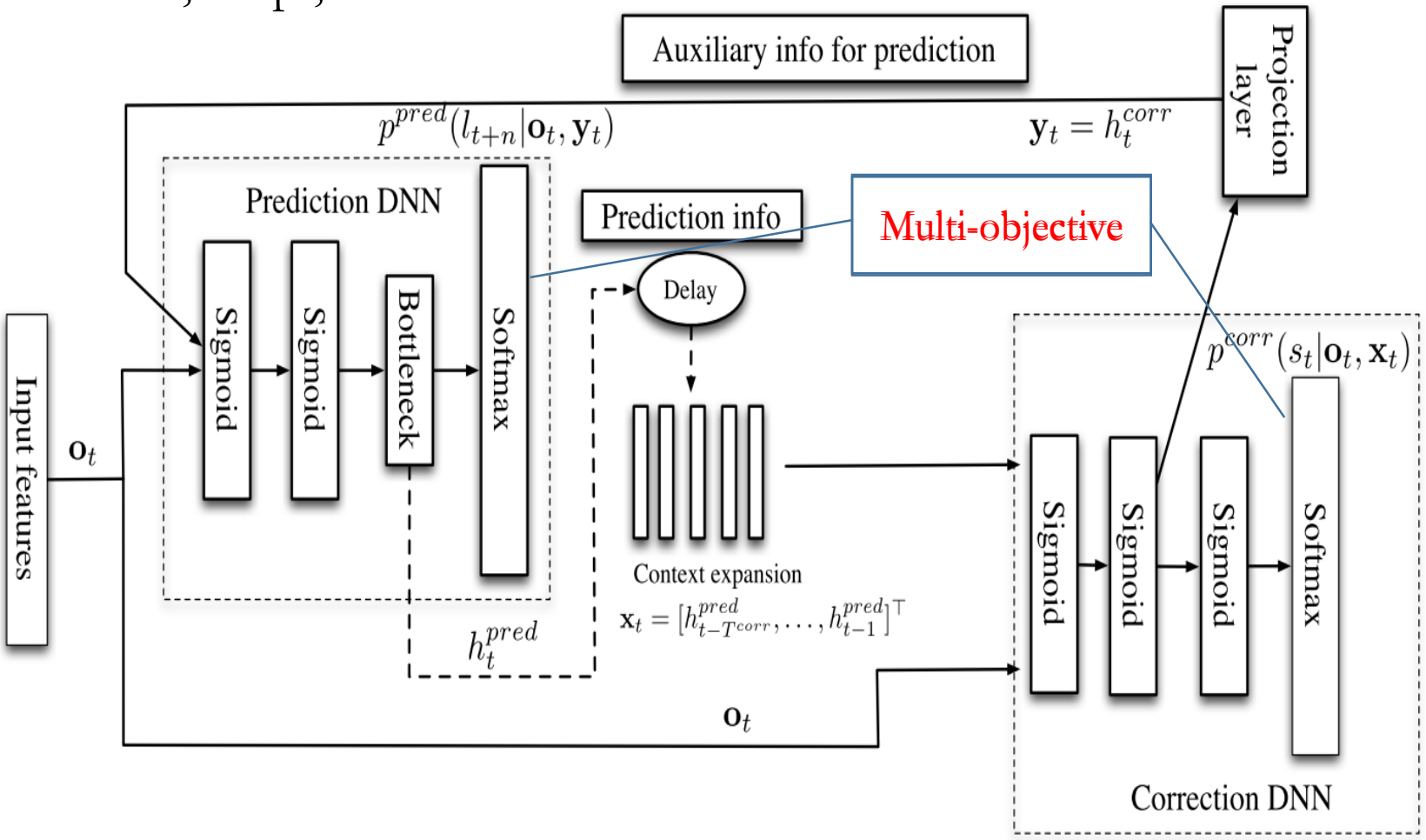
```
ot = Sigmoid( Plus( Plus( Plus(Wxoinput, bo), WhodelayHO), Wcoct))

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

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

NDL Example: Prediction Based AM

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



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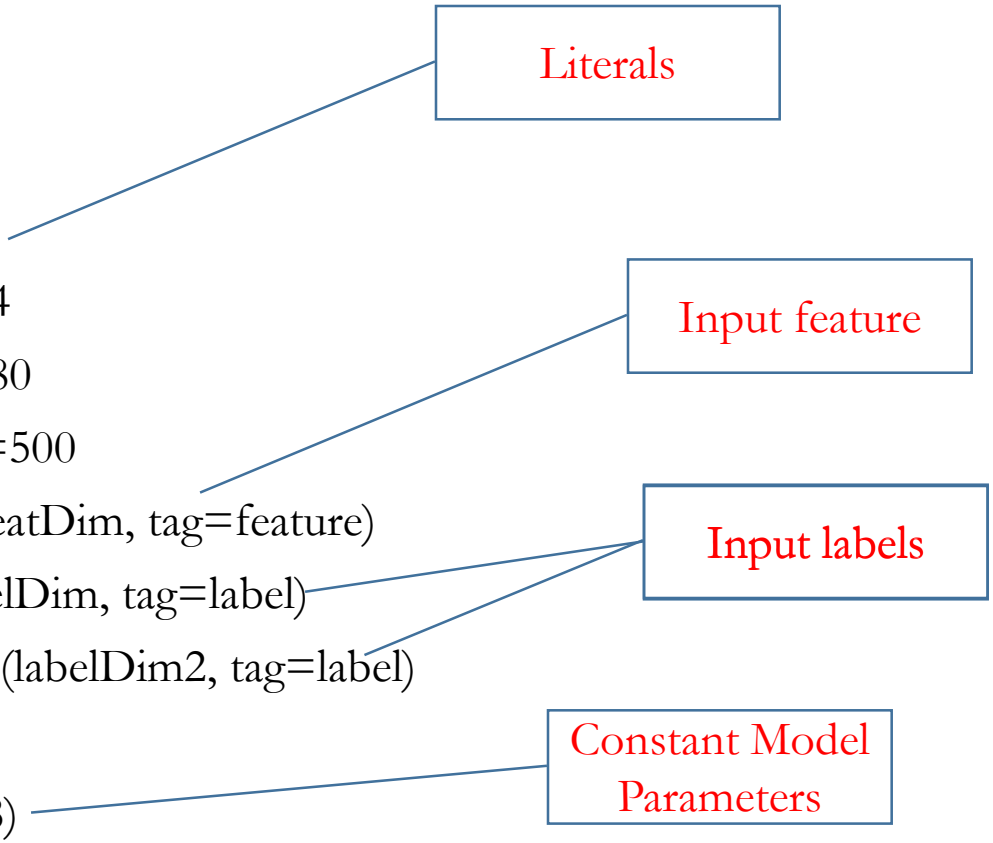
NDL Example: Prediction Based AM

```
#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)
```



NDL Example: Prediction Based AM

```
# 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

NDL Example: Prediction Based AM

```
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)
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)


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)
```

Concatenate information from past

Multiple criteria

Combine criteria

NDL Example: Prediction Based AM

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

    frameMode=false
    Truncated=true

    nbruttsineachrecurrentiter=32
    features=[
        dim=1845
        scpFile=$scpFilePath$
    ]
    labelDim=183
    labelType=Category

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

Utterance mode for RNN

Truncated BPTT

# of parallel utterances

Main label

Prediction label

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  - Stochastic Gradient Descent (SGD)
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Model Editing Language

- Provides a means to modify both the structure and the model parameters of an existing network
- Can use NDL to define new elements
- Supports the use of the '*' wildcard in the commands
  - If available nodes are
    - L3.RL: RectifiedLinear node
    - L3.BFF.B: Parameter node - used for bias
    - L3.BFF.W: Parameter node - used for weight
    - L3.BFF.FF.T: Times node
    - L3.BFF.FF.P: Plus node
  - Then
    - L3.*: Select all the L3 nodes
    - L3.*.P: Select the L3.BFF.FF.P node
    - L3.*: All the L3 nodes in the model

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MEL Commands

- CreateModel, CreateModelWithName
- LoadModel, LoadModelWithName
- SaveDefaultModel, SaveModel
- UnloadModel
- LoadNDLSnippet
- Dump, DumpModel, DumpNode
- Copy, CopyNode, CopySubTree
- SetInput, SetNodeInput, SetInputs, SetNodeInputs
- SetProperty
- SetPropertyForSubTree
- Remove, RemoveNode, Delete, DeleteNode
- Rename

MEL Commands

- Copy, CopyNode, CopySubTree
  - Copy a node, a group of nodes, or all nodes in a subtree from one location to another
  - Format:
    - Copy(fromNode, toNode, [copy=all|value])
    - CopyNode(fromNode, toNode, [copy=all|value])
    - CopyNode(fromNode, toNode, [copy=all|value])
  - Copy=all (default. copies both values and links)
  - Copy=value (copies only the values of a node)
- SetInput, SetNodeInput, SetInputs, SetNodeInputs
  - change connections between nodes
  - Formats
    - SetInput(node, inputNumber, inputNode)
    - SetInputs(node, inputNode1[, inputNode2, inputNode3])

•ComputeGradient

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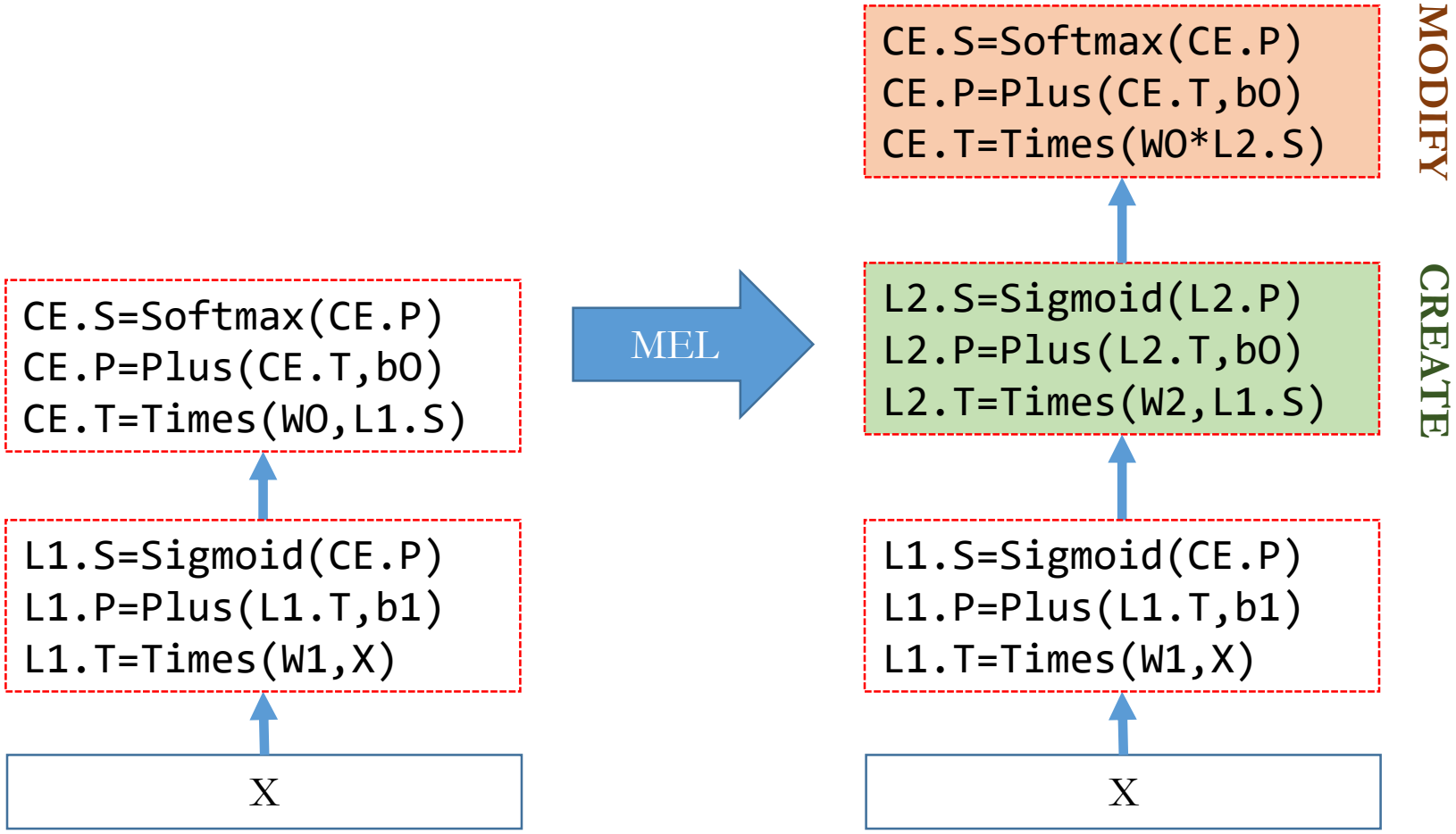
MEL Commands

- SetProperty, SetPropertyForSubTree
  - Set the property of a node or a subtree to a specific value
  - Format
    - SetProperty(node, propertyName, propertyValue)
    - SetProperty(rootNode, propertyName, propertyValue)
  - propertyName: ComputeGradient and tags
- Remove, RemoveNode, Delete, DeleteNode
  - Delete node(s) from a model
  - Format (all have the same effect)
    - Remove(node, [node2, node3])
    - Delete(node, [node2, node3])
    - RemoveNode(node, [node2, node3])
    - DeleteNode(node, [node2, node3])

MEL Example: DPT



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)
```

Outline

- Major Modeling Techniques in ASR
  - Deep Neural Networks (DNNs)
  - Convolutional Neural Networks (CNNs)
  - Long Short-Term Memory (LSTM) RNNs
  - Model Adaptation
- **Build Deep ASR Models Using CNTK**
  - Computational Networks and CNTK
  - Network Definition Language (NDL)
  - Examples: DNN, LSTM and PAC-RNN
  - Model Editing Language (MEL)
  - **Stochastic Gradient Descent (SGD)**
- Summary

Learner

- Given a training set and an optimization criterion, the learner finds a set of model parameters that optimizes the criterion.
- In CNTK the learner always minimizes the criterion.
  - If you want to maximize an objective function, you must first convert it to a minimization problem:

$$argmax(a) = argmin(-a)$$

- CNTK supports the stochastic gradient descent (SGD) learner and its variants AdaGrad and RmsProp

$$\mathbf{W}_{t+1}^{\ell} \leftarrow \mathbf{W}_{t}^{\ell} - \varepsilon \triangle \mathbf{W}_{t}^{\ell}$$

  - Used to support L-BFGS as well. Removed when we make it open source to public
  - Can add other learners relatively easily as long as it requires only the first-order gradient.

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SGD Learner Configuration

- The behavior of the SGD algorithm is controlled by the SGD block of the options.
- These options can be classified as:
  - Training process control
  - Learning rate and momentum control
  - Gradient control
  - Others

```
SGD=[
        epochSize=0
        minibatchSize=256:1024
        learningRatesPerMB=0.8:3.2*14:0.08
        momentumPerMB=0.9
        dropoutRate=0.0
        maxEpochs=$MaxNumEpochs$
    ]
```

Training Process Control

- **modelPath**
  - The full path used to save the final model.
  - Must be provided and points to a valid file name.
- **epochSize**
  - The number of samples in each epoch. In CNTK epoch can be different from the sweep of the full dataset.
  - When set to 0 the whole dataset size is used (handled by the data reader)
  - An intermediate model and check point info is saved for each epoch.
- **maxEpochs**
  - Maximum number of epochs to run.
  - May terminate earlier if learning rate becomes too small
- **minibatchSize**
  - Minibatch size for each epoch. Default value is 256.
  - Supports different size for different epochs. E.g., 128*2:1024 (128 for 2 epochs and then 1024 for the rest).
- **keepCheckPointFiles**
  - Whether you want to keep the check point file after a new epoch starts.
  - Default is false so that the previous check point files are deleted.

Training Process Control

- **trainCriterionNodeName**
  - The name of the training criterion node.
  - If not provided the default training criterion node is used.
- **evalCriterionNodeName**
  - The name of the evaluation criterion node.
  - If not provided the default evaluation criterion is used.
- **dropoutRate**
  - Dropout rate during the training procedure. Default is 0.0.
  - Different epoch can have different dropout rate but all dropout nodes share the same rate for the same epoch.
  - Has no effect if there is no dropout node
- **maxTempMemSizeInSamplesForCNN**
  - Maximum temporary memory used (in number of samples) when packaging and unpackaging input features for CNN.
  - Default is 0: means using any value as needed.
  - Useful to control the memory foot print esp. when run under GPU.
- **executionEngine**
  - The execution engine to use. Valid value is synchronous (default).

Learning Rate and Momentum Control

- **learningRatesPerMB**
  - Learning rates per minibatch. Useful when you want to use the same learning rate while the minibatch size is changed.
  - Different epochs can have different rates, e.g., 0.8*10:0.2
- **learningRatesPerSample**
  - Learning rates per sample. The effective learning rate equals to $minibatchSize \times learningRatesPerSample$
  - Useful when you want to keep the learning rates per sample constant, i.e., automatically increases effective learning rate for the minibatch when the minibatch size is increased.
  - Different epochs can have different rates
- **momentumPerMB**
  - Momentum per minibatch. Default is 0.9.
  - Different epochs can have different momentum, e.g., 0.1*2:0.9

Learning Rate and Momentum Control

- **autoAdjust**
  - Information related to automatic learning rate control.
  - Default value is empty (“”) no auto learning rate control.
- **autoAdjustLR**
  - Which learning rate adjustment algorithm to use.
  - Valid values are
    - None: default, don't auto adjust learning rate
    - AdjustAfterEpoch: check the training criterion after each epoch using the development set (if available) or the training set to decide whether to adjust the learning rate
    - SearchBeforeEpoch: search the learning rate based on performance on a small portion of the training set before each epoch starts
  - Automatic learning rate adjustment is applied only if the learning rate for the epoch is not provided explicitly.

If AutoAdjustLR Set to AdjustAfterEpoch

```
autoAdjust=[
    autoAdjustLR=AdjustAfterEpoch

    reduceLearnRateIfImproveLessThan=0

    learnRateDecreaseFactor=0.618

    increaseLearnRateIfImproveMoreThan= 1#INF

    learnRateIncreaseFactor=1.382

    loadBestModel=true

    learnRateAdjustInterval=1
]
```

Reduce learning rate if the improvement is less than this value. Default is 0.

Reduce learning rate by this factor. Default is 0.618.

Increase learning rate if the improvement is larger than this value. Default is 1#INF

Increase learning rate by this factor. Default is 1.382.

Weather to load the best model if the current model decreases the performance. Default is true

The frequency of applying the learning rate adjustment check. Default is 1 epoch.

Gradient Control

- **gradientClippingWithTruncation**
  - True (default): use the truncation based gradient clipping to control gradient explosion.
  - False: use the norm based clipping which is more expensive
- **clippingThresholdPerSample**
  - The clipping thread for each sample. Default value is 1#INF
- **L2RegWeight**
  - The L2 regularization weight. Default is 0.
  - Adds a scaled version of the parameters into the gradient, biasing parameter values to zero
- **L1RegWeight**
  - The L1 regularization weight. Default is 0.
  - Uses the proximal gradient descent algorithm to shrink the weights, i.e., with the soft-threshold function
- **gaussianNoiseInjectStd**
  - The standard deviation of the Gaussian noise added to the gradient. Default is 0.

Gradient Update Variations

- **gradUpdateType**
  - Gradient update type
  - Valid values are none (default, normal SGD), Adagrad, or rmsprop.
- Default SGD learner
  - Apply learning rate to gradients.
  - Apply momentum to gradients.
  - Subtract result from parameter values.

Gradient Update: RMSProp

- rms_wgt_inc
  - multiplicative increment of the learning rate scale. Default is 1.2.
- rms_wgt_dec
  - multiplicative decrement of the learning rate scale. Default is 0.75.
- rms_wgt_max
  - maximum learning rate scale allowed.
  - A value closer to 1 makes the learning rate adjustment more stable but slower. Default is 10.
- rms_wgt_min
  - minimum learning rate scale allowed.
  - A value closer to 1 makes the learning rate adjustment more stable but slower. Default is 0.1.
- rms_gamma
  - smoothing factor used to estimate the moving average of the variance.
  - The smaller the value, the quicker it forgets the past information. Default is 0.99.

Other Info

- **traceLevel**
  - Trace level to decide what information to print out in the stderr.
  - Valid values are 0 (default) and 1 (more info).
- **numMBsToShowResult**
  - Display training statistics after how many minibatches.
  - Default is 10. larger values update information slower but require less IO and thus are faster.
- **gradientCheck**
  - Determines whether to use the gradient checker. Default is false
  - When using the gradient checker you need to use a minibatch size that is larger than the sequence length for RNNs due to the truncated back-propagation through time (BPTT) algorithm used to train RNNs, and a smaller learning rate to prevent numerical issues caused by divergence. In addition, precision should be set to double.
  - Should be used to check your implementation when new nodes are added

Hyper-Parameter search

- Manual search
  - Based on experience
  - Start from hyper-parameters known to work well for similar problems
  - Analyze the result and adjust the hyper-parameters accordingly
- Automatic search
  - Often based on the Bayesian optimization algorithms http://www.iro.umontreal.ca/~bengioy/cifar/NCAP2014-summerschool/slides/Ryan_adams_140814_bayesopt_ncap.pdf
  - Basic idea: Given the set of hyper-parameter-result pairs, adjust the distribution of good parameters and randomly select from it
  - Many tools available
  - (tool) spearmint /whetlab https://github.com/HIPS/Spearmint and whetlab.com

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

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- **Summary**

Summary

- Significant progress has been made in the recent years with the integration of deep learning models such as as DNNs, CNNs and LSTMs.
- 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
- CNTK implements CNs so that you only need to focus on designing the CNs instead of implementing learning algorithms for your specific CN