
Microsoft
Cognitive
Toolkit
aka.ms/CognitiveToolkit
Microsoft

The Microsoft Cognitive Toolkit (CNTK)

Training Deep Models Like Microsoft Product Groups

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Microsoft

deep learning at Microsoft

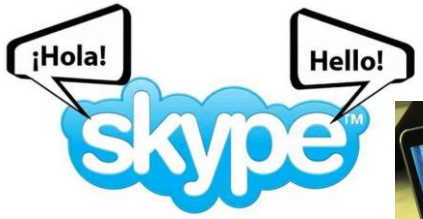
- Microsoft Cognitive Services
- Skype Translator
- Cortana
- Bing
- HoloLens
- Microsoft Research

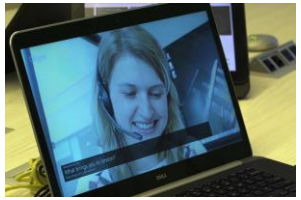
Cortana

Bing

Bing ads

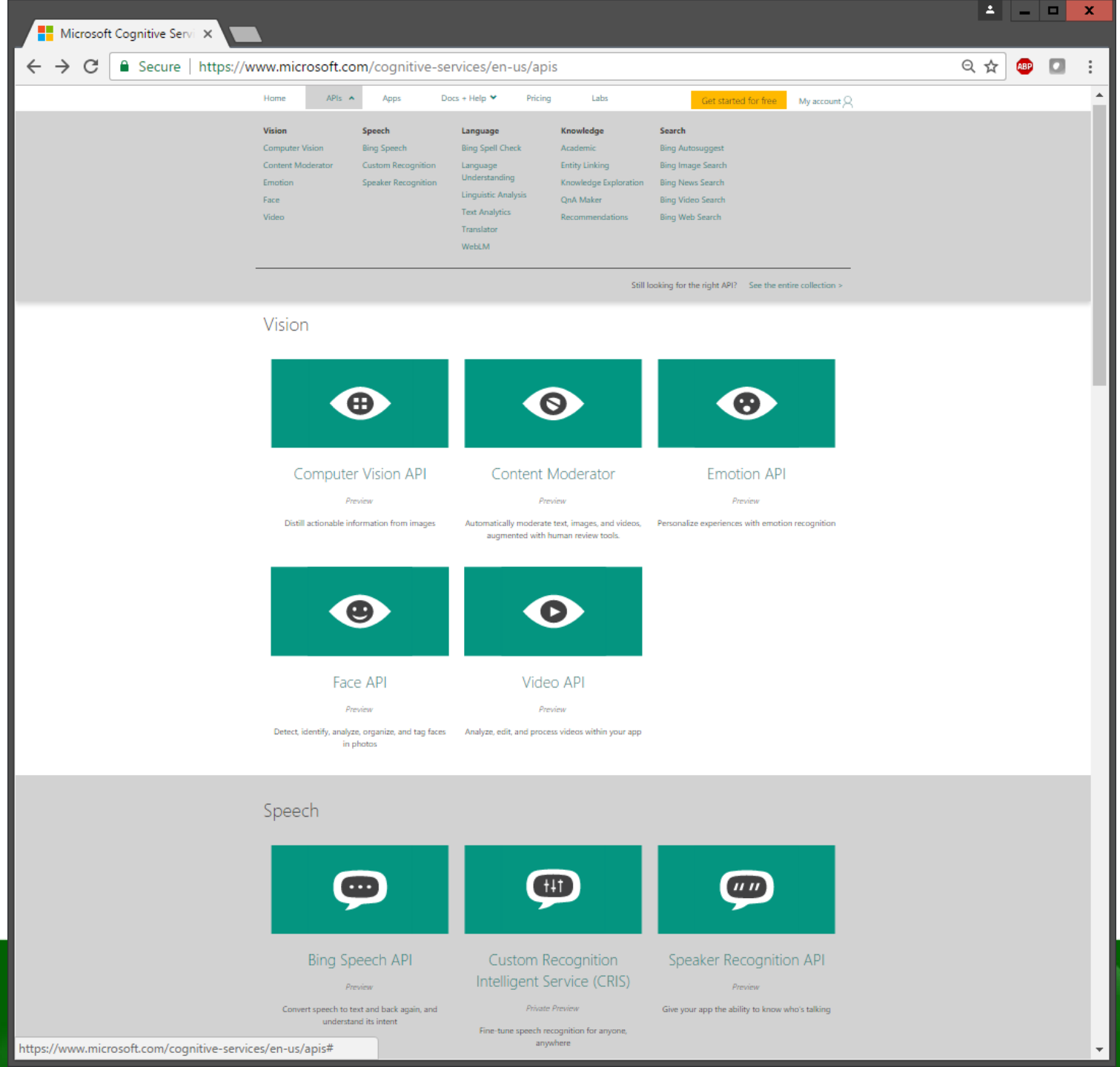
Microsoft HoloLens





XBOX

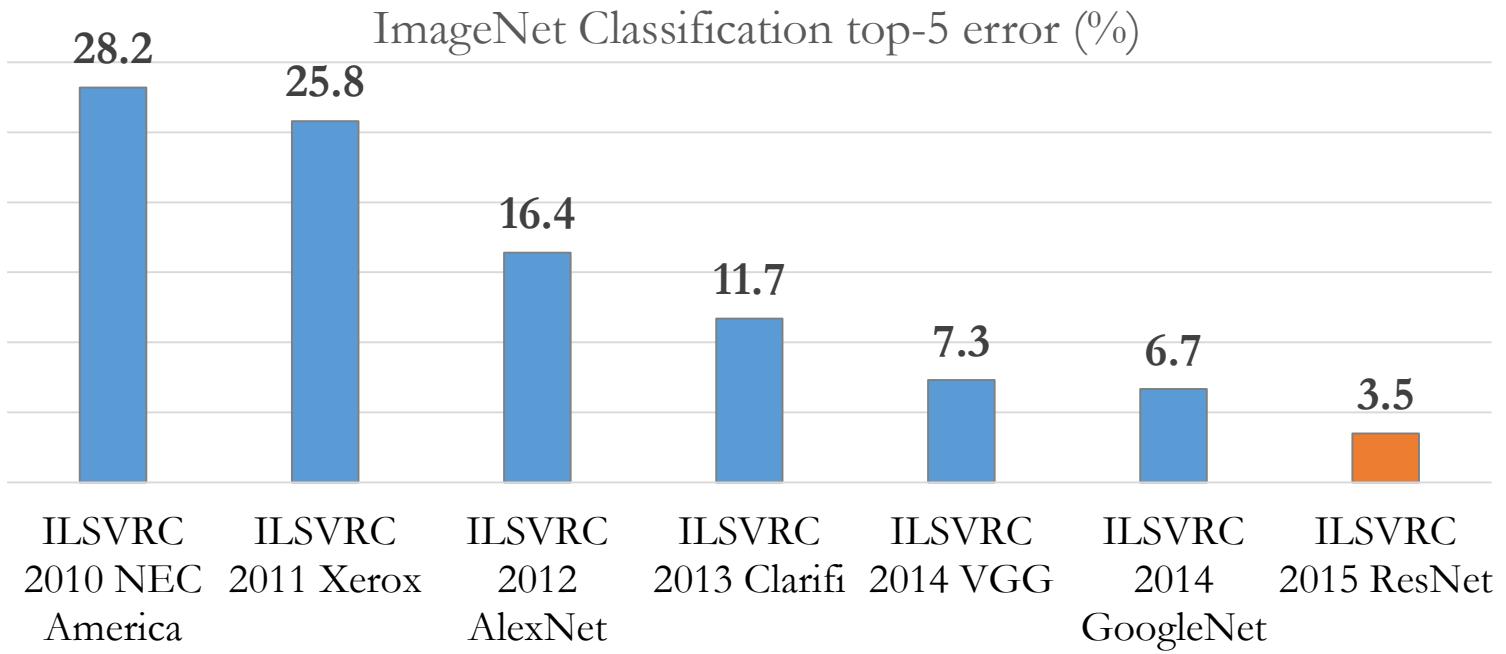
Microsoft Research



Microsoft Cognitive Toolkit

Microsoft

ImageNet: Microsoft 2015 ResNet



Microsoft had all **5 entries** being the 1-st places this year: ImageNet classification, ImageNet localization, ImageNet detection, COCO detection, and COCO segmentation

http://how-old.net/#resul

How old do I look?

How-Old.net

How old do I look? #HowOldRobot

Sorry if we didn't quite get it right - we are still improving this feature.

Try Another Photo!

Microsoft

P.S. We don't keep the photo

Share 2.3M Tweet

The magic behind How-Old.net

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https://www.caption...

CaptionBot - For pictures w...

Microsoft

CaptionBot

I am not really confident, but I think it's a group of young children sitting next to a child and they seem 😐😐.

How did I do?

★ ★ ★ ★ ★

Uber to require selfie security check from drivers

Using Microsoft Cognitive Services, Uber hopes to make riders feel safer by verifying the ID of drivers before rides are given.

By Jake Smith for iGeneration | September 23, 2016 -- 19:59 GMT (03:59 GMT+08:00) | Topic: Innovation

Uber announced on Friday a new security feature called Real-Time ID Check that will require drivers to periodically take a selfie before starting their driving shift.

The feature, which begins rolling out to US cities on Friday, uses Microsoft Cognitive Services to reduce fraud and give riders an extra sense of security.

Uber says Microsoft's feature instantly compares the selfie to the one corresponding with the account on file. If the two

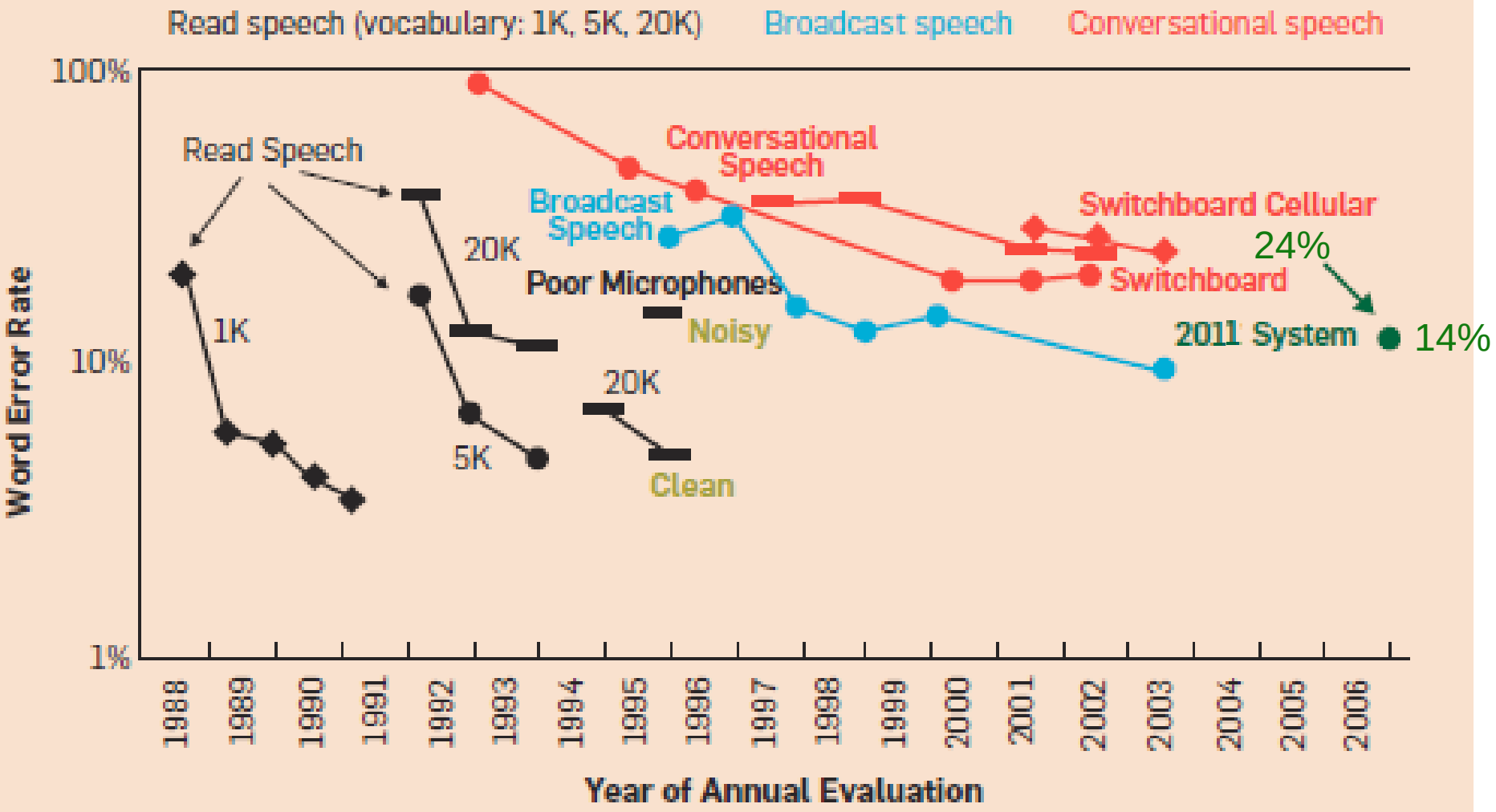
SHARING ECONOMY

RELATED STORIES

Innovation

Victoria partners with Bosch for self-

Figure 1. Historical progress of speech recognition word error rate on more and more difficult tasks.[18] The latest system for the switchboard task is marked with the green dot.



Microsoft's historic speech breakthrough

- Microsoft 2016 research system for conversational speech recognition
- 5.9% word-error rate
- enabled by CNTK's multi-server scalability

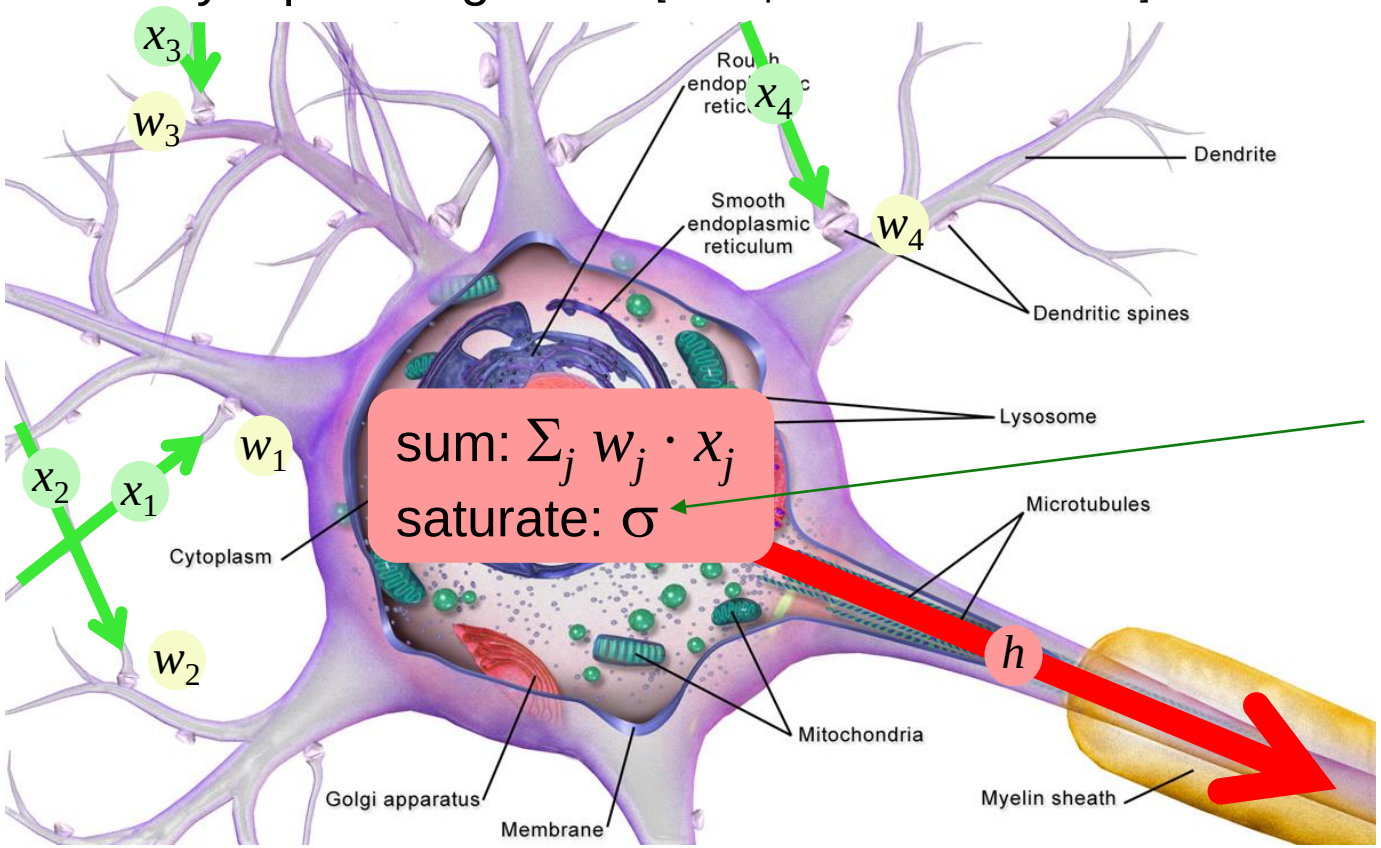
[W. Xiong, J. Droppo, X. Huang, F. Seide, M. Seltzer, A. Stolcke, D. Yu, G. Zweig: "Achieving Human Parity in Conversational Speech Recognition," https://arxiv.org/abs/1610.05256]

Youtube Link

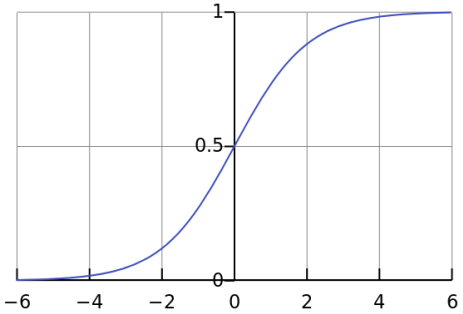
I. deep neural networks crash course
II. Microsoft Cognitive Toolkit (CNTK)
III. defining neural networks in CNTK
IV. deep dive: how CNTK gets so fast
V. conclusion

deep neural networks in a single slide

- neurons are simple pattern detectors, measure how well inputs x_j **correlate** with synaptic weights w [Perceptron, Rosenblatt 1957]



example saturation: sigmoid function



[images from Wikipedia]

deep neural networks in a single slide

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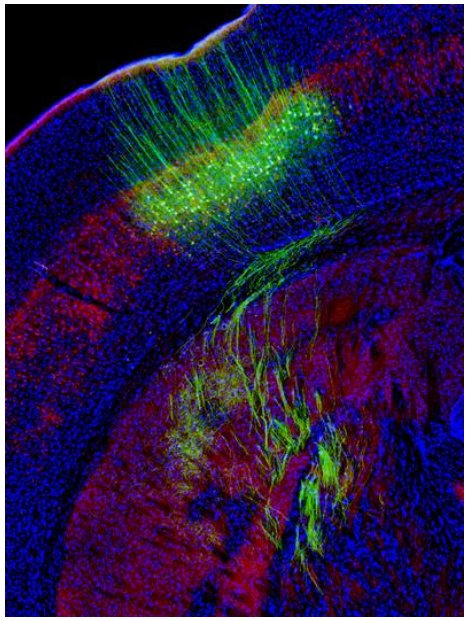
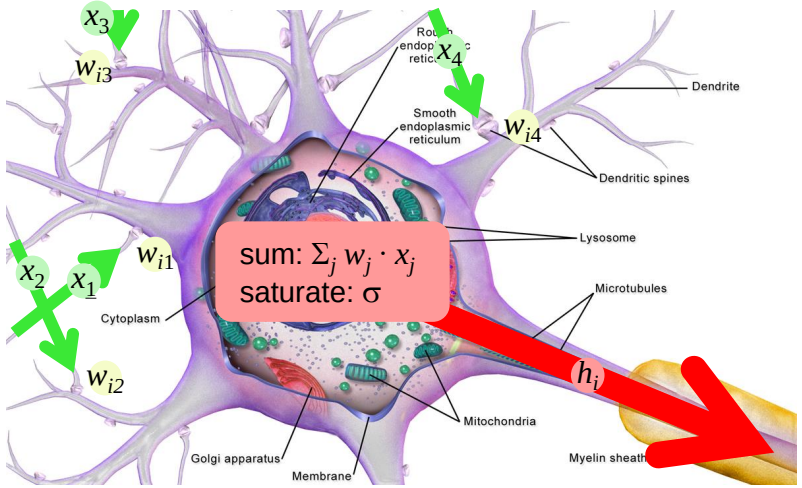
$$h_i = \sigma(\Sigma_j\, w_{ij} \cdot x_j + b_i)$$

- operate as **collections**, or vectors

$$h = \sigma(\mathbf{W}\, x + b)$$





correlate with patterns

$$\mathbf{W}\, x = \begin{pmatrix} w_{11}, w_{12}, ..w_{1N} \\ w_{21}, w_{22}, ..w_{2N} \\ \dots \\ w_{M1}, w_{M2}, ..w_{MN} \end{pmatrix} x = \begin{pmatrix} \text{pattern}_1 \\ \text{pattern}_2 \\ \dots \\ \text{pattern}_N \end{pmatrix} x$$

e.g. 2000 neurons

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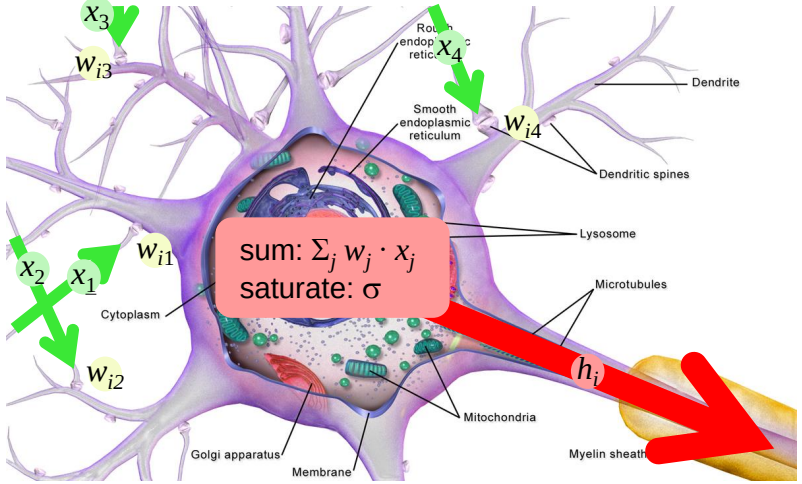
- operate as **collections**, or vectors

$$h = \sigma(\mathbf{W}\, x + b)$$

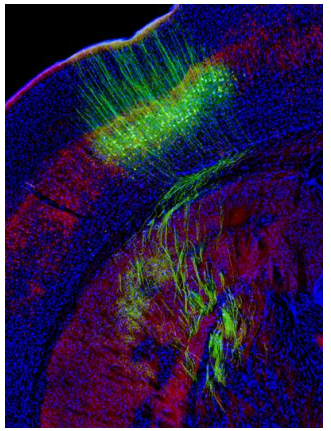
- arranged in **layers** → increasingly abstract representation

$$h^{(1)} = \sigma(\mathbf{W}^{(1)}\, x \quad + b^{(1)})$$
$$h^{(2)} = \sigma(\mathbf{W}^{(2)}\, h^{(1)} + b^{(2)})$$



$$\mathbf{W}^{(1)} = \begin{pmatrix} \text{pattern}_1 \\ \text{pattern}_2 \\ \dots \\ \text{pattern}_N \end{pmatrix}$$

$$\mathbf{W}^{(2)} = \begin{pmatrix} \text{abstract pattern}_1 \\ \text{abstract pattern}_2 \\ \dots \\ \text{abstract pattern}_N \end{pmatrix}$$



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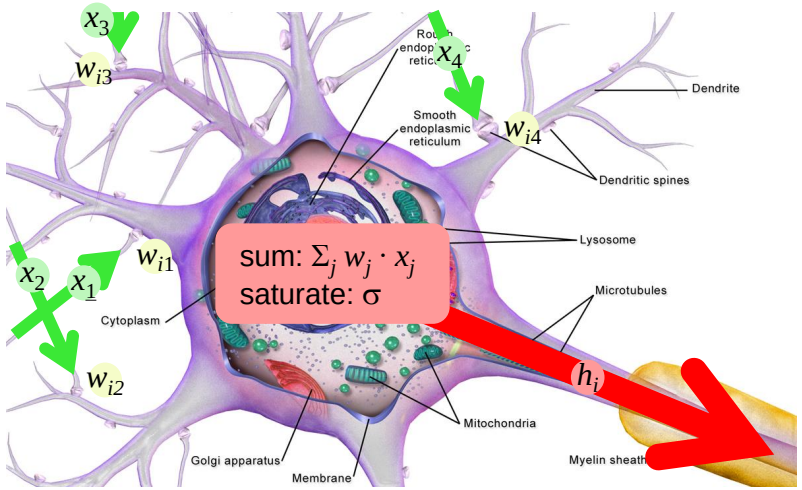
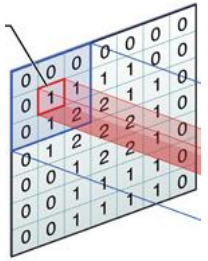
- connectivity **can be local** (spatial receptive fields)

$$h(c,r) = \sigma(\mathbf{W}\, x(c\text{-}\Delta c..c\text{+}\Delta c, r\text{-}\Delta r..r\text{+}\Delta r) + b)$$





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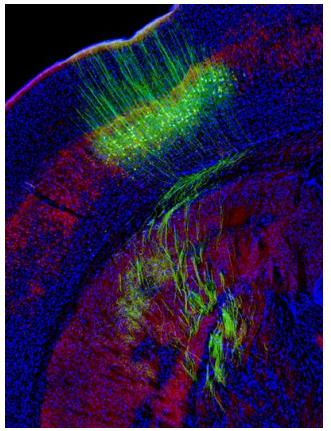

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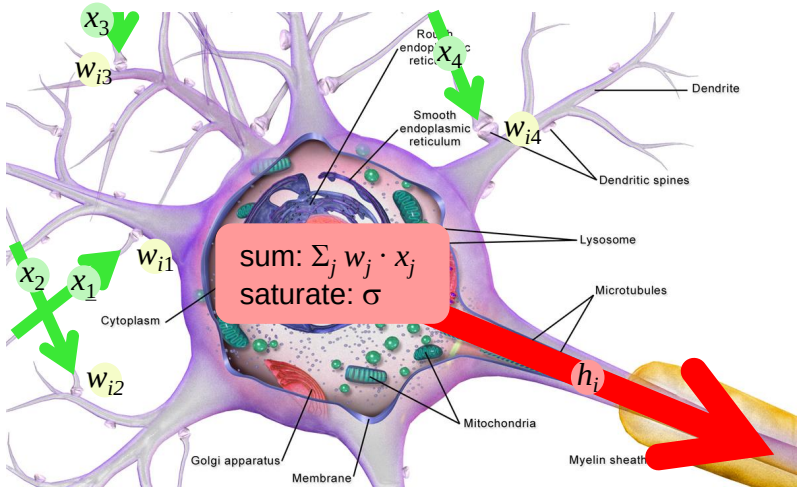
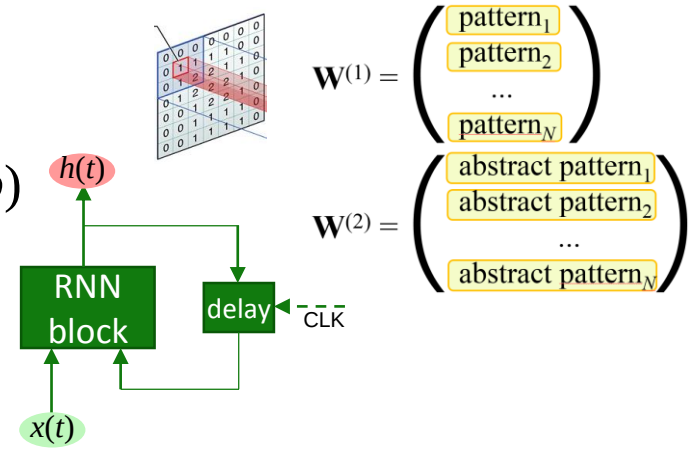
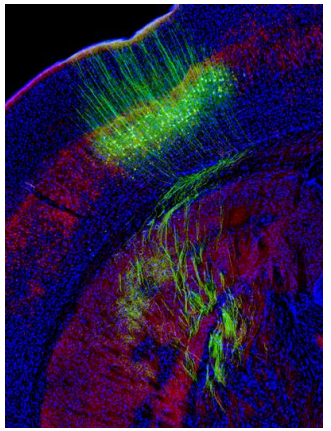
$$h(c,r) = \sigma(\mathbf{W}\, x(c\text{-}\Delta c..c\text{+}\Delta c, r\text{-}\Delta r..r\text{+}\Delta r) + b)$$

- can form **feedback loops**

$$h(t) = \sigma(\mathbf{W}\, x(t) + \mathbf{R}\, h(t\text{-}1) + b)$$







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  deep

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  convolutional $h(c,r) = \sigma(\mathbf{W}\, x(c\text{-}\Delta c..c\text{+}\Delta c, r\text{-}\Delta r..r\text{+}\Delta r) + b)$

- can form **feedback loops**

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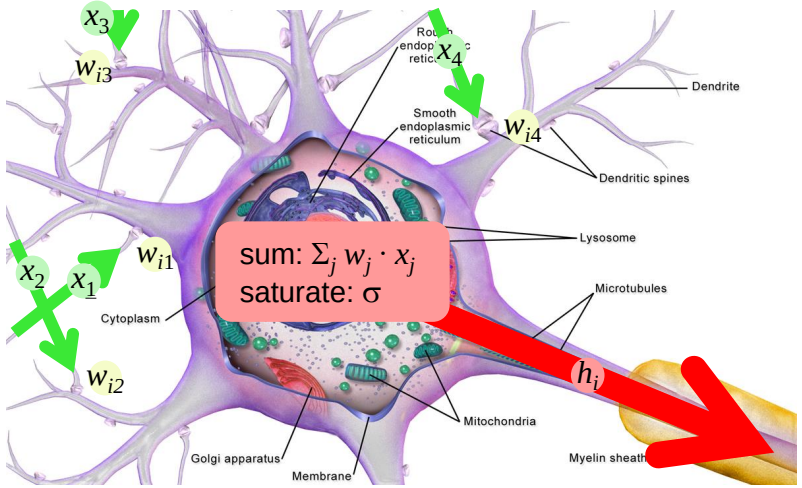
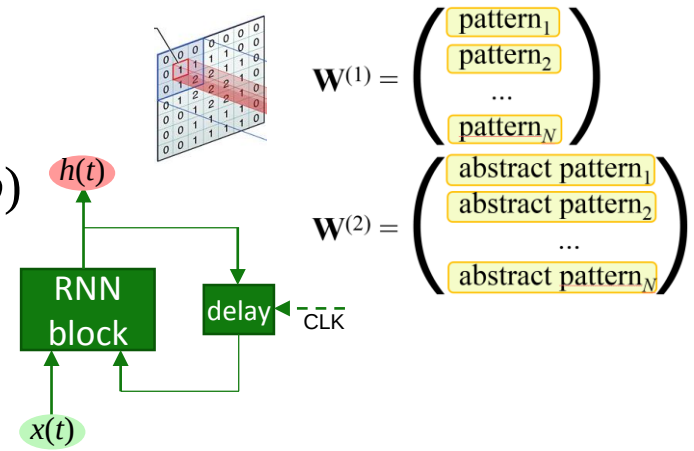
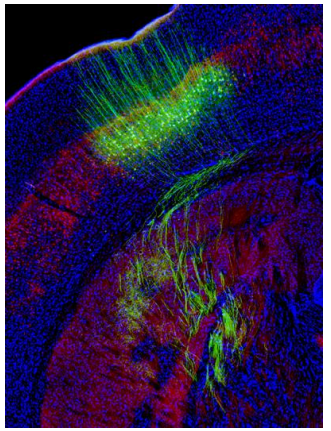
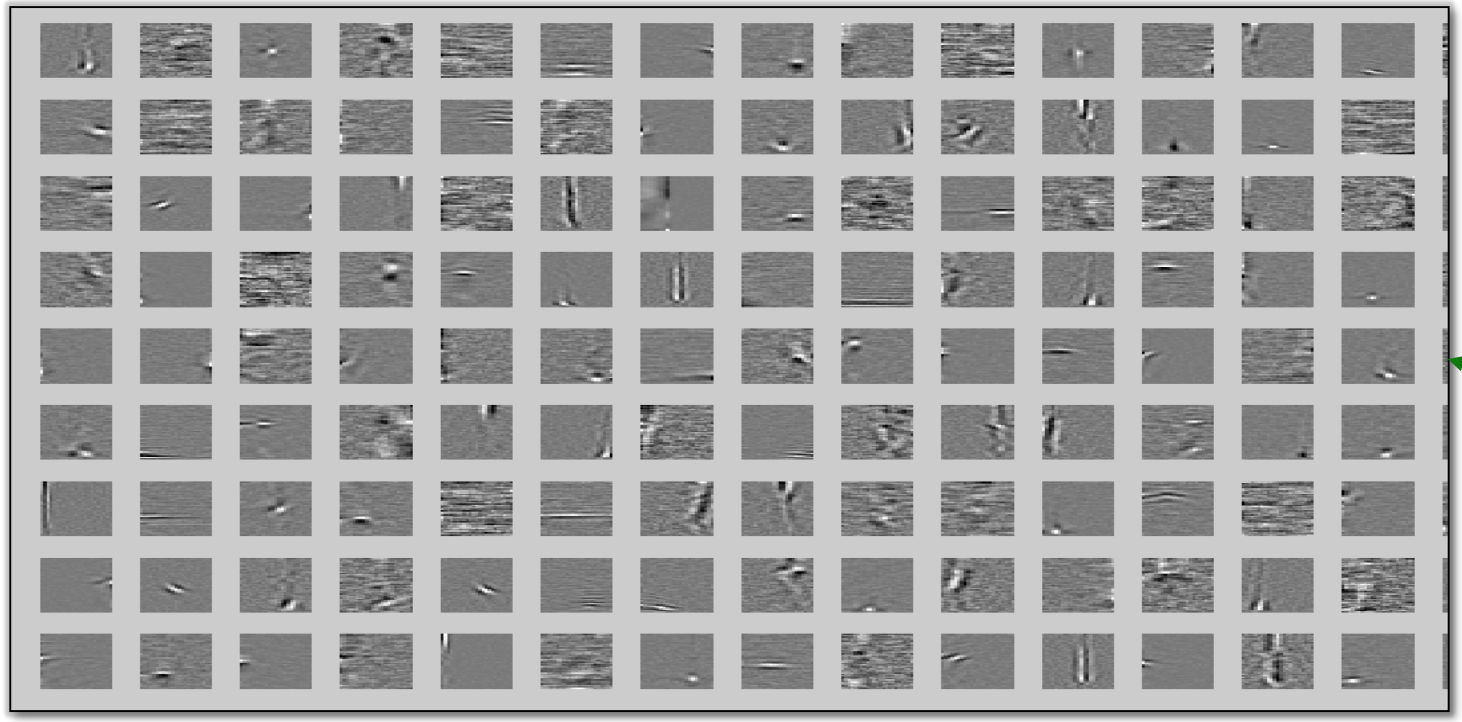


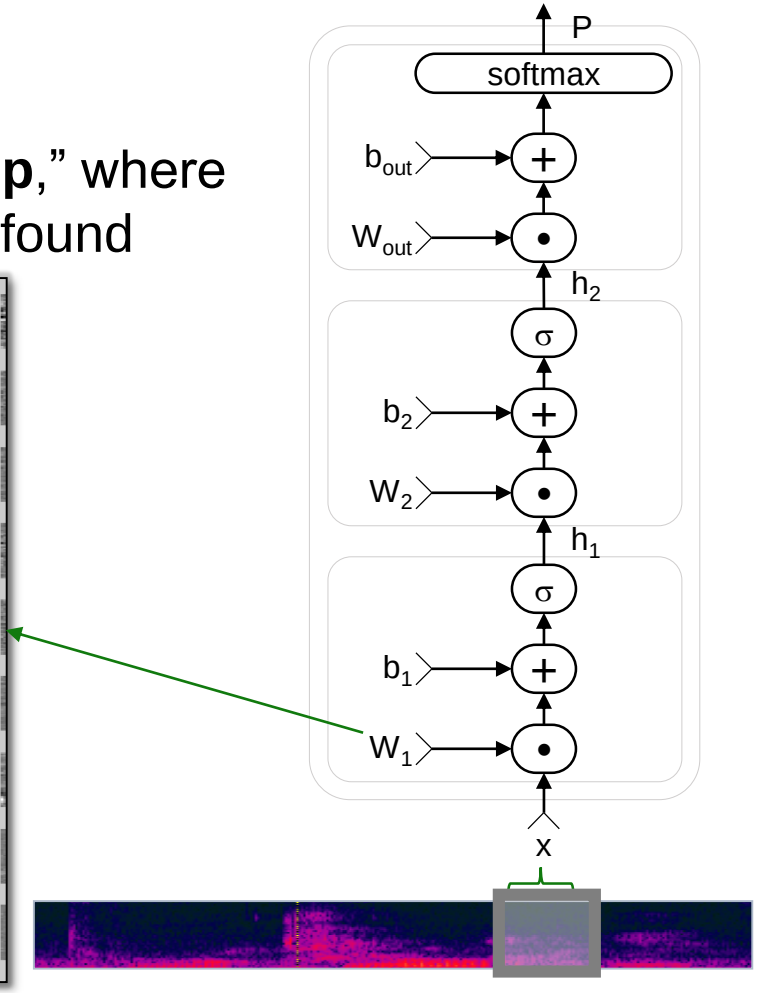




fully connected (FCN), convolutional (CNN), recurrent (RNN)

- fully connected (FCN) $h = \sigma(\mathbf{W}\, x + b)$
  - describes objects through probabilities of "**class membership**," where the N classes overlap and are whatever the training process found





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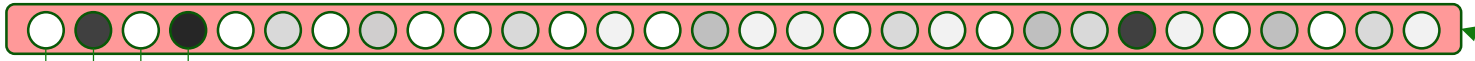
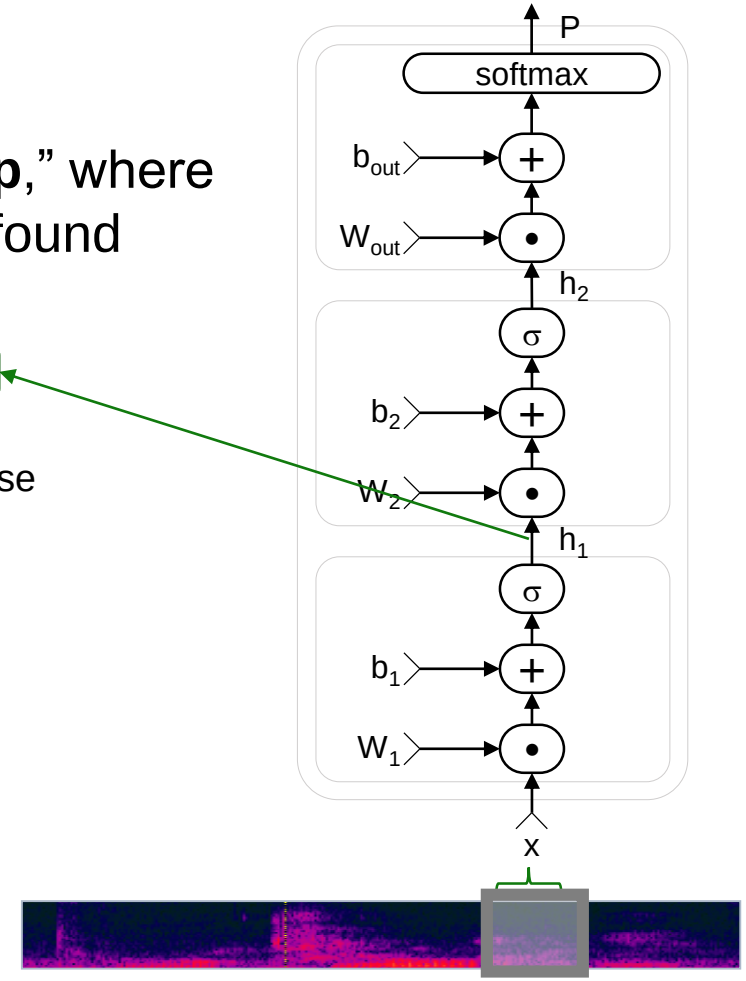


- is something with a sharp increase of higher-frequency broadband noise
- is something with a broad spectral peak at 820 Hz
- is something with broadly low energy
- is something with a spectral peak at 1 kHz moving up
- …



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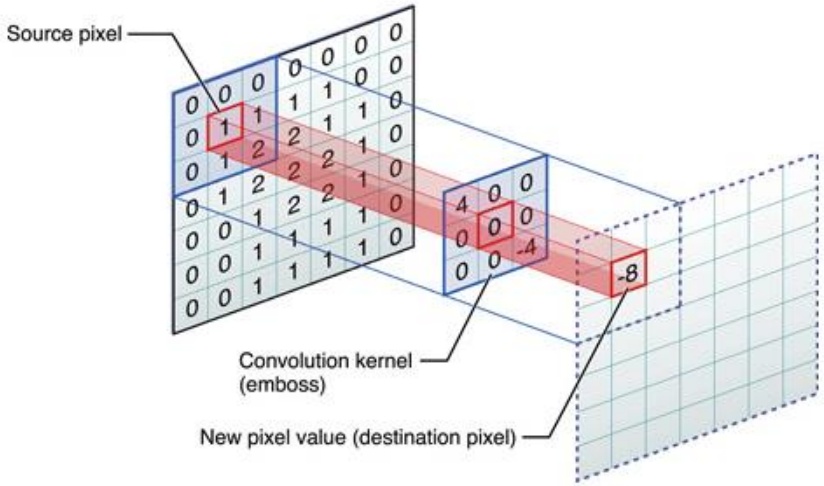
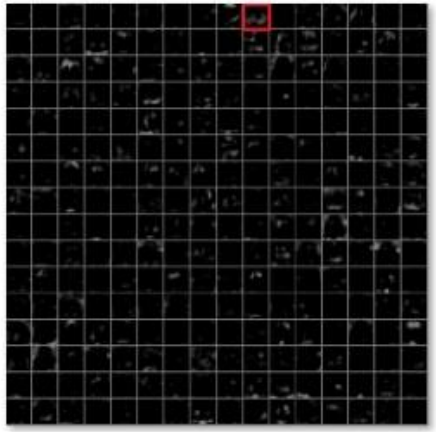
  - describes objects through probabilities of "**class membership.**"
- convolutional (CNN) $h(c,r) = \sigma(\mathbf{W}\ x(c\text{-}\Delta c..c\text{+}\Delta c, r\text{-}\Delta r..r\text{+}\Delta r) + b)$
  - repeatedly applies a little FCN over images or other **repetitive structures**



fully conne current (RNN)

- fully connect
  - describes c
- convolutiona
  - repeatedly tures


1.png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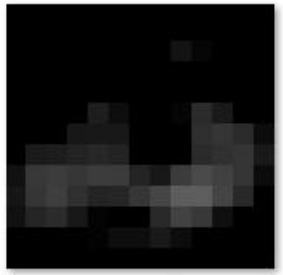
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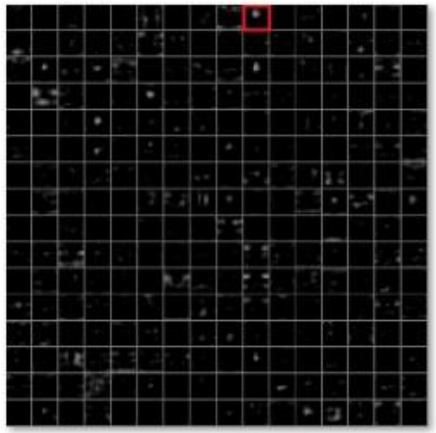
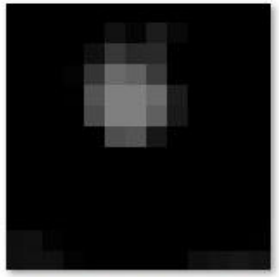
2.png


2_conv5.png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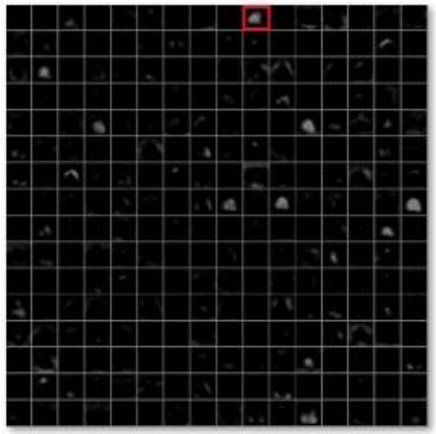
3.png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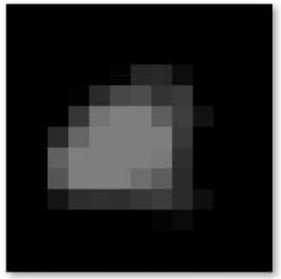
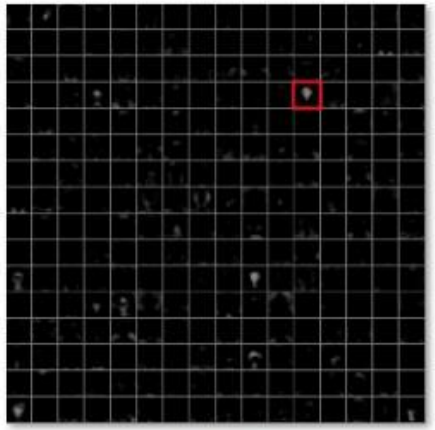

3_conv5_selected.png

fully conne current (RNN)

- fully connect
  - describes
- convolutiona
  - repeatedly ures


1.png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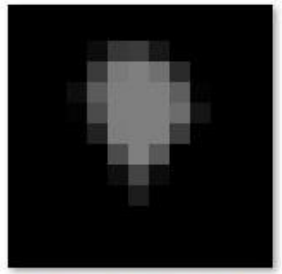
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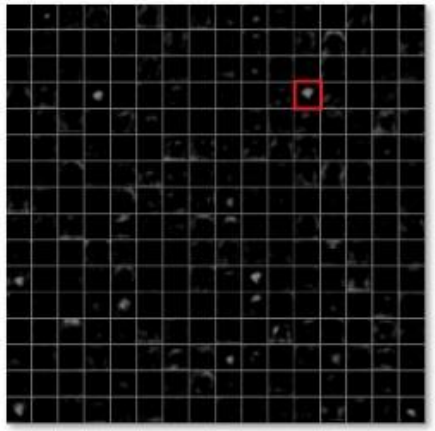
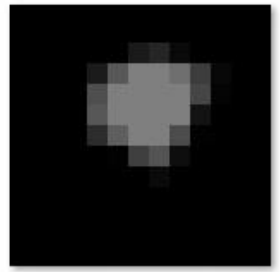
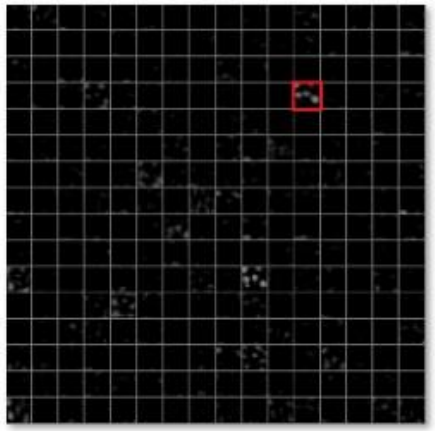
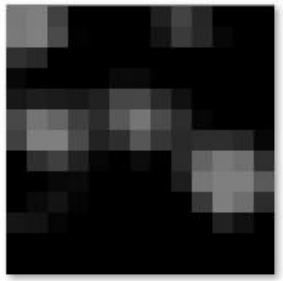
2.png


2_conv5.png


2_conv5_selected.png


4.png


4_conv5.png

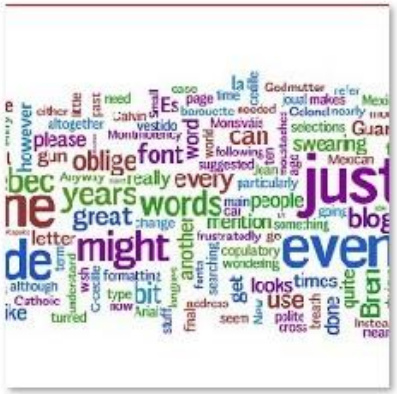

4_conv5_selected.png

Microsoft Cognitive Toolkit

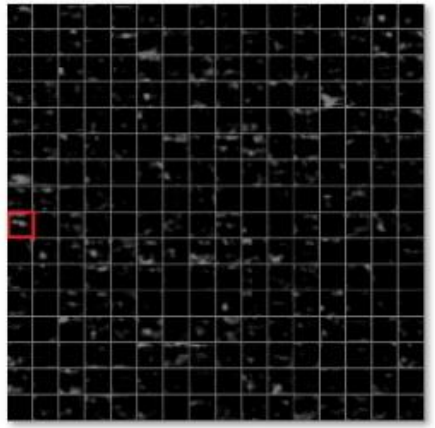
Microsoft

fully conne current (RNN)

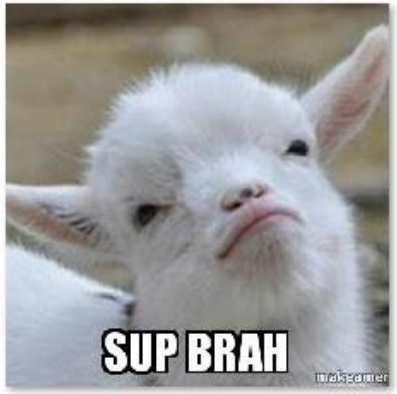
- fully connect
  - describes
- convolutiona
  - repeatedly ures



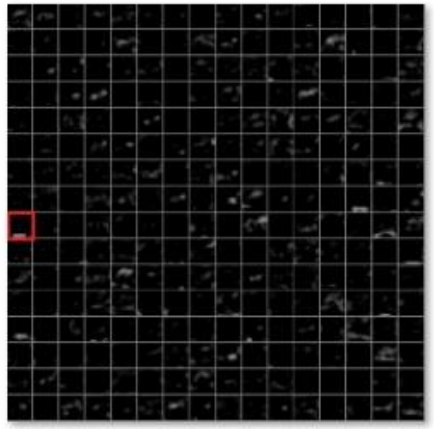
2.png


2_conv5.png

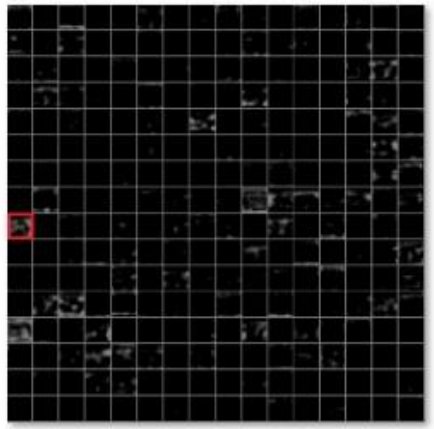

2_conv5_selected.png

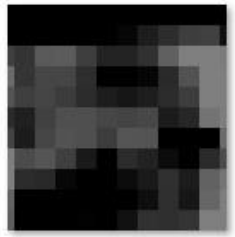


3.png


3_conv5.png


3_conv5_selected.png


1_conv5.png


1_conv5_selected.png

Microsoft Cognitive Toolkit

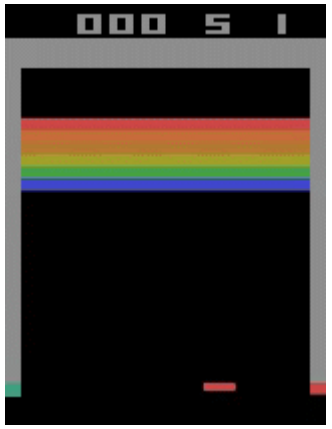
Microsoft

fully connected (FCN), convolutional (CNN), recurrent (RNN)

- fully connected (FCN) $h = \sigma(\mathbf{W}\ x + b)$
  - describes objects through probabilities of "**class membership.**"
- convolutional (CNN) $h(c,r) = \sigma(\mathbf{W}\ x(c\text{-}\Delta c..c\text{+}\Delta c, r\text{-}\Delta r..r\text{+}\Delta r) + b)$
  - repeatedly applies a little FCN over images or other **repetitive structures**
- recurrent (RNN) $h(t) = \sigma(\mathbf{W}\ x(t) + \mathbf{R}\ h(t\text{-}1) + b)$
  - repeatedly applies a FCN over a **sequence**, using its **own previous output**

training deep neural networks with SGD

- training
  - find weight parameters ($\mathbf{W}^{(n)}$, $b^{(n)}$) as to match some **criterion function**
  - **supervised learning** → **classify** an input
  - **unsupervised learning** → **discover** hidden structure in data
  - **reinforcement learning** → interact with an environment to **maximize reward**



CNTK / OpenAI Gym
[Morgan Funtowicz]

- stochastic gradient descent (SGD)
  - feed input sample, compare to desired output
  - iteratively take a step in the direction of the **gradient** of the criterion function w.r.t. a weight parameter

- SGD training is VERY expensive
  - speech: **10^{18} FLOPSs**
  - image: **10^{19} FLOPS**
  - Titan X GPU (3840 CUDA cores): peak 7 10^{12} FLOPS → 1+ weeks

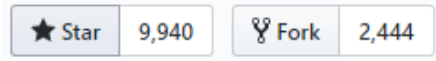
deep-learning toolkits must address two questions:

- **how to author neural networks?** ← user's job
- **how to execute them efficiently? (training/test)** ← *tool*'s job*!!*

I. deep neural networks crash course
II. Microsoft Cognitive Toolkit (CNTK)
III. defining neural networks in CNTK
IV. deep dive: how CNTK gets so fast
V. conclusion

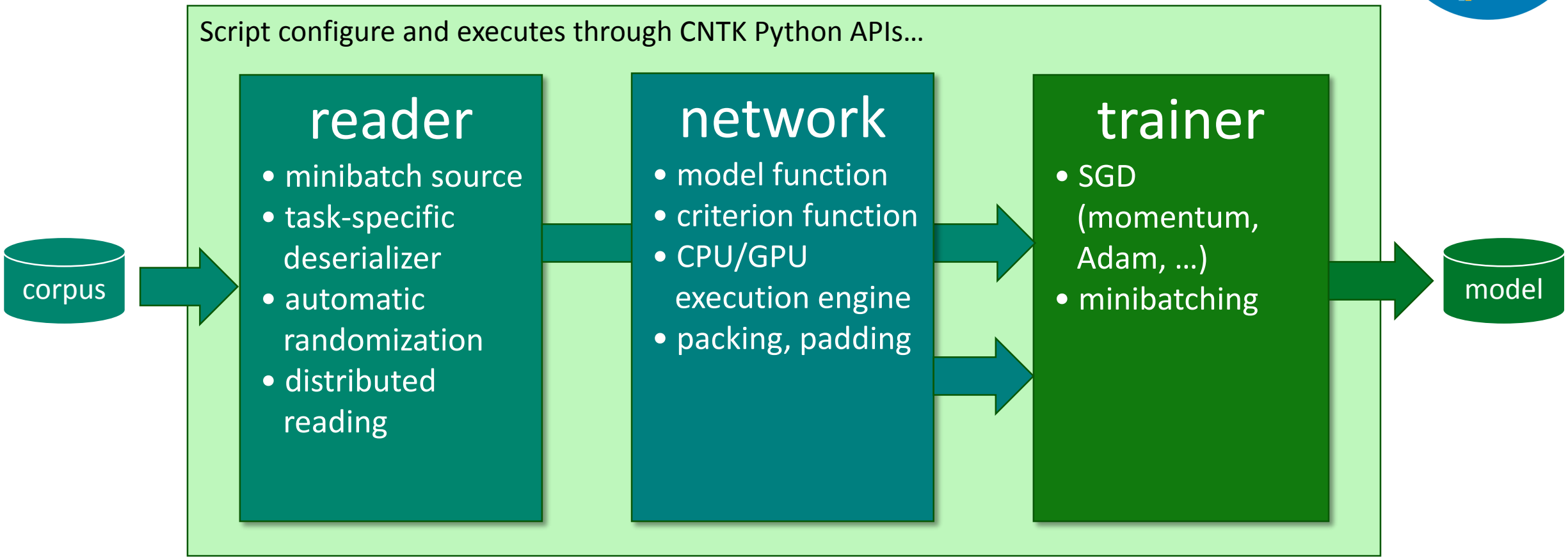
Microsoft Cognitive Toolkit, CNTK

- CNTK is a library for deep neural networks
  - model definition
  - scalable training
  - efficient I/O
- easy to author, train, and use neural networks
  - think “what” not “how”
  - focus on composability
- Python, C++, C#, Java
- open source since 2015 https://github.com/Microsoft/CNTK



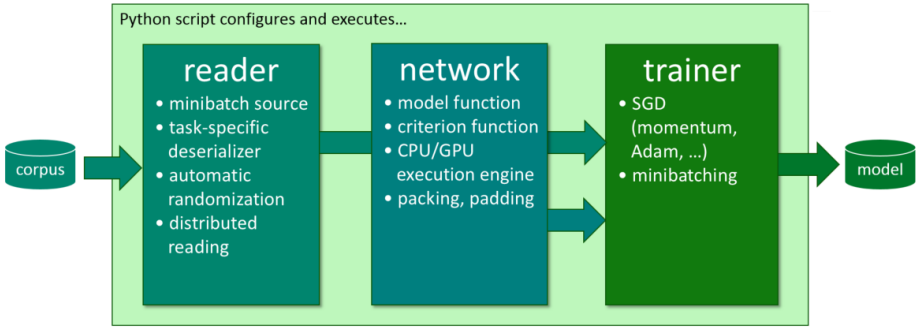
  - created by Microsoft Speech researchers (Dong Yu et al.) in 2012, “Computational Network Toolkit”
  - contributions from MS product groups and external (e.g. MIT, Stanford), development is visible on Github
  - Linux, Windows, docker, cudnn5, CUDA 8

Microsoft Cognitive Toolkit, CNTK

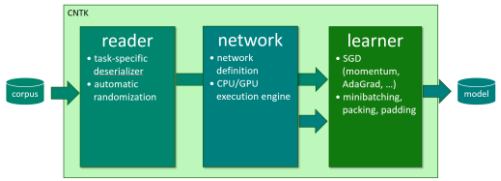


As easy as 1-2-3

```
from cntk import *

# reader
def create_reader(path, is_training):
    ...

# network
def create_model_function():
    ...
def create_criterion_function(model):
    ...

# trainer (and evaluator)
def train(reader, model):
    ...
def evaluate(reader, model):
    ...

# main function
model = create_model_function()

reader = create_reader(..., is_training=True)
train(reader, model)

reader = create_reader(..., is_training=False)
evaluate(reader, model)
```



workflow



- prepare data
- configure reader, network, learner (Python)
- train:

```
mpiexec --np 16 --hosts server1,server2,server3,server4    \
python my_cntk_script.py
```

- deploy
  - offline (Python): apply model file-to-file
  - your code: embed model through C++ API
  - online: web service wrapper through C#/Java API

CNTK performs!

TABLE 7. COMPARATIVE EXPERIMENT RESULTS (TIME PER MINI-BATCH IN SECOND)

		Desktop CPU (Threads used)				Server CPU (Threads used)						Single GPU		
		1	2	4	8	1	2	4	8	16	32	G980	G1080	K80
FCN-S	Caffe	1.324	0.790	**0.578**	-	1.355	0.997	0.745	**0.573**	0.608	1.130	0.041	**0.030**	0.071
	CNTK	1.227	0.660	**0.435**	-	1.340	0.909	0.634	0.488	**0.441**	1.000	0.045	**0.033**	0.074
	TF	7.062	4.789	2.648	**1.938**	9.571	6.569	3.399	1.710	0.946	**0.630**	0.060	**0.048**	0.109
	MXNet	4.621	2.607	2.162	**1.831**	5.824	3.356	2.395	2.040	**1.945**	2.670	-	**0.106**	0.216
	Torch	1.329	0.710	**0.423**	-	1.279	1.131	0.595	0.433	**0.382**	1.034	0.040	**0.031**	0.070
AlexNet-S	Caffe	1.606	0.999	**0.719**	-	1.533	1.045	**0.797**	0.850	0.903	1.124	0.034	**0.021**	0.073
	CNTK	3.761	1.974	**1.276**	-	3.852	2.600	1.567	1.347	**1.168**	1.579	0.045	**0.032**	0.091
	TF	6.525	2.936	1.749	**1.535**	5.741	4.216	2.202	1.160	**0.701**	0.962	0.059	**0.042**	0.130
	MXNet	2.977	2.340	2.250	**2.163**	3.518	3.203	2.926	2.828	**2.827**	2.887	0.020	**0.014**	0.042
	Torch	4.645	2.429	**1.424**	-	4.336	2.468	1.543	1.248	**1.090**	1.214	0.033	**0.023**	0.070
RenNet-50	Caffe	11.554	7.671	**5.652**	-	10.643	8.600	6.723	**6.019**	6.654	8.220	-	**0.254**	0.766
	CNTK	-	-	-	-	-	-	-	-	-	-	0.240	**0.168**	0.638
	TF	23.905	16.435	10.206	**7.816**	29.960	21.846	11.512	6.294	**4.130**	4.351	0.327	**0.227**	0.702
	MXNet	**14.035**	16.053	16.162	15.000	**17.910**	19.277	19.123	18.898	19.048	19.355	0.059	**0.041**	0.132
	Torch	13.178	7.500	**4.736**	4.948	12.807	8.391	5.471	4.164	**3.683**	4.422	0.208	**0.144**	0.523
FCN-R	Caffe	2.476	1.499	**1.149**	-	2.282	1.748	1.403	1.211	1.127	**1.127**	0.025	**0.017**	0.055
	CNTK	1.845	0.970	0.661	**0.571**	1.592	0.857	0.501	0.323	**0.252**	0.280	0.025	**0.017**	0.053
	TF	2.647	1.913	1.157	**0.919**	3.410	2.541	1.297	0.661	0.361	**0.325**	0.033	**0.020**	0.063
	MXNet	1.914	1.072	0.719	**0.702**	1.609	1.065	0.731	0.534	0.451	**0.447**	0.029	**0.019**	0.060
	Torch	1.670	0.926	**0.565**	0.611	1.379	0.915	0.662	0.440	0.402	**0.366**	0.025	**0.016**	0.051
AlexNet-R	Caffe	3.558	2.587	**2.157**	2.963	4.270	3.514	3.381	**3.364**	4.139	4.930	0.041	**0.027**	0.137
	CNTK	9.956	7.263	**5.519**	6.015	9.381	6.078	4.984	**4.765**	6.256	6.199	0.045	**0.031**	0.108
	TF	4.535	3.225	1.911	**1.565**	6.124	4.229	2.200	1.396	1.036	**0.971**	**0.227**	0.317	0.385
	MXNet	13.401	12.305	12.278	**11.950**	17.994	17.128	16.764	**16.471**	17.471	17.770	0.060	**0.032**	0.122
	Torch	5.352	3.866	**3.162**	3.259	6.554	5.288	4.365	**3.940**	4.157	4.165	0.069	**0.043**	0.141
RenNet-56	Caffe	6.741	5.451	**4.989**	6.691	7.513	**6.119**	6.232	6.689	7.313	9.302	-	**0.116**	0.378
	CNTK	-	-	-	-	-	-	-	-	-	-	0.206	**0.138**	0.562
	TF	-	-	-	-	-	-	-	-	-	-	0.225	**0.152**	0.523
	MXNet	34.409	31.255	**30.069**	31.388	44.878	43.775	**42.299**	42.965	43.854	44.367	0.105	**0.074**	0.270
	Torch	5.758	3.222	**2.368**	2.475	8.691	4.965	3.040	**2.560**	2.575	2.811	0.150	**0.101**	0.301
LSTM	Caffe	-	-	-	-	-	-	-	-	-	-	-	-	-
	CNTK	0.186	0.120	**0.090**	0.118	0.211	0.139	0.117	0.114	**0.114**	0.198	0.018	**0.017**	0.043
	TF	4.662	3.385	1.935	**1.532**	6.449	4.351	2.238	1.183	0.702	**0.598**	0.133	**0.065**	0.140
	MXNet	-	-	-	-	-	-	-	-	-	-	0.089	**0.079**	0.149
	Torch	6.921	3.831	**2.682**	3.127	7.471	4.641	3.580	**3.260**	5.148	5.851	0.399	**0.324**	0.560

["Benchmarking State-of-the-Art Deep Learning Software Tools," HKBU, https://arxiv.org/pdf/1608.07249v6.pd]

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neural networks as graphs

example: 2-hidden layer feed-forward NN

$$h_1 = \sigma(\mathbf{W}_1 x + b_1)$$
$$h_2 = \sigma(\mathbf{W}_2 h_1 + b_2)$$
$$P = \mathrm{softmax}(\mathbf{W}_{\mathrm{out}} h_2 + b_{\mathrm{out}})$$

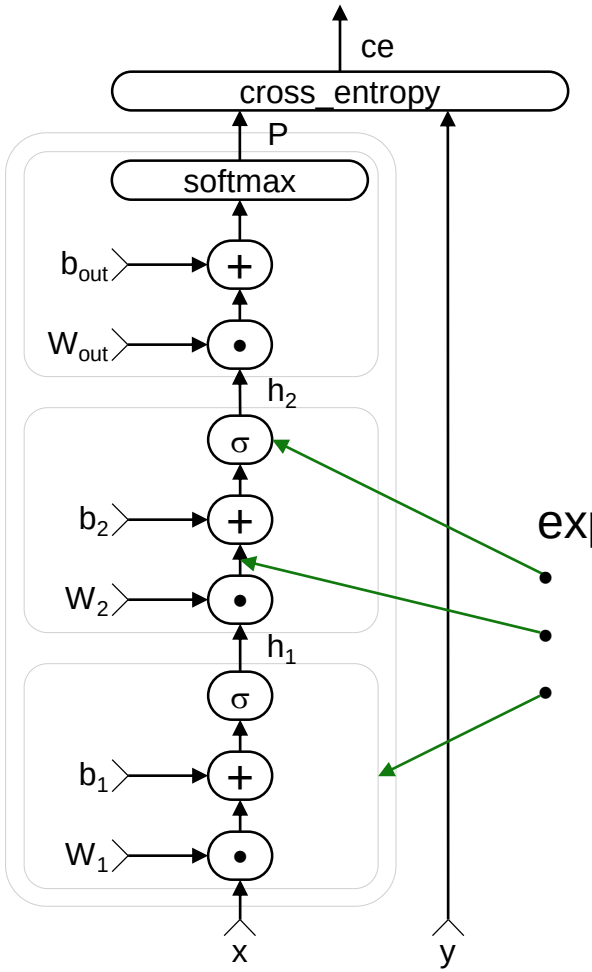
```
h1 = sigmoid (x  @ W1   + b1)
h2 = sigmoid (h1 @ W2   + b2)
P  = softmax (h2 @ Wout + bout)
```

with input $x \in \mathrm{R}^M$ and one-hot label $y \in \mathrm{R}^J$
and cross-entropy training criterion

$$ce = y^{\mathrm{T}} \log P$$
$$\sum_{\mathrm{corpus}} ce = \max$$

```
ce = cross_entropy (P, y)
```

neural networks as graphs

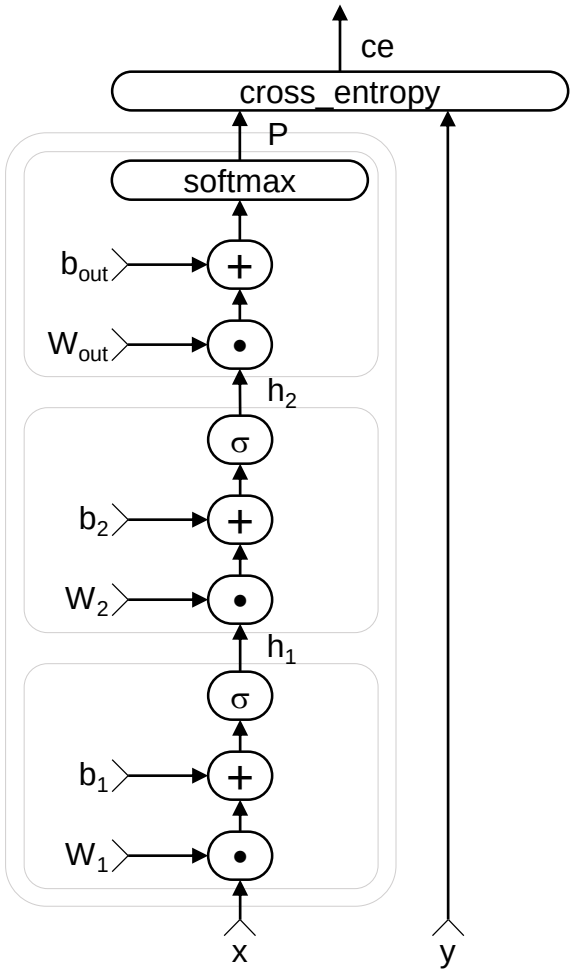


expression tree with

- primitive ops
- values (tensors)
- composite ops

```
h1 = sigmoid (x  @ W1   + b1)
h2 = sigmoid (h1 @ W2   + b2)
P  = softmax (h2 @ Wout + bout)
ce = cross_entropy (P, y)
```

neural networks as graphs



why graphs?

- automatic differentiation*!!*
  - chain rule: $\partial \mathcal{F} / \partial \text{in} = \partial \mathcal{F} / \partial \text{out} \cdot \partial \text{out} / \partial \text{in}$
  - run graph backwards

→ **“back propagation”**

graphs are the “assembly language” of DNN tools

authoring neural networks

- **Theano, TensorFlow**:
  - **expression graph is user surface**; user builds the graph
  - your script generates “assembly language” (graph) like a compiler backend
  - code does not really do what it looks like (“referential transparency problem”)

```
y = tf.contrib.layers.fully_connected(x, num_outputs=512, scope=variable_scope)
```

→ abstraction level **too low**

- **Chainer, DyNet, PyTorch**:
  - **imperative computation** (builds a hidden graph for gradient only)
  - Turing complete
  - but: no automatic batching → inefficient on GPUs

→ abstraction level **too high**

authoring networks as functions

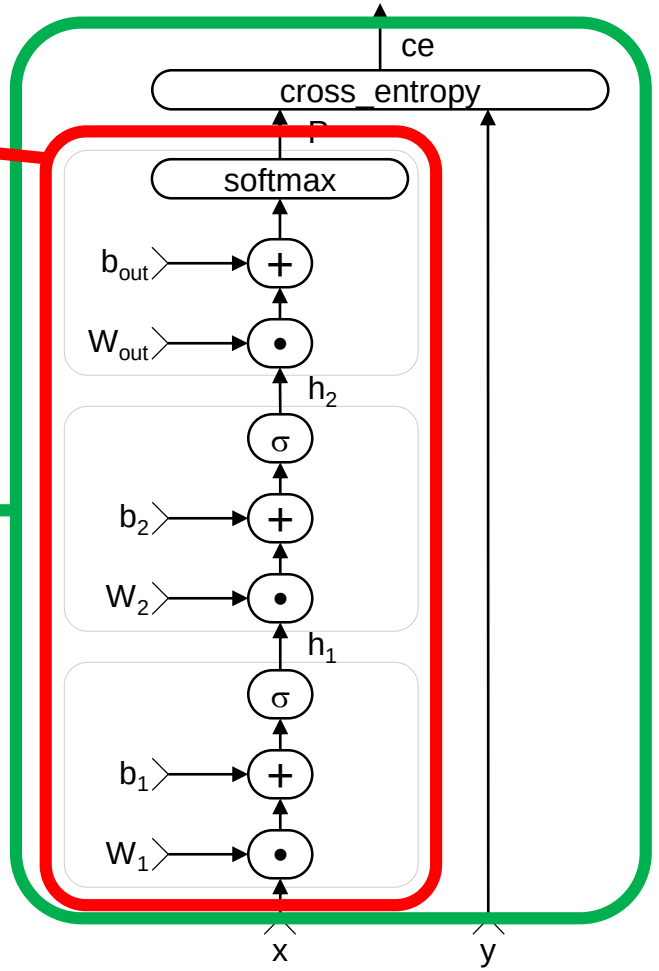
- **CNTK** model: neural networks are functions
  - pure functions
  - with “special powers”:
    - can compute a gradient w.r.t. any of its nodes
    - external deity can update model parameters

- user specifies network as function objects:
  - formula as a Python function (low level, e.g. LSTM)
  - function composition of smaller sub-networks (layering)
  - higher-order functions (equiv. of scan, fold, unfold)
  - model parameters held by function objects

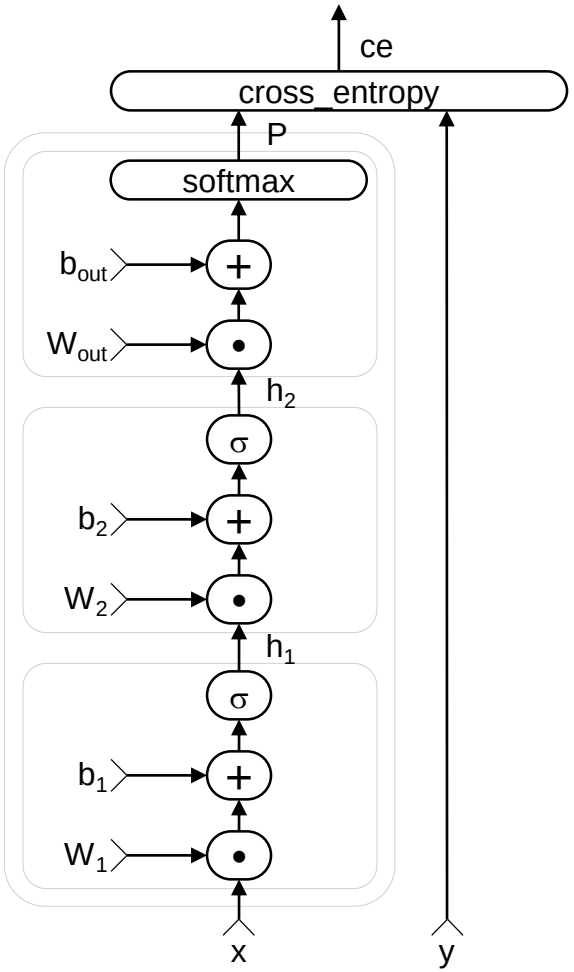
- “compiled” into the static execution graph under the hood

authoring networks as functions

- "model function"
  - *features → predictions*
  - defines the **model structure** & parameter initialization
  - holds parameters that will be learned by training
- "criterion function"
  - (*features*, *labels*) → (*training loss*, *additional metrics*)
  - defines **training and evaluation criteria** on top of the model function
  - provides gradients w.r.t. training criteria

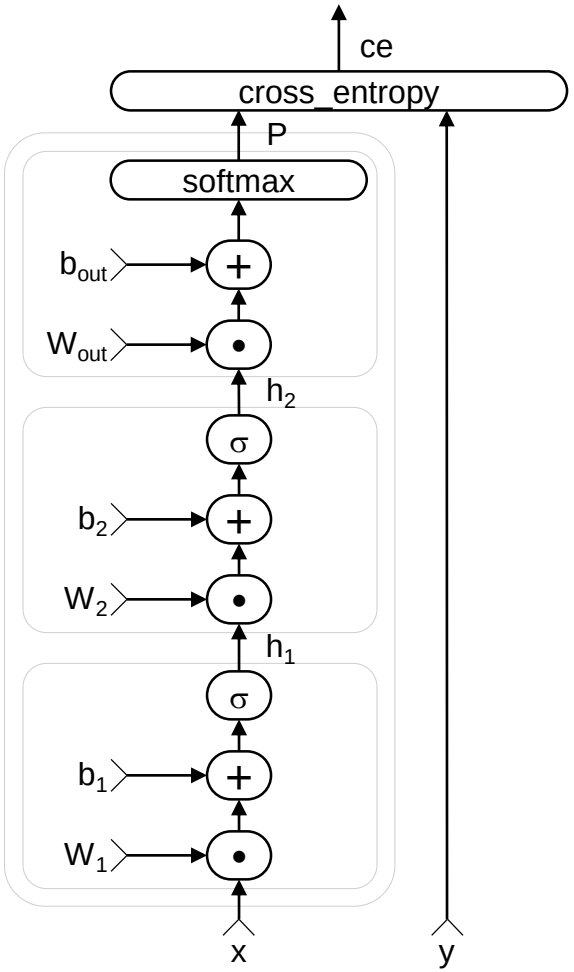


authoring networks as functions



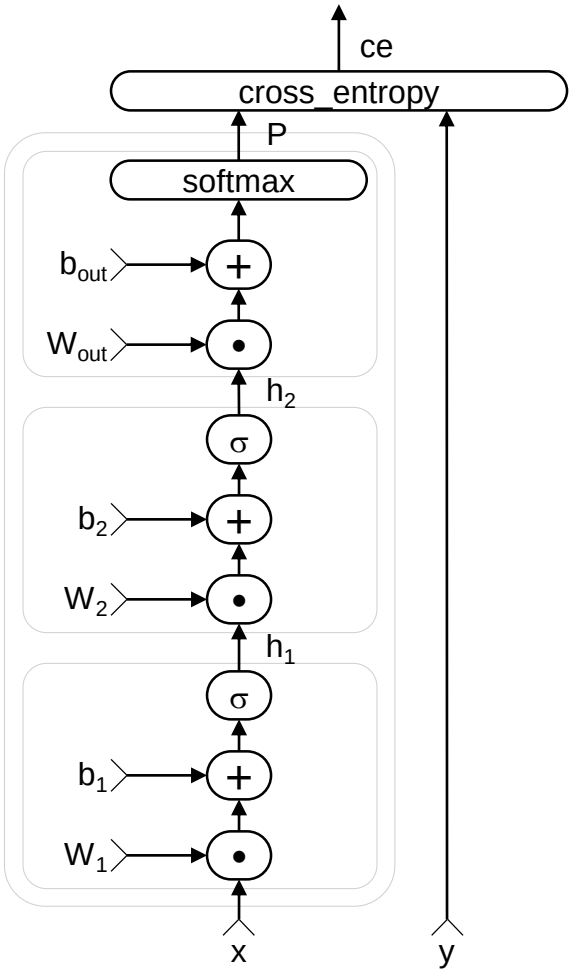

```
# --- graph building ---
M = 40 ; H = 512 ; J = 9000  # feat/hid/out dim
# define learnable parameters
W1   = Parameter((M,H)); b1   = Parameter(H)
W2   = Parameter((H,H)); b2   = Parameter(H)
Wout = Parameter((H,J)); bout = Parameter(J)
# build the graph
x = Input(M) ; y = Input(J)  # feat/labels
h1 = sigmoid(x  @ W1   + b1)
h2 = sigmoid(h1 @ W2   + b2)
P  = softmax(h2 @ Wout + bout)
ce = cross_entropy(P, y)
```

authoring networks as functions




```
# --- graph building with function objects ---
M = 40 ; H = 512 ; J = 9000  # feat/hid/out dim
#  - function objects own the learnable parameters
#  - here used as blocks in graph building
x = Input(M) ;  y = Input(J)  # feat/labels
h1 = Dense(H, activation=sigmoid)(x)
h2 = Dense(H, activation=sigmoid)(h1)
P  = Dense(J, activation=softmax)(h2)
ce = cross_entropy(P, y)
```

authoring networks as functions




```
M = 40 ; H = 512 ; J = 9000  # feat/hid/out dim
# compose model from function objects
model = Sequential([Dense(H, activation=sigmoid),
                    Dense(H, activation=sigmoid),
                    Dense(J, activation=softmax)])
# criterion function (invokes model function)
@Function
def criterion(x: Tensor[M], y: Tensor[J]):
    P = model(x)
    return cross_entropy(P, y)
# function is passed to trainer
tr = Trainer(criterion, Learner(model.parameters), …)
```

composition

- stacking layers:

```
model = Sequential([Dense(H, activation=sigmoid),
                    Dense(H, activation=sigmoid),
                    Dense(J)])
```

- recurrence:

```
model = Sequential([Embedding(emb_dim, name='embed'),
                    Recurrence(GRU(hidden_dim)),
                    Dense(num_labels, name='out_projection')])
```

- unfold:

```
model = UnfoldFrom(lambda history: s2smodel(history, input) >> hardmax,
                   until_predicate=lambda w: w[...,sentence_end_index],
                   length_increase=length_increase)
output = model(START_SYMBOL)
```

Layers API

- basic blocks:
  - `LSTM(), GRU(), RNNUnit()`
  - `Stabilizer(), identity`
  - `ForwardDeclaration(), Tensor[], SparseTensor[], Sequence[], SequenceOver[]`
- layers:
  - `Dense(), Embedding()`
  - `Convolution(), Convolution1D(), Convolution2D(), Convolution3D(), Deconvolution()`
  - `MaxPooling(), AveragePooling(), GlobalMaxPooling(), GlobalAveragePooling(), MaxUnpooling()`
  - `BatchNormalization(), LayerNormalization()`
  - `Dropout(), Activation()`
  - `Label()`
- composition:
  - `Sequential(), For(), operator >>, (function tuples)`
  - `ResNetBlock(), SequentialClique()`
- sequences:
  - `Delay(), PastValueWindow()`
  - `Recurrence(), RecurrenceFrom(), Fold(), UnfoldFrom()`
- models:
  - `AttentionModel()`

Layers Library Reference

Note: This documentation has not yet been completely updated with respect to the latest update of the Layers library. It should be correct but misses several new options and layer types.

CNTK predefines a number of common "layers," which makes it very easy to write simple networks that consist of standard layers layered on top of each other. Layers are function objects that can be used like a regular `Function` but hold learnable parameters and have an additional pair of `()` to pass construction parameters or attributes.

For example, this is the network description for a simple 1-hidden layer model using the `Dense` layer:

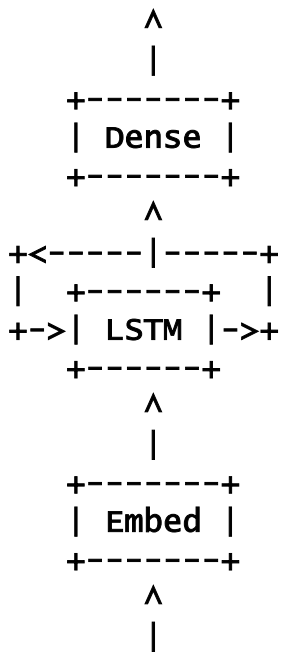
```
h = Dense(1024, activation=relu)(features)
p = Dense(9000, activation=softmax)(h)
```

which can then, e.g., be used for training against a cross-entropy criterion:

examples: language understanding

Task: Slot tagging with an LSTM

show	O
flights	O
from	O
burbank	B-fromloc.city_name
to	O
st.	B-toloc.city_name
louis	I-toloc.city_name
on	O
monday	B-depart_date.day_name



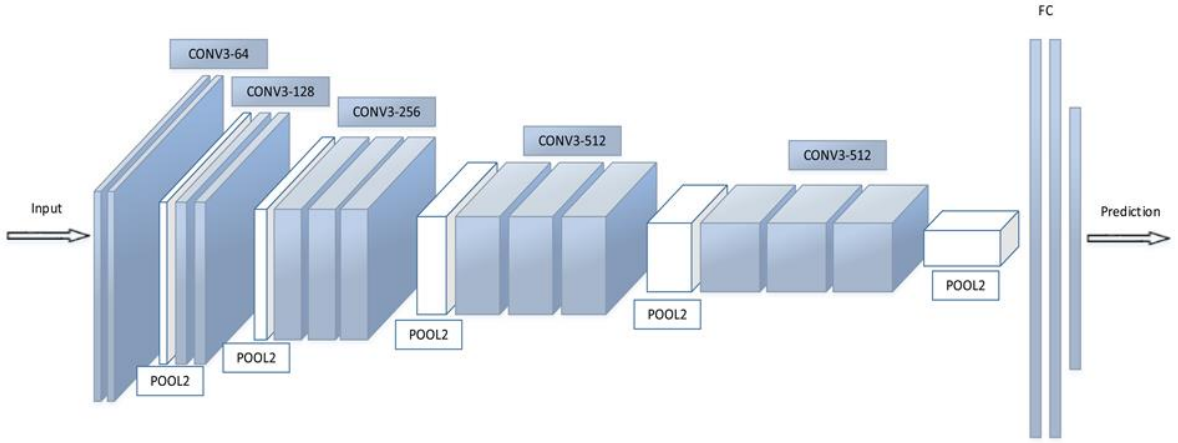

```
# model function: input -> prediction
model = Sequential([
    Embedding(300),
    Recurrence(LSTM(256))
    Dense(num_labels),
])

# criterion func: (input, labels) -> (loss, metric)
@Function
def crit(query: Sequence[SparseTensor[vocab_size]],
         labels:Sequence[SparseTensor[num_labels]]):
    z = model(query)
    ce   = cross_entropy_with_softmax(z, labels)
    errs = classification_error      (z, labels)
    return (ce, errs)

# train it
trainer = Trainer(crit, ...)
...
    train_minibatch(data)
```

examples: image (conv net)

```
# model function
with default_options(activation=relu, pad=True):
    model = Sequential([
        For(range(5), lambda i: [
            Convolution((3,3), 64 * 2**i),
            Convolution((3,3), 64 * 2**i),
            MaxPooling((3,3), strides=2)
        ]),
        For(range(3), lambda i: [
            Dense([4096,4096,2048][i]),
            Dropout(0.5)
        ]),
        Dense(num_classes, activation=None)
    ])
```



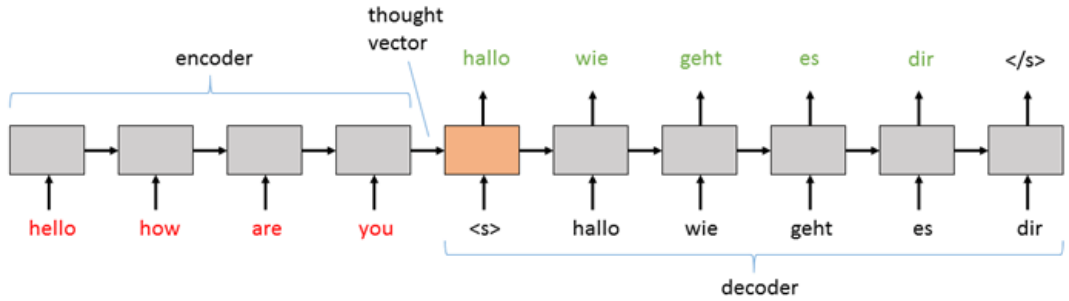
[VGG network, Simonyan *et al.*, 2015]

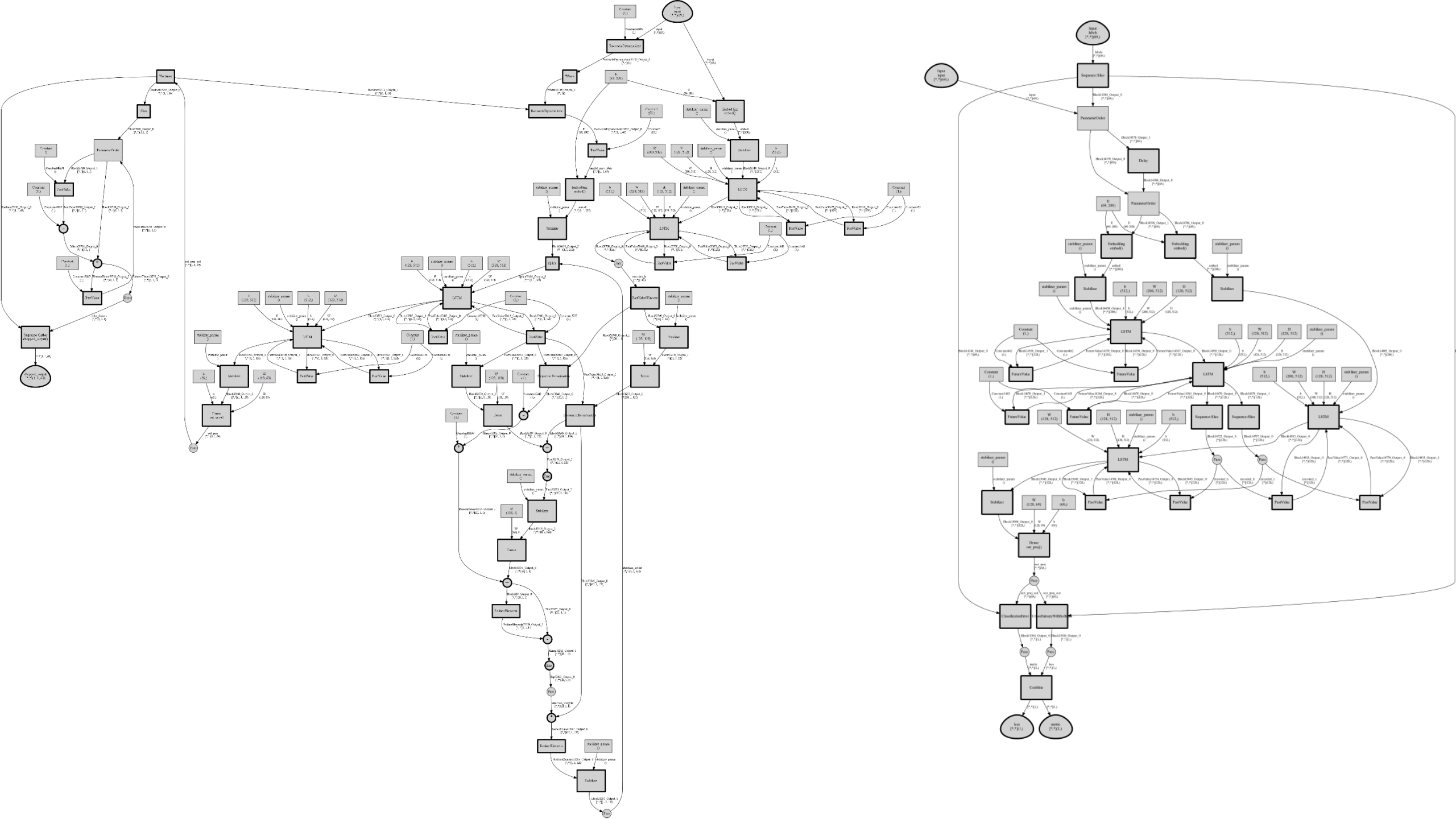
```
# criterion function
@Function
def criterion(x: Tensor[3, image_height, image_width], y: Tensor[num_classes]):
    z = model(normalize(x))
    ce   = cross_entropy_with_softmax(z, y)
    errs = classification_error      (z, y)
    return (ce, errs)
```

examples: sequence-to-sequence translation

```
# Encoder: (input*) --> (h0)
encode = Sequential([
    Embedding(300),
    Fold(GRU(128))
])

# Decoder: (history*, input*) --> z*
embed = Embedding(300)
gru = GRU(128)
proj_out = Dense(label_vocab_dim)
@Function
def decode(history, input):
    thought_vector = encode(input)
    r = embed(history)
    r = RecurrenceFrom(gru)(thought_vector, r) # :: h, r -> h
    r = proj_out(r)
    return proj_out(r)
```





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  -- GPU execution
  -- optimization
  -- parallelization
V. conclusion

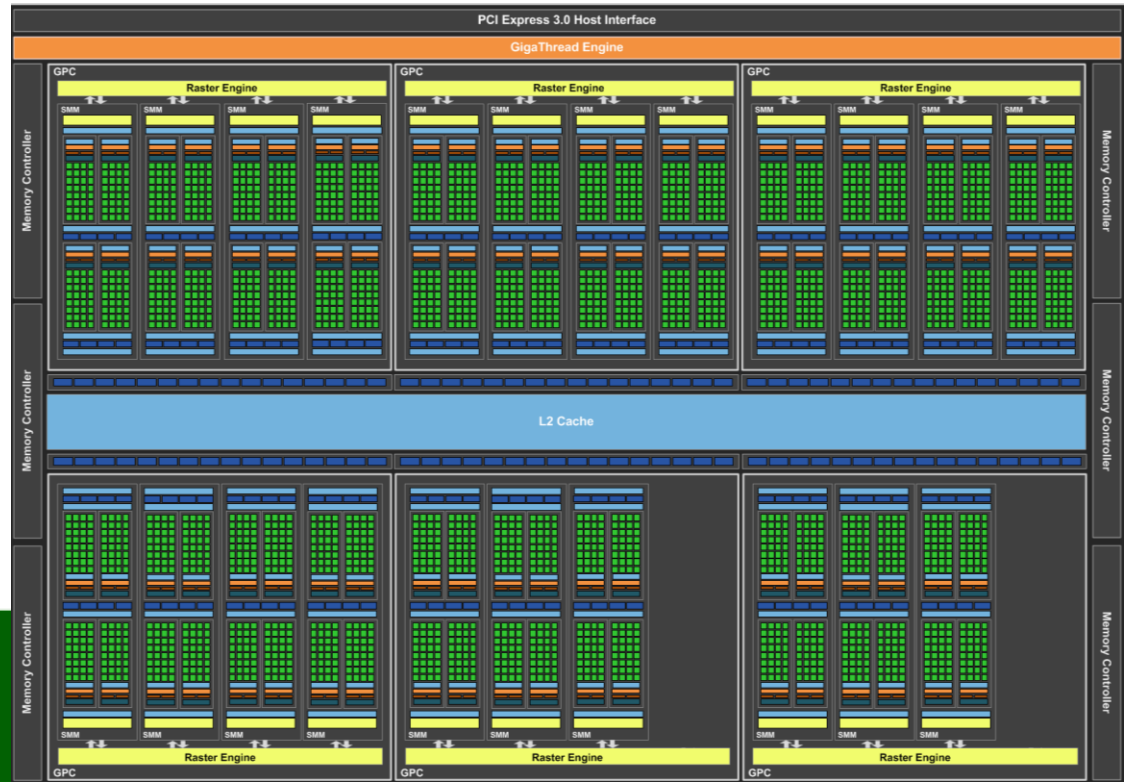
high performance with GPUs

- GPUs are massively parallel super-computers
  - Nvidia Titan X: 3072 parallel processors
  - GPUs made NN research and experimentation productive

- CNTK must turn DNNs into **parallel programs**

- two main priorities in GPU computing:
  1. make sure all CUDA cores are always busy
  2. read from GPU RAM as little as possible

[Jacob Devlin, NLPCC 2016 Tutorial]



minibatching

- **minibatching :=** batch N samples, e.g. N=256; execute in lockstep
  - turns N matrix-vector products into one matrix-matrix product → peak GPU performance
  - element-wise ops and reductions benefit, too
  - has limits (convergence, dependencies, memory)
- critical for GPU performance
  - difficult to get right

→ CNTK makes batching fully transparent

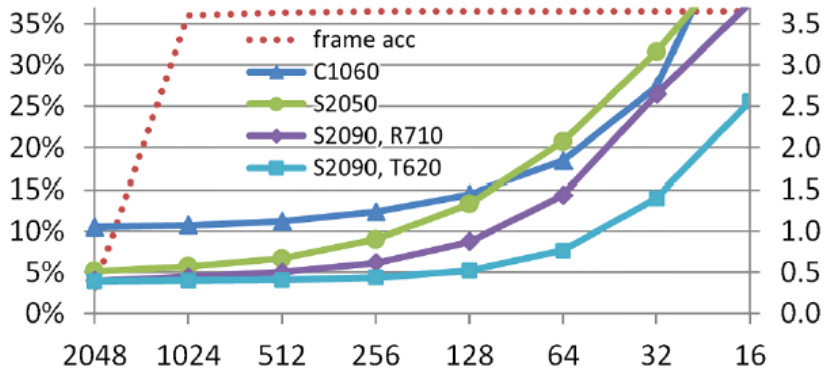


Figure 1: *Relative runtime for different minibatch sizes and GPU/server model types, and corresponding frame accuracy measured after seeing 12 hours of data.*[7]

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symbolic loops over sequential data

extend our example to a recurrent network (RNN)

$$
\begin{aligned}
h_1 &= \sigma(\mathbf{W}_1\, x + b_1) \\
h_2 &= \sigma(\mathbf{W}_2\, h_1 + b_2) \\
P &= \mathrm{softmax}(\mathbf{W}_{\mathrm{out}}\, h_2 + b_{\mathrm{out}}) \\
ce &= L^{\mathrm{T}} \log P \\
\textstyle\sum_{\mathrm{corpus}} ce &= \max
\end{aligned}
$$

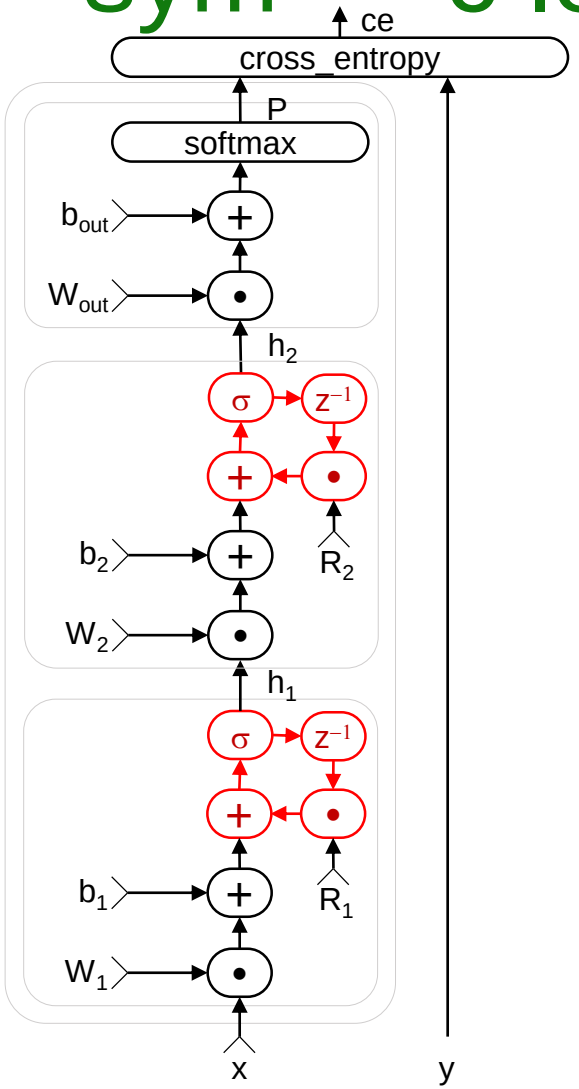
symbolic loops over sequential data

extend our example to a recurrent network (RNN)

$$h_1(t) = \sigma(\mathbf{W}_1\, x(t) + \mathbf{R}_1\, h_1(t\text{-}1) + b_1)$$
$$h_2(t) = \sigma(\mathbf{W}_2\, h_1(t) + \mathbf{R}_2\, h_2(t\text{-}1) + b_2)$$
$$P(t) = \mathrm{softmax}(\mathbf{W}_{\mathrm{out}}\, h_2(t) + b_{\mathrm{out}})$$
$$ce(t) = L^{\mathrm{T}}(t) \log P(t)$$
$$\sum_{\mathrm{corpus}} ce(t) = \max$$

```
h1 = sigmoid(x  @ W1 + past_value(h1) @ R1 + b1)
h2 = sigmoid(h1 @ W2 + past_value(h2) @ R2 + b2)
P  = softmax(h2 @ Wout + bout)
ce = cross_entropy(P, L)
```

symbolic loops over sequential data



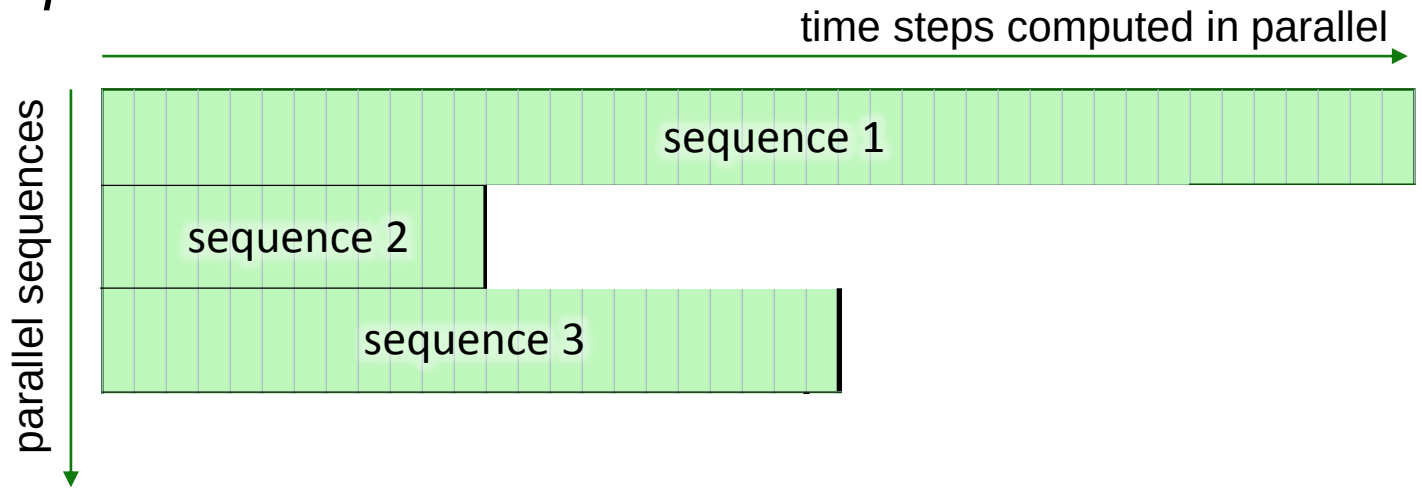

```
h1 = sigmoid(x  @ W1 + past_value(h1) @ R1 + b1)
h2 = sigmoid(h1 @ W2 + past_value(h2) @ R2 + b2)
P  = softmax(h2 @ Wout + bout)
ce = cross_entropy(P, L)
```

- CNTK automatically unrolls cycles at *execution time*
- efficient and composable
  - cf. TensorFlow: [https://www.tensorflow.org/versions/r1.0/tutorials/recurrent/index.html]

```
lstm = rnn_cell.BasicLSTMCell(lstm_size)
state = tf.zeros([batch_size, lstm.state_size]
probabilities = []
loss = 0.0
for current_batch_of_words in words_in_dataset:
    output, state = lstm(current_batch_of_words, state)
    logits = tf.matmul(output, softmax_w) + softmax_b
    probabilities.append(tf.nn.softmax(logits))
    loss += loss_function(probabilities, target_words)
```

batching variable-length sequences

- minibatches containing sequences of different lengths are automatically packed *and padded*



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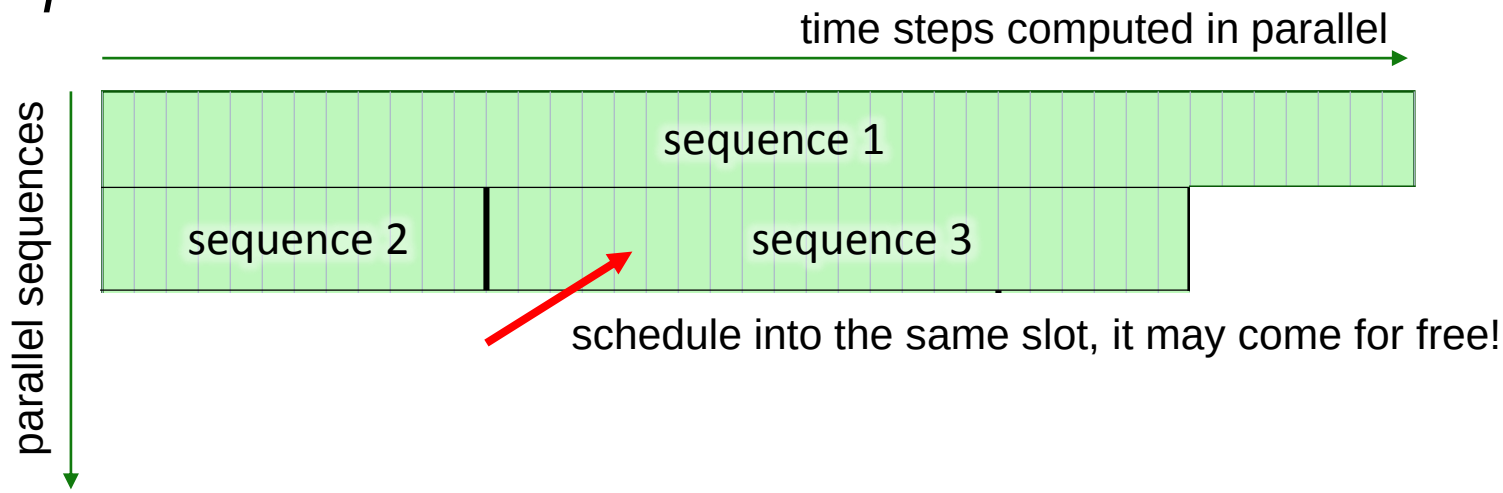

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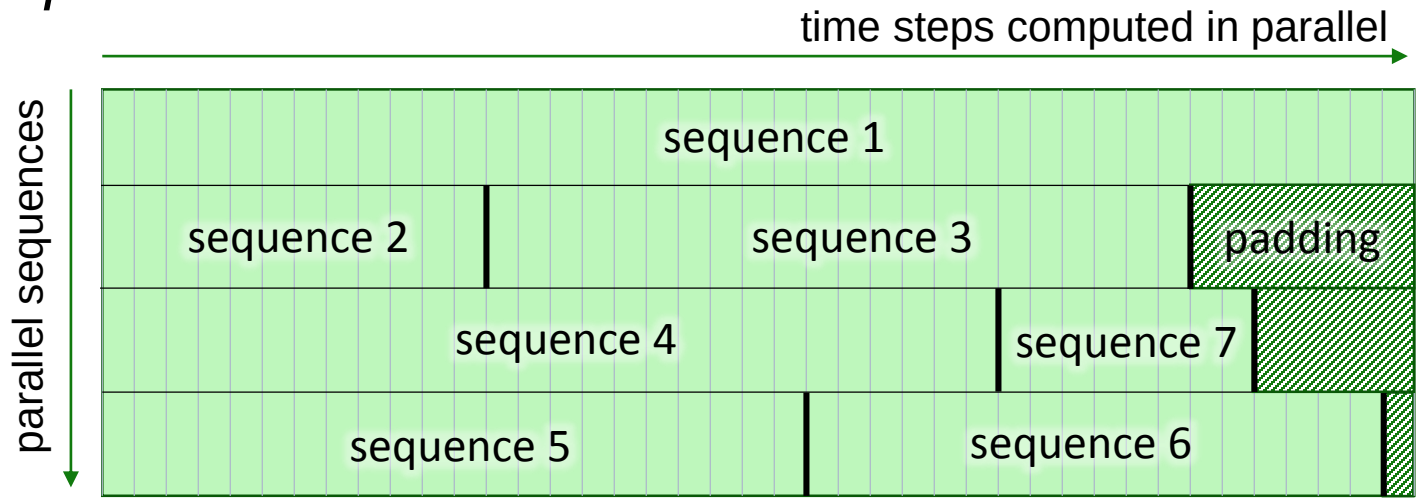

- fully transparent batching
  - recurrent → CNTK unrolls, handles sequence boundaries
  - non-recurrent operations → parallel
  - sequence reductions → mask

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data-parallel training

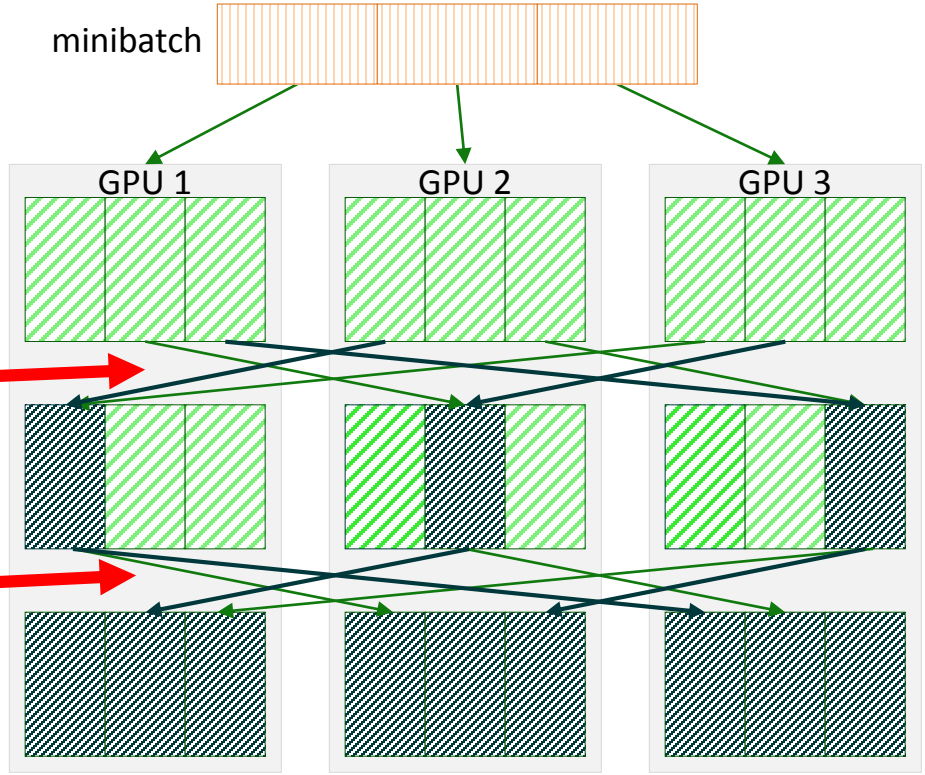
how to reduce communication cost:

communicate less each time

- 1-bit SGD:
  [F. Seide, H. Fu, J. Droppo, G. Li, D. Yu: "1-Bit Stochastic Gradient Descent... Distributed Training of Speech DNNs", Interspeech 2014]
  - quantize gradients to 1 bit per value
  - trick: carry over quantization error to next minibatch

1-bit quantized with residual

1-bit quantized with residual



data-parallel training

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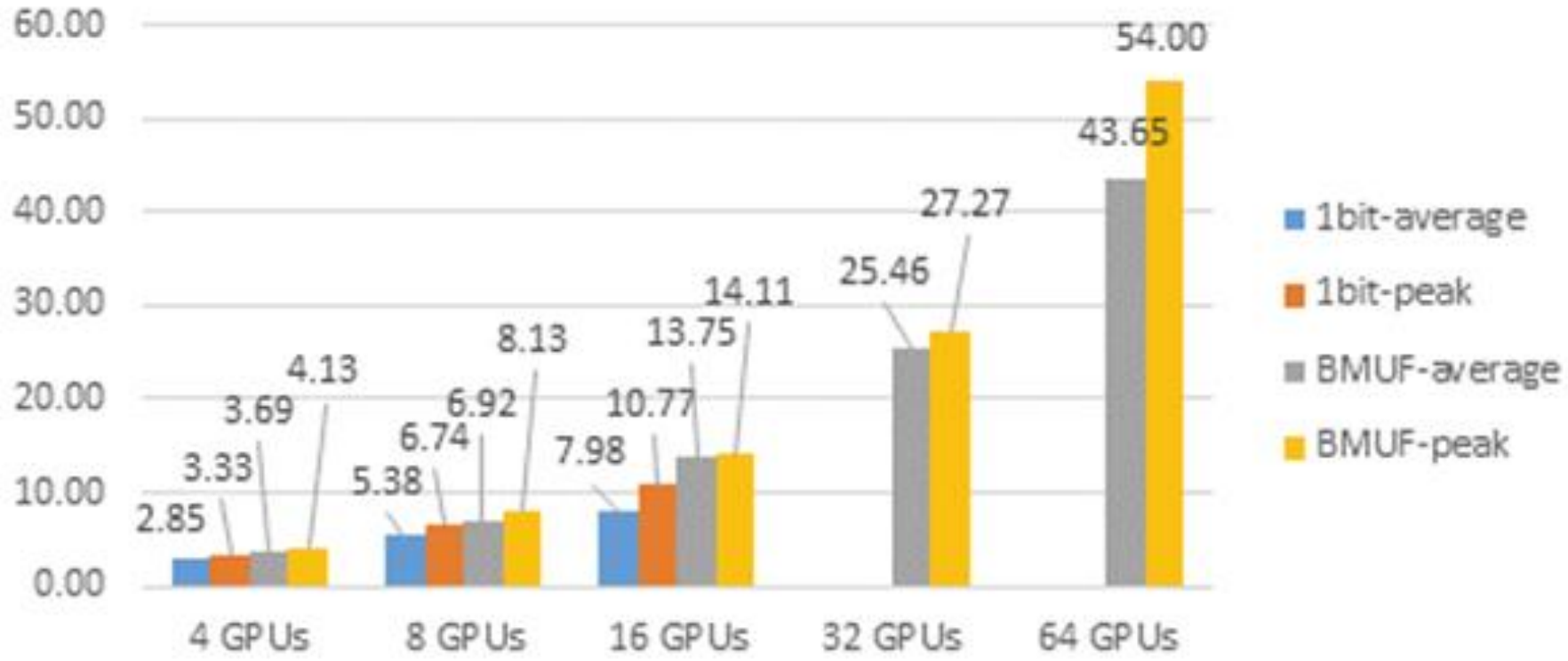
  - quantize gradients to 1 bit per value
  - trick: carry over quantization error to next minibatch

communicate less often

- automatic MB sizing [F. Seide, H. Fu, J. Droppo, G. Li, D. Yu: “ON Parallelizability of Stochastic Gradient Descent...”, ICASSP 2014]
- block momentum [K. Chen, Q. Huo: “Scalable training of deep learning machines by incremental block training…,” ICASSP 2016]
  - very recent, very effective parallelization method
  - combines model averaging with error-residual idea

data-parallel training



LSTM SGD baseline	11.08				
Parallel Algorithms	4-GPU	8-GPU	16-GPU	32-GPU	64-GPU
1bit	10.79	10.59	11.02		
BMUF	10.82	10.82	10.85	10.92	11.08

Table 2: WERs (%) of parallel training for LSTMs

[Yongqiang Wang, IPG; internal communication]

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CNTK's approach to the two key questions:

- **efficient network authoring**
  - **networks as function objects**, well-matching the nature of DNNs
  - focus on **what, not how**
  - familiar syntax and flexibility **in Python**
- **efficient execution**
  - graph → parallel program through **automatic minibatching**
  - **symbolic loops** with dynamic scheduling
  - unique **parallel training algorithms** (1-bit SGD, Block Momentum)

on our roadmap

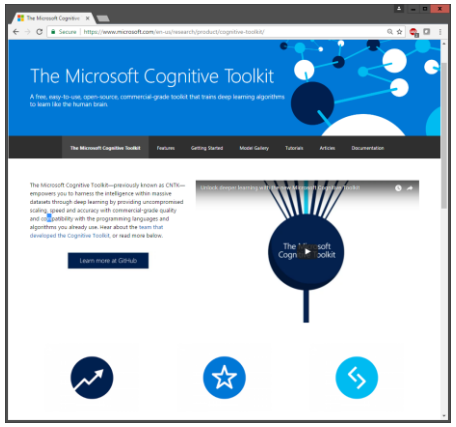
- integration with C#/.Net, R, Keras, HDFS, and Spark
  - continued C#/.Net integration; R
  - Keras back-end
  - HDFS
  - Spark
- technology
  - handle models too large for GPU
  - optimized nested recurrence
  - ASGD
  - 16-bit support, ARM, FPGA

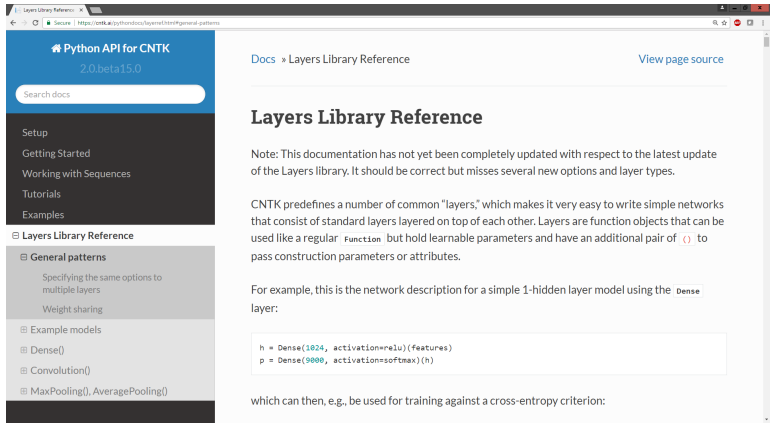
Cognitive Toolkit:
deep learning like Microsoft product groups

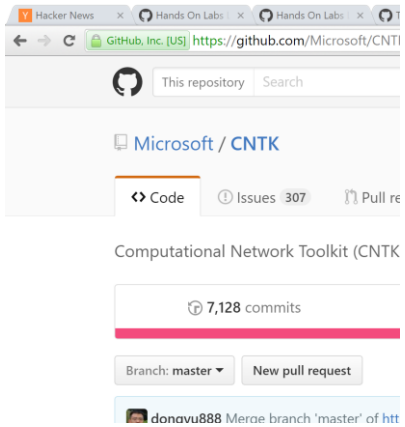
- ease of use
  - *what*, not *how*
  - powerful library
  - minibatching is automatic
- fast
  - optimized for NVidia GPUs & libraries
  - easy yet best-in-class multi-GPU/multi-server support
- flexible
  - Python and C++ API, powerful & composable
- 1st-class on Linux and Windows
- train like MS product groups: internal=external version

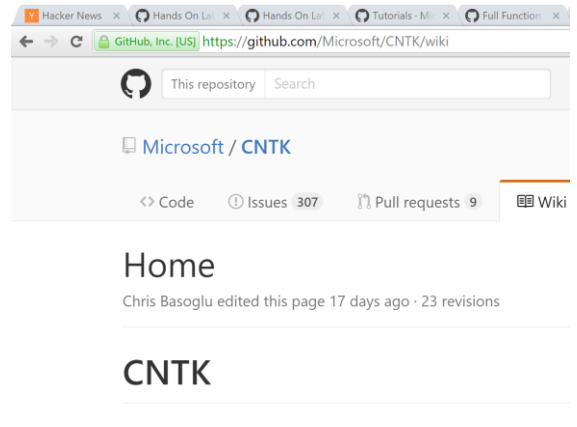
Cognitive Toolkit: democratizing the AI tool chain

- Web site: https://cntk.ai/
- Docs: https://cntk.ai/pythondocs
- Github: https://github.com/Microsoft/CNTK
- Wiki: https://github.com/Microsoft/CNTK/wiki









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