Deep Learning in Action

Current state of AI

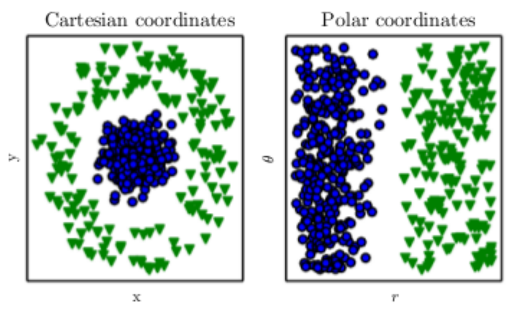
> In the early days of artificial intelligence, the field rapidly tackled and solved problems that are intellectually difficult for human beings but relatively straightforward for computers - problems that can be described by a list of formal, mathematical rules. The true challenge to artificial intelligence proved to be solving the tasks that are easy for people to perform but hard for people to describe formally —problems that we solve intuitively, that feel automatic, like recognizing spoken words or faces in images.

Goodfellow et al. 2016, Deep Learning (http://www.deeplearningbook.org/)

Easy for us. Difficult for computers

- object recognition
- speech recognition
- speech *generation*
- labeling images

Representations matter



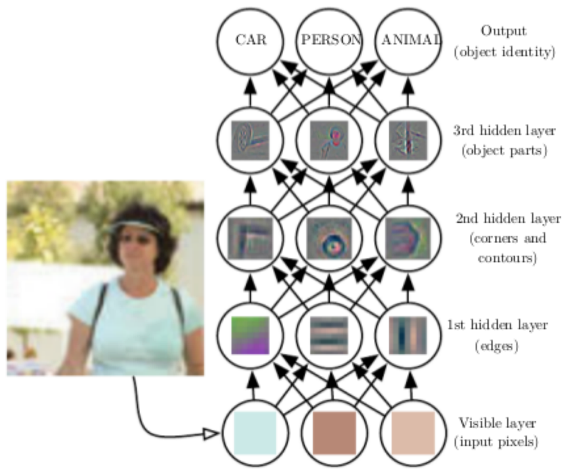
Source: Goodfellow et al. 2016, Deep Learning (http://www.deeplearningbook.org/)

Just feed the network the right features?

- What are the correct pixel values for a "bike" feature?
  - race bike, mountain bike, e-bike?
  - pixels in the shadow may be *much* darker
  - what if bike is mostly obscured by rider standing in front?

Let the network pick the features

... a layer at a time


CAR
PERSON
ANIMAL
Output (object identity)
3rd hidden layer (object parts)
2nd hidden layer (corners and contours)
1st hidden layer (edges)
Visible layer (input pixels)

Source: Goodfellow et al. 2016, Deep Learning (http://www.deeplearningbook.org/)

Deep Learning, 2 ways to think about it

- hierarchical feature extraction (start simple, end complex)
- function composition (see http://colah.github.io/posts/2015-09-NN-Types-FP/ (http://colah.github.io/posts/2015-09-NN-Types-FP/))

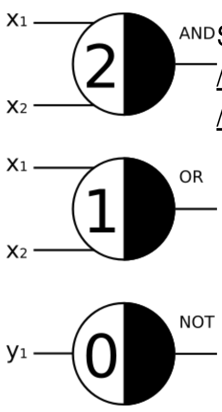
A Short History of (Deep) Learning

The first wave: cybernetics (1940s - 1960s)

- neuroscientific motivation
- linear models

McCulloch-Pitts Neuron (MCP, 1943, a.k.a. Logic Circuit)

- binary output (0 or 1)
- neurons may have inhibiting (negative) and excitatory (positive) inputs
- each neuron has a threshold that has to be surpassed by the sum of activations for the neuron to get active (output 1)
- if just one input is inhibitory, the neuron will not activate



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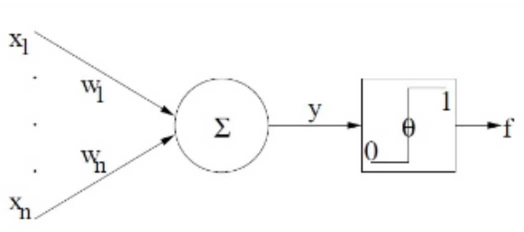
Perceptron (Rosenblatt, 1958): Great expectations

- compute linear combination of inputs
- return +1 if result is positive, -1 if result is negative



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Minsky & Papert (1969), "Perceptrons": the great disappointment

- Perceptrons can only solve linearly separable problems
- Big loss of interest in neural networks

The second wave: Connectionism (1980s, mid-1990s)

- distributed representations
- backpropagation gets popular

The magic ingredient: backpropagation

Several "origins" in different fields, see e.g.

- Henry J. Kelley (1960). Gradient theory of optimal flight paths. Ars Journal, 30(10), 947-954.
- Arthur E. Bryson (1961, April). A gradient method for optimizing multi-stage allocation processes. In Proceedings of the Harvard Univ. Symposium on digital computers and their applications.
- Paul Werbos (1974). Beyond regression: New tools for prediction and analysis in the behavioral sciences. PhD thesis, Harvard University.
- Rumelhart, David E.; Hinton, Geoffrey E.; Williams, Ronald J. (8 October 1986). "Learning representations by back-propagating errors". Nature. 323 (6088): 533–536.

Backprop: How could the magic fail?

- Only applicable in case of supervised learning
- Doesn't scale well to multiple layers (as they thought *at the time*)
- Can converge to poor local minima (as they thought *at the time*)

The third wave: Deep Learning

- everything starts with: Hinton, G. E., Osindero, S., & Teh, Y. W. (2006). A fast learning algorithm for deep belief nets. Neural computation, 18(7), 1527-1554.
- deep neural networks can be trained efficiently, if the weights are initialized intelligently
- return of backpropagation

The architectures en vogue now (CNN, RNN, LSTM...) have mostly been around since the 1980s/1990s.

So why the ~~hype~~ success *now*?

Big data

> It is true that some skill is required to get good performance from a deep learning algorithm. Fortunately, the amount of skill required reduces as the amount of training data increases. The learning algorithms reaching human performance on complex tasks today are nearly identical to the learning algorithms that struggled to solve toy problems in the 1980s [...].

Goodfellow et al. 2016, Deep Learning (http://www.deeplearningbook.org/)

Dataset size - rule of thumb

> As of 2016, a rough rule of thumb is that a supervised deep learning algorithm will generally achieve acceptable performance with around 5,000 labeled examples per category, and will match or exceed human performance when trained with a dataset containing at least 10 million labeled examples.

Goodfellow et al. 2016, Deep Learning (http://www.deeplearningbook.org/)

Big models

thanks to faster/better

- hardware (CPUs, GPUs)
- network infrastructure
- software implementations

> Since the introduction of hidden units, artificial neural networks have doubled in size roughly every 2.4 years.

Goodfellow et al. 2016, Deep Learning (http://www.deeplearningbook.org/)

Big impact

- deep networks consistently win prestigious competitions (e.g., ImageNet)
- deep learning solves increasingly complex problems (e.g., sequence-to-sequence learning)
- deep learning has started to fuel *other research areas*

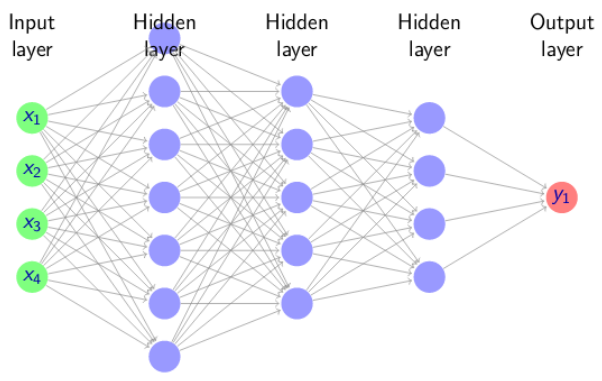
and most importantly: Deep learning is *highly profitable*

> Deep learning is now used by many top technology companies including Google, Microsoft, Facebook, IBM, Baidu, Apple, Adobe, Netflix, NVIDIA and NEC.

Goodfellow et al. 2016, Deep Learning (http://www.deeplearningbook.org/)

Deep Learning Architectures

Feedforward Deep Neural Network



Source: https://uwaterloo.ca/data-science/sites/ca.data-science/files/uploads/files/lecture_1_0.pdf (https://uwaterloo.ca/data-science/sites/ca.data-science/files/uploads/files/lecture_1_0.pdf)

Multi-layer Perceptron (MLP)

Caveat (terminology-related)

> So “multi-layer” neural networks do not use the perceptron learning procedure.
>
> They should never have been called multi-layer perceptrons.

Geoffrey Hinton, Neural Networks for Machine Learning Lec. 3 (http://www.cs.toronto.edu/~tijmen/csc321/slides/lecture_slides_lec3.pdf)

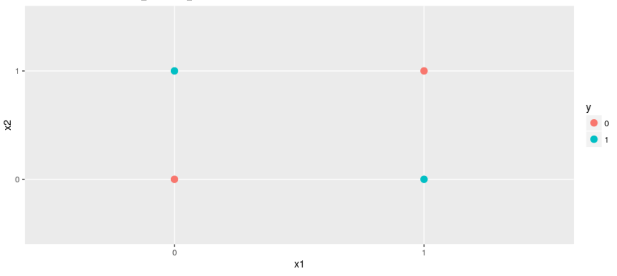
What people mean by MLP is just a deep feedforward neural network.

Why hidden layers?

Learning XOR

We want to predict

- 0 from [0,0]
- 0 from [1,1]
- 1 from [0,1]
- 1 from [1,0]

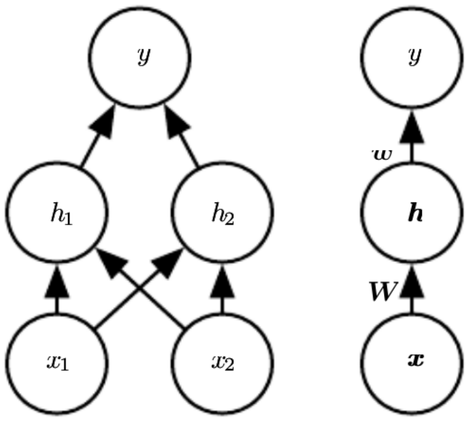


Trying a linear model

$f(\mathbf{x}; \mathbf{w}, b) = \mathbf{x}^T \mathbf{w} + b$

- with Mean Squared Error cost (MSE), this leads to: $\mathbf{w} = 0, b = 0.5$
- mapping every point to 0.5!

Introduce hidden layer



Source: Goodfellow et al. 2016, Deep Learning (http://www.deeplearningbook.org/)

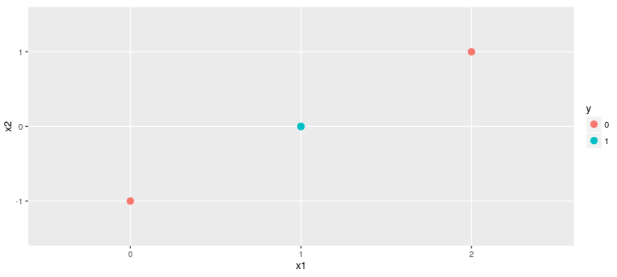
Calculation with hidden layer

$f(\mathbf{x}; \mathbf{W}, \mathbf{c}, \mathbf{w}, b) = \mathbf{w}^T(\mathbf{W}^T\mathbf{x} + \mathbf{c}) + b$

- Design matrix: $\mathbf{X} = \begin{bmatrix} 0 & 0 \\ 0 & 1 \\ 1 & 0 \\ 1 & 1 \end{bmatrix}$
- Parameters: $\mathbf{W} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$, $\mathbf{c} = \begin{bmatrix} 0 \\ -1 \end{bmatrix}$, $\mathbf{w} = \begin{bmatrix} 1 \\ -2 \end{bmatrix}$
- Input to hidden layer: $\mathbf{XW} = \begin{bmatrix} 0 & 0 \\ 1 & 1 \\ 1 & 1 \\ 2 & 2 \end{bmatrix}$, add $\mathbf{c}$ to every row ==>

$$\begin{bmatrix} 0 & -1 \\ 1 & 0 \\ 1 & 0 \\ 2 & 1 \end{bmatrix}$$

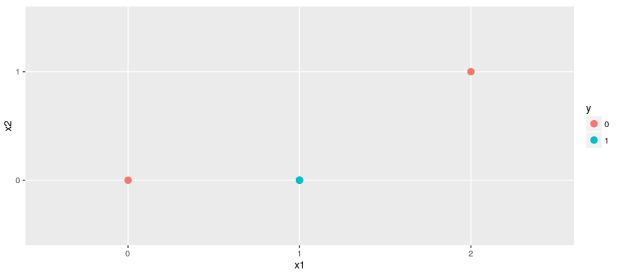
Which gives us...



Introducing nonlinearity

$f(\mathbf{x}; \mathbf{W}, \mathbf{c}, \mathbf{w}, b) = \mathbf{w}^T max(0, \mathbf{W}^T \mathbf{x} + \mathbf{c}) + b$

Output of rectified linear transformation: $\begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 1 & 0 \\ 2 & 1 \end{bmatrix}$

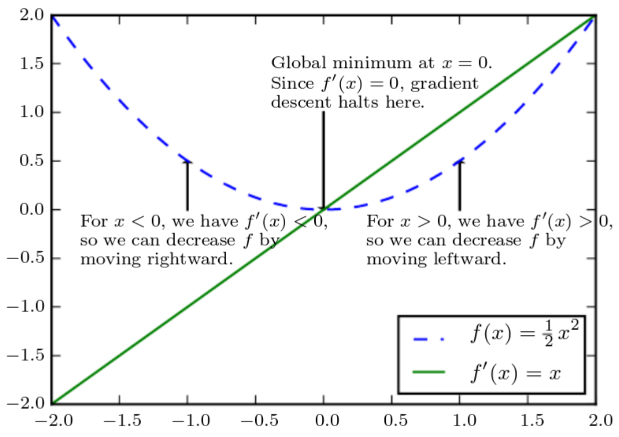


The remaining hidden-to-output transformation is linear, but the classes are already linearly separable.

How to train a deep network (1): Gradient Descent

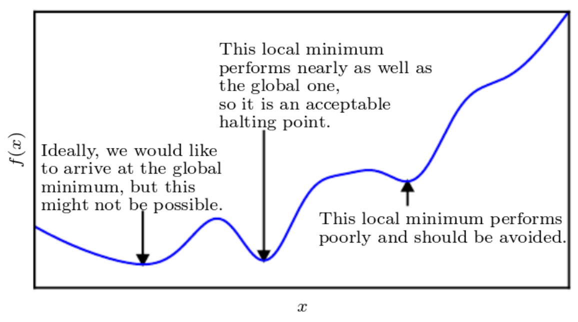
Optimization

- Like other machine learning algorithms, neural networks learn by *minimizing a cost function*.
- Cost functions in neural networks normally are not convex and so, cannot be optimized in closed form.
- The solution is to do gradient descent.



Source: Goodfellow et al. 2016, Deep Learning (http://www.deeplearningbook.org/)

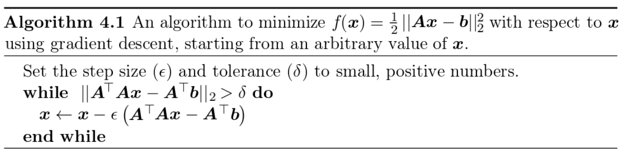
Local minima



Source: Goodfellow et al. 2016, Deep Learning (http://www.deeplearningbook.org/)

Closed-form vs. gradient descent optimization by example: Least Squares

- Minimize squared error $f(\mathbf{x}) = ||\mathbf{X}\hat{\beta} - \mathbf{y}||_2^2$
- Closed form: solve **normal equations** $\hat{\beta} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{y}$
- Alternatively, follow the gradient: $\nabla_x f(\mathbf{x}) = \mathbf{X}^T\mathbf{X}\hat{\beta} - \mathbf{X}^\mathbf{T}\mathbf{y}$



Algorithm 4.1 An algorithm to minimize $f(\boldsymbol{x}) = \frac{1}{2}||\boldsymbol{A}\boldsymbol{x} - \boldsymbol{b}||_2^2$ with respect to $\boldsymbol{x}$ using gradient descent, starting from an arbitrary value of $\boldsymbol{x}$.

```
Set the step size ($\epsilon$) and tolerance ($\delta$) to small, positive numbers.
while $||\boldsymbol{A}^\top\boldsymbol{A}\boldsymbol{x} - \boldsymbol{A}^\top\boldsymbol{b}||_2 > \delta$ do
  $\boldsymbol{x} \leftarrow \boldsymbol{x} - \epsilon\left(\boldsymbol{A}^\top\boldsymbol{A}\boldsymbol{x} - \boldsymbol{A}^\top\boldsymbol{b}\right)$
end while
```

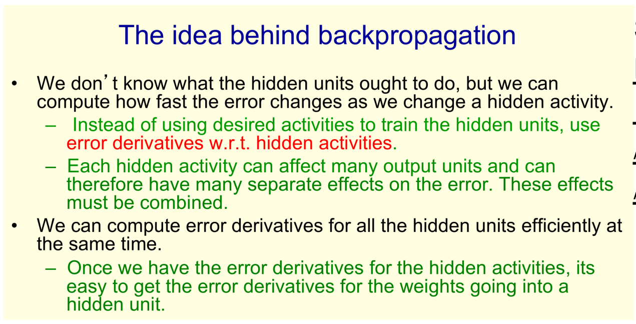
Source: Goodfellow et al. 2016, Deep Learning (http://www.deeplearningbook.org/)

This gives us a way to train one weight matrix.

How about a net with several layers?

How to train a deep network (2): Backpropagation

Who else to ask but Geoff Hinton...



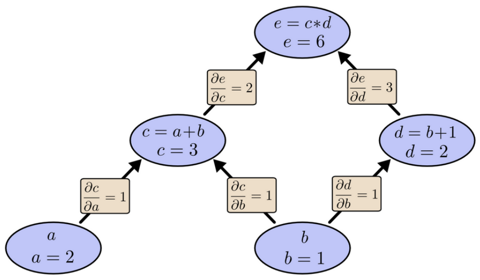
The idea behind backpropagation

- We don't know what the hidden units ought to do, but we can compute how fast the error changes as we change a hidden activity.
  - Instead of using desired activities to train the hidden units, use error derivatives w.r.t. hidden activities.
  - Each hidden activity can affect many output units and can therefore have many separate effects on the error. These effects must be combined.
- We can compute error derivatives for all the hidden units efficiently at the same time.
  - Once we have the error derivatives for the hidden activities, its easy to get the error derivatives for the weights going into a hidden unit.

Source: Geoffrey Hinton, Neural Networks for Machine Learning Lec. 3 (http://www.cs.toronto.edu/~tijmen/csc321/slides/lecture_slides_lec3.pdf)

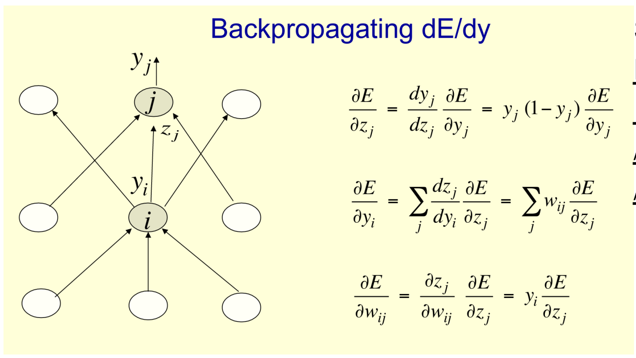
The mechanics of backprop

- basically, just the chain rule: $\frac{dz}{dx} = \frac{dz}{dy}\frac{dy}{dx}$
- chained over several layers:


$e = c*d$
$e = 6$
$\frac{\partial e}{\partial c} = 2$
$\frac{\partial e}{\partial d} = 3$
$c = a+b$
$c = 3$
$d = b+1$
$d = 2$
$\frac{\partial c}{\partial a} = 1$
$\frac{\partial c}{\partial b} = 1$
$\frac{\partial d}{\partial b} = 1$
a
$a = 2$
b
$b = 1$

Source: https://colah.github.io/posts/2015-08-Backprop/ (https://colah.github.io/posts/2015-08-Backprop/)

Backprop example: logistic neuron



Backpropagating dE/dy

$$\frac{\partial E}{\partial z_j} = \frac{dy_j}{dz_j}\frac{\partial E}{\partial y_j} = y_j(1-y_j)\frac{\partial E}{\partial y_j}$$

$$\frac{\partial E}{\partial y_i} = \sum_j \frac{dz_j}{dy_i}\frac{\partial E}{\partial z_j} = \sum_j w_{ij}\frac{\partial E}{\partial z_j}$$

$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial z_j}{\partial w_{ij}}\frac{\partial E}{\partial z_j} = y_i\frac{\partial E}{\partial z_j}$$

Source: Geoffrey Hinton, Neural Networks for Machine Learning Lec. 3 (http://www.cs.toronto.edu/~tijmen/csc321/slides/lecture_slides_lec3.pdf)

Decisions (1): Which loss function should I choose?

- the *loss* (or *cost*) function indicates the cost incurred from false prediction / misclassification
- probably the best-known loss function in machine learning is **mean squared error**:

$\frac{1}{n} \sum_n (\hat{y} - y)^2$

- most of the time, in deep learning we use **cross entropy**:

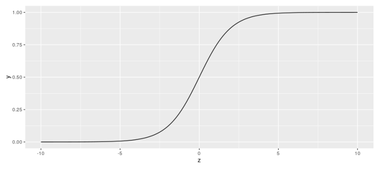
$- \sum_j t_j log(y_j)$

This is the negative log probability of the right answer.

Decisions (2): Which activation function to choose?

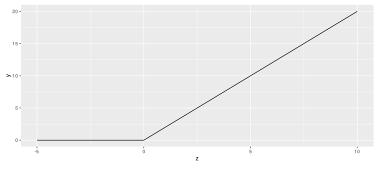
- purpose of activation function: introduce nonlinearity (see above)
- for a long time, the sigmoid (logistic) activation function was used a lot:

$y = \frac{1}{1+e^{-z}}$



- now *rectified linear units* (ReLUs) are preferred:

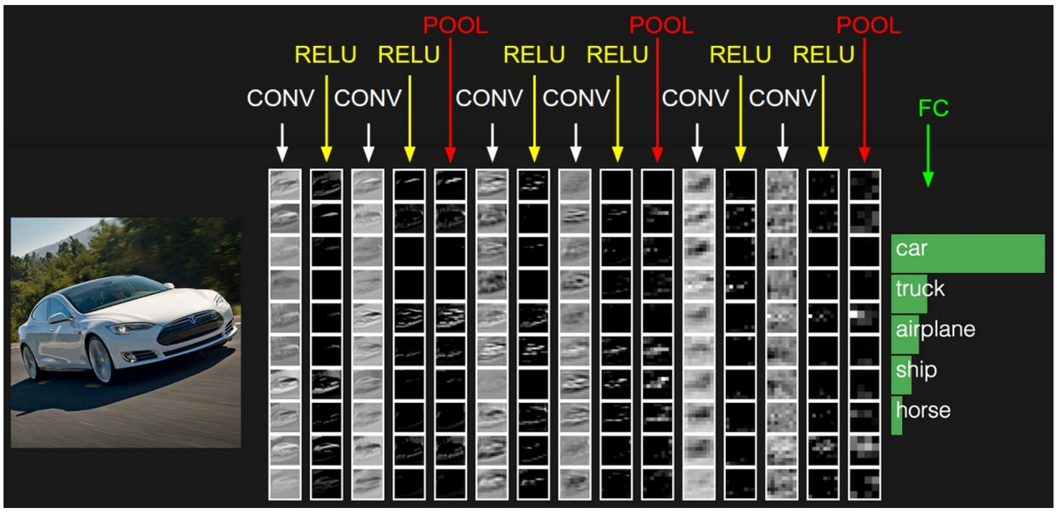
$y = max(0, z)$



Convolutional Neural Networks

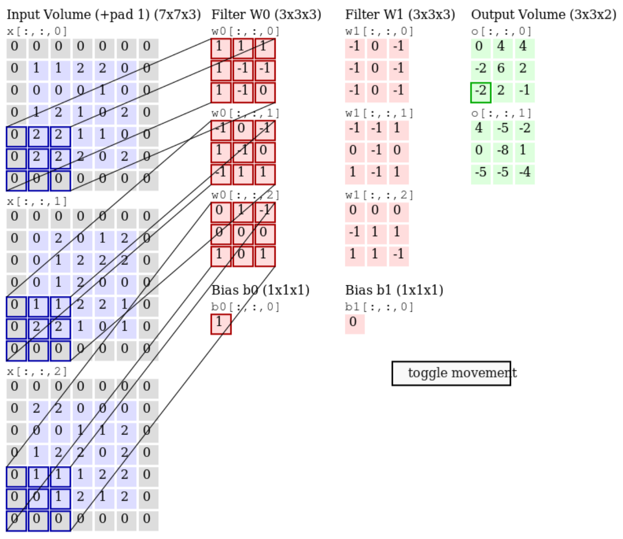
Why Conv Nets?

- conventional feedforward networks need equally sized input (images for example normally aren't!)
- convolution operation extracts image features



Source: http://cs231n.github.io/convolutional-networks/ (http://cs231n.github.io/convolutional-networks/)

The Convolution Operation



Source: http://cs231n.github.io/convolutional-networks/ (http://cs231n.github.io/convolutional-networks/) (Live Demo on website!)

Convolution and cross-correlation

- Strictly, the operation shown above (and implemented in most DL libraries) is not convolution, but cross-correlation
- 1-dimensional discrete convolution: $s(t) = (x * w)(t) = \sum_a x(a)w(t-a)$
- 2-dimensional convolution: $S(i,j) = I * K(i,j) = \sum_m \sum_n I(m,n)K(i-m,j-n)$
- 2-dimensional cross-correlation: $S(i,j) = I * K(i,j) = \sum_m \sum_n I(i+m,j+n)K(m,n)$

Octave demo

```
A = [1,2,3;4,5,6;7,8,9] # input "image"
# padded input matrix, for easier visualization
A_padded = [zeros(1,size(A,2)+2); [zeros(size(A,1),1)
, A, zeros(size(A,1),1)]; zeros(1,size(A,2)+2)]
B = [1,0;0,0] # kernel

# real convolution
C_full = conv2(A,B,'full') # default
C_same = conv2(A,B,'same')
C_valid = conv2(A,B,'valid')

# cross-correlation
XC = xcorr2(A,B)
```

Gimp demo

- Edge enhance: $\begin{bmatrix} 0 & 0 & 0 \\ -1 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$, edge detect: $\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$

- Blur: $\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$, sharpen: $\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$

see: https://docs.gimp.org/en/plug-in-convmatrix.html (https://docs.gimp.org/en/plug-in-convmatrix.html)

Language modeling and word vectors

Language modeling

- predict next word given preceding ones
- based on statistical properties of the distribution of sequences of words

Distributional hypothesis: linguistic items with similar distributions have similar meanings

- n-gram/count-based (e.g., Latent Semantic Analysis)
- predictive (neural network language models, e.g., word2vec)

ngram-based

- choose ngram-size n
- estimate the probability $P(w_{t+1}|w_1, \ldots, w_{t-2}, w_{t-1}, w_t)$ by ignoring context beyond n−1 words and dividing by the count of all given words up till w_t
- e.g., with bigrams: $P(w_{t+1}|w_t = \frac{count(w_{t+1}, w_t)}{count(w_t)})$

neural network example (Bengio et al 2001, Bengio et al 2003)

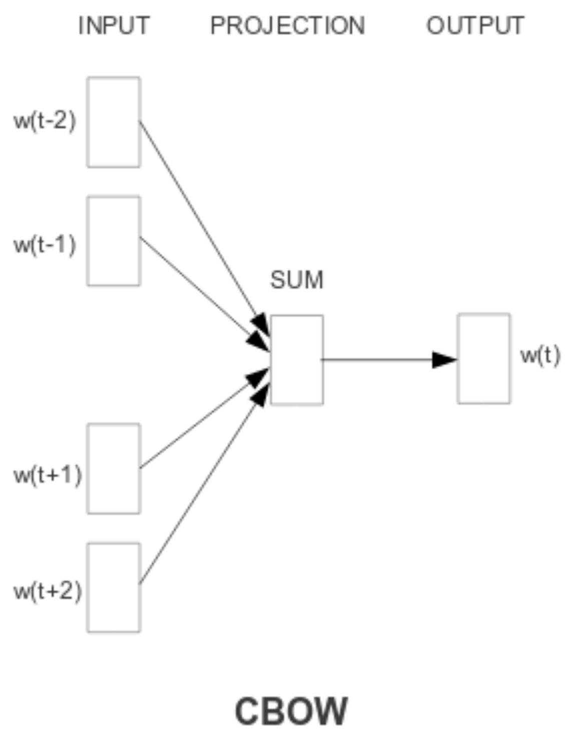
- choose a context size n, as in ngrams
- map each word w_{t-i} in the $n - 1$ - word context to an associated d-dimensional feature vector $C_{w_{t-i}}$
- predict next word using standard NN architecture with tanh (hidden layer) resp. softmax (output layer) activation functions
- train network to maximize log likelihood $L(\theta) = \sum_t logP(w_t|w_{t-n+1}, \ldots, w_{t-1})$ using stochastic gradient descent

Word embeddings: word2vec

Mikolov et al (2013a). Efficient estimation of word representations in vector space. arXiv:1301.3781.

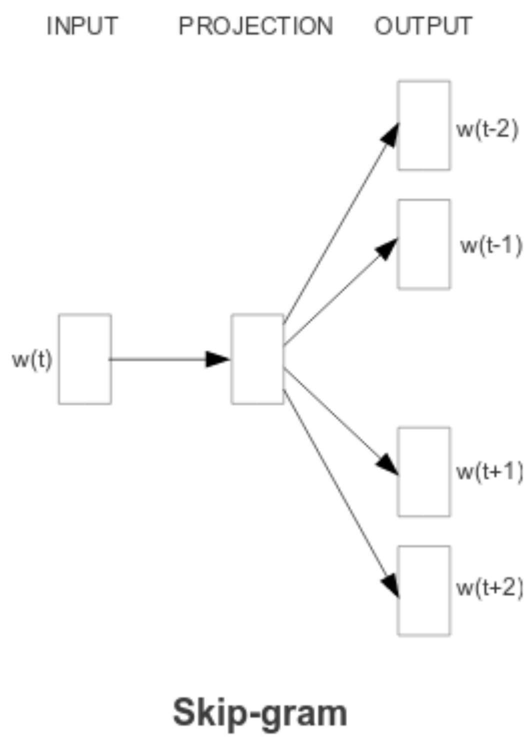
- Continuous Bag of Words (CBOW)
- Skip-Gram

Continuous Bag of Words



Source: Mikolov et al. 2013, Efficient estimation of word representations in vector space. arXiv:1301.3781.

Skip-gram



Source: Mikolov et al. 2013, Efficient estimation of word representations in vector space. arXiv:1301.3781.

Semantic & syntactic relationships

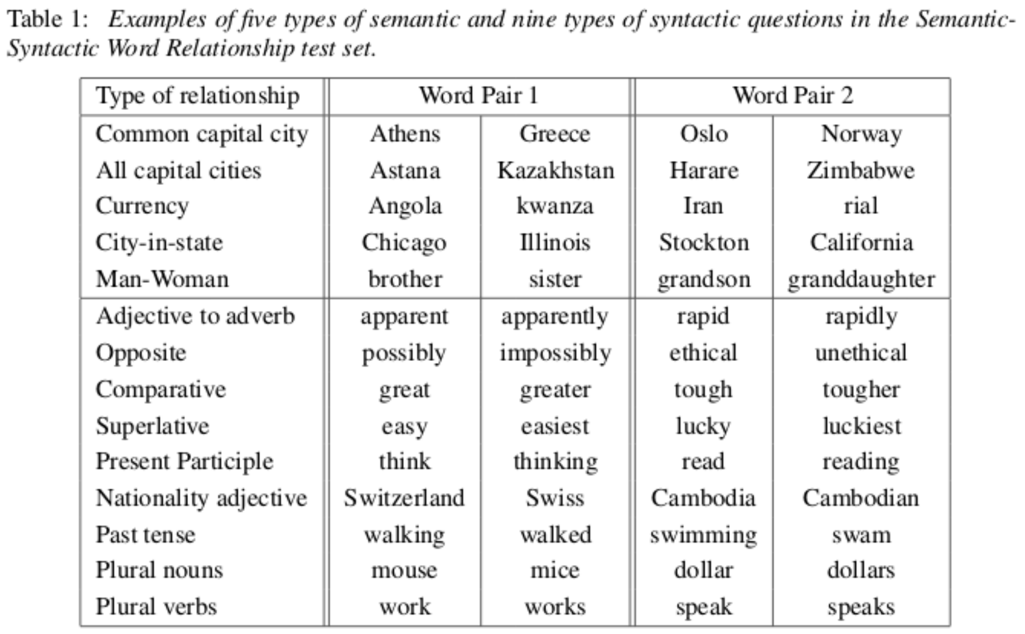
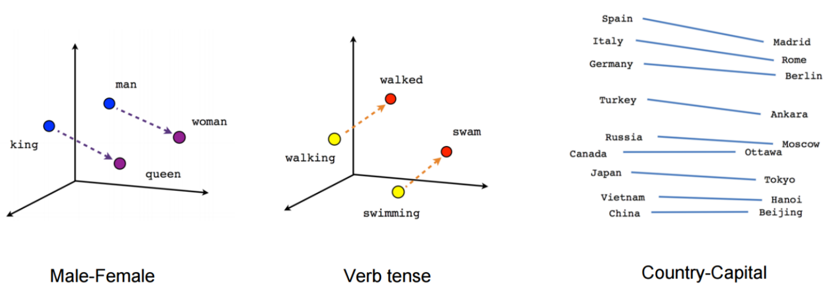


Table 1: *Examples of five types of semantic and nine types of syntactic questions in the Semantic-Syntactic Word Relationship test set.*

Type of relationship	Word Pair 1		Word Pair 2	
Common capital city	Athens	Greece	Oslo	Norway
All capital cities	Astana	Kazakhstan	Harare	Zimbabwe
Currency	Angola	kwanza	Iran	rial
City-in-state	Chicago	Illinois	Stockton	California
Man-Woman	brother	sister	grandson	granddaughter
Adjective to adverb	apparent	apparently	rapid	rapidly
Opposite	possibly	impossibly	ethical	unethical
Comparative	great	greater	tough	tougher
Superlative	easy	easiest	lucky	luckiest
Present Participle	think	thinking	read	reading
Nationality adjective	Switzerland	Swiss	Cambodia	Cambodian
Past tense	walking	walked	swimming	swam
Plural nouns	mouse	mice	dollar	dollars
Plural verbs	work	works	speak	speaks

Source: Mikolov et al. 2013, Efficient estimation of word representations in vector space. arXiv:1301.3781.

word2vec visualizations



Source: [https://www.tensorflow.org/versions/r0.11/tutorials/word2vec/index.html (https://www.tensorflow.org/versions/r0.11/tutorials/word2vec/index.html)]

Recurrent neural networks (RNNs)

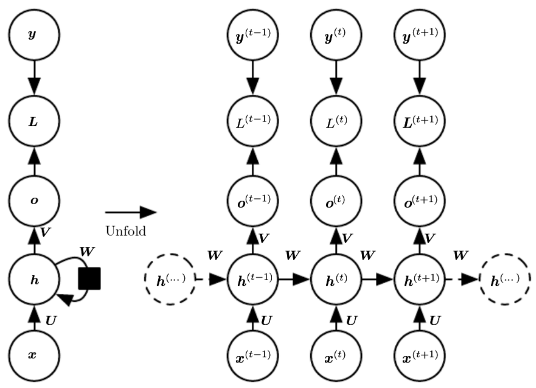
Why have recursion ?

- cannot process sequential data with "normal" feedforward networks
- in NLP, the n-gram approach cannot handle long-term relationships

> Jane walked into the room. John walked in too. It was late in the day, and everyone was walking home after a long day at work. Jane said hi to ___

(Stanford CS 224D Deep Learning for NLP Lecture Notes (http://cs224d.stanford.edu/lecture_notes/LectureNotes4.pdf))

Two representations of RNNs



Source: Goodfellow et al. 2016, Deep Learning (http://www.deeplearningbook.org/)

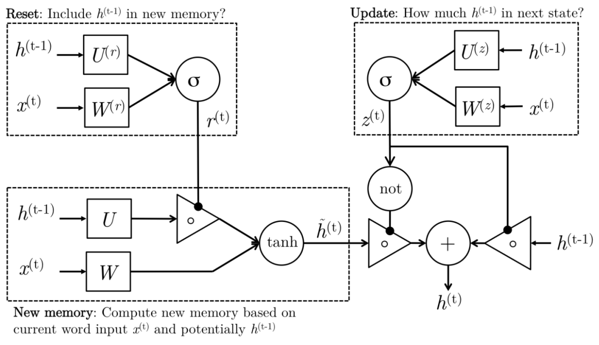
The recursion: example code

```
def rnn_cell(rnn_input, state):
    with tf.variable_scope('rnn_cell', reuse=True):
        W = tf.get_variable('W', [num_classes + state
_size, state_size])
        b = tf.get_variable('b', [state_size], initia
lizer=tf.constant_initializer(0.0))
    return tf.tanh(tf.matmul(tf.concat(1, [rnn_input,
 state]), W) + b)

state = init_state
rnn_outputs = []
for rnn_input in rnn_inputs:
    state = rnn_cell(rnn_input, state)
    rnn_outputs.append(state)
final_state = rnn_outputs[-1]
```

from: http://r2rt.com/recurrent-neural-networks-in-tensorflow-i.html (http://r2rt.com/recurrent-neural-networks-in-tensorflow-i.html)

RNNs in practice: The need to forget

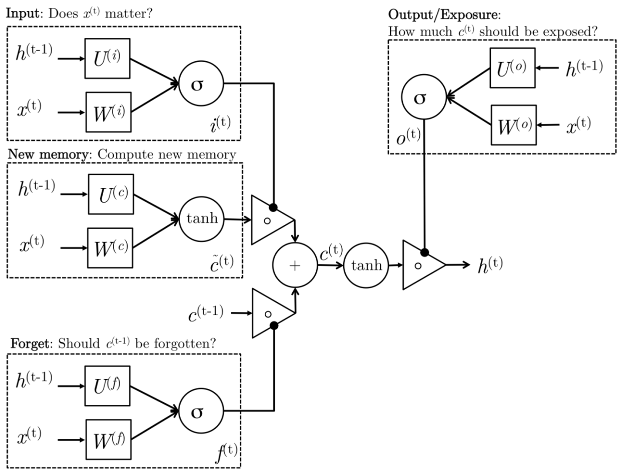
Gated Recurrent Units (GRUs)


Reset: Include $h^{(t-1)}$ in new memory?
$h^{(t-1)}$
$x^{(t)}$
$U^{(r)}$
$W^{(r)}$
σ
$r^{(t)}$
Update: How much $h^{(t-1)}$ in next state?
$U^{(z)}$
$W^{(z)}$
σ
$z^{(t)}$
not
$h^{(t-1)}$
$x^{(t)}$
U
W
tanh
$\tilde{h}^{(t)}$
+
$h^{(t)}$
New memory: Compute new memory based on current word input $x^{(t)}$ and potentially $h^{(t-1)}$

$$z^{(t)} = \sigma(W^{(z)}x^{(t)} + U^{(z)}h^{(t-1)}) \qquad \text{(Update gate)}$$
$$r^{(t)} = \sigma(W^{(r)}x^{(t)} + U^{(r)}h^{(t-1)}) \qquad \text{(Reset gate)}$$
$$\tilde{h}^{(t)} = \tanh(r^{(t)} \circ Uh^{(t-1)} + Wx^{(t)}) \qquad \text{(New memory)}$$
$$h^{(t)} = (1 - z^{(t)}) \circ \tilde{h}^{(t)} + z^{(t)} \circ h^{(t-1)} \qquad \text{(Hidden state)}$$

Source: Stanford CS 224D Deep Learning for NLP Lecture Notes (http://cs224d.stanford.edu/lecture_notes/LectureNotes4.pdf))

Long Short Term Memory (LSTM)



$$i^{(t)} = \sigma(W^{(i)}x^{(t)} + U^{(i)}h^{(t-1)}) \qquad \text{(Input gate)}$$
$$f^{(t)} = \sigma(W^{(f)}x^{(t)} + U^{(f)}h^{(t-1)}) \qquad \text{(Forget gate)}$$
$$o^{(t)} = \sigma(W^{(o)}x^{(t)} + U^{(o)}h^{(t-1)}) \qquad \text{(Output/Exposure gate)}$$
$$\tilde{c}^{(t)} = \tanh(W^{(c)}x^{(t)} + U^{(c)}h^{(t-1)}) \qquad \text{(New memory cell)}$$
$$c^{(t)} = f^{(t)} \circ \tilde{c}^{(t-1)} + i^{(t)} \circ \tilde{c}^{(t)} \qquad \text{(Final memory cell)}$$
$$h^{(t)} = o^{(t)} \circ \tanh(c^{(t)})$$

Source: Stanford CS 224D Deep Learning for NLP Lecture Notes (http://cs224d.stanford.edu/lecture_notes/LectureNotes4.pdf)

GRU vs. LSTM: code example (Tensorflow)

Baseline: Simple RNN Cell

```
class BasicRNNCell(RNNCell):
  """The most basic RNN cell."""

  def __init__(self, num_units, input_size=None, acti
vation=tanh):
    self._num_units = num_units
    self._activation = activation

  @property
  def state_size(self):
    return self._num_units

  def __call__(self, inputs, state, scope=None):
    """Most basic RNN: output = new_state = act(W * i
nput + U * state + B)."""
    with vs.variable_scope(scope or "basic_rnn_cell")
:
      output = self._activation(
          _linear([inputs, state], self._num_units, T
rue, scope=scope))
return output, output
```

GRU vs. LSTM: code example (Tensorflow)

GRU Cell

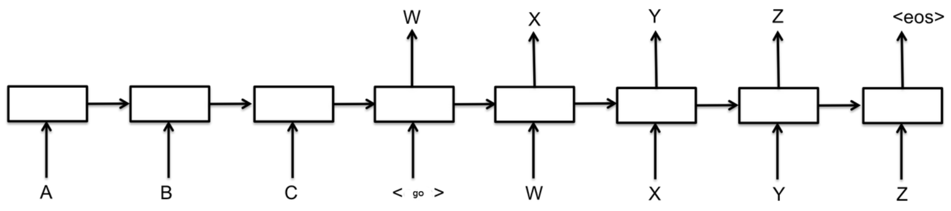
```
class GRUCell(RNNCell):
  """Gated Recurrent Unit cell (cf. http://arxiv.org/
abs/1406.1078)."""

  def __call__(self, inputs, state, scope=None):
    """Gated recurrent unit (GRU) with nunits cells."
""
    with vs.variable_scope(scope or "gru_cell"):
      with vs.variable_scope("gates"):  # Reset gate
and update gate.
        # We start with bias of 1.0 to not reset and
not update.
        r, u = array_ops.split(value=_linear([inputs,
 state],
                                             2 * self
._num_units,
                                             True,
                                             1.0,
                                             scope=sc
ope),
                              num_or_size_splits=2,
                              axis=1)
        r, u = sigmoid(r), sigmoid(u)

      with vs.variable_scope("candidate"):
        c = self._activation(_linear([inputs, r * sta
te],
                                    self._num_units,
                                    True, scope=scop
e))

      new_h = u * state + (1 - u) * c

return new_h, new_h
```

GRU vs. LSTM: code example (Tensorflow)

LSTM Cell

```
class BasicLSTMCell(RNNCell):

  def __call__(self, inputs, state, scope=None):
    with vs.variable_scope(scope or "basic_lstm_cell"
):

      c, h = array_ops.split(1, 2, state)
      concat = _linear([inputs, h], 4 * self._num_uni
ts, True, scope=scope)

      # i = input_gate, j = new_input, f = forget_gat
e, o = output_gate
      i, j, f, o = array_ops.split(1, 4, concat)

      new_c = (c * sigmoid(f + self._forget_bias) + s
igmoid(i) * self._activation(j))
      new_h = self._activation(new_c) * sigmoid(o)

      new_state = array_ops.concat_v2([new_c, new_h],
 1)
      return new_h, new_state
```

Mapping sequences to sequences: seq2seq

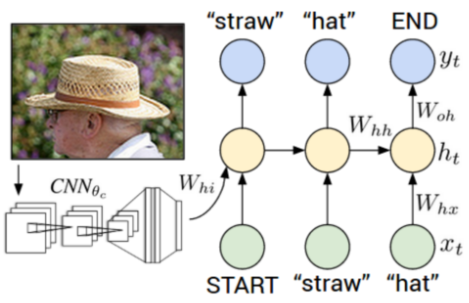


Source: Tensorflow seq2seq tutorial (https://www.tensorflow.org/versions/master/tutorials/seq2seq/index.html)

- first RNN encodes the input, second decodes the output
- applications: e.g., machine translation - though basically, all sequence-to-sequence translation!

Combining modes/models example: Images and Descriptions

- Andrej Karpathy, Li Fei-Fei: Deep Visual-Semantic Alignments for Generating Image Descriptions (http://cs.stanford.edu/people/karpathy/cvpr2015.pdf)
- combining CNNs, bidirectional RNNs, and multimodal embeddings
- Demo (http://cs.stanford.edu/people/karpathy/deepimagesent/rankingdemo/)

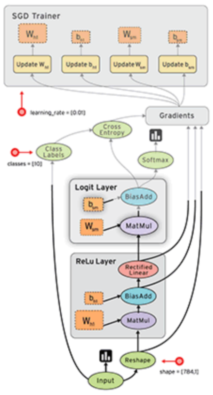


Source: Deep Visual-Semantic Alignments for Generating Image Descriptions (http://cs.stanford.edu/people/karpathy/cvpr2015.pdf)

Tensorflow Demo: Generating text

What is TensorFlow?

> "If you can express your computation as a data flow graph, you can use TensorFlow."



Source: www.tensorflow.org (https://www.tensorflow.org/)

- represent computations as graphs
- nodes are operations
- edges are *Tensors* (multidimensional matrices) input to/output from operations
- to make anything happen, execute the graph in a *Session*
- a *Session* places and runs a graph on a *Device* (GPU, CPU)

Basic TensorFlow workflow

demo (tf_workflow.ipynb)

Let's generate some text!

char-rnn demo

(based on https://github.com/sherjilozair/char-rnn-tensorflow (https://github.com/sherjilozair/char-rnn-tensorflow))

Questions? Thank you!