The Deep Learning Revolution

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Deep Learning Revolution

- Recent machine learning methods for training "deep" neural networks (NNs) have demonstrated remarkable progress on many challenging AI problems (e.g. speech recognition, visual object recognition, machine translation, game playing).
- However, their capabilities are prone to "hype."
- Deep learning has not "solved" AI and current methods have clear limitations.

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Very Brief History of Machine Learning

- Single-layer neural networks (1957-1969)
- Symbolic AI & knowledge engineering (1970-1985)
- Multi-layer NNs and symbolic learning (1985-1995)
- Statistical (Bayesian) learning and kernel methods (1995-2010)
- Deep learning (CNNs and RNNs) (2010-?)

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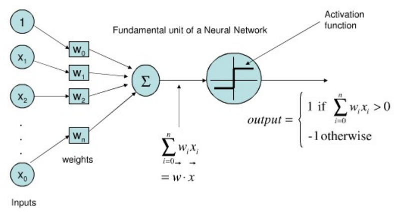
Single-Layer Neural Network
(Linear Threshold Unit)

- Mathematical model of an individual neuron.



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Perceptron

- Rosenblatt (1957) developed an iterative, hill-climbing algorithm for learning the weights of single-layer NN to try to fit a set of training examples.
- Unable to learn or represent many classification functions (e.g. XOR), only the "linearly separable" ones are learnable.

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Perceptron Learning Rule

- Update weights by:

$$w_i = w_i + \eta(t - o)x_i$$

where η is the "learning rate," *t* is the teacher output, and *o* is the network output.
- Equivalent to rules:
  – If output is correct do nothing.
  – If output is high, lower weights on active inputs
  – If output is low, increase weights on active inputs

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Perceptron Learning Algorithm

- Iteratively update weights until convergence.

Initialize weights to random values
Until outputs of all training examples are correct
    For each training pair, *E*, do:
        Compute current output *o* for *E* given its inputs
        Compare current output to target value, *t*, for *E*
        Update weights using learning rule

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Perceptron Demise

- *Perceptons* (1969) by Minksy and Papert illuminated the limitations of the perceptron.
- Work on neural-networks dissipated during the 70's and early 80's.

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Neural Net Resurgence (1986)

- Interest in NNs revived in the mid 1980's due to the rise of "connectionism."
- Backpropagation algorithm popularized for training three-layer NN's.
- Generalized the iterative "hill climbing" method to approximate fitting two layers of synaptic connections, but no convergence guarantees.

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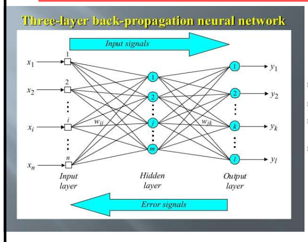
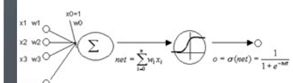
3-Layer NN Backpropagation





[The sigmoid threshold unit]

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Second NN Demise (1995-2010)

- Generic backpropagation did not generalize that well to training deeper networks.
- Little theoretical justification for underlying methods.
- Machine learning research moved to graphical models and kernel methods.

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Deep Learning Revolution (2010…)

- Improved methods developed for training deep neural works.
- Particular successes with:
  - Convolutional neural nets (CNNs) for vision.
  - Recurrent neural nets (RNNs) for machine translation and speech recognition.
  - Deep reinforcement learning for game playing.

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Massive Data and Specialized Hardware

- Large collections of supervised (crowdsourced) training data has been critical.
- Efficient processing of this big data using specialized hardware (Graphics Processing Units, GPUs) has been critical.

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CNNs

- Convolutional layers learn to extract local features from image regions (receptive fields) analogous to human vision (LeCun, et al., 1998).
- Deeper layers extract higher-level features.
- Pool activity of multiple neurons into one at the next layer using max or mean.
- Nonlinear processing with Rectified Linear Units (ReLUs)
- Decision made using final fully connected layers.

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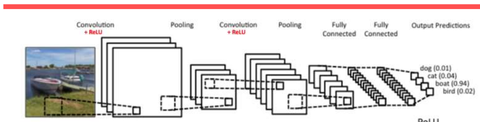
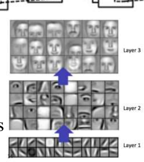
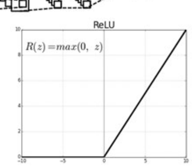
CNNs



Increasingly broader local features extracted from image regions





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ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

- Recognize 1,000 categories of objects in 150K test images (given 1.2M training images).

Mongoose

Canoe

Missile

Trombone

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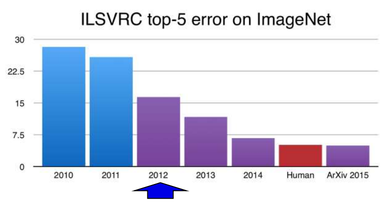
ImageNet Performance Over Time



CNNs introduced

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Recurrent Neural Networks (RNNs)

- Add feedback loops where some units' current outputs determine some future network inputs.
- RNNs can model dynamic finite-state machines, beyond the static combinatorial circuits modeled by feed-forward networks.

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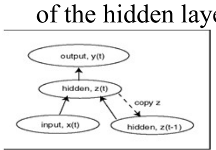
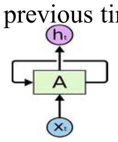
Simple Recurrent Network (SRN)

- Initially developed by Jeff Elman (“*Finding structure in time*,” 1990).
- Additional input to hidden layer is the state of the hidden layer in the previous time





http://colah.github.io/posts/2015-08-Understanding-LSTMs/ 19

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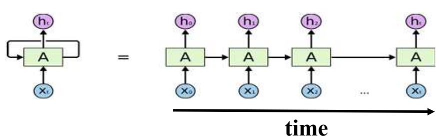
Unrolled RNN

- Behavior of RNN is perhaps best viewed by “unrolling” the network over time.



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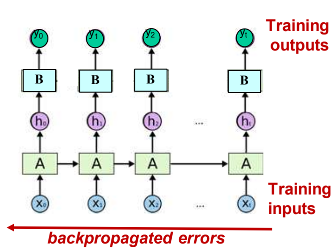
Training RNN’s

- RNNs can be trained using “backpropagation through time.”
- Can viewed as applying normal backprop to the unrolled network.



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Vanishing/Exploding Gradient Problem

- Backpropagated errors multiply at each layer, resulting in exponential decay (if derivative is small) or growth (if derivative is large).
- Makes it very difficult train deep networks, or simple recurrent networks over many time steps.

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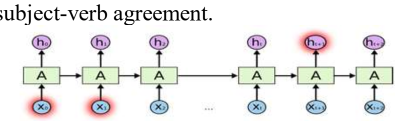
Long Distance Dependencies

- It is very difficult to train SRNs to retain information over many time steps.
- This make is very difficult to learn SRNs that handle long-distance dependencies, such as subject-verb agreement.



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Long Short Term Memory (LSTM)

- LSTM networks, add additional gating units in each memory cell (Hochreiter & Schmidhuber, 1997).
  - Forget gate
  - Input gate
  - Output gate
- Prevents vanishing/exploding gradient problem and allows network to retain state information over longer periods of time.

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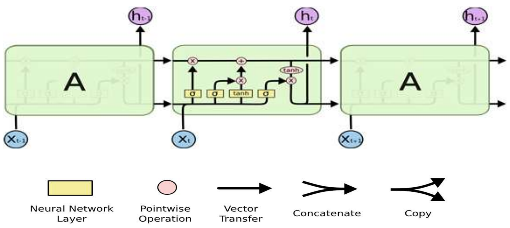
LSTM Network Architecture



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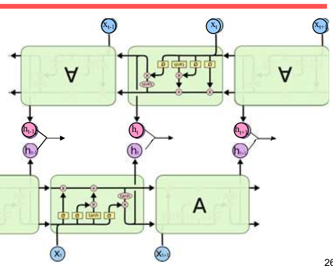
Bi-directional LSTM (Bi-LSTM)

- Separate LSTMs process sequence forward and backward and hidden layers at each time step are concatenated to form the cell output.



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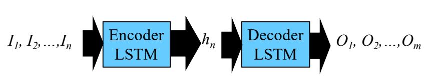
Sequence to Sequence (Seq2Seq) Transduction

- Encoder/Decoder framework maps one sequence to a "deep vector" then another LSTM maps this vector to an output sequence (Sutskever et al., 2014).



- Train model "end to end" on I/O pairs of sequences.

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Neural Machine Translation (NMT)

- LSTM Seq2Seq has lead to a new approach to translating human language.
- NMT modestly outperforms previous statistical learning approaches to MT (SMT).

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NMT Results (Wu et al., 2016)

- Experimental results using automated (BLEU) and human evaluation for English→ French translation.

Method	BLEU	Human Rating
SMT	37.0	3.87
NMT	40.35	4.46
Human		4.82

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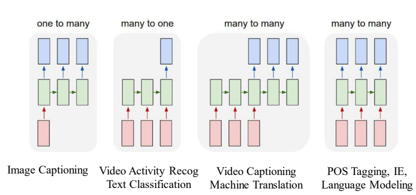
LSTM Application Architectures



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Independent Word Vectors

- Represent word meanings as vectors based on words with which they co-occur.
- Neural approaches based on predicting a word's context (skip-grams) from its vector (Word2Vec, Mikolov et al., 2013).
- Fails to account for lexical ambiguity or dependence of word meaning on context.

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Bidirectional Language Model

- A standard statistical language model predicts the probability of the next word based on the previous context.
  - Your program for Project 4 does not _____
- A bidirectional language model (BiLM) predicts the word at each position based on both prior and posterior context encoded using an RNN (e.g. LSTM).

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Contextualized Word Embeddings

- Produce a vector representation for a specific occurrence of a word, by using textual context to compute its meaning.
- ELMo (Embeddings from Language Models, Peters et al., 2018) uses the hidden state of a BiLM to compute contextualized word embeddings.

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Transformer Networks

- An alternate Seq2Seq neural architecture based on attention rather than recurrence (Vaswani et al., 2017).
- Attention mechanisms compute the output at each position in the sequence by varying “attention” across different positions in the input sequence.

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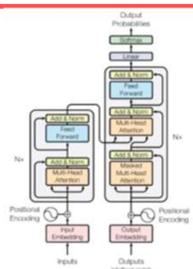
Transformer Architecture



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BERT Contextualized Embeddings

- Bidirectional Encoder Representations from Transformers (BERT, Devlin et al., 2018)
- Trains a transformer network to predict a fraction of “masked” tokens in an input sentence, or predict the next sentence.

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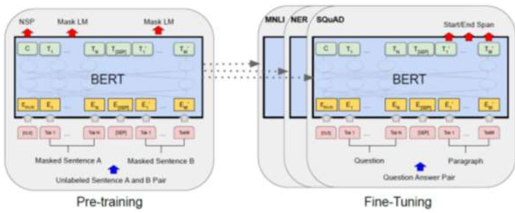
BERT Architecture



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Neural Information Retrieval

- Word embeddings have been used to improve IR by allowing matching words based on semantic similarity.
- Most recent results (Dai & Callan, SIGIR-2019) show improvements to ad-hoc document retrieval using BERT transformer approach.

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BERT IR Results

Table 2: Search accuracy on Robust04 and ClueWeb09-B. † indicates statistically significant improvements over Coor-Ascent by permutation test with p< 0.05.

	nDCG@20			
	Robust04		ClueWeb09-B	
Model	Title	Description	Title	Description
BOW	0.417	0.409	0.268	0.234
SDM	0.427	0.427	0.279	0.235
RankSVM	0.420	0.435	0.289	0.245
Coor-Ascent	0.427	0.441	**0.295**	0.251
DRMM	0.422	0.412	0.275	0.245
Conv-KNRM	0.416	0.406	0.270	0.242
BERT-FirstP	0.444†	0.491†	0.286	**0.272**†
BERT-MaxP	**0.469**†	**0.529**†	0.293	0.262†
BERT-SumP	0.467†	0.524†	0.289	0.261

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"Cramming" Meaning into Vectors

- DNNs force semantics to be encoded into real-valued vectors.
- Structured meaning representations that exploit trees, graphs, and logical representations are only imperfectly encoded as vectors.

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Complex Compositional Questions

"Has Woody Allen made more movies with Diane Keaton or Mia Farrow."

$$\underset{X \in \{DianeKeaton, MiaFarrow\}}{argmax} \; count(Y, Director(Y, WoodyAllen) \wedge Cast(Y, X))$$

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Conclusions

- Machine learning, and specifically neural nets, has a a long, rich, varied history.
- Deep learning has made significant recent progress.
- Progress is continuing and holds promise of enabling revolutionary technology.
- However, progress has been exaggerated and core AI problems are a long way from completely solved.

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