CS 474/574 Machine Learning
8. Deep Learning

Prof. Dr. Forrest Sheng Bao
Dept. of Computer Science
Iowa State University
Ames, IA, USA

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Images that were not created by the instructor but from the web are cited in the Markdown source code in the syntax:

```
![a web image](URL)
```

Deep learning (DL)

- Deep neural networks (DNNs): extensive amounts of layers.

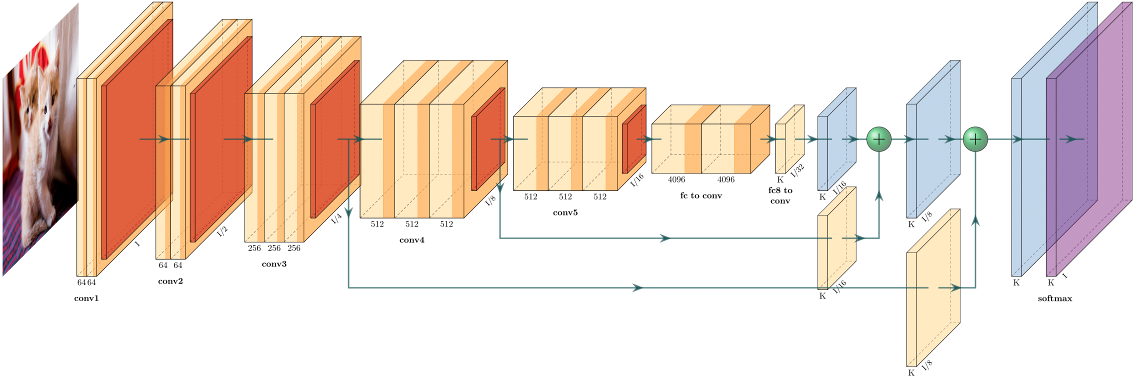

Figure 1: a web image

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- New techniques have been developed to speed up the training of DNNs and/or to avoid overfitting: dropout, batch normalization, stochastic pooling, etc. They are used for other DNNs as well.

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- Many DL tasks are end-to-end and hence are more black-box.

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- Using DL requires creative ways to prepare training data (e.g., negative sampling), not straightforward pairs of feature/input vectors and labels/output vectors).

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- Filters trained for a task can be reused or fine-tuned for another task. (**transfer learning**)

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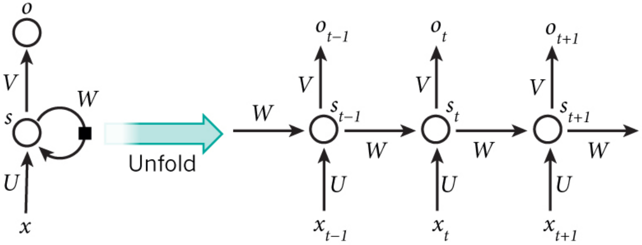

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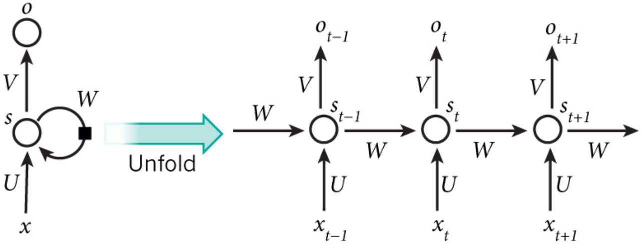

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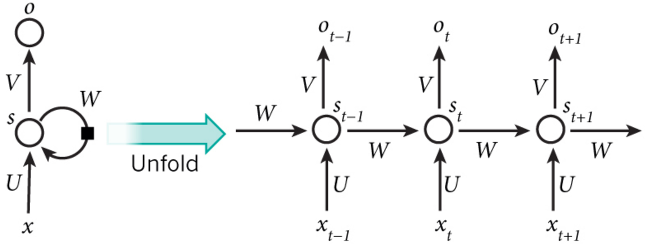

- Examples: Elman network 1 2, Hopfiled Network
- An RNN is just an IIR filter (are you also a EE major?):

$$y[n] = \sum_{l=1}^{N} a_l y[n-l] + \sum_{k=0}^{M} b_k x[n-k]$$

where $x[i]$ (or $y[i]$) is the i-th element (a scalar) in the input (or output) sequence.

LTSM and GRU networks: two special kind of RNNs

- Vanilla (basic, plain) RNNs are not good at modeling long-term dependencies which is especially common in text. E.g., in the sentence, “Unlike what he said, I did NOT eat the pizza”, “Unlike” and “not”, two words separated far, need to be jointly considered to infer whether the subject ate the pizza.

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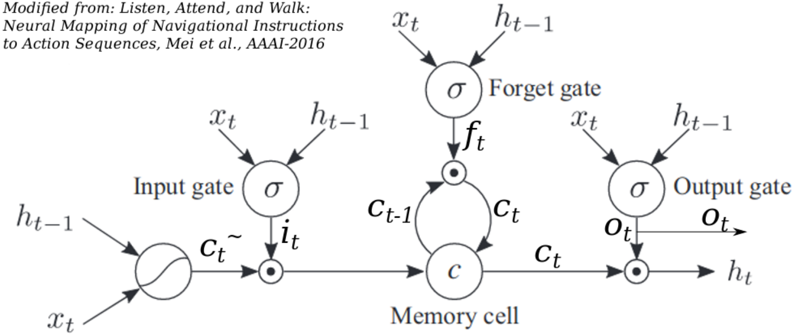
- Gated Recurrent Unit (GRU): simpler, just reset gate and update gate.

LSTM gates

An LSTM neuron is a **cell** or **unit**. Each LSTM cell has 3 **gates**: forget gate, input gate, and output gate. The 3 gates are all computed from current input $\mathbf{x}(t)$ and hidden state vector (NOT output) from previous time-step $\mathbf{h}(t-1)$, but with different transfer matrixes/weights.

Modified from: Listen, Attend, and Walk: Neural Mapping of Navigational Instructions to Action Sequences, Mei et al., AAAI-2016



$$f_t = \sigma_g(W_f x_t + U_f h_{t-1} + b_f)$$
$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i)$$
$$o_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o)$$
$$\tilde{c}_t = \sigma_c(W_c x_t + U_c h_{t-1} + b_c)$$
$$c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t$$
$$h_t = o_t \circ \sigma_h(c_t)$$

Note that the activation functions $\sigma_g, \sigma_c, \sigma_h$ may not all be the same. Usually σ_c and σ_h are $\tanh$ and gate activations are logistic.

Units vs. Layers

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- The term "cell" in literature is a unit. But in many ML frameworks, including Tensorflow, it could mean a layer of units.

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  - hidden/context layer: $\mathbf{s}(t) = f\left(\mathbb{X}\mathbf{x}(t)\right)$ where $\mathbb{X}$ is the matrix of weights from the input layer to hidden layer.

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  - hidden/context layer: $\mathbf{s}(t) = f(\mathbb{X}\mathbf{x}(t))$ where $\mathbb{X}$ is the matrix of weights from the input layer to hidden layer.
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- The new language model: $P(w_{t+1}|\mathbf{w}(t), \mathbf{s}(t-1))$, predicting the next output word given a short history $\mathbf{w}(t)$ up to current step t and the hidden layer up to previous step $t-1$.

Neural language models – additional reading

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- See also: https://www.tensorflow.org/api_docs/python/tf/keras/layers/Embedding

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- Although still supervised, the expected output is not manually provided but given from data automatically – semi-supervised.

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- Other applications: seizure prediction, speech recognition or synthesis, e.g., Boss Wang et al., 2017, Tacotron: Towards End-to-end Speech Synthesis

Autoencoders: representation learning

- Let's bring DL-based generation to another level: can we re-produce the input data from the output layer?

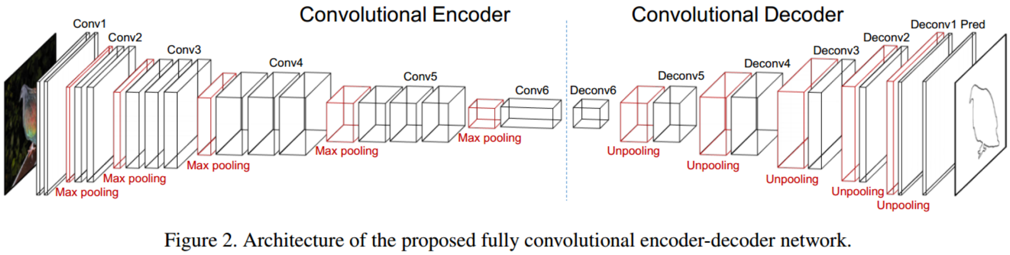

Figure 2: Object Contour Detection with a Fully Convolutional Encoder-Decoder Network, Yang et al., CVPR 2016

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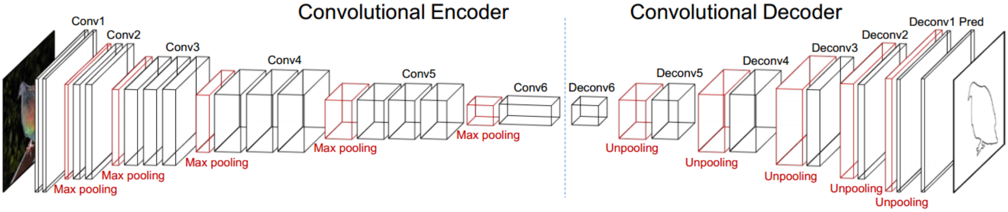

Figure 2. Architecture of the proposed fully convolutional encoder-decoder network.

Figure 2: Object Contour Detection with a Fully Convolutional Encoder-Decoder Network, Yang et al., CVPR 2016

- Applications: data compression. More applications: image deblurring. Lots of illegal things: courterfeit signatures/voices (don't worry, we will talk about how to catch them in GANs)

Generative adversarial networks (GANs)

- A GAN has two NNs: generator and discriminator/classifier. They push the limit of each other to find the essence of data.

See Google's tutorial

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- Multitask learning

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- Long et al., Conditional Adversarial Domain Adaptation, NIPS 2018

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