Recap: Long Short-Term Memory

- **LSTMs**
  - Inspired by the design of memory cells
  - Each module has 4 layers, interacting in a special way.

Recap: Elements of LSTMs

- **Forget gate layer**
  - Look at $h_{t-1}$ and $x_t$ and output a number between 0 and 1 for each dimension in the cell state $C_{t-1}$.
  - 0: completely delete this, 1: completely keep this.

- **Update gate layer**
  - Decide what information to store in the cell state.
  - Sigmoid network (input gate layer) decides which values are updated.
  - tanh layer creates a vector of new candidate values that could be added to the state.

Recap: Gated Recurrent Units (GRU)

- **Simpler model than LSTM**
  - Combines the forget and input gates into a single update gate $z_t$.
  - Similar definition for a reset gate $r_t$, but with different weights.
  - In both cases, merge the cell state and hidden state.

- **Empirical results**
  - Both LSTM and GRU can learn much longer-term dependencies than regular RNNs.
  - GRU performance similar to LSTM (no clear winner yet), but fewer parameters.
Currently Hot Research Directions

- Generative Models
  - Networks for image generation
  - Generative Adversarial Networks (GAN)
- Towards General Models of Computation
  - Memory Networks
  - Neural Turing Machines
- Deep Reinforcement Learning

Generative Networks

- Using a network to generate images
  - Sampling from noise distribution
  - Sequence of upsampling layers to generate an output image
  - How can we train such a model to produce the desired output?

Generative Adversarial Networks (GAN)

- Conceptual view
  - Main idea
    - Simultaneously train an image generator and a discriminator.
    - Interpreted as a two-player game
    - Very tricky to train...

Memory Networks

- Soft, differentiable memory
  - Stores <key, value> pairs
  - Input is matched to the stored keys
  - Output is the average over all values that correspond to the matched keys

- Key Idea
  - Make all steps differentiable.
  - Then all parameters (including access keys, stored values, etc.) can be learned with end-to-end supervised learning.

End-to-End Memory Networks

- A closer look at the memory mechanism
  - Rely on sparsity of softmax to select a unique output value.
  - \[ a = \sum p_i c_i \]
  - \[ p_i = \text{softmax}(a \cdot m_i) \]

Memory Networks

- Problem with this design
  - Softmax used for the selection involves a normalization over all stored keys.
  - Memory cells that are not accessed get almost zero gradient.
  - When a backpropagation step causes the accessed memory cell to change, this massively affects the gradient flow.

  ⇒ Together, this results in bad gradient propagation during learning.
  ⇒ Very finicky behavior...

Improved Design

- Gated memory (e.g., Recurrent Entity Network)

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Neural Turing Machines

- Goal: Enable general computation with Neural Nets
  - Again key is to make all operations differentiable.
  - Memory + Access operators + Controller
  - Learn entire algorithms from examples.

A. Graves, G. Wayne, I. Danihelka, Neural Turing Machines, arXiv 1410.5401, 2014

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Deep Reinforcement Learning

- Example application: Learning to play Atari games


Idea Behind the Model

- Interpretation
  - Assume finite number of actions
  - Each number here is a real-valued quantity that represents the Q function in Reinforcement Learning

- Collect experience dataset:
  - Set of tuples \((s, a, s', r, \ldots)\)
  - (State, Action taken, New state, Reward received)

- L2 Regression Loss

\[
L_2(\theta) = \sum_{(s,a,r,s')} (Q(s,a; \theta) - target) \rightarrow \text{minimize}
\]

Current reward + estimate of future reward, discounted by \( \gamma \)

Slide credit: Andrej Karpathy
Results: Space Invaders

Comparison with Human Performance

Learned Representation

Success Story: Alpha Go

References and Further Reading

• Generative Adversarial Networks (GANs)
References and Further Reading

• Memory Networks

• Neural Turing Machines

References and Further Reading

• DQN paper
  - [www.nature.com/articles/nature14236](http://www.nature.com/articles/nature14236)

• AlphaGo paper
  - [www.nature.com/articles/nature16961](http://www.nature.com/articles/nature16961)