Recursive Neural Networks

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Topics

- Sequence Modeling: Recurrent and Recursive Nets

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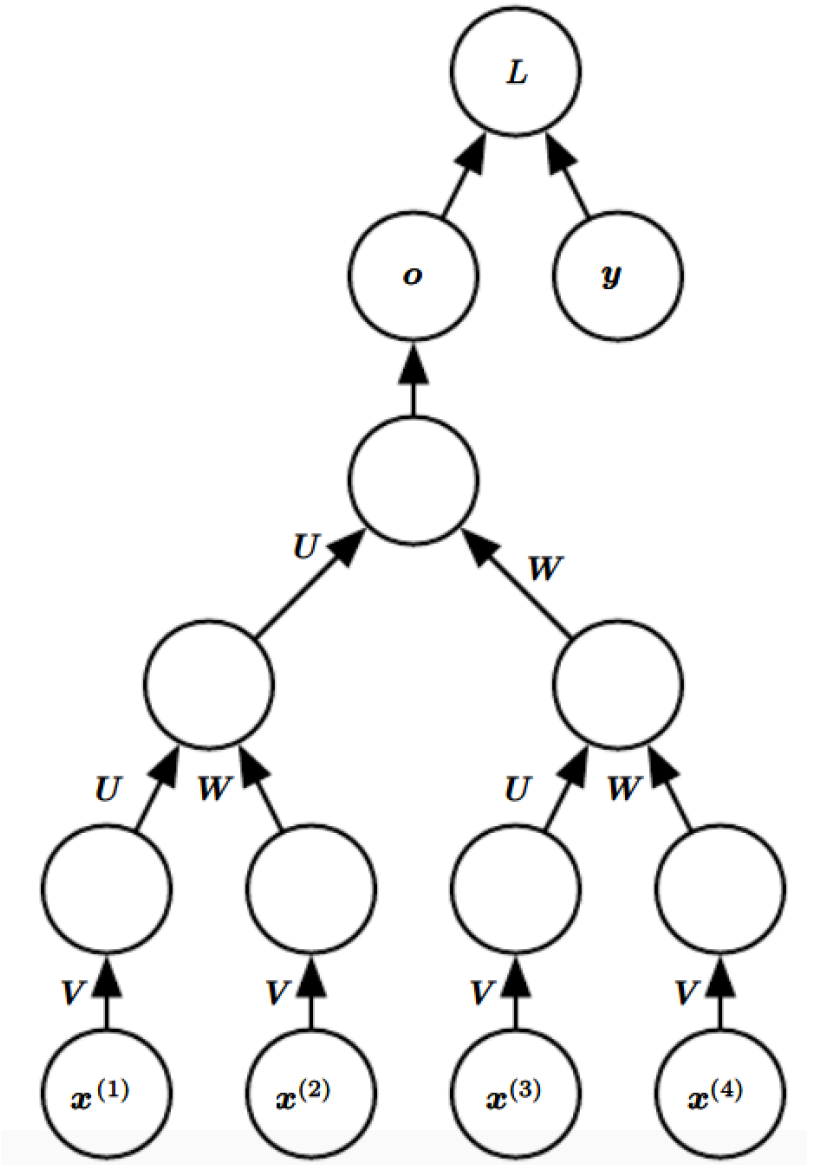
Recursive Neural Networks

- They are yet another generalization of recurrent networks with a different kind of computational graph
- It is structured as a deep tree, rather than the chain structure of RNNs
- The typical computational graph for a recursive network is shown next

Computational graph of a Recursive Network

- It generalizes a recurrent network from a chain to a tree
- A variable sequence $\boldsymbol{x}^{(1)},\boldsymbol{x}^{(2)},,\boldsymbol{x}^{(t)}$ can be mapped to a fixed size representation (the output $\boldsymbol{o}$), with a fixed set of parameters (the weight matrices U, V, W)
- Figure illustrates supervised learning case in which target $\boldsymbol{y}$ is provided that is associated with the whole sequence



Advantage of Recursive over Recurrent Nets

- For a sequence of the same length τ, the depth (measured as the no. of compositions of nonlinear operations) can be reduced from τ to $O(\log \tau)$, which might help deal with long-term dependencies
- An open question is how best to structure the tree

Need for Recursive nets in NLP

- Deep learning based methods learn low-dimensional, real-valued vectors for word tokens, mostly from a large data corpus, successfully capturing syntactic and semantic aspects of text
- For tasks where the inputs are larger text units, e.g., phrases, sentences or documents, a compositional model is first needed to aggregate tokens into a vector with fixed dimensionality that can be used for other NLP tasks
- Models for achieving this fall into two categories: recurrent models and recursive models

Recurrent Model for NLP

- Recurrent models deal successfully with time series data
- The recurrent models generally consider no linguistic structure aside from the word order
- They were applied early on to NLP by modeling a sentence as tokens processed sequentially and at each step combining the current token with previously built embeddings
- Recurrent models can be extended to bidirectional ones from both left to right and right to left
- These models consider no linguistic structure aside from word order

Recursive Models for NLP

- Recursive neural models (also referred to as tree models) by contrast are structured by syntactic parse trees
- Instead of considering tokens sequentially, recursive models combine neighbors based on the recursive structure of parse trees, starting from the leaves and proceeding recursively in a bottom-up fashion until the root of the parse tree is reached
  - Ex: for the phrase the food is delicious, following the operation sequence ((the food) (is delicious)) rather than the sequential order (((the food) is) delicious)

Advantage of Recursive Model for NLP

- They have the potential of capturing long-distance dependencies
- Two tokens may be structurally closer to each other even though they are far away in word sequence
- Ex: a verb and its corresponding direct object can be far away in terms of tokens if many adjectives lie inbetween, but they are adjacent in the parse tree
- However parsing is slow and domain dependent
- See performance comparison with LSTM on four NLP tasks at https://nlp.stanford.edu/pubemnlp2015_2_jiwei.pdf

Structure of the Tree

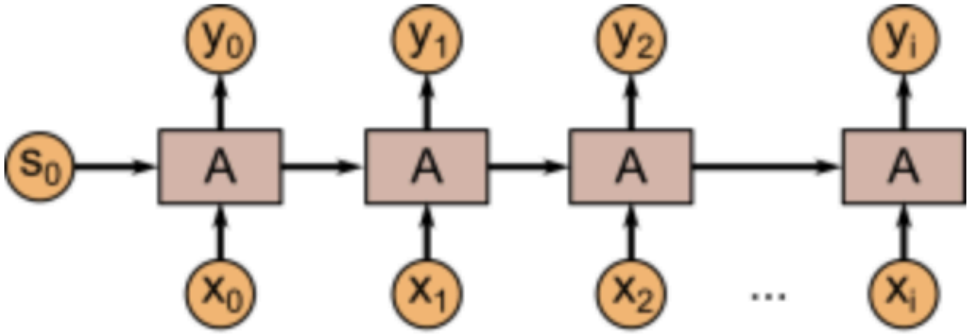
- One option is to have a tree structure that does not depend on the data, such as a balanced binary tree
- In some application domains, external methods can suggest the appropriate tree structure
  - Ex: when processing natural language sentences, the tree structure for the recursive network can be fixed to the structure of the parse tree of the sentence provided by a natural language parse
- Ideally, one would like the learner itself to discover and infer the tree structure that is appropriate for any given input

Variants of Recursive Net idea

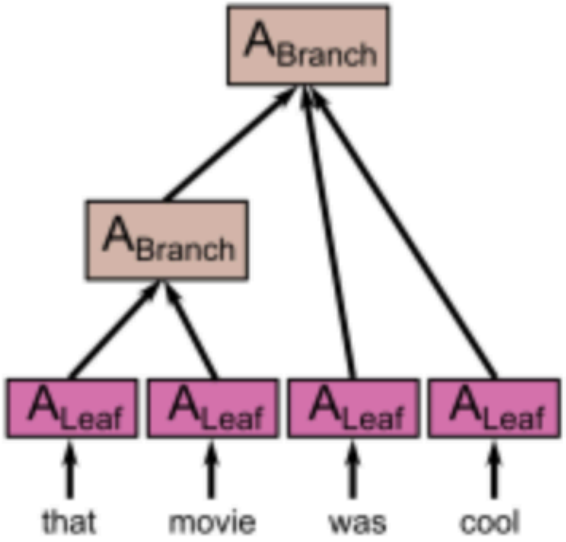
- Associate data with a tree structure and associate inputs and targets with individual nodes of the tree
  - The computation performed for each node does not have to be the artificial neuron computation (affine transformation of all inputs followed by a monotone nonlinearity)
  - Can use a tensor operations of bilinear forms
    - Previously found useful to model linear relationships between concepts when the concepts are represented by continuous vectors

Recursive Neural Networks

- Recursive neural networks are also called Tree Nets
  - Useful for learning tree-like structures
  - They are highly useful for parsing natural scenes and language



Recurrent Neural Net



Recursive Neural Net

Unrolling Recurrent and Tree Nets

- In RNNs, at each time step the network takes as input its previous state $\mathrm{s}^{(t-1)}$ and its current input $\mathrm{x}^{(t)}$ and produces an output $\mathrm{y}^{(t)}$ and a new hidden state $\mathrm{s}^{(t)}$.
- TreeNets, on the other hand, don't have a simple linear structure like that.
- With RNNs, you can 'unroll' the net and think of it as a large feedforward net with inputs $\mathrm{x}^{(0)}$, $\mathrm{x}^{(1)}$, …, $\mathrm{x}^{(T)}$, initial state $\mathrm{s}^{(0)}$, and outputs $\mathrm{y}^{(0)}$,$\mathrm{y}^{(1)}$,…,$\mathrm{y}^{(T)}$, with T varying depending on the input data stream, and the weights in each of the cells tied with each other.
- You can also think of TreeNets by unrolling them – the weights in each branch node are tied with each other, and the weights in each leaf node are tied with each other.

Advantage of Recursive Nets

- The advantage of Recursive Nets is that they can be very powerful in learning hierarchical, tree-like structure.
- The disadvantages are, firstly, that the tree structure of every input sample must be known at training time.