An introduction to Deep Learning for NLP

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Outline

Deep Learning Era

What?

- Many layers of non-linear units for feature extraction and transformation
- Lower level to higher level features form hierarchy of concepts

Why now?

- Large data available
- Computational resources (CPUs and GPUs)

Most used models:

- Convolutional Neural Network (CNNs)
- Long Short Term Memory network-LSTM (variant of RNN)
- Gated Recurrent Unit (GRU)

Sparse vs. dense feature representations

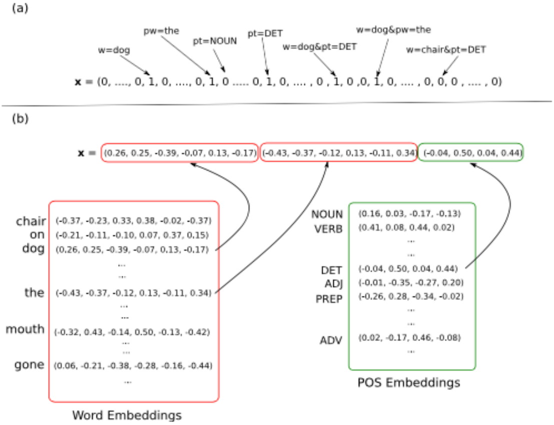


Figure: Two encodings of the information: current word is “dog”; previous word is “the”; previous pos-tag is “DET”. (a) Sparse feature vector. (b) Dense, embeddings-based feature vector.

What to use?

One Hot: Each feature is its own dimension.

- Dimensionality of one-hot vector is same as number of distinct features.
- Features are completely independent from one another.
  Example: "word is 'dog' " is as dis-similar to "word is 'thinking' " than it is to "word is 'cat' ".

Dense: Each feature is a d-dimensional vector.

- Model training will cause similar features to have similar vectors - information is shared between similar features

Benefits of dense and low-dimensional vectors

- Computational efficient
- Generalization power
- Collobert & Weston, 2008; Collobert et al. 2011; Chen & Manning, 2014 ... advocate the use of dense, trainable embedding vectors for all features.

Word Embeddings

Initialization:

- word2vec: initialize the word vectors to uniformly sampled random numbers in the range $[-\frac{1}{2d}, \frac{1}{2d}]$ where d is the number of dimensions.
- xavier initialization: $[-\frac{\sqrt{6}}{\sqrt{d}}, \frac{\sqrt{6}}{\sqrt{d}}]$

Problems:

- Word similarity is hard to define and is usually very task-dependent

Missing words in pre-trained vectors?

- Retrain with training data
- Find synonyms?
- Open research problem...

Convolutional Neural Networks

Definition

Multiple-layer feedforward neural networks where each neuron in a layer receives input from a neighborhood of the neurons in the previous layer. (Lecun, 1998)

From Computer Vision to NLP: 2d grid $\rightarrow$ 1d sequence

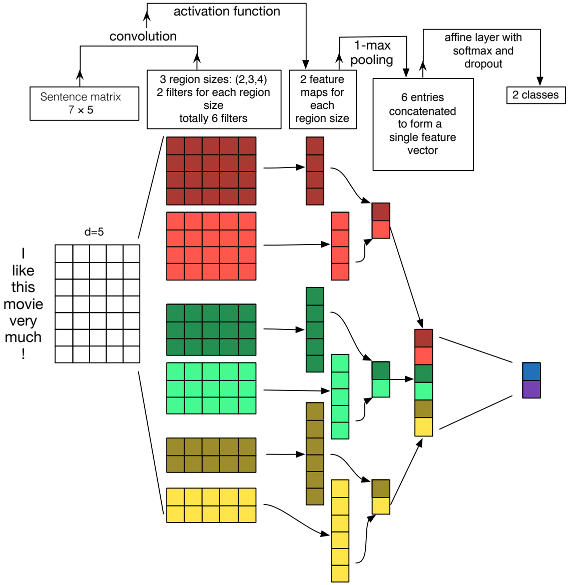
Properties

- Compositionality: learn complex features starting from small regions $\hookrightarrow$ higher-order features (n-grams) can be constructed from basic unigrams
- Local invariance: detect an object regardless the position in image $\hookrightarrow$ ordering is crucial locally and not globally

Convolutional Neural Networks (2)

- A sequence of words $x = x_1, ..., x_n$, each with their corresponding d_{emb} dimensional word embedding $v(x_i)$
- 1d convolution layer of width k works by moving a sliding window of size k over the sentence, and applying the same "filter" to each window in the sequence $[v(x_i); v(x_{i+1}); ...; v(x_{i+k-1})]$
- Depending on whether we pad the sentence with $k-1$ words to each side, we may get either $m = n - k + 1$ (narrow convolution) or $m = n + k + 1$ windows (wide convolution)
- Result of the convolution layer is m vectors $p_1, ..., p_m \in \mathbb{R}^{d_{conv}}$: $p_i = g(w_i W + b)$ where g is a non-linear activation function that is applied element-wise, $W \in \mathbb{R}^{k d_{emb} \times d_{conv}}$ and $b \in \mathbb{R}^{d_{conv}}$ are parameters of the network.

CNN for sentence classification (Zhang and Wallace, 2015)



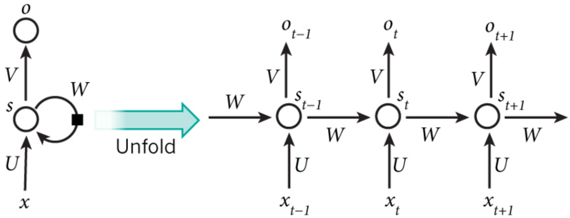
Recurrent Neural Networks

- CNNs are limited to local patterns
- RNNs were specifically developed to be used with sequences
- The task of *language modeling* consists in learning the probability of observing the next word in a sentence given the $n-1$ preceding words, that is $P[w_n|w_1, ..., w_{n-1}]$.
- At given time step: $s_t = f(U_{x_t} + W_{s_{t-1}})$

Example

If the sequence is a sentence of 5 words, the network would be unrolled into a 5-layer neural network, one layer for each word.

RNN Architecture



- x_t is the input at time step t. For example, x_1 could be a one-hot vector corresponding to the second word of a sentence.
- s_t is the hidden state at time step t (memory). s_t is calculated based on the previous hidden state and the input at the current step: $s_t = f(U_{x_t} + W_{s_{t-1}})$. f is usually a nonlinearity(tanh or ReLU). s_{-1}, which is required to calculate the first hidden state, is typically initialized to all zeroes.
- o_t is the output at step t. I.e. if we wanted to predict the next word in a sentence it would be a vector of probabilities across our vocabulary. $o_t = \text{softmax}(V_{s_t})$.

Long Short Term Memory Networks

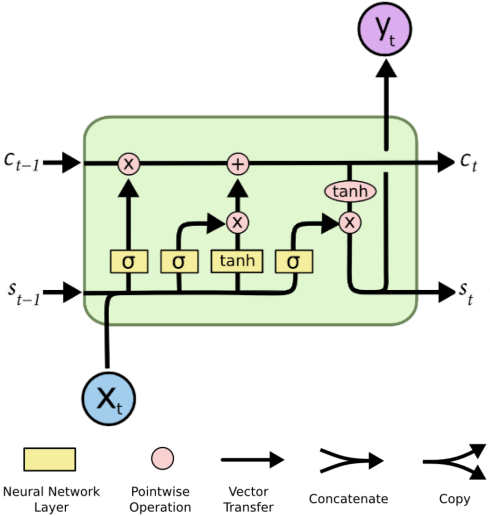
Hochreiter & Schmidhuber (1997)

LSTM is explicitly designed to avoid the long-term dependency problem.

Properties

- Chain like structure
- Instead of having a single neural network layer, there are four
- Remove or add information to the cell state, carefully regulated by structures called gates
- Three sigmoid gates, to protect and control the cell state

LSTM architecture



(1) forget gate layer: $f_t = \sigma(U_f x_t + W_f s_{t-1})$

(2) input gate layer: $i_t = \sigma(U_i x_t + W_i s_{t-1})$

(3) candidate values computation layer: $\tilde{c}_t = \tanh(U_c x_t + W_c s_{t-1})$

(4) $c_t = f_t \times C_{t-1} + i_t \times \tilde{c}_t$

(5) output gate layer: $o_t = \sigma(U_o x_t + W_o s_{t-1})$

(6) $y_t = o_t \times \text{tanh}(C_t)$

Optimization Issues

$$\mathbb{E}_{x,y\sim\hat{p}_{data(x,y)}}[L(f(x;\theta),y)] = \frac{1}{m}\sum_{i=1}^{m} L(f(x^{(i)};\theta),y^{(i)})$$

Learning $\neq$ Pure optimization

- Performance measure P, that is defined with respect to the test set
- May also be intractable
- Reduce a different cost function $J(\theta)$ hoping it will improve P

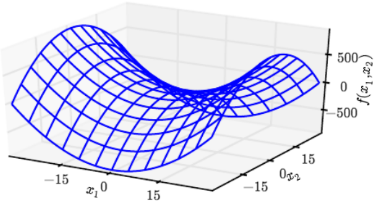
Properties

- Usually **non-convex**
- Any deep model is essentially guaranteed to have an extremely large number of local minima
- Model identifiability: a sufficiently large training set can rule out all but one setting of parameters $\rightarrow$ weight space symmetry
- Local minima is a good approximation to global minima

More Optimization

Issues

- All of these local minima arising from non-identifiability are equivalent to each other in cost value → not a problematic form of non-convexity
- Local minima can be problematic if they have high cost in comparison to the global minimum
- Saddle point as being a local minimum along one cross-section of the cost function and a local maximum along another cross-section



More...

Initialization of weights

- May get stuck in a local minimum or a saddle point
- Starting from different initial points (e.g. parameters) may result in different results
- Random values has an important effect on the success of training
- Xavier initialization, Glorot and Bengio (2010):

$$\mathrm{W} \sim U\left[-\frac{\sqrt{6}}{\sqrt{d_{in}+d_{out}}}, +\frac{\sqrt{6}}{\sqrt{d_{in}+d_{out}}}\right]$$

- When using ReLU non-linearities $\rightarrow$ sampling from a zero-mean Gaussian distribution whose standard deviation is $\sqrt{\frac{2}{d_{in}}}$, He et al. (2015)

Vanishing and Exploding Gradients

- Error gradients to either vanish (become exceedingly close to 0) or explode (become exceedingly high) in backpropagation

Regularization

Overfitting

- Many parameters
- Prune to overfitting

Example: LSTM has a set of 2 matrices: U and W for each of the 3 gates. n is the hidden layer size and m is the vocabulary size. (ie $n = 100$, $m = 8000$)

- U has dimensions $n \times m$
- W has dimensions $n \times n$
- there is a different set of these matrices for each of the three gates(like U_{forget} for the forget gate)
- there is another set of these matrices for updating the cell state S

$\hookrightarrow$ total number of parameters = $\underline{4(nm + n^2) = 3{,}240{,}000\ !}$

Solution

- Dropout: randomly dropping (setting to 0) half of the neurons in the network (or in a specific layer) in each training example. (Hinton, Srivastava, Krizhevsky, Sutskever, & Salakhutdinov, 2012)

Deep Learning models for numerous tasks

- **CNNs:** document classification, short-text categorization, sentiment classification, relation type classification between entities, event detection, paraphrase identification, semantic role labelling, qa
- **Recurrent:** language modeling, sequence tagging, machine translation, dependency parsing, sentiment analysis, noisy text normalization, dialog state tracking, response generation
- **Recursive**(generalization of RNN that can handle trees): constituency-dependency parse re-ranking, discourse parsing, semantic relation classification, political ideology detection based on parse trees, sentiment classification, target-dependent sentiment classification, qa

Understanding Neural Networks

Deep "dark" networks

If the network fails, it is hard to understand what went wrong!

- Hard to provide concrete interpretation
- Visualization to the rescue!
- http://colah.github.io/
- Visualizing and understanding convolutional networks, M. Zeiler and R. Fergus (2014)

The end!

Future: Deep Generative Models

- Probability distributions over multiple variables
- Boltzmann Machines, RBM, Deep Belief Networks

Resources

- Natural language processing (almost) from scratch, R. Collobert et al., 2011
- A Primer on Neural Network Models for Natural Language Processing, Goldberd, 2015
- Deep Learning, Ian Goodfellow and Yoshua Bengio and Aaron Courville, 2016

Conference

- International Conference on Learning Representations (ICLR)

Thank you!