Overview of LSTMs and word2vec

and a bit about compositional distributional semantics if there's time

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Outline

RNNs and LSTMs

Word2vec

Compositional distributional semantics

Some slides adapted from Aurelie Herbelot.

Outline.

RNNs and LSTMs

Word2vec

Compositional distributional semantics

Motivation

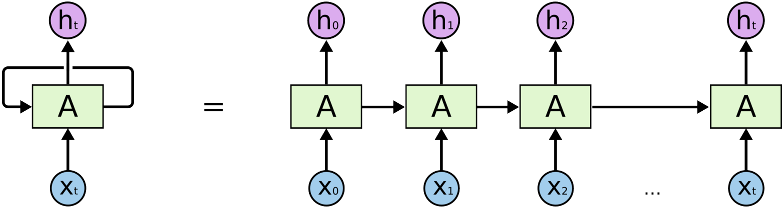
- Standard NNs cannot handle sequence information well.
- Can pass them sequences encoded as vectors, but input vectors are fixed length.
- Models are needed which are sensitive to sequence input and can output sequences.
- RNN: Recurrent neural network.
- Long short term memory (LSTM): development of RNN, more effective for most language applications.
- More info: `http://neuralnetworksanddeeplearning.com/` (mostly about simpler models and CNNs)
  `https://karpathy.github.io/2015/05/21/rnn-effectiveness/`

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

Sequences

- Video frame categorization: strict time sequence, one output per input.
- Real-time speech recognition: strict time sequence.
- Neural MT: target not one-to-one with source, order differences.
- Many language tasks: best to operate left-to-right and right-to-left (e.g., bi-LSTM).
- attention: model 'concentrates' on part of input relevant at a particular point. Caption generation: treat image data as ordered, align parts of image with parts of caption.

Recurrent Neural Networks



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RNN language model: Mikolov et al, 2010

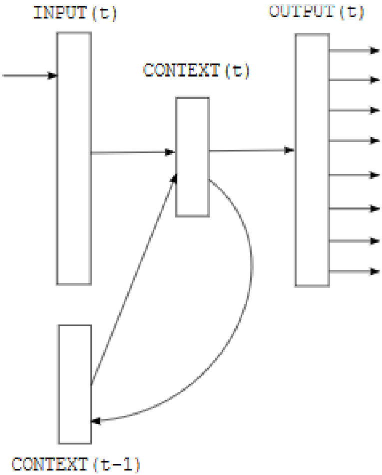


Figure 1: *Simple recurrent neural network.*

RNN as a language model

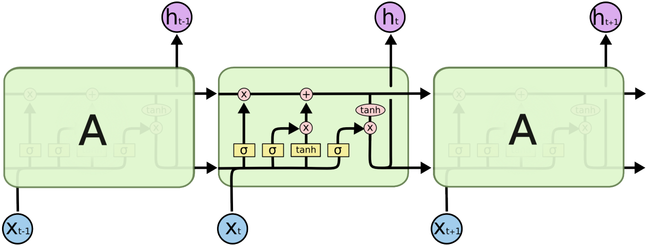
- Input vector: vector for word at t concatenated to vector which is output from context layer at $t-1$.
- Performance better than n-grams but won't capture 'long-term' dependencies:

  She shook her head.
  She decided she did not want any more tea, so shook her head when the waiter reappeared.
- not the same as long distance dependency in linguistics

Long Short Term Memory Networks (A)

- An RNN has just one layer in its repeating module.
- An LSTM has four layers that interact, each one with a gate. Gates are ways to let information through (or not):
  - Forget gate layer: look at previous cell state and current input, and decide which information to throw away.
  - Input gate layer: see which information in the current state we want to update.
  - Update layer: propose new values for the cell state.
  - Output layer: Filter cell state and output the filtered result.
- For instance: store gender of subject until another subject is seen.

Long Short Term Memory Networks



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State-of-the-art (possibly out of date already . . .)

- LSTMs have essentially replaced n-grams as language models for speech.
- Image captioning and other multi-modal tasks which were very difficult with previous methods are now feasible.
- Many traditional NLP tasks work very well with LSTMs, but not necessarily the top performers: e.g., POS tagging and NER: Choi 2016 — dynamic feature induction.
- Neural MT: broken away from plateau of SMT, especially for grammaticality (partly because of characters/subwords), but not yet industry strength.
- Definitely not there yet for text normalization: '33rpm' normalized to 'thirty two revolutions per minute'

https://arxiv.org/ftp/arxiv/papers/1611/1611.00068.pdf

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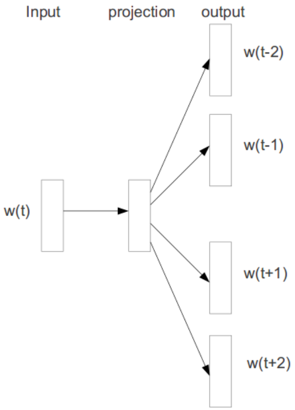
Embeddings

- embeddings: distributional models with dimensionality reduction, based on prediction
- word2vec: as originally described (Mikolov et al 2013), a NN model using a two-layer network (i.e., not deep!) to perform dimensionality reduction.
- two possible architectures:
  - given some context words, predict the target (CBOW)
  - given a target word, predict the contexts (Skip-gram)
- Very computationally efficient, good all-round model (good hyperparameters already selected).

The Skip-gram model (A)



Features of Word2Vec representations (A)

- A representation is learnt at the reduced dimensionality straightaway: we are outputting vectors of a chosen dimensionality (parameter of the system).
- Usually, a few hundred dimensions: dense vectors.
- The dimensions are not interpretable: it is impossible to look into ‘characteristic contexts’.
- For many tasks, word2vec (skip-gram) outperforms standard count-based vectors.
- But mainly due to the hyperparameters and these can be emulated in standard count models (see Levy et al).

What Word2Vec is famous for (A)

BUT . . . see Levy et al and Levy and Goldberg for discussion

The actual components of Word2Vec (A)

- A vocabulary. (Which words do I have in my corpus?)
- A table of word probabilities.
- Negative sampling: tell the network what *not* to predict.
- Subsampling: don't look at all words and all contexts.

Negative sampling (A)

Instead of doing full softmax (very expensive), word2vec is trained using logistic regression to discriminate between real and fake words:

- Whenever considering a word-context pair, also give the network contexts which are not the actual observed word.
- Sample from the vocabulary. The probability to sample something more frequent in the corpus is higher.
- The number of negative samples will affect results.

Subsampling (A)

- Instead of considering all words in the sentence, transform it by randomly removing words from it:
  considering all sentence transform randomly words
- The subsampling function makes it more likely to remove a frequent word.
- Note that word2vec does not use a stop list.
- Note that subsampling affects the window size around the target (i.e., means word2vec window size is not fixed).
- Also: weights of elements in context window vary.

Using word2vec

- predefined vectors or create your own
- can be used as input to NN model
- many researchers use the gensim Python library
  `https://radimrehurek.com/gensim/`
- Emerson and Copestake (2016) find significantly better performance on some tests using parsed data
- Levy et al's papers are very helpful in clarifying word2vec behaviour
- Bayesian version: Barkan (2016)

  `https://arxiv.org/ftp/arxiv/papers/1603/1603.06571.pdf`

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Compositional semantics

- Compositional semantics is about providing a meaning representation for an entire sentence.
- Classically (e.g., Montague) based on syntax and morphology, meaning expressed as in logic:

  every white cat is asleep

  $\forall x[[\mathit{white}'(x) \wedge \mathit{cat}'(x)] \rightarrow \mathit{asleep}'(x)]$

- Structures built deterministically from a rich syntactic analysis (quantifier scope possibly underspecified).
- Useful in applications like database interfaces where predicates can be grounded.
- Can be automatically induced for limited domains.

Compositional distributional semantics

- Compositional distributional semantics is typically about the meaning of short phrases: e.g., *white cat*.
- Not so good at full sentences, or quantifiers, modals etc, which compositional semantics deals with.
- In standard compositional distributional semantics, *white cats* does not refer to entities which are white and cats, but is more like creation of a new concept.
- Hence (perhaps) success of additive models.
- Unlike formal semantics, compositional distributional semantics is good at semi-compositionality (compound nouns, *heavy table* vs *heavy rain* vs *heavy taxation* etc).

Next time

- In two weeks ...
- Possibly: more advanced distributional semantics techniques ...