COMP3220 — Document Processing and the Semantic Web

Week 05 Lecture 1: Processing Text Sequences

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Abstract

This lecture focuses on some of the key aspects of text that make it different, and difficult, from other unstructured data from the point of machine learning, and how deep learning handles them. The first solution is to map words into continuous representations called embeddings. Using embeddings usually improves the quality of most text processing tasks. The second solution is the use of recurrent neural networks that can handle sequences of text.

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Contents

Reading

- Deep Learning book, chapter 6.
- Understanding LSTM Networks, `https://colah.github.io/posts/2015-08-Understanding-LSTMs/`.

1 Word Embeddings

1.1 Challenges of Text for Machine Learning

Words as Arbitrary Symbols

- Words are encoded as arbitrary symbols.
- Within one language there is no clear correspondence between a word symbol and its meaning.
  - "dig" vs. "dog"
  - "car" vs. "automobile"
- Different languages may use different representations of the same word.

https://en.wikipedia.org/wiki/File:Hello_in_different_languages_word_cloud.jpeg

Ambiguities Everywhere

Language features ambiguity at multiple levels.

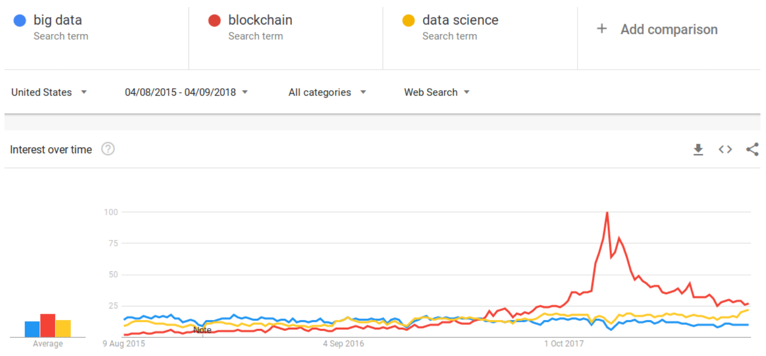
Lexical Ambiguity

Example from Google's dictionary:

- bank (n): the land alongside or sloping down a river or lake.
- bank (n): financial establishment that uses money deposited by customers for investment, . . .
- bank (v): form in to a mass or mound.
- bank (v): build (a road, railway, or sports track) higher at the outer edge of a bend to facilitate fast cornering.
- . . .

So many words!

- Any language features a large number of distinct words.
- New words are coined.
- Words change their use in time.
- There are also names, numbers, dates... an infinite number.



● big data
Search term
● blockchain
Search term
● data science
Search term
+ Add comparison

United States ▾ 04/08/2015 - 04/09/2018 ▾ All categories ▾ Web Search ▾

Interest over time

https://trends.google.com

Long-distance Dependencies

- Sentences are sequences of words.
- Words close in the sentence are often related.
- But sometimes there are relations between words far apart.

grammatical: “The man living upstairs is very cheerful” “The people living upstairs are very cheerful”

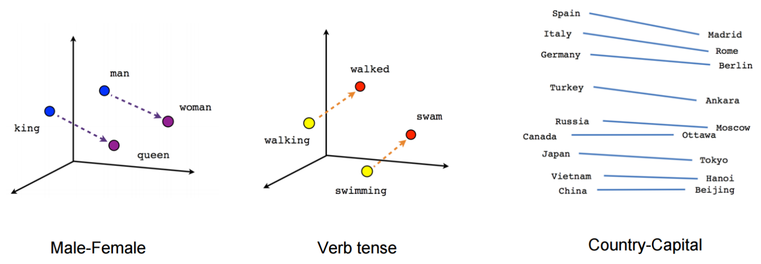
reference: “I bought a book from the bookshp and I liked it”

knowledge: “I was born in France and I speak fluent French”

1.2 Word Embeddings

Word Embeddings

- First introduced in 2013, nowadays is one of the most common ingredients in text processing systems.
- Word embeddings squarely aim at addressing the issue of representing words as continuous vectors of integers.
- Words with similar context are mapped to similar vectors.
- Embeddings are learnt using large, unlabelled training data.



https://www.tensorflow.org/tutorials/representation/word2vec

One-hot vs. word embeddings

One-hot

- Sparse
- Binary values (typically)
- High-dimensional
- Hard-coded

Word embeddings

- Dense
- Continous values
- Lower-dimensional

- Learned from data

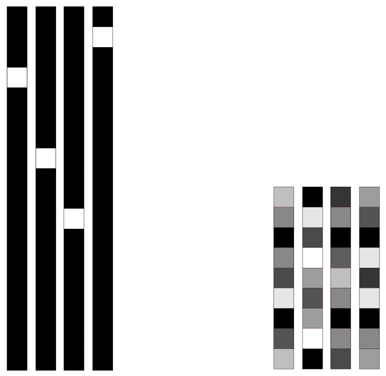


Image from Chollet (2018) "Dee Learning with Python:", Manning. Figure 6.2, page 184.

Two Ways to Obtain Word Embeddings

1. Learn the word embeddings jointly with the task you care about (e.g. document classification).
2. Use pre-trained word embeddings.

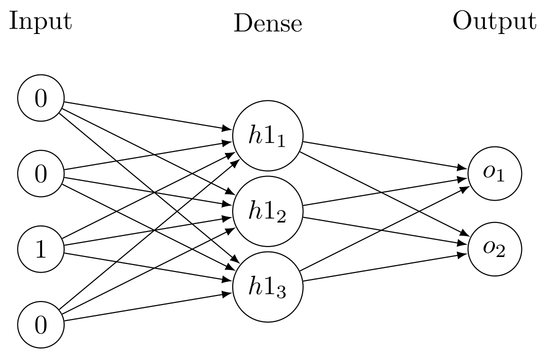
Learning Word Embeddings

- You can add a dense layer as the first layer of your network and let the system learn the optimal weights.
- This approach is so useful and common that many deep learning frameworks define an "embedding" layer that facilitates this.
- The input to the "embedding" layer is the word index.
- The output is the word embedding.

Embedding Layer as a Dense Layer

The input of the dense layer is the one-hot encoding of the word

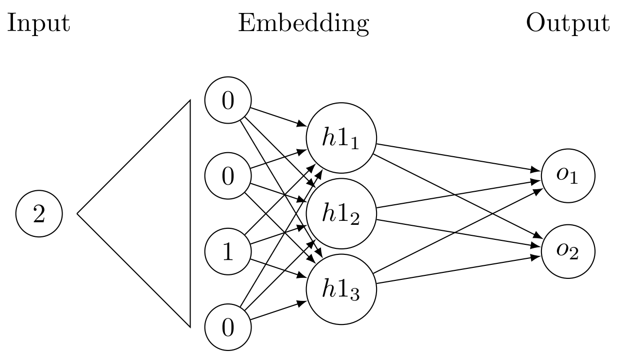
A Dense Layer



Embedding Layer in Keras

The input of a Keras embedding layer is a word index which will be internally converted into its one-hot representation.

An Embedding Layer



Using pre-trained word embeddings

The Problem: Data Sparsity

- Sometimes we have so little training data that many words are poorly represented.
- Often, words in the training data do not occur in the test data.
- For these words we would not be able to learn the embeddings.

A Solution: Pre-training

- Several people have computed word embeddings for large vocabularies using large data sets.
- We can then use these pre-trained embeddings to map from the word index to the word embedding.

Using Word Embeddings in Keras

- The following notebook is based on the jupyter notebooks provided by the Deep Learning book: `https://github.com/fchollet/deep-learning-with-python-notebooks`
  - Using word embeddings.
- The notebook illustrates how you can use an embeddings layer for text classification, and how to load pre-trained word embeddings.
- This notebook is important because it also illustrates Keras' text tokenisation techniques.

2 Text Sequences

2.1 Modelling Text Sequences

Handling Text Sequences

- A document is a sequence of words.

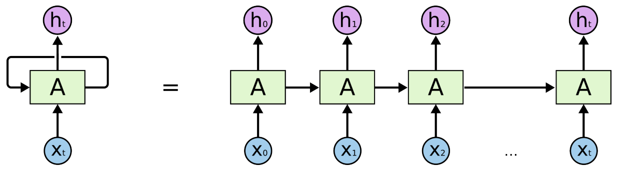
- Many document representations are based on a bag-of-words approach.
  - Word order is ignored.
  - The context around a word is ignored.
- Even word embeddings ignore word order.

Why context matters
"I can_1 kick the can_2"

- The meaning of "can_1" is different from that of "can_2".
- "can_1" and "can_2" should have different word embeddings.
- We can tell the meaning because of the context:
  - "I can kick ..."
  - "... kick the can"

Recurrent Neural Networks

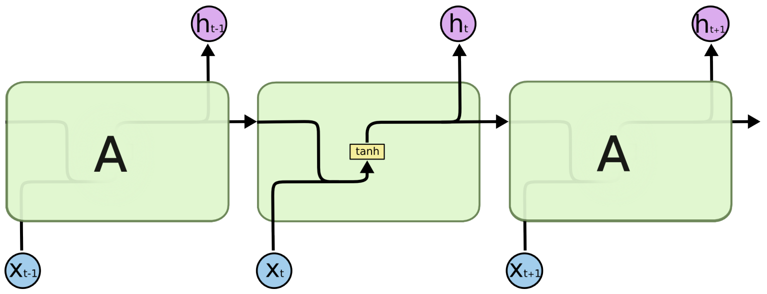
- A Recurrent Neural Network (RNN) is designed to process sequences.
- A RNN is a neural network that is composed of RNN cells.
- Each RNN cell takes as input two pieces of information:
  1. A vector representing an item x_i in the sequence.
  2. The state resulting from processing the previous items.
- The output of the RNN cell is a state that can be fed to the next cell in the sequence.
- All cells in an RNN chain share the same parameters.
- In a sense, we can say that an RNN cell is the same for all words in the sequence, but now context also matters.



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

A Simple Recurrent Neural Networks

- A simple RNN cell ("vanilla RNN") has just a dense layer with an activation function (hyperbolic tangent, or "tanh" in the drawing below).
- Vanilla RNN cells have been used since 1990s.



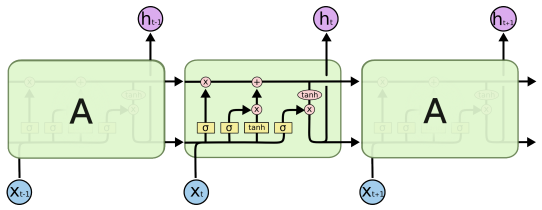
https://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTMs and GRUs

- Vanilla RNN cells are still too simple and they do not handle long-distance dependencies easily.
- More complex RNN cells have been designed specifically to address this issue.
- Current most popular RNN cells are:

  LSTM Long Short Term Memory (picture).

  GRU Gated Recurrent Unit; a more recent, simpler cell.



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

RNNs in Practice

- Most deep learning frameworks include special layers for RNNs.
- When you use an RNN layer, you have the option to specify the type of RNN cell.
- You often have the option to use the state of the last cell, or the state of all cells.

Recurrent Neural Networks in Keras

The following notebook is based on the jupyter notebooks provided by the Deep Learning book: `https://github.com/fchollet/deep-learning-with-python-notebooks`

- Understanding Recurrent Neural Networks.

The notebook illustrates how you can use an embeddings layer for text classification, and how to load pre-trained word embeddings.

2.2 Sequence Labelling

What is Sequence Labelling?

- A sequence labelling problem is one where:
  - the input consists of a sequence $\boldsymbol{X} = (X_1, \ldots, X_n)$, and
  - the output consists of a sequence $\boldsymbol{Y} = (Y_1, \ldots, Y_n)$ of labels, where:

  - Y_i is the label for element X_i

- Example: Part-of-speech tagging

$$\begin{pmatrix} \boldsymbol{Y} \\ \boldsymbol{X} \end{pmatrix} = \begin{pmatrix} \text{Verb,} & \text{Determiner,} & \text{Noun} \\ \text{spread,} & \text{the,} & \text{butter} \end{pmatrix}$$

- Example: Spelling correction

$$\begin{pmatrix} \boldsymbol{Y} \\ \boldsymbol{X} \end{pmatrix} = \begin{pmatrix} \text{write,} & \text{a,} & \text{book} \\ \text{rite,} & \text{a,} & \text{buk} \end{pmatrix}$$

Other applications of sequence labelling

- Named entity recognition and classification (NER) involves finding the named entities in a text and identifying what type of entity they are (e.g., person, location, corporation, dates, etc.).
- Speech transcription can be seen as a sequence labelling task:
  - The input $\boldsymbol{X} = (X_1, \ldots, X_n)$ is a sequence of acoustic frames X_i, where X_i is a set of features extracted from a 50msec window of the speech signal.
  - The output $\boldsymbol{Y}$ is a sequence of words (the transcript of the speech signal).
- Financial applications of sequence labelling:
  - Identifying trends in price movements.
- Biological applications of sequence labelling:
  - Gene-finding in DNA or RNA sequences.

Sequence Labelling as Classification

Can we just use a standard classifier?

- Standard classifiers (such as those we have seen so far) assume independence between samples:
  - The probability of the label assigned to sample i is independent to the probability of the label assigned to sample j.
- But in sequence labelling there is interdependence between the labels of different samples.

Modelling Context

Classifier with context features

- A (crude) approach to model interdependence between samples is to add context features.
- For example, we can use features based on previous words and following words.
- We can even incorporate the label of the previous word as a feature.
- But it is not so easy to incorporate the label of *both* the previous word and the following word.

Using Recurrent Neural Networks for Sequence Labelling

- We have seen how RNNs can be used to classify documents.
- Similarly, we can use RNNs to classify sequences of words.
- Keras provides 'TimeDistributed', which assigns a copy of a layer to the output of each recurrent cell.

```
model = Sequential()
model.add(Embedding(max_words, 32))
model.add(LSTM(32, return_sequences=True))
model.add(TimeDistributed(Dense(num_tags,
                          activation='softmax')))

model.compile(optimizer='Adam',
              loss='categorical_crossentropy',
              metrics=['acc'])
```

```
Layer (type)                 Output Shape              Param #
=================================================================
embedding_1 (Embedding)      (None, None, 32)          320000
_________________________________________________________________
lstm_1 (LSTM)                (None, None, 32)          8320
_________________________________________________________________
time_distributed_1 (TimeDist (None, None, 20)          660
=================================================================
```

The resulting neural network will output sequences of labels and therefore the output shape is a tensor with three dimensions:

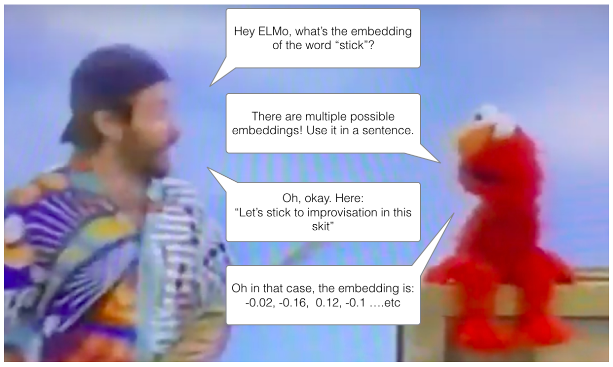
1. The number of samples in the batch.
2. The number of labels per sample (the length of the sentence).
3. The number of label categories (20 in this example).

Sequence Labelling in Keras

- The following notebook is based on nlpforhackers' post: `https://nlpforhackers.io/lstm-pos-tagger-keras/`
  - Building a Part of Speech Tagger with Keras
- We will look at how to build a Part of Speech tagger using a LSTM layer.
- The notebook uses NLTK's treebank corpus, which contains annotations with the parts of speech of the words.

Final Note: Contextualised Word Embeddings!

Recent research deviced a way to combine RNN and word embeddings to produce context-dependent word embeddings. The resulting systems are beating state of the art in many applications!


Hey ELMo, what's the embedding of the word "stick"?
There are multiple possible embeddings! Use it in a sentence.
Oh, okay. Here: "Let's stick to improvisation in this skit"
Oh in that case, the embedding is: -0.02, -0.16, 0.12, -0.1 ....etc

`http://jalammar.github.io/illustrated-bert/`

Take-home Messages

1. Explain some of the fundamental challenges that plain text represents to machine learning.
2. Apply word embeddings in deep learning.
3. Use recurrent neural networks for text classification.
4. Comment on the issues of sequence labelling.

What's Next

Week 6

- Generating text.
- Reading: Deep Learning book, chapter 8.1