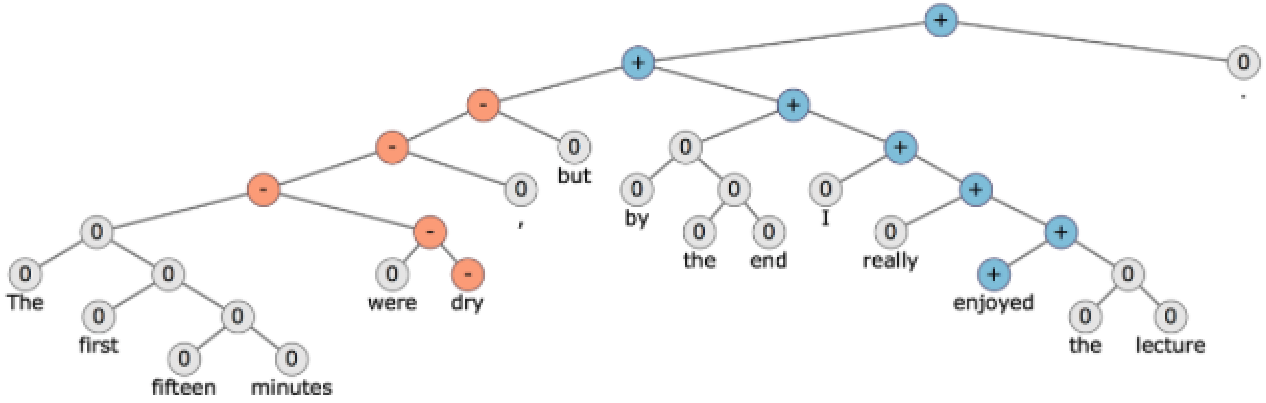
Deep Learning: Natural Language Processing with Deep Learning

```
$ echo "Data Sciences Institute"
```

Natural Language Processing

[Google Translate System - 2016]



[Socher 2015]

Natural Language Processing

- Sentence/Document level Classification (topic, sentiment)
- Topic modeling (LDA, ...)
- Translation
- Chatbots / dialogue systems / assistants (Alexa, ...)
- Summarization

Useful open source projects

gensim spaCy

scikit learn HUGGING FACE

Outline

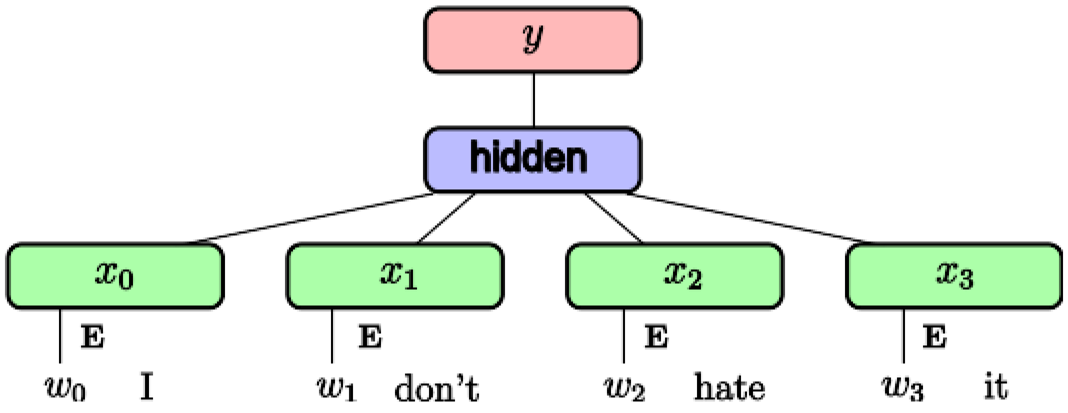
- Classification and word representation
- Word2Vec
- Language Modelling
- Recurrent neural networks

Word Representation and Word2Vec

Word representation

- Words are indexed and represented as 1-hot vectors
- Large Vocabulary of possible words $|V|$
- Use of **Embeddings** as inputs in all Deep NLP tasks
- Word embeddings usually have dimensions 50, 100, 200, 300

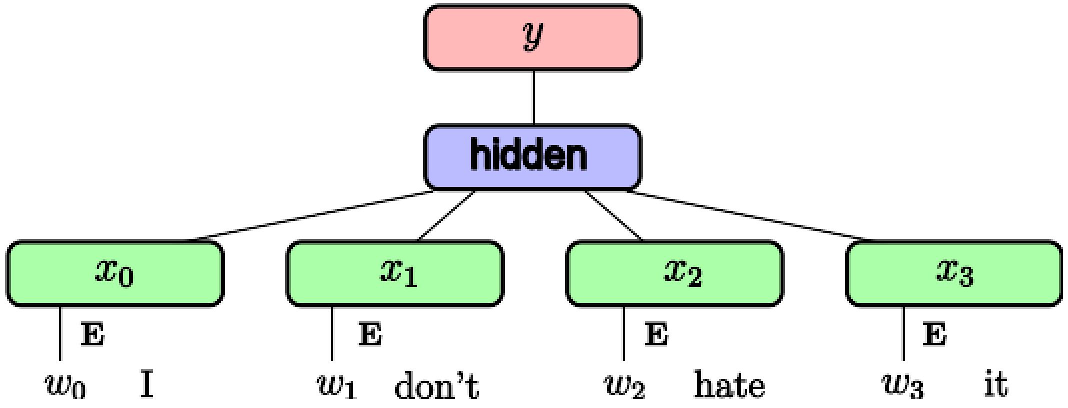
Supervised Text Classification



- $\mathbf{E}$ embedding (linear projection) $\rightarrow$ `|V| x H`
- Embeddings are averaged $\rightarrow$ hidden activation size: `H`
- Dense output connection $\mathbf{W}, \mathbf{b} \rightarrow$ `H x K`
- Softmax and **cross-entropy** loss

Joulin, Armand, et al. "Bag of tricks for efficient text classification." FAIR 2016

Supervised Text Classification



- Very efficient (**speed** and **accuracy**) on large datasets
- State-of-the-art (or close to) on several classification, when adding **bigrams/trigrams**
- Little gains from depth

Joulin, Armand, et al. "Bag of tricks for efficient text classification." FAIR 2016

Transfer Learning for Text

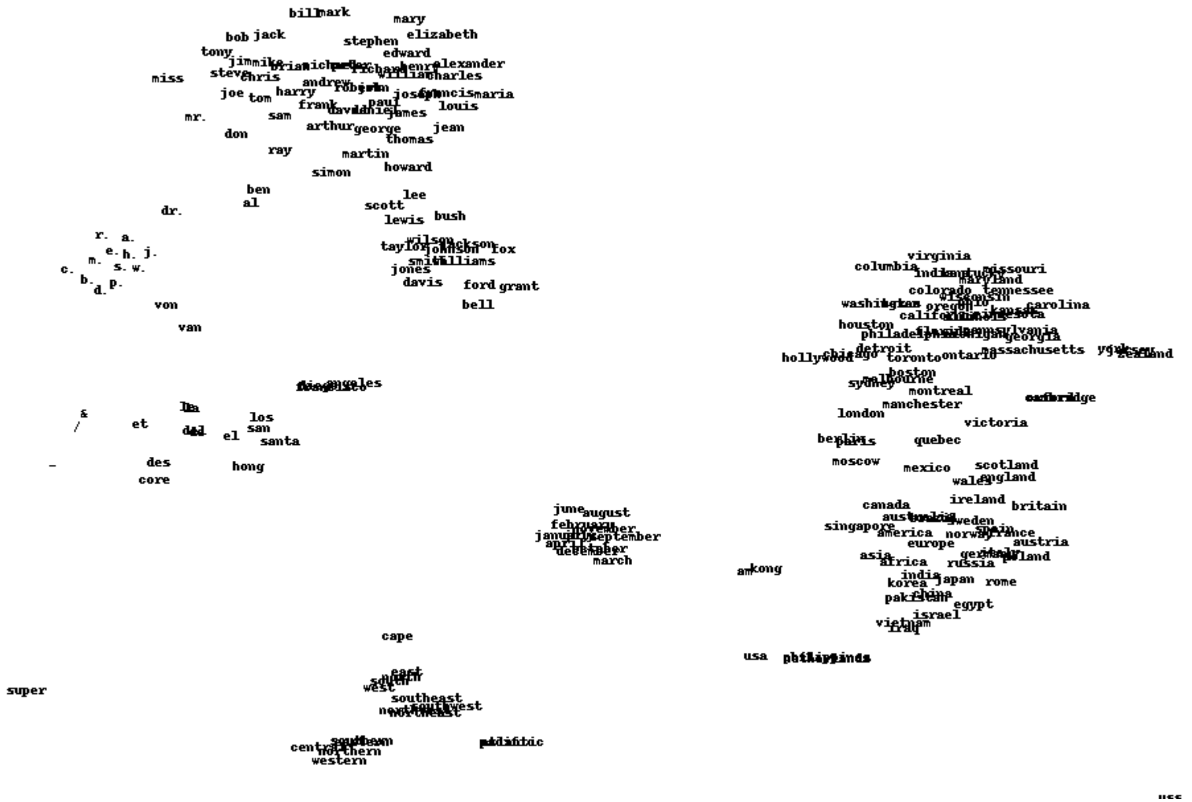
Similar to image: can we have word representations that are generic enough to **transfer** from one task to another?

Unsupervised / self-supervised learning of word representations

Unlabelled text data is almost infinite:

- Wikipedia dumps
- Project Gutenberg
- Social Networks
- Common Crawl

Word Vectors



excerpt from work by J. Turian on a model trained by R. Collobert et al. 2008

Word2Vec

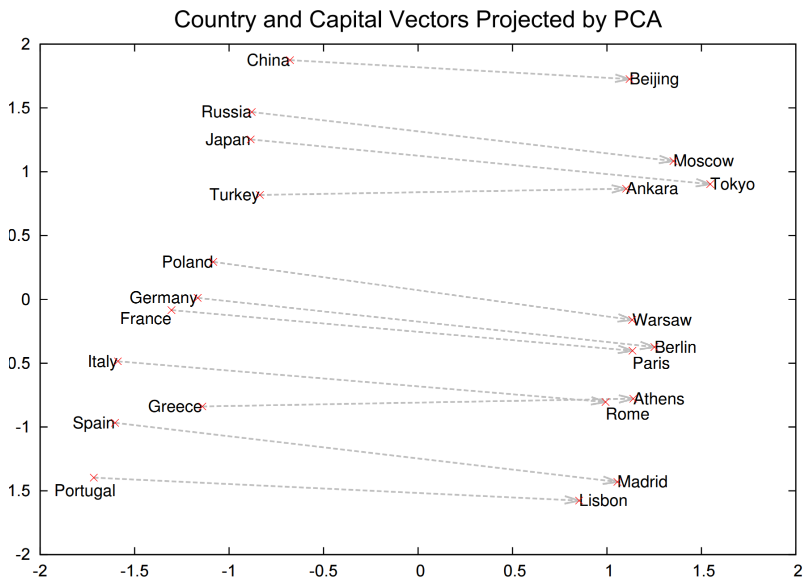
FRANCE	JESUS	XBOX	REDDISH	SCRATCHED	MEGABITS
AUSTRIA	GOD	AMIGA	GREENISH	NAILED	OCTETS
BELGIUM	SATI	PLAYSTATION	BLUISH	SMASHED	MB/S
GERMANY	CHRIST	MSX	PINKISH	PUNCHED	BIT/S
ITALY	SATAN	IPOD	PURPLISH	POPPED	BAUD
GREECE	KALI	SEGA	BROWNISH	CRIMPED	CARATS
SWEDEN	INDRA	PSNUMBER	GREYISH	SCRAPED	KBIT/S
NORWAY	VISHNU	HD	GRAYISH	SCREWED	MEGAHERTZ
EUROPE	ANANDA	DREAMCAST	WHITISH	SECTIONED	MEGAPIXELS
HUNGARY	PARVATI	GEFORCE	SILVERY	SLASHED	GBIT/S
SWITZERLAND	GRACE	CAPCOM	YELLOWISH	RIPPED	AMPERES

Compositionality

Czech + currency	Vietnam + capital	German + airlines	Russian + river	French + actress
koruna	Hanoi	airline Lufthansa	Moscow	Juliette Binoche
Check crown	Ho Chi Minh City	carrier Lufthansa	Volga River	Vanessa Paradis
Polish zolty	Viet Nam	flag carrier Lufthansa	upriver	Charlotte Gainsbourg
CTK	Vietnamese	Lufthansa	Russia	Cecile De

Colobert et al. 2011, Mikolov, et al. 2013

Word Analogies



- Linear relations in Word2Vec embeddings
- Many come from text structure (e.g. Wikipedia)

Mikolov, Tomas, et al. "Distributed representations of words and phrases and their compositionality." NIPS 2013

Self-supervised training

Distributional Hypothesis (Harris, 1954):

“words are characterized by the company that they keep”

Main idea: learning word embeddings by **predicting word contexts**

Given a word e.g. “carrot” and any other word $w \in V$ predict probability $P(w|\text{carrot})$ that w occurs in the context of “carrot”.

- **Unsupervised / self-supervised**: no need for class labels.
- (Self-)supervision comes from **context**.
- Requires a lot of text data to cover rare words correctly.

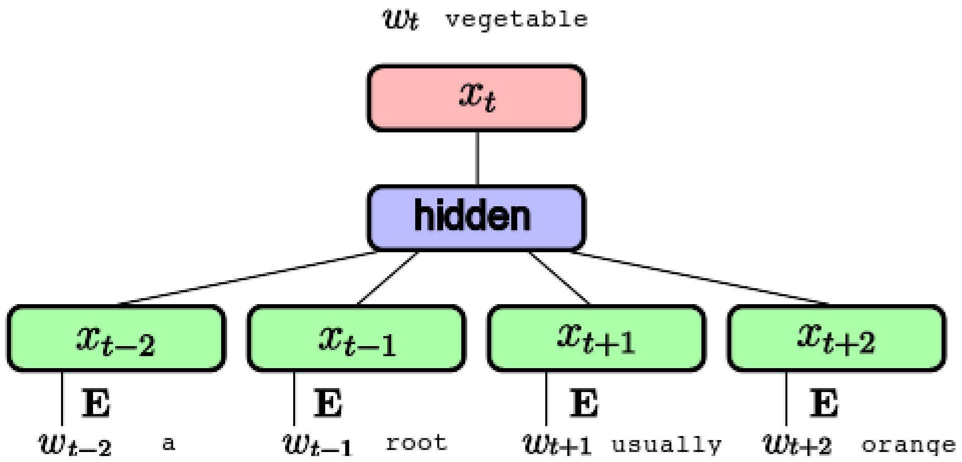
Mikolov, Tomas, et al. "Distributed representations of words and phrases and their compositionality." NIPS 2013

Word2Vec: CBoW

CBoW: representing the context as **Continuous Bag-of-Words**

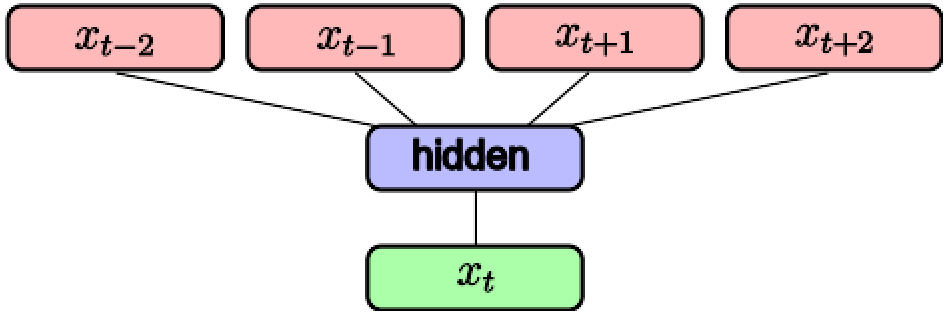
Self-supervision from large unlabeled corpus of text: *slide* over an **anchor word** and its **context**:

`the carrot is a root vegetable, usually orang`



Mikolov, Tomas, et al. "Distributed representations of words and phrases and their compositionality." NIPS 2013

Word2Vec: Skip Gram



- Given the central word, predict occurrence of other words in its context.
- Widely used in practice

Word2Vec: Negative Sampling

- Task is simplified further: **binary classification** of word pairs
- For the sentence "The quick brown fox jumps over the lazy dog":
- "quick" and "fox" are positive examples (if context window is 2)
- "quick" and "apple" are negative examples
- By sampling negative examples, we don't just bring similar words' embeddings closer, but also push away dissimilar words' embeddings.

Transformer-based methods

- **Attention** mechanism: more recent and more powerful than Word2Vec
- **BERT** (Bidirectional Encoder Representations from Transformers) allows for **contextual embeddings** (different embeddings for the same word in different contexts)
- For example, "bank" in "river bank" and "bank account" will have different embeddings
- This means converting a word to a vector is no longer a simple lookup in a table, but a function of the entire sentence

Transformer-based methods

- **Sub-word tokenization**: BERT uses a sub-word tokenization, which allows it to handle out-of-vocabulary words better than Word2Vec
- For example, "unbelievable" can be split into "un" and "believable"
- This means that the model can guess the meaning of words it has never seen before, based on the meanings of their parts
- OpenAI tokenization example: https://platform.openai.com/tokenizer

Take Away on Embeddings

For text applications, inputs of Neural Networks are Embeddings

- If **little training data** and a wide vocabulary not well covered by training data, use **pre-trained self-supervised embeddings** (word2vec, or with more time and resources, BERT, GPT, etc.)
- If **large training data** with labels, directly learn task-specific embedding for more precise representation.
- word2vec uses **Bag-of-Words** (BoW): they **ignore the order** in word sequences
- Depth & non-linear activations on hidden layers are not that useful for BoW text classification.

Language Modelling and Recurrent Neural Networks

Language Models

Assign a probability to a sequence of words, such that plausible sequences have higher probabilities e.g:

- $p(\text{"I like cats"}) > p(\text{"I table cats"})$
- $p(\text{"I like cats"}) > p(\text{"like I cats"})$

Likelihoods are factorized:

$$p_\theta(w_0) \cdot p_\theta(w_1|w_0) \cdot \ldots \cdot p_\theta(w_n|w_{n-1}, w_{n-2}, \ldots, w_0)$$

p_θ is parametrized by a neural network.

The internal representation of the model can better capture the meaning of a sequence than a simple Bag-of-Words.

Conditional Language Models

NLP problems expressed as **Conditional Language Models**:

Translation: $p(Target|Source)$

- *Source*: "J'aime les chats"
- *Target*: "I like cats"

Model the output word by word:

$$p_\theta(w_0|Source) \cdot p_\theta(w_1|w_0, Source) \cdot \ldots$$

Conditional Language Models

Question Answering / Dialogue:

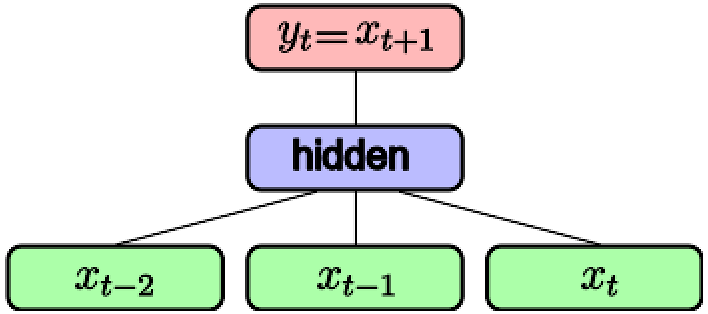
$$p(Answer|Question, Context)$$

- *Context*:
  - "John puts two glasses on the table."
  - "Bob adds two more glasses."
  - "Bob leaves the kitchen to play baseball in the garden."
- *Question*: "How many glasses are there?"
- *Answer*: "There are four glasses."

Image Captionning: $p(Caption|Image)$

- Image is usually the 2048-d representation from a CNN

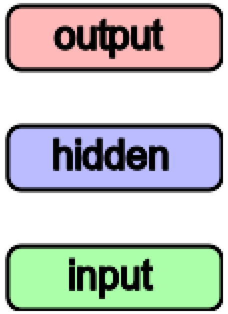
Simple Language Model



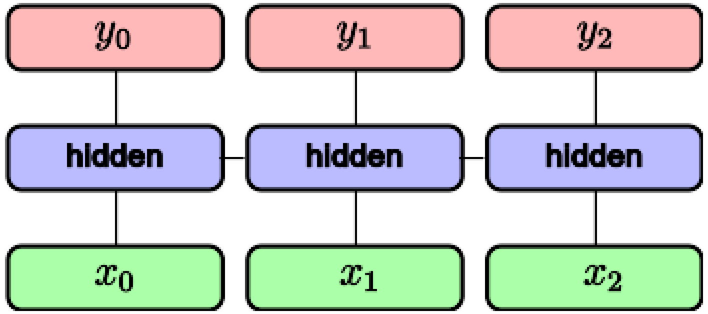
Fixed context size

- **Average embeddings**: (same as CBoW) no sequence information
- **Concatenate embeddings**: introduces many parameters
- Still does not take well into account varying sequence sizes and sequence dependencies

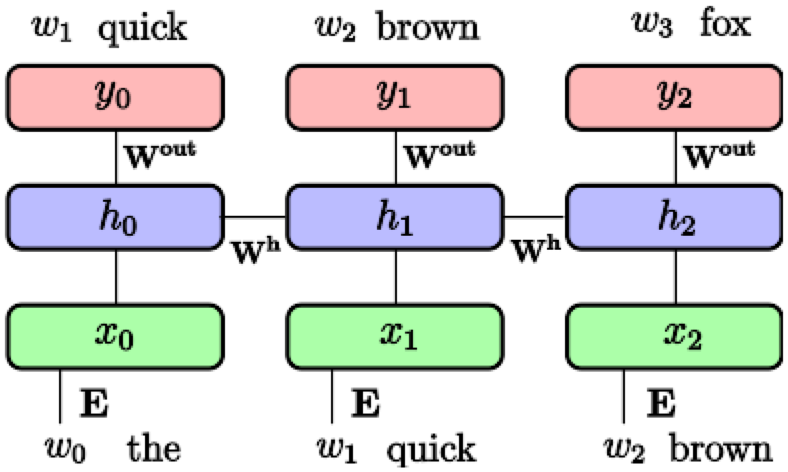
Recurrent Neural Network



Unroll over a sequence (x_0, x_1, x_2):



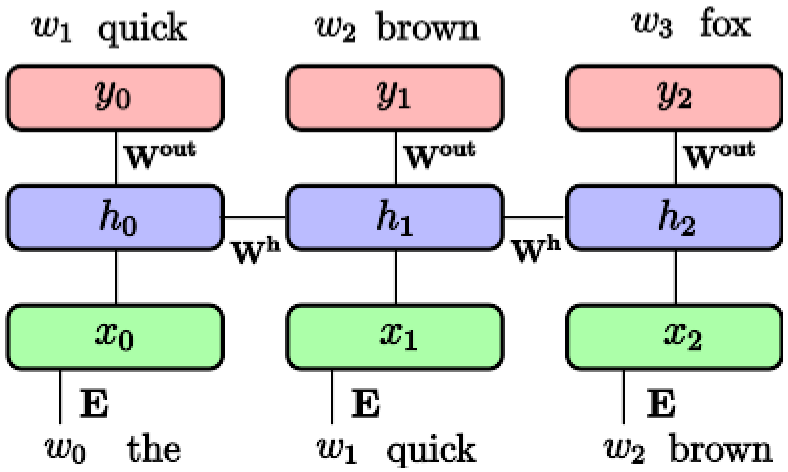
Language Modelling



input $(w_0, w_1, \ldots, w_t)$ sequence of words (1-hot encoded)

output $(w_1, w_2, \ldots, w_{t+1})$ shifted sequence of words (1-hot encoded)

Language Modelling

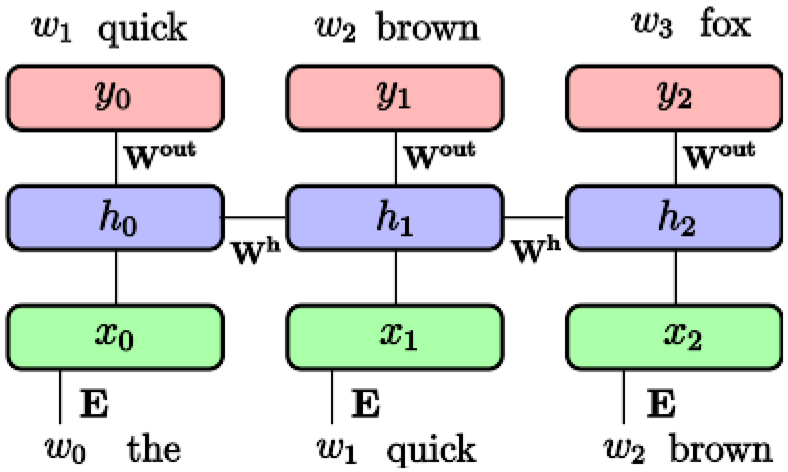


$x_t = \mathrm{Emb}(w_t) = \mathbf{E}w_t \rightarrow$ input projection `H`

$h_t = g(\mathbf{W^h}h_{t-1} + x_t + b^h) \rightarrow$ recurrent connection `H`

$y = \mathrm{softmax}(\mathbf{W^o}h_t + b^o) \rightarrow$ output projection `K = |V|`

Recurrent Neural Network



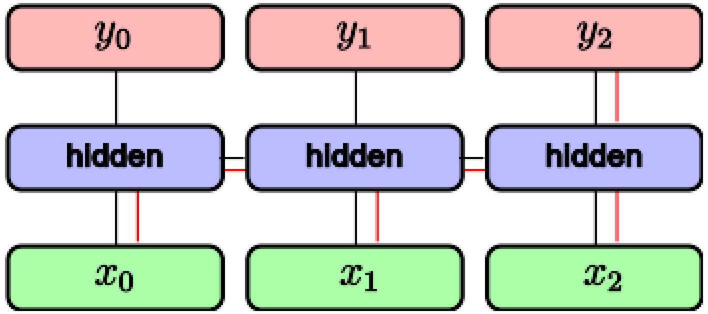
Input embedding $\mathbf{E} \rightarrow$ `|V| x H`

Recurrent weights $\mathbf{W^h} \rightarrow$ `H x H`

Output weights $\mathbf{W^{out}} \rightarrow$ `H x K = H x |V|`

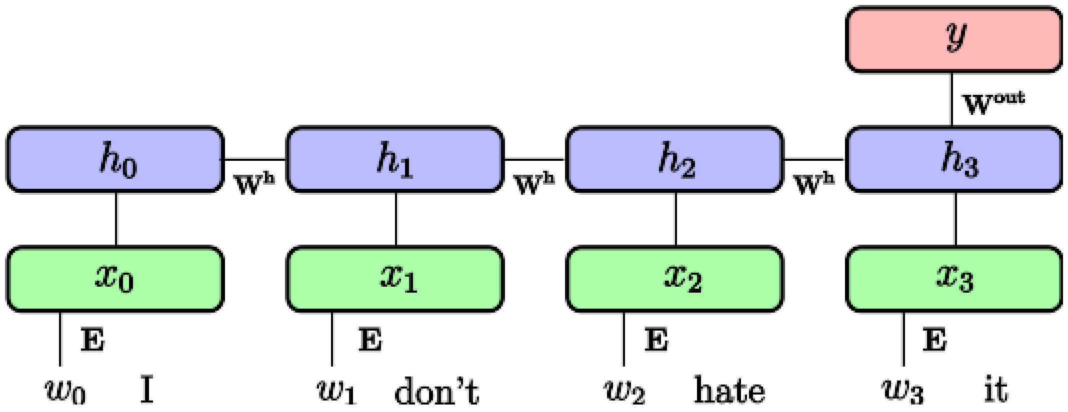
Backpropagation through time

Similar as standard backpropagation on unrolled network



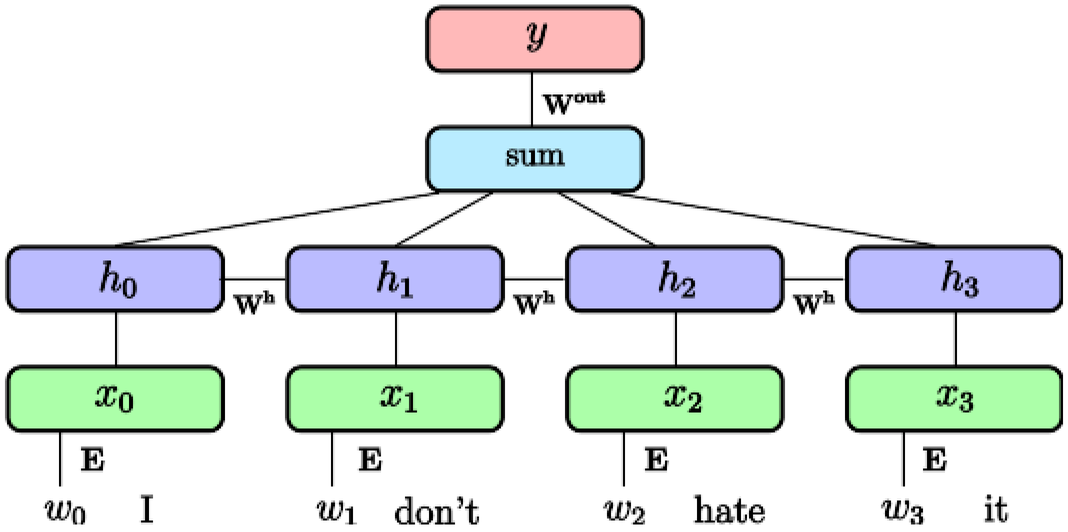
- Similar as training **very deep networks** with tied parameters
- Example between x_0 and y_2: W^h is used twice
- Usually truncate the backprop after T timesteps
- Difficulties to train long-term dependencies

Other uses: Sentiment Analysis



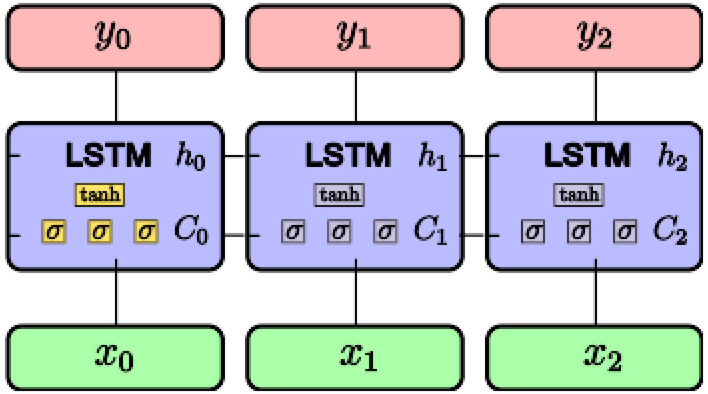
- Output is sentiment (1 for positive, 0 for negative)
- Very dependent on words order
- Very flexible network architectures

Other uses: Sentiment analysis



- Output is sentiment (1 for positive, 0 for negative)
- Very dependent on words order
- Very flexible network architectures

LSTM



- 4 times more parameters than RNN
- Mitigates **vanishing gradient** problem through **gating**
- Widely used and SOTA in many sequence learning problems

Hochreiter, Sepp, and Jürgen Schmidhuber. "Long short-term memory." Neural computation 1997

Vanishing / Exploding Gradients

Passing through t time-steps, the resulting gradient is the **product** of many gradients and activations.

- Gradient messages close to 0 can shrink be 0
- Gradient messages larger than 1 can explode
- **LSTM** mitigates that in RNNs
- **Additive path** between c_t and c_{t-1}
- **Gradient clipping** prevents gradient explosion
- Well chosen **activation function** is critical (tanh)

  Skip connections in ResNet also alleviate a similar optimization problem.

Next: Lab 6!