Natural Language Processing and Machine Translation

Language Models

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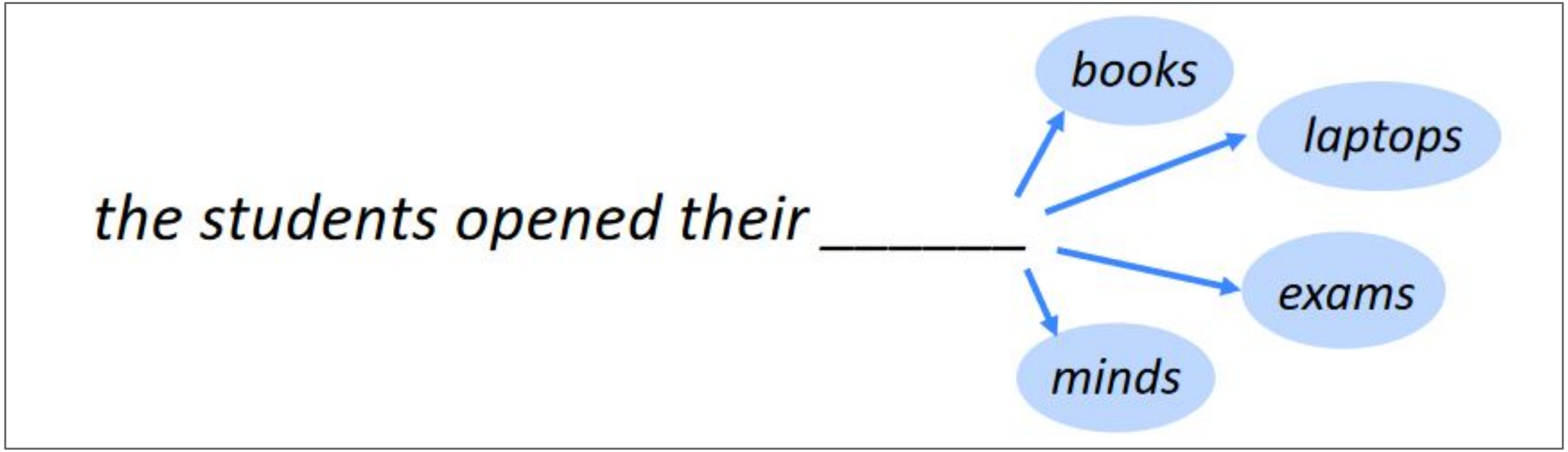
Introduction

- Use of various statistical and probabilistic techniques to determine the probability of a given sequence of words occurring in a sentence
- Analyze bodies of text data to provide a base for word predictions



https://medium.com/@antonio.lopardo/the-basics-of-language-modeling-1c8832f21079

N-gram

The cow jumps over the moon

Unigram/ 1-gram	Bigram/2-gram	3-gram	4-gram
The cow jumps over the moon	The cow cow jumps jumps over over the the moon	The cow jumps cow jumps over jumps over the over the moon	The cow jumps over cow jumps over the jumps over the moon

If X=Num of words in a given sentence K, the number of n-grams for sentence K would be:

$$Ngrams_K = X - (N - 1)$$

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N-gram Language Models

Its water is so transparent that ....

$$P(the|its\ water\ is\ so\ transparent\ that).$$

One approach to calculate this using frequency approach

$$P(the|its\ water\ is\ so\ transparent\ that) = \frac{C(its\ water\ is\ so\ transparent\ that\ the)}{C(its\ water\ is\ so\ transparent\ that)}$$

Will this give us a good estimate in all possible scenarios ??

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N-gram Language Models

Another way to do this is using **chain rule of probability**

p(w1...ws) = p(w1) . p(w2 | w1) . p(w3 | w1 w2) . p(w4 | w1 w2 w3) ..... p(wn | w1...wn-1)

But this is again computationally expensive

We make this more simpler with an assumption:

- We approximate the context of the word wk by looking at the last word of the context. (**Markov Assumption**)

Eg. for bigram

$$p(w) = \prod_{i=1}^{k+1} p(w_i | w_{i-1})$$

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N-gram language models

<s> I am a human </s>
<s> I am not a stone </s>
<s> I live in Lahore </s>

P(I|<S>)=C(<s>|I)/C(<s>)=3/3=1

P(am|I)=C(I|am)/C(I)=⅔

P(a|am)=C(am|a)/C(a)=½

P(human|a)=C(a|human)/C(a)=½

P(</s>|human)=C(human|</s>)/C(human)=1

P(not|am)=C(am|not)/C(am)=½

P(a|not)=C(not|a)/C(not)=1

P(stone|a)=C(a|stone)/C(a)=½

P(</s>|stone)=C(stone|</s>)/C(stone)=1

P(live|I)=C(I|live)/C(I)=⅓

P(in|live)=C(live|in)/C(live)=1

P(Lahore|in)=C(in|Lahore)/C(in)=1

P(</s>|Lahore)=C(Lahore|</s>)/C(Lahore)=1

P(I am a human)
= P(I|<s>) P(am|I) P(a|am) P(human|a) P(</s>|human)
= 1 * ⅔ * ½ *½ * 1
= ⅙

P(I am human)
= P(I|<s>) P(am|I) P(human|am) P(</s>|human)
= 1 * ⅔ * 0 * 1
= 0 => Does this seem correct?

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Laplace Smoothing

<s> I am a human </s>
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P(a|not)=C(not|a)/C(not)=1

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P(live|I)=C(I|live)/C(I)=⅓

P(in|live)=C(live|in)/C(live)=1

P(Lahore|in)=C(in|Lahore)/C(in)=1

P(</s>|Lahore)=C(Lahore|</s>)/C(Lahore)=1

The solution to the problem of unseen N-grams is to re-distribute some of the probability mass from the observed frequencies to unseen N-grams. This is a general problem in probabilistic modeling called **smoothing**.

$$P_{\text{Laplace}}(w_i) = \frac{c_i + 1}{N + V}$$

Using laplace smoothing (Vocab = 11)

P(I am human)
= P(I|<s>) P(am|I) P(human|am) P(</s>|human)
= (3+1)/(3+11) * (2+1)/(3+11) * (0+1)/(2+11) * (1+1)/(1+11)
= 4/14 * 3/14 * 1/13 * 2/12
= 0.00078

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Good Turing Discounting

- Re-estimate the amount of probability mass to assign N-gram with zero or low counts by looking at the number of N-grams with higher counts
- Use the count of things which are seen once to help estimates the count of things never seen.
- Let Nc be number of N-grams that occur c times
  - For bigrams, No, is the number of bigrams of count 0, N1, is the number of bigrams with count 1, etc
- Revised count

$$\boxed{c^{*} = (c+1)\frac{N_{c+1}}{N_c}}$$

Kneser Ney Smoothing

- Let the count assigned to each unigram be the number of different words that it follows. Define:

$$N_{1+}(\bullet\ w_i) = |\{w_{i-1} : c(w_{i-1}w_i) > 0\}|$$

$$N_{1+}(\bullet\ \bullet) = \sum_{w_i} N_{1+}(\bullet\ w_i)$$

- Let lower-order distribution be:

$$p_{KN}(w_i) = \frac{N_{1+}(\bullet\ w_i)}{N_{1+}(\bullet\ \bullet)}$$

- Put it all together:

$$p_{KN}(w_i|w_{i-n+1}^{i-1}) = \frac{\max\{c(w_{i-n+1}^{i}) - \delta, 0\}}{\sum_{w_i} c(w_{i-n+1}^{i})} + \frac{\delta}{\sum_{w_i} c(w_{i-n+1}^{i})} N_{1+}(w_{i-n+1}^{i-1}\ \bullet) p_{KN}(w_i|w_{i-n+2}^{i-1})$$

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Evaluating Language Models

2 types of evaluation

- Extrinsic evaluation
- Intrinsic evaluation

Extrinsic Evaluation

- Model metrics compared with respect to applications implemented in

Intrinsic Evaluation

- Single model evaluation
  - Perplexity

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Perplexity

I always order burger with ....

fries
drinks
sausage
....
....
burgers
with burgers

A good language models with add words like fries, drinks or sausage to the above sentence while a bad language model could add completely random words

A better model of text is the one that assigns a higher probability to the words that actually occurs.

Perplexity is the probability of test set normalized by the number of words

$$PP(W) = P(w_1 w_2 \ldots w_N)^{-\frac{1}{N}}$$

$$= \sqrt[N]{\frac{1}{P(w_1 w_2 \ldots w_N)}}$$

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Perplexity as average branching factor

How hard is the task of recognizing digits ‘0’, ‘1’,‘2’,‘3’,‘4’,‘5’,‘6’,‘8’,‘8’,‘9’ ?

There were …….. people in the room.

Assuming that the above space can be filled with any digit from 0-9 and probability of all these digits are equally likely

P(any digit) = 1/10

PP(any digit)= (1/10)^-1

= 10

Lower the perplexity, better the model

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Backoff

- Non linear method
- Estimate for an n-gram is allowed to back off through progressively shorter histories
- Trigram version

$$\hat{P}(w_i \mid w_{i-2}w_{i-1}) = \begin{cases} P(w_i \mid w_{i-2}w_{i-1}), & \text{if } C(w_{i-2}w_{i-1}w_i) > 0 \\ \alpha_1 P(w_i \mid w_{i-1}), & \text{if } C(w_{i-2}w_{i-1}w_i) = 0 \\ & \text{and } C(w_{i-1}w_i) > 0 \\ \alpha_2 P(w_i), & \text{otherwise.} \end{cases}$$

Word Representation

How do we represent the meaning of a wod?

⇒ One common NLP solution: Use a taxonomic resource(eg. **WordNet**), a thesaurus containing a list of synonyms set and hypernyms set (“is a” relationships)

E.g., synonyms set containing “good”:

```
noun: good
noun: good, goodness
noun: good, goodness
noun: commodity, trade_good, good
adj: good
adj (sat): full, good
adj: good
adj (sat): estimable, good, honorable, respectable
adj (sat): beneficial, good
adj (sat): good
adj (sat): good, just, upright
…
adverb: well, good
adverb: thoroughly, soundly, good
```

E.g., hypernyms of “panda”

```
[Synset('procyonid.n.01'),
Synset('carnivore.n.01'),
Synset('placental.n.01'),
Synset('mammal.n.01'),
Synset('vertebrate.n.01'),
Synset('chordate.n.01'),
Synset('animal.n.01'),
Synset('organism.n.01'),
Synset('living_thing.n.01'),
Synset('whole.n.02'),
Synset('object.n.01'),
Synset('physical_entity.n.01'),
Synset('entity.n.01')]
```

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Word Representation

Problems with such discrete representation

- Missing context and nuances
  - Eg. “There is a stone in river ***bank***”, “The **bank** should be closed by now”.
- Missing new meanings of words
  - Eg. wicked, badass, wizard, ninja
  - Impossible to keep up-to-date forever
- Requires human labor to maintain
- Cannot compute accurate word similarity

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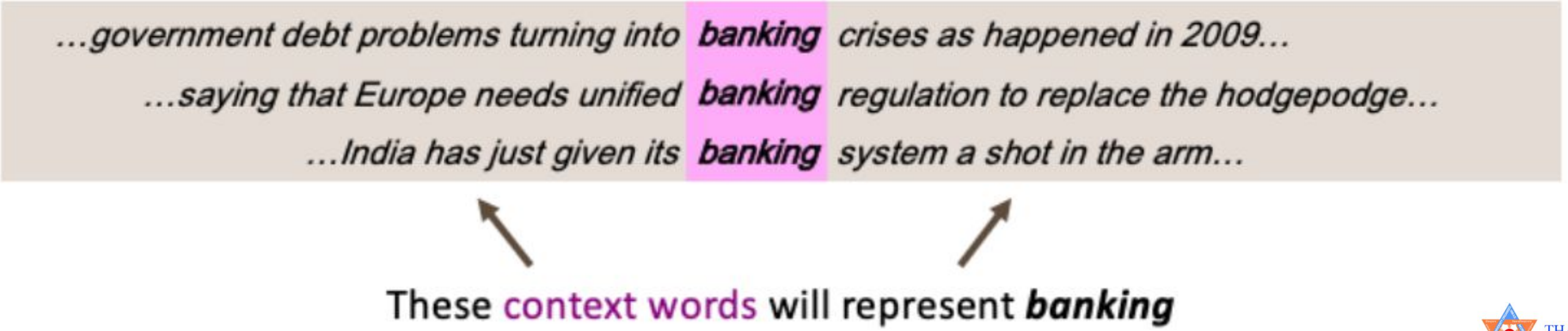
Word Similarity

- Naively, words can be represented by one-hot vectors
  - motel = [0 0 1 0 0 0 0 0 0 0 0]
  - hotel = [0 0 0 0 0 0 0 0 1 0 0]
- Dot products of these two vectors = 0 (orthogonal)
- Thus, there is no natural notion of similarity for one-hot vectors
- Solution?
  - Rely on WordNet to get similarity?
    - Incompleteness, inconsistency, difficult to maintain
  - **Actual Solution: Learn to encode similarity in the vectors**

Word Similarity

- How to encode similarity?
    - Distributional semantics: **A word's meaning is given by the words that frequently appear close-by**
        - "*You shall know a word by the company it keeps*" (J.R Firth 1957)
        - One of the most successful ideas of modern NLP
    - When a word *w* appears in a text, its context is the set of words that appear nearby (within a fixed size window)



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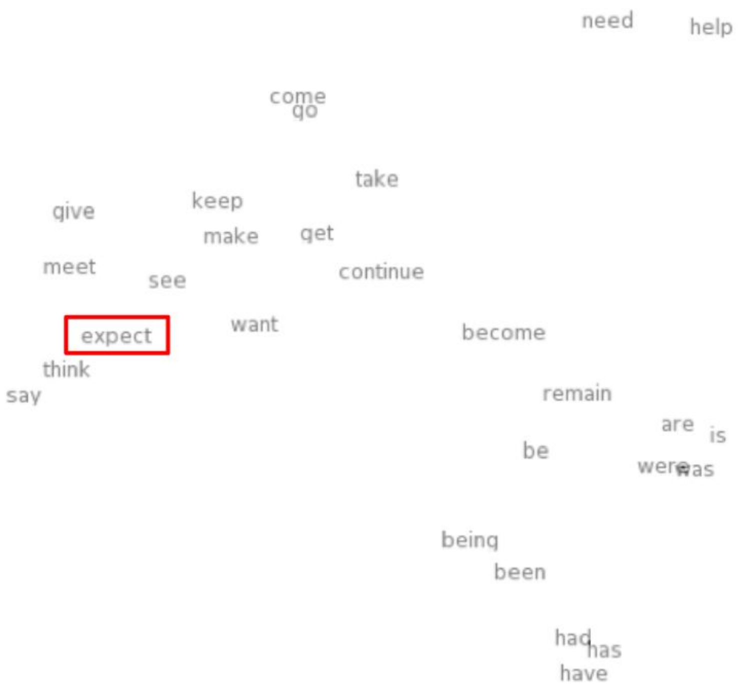
Word Vectors

$$expect = \begin{pmatrix} 0.286 \\ 0.792 \\ -0.177 \\ -0.107 \\ 0.109 \\ -0.542 \\ 0.349 \\ 0.271 \\ 0.487 \end{pmatrix}$$



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Suggested Readings

1. https://web.stanford.edu/~jurafsky/slp3/6.pdf (vector semantics and embeddings)
2. Efficient Estimation of Word Representations in Vector Space (original word2vec paper)

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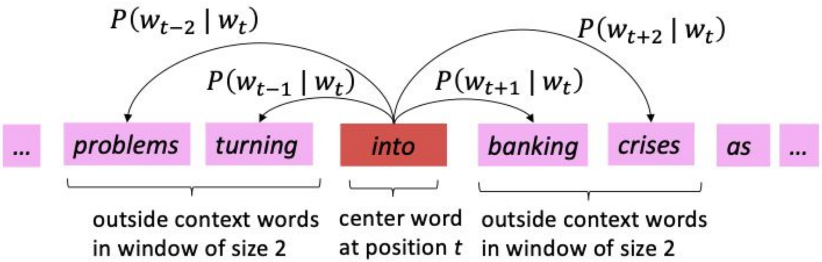
Word2Vec is an initial framework for learning word vectors

- We got large corpus of text
- Go through each position *t* in the text, which has a **center word c**, and **context ("outside") words o**
- Calculate the **probability** of *o* given *c* (or vice versa)
- **Gradient descent** to maximize this probability
- Example windows for $P(w_{t+j}|w_t)$



Efficient Estimation of Word Representations in Vector Space, Mikolov et al., 2013, https://arxiv.org/pdf/1301.3781.pdf

Word2Vec: Objective Function

For each position t = 1,...T, predict context words within a window of fixed size m, given center word w_j, the likelihood is

$$L(\theta) = \prod_{t=1}^{T} \prod_{\substack{-m \le j \le m \\ j \ne 0}} \log P(w_{t+j} | w_t; \theta)$$

The objective function $J(\theta)$ is the average negative log likelihood:

$$J(\theta) = -\frac{1}{T} \sum_{t=1}^{T} \sum_{\substack{-m \le j \le m \\ j \ne 0}} \log P(w_{t+j} | w_t; \theta)$$

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Word2Vec

Two flavors of Word2Vec algorithm

- **CBOW (Continuous Bag of words)**
  - Uses the context words to predict current word
- **Skip-gram**
  - Use the current word to predict its context

Word2Vec

A closer look...

The probability of a predicted word occurring given a center word:

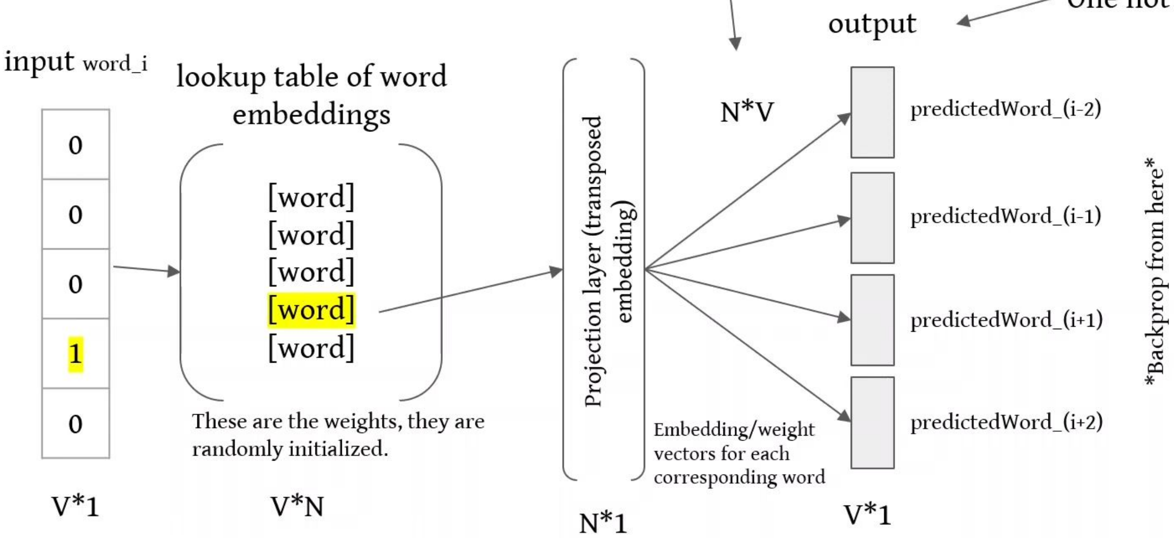
$$P\left(predictedWord_n \mid centerWord\right) = \frac{e^{dot(predictedWord_n,\ centerWord)}}{\sum_i e^{dot(predictedWord_i,\ centerWord)}}$$

Activation function:

$$softmax\left(predictedWord_n\right) = \frac{e^{predictedWord_n}}{\sum_i e^{predictedWord_i}}$$

One hot vector in:

One hot vector out



The softmax activation normalizes the outputs as a probability distribution. This means a percentage is associated with each predicted word.

The weight vector is actually what becomes your word embedding!

V: # of words in the corpus, N: # of values in our vectors

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Word2Vec

```
[12] from gensim.models import Word2Vec
     import numpy as np
```

```
[13] sentences=[['this','is','a','sentence','about','school'],
                ['school','has','students','and','teachers'],
                ['the','students','learn'],
                ['the','teachers','make','money']]
```

```
[28] model=Word2Vec(sentences, min_count=1, window=3)
```

```
first=model['students']
target=model['learn']
second=model['teachers']

print("First: ", np.linalg.norm(target-first))
print("Second: ", np.linalg.norm(target-second))
```

```
First:  0.04220174
Second:  0.03774856
```

```
model.most_similar('school')
```

```
[('has', 0.17184367775917053),
 ('the', 0.1533074080944061З),
 ('this', 0.12881389260292053),
 ('students', 0.08287020027637482),
 ('a', 0.06733693182468414),
 ('sentence', 0.05654553323984146),
 ('and', 0.008189082145690918),
 ('money', -0.0024816691875457764),
 ('teachers', -0.029205819591879845),
 ('learn', -0.06788718700408936)]
```

sg parameter in Word2Vec( ):

sg →0 (CBOW)

sg → 1 (Skipgrams)

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Word2Vec : Skip-gram vs CBOW

- **CBOW** (Predict center word given outside words) and **Skip-gram** (Predict context ("outside") words given center word) uses the **same training procedure.**
- **CBOW** is much simpler, this implies a **much faster convergence** for CBOW than for Skip-gram, in the original paper, CBOW took hours to train, Skip-gram 3 days.
- CBOW learns better **syntactic relationships** between words while Skip-gram is better in capturing better **semantic relationships**. For the word 'cat':
  - CBOW would retrieve as closest vectors morphologically like plurals, i.e. **'cats'**
  - Skip-gram would consider morphologically different words (but semantically relevant) like **'dog' much closer to 'cat'** in comparison.
- Because Skip-gram rely on single word input, it is **less sensitive to overfit frequent words** (and it's also the reason of the better performances of Skip-gram in capturing semantic relationships).

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Word2Vec : Summary

- **Word2Vec** is the the first framework to encode word vectors using nearby words
    - Comes in 2 variants : **Skip-gram** and **CBOW**
    - Skip gram seems better but takes longer time to train
    - Amazingly effective to capture word similarity
- The current approach is inefficient given the huge computational cost in the lower term. We can revisit this using **negative sampling** instead

$$\frac{\exp(\mathbf{u_o}^\top \mathbf{v_c})}{\sum_{w=1}^{V} \exp(\mathbf{u_w}^\top \mathbf{v_c})}$$

Huge cost!

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Negative Sampling

- Instead of using all vocabularies, we can just pick some “negative” samples
- Steps:
  - We draw k random negative samples
  - We maximize the probability of real outside word appearing and minimize the probability of random words appearing around the center word.

$$\mathbf{J}_{\text{neg-sample}}(\mathbf{v}_c, o, \mathbf{U}) = -\log(\sigma(\mathbf{u}_o^T \mathbf{v}_c)) - \sum_{k=1}^{K} \log(\sigma(-\mathbf{u}_k^T \mathbf{v}_c))$$

- Since we are not normalizing, we use sigmoid instead to turn the dot product to probabilities.
- Negative sampling technique is a widely used technique in deep learning field.

Limitations of Word2Vec

- Only looks at local words
  - Does not utilize global co occurrence statistics
  - **Possible solution:** Use co occurrence counts **(GloVe)**

- Does not work well with OOV tokens
  - **Possible solution:** Use character based or sub-words based embeddings (eg. FastText)

- Unsure whether contextual information was fully captured
  - **Possible solution:**
    - Pass these trained embeddings through some RNN/LSTM and get the resulting encodings as embeddings (ELMo)
    - Provide some prediction task, so that the model can capture better context (BERT)

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Co-occurrence matrix

- 2 options
  - Window
  - Full document

- **Window:** Similar to Word2Vec, use window around each word -> capture some syntactic and semantic information, (Use window-based for word embedding)
- **Document:** similar to Latent Semantic Analysis

Co-occurrence matrix

- Example : Window length 1 (common: 5-10)

- Example corpus:
    - *" I like deep learning. "*
    - *" I like NLP."*
    - *" I enjoy flying. "*

counts	I	like	enjoy	deep	learning	NLP	flying	.
I	0	2	1	0	0	0	0	0
like	2	0	0	1	0	1	0	0
enjoy	1	0	0	0	0	0	1	0
deep	0	1	0	0	1	0	0	0
learning	0	0	0	1	0	0	0	1
NLP	0	1	0	0	0	0	0	1
flying	0	0	1	0	0	0	0	1
.	0	0	0	0	1	1	1	0

Also has its own problem !!

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Global Vectors for word representation (GloVe)

- Paper : https://aclanthology.org/D14-1162.pdf

- Mathematical explanation and derivation : https://towardsdatascience.com/light-on-math-ml-intuitive-guide-to-understanding-glove-embeddings-b13b4f19c010

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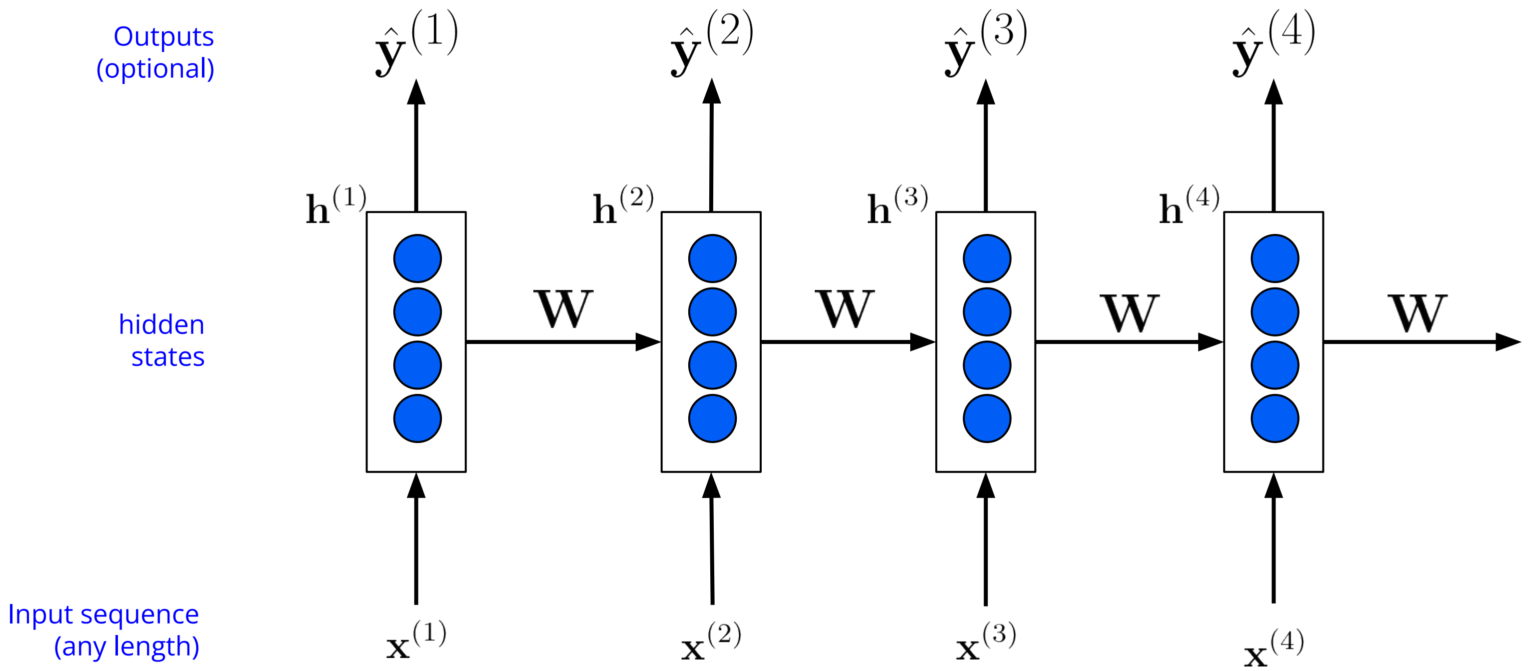
Recurrent Neural Network

- **Suggested Readings**
  - N-gram Language Models (textbook chapter)
  - The Unreasonable Effectiveness of Recurrent Neural Networks (blog post overview about RNN)
  - Sequence Modeling: Recurrent and Recursive Neural Nets (Sections 10.1 and 10.2)
  - On Chomsky and the Two Cultures of Statistical Learning (some cool stuffs about LM)

Recurrent Neural Network



Recurrent Neural Network

output distribution

$$\hat{\mathbf{y}}^{(t)} = \text{softmax}(\mathbf{U}\mathbf{h}^{(t)} + \mathbf{b_2}) \in \mathbb{R}^{|V|}$$

hidden states

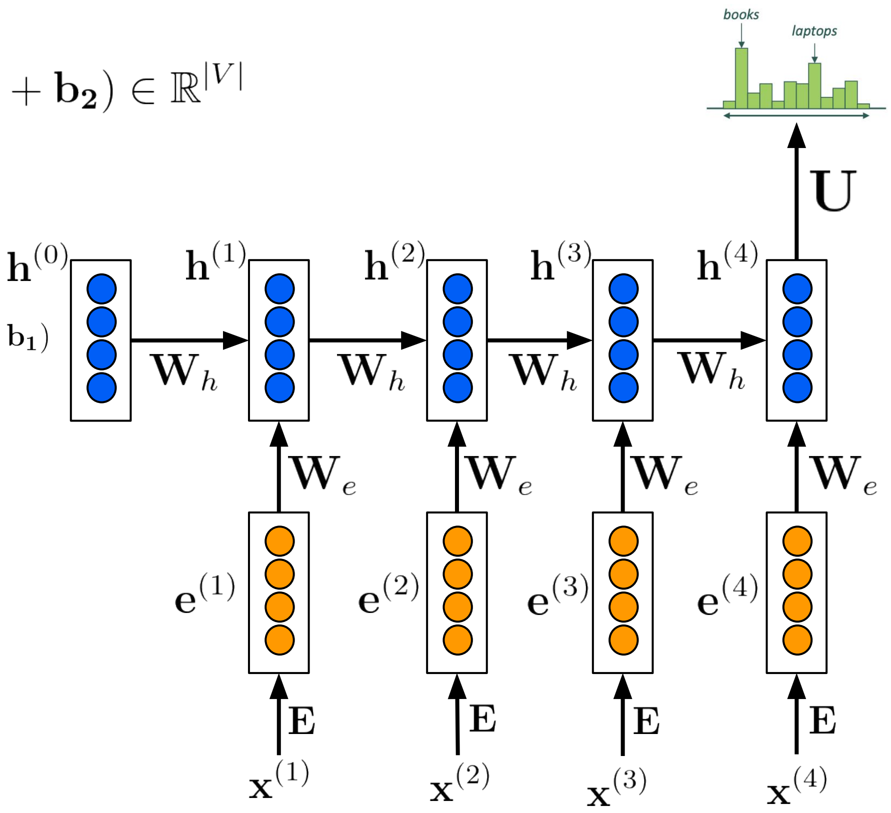
$$\mathbf{h}^{(t)} = f(\mathbf{W}_h \mathbf{h}^{(t-1)} + \mathbf{W}_e \mathbf{e}^{(t)} + \mathbf{b}_1)$$

words embeddings

$$\mathbf{e}^{(t)} = \mathbf{E}\mathbf{x}^{(\mathbf{t})}$$

words/one-hot vectors

$$\mathbf{x}^{(t)} \in \mathbb{R}^{|V|}$$



- Can process any length input
- Can use information from many steps back
- Model size does not increase because W is shared

Remaining problems:

- Recurrent computation is **slow** because it's sequential
- In reality, **difficult to access information from many steps back** (more on this later in the course)

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Training a RNN LM

- Get a **big corpus of text** which is a sequence of words
- Feed into RNN-LM; compute output distribution for **every step t**
  - i.e., predict probability dist of every word, given words so far

- **Loss function** on step t is **cross-entropy** between predicted probability distribution , and the true next word (one hot for):

$$J^{(t)}(\theta) = CE(\mathbf{y}^{t}, \hat{\mathbf{y}}^{(t)}) = -\sum_{w \in V} \mathbf{y}_w^{(t)} \log \hat{\mathbf{y}}_w^{(t)} = -\log \hat{\mathbf{y}}_{\mathbf{x}_{t+1}}^{(t)}$$

- Average this to get overall loss for the entire training set

$$J(\theta) = \frac{1}{T}\sum_{t=1}^{T} J^{(t)}(\theta) = \frac{1}{T}\sum_{t=1}^{T} -\log \hat{\mathbf{y}}_{\mathbf{x}_{t+1}}^{(t)}$$

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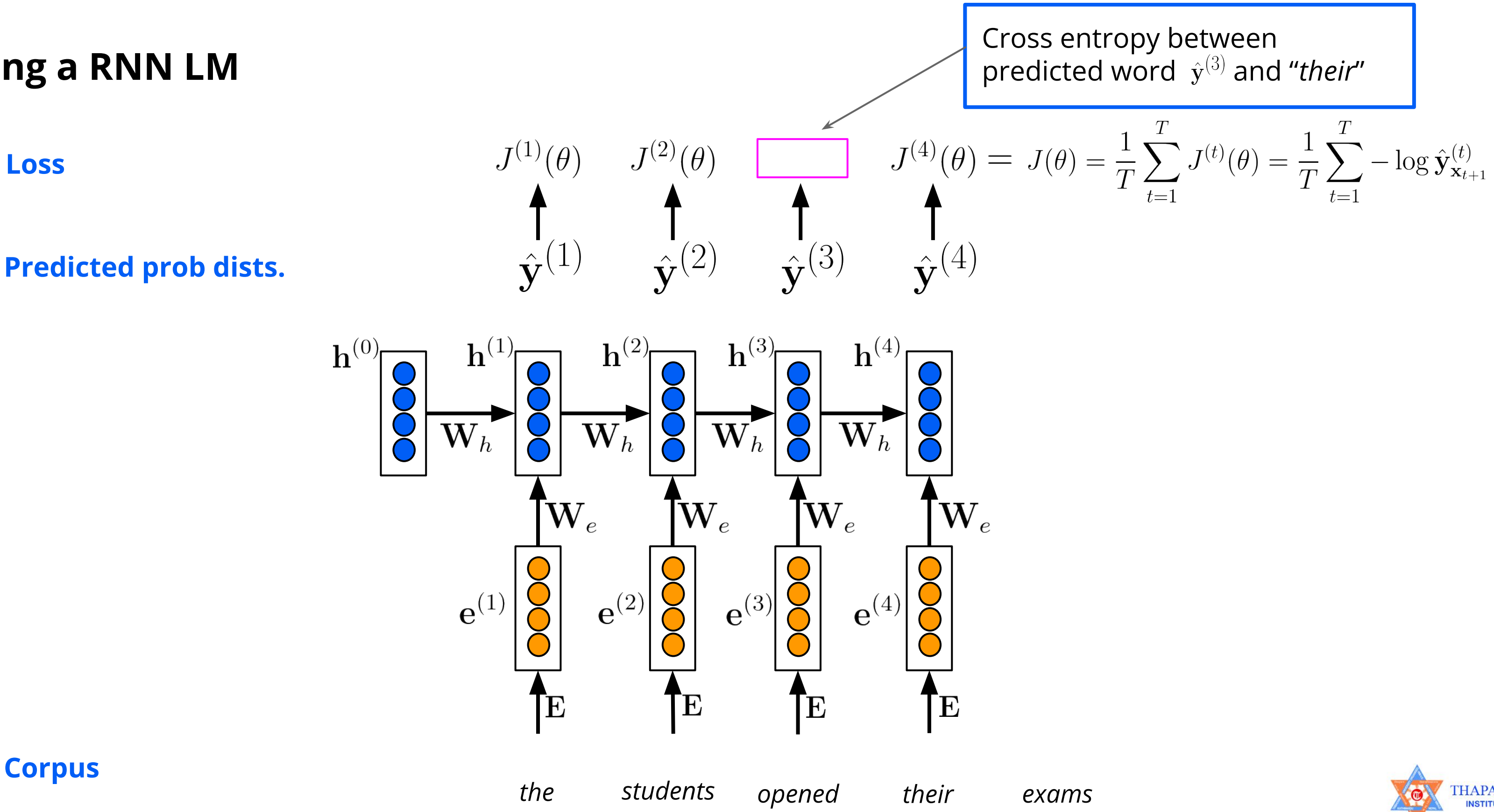
Training a RNN LM



Training a RNN LM

- Better to perform **stochastic gradient descent** instead to save computational time
    - Use batch of sentences, instead of the whole corpus
- The derivative w.r.t the repeated weight matrix is simply the sum of all gradients of each time step

$$\frac{\partial J^{(t)}}{\partial \mathbf{W}_h} = \sum_{i=1}^{t} \frac{\partial J^{(t)}}{\partial \mathbf{W}_h}\bigg|_{(i)}$$

This is also known as "**backpropagation through time**"

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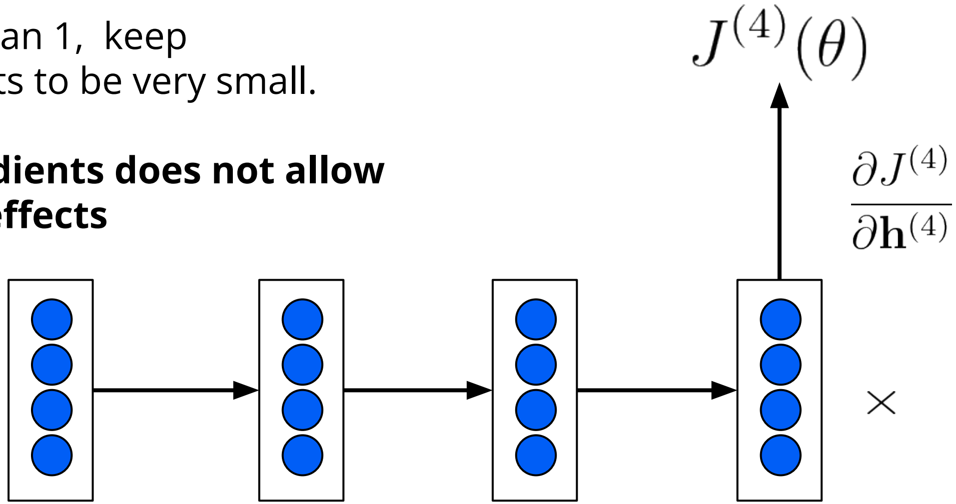
Vanishing Gradients

Imagine if all these gradients are less than 1, keep multiplying them will cause the gradients to be very small.

The real problem is that **vanishing gradients does not allow the network to learn any long-term effects**



$$\frac{\partial J^{(4)}}{\partial \mathbf{h}^{(1)}} = \frac{\partial \mathbf{h}^{(2)}}{\partial \mathbf{h}^{(1)}} \times \frac{\partial \mathbf{h}^{(3)}}{\partial \mathbf{h}^{(2)}} \times \frac{\partial \mathbf{h}^{(4)}}{\partial \mathbf{h}^{(3)}}$$

Effect of vanishing gradients

- **LM task**: "*The writer of the books* _______" (possible words: is, are)
- **Correct answer**: *The writer of the books is planning a sequel*
- **Syntactic** recency: The writer of the book is (correct)
- **Sequential** recency: The writer of the books are (incorrect)
- Due to vanishing gradient, RNN-LMs are better at learning from sequential recency than syntactic recency, so they make this type of error more often [Linzen et al. 2016]

Exploding Gradient

- If the gradient becomes too big, the SGD update can easily overshoot:

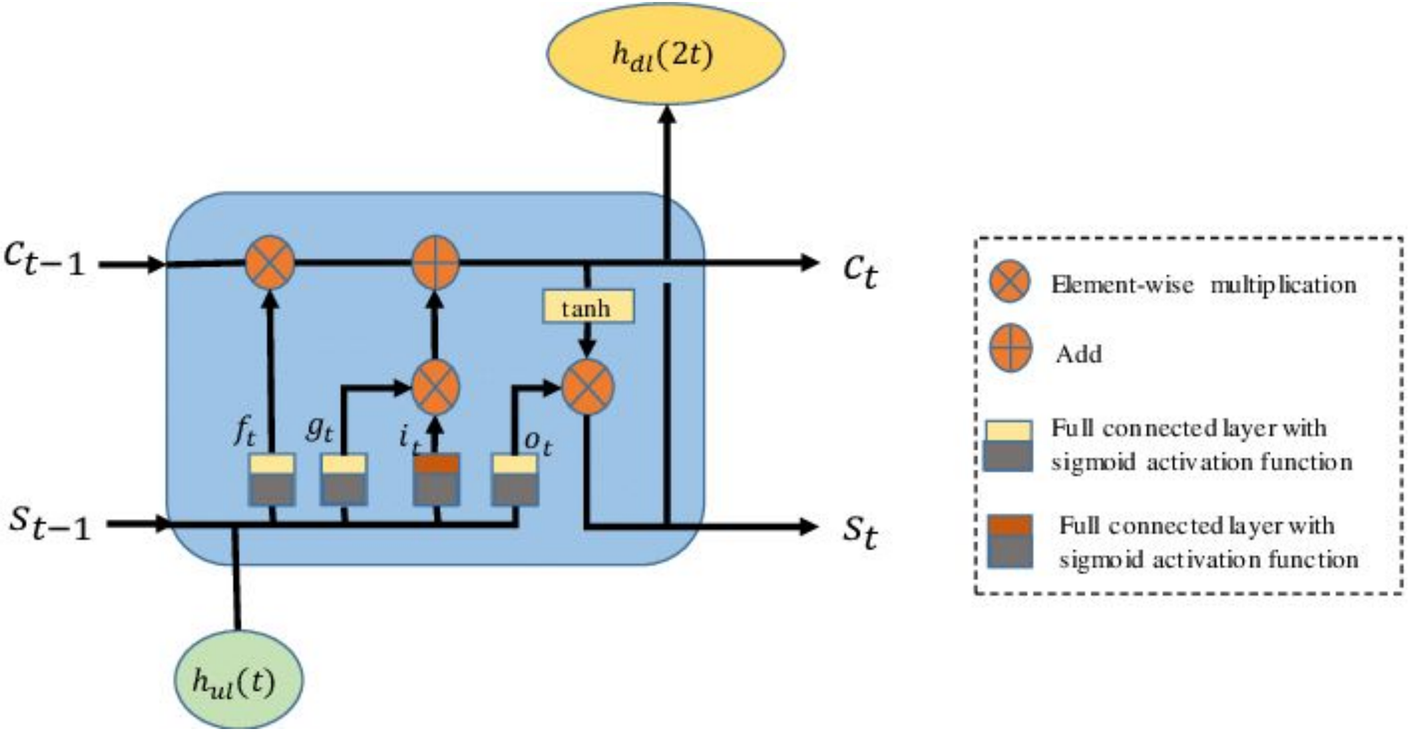
$$\theta^{\text{new}} = \theta^{\text{old}} - \alpha \nabla_\theta J(\theta)$$

- This can cause bad updates: we take too large a step and reach a weird and bad parameter configuration (with large loss)
- In the worst case, this will result in **Inf** or **NaN** in your network
  a. (then you have to restart training from an earlier checkpoint)

Solving vanishing gradient

- As hinted earlier, vanishing gradients cause the model **inability to learn long-term relationships**
- Instead of trying to fix vanishing gradients which is difficult, can we try to **preserve long-term relationships better**?
- How about a RNN with a separate **memory**?

Long Short Term Memory (LSTM)



Long Short Term Memory (LSTM)

A type of RNN proposed by Hochreiter and Schmidhuber in 1997 as a solution to the vanishing gradients problem. Everyone cites that paper but really a crucial part of the modern LSTM is from Gersetal.(2000) :-)

Forget gate: controls what is kept vs. forgotten, from previous cell state

Input gate: controls what parts of the new cell contents are written to cell

Output gate: controls what parts of cell are output to hidden state

New cell content: this is the new content to be written to the cell

Cell state: erase ("forget") some content from last cell state, write ("input") some new cell state

Hidden state: read ("output") some content from the cell

$$
\left.
\begin{aligned}
\mathbf{f}^{(t)} &= \sigma\left(\mathbf{W}_f \mathbf{h}^{(t-1)} + \mathbf{U}_f \mathbf{x}^{(t)} + \mathbf{b}_f\right) \\
\mathbf{i}^{(t)} &= \sigma\left(\mathbf{W}_i \mathbf{h}^{(t-1)} + \mathbf{U}_i \mathbf{x}^{(t)} + \mathbf{b}_i\right) \\
\mathbf{o}^{(t)} &= \sigma\left(\mathbf{W}_o \mathbf{h}^{(t-1)} + \mathbf{U}_o \mathbf{x}^{(t)} + \mathbf{b}_o\right) \\
\\
\tilde{\mathbf{c}}^{(t)} &= \tanh\left(\mathbf{W}_c \mathbf{h}^{(t-1)} + \mathbf{U}_c \mathbf{x}^{(t)} + \mathbf{b}_c\right) \\
\mathbf{c}^{(t)} &= \mathbf{f}^{(t)} \circ \mathbf{c}^{(t-1)} + \mathbf{i}^{(t)} \circ \tilde{\mathbf{c}}^{(t)} \\
\mathbf{h}^{(t)} &= \mathbf{o}^{(t)} \circ \tanh \mathbf{c}^{(t)}
\end{aligned}
\right\}
$$

All these vectors are of same length

Gates are applied using element-wise (Hadamard product)

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Long Short Term Memory (LSTM)

- In **2013-2015**, LSTMs started achieving **state-of-the-art** results
  - Successful tasks: handwriting recognition, speech recognition, machine translation, parsing, and image captioning, as well as language models
  - LSTMs became the dominanch approach for most NLP tasks

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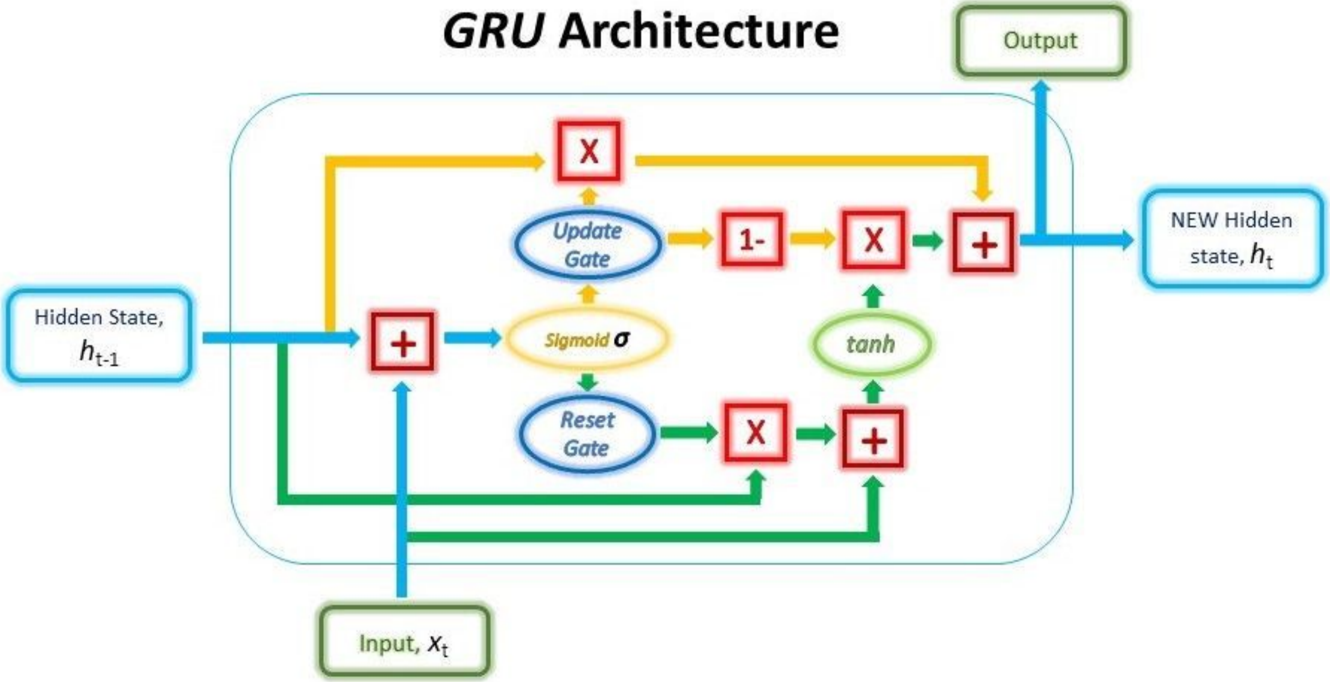
Gated Recurrent Unit (GRU)

Paper: https://arxiv.org/pdf/1406.1078v3.pdf

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