Generative Artificial Intelligence

Word Embeddings and Language Modeling

GAI Motivation (for NLP tasks)

Supervised learning

- Text classification
- QA system
- …

Think about your learning strategies !

Issues

- Lack of training data
- Limitation of domain knowledge

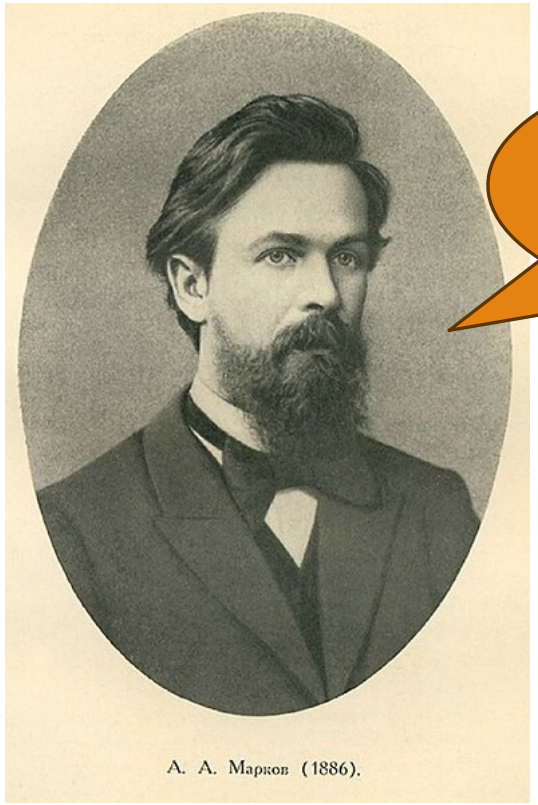
Natural Language Generation

The commonest way to generate sentences is by **writing the words down, one after another**.

e.g. Please turn your homework …

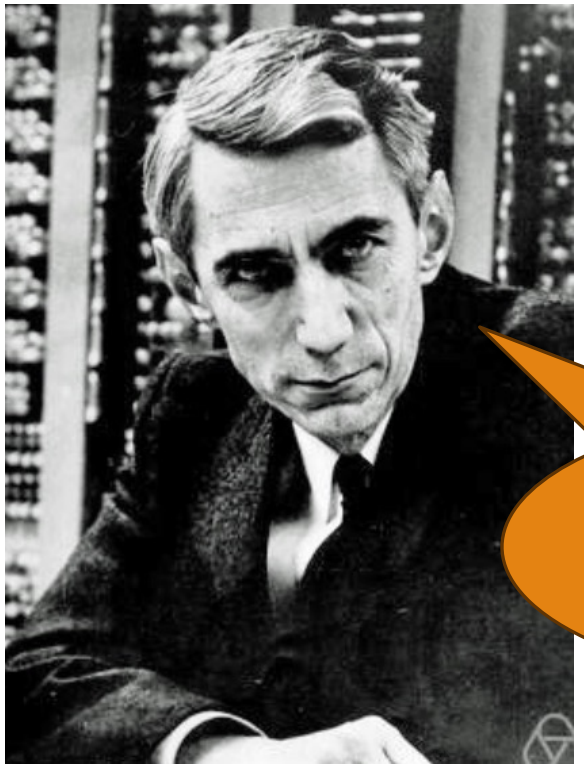
The next could be ?

語言模型 (Language Model)



[1913] The chance of a letter appearing depends on the letter before it.

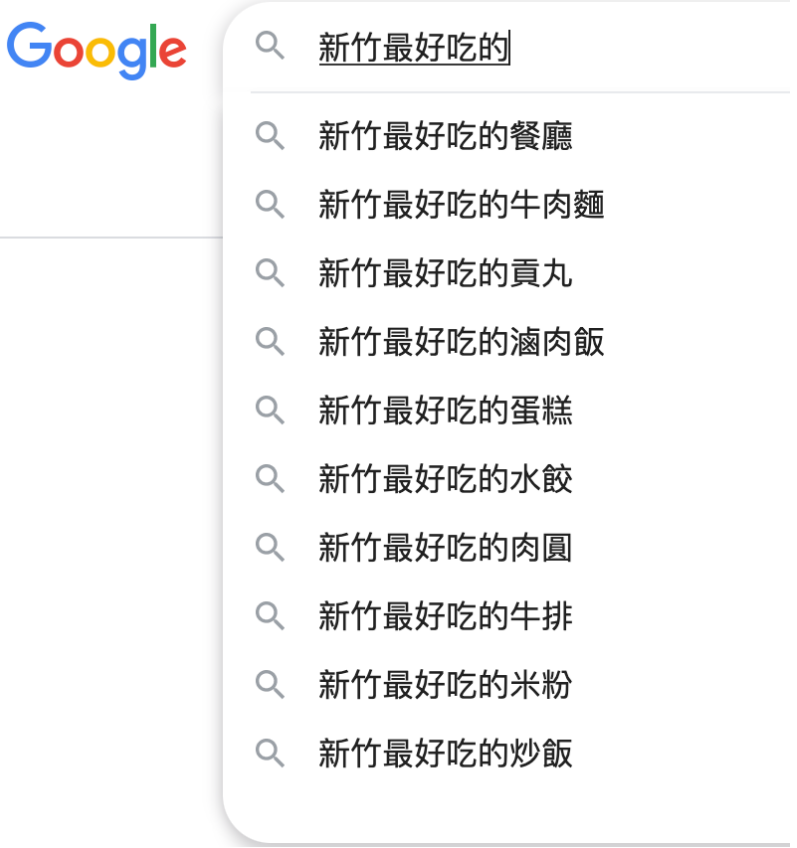
Andrey Markov
1856 - 1922

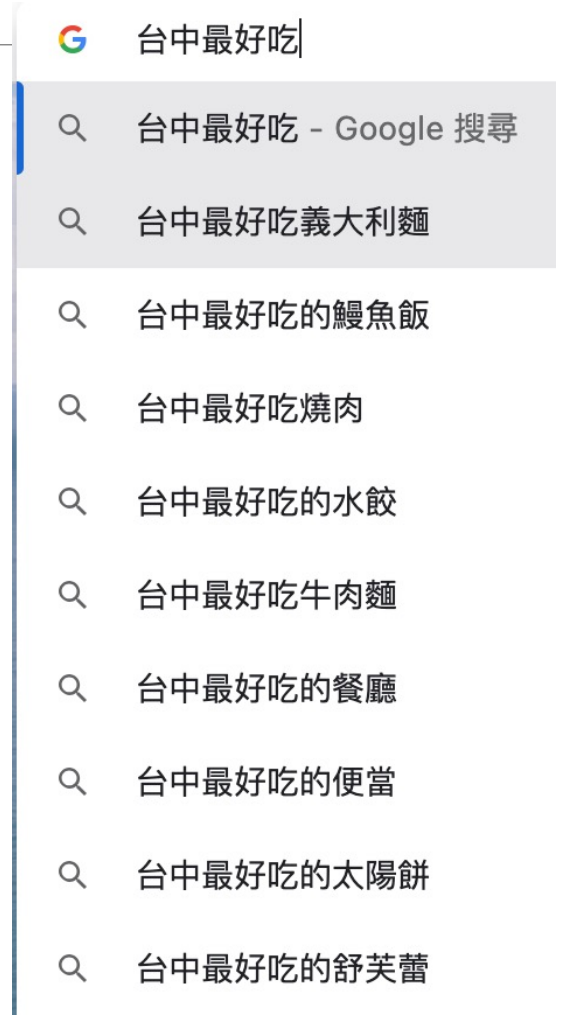


[1951] Prediction and Entropy of Printed English

Claude Shannon
1916 – 2001

Language Model





妳說這一句　很有夏天的感覺

消失的下雨天

我用幾行字形容妳是我的誰

為妳翹課的那一天　花落的那一天

怎麼這樣子　雨還沒停妳就撐傘要走

童年的紙飛機 現在終於飛回我手裡

天青色等煙雨 而我在等妳

P (b | a)

P (c | ab)

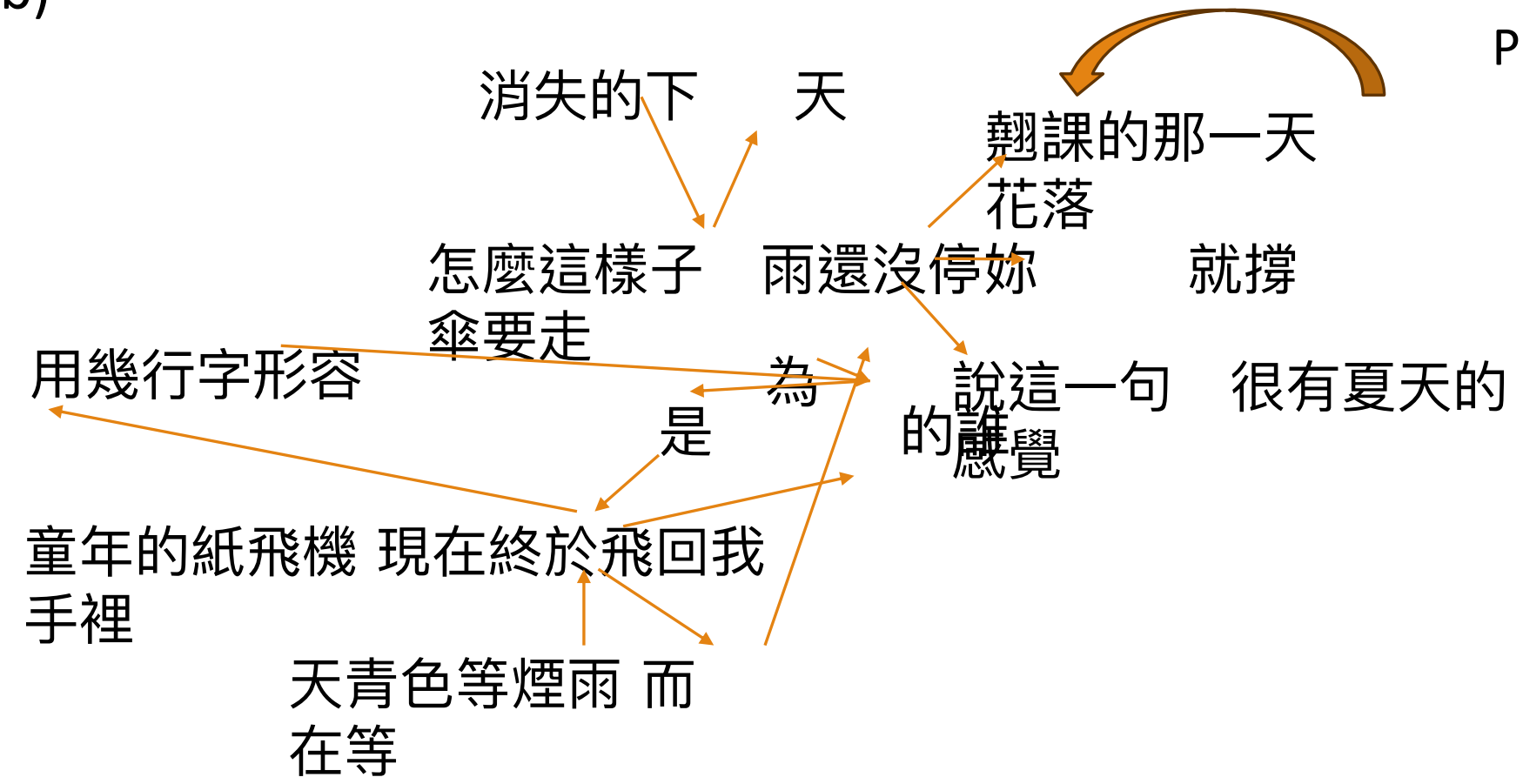
.

.

.

P (說 | 妳) = 1/4

P (說 | 沒停妳) =



N-grams

An n-gram is a sequence of n words:

e.g. Please turn your homework …

1-gram (unigram): "please", "turn", "your", or "homework"

2-gram (bigram): "please turn", "turn your", or "your homework"

3-gram (trigram): "please turn your", or "turn your homework"

…

N-gram Language Models

We can use a naïve statistic method to model the language

In a bi-gram model we have to count the occurrences of each bi-gram.

e.g.
C(I want) = 2
C(want to) = 3
C(spend time) = 1
...

N-gram Language Models

An example of bi-gram LM.

Draw a table of bigram counts for eight of the words in all of the sentences

	i	want	to	eat	chinese	food	lunch	spend
i	5	827	0	9	0	0	0	2
want	2	0	608	1	6	6	5	1
to	2	0	4	686	2	0	6	211
eat	0	0	2	0	16	2	42	0
chinese	1	0	0	0	0	82	1	0
food	15	0	15	0	1	4	0	0
lunch	2	0	0	0	0	1	0	0
spend	1	0	1	0	0	0	0	0

From: Stanford NLP

N-gram Language Models

Apply add-k smoothing (k=1):

	i	want	to	eat	chinese	food	lunch	spend
i	6	828	1	10	1	1	1	3
want	3	1	609	2	7	7	6	2
to	3	1	5	687	3	1	7	212
eat	1	1	3	1	17	3	43	1
chinese	2	1	1	1	1	83	2	1
food	16	1	16	1	2	5	1	1
lunch	3	1	1	1	1	2	1	1
spend	2	1	2	1	1	1	1	1

Compute Probability (relative frequency):

	i	want	to	eat	chinese	food	lunch	spend
i	0.0015	0.21	0.00025	0.0025	0.00025	0.00025	0.00025	0.00075
want	0.0013	0.00042	0.26	0.00084	0.0029	0.0029	0.0025	0.00084
to	0.00078	0.00026	0.0013	0.18	0.00078	0.00026	0.0018	0.055
eat	0.00046	0.00046	0.0014	0.00046	0.0078	0.0014	0.02	0.00046
chinese	0.0012	0.00062	0.00062	0.00062	0.00062	0.052	0.0012	0.00062
food	0.0063	0.00039	0.0063	0.00039	0.00079	0.002	0.00039	0.00039
lunch	0.0017	0.00056	0.00056	0.00056	0.00056	0.0011	0.00056	0.00056
spend	0.0012	0.00058	0.0012	0.00058	0.00058	0.00058	0.00058	0.00058

From: Stanford NLP

Probability of a Sequence

Let's begin with the task of computing the probability

$$P(w|h) = \frac{C(w,h)}{C(h)}$$

w: the word to be generated
h: some history
C: the times the pattern show up in the dataset

e.g. Compute the probability of the word "the" given the history "its water is so transparent that".

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

Probability of a Sequence

Compute probabilities of entire sequences like $w_1 \dots w_n$ N-gram model(Chain Rule of Probabilities)

$$P(w_1 \dots w_n) = P(w_1)P(w_2|w_1)P(w_3|w_{1:2}) \dots P(w_n|w_{n-N+1})$$

$$= \prod_{k=1}^{n} P(w_k|w_{k-N+1})$$

e.g. Bi-gram model

$$P(w_1 \dots w_n) = P(w_1)P(w_2|w_1)P(w_3|w_2) \dots P(w_n|w_{n-1})$$

$$= \prod_{k=1}^{n} P(w_k|w_{k-1})$$

Language Models

Language Models (LMs) :

Models that assign probabilities to sequences of words are called LMs.

Including:

N-Gram Language Models:

A purely statistical model of language.

Neural Language Models:

Use neural networks to predict the likelihood of sequences.

N-gram Language Models

Bigram model

Approximates the probability of a word given all the previous words $P(w_n|w_{1:n-1})$ by using only the conditional probability of the preceding word $P(w_n|w_{n-1})$

i.e. Instead of computing the probability $P(the|its\ water\ is\ so\ transparent\ that)$
Bigram model approximate it with the probability $P(the|that)$

The assumption that the probability of a word depends only on the previous word is called a Markov assumption.

Shortcomings of N-gram LMs

Limited context

- N-gram models are unable to capture longer-distance (>>N) language dependencies.

Data sparsity (High time/space complexity)

- As the N value increases, the number of parameters to store and compute grows exponentially.

Ignoring word order / context information

- N-gram models assume independence between words, neglecting the influence of word order on semantics.

Low flexibility

N-gram language models struggle with *synonyms* and have limited ability to adapt to varying conditions. (e.g. dialogue).

Bag of Words

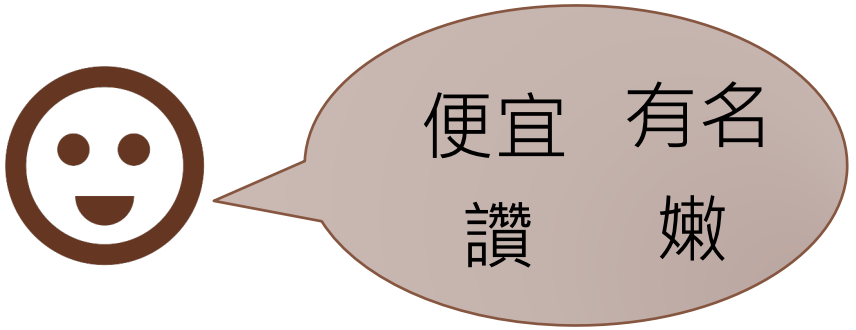
Very good drama although it appeared to have a few blank areas leaving the viewers to fill in the action for themselves. I can imagine life being this way for someone who can neither read nor write. This film simply smacked of the real world: the wife who is suddenly the sole supporter, the live-in relatives and their quarrels, the troubled child who gets knocked up and then, typically, drops out of school, a jackass husband who takes the nest egg and buys beer with it. 2 thumbs up… very very very good movie.

('the', 8),
(',', 5),
('very', 4),
('.', 4),
('who', 4),
('and', 3),
('good', 2),
('it', 2),
('to', 2),
('a', 2),
('for', 2),
('can', 2),
('this', 2),
('of', 2),
('drama', 1),
('although', 1),
('appeared', 1),
('have', 1),
('few', 1),
('blank', 1)
…..

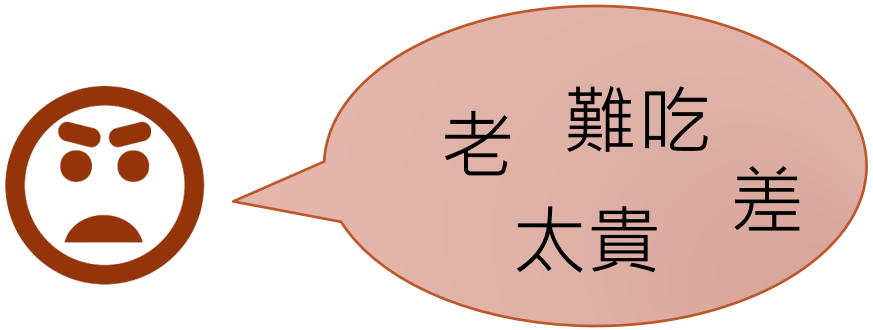
錢, 不是問題　　不, 錢是問題

Example: Opinion Mining

今天的牛排很讚又便宜
這家餐廳的前菜很有名
肉質很嫩



牛小排煮的有點太老
難吃又貴
價格太貴服務又差



One-hot encoding

Vocabulary space

Term vector

	便宜	有名	讚	嫩	難吃	太貴	差	老
便宜	1	0	0	0	0	0	0	0
有名	0	1	0	0	0	0	0	0
讚	0	0	1	0	0	0	0	0
嫩	0	0	0	1	0	0	0	0
難吃	0	0	0	0	1	0	0	0
太貴	0	0	0	0	0	1	0	0
差	0	0	0	0	0	0	1	0
老	0	0	0	0	0	0	0	1

Sparse Vectors

Sparse vector embeddings represent words as high-dimensional vectors with mostly zero values.

Each dimension corresponds to a unique feature (word), measured by some well-designed methods.

- TF-IDF
- PPMI

Distributional Hypothesis

Words that occur in similar contexts tend to have similar meanings.

The NLP approaches utilize the context around the word to define its meaning.

e.g.

- I enjoy coding and I do it everyday!
- I like coding and I do it everyday!

"enjoy" and "like" are synonym and they are in the same context.

TF-IDF

The mathematical representation of TF-IDF:

$$TF - IDF = TF \times IDF$$

where

$$TF_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}} \qquad IDF_i = lg \frac{|D|}{|\{j : t_i \in d_j\}|}$$

- Where $n_{i,j}$ i-th word in j-th text in the dataset.

TF (Term Frequency)

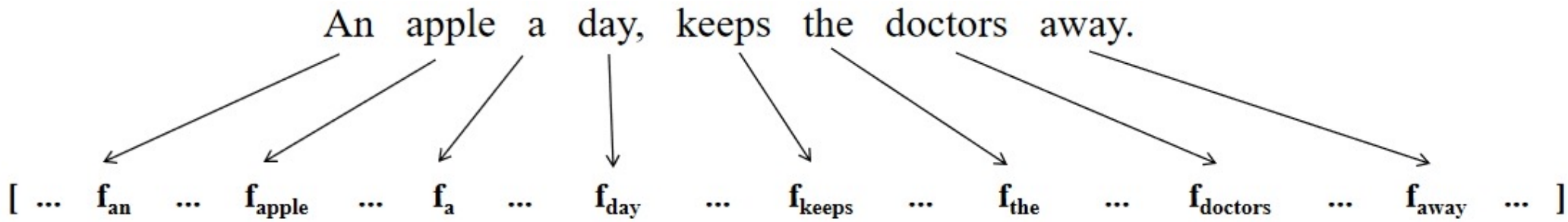
- Represents the "frequency" of a term appearing in a text.

IDF (Inverse Document Frequency)

- Aims for terms to have higher specificity, meaning the fewer texts in the dataset contain the term, the better.

TF-IDF

After computing the scores of every terms, we get a sparse vector to represent the text.



TF-IDF

Preprocessing text (optional)

Stemming

- By removing the suffixes from words (e.g."cats," "catlike," "catty" all have "cat" as their base), we can revert the words back to their root forms.

Feature Selection

- Filter and select which parts of speech to retain, such as verbs or nouns.
- Analyze the frequency of the terms using statistical methods or algorithms like TF-IDF.

PPMI

Mutual Information (MI)

- It is a measure of how often two events x and y occur:

$$I(x,y) = log_2 \frac{P(x,y)}{P(x)P(y)}$$

PMI (Pointwise MI)

- The mutual information between a target word w and a context word c:

$$PMI(w,c) = I(w,c)$$

PPMI

PPMI (Positive PMI)

- PPMI replaces all negative PMI values with zero

$$PPMI(w,c) = max(PMI(w,c), 0)$$

e.g. Co-occurrence counts for 4 words in 5 contexts

	computer	data	result	pie	sugar	count(w)
cherry	2	8	9	442	25	486
strawberry	0	0	1	60	19	80
digital	1670	1683	85	5	4	3447
information	3325	3982	378	5	13	7703
count(context)	4997	5673	473	512	61	11716

From: Stanford NLP

PPMI

Replacing the counts in with joint probabilities:

	p(w,context)					p(w)
	computer	**data**	**result**	**pie**	**sugar**	**p(w)**
cherry	0.0002	0.0007	0.0008	0.0377	0.0021	0.0415
strawberry	0.0000	0.0000	0.0001	0.0051	0.0016	0.0068
digital	0.1425	0.1436	0.0073	0.0004	0.0003	0.2942
information	0.2838	0.3399	0.0323	0.0004	0.0011	0.6575
p(context)	0.4265	0.4842	0.0404	0.0437	0.0052	

Compute the PPMI matrix

	computer	**data**	**result**	**pie**	**sugar**
cherry	0	0	0	4.38	3.30
strawberry	0	0	0	4.10	5.51
digital	0.18	0.01	0	0	0
information	0.02	0.09	0.28	0	0

Sparse vectors are obtained

From: Stanford NLP

Word embedding

Concept space

	d_1	d_2	d_3	d_4	d_5	d_6	d_7	d_8
便宜	1	3	2	3	0	-2	2	0
有名	3	1	4	2	0	2	0	1
讚	0	0	1	0	0	1	-1	0
嫩	1	3	0	1	0	0	0	0
難吃	0	0	0	0	1	0	2	0
太貴	0	0	0	0	3	1	0	1
差	-1	0	1	-1	0	2	1	0
老	0	-2	-1	0	1	3	2	1

Term vector

Dense Vectors

Dense vector embeddings represent words in a continuous vector space

Semantically similar words are closer together.

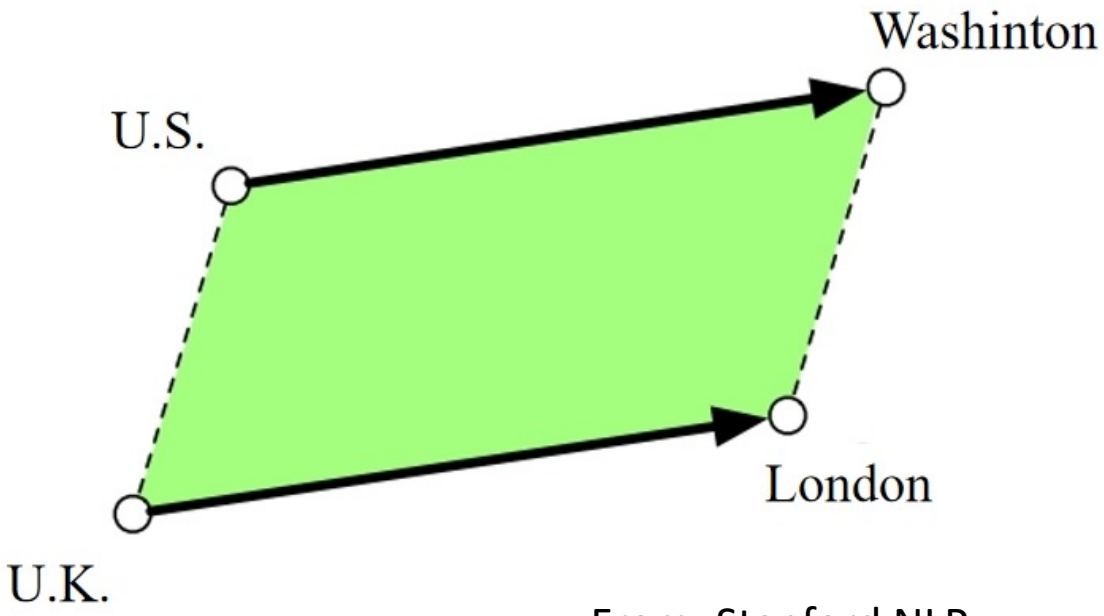
Word2Vec

Contextualized Embeddings

Properties of Embeddings

Vectors for representing words are called **embeddings**

- Analogy/Relational Similarity

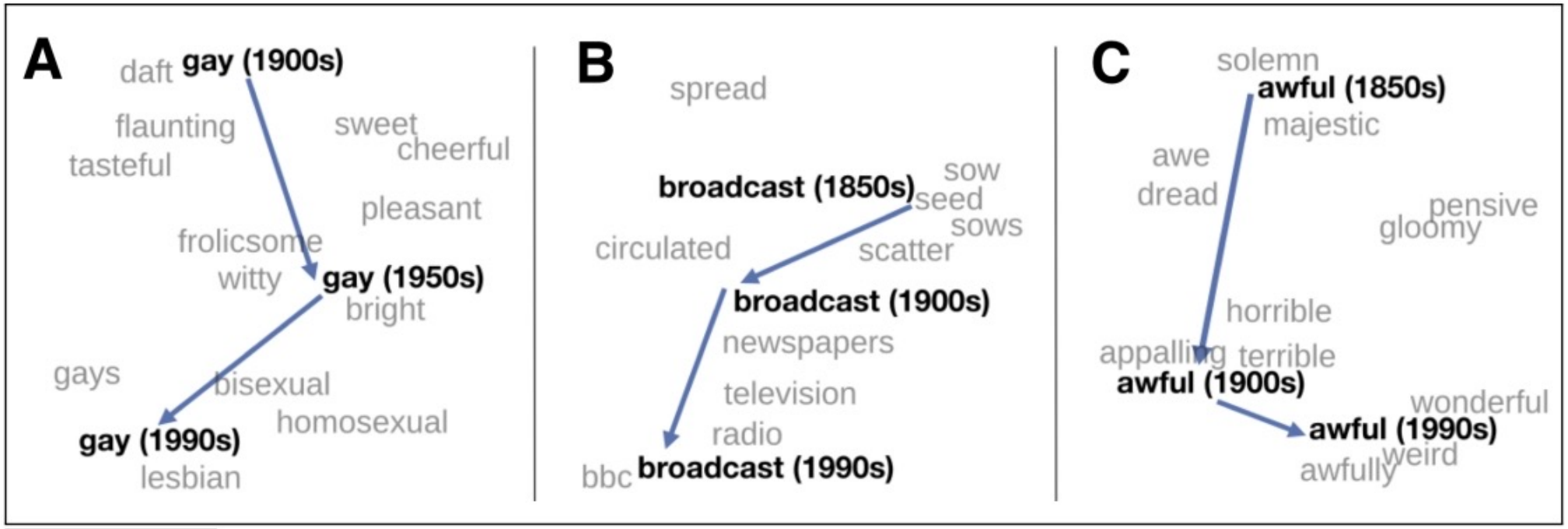


From: Stanford NLP

Washinton - U.S. = London - U.K.
Washinton - U.S. + U.K. = London

Properties of Embeddings

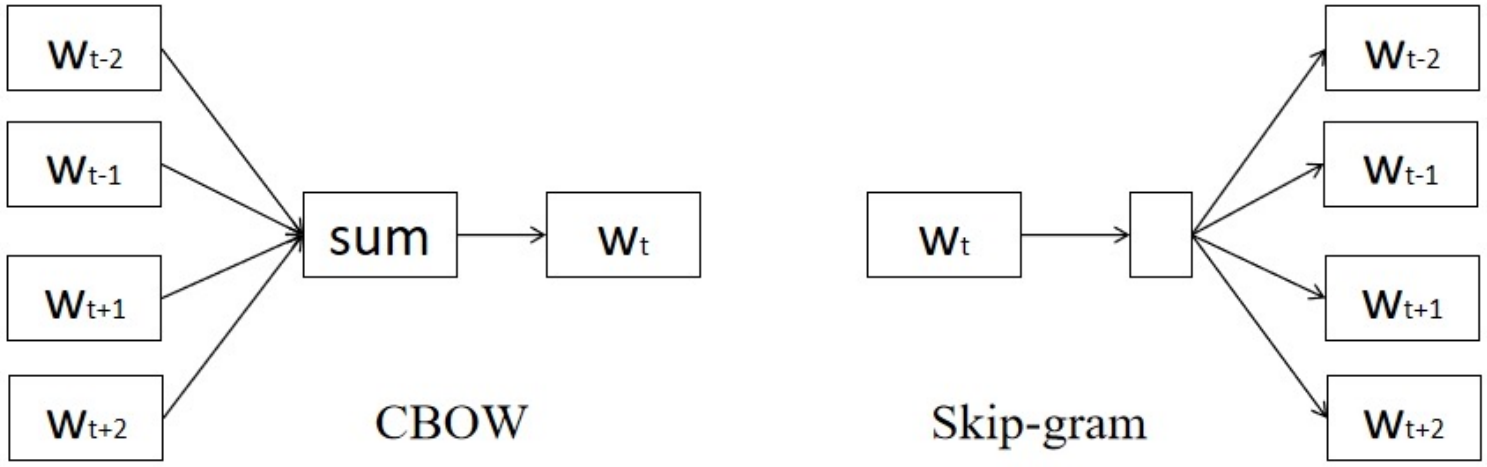
- Historical Semantics
  - Embeddings can also be a useful tool for studying how meaning changes over time



From: Stanford NLP

Word2Vec

- Skip-gram
  - Use words to predict their contexts.
- CBOW
  - Use the context to predict the target word.



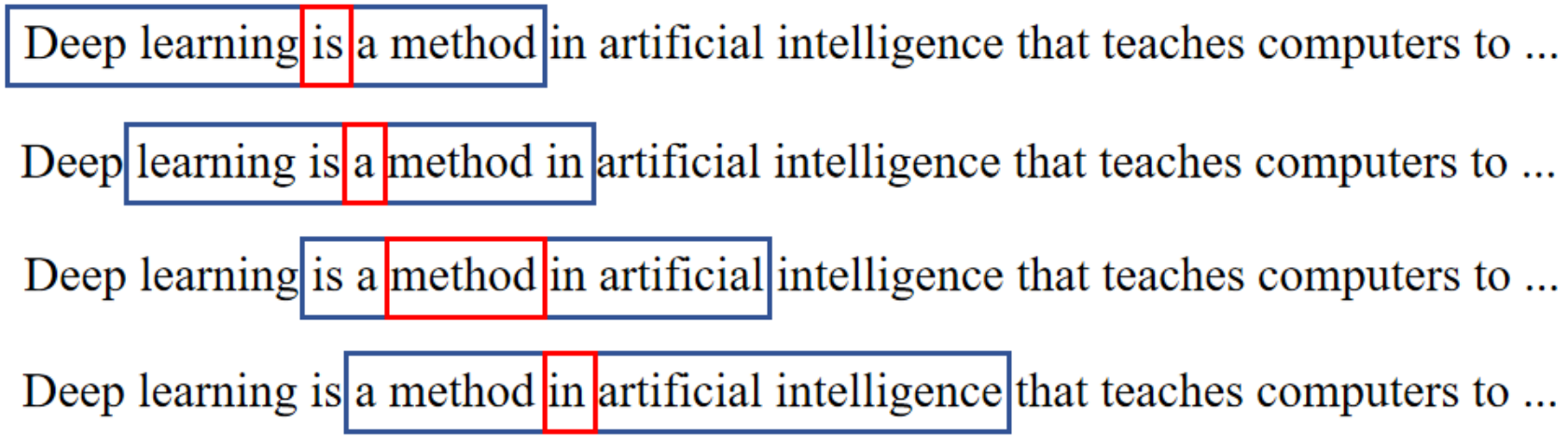
Word2Vec

1. Treat the target word and a neighboring context word as **positive examples**.
2. Randomly sample other words in the lexicon to get **negative samples**.
3. Use **logistic regression** to train a classifier to distinguish those two cases.
4. Use the learned weights as the embeddings.

Word2Vec

Calculate the co-occurrence matrix from the corpus, where each element represents how often a word appears in the context of another word within a certain window size.

Assume window size = 2



Word2Vec

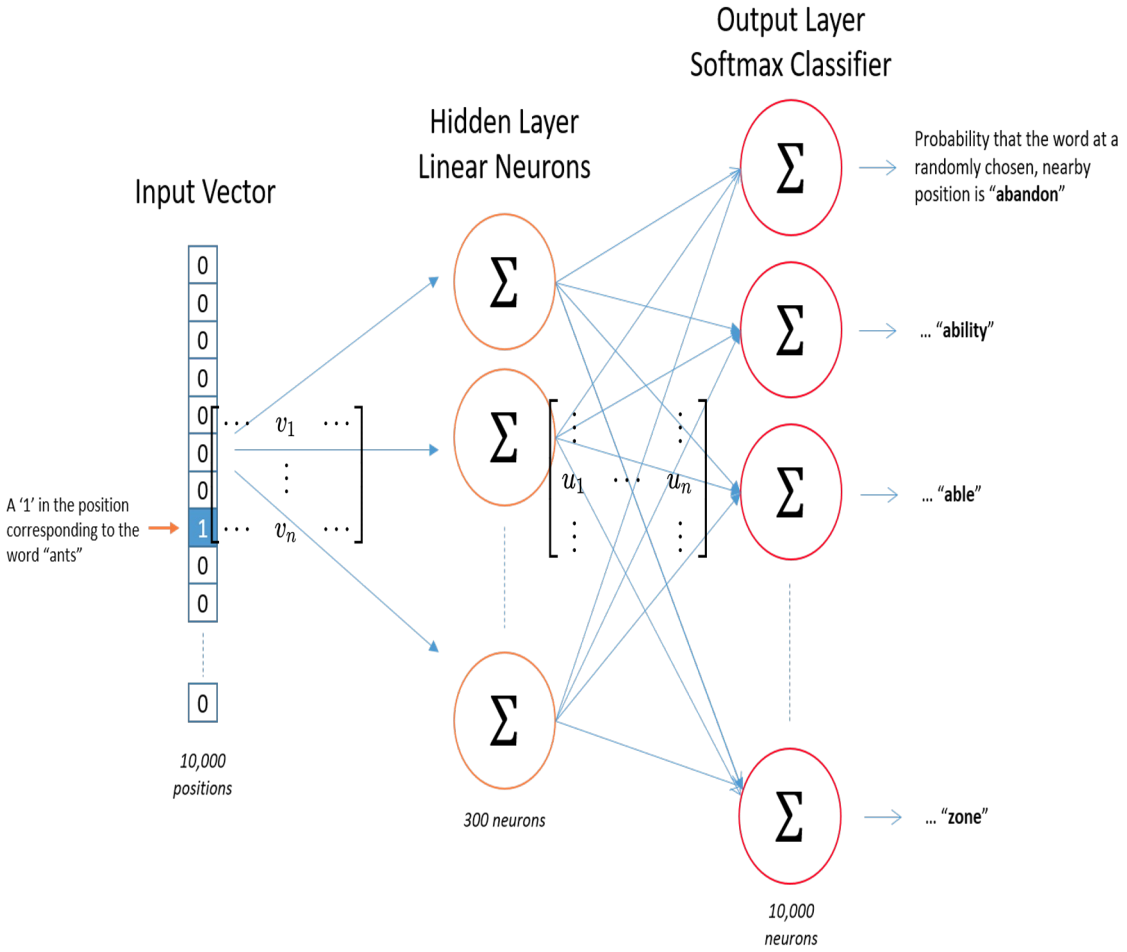
Skip-gram:

Assume c is the word id in the context, w is the center word, u and v are vectors of c and w.

$$P(c|w) = \frac{exp(u_c^\top v_w)}{\sum_t exp(u_{c_t}^\top v_w)}$$

Model Parameters

word2vec uses a single hidden layer feedforward neural network



Input to hidden layer matrix has our target word embeddings $\mathbf{v}_i$

Hidden to output layer matrix has another set of word embeddings called output embeddings $\mathbf{u}_i$

http://mccormickml.com/2016/04/19/word2vec-tutorial-the-skip-gram-model/

Contextualized Word Embeddings

- Learn word vectors using long contexts instead of a context window
- Learn a deep Neural LM and use all its layers in prediction

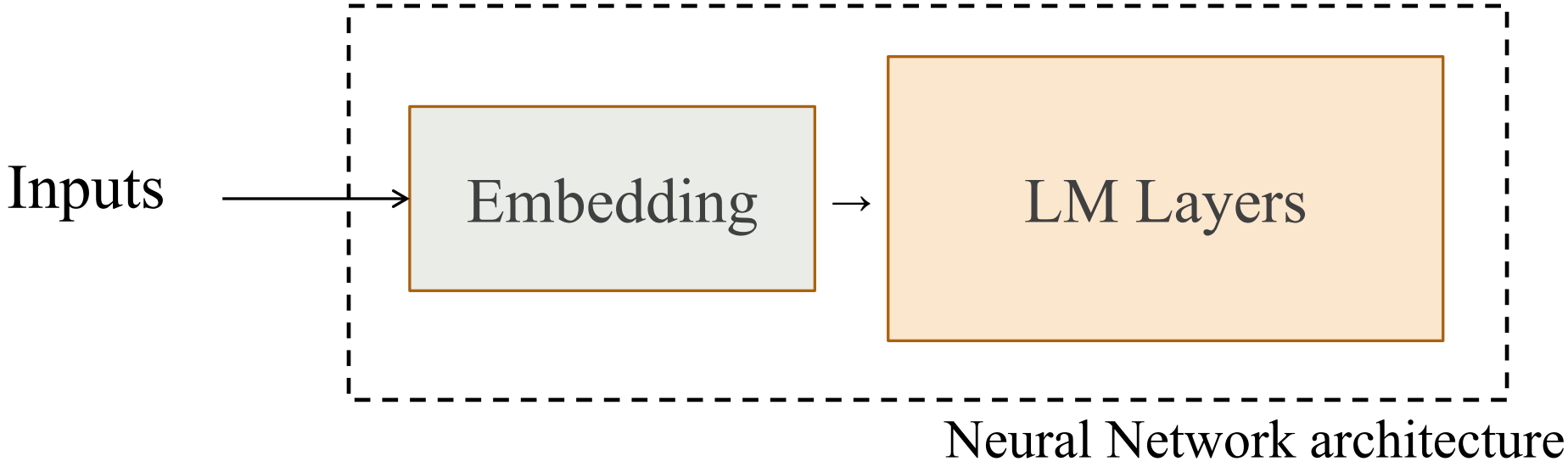
The probability of a sequence becomes:

$$P(w_1 \dots w_n) = P(w_1)P(w_2|w_1)P(w_3|w_{1:2}) \dots P(w_n|w_{1:n-1})$$

$$= \prod_{k=1}^{n} P(w_k|w_{1:k-1})$$

Contextualized Word Embeddings

- The embedding is designed to be a part of the model.
- When the downstream task provides a preferred context, it can be adjusted during the training process, incorporating the relevant information from the task context.



Neural Language Models

A model structure is needed to process the hidden feature in the embeddings.

Neural LMs leverage neural networks to learn and represent complex language patterns.

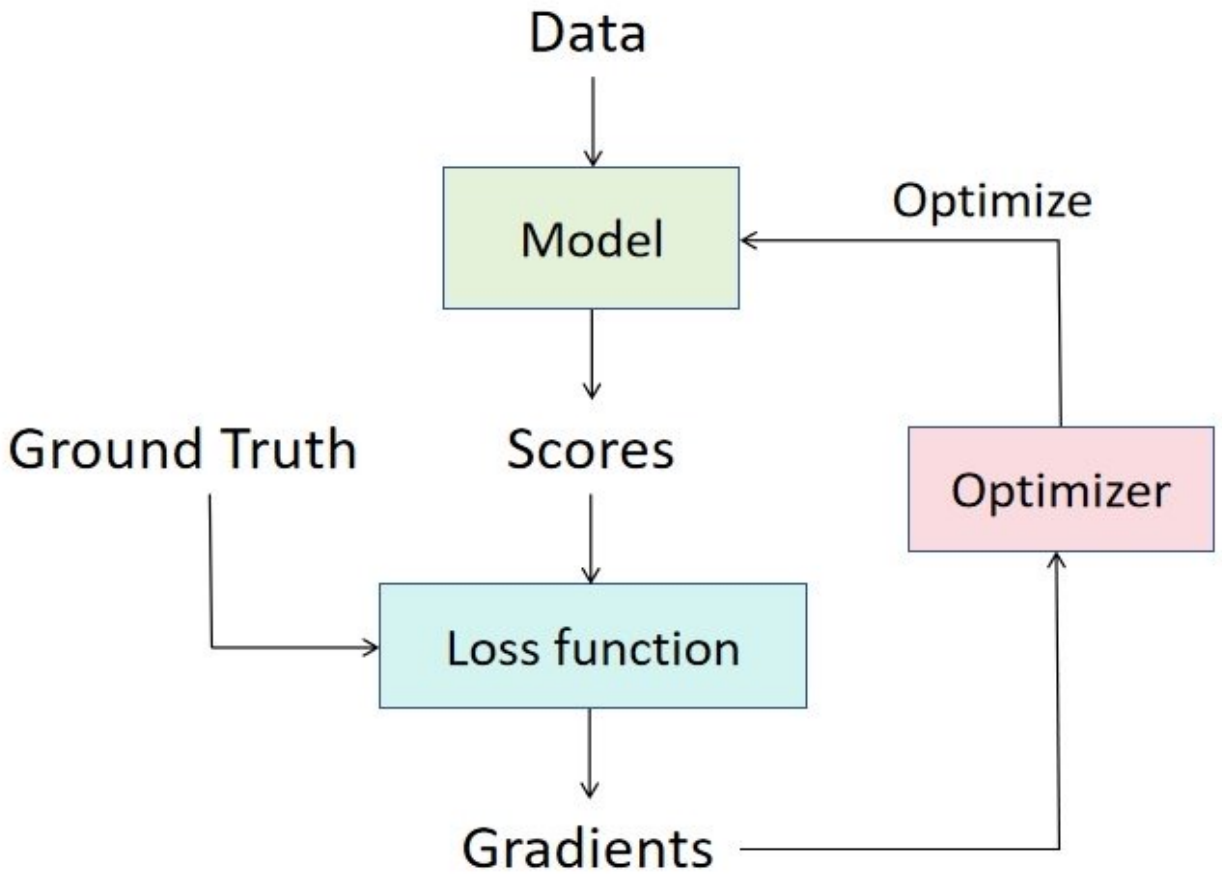
Basic Definitions

- FFN
- RNN

Basic Definitions

- In a deep learning project, there are some fundamental components.
  1. Model
     - A model refers to the architecture or structure used to **represent relationships between input data and output predictions**.
  2. Optimizer
     - An optimizer is an algorithm used to adjust the parameters of the model during training in order to **minimize the error** between predicted and actual output values.
  3. Loss function
     - A loss function (objective function) **measures the difference** between the predicted output of a model and the true target output.

Training Neural Networks



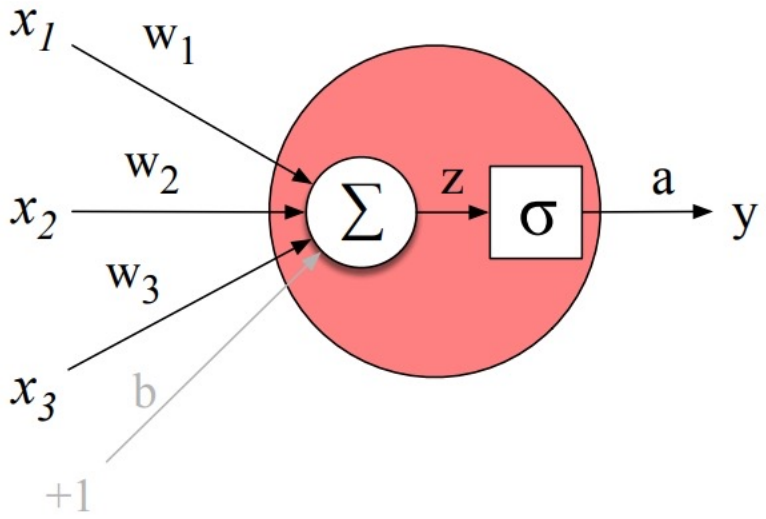
Training Neural Networks

The training process typically involves the following steps:

1. **Data Preparation:** Prepare training and testing datasets.
2. **Model Construction:** Construct the model using a deep learning framework (TensorFlow, PyTorch, ...)
3. **Loss Function Definition:** Select an appropriate loss function. (Cross-entropy, Logloss, ...)
4. **Optimizer Selection:** Choose a suitable optimization algorithm. (Adam, SGD, ...)
5. **Model Training:** Train the model using the training dataset.
6. **Model Evaluation:** Evaluate the trained model using the testing dataset. (F1, LCS, ...)

Neurons

- Neurons are the basic building blocks of the nervous system in biology.
  - They receive signals from other neurons and transmit them towards the cell body.
- Similar to biological neurons, the basic computational unit (neuron) **receives inputs**, **perform computations**, and **produce outputs**.

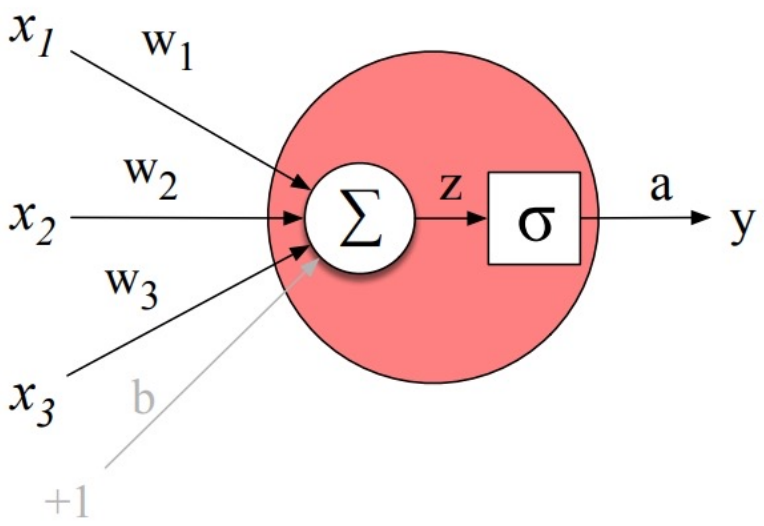


Neurons

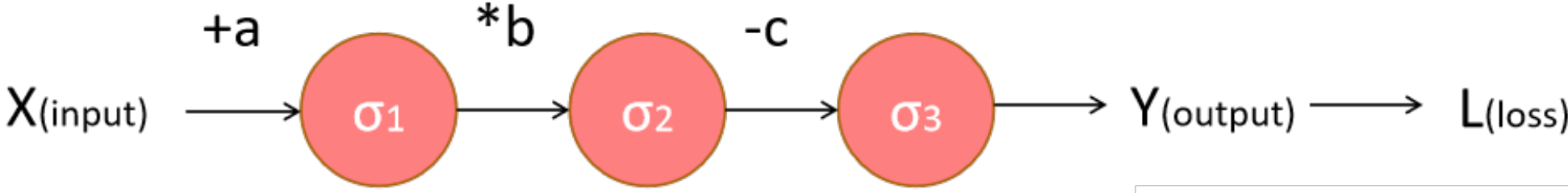
- The computation process is represented as:

$$y = \sigma(Wx + b)$$

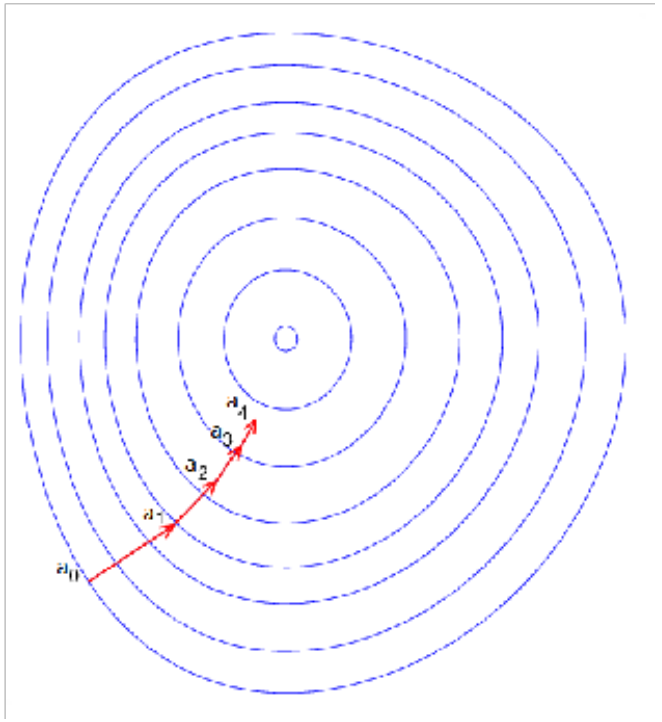
where σ is the an activation function (softmax, sigmoid, relu, ...)



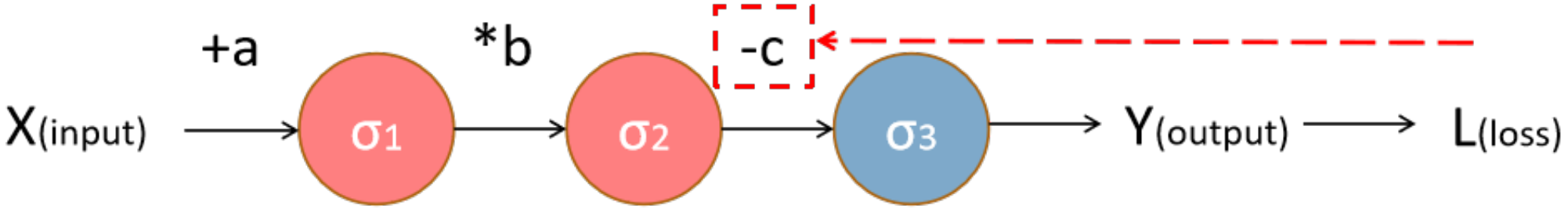
Back Propagation



- Neural networks utilize gradient descent to optimize the parameters (a, b, c) in the model.



Back Propagation

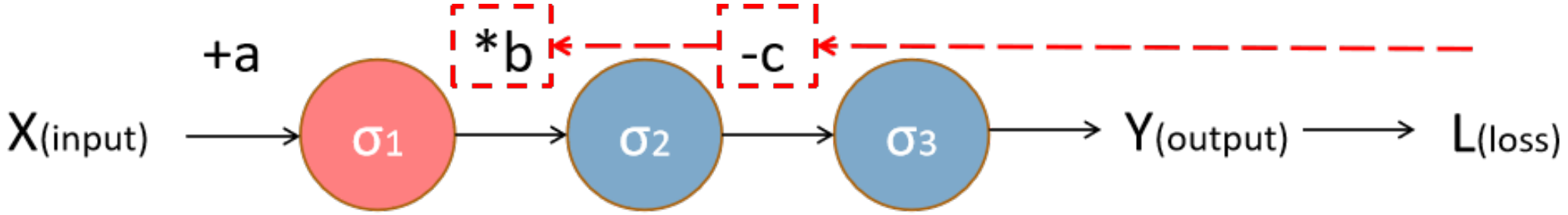


Learning rate (step length)

$$c' = c + \lambda \nabla F(c)$$

$$\nabla F(c) = \frac{\partial L}{\partial c}$$

Back Propagation

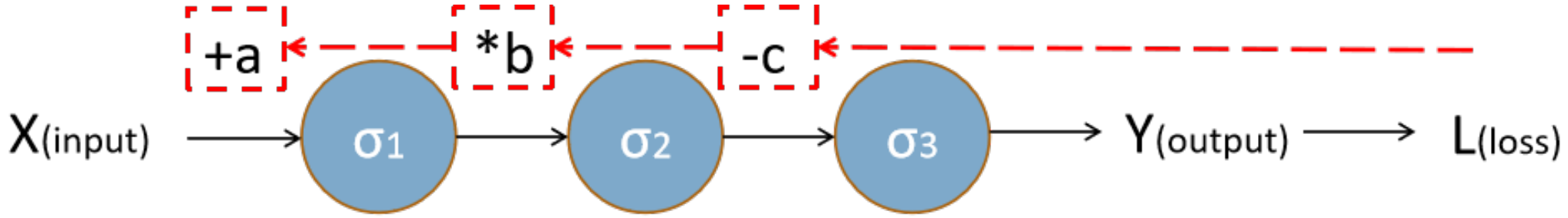


$$b' = b + \lambda \nabla F(b)$$

$$\nabla F(b) = \frac{\partial L}{\partial b} = \frac{\partial L}{\partial c}\frac{\partial c}{\partial b}$$

Chain rule

Back Propagation



$$a' = a + \lambda \nabla F(a)$$

$$\nabla F(a) = \frac{\partial L}{\partial a} = \frac{\partial L}{\partial c} \frac{\partial c}{\partial b} \frac{\partial b}{\partial a}$$

Activation functions

- The core idea of using activation functions is to introduce **nonlinearity** into neural networks.
- Neural network models aim to **avoid the final processing stage being merely a linear transformation of the inputs, s**o that the model is able to have good performance on complex problems.
- Commonly used activation functions include: Sigmoid, ReLU, tanh, GeLU...

Activation functions

	Range	Applications
softmax	[0, 1] (sum up to 1)	It is commonly used in multi-class classification tasks where the model needs to predict the probability distribution over classes.
sigmoid	[0, 1]	It often used in binary classification tasks where a threshold is needed to predict probabilities of belonging to one of the two classes.
tanh	[-1, 1]	It is often preferred over sigmoid for hidden layers as it produces zero-centered output
ReLU	[0, +inf]	It introduce nonlinearity and avoid gradient vanishing

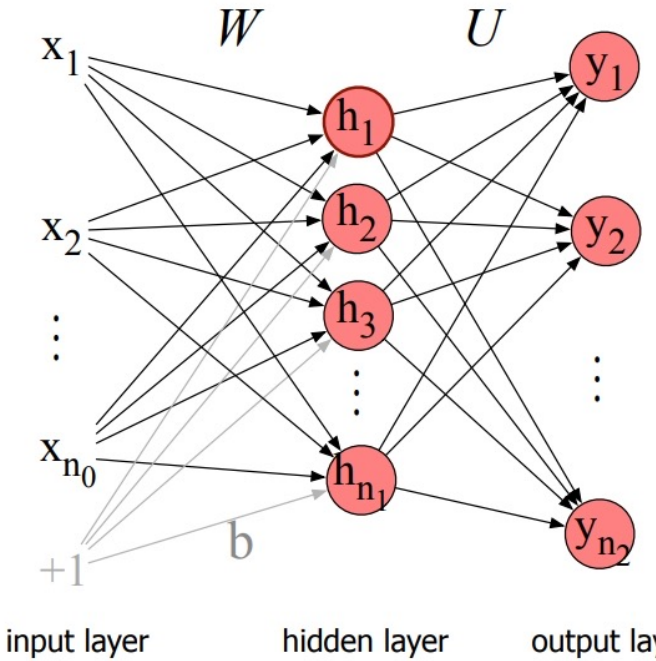
FFN

- Feedforward network (FFN) is a multilayer feedforward network in which the units are connected with no cycles.

$$h = \sigma(Wx + b)$$

$$z = Uh$$

$$y = softmax(z)$$



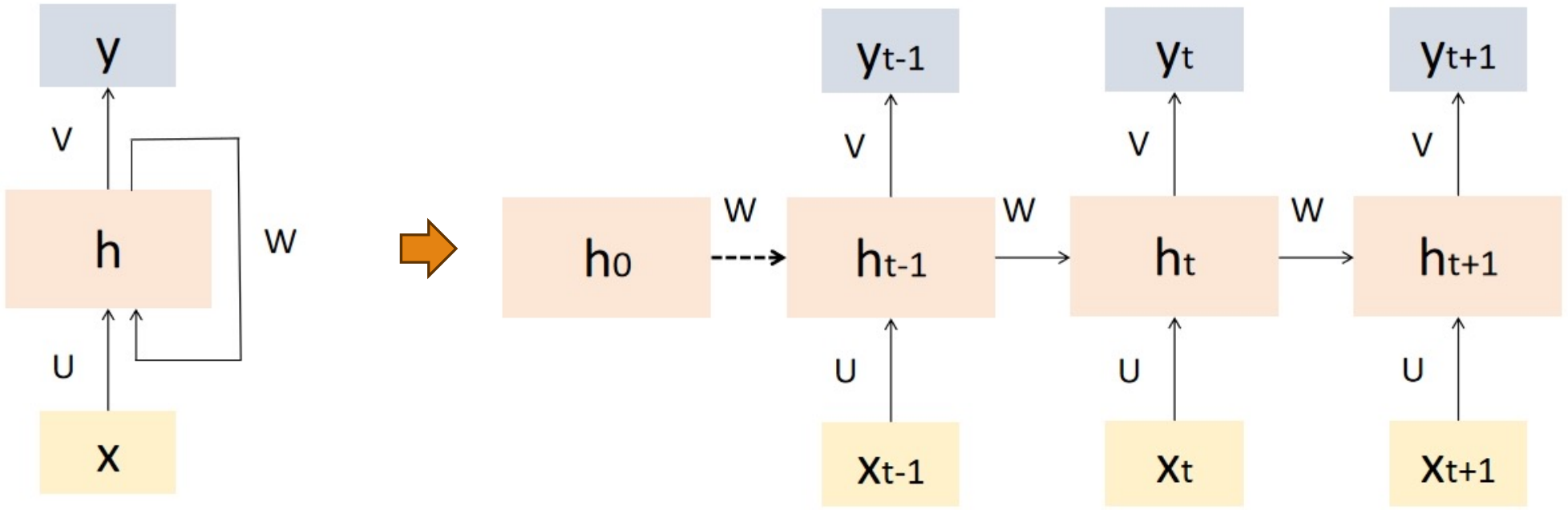
From: Stanford NLP

Short comings of FFN

- Lack of Sequence Modeling:
  - In NLP tasks, understanding the sequence of words and their dependencies is crucial for accurate predictions.
- Fixed Input Size:
  - FFNs require fixed-size inputs, which can be problematic for NLP tasks where input sequences vary in length.
- Limited Contextual Information:
  - Many NLP tasks benefit from capturing long-range dependencies and understanding the broader context of a text, which is better addressed by models capable of modeling sequential data effectively.

RNN

- Recurrent Neural Networks (RNNs) are a type of artificial neural network designed to handle sequential data by **capturing temporal dependencies**.
  - The same set of weights and biases are used across all time steps



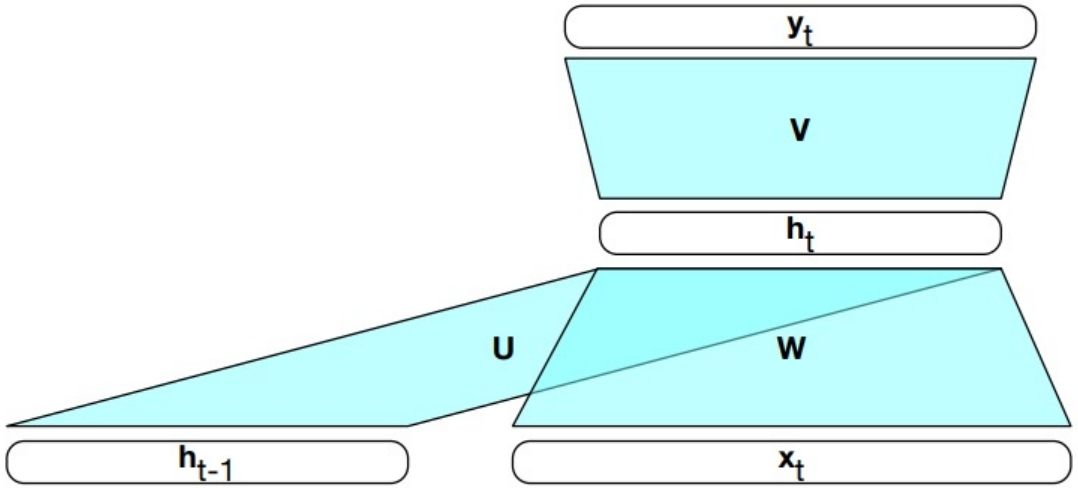
RNN

- The equation on step t is:

$$y_t = g(Vh_t)$$

$$h_t = f(Ux_t + Wh_{t-1})$$

where f and g are activation functions



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Properties of RNNs

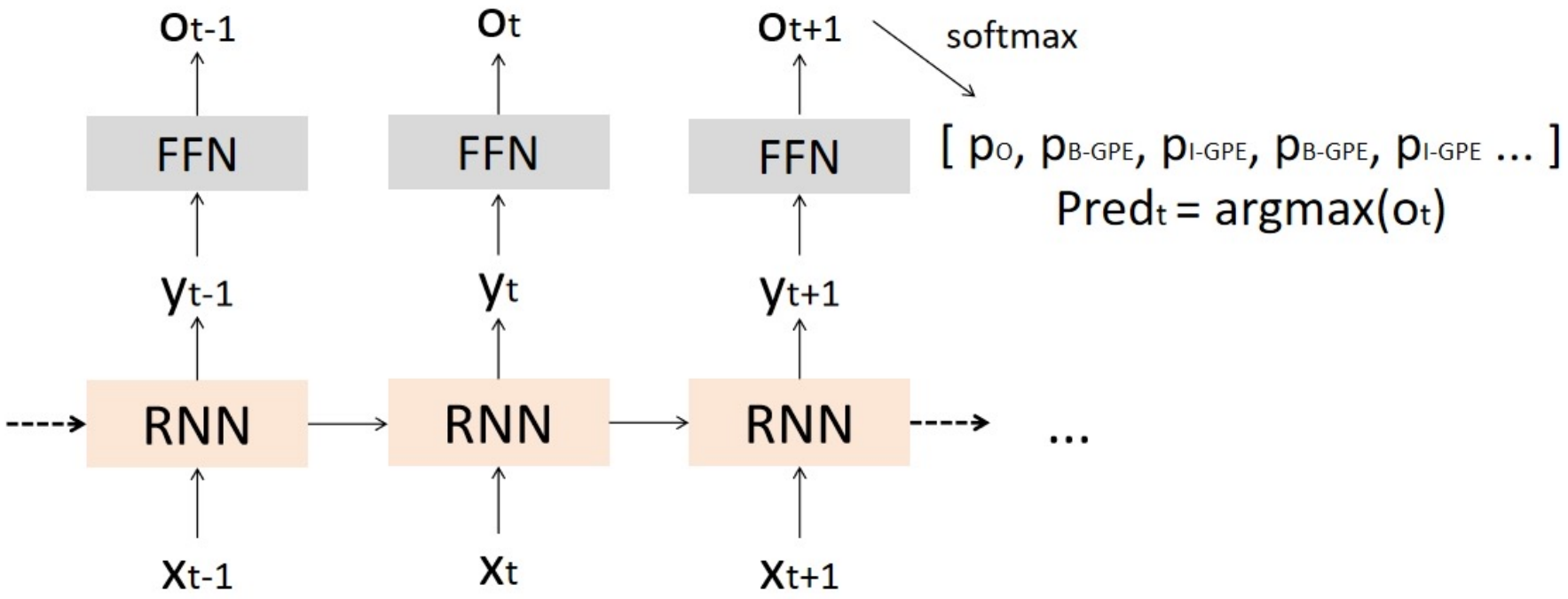
- **Sequential Processing:**
  - RNNs handle sequences, allowing them to model temporal dependencies in data.
- **Recurrent Connections:**
  - RNNs maintain internal memory, facilitating the capture of long-term dependencies.
- **Parameter Sharing:**
  - RNNs share parameters across time steps, enhancing efficiency in learning sequential data.
- **Vanishing Gradient Problem:**
  - Traditional RNNs may face vanishing gradient issues, hindering learning of long-term dependencies.

Name Entity Recognition

- Name Entity Recognition (NER) is a fundamental task in NLP.
- The model needs to identify named entities within the sequence, such as countries, organizations, and individuals.

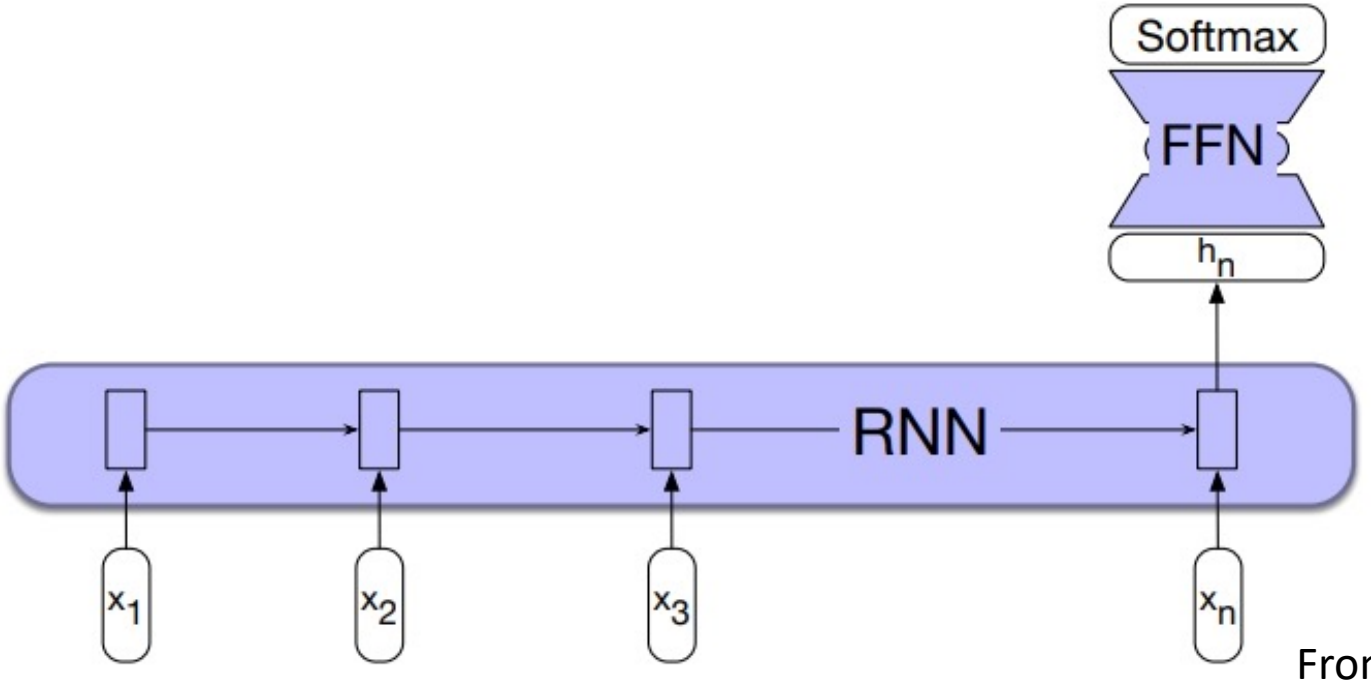
RNNs for NER

- In token classification task, every output should be mapped to a one-hot vector.
- A feed forward network is added to the RNN model.



RNNs for Sequence Classification

- RNNs classify the entire sequences rather than the tokens within them.
- Take the hidden layer for the last token of the text.



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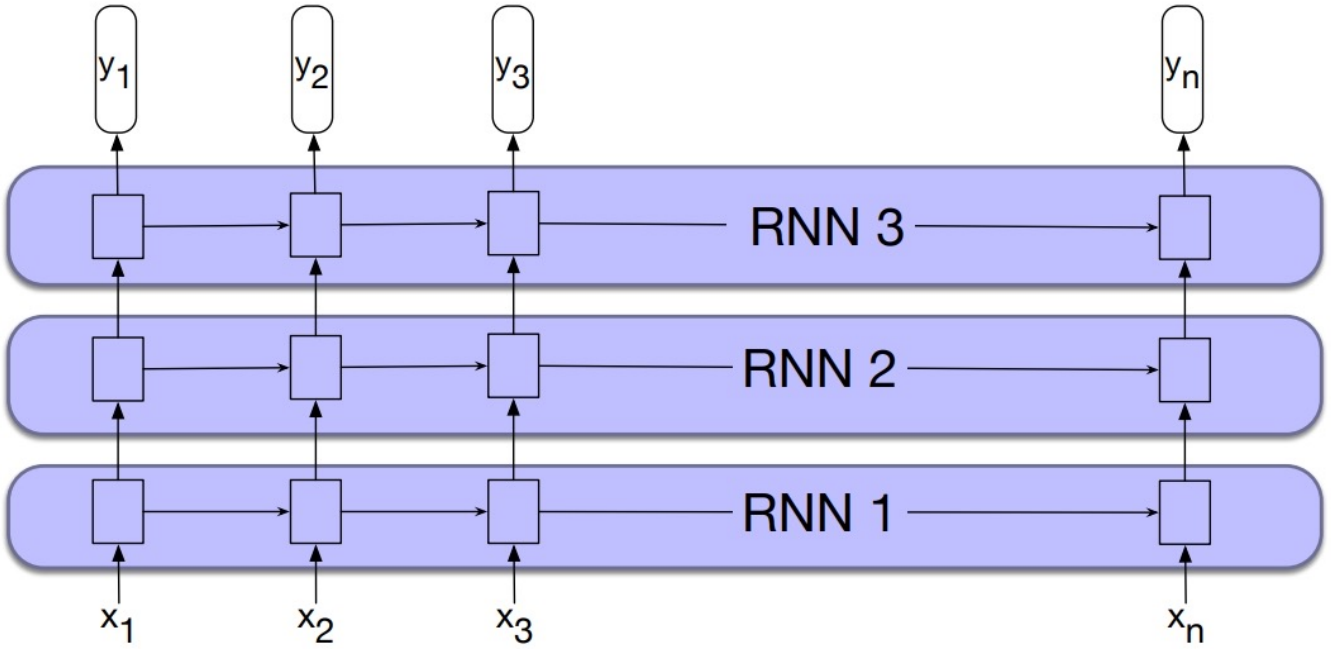
Stacked RNNs

- Stacked RNNs consist of multiple networks where the output of one layer serves as the input to a subsequent layer

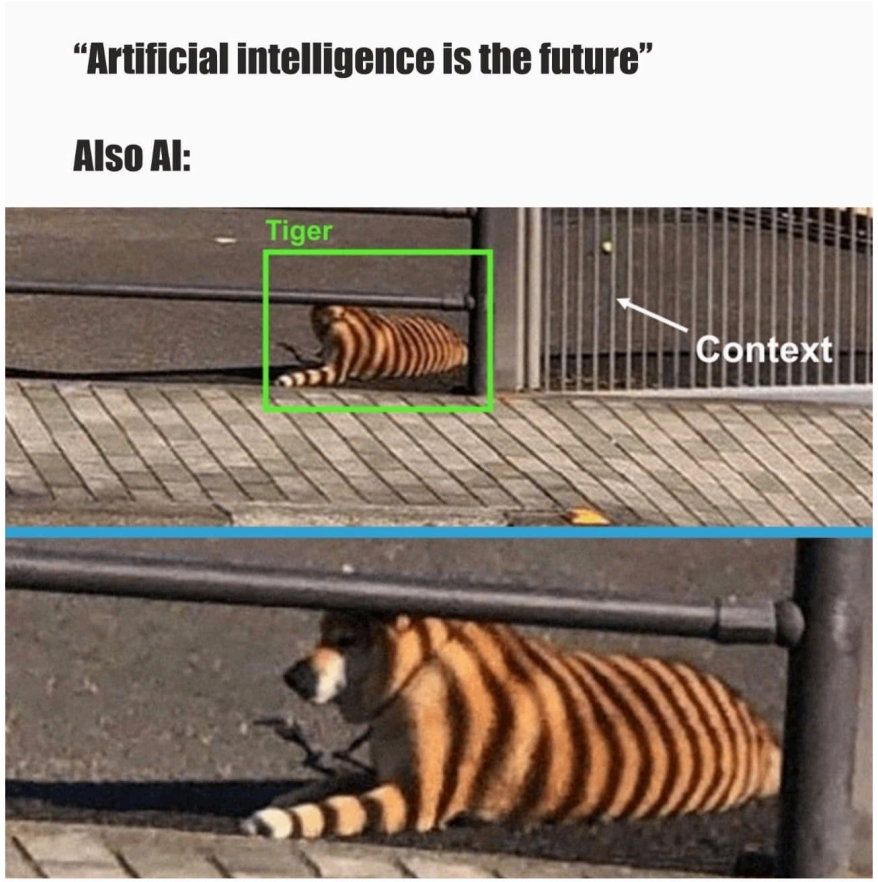


Figures are from https://reurl.cc/1389mD

Stacked RNNs

- Stacked RNNs generally outperform single-layer networks.
  - The network induces representations at differing levels of abstraction across layers
  - The initial layers of stacked networks induce representations that serve as useful abstractions for further layers
- However, as the number of stacks is increased the training costs rise quickly.

Word context

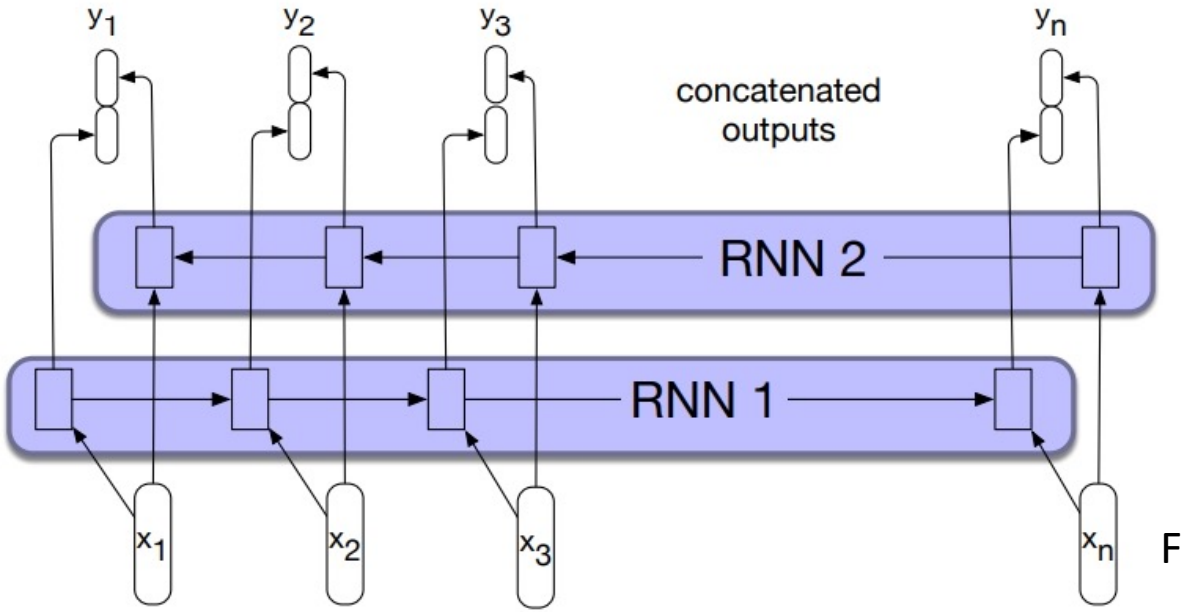


蘋 果	公司
蘋 果	派

蘋果改變了他的一生,	對牛頓來說
蘋果改變了他的一生,	對賈伯斯來說

Bidirectional RNNs

- In many applications RNNs have to access the entire input sequence.
- Bidirectional RNN was introduced.
  - It combines two independent bidirectional RNNs, one where the input is processed from the start to the end, and the other from the end to the start



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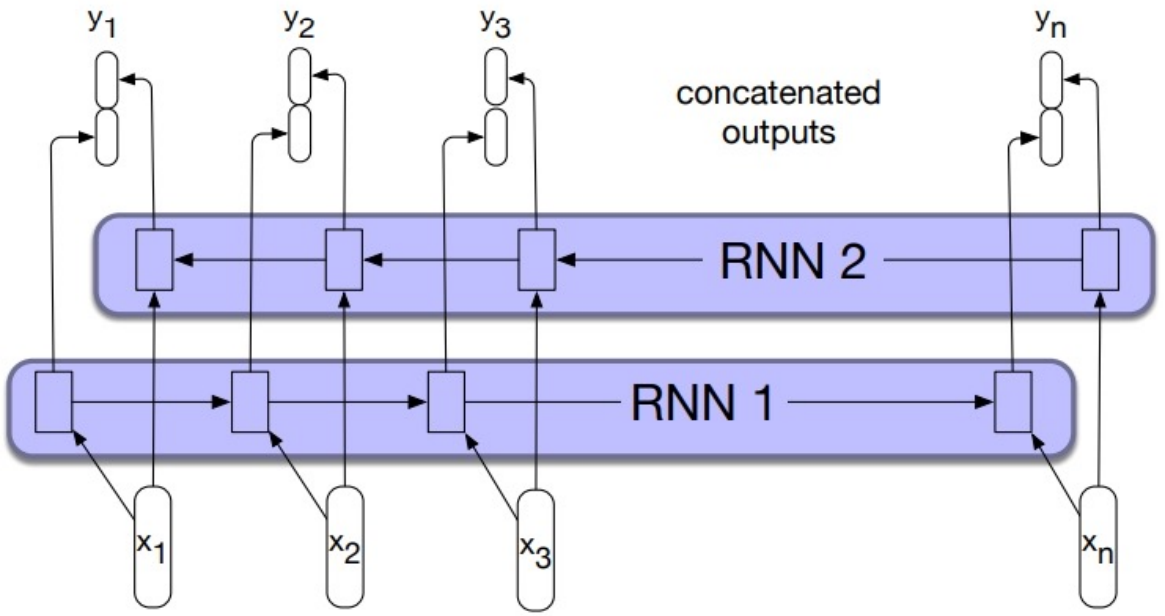
Bidirectional RNNs

- The representations:

$$h_t^f = RNN_1(x_1, \ldots, x_t)$$

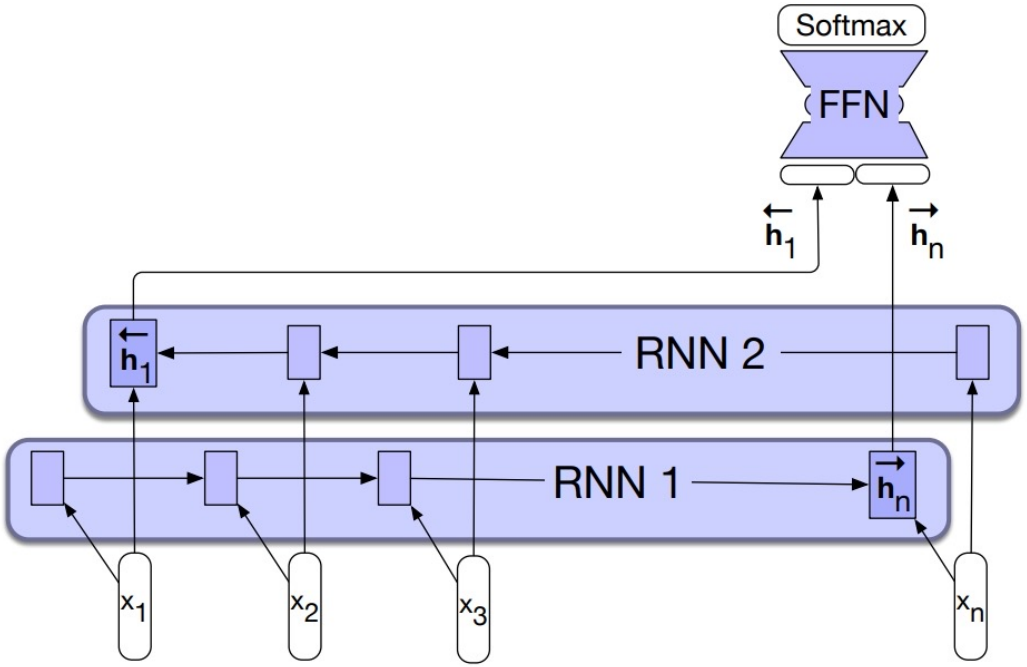
$$h_t^b = RNN_2(x_t, \ldots, x_n)$$

$$y_t = [h_t^f; h_t^b]$$



Bidirectional RNNs for Sequence Classification

- The final hidden units from the forward and backward passes are combined to represent the entire sequence.
- This combined representation serves as input to the subsequent classifier.



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Summary

- **LM:** Models that assign probabilities to sequences of words
- **N-gram LM:** Traditional statistical model of language

Embedding approaches:

- **Sparse vectors:** Use contexts to encode the word embedding. (TF-IDF, PPMI)
- **Dense vectors:** Apply self-supervised training. (Word2Vec, Contextualized Embeddings)

Neural LMs:

- **FFN:** Fully-connected dense neural network.
- **RNN:** Recurrent, store temporal hidden-state.

Reference

Stanford NLP:

- https://web.stanford.edu/~jurafsky/slp3/