Introduction to Word Embeddings

Yogesh Kulkarni

November 1, 2020

Word Vectors

What are Word Vectors/Embeddings?

- Word Embeddings are the texts converted into numbers
- There may be different numerical representations of same text.
- Many Machine Learning algorithms and almost all Deep Learning Architectures are incapable of processing strings or plain text in their raw form.
- They require numbers as inputs to perform any sort of job, be it classification, regression etc. in broad terms.
- So, for the computer to be able to "understand" a vector representation of a word is required.

Different types of Word Vectors

- (Traditional) Frequency based Embedding:
  - One-hot
  - Count Vector
  - TF-IDF Vector
  - Co-Occurrence Vector
- (Modern) Prediction based Embedding:
  - Word2vec (Google)
  - Global Vector Representations (GloVe) (Stanford)

Murthy's Visualization Strategy

- X axis :Different models chronologically
- Y axis: Scale of understanding words
- Color: How well it learns trends (auto-regresses)
- Shape: How complicated are the parsers and rules
- Size: How is the performance

(Ref: Understanding "Understanding language" - Murthy Kolluru

One Hot

In traditional NLP, we regard words as discrete symbols: **hotel, conference, motel**

Means one 1, the rest 0s

Words can be represented by **one-hot** vectors:

motel = [0 0 0 0 0 0 0 0 0 0 1 0 0 0 0]
hotel = [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0]

Vector dimension = number of words in vocabulary (e.g. 500,000)

(Ref: Word Embeddings - Elena Voita, Yandex Research

One Hot: Problem

Example: in web search, if user searches for "Seattle motel", we would like to match documents containing "Seattle hotel".

But:

motel = [0 0 0 0 0 0 0 0 0 0 1 0 0 0 0]
hotel = [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0]

These two vectors are orthogonal.

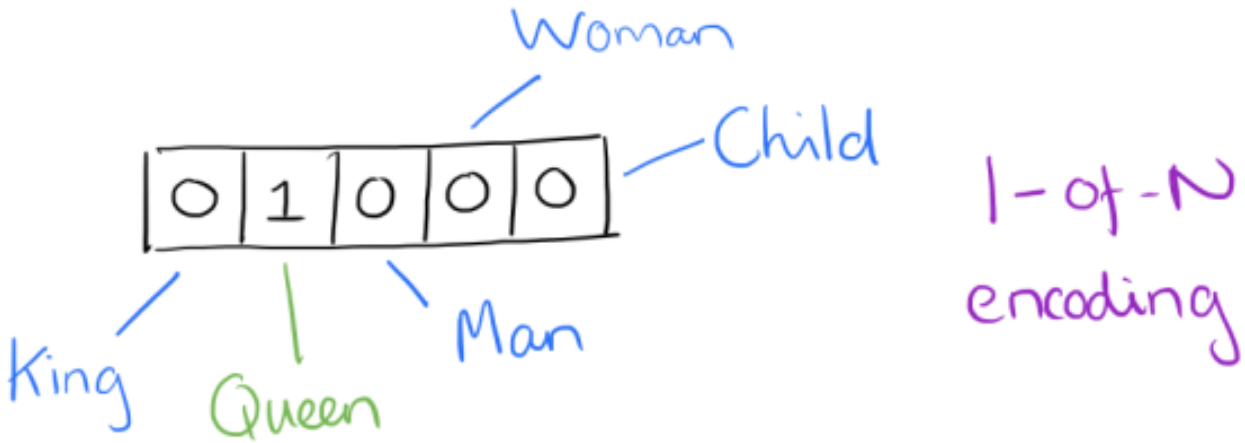
There is no natural notion of **similarity** for one-hot vectors!

These vectors do not contain information about a **meaning** of a word.

(Ref: Word Embeddings - Elena Voita, Yandex Research)

One Hot: Example

One-hot: Suppose our vocabulary has only five words: King, Queen, Man, Woman, and Child. We could encode the word 'Queen' as:



No meaningful comparison possible. We will look at some vectorization schemes that can capture "meaning", somewhat.

Murthy's Visualization

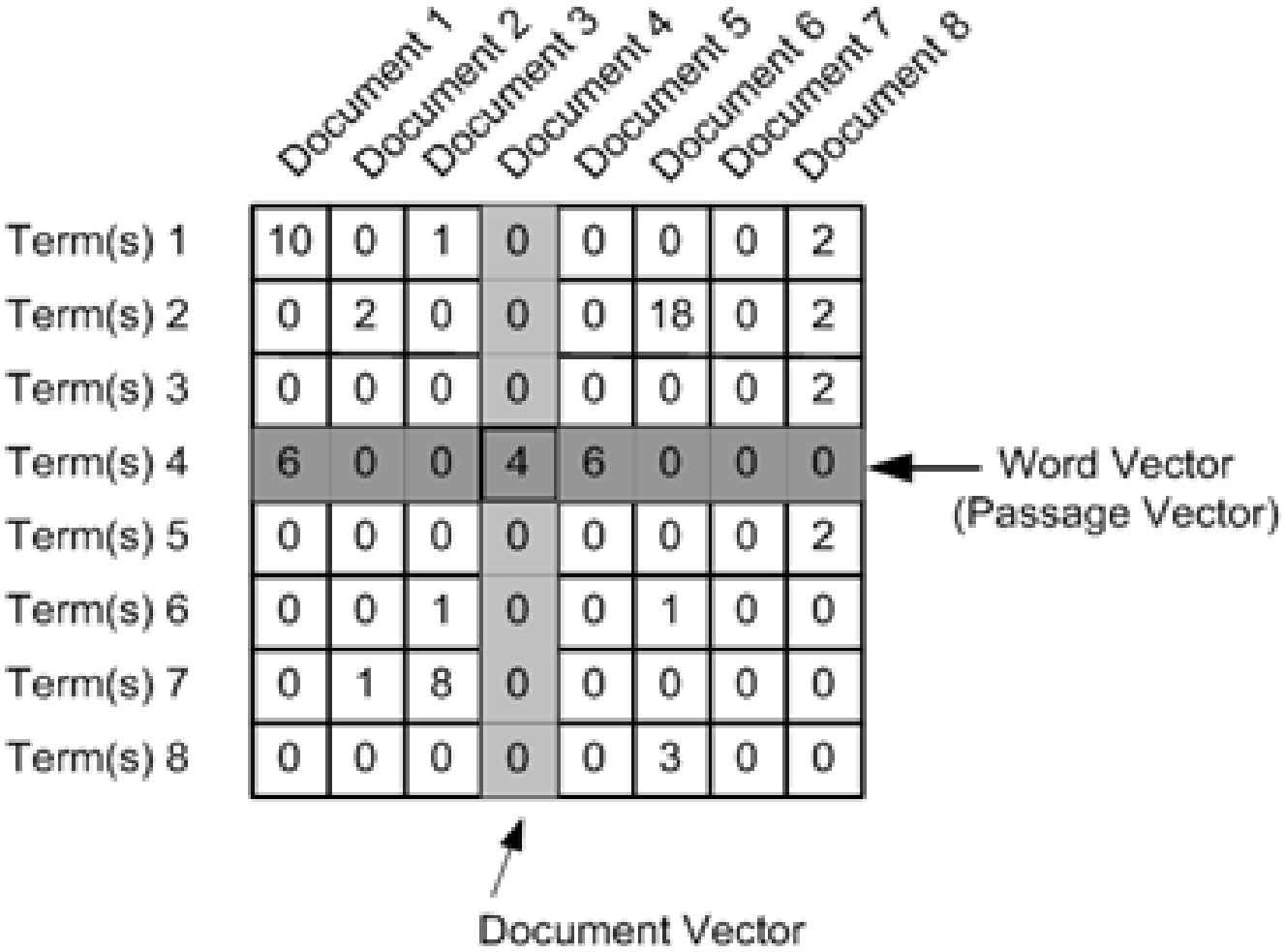
(Ref: Understanding "Understanding language" - Murthy Kolluru

Count Vector

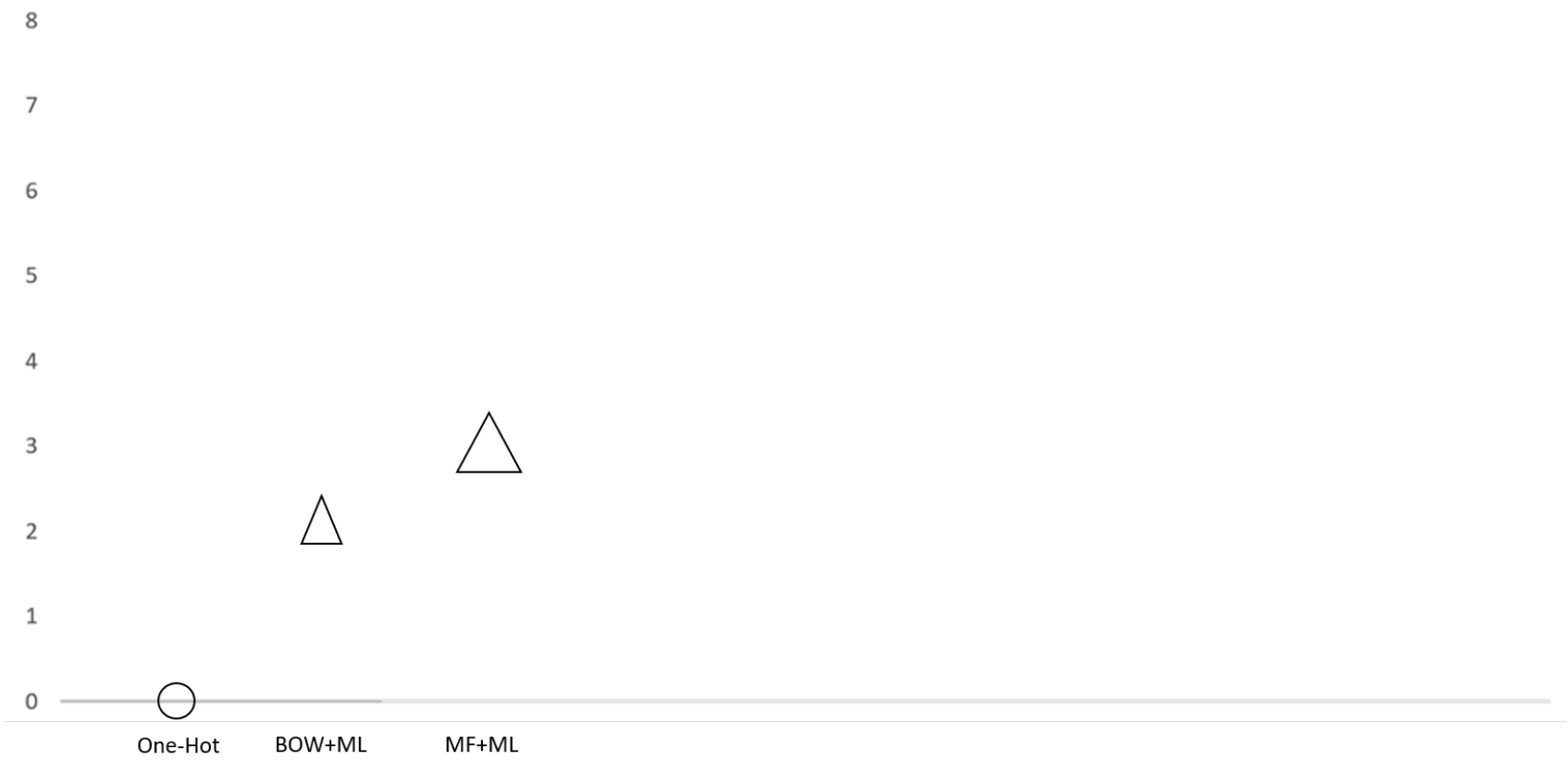
- Corpus:
  - D1: He is a lazy boy. She is also lazy.
  - D2: Neeraj is a lazy person.
- Dictionary is a list of unique tokens(words)
  =['He','She','lazy','boy','Neeraj','person']
- Count Matrix:

	He	She	lazy	boy	Neeraj	person
D1	1	1	2	1	0	0
D2	0	0	1	0	1	1

Count Vector



Murthy's Visualization



(Ref: Understanding "Understanding language" - Murthy Kolluru

TF-IDF vectorization

- It takes into account not just the occurrence of a word in a single document but in the entire corpus.
- Down weight the common words occurring in almost all documents and give more importance to words that appear in a subset of documents.
- Corpus:

Document 1

Term	Count
This	1
is	1
about	2
Messi	4

Document 2

Term	Count
This	1
is	2
about	1
Tf-idf	1

TF-IDF vectorization

- TF = (Number of times term t appears in a document)/(Number of terms in the document)
- So, TF(This,Document1) = 1/8 and TF(This, Document2)=1/5
- IDF = log(N/n), where, N is the number of documents and n is the number of documents a term t has appeared in.
- So, IDF(This) = log(2/2) = 0.
- TFIDF = TF*IDF
- Dictionary is made of a list of unique tokens(words)
- Similar to Count Matrix, TFIDF matrix is made with TFIDF values in it.

TF-IDF Inferencing

Once tf-idf model is trained on a corpus of documents, what happens when a test word or a document is given? How does it calculate tf-idf vector for it?

- For just one test word, its tf would be 1, then do we just mulitply idf of that word from trained model? Are tf values in trained model irrelevant?
- Even for test document, does `inverse_transform` take into account tfs of current test document or tfs within trained model?
- Answer: the test word or document is 'ADDED' to the corpus are retraining/calculation is done to arrive at meaningful numbers.

(Ref: https://stackoverflow.com/questions/55707577/how-does-tfidfvectorizer-compute-scores-on-test-data)

Co-Occurrence Matrix

- Co-occurrence ' For a given corpus, the co-occurrence of a pair of words say w1 and w2 is the number of times they have appeared together in a Context Window.
- Context Window ' Context window is specified by a number and the direction. So what does a context window of 2 (around) means?

Quick	Brown	Fox	Jump	Over	The	Lazy	Dog

- For Corpus =" He is not lazy. He is intelligent. He is smart."

	He	is	not	lazy	intelligent	smart
He	0	4	2	1	2	1
is	4	0	1	2	2	1
not	2	1	0	1	0	0
lazy	1	2	1	0	0	0
intelligent	2	2	0	0	0	0
smart	1	1	0	0	0	0

Co-Occurrence Matrix

Red box- It is the number of times 'He' and 'is' have appeared in the context window 2 and it can be seen that the count turns out to be 4.

He	is	not	lazy	He	is	intelligent	He	is	smart
He	is	not	lazy	He	is	intelligent	He	is	smart
He	is	not	lazy	He	is	intelligent	He	is	smart
He	is	not	lazy	He	is	intelligent	He	is	smart

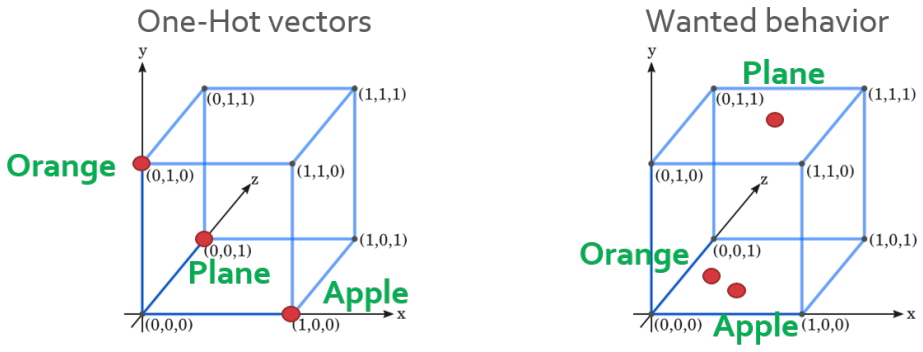
While the word 'lazy' has never appeared with'intelligent' in the context window and therefore has been assigned 0 in the blue box.

Good Vector Representation

- To have "Semantic" (meaning-wise) representation, the Similar words should be close to each other in the hyper dimensional space.
- Non-similar words should be far apart from each other in the hyper dimensional space.

Good Vector Representation

- Traditional One Hot Encoding:
  - Apple = [1, 0, 0]
  - Orange = [0, 1, 0]
  - Plane = [0, 0, 1]



- Very few cells participate in the representation.

But, What is “meaning”?

What is “bardiwac”?
Anyone?

Lets try again, with examples

What is "bardiwac"?

- He handed her a glass of bardiwac.
- Beef dishes are made to complement the bardiwac.
- Nigel staggered to his feet, face flushed from too much bardiwac.
- Malbec, one of the lesser-known bardiwac grapes, responds well to Australia's sunshine.
- I dined off bread and cheese and this excellent bardiwac.
- The drinks were delicious: blood-red bardiwac as well as light, sweet Rhenish.

Now, anyone?

At least one can guess now

What is “bardiwac”?
“Bardiwac is a red alcoholic beverage made from grapes ”
Context helps . . .

Distributed Semantics/Meaning

- A bottle of bardiwac is on the table.
- Everybody likes bardiwac.
- Don't have bardiwac before you drive.
- We make bardiwac out of corn.

Distributed Semantics/Meaning

- A bottle of xxxxxxxx is on the table.
- Everybody likes xxxxxxxx.
- Don't have xxxxxxxx before you drive.
- We make xxxxxxxx out of corn.

What other words fit into these places?
Won't they be similar to bardiwac?

Distributed Semantics/Meaning

- A bottle of _____ is on the table. (1)
- Everybody likes _____. (2)
- Don't have _____ before you drive. (3)
- We make _____ out of corn. (4)

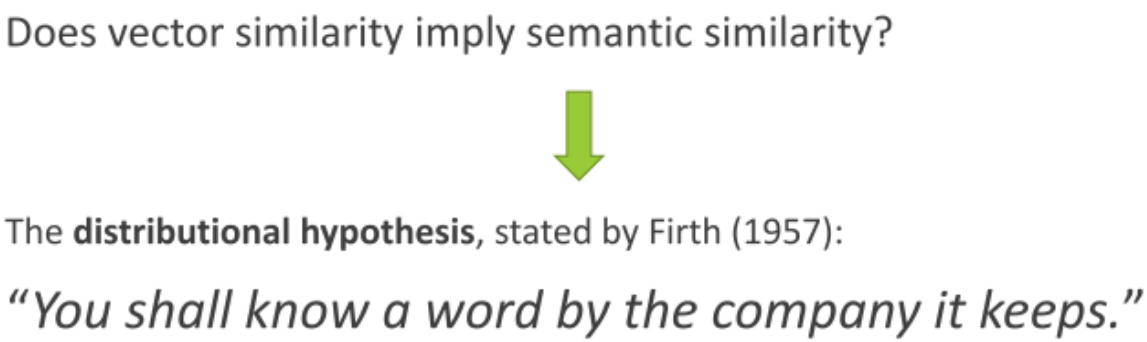
What other words fit into these contexts?

	(1)	(2)	(3)	(4)	...
bardiwac	1	1	1	1	
loud	0	0	0	0	
motor oil	1	0	0	1	
tortillas	0	1	0	1	
wine	1	1	1	0	
choices	0	1	0	0	

(Ref: Word Embeddings - Elena Voita, Yandex Research

Distributed Semantics/Meaning

Closer ones are . . .



(Ref: Word Embeddings - Elena Voita, Yandex Research)

Distributed Semantics/Meaning

Closer ones are . . .

Does vector similarity imply semantic similarity?

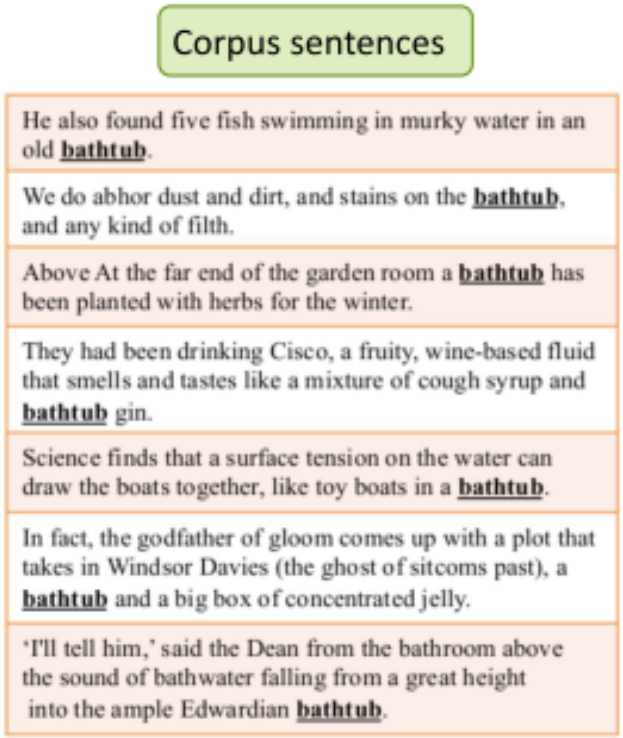
The **distributional hypothesis**, stated by Firth (1957):

"You shall know a word by the company it keeps."

(Ref: Word Embeddings - Elena Voita, Yandex Research

Distributed Semantics/Meaning

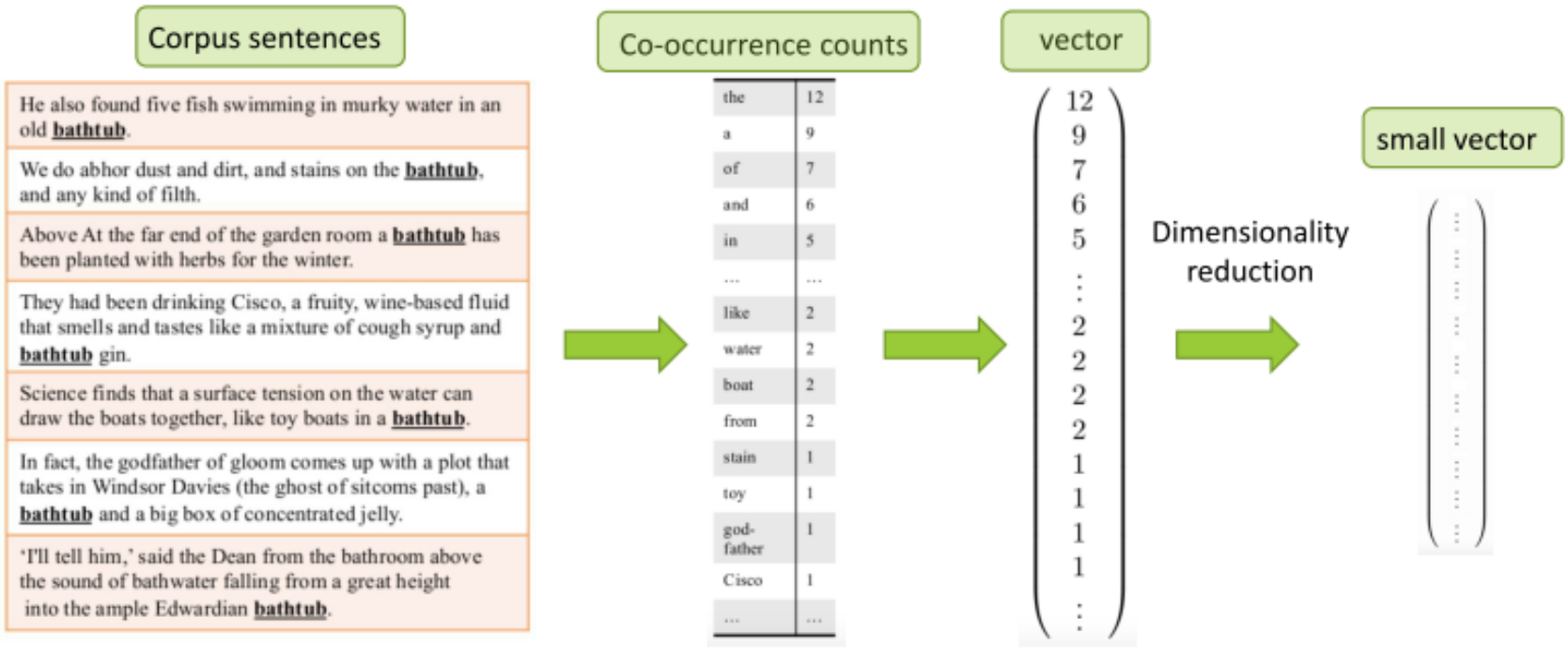
Idea of Co-occurance counts . . .



(Ref: Word Embeddings - Elena Voita, Yandex Research)

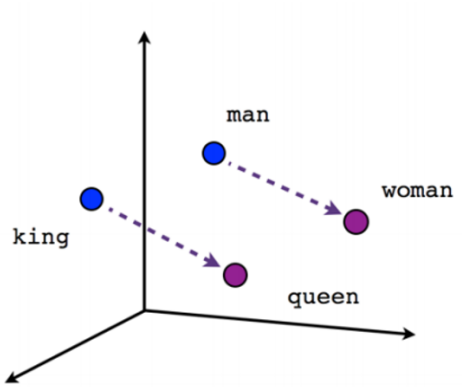
Distributed Semantics/Meaning

Calculate Co-occurrences for the context word, that itself becomes its own representation!!!

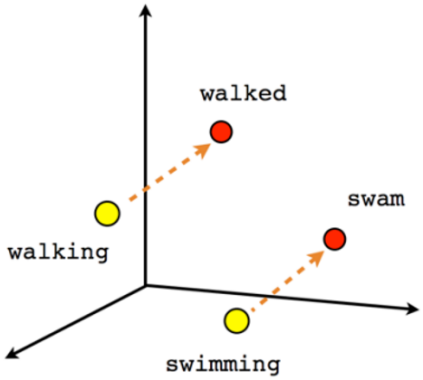


(Ref: Word Embeddings - Elena Voita, Yandex Research)

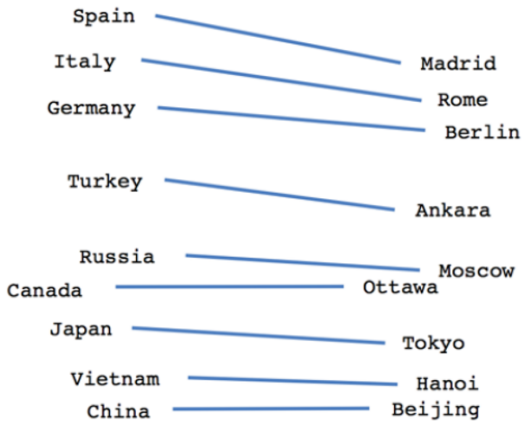
Examples



Male-Female



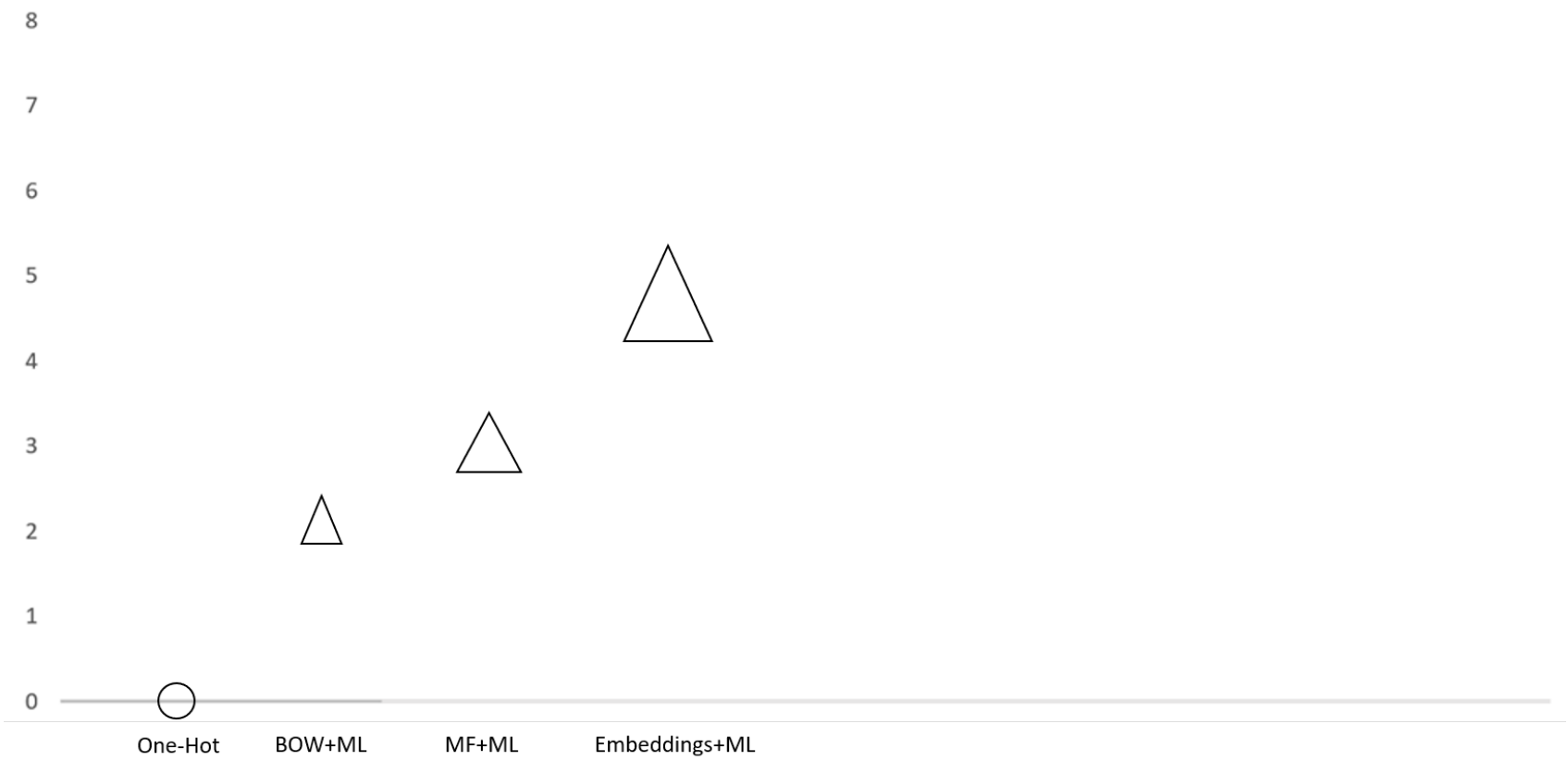
Verb tense



Country-Capital

vector[Queen] = vector[King] - vector[Man] + vector[Woman]

Murthy's Visualization



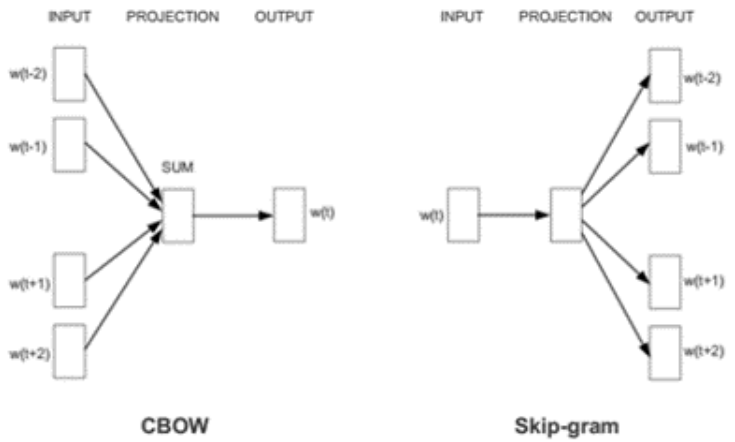
(Ref: Understanding "Understanding language" - Murthy Kolluru

Building these magical vectors

- How do we actually build these super-intelligent vectors, that seem to have such magical powers?
- How to find a word's friends?
- We will discuss the most famous methods to build such lower-dimension vector representations for words based on their context
  - Co-occurrence Matrix with SVD
  - word2vec (Google)
  - Global Vector Representations (GloVe) (Stanford)

Language Model

- A good statistical model for NLP is the conditional probability of the next word w given its previous ones
- Takes advantage of both word order, and the fact that temporally closer words have a stronger dependency.
- Continues Bag - of - Words (CBOW): predicts a word given its context (bidirectional).
- Skip - Gram: predicts the context given a word (bidirectional).

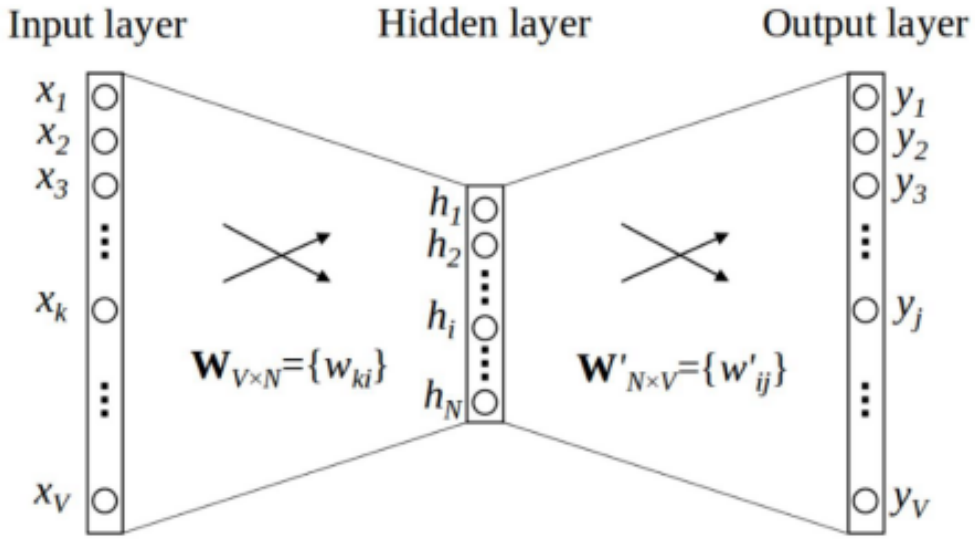


(Ref: Distributed Representations of Words and Phrases and their Compositionality. Mikolov at al., 2013)

Context windows

- Context can be anything - a surrounding n-gram, a randomly sampled set of words from a fixed size window around the word
- For example, assume context is defined as the word following a word. $context(w_i) = w_{i+1}$
- Corpus : I ate the cat
- Training Set : $I|ate, ate|the, the|cat, cat|$.

Google's Word2Vec

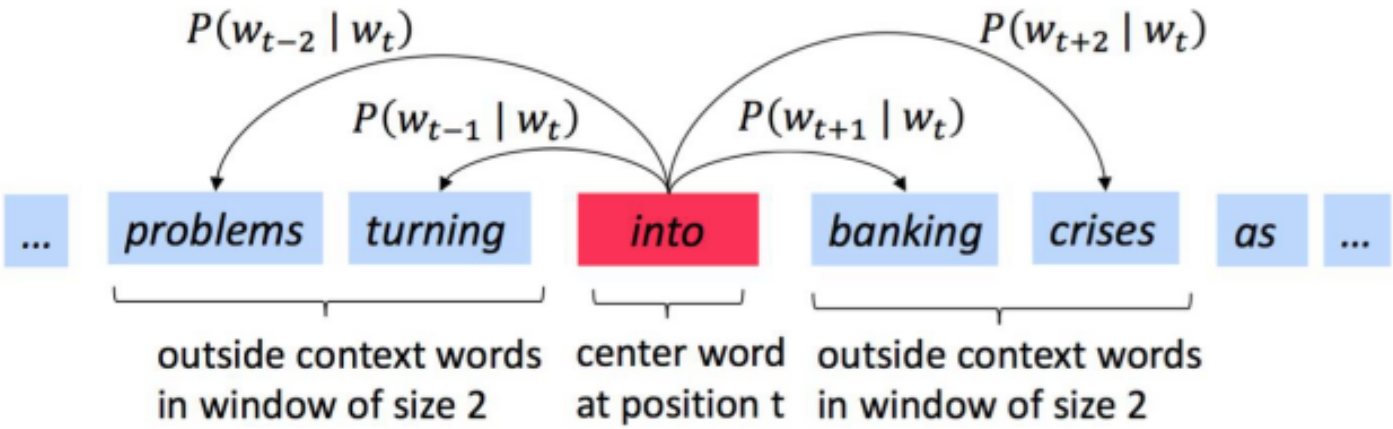


- a large corpus of text
- Every word in a fixed vocabulary is represented by a vector
- Go through each position t in the text, which has a center word c and context ("outside") words o
- Use the similarity of the word vectors for *c* and *o* to calculate the probability of *o* given *c* (or vice versa)
- Keep adjusting the word vectors to maximize this probability

Mikolov et al, 2013, https://arxiv.org/pdf/1310.4546.pdf

(Ref: Word Embeddings - Elena Voita, Yandex Research)

Word2Vec Procedure



http://web.stanford.edu/class/cs224n/syllabus.html

(Ref: Word Embeddings - Elena Voita, Yandex Research)

Word2Vec Optimization

The **objective function (or loss, or cost function)** $J(\theta)$ is the (average) negative log likelihood

$$J(\theta) = -\frac{1}{T}\log L(\theta) = -\frac{1}{T}\sum_{t=1}^{T}\sum_{\substack{-m\le j\le m \\ j\neq 0}} \log P\left(w_{t+j} \mid w_t; \theta\right)$$

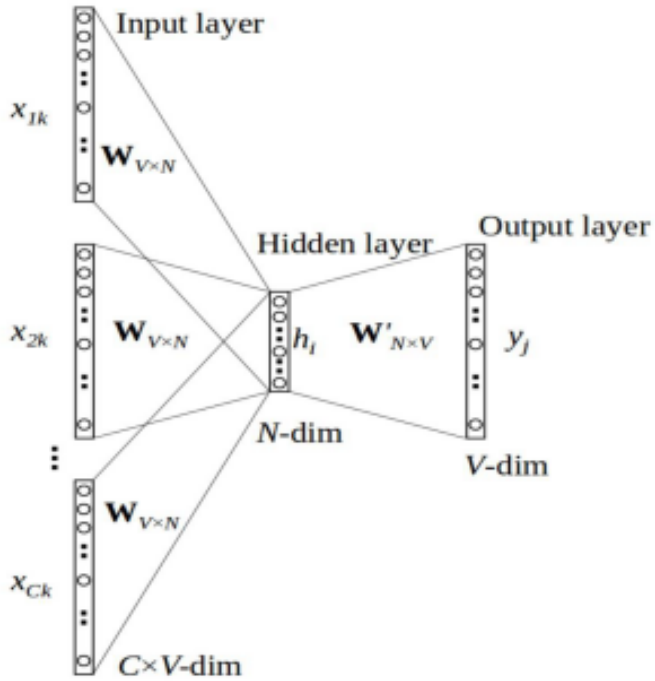
Minimizing objective function $\Longleftrightarrow$ Maximizing predictive accuracy

θs are all the weights in the neural network.

(Ref: Word Embeddings - Elena Voita, Yandex Research)

Word2Vec: CBOW

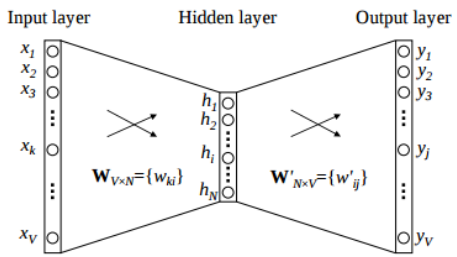
- Predict center word from (bag of) context words



(Ref: Word Embeddings - Elena Voita, Yandex Research)

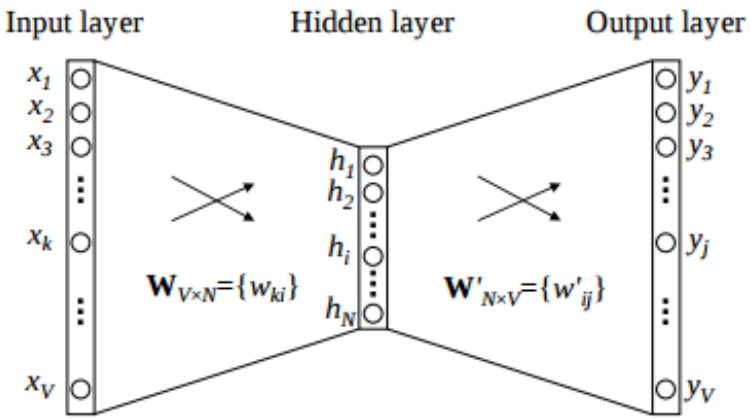
CBOW (Continuous Bag of words)

- Predicts the probability of a word given a context.
- A context may be a single word or a group of words.
- Corpus =“Hey, this is sample corpus using only one context word.”
- training set with window 1
- The input layer and the target, both are one- hot encoded of size [1 X V]. Here V=10 in the above example.
- There are two sets of weights. one is between the input and the hidden layer and second between hidden and output layer.
- N is the number of dimensions, say 4.

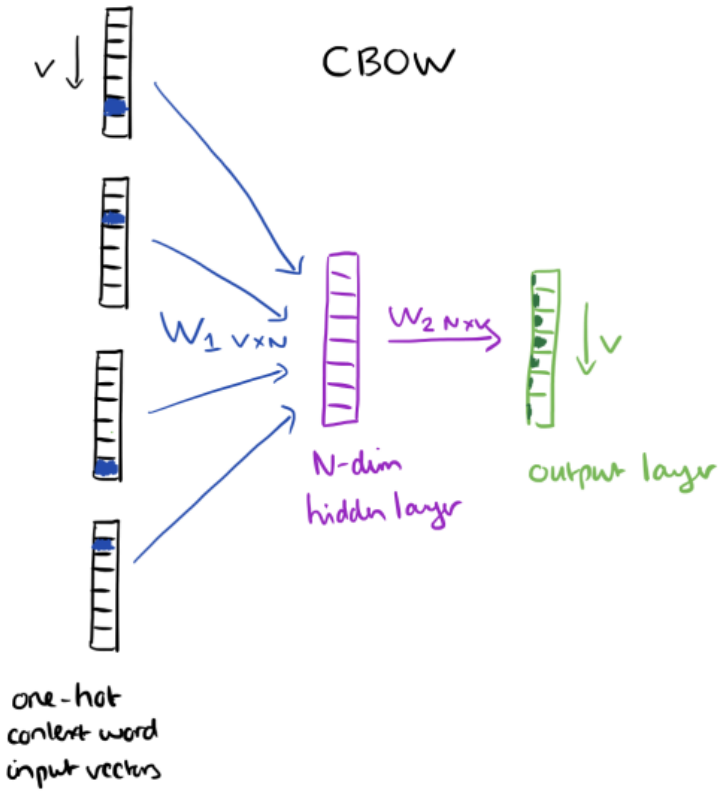


CBOW (Continuous Bag of words)

- The context words form the input layer.
- Each word is encoded in one-hot form.
- There is a single hidden layer and an output layer.



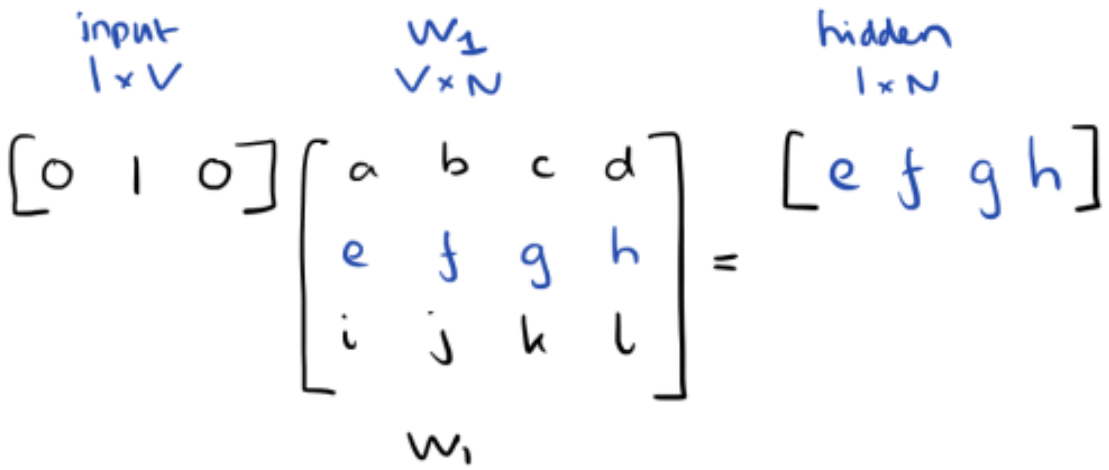
CBOW (Continuous Bag of words)



- $V^T(1xv) \times W_1(vxN) = Hidden(1xN)$
- $Hidden(1xN) \times W_2(Nxv) = Output(1xv)$

CBOW (Continuous Bag of words)

- The training objective is to maximize the conditional probability of observing the actual output word (the focus word) given the input context words, with regard to the weights.
- Since our input vectors are one-hot, multiplying an input vector by the weight matrix W1 amounts to simply selecting a row from W1.



CBOW (Continuous Bag of words)

- Lets say V=8, N=3
- Means that W_1 and W_2 will be 8 x 3 and 3x 8 matrices,

W_1

-0.094491	-0.443977	0.313917
-0.490796	-0.229903	0.065460
0.072921	0.172246	-0.357751
0.104514	-0.463000	0.079367
-0.226080	-0.154659	-0.038422
0.406115	-0.192794	-0.441992
0.181755	0.088268	0.277574
-0.055334	0.491792	0.263102

W_2

0.023074	0.479901	0.432148	0.375480	-0.364732	-0.119840	0.266070	-0.351000
-0.368008	0.424778	-0.257104	-0.148817	0.033922	0.353874	-0.144942	0.130904
0.422434	0.364503	0.467865	-0.020302	-0.423890	-0.438777	0.268529	-0.446787

- Input is "cat"' $[01000000]^T$
- Target is "climbed" $= [00010000]t$

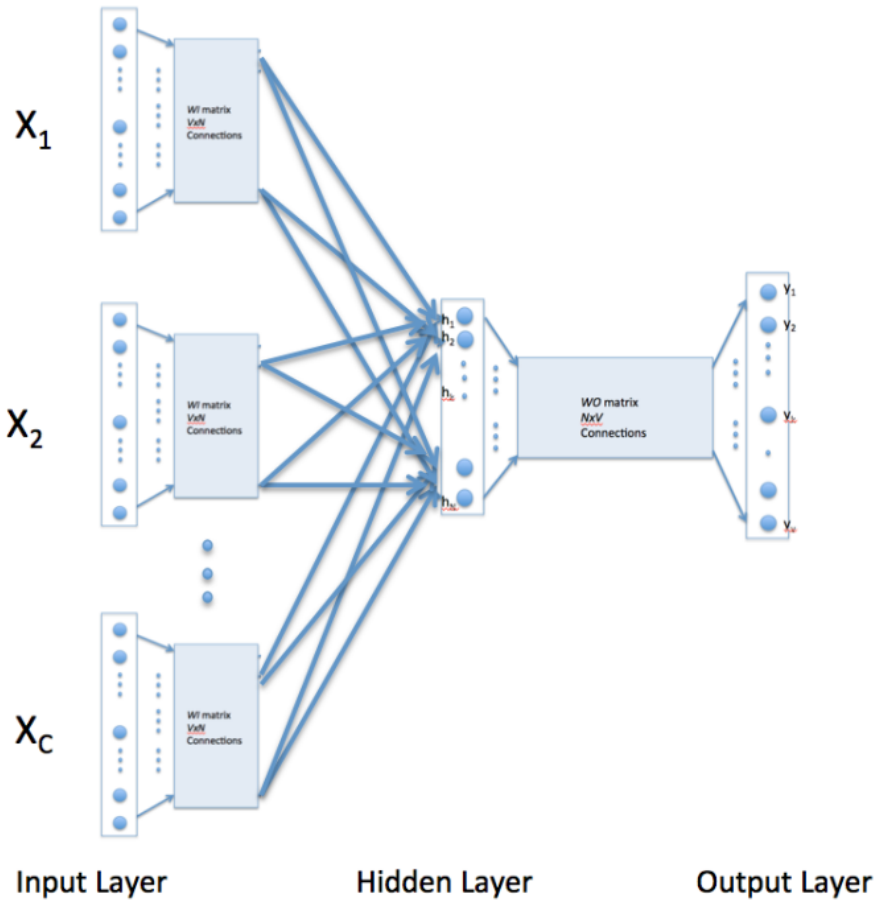
CBOW (Continuous Bag of words)

- Output at the hidden layer neurons can be computed as: $H^t = X^t W_1 = [-0.490796, -0.229903, 0.065460]$
- Similarly for hidden to output layer: $H^t W_2 =$ [0.100934, -0.309331, -0.122361, -0.151399, 0.143463, -0.051262, -0.079686, 0.112928]
- Since the goal is produce probabilities for words in the output layer, softmax is used
- Thus, the probabilities for eight words in the corpus are:0.143073, 0.094925, 0.114441, 0.111166, 0.149289, 0.122874, 0.119431, 0.144800
- Error is by subtracting probability vector from the target vector.
- Once the error is known, the weights in the matrices W_2 and W_1 can be updated using backpropagation.

CBOW (Continuous Bag of words)

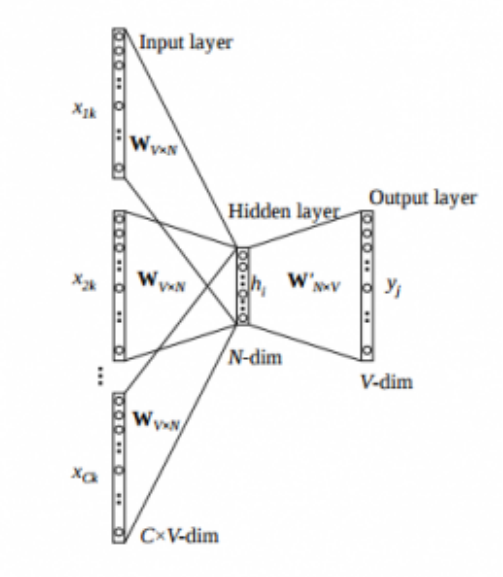
- Given C input word vectors, the activation function for the hidden layer h amounts to simply summing the corresponding 'hot' rows in W1, and dividing by C to take their average.
- This implies that the link (activation) function of the hidden layer units is simply linear (i.e., directly passing its weighted sum of inputs to the next layer).
- From the hidden layer to the output layer, the second weight matrix W2 can be used to compute a score for each word in the vocabulary, and softmax can be used to obtain the posterior distribution of words.

CBOW (Continuous Bag of words)



CBOW (Continuous Bag of words)

- The input is multiplied by the input-hidden weights and called hidden activation.
- The hidden input gets multiplied by hidden- output weights and output is calculated.
- Error between output and target is calculated and propagated back to re-adjust the weights.



CBOW

Advantages of CBOW:

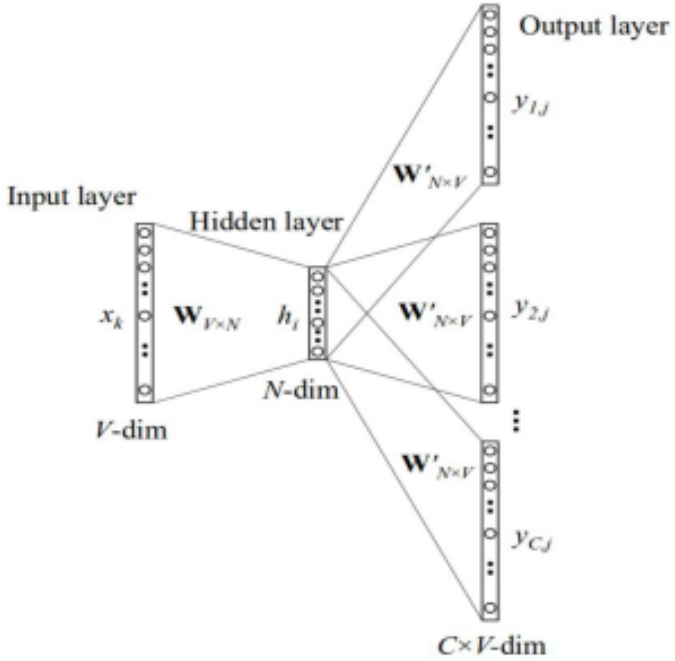
- Being probabilistic is nature, it is supposed to perform superior to deterministic methods(generally).
- It is low on memory. It does not need to have huge RAM requirements like that of co-occurrence matrix where it needs to store three huge matrices.

Disadvantages of CBOW:

- CBOW takes the average of the context of a word (as seen above in calculation of hidden activation). For example, Apple can be both a fruit and a company but CBOW takes an average of both the contexts and places it in between a cluster for fruits and companies.
- Training a CBOW from scratch can take forever if not properly optimized.

Word2Vec: Skip-Gram

- Predict context ("outside") words (position independent) given center word



(Ref: Word Embeddings - Elena Voita, Yandex Research)

Skip-Gram Model

- Skip-gram follows the same topology as of CBOW.
- It just flips CBOW's architecture on its head. The aim of skip-gram is to predict the context given a word.
- C="Hey, this is sample corpus using only one context word."

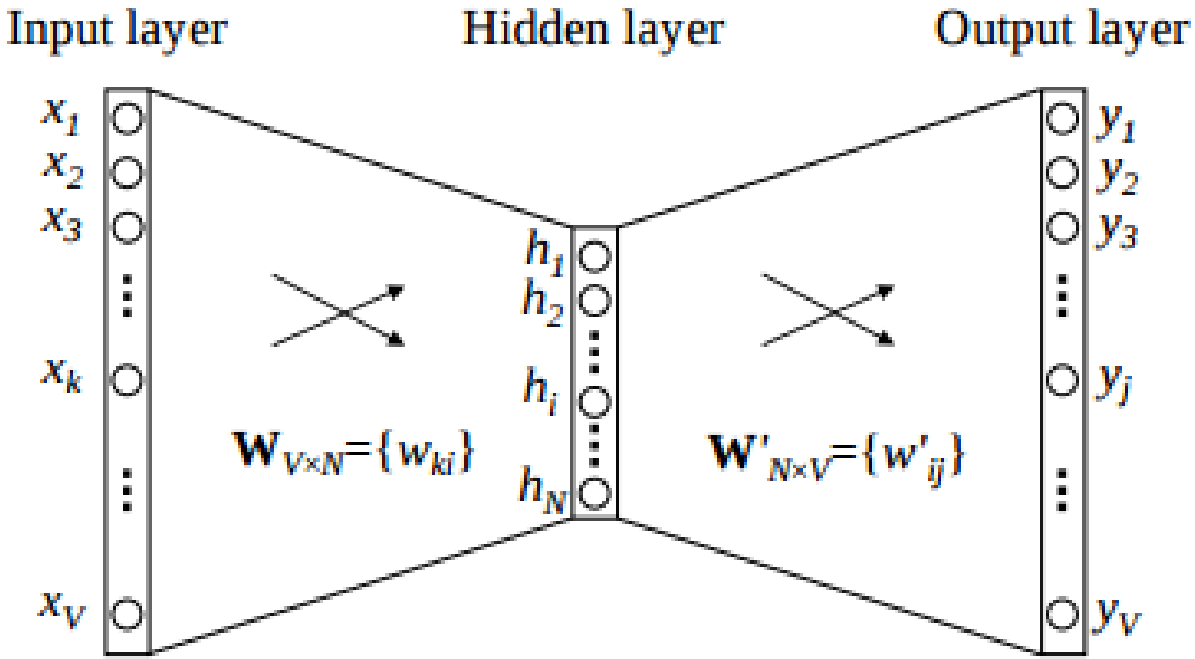
Input	Output(Context1)	Output(Context2)
Hey	this	<padding>
this	Hey	is
is	this	sample
sample	is	corpus
corpus	sample	corpus
using	corpus	only
only	using	one
one	only	context
context	one	word
word	context	<padding>

Skip-Gram Model

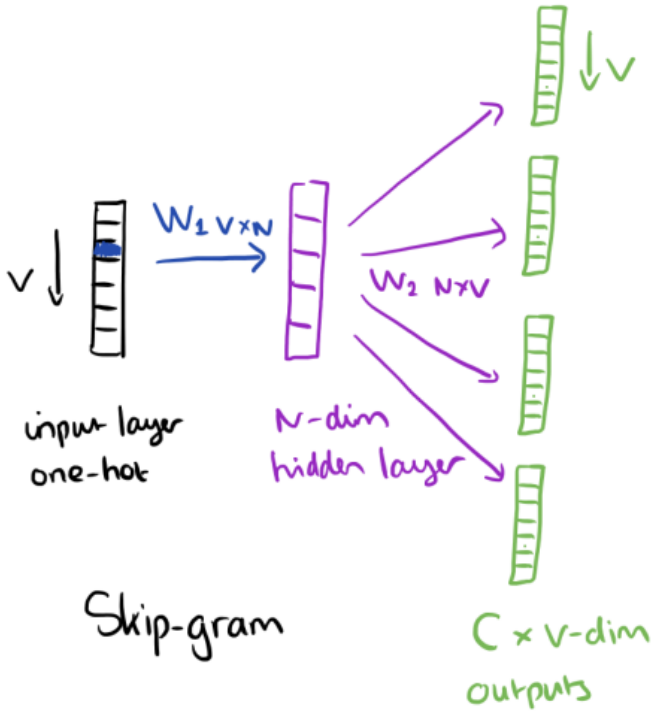
- Since context window is of 1 on both the sides, there will be “two” one hot encoded target variables and “two” corresponding outputs as can be seen by the blue section in the image.
- Two separate errors are calculated with respect to the two target variables and the two error vectors obtained are added element-wise to obtain a final error vector which is propagated back to update the weights.
- The weights between the input and the hidden layer are taken as the word vector representation after training.

Skip-Gram Model

- Constructed with the focus word as the single input vector, and
- the target context words are now at the output layer



Skip-Gram Model



- $V^T(1xv) \times W_1(vxN) = Hidden(1xN)$
- $Hidden(1xN) \times W_2(Nxv) = Output(1xv) \quad C \quad times$

Skip-Gram Model

- At the output layer, we now output C multinomial distributions instead of just one.
- The training objective is to minimize the summed prediction error across all context words in the output layer.

Skip-Gram Model

Context words=2, V= 10, N=4

- Input one-hot encoded vector.
- Weight matrix between the hidden layer and the output layer.
- Matrix multiplication of hidden activation and the hidden output weights. There will be two rows calculated for two target(context) words.
- Each output is converted into its softmax probabilities
- Error is calculated for all output

Skip-Gram Model

Advantages of Skip-Gram Model

- Skip-gram model can capture two semantics for a single word. i.e it will have two vector representations of Apple. One for the company and other for the fruit.
- Skip-gram with negative sub-sampling outperforms every other method generally.

Disadvantages of Skip-Gram Model:

- Very vulnerable, and not a robust concept
- Can take a long time to train
- Non-uniform results
- Hard to understand

Skip-Gram Model

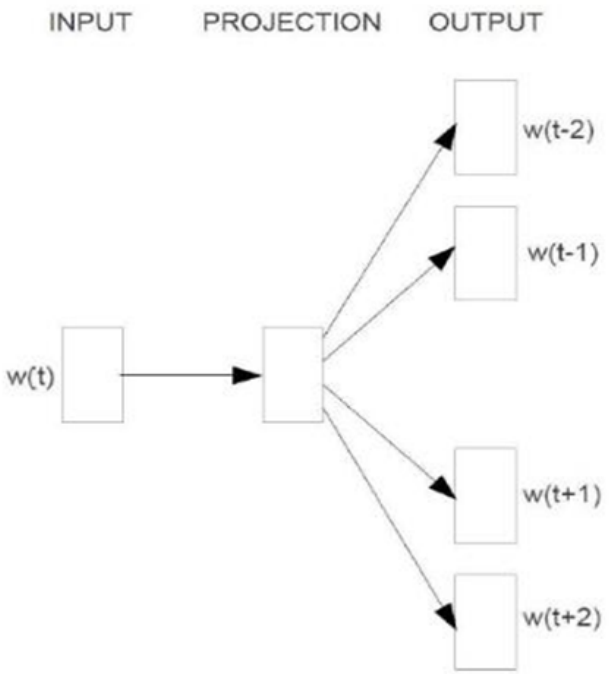
- Skip- Gram maximizes the log - likelihood:

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq j\leq c, j\neq 0}\log p(w_{t+j}|w_t)$$

- Where:
  - T - # of words in the corpus.
  - c - unidirectional window size of the context.

Skip-Gram Model

- Corpus: "If a dog chews shoes, whose shoes does he choose?"



- Where:
  - Input word: shoes
  - Window size: 2.

Word2Vec

Word2vec (Google): a distributed representation of a word is used and not sparse like One-Hot.

Represent in some abstract way the 'meaning' of a word.

Word Distributed Representation - Word2Vec

- All vector cells participate in representing each word.
- Words are represented by real valued dense vectors of significantly smaller dimensions (e.g. 100 - 1000).
- Intuition: consider each vector cell as a representative of some feature.

Word Representations Comparison

Traditional Method - Bag of Words Model

- Uses one hot encoding
- Each word in the vocabulary is represented by one bit position in a HUGE vector.
- For example, with a vocabulary of 10000 words, and "Hello" is the 4th word in the dictionary: `0 0 0 1 0 0 . . . . . 0 0 0 0`
- Context information is not utilized

Modern - Word Vectors

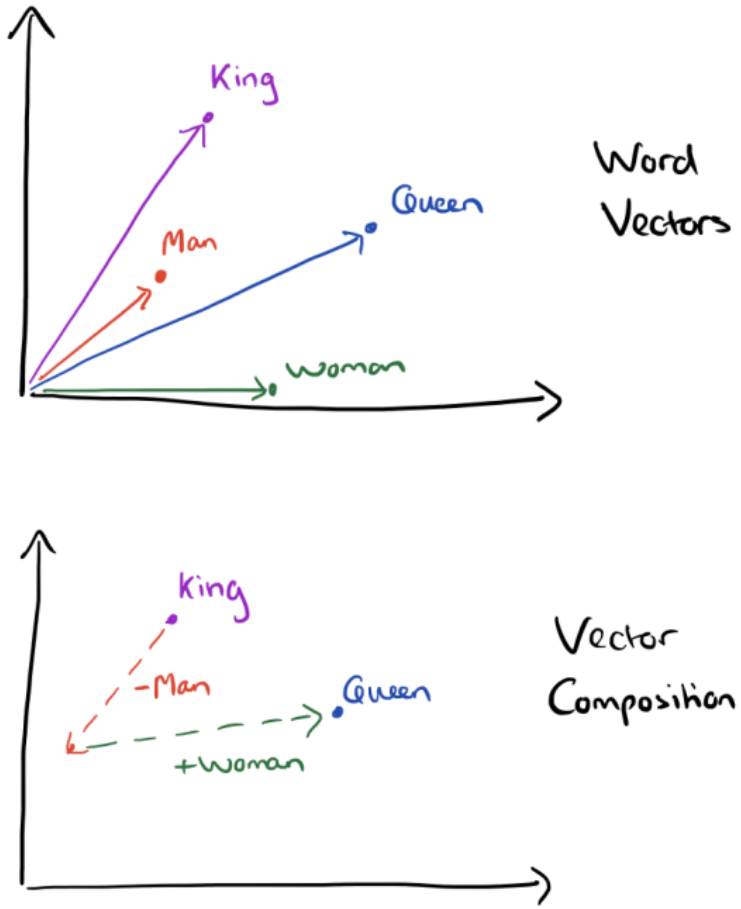
- Stores each word in as a point in space, represented by a vector of fixed number of dimensions (generally 300)
- Unsupervised, built just by reading huge corpus
- For example, "Hello" might be represented as : `[0.4, -0.11, 0.55, 0.3 . . . 0.1, 0.02]`
- Context information is utilized

The Power of Word2Vecs

- They provide a fresh perspective to ALL problems in NLP, and not just solve one problem.
- Technological Improvement
- Rise of deep learning since 2006 (Big Data + GPUs + Work done by Andrew Ng, Yoshua Bengio, Yann Lecun and Geoff Hinton)
- Application of Deep Learning to NLP - led by Yoshua Bengio, Christopher Manning, Richard Socher, Tomas Mikalov
- The need for unsupervised learning . (Supervised learning tends to be excessively dependent on hand-labeled data and often does not scale)

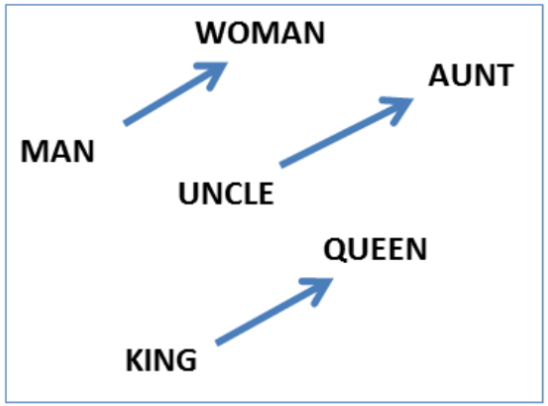
Examples

Vectors for King, Man, Queen, & Woman:

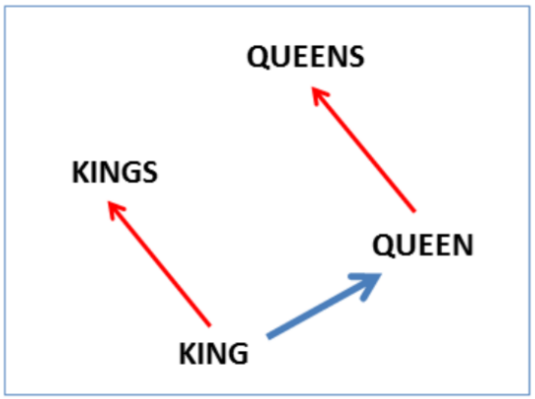


Examples

Gender relation:



Plural relation:



Examples

Word pair relationships:

Table 8: *Examples of the word pair relationships, using the best word vectors from Table 4 (Skip-gram model trained on 783M words with 300 dimensionality).*

Relationship	Example 1	Example 2	Example 3
France - Paris	Italy: Rome	Japan: Tokyo	Florida: Tallahassee
big - bigger	small: larger	cold: colder	quick: quicker
Miami - Florida	Baltimore: Maryland	Dallas: Texas	Kona: Hawaii
Einstein - scientist	Messi: midfielder	Mozart: violinist	Picasso: painter
Sarkozy - France	Berlusconi: Italy	Merkel: Germany	Koizumi: Japan
copper - Cu	zinc: Zn	gold: Au	uranium: plutonium
Berlusconi - Silvio	Sarkozy: Nicolas	Putin: Medvedev	Obama: Barack
Microsoft - Windows	Google: Android	IBM: Linux	Apple: iPhone
Microsoft - Ballmer	Google: Yahoo	IBM: McNealy	Apple: Jobs
Japan - sushi	Germany: bratwurst	France: tapas	USA: pizza

Country-capital city relationship:

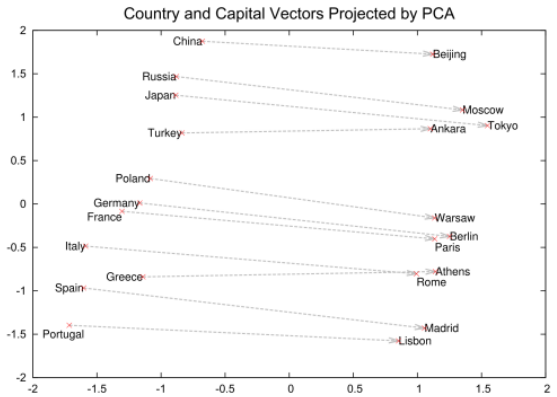


Figure 2: Two-dimensional PCA projection of the 1000-dimensional Skip-gram vectors of countries and their capital cities. The figure illustrates ability of the model to automatically organize concepts and learn implicitly the relationships between them, as during the training we did not provide any supervised information about what a capital city means.

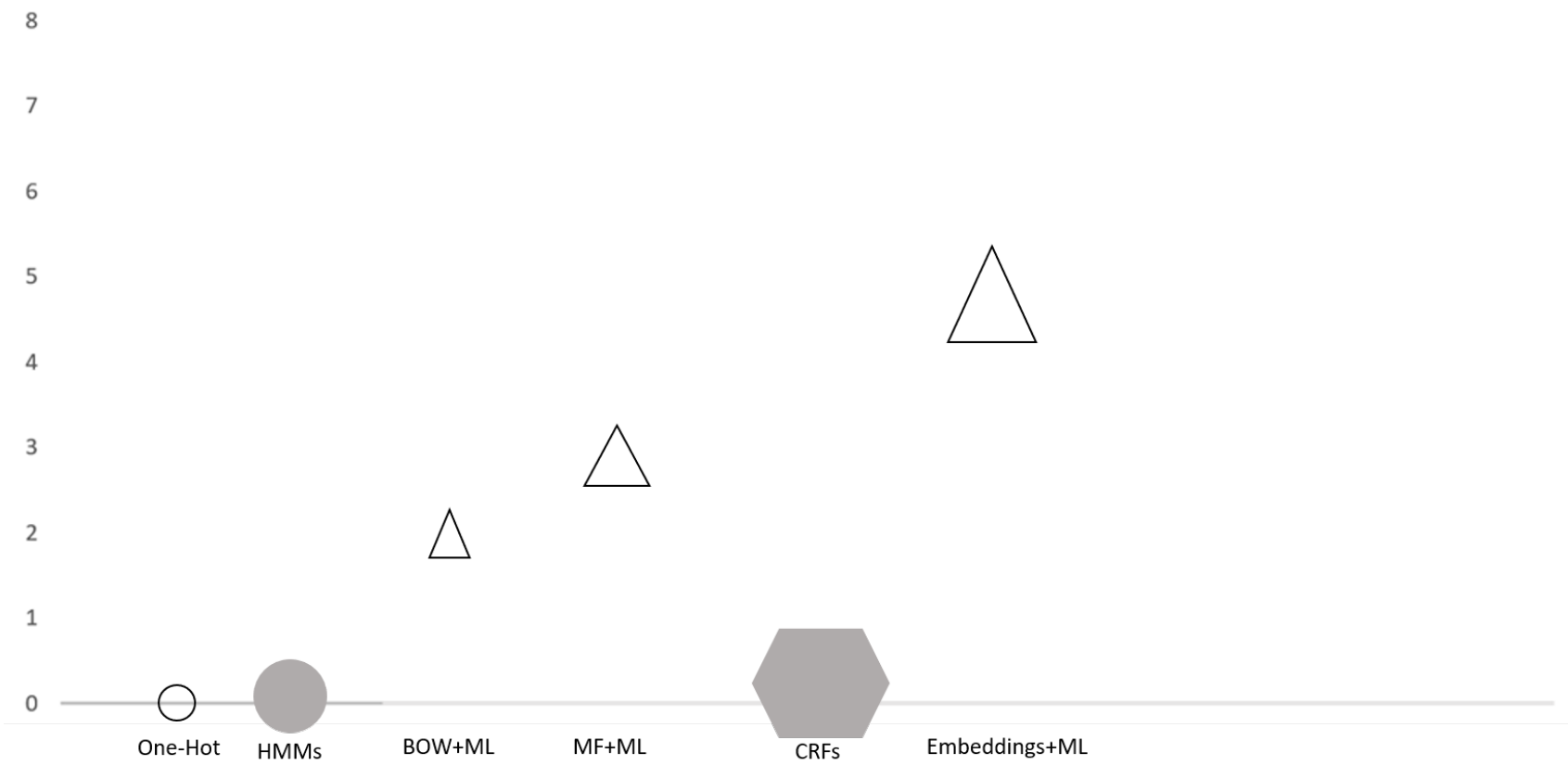
Probabilistic Graphical Models

Markov process based Language Models also capture semantics

- Hidden Markov models
- Conditional Random Fields

(Ref: Understanding "Understanding language" - Murthy Kolluru

Murthy's Visualization



(Ref: Understanding "Understanding language" - Murthy Kolluru

Other than Words . . .

What if . . .

We want to use subword information?

FastText

Adding subword information

- Model: SG-NS (skip-gram with negative sampling)
- Change the way word vectors are formed
- each word represented as a bag of character n-gram: eg “where” : ”wh”,”whe”,”her”,”ere”,”re”
- associate a vector representation to each n- gram
- represent a word by the sum of the vector representations of its n-grams

(Ref: Bojanovsky et al, TACL 2017 http://aclweb.org/anthology/Q17-1010)

What if . . .

We abstract the skip-gram model to the sentence level?

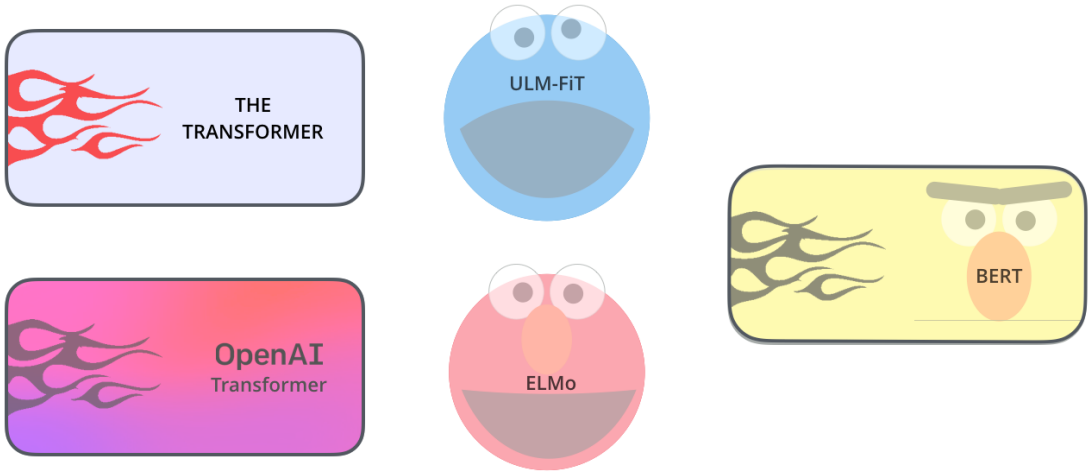
Sentence Embedding

- Before: use a word to predict its surrounding context
- Now: encode a sentence to predict the sentences around it

(Ref: Kiros et al., NIPS 2015 https://papers.nips.cc/paper/5950-skip-thought-vectors.pdf)

Latest embeddings

- The year 2018 has been an inflection point for machine learning models in NLP
- It's been referred to as NLP's ImageNet moment,



(Ref: The Illustrated BERT, ELMo, and co. (How NLP Cracked Transfer Learning) -Jay Alammar)

ELMo: Context Matters

- Say, a word "stick" would be represented by a Word2Vec vector no-matter what the context was.
- "stick"" has multiple meanings depending on where it's used.
- Why not give it an embedding based on the context it's used in – to both capture the word meaning in that context as well as other contextual information?".
- Instead of using a fixed embedding for each word, ELMo looks at the entire sentence before assigning each word in it an embedding. It uses a bi-directional LSTM trained on a specific task to be able to create those embeddings.

(Ref: The Illustrated BERT, ELMo, and co. (How NLP Cracked Transfer Learning) -Jay Alammar)

ULM-FiT: Nailing down Transfer Learning in NLP

- ULM-FiT introduced methods to effectively utilize a lot of what the model learns during pre-training – more than just embeddings, and more than contextualized embeddings. ULM-FiT introduced a language model and a process to effectively fine-tune that language model for various tasks.
- NLP finally had a way to do transfer learning probably as well as Computer Vision could

(Ref: The Illustrated BERT, ELMo, and co. (How NLP Cracked Transfer Learning) -Jay Alammar)

The Transformer: Going beyond LSTMs

- The Encoder-Decoder structure of the transformer made it perfect for machine translation. But how would you use it for sentence classification?
- How would you use it to pre-train a language model that can be fine-tuned for other tasks?

(Ref: The Illustrated BERT, ELMo, and co. (How NLP Cracked Transfer Learning) -Jay Alammar)

OpenAI Transformer

Pre-training a Transformer Decoder for Language Modeling

- It turns out we don't need an entire Transformer to adopt transfer learning and a fine-tunable language model for NLP tasks.
- We can do with just the decoder of the transformer. The decoder is a good choice because it's a natural choice for language modeling (predicting the next word) since it's built to mask future tokens – a valuable feature when it's generating a translation word by word.
- Now that the OpenAI transformer is pre-trained and its layers have been tuned to reasonably handle language, we can start using it for downstream tasks.

(Ref: The Illustrated BERT, ELMo, and co. (How NLP Cracked Transfer Learning) -Jay Alammar)

BERT: From Decoders to Encoders

- The openAI transformer gave us a fine-tunable pre-trained model based on the Transformer. But something went missing in this transition from LSTMs to Transformers.
- ELMo's language model was bi-directional, but the openAI transformer only trains a forward language model.
- Could we build a transformer-based model whose language model looks both forward and backwards (in the technical jargon – "is conditioned on both left and right context")?
- "Hold my beer", said R-rated BERT. Everybody knows bidirectional conditioning would allow each word to indirectly see itself in a multi-layered context." "We'll use masks", said BERT confidently.

(Ref: The Illustrated BERT, ELMo, and co. (How NLP Cracked Transfer Learning) -Jay Alammar)

BERT

So, BERT builds on top of a number of clever ideas that have been bubbling up in the NLP community recently – including but not limited to

- Semi-supervised Sequence Learning (by Andrew Dai and Quoc Le),
- ELMo (by Matthew Peters and researchers from AI2 and UW CSE),
- ULMFiT (by fast.ai founder Jeremy Howard and Sebastian Ruder),
- the OpenAI transformer (by OpenAI researchers Radford, Narasimhan, Salimans, and Sutskever), and
- the Transformer (Vaswani et al).

You can use the pre-trained BERT to create contextualized word embeddings

(Ref: The Illustrated BERT, ELMo, and co. (How NLP Cracked Transfer Learning) -Jay Alammar)

How to evaluate embeddings

Intrinsic: evaluation on a specific/intermediate subtask

- word analogies: "a is to b as c is to xxxx?"
- word similarity: correlation of the rankings

Extrinsic: evaluation on a real task

- take some task (MT, NER, coreference resolution, . . .) or several tasks
- train with different pretrained word embeddings
- if the task quality is better -¿ win!

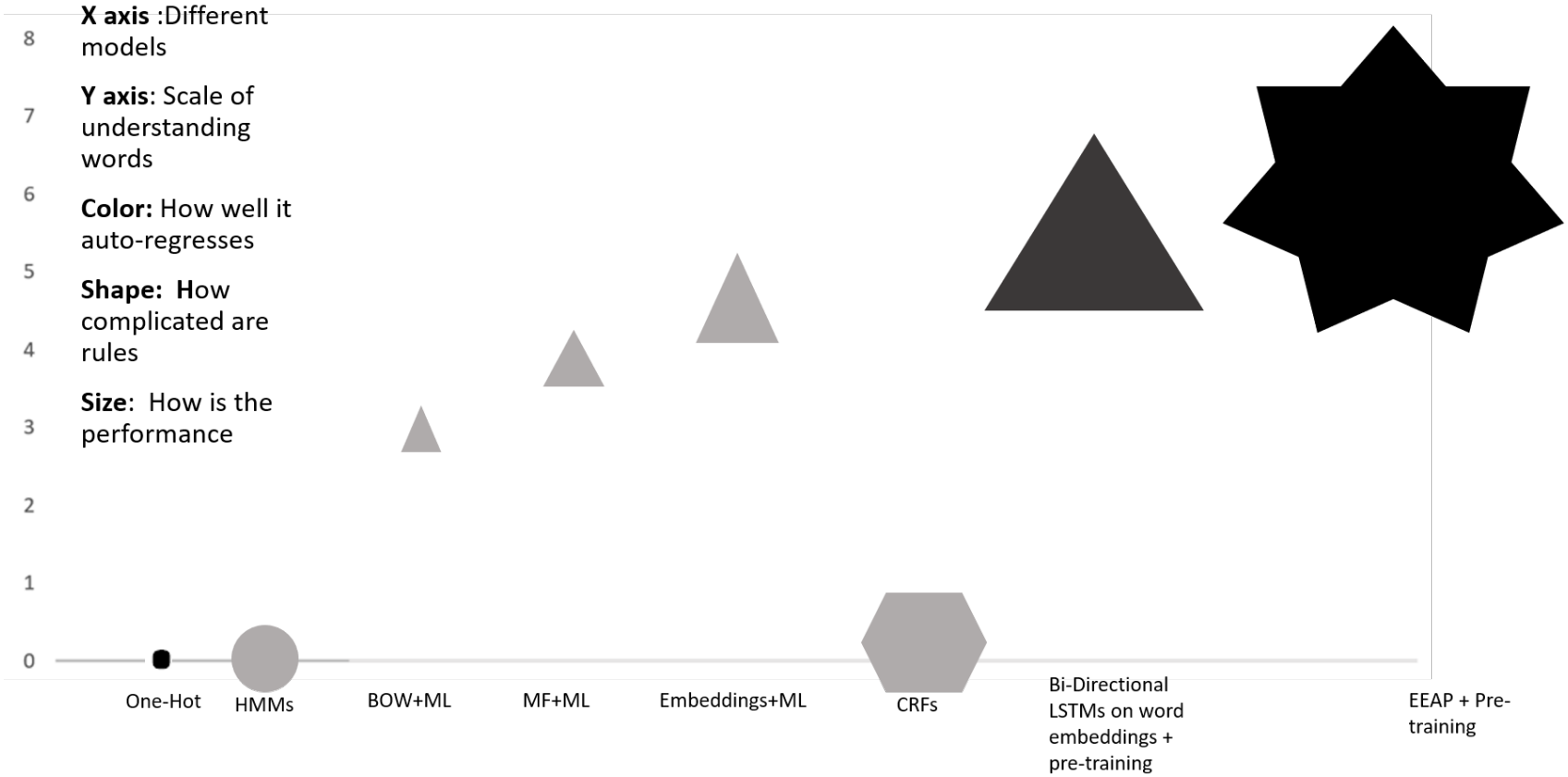
Transfer learning

Very popular in Image processing but a late entry into NLP world

- Pre-train with language models
- Train same net on multiple tasks

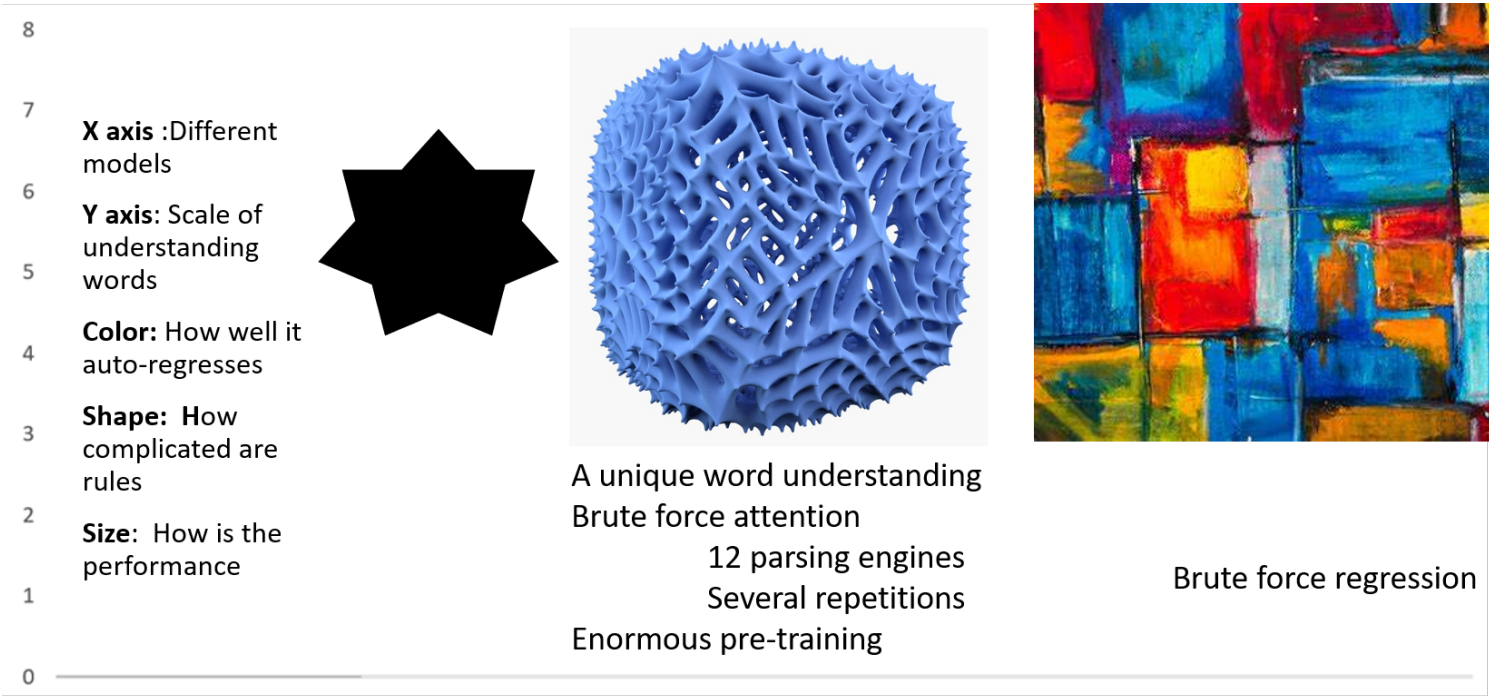
(Ref: Understanding "Understanding language" - Murthy Kolluru

Murthy's Visualization



(Ref: Understanding "Understanding language" - Murthy Kolluru

Murthy's Visualization



(Ref: Understanding "Understanding language" - Murthy Kolluru

Applications of Word Vectors

Applications of Word Vectors

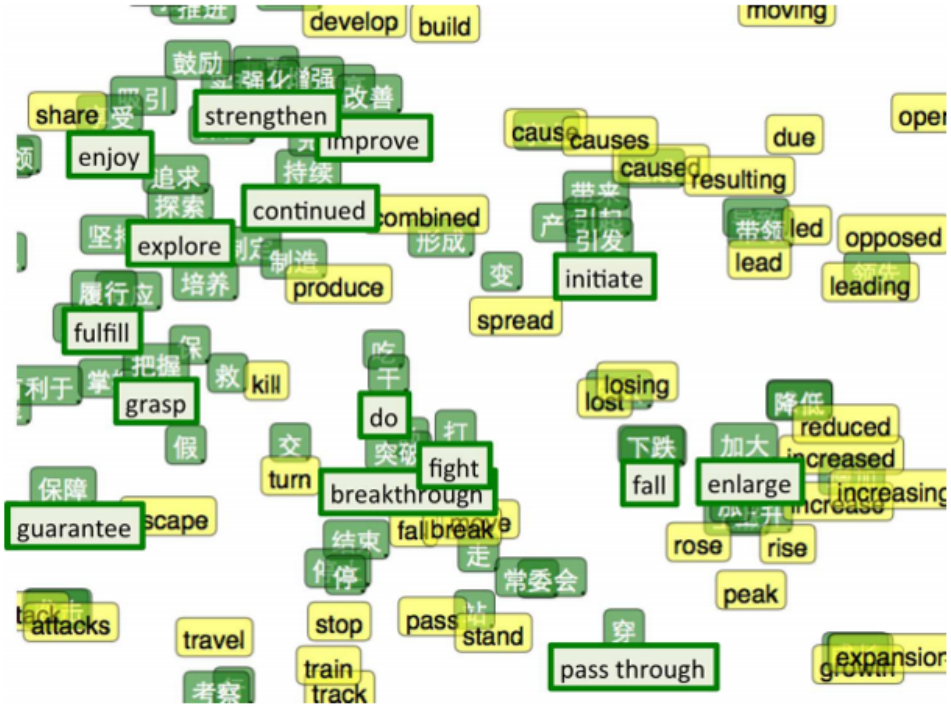
Word Similarity:

- Classic Methods : Edit Distance, WordNet, Porter's Stemmer, Lemmatization using dictionaries
- Easily identifies similar words and synonyms since they occur in similar contexts
- Stemming (thought $\rightarrow$ think)
- Inflections, Tense forms
- eg. Think, thought, ponder, pondering,
- eg. Plane, Aircraft, Flight

Applications of Word Vectors

Machine Translation:

- Classic Methods : Rule-based machine translation, morphological transformation



Applications of Word Vectors

Part-of-Speech and Named Entity Recognition:

- Classic Methods : Sequential Models (MEMM , Conditional Random Fields), Logistic Regression

	POS WSJ (acc.)	NER CoNLL (F1)
State-of-the-art*	97.24	89.31
Supervised NN	**96.37**	**81.47**
Unsupervised pre-training followed by supervised NN**	**97.20**	**88.87**
+ hand-crafted features***	97.29	89.59

Applications of Word Vectors

Sentiment Analysis:

- Classic Methods : Naive Bayes, Random Forests/SVM
- Classifying sentences as positive and negative
- Building sentiment lexicons using seed sentiment sets
- No need for classifiers, we can just use cosine distances to compare unseen reviews to known reviews.

```
Enter word or sentence (EXIT to break): sad

Word: sad  Position in vocabulary: 4067

                                             Word       Cosine distance
--------------------------------------------------------------------------
                                        saddening              0.727309
                                              Sad              0.661083
                                         saddened              0.660439
                                     heartbreaking             0.657351
                                     disheartening             0.650732
                                     Meny_Friedman             0.648706
                              parishioner_Pat_Patello          0.647586
                                        saddens_me             0.640712
                                      distressing              0.639909
                                  reminders_bobbing            0.635772
                                   Turkoman_Shiites            0.635577
                                          saddest              0.634551
                                       unfortunate             0.627209
                                            sorry              0.619405
                                       bittersweet             0.617521
                                            tragic             0.611279
                                         regretful             0.603472
```

Applications of Word Vectors

Sentiment Analysis:

- Co-reference Resolution: Chaining entity mentions across multiple documents - can we find and unify the multiple contexts in which mentions occurs?
- Clustering: Words in the same class naturally occur in similar contexts, and this feature vector can directly be used with any conventional clustering algorithms (K-Means, agglomerative, etc). Human doesn't have to waste time hand-picking useful word features to cluster on.
- Semantic Analysis of Documents: Build word distributions for various topics, etc.

Weakness of Word Embedding

- Very vulnerable, and not a robust concept
- Can take a long time to train
- Non-uniform results
- Hard to understand and visualize

Summary

Machines like humans need four things to understand language

- Understand the words (semantics)
- Build the ability to guess (language model)
- Parse language specific rules and patterns (encoder-decoder, transformers)
- Build on the experience (pre-training)

Ability to include non-language information (culture, visuals, etc) will improve language models.

Word Embeddings in Tensorflow

(Ref: How to Use Word Embedding Layers for Deep Learning with Keras by Jason Brownlee)

Word Embedding (Recap)

- Word embeddings provide a dense representation of words and their relative similarity.
- Improvement over sparse representations like Bag of Words
- Can be pre-built on generic corpus or built from scratch with own corpus

Tensorflow/Keras Embedding Layer

- Requires that the input data be integer encoded, so that each word is represented by a unique integer. Tokenizer API can be used to generate this format.
- Like a lookup table that maps from integer indices (which stand for specific words) to dense vectors (their embeddings).
- Usage:
  - Used alone to learn a word embedding that can be saved and used in another model later.
  - Used as part of a deep learning model where the embedding is learned along with the model itself.
  - Used to load a pre-trained word embedding model, a type of transfer learning.

Embedding Layer Input Specification

- **input_dim**: Size of the vocabulary. For example, if your data is integer encoded to values between 0-10, then the size of the vocabulary would be 11 words.
- **output_dim**: Size of the vector space in which words will be embedded, ie size of the output vectors from this layer for each word. For example, it could be 32 or 100 or even larger.
- **input_length**: This is the length of input sequences, as you would define for any input layer of a Keras model. For example, if all of your input documents are comprised of 1000 words, this would be 1000.

```
e = Embedding(200, 32, input_length=50)
```

Above Embedding layer is with a vocabulary of 200 (e.g. integer encoded words from 0 to 199, inclusive), a vector space of 32 dimensions in which words will be embedded, and input documents that have 50 words each.

Embedding Layer

```
# Embed a 1,000 word vocabulary into 5 dimensions.
embedding_layer = tf.keras.layers.Embedding(1000, 5)
```

- Initially all 5000 weights are initialized randomly (just like any other layer).
- During training, they are gradually adjusted via backpropagation.
- Once trained, the learned word embeddings will roughly encode similarities between words (as they were learned for the specific problem your model is trained on).

(Ref: https://www.tensorflow.org/tutorials/text/word_embeddings)

Embedding Layer Output

- The output of the Embedding layer is a 2D vector with one embedding for each word in the input sequence of words (input document).
- If you wish to connect a Dense layer directly to an Embedding layer, you must first flatten the 2D output matrix to a 1D vector using the Flatten layer.

Word Embeddings via Layers in Keras/Tensorflow

(Ref: How to Use Word Embedding Layers for Deep Learning with Keras by Jason Brownlee)

Embedding Layer Example: Inputs

Sentiment analysis classification on 10 documents.

```
# define documents
docs = ['Well done!',
    'Good work',
    'Great effort',
    'nice work',
    'Excellent!',
    'Weak',
    'Poor effort!',
    'not good',
    'poor work',
    'Could have done better.']
# define class labels
labels = array([1,1,1,1,1,0,0,0,0,0])
```

Embedding Layer Example: Encoding

Integer encoding. Estimating the vocabulary size of 50, which is much larger than needed, but thats ok.
Keras provides the one_hot() function that creates a hash of each word as an efficient integer encoding.

```
# integer encode the documents
vocab_size = 50
encoded_docs = [one_hot(d, vocab_size) for d in docs]
print(encoded_docs)

[[6, 16], [42, 24], [2, 17], [42, 24], [18], [17], [22, 17], [27, 42], [22,
     24], [49, 46, 16, 34]]
```

Embedding Layer Example: Padding

- The sequences have different lengths and Keras prefers inputs to be vectorized and all inputs to have the same length.
- Pad all input sequences to have the length of 4.
- Again, we can do this with a built in Keras function, in this case the pad_sequences() function.

```
# pad documents to a max length of 4 words
max_length = 4
padded_docs = pad_sequences(encoded_docs, maxlen=max_length, padding='post')
print(padded_docs)

[[ 6 16  0  0]
 [42 24  0  0]
 [ 2 17  0  0]
 [42 24  0  0]
 [18  0  0  0]
 [17  0  0  0]
 [22 17  0  0]
 [27 42  0  0]
 [22 24  0  0]
 [49 46 16 34]]
```

Embedding Layer Example: Model

The Embedding has a vocabulary of 50 and an input length of 4. Lets choose a small embedding space of 8 dimensions. The output from the Embedding layer will be 4 vectors of 8 dimensions each, one for each word. We flatten this to a one 32-element vector to pass on to the Dense output layer.

```
# define the model
model = Sequential()
model.add(Embedding(vocab_size, 8, input_length=max_length))
model.add(Flatten())
model.add(Dense(1, activation='sigmoid'))
# compile the model
model.compile(optimizer='adam', loss='binary_crossentropy',
     metrics=['accuracy'])
# summarize the model
print(model.summary())

Layer (type)                 Output Shape              Param #
=================================================================
embedding_1 (Embedding)      (None, 4, 8)              400
_________________________________________________________________
flatten_1 (Flatten)          (None, 32)                0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 33
=================================================================
```

Embedding Layer Example: Evaluation

```
# fit the model
model.fit(padded_docs, labels, epochs=50, verbose=0)
# evaluate the model
loss, accuracy = model.evaluate(padded_docs, labels, verbose=0)
print('Accuracy: %f' % (accuracy*100))

Accuracy: 100.000000
```

Glove Keras/Tensorflow

(Ref: How to Use Word Embedding Layers for Deep Learning with Keras by Jason Brownlee)

Glove Word Embedding

- Glove provides a suite of pre-trained word embeddings on their website released under a public domain license
- The smallest package of embeddings is 822Mb, called “glove.6B.zip“. It was trained on a dataset of one billion tokens (words) with a vocabulary of 400 thousand words.
- There are a few different embedding vector sizes, including 50, 100, 200 and 300 dimensions.
- You can download this collection of embeddings and we can seed the Keras Embedding layer with weights from the pre-trained embedding for the words in your training dataset.

Glove Embedding Example: Input

```
# define documents
docs = ['Well done!',
    'Good work',
    'Great effort',
    'nice work',
    'Excellent!',
    'Weak',
    'Poor effort!',
    'not good',
    'poor work',
    'Could have done better.']
# define class labels
labels = array([1,1,1,1,1,0,0,0,0,0])
# prepare tokenizer
t = Tokenizer()
t.fit_on_texts(docs)
vocab_size = len(t.word_index) + 1
# integer encode the documents
encoded_docs = t.texts_to_sequences(docs)
print(encoded_docs)
# pad documents to a max length of 4 words
max_length = 4
padded_docs = pad_sequences(encoded_docs, maxlen=max_length, padding='post')
print(padded_docs)
```

Glove Embedding Example: Load Glove

Load the entire GloVe word embedding file into memory as a dictionary of word to embedding array.

```
# load the whole embedding into memory
embeddings_index = dict()
f = open('glove.6B.100d.txt')
for line in f:
  values = line.split()
  word = values[0]
  coefs = asarray(values[1:], dtype='float32')
  embeddings_index[word] = coefs
f.close()
print('Loaded %s word vectors.' % len(embeddings_index))
```

Glove Embedding Example: Prep Input

Create a matrix of one embedding for each word in the training dataset. We can do that by enumerating all unique words in the Tokenizer.word_index and locating the embedding weight vector from the loaded GloVe embedding.

```
# create a weight matrix for words in training docs
embedding_matrix = zeros((vocab_size, 100))
for word, i in t.word_index.items():
  embedding_vector = embeddings_index.get(word)
  if embedding_vector is not None:
    embedding_matrix[i] = embedding_vector
```

The result is a matrix of weights only for words we will see during training.

Glove Embedding Example: Embedding Layer

The embedding layer can be seeded with the GloVe word embedding weights. We chose the 100-dimensional version, therefore the Embedding layer must be defined with output_dim set to 100. Finally, we do not want to update the learned word weights in this model, therefore we will set the trainable attribute for the model to be False.

```
# define model
model = Sequential()
e = Embedding(vocab_size, 100, weights=[embedding_matrix], input_length=4,
      trainable=False)
model.add(e)
model.add(Flatten())
model.add(Dense(1, activation='sigmoid'))
# compile the model
model.compile(optimizer='adam', loss='binary_crossentropy',
      metrics=['accuracy'])
# summarize the model
print(model.summary())
# fit the model
model.fit(padded_docs, labels, epochs=50, verbose=0)
# evaluate the model
loss, accuracy = model.evaluate(padded_docs, labels, verbose=0)
print('Accuracy: %f' % (accuracy*100))
```

Summary

- Keras supports word embeddings via the Embedding layer.
- How to learn a word embedding while fitting a neural network.
- How to use a pre-trained word embedding in a neural network.

Thanks ... yogeshkulkarni@yahoo.com