Word 2 Vec

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ODH

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Motivation

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  - s1: Monday, Monday!
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  - s4: Is today a Monday
- First order of business: Find a good representation of the text

Proposed Solution

- One-hot encoded vector for the entire vocabulary

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  `vocab` $\sim$ `[Monday, Tuesday, is, a, today]`

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s1:  Monday, Monday!  ~              [1, 0, 0, 0, 0]
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- Need to learn a low-dimensional representation: Word2Vec

Neural Network

- Neural network as a black box

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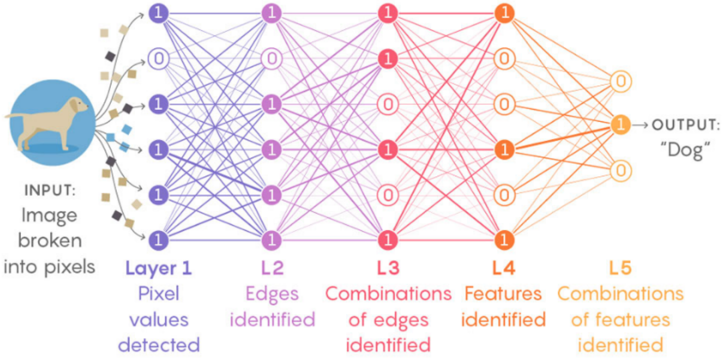
Neural Network

- Internal structure of a neural network is able to represent information



Internal representation of a Neural Network

Source: https://www.quantamagazine.org/new-theory-cracks-open-the-black-box-of-deep-learning-20170921/

Word Vectors

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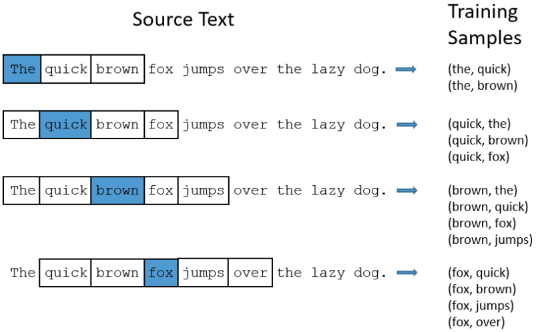
- Auxiliary Task: Given a specific input word, compute probability for every word in our vocabulary of being the neighbor

Word Vectors

- Intuition: Train a neural network for an “auxiliary” task, and use the learned weights as a representation(word-vectors)
- Break the sentence into small windows(size=2), and create training set for each input word(in blue)

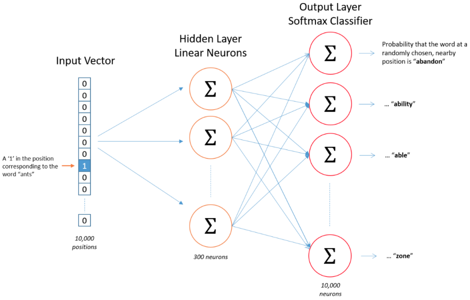


Generating Training Data

Source: *McCormick, C. (2016, April 19). Word2Vec Tutorial - The Skip-Gram Model*

Word Vectors

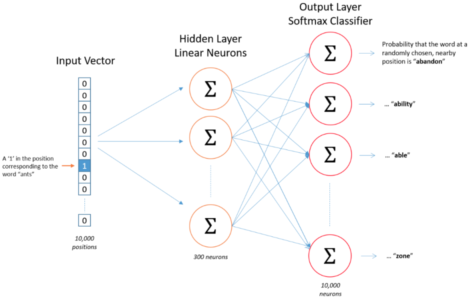
- Intuition: Train a neural network for an “auxiliary” task, and use the learned weights as a representation(word-vectors)
- Feed the training data as one-hot encoded vectors to the model, such that the output is a the probability of a word being the neighbor of target.



Neural Network for training the auxiliary task

Word Vectors

- Intuition: Train a neural network for an "auxiliary" task, and use the learned weights as a representation(word-vectors)
- Use the hidden layer as the word-representation



Word vectors as the hidden layer

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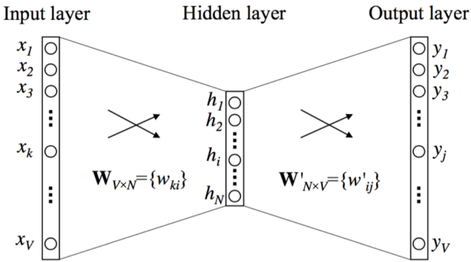

Single context word model

Source: David Meyer, How exactly does word2vec work?

How does Word2Vec work?

- Given an input word, predict single target word
- $X = (x_1, x_2, ...x_V)$, $Y = (y_1, y_2...y_V)$, where V is the size of vocabulary, $x_i \in X$ and $y_i \in Y$ are one-hot encoded vectors

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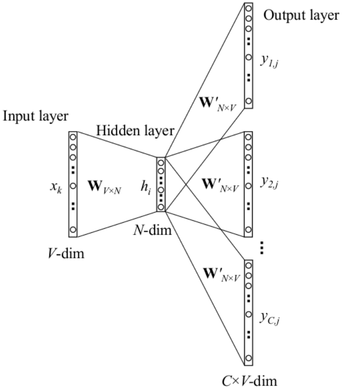
- The training objective, therefore, is to maximize the conditional probability of observing the actual output word, given the input context word

Word2Vec

- Skip-gram (SG): use a word to predict the surrounding ones in window.

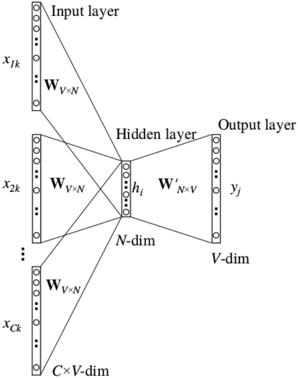


Structure of a Skip-gram model

Source: Xin Rong, Word2Vec Parameter Learning Explained

Word2Vec

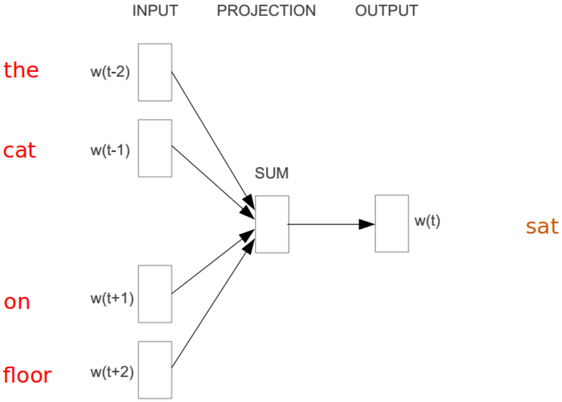
- Skip-gram (SG): use a word to predict the surrounding ones in window.
- Continuous Bag of Words (CBOW): use a window of word to predict the middle word



Structure of a Continuous Bag-Of-Words Model

CBOW

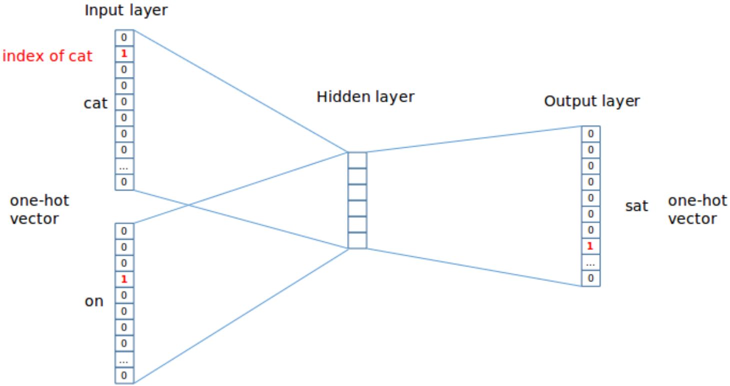
- e.g. "The cat sat on floor" (window = 2)



Sentence Structure

Source: Vagelis Hristidis, Vector Representation of Text

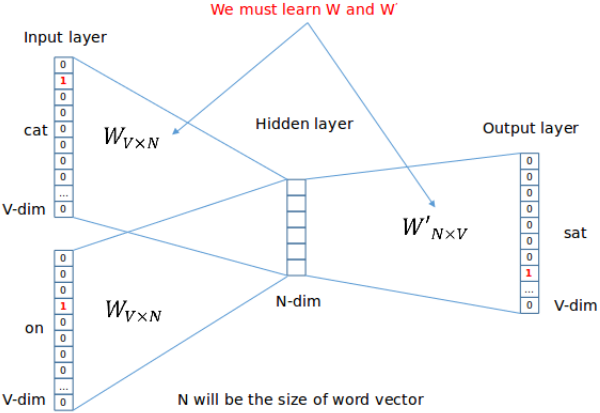
CBOW



One hot encoded input and output

Source: Vagelis Hristidis, Vector Representation of Text

CBOW



Learning W, W' matrices

Source: Vagelis Hristidis, Vector Representation of Text

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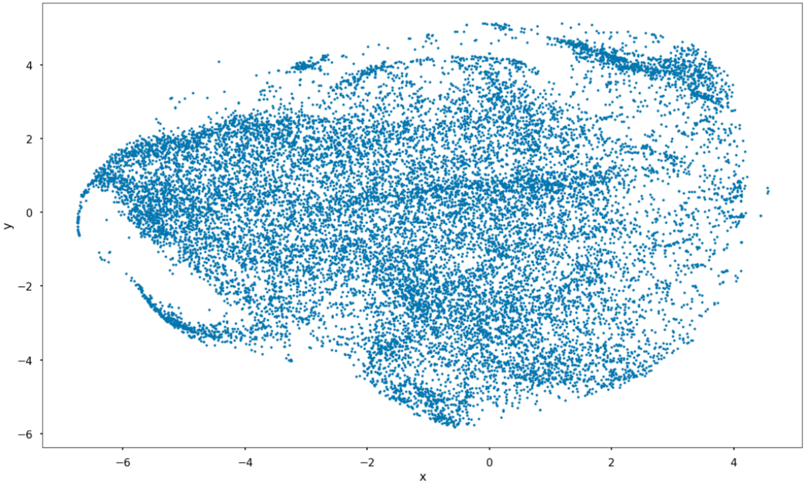
- Build the vocabulary using the window size of 7 units, and minimum word count of 3 units
- Train a skip-gram model using gensim on the entire vocabulary to obtain a 300-dimensional feature(word)-vector

Thrones2Vec

- Load all text from “Song of Ice and Fire” GoT books
  - “A Clash of Kings”, “A Storm of Swords”, “ A Song of Ice and Fire ”, “ A Feast for Crows”, “ A Game of Thrones”
- Convert the book into sentences by using tokenizer used in English such as period, question mark etc
- Clean each sentence to remove unnecessary words, punctuations, hyphens etc and split into words
  - `Heraldic crest by Virginia Norey.`
  - `['Heraldic', 'crest', 'by', 'Virginia', 'Norey']`
- Build the vocabulary using the window size of 7 units, and minimum word count of 3 units
- Train a skip-gram model using gensim on the entire vocabulary to obtain a 300-dimensional feature(word)-vector
- Compress the word-vectors into a 2D space for visualization

The Big Picture



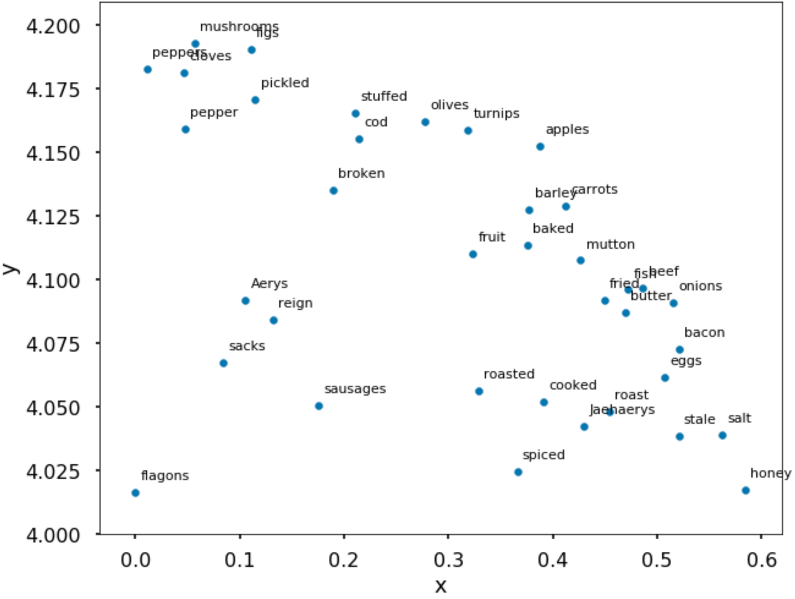
Embedding of the entire vocabulary space onto 2-D

Word Mappings

	word	x	y
0	fawn	-4.470860	-0.406855
1	raining	2.432409	-1.825349
2	writings	-3.212095	1.967637
3	Ysilla	1.436866	-2.421560
4	Rory	-1.090941	-2.569549
5	hordes	-2.204853	2.614524
6	mustachio	-1.086925	-3.887781
7	Greyjoy	1.585396	3.667034
8	yellow	-0.813293	-5.425221
9	four	1.871287	2.557694

Mapping of words on x,y axis from t-SNE

Similar objects cluster together



Food Items group together

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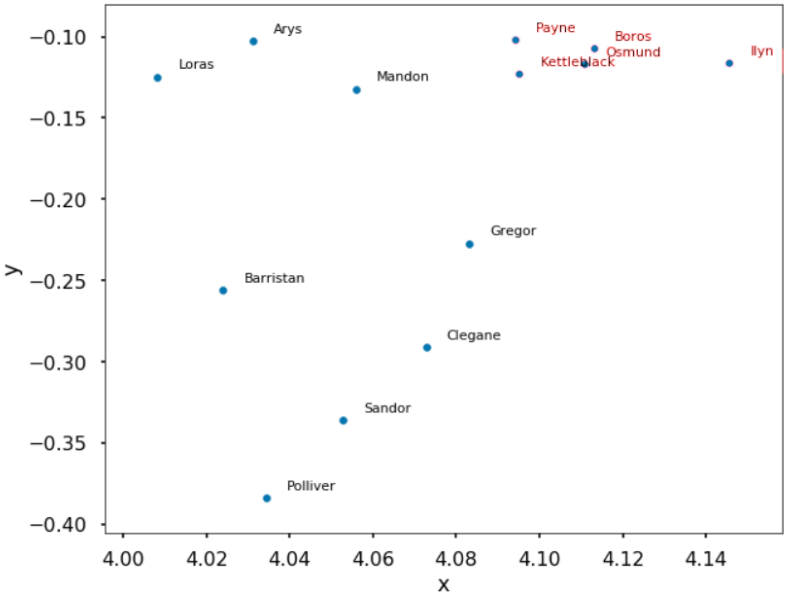

People related to Kingsguard ended up together

Most Similar To

- `thrones2vec.most_similar("Stark")`

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  ('Eddard', 0.7424380779266357),
  ('Winterfell', 0.6484879851341248),
  ('Brandon', 0.643855094909668),
  ('Lyanna', 0.6438395977020264),
  ('Robb', 0.6242259740829468),
  ('executed', 0.6220564842224121),
  ('Arryn', 0.6189972162246704),
  ('Benjen', 0.6188897490501404),
  ('direwolf', 0.6143664121627808),
  ('beheaded', 0.6046537756919861)

Most Similar to

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  (‘Unburnt’, 0.8507828712463379),
  (‘Stormborn’, 0.815880537033081),
  (‘Khaleesi’, 0.7907167673110962),
  (‘Mother’, 0.7906662225723267),
  (‘khaleesi’, 0.7895367741584778),
  (‘Shackles’, 0.7814539074897766),
  (‘Breaker’, 0.7562315464019775),
  (‘warlocks’, 0.7459860444068909),
  (‘fairest’, 0.7372589111328125),
  (‘Grass’, 0.7342460751533508)

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Conclusions

- Word2Vec can efficiently learn word-embeddings in a lower-dimension space such that similar words cluster together

Questions?