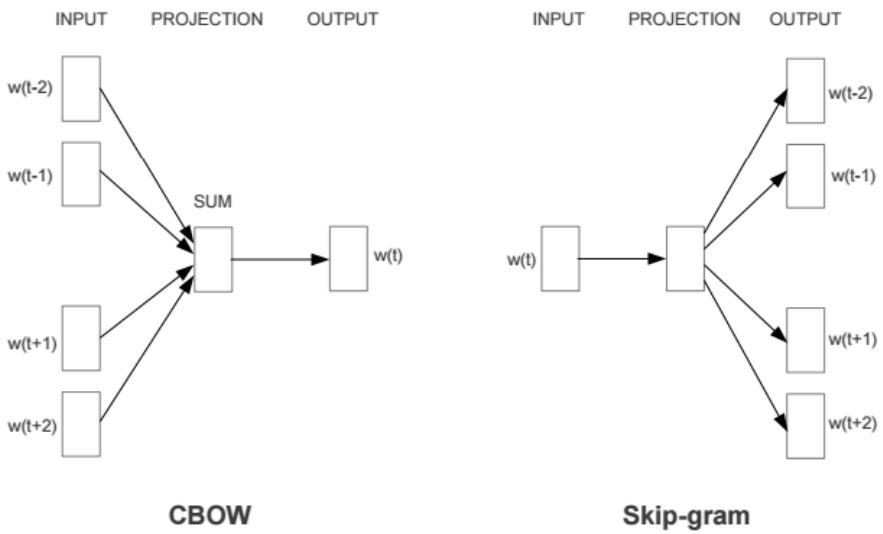

Word Representations

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EMBEDDINGS

WORKING WITH TEXT

- Neural networks don't take raw text as input. Only numeric tensors.
- *Vectorizing* text is the process of transforming text into numeric tensors. This can be done in multiple ways:
  - **Segment text into words, and transform each word into a vector.**
  - Segment text into characters, and transform each character into a vector.
  - Extract n-grams of words or characters, and transform each n-gram into a vector.
- Apply categorical transformation:
  - One-hot encoding
  - Word embedding

ONE-HOT ENCODING

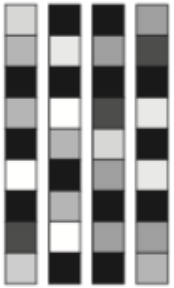
- Words are categorical, they have no *ordinal* relationship. So they can't just be numerically encoded.
- For each word:
  - Numerically encode each word: {red:0, green:1, blue:2}
  - Generate vector of zeros the length of all possible words/categories
  - Set the index value for the word in the vector

red,	green,	blue
1,	0,	0
0,	1,	0
0,	0,	1

WORD EMBEDDINGS

- One-hot results in *sparse vector representation* (mostly zeros, hi dimensions).
- Word embeddings provide *dense vector representations*.
- Idea is to “embed” words into a lower-dimensionality space.
- The dimensions of this space are typically defined by word context, i.e., semantically similar words are embedded near each other.
- Popular algorithms:
  - PMI,Word2Vec: Skip-gram or CBOW, GLoVE, fasttext, …

One-hot word vectors:
- Sparse
- High-dimensional
- Hardcoded



Word embeddings:
- Dense
- Lower-dimensional
- Learned from data

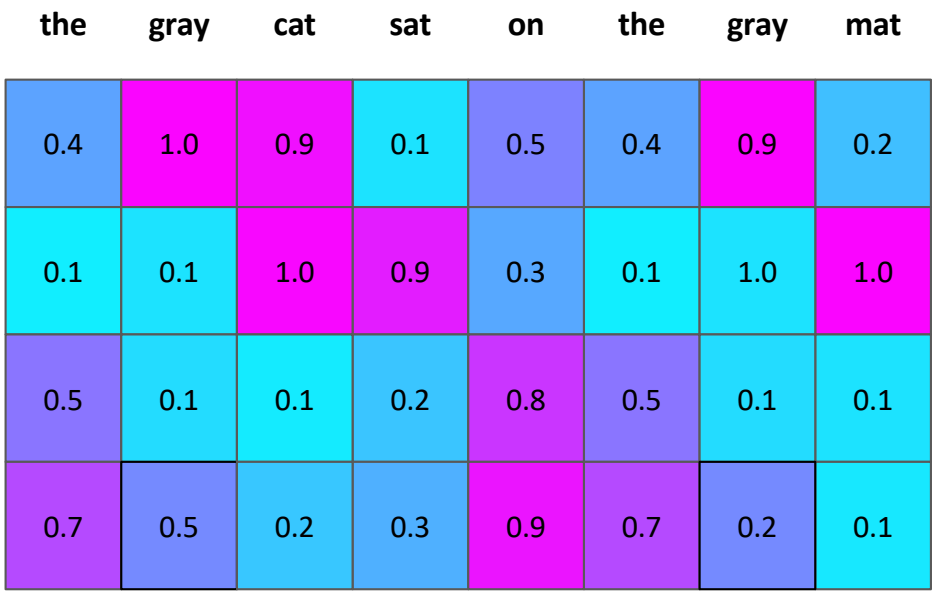
The Distributional Hypothesis (Firth, 1957)

- ‘You can tell a word by the company it keeps’

  - *The cat sat on the mat*
  - *The dog sat on the mat*
  - *The elephant sat on the mat*
  - *The quickly sat on the mat*

Embeddings: distributed representation of text

Text is represented *categorically*, but we want similar words to have similar representations




```
embedding_layer = nn.Embedding(num_embeddings=vocab_size, embedding_dim=4)
embeddings = embedding_layer('the gray cat sat on the gray mat'.split())
```

Embeddings: Word2Vec

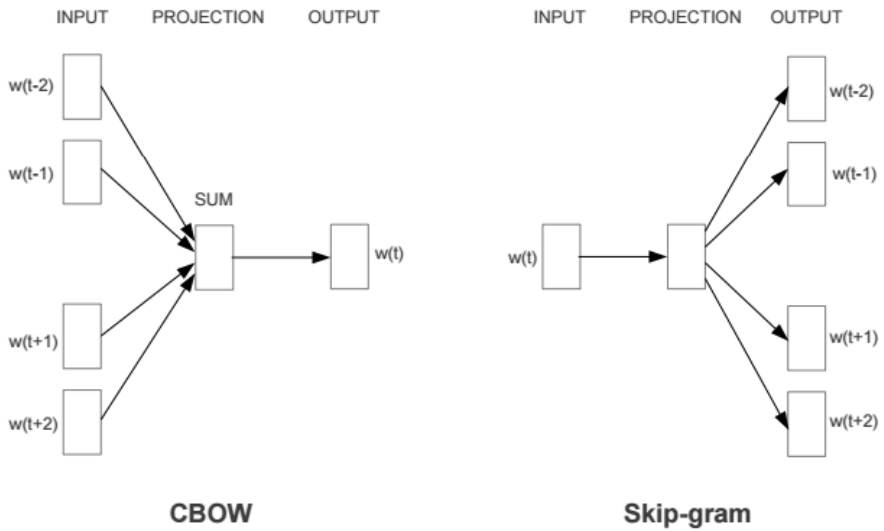
Idea: Maximize the probability of any context word given the current center word:

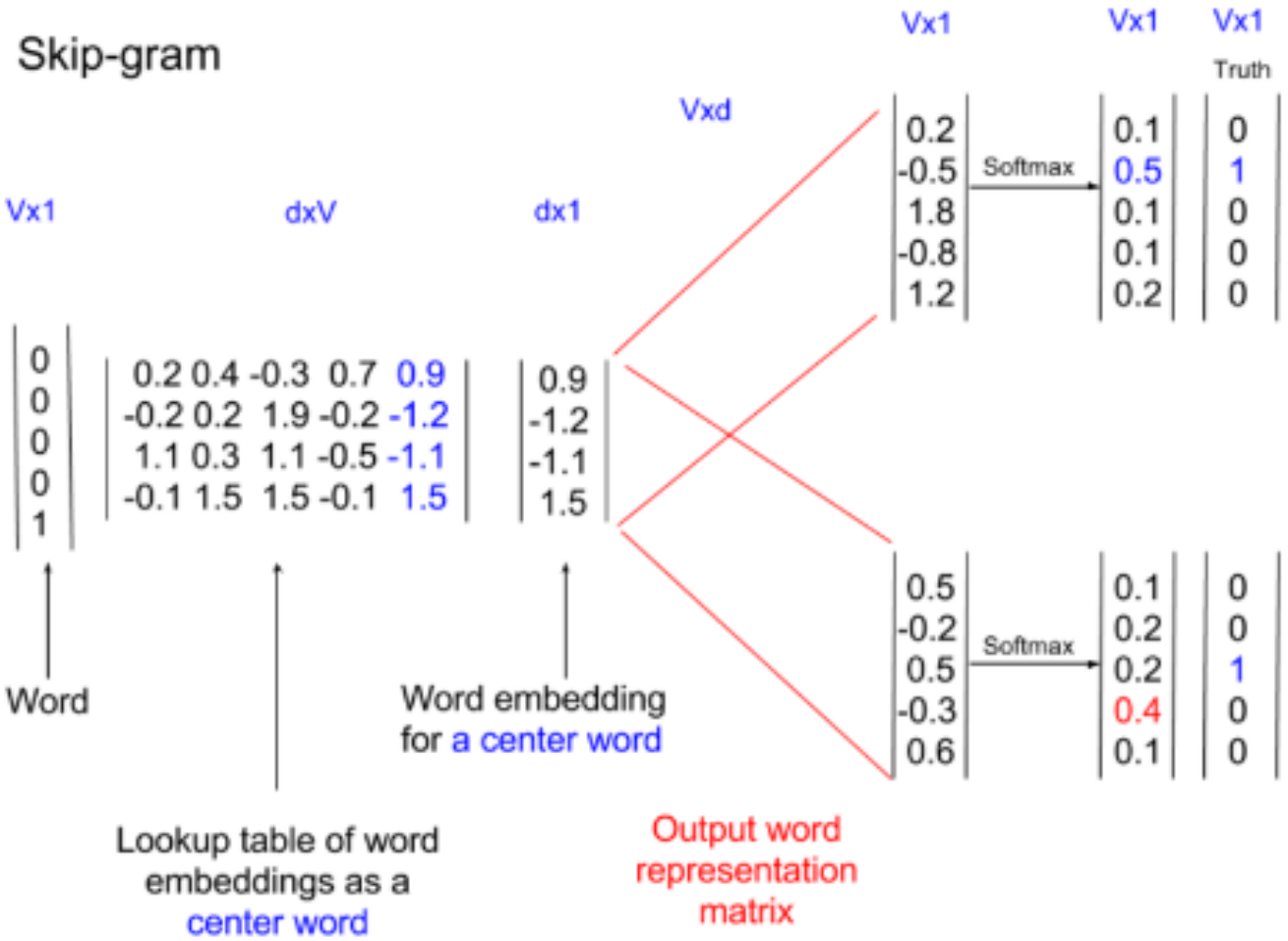
$$J'(\theta) = \prod_{t=1}^{T} \prod_{\substack{-m \leq j \leq m, \\ j \neq 0}} p(w_{t+j}|w_t;\theta)$$

- T - our text(corpus). For each word t=1...T, we try to predict surrounding words
- m - size of our window
- θ represents all variables we will optimize

Embeddings: Word2Vec

- **CBOW** model predict missing word (focus word) using context (surrounding words).
- **Skip gram** model predicts context based on the word in focus.
- Context is a fixed number of words to the left and right of the word in focus.
- Maximize average log probability of context words co-occurring with focus words.




Skip-gram
Vx1
dxV
dx1
Vxd
Vx1
Vx1
Vx1
Truth
0
0
0
0
1
0.2 0.4 -0.3 0.7 0.9
-0.2 0.2 1.9 -0.2 -1.2
1.1 0.3 1.1 -0.5 -1.1
-0.1 1.5 1.5 -0.1 1.5
0.9
-1.2
-1.1
1.5
0.2
-0.5
1.8
-0.8
1.2
Softmax
0.1
0.5
0.1
0.1
0.2
0
1
0
0
0
0.5
-0.2
0.5
-0.3
0.6
Softmax
0.1
0.2
0.2
0.4
0.1
0
0
1
0
0
Word
Word embedding
for a center word
Lookup table of word
embeddings as a
center word
Output word
representation
matrix

Pointwise Mutual Information

- Normalized skip gram probability
- Log probability of context word, x, co-occurring with target word y.

$$\mathrm{pmi}(x;y) \equiv \log \frac{p(x,y)}{p(x)p(y)}$$

- Urbain, J., Bushnee, G., Knudson, Kowalski, G., P., Taylor, B. “Distributional Semantic Concept Models for Entity Relation Discovery,” NAACL VSM-NLP (National Association of Computational Linguistics workshop on Vector Space Modeling in Natural Language Processing), June 2015.
- Levy, O., and Goldberg, Y., Neural Word Embedding as Implicit Matrix Factorization, NIPS, 2014.
- Urbain, J. A Distributed Dimensional Indexing Model for Information Retrieval and Extraction. NLM/NIBIB Workshop on Natural Language Processing: State of the Art, Future Directions and Applications for Enhancing Clinical Decision-Making, (April 23-24, 2012).

GloVe Word Embeddings

1. Collect word co-occurrence statistics in a word co-occurrence matrix X. Where each element Xij represents how often work I appears in context of word j.
2. Define soft constraints foreach word pair. Word vectors ~= log probability of co-occurrence.

$$w_i^T w_j + b_i + b_j = log(X_{ij})$$

3. Define a cost function to optimize.

$$J = \sum_{i=1}^{V} \sum_{j=1}^{V} f(X_{ij})(w_i^T w_j + b_i + b_j - \log X_{ij})^2$$

f(X) is a weighting function to prevent learning only extremely common word pairs.

https://nlp.stanford.edu/projects/glove/

$$f(X_{ij}) = \begin{cases} (\frac{X_{ij}}{x_{max}})^{\alpha} & \text{if } X_{ij} < XMAX \\ 1 & \text{otherwise} \end{cases}$$

FastText

- Each word is represented as a bag of character n-grams.
- Words are represented as the sum of their character n-grams.
- Captures morphology of words.
- Provides a representation for rare and out-of-vocabulary words.
- Very fast.
- Outperforms Word2Vec and GloVe in most benchmarks.

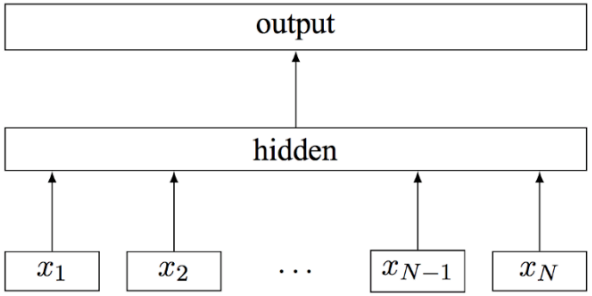


Figure 1: Model architecture of `fastText` for a sentence with N ngram features $x_1, \ldots, x_N$. The features are embedded and averaged to form the hidden variable.

Image taken from the original paper

E.g., tri-grams for the word *apple* are *{_ap, app, ppl, ple, le_}*.

Bojanowski, P., Grave, E., Jouln, A, Mikolov, T. Enhancing Wore Vectors with Subword Information, 2017.

Selected word embedding: GloVe + Character Embedding

- Embedding for each word *w* is created by concatenating pretrained *p1=300* GloVe vector (Pennington et al., 2014) and the word's character embedding.
- GloVe word vectors are fixed during training.
- All the out-of-vocabulary words are mapped to a token, whose embedding is trainable with random initialization.
- Character embedding:
    - Each character is represented as a trainable vector of dimension *p2 = 200*, meaning each word can be viewed as the concatenation of the embedding vectors for each of its characters.
    - The length of each word is either truncated or padded to 16.
    - Take maximum value of each row of this matrix to get a fixed-size vector representation of each word.
    - Finally, the output of a given word *x* from this layer is the concatenation [xw; xc] ∈ Rp1+p2 , where xw and xc are the word embedding and the convolution output of character embedding of x respectively.
- Adapted from Seo et al., 2016, and Srivastava et al., 2015).

Problems with word embeddings?

Synonyms:

- River *bank*, *Bank* shot, *bank* deposit all have the same word representations.

- *… more on learning general models of language later.*

Properties of embeddings

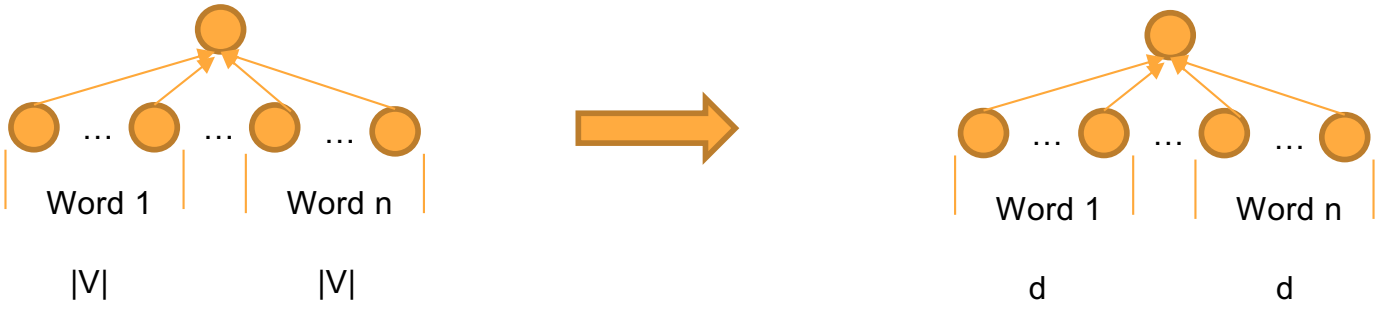
- They are dense: 0.53, 0.2, -1.2, ….
- They are low dimensional: (typically 50 <= d <= 300)
- Embed domain semantics:

  `king' - `man` + `woman` ≈ `queen`

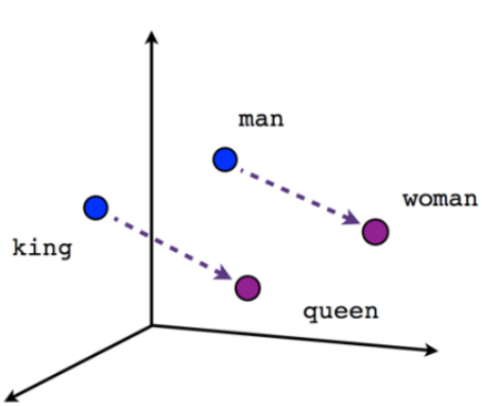
  `paris` - `france` + `spain` ≈ `madrid`
- Generalize easily!

Properties of embeddings (cont.)

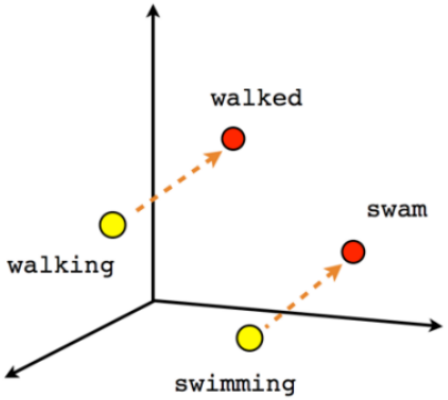
- They are used as input across a variety NLP tasks (transfer learning!):



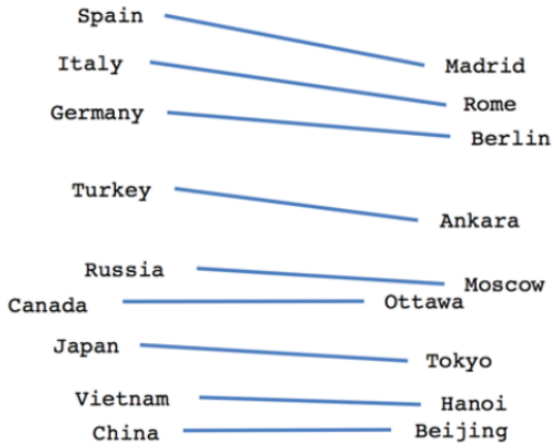
Total # of input parameters:	n * |V|	>>	n * d



Male-Female



Verb tense



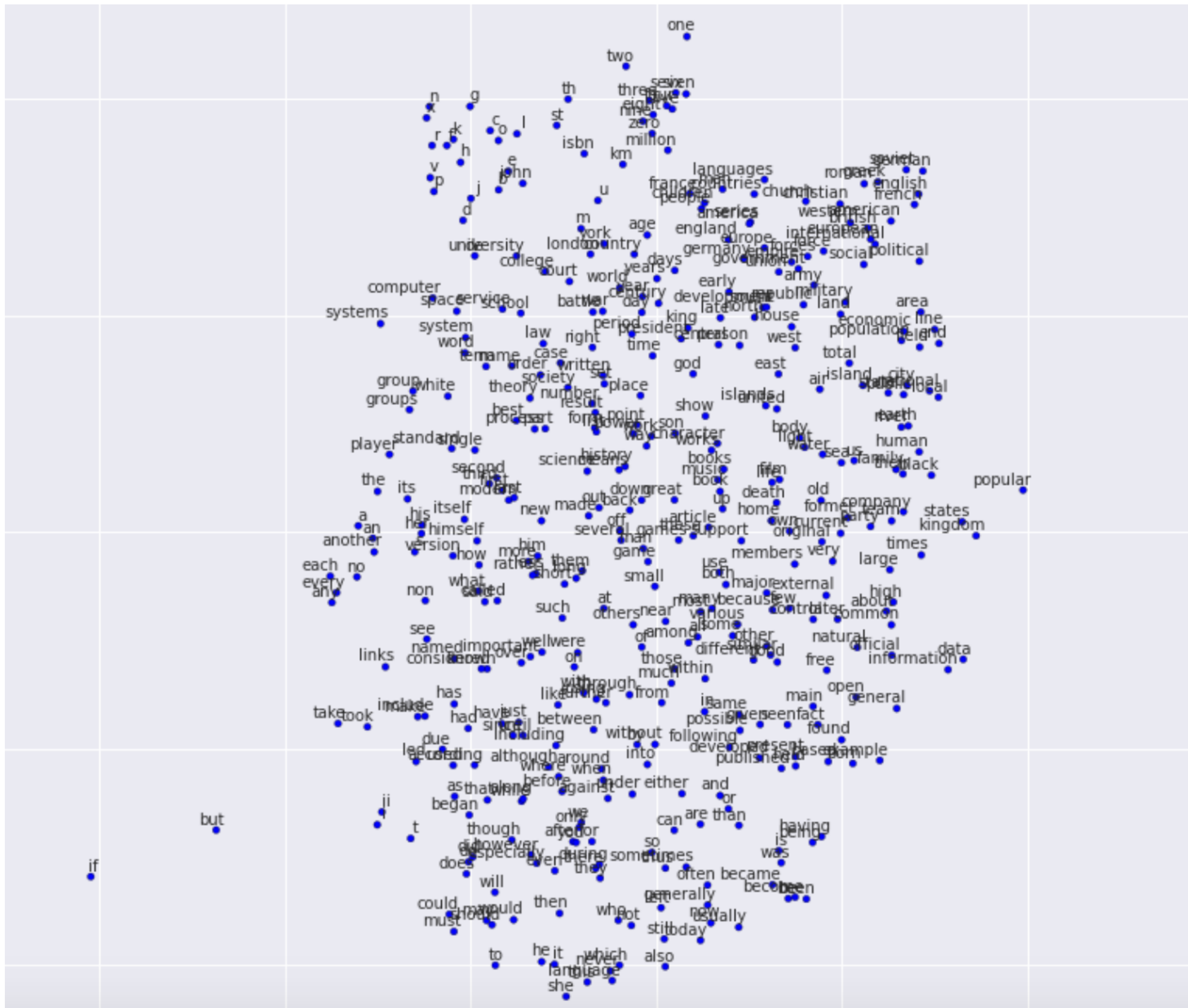
Country-Capital

https://www.tensorflow.org/tutorials/representation/word2vec

Word2Vec Galaxy

- https://www.youtube.com/watch?v=SnmQdKq_2hk

https://www.youtube.com/watch?v=SnmQdKq_2hk



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USING WORD EMBEDDINGS

1. Learn an Embedding
   - Use embedding layer in your deep learning model

2. Reuse an Embedding
   - Download pre-trained word vectors

Lab 2 – Word Representations