Machine Learning (CE 40717)

Fall 2025

Ali Sharifi-Zarchi

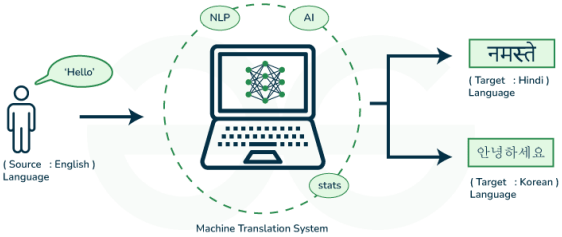
CE Department
Sharif University of Technology

December 23, 2025

Natural Language Processing

- Language is central to human interaction; many of our daily activities revolve around text and language.
- Natural Language Processing (NLP) enables computers to understand and generate human language.

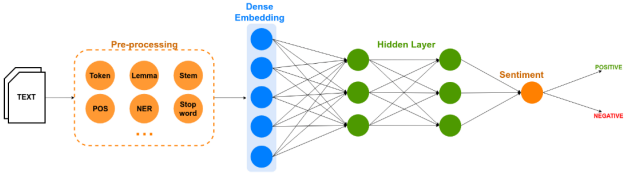
Translation



- NLP helps translate text from one language to another.

Figure adapted from geeksforgeeks.org/machine-translation-of-languages-in-artificial-intelligence/

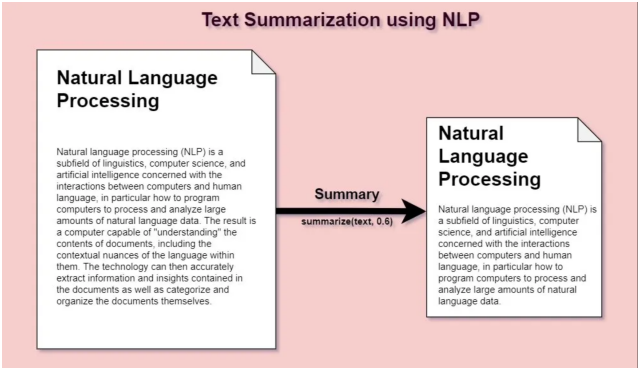
Sentiment Analysis



- Determines the sentiment (e.g., positive or negative) expressed in a text.

Figure adapted from www.mdpi.com/2079-9292/9/3/483

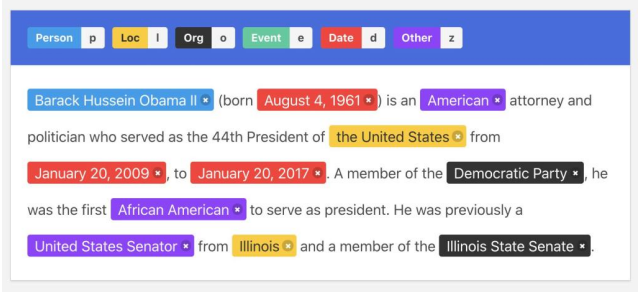
Text Summarization



- Automatically generates a concise summary of longer text.

Figure adapted from turbolab.in/types-of-text-summarization-extractive-and-abstractive-summarization-basics/

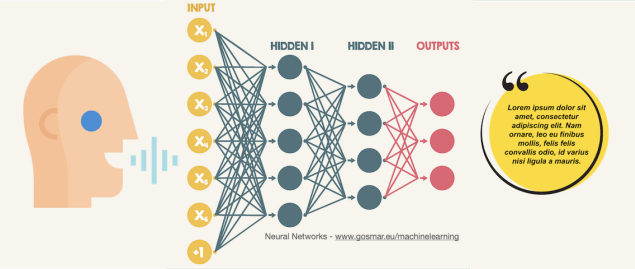
Named Entity Recognition (NER)



- Identifies and classifies entities (e.g., names, dates) in text.

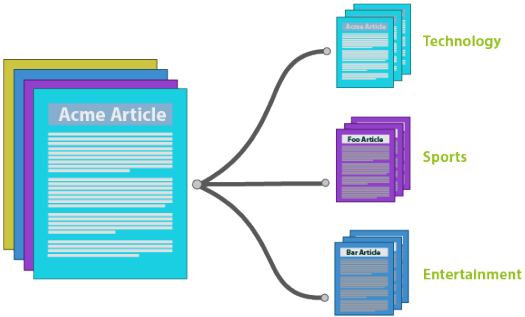
Figure adapted from analyticsvidhya.com/blog/2021/11/a-beginners-introduction-to-ner-named-entity-recognition/

Speech Recognition



- Converts spoken language into text.

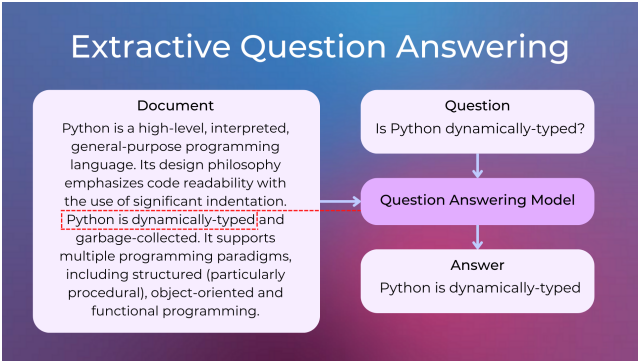
Text Classification



- Categorizes text into predefined groups or topics.

Figure adapted from towardsdatascience.com/machine-learning-nlp-text-classification-using-scikit-learn-python-and-nltk-c52b92a7c73a

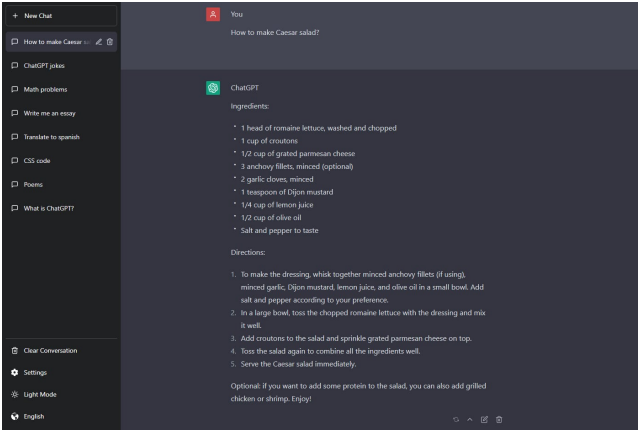
Question Answering



- Answers questions based on a given text or dataset.

Figure adapted from nlplanet.org/course-practical-nlp/02-practical-nlp-first-tasks/17-question-answering

Chatbots and Dialogue Systems



- NLP powers chatbots that can interact with users through text or speech.

Figure adapted from chatgpt.org/

The Importance of Word Representation

- To process text effectively, the first step is to represent words in a way that models can understand.
- We need to transform words into vectors or dense representations to capture their meaning and relationships.
- This is crucial for enabling machines to understand and use language as humans do.

Motivation and One-Hot Encoding

- Traditional models like one-hot encoding lack semantic understanding and fail to capture word relationships.
- One-hot encoding represents words as binary vectors where only one position is 1, making the representation sparse and non-semantic.
- We need dense, semantic word representations to improve natural language processing tasks.

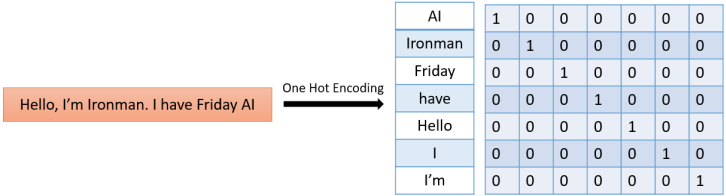


Figure adapted from medium.com/@kalyan45/natural-language-processing-one-hot-encoding-5b31f76b09a0

Example of One-Hot Encoding

- For example, given a vocabulary of 5 words:
  - `apple` = [1, 0, 0, 0, 0]
  - `banana` = [0, 1, 0, 0, 0]
  - `cherry` = [0, 0, 1, 0, 0]
  - `date` = [0, 0, 0, 1, 0]
  - `elderberry` = [0, 0, 0, 0, 1]
- The length of the one-hot vector depends on the number of unique words in the vocabulary.

Strengths and Limitations of One-Hot Encoding

- **Strengths:**
  - One-hot encoding is a simple and intuitive representation that can be effective in certain models, especially smaller neural networks.
  - It requires minimal computation and works well for small vocabularies or categorical features in simpler tasks.
- **Limitations:**
  - One-hot encoding does not capture semantic relationships, so similar words (e.g., `hotel` and `motel`) appear unrelated.
  - The vectors are sparse, containing mostly zeros, making it inefficient for large vocabularies and prone to overfitting due to the large number of parameters in downstream models.

Example: Similar Words, Zero Cosine Similarity

- Consider the following one-hot vectors:
  - `hotel` = [0, 0, 0, 1, 0]
  - `motel` = [0, 0, 0, 0, 1]
- Even though `hotel` and `motel` are semantically similar, their cosine similarity is 0 because their vectors are orthogonal.
- **Cosine Similarity:**

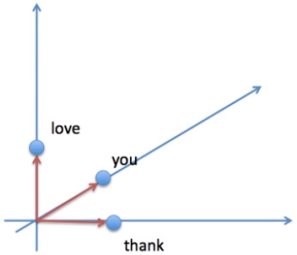
$$\cos(\theta) = \frac{\mathbf{v}_1 \cdot \mathbf{v}_2}{\|\mathbf{v}_1\| \|\mathbf{v}_2\|}$$

- In this case, the dot product of the one-hot vectors is zero, leading to a cosine similarity of zero.

Example: One-Hot Encoding for Different Words

	thank	you	love
thank	1	0	0
you	0	1	0
love	0	0	1

unique word	encoding
thank	[1, 0, 0]
you	[0, 1, 0]
love	[0, 0, 1]



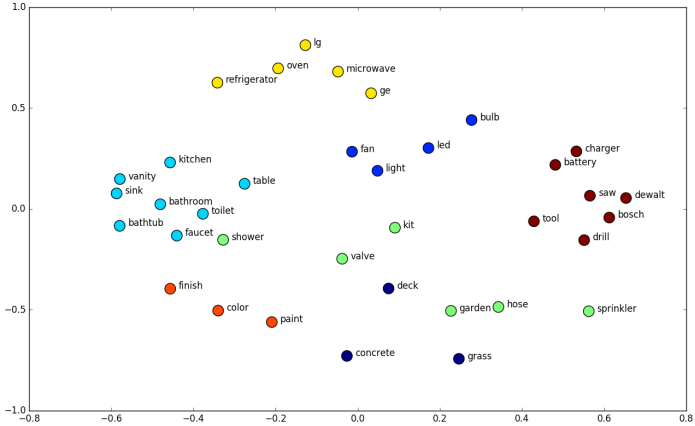
- Different words can be perpendicular to each other in space regardless of their meanings.

Figure adapted from andreaperlato.com/theorypost/introduction-to-word2vec/

Word Embedding

- To process text data, we need to represent words in a form that a machine can understand—numerical vectors.
- Word2Vec uses a neural network to learn **word embedding**s that capture semantic similarities.
- These embeddings allow words with similar meanings to be represented by vectors close to each other in a high-dimensional space.

Example: Word Embedding



Word2Vec as a Neural Network

- Word2Vec is a shallow neural network, with an input, hidden, and output layer.
- It takes in a target word and learns to predict either the surrounding context words or the target word from a set of context words.
- Through training, the network adjusts weights to create meaningful vector representations of words.

Word2Vec as a Neural Network

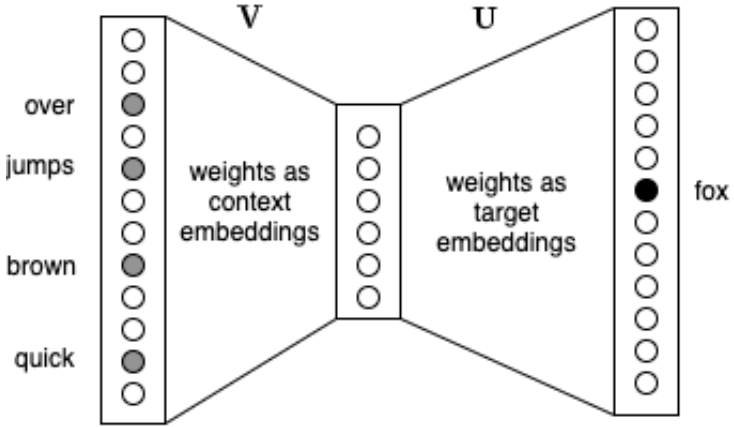


Figure adapted from machinelearningcoban.com/tabml_book/ch_embedding/word2vec.html

Expected Outcome of Word2Vec

- Word2Vec aims to create a vector space where words with similar meanings or contexts are located close to each other.
- **Expected Result:** Semantically related words—such as “king” and “queen” or “dog” and “puppy”—should have similar vector representations.
- This proximity allows for various NLP tasks, such as:
  - **Synonym detection:** Identifying words with similar meanings.
  - **Analogy tasks:** Solving analogies by vector arithmetic (e.g., “king” - “man” + “woman” $\approx$ “queen”).
  - **Clustering of concepts:** Grouping related concepts together in the embedding space.
- By representing words in this way, Word2Vec enables models to make use of semantic relationships between words.

Expected Outcome of Word2Vec

Hypothetical features to understand word embeddings

Figure adapted from medium.com/@manansuri/a-dummys-guide-to-word2vec-456444f3c673

Word2Vec: Contextual Word Representation

- The core idea is based on distributional semantics: "You shall know a word by the company it keeps."
- Word2Vec uses two main algorithms for learning word vectors:
  - Continuous Bag of Words (CBOW)
  - Skip-gram Model

CBOW: How It Works

- CBOW predicts the target word using the context (surrounding words) in a fixed window.
- For each word in the corpus, CBOW takes a set of context words and predicts the center word.
- Example: Given the context words {“the”, “brown”, “fox”, “over”}, CBOW predicts the center word “jumps.”
- CBOW tends to perform better on smaller datasets and is computationally more efficient.

Example: Continuous Bag of Words

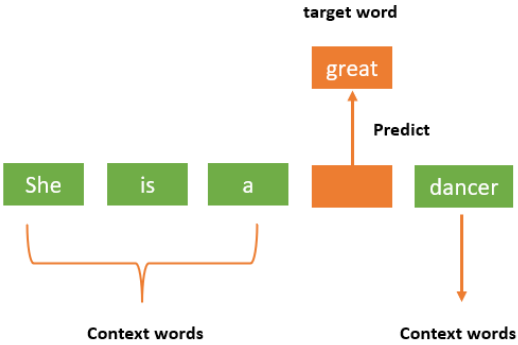


Figure adapted from geeksforgeeks.org/continuous-bag-of-words-cbow-in-nlp/

Skip-gram: How It Works

- Skip-gram is the reverse of CBOW. It predicts the surrounding context words given a target word.
- For each word w_t, the model predicts the words in the window of size m around it (e.g., words $w_{t-2}, w_{t-1}, w_{t+1}, w_{t+2}$).
- Example: If the center word is “jumps,” Skip-gram predicts the context words “the,” “brown,” “fox,” and “over.”
- Skip-gram is better suited for larger datasets and can capture rare words more effectively.

Why Skip-gram?

- Skip-gram is preferred for large datasets because it handles rare words more effectively than CBOW.
- It captures detailed information about the surrounding words, leading to better word representations in the vector space.
- Word2Vec embeddings from Skip-gram have been widely adopted in various NLP tasks such as machine translation, sentiment analysis, and document classification.

Skip-gram Example

Window Size	Text	Skip-grams
2	[The **wide** road shimmered] in the hot sun.	wide, the wide, road wide, shimmered
	The [wide road **shimmered** in the] hot sun.	shimmered, wide shimmered, road shimmered, in shimmered, the
	The wide road shimmered in [the hot **sun**].	sun, the sun, hot
3	[The **wide** road shimmered in] the hot sun.	wide, the wide, road wide, shimmered wide, in
	[The wide road **shimmered** in the hot] sun.	shimmered, the shimmered, wide shimmered, road shimmered, in shimmered, the shimmered, hot
	The wide road shimmered [in the hot **sun**].	sun, in sun, the sun, hot

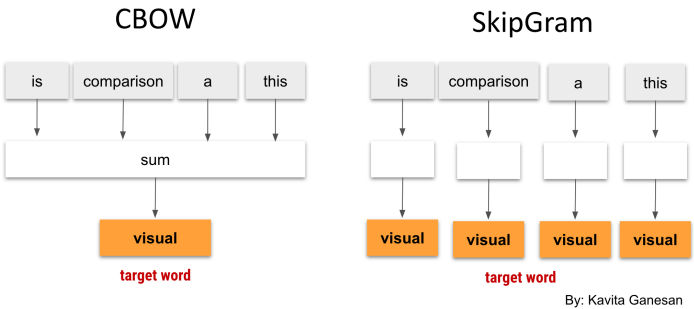
Different window sizes and samples drawn from context words and their target

Figure adapted from tensorflow.org/text/tutorials/word2vec

CBOW vs. Skip-gram

- CBOW and Skip-gram are the two primary architectures for Word2Vec.
- **CBOW** predicts a target word given its surrounding context, making it efficient and effective for smaller datasets.
- **Skip-gram**, on the other hand, predicts the surrounding words for a given target word. It is well-suited for larger datasets and can handle rare words more effectively.
- In essence, the Skip-gram model captures more detailed word relationships and is robust in large vocabularies.

CBOW vs. Skip-gram



This is a visual comparison

Difference between CBOW and Skip-gram

Figure adapted from kavita-ganesan.com/comparison-between-cbow-skipgram-subword/

Skip-gram: Objective Function

- The Skip-gram model learns word representations by predicting context words w_o given a center word w_c.
- Each word has two embeddings:
  - **Input (center) embedding**: $\mathbf{v}_w$
  - **Output (context) embedding**: $\mathbf{u}_w$
- The conditional probability of a context word is:

$$P(w_o \mid w_c) = \frac{\exp(\mathbf{u}_{w_o}^\top \mathbf{v}_{w_c})}{\sum_{x \in V} \exp(\mathbf{u}_x^\top \mathbf{v}_{w_c})}$$

- Intuition: words that co-occur should have large dot products.

Skip-gram as a 2-Layer Neural Network

- Word2Vec is a shallow neural network:

$$\text{one-hot}(w_c) \rightarrow \mathbf{W}_{\text{in}} \rightarrow \mathbf{h} \rightarrow \mathbf{W}_{\text{out}} \rightarrow \text{softmax}$$

- Weight matrices:

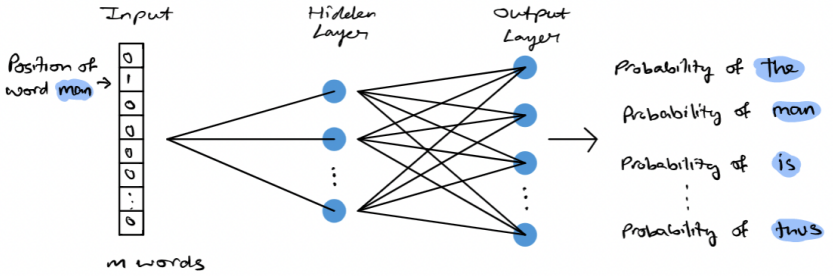
$$\mathbf{W}_{\text{in}} \in \mathbb{R}^{|V| \times d}, \quad \mathbf{W}_{\text{out}} \in \mathbb{R}^{d \times |V|}$$

- Because the input is one-hot:

$$\mathbf{h} = \mathbf{W}_{\text{in}}^{\top} \mathbf{x} = \mathbf{v}_{w_c}$$

- **Key point:**
  - $\mathbf{v}_w$ = row of $\mathbf{W}_{\text{in}}$
  - $\mathbf{u}_w$ = column of $\mathbf{W}_{\text{out}}$
- Updating embeddings = updating network weights.

Skip-gram as a Neural Network



Skip-gram Model as Neural Network

Figure adapted from towardsdatascience.com/word2vec-explained-49c52b4ccb71

Skip-gram: Loss Function

- Training maximizes likelihood of observed center–context pairs.
- Equivalent objective (negative log-likelihood):

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

- T: corpus size, m: window size.

Skip-gram: Gradient Calculation

- For one training pair (w_c, w_o):

$$\log P(w_o \mid w_c) = \mathbf{u}_{w_o}^\top \mathbf{v}_{w_c} - \log \sum_x \exp(\mathbf{u}_x^\top \mathbf{v}_{w_c})$$

- Gradient w.r.t. center embedding:

$$\frac{\partial \log P(w_o \mid w_c)}{\partial \mathbf{v}_{w_c}} = \mathbf{u}_{w_o} - \sum_x P(w_x \mid w_c)\, \mathbf{u}_x$$

- Same result as backprop through $\mathbf{W}_{\text{in}}$.

Skip-gram: Gradient Update (Intuition)

- Gradient ascent update:

$$\mathbf{v}_{w_c} \leftarrow \mathbf{v}_{w_c} + \eta \left(\mathbf{u}_{w_o} - \sum_x P(w_x \mid w_c)\, \mathbf{u}_x \right)$$

- Interpretation:
  - Pull center word toward true context word
  - Push it away from other words
- Output embeddings $\mathbf{u}_x$ are updated analogously.

Skip-gram Example with Gradient Intuition

- Sentence: “Cats chase mice in the dark night.”
- Center word: w_c = “chase”
- Context word: w_o = “cats”
- Example embeddings (2D for illustration):

$$\mathbf{v}_{\text{chase}} = [0.1, 0.2], \quad \mathbf{u}_{\text{cats}} = [0.3, 0.4]$$

- Dot product:

$$\mathbf{u}_{\text{cats}}^{\top} \mathbf{v}_{\text{chase}} = 0.11$$

- If $P(\text{cats} \mid \text{chase}) = 0.493$, the error is:

$$1 - 0.493 = 0.507$$

- The update moves $\mathbf{v}_{\text{chase}}$ closer to $\mathbf{u}_{\text{cats}}$.

Skip-gram Pseudocode

Algorithm 1 Skip-gram Model

Require: Corpus D, window size w, embedding dimension d, learning rate η, epochs n
  Initialize input embeddings $\mathbf{V}$ and output embeddings $\mathbf{U}$ randomly
  for epoch = 1 to n **do**
    for each sentence S in D **do**
      for each center word w_C in S **do**
        for each context word w_O within window w **do**
          Compute score $\mathbf{u}_{w_O}^{\top}\mathbf{v}_{w_C}$
          Compute $P(w_O \mid w_C)$ using softmax
          Update $\mathbf{v}_{w_C}$ and $\mathbf{u}_{w_O}$ using gradients
        end for
      end for
    end for
  end for
  return input embeddings $\mathbf{V}$

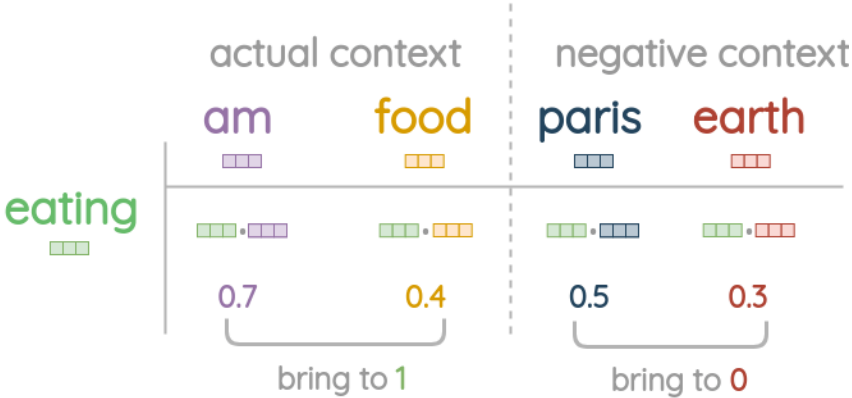
Why Do We Need Negative Sampling?

- The softmax denominator sums over the entire vocabulary V.
- For large vocabularies, this is computationally expensive.
- **Key idea**: update only a few words instead of all words.
- **Negative sampling** provides an efficient approximation.

Skip-gram: Negative Sampling

- For each positive pair (w_c, w_o), sample k negative words.
- The objective becomes binary classification:
  - Maximize similarity for true context words
  - Minimize similarity for randomly sampled words
- Example:
  - Center word: “cat”
  - Positive context: “cute”
  - Negative samples: “table”, “sky”, “computer”

Skip-gram: Negative Sampling



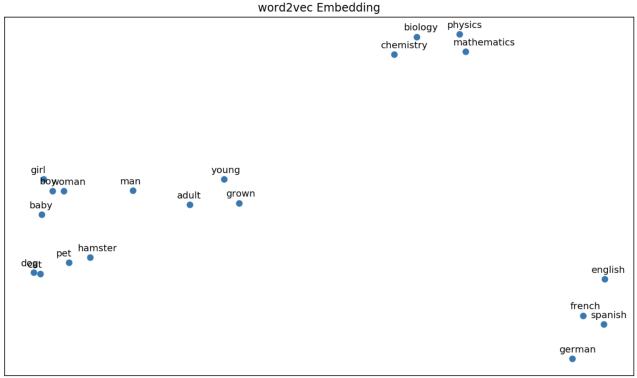
Negative sampling

Figure adapted from amitness.com/posts/fasttext-embeddings

Visualizing Words in 2D

- After training the model, words are mapped into a high-dimensional vector space.
- Using techniques like PCA or t-SNE, these vectors can be reduced to 2D for visualization, where similar words appear closer together.

Visualizing Words in 2D



Words represented in a 2D space after dimensionality reduction

Figure adapted from jramkiss.github.io/2019/08/21/word-embeddings/

Word Analogy: Vector Arithmetic in Word2Vec

- Word2Vec embeddings can solve analogy tasks by performing vector arithmetic.
- The analogy task takes the form:

$$\text{king} - \text{man} + \text{woman} \approx \text{queen}$$

- The analogy is solved by finding the word vector closest to $\mathbf{v}_{king} - \mathbf{v}_{man} + \mathbf{v}_{woman}$.

Word Analogy Formula

- The formal formula for solving word analogies is:

$$d = \arg\max_i \frac{(x_b - x_a + x_c)^T x_i}{\|x_b - x_a + x_c\|}$$

- Definitions:
  - x_a: Vector for the first word (e.g., "man").
  - x_b: Vector for the second word (e.g., "woman").
  - x_c: Vector for the third word (e.g., "king").
  - x_i: Candidate word vectors in the vocabulary.
- Example: To solve "man is to woman as king is to ?", the formula computes a vector closest to $x_b - x_a + x_c$ (e.g., "queen").

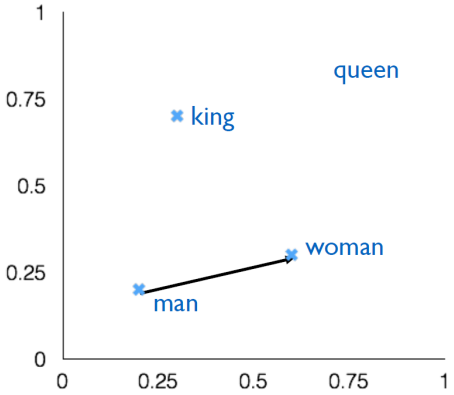
Word Analogy Example

- Example:

$$\text{king}[0.30, 0.70] - \text{man}[0.20, 0.20] + \text{woman}[0.60, 0.30] \approx \text{queen}[0.70, 0.80]$$

- This means the vector difference between "king" and "man" is similar to the difference between "queen" and "woman."

Word Analogy Example



Word analogy example

Contribution

- **These slides were prepared with contribution from:**
  - Omid Daliran
  - Armin Geramirad

References