MO434 - Deep Learning
Text Representation

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- In this context, feature engineering plays a crucial role to convert text into numbers.
- Even if you use a model that learns features from textual data, you still need to understand the concepts behind this process.
- This module then covers some popular feature engineering techniques.

Agenda

- Concept of vector space model.
- Bag of words, Bag of N-Grams and TF-IDF.
- Word2Vec: CBOW and Skip-Gram.
- GloVe and FastText.

Vector space model

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This concept is adopted in feature engineering techniques.

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- TF-IDF – it accounts for relevant words that are not very frequent in the documents.

$$
\begin{aligned}
w_i &= tf(W_i) \times idf(W_i), \\
idf(W_i) &= 1 + \log \frac{|\mathcal{D}|}{1 + df(W_i)},
\end{aligned}
$$

  where $tf(W_i)$ is the term frequency of W_i in D (w_i in BOW), $idf(W_i)$ is the inverse document frequency with $df(W_i)$ being the number of documents in $\mathcal{D}$ in which W_i occurs.

Traditional feature engineering techniques

Let's see the following notebook with traditional feature engineering techniques (TRADITIONAL FEATURE ENGINEERING).

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Traditional techniques generate long and sparse feature vectors. Advanced methods can create dense embeddings, considerably shorter, by exploring unsupervised neural networks and capturing contextual and semantic similarity. We will see the following examples.

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- Word2Vec – it is divided into two strategies:
  - Skip-Gram and
  - Continous-Bag-Of-Words (CBOW).
- GloVe.
- FastText.

Let $W_{i-k}, W_{i-k+1}, \ldots, W_{i+k-1}, W_{i+k}$ be the surrounding words of a given central word W_i within an observation window of size $2k+1$ in a document D of our vocabulary $\mathcal{D}$.

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Word2Vec

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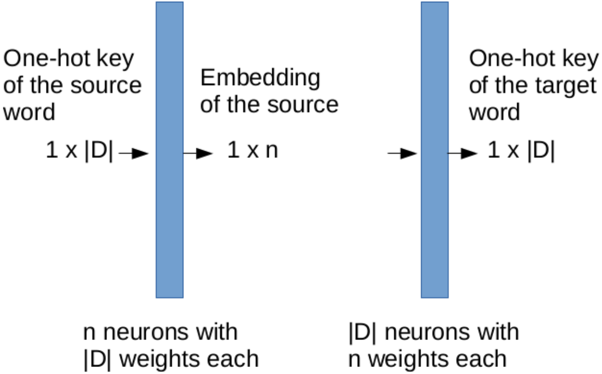
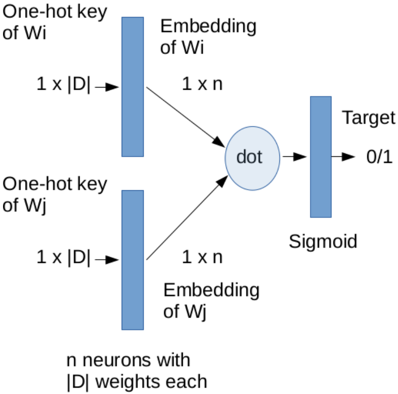
A CBOW model learns to predict W_i from the input $[W_{i-1}, W_{i+1}]$ – i.e., it predicts the central word from the surrounding ones.

Skip-Gram: the input is the one-hot key of a central word (source) W_i and a hidden layer with n neurons with no activation transforms it into an embedding $1 \times n$ for W_i, while the output layer with $|\mathcal{D}|$ neurons and softmax creates the one-hot key of the surrounding word used as target.

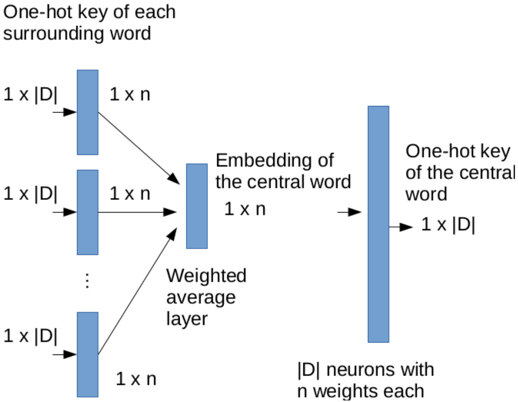


Skip-Gram model

Skip-Gram: another possibility is to input pairs $[W_i, W_j]$ of words with a target label equal to 1, when W_j is a surrounding word of W_i, and 0, otherwise. The one-hot keys of W_i and W_j pass through one hidden layer each and the inner product between their $1 \times n$ embeddings passes through a sigmoid to estimate the target.



CBOW: The one-hot keys of all surrounding words pass through a hidden layer with no activation each, creating one embedding per surrounding word. Those embeddings are averaged, creating an embedding $1 \times n$ for W_i and the output layer with softmax transforms it into the one-hot key of W_i.



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- The idea is to apply matrix factorization to compute $WC = WF \times FC$, where WF is a word-feature matrix and FC is a feature-context matrix.

- The SGD algorithm is used to minimize the error and, finally, WF provides the embeddings for all words in $\mathcal{D}$.

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Finally, advanced feature engineering techniques are illustrated in (ADVANCED FEATURE ENGINEERING).