>>> Introduction to Natural Language Processing

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>>> Machine Learning Tools Used In this Tutorial[1]

* torch v1.9.0
* torchtext v0.10.0
* nltk v3.6
* gensim v4.1.2
* matplotlib v3.4
* numpy v1.22
* CUDA driver v11.4

[1] code available at: https://github.com/abidikhairi/introduction-nlp

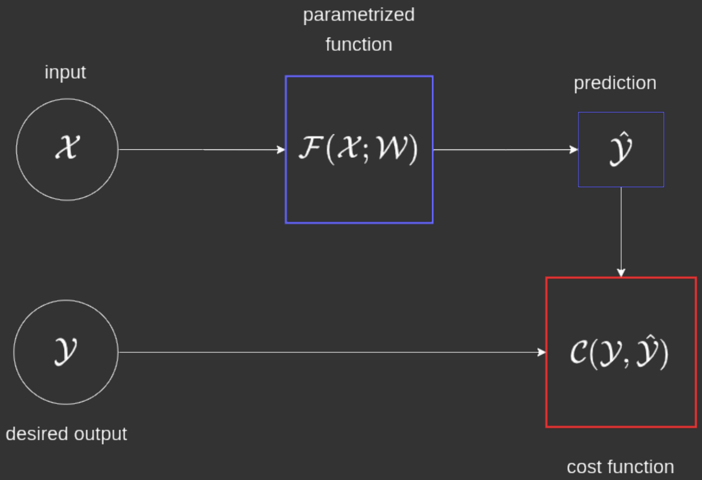


Figure: training neural networks

>>> Introduction

Natural language processing is the intersection of linguistics, computer science, and artificial intelligence.

>>> Introduction

Its principal purpose is to design computer programs that can understand natural language. Such as understanding the semantic of phrases.

>>> Introduction

for the sake of understanding natural language. we next introduce the words embedding techniques.

>>> Embbeding: Definition

Before going deeper into word embedding methods, before all else, we outline the notion of embedding.

>>> Embedding: Definition

Mathematically speaking, an embedding is a mapping $\mathcal{G}$ from one space E to another space F. in such a way that $dim(F) << dim(E)$. and $\mathcal{G}$ must preserve the structure of E.

$$\mathcal{G} : E \longmapsto F \tag{1}$$

>>> Embedding: Machine Learning

From the perspective of machine learning, embedding is considered a dimensionality reduction technique. In the following, we present some experiments on dimensionality reduction using TSNE [10].

>>> Embedding: MNIST dataset

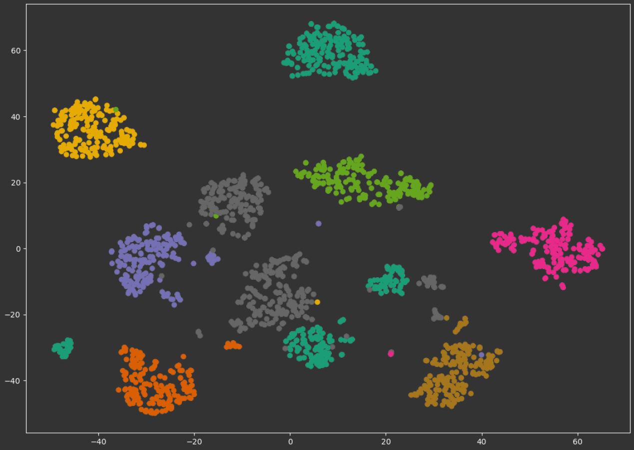


Figure: Embedding of MNIST dataset [4]

\>>> Embedding: Iris dataset

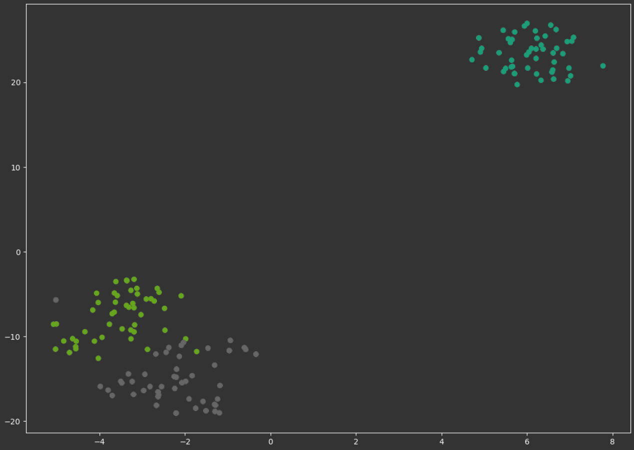
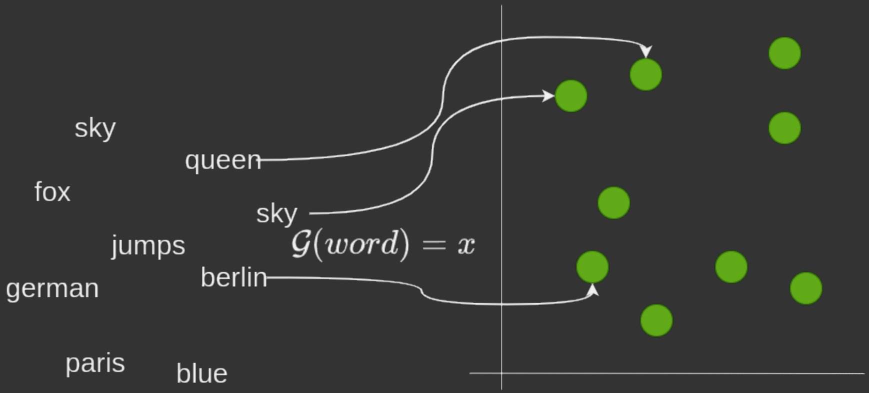


Figure: Embedding of Iris dataset [9]

>>> Word Embedding

Word embedding is a technique applied by text processing models to transform the text into real-valued vectors by capturing the semantic and syntactic relations between words. Later, those vectors will be in use by downstream tasks. Such as sentiment analysis [7], [8] or fake news detection [3].

>>> Word Embedding



$$\mathcal{G} : E \longmapsto \mathbb{R}^2$$

Figure: Example of word embedding

>>> Word Embedding: Complete Process

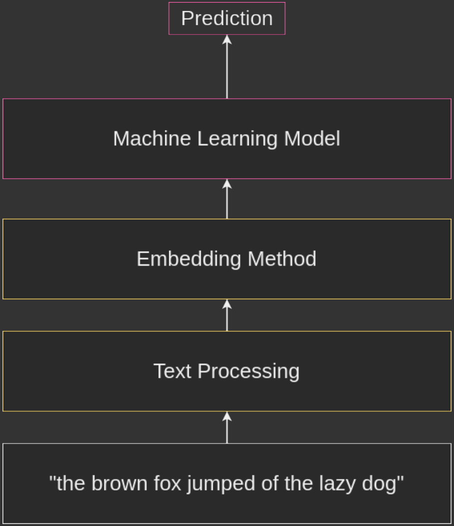


Figure: Machine learning on Text

>>> Word Embedding: Methods

* Latent Semantic Analysis [2] (Matrix Factorization)
* Term-Frequency Inverse Document Frequency [1] (Frequentist Approach)
* Word2Vec [5] (Probabilistic Neural Network Model)

>>> Word2Vec

In 2013, Tomas Mikolov (Google Researcher) proposed a simple and efficient neural network architecture called Word2vec [5] for estimating word representations (embedding).

Word2Vec estimates word representation by maximizing the likelihood of seeing a context given the center word.

$$\underset{\theta}{\operatorname{argmax}}\, log(p(w_c|w_t;\theta)) \tag{2}$$

>>> Word2Vec: SkipGram

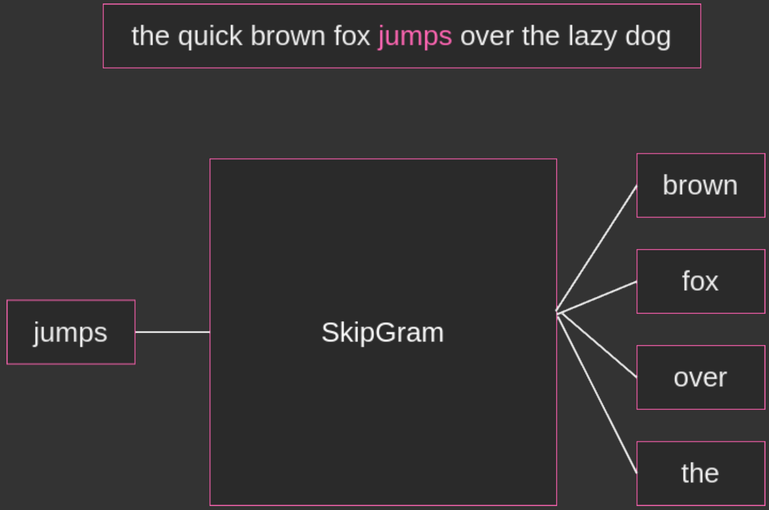


Figure: Skip-Gram Architecture

>>> Word2Vec: Probability Estimation Function

Word2Vec defines the probability function to be the softmax function.

$$p(w_c|w_t) = \frac{exp(w_c.w_t)}{\sum_{i=0}^{W} exp(w_i.w_c)} \tag{3}$$

>>> Word2Vec: Softmax

As we note, the time complexity of the softmax grows exponentially as the dataset grows. Given that text, datasets have 10^6 - 10^9 words. Therefore, the computation of the softmax functions becomes very expensive.

>>> Word2Vec: Noise Contrastive Estimation

In [6], Tomas Mikolov presented new methods to overcome the exorbitance cost of the softmax function.

$$log\ \sigma(w_c^T.w_t) + \sum_{i=1}^{k} \mathbb{E}_{w_i \sim P(n)} \left[log\ \sigma(-w_i^T.w_t)\right] \tag{4}$$

>>> Recurrent Neural Networks

Recurrent Neural Networks are class of Deep Learning architectures that operates on sequential inputs, such as time series, text, and voice.

>>> RNN Cell

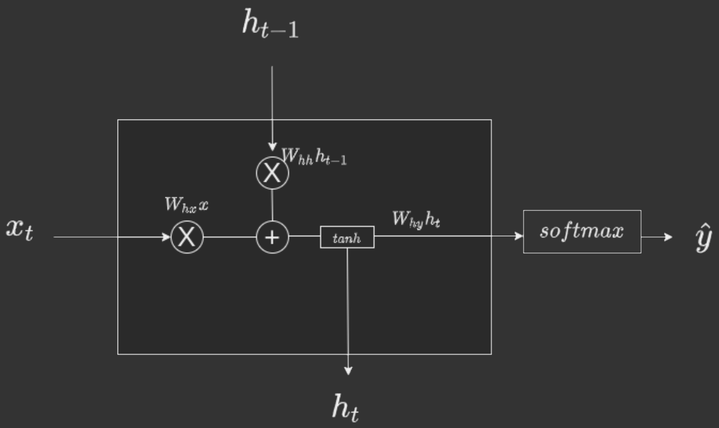


Figure: RNN Cell

>>> RNN Layer

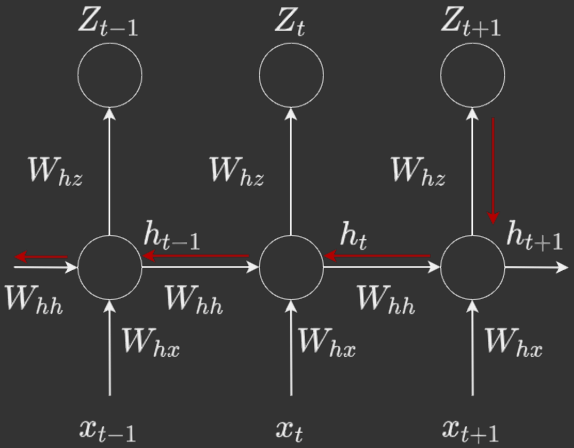


Figure: RNN Layer

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