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NATURAL LANGUAGE PROCESSING

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Agenda

1. Intro to Natural Language Processing (NLP)

2. Basics of Data Preprocessing in NLP
   - Tokenization
   - Normalization

3. Vectorization
   - Frequency Vectors
   - TFIDF Vectors

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1. Natural Language Processing

1.1 What is Natural Language Processing?

"*Natural Language Processing (NLP) is a subfield of linguistics, computer science, information engineering, and artificial intelligence concerned with the interactions between computers and human (natural) languages*".

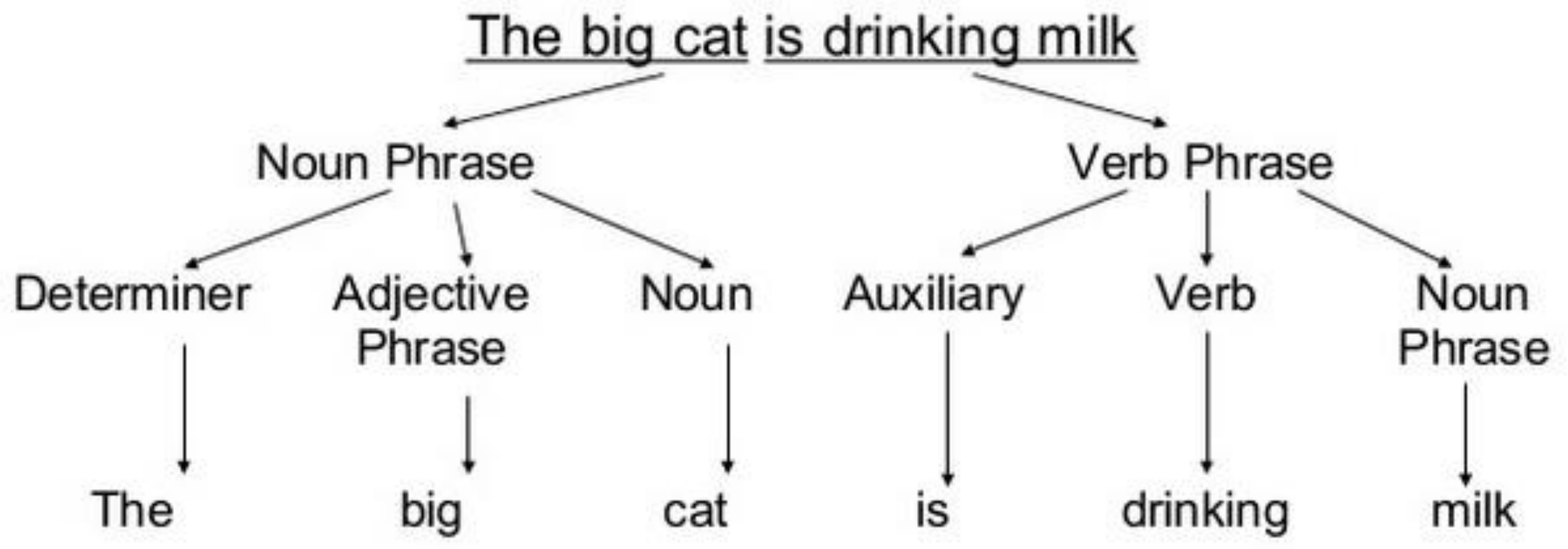
- Wikipedia

1.2 What is Natural Language?

- Human languages

- Consists of :
  - Vocabulary, set of words
  - Text made of sequence of words from vocabulary
  - Language is constructed of a set of all possible texts

1.3 Syntactic Analysis of Natural Language



1.4 Why NLP is useful?

- Applications of NLP include
  - ➢ spam filtering
  - ➢ search engines,
  - ➢ checking spelling and grammar,
  - ➢ social website feeds,
  - ➢ speech recognition,
  - ➢ language translation, etc.

- Google Translate, for instance, is an example of NLP model

1.5 NLP Libraries in Python

- Natural language toolkit (NLTK)
- Scikit-Learn
- Gensim
- SpaCy
- TextBlob
- CoreNLP

1.6 What is NLTK?

- leading platform in Python NLP library
- provides easy-to-use interfaces to over 50 corpora and lexical resources such as WordNet
- provides a suite of text processing libraries for tokenization, stemming, tagging, parsing, semantic reasoning and an active discussion forum

2. Basic Data Preprocessing for NLP

2.1 Tokenization

- Splitting text into sections

- Tokenization is the process of breaking a stream of text up into words, phrases, symbols and other meaningful elements called tokens

2.1 Tokenization – an example

- Using NLTK's "word_tokenize" function -

I haven't watched the show at the theatre.

['I', 'have', "n't", 'watched', 'the', 'show', 'at', 'the', 'theatre', '.']

2.2 Normalization

- Process of transforming text into a single canonical form

- Tokenization + more
  - Convert all letters to lower or upper case
  - Removing punctuations
  - Removing white spaces
  - Removing stops words
  - Part of speech (POS) tagging

- Process of normalization is different for different corpus

2.2 Normalization

Stop words

['I', 'have', "n't", 'watched', 'the', 'show', 'at', 'the', 'theatre', '.']

Punctuations

There is no universal list of stop words

2.3 Normalization – Stemming

- Process of reducing a word to its stem, base of root form
  - ➢ Stemmer, stemming, stemmed → stem
  - ➢ Girls, girl → girl

- Goal is to remove word affixes, which generally indicate plurality in Latin languages

- Stemming is useful because it is a fast feature reduction method

2.3 Normalization – Lemmatization

- Process of reducing a word to its lemma
  - gardening → to garden
  - Gardener, garden → gardener, garden

- It can handle irregular cases as well as handle tokens with different parts of speech

- Lemmatization takes time but is generally more effective in its representation

2.5 Normalization – POS Tagging

- Assigning syntactic tag to each word in a sentence

Stanford Parser

Please enter a sentence to be parsed:

Surgical resection specimens of 85 invasive ductal carcinomas of 85 women who had undergone 3D ultrasound were included.

Language: English   Sample Sentence   Parse

Your query

Surgical resection specimens of 85 invasive ductal carcinomas of 85 women who had undergone 3D ultrasound were included.

Tagging

Surgical/NNP resection/NN specimens/NNS of/IN 85/CD invasive/JJ ductal/JJ carcinomas/NNS of/IN 85/CD women/NNS who/WP had/VBD undergone/VBN 3D/CD ultrasound/NN were/VBD included/VBN ./.

- NNP: Proper Noun, singular
- JJ: Adjective
- VBN: Verb, past participle

3. Vectorization

3.1 Vectorization

- To apply machine learning to NLP, we must convert the natural texts into numeric data i.e vectorization

- Features must represent attributes and properties of documents, such as its content as well as meta data - document length, author, source, etc.

- Vectorization creates a high-dimensional semantic space where documents that have similar meaning are closer together and those that are different are farther apart

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3.2 Methods of Vectorization

- Frequency vector
- One-Hot Encoding
- TFIDF
- Distributed Representation
    - Word2vec
    - Doc2vec

3.3 Vectorization – Frequency Vectors

- The simplest vectorization method is the bag of words (BOW) model that encodes meaning and similarity based on vocabulary

- Every document from the corpus is represented as a vector whose length is equal to the vocabulary of the corpus

- The simplest vector encoding model is to simply fill in the vector with the frequency of each word as it appears in the document

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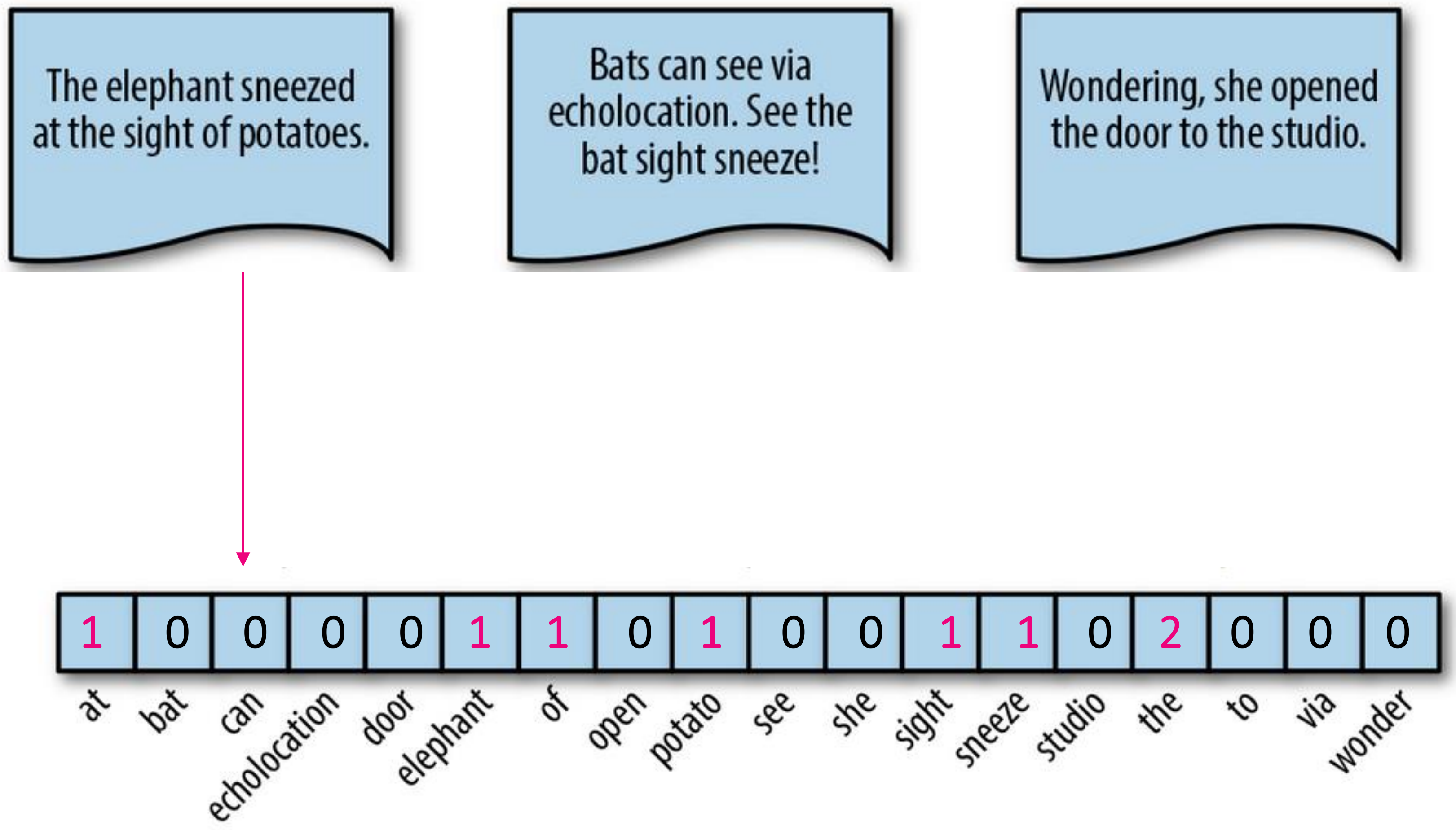
3.3 Vectorization – Frequency Vectors



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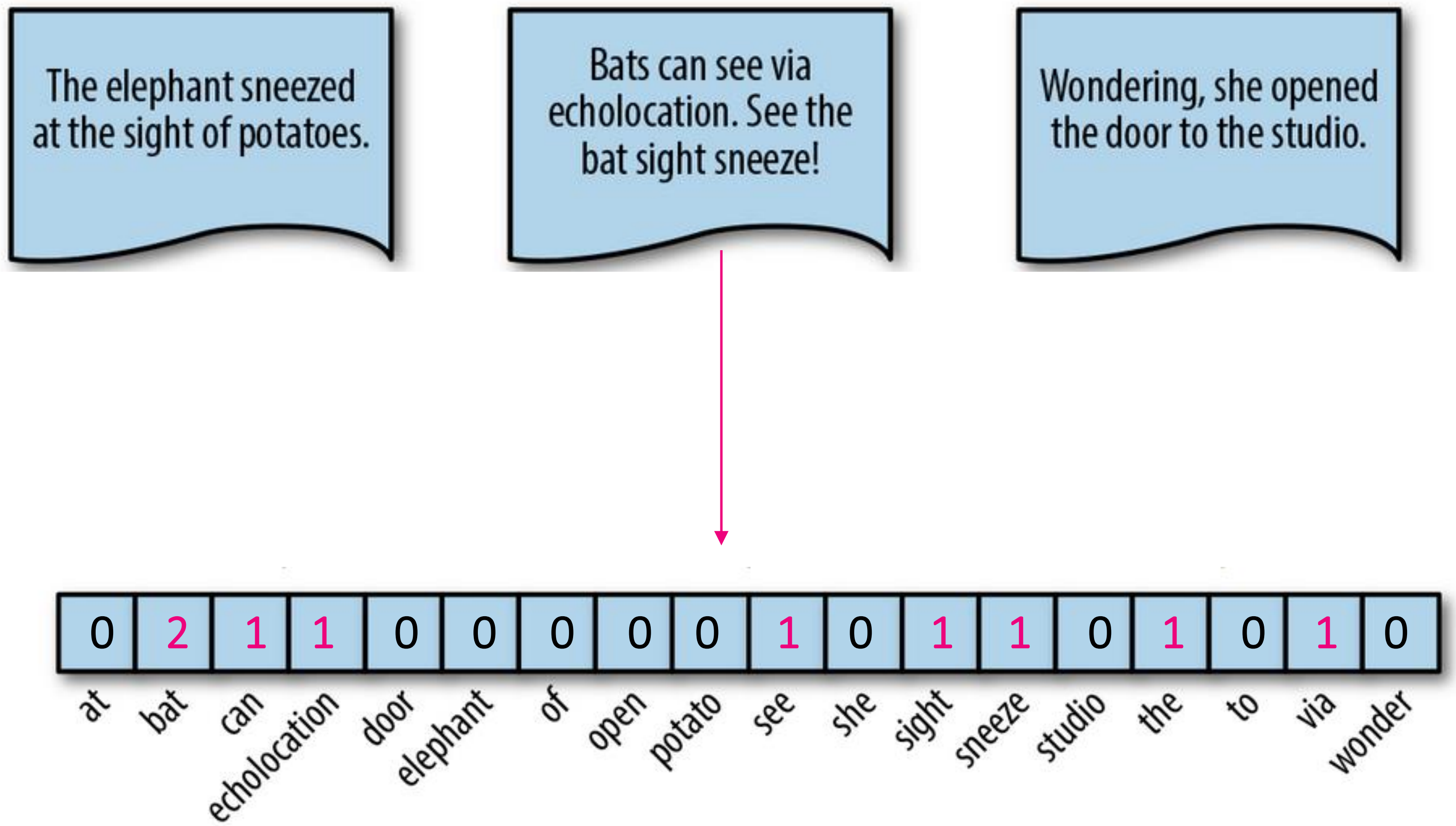

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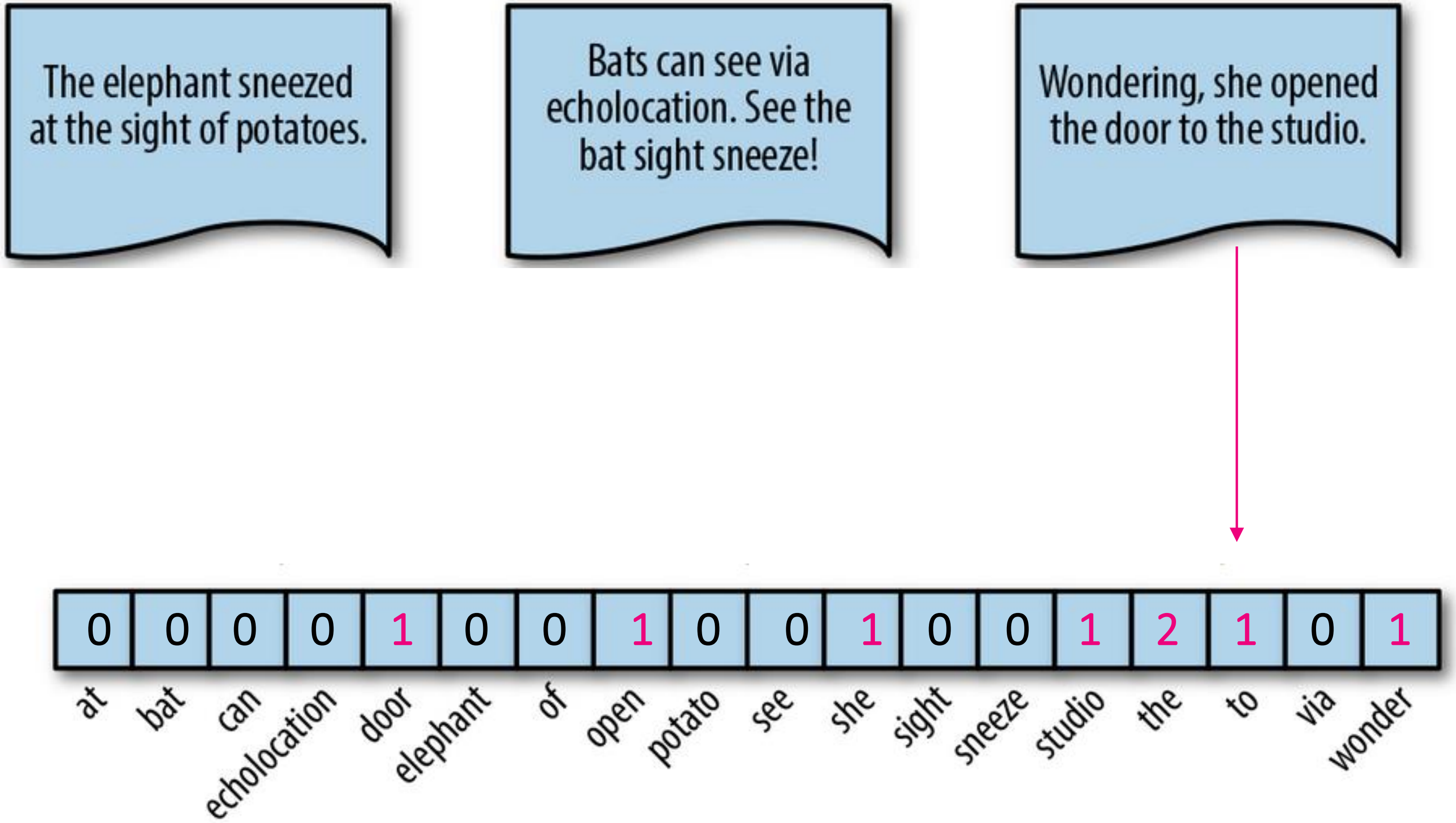

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3.3 Vectorization – Frequency Vectors

Drawbacks:

- can be extremely sparse when vocabularies get larger
- significant impact on speed of ML model
- disregard grammar and the relative position of words in documents
- frequently appearing tokens are considered significant than less frequent tokens
- context of the corpus is ignored

3.4 Vectorization – TFIDF Vectors

- Are meanings most likely encoded in more rare terms from a document?

- Term Frequency - Inverse Document Frequency

- Normalizes the frequency of tokens in a document with respect to the rest of the corpus

- Emphasizes terms that are very relevant to a specific document

3.4 Vectorization – TFIDF Vectors

Two steps to measure the relevance of a token to a document

$$\text{TF- IDF} = \text{TF}(t, d) \times \text{IDF}(t)$$

Term Frequency

Number of times term, t appears in a document, d

Inverse Document Frequency

$$\log \frac{1 + \text{no. of documents}}{1 + \text{df}(d, t)}$$

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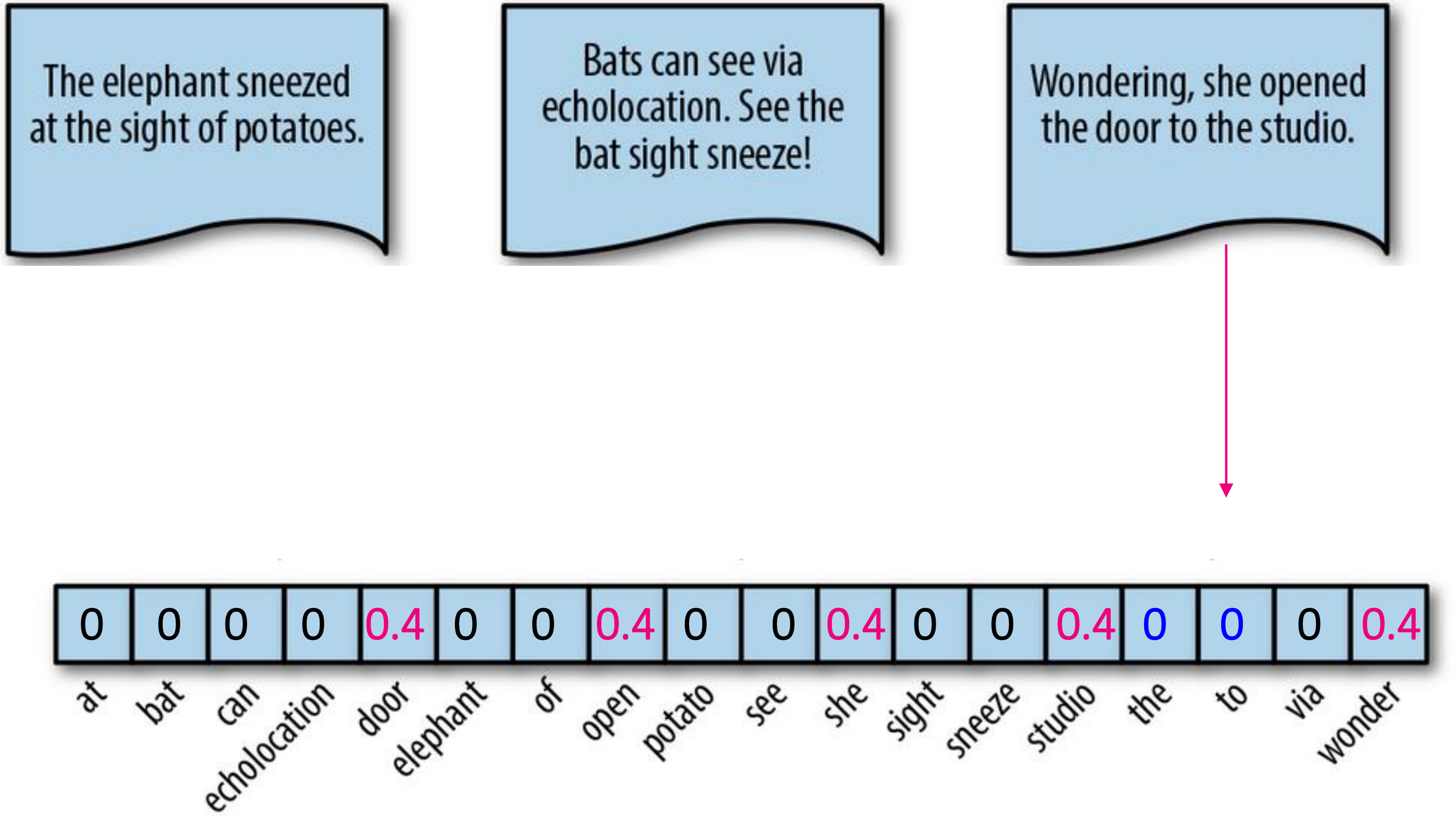
3.4 Vectorization – TFIDF Vectors



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Questions?

Thank you