THINKFUL

Text Vectorization & Feature Engineering

DATA SCIENCE

Warm Up

- How many ways can you think of to convert text data into numbers that can be computed upon?

Agenda

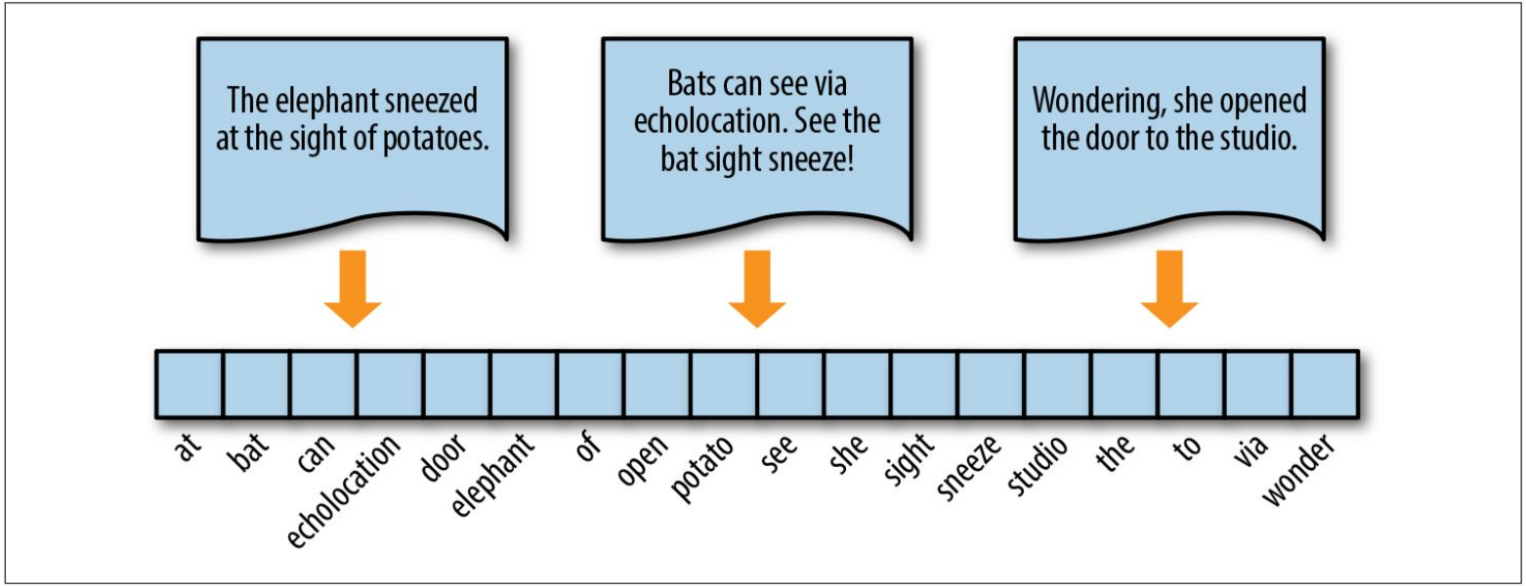
- Feature Engineering for Text Data
- Bag of Words Vectorization
- Vectorization Methods
- Count Vectorization
- One Hot Vectorization
- TF-IDF Vectorization
- Distributed Representation Vectorization
- Important Considerations for Vectorization

Feature Engineering For Text Data

- Machine learning algorithms operate on a numeric feature space, expecting input as a two-dimensional array where rows are instances and columns are features.
- In order to perform machine learning on text, we need to transform our documents into numeric vector representations.
- This process is called feature extraction and engineering or, more simply, vectorization.

Bag of Words (BOW) Vectorization

- Bag of Words vectorization represents each document in the corpus as a vector whose length is equal to the vocabulary of the corpus.

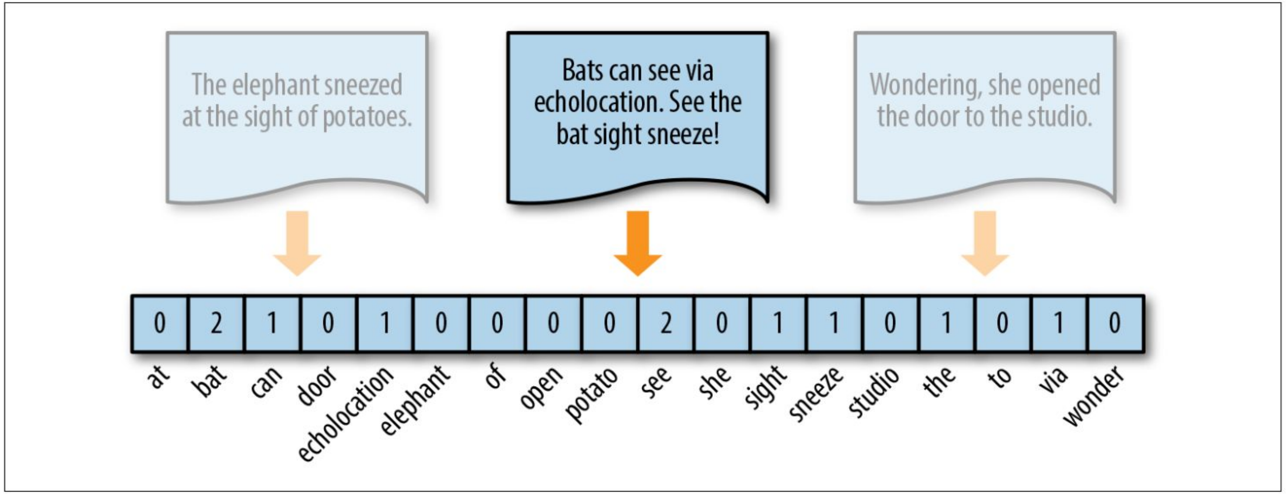


Vectorization Methods

- What should each element in the document vector be?
- There are a few different approaches, each of which extends or modifies the base bag of words model to describe semantic space.
- Count/Frequency Vectorization
- One Hot Vectorization
- TF-IDF Vectorization
- Distributed Representation Vectorization

Count Vectorization

- The simplest vector encoding method is to simply fill in the vector with the frequency of each word as it appears in the document.
- Can either be a straight integer encoding or a normalized encoding where each word is weighted by the total number of words in the document.



Count Vectorization

- We can use Scikit-Learn's `CountVectorizer` to perform count vectorization on a list of tokenized, normalized, and cleaned documents.
- After instantiating the CountVectorizer, we call the fit_transform method, pass it our list of documents, and save the results in a data frame.

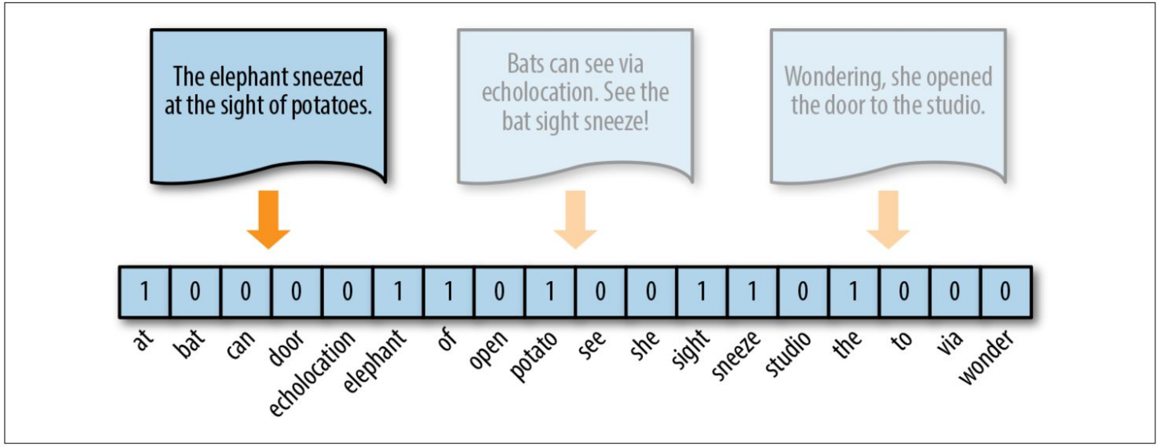
```
from sklearn.feature_extraction.text import CountVectorizer

vectorizer = CountVectorizer()
vectors = vectorizer.fit_transform(documents)

count = pd.DataFrame(vectors.toarray(),
                     columns=vectorizer.get_feature_names())
```

One Hot Vectorization

- Count vectorization - tokens that occur very frequently are considered much more significant than less frequent tokens, which may not be desirable.
- A solution to this problem is one hot encoding, which simply assigns a 1 if the token exists in the document and a 0 otherwise.



One Hot Vectorization

- We can use the same `CountVectorizer` from Scikit-Learn to perform one hot vectorization - we just need to set its `binary` parameter equal to `True`.
- We can then proceed just like we did before, calling the fit_transform, passing it the list of cleaned documents, and loading the results into a data frame.

```
vectorizer = CountVectorizer(binary=True)
vectors = vectorizer.fit_transform(documents)

one_hot = pd.DataFrame(vectors.toarray(),
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TF-IDF Vectorization

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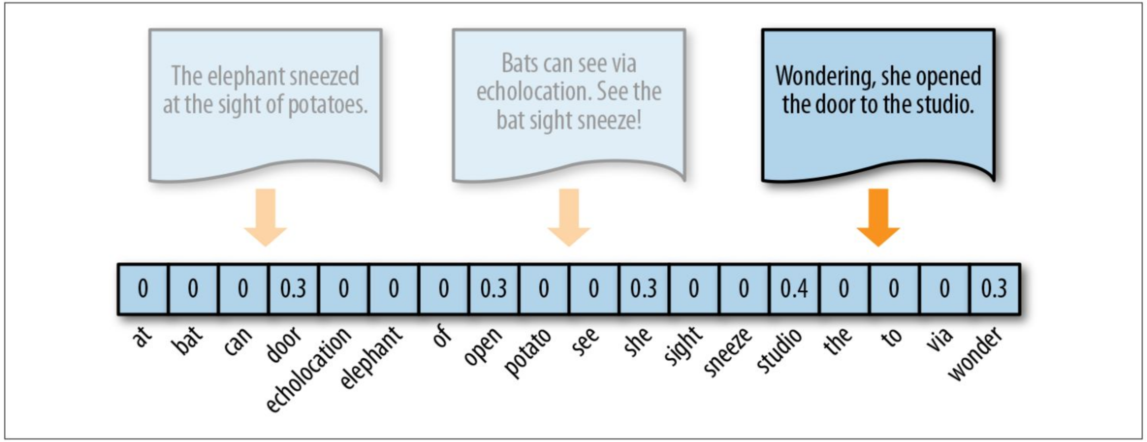

TF-IDF Vectorization

- To perform TF-IDF vectorization in Python, we need to import Scikit-Learn's `TfidfVectorizer` and use it in place of the `CountVectorizer`.
- We can then call the `fit_transform` method, pass it our list of documents, and load the results into a data frame just like we did with the other methods.

```
from sklearn.feature_extraction.text import TfidfVectorizer

vectorizer = TfidfVectorizer()
vectors = vectorizer.fit_transform(documents)

tfidf = pd.DataFrame(vectors.toarray(),
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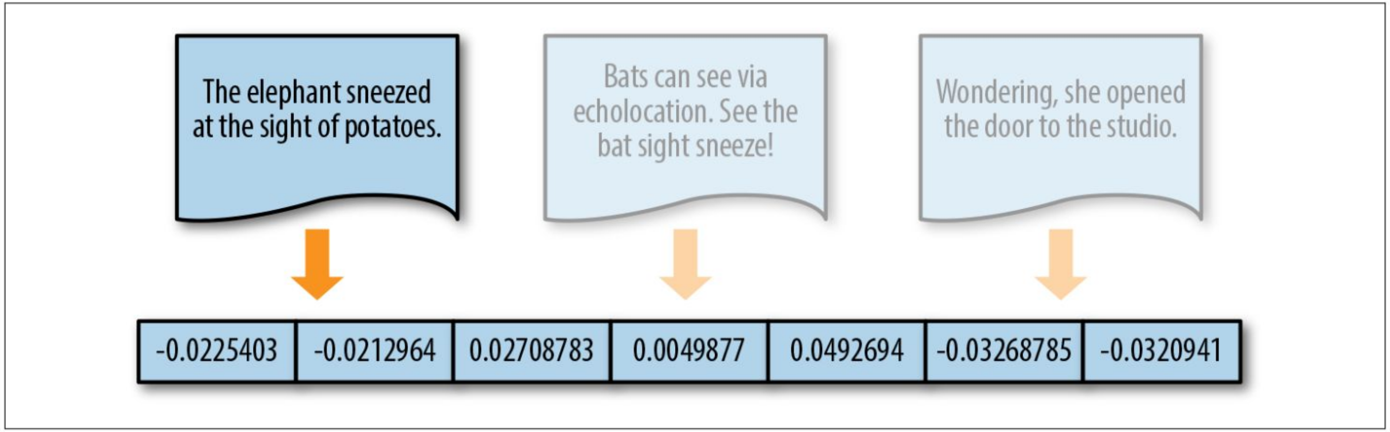
```

Distributed Representations

- When document similarity is important, we must encode our text data along a continuous scale with a distributed representation.
- In the resulting vector, each document is represented in a feature space with word similarities embedded based on how the representation was trained and not directly tied to the document itself.



Word2Vec & Doc2Vec

- Word2Vec is a word embedding model that trains word representations based on either a continuous bag-of-words (CBOW) or skip-gram model, such that words are embedded in space along with similar words based on their context.
- Doc2Vec is an extension of Word2Vec that learns fixed-length feature representations from variable length documents, attempts to inherit the semantic properties of words, and takes into consideration the ordering of words within a narrow context.
- The Gensim library has implementations of both of these, and we will use Doc2Vec to vectorize our text.

Doc2Vec Vectorization

- To perform this type of vectorization, we need to import Gensim's `Doc2Vec` and `TaggedDocument` functions.
- First, we need to convert our list of documents into a list of `TaggedDocument` objects.
- Then, we can call the `Doc2Vec` function, pass it the converted documents, and load the results into a data frame as follows.

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from gensim.models.doc2vec import Doc2Vec, TaggedDocument

documents = [TaggedDocument(doc, [i])
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model = Doc2Vec(documents)

doc2vec = pd.DataFrame([[document]+list(model[document])
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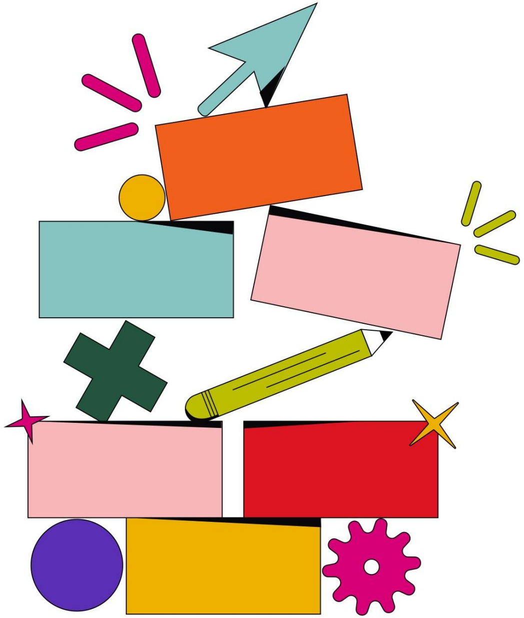
Considerations For Vectorization

- Which stop words to include and which to filter out.
- Whether we should we vectorize based on individual terms or n-grams.
  - Vectorizing based on individual terms leaves out potentially important word combinations and phrases, but vectorizing based on n-grams makes the data very sparse and potentially more difficult to model (especially with a limited amount of data).
- Whether we should remove infrequent words and if so, what the threshold should be.
- What vectorization approach aligns best with our data and our goals.

Questions?



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Summary

Brief review, should call back to the objective and make the direct connection for how the objective has now been achieved.

- Feature engineering for text data.
- An overview of the different text vectorization methods.
- How to perform each vectorization method in Python.
- Some important considerations for vectorizing text data.

Assignment

1. See Jupyter Notebook.

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Thank You

Text Vectorization and Feature Engineering

Warm Up

- How many ways can you think of to convert text data into numbers that can be computed upon?

High Level Agenda

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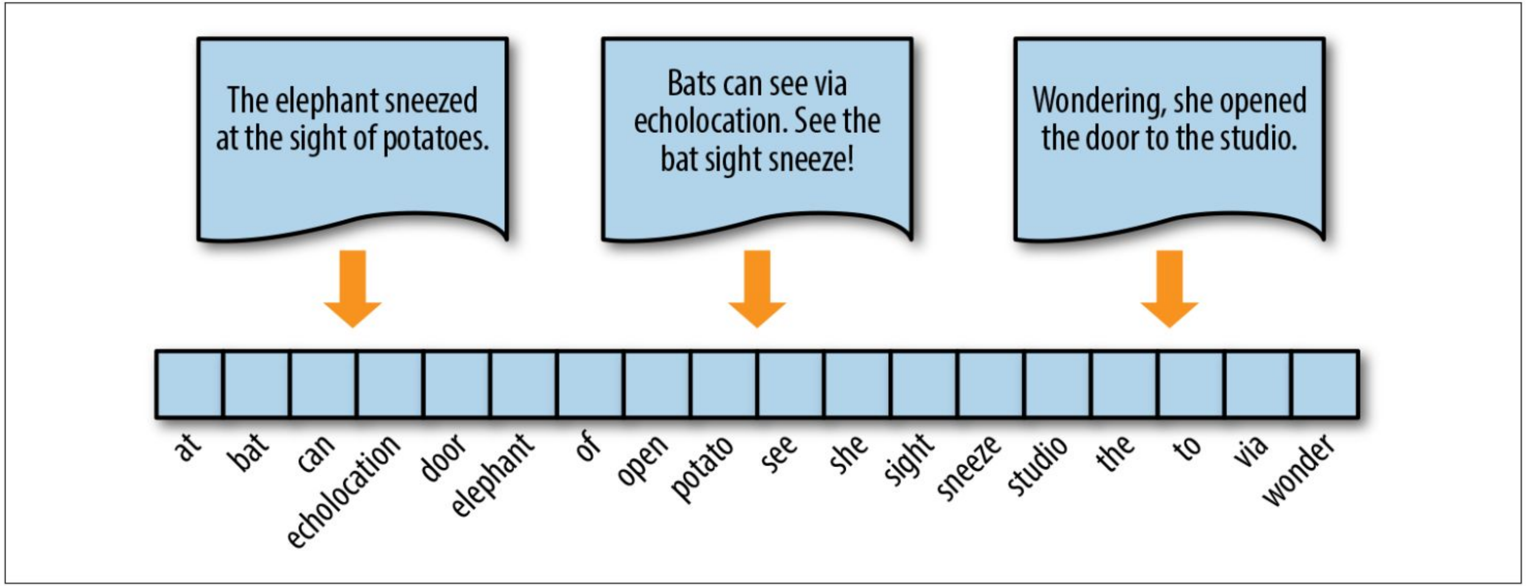

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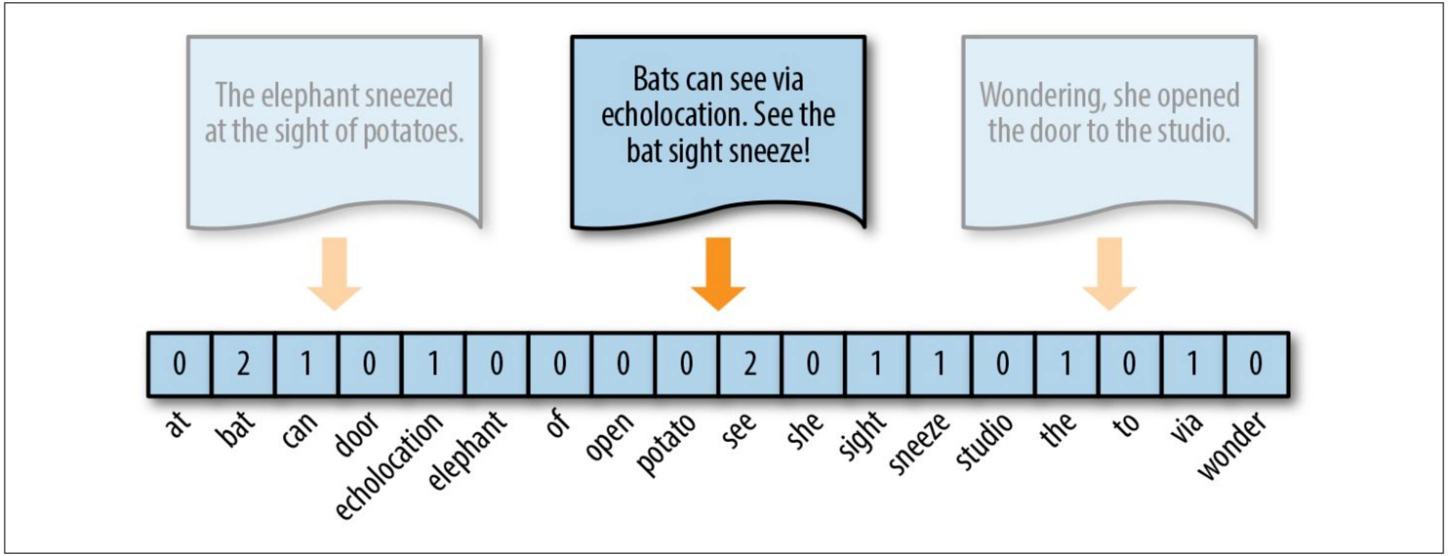

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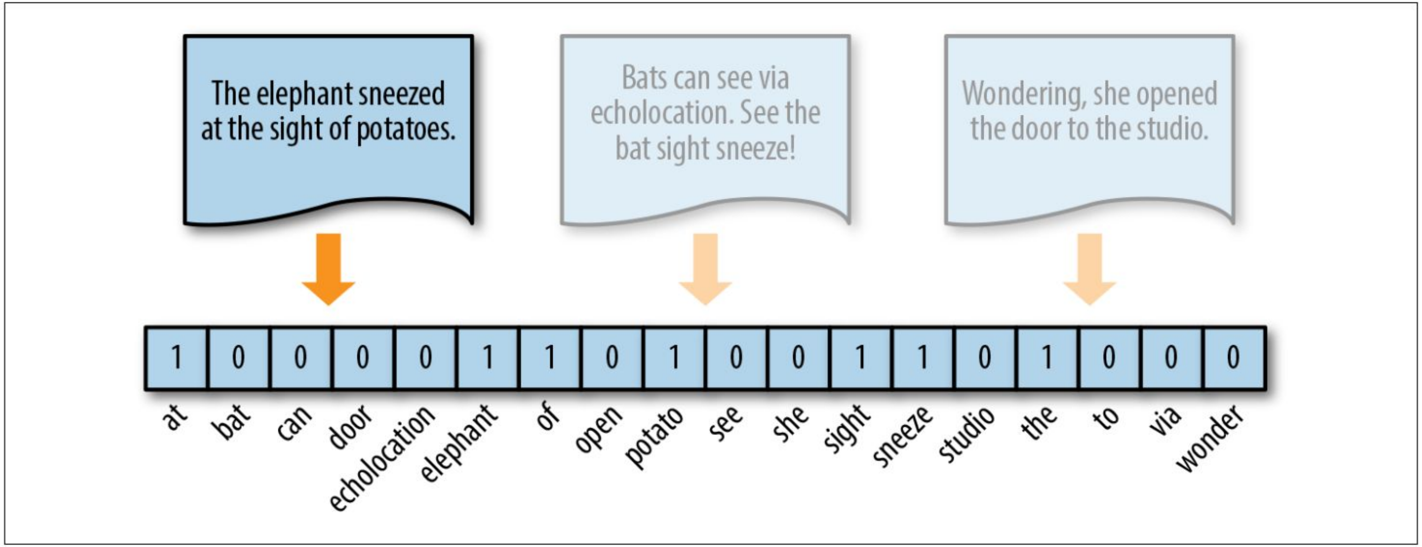

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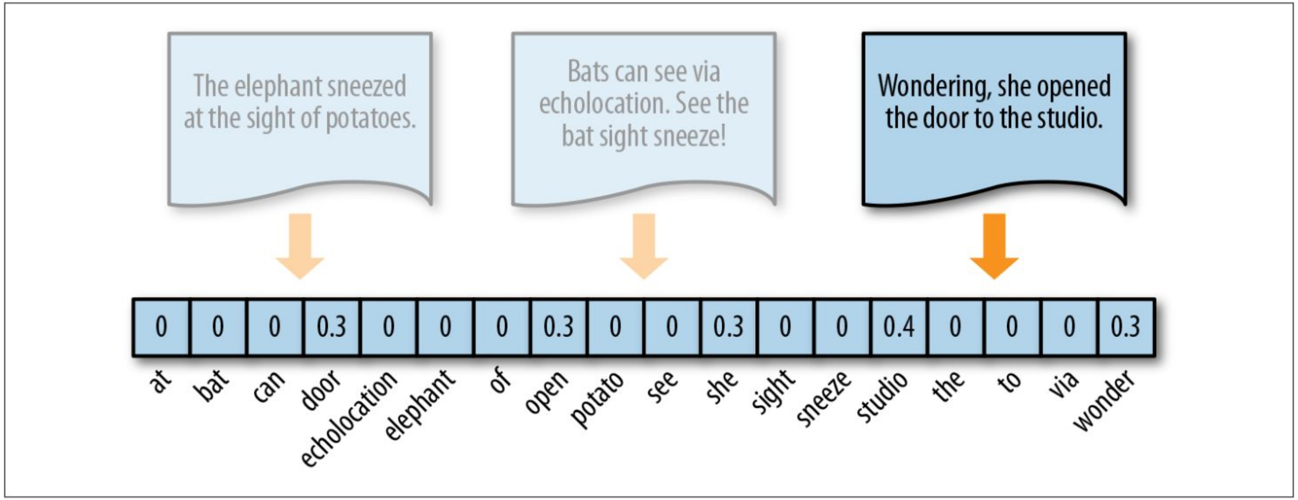

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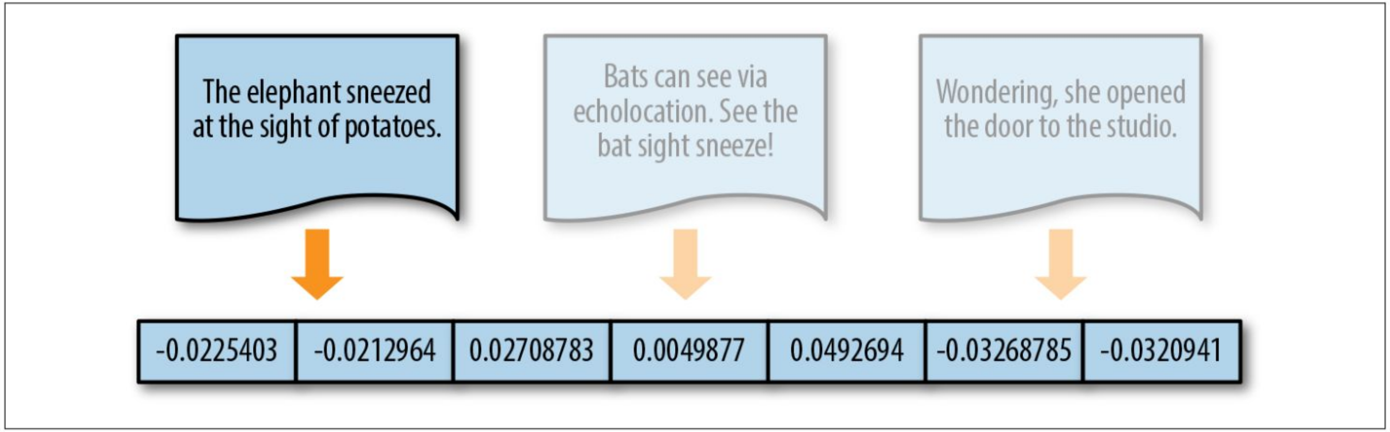

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Recap

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