

Preparing Text Data for Machine Learning



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Overview

Representing text in numeric form

One-hot, frequency-based and prediction-based embeddings

Bag-of-words and bag-of-ngrams modeling of text

Building feature vectors from text data using CountVectorizer, TfidfVectorizer and HashingVectorizer

Performing feature extraction on a Python dictionary

Encoding Text Data in Numeric Form

d = “This is not the worst restaurant in the metropolis,
not by a long way”

Document as Word Sequence

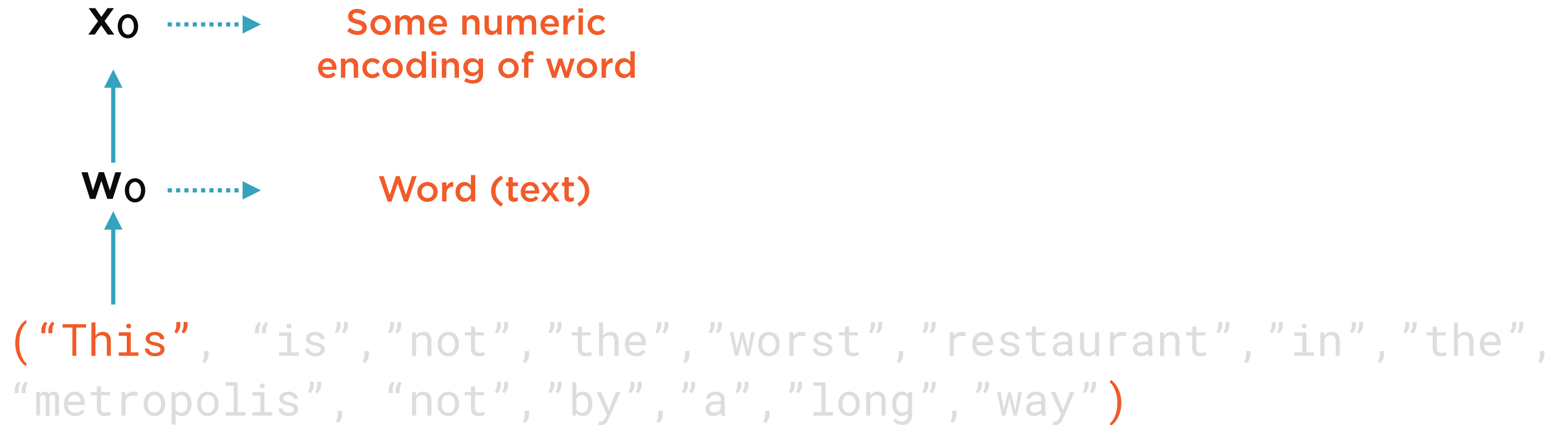
Model a document as an ordered sequence of words

`d = "This is not the worst restaurant in the metropolis,
not by a long way"`

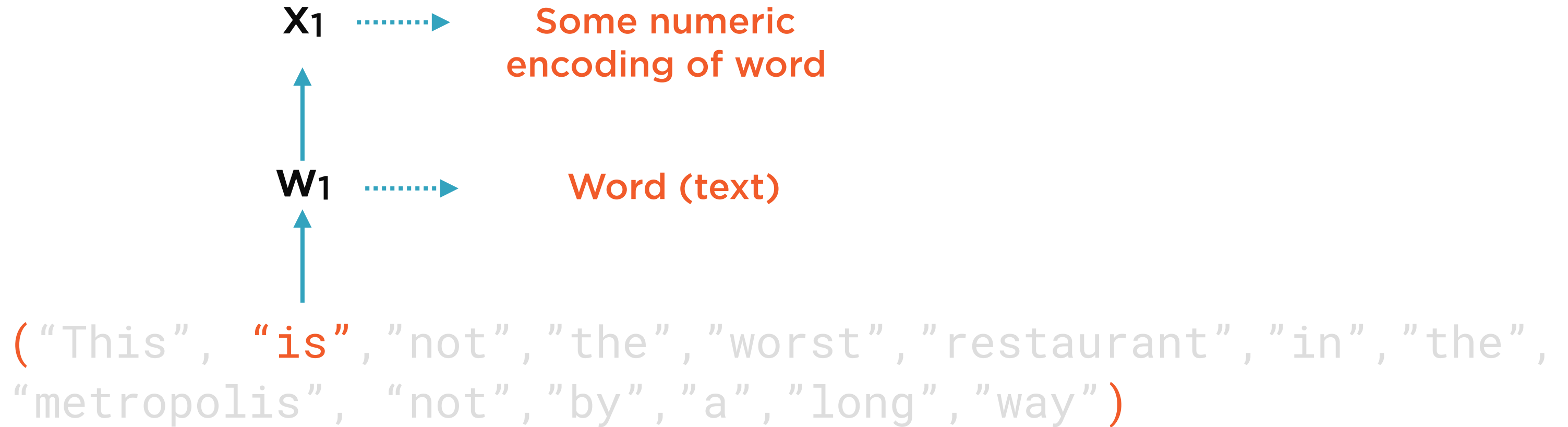
`("This", "is", "not", "the", "worst", "restaurant", "in", "the",
"metropolis", "not", "by", "a", "long", "way")`

Document as Word Sequence

Tokenize document into individual words



Represent Each Word as a Number



Represent Each Word as a Number



Represent Each Word as a Number

$$d = [x_0, x_1, \dots x_n]$$

Document as Tensor

Represent each word as numeric data, aggregate into tensor

Numeric Representations of Text



One-hot

Frequency-based

Prediction-based

Numeric Representations of Text

One-hot

Frequency-based

Prediction-based

Represent each word in text by its
presence or absence

Numeric Representations of Text

One-hot

Frequency-based

Prediction-based

Frequency-based Embeddings

Count

TF-IDF

Co-occurrence

Frequency-based Embeddings

Count

TF-IDF

Co-occurrence

Capture how often a word occurs in a document i.e. the **counts** or the **frequency**

Frequency-based Embeddings

Count

TF-IDF

Co-occurrence

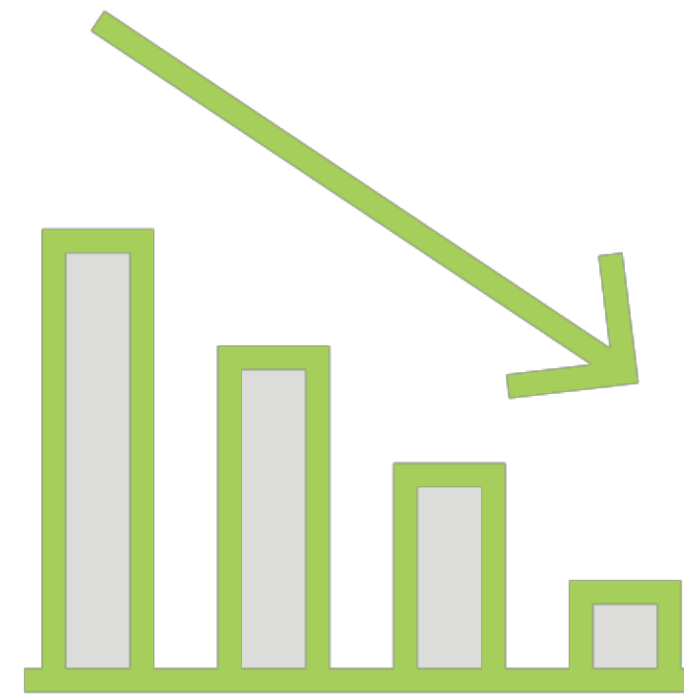
Captures how often a word
occurs in a **document** as well as
the **entire corpus**

Tf-Idf



Frequently in a single document

Might be important



Frequently in the corpus

**Probably a common word like
“a”, “an”, “the”**

Frequency-based Embeddings

Count

TF-IDF

Co-occurrence

Similar words will occur
together and will have similar
context

Context Window

A window centered around a word, which includes a certain number of neighboring words

Co-occurrence

The number of times two words w_1 and w_2 have occurred together in a context window

Word Embeddings

One-hot

Frequency-based

Prediction-based

1
2 3

Predictions-based embeddings

Numerical representations of
text which capture meanings
and semantic relationships,
generated using ML models

Magic



Word embeddings capture meaning

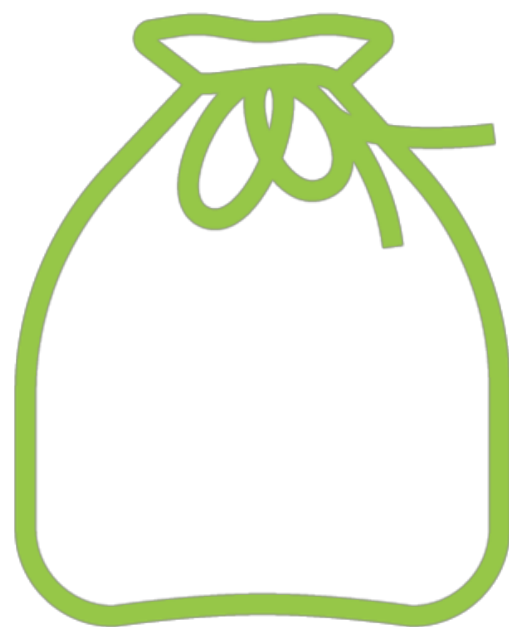
“Queen” ~ “King” == “Woman” ~ “Man”

“Paris” ~ “France” == “London” ~ “England”

Dramatic dimensionality reduction

Bag-based Models for Text

Bag-based Models for Text



Bag-of-words



Bag of n-grams

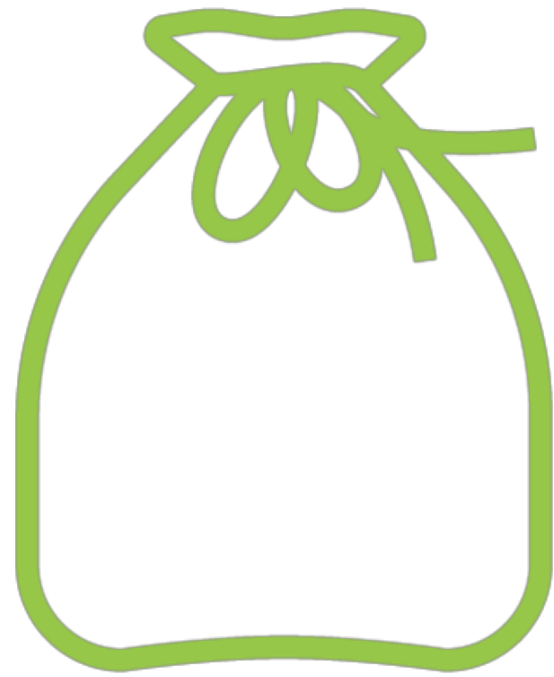
Bag-of-words Model

Any model that represents the document as a bag (multiset) of its constituent words, disregarding order but maintaining multiplicity

Bag-of-words Model

Any model that represents the document as a bag (multiset) of its constituent words, **disregarding order but maintaining multiplicity**

Bag-of-words Models



Examples of bag-of-words models

- Count Vectorization
- TF-IDF Vectorization

Examples that are not bag-of-words models

- One-hot encoding (no multiplicity)
- Word embeddings

Bag-of-n-grams Model

Any model that represents the document as a bag (multiset) of its constituent **n-grams**, disregarding order but maintaining multiplicity

Bag-of-n-grams Model

Any model that represents the document as a bag (multiset) of its constituent n-grams, disregarding order but maintaining multiplicity

Bag-of-n-grams



Bag is a set with duplicates (i.e. multiset)

Bag-of-words models contain only individual words

Bag-of-n-gram models contain n-grams

Bag-of-n-grams



An n-gram model store additional spatial information for a word

Words that occur together

Demo

**Vectorize text data using the
bag-of-words model**

Demo

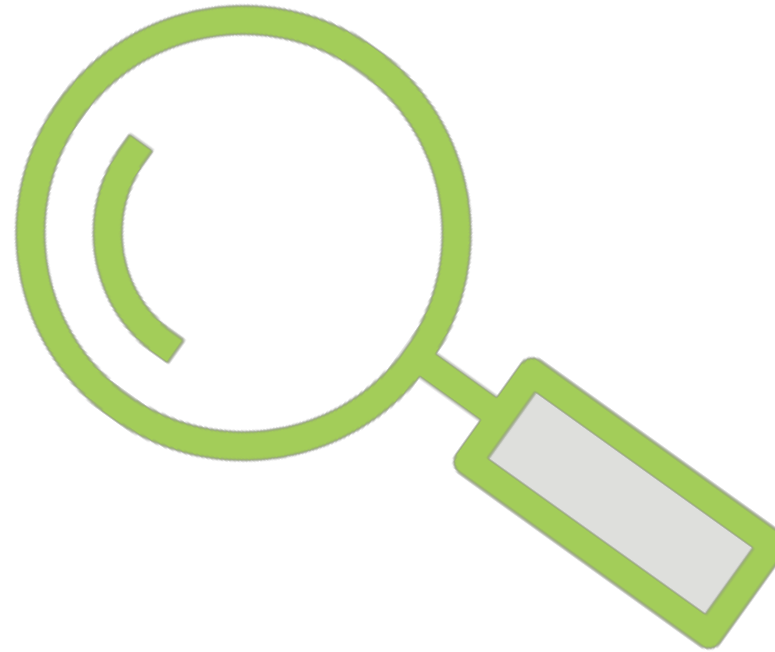
**Vectorize text data using the
bag-of-n-grams model**

Demo

Vectorize text data using tf-idf scores

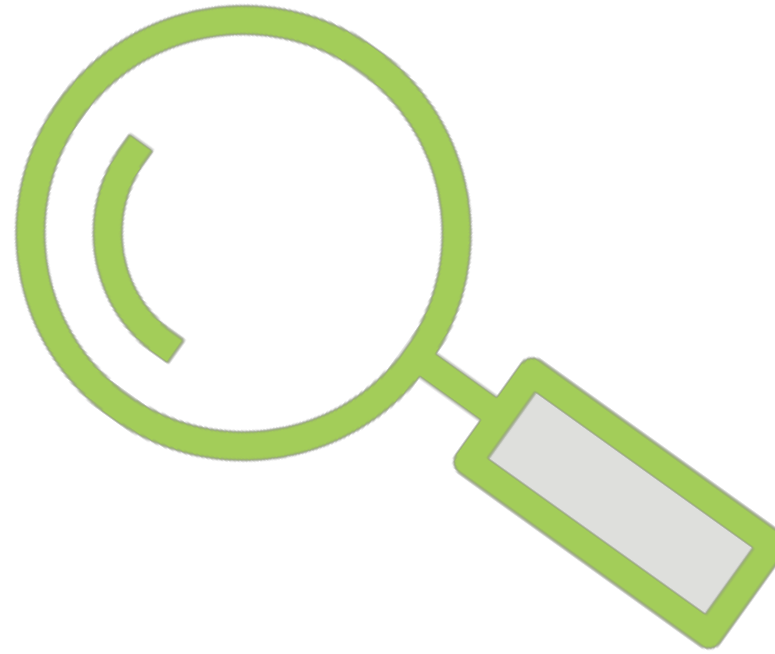
Hashing

Hashing



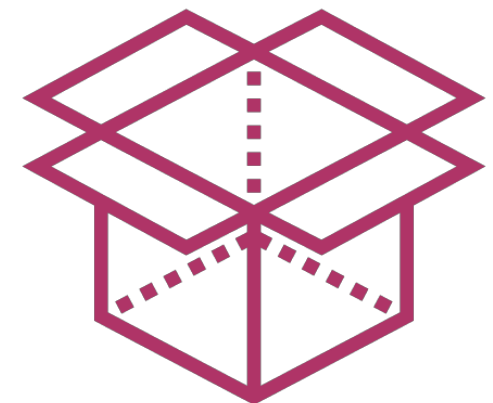
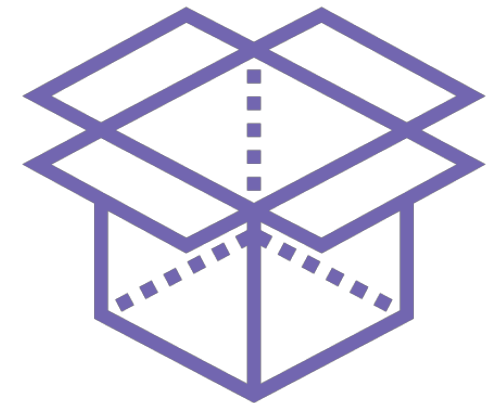
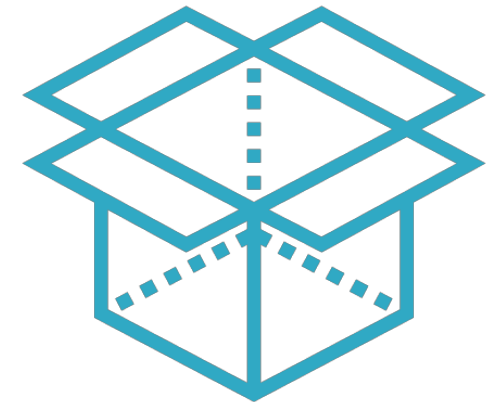
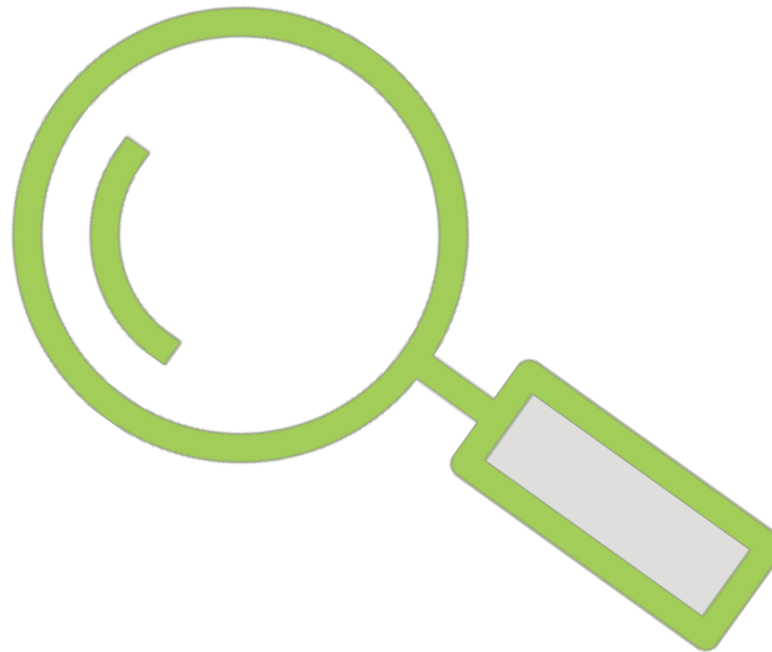
**A technique that allows you to lookup
specific values very quickly**

Hashing



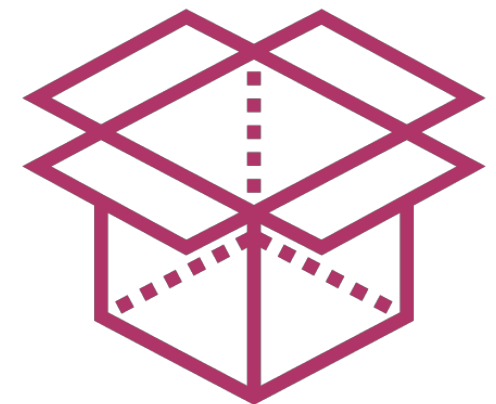
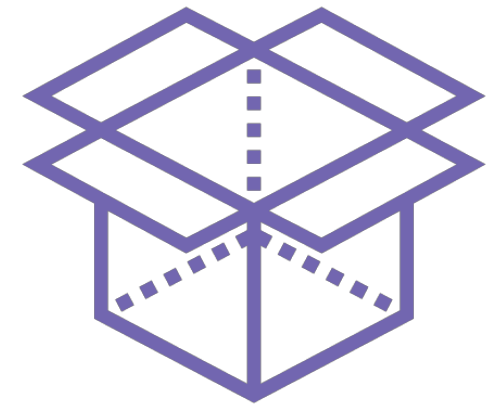
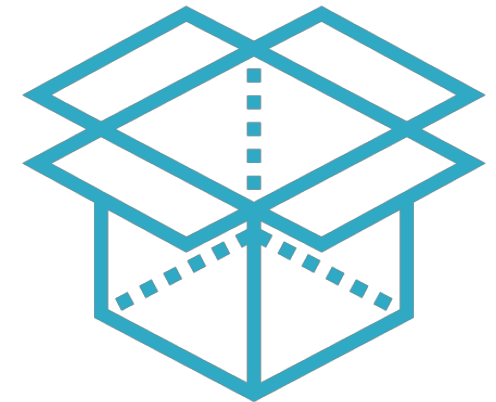
Also can be used to perform dimensionality reduction

Hashing



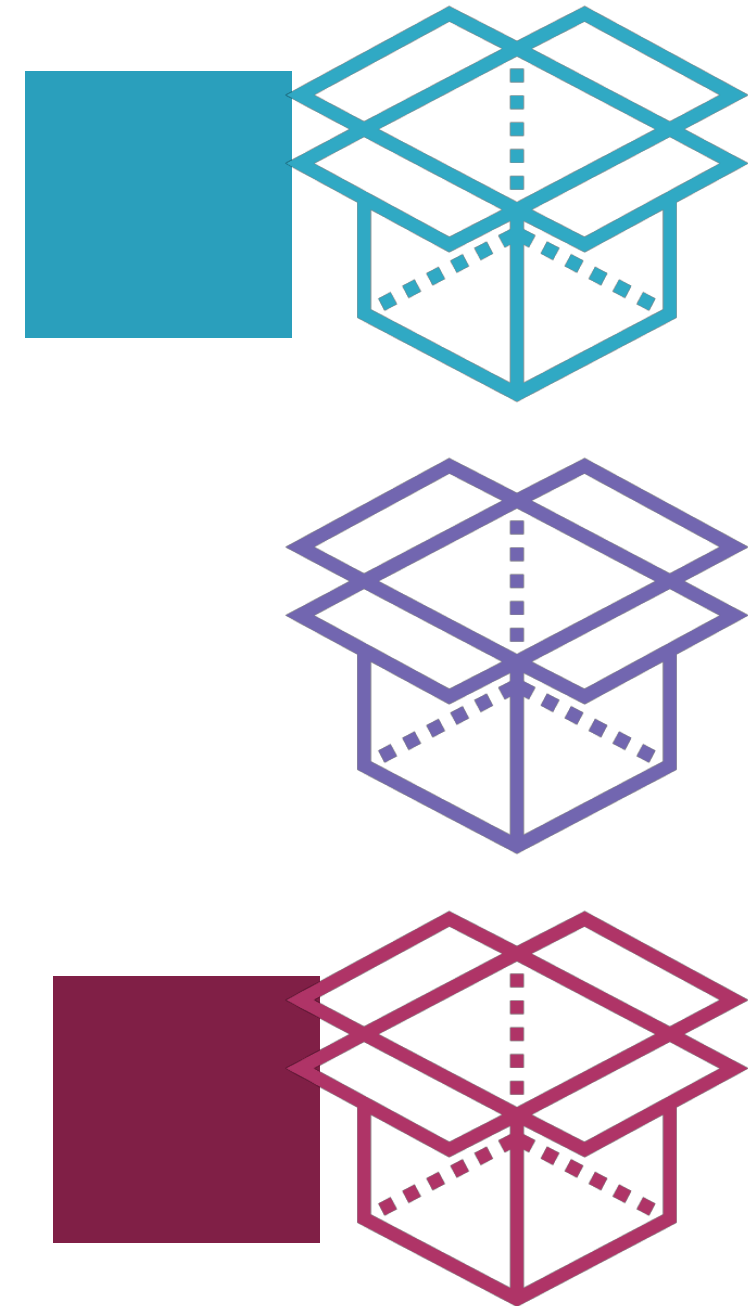
Have a fixed number of categories or buckets

Hashing

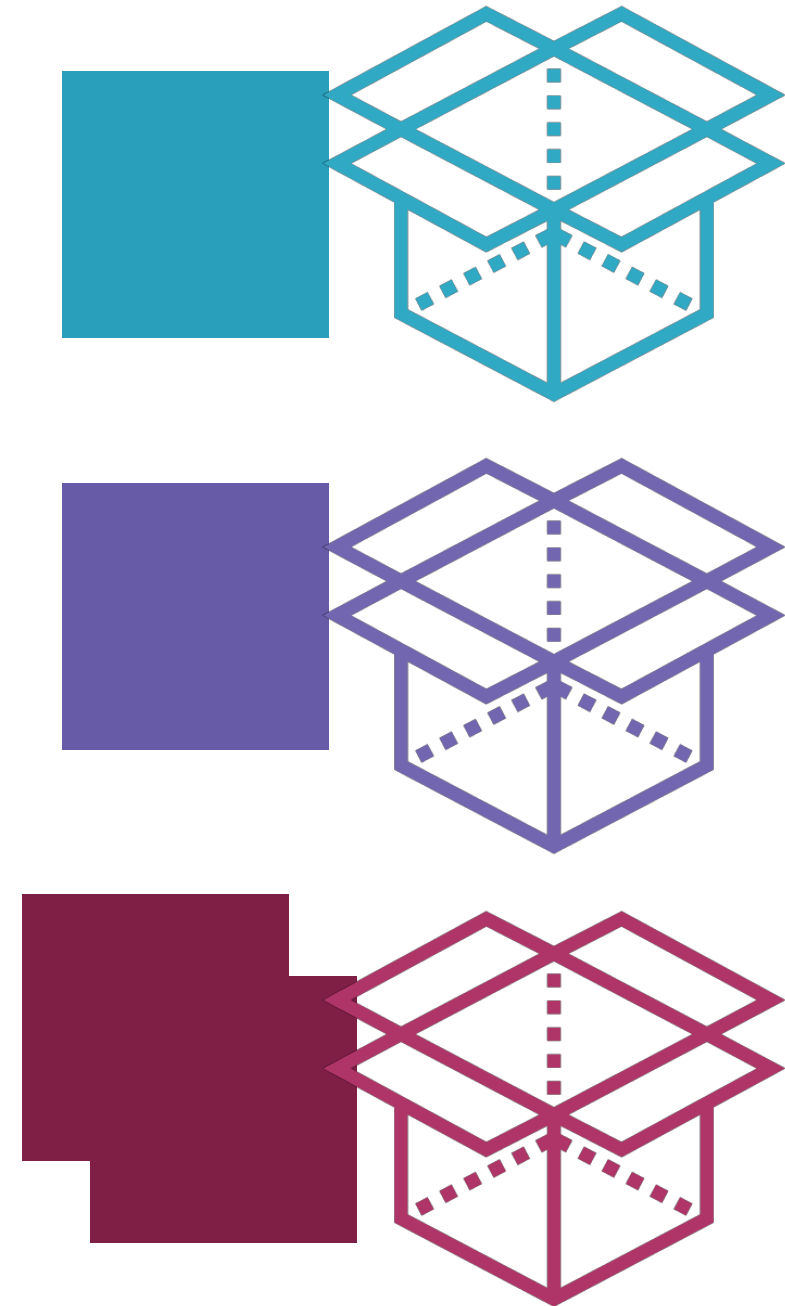


A hash function determines which bucket each value belongs to

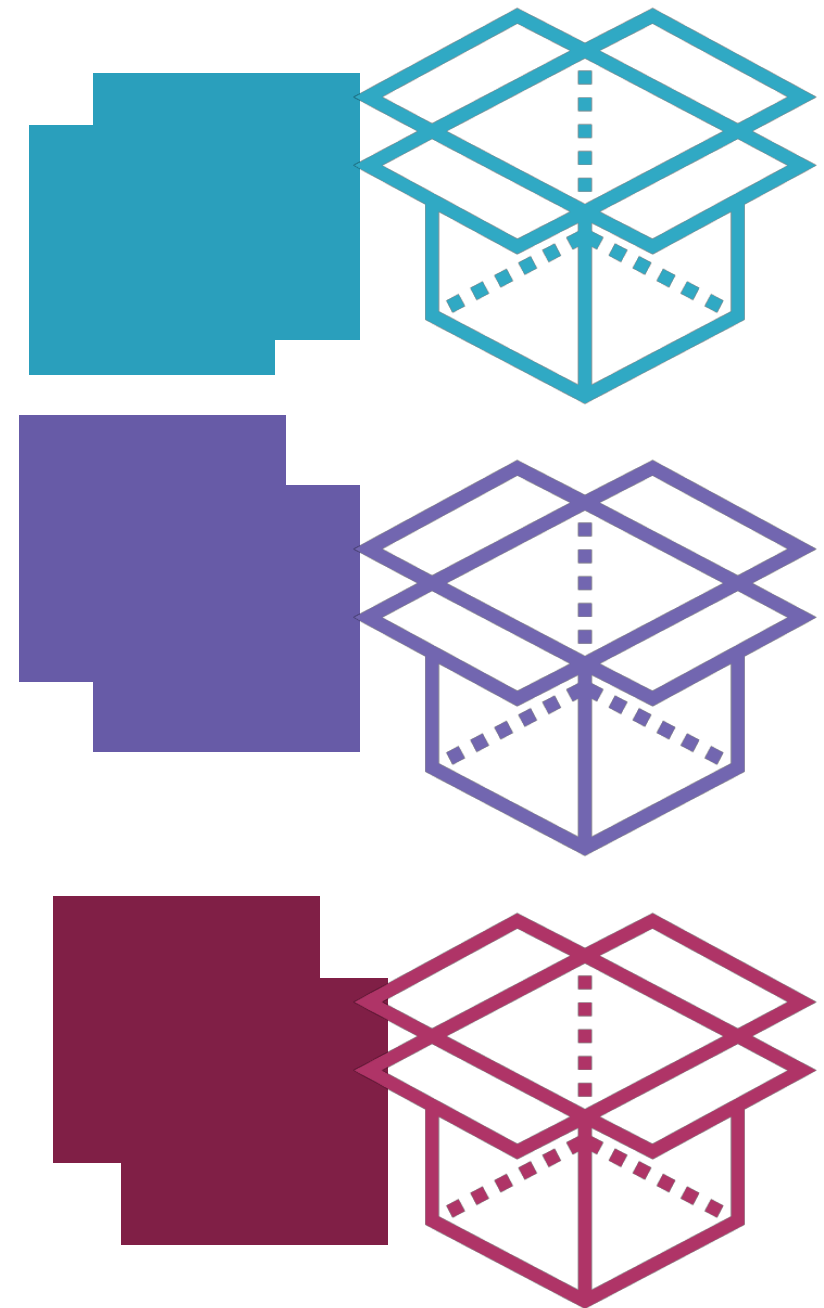
Hashing



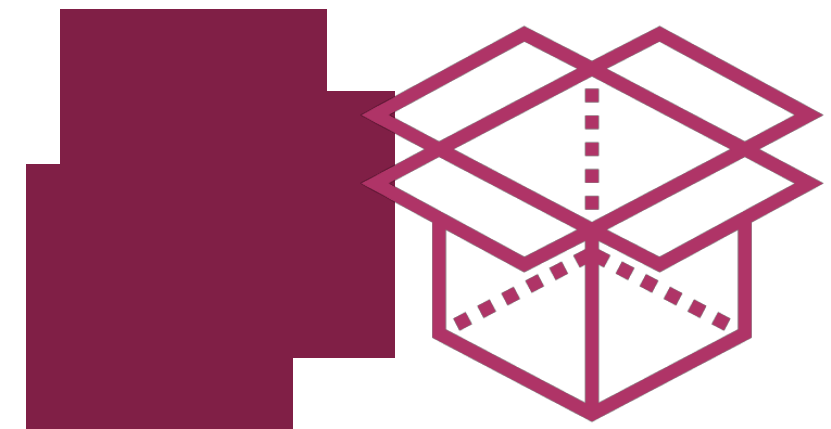
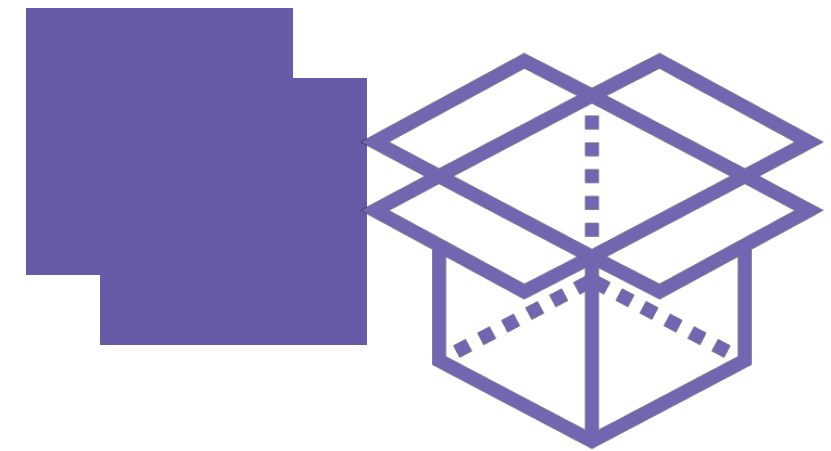
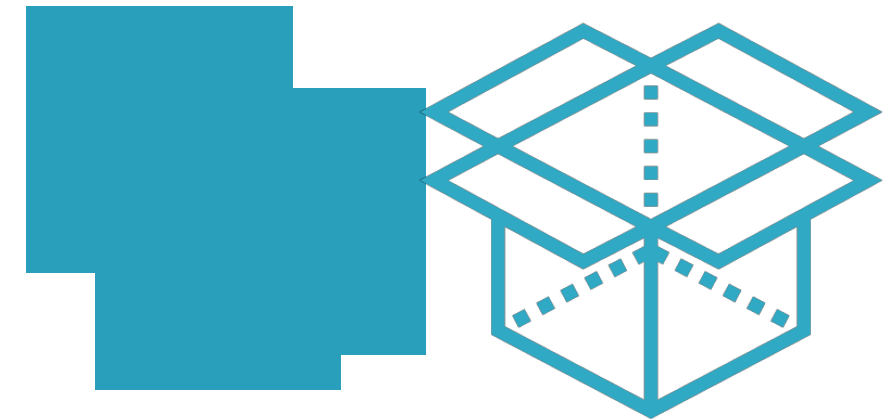
Hashing



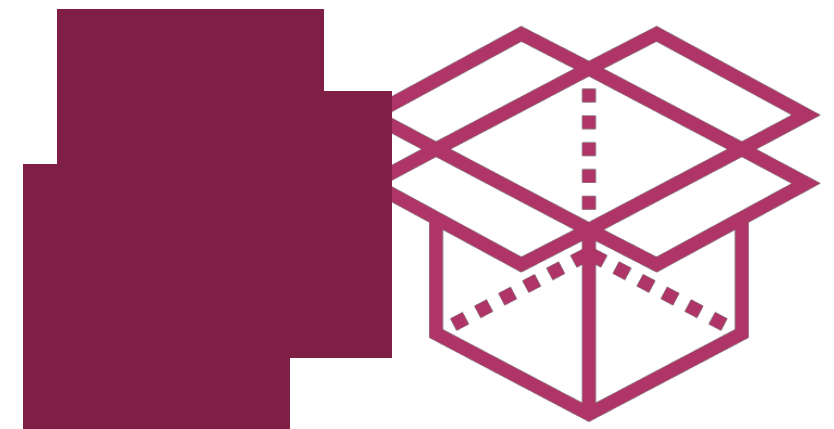
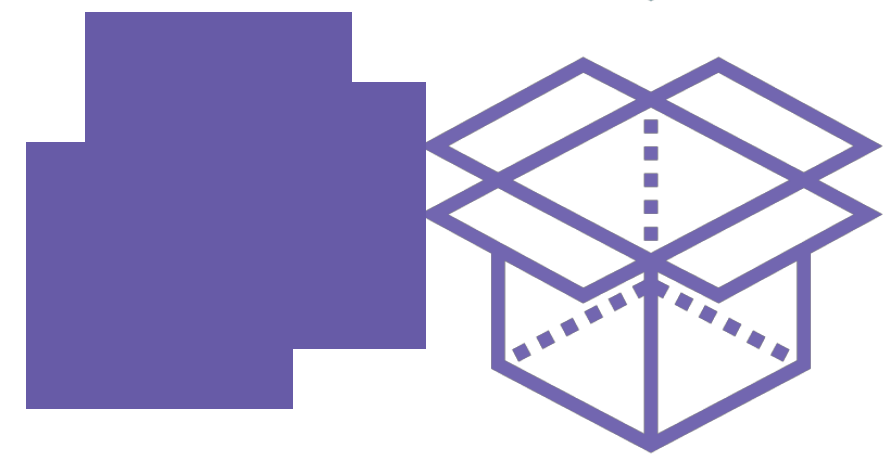
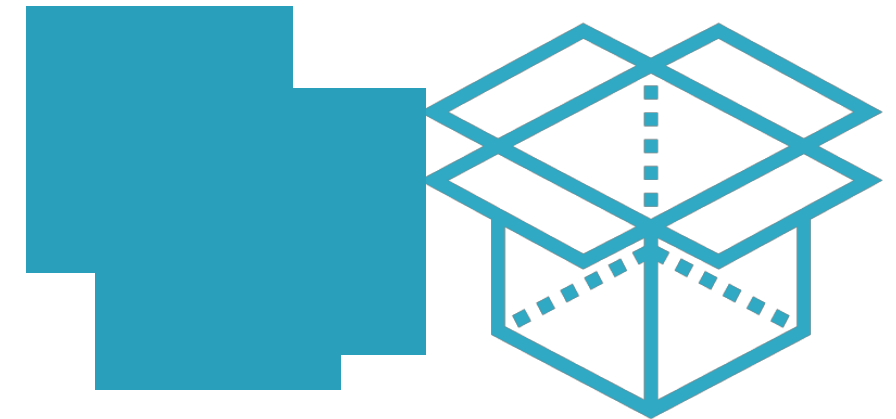
Hashing



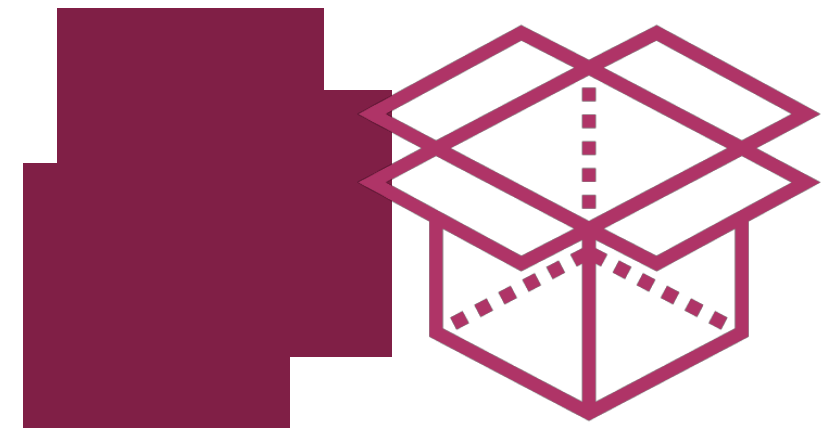
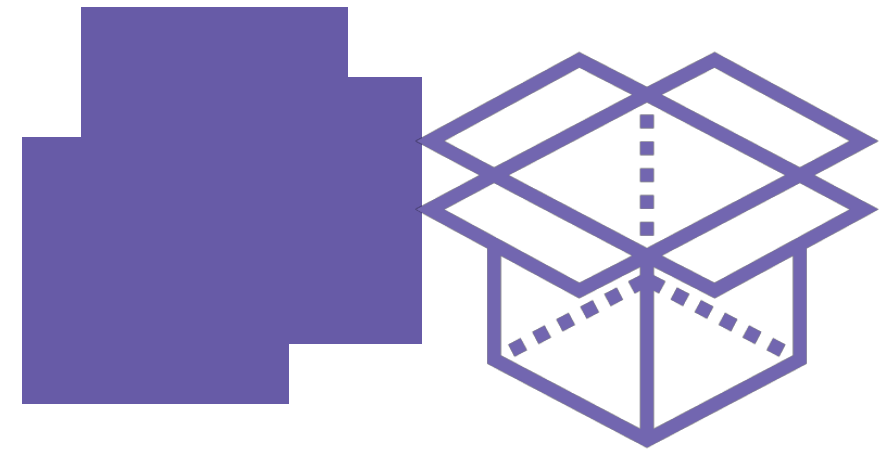
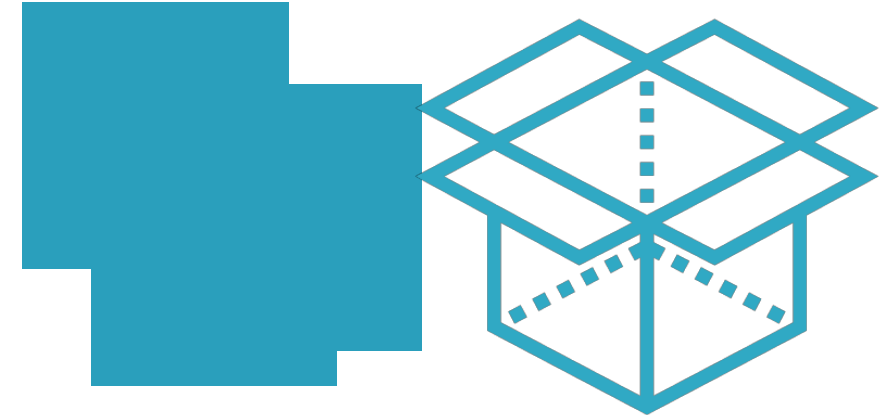
Hashing



Hashing

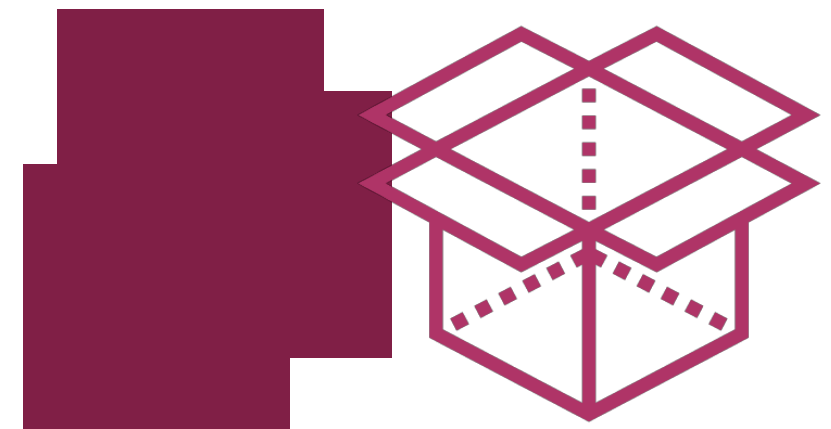
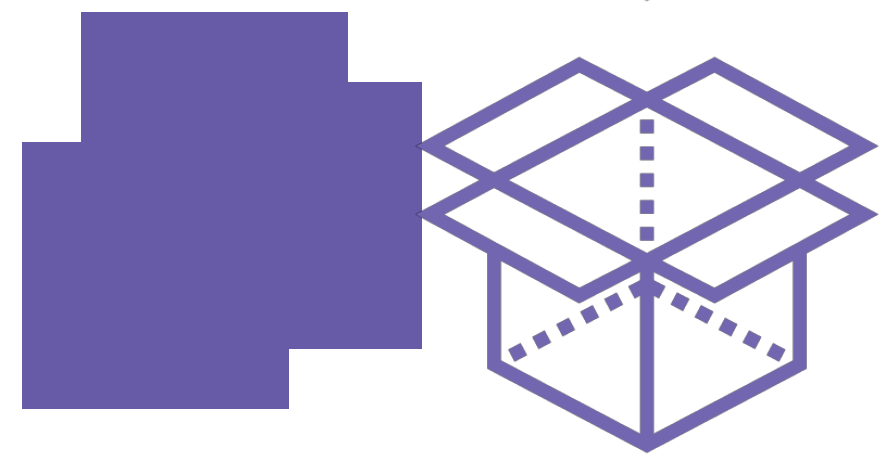
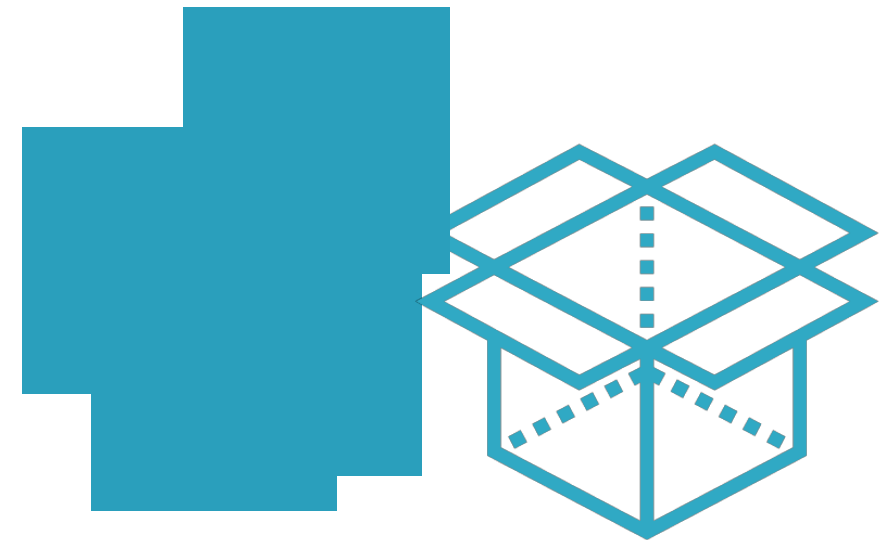


Hashing



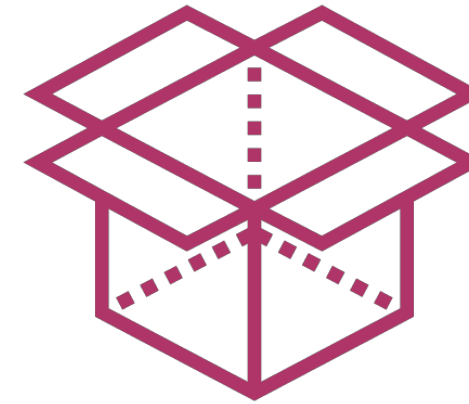
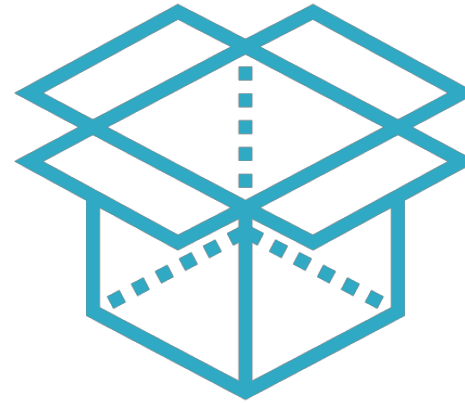
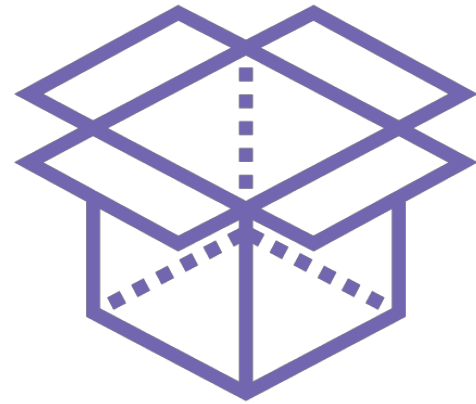
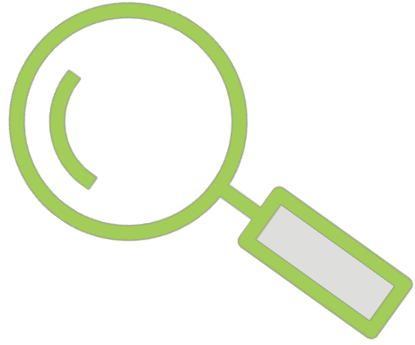
For any new value we know immediately which bucket it belongs to

Hashing



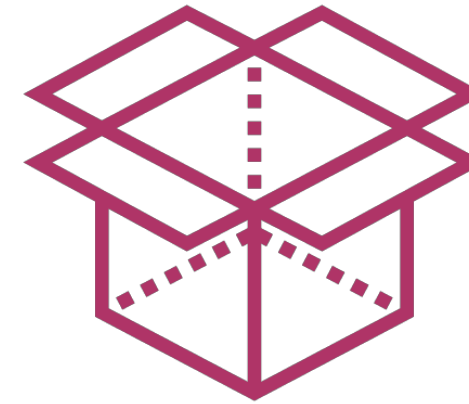
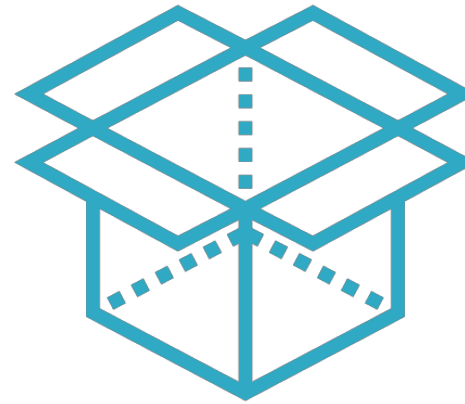
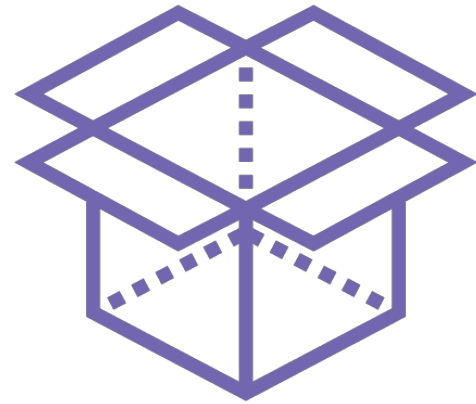
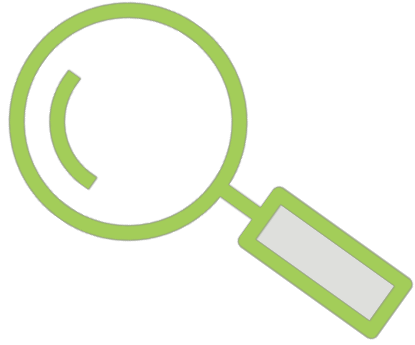
For any new value we know immediately which bucket it belongs to

Hashing



Each value is **hashed** so it falls in one of these buckets

Hashing



A value can only belong to **one bucket** and always belongs to the **same bucket**

Feature Hashing in Text

Apply a hash function to words to determine their location in the feature vector representing a document.
Fast and memory efficient but has no inverse transform.

Feature hashing uses the
“**hashing trick**” for
dimensionality reduction

Dimensionality Reduction



Input: N-dimensional data

Output: k-dimensional data

Where $k < N$

Hashing



Input: N-dimensional data

Output: 1-dimensional data

Output is the hash bucket the data maps to

Hashing



Input: N-dimensional data

Output: k-dimensional data

Can easily extend hashing to output desired dimensionality

Hashing



Thus hashing is a simple form of dimensionality reduction

However, very similar inputs may be mapped to very different hash values

Hashing performs dimensionality reduction but does not keep similar data points together

Demo

**Reducing dimensions in text using the
hashing vectorizer**

Demo

**Performing feature extraction on a
Python dictionary**

Summary

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One-hot, frequency-based and prediction-based embeddings

Bag-of-words and bag-of-ngrams modeling of text

Building feature vectors from text data using CountVectorizer, TfidfVectorizer and HashingVectorizer

Performing feature extraction on a Python dictionary