TOPIC MODELING

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Introduction

- Topic Modeling is an unsupervised machine learning technique aimed at:
  - Scanning a set of documents, detecting word and phrase patterns within them;
  - Automatically clustering word groups and similar expressions that best characterize a set of documents.

Topic Modeling

- Topic Modeling provides collections of words that make sense together, which are interpreted as topics.

Example: Five topics from a twenty-five topic model fit on Enron e-mails. Example topics concern financial transactions, natural gas, the California utilities, federal regulation, and planning meetings. We provide the five most probable words from each topic (each topic is a distribution over all words).

Topic	Terms
3	trading financial trade product price
6	gas capacity deal pipeline contract
9	state california davis power utilities
14	ferc issue order party case
22	group meeting team process plan

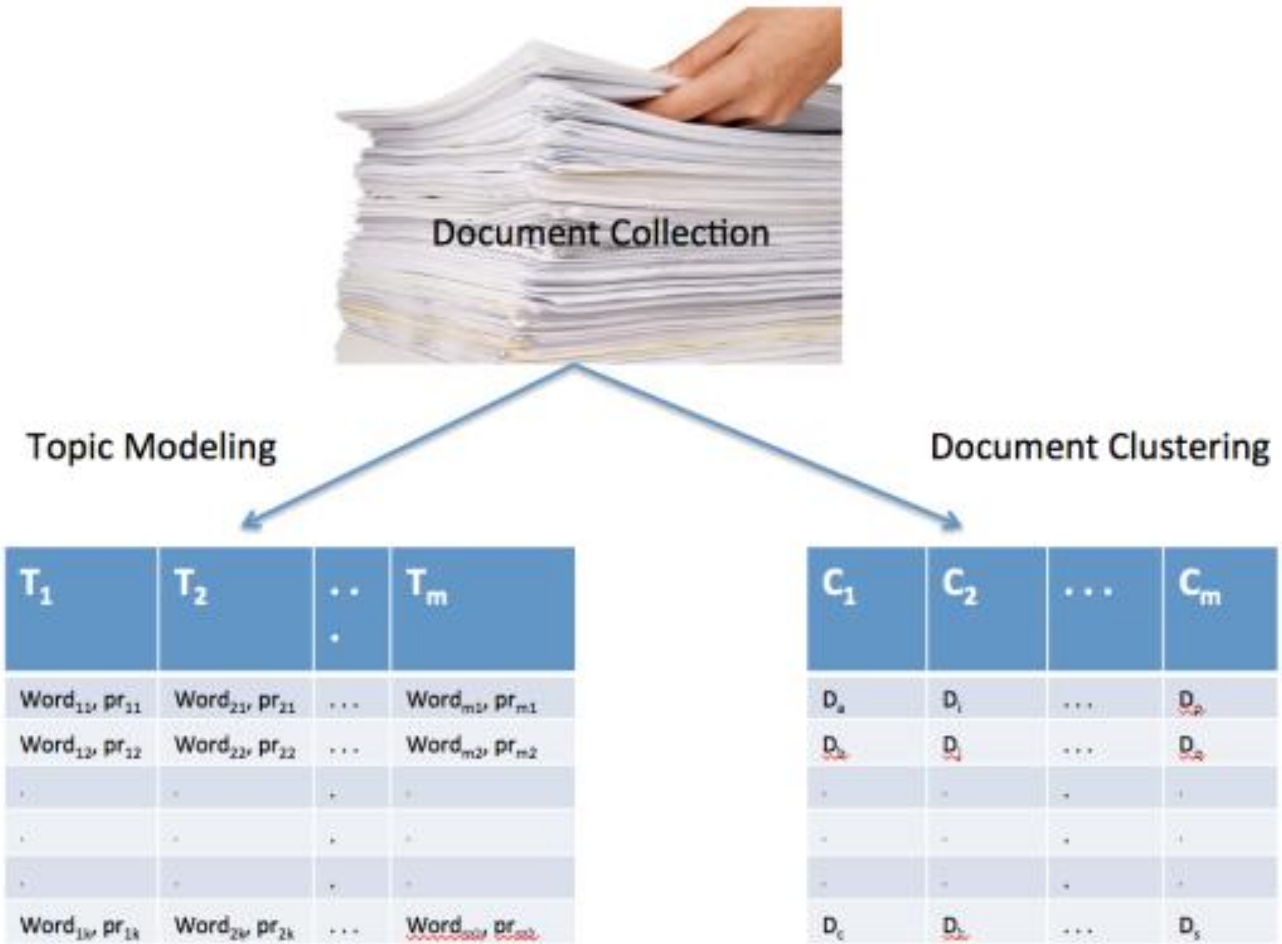
Text Clustering and Topic Modeling
What's the difference?

- In Text Clustering, the basic idea is to group documents into different clusters based on a suitable similarity measure (or distance).

- In Topic Modeling, the basic idea is to group words into different clusters, where:
  - Each word in the cluster is likely to occur "more" (have a probability of occurrence) for the given topic;
  - Different topics have their respective clusters of words along with corresponding probabilities;
  - Different topics may share some words and a document can have more than one topic associated with it.

Text Clustering and Topic Modeling

What's the difference?



An example of Topic Modeling

"Manipulating facial expressions and body movements in videos has become so advanced that most people struggle to tell the difference between fake and real. A fake video of Barack Obama went viral last year where you see the former President addressing the camera. If you turn off the sound, you will not even realize it's a fake video!"

	Topic 1
	Topic 2
	Topic 3

- There are three topics (or concepts) – Topic 1, Topic 2, and Topic 3.
- The most dominant topic in the above example is Topic 2, which indicates that this piece of text is primarily about fake videos.

Another example of Topic Modeling

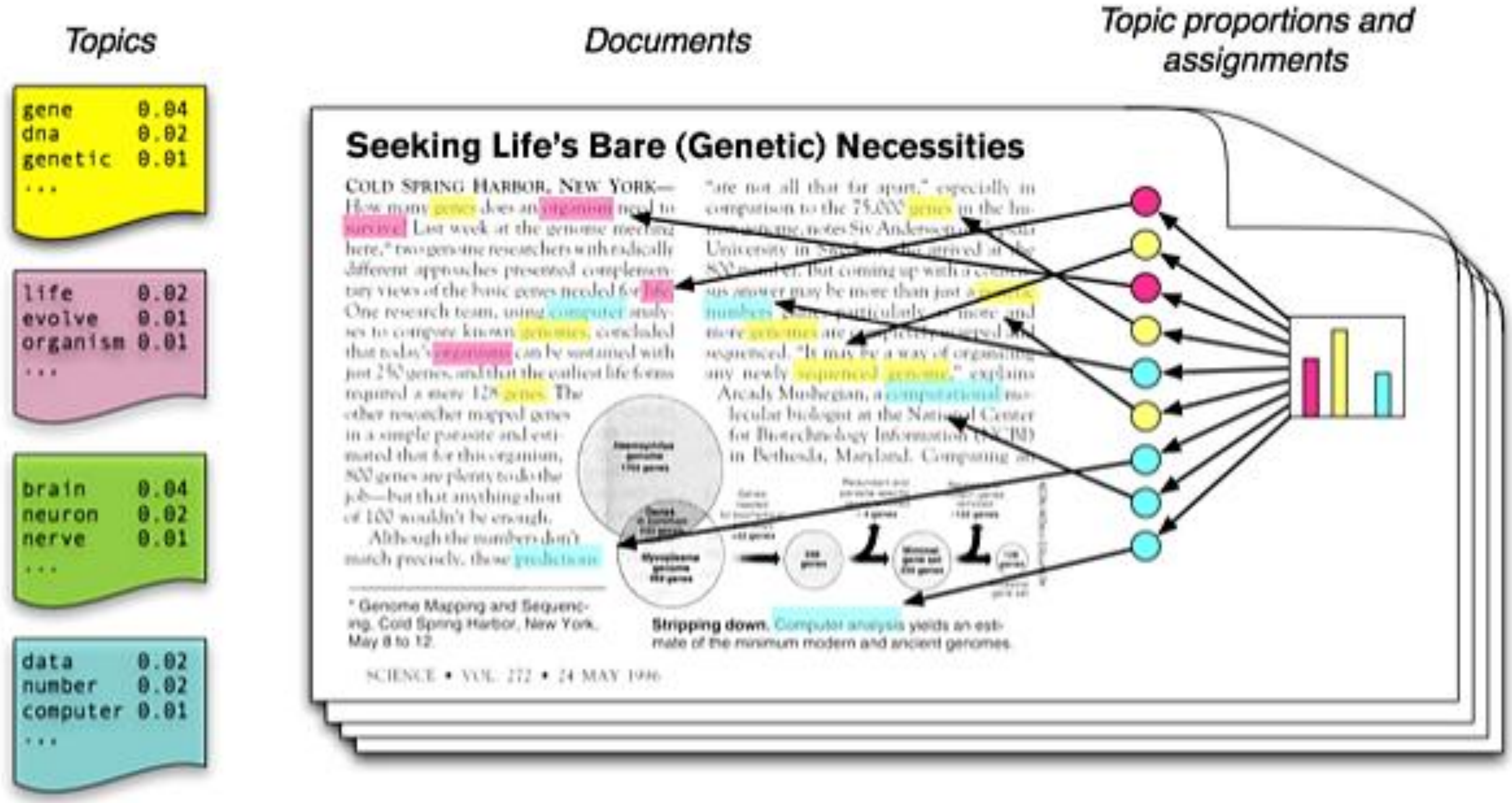
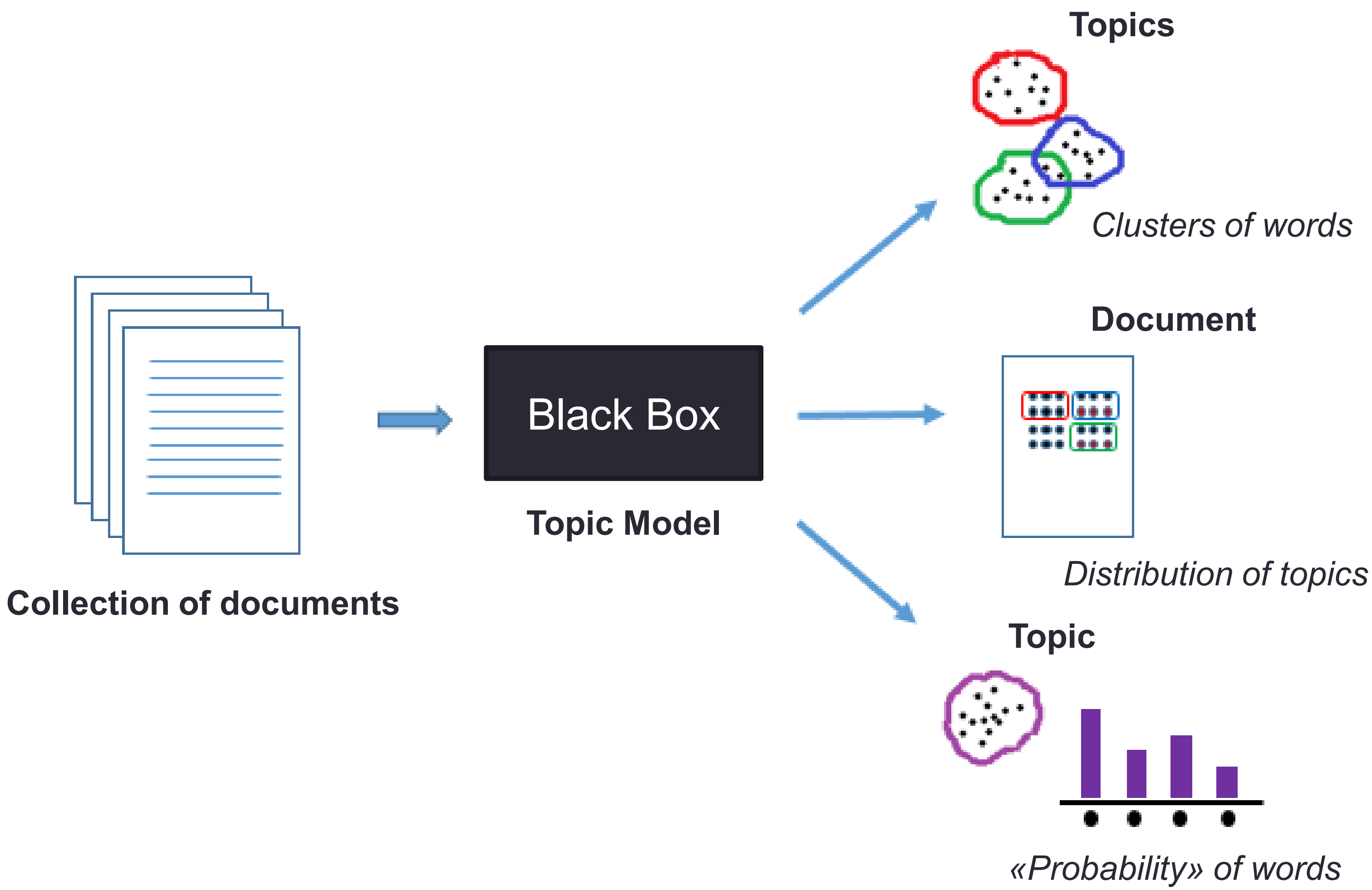


Figure source: Blei, D. M. (2012). Probabilistic topic models. *Communications of the ACM*, *55*(4), 77-84.

From Documents to Topics



Main techniques for Topic Modeling

- Latent Semantic Analysis (LSA)
  - The core idea is to take the Document-Term matrix and decompose it into a separate Document-Topic matrix and a Topic-Term matrix.
  - And its probabilistic version → pLSA.

- Latent Dirichlet Allocation (LDA)
  - Each **document** is considered a mixture of topics and each **word** in a document is considered randomly drawn from document's topics;
  - The **topics** are considered hidden (latent) and must be uncovered via analyzing joint distribution to compute the conditional distribution of hidden variables (**topics**) given the observed variables, **words in documents**.

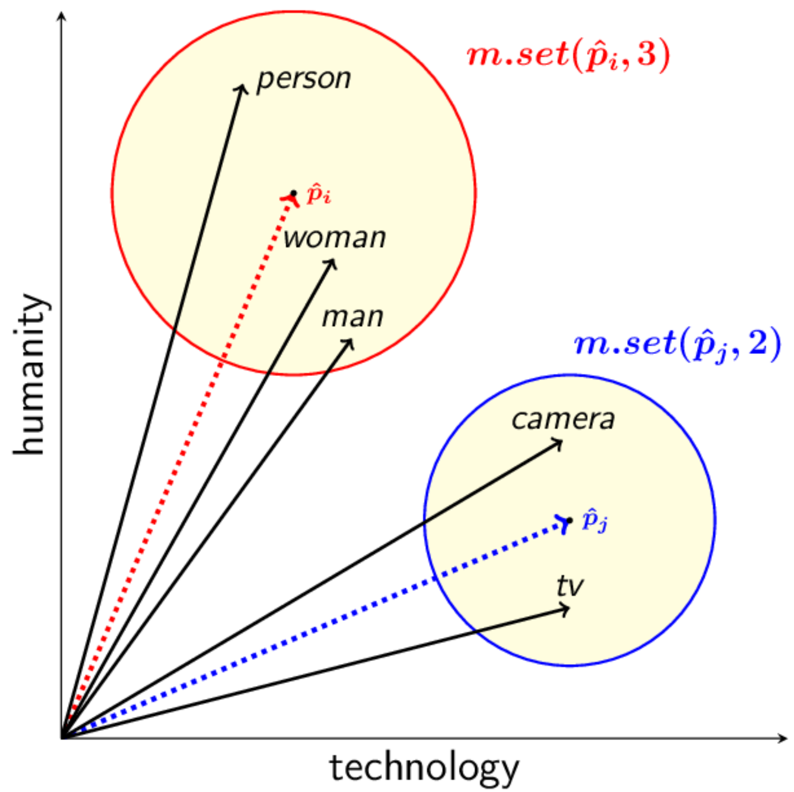
- Disregarding the approach, the output of a topic modeling algorithm is a list of topics with associated clusters of words (and their probabilities).

LATENT SEMANTIC ANALYSIS (LSA)

Latent Semantic Analysis (LSA)

- Latent Semantic Analysis (LSA) is one of the simplest Topic Modeling methods.

- It is based on the distributional hypothesis:
  - The semantics of words can be grasped by looking at the contexts the words appear in;
  - Under this hypothesis, the semantics of two words will be similar if they tend to occur in similar contexts.



Latent Semantic Analysis (LSA)

- LSA computes how frequently words occur in the documents – and the whole corpus – and assumes that similar documents will contain approximately the same distribution of word frequencies for certain words.

- In this case, syntactic information (e.g., word order) and semantic information (e.g., the multiplicity of meanings of a given word) are ignored, and each document is represented as a Bag of Words vector → It must be weighted! → Which **weighting** function?

Latent Semantic Analysis (LSA)

- The standard method for computing word frequencies in LSA applied to topic modeling is TF-IDF.

- Once TF-IDF frequencies have been computed, we can create a Document-Term matrix that contains the TF-IDF values for each term in a given document.

Latent Semantic Analysis (LSA)

Document-Term Matrix	Lebron	Senate	Celtics	Sprain	Cancer
Document 1	0.4	0.01	0.2	0	0
Document 2	0	0.9	0	0	0.02
Document 3	0	0	0	0.2	0.3
Document 4	0	0	0	0.2	0.3

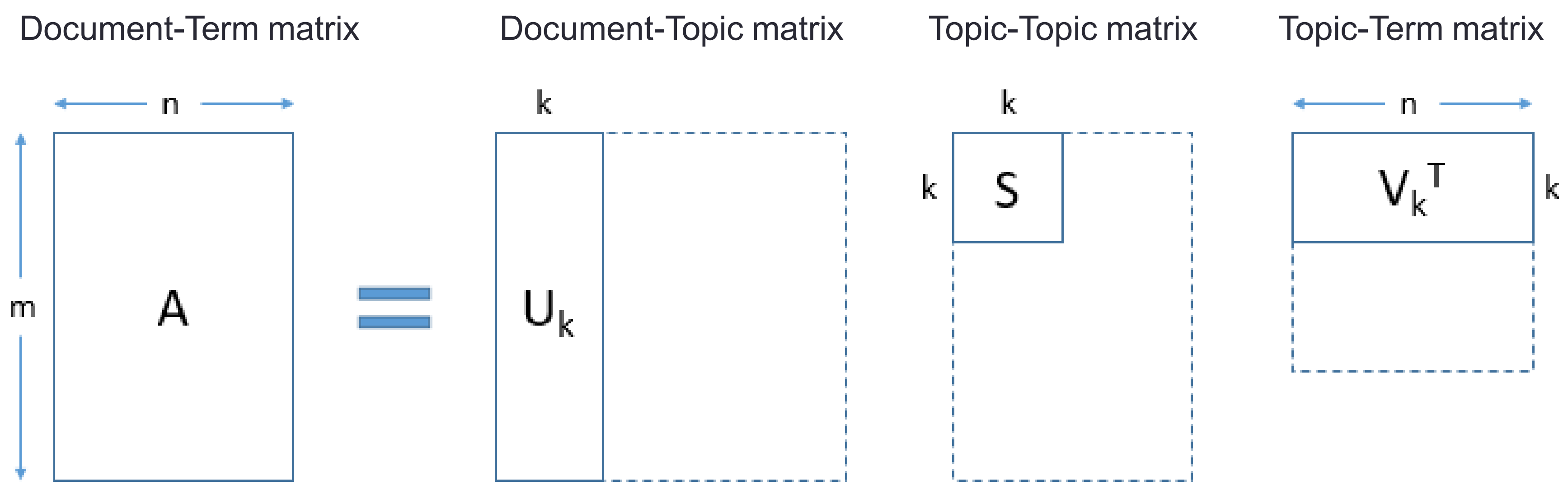
Latent Semantic Analysis (LSA)

- The Document-Term matrix can be decomposed into the product of 3 matrices (USV^T) by using Singular Value Decomposition (SVD).

- The U matrix is known as the Document-Topic matrix and the V^T matrix is known as the Topic-Term matrix.

- Linear algebra guarantees that the S matrix will be diagonal, and LSA will consider each singular value, i.e., each of the numbers in the main diagonal of matrix S, as a potential topic found in the documents.

Latent Semantic Analysis (LSA)



Latent Semantic Analysis (LSA)

	Term1	Term2	Term3	Term4
Doc1				
Doc2				
Doc3				
Doc4				

m x *m* matrix

=

Topic distribution across documents

	Topic1	Topic2
Doc1		
Doc2		
Doc3		
Doc4		

m x *n* singular matrix

×

Topic importance

	Topic1	Topic2
Topic1		
Topic2		

n x *n* diagonal matrix

×

Word assignment to topics

	Term1	Term2	Term3	Term4
Topic1				
Topic2				

n x *m* singular matrix

Latent Semantic Analysis (LSA)

Document-Term Matrix	Lebron	Senate	Celtics	Sprain	Cancer
Document 1	0.4	0.01	0.2	0	0
Document 2	0	0.9	0	0	0.02
Document 3	0	0	0	0.2	0.3
Document 4	0	0	0	0.2	0.3

Document-Topic Matrix	T1	T2	T3	T4
Document 1	0.8	0.2	0	0
Document 2	0	0.7	0	0
Document 3	0.1	0	0	0
Document 4	0.6	0	0.2	0.2

Topic-Term Matrix	Lebron	Senate	Celtisc	Sprain	Cancer
T1	0.8	0	0.9	0.6	0
T2	0.1	0.7	0.1	0	0
T3	0.1	0.3	0	0.4	0.7
…	…	…	…	…	…

Implementation of LSA in Python

```
#IMPORTING DATA

import pandas as pd
pd.set_option("display.max_colwidth", 200)

from sklearn.datasets import fetch_20newsgroups

dataset = fetch_20newsgroups(shuffle = True,
random_state=1, remove=('headers', 'footers', 'quotes'))

documents = dataset.data

#print(len(documents))

#print(dataset.target_names)
```

WARNING:
NOT to be used for
Projects !!!

Implementation of LSA in Python

```
11,314

['alt.atheism','comp.graphics','comp.os.ms-
windows.misc','comp.sys.ibm.pc.hardware','comp.sys.mac.har
dware','comp.windows.x','misc.forsale','rec.autos','rec.mo
torcycles','rec.sport.baseball','rec.sport.hockey','sci.cr
ypt','sci.electronics','sci.med','sci.space','soc.religion
.christian','talk.politics.guns','talk.politics.mideast','
talk.politics.misc','talk.religion.misc']
```

Implementation of LSA in Python

```
#BUILDING THE MATRIX

from sklearn.feature_extraction.text import
TfidfVectorizer

vectorizer = TfidfVectorizer(stop_words='english',
max_features= 1000, # keep top 1000 terms
max_df = 0.5,
smooth_idf = True)

X = vectorizer.fit_transform(news_df['clean_doc'])
```

Implementation of LSA in Python

```
#PERFORMING TOPIC MODELING

from sklearn.decomposition import TruncatedSVD

# SVD represent documents and terms in vectors
svd_model = TruncatedSVD(n_components = 20, algorithm =
'randomized', n_iter = 100, random_state = 122)

svd_model.fit(X)

#print(len(svd_model.components_))
```

Implementation of LSA in Python

```
#PRINTING TOPICS

terms = vectorizer.get_feature_names()

for i, comp in enumerate(svd_model.components_):
    terms_comp = zip(terms, comp)
    sorted_terms = sorted(terms_comp, key= lambda x:x[1], 
reverse=True)[:7]
    print("Topic "+str(i)+": ")
    for t in sorted_terms:
        print(t[0])
        print(" ")
```

Implementation of LSA in Python

```
Topic 0: like know people think good time thanks
Topic 1: thanks windows card drive mail file advance
Topic 2: game team year games season players good
Topic 3: drive scsi disk hard card drives problem
Topic 4: windows file window files program using problem
Topic 5: government chip mail space information encryption data
Topic 6: like bike know chip sounds looks look
Topic 7: card sale video offer monitor price jesus
Topic 8: know card chip video government people clipper
Topic 9: good know time bike jesus problem work
Topic 10: think chip good thanks clipper need encryption
Topic 11: thanks right problem good bike time window
Topic 12: good people windows know file sale files
Topic 13: space think know nasa problem year israel
Topic 14: space good card people time nasa thanks
Topic 15: people problem window time game want bike
Topic 16: time bike right windows file need really
Topic 17: time problem file think israel long mail
Topic 18: file need card files problem right good
Topic 19: problem file thanks used space chip sale
```

Some of LSA's Drawbacks

- Results that can be justified on the mathematical level, may have **no interpretable meaning** in natural language.

- LSA can only partially capture polysemy.
  - This is not always a problem due to words having a predominant sense throughout a corpus (i.e., not all meanings are equally likely).

- Limitations of the Bag of Words (BoW) model → unordered collection of words. Possible solutions:
  - Multi-gram dictionary can be used to find direct and indirect association;
  - Higher-order co-occurrences among terms → It analyzes indirect associations between words.

PROBABILISTIC LSA (pLSA)

High-level Description of pLSA

- pLSA uses a probabilistic method instead of SVD to tackle the problem.
- The core idea is to find a probabilistic model with latent topics that can generate the data we observe in our document-term matrix.
- In particular, we want a model $P(D, W)$ such that for any document $d \in D$ and word $w \in W$, $P(d, w)$ corresponds to that entry in the Document-Term matrix.

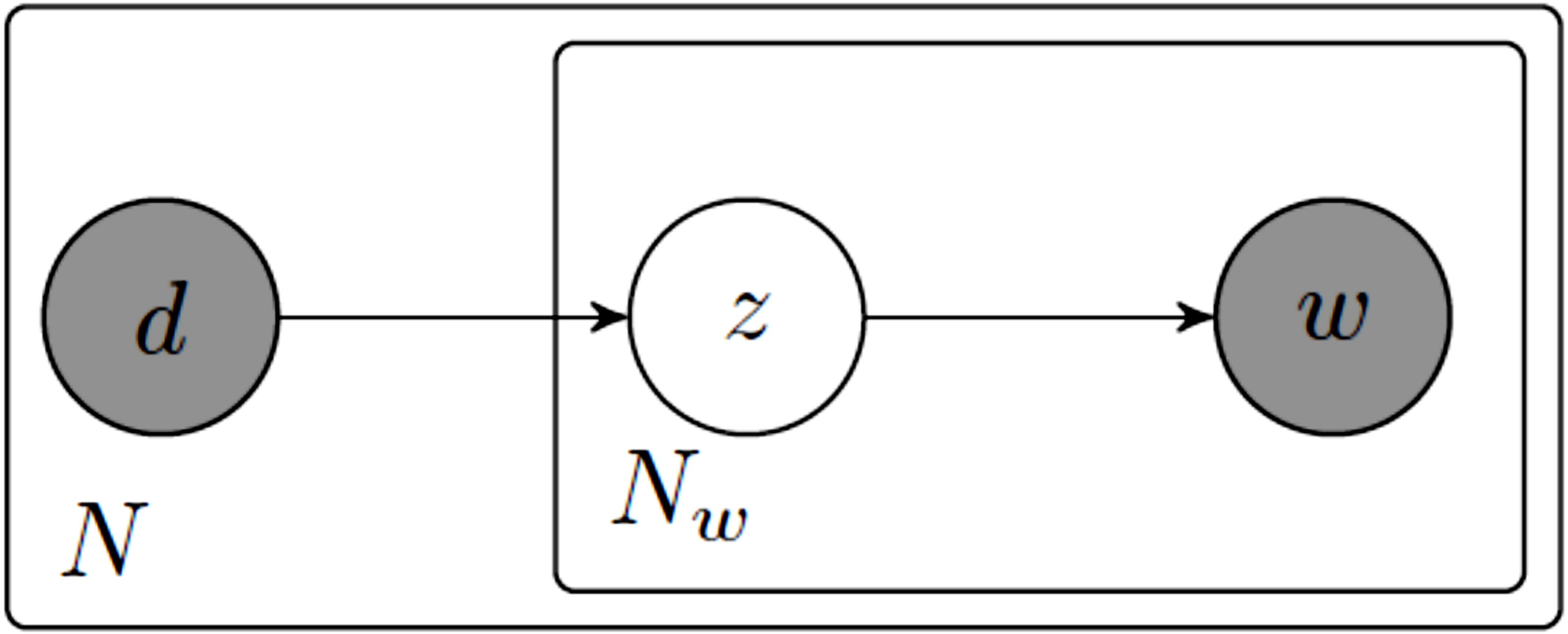
High-level Description of pLSA

- pLSA considers that our data can be expressed in terms of 3 sets of variables:
  - Documents: $d \in D = \{d_1, \dots, d_N\}$ observed variables. Let N be their number, defined by the size of our given corpus.
  - Words: $w \in W = \{w_1, \dots, w_M\}$ observed variables. Let M be the number of distinct words from the corpus.
  - Topics: $z \in Z = \{z_1, \dots, z_K\}$ latent (or hidden) variables. Their number, K, has to be specified a priori.

- $P(D, W) = \prod_{(d,w)} P(d, w)$

For more details:
http://homepages.inf.ed.ac.uk/rbf/CVonline/LOCAL_COPIES/AV1011/oneata.pdf

High-level Description of pLSA



High-level Description of pLSA

Probability theory

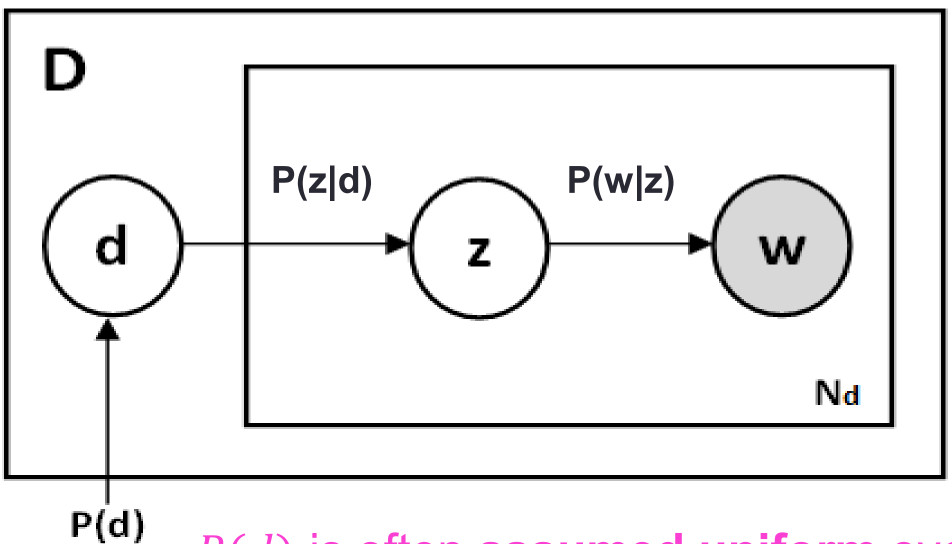
- $P(d, w)$ → Under conditional independence and using the Bayesian rule:

  → $P(w, d) = \sum_{z \in Z} P(z) P(d|z) P(w|z)$

  → $P(w, d) = P(d) \sum_{z \in Z} \underbrace{P(z|d)} \underbrace{P(w|z)}$

Probability of observing word w given topic z

Probability of topic z occurring in document d



$P(d)$ is often **assumed uniform** over all documents → $P(d) = 1/N$

Probabilistic LSA (Some details) (1)

From

$$P(w,d) = \sum_{z \in Z} P(z)P(d|z)P(w|z)$$

to?

$$P(w,d) = P(d)\sum_{z \in Z} P(z|d)P(w|z)$$

Probabilistic LSA (Some details) (2)

$$P(w,d) = \sum_{z \in Z} P(z)\boxed{P(d|z)}P(w|z) =$$

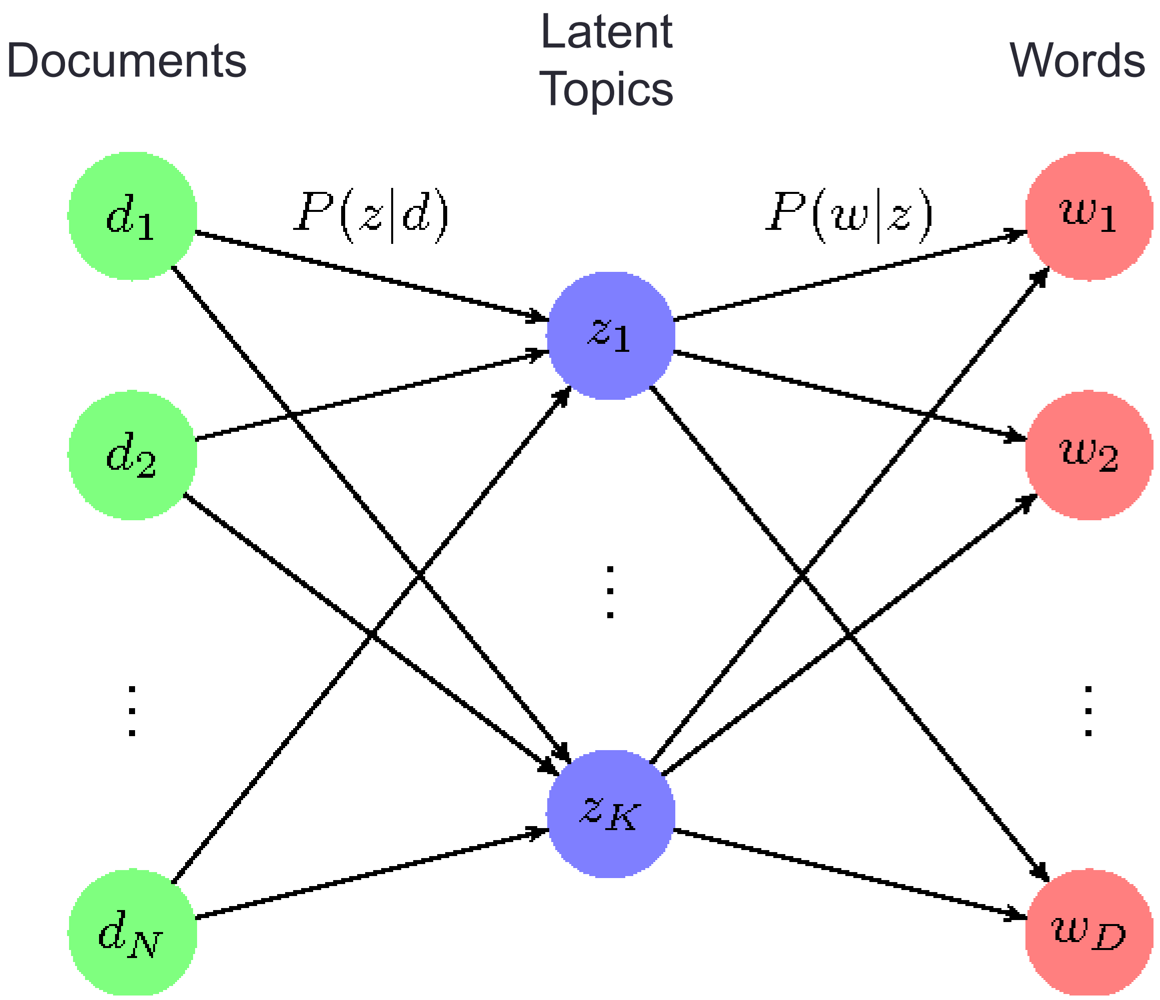
$$= \sum_{z \in Z} \cancel{P(z)} \frac{P(z|d)P(d)}{\cancel{P(z)}} P(w|z) =$$

$$= P(d) \sum_{z \in Z} P(z|d)P(w|z)$$

Bayes' Theorem

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

High-level Description of pLSA



High-level Description of pLSA

- If we reason in terms of matrix decomposition:

$$P(w,d) = \sum_{z \in Z} \underline{P(z)}\,\underline{P(d|z)}\,\underline{P(w|z)}$$

$$A \approx \underline{U_k}\,\underline{S_k}\,\underline{V_k^T}$$

- The distributions $P(z|d)$ and $P(w|z)$ are estimated in a way that maximizes the likelihood of the observed document-term matrix.

pLSA: Syntesis (1)

- Document-Term Matrix
  - Imagine to have a large collection of documents.
  - Each document can be represented as a Bag of Words vector → Must be **weigthed**!
  - We create a matrix where rows represent documents, columns represent unique words, and the cells contain the term frequency of each word (TF) in the corresponding document.

- Latent Semantic Analysis (LSA)
  - It analyzes the relationships between terms and documents by performing SVD on the document-term matrix (TF-IDF weights).
  - This helps identify latent (hidden) semantic patterns.

- pLSA, probabilistic aspect
  - In pLSA, the idea is to introduce a probabilistic model to the latent structure.
  - Instead of treating the relationships between terms and documents as fixed values, pLSA introduces probabilities.
  - It assumes that there are latent (hidden) variables governing the generation of terms within a document.

pLSA: Syntesis (2)

- Generative model
  - pLSA assumes that documents are generated by a mixture of latent topics, and each topic is associated with a probability distribution over terms.
  - The process of generating a document involves choosing a topic according to a probability distribution and then selecting words from the corresponding topic's distribution.
  - pLSA describes a process that "could have generated" the observed data.

- Estimating parameters
  - The goal in pLSA is to estimate the parameters of the model, which include the probability distributions over terms for each topic and the probability of each document belonging to a particular topic.
  - This is typically done using the Expectation-Maximization (EM) algorithm.
    - A statistical method used for finding maximum likelihood estimates of parameters in models with latent variables.

Expectation-Maximization

- The **Expectation–Maximization (EM)** algorithm is a general iterative optimization technique used to estimate parameters of probabilistic models — especially when there are latent (hidden) variables that we can not directly observe.

- E-Step (Expectation Step)
  - Based on a guess of the model's parameters, the algorithm calculates the expected value of the hidden variables.

- M-Step (Maximization Step):
  - Using the estimates from the E-step, the algorithm updates the parameters to maximize the likelihood of the observed data.
    - Mean, variance, etc.

Implementation of pLSA in Python

- Exercise.

- It can be part of your projects.

Probabilistic LSA (References)

- Hofmann, T. (1999, August). Probabilistic Latent Semantic Indexing. In Proceedings of the 22nd annual international ACM SIGIR conference on Research and development in information retrieval (pp. 50-57).
- Hofmann, T. (2013). Probabilistic latent semantic analysis. arXiv preprint arXiv:1301.6705.
- http://homepages.inf.ed.ac.uk/rbf/CVonline/LOCAL_COPIES/AV1011/oneata.pdf

LATENT DIRICHLET ALLOCATION (LDA)

High-level Description of LDA

- Latent Dirichlet Allocation (LDA) is a Bayesian version of pLSA.
  - LDA treats documents as Bags of Words → Which weight?
    - It is designed to discover topics based on term frequencies (TF).
  - LDA assumes documents are produced from a mixture of topics;
  - LDA categorizes documents by topic via a generative probabilistic model;
  - Distribution of topics in a document and the distribution of words in topics are Dirichlet distributions.

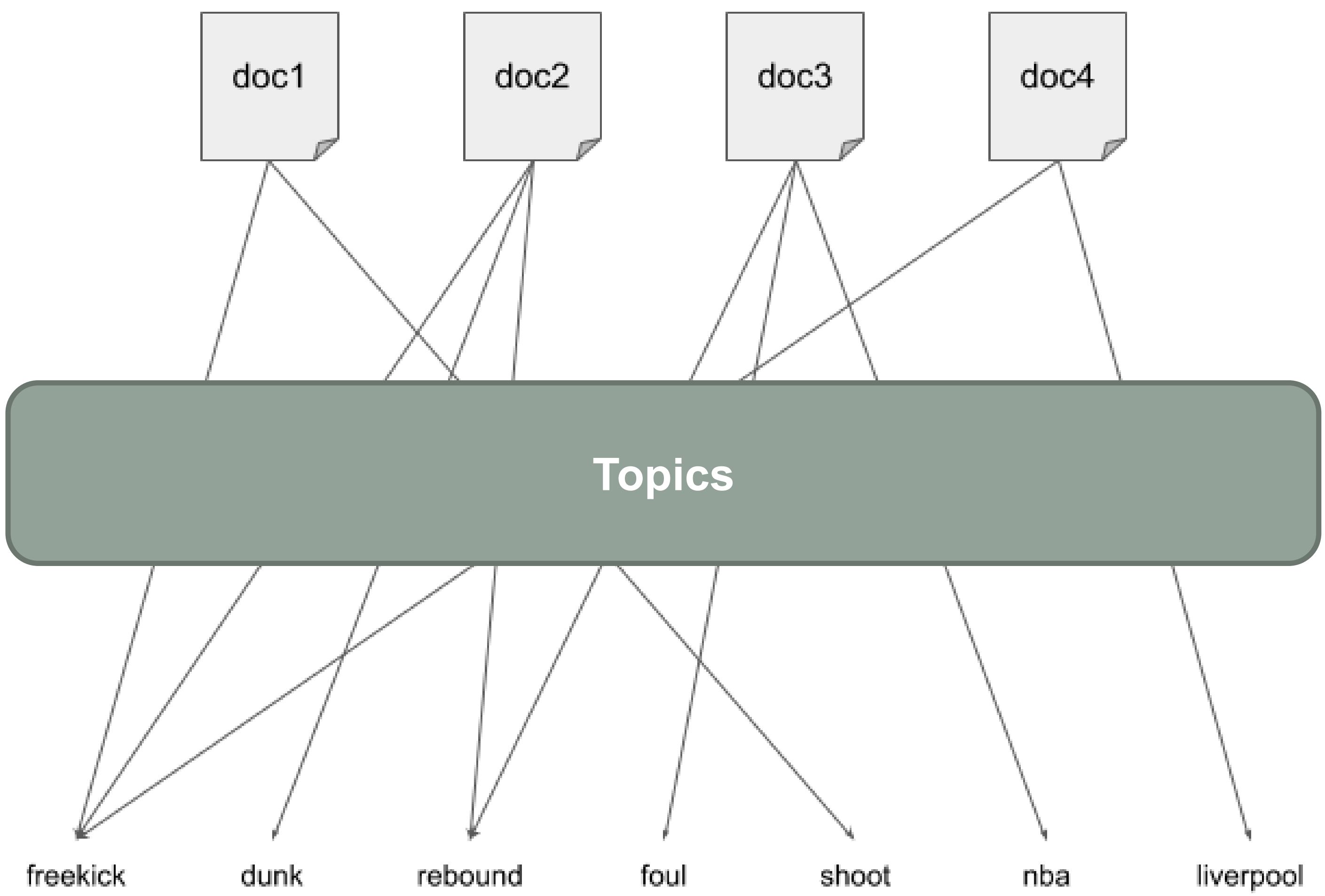
High-level Description of LDA

- The idea is that:
  - Words are generated from topics;
  - Each document has a particular probability of using particular topics to generate a given word;
  - We seek to find which topics given documents are likely to use to generate words.

High-level Description of LDA

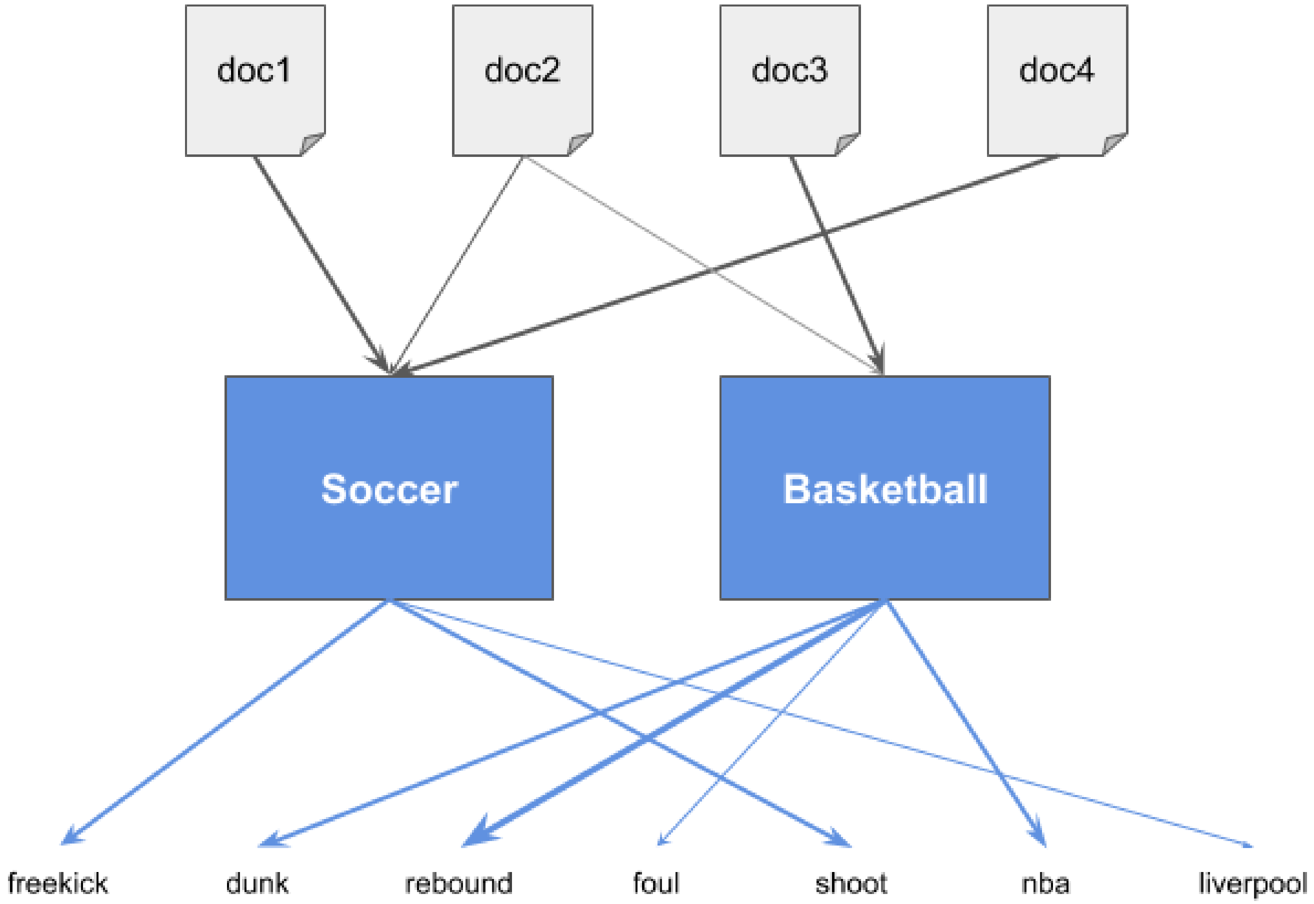
- INPUT: We start with a corpus of M documents and choose how many k topics we want to discover out of this corpus.
- OUTPUT: the topic model, and the M documents expressed as a combination of the k topics.
- OPERATION: the algorithm finds the weight of connections between documents and topics and between topics and words.

High-level Description of LDA



High-level Description of LDA

- For $k = 2$, an LDA model could look like this:



High-level Description of LDA

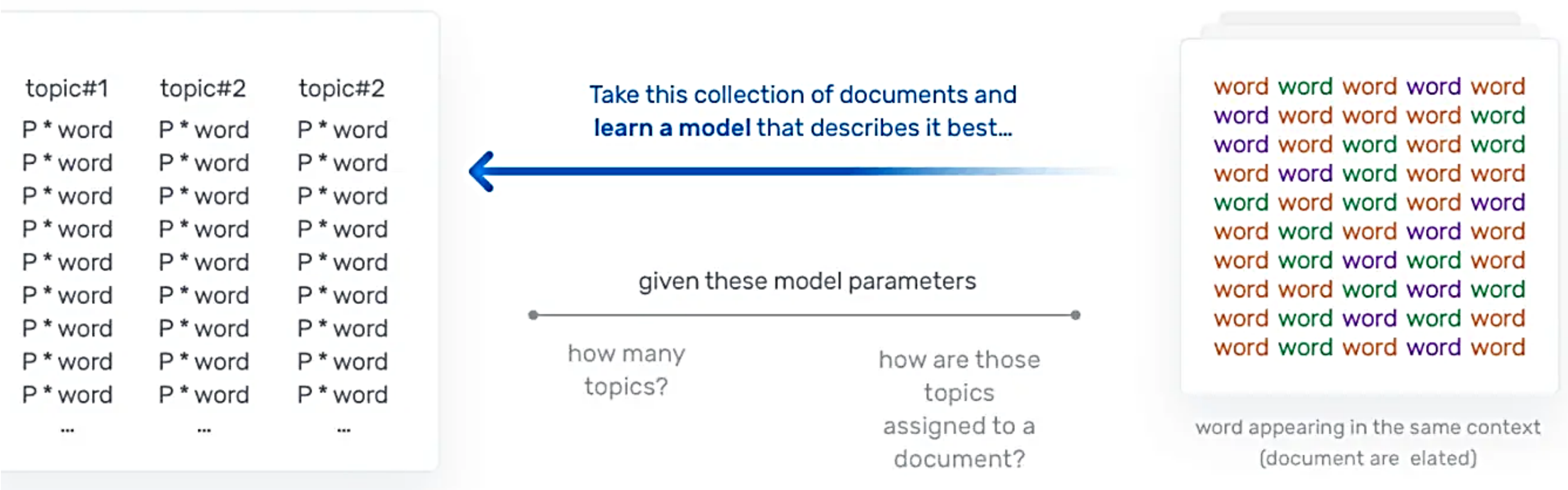
- The algorithm created an intermediate layer with topics and figured out the weights between documents and topics and between topics and words.

- Documents are no longer connected to words but to topics.

- In the previous example, each topic was named for clarity, but in real life, we would not know exactly what they represent.
  - We would have topics 1, 2, …, up to k, that's all.

High-level Description of LDA

- When LDA models a new document, it works in the following way:



Why Dirichlet Distributions?

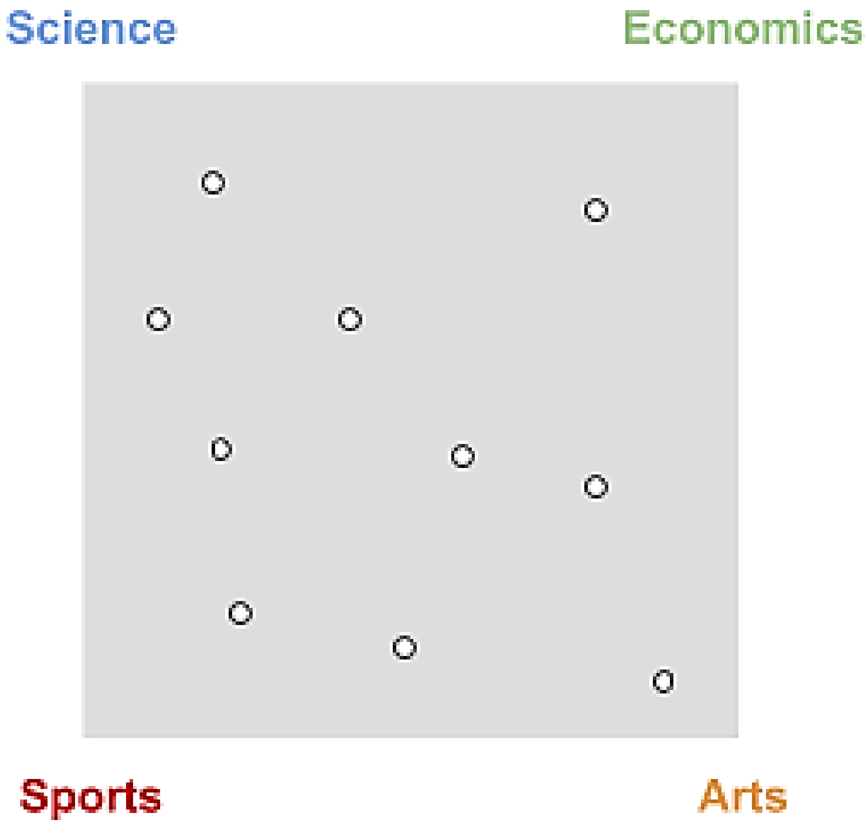
- Dirichlet distributions encode the intuition that documents are related to a few topics.

- In practical terms, this results in better disambiguation of words and a more precise assignment of documents to topics.

- Let us suppose to have four topics:
  - Science
  - Sports
  - Arts
  - Economics

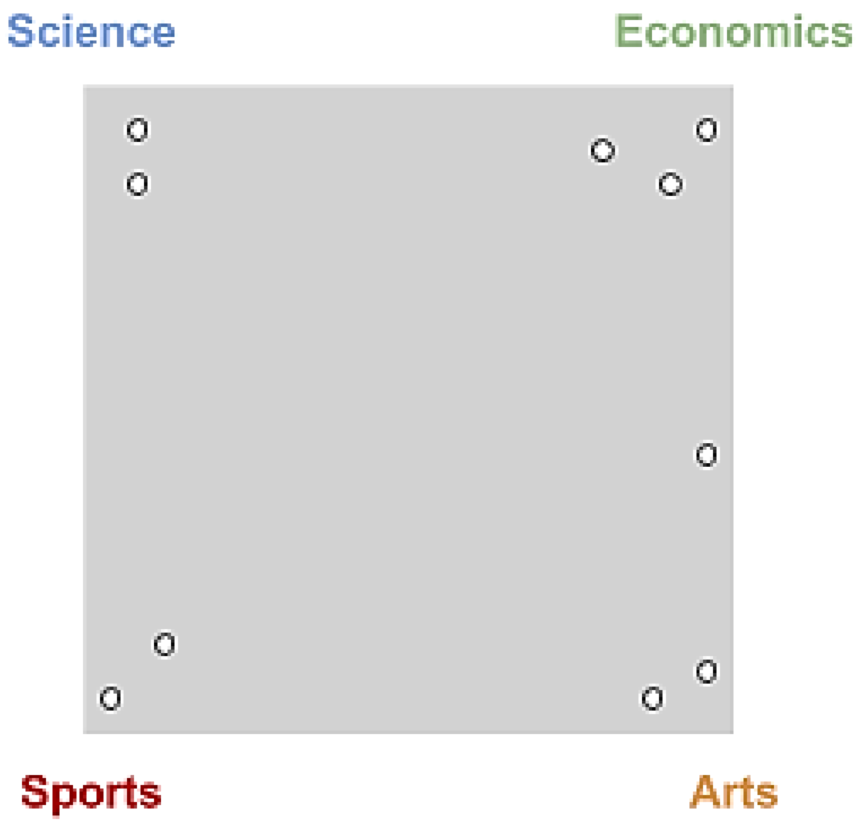
Why Dirichlet Distributions?

- In a random distribution, documents would be evenly distributed across the four topics:



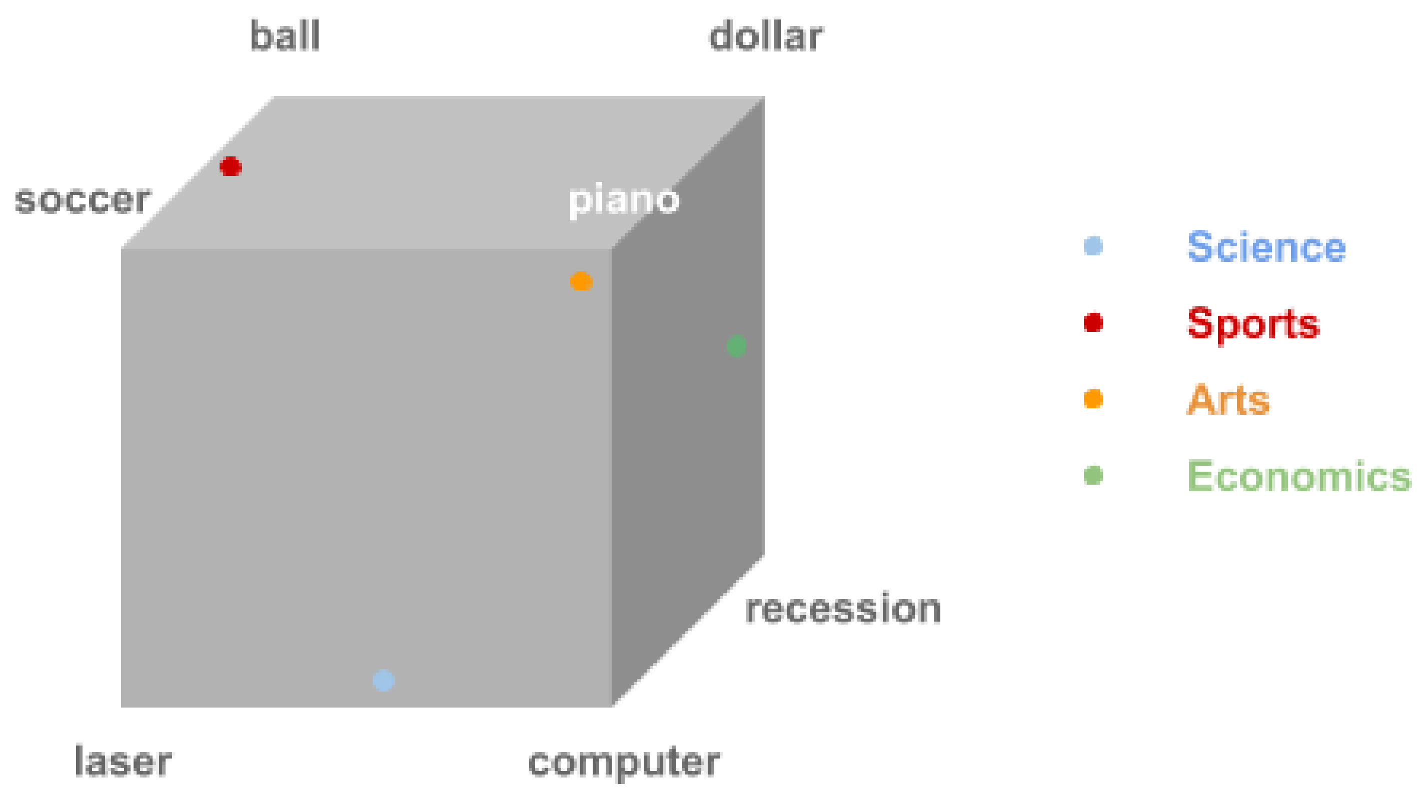
Why Dirichlet Distributions?

- In real life, however, we know they are more sparsely distributed, like this:



What are Dirichlet Distributions?

- This also happens between topics and words:



What are Dirichlet Distributions?

- A Dirichlet distribution $Dir(p)$ is a way to model a probability function (PF) which gives probabilities for discrete random variables.

- Example: rolling a die
  - It is a discrete random variable: The result is unpredictable, and the values can be 1, 2, 3, 4, 5, or 6.
  - For a fair die, a PF would give these probabilities: [0.16, 0.16, 0.16, 0.16, 0.16, 0.16].
  - For a biased die, a PF could return these probabilities: [0.25, 0.15, 0.15, 0.15, 0.15, 0.15], where obtaining a one is higher than the other sides.

What are Dirichlet Distributions?

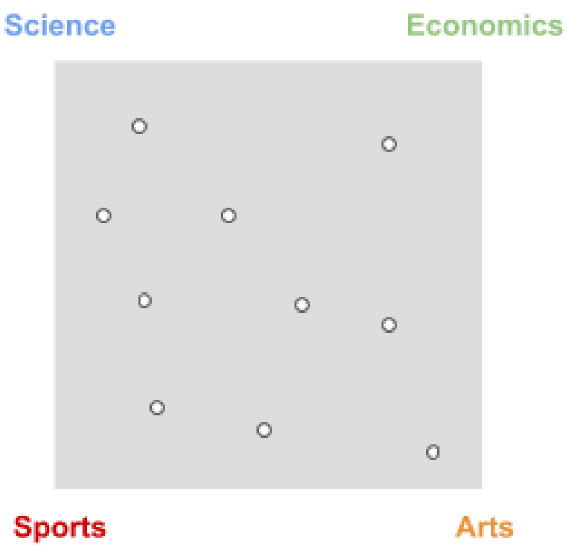
- In the example with documents, topics, and words, we have two PFs:
  - θ_d: the probability of topic k occurring in document d;
  - φ_k: the probability of word w occurring in topic k.

- The p parameter in $Dir(p)$ is named concentration parameter, and rules the trend of the distribution to be:
  - uniform ($p = 1$)
  - concentrated ($p > 1$)
  - sparse ($p < 1$)

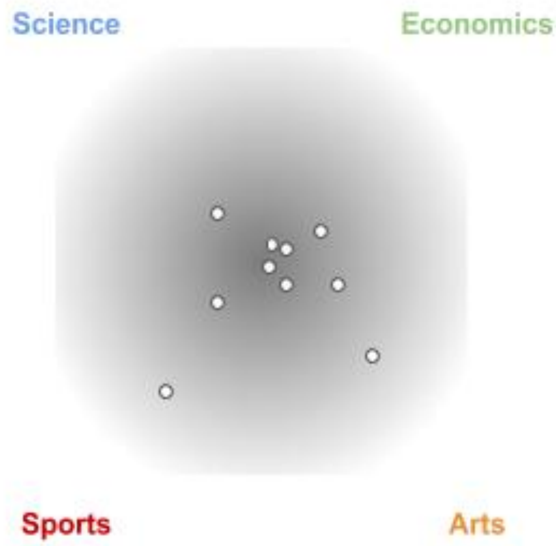
What are Dirichlet Distributions?

- When we consider document and topics, we denote $p = \alpha$.

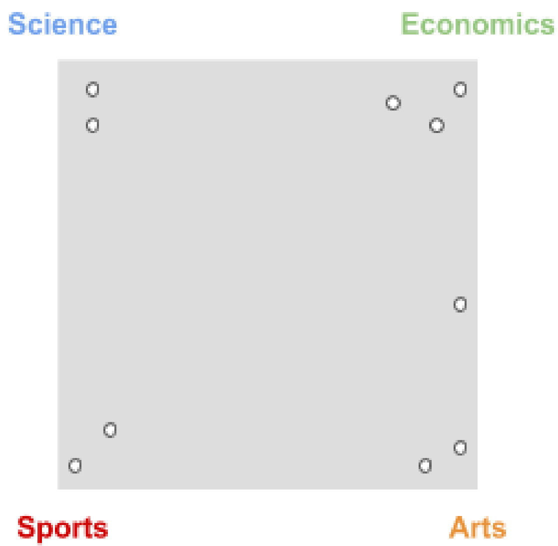
distribution with $\alpha = 1$



distribution with $\alpha > 1$



distribution with $\alpha < 1$



What are Dirichlet Distributions?

- When we consider topics and words, we denote $p = \beta$.

- By using concentration parameters $\alpha, \beta < 1$, these probabilities will be closer to the real world.

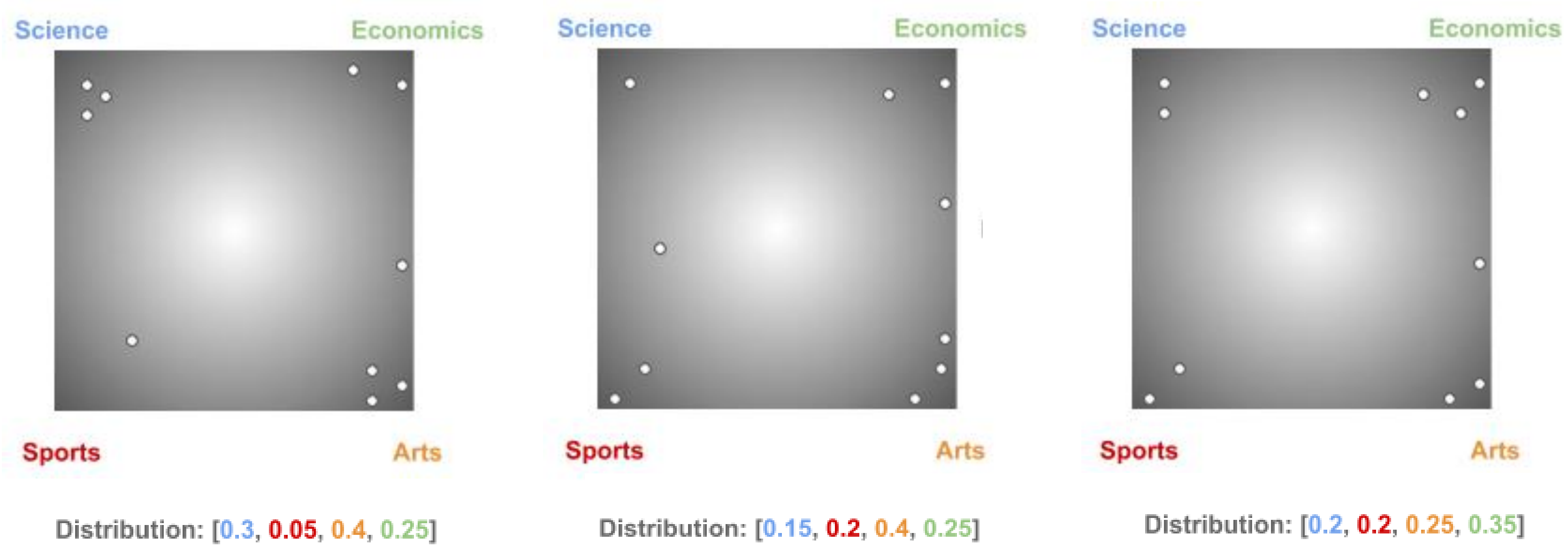
- In other words, they follow Dirichlet distributions:

$$\theta_d \approx Dir(\alpha)$$
$$\varphi_k \approx Dir(\beta)$$

where α and β rule each distribution, and both have values < 1.

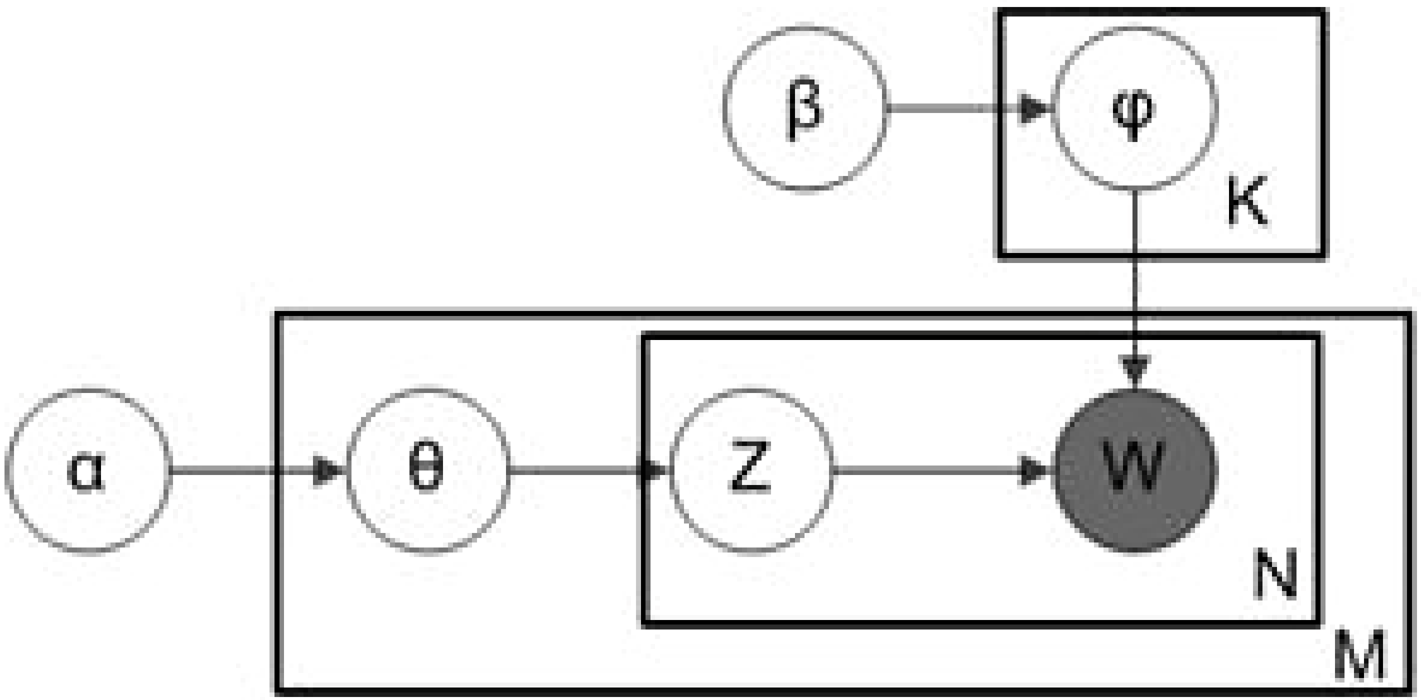
What are Dirichlet Distributions?

- IMPORTANT. Using the same concentration parameter, e.g., α, we obtain many different distributions of documents over topics



- They get adjusted during the training process to make the model better.

High-level Description of LDA



Parameters of LDA (1)

- Alpha and Beta Hyperparameters
  - Alpha represents document-topic density.
    - Higher the value of alpha, documents are composed of more topics and lower the value of alpha, documents contain fewer topics.
  - Beta represents topic-word density.
    - Higher the beta, topics are composed of a large number of words in the corpus, and with the lower value of beta, they are composed of few words.

- Number of Topics
  - Selected randomly.
  - By using the Kullback-Leibler (KL) Divergence Score.

Parameters of LDA (2)

- Number of Topic Terms
  - Generally decided according to the requirement.
    - If the problem statement talks about extracting themes or concepts, it is recommended to choose a higher number;
    - If problem statement talks about extracting features or terms, a low number is recommended.

- Number of Iterations
  - Maximum number of iterations allowed to LDA algorithm for convergence.

Implementation of LDA in Python

```
#IMPORTING DATA - AS IN THE LSA EXAMPLE

#PREPROCESSING - LDA requires some basic pre-processing of text data

def tokenize_lemma_stopwords(text):
        tokens = nltk.tokenize.word_tokenize(text.lower())
        # split string into words (tokens)
        tokens = [t for t in tokens if t.isalpha()]
        # keep strings with only alphabets
        tokens = [wordnet_lemmatizer.lemmatize(t) for t in tokens]
        # put words into base form
        tokens = [stemmer.stem(t) for t in tokens]
        tokens = [t for t in tokens if len(t) > 2]
        # remove short words, they're probably not useful
        tokens = [t for t in tokens if t not in stopwords]
        # remove stopwords

        return tokens

def dataCleaning(data):
        data["content"] = data["content"].apply(tokenize_lemma_stopwords)
        return data
```

Implementation of LDA in Python

```
#Convert pre-processed tokens into a dictionary with word index
and it's count in the corpus
#We can use gensim package to create this dictionary then to
create bag-of-words

dictionary = gensim.corpora.Dictionary(X)

dictionary.filter_extremes(no_below=5, no_above=0.5,
keep_n=100000)
# filter words that occurs in less than 5 documents and words
that occurs in more than 50% of total documents
# keep top 100000 frequent words

bow_corpus = [dictionary.doc2bow(doc) for doc in X]
# create bag-of-words ==> list(index, count) for words in
doctionary
```

Implementation of LDA in Python

```
# Create lda model with gensim library
# Manually pick number of topic

lda_model = gensim.models.LdaModel(bow_corpus,
                                   id2word=dictionary,
                                   num_topics=5,
                                   offset=2,
                                   random_state=100,
                                   update_every=1,
                                   passes=10,
                                   alpha='auto',
                                   beta="auto",
                                   per_word_topics=True)
```

Implementation of LDA in Python

```
from pprint import pprint
pprint(lda_model.print_topics())

[(0, # Seems to be Computer and Technology
  '0.014*"key" + 0.007*"chip" + 0.006*"encryption" + 0.006*"system" + '
  '0.005*"clipper" + 0.005*"article" + 0.004*"university" + '
  '0.004*"information" + 0.004*"government" + 0.004*"time"'),
 (1, # Seems to be Science and Technology
  '0.008*"drive" + 0.007*"university" + 0.007*"window" + 0.007*"system" + '
  '0.006*"doe" + 0.005*"card" + 0.005*"thanks" + 0.005*"space" + '
  '0.004*"article" + 0.004*"computer"'),
 (2, # Seems to be politics
  '0.010*"people" + 0.006*"gun" + 0.006*"armenian" + 0.005*"time" + '
  '0.005*"article" + 0.005*"then" + 0.005*"israel" + 0.004*"war" + '
  '0.004*"government" + 0.004*"israeli"'),
 (3, # Seems to be sports
  '0.013*"game" + 0.011*"team" + 0.008*"article" + 0.007*"university" + '
  '0.006*"player" + 0.006*"time" + 0.005*"play" + 0.005*"season" + '
  '0.004*"hockey" + 0.004*"win"'),
 (4, # Seems to be religion
  '0.018*"god" + 0.011*"people" + 0.008*"doe" + 0.008*"christian" + '
  '0.007*"jesus" + 0.006*"believe" + 0.006*"then" + 0.006*"article" + '
  '0.005*"life" + 0.005*"time"')]
```

RECAP: TF-IDF or just TF?

- The use of **TF-IDF (Term Frequency-Inverse Document Frequency)** in Latent Semantic Analysis (LSA) versus **TF (Term Frequency)** in Probabilistic Latent Semantic Analysis (PLSA) and Latent Dirichlet Allocation (LDA) stems from the underlying methodologies and objectives of these models.

RECAP: TF-IDF in LSA

- **LSA** is a linear algebra-based technique that applies **Singular Value Decomposition (SVD)** to a term-document matrix.
  - The goal of LSA is to reduce dimensionality and uncover latent semantic structures by finding patterns of co-occurrence in the matrix.

- **TF-IDF is used in LSA** to enhance the term-document matrix before applying SVD:
  - **TF-IDF weighting** helps balance term importance:
    - Terms frequent in a document (high term frequency, TF) are given more weight.
    - Terms that are too common across all documents (low inverse document frequency, IDF) are downweighted.
  - By emphasizing terms that are both relevant (high TF) and distinctive (high IDF), TF-IDF helps LSA focus on meaningful semantic patterns.

RECAP: TF in pLSA and LDA

- **PLSA and LDA** are probabilistic models that treat documents as mixtures of latent topics and aim to infer these topic distributions. They use the **bag-of-words representation** (TF-based counts) as input.

- **Generative model framework**: These methods model the generative process of text:
  - For a given topic, words are sampled based on their probability distributions.
  - Incorporating TF-IDF would interfere with the probabilistic interpretation of word frequencies since TF-IDF normalizes and scales raw counts.

- **Statistical foundation**: LDA relies on word counts to estimate Dirichlet distributions over topics and words. Modifying these counts with TF-IDF would disrupt this statistical foundation.

NOWADAYS: Embedding-based approaches

- BERTopic
  - Grootendorst, M. (2022). BERTopic: Neural topic modeling with a class-based TF-IDF procedure. *arXiv preprint arXiv:2203.05794*.
  - Uses BERT embeddings + HDBSCAN clustering + TF-IDF for topic representation.
  - Excellent for capturing semantic similarity.
  - Handles short texts and multilingual corpora.

- Top2Vec
  - Angelov, D. (2020). Top2vec: Distributed representations of topics. *arXiv preprint arXiv:2008.09470*.
  - Learns joint embeddings of documents and words.
  - Finds dense clusters of semantically similar documents.
  - Produces topics automatically without specifying the topic count upfront.

EVALUATING TOPIC MODELING

Evaluation Approaches

- Eye Balling Models
  - Top-*n* words
  - Topics/Documents

- Intrinsic Evaluation Metrics
  - Capturing model semantics
  - Topics interpretability

Internal coherence of topic models

- Human Judgements
  - Quantitative methods for evaluating human judgement

- Extrinsic Evaluation Metrics/Evaluation at task
  - Is the model good at performing predefined tasks, such as classification?

Intrinsic Evaluation Metrics

- Intrinsic Evaluation metrics that best describe the performance of a topic model:
    - Perplexity
    - Coherence
    - Diversity

Measure Details

- Perplexity is a measure of uncertainty, meaning lower the perplexity better the model.
- Coherence is the measure of semantic similarity between top words in our topic. Higher the coherence better the model performance.
- Diversity evaluates whether topics are diverse and not redundant.

Perplexity

- Perplexity is a statistical measure of how well a probability model predicts a sample.

- It aims to capture how “surprised” a model is of new data it has not seen before.

- This metric is measuring “how probable” some new unseen data is given the model that was learned earlier.

```
#COMPUTING PERPLEXITY

print('Perplexity: ',
lda_model.log_perplexity(bow_corpus))
```

Coherence

- Topic Coherence measures score a single topic by measuring the degree of semantic similarity between high scoring words in the topic.

- These measurements help distinguish between topics that are semantically interpretable topics and topics that are artifacts of statistical inference.

```
#COMPUTING COHERENCE

coherence_model_lda =
models.CoherenceModel(model=lda_model, texts=X,
dictionary=dictionary, coherence='c_v’)

coherence_lda = coherence_model_lda.get_coherence()
print('Coherence Score: ', coherence_lda)
```

Distinct Coherence measures

- **`c_v`**
  - based on a sliding window, one-set segmentation of the top words and an indirect confirmation measure that uses normalized pointwise mutual information (NPMI) and the cosine similarity.
- **`c_p`**
  - based on a sliding window, one-preceding segmentation of the top words and the confirmation measure of Fitelson’s coherence.
- **`c_uci`**
  - based on a sliding window and the pointwise mutual information (PMI) of all word pairs of the given top words.

Distinct Coherence measures

- **`c_umass`**
  - based on document cooccurrence counts, a one-preceding segmentation and a logarithmic conditional probability as confirmation measure.
- **`c_npmi`**
  - enhanced version of the `c_uci` coherence using the normalized pointwise mutual information (NPMI).
- **`c_a`**
  - baseed on a context window, a pairwise comparison of the top words and an indirect confirmation measure that uses normalized pointwise mutual information (NPMI) and the cosine similarity.

Diversity

- Metrics for diversity could include measuring the cosine similarity between topic vectors or quantifying the spread of topics across documents.

- Redundant topics might occur when the model identifies similar topics with slight variations.

```
#COMPUTING DIVERSITY

doc_topic_matrix =
lda_model.get_document_topics(corpus)
doc_topic_array = np.array([np.array(doc_topic)[:, 1]
for doc_topic in doc_topic_matrix])
cosine_sim_matrix = cosine_similarity(doc_topic_array)

topic_diversity = 1 - np.mean(np.max(cosine_sim_matrix,
axis=1))
print("Topic Diversity: {topic_diversity}")
```

A (VERY) BRIEF INTRODUCTION TO TOPIC CLASSIFICATION

Topic Modeling VS Topic Classification

- Topic Modeling is an unsupervised machine learning technique (i.e., it does not require training).
  - If there is not the possibility to priorly analyze texts (to label it), or if the aim is not looking for a fine-grained analysis, topic modeling algorithms are indicated.

- Topic Classification is a supervised machine learning technique, i.e., it needs training before being able to automatically analyze texts.
  - If there is a list of predefined topics for a set of texts, and the aim is to gain accurate insights, topic classification is more suitable.

Topic Classification Approaches

- Rule-based systems
  - Human-based
- Machine learning systems
  - Automatic supervised approaches
- Hybrid systems
  - A mix of the previous two

Rule-Based Systems

- They works by directly programming a set of hand-made rules, based on the content of the documents that a human expert has read.

- Each one of these rules is made up of a pattern and a prediction. Since we are focusing on topic analysis, the prediction will be the topic.

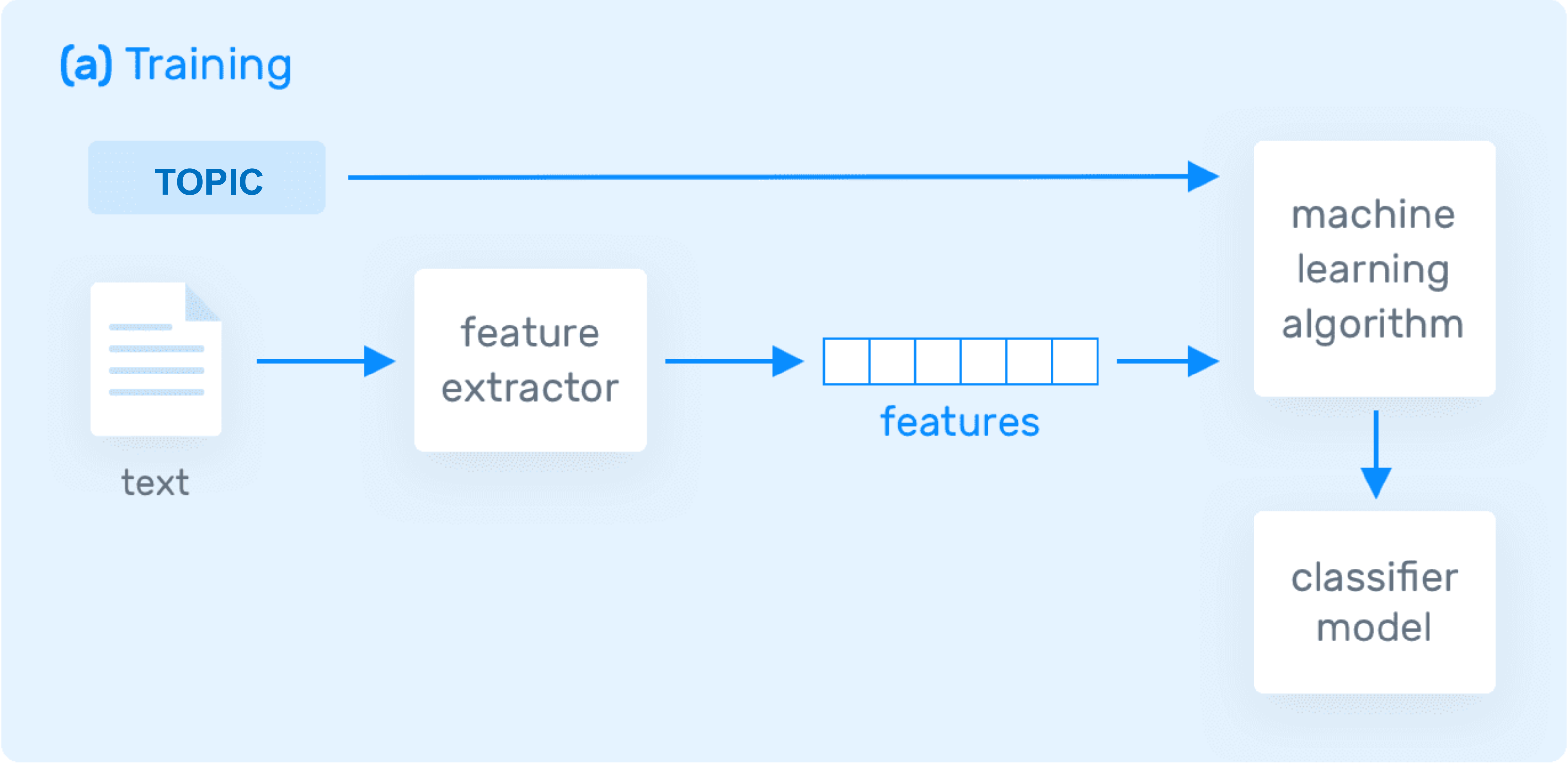
- Downsides:
  - Too complex for someone without expert knowledge;
  - Require constant analysis and testing to ensure they are functioning in the correct way;
  - When adding new rules, existing rules are altered;
  - In short, these systems are high-maintenance and unscalable.

Machine Learning Systems

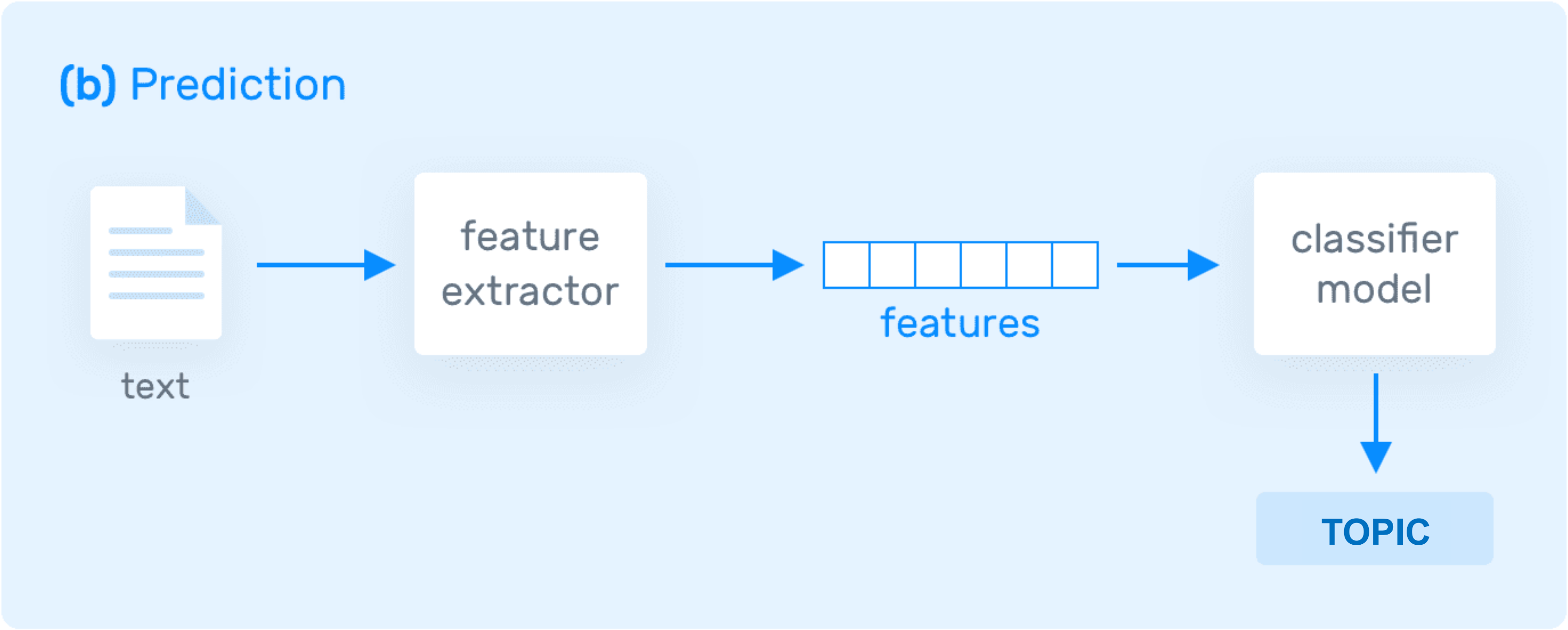
- A topic classification machine learning model needs to be fed examples of text and a list of predefined tags, known as training data.

- Once the text is transformed into vectors and the training data is tagged with the expected tags, this information is fed to an algorithm to create the classification model.

Machine Learning Systems



Machine Learning Systems



Machine Learning Systems

- Naive Bayes
  - Family of that deliver good results even when dealing with small amounts of data, say between 1,000 and 10,000 texts;
  - It works by correlating the probability of words appearing in a text with the probability of that text being about a certain topic.

- Support Vector Machines (SVM)
  - Slightly more complex than Naive Bayes;
  - They often deliver better results than NB for topic classification;
  - Downside: they require complex programming and require more computing resources.
    - It is possible to speed up the training process of an SVM by optimizing the algorithm by feature selection, in addition to running an optimized linear kernel such as scikit-learn's Linear SVC.

Machine Learning Systems

- Deep Learning
  - Topic Classification benefit from Deep Learning;
  - It employs two main deep learning architectures:
    - Convolutional Neural Networks (CNN);
    - Recurrent Neural Networks (RNN).
    - Downside: They require much more training data than traditional machine learning algorithms.
      - Instead of, for example, 1,000 training samples, it is necessary to have millions of samples.

Hybrid Systems

- These are simply combinations of machine learning classifiers and rule-based systems, which improve results as you fine-tune rules.

- You can use these to rules to tweak topics that have been incorrectly modeled by the machine learning classifier.

Metrics and Evaluation

- As in many other classification tasks, in Topic Classification it is necessary to test the actual label (topic) for a specific text and compare it to the predicted label (topic).

- With the results, it is possible to compute the following (well-known) evaluation metrics:
  - Accuracy: the percentage of texts that were assigned the correct topic;
  - Precision: the percentage of texts the classifier tagged correctly out of the total number of texts it predicted for each topic;
  - Recall: the percentage of texts the model predicted for each topic out of the total number of texts it should have predicted for that topic;
  - F1 Score: the average of both Precision and Recall.