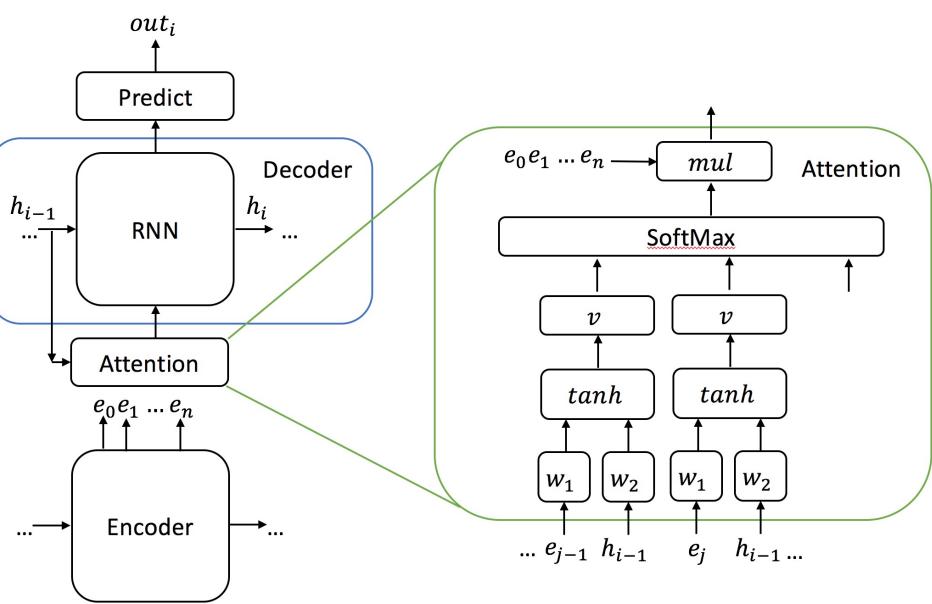
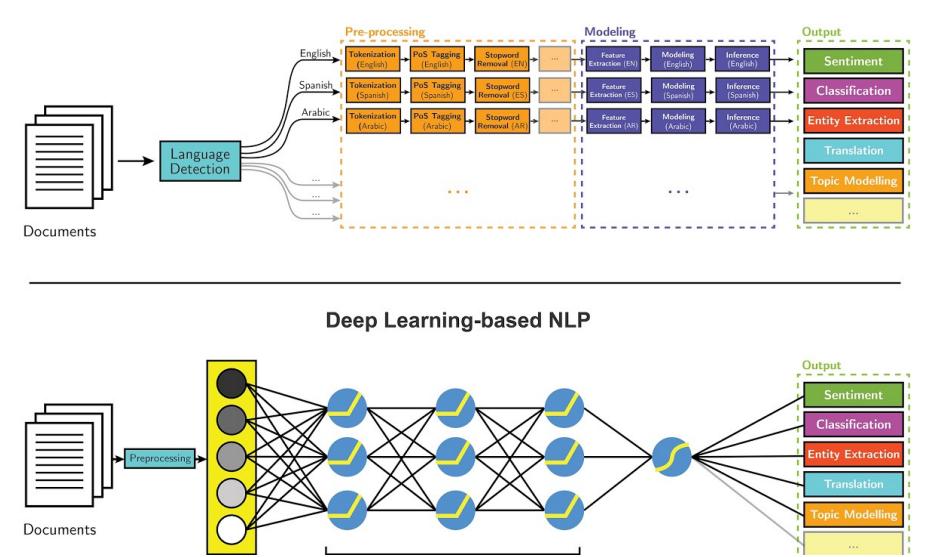
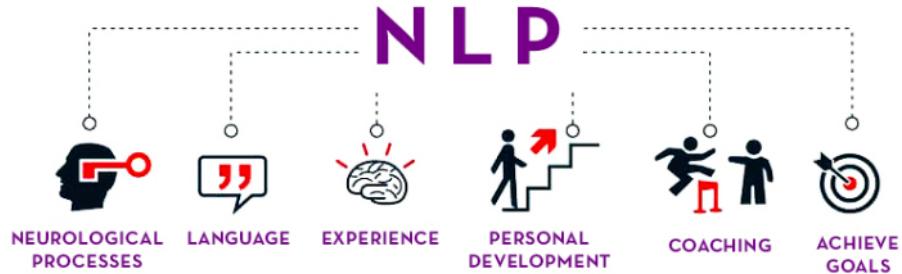
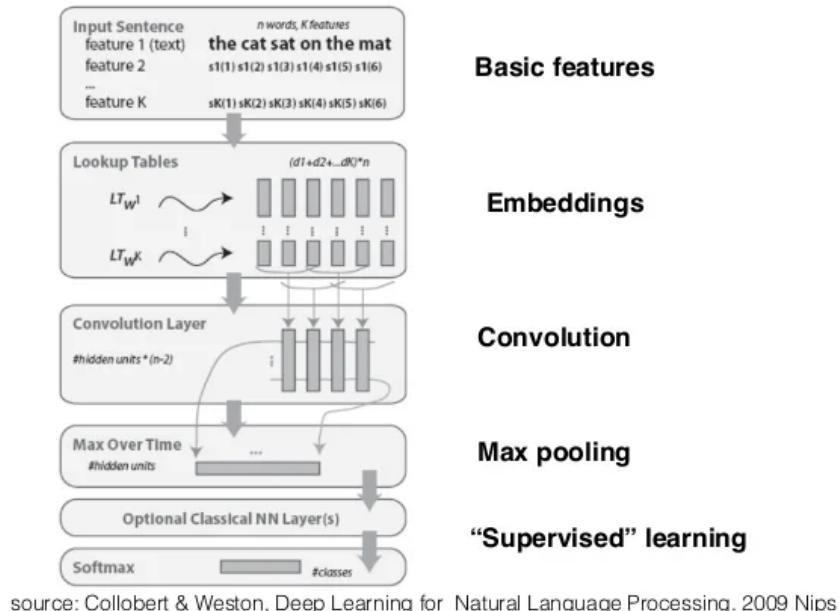


Memo - Natural Language Processing

Natural Language Processing Introduction



General Deep Architecture for NLP



source: Collobert & Weston, Deep Learning for Natural Language Processing. 2009 Nips

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Deep Learning vs NLP

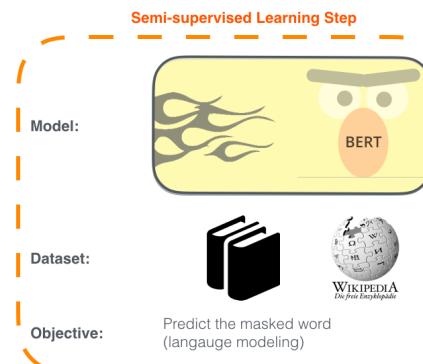
Comparison Chart

Deep Learning	NLP
Deep learning is a subset of the field of machine learning based on artificial neural networks that teaches computers to learn by example.	Natural Language Processing is the ability of a computer program to understand human language as it is spoken.
It is a function of artificial intelligence that imitates human brain in processing data and creating patterns for decision making uses.	It investigates the use of computers to process or to understand human languages for the purpose of performing useful tasks.
It is an AI function that mimics human learning and thinking process to process data that is both unstructured and unlabeled.	NLP is the relationship between computers and human language.
Deep learning algorithms are used in Google language translation services, Alexa, self-driving cars, voice synthesis, facial recognition, etc.	Applications include machine translation, automatic summarization, automatic speech recognition, chatbots, market intelligence, customer service, etc.



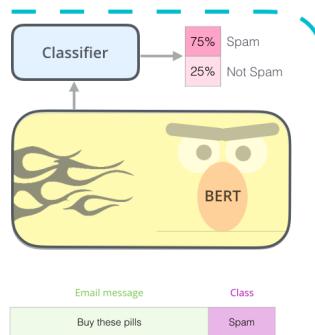
1 - **Semi-supervised** training on large amounts of text (books, wikipedia..etc).

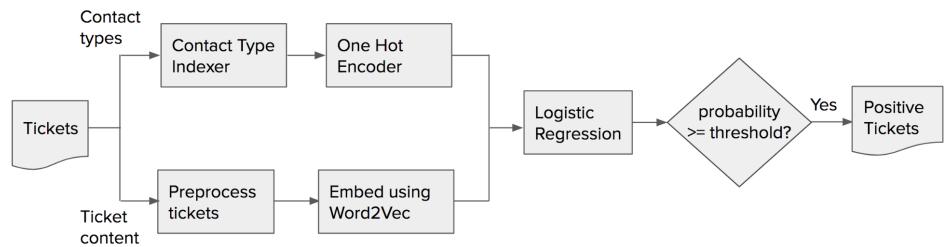
The model is trained on a certain task that enables it to grasp patterns in language. By the end of the training process, BERT has language-processing abilities capable of empowering many models we later need to build and train in a supervised way.



2 - **Supervised** training on a specific task with a labeled dataset.

Supervised Learning Step





```
from google.colab import drive
drive.mount('/content/drive', force_remount=True)
```

Model Resources

[TensorFlow Hub](#)

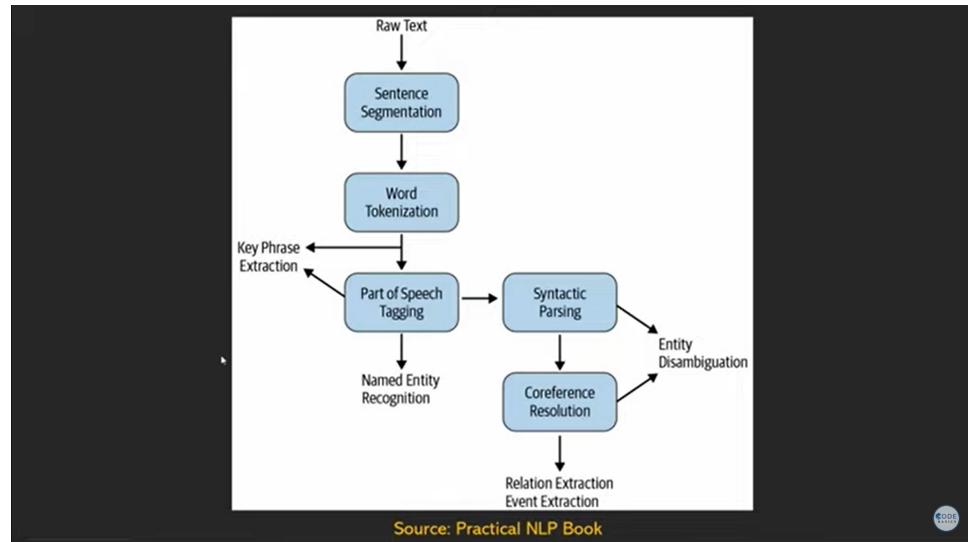
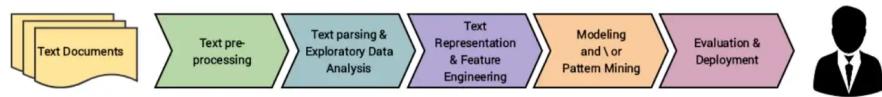
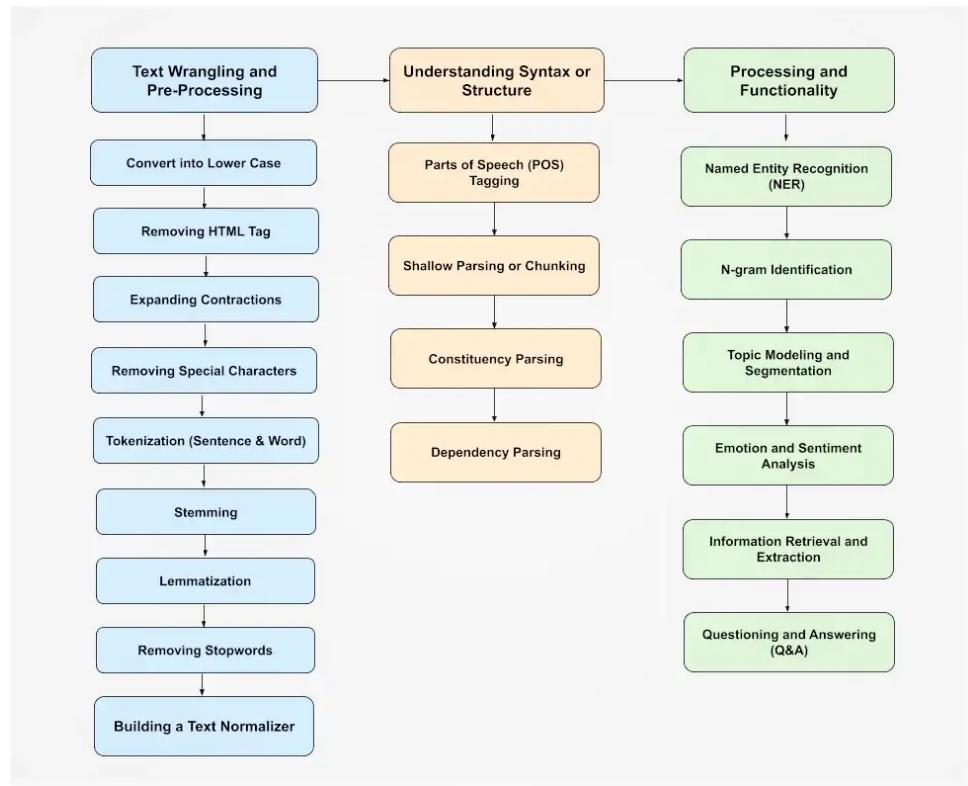
[fastText](#)

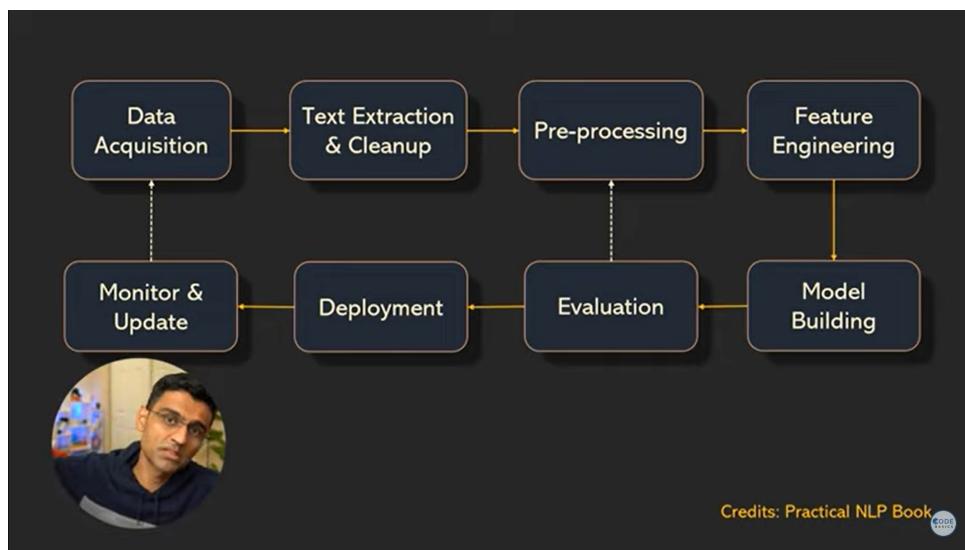
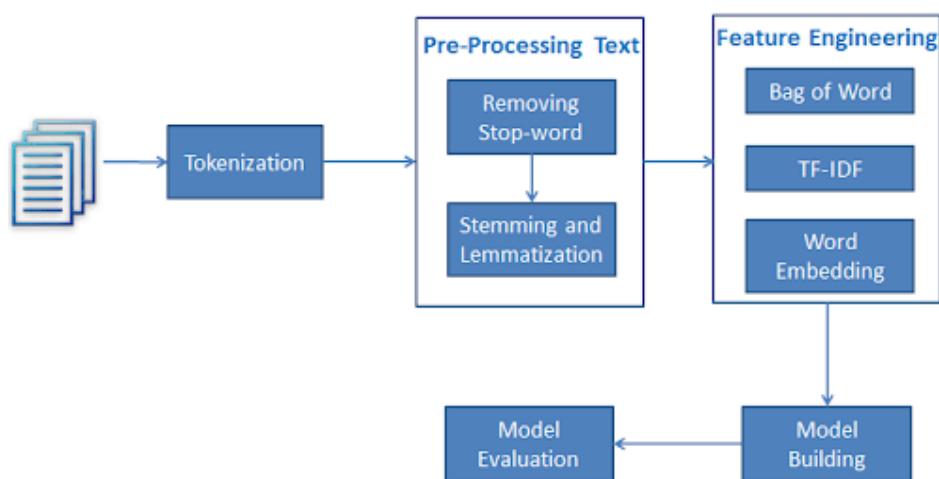
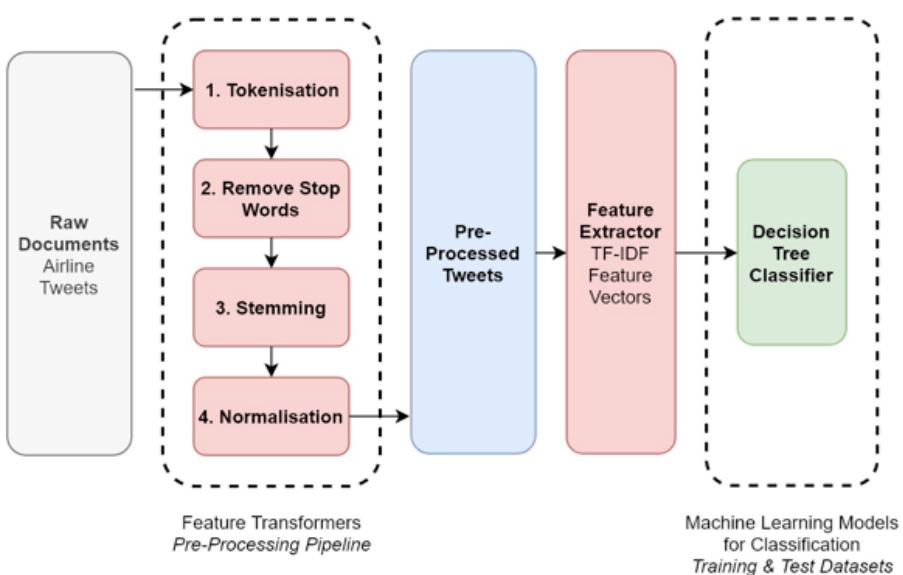
[GPT-3](#)

OpenSource Ecosystem - Libraries



Workflow





Pre-processing - Spacy vs NLTK

Spacy	NLTK
Spacy is Object Oriented	NLTK is mainly a string processing library
Spacy is user friendly	NLTK is also user friendly but probably less user friendly compared to Spacy
Provides most efficient NLP algorithm for a given task. Hence if you care about the end result, go with Spacy	Provides access to many algorithms. If you care about specific algo and customizations go with NLTK
Spacy is new library and has a very active user community	NLTK is old library. User community as active as Spacy
	
the differences. I hope you like this	

NLTK

```
In [ ]: import nltk
```

```
In [ ]: nltk.download('punkt')
```

```
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\User\AppData\Roaming\nltk_data...
[nltk_data]     Package punkt is already up-to-date!
```

```
Out[ ]: True
```

```
In [ ]: from nltk.tokenize import sent_tokenize
```

```
In [ ]: sent_tokenize("An end to end NLP project consists of many steps. These steps together forms an NLP pipeline. The pipeline has various stages such as data acquisition, data cleaning, pre-processing, model building, deployment, monitor and update etc.")
```

```
Out[ ]: ['An end to end NLP project consists of many steps.',  
        'These steps together forms an NLP pipeline.',  
        'The pipeline has various stages such as data acquisition, data cleaning, pre-processing, model building, deployment, monitor and update etc.']
```

```
In [ ]: from nltk.tokenize import word_tokenize  
word_tokenize("An end to end NLP project consists of many steps.")
```

```
Out[ ]: ['An',  
        'end',  
        'to',  
        'end',  
        'NLP',  
        'project',  
        'consists',  
        'of',  
        'many',  
        'steps',  
        '.']
```

Spacy

```
In [ ]: import spacy
```

```
In [ ]: !python -m spacy download en
```

```
In [ ]: nlp = spacy.load('en_core_web_sm')
#nlp = spacy.blank("en")
```

```
In [ ]: type(nlp)
```

```
Out[ ]: spacy.lang.en.English
```

```
In [ ]: text = "An end to end NLP project consists of many steps. These steps together form
```

```
In [ ]: doc = nlp(text)
type(doc)
```

```
Out[ ]: spacy.tokens.doc.Doc
```

```
In [ ]: for sentence in doc.sents:
    print(sentence)
```

An end to end NLP project consists of many steps.

These steps together forms an NLP pipeline.

The pipeline has various stages such as data acquisition, data cleaning, pre-processing, model building, deployment, monitor and update etc.

```
In [ ]: for word in sentence:
    print(word)
```

The
pipeline
has
various
stages
such
as
data
acquisition
,

data
cleaning
,

pre
-
processing
,

model
building
,

deployment
,

monitor
and
update
etc
.

```
In [ ]: for token in doc:
    print(token)
```

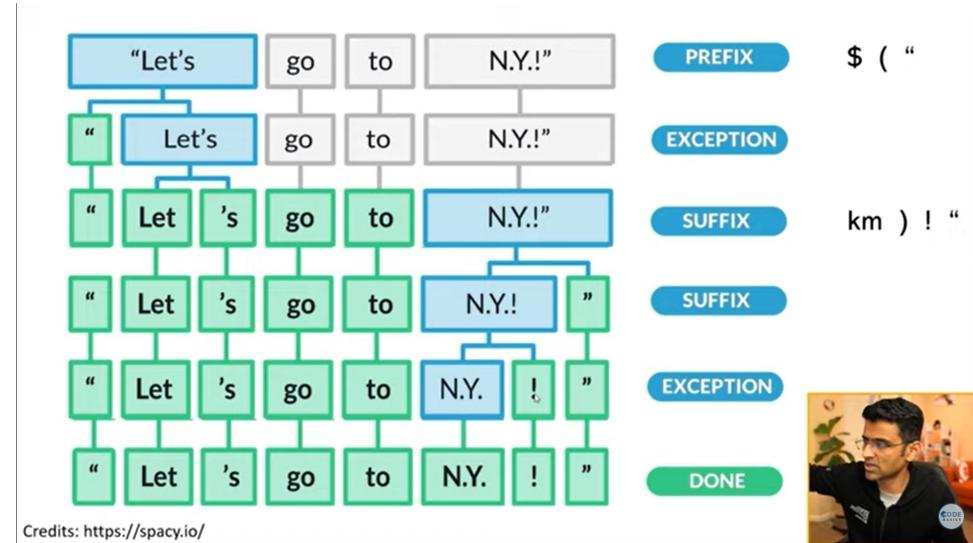
```
An  
end  
to  
end  
NLP  
project  
consists  
of  
many  
steps  
. .  
These  
steps  
together  
forms  
an  
NLP  
pipeline  
. .  
The  
pipeline  
has  
various  
stages  
such  
as  
data  
acquisition  
,,  
data  
cleaning  
,,  
pre  
-  
processing  
,,  
model  
building  
,,  
deployment  
,,  
monitor  
and  
update  
etc  
. .
```

In []: doc[0]

Out[]: An

In []: doc[-1]

Out[]: .



```
In [ ]: token_0 = doc[0]  
token_0
```

Out[]: An

In []: type(token 0)

Out[]: spacy.tokens.token.Token

```
In [ ]: dir(token 0)
```

```
Out[ ]: ['_',
 '_bytes_',
 '_class_',
 '_delattr_',
 '_dir_',
 '_doc_',
 '_eq_',
 '_format_',
 '_ge_',
 '_getattribute_',
 '_gt_',
 '_hash_',
 '_init_',
 '_init_subclass_',
 '_le_',
 '_len_',
 '_lt_',
 '_ne_',
 '_new_',
 '_pyx_vtable_',
 '_reduce_',
 '_reduce_ex_',
 '_repr_',
 '_setattr_',
 '_sizeof_',
 '_str_',
 '_subclasshook_',
 '_unicode_',
 'ancestors',
 'check_flag',
 'children',
 'cluster',
 'conjuncts',
 'dep',
 'dep_',
 'doc',
 'ent_id',
 'ent_id_',
 'ent_iob',
 'ent_iob_',
 'ent_kb_id',
 'ent_kb_id_',
 'ent_type',
 'ent_type_',
 'get_extension',
 'has_dep',
 'has_extension',
 'has_head',
 'has_morph',
 'has_vector',
 'head',
 'i',
 'idx',
 'iob_strings',
 'is_alpha',
 'is_ancestor',
 'is_ascii',
 'is_bracket',
 'is_currency',
 'is_digit',
 'is_left_punct',
```

```
'is_lower',
'is_oov',
'is_punct',
'is_quote',
'is_right_punct',
'is_sent_end',
'is_sent_start',
'is_space',
'is_stop',
'is_title',
'is_upper',
'lang',
'lang_',
'left_edge',
'lefts',
'lemma',
'lemma_',
'lex',
'lex_id',
'like_email',
'like_num',
'like_url',
'lower',
'lower_',
'morph',
'n_lefts',
'n_rights',
'nbor',
'norm',
'norm_',
'orth',
'orth_',
'pos',
'pos_',
'prefix',
'prefix_',
'prob',
'rank',
'remove_extension',
'right_edge',
'rights',
'sent',
'sent_start',
'sentiment',
'set_extension',
'set_morph',
'shape',
'shape_',
'similarity',
'subtree',
'suffix',
'suffix_',
'tag',
'tag_',
'tensor',
'text',
'text_with_ws',
'vector',
'vector_norm',
'vocab',
'whitespace_']
```

```
In [ ]: token_0.text
```

```
Out[ ]: 'An'
```

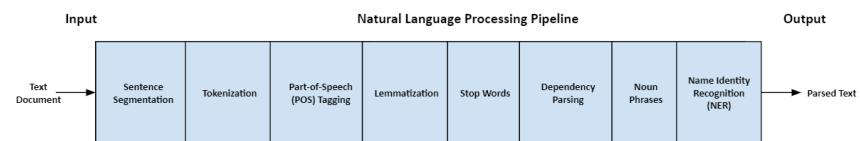
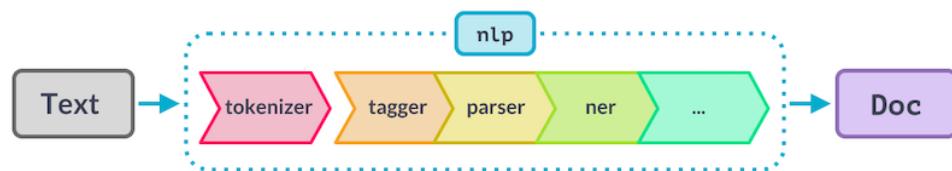
```
In [ ]: token_0.like_num
```

```
Out[ ]: False
```

Pipeline in Spacy

```
!pip intall spacy
!python -m spacy download en
import spacy
nlp = spacy.load("en_core_web_sm")
```

NLP Pipeline: Building an NLP Pipeline, Step-by-Step



NAME	COMPONENT	CREATES	DESCRIPTION
tokenizer	<code>Tokenizer</code>	<code>Doc</code>	Segment text into tokens.
tagger	<code>Tagger</code>	<code>Doc[i].tag</code>	Assign part-of-speech tags.
parser	<code>DependencyParser</code>	<code>Doc[i].head</code> , <code>Doc[i].dep</code> , <code>Doc.sents</code> , <code>Doc.noun_chunks</code>	Assign dependency labels.
ner	<code>EntityRecognizer</code>	<code>Doc.ents</code> , <code>Doc[i].ent_iob</code> , <code>Doc[i].ent_type</code>	Detect and label named entities.
textcat	<code>TextCategorizer</code>	<code>Doc.cats</code>	Assign document labels.
...	<code>custom components</code>	<code>Doc._.xxx</code> , <code>Token._.xxx</code> , <code>Span._.xxx</code>	Assign custom attributes, methods or properties.

```
In [ ]: import spacy
nlp = spacy.blank("en")

In [ ]: with open("data/student.txt", "r") as f:
    text = f.readlines()
print(text)

['Dayton high school, 8th grade students information\n', '=====
=====\\n', '\\n', 'Name\\tbirth day \\temail\\n', '----\\t----\n-----\\t----\\n', 'Virat 5 June, 1882 virat@kohli.com\\n', 'Maria\\t12 April, 2001 maria@sharapova.com\\n', 'Serena 24 June, 1998 serena@williams.com \\n', 'Joe 1 May, 1997 joe@root.com']

In [ ]: text = " ".join(text)
text

Out[ ]: 'Dayton high school, 8th grade students information\n =====\n =====\\n Name\\tbirth day \\temail\\n ----\\t-----\\t----\n -\\n Virat 5 June, 1882 virat@kohli.com\\n Maria\\t12 April, 2001 maria@sharapova.com\\n Serena 24 June, 1998 serena@williams.com \\n Joe 1 May, 1997 joe@root.com'

In [ ]: doc = nlp(text)
emails = []
for token in doc:
    if token.like_email:
        emails.append(token)
emails

Out[ ]: [virat@kohli.com, maria@sharapova.com, serena@williams.com, joe@root.com]
```

Customizing tokenizer

```
In [ ]: doc = nlp("gimme double cheese extra large healthy pizza")

In [ ]: tokens = [token for token in doc]
tokens

Out[ ]: [gimme, double, cheese, extra, large, healthy, pizza]

In [ ]: from spacy.symbols import ORTH

nlp.tokenizer.add_special_case("gimme", [
    {ORTH: "gim"}, 
    {ORTH: "me"}, 
])
doc = nlp("gimme double cheese extra large healthy pizza")
tokens = [token for token in doc]
tokens

Out[ ]: [gim, me, double, cheese, extra, large, healthy, pizza]

In [ ]: import spacy
nlp = spacy.blank("en")

doc = nlp("Captain america ate 100$ of samosa. Then he said I can do this all day.")
```

```
for token in doc:  
    print(token)
```

```
Captain  
america  
ate  
100  
$  
of  
samosa  
. .  
Then  
he  
said  
I  
can  
do  
this  
all  
day  
. .
```

```
In [ ]: nlp = spacy.blank("en")  
  
nlp.pipe_names
```

```
Out[ ]: []
```

```
In [ ]: nlp = spacy.load('en_core_web_sm')  
  
nlp.pipe_names
```

```
Out[ ]: ['tok2vec', 'tagger', 'parser', 'attribute_ruler', 'lemmatizer', 'ner']
```

```
In [ ]: nlp.pipeline
```

```
Out[ ]: [('tok2vec', <spacy.pipeline.tok2vec.Tok2Vec at 0x2351d837dc0>),  
         ('tagger', <spacy.pipeline.tagger.Tagger at 0x2351d837fa0>),  
         ('parser', <spacy.pipeline.dep_parser.DependencyParser at 0x2351d74a490>),  
         ('attribute_ruler',  
          <spacy.pipeline.attributeruler.AttributeRuler at 0x2351da6dd80>),  
         ('lemmatizer', <spacy.lang.en.lemmatizer.EnglishLemmatizer at 0x2351da97980>),  
         ('ner', <spacy.pipeline.ner.EntityRecognizer at 0x2351d74a420>)]
```

```
In [ ]: doc = nlp("Captain america ate 100$ of samosa. Then he said I can do this all day.")  
  
for token in doc:  
    print(token, " ", token.pos_, " ", token.lemma_)
```

```

Captain      PROPN      Captain
america     PROPN      america
ate         VERB       eat
100        NUM        100
$           NOUN       $
of          ADP        of
samosa     PROPN      samosa
.          PUNCT      .
Then        ADV        then
he          PRON      he
said       VERB       say
I           PRON      I
can         AUX        can
do          VERB       do
this       PRON      this
all         DET        all
day         NOUN      day
.          PUNCT      .

```

```
In [ ]: doc = nlp("Captain america ate 100$ of samosa. Then he said I can do this all day.")

for token in doc:
    print(token, " ", spacy.explain(token.pos_), " ", token.lemma_)
```

```

Captain      proper noun      Captain
america     proper noun      america
ate         verb       eat
100        numeral      100
$           noun       $
of          adposition    of
samosa     proper noun      samosa
.          punctuation   .
Then        adverb      then
he          pronoun     he
said       verb       say
I           pronoun     I
can         auxiliary   can
do          verb       do
this       pronoun     this
all         determiner   all
day         noun       day
.          punctuation   .

```

Adding a Customizing Component to a blank pipeline

```
In [ ]: nlp_source = spacy.load("en_core_web_sm")

nlp = spacy.blank("en")

nlp.add_pipe("ner", source=nlp_source)

nlp.pipe_names
```

```
Out[ ]: ['ner']
```

```
In [ ]: nlp.pipe_names
```

```
Out[ ]: ['ner']
```

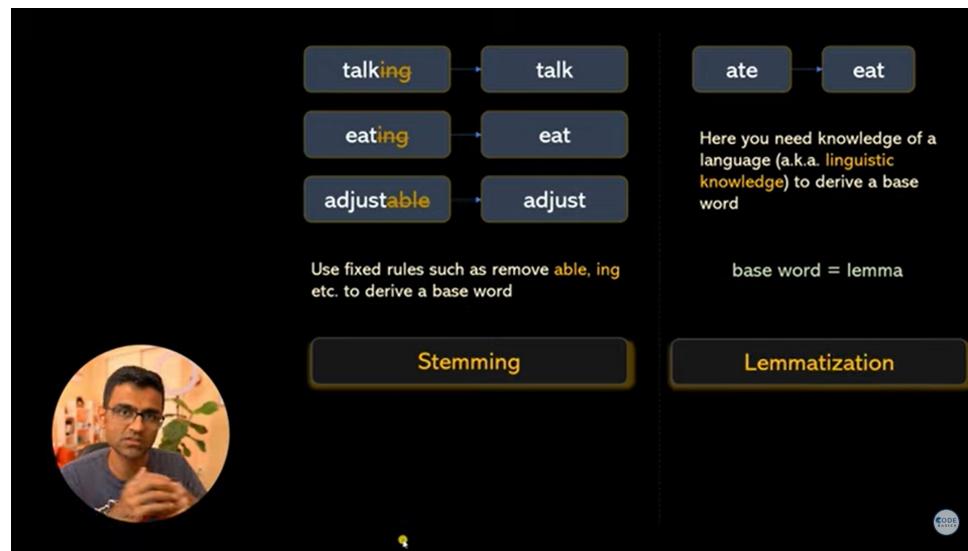
```
In [ ]: nlp_source = spacy.load("en_core_web_sm")
nlp = spacy.blank("en")
nlp.add_pipe("ner", source=nlp_source)

doc = nlp("Tesla Inc is going to acquire twitter for $45 billion")

for entity in doc.ents:
    print(entity.text, " ", entity.label_, " ", spacy.explain(entity.label_))

Tesla Inc      ORG      Companies, agencies, institutions, etc.
$45 billion    MONEY    Monetary values, including unit
```

Stemming and Lemmatization



```
In [ ]: import nltk
import spacy
```

```
In [ ]: from nltk.stem import PorterStemmer
stemmer = PorterStemmer()
```

```
In [ ]: words = ["eating", "eats", "eat", "ate", "adjustable", "rafting", "ability", "meeting"]

for word in words:
    print(word, " ", stemmer.stem(word))

eating      eat
eats       eat
eat        eat
ate        ate
adjustable   adjust
rafting     raft
ability     abil
meeting     meet
```

```
In [ ]: nlp = spacy.load("en_core_web_sm")

doc = nlp("eating eats eat ate adjustable rafting ability meeting better")

for token in doc:
    print(token, " ", token.lemma_, " ", token.lemma)
```

```

eating      eating      12092082220177030354
eats       eat        9837207709914848172
eat        eat        9837207709914848172
ate        eat        9837207709914848172
adjustable   adjustable  6033511944150694480
rafting     raft       7154368781129989833
ability     ability     11565809527369121409
meeting    meeting    14798207169164081740
better      well       4525988469032889948

```

```
In [ ]: doc = nlp("Mando talked for 3 hours although talking isn't his thing")

for token in doc:
    print(token, " ", token.lemma_, " ", token.lemma)
```

```

Mando      mando      10991835832878170099
talked     talk       13939146775466599234
for        for        16037325823156266367
3          3          602994839685422785
hours      hour       9748623380567160636
although   although   343236316598008647
talking    talking   3577425109143670181
is         be         10382539506755952630
n't        not        447765159362469301
his        his        2661093235354845946
thing      thing      2473243759842082748

```

Adding a Customizing token Component to pipeline

```
In [ ]: nlp.pipe_names
```

```
Out[ ]: ['tok2vec', 'tagger', 'parser', 'attribute_ruler', 'lemmatizer', 'ner']
```

```
In [ ]: ar = nlp.get_pipe("attribute_ruler")

doc = nlp("Bro, you wanna go? Brah, don't say no! I am exhausted")

for token in doc:
    print(token, " ", token.lemma_, " ", token.lemma)
```

```

Bro      Bro      16427154408071002123
,        ,        2593208677638477497
you     you      7624161793554793053
wanna   wanna   13000462173222681081
go      go       8004577259940138793
?        ?        8205403955989537350
Brah    Brah    5645766505577852541
,        ,        2593208677638477497
do      do       2158845516055552166
n't     not     447765159362469301
say     say     8685289367999165211
no      no      13055779130471031426
!        !        17494803046312582752
I        I        4690420944186131903
am      be      10382539506755952630
exhaust exhaust 5738807065439247694

```

```
In [ ]: ar = nlp.get_pipe("attribute_ruler")
```

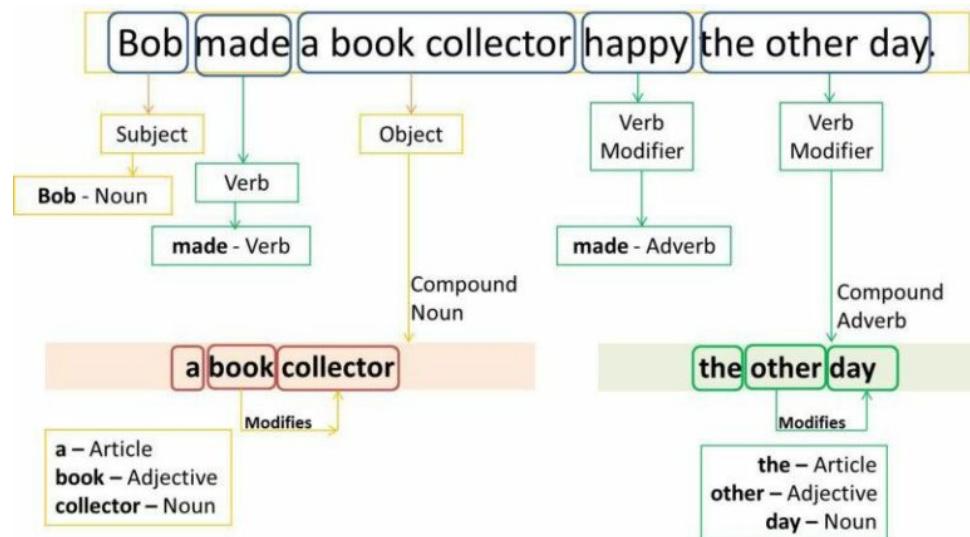
```
ar.add([{"TEXT": "Bro"}, {"TEXT": "Brah"}], {"LEMMA": "Brother"})

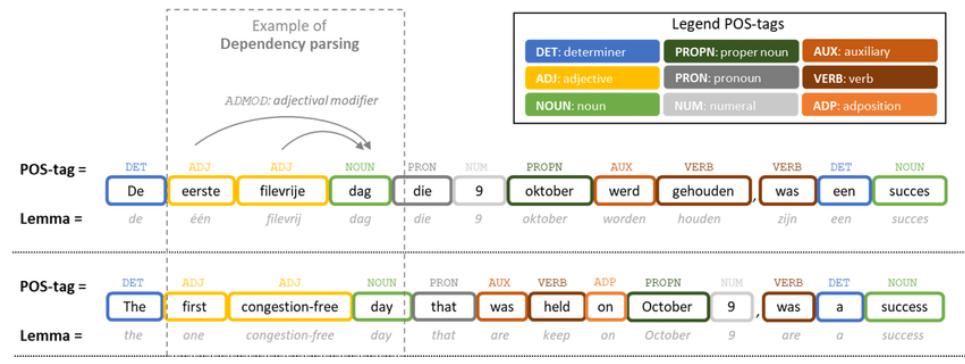
doc = nlp("Bro, you wanna go? Brah, don't say no! I am exhausted")

for token in doc:
    print(token, " ", token.lemma_, " ", token.lemma)
```

Bro	Brother	4347558510128575363
,	,	2593208677638477497
you	you	7624161793554793053
wanna	wanna	13000462173222681081
go	go	8004577259940138793
?	?	8205403955989537350
Brah	Brother	4347558510128575363
,	,	2593208677638477497
do	do	2158845516055552166
n't	not	447765159362469301
say	say	8685289367999165211
no	no	13055779130471031426
!	!	17494803046312582752
I	I	4690420944186131903
am	be	10382539506755952630
exhausted	exhaust	5738807065439247694

Part Of Speech(POS) Tagging





```
In [ ]: nlp = spacy.load("en_core_web_sm")
doc = nlp("Elon flew to mars yesterday. He carried biryani masala with him")

for token in doc:
    print(token, " ", token.pos_, " ", spacy.explain(token.pos_), " ", token.lemma_)
```

Elon	PROPN	proper noun	NNP	noun, proper singular
flew	VERB	verb	VBD	verb, past tense
to	ADP	adposition	IN	conjunction, subordinating or preposition
mars	NOUN	noun	NNS	noun, plural
yesterday	NOUN	noun	NN	noun, singular or mass
.	PUNCT	punctuation	.	punctuation mark, sentence closer
He	PRON	pronoun	PRP	pronoun, personal
carried	VERB	verb	VBD	verb, past tense
biryani	NOUN	noun	NN	noun, singular or mass
masala	NOUN	noun	NN	noun, singular or mass
with	ADP	adposition	IN	conjunction, subordinating or preposition
him	PRON	pronoun	PRP	pronoun, personal

```
In [ ]: earnings_text="""Microsoft Corp. today announced the following results for the quar

.
.
.
.
.

"Digital technology is the most malleable resource at the world's disposal to over
"Solid commercial execution, represented by strong bookings growth driven by long-t

doc = nlp(earnings_text)

filtered_tokens = []

for token in doc:
    if token.pos_ not in ["SACE", "PUNC"]:
        filtered_tokens.append(token)

filtered_tokens[:10]
```

```
Out[ ]: [Microsoft,
Corp.,
today,
announced,
the,
following,
results,
for,
the,
quarter]
```

```
In [ ]: count = doc.count_by(spacy.attrs.POS)
count
```

```
Out[ ]: {96: 15,
92: 45,
100: 22,
90: 9,
85: 16,
93: 16,
97: 27,
98: 1,
84: 21,
103: 10,
87: 6,
99: 5,
89: 12,
86: 3,
94: 3,
95: 2}
```

```
In [ ]: for k, v in count.items():
    print(doc.vocab[k].text, " ", v)
```

PROPN	15
NOUN	45
VERB	22
DET	9
ADP	16
NUM	16
PUNCT	27
SCONJ	1
ADJ	21
SPACE	10
AUX	6
SYM	5
CCONJ	12
ADV	3
PART	3
PRON	2

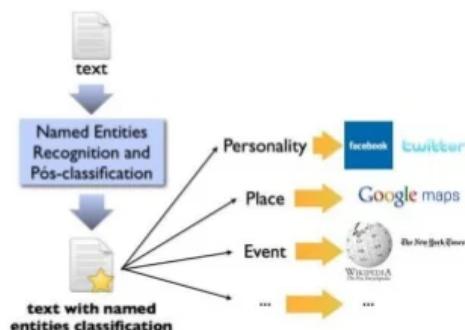
Named Entity Recognition (NER)

[Introduction to Named Entity Recognition](#)

[Hugging Face](#)



TYPES OF NAMED ENTITIES



➤ GENERIC NE:

Includes names of persons , organizations, etc.
For Example, any general requirement consisting of names of persons, organization , URLs, Location and so on.

➤ DOMAIN SPECIFIC NE:

Consists of entities related to domains
For example,
In a medical domain, names of diseases , names of medicines form the entities whereas
In a manufacturing domain names of products , manufacturers , attributes of products form the named entities.

```
In [ ]: import spacy
nlp = spacy.load("en_core_web_sm")
```

```
In [ ]: nlp.pipe_names
```

```
Out[ ]: ['tok2vec', 'tagger', 'parser', 'attribute_ruler', 'lemmatizer', 'ner']
```

```
In [ ]: doc = nlp("Tesla Inc is going to acquire twitter for $45 billion")

for entity in doc.ents:
    print(entity.text, " ", entity.label_, " ", spacy.explain(entity.label_))

Tesla Inc      ORG      Companies, agencies, institutions, etc.
$45 billion    MONEY    Monetary values, including unit
```

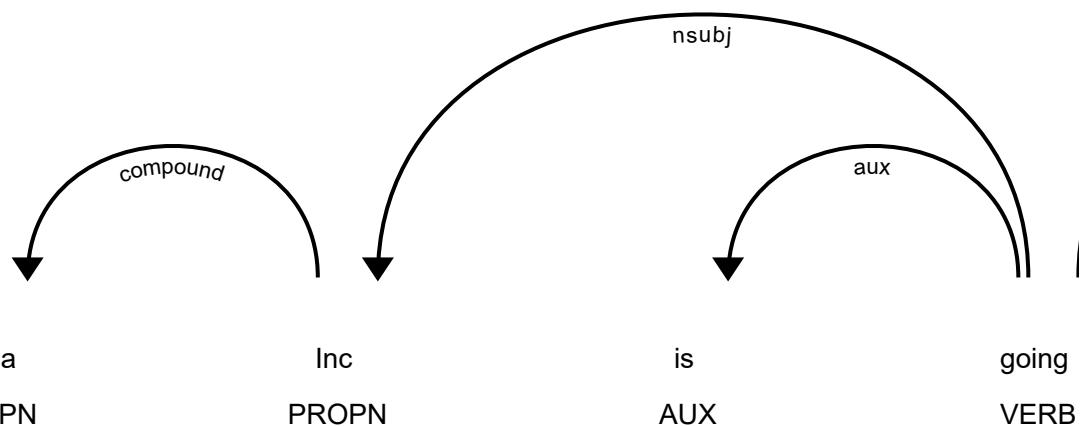
```
In [ ]: from spacy import displacy

displacy.render(doc, style="ent")
```

Tesla Inc **ORG** is going to acquire twitter for **\$45 billion MONEY**

```
In [ ]: from spacy import displacy

displacy.render(doc, style="dep")
```



```
In [ ]: nlp.pipe_labels["ner"]
```

```
Out[ ]: ['CARDINAL',
          'DATE',
          'EVENT',
          'FAC',
          'GPE',
          'LANGUAGE',
          'LAW',
          'LOC',
          'MONEY',
          'NORP',
          'ORDINAL',
          'ORG',
          'PERCENT',
          'PERSON',
          'PRODUCT',
          'QUANTITY',
          'TIME',
          'WORK_OF_ART']
```

```
In [ ]: doc = nlp("Michael Bloomberg founded Bloomberg in 1982")
```

```
for entity in doc.ents:
    print(entity.text, " ", entity.label_, " ", spacy.explain(entity.label_))
```

```
Michael Bloomberg     PERSON     People, including fictional
Bloomberg            GPE     Countries, cities, states
1982                DATE     Absolute or relative dates or periods
```

Adding a Customizing NER Component to pipeline

```
In [ ]: doc = nlp("Tesla is going to acquire Twitter for $45 billion")
```

```
for entity in doc.ents:
    print(entity.text, " ", entity.label_, " ", spacy.explain(entity.label_))
```

Twitter PERSON People, including fictional
\$45 billion MONEY Monetary values, including unit

In []: type(doc[0])

Out[]: spacy.tokens.token.Token

In []: type(doc[2:5])

Out[]: spacy.tokens.span.Span

In []: from spacy.tokens import Span

```
s1 = Span(doc, 0, 1, label="ORG")
s2 = Span(doc, 5, 6, label="ORG")

doc.set_ents([s1, s2], default="unmodified")
```

In []: for entity in doc.ents:

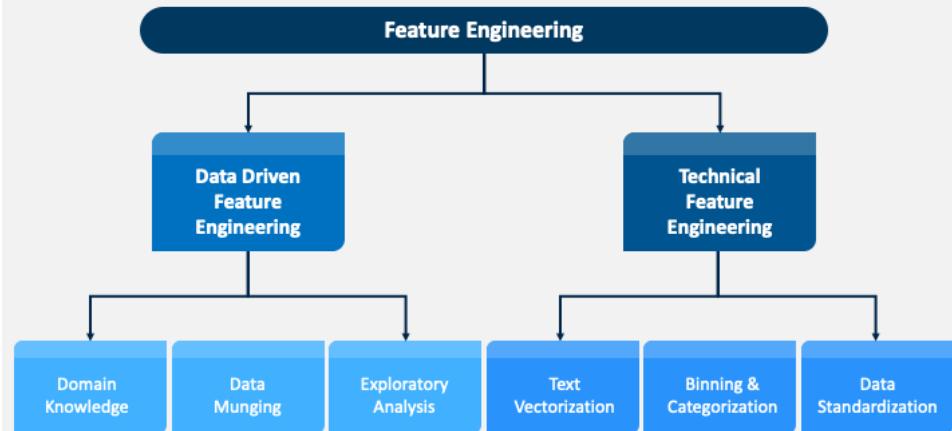
```
    print(entity.text, " ", entity.label_, " ", spacy.explain(entity.label_))
```

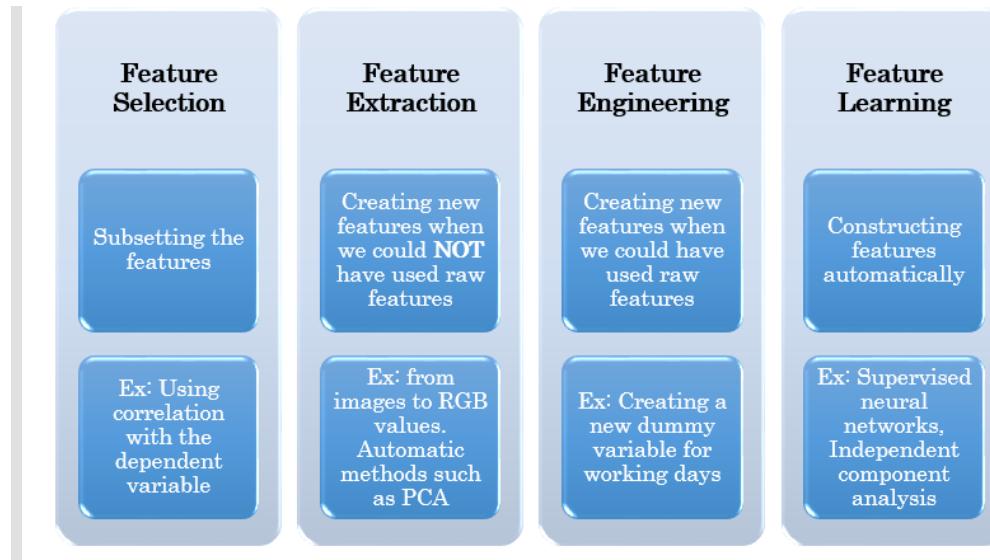
Tesla ORG Companies, agencies, institutions, etc.
Twitter ORG Companies, agencies, institutions, etc.
\$45 billion MONEY Monetary values, including unit

Feature Engineering

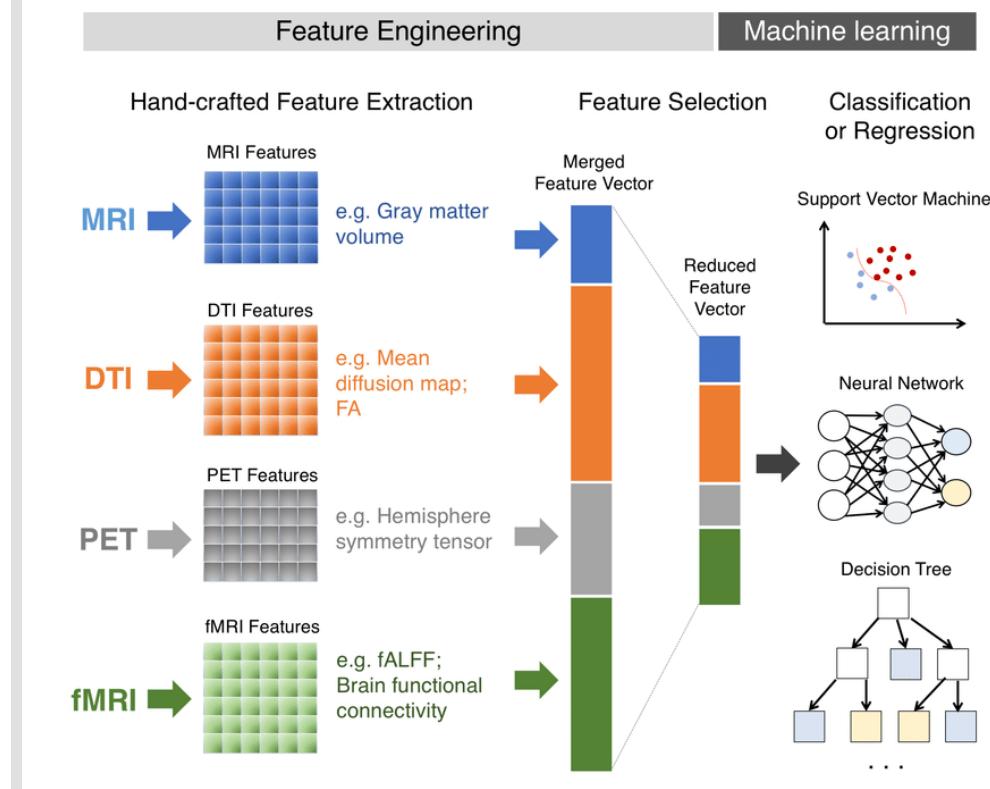
FEATURE ENGINEERING

Enter your sub headline here

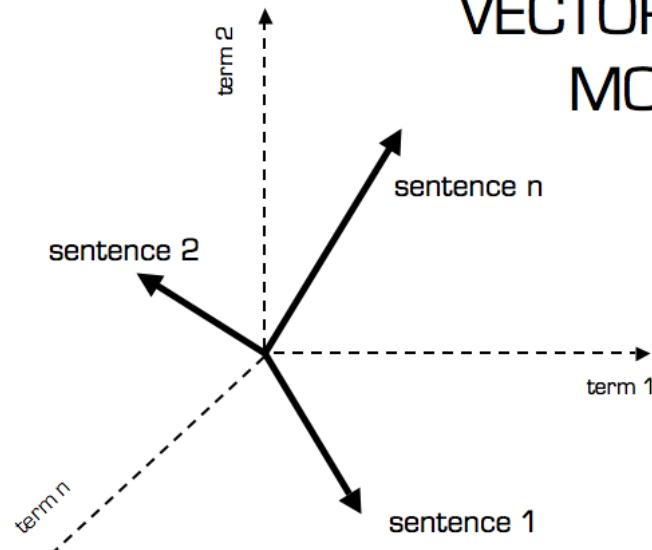




Convert Text to Vector

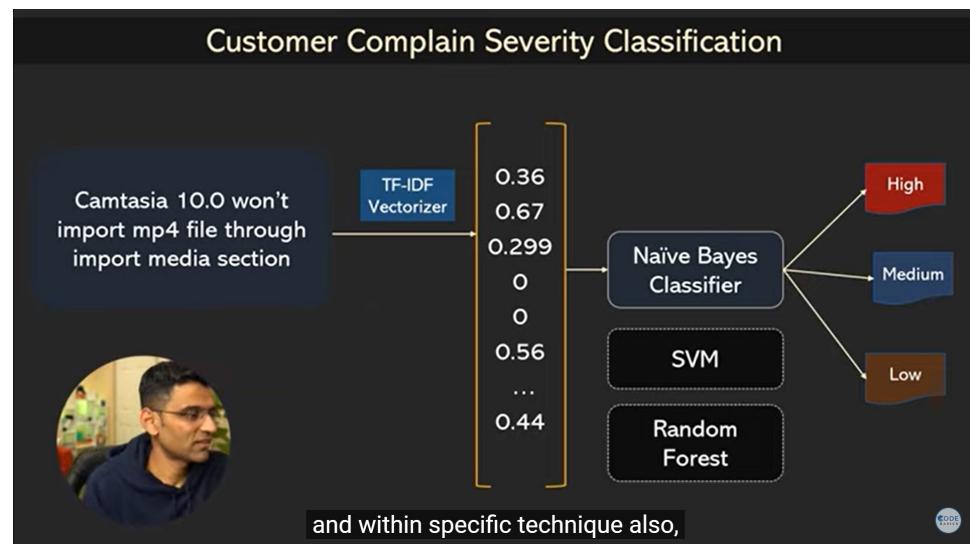
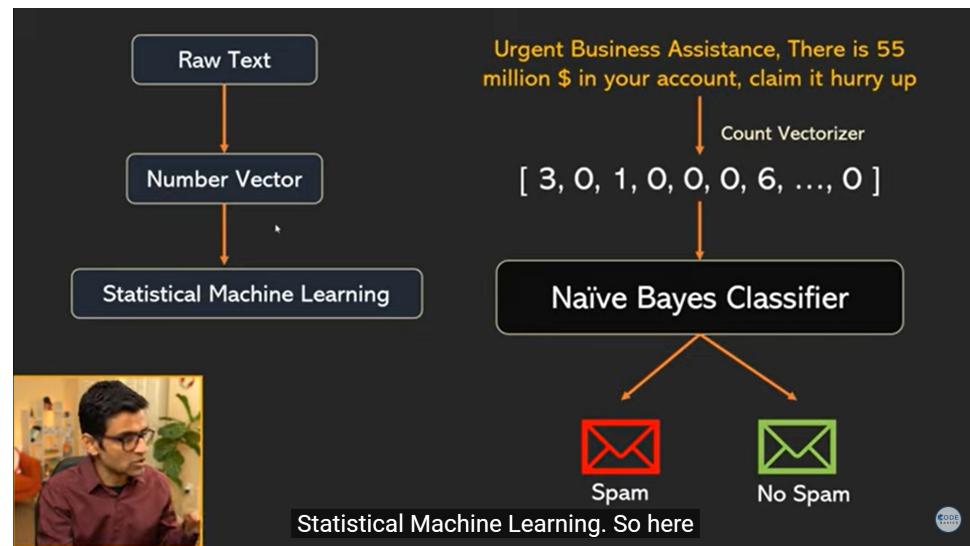


VECTOR SPACE MODEL



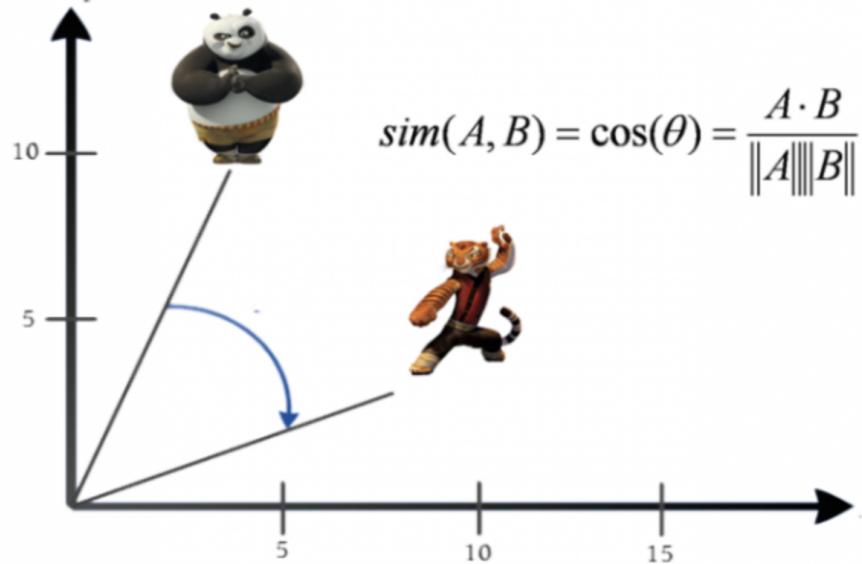
Text Classification

[sentence-transformers/paraphrase-multilingual-MiniLM-L12-v2](https://pypi.org/project/sentence-transformers/)

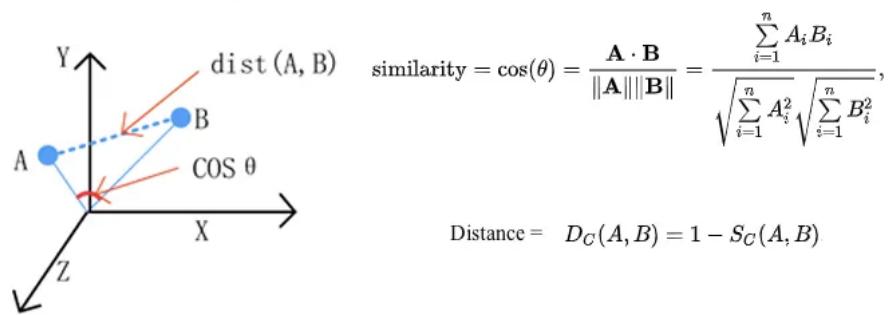


Cosine similarity, cosine distance explained

Cosine Similarity



Cosine Similarity & Cosine Distance



```
In [ ]: from sklearn.metrics.pairwise import cosine_similarity, cosine_distances
```

```
In [ ]: cosine_similarity([[3,1]],[[6,2]])
```

```
Out[ ]: array([[1.]])
```

```
In [ ]: cosine_distances([[3,1]],[[6,2]])
```

```
Out[ ]: array([[1.11022302e-16]])
```

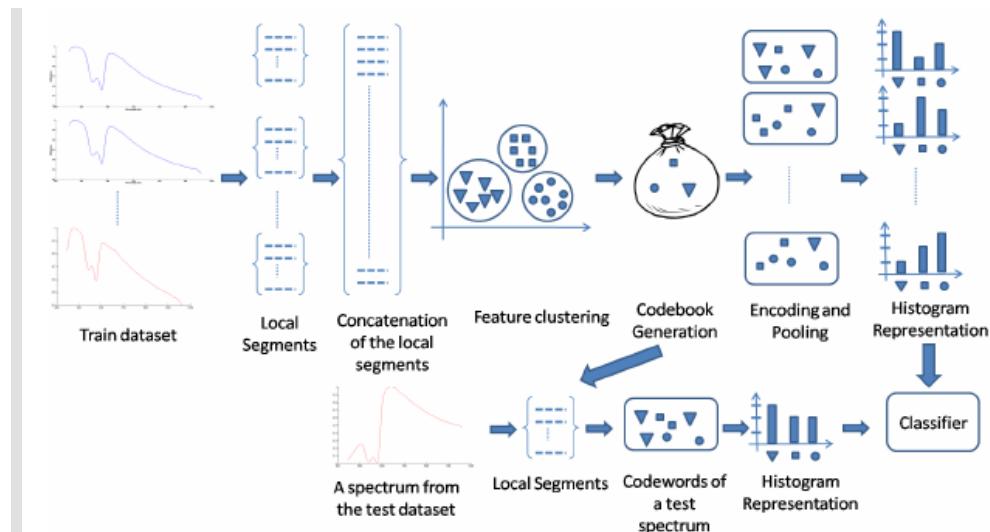
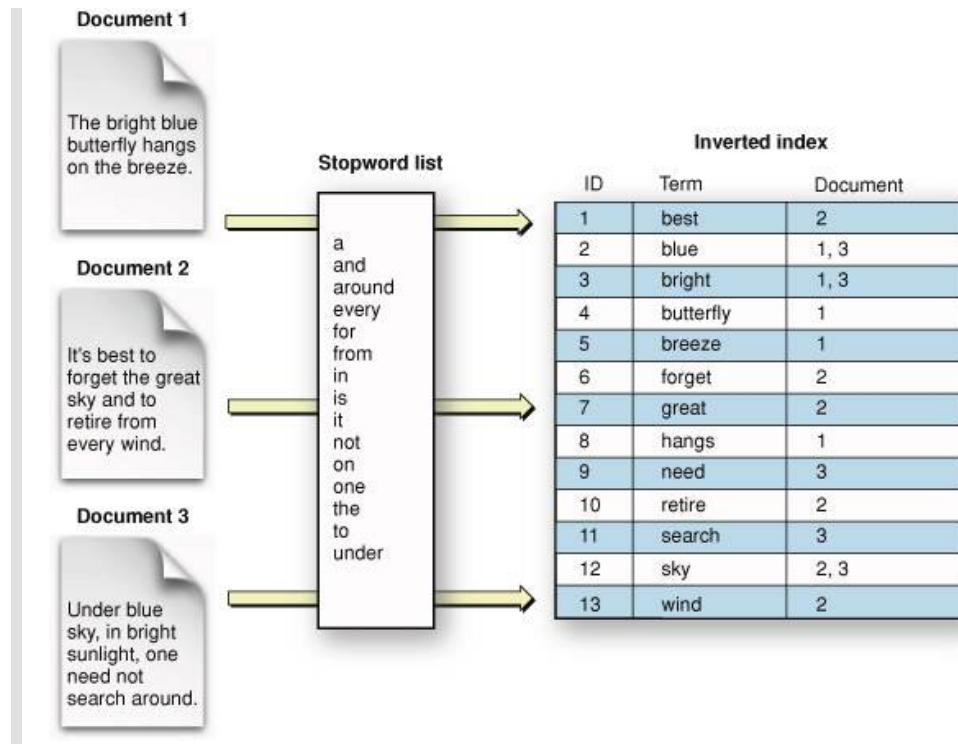
```
In [ ]: cosine_similarity([[3,0]],[[0,8]])
```

```
Out[ ]: array([[0.]])
```

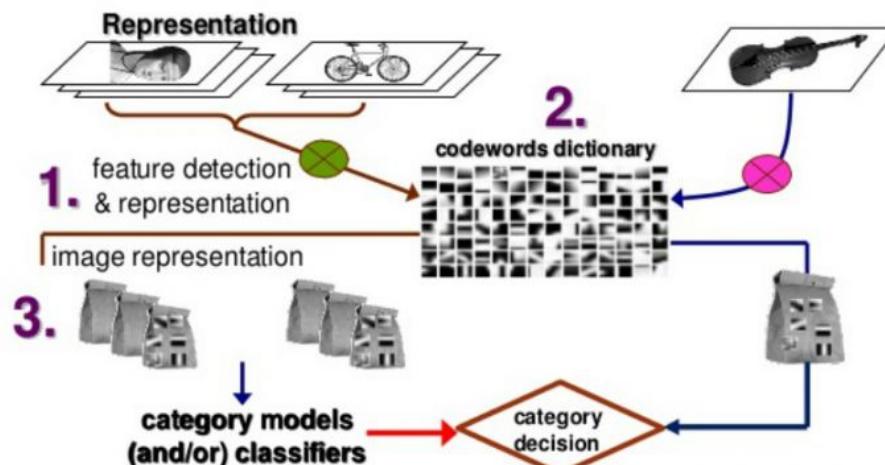
```
In [ ]: cosine_distances([[3,0]],[[0,8]])
```

```
Out[ ]: array([[1.]])
```

Text Representation - Bag Of Words (BOW)



Bag of Visual Words



In []: `import numpy as np`
`import pandas as pd`

```
In [ ]: df = pd.read_csv('data/spam.csv')
df.head()
```

	Category	Message
0	ham	Go until jurong point, crazy.. Available only ...
1	ham	Ok lar... Joking wif u oni...
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...
3	ham	U dun say so early hor... U c already then say...
4	ham	Nah I don't think he goes to usf, he lives aro...

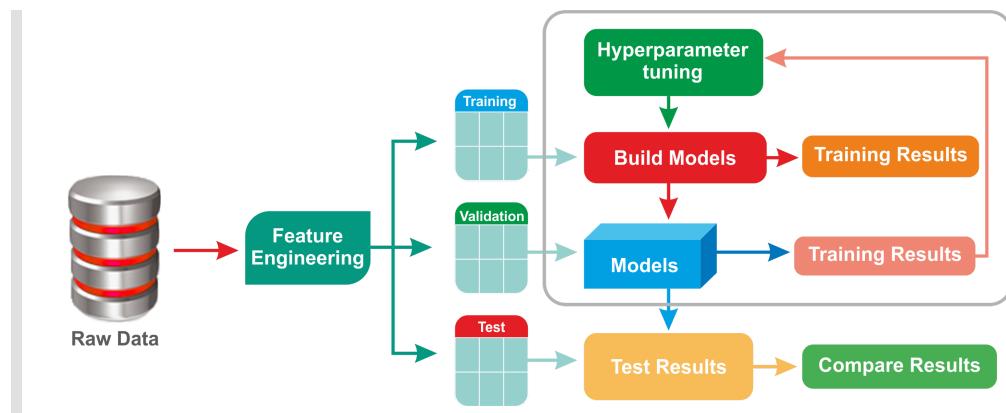
```
In [ ]: df['Category'].value_counts()
```

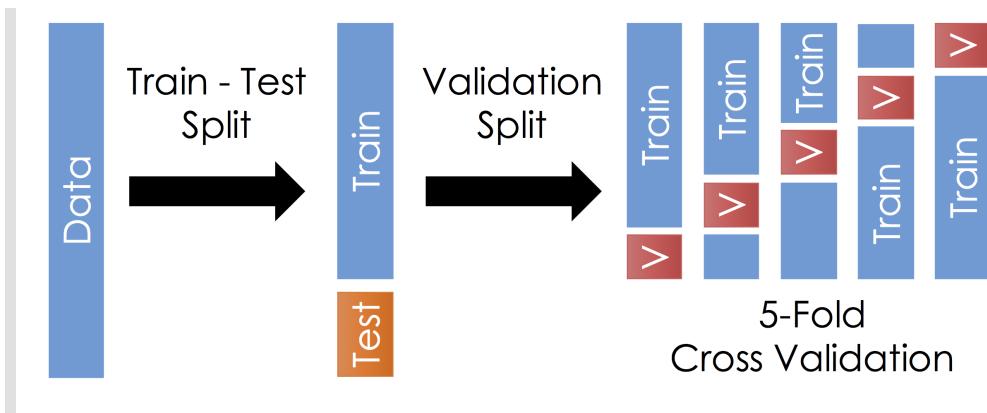
```
Out[ ]: ham    4825
spam     747
Name: Category, dtype: int64
```

```
In [ ]: df['Spam'] = df['Category'].apply(lambda x: 1 if x=='spam' else 0)
df.head()
```

	Category	Message	Spam
0	ham	Go until jurong point, crazy.. Available only ...	0
1	ham	Ok lar... Joking wif u oni...	0
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...	1
3	ham	U dun say so early hor... U c already then say...	0
4	ham	Nah I don't think he goes to usf, he lives aro...	0

Model Building and Training





```
In [ ]: from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(df['Message'], df['Spam'], test_size=0.2, random_state=42)
```

```
In [ ]: type(X_train)
```

```
Out[ ]: pandas.core.series.Series
```

```
In [ ]: type(y_train)
```

```
Out[ ]: pandas.core.series.Series
```

```
In [ ]: type(X_train.values)
```

```
Out[ ]: numpy.ndarray
```

```
In [ ]: type(y_train.values)
```

```
Out[ ]: numpy.ndarray
```

Create bag of words representation using CountVectorizer

```
In [ ]: from sklearn.feature_extraction.text import CountVectorizer
v = CountVectorizer()
X_train_cv = v.fit_transform(X_train.values)
```

```
In [ ]: type(X_train_cv)
```

```
Out[ ]: scipy.sparse._csr.csr_matrix
```

```
In [ ]: X_train_cv.shape
```

```
Out[ ]: (4457, 7799)
```

```
In [ ]: dir(v)
```

```
In [ ]: v.vocabulary_
```

```
In [ ]: v.get_feature_names_out()[1000:1010]
```

```
Out[ ]: array(['anything', 'anythingtomorrow', 'anytime', 'anyway', 'anyways',
   'anywhere', 'apart', 'apartment', 'apeshit', 'aphex'], dtype=object)
```

```
In [ ]: X_train_np = X_train_cv.toarray()
X_train_np
```

```
Out[ ]: array([[0, 0, 0, ..., 0, 0, 0],
   [0, 0, 0, ..., 0, 0, 0],
   [0, 0, 0, ..., 0, 0, 0],
   ...,
   [0, 0, 0, ..., 0, 0, 0],
   [0, 0, 0, ..., 0, 0, 0],
   [0, 0, 0, ..., 0, 0, 0]], dtype=int64)
```

```
In [ ]: type(X_train_np)
```

```
Out[ ]: numpy.ndarray
```

```
In [ ]: np.where(X_train_np[0] != 0)
```

```
Out[ ]: (array([3907, 4663, 4693, 4849, 5173, 5886, 6137, 6306, 6308, 6978, 7018,
   7262, 7541, 7696], dtype=int64),)
```

```
In [ ]: X_train_np[0][1054]
```

```
Out[ ]: 0
```

```
In [ ]: X_train[:4]
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_23912\2167669864.py:1: FutureWarning: T
he behavior of `series[i:j]` with an integer-dtype index is deprecated. In a futur
e version, this will be treated as *label-based* indexing, consistent with e.g. `s
eries[i]` lookups. To retain the old behavior, use `series.iloc[i:j]`. To get the
future behavior, use `series.loc[i:j]`.
X_train[:4]
```

```
Out[ ]: 3292    I'm not smoking while people use "wylie smokes...
          That is wondar full flim.
      723
      5249      K I'm leaving soon, be there a little after 9
      5253      Please tell me not all of my car keys are in y...
Name: Message, dtype: object
```

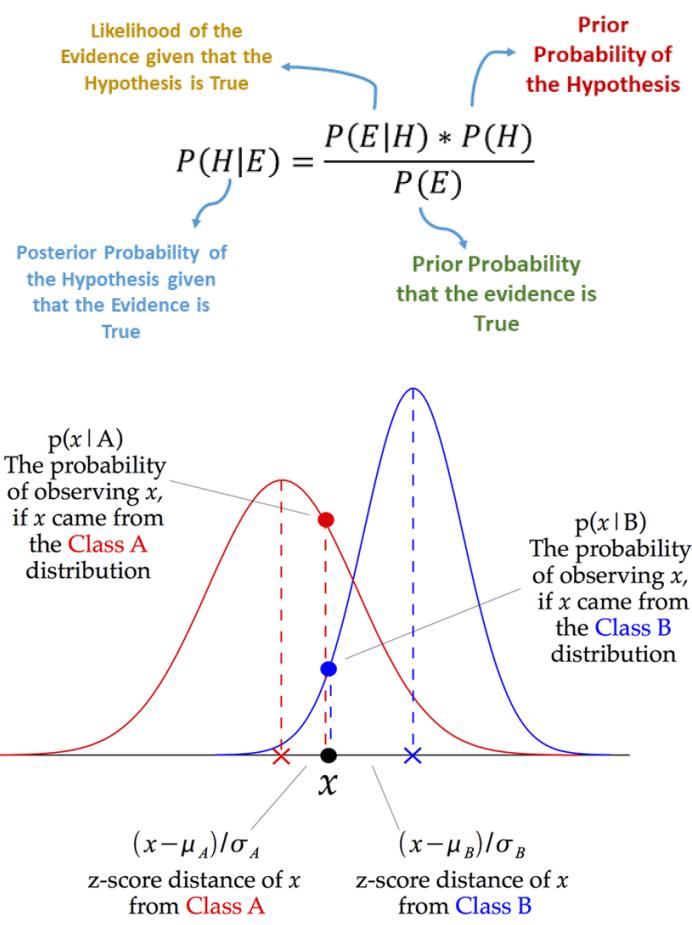
```
In [ ]: v.get_feature_names_out()[2333]
```

```
Out[ ]: 'different'
```

```
In [ ]: v.get_feature_names_out()[4539]
```

```
Out[ ]: 'missin'
```

Naive Bayes Classifier



```
In [ ]: from sklearn.naive_bayes import MultinomialNB
model = MultinomialNB()
model.fit(X_train_cv, y_train)
```

```
Out[ ]: ▾ MultinomialNB
MultinomialNB()
```

```
In [ ]: X_test_cv = v.transform(X_test)
```

```
In [ ]: y_preds = model.predict(X_test_cv)
```

```
In [ ]: model.score(X_test_cv, y_test)
```

```
Out[ ]: 0.9847533632286996
```

```
In [ ]: model.predict_proba(X_test_cv[:10])
```

```
Out[ ]: array([[3.01293305e-02, 9.69870669e-01],
 [9.99410799e-01, 5.89201334e-04],
 [9.99999703e-01, 2.96768149e-07],
 [3.93373327e-11, 1.00000000e+00],
 [9.99999684e-01, 3.16156187e-07],
 [1.00000000e+00, 3.11023360e-15],
 [6.17426315e-15, 1.00000000e+00],
 [9.99999875e-01, 1.24821298e-07],
 [9.99999948e-01, 5.23724766e-08],
 [9.99999974e-01, 2.59966712e-08]])
```

```
In [ ]: from sklearn.metrics import classification_report
print(classification_report(y_test, y_preds))

precision    recall   f1-score   support
0            0.99    1.00      0.99     968
1            0.97    0.91      0.94     147

accuracy                           0.98      1115
macro avg                  0.98    0.95      0.97     1115
weighted avg                 0.98    0.98      0.98     1115
```

```
In [ ]: emails = [
    'Hey mohan, can we get together to watch footbal game tomorrow?',
    'Upto 20% discount on parking, exclusive offer just for you. Dont miss this rev
]

emails_cv = v.transform(emails)

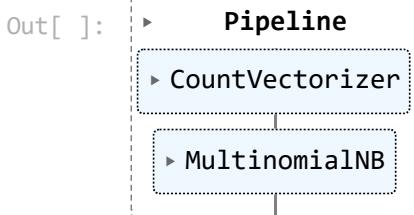
model.predict(emails_cv)
```

Out[]: array([0, 1], dtype=int64)

```
In [ ]: from sklearn.pipeline import Pipeline

model = Pipeline([
    ('vectorizer', CountVectorizer()),
    ('nb', MultinomialNB()),
])

model.fit(X_train, y_train)
```



```
In [ ]: model.score(X_test, y_test)
```

Out[]: 0.9847533632286996

```
In [ ]: from sklearn.metrics import classification_report
y_preds = model.predict(X_test)
print(classification_report(y_test, y_preds))
```

	precision	recall	f1-score	support
0	0.99	1.00	0.99	968
1	0.97	0.91	0.94	147
accuracy			0.98	1115
macro avg	0.98	0.95	0.97	1115
weighted avg	0.98	0.98	0.98	1115

Text Representation - Stop Words

```
In [ ]: from spacy.lang.en.stop_words import STOP_WORDS
```

```
In [ ]: len(STOP_WORDS)
```

```
Out[ ]: 326
```

```
In [ ]: nlp = spacy.load("en_core_web_sm")
```

```
In [ ]: doc = nlp("We just opened our wings, the flying part is coming soon")

for token in doc:
    if not token.is_stop and not token.is_punct:
        print(token)
```

```
opened
wings
flying
coming
soon
```

```
In [ ]: def preprocess(text):
    doc = nlp(text)
    no_stop_words = [token.text for token in doc if not token.is_stop and not token.is_punct]
    return " ".join(no_stop_words)
```

```
In [ ]: preprocess("We just opened our wings, the flying part is coming soon")
```

```
Out[ ]: 'opened wings flying coming soon'
```

```
In [ ]: preprocess("Musk wants time to prepare for a trial over his")
```

```
Out[ ]: 'Musk wants time prepare trial'
```

```
In [ ]: import numpy as np
import pandas as pd
```

```
In [ ]: df = pd.read_json('data/doj_press.json', lines=True)
df.head()
```

Out[]:	id	title	contents	date	topics	components
0	None	Convicted Bomb Plotter Sentenced to 30 Years	PORTLAND, Oregon. – Mohamed Osman Mohamud, 23,...	2014-10-01T00:00:00-04:00	[]	[National Security Division (NSD)]
1	12-919	\$1 Million in Restitution Payments Announced t...	WASHINGTON – North Carolina's Waccamaw River...	2012-07-25T00:00:00-04:00	[]	[Environment and Natural Resources Division]
2	11-1002	\$1 Million Settlement Reached for Natural Reso...	BOSTON– A \$1-million settlement has been...	2011-08-03T00:00:00-04:00	[]	[Environment and Natural Resources Division]
3	10-015	10 Las Vegas Men Indicted \r\nfor Falsifying V...	WASHINGTON—A federal grand jury in Las Vegas...	2010-01-08T00:00:00-05:00	[]	[Environment and Natural Resources Division]
4	18-898	\$100 Million Settlement Will Speed Cleanup Wor...	The U.S. Department of Justice, the U.S. Envir...	2018-07-09T00:00:00-04:00	[Environment]	[Environment and Natural Resources Division]

In []: `df.info()`

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 13087 entries, 0 to 13086
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype  
--- 
 0   id          12810 non-null   object 
 1   title        13087 non-null   object 
 2   contents     13087 non-null   object 
 3   date         13087 non-null   object 
 4   topics       13087 non-null   object 
 5   components   13087 non-null   object 
dtypes: object(6)
memory usage: 613.6+ KB
```

In []: `df = df[df['topics'].str.len() != 0]`
`df.head()`

Out[]:		id	title	contents	date	topics	components
	4	18-898	\$100 Million Settlement Will Speed Cleanup Work...	The U.S. Department of Justice, the U.S. Envir...	2018-07-09T00:00:00-04:00	[Environment]	[Environment and Natural Resources Division]
	7	14-1412	14 Indicted in Connection with New England Com...	A 131-count criminal indictment was unsealed t...	2014-12-17T00:00:00-05:00	[Consumer Protection]	[Civil Division]
	19	17-1419	2017 Southeast Regional Animal Cruelty Prosecu...	The United States Attorney's Office for the Mi...	2017-12-14T00:00:00-05:00	[Environment]	[Environment and Natural Resources Division, U...
	22	15-1562	21st Century Oncology to Pay \$19.75 Million to...	21st Century Oncology LLC, has agreed to pay \$...	2015-12-18T00:00:00-05:00	[False Claims Act, Health Care Fraud]	[Civil Division]
	23	17-1404	21st Century Oncology to Pay \$26 Million to Se...	21st Century Oncology Inc. and certain of its ...	2017-12-12T00:00:00-05:00	[Health Care Fraud, False Claims Act]	[Civil Division, USAO - Florida, Middle]

In []: `df.info()`

```

<class 'pandas.core.frame.DataFrame'>
Int64Index: 4688 entries, 4 to 13086
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype  
--- 
 0   id          4560 non-null    object 
 1   title        4688 non-null    object 
 2   contents     4688 non-null    object 
 3   date         4688 non-null    object 
 4   topics       4688 non-null    object 
 5   components   4688 non-null    object 
dtypes: object(6)
memory usage: 256.4+ KB

```

In []: `df = df.head(100)`
`df["contents_new"] = df["contents"].apply(preprocess)`
`df.head()`

Out[]:	id	title	contents	date	topics	components	contents_new
	4	\$100 Million Settlement Will Speed Cleanup Wor...	The U.S. Department of Justice, the U.S. Envir...	2018-07-09T00:00:00-04:00	[Environment]	[Environment and Natural Resources Division]	U.S. Department Justice U.S. Environmental Pro...
	7	14-1412 14 Indicted in Connection with New England Com...	A 131-count criminal indictment was unsealed t...	2014-12-17T00:00:00-05:00	[Consumer Protection]	[Civil Division]	131 count criminal indictment unsealed today B...
	19	17-1419 2017 Southeast Regional Animal Cruelty Prosecu...	The United States Attorney's Office for the Mi...	2017-12-14T00:00:00-05:00	[Environment]	[Environment and Natural Resources Division, U...	United States Attorney Office Middle District ...
	22	15-1562 21st Century Oncology to Pay \$19.75 Million to...	21st Century Oncology LLC, has agreed to pay \$...	2015-12-18T00:00:00-05:00	[False Claims Act, Health Care Fraud]	[Civil Division]	21st Century Oncology LLC agreed pay \$ 19.75 m...
	23	17-1404 21st Century Oncology to Pay \$26 Million to Se...	21st Century Oncology Inc. and certain of its ...	2017-12-12T00:00:00-05:00	[Health Care Fraud, False Claims Act]	[Civil Division, USAO - Florida, Middle]	21st Century Oncology Inc. certain subsidiarie...

In []: len(preprocess(df['contents'].iloc[4]))

Out[]: 4217

In []: len(df['contents'].iloc[4])

Out[]: 5504

Text Representation - Bag Of n-grams

```
In [ ]: from sklearn.feature_extraction.text import CountVectorizer
v = CountVectorizer()
v.fit(["Thor Hathodawala is looking for a job"])
```

Out[]: ▾ CountVectorizer
CountVectorizer()

In []: v.vocabulary_

Out[]: {'thor': 5, 'hathodawala': 1, 'is': 2, 'looking': 4, 'for': 0, 'job': 3}

```
In [ ]: v = CountVectorizer(ngram_range=(2, 2))

v.fit(["Thor Hathodawala is looking for a job"])

v.vocabulary_
```

```
Out[ ]: {'thor hathodawala': 4,
         'hathodawala is': 1,
         'is looking': 2,
         'looking for': 3,
         'for job': 0}
```

```
In [ ]: import spacy

nlp = spacy.load("en_core_web_sm")

def preprocess(text):
    doc = nlp(text)
    filtered_tokens = []
    for token in doc:
        if token.is_stop or token.is_punct:
            continue
        filtered_tokens.append(token.lemma_)
    return " ".join(filtered_tokens)
```

```
In [ ]: corpus = [
        "Thor ate pizza",
        "Loki is tall",
        "Loki is eating pizza"
]

corpus_processed = [preprocess(text) for text in corpus]
corpus_processed
```

```
Out[ ]: ['Thor eat pizza', 'Loki tall', 'Loki eat pizza']
```

```
In [ ]: v = CountVectorizer(ngram_range=(1, 2))
v.fit(corpus_processed)
v.vocabulary_
```

```
Out[ ]: {'thor': 7,
         'eat': 0,
         'pizza': 5,
         'thor eat': 8,
         'eat pizza': 1,
         'loki': 2,
         'tall': 6,
         'loki tall': 4,
         'loki eat': 3}
```

```
In [ ]: v.transform(["Thor ate pizza"]).toarray()
```

```
Out[ ]: array([[0, 0, 0, 0, 0, 1, 0, 1, 0]], dtype=int64)
```

Categories Classification

```
In [ ]: import numpy as np
import pandas as pd
```

```
In [ ]: df = pd.read_json('data/news_dataset.json')
df.head()
```

Out[]:

	text	category
0	Watching Schrödinger's Cat Die University of C...	SCIENCE
1	WATCH: Freaky Vortex Opens Up In Flooded Lake	SCIENCE
2	Entrepreneurs Today Don't Need a Big Budget to...	BUSINESS
3	These Roads Could Recharge Your Electric Car A...	BUSINESS
4	Civilian 'Guard' Fires Gun While 'Protecting' ...	CRIME

```
In [ ]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 12695 entries, 0 to 12694
Data columns (total 2 columns):
 #   Column      Non-Null Count  Dtype  
---  --          --          --      
 0   text        12695 non-null   object 
 1   category    12695 non-null   object 
dtypes: object(2)
memory usage: 297.5+ KB
```

```
In [ ]: df['category'].value_counts()
```

```
Out[ ]: BUSINESS    4254
        SPORTS     4167
        CRIME      2893
        SCIENCE    1381
Name: category, dtype: int64
```

```
In [ ]: min_samples = 1381
df_BUSINESS = df[df['category']=='BUSINESS'].sample(min_samples, random_state=2022)
df_BUSINESS.shape
```

```
Out[ ]: (1381, 2)
```

```
In [ ]: df_SPORTS = df[df['category']=='SPORTS'].sample(min_samples, random_state=2022)
df_CRIME = df[df['category']=='CRIME'].sample(min_samples, random_state=2022)
df_SCIENCE = df[df['category']=='SCIENCE'].sample(min_samples, random_state=2022)
```

```
In [ ]: df_balanced = pd.concat([df_BUSINESS, df_SPORTS, df_CRIME, df_SCIENCE], axis=0)
df_balanced['category'].value_counts()
```

```
Out[ ]: BUSINESS    1381
        SPORTS     1381
        CRIME      1381
        SCIENCE    1381
Name: category, dtype: int64
```

Model Build and Train

```
In [ ]: df_balanced['category_new'] = df_balanced['category'].map({
    "BUSINESS": 0,
    "SPORTS" : 1,
    "CRIME": 3,
```

```
"SCIENCE": 4,
})
```

```
In [ ]: from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(
    df_balanced['text'],
    df_balanced['category_new'],
    test_size=0.2,
    random_state=2022,
    stratify=df_balanced['category_new']
)
```

```
In [ ]: y_train.value_counts()
```

```
Out[ ]: 4    1105
3    1105
0    1105
1    1104
Name: category_new, dtype: int64
```

```
In [ ]: from sklearn.naive_bayes import MultinomialNB
from sklearn.pipeline import Pipeline
from sklearn.metrics import classification_report

model = Pipeline([
    ('vectorizer_bow', CountVectorizer(ngram_range=(1, 2))),
    ('multi NB', MultinomialNB()),
])
model.fit(X_train, y_train)
```

```
Out[ ]: Pipeline
        |
        +-- CountVectorizer
        |
        +-- MultinomialNB
```

```
In [ ]: model.score(X_test, y_test)
```

```
Out[ ]: 0.8244343891402715
```

```
In [ ]: y_preds = model.predict(X_test)
```

```
In [ ]: print(classification_report(y_test, y_preds))
```

	precision	recall	f1-score	support
0	0.69	0.90	0.78	276
1	0.95	0.74	0.83	277
3	0.82	0.88	0.85	276
4	0.92	0.78	0.84	276
accuracy			0.82	1105
macro avg	0.85	0.82	0.83	1105
weighted avg	0.85	0.82	0.83	1105

Using preprocessed text to train

```
In [ ]: df_balanced['text_processed'] = df_balanced['text'].apply(preprocess)
```

```
In [ ]: df_balanced.head()
```

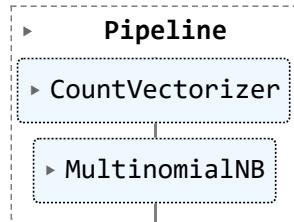
Out[]:

		text	category	category_new	text_processed
11967	GCC Business Leaders Remain Confident in the F...	BUSINESS	0		gcc Business leader remain Confident face Regi...
2912	From the Other Side; an Honest Review from Emp...	BUSINESS	0		Honest Review employee wake morning love impor...
3408	Mike McDerment, CEO of FreshBooks, Talks About...	BUSINESS	0		Mike McDerment ceo FreshBooks talk give build ...
502	How to Market Your Business While Traveling th...	BUSINESS	0		market business travel World recently amazing ...
5279	How to Leverage Intuition in Decision-making I...	BUSINESS	0		Leverage intuition decision making feel safe r...

```
In [ ]: from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(
    df_balanced['text_processed'],
    df_balanced['category_new'],
    test_size=0.2,
    random_state=2022,
    stratify=df_balanced['category_new']
)
```

```
In [ ]: model = Pipeline([
    ('vectorizer_bow', CountVectorizer(ngram_range=(1, 2))),
    ('multi NB', MultinomialNB()),
])
model.fit(X_train, y_train)
```

Out[]:



```
In [ ]: model.score(X_test, y_test)
```

Out[]: 0.860633484162896

```
In [ ]: y_preds = model.predict(X_test)
print(classification_report(y_test, y_preds))
```

	precision	recall	f1-score	support
0	0.80	0.88	0.84	276
1	0.92	0.83	0.87	277
3	0.83	0.92	0.87	276
4	0.91	0.81	0.86	276
accuracy			0.86	1105
macro avg	0.87	0.86	0.86	1105
weighted avg	0.87	0.86	0.86	1105

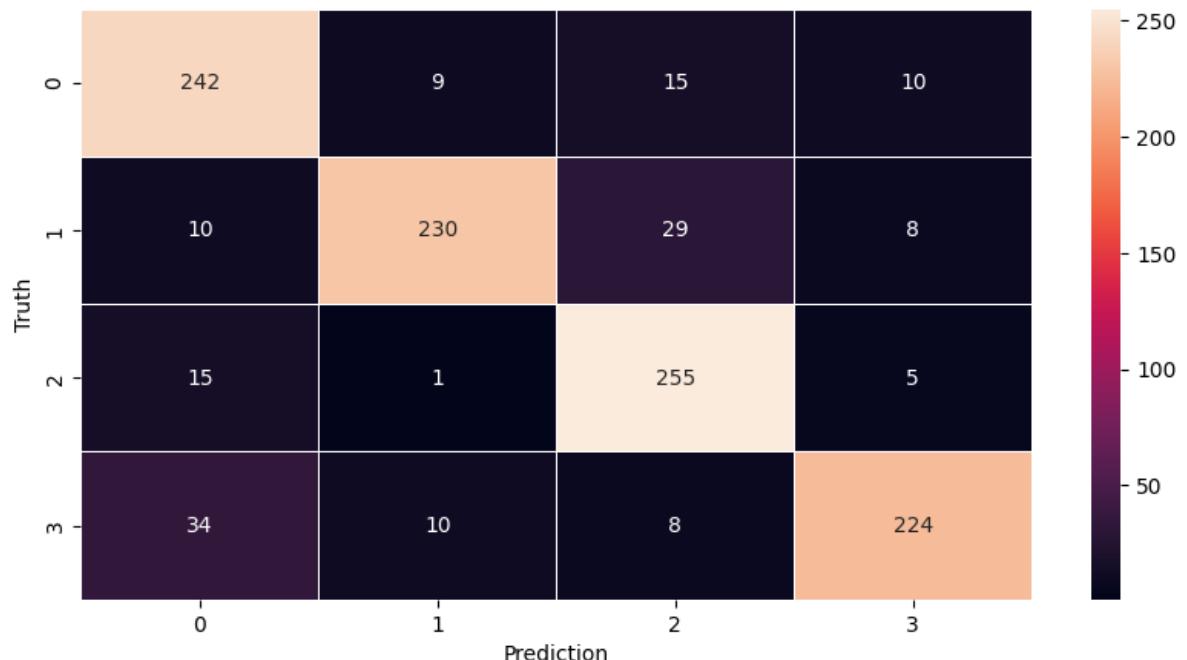
```
In [ ]: from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_preds)
cm
```

```
Out[ ]: array([[242,    9,   15,   10],
               [ 10, 230,   29,    8],
               [ 15,    1, 255,    5],
               [ 34,   10,    8, 224]], dtype=int64)
```

```
In [ ]: import matplotlib.pyplot as plt
import seaborn as sn

plt.figure(figsize=(10,5))
sn.heatmap(
    cm,
    annot=True,
    fmt='d',
    linewidth=0.5
)
plt.xlabel('Prediction')
plt.ylabel('Truth')
```

```
Out[ ]: Text(95.7222222222221, 0.5, 'Truth')
```



Text Representation - TF-IDF

TF*IDF

TF*IDF = TERM FREQUENCY * INVERSE DOCUMENT FREQUENCY

TERM FREQUENCY =
THE AMOUNT OF TIMES A TERM APPEARS IN A DOCUMENT



INVERSE DOCUMENT FREQUENCY =
A MEASURE OF WHETHER A TERM IS RARE OR COMMON IN A COLLECTION OF DOCUMENTS.

TF-IDF

TF-IDF is a measure of originality of a word by comparing the number of times a word appears in a doc with the number of docs the word appears in.

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

$$\text{Term frequency} \quad \text{Inverse document frequency}$$

Number of times term t appears in a doc, d $\log \frac{1 + n}{1 + df(d, t)} + 1$

of documents

Document frequency of the term t

```
In [ ]: from sklearn.feature_extraction.text import TfidfVectorizer
```

```
v = TfidfVectorizer()
```

```
dir(v)
```

```
In [ ]: corpus = [
    "Thor eating pizza, Loki is eating pizza, Ironman ate pizza already",
    "Apple is announcing new iphone tomorrow",
    "Tesla is announcing new model-3 tomorrow",
    "Google is announcing new pixel-6 tomorrow",
    "Microsoft is announcing new surface tomorrow",
    "Amazon is announcing new eco-dot tomorrow",
    "I am eating biryani and you are eating grapes"
]
```

```
In [ ]: output_transformed = v.fit_transform(corpus)
```

```
In [ ]: type(output_transformed)
```

```
Out[ ]: scipy.sparse._csr.csr_matrix
```

```
In [ ]: v.vocabulary_
```

```
Out[ ]: {'thor': 25,
          'eating': 10,
          'pizza': 22,
          'loki': 17,
          'is': 16,
          'ironman': 15,
          'ate': 7,
          'already': 0,
          'apple': 5,
          'announcing': 4,
          'new': 20,
          'iphone': 14,
          'tomorrow': 26,
          'tesla': 24,
          'model': 19,
          'google': 12,
          'pixel': 21,
          'microsoft': 18,
          'surface': 23,
          'amazon': 2,
          'eco': 11,
          'dot': 9,
          'am': 1,
          'biryani': 8,
          'and': 3,
          'you': 27,
          'are': 6,
          'grapes': 13}
```

```
In [ ]: all_feature_names = v.get_feature_names_out()
all_feature_names
```

```
Out[ ]: array(['already', 'am', 'amazon', 'and', 'announcing', 'apple', 'are',
               'ate', 'biryani', 'dot', 'eating', 'eco', 'google', 'grapes',
               'iphone', 'ironman', 'is', 'loki', 'microsoft', 'model', 'new',
               'pixel', 'pizza', 'surface', 'tesla', 'thor', 'tomorrow', 'you'],
               dtype=object)
```

```
In [ ]: v.idf_
```

```
Out[ ]: array([2.38629436, 2.38629436, 2.38629436, 2.38629436, 1.28768207,
               2.38629436, 2.38629436, 2.38629436, 2.38629436, 2.38629436,
               1.98082925, 2.38629436, 2.38629436, 2.38629436, 2.38629436,
               2.38629436, 1.13353139, 2.38629436, 2.38629436, 2.38629436,
               1.28768207, 2.38629436, 2.38629436, 2.38629436, 2.38629436,
               2.38629436, 1.28768207, 2.38629436])
```

```
In [ ]: for word in all_feature_names:
           index = v.vocabulary_.get(word)
           print(f"{word}: {v.idf_[index]}")
```

```
already: 2.386294361119891
am: 2.386294361119891
amazon: 2.386294361119891
and: 2.386294361119891
announcing: 1.2876820724517808
apple: 2.386294361119891
are: 2.386294361119891
ate: 2.386294361119891
biryani: 2.386294361119891
dot: 2.386294361119891
eating: 1.9808292530117262
eco: 2.386294361119891
google: 2.386294361119891
grapes: 2.386294361119891
iphone: 2.386294361119891
ironman: 2.386294361119891
is: 1.1335313926245225
loki: 2.386294361119891
microsoft: 2.386294361119891
model: 2.386294361119891
new: 1.2876820724517808
pixel: 2.386294361119891
pizza: 2.386294361119891
surface: 2.386294361119891
tesla: 2.386294361119891
thor: 2.386294361119891
tomorrow: 1.2876820724517808
you: 2.386294361119891
```

In []: `output_transformed[:2]`

Out[]: <2x28 sparse matrix of type '<class 'numpy.float64'>'
with 14 stored elements in Compressed Sparse Row format>

In []: `output_transformed.toarray()[:2]`

Out[]: array([[0.24266547, 0. , 0. , 0. , 0. ,
 0. , 0. , 0.24266547, 0. , 0. ,
 0.40286636, 0. , 0. , 0. , 0. ,
 0.24266547, 0.11527033, 0.24266547, 0. , 0. ,
 0. , 0. , 0.72799642, 0. , 0. ,
 0.24266547, 0. , 0. , 0. , 0. ,
 [0. , 0. , 0. , 0. , 0.30652086,
 0.5680354 , 0. , 0. , 0. , 0. ,
 0. , 0. , 0. , 0. , 0.5680354 ,
 0. , 0.26982671, 0. , 0. , 0. ,
 0.30652086, 0. , 0. , 0. , 0. ,
 0. , 0.30652086, 0. , 0. , 0. ,
]])

In []: `corpus[:2]`

Out[]: ['Thor eating pizza, Loki is eating pizza, Ironman ate pizza already',
'Apple is announcing new iphone tomorrow']

In []: `df = pd.read_csv("data/Ecommerce_data.csv")
df.head()`

Out[]:

	Text	label
0	Urban Ladder Eisner Low Back Study-Office Comp...	Household
1	Contrast living Wooden Decorative Box,Painted ...	Household
2	IO Crest SY-PCI40010 PCI RAID Host Controller ...	Electronics
3	ISAKAA Baby Socks from Just Born to 8 Years- P... Clothing & Accessories	Clothing & Accessories
4	Indira Designer Women's Art Mysore Silk Saree ... Clothing & Accessories	Clothing & Accessories

In []: df['label'].value_counts()

```
Out[ ]: Household      6000
Electronics      6000
Clothing & Accessories 6000
Books            6000
Name: label, dtype: int64
```

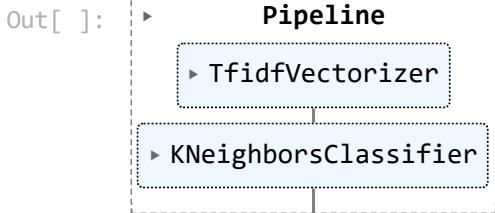
```
In [ ]: df['label_num'] = df['label'].map({
    'Household' : 0,
    'Books' : 1,
    'Electronics': 2,
    'Clothing & Accessories': 3
})
df.head()
```

	Text	label	label_num
0	Urban Ladder Eisner Low Back Study-Office Comp...	Household	0
1	Contrast living Wooden Decorative Box,Painted ...	Household	0
2	IO Crest SY-PCI40010 PCI RAID Host Controller ...	Electronics	2
3	ISAKAA Baby Socks from Just Born to 8 Years- P... Clothing & Accessories	Clothing & Accessories	3
4	Indira Designer Women's Art Mysore Silk Saree ... Clothing & Accessories	Clothing & Accessories	3

```
In [ ]: X_train, X_test, y_train, y_test = train_test_split(
    df['Text'],
    df['label_num'],
    test_size=0.2, # 20% samples will go to test dataset
    random_state=2022,
    stratify=df.label_num
)
```

```
In [ ]: from sklearn.neighbors import KNeighborsClassifier
from sklearn.pipeline import Pipeline

model = Pipeline([
    ('vectorizer_tfidf', TfidfVectorizer()),
    ('KNN', KNeighborsClassifier()),
])
model.fit(X_train, y_train)
```



In []: `model.score(X_test, y_test)`

Out[]: 0.9641666666666666

In []: `from sklearn.metrics import classification_report`

```

y_preds = model.predict(X_test)
print(classification_report(y_test, y_preds))
  
```

	precision	recall	f1-score	support
0	0.95	0.96	0.95	1200
1	0.97	0.95	0.96	1200
2	0.97	0.97	0.97	1200
3	0.97	0.98	0.97	1200
accuracy			0.96	4800
macro avg	0.96	0.96	0.96	4800
weighted avg	0.96	0.96	0.96	4800

In []: `y_test[:5]`

```
C:\Users\User\AppData\Local\Temp\ipykernel_23912\1754177261.py:1: FutureWarning: The behavior of `series[i:j]` with an integer-dtype index is deprecated. In a future version, this will be treated as *label-based* indexing, consistent with e.g. `series[i]` lookups. To retain the old behavior, use `series.iloc[i:j]`. To get the future behavior, use `series.loc[i:j]`.
  y_test[:5]
```

Out[]: 20706 0
19166 2
15209 3
2462 1
6621 3
Name: label_num, dtype: int64

In []: `y_preds[:5]`

Out[]: array([0, 2, 3, 1, 0], dtype=int64)

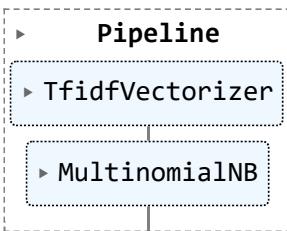
In []: `from sklearn.naive_bayes import MultinomialNB`
`from sklearn.pipeline import Pipeline`

```

model = Pipeline([
    ('vectorizer_tfidf', TfidfVectorizer()),
    ('Multi NB', MultinomialNB()),
])
  
```

`model.fit(X_train, y_train)`

Out[]:

In []: `model.score(X_test, y_test)`

Out[]: 0.9602083333333333

In []: `from sklearn.metrics import classification_report`

```

y_preds = model.predict(X_test)
print(classification_report(y_test, y_preds))
  
```

	precision	recall	f1-score	support
0	0.92	0.96	0.94	1200
1	0.98	0.92	0.95	1200
2	0.97	0.97	0.97	1200
3	0.97	0.99	0.98	1200
accuracy			0.96	4800
macro avg	0.96	0.96	0.96	4800
weighted avg	0.96	0.96	0.96	4800

In []: `df['Text_processed'] = df['Text'].apply(preprocess)`

```

X_train, X_test, y_train, y_test = train_test_split(
    df['Text_processed'],
    df['label_num'],
    test_size=0.2, # 20% samples will go to test dataset
    random_state=2022,
    stratify=df.label_num
)
  
```

```

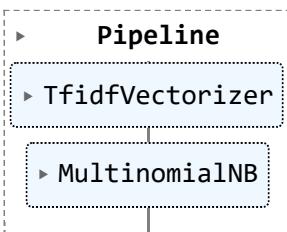
from sklearn.naive_bayes import MultinomialNB
from sklearn.pipeline import Pipeline
  
```

```

model = Pipeline([
    ('vectorizer_tfidf', TfidfVectorizer()),
    ('Multi NB', MultinomialNB()),
])
  
```

```
model.fit(X_train, y_train)
```

Out[]:



```

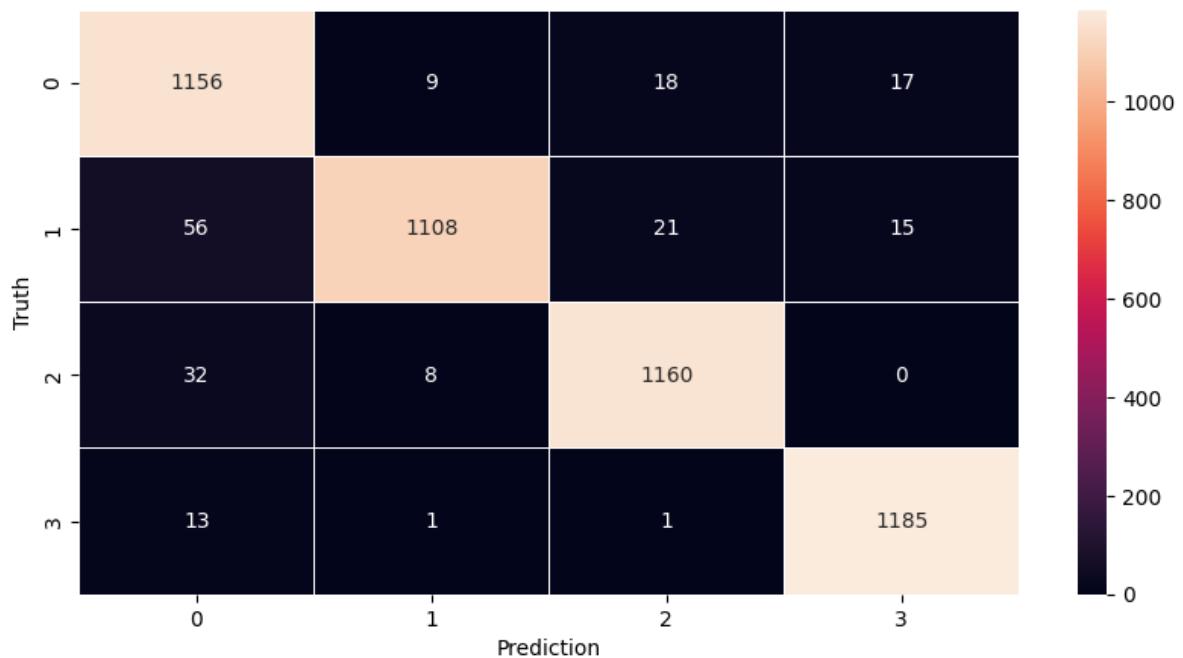
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_preds)
cm
  
```

```
Out[ ]: array([[1156,    9,   18,   17],
   [ 56, 1108,   21,   15],
   [ 32,    8, 1160,    0],
   [ 13,    1,    1, 1185]], dtype=int64)
```

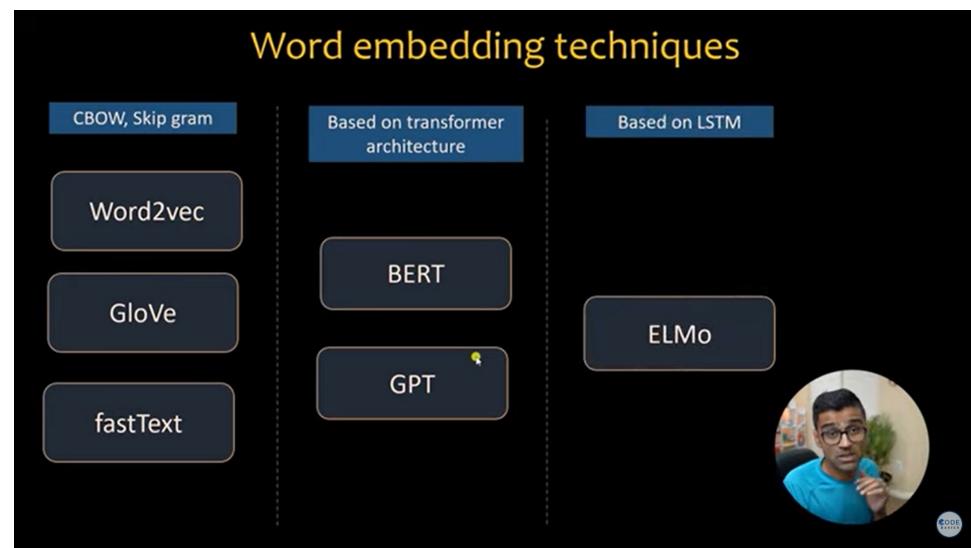
```
In [ ]: import matplotlib.pyplot as plt
import seaborn as sn

plt.figure(figsize=(10,5))
sn.heatmap(
    cm,
    annot=True,
    fmt='d',
    linewidth=0.5
)
plt.xlabel('Prediction')
plt.ylabel('Truth')
```

```
Out[ ]: Text(95.72222222222221, 0.5, 'Truth')
```



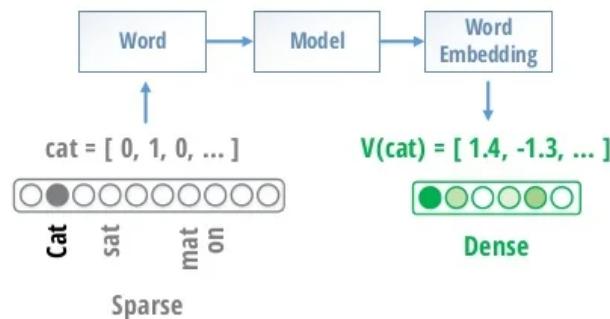
Text Representation - Word Embeddings



	Words Embed.	Sentences Embed.
Strong baselines	FastText	Bag-of-Words
State-of the-art	ELMo	<p>Unsupervised Uses unannotated or weakly-annotated dataset</p> <p>Skip-Thoughts Quick-Thoughts DiscSent Google's dialog input-output</p> <p>Supervised Uses annotated dataset</p> <p>InferSent Machine translation</p> <p>recent trend</p>
		<p>Multi-task learning Uses several annotated or unannotated datasets</p> <p>MILA/MSR's General Purpose Sent. Google's Universal Sentence Enc.</p>



WORD EMBEDDINGS



- From a sparse representation (usually one-hot encoding) to a dense representation
- Embeddings created as by-product vs explicit model



```
!python -m spacy download en_core_web_lg
```

```
In [ ]: nlp = spacy.load("en_core_web_lg")
```

```
In [ ]: doc = nlp("dog cat banana abcde")

for token in doc:
    print (token, " Vector: ", token.has_vector, " OOV: ", token.is_oov)
```

```
dog  Vector:  True  OOV:  False
cat  Vector:  True  OOV:  False
banana  Vector:  True  OOV:  False
abcde  Vector:  False  OOV:  True
```

```
In [ ]: doc[0].vector.shape
```

```
Out[ ]: (300, )
```

```
In [ ]: token_base = nlp("bread")
token_base.vector.shape
```

Out[]: (300,)

```
In [ ]: doc = nlp("bread sandwich burger car tiger human wheat")

for token in doc:
    print(f"{token.text} <-> {token_base.text}, Similarity:", token.similarity(token_base))

bread <-> bread, Similarity: 1.0
sandwich <-> bread, Similarity: 0.6341067010130894
burger <-> bread, Similarity: 0.47520687769584247
car <-> bread, Similarity: 0.06451533308853552
tiger <-> bread, Similarity: 0.04764611675903374
human <-> bread, Similarity: 0.2151154210812192
wheat <-> bread, Similarity: 0.6150360888607199
```

```
In [ ]: def print_similarity(word_base, words_to_compare):
    token_base = nlp(word_base)
    doc = nlp(words_to_compare)
    for token in doc:
        print(f"{token.text} <-> {token_base.text}, Similarity:", token.similarity(token_base))

print_similarity("iphone", "apple samsung iphone dog kitten")
```

```
apple <-> iphone, Similarity: 0.4387907401919904
samsung <-> iphone, Similarity: 0.670859081425417
iphone <-> iphone, Similarity: 1.0
dog <-> iphone, Similarity: 0.08211864228011527
kitten <-> iphone, Similarity: 0.10222317834969896
```

```
In [ ]: king = nlp.vocab["king"].vector
man = nlp.vocab["man"].vector
woman = nlp.vocab["woman"].vector
queen = nlp.vocab["queen"].vector

result = king - man + woman
```

```
In [ ]: from sklearn.metrics.pairwise import cosine_similarity

cosine_similarity([result], [queen])
```

Out[]: array([[0.61780137]], dtype=float32)

Text Classification Using Spacy Word Embeddings

```
In [ ]: import numpy as np
import pandas as pd
```

```
In [ ]: df = pd.read_csv("data/Fake_Real_Data.csv")
df.head()
```

Out[]:

	Text	label
0	Top Trump Surrogate BRUTALLY Stabs Him In The...	Fake
1	U.S. conservative leader optimistic of common ...	Real
2	Trump proposes U.S. tax overhaul, stirs concer...	Real
3	Court Forces Ohio To Allow Millions Of Illega...	Fake
4	Democrats say Trump agrees to work on immigrat...	Real

In []: df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9900 entries, 0 to 9899
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype  
---  -- 
 0   Text    9900 non-null   object 
 1   label   9900 non-null   object 
dtypes: object(2)
memory usage: 154.8+ KB
```

In []: df['label'].value_counts()

```
Out[ ]: Fake    5000
        Real    4900
        Name: label, dtype: int64
```

In []: df['label_num'] = df['label'].map({'Fake': 0, 'Real': 1})

In []: df.sample(5)

Out[]:

	Text	label	label_num
8961	Gala glitz masks Asia's tensions as Trump wind...	Real	1
3230	Kellyanne Conway Announces Trump's HUGE 'Than...	Fake	0
2944	Trump Boasts About Opening Of First New Coal ...	Fake	0
8488	U.S. taxpayers rush to claim deductions under ...	Real	1
1661	Trump faces obstacles in bid to re-shape key U...	Real	1

In []: nlp = spacy.load("en_core_web_lg")

In []: df['vector'] = df['Text'].apply(lambda text: nlp(text).vector)

In []: df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9900 entries, 0 to 9899
Data columns (total 4 columns):
 #   Column      Non-Null Count  Dtype  
---  --          -----          --    
 0   Text        9900 non-null    object  
 1   label       9900 non-null    object  
 2   label_num   9900 non-null    int64  
 3   vector      9900 non-null    object  
dtypes: int64(1), object(3)
memory usage: 309.5+ KB
```

Train-Test splitting

```
In [ ]: from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(
    df['vector'].values,
    df['label_num'],
    test_size=0.2,
    random_state=2022,
)
```



```
In [ ]: X_train[0].shape
```



```
Out[ ]: (300,)
```

Reshaping the X_train and X_test so as to fit for models

```
In [ ]: X_train_2d = np.stack(X_train)
X_test_2d = np.stack(X_test)
```



```
In [ ]: X_train_2d.shape
```



```
Out[ ]: (7920, 300)
```



```
In [ ]: X_test_2d.shape
```



```
Out[ ]: (1980, 300)
```

Model Building and Training

```
In [ ]: from sklearn.preprocessing import MinMaxScaler
from sklearn.naive_bayes import MultinomialNB

scaler = MinMaxScaler()
scaled_train_embed = scaler.fit_transform(X_train_2d)
scaled_test_embed = scaler.transform(X_test_2d)

model = MultinomialNB()
model.fit(scaled_train_embed, y_train)
```

Out[]:

MultinomialNB

MultinomialNB()

MIN MAX SCALING

Rescales feature values to between 0 and 1

$$\text{Rescaled value } X'_i = \frac{x_i - \min(x)}{\max(x) - \min(x)}$$

Original value

Minimum value in feature

Maximum value in feature

ChrisAlbon

In []: model.score(scaled_test_embed, y_test)

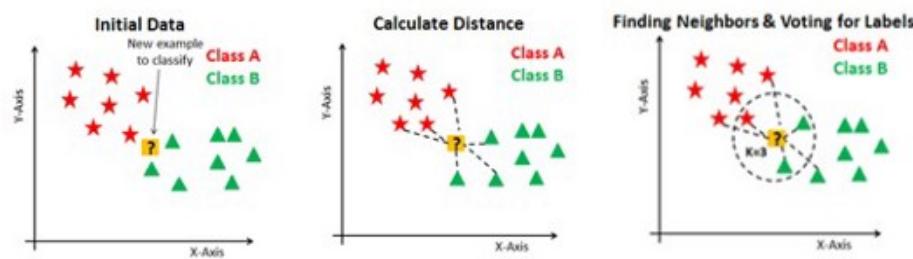
Out[]: 0.943939393939394

In []: y_preds = model.predict(scaled_test_embed)

print(classification_report(y_test, y_preds))

	precision	recall	f1-score	support
0	0.95	0.94	0.95	1024
1	0.94	0.95	0.94	956
accuracy			0.94	1980
macro avg	0.94	0.94	0.94	1980
weighted avg	0.94	0.94	0.94	1980

KNN K nearest neighbors Classification



In []: from sklearn.neighbors import KNeighborsClassifier

model = KNeighborsClassifier(n_neighbors = 5, metric = 'euclidean')

```
model.fit(X_train_2d, y_train)
```

Out[]: ▾ KNeighborsClassifier

```
KNeighborsClassifier(metric='euclidean')
```

In []: model.score(X_test_2d, y_test)

Out[]: 0.9909090909090909

In []: y_preds = model.predict(X_test_2d)

```
print(classification_report(y_test, y_preds))
```

	precision	recall	f1-score	support
0	1.00	0.99	0.99	1024
1	0.99	0.99	0.99	956
accuracy			0.99	1980
macro avg	0.99	0.99	0.99	1980
weighted avg	0.99	0.99	0.99	1980

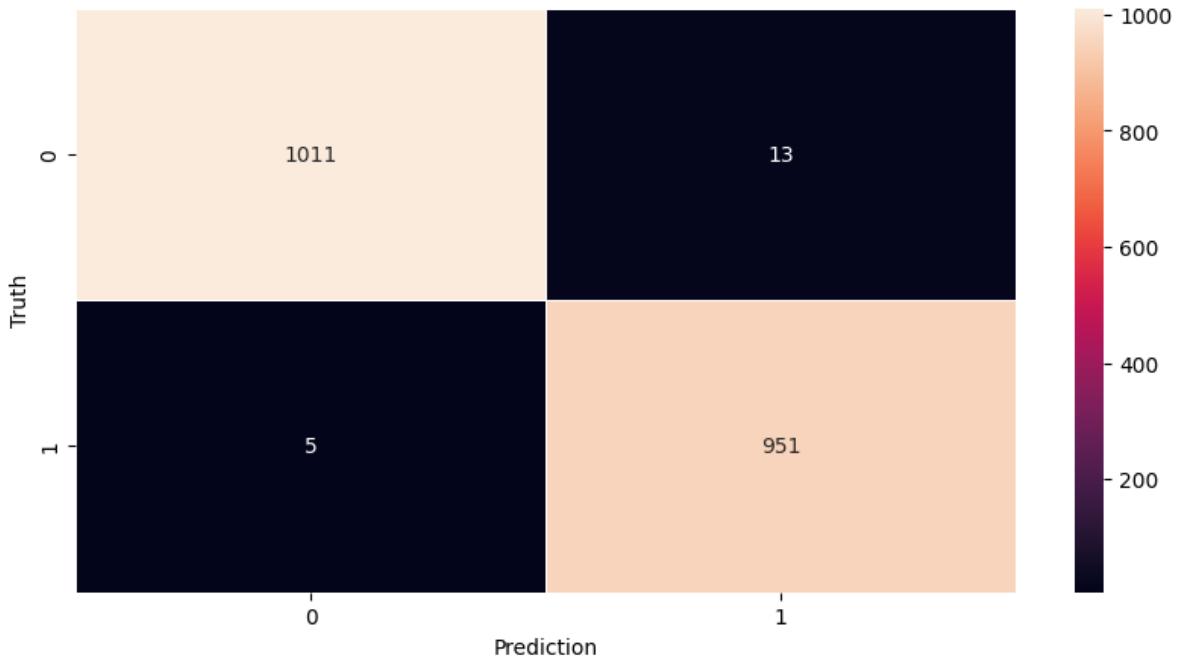
In []: from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_preds)
cm

Out[]: array([[1011, 13],
 [5, 951]], dtype=int64)

In []: plt.figure(figsize=(10,5))

```
sn.heatmap(  
    cm,  
    annot=True,  
    fmt='d',  
    linewidth=0.5  
)  
  
plt.xlabel('Prediction')  
plt.ylabel('Truth')
```

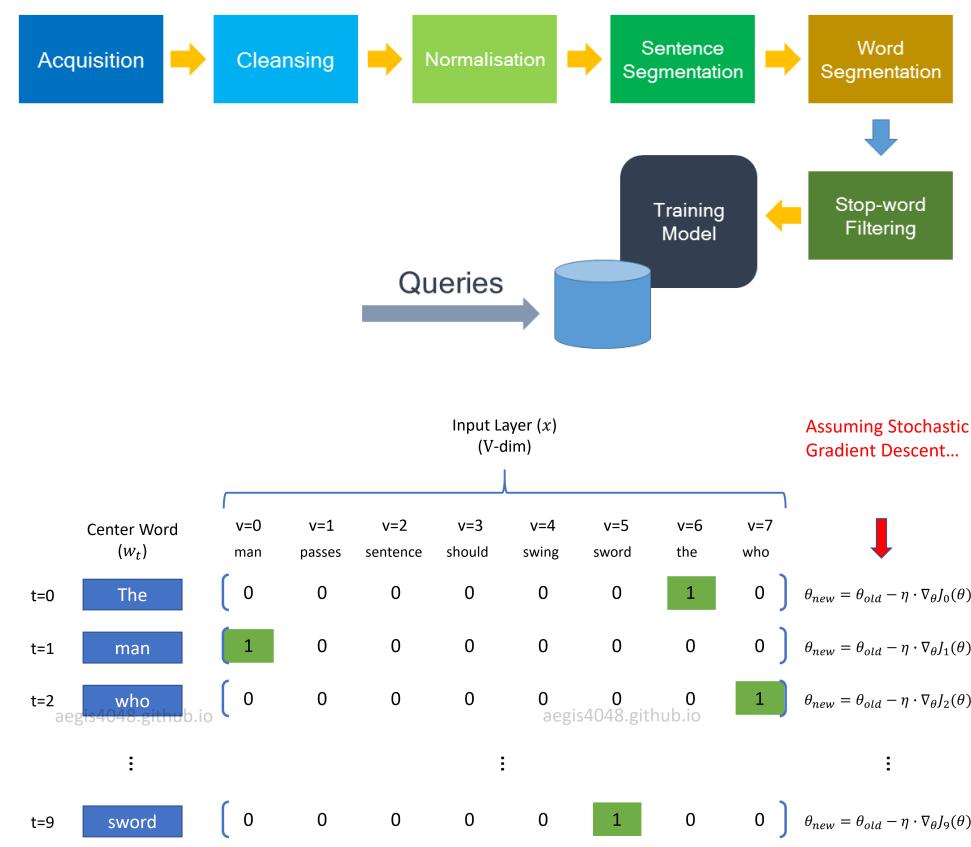
Out[]: Text(95.7222222222221, 0.5, 'Truth')



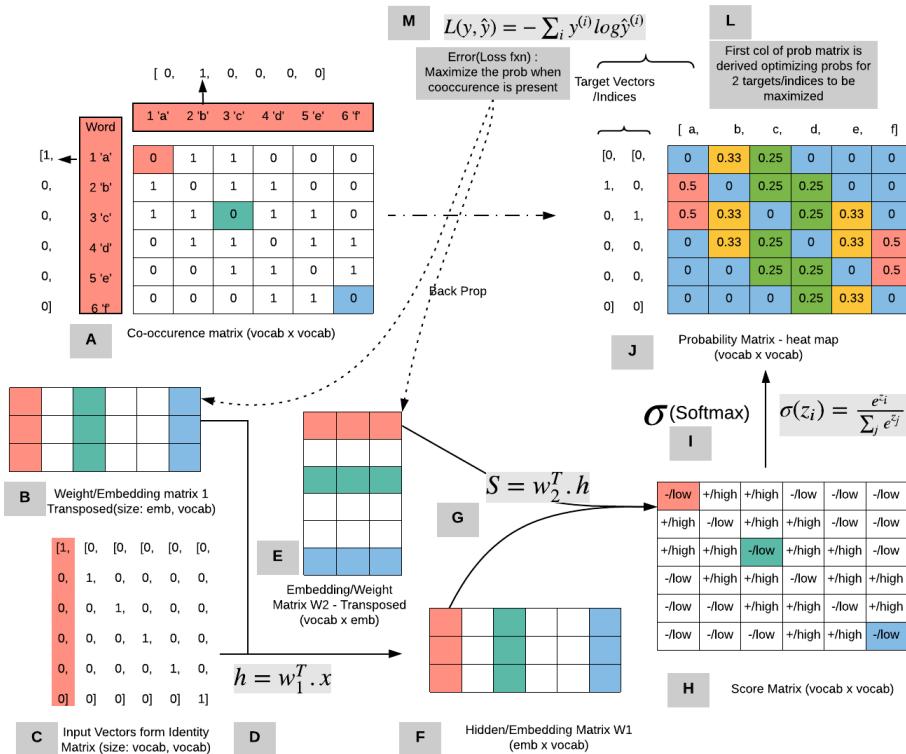
Word Vectors Overview Using Gensim Library

[gensim models](#)

`!pip install gensim`



Word2Vec - Information Flow



```
In [ ]: import gensim.downloader as api
```

```
In [ ]: wv = api.load('word2vec-google-news-300')
```

```
In [ ]: wv.similarity(w1="great", w2="good")
```

```
Out[ ]: 0.729151
```

```
In [ ]: wv.most_similar("good")
```

```
Out[ ]: [('great', 0.7291510105133057),
 ('bad', 0.7190051078796387),
 ('terrific', 0.6889115571975708),
 ('decent', 0.6837348341941833),
 ('nice', 0.6836092472076416),
 ('excellent', 0.644292950630188),
 ('fantastic', 0.6407778263092041),
 ('better', 0.6120728850364685),
 ('solid', 0.5806034803390503),
 ('lousy', 0.576420247554779)]
```

```
In [ ]: wv.most_similar(positive=['king', 'woman'], negative=['man'])
```

```
Out[ ]: [('queen', 0.7118193507194519),
          ('monarch', 0.6189674139022827),
          ('princess', 0.5902431011199951),
          ('crown_prince', 0.5499460697174072),
          ('prince', 0.5377321839332581),
          ('kings', 0.5236844420433044),
          ('Queen_Consort', 0.5235945582389832),
          ('queens', 0.5181134343147278),
          ('sultan', 0.5098593831062317),
          ('monarchy', 0.5087411999702454)]
```

```
In [ ]: wv.most_similar(positive=['king', 'woman'], negative=['man'], topn=5)
```

```
Out[ ]: [('queen', 0.7118193507194519),
          ('monarch', 0.6189674139022827),
          ('princess', 0.5902431011199951),
          ('crown_prince', 0.5499460697174072),
          ('prince', 0.5377321839332581)]
```

```
In [ ]: wv.most_similar(positive=['France', 'Berlin'], negative=['Paris'], topn=5)
```

```
Out[ ]: [('Germany', 0.7901254892349243),
          ('Austria', 0.6026812195777893),
          ('German', 0.6004959940910339),
          ('Germans', 0.5851002931594849),
          ('Poland', 0.5847075581550598)]
```

```
In [ ]: wv.doesnt_match(["facebook", "cat", "google", "microsoft"])
```

```
Out[ ]: 'cat'
```

```
In [ ]: wv.doesnt_match(["dog", "cat", "google", "mouse"])
```

```
Out[ ]: 'google'
```

Gensim: Glove

GloVe

```
In [ ]: glv = api.load("glove-twitter-25")
```

```
In [ ]: glv.most_similar("good")
```

```
Out[ ]: [('too', 0.9648017287254333),
          ('day', 0.9533665180206299),
          ('well', 0.9503170847892761),
          ('nice', 0.9438973665237427),
          ('better', 0.9425962567329407),
          ('fun', 0.9418926239013672),
          ('much', 0.9413353800773621),
          ('this', 0.9387555122375488),
          ('hope', 0.9383506774902344),
          ('great', 0.9378516674041748)]
```

```
In [ ]: glv.doesnt_match("breakfast cereal dinner lunch".split())
```

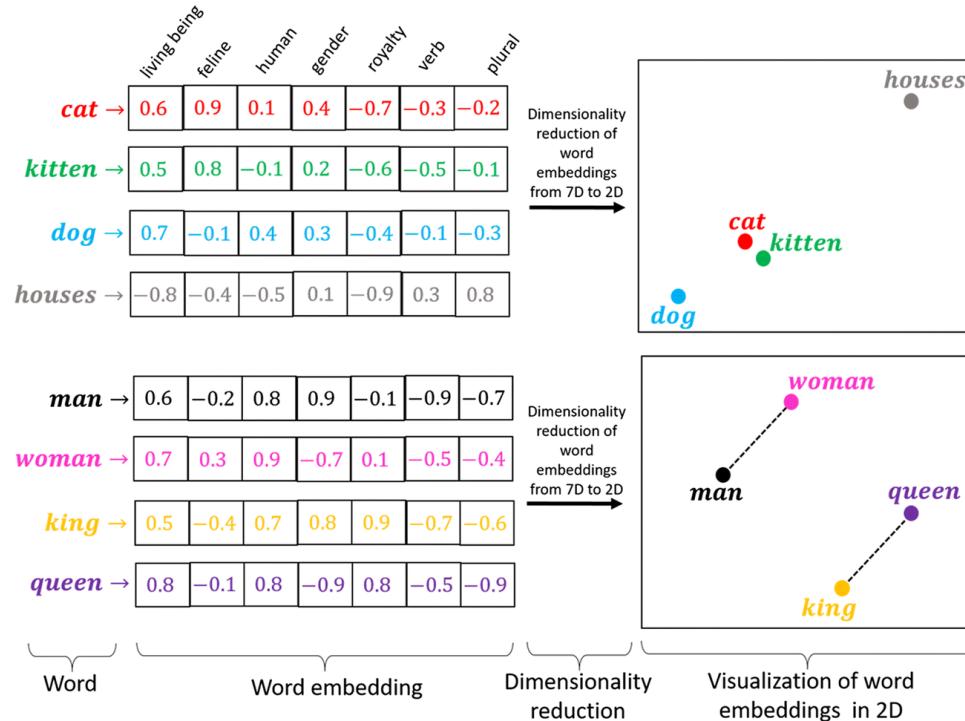
```
Out[ ]: 'cereal'
```

```
In [ ]: g1v.doesnt_match("facebook cat google microsoft".split())
```

```
Out[ ]: 'cat'
```

Text Classification USing Gensim Word Embeddings

Dataset



word2vec

Input:
text

Latin text sample:
Lorem ipsum dolor sit amet, conse-
etur adipiscing elit, sed diam nonum
i tempor in euismod tempor
invidunt ut labore et dolore magna
aliquam erat volutpat. At vero eos et
aliquid vel.

train for
each word
a word vector

Model:

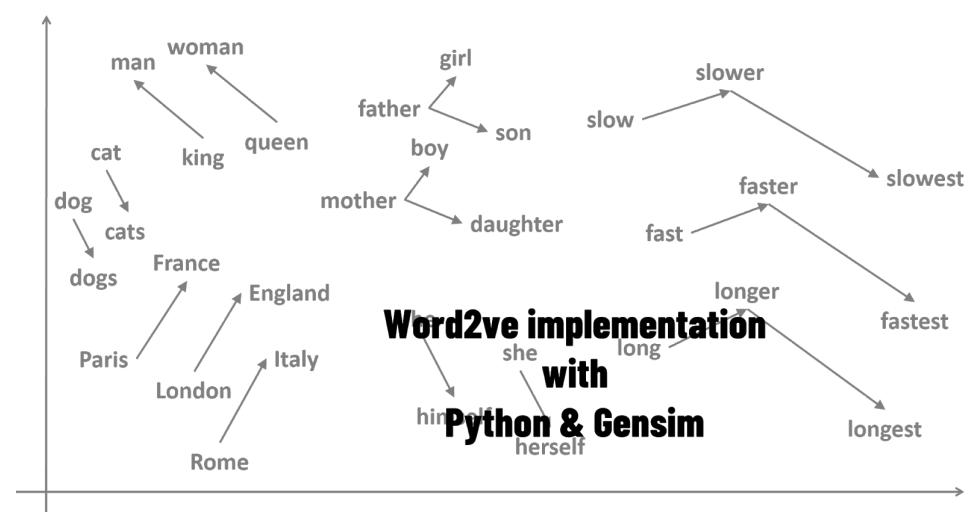
wv_kite
wv_space
wv_dog
wv_water
wv_house
wv_netherlands
wv_spain wv_france
wv_italy
wv_belgium

vector space:
consists of word vectors
for each word

most_similar('france'):

spain	0.678515
belgium	0.665923
netherlands	0.652428
italy	0.633130

highest cosine
distance values
in vector space
of the nearest
words



Using gensim's word2vec embeddings to convert text into vector

1. Preprocess the text to remove stop words, punctuations and get lemma for each word
2. Get word vectors for each of the words in a pre-processed sentence
3. Take a mean of all word vectors to derive the numeric representation of the entire news article

```
import gensim.downloader as api
wv = api.load('word2vec-google-news-300')
```

```
In [ ]: wv.similarity(w1="great", w2="good")
```

```
Out[ ]: 0.729151
```

```
In [ ]: wv_great = wv["great"]
wv_good = wv["good"]
```

```
In [ ]: wv_great.shape
```

```
Out[ ]: (300,)
```

```
In [ ]: type(wv_great)
```

```
Out[ ]: numpy.ndarray
```

Get Data

```
In [ ]: df = pd.read_csv("data/fake_and_real_news.csv")
df.head()
```

Out[]:

		Text	label
0	Top Trump Surrogate BRUTALLY Stabs Him In The...	Fake	
1	U.S. conservative leader optimistic of common ...	Real	
2	Trump proposes U.S. tax overhaul, stirs concer...	Real	
3	Court Forces Ohio To Allow Millions Of Illega...	Fake	
4	Democrats say Trump agrees to work on immigrat...	Real	

In []: df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9900 entries, 0 to 9899
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype  
 ---  --     --           --    
 0   Text    9900 non-null   object 
 1   label   9900 non-null   object 
dtypes: object(2)
memory usage: 154.8+ KB
```

In []: df['label'].value_counts()

```
Out[ ]: Fake    5000
        Real    4900
Name: label, dtype: int64
```

```
In [ ]: df['label_num'] = df['label'].map({
        "Fake": 0,
        "Real": 1
    })
df.head()
```

Out[]:

		Text	label	label_num
0	Top Trump Surrogate BRUTALLY Stabs Him In The...	Fake		0
1	U.S. conservative leader optimistic of common ...	Real		1
2	Trump proposes U.S. tax overhaul, stirs concer...	Real		1
3	Court Forces Ohio To Allow Millions Of Illega...	Fake		0
4	Democrats say Trump agrees to work on immigrat...	Real		1

In []: df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9900 entries, 0 to 9899
Data columns (total 3 columns):
 #   Column      Non-Null Count  Dtype  
 ---  --         --           --    
 0   Text        9900 non-null   object 
 1   label       9900 non-null   object 
 2   label_num   9900 non-null   int64  
dtypes: int64(1), object(2)
memory usage: 232.2+ KB
```

convert the text into a vector

```
In [ ]: import spacy
nlp = spacy.load("en_core_web_lg")

def preprocess_and_vectorize(text):
    doc = nlp(text)

    filtered_tokens = []

    for token in doc:
        if token.is_punct or token.is_stop:
            continue
        filtered_tokens.append(token.lemma_)

    return filtered_tokens
```

```
In [ ]: preprocess_and_vectorize("Don't worry if you don't understand")
```

```
Out[ ]: ['worry', 'understand']
```

```
In [ ]: wv.get_mean_vector(['worry', 'understand'], pre_normalize=False)[:5]
```

```
Out[ ]: array([ 0.00976562, -0.00561523, -0.08905029,  0.01330566, -0.2709961 ],  
           dtype=float32)
```

```
In [ ]: v1 = wv['worry']
v2 = wv['understand']
np.mean([v1, v2], axis=0)[:5]
```

```
Out[ ]: array([ 0.00976562, -0.00561523, -0.08905029,  0.01330566, -0.2709961 ],  
           dtype=float32)
```

```
In [ ]: import spacy
nlp = spacy.load("en_core_web_lg")

def preprocess_and_vectorize(text):
    doc = nlp(text)

    filtered_tokens = []

    for token in doc:
        if token.is_punct or token.is_stop:
            continue
        filtered_tokens.append(token.lemma_)

    return wv.get_mean_vector(filtered_tokens)
```

```
In [ ]: v = preprocess_and_vectorize("Don't worry if you don't understand")
v.shape
```

```
Out[ ]: (300,)
```

```
In [ ]: df['vector'] = df['Text'].apply(preprocess_and_vectorize)
#df['vector_text'] = df['Text'].apply(lambda text: preprocess_and_vectorize(text))
```

```
In [ ]: df.head()
```

Out[]:

		Text	label	label_num	vector
0	Top Trump Surrogate BRUTALLY Stabs Him In The...	Fake	0	[0.008145372, 0.019952843, -0.00989356, 0.0344...	
1	U.S. conservative leader optimistic of common ...	Real	1	[0.00861828, 0.007408227, 0.0007675802, 0.0138...	
2	Trump proposes U.S. tax overhaul, stirs concer...	Real	1	[0.01823076, 0.0063306373, -0.0058634086, 0.03...	
3	Court Forces Ohio To Allow Millions Of Illega...	Fake	0	[0.012453172, 0.0122098895, 6.3027373e-06, 0.0...	
4	Democrats say Trump agrees to work on immigrat...	Real	1	[-0.0022669104, 0.011340516, 0.003596399, 0.02...	

Train-Test splitting

```
In [ ]: from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(
    df['vector'].values,
    df['label_num'],
    test_size=0.2,
    random_state=2022,
    stratify=df['label_num']
)
```

Reshaping the X_train and X_test to fit model

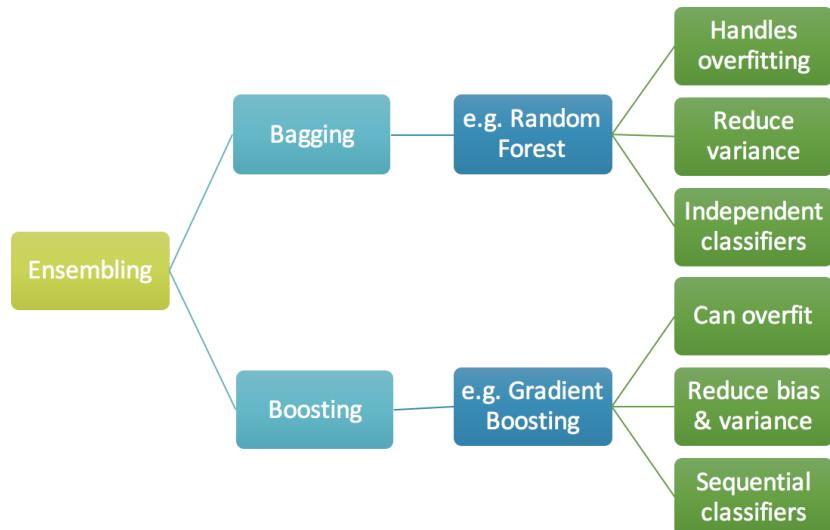
```
In [ ]: X_train[:3]
```

```
In [ ]: X_train_2d = np.stack(X_train)
X_test_2d = np.stack(X_test)
```

```
In [ ]: X_train_2d[:3]
```

Model Building and Training

Gradient Boosting Classifier

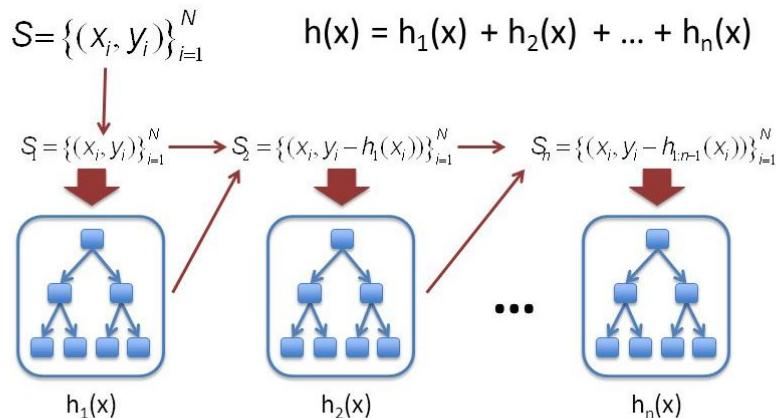


Gradient Boosting (Simple Version)

(Why is it called “gradient”?)

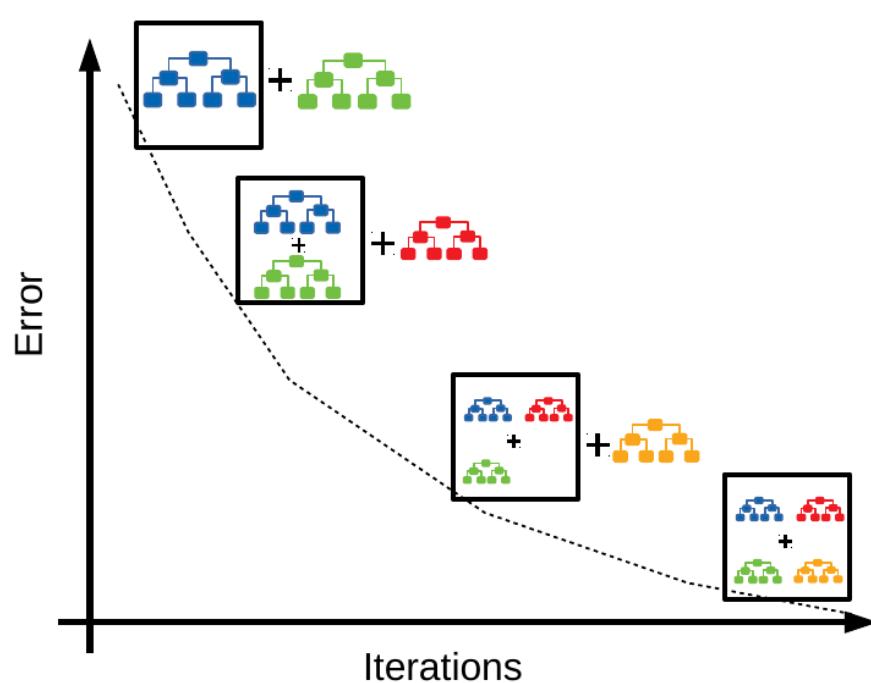
(For Regression Only)

(Answer next slides.)



<http://statweb.stanford.edu/~jhf/ftp/trebst.pdf>

24



```
In [ ]: from sklearn.ensemble import GradientBoostingClassifier
model = GradientBoostingClassifier()
model.fit(X_train_2d, y_train)
```

```
Out[ ]: ▾ GradientBoostingClassifier
GradientBoostingClassifier()
```

```
In [ ]: model.score(X_test_2d, y_test)
```

```
Out[ ]: 0.9782828282828283
```

```
In [ ]: y_preds = model.predict(X_test_2d)
```

```
In [ ]: from sklearn.metrics import classification_report
print(classification_report(y_test, y_preds))
```

	precision	recall	f1-score	support
0	0.98	0.97	0.98	1000
1	0.97	0.98	0.98	980
accuracy			0.98	1980
macro avg	0.98	0.98	0.98	1980
weighted avg	0.98	0.98	0.98	1980

Test

```
In [ ]: test_news = [
    "Michigan governor denies misleading U.S. House on Flint water (Reuters) - Mich"
    " WATCH: Fox News Host Loses Her Sh*t, Says Investigating Russia For Hacking Ou"
    " Sarah Palin Celebrates After White Man Who Pulled Gun On Black Protesters Go"
]
```

```
In [ ]: test_news_vectors = [preprocess_and_vectorize(n) for n in test_news]
```

```
In [ ]: model.predict(test_news_vectors)
```

```
Out[ ]: array([1, 0, 0], dtype=int64)
```

```
In [ ]: from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_preds)
cm
```

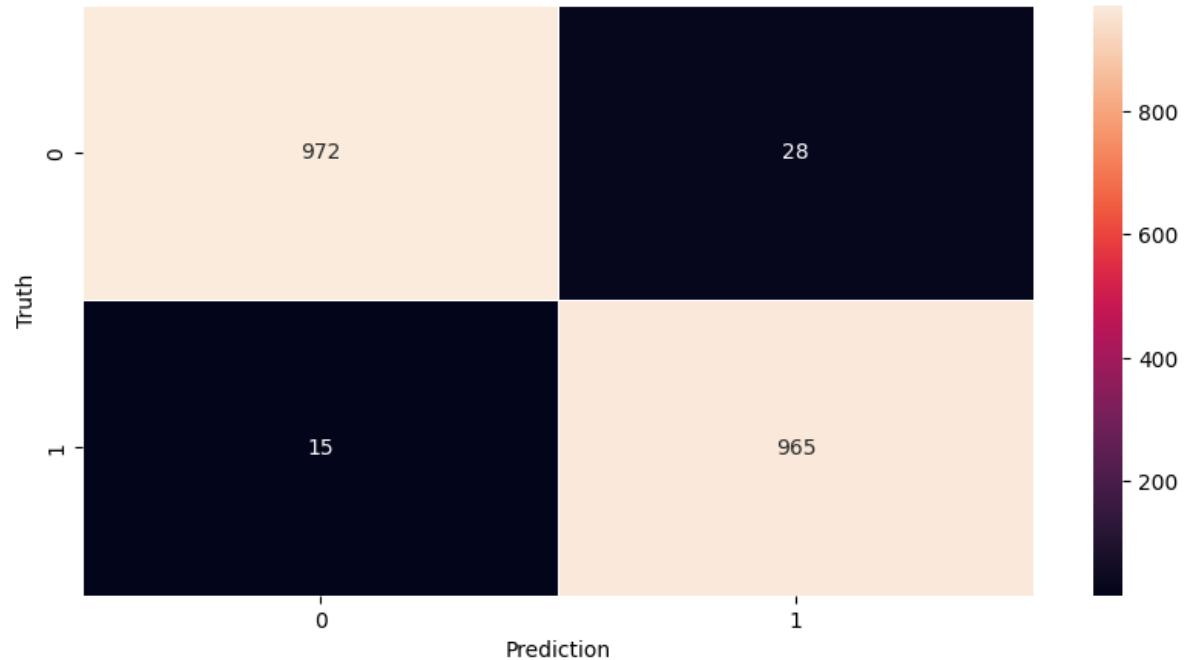
```
Out[ ]: array([[972, 28],
   [15, 965]], dtype=int64)
```

```
In [ ]: plt.figure(figsize=(10,5))
```

```
sn.heatmap(
    cm,
    annot=True,
    fmt='d',
    linewidth=0.5
)

plt.xlabel('Prediction')
plt.ylabel('Truth')
```

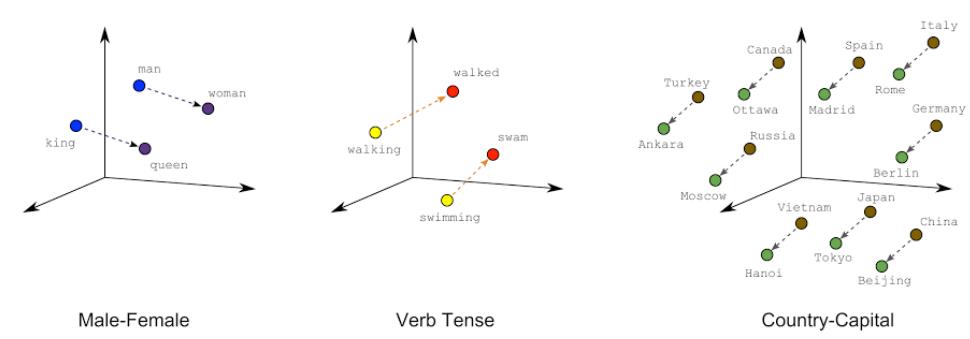
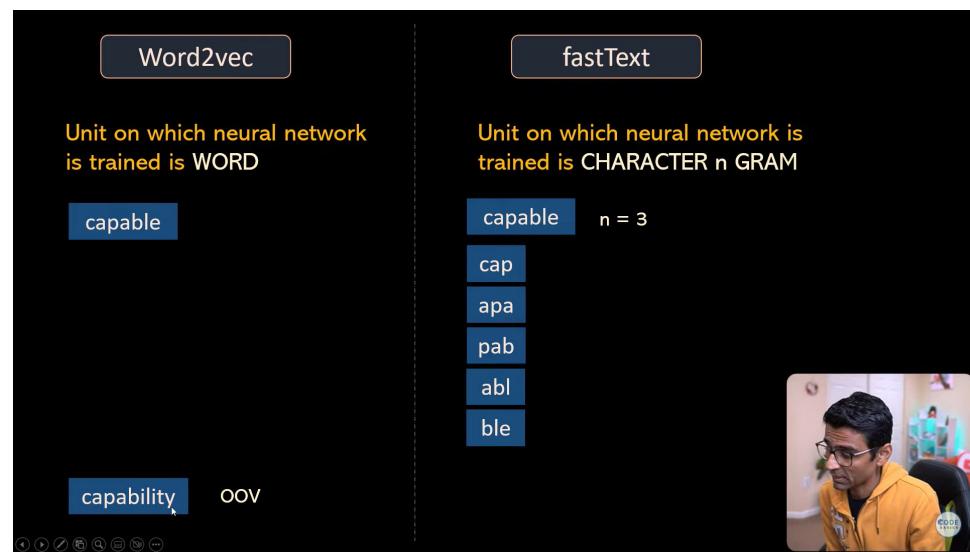
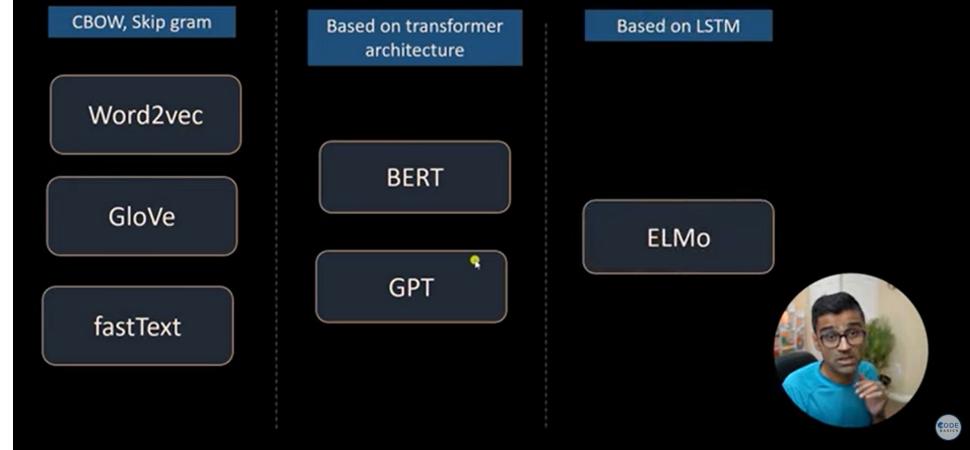
```
Out[ ]: Text(95.72222222222221, 0.5, 'Truth')
```



Train Custom Word Vectors in fastText

```
git clone https://github.com/facebookresearch/fastText.git
cd fastText
pip install .
pip install fasttext pip install fastText
```

Word embedding techniques



```
In [ ]: df = pd.read_csv("data/Cleaned_Indian_Food_Dataset.csv")
df.head(3)
```

Out[]:

		TranslatedRecipeName	TranslatedIngredients	TotalTimeInMins	Cuisine	TranslatedInstructions
0	Masala Karela Recipe	1 tablespoon Red Chilli powder,3 tablespoon Gr...		45	Indian	To begin making the Masala Karela Recipe,de-se...
1	Spicy Tomato Rice (Recipe)	2 teaspoon cashew - or peanuts, 1/2 Teaspoon ...		15	South Indian Recipes	To make tomato puliogere, first cut the tomato...
2	Ragi Semiya Upma Recipe - Ragi Millet Vermicel...	1 Onion - sliced,1 teaspoon White Urad Dal (Sp...		50	South Indian Recipes	To begin making the Ragi Vermicelli Recipe, fi...

In []: df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5938 entries, 0 to 5937
Data columns (total 9 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   TranslatedRecipeName    5938 non-null   object 
 1   TranslatedIngredients   5938 non-null   object 
 2   TotalTimeInMins        5938 non-null   int64  
 3   Cuisine                5938 non-null   object 
 4   TranslatedInstructions 5938 non-null   object 
 5   URL                   5938 non-null   object 
 6   Cleaned-Ingredients   5938 non-null   object 
 7   image-url             5938 non-null   object 
 8   Ingredient-count      5938 non-null   int64  
dtypes: int64(2), object(7)
memory usage: 417.6+ KB
```

In []: df['TranslatedInstructions'][0]

Out[]: 'To begin making the Masala Karela Recipe,de-seed the karela and slice.\r\nDo not remove the skin as the skin has all the nutrients.\r\nAdd the karela to the pressure cooker with 3 tablespoon of water, salt and turmeric powder and pressure cook for three whistles.\r\nRelease the pressure immediately and open the lids.\r\nKeep aside.Heat oil in a heavy bottomed pan or a kadhai.\r\nAdd cumin seeds and let it sizzle.Once the cumin seeds have sizzled, add onions and saute them till it turns golden brown in color.Add the karela, red chilli powder, amchur powder, coriander powder and besan.\r\nStir to combine the masalas into the karela.Drizzle a little extra oil on the top and mix again.\r\nCover the pan and simmer Masala Karela stirring occasionally until everything comes together well.\r\nTurn off the heat.Transfer Masala Karela into a serving bowl and serve.Serve Masala Karela along with Pan chmel Dal and Phulka for a weekday meal with your family.\r\n'

Pre-processing - Use Regular Expression to Clean Data

- 1.Remove punctuation
- 2.Remove extra space
- 3.Make the entire sentence lower case

```
In [ ]: import re
```

```
def preprocess(text):
    text = re.sub(r'^\w\s]', ' ', text)
    text = re.sub(r'[ \r\n]+', ' ', text)
    return text.strip().lower()
```

```
In [ ]: text = "To begin making the Masala Karela Recipe, de-seed the karela and slice.\r\n\r\n"
```

```
In [ ]: preprocess(text)
```

Out[]: 'to begin making the masala karela recipe de seed the karela and slice do not remove the skin as the skin has all the nutrients add the karela to the pressure cooker with 3 tablespoon of water salt and turmeric powder and pressure cook for three whistles release the pressure immediately and open the lids keep aside heat oil in a heavy bottomed pan or a kadhai add cumin seeds and let it sizzle once the cumin seeds have sizzled add onions and saute them till it turns golden brown in color add the karela red chilli powder amchur powder coriander powder and besan stir to combine the masalas into the karela drizzle a little extra oil on the top and mix again cover the pan and simmer masala karela stirring occasionally until everything comes together well turn off the heat transfer masala karela into a serving bowl and serve serve masala karela along with panchmel dal and phulka for a weekday meal with your family'

```
In [ ]: df['TranslatedInstructions'] = df['TranslatedInstructions'].apply(preprocess)
```

```
In [ ]: df.head()
```

	TranslatedRecipeName	TranslatedIngredients	TotalTimeInMins	Cuisine	TranslatedInstructions
0	Masala Karela Recipe	1 tablespoon Red Chilli powder,3 tablespoon Gr...	45	Indian	to begin making the masala karela recipe de se...
1	Spicy Tomato Rice (Recipe)	2 teaspoon cashew - or peanuts, 1/2 Teaspoon ...	15	South Indian Recipes	to make tomato puliogere first cut the tomatoe...
2	Ragi Semiya Upma Recipe - Ragi Millet Vermicel...	1 Onion - sliced,1 teaspoon White Urad Dal (Sp...	50	South Indian Recipes	to begin making the ragi vermicelli recipe fir...
3	Gongura Chicken Curry Recipe - Andhra Style Go...	1/2 teaspoon Turmeric powder (Haldi),1 tablesp...	45	Andhra	to begin making gongura chicken curry recipe f...
4	Andhra Style Alam Pachadi Recipe - Adrak Chutn...	oil - as per use, 1 tablespoon coriander seed...	30	Andhra	to make andhra style alam pachadi first heat o...

```
In [ ]: df['TranslatedInstructions'][0]
```

Out[]: 'to begin making the masala karela recipe de seed the karela and slice do not remove the skin as the skin has all the nutrients add the karela to the pressure cooker with 3 tablespoon of water salt and turmeric powder and pressure cook for three whistles release the pressure immediately and open the lids keep aside heat oil in a heavy bottomed pan or a kadhai add cumin seeds and let it sizzle once the cumin seeds have sizzled add onions and saute them till it turns golden brown in color add the karela red chilli powder amchur powder coriander powder and besan stir to combine the masalas into the karela drizzle a little extra oil on the top and mix again cover the pan and simmer masala karela stirring occasionally until everything comes together well turn off the heat transfer masala karela into a serving bowl and serve serve masala karela along with panchmel dal and phulka for a weekday meal with your family'

```
In [ ]: df.to_csv("data/food_recipes.csv", columns=['TranslatedInstructions'], header=None)
```

```
In [ ]: import fasttext

model = fasttext.train_unsupervised("data/food_recipes.csv")
```

```
In [ ]: model.get_nearest_neighbors("paneer")
```

Out[]: [(0.6278824806213379, 'bhurji'),
(0.6183227896690369, 'tikka'),
(0.6128366589546204, 'makhanwala'),
(0.5976285934448242, 'tikkas'),
(0.5888250470161438, 'makhan'),
(0.5729339718818665, 'tandoori'),
(0.568075954914093, 'reshmi'),
(0.5664334297180176, 'makhani'),
(0.5645010471343994, 'burji'),
(0.5590397715568542, 'satay')]

```
In [ ]: model.get_word_vector("dosa").shape
```

Out[]: (100,)

Text Classification Using fastText

```
In [ ]: df= pd.read_csv("data/e-commerce_dataset.csv", header=None)
df.head()
```

	0	1
0	Household Paper Plane Design Framed Wall Hanging Motivational Artwork	
1	Household S AF 'Floral' Framed Painting (Wood, 30 inch x 20 inch)	
2	Household S AF 'UV Textured Modern Art Print Framed' Painting	
3	Household S AF Flower Print Framed Painting (Synthetic, 12 inch x 16 inch)	
4	Household Incredible Gifts India Wooden Happy Birthday Unique Wall Art	

```
In [ ]: df.columns=["category", "description"]
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50425 entries, 0 to 50424
Data columns (total 2 columns):
 #   Column      Non-Null Count  Dtype  
---  --  
 0   category    50425 non-null   object 
 1   description  50424 non-null   object 
dtypes: object(2)
memory usage: 788.0+ KB
```

In []: df['category'].value_counts()

```
Out[ ]: Household           19313
         Books              11820
         Electronics        10621
         Clothing & Accessories 8671
Name: category, dtype: int64
```

In []: df.dropna(inplace=True)
df.shape

```
Out[ ]: (50424, 2)
```

In []: df['category'].replace("Clothing & Accessories", "Clothing_Accessories", inplace=True)
df['category'].unique()

```
Out[ ]: array(['Household', 'Books', 'Clothing_Accessories', 'Electronics'],
              dtype=object)
```

In []: df['category'] = "__label__" + df['category'].astype(str)
df.head()

	category	description
0	__label_Household	Paper Plane Design Framed Wall Hanging Motiv...
1	__label_Household	SAF 'Floral' Framed Painting (Wood, 30 inch x ...
2	__label_Household	SAF 'UV Textured Modern Art Print Framed' Pain...
3	__label_Household	SAF Flower Print Framed Painting (Synthetic, 1...
4	__label_Household	Incredible Gifts India Wooden Happy Birthday U...

In []: df.info()

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 50424 entries, 0 to 50424
Data columns (total 2 columns):
 #   Column      Non-Null Count  Dtype  
---  --  
 0   category    50424 non-null   object 
 1   description  50424 non-null   object 
dtypes: object(2)
memory usage: 1.2+ MB
```

In []: df['category_description'] = df['category'] + ' ' + df['description']
df.head()

Out[]:

	category	description	category_description
0	_label_Household	Paper Plane Design Framed Wall Hanging Motivat...	_label_Household Paper Plane Design Framed W...
1	_label_Household	SAF 'Floral' Framed Painting (Wood, 30 inch x ...	_label_Household SAF 'Floral' Framed Paintin...
2	_label_Household	SAF 'UV Textured Modern Art Print Framed' Pain...	_label_Household SAF 'UV Textured Modern Art...
3	_label_Household	SAF Flower Print Framed Painting (Synthetic, 1...	_label_Household SAF Flower Print Framed Pai...
4	_label_Household	Incredible Gifts India Wooden Happy Birthday U...	_label_Household Incredible Gifts India Wood...

In []: df['category_description'][0]

```
'_label_Household Paper Plane Design Framed Wall Hanging Motivational Office Dec or Art Prints (8.7 X 8.7 inch) - Set of 4 Painting made up in synthetic frame with uv textured print which gives multi effects and attracts towards it. This is an sp ecial series of paintings which makes your wall very beautiful and gives a royal t ouch. This painting is ready to hang, you would be proud to possess this unique pa inting that is a niche apart. We use only the most modern and efficient printing t echnology on our prints, with only the and inks and precision epson, roland and hp printers. This innovative hd printing technique results in durable and spectacular looking prints of the highest that last a lifetime. We print solely with top-notch 100% inks, to achieve brilliant and true colours. Due to their high level of uv re sistance, our prints retain their beautiful colours for many years. Add colour and style to your living space with this digitally printed painting. Some are for plea sure and some for eternal bliss.so bring home this elegant print that is lushed wi th rich colors that makes it nothing but sheer elegance to be to your friends and family.it would be treasured forever by whoever your lucky recipient is. Liven up your place with these intriguing paintings that are high definition hd graphic dig ital prints for home, office or any room.'
```

Pre-processing - Use Regular Expression to Clean Data

- 1.Remove punctuation
- 2.Remove extra space
- 3.Make the entire sentence lower case

In []: df['category_description'] = df['category_description'].apply(preprocess)

In []: df['category_description'][0]

```
Out[ ]: '__label__household paper plane design framed wall hanging motivational office dec  
or art prints 8 7 x 8 7 inch set of 4 painting made up in synthetic frame with uv  
textured print which gives multi effects and attracts towards it this is an specia  
l series of paintings which makes your wall very beautiful and gives a royal touch  
this painting is ready to hang you would be proud to possess this unique painting  
that is a niche apart we use only the most modern and efficient printing technolog  
y on our prints with only the and inks and precision epson roland and hp printers  
this innovative hd printing technique results in durable and spectacular looking p  
rints of the highest that last a lifetime we print solely with top notch 100 inks  
to achieve brilliant and true colours due to their high level of uv resistance our  
prints retain their beautiful colours for many years add colour and style to your  
living space with this digitally printed painting some are for pleasure and some f  
or eternal bliss so bring home this elegant print that is lushed with rich colors  
that makes it nothing but sheer elegance to be to your friends and family it would  
be treasured forever by whoever your lucky recipient is liven up your place with t  
hese intriguing paintings that are high definition hd graphic digital prints for h  
ome office or any room'
```

Train Test Split

```
In [ ]: from sklearn.model_selection import train_test_split
```

```
train, test = train_test_split(df, test_size=0.2)
```

```
In [ ]: train.shape, test.shape
```

```
Out[ ]: ((40339, 3), (10085, 3))
```

```
In [ ]: train.to_csv("data/e-commerce_train.csv", columns=["category_description"], index=False)  
test.to_csv("data/e-commerce_test.csv", columns=["category_description"], index=False)
```

```
In [ ]: import fasttext
```

```
model = fasttext.train_supervised(input="data/e-commerce_train.csv")
```

```
In [ ]: model.test("data/e-commerce_test.csv")
```

```
Out[ ]: (10085, 0.9699553792761527, 0.9699553792761527)
```

- First parameter (10085) is test size. Second and third parameters are precision and recall respectively.

```
In [ ]: model.predict("wintech assemble desktop pc cpu 500 gb sata hdd 4 gb ram intel c2d r
```

```
Out[ ]: ('__label__electronics',), array([0.99772298]))
```

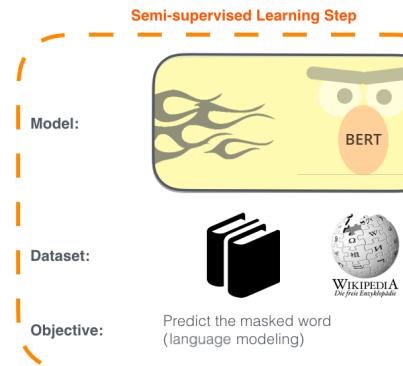
```
In [ ]: model.predict("ockey men's cotton t shirt fabric details 80 cotton 20 polyester sup
```

```
Out[ ]: ('__label__clothing_accessories',), array([1.00000703]))
```

BERT (Bidirectional Encoder Representations From Transformers)

1 - **Semi-supervised** training on large amounts of text (books, wikipedia..etc.).

The model is trained on a certain task that enables it to grasp patterns in language. By the end of the training process, BERT has language-processing abilities capable of empowering many models we later need to build and train in a supervised way.



2 - **Supervised** training on a specific task with a labeled dataset.

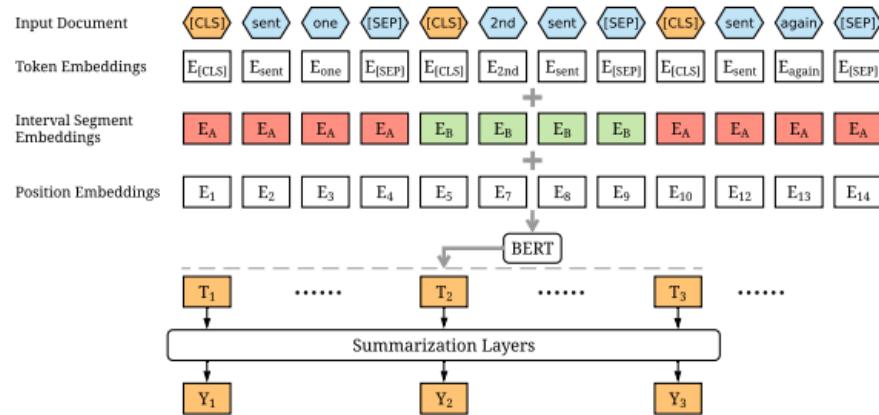
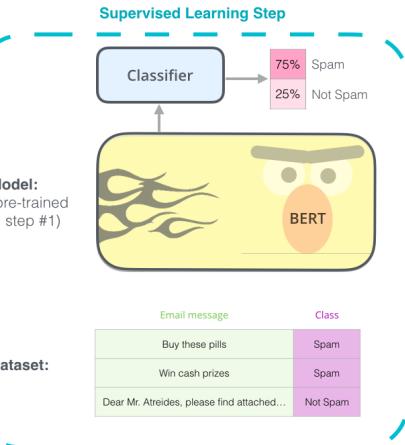
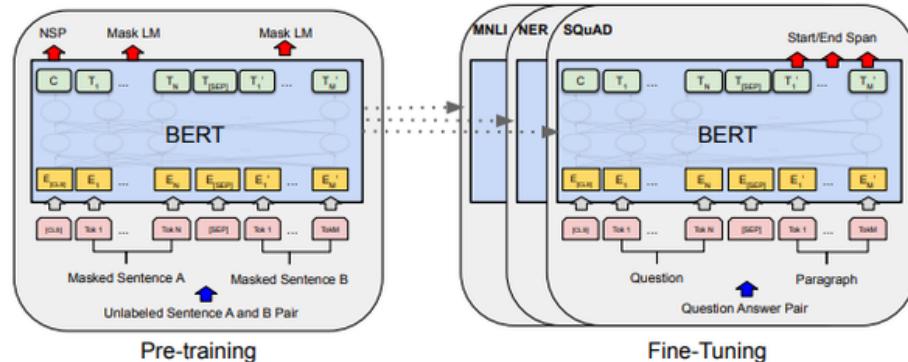


Figure 1: The overview architecture of the BERTSUM model.



Regular Expression Tutorial

regular expressions 101

Tesla Company Filings

In []: `import re`

In []: `text = ''`

`Elon musk's phone number is 9991116666, call him if you have any questions on dodge
Tesla's CFO number (999)-333-7777`

```
In [ ]: pattern = '\((\d{3})\)-\d{3}-\d{4}|\d{10}'
matches = re.findall(pattern, text)
matches
```

```
Out[ ]: ['9991116666', '(999)-333-7777']
```

```
In [ ]: text = '''
Note 1 - Overview
Tesla, Inc. ("Tesla", the "Company", "we", "us" or "our") was incorporated in the S
products. Our Chief Executive Officer, as the chief operating decision maker ("CODM
Beginning in the first quarter of 2021, there has been a trend in many parts of the
against COVID-19, as well as an easing of restrictions on social, business, travel
rates and regulations continue to fluctuate in various regions and there are ongoing
and increases in costs for logistics and supply chains, such as increased port congest
supply. We have also previously been affected by temporary manufacturing closures,
administrative activities supporting our product deliveries and deployments.

Note 2 - Summary of Significant Accounting Policies
Unaudited Interim Financial Statements
The consolidated balance sheet as of September 30, 2021, the consolidated statement
comprehensive income, the consolidated statements of redeemable noncontrolling inter
30, 2021 and 2020 and the consolidated statements of cash flows for the nine months
disclosed in the accompanying notes, are unaudited. The consolidated balance sheet
consolidated financial statements as of that date. The interim consolidated financi
conjunction with the annual consolidated financial statements and the accompanying
ended December 31, 2020.
'''
```

```
In [ ]: pattern = 'Note \d - ([^\n]*)'
matches = re.findall(pattern, text)
matches
```

```
Out[ ]: ['Overview', 'Summary of Significant Accounting Policies']
```

```
In [ ]: text = '''
The gross cost of operating lease vehicles in FY2021 Q1 was $4.85 billion.
In previous quarter i.e. FY2020 Q4 it was $3 billion.
'''
```

```
In [ ]: pattern = 'FY\d{4} Q[1-4]'
matches = re.findall(pattern, text)
matches
```

```
Out[ ]: ['FY2021 Q1', 'FY2020 Q4']
```

```
In [ ]: text = '''
The gross cost of operating lease vehicles in FY2021 Q1 was $4.85 billion.
In previous quarter i.e. fy2020 Q4 it was $3 billion.
'''
```

```
In [ ]: pattern = 'FY\d{4} Q[1-4]'
matches = re.findall(pattern, text)
matches
```

```
Out[ ]: ['FY2021 Q1']
```

```
In [ ]: plt.figure(figsize=(10,5))
sn.heatmap(
```

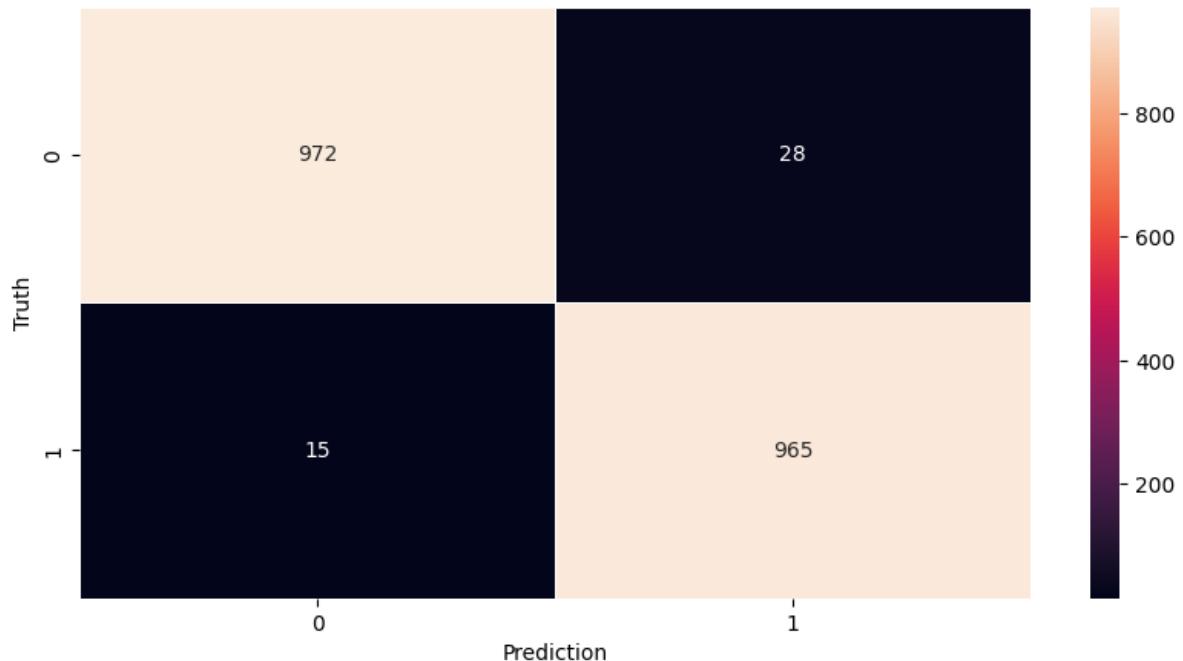
```

        cm,
        annot=True,
        fmt='d',
        linewidth=0.5
    )

plt.xlabel('Prediction')
plt.ylabel('Truth')

```

Out[]: Text(95.72222222222221, 0.5, 'Truth')



Case insensitive pattern match using flags=re.IGNORECASE

```
In [ ]: pattern = 'FY\d{4} Q[1-4]'
matches = re.findall(pattern, text, flags=re.IGNORECASE)
matches
```

Out[]: ['FY2021 Q1', 'fy2020 Q4']

```
In [ ]: pattern = 'FY(\d{4} Q[1-4])'
matches = re.findall(pattern, text, flags=re.IGNORECASE)
matches
```

Out[]: ['2021 Q1', '2020 Q4']

```
In [ ]: pattern = '\$([\d\.]+)'
matches = re.findall(pattern, text, flags=re.IGNORECASE)
matches
```

Out[]: ['4.85', '3']

```
In [ ]: pattern = 'FY(\d{4} Q[1-4])|\$([\d\.]+)'
matches = re.findall(pattern, text, flags=re.IGNORECASE)
matches
```

Out[]: [('2021 Q1', ''), ('', '4.85'), ('2020 Q4', ''), ('', '3')]

```
In [ ]: pattern = 'FY(\d{4} Q[1-4])[\^\$]+\$(\[\d\.\]+)'
matches = re.findall(pattern, text, flags=re.IGNORECASE)
matches
```

```
Out[ ]: [('2021 Q1', '4.85'), ('2020 Q4', '3')]
```

```
In [ ]: def get_pattern_match(pattern, text):
    matches = re.findall(pattern, text, flags=re.IGNORECASE)
    if matches:
        return matches
```

```
In [ ]: chat1='codebasics: Hello, I am having an issue with my order # 412889912'
chat2='codebasics: I have a problem with my order number 412889912'
chat3='codebasics: My order 412889912 is having an issue, I was charged 300$ when c
```

```
In [ ]: pattern = 'order[^\\d]*(\\d*)'
get_pattern_match(pattern, chat1)
```

```
Out[ ]: ['412889912']
```

```
In [ ]: chat1 = 'codebasics: you ask lot of questions 😞 1235678912, abc@xyz.com'
chat2 = 'codebasics: here it is: (123)-567-8912, abcX@xyz.com'
chat3 = 'codebasics: yes, phone: 1235678912 email: abc_82@xyz.com'
```

```
In [ ]: pattern = '(\d{10})|((\d{3})-\d{3}-\d{4})|([a-zA-Z0-9_]*@[a-z]*\.[a-zA-Z0-9]*)'
```

```
In [ ]: get_pattern_match(pattern, chat1)
```

```
Out[ ]: [('1235678912', '', ''), ('', '', 'abc@xyz.com')]
```

```
In [ ]: get_pattern_match(pattern, chat2)
```

```
Out[ ]: [('', '(123)-567-8912', ''), ('', '', 'abcX@xyz.com')]
```

```
In [ ]: get_pattern_match(pattern, chat3)
```

```
Out[ ]: [('1235678912', '', ''), ('', '', 'abc_82@xyz.com')]
```

```
In [ ]: text = '''
Born      Mukesh Dhirubhai Ambani
19 April 1957 (age 64)
Aden, Colony of Aden
(present-day Yemen)[1][2]
Nationality      Indian
Alma mater
St. Xavier's College, Mumbai
Institute of Chemical Technology (B.E.)
Stanford University (drop-out)
Occupation      Chairman and MD, Reliance Industries
Spouse(s)        Nita Ambani (m. 1985)[3]
Children         3
Parent(s)
Dhirubhai Ambani (father)
Kokilaben Ambani (mother)
Relatives        Anil Ambani (brother)
Tina Ambani (sister-in-law)
'''
```

```
In [ ]: def get_pattern_match(pattern, text):
    matches = re.findall(pattern, text, flags=re.IGNORECASE)
    if matches:
        return matches[0]

def extract_personal_information(text):
    age = get_pattern_match('age (\d+)', text)
    full_name = get_pattern_match('Born(.*)\n', text)
    birth_date = get_pattern_match('Born.*\n(.*)\n(age', text)
    birth_place = get_pattern_match('\n(age.*\n(.*)', text)
    return {
        'age': int(age),
        'name': full_name.strip(),
        'birth_date': birth_date.strip(),
        'birth_place': birth_place.strip(),
    }
```

```
In [ ]: extract_personal_information(text)
```

```
Out[ ]: {'age': 64,
          'name': 'Mukesh Dhirubhai Ambani',
          'birth_date': '19 April 1957',
          'birth_place': 'Aden, Colony of Aden'}
```

Future Plan

- Integrate with Industry Domain Knowledge

-- Memo End --