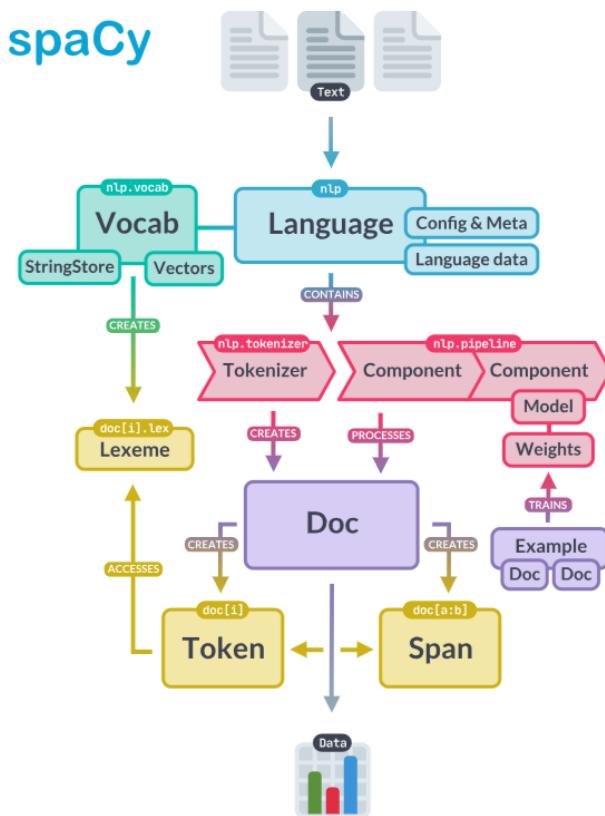


01 Spacy Tokenization

December 20, 2025

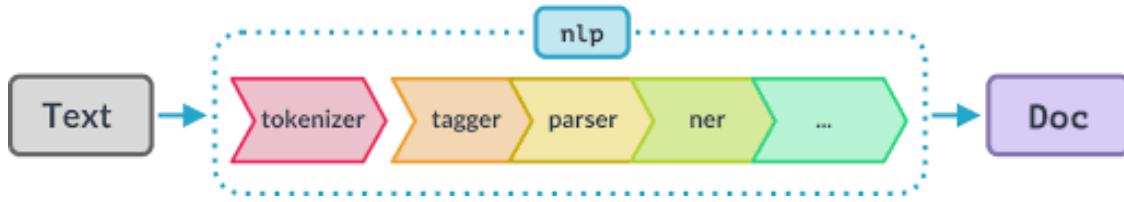
1 Tokenization



```
[1]: import spacy
from prettytable import PrettyTable
```

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

```
[3]: text = "Hello Uditya Narayan Tiwari! let's learn NLP together i am 21"
```



```
[4]: doc = nlp(text)
doc
```

[4]: Hello Uditya Narayan Tiwari! let's learn NLP together i am 21

```
[5]: doc.to_dict()
```

```
[5]: {'text': "Hello Uditya Narayan Tiwari! let's learn NLP together i am 21",
  'array_head': (71, 81, 65, 67, 75, 79, 76, 77, 78, 452, 454, 73, 453, 74, 80),
  'array_body': array([[ 5, 1,
  15777305708150031551,
  5983625672228268878, 3252815442139690129, 0,
  8206900633647566924, 2, 0,
  0, 0, 5983625672228268878,
  456, 91, 1],
 [ 6, 1, 621519759253969662,
  12044956042206692584, 15794550382381185553, 2,
  7037928807040764755, 3, 380,
  0, 0, 621519759253969662,
  11292551915497242671, 96, 18446744073709551615],
 [ 7, 1, 17937943263439891957,
  1332317125561210957, 15794550382381185553, 1,
  7037928807040764755, 1, 380,
  0, 0, 17937943263439891957,
  11292551915497242671, 96, 18446744073709551615],
 [ 6, 0, 7708786325424957310,
  17610643503028872449, 15794550382381185553, 18446744073709551613,
  428, 1, 380,
  0, 0, 7708786325424957310,
  11292551915497242671, 96, 18446744073709551615],
 [ 1, 1, 17494803046312582752,
  17494803046312582752, 12646065887601541794, 18446744073709551612,
  445, 2, 0,
  0, 0, 17494803046312582752,
  6739740606194143788, 97, 18446744073709551615],
 [ 3, 0, 278066919066513387,
  278066919066513387, 14200088355797579614, 0,
  8206900633647566924, 2, 0,
  0, 0, 278066919066513387,
  4068996703163926224, 100, 1],
```

```

[          2,           1, 16428057658620181782,
4950757572332304006, 13656873538139661788,           1,
          429,           2,           0,
          0,           0, 4950757572332304006,
12523944338091500347,           95, 18446744073709551615],
[          5,           1, 9664905639869093544,
9664905639869093544, 14200088355797579614, 18446744073709551614,
          408,           2,           0,
          0,           0, 9664905639869093544,
4068996703163926224,           100, 18446744073709551615],
[          3,           1, 15832915187156881108,
11273594034978133401, 15794550382381185553, 18446744073709551615,
          416,           3,           383,
          0,           0, 15832915187156881108,
11292551915497242671,           96, 18446744073709551615],
[          8,           1, 12060003407050460571,
12060003407050460571, 164681854541413346, 18446744073709551614,
          400,           2,           0,
          0,           0, 12060003407050460571,
          456,           86, 18446744073709551615],
[          1,           1, 5097672513440128799,
5097672513440128799, 13656873538139661788,           1,
          429,           2,           0,
          0,           0, 4690420944186131903,
8572492957087256302,           95, 18446744073709551615],
[          2,           1, 959164148857638496,
959164148857638496, 9188597074677201817, 18446744073709551612,
          408,           2,           0,
          0,           0, 10382539506755952630,
1447802835980306976,           87, 18446744073709551615],
[          2,           0, 4686009691886217934,
4686009691886217934, 8427216679587749980, 18446744073709551615,
          404,           2,           0,
          0,           0, 4686009691886217934,
1599824077107694006,           93, 18446744073709551615]],
      dtype=uint64),
'sentiment': 0.0,
'tensor': array([[ 0.05445875, -0.59416246,  0.818173 , ...,  0.38977188,
-0.40392596,  1.4487071 ],
[-0.04225922, -1.1231196 ,  1.6962935 , ...,  0.59242487,
 0.6001835 ,  0.16076504],
[ 0.24459338, -1.140665 ,  0.28151155, ...,  0.08815472,
 0.8826299 , -0.05909336],
...,
[-1.0578656 , -0.7674625 , -0.77184594, ...,  0.47284043,
-0.36860317,  0.25863093],
[-0.13910657, -0.273593 , -0.9564745 , ...,  0.04795459,

```

```

-0.00504667,  2.2988346 ],
[-0.23384394,  0.4510045 ,  0.6332393 , ...,  0.61563087,
 -0.33255428, -0.26758942]], dtype=float32),
'cats': {},
'spans': b'\x90',
'strings': ['',
'PERSON',
'narayan',
'ROOT',
'PronType=Prs',
'21',
'npadvmod',
'tiwari',
'hello',
'attr',
'VB',
'ORG',
'Number=Sing',
'dobj',
'VBP',
'Mood=Ind|Number=Sing|Person=1|Tense=Pres|VerbForm=Fin',
'Narayan',
'learn',
'..',
'Uditya',
'NumType=Card',
'NNP',
'Tiware',
'I',
'punct',
'advmod',
'NLP',
'!',
'let',
'compound',
'be',
'CD',
'VerbForm=Inf',
'us',
'nlp',
'PunctType=Peri',
'UH',
'together',
'i',
'am',
'uditya',
'ccomp',

```

```
'RB',
'nsubj',
'Case=Nom|Number=Sing|Person=1|PronType=Prs',
'PRP'],
'has_unknown_spaces': False}
```

[6]: `for token in doc:
 print(token.text, token.is_alpha, token.is_punct, token.like_num)`

```
Hello True False False
Uditya True False False
Narayan True False False
Tiwari True False False
! False True False
let True False False
's False False False
learn True False False
NLP True False False
together True False False
i True False False
am True False False
21 False False True
```

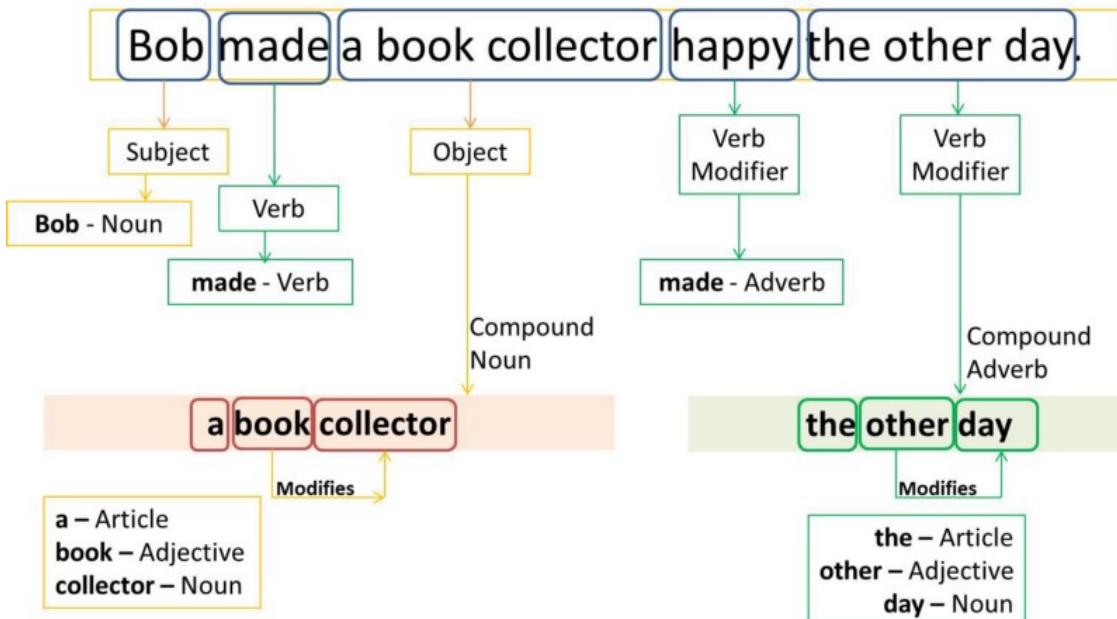
[7]: `table = PrettyTable()
table.field_names = ['token', 'is alpha', 'is punct', 'is number']
for token in doc:
 table.add_row([token.text, token.is_alpha, token.is_punct, token.
 ↪like_num])`

[8]: `print(table) # so using pretty table we can see the things proper in the
↪formatted way`

token	is alpha	is punct	is number
Hello	True	False	False
Uditya	True	False	False
Narayan	True	False	False
Tiwari	True	False	False
!	False	True	False
let	True	False	False
's	False	False	False
learn	True	False	False
NLP	True	False	False
together	True	False	False
i	True	False	False
am	True	False	False
21	False	False	True

```
+-----+-----+-----+
```

2 Part Of Speech(POS) Tagging



[9] : doc

[9] : Hello Uditya Narayan Tiwari! let's learn NLP together i am 21

```
[10]: table = PrettyTable()
table.field_names = ['token', 'pos', 'details', 'explanation']

for token in doc:
    table.add_row([token.text, token.pos_, token.tag_, spacy.explain(token.
tag_)])

print(table)
```

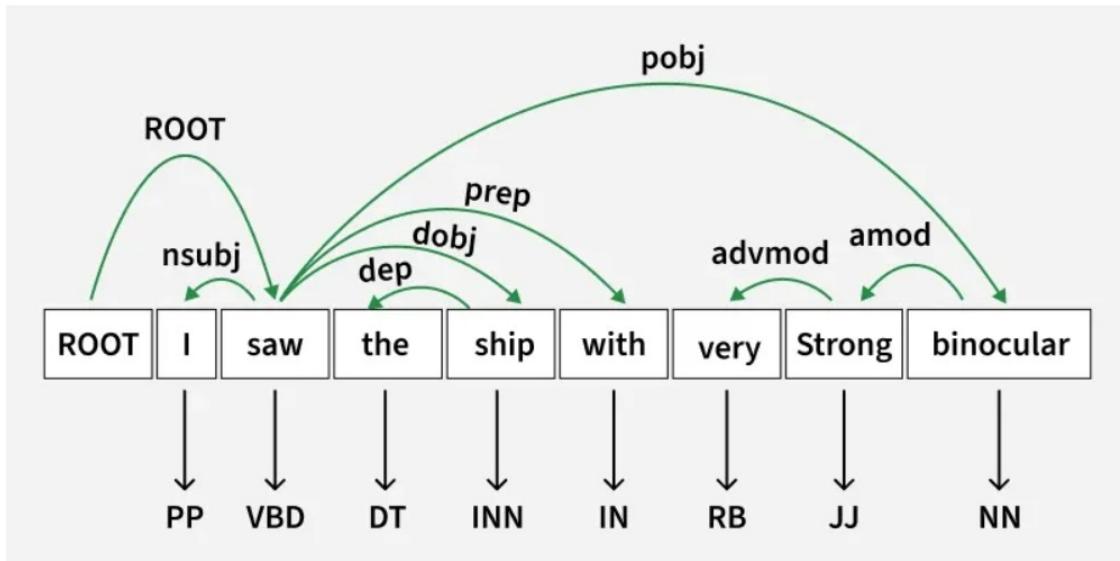
token	pos	details	explanation
Hello	INTJ	UH	interjection
Uditya	PROPN	NNP	noun, proper singular
Narayan	PROPN	NNP	noun, proper singular
Tiwari	PROPN	NNP	noun, proper singular
!	PUNCT	.	punctuation mark, sentence closer
let	VERB	VB	verb, base form
's	PRON	PRP	pronoun, personal
learn	VERB	VB	verb, base form

	NLP		PROPN		NNP		noun, proper singular	
	together		ADV		RB		adverb	
	i		PRON		PRP		pronoun, personal	
	am		AUX		VBP		verb, non-3rd person singular present	
	21		NUM		CD		cardinal number	
+-----+-----+-----+-----+-----+-----+-----+-----+								

02 Dependency Parsing

December 20, 2025

1 Dependency Parsing



```
[1]: import spacy
from prettytable import PrettyTable

[2]: nlp = spacy.load('en_core_web_sm')

[3]: text = "Spot Intelligence is a NLP company that builds custom models"

[4]: doc = nlp(text)
doc

[4]: Spot Intelligence is a NLP company that builds custom models

[5]: table = PrettyTable()
table.field_names = ['token', 'dep', 'head text', 'head pos', 'children']

for token in doc:
    children = [child.text for child in token.children]
```

```

        table.add_row([token.text, token.dep_, token.head.text, token.head.
        ↪pos_, children])

print(table)

```

token	dep	head text	head pos	children
Spot	compound	Intelligence	PROPN	[]
Intelligence	nsubj	is	AUX	['Spot']
is	ROOT	is	AUX	['Intelligence', 'company']
a	det	company	NOUN	[]
NLP	compound	company	NOUN	[]
company	attr	is	AUX	['a', 'NLP', 'builds']
that	nsubj	builds	VERB	[]
builds	relcl	company	NOUN	['that', 'models']
custom	compound	models	NOUN	[]
models	dobj	builds	VERB	['custom']

[6]: `from spacy import displacy
displacy.render(doc, style = 'dep', jupyter=True, options={})`

<IPython.core.display.HTML object>

[7]: `from spacy import displacy
displacy.render(doc, style = 'dep', jupyter=True, options={'distance':85, ↪'compact':True, 'bg':'#09a3d3', 'color': '#ffffff'})`

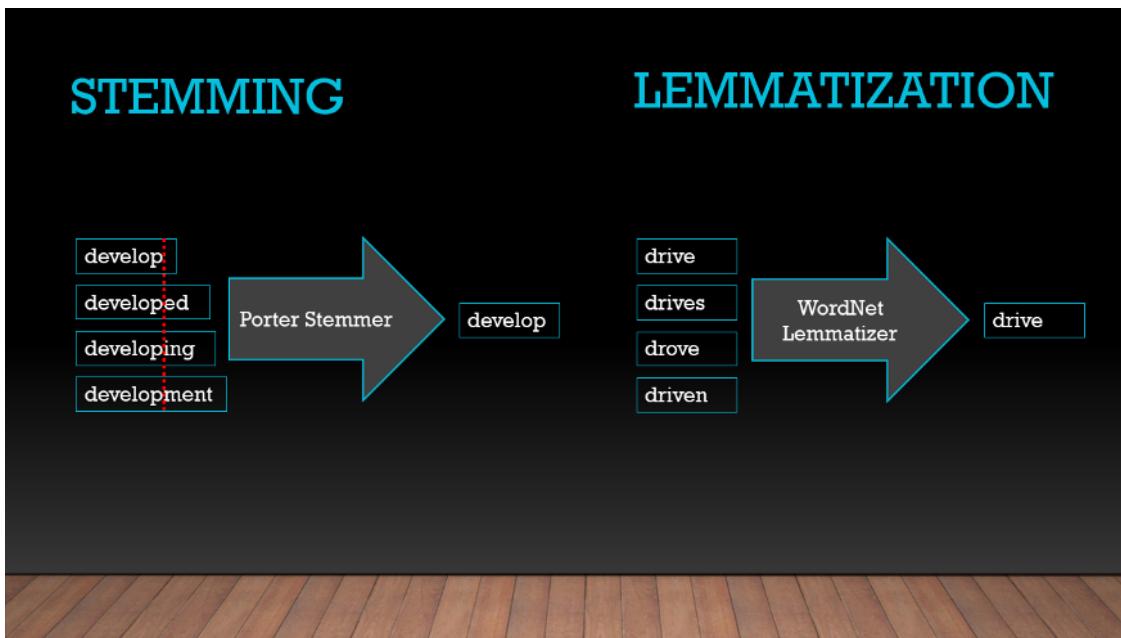
<IPython.core.display.HTML object>

03 Lemmatization

December 20, 2025

1 Lemmatization

- **Base Form Reduction:** Lemmatization reduces words to their meaningful base form(e.g., “running” to “run”)
- **Enhances NLP Accuracy:** It normalizes words variations, improving the accuracy of NLP tasks by treating different word forms as the same.



```
[1]: import spacy
from prettytable import PrettyTable
nlp = spacy.load('en_core_web_sm')

[2]: text = 'run ran running'
doc = nlp(text)

table = PrettyTable(field_names=['token', 'lemma']) # here lemma means root↳words

for token in doc:
    table.add_row([token.text, token.lemma_])
```

```
print(table)
```

token	lemma
run	run
ran	run
running	run

```
[3]: text = 'The scientists discover new species every year, Last year, they  
↳discovered an ancient artifact. they are discovering new techniques with  
↳their recent discovery'
```

```
doc = nlp(text)
```

```
table = PrettyTable(field_names=['token', 'lemma', 'pos']) # here lemma means  
↳root words
```

```
for token in doc:  
    table.add_row([token.text, token.lemma_, token.pos_])
```

```
print(table)
```

token	lemma	pos
The	the	DET
scientists	scientist	NOUN
discover	discover	VERB
new	new	ADJ
species	specie	NOUN
every	every	DET
year	year	NOUN
,	,	PUNCT
Last	last	ADJ
year	year	NOUN
,	,	PUNCT
they	they	PRON
discovered	discover	VERB
an	an	DET
ancient	ancient	ADJ
artifact	artifact	NOUN
.	.	PUNCT
they	they	PRON
are	be	AUX
discovering	discover	VERB
new	new	ADJ

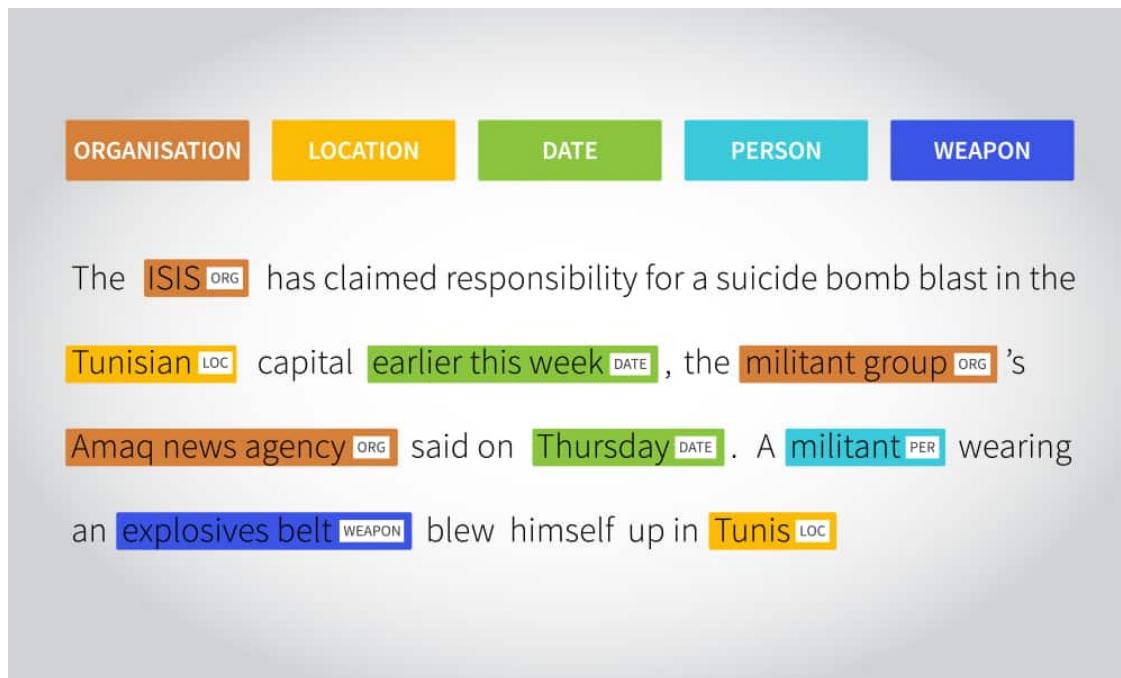
	techniques		technique		NOUN	
	with		with		ADP	
	their		their		PRON	
	recent		recent		ADJ	
	discovery		discovery		NOUN	
+	-----+	-----+	-----+	-----+	-----+	-----+

04 Named Entity Recognition

December 20, 2025

1 Named Entity Recognition(NER)

- **Entity Classification:** NER identifies and categorizes entities like names, locations, and dates in text, helping to extract key information.
- **Broad Application:** It enhances tasks like information extraction , question answering, and summarization by highlighting important entities in the text.



```
[1]: import spacy
from prettytable import PrettyTable

nlp = spacy.load('en_core_web_sm')
```

```
[2]: nlp.get_pipe('ner').labels # pre-trained model --> ner
```

```
[2]: ('CARDINAL',
'DATE',
'EVENT',
'FAC',
```

```
'GPE',
'LANGUAGE',
'LAW',
'LOC',
'MONEY',
'NORP',
'ORDINAL',
'ORG',
'PERCENT',
'PERSON',
'PRODUCT',
'QUANTITY',
'TIME',
'WORK_OF_ART')
```

```
[3]: text = """
On December 20, 2025, Satya Nadella announced that Microsoft would invest $5_
↳ billion to build a new research hub in London. This facility, located near_
↳ Kings Cross, aims to rival the innovation seen at Google in Mountain View,_
↳ California.
"""


```

```
[4]: from spacy import displacy
doc = nlp(text = text)
displacy.render(doc, style = 'ent', jupyter = True)
```

```
<IPython.core.display.HTML object>
```

```
[5]: table = PrettyTable()
table.field_names=['token', 'label', 'explanation', 'Star Char', 'End Char']
for ent in doc.ents:
    table.add_row([ent.text, ent.label_, spacy.explain(ent.label_), ent.
    ↳start_char, ent.end_char])

print(table)
```

token	label	explanation	Star Char	End Char
December 20, 2025	DATE	Absolute or relative dates or periods		4
21				
Satya Nadella	PERSON	People, including fictional		23
36				
Microsoft	ORG	Companies, agencies, institutions, etc.		52
61				

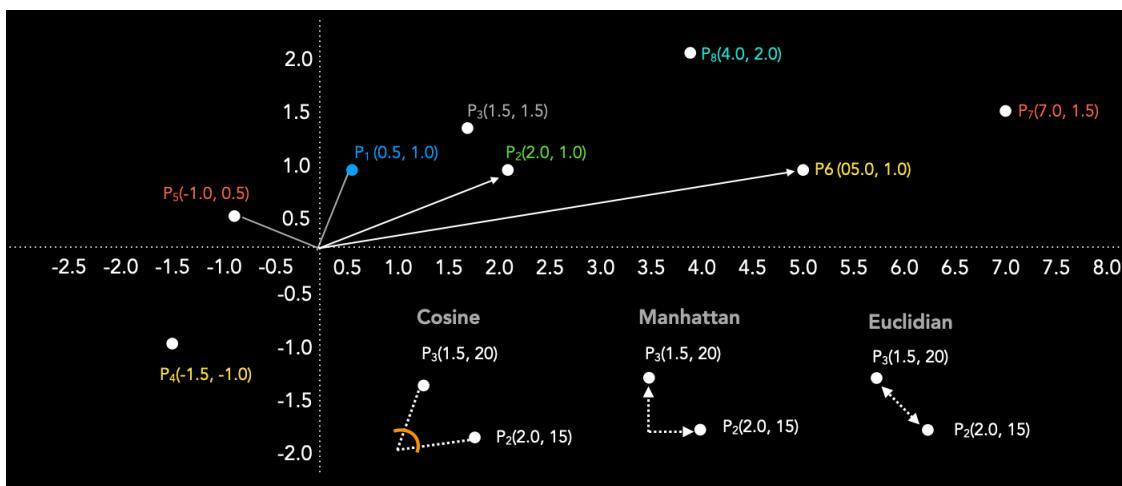
	\$5 billion	MONEY	Monetary values, including unit		75
	85				
	London	GPE	Countries, cities, states		117
	123				
	Kings Cross	ORG	Companies, agencies, institutions, etc.		153
	164				
	Google	ORG	Companies, agencies, institutions, etc.		203
	209				
	Mountain View	GPE	Countries, cities, states		213
	226				
	California	GPE	Countries, cities, states		228
	238				
+-----+-----+-----+-----+					
-----+-----+					

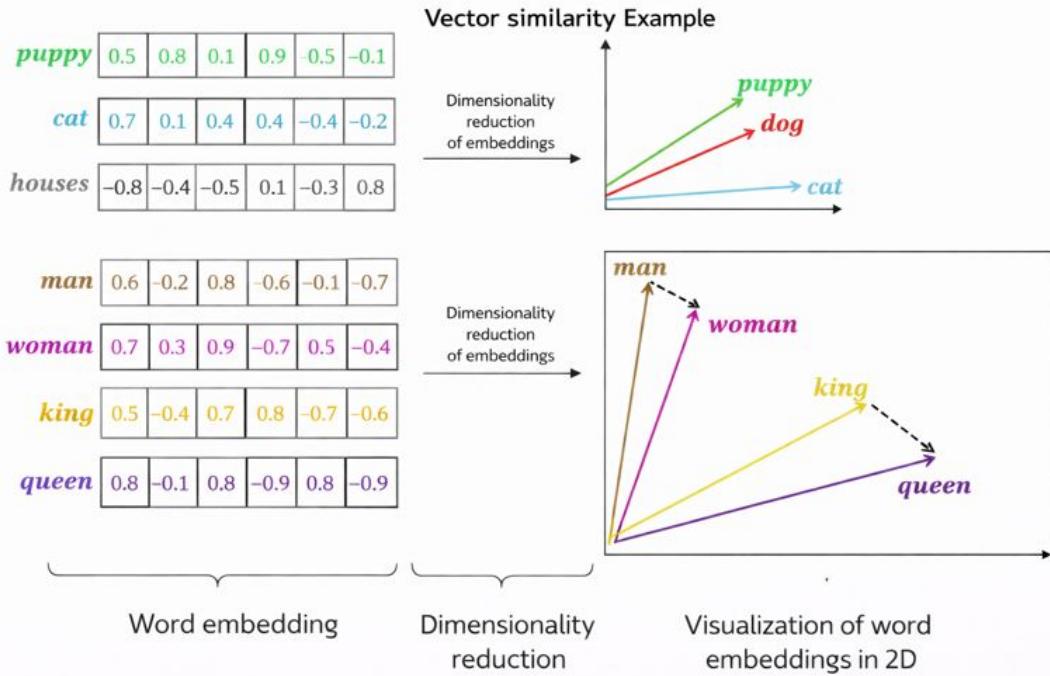
05 Vector Similarity

December 20, 2025

1 Vector Similarity

- **Measures Textual Relatedness:** Similarity in NLP quantifies how closely related two pieces of text are, based on factors like words choice, context, and meaning.
- **Used in Various Applications:** It's Crucial for tasks such as document clustering, recommendations systems, and paraphrase detection, where understanding the degree of similarity between texts is essential.
- **Different Methods:** Similarity can be measured using various approaches, from simple techniques like cosine similarity on word vectors to more advanced methods involving contextual embeddings from models like BERT.





```
[1]: import spacy
from prettytable import PrettyTable
from spacy import displacy
```

```
[2]: nlp = spacy.load('en_core_web_lg')
```

```
[3]: doc = nlp('cat')
vec1 = doc.vector
```

```
[4]: doc.vector.shape
```

```
[4]: (300,)
```

```
[5]: # doc.vector
```

```
[6]: doc = nlp('dog')
vec2 = doc.vector
```

```
[7]: doc.vector.shape
```

```
[7]: (300,)
```

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

```
sim = cosine_similarity([vec1], [vec2])
print(sim)
```

```

[[0.80168545]]

[9]: words = ['dog', 'cat', 'man', 'woman', 'king', 'queen', 'houses']
table = PrettyTable(field_names=['word 1', 'word 2', 'score'])

[10]: from itertools import combinations
list(combinations(words, 2))

[10]: [('dog', 'cat'),
        ('dog', 'man'),
        ('dog', 'woman'),
        ('dog', 'king'),
        ('dog', 'queen'),
        ('dog', 'houses'),
        ('cat', 'man'),
        ('cat', 'woman'),
        ('cat', 'king'),
        ('cat', 'queen'),
        ('cat', 'houses'),
        ('man', 'woman'),
        ('man', 'king'),
        ('man', 'queen'),
        ('man', 'houses'),
        ('woman', 'king'),
        ('woman', 'queen'),
        ('woman', 'houses'),
        ('king', 'queen'),
        ('king', 'houses'),
        ('queen', 'houses')]

[11]: words = ['dog', 'cat', 'man', 'woman', 'king', 'queen', 'houses']
table = PrettyTable(field_names=['word 1', 'word 2', 'score'])
for word1, word2 in combinations(words, 2):
    token1 = nlp(word1)
    token2 = nlp(word2)

    sim = token1.similarity(token2)
    table.add_row([word1, word2, f"{sim:.2f}"])

print(table)

+-----+-----+-----+
| word 1 | word 2 | score |
+-----+-----+-----+
| dog    | cat    | 0.80 |
| dog    | man    | 0.42 |
| dog    | woman  | 0.39 |

```

	dog		king		0.25	
	dog		queen		0.23	
	dog		houses		0.23	
	cat		man		0.36	
	cat		woman		0.36	
	cat		king		0.28	
	cat		queen		0.31	
	cat		houses		0.20	
	man		woman		0.74	
	man		king		0.41	
	man		queen		0.27	
	man		houses		0.24	
	woman		king		0.27	
	woman		queen		0.41	
	woman		houses		0.21	
	king		queen		0.73	
	king		houses		0.21	
	queen		houses		0.21	
+-----+-----+-----+						