

Natural Language
Processing

Session-3





Word Embedding







Word Embedding (Feature Representation)

```
In [6]: model.wv['ankara']
Out[6]: array([ 0.28124622, -0.40046975, 0.4623563 , -0.26006582, 0.4291707 ,
               -0.5458609 , -0.36119318, -0.28867924, -0.60250515, 0.4237076 ,
                0.28818154, -0.17176527, 0.19708447, -0.37333247, -0.5264093,
               -0.6427167 , 0.14568327 , 0.17329371 , -0.5378837 , -0.3682972 ,
               -0.15588258, -0.20114157, 0.67830926, 0.04082025, -0.19011535,
                0.59075046, -0.6102628, -0.42992386, -0.12169785, -0.2939379,
               -0.13670284, -0.13515596, -0.1399645, -0.72388405, -0.7582215,
                0.10269422, 0.23371245, 0.02973733, 0.10352834, 0.17330961,
                0.31032264, -0.00689159, -0.51990616, 0.4342847, 0.24778119,
                0.08977021, 0.37872604, 0.2631365, 0.11655401, 0.02951079,
                0.2531644 , 0.03372194, -0.35848543, -0.21600617, 0.33282214,
                0.27077678, 0.53709596, 0.26062086, -0.24004991, 0.10561307,
                0.36568683, -0.8039388, 0.41826522, -0.32496533, 0.21453372,
               -0.1572319 , -0.7251499 , 0.08052048, 0.08987505, 0.1112271 ,
                0.14825632, 0.58504164, 0.684992 , 0.00776701, 0.18076658,
               -0.09477395, -0.1137936, 0.5623219, -0.3188122, 0.5662095,
                0.32072476, 0.17244305, -0.58838886, -0.05057955, -0.47085264,
               -0.17080188, -0.17386362, -0.12876017, -0.02662375, 0.36869773,
               -0.23252094, -0.10350469, -0.09519712, -0.09009365, -0.2726341,
               -0.04719334, -0.25645226, -0.03347286, 0.10456851,
                                                                  0.06934233],
              dtype=float32)
```



Word Embedding (Feature Representation)

Word Embeddings

Rome =
$$(0.91, 0.83, 0.17, ..., 0.41]$$

Paris =
$$(0.92, 0.82, 0.17, ..., 0.98)$$

Italy =
$$[0.32, 0.77, 0.67, ..., 0.42]$$

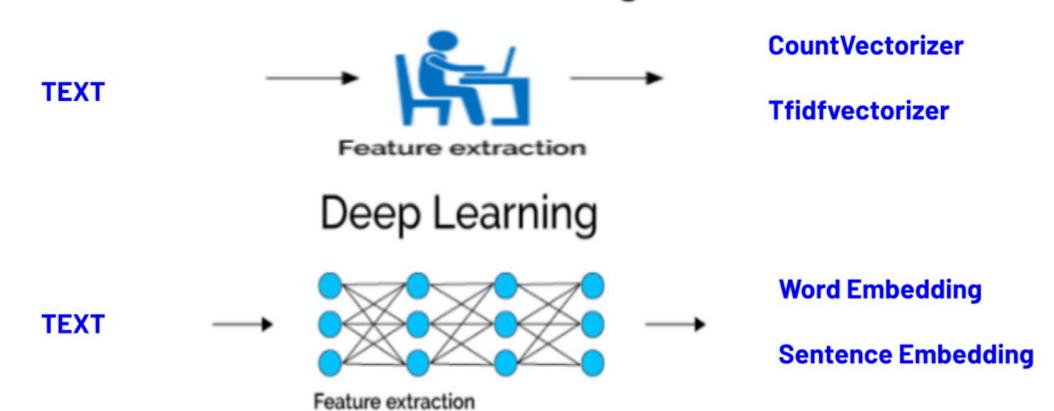
France =
$$[0.33, 0.78, 0.66, ..., 0.97]$$

Word embeddings are numeric vectors that show semantic relationships between words.



Word Embedding (Feature Representation) Feature Extraction

Machine Learning





Word Embedding (Feature Representation)

For example;

- -The teacher made a test to the students in school
- -The teacher graded the students
- -The teacher assigned a project to the student
- -The instructor gave a quiz to the learners at the university
- -The instructor made an verbal to the learner
- -The learners graduated from the university
- -The learners received diplomas



Word Embedding (Feature Representation)

Unique Tokens:

-the

-school

-university

-teacher

-graded

-verbal

-made

-assigned

-graduated

-a

-project

-from

-test

-instructor

-received

-to

-quiz

-gave

-students

-learners

-diplomas

-in

-at

-learner

-student

Feature Representation:

education, teaching, organisation, article, verb, preposition



Word Embedding (Feature Representation)

Unique Tokens Feature Representations	the	teacher	made	а	test	to	student/s	in	school	graded	assigned	project
teaching	0.02	-0.90	0.02	0.01	0.89	0.03	-0.95	0.02	0.90	0.87	-0.02	0.88
organisation	0.5	0.02	0.03	0.45	0.01	0.40	0.01	0.42	0.91	-0.02	0.02	0.01
article	1	0.60	0.01	1	0.02	-0.01	0.48	0.01	0.50	-0.01	0.01	0.10
verb	0.01	0.53	1	0.20	1	0.40	0.49	0.02	0.40	1	1	0.80
preposition	0.02	0.03	-0.02	-0.01	0.02	1	0.01	1	0.02	0.01	0.04	0.02

Unique Tokens	instructor	quiz	learner/s	at	university	verbal	graduated	from	received	gave	diplomas
Feature Representations											
education	-0.93	0.91	-0.93	0.01	0.90	0.85	0.83	-0.01	0.03	0.02	0.82
teaching	-0.88	0.92	-0.94	0.02	0.89	0.86	0.87	-0.03	0.04	0.03	0.85
organisation	0.01	-0.02	0.02	0.45	0.92	-0.02	-0.02	0.30	-0.02	-0.02	0.02
article	0.55	0.05	0.60	0.01	0.45	0.01	0.03	0.02	0.01	0.03	-0.03
verb	0.52	0.85	0.51	0.02	0.45	0.70	1	0.01	1	1	-0.42
preposition	0.01	0.03	0.02	1	0.01	0.01	0.02	1	0.02	0.03	0.02

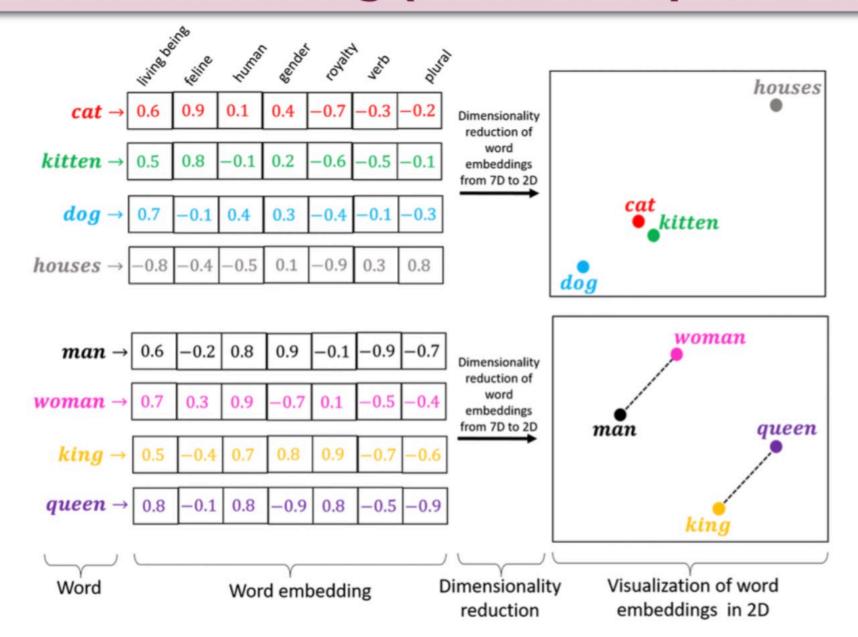


Word Embedding-Feature Representation

	Man (5391)	Woman (9853)	King (4914)	Queen (7157)	Apple (456)	Orange (6257)
1 Garder	-1	1	-0.95	0.97	0.00	0.01
300 Royal	0.01	0.62	0.93	0.95	-0.01	0.00
Age	0.03	0.02	0.7	0.69	0.03	-0.02
Food	6.09	0.01	0.02	0.01	0.95	0.97
of alix- volo	62341	@9853				Andrev



Word Embedding (Feature Representation)



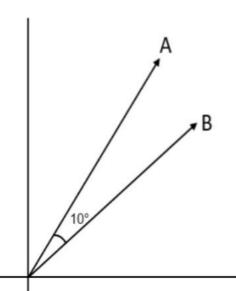


Cosine Similarity

- -Cosine similarity is a measurement that quantifies the similarity between two or more vectors.
- -The cosine similarity is the cosine of the angle between vectors. The cosine similarity is a value that is bound by a constrained range of -1 and 1.



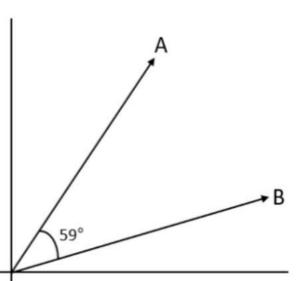
Cosine Similarity



The angle between vector A and B is 10 deg.

Cos(10) = 0.9848...

The angles could be said to be 98% similar



The angle between vector A and B is 59 deg.

Cos(59) = 0.559...

The angles could be said to be 55% similar

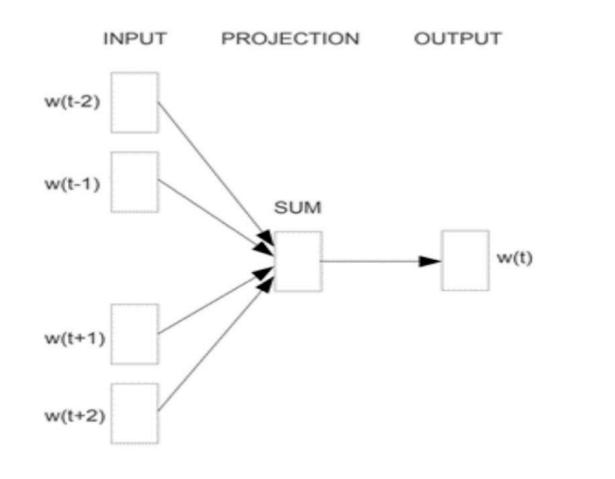


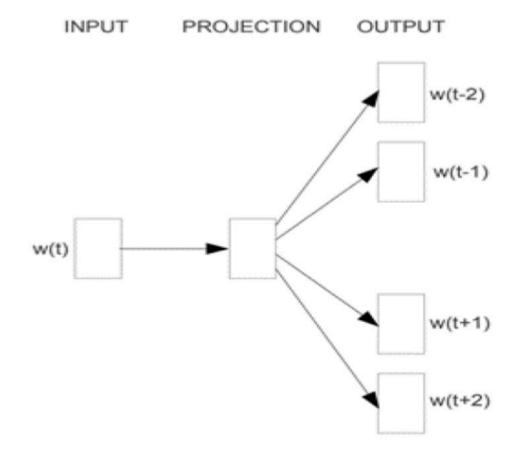
Word Embedding Algorithms

- -Embedding Layer
- -Word2Vec
 - Continuous Bag of Words (CBOW Model)
 - Skip-Gram Model
- -Global Vectors (Glove)
- -Embeddings from Language Models (ELMo)
- -Bidirectional Encoder Representations from Transformers (BERT)
- -Generative Pre-trained Transformer (GPT-2/3)



Word2Vec





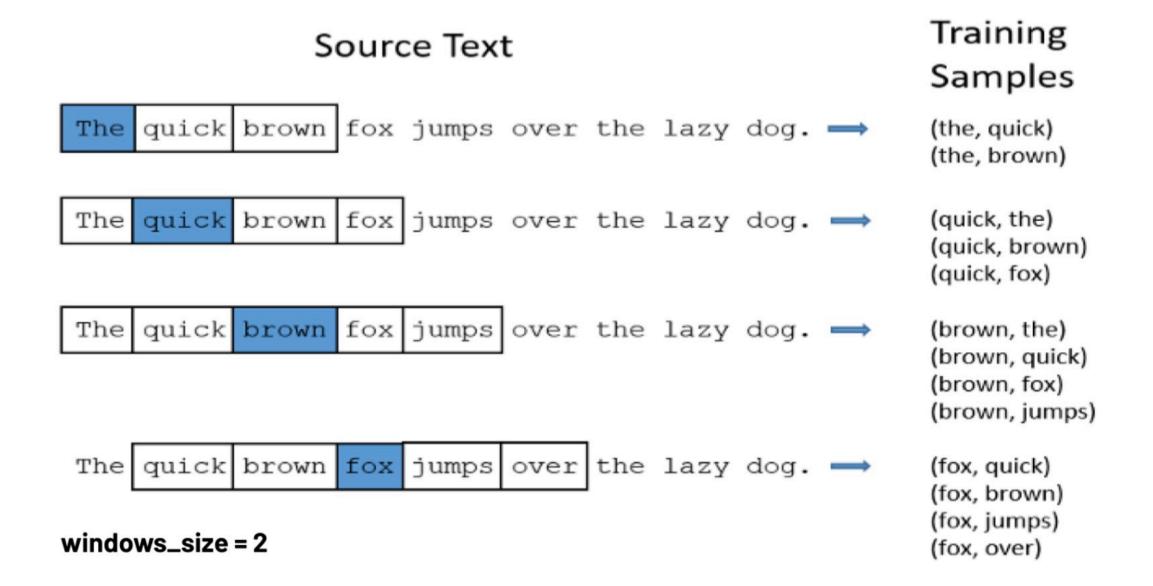
CBOW

Skip-gram

windows_size = 2



Word2Vec-window_size parameter





ELMO and BERT

- -The word2vec and glove models are unfortunately unsuccessful in capturing homophones with different meanings.
- -However, the **ELMO** and **BERT** model is quite successful in capturing the semantic differences between words.

I love **the apple** that my mother bought from the market.

I love the apple, the biggest company in the world.