Universidad EAFIT
Escuela de Ciencias Aplicadas e Ingeniería

Artificial Intelligence

Lecture05 – NLP Word2vec

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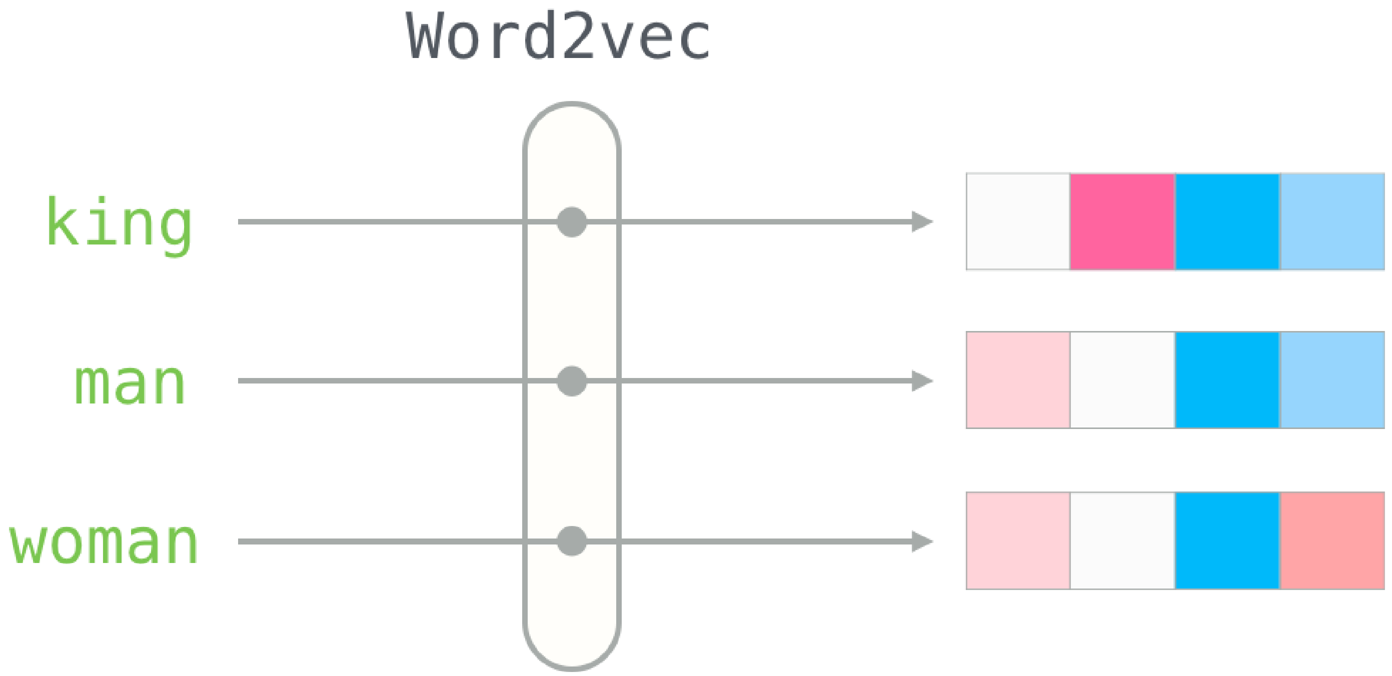
Word Embeddings



Efficient Estimation of Word Representations in Vector Space

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Distributed Representations of Words and Phrases and their Compositionality

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Word Embeddings

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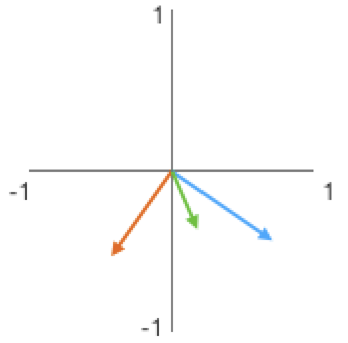


	Trait #1	Trait #2			
Jay	-0.4	0.8			
Person #1	-0.3	0.2			
Person #2	-0.5	-0.4			

Openness to experience	79 out of 100
Agreeableness	75 out of 100
Conscientiousness	42 out of 100
Negative emotionality	50 out of 100
Extraversion	58 out of 100

	Trait #1	Trait #2	Trait #3	Trait #4	Trait #5
Jay	-0.4	0.8	0.5	-0.2	0.3
Person #1	-0.3	0.2	0.3	-0.4	0.9
Person #2	-0.5	-0.4	-0.2	0.7	-0.1

$$\text{cosine similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|}$$

```
cosine_similarity( Jay [-0.4, 0.8] , Person #1 [-0.3, 0.2] ) = 0.87 ✓
cosine_similarity( Jay [-0.4, 0.8] , Person #2 [-0.5, -0.4] ) = -0.20
```

```
cosine_similarity( Jay [-0.4, 0.8, 0.5, -0.2, 0.3] , Person #1 [-0.3, 0.2, 0.3, -0.4, 0.9] ) = 0.66 ✓
cosine_similarity( Jay [-0.4, 0.8, 0.5, -0.2, 0.3] , Person #2 [-0.5, -0.4, -0.2, 0.7, -0.1] ) = -0.37
```

Word Embeddings

Two central ideas:

1. We can represent things as vectors

Jay	-0.4	0.8	0.5	-0.2	0.3

2. We can easily calculate how similar vectors are to each other:

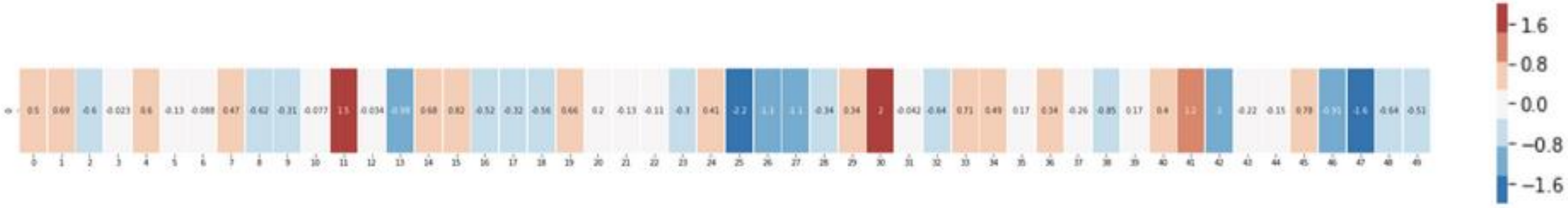
The people most similar to Jay are:

	cosine_similarity ▼
Person #1	0.86
Person #2	0.5
Person #3	-0.20

Word Embeddings

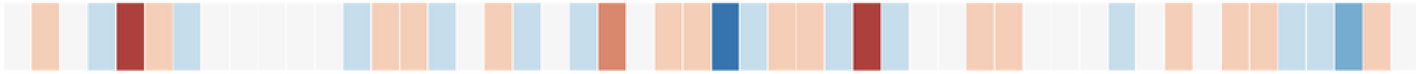
King (GloVe vector trained on Wikipedia):

```
[ 0.50451 , 0.68607 , -0.59517 , -0.022801, 0.60046 , -0.13498 , -0.08813 , 0.47377 , -0.61798 , -0.31012 ,
-0.076666, 1.493 , -0.034189, -0.98173 , 0.68229 , 0.81722 , -0.51874 , -0.31503 , -0.55809 , 0.66421 , 0.1961
, -0.13495 , -0.11476 , -0.30344 , 0.41177 , -2.223 , -1.0756 , -1.0783 , -0.34354 , 0.33505 , 1.9927 ,
-0.04234 , -0.64319 , 0.71125 , 0.49159 , 0.16754 , 0.34344 , -0.25663 , -0.8523 , 0.1661 , 0.40102 , 1.1685 ,
```

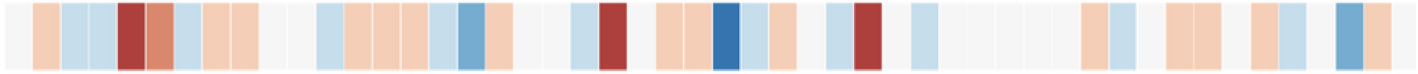


“king”

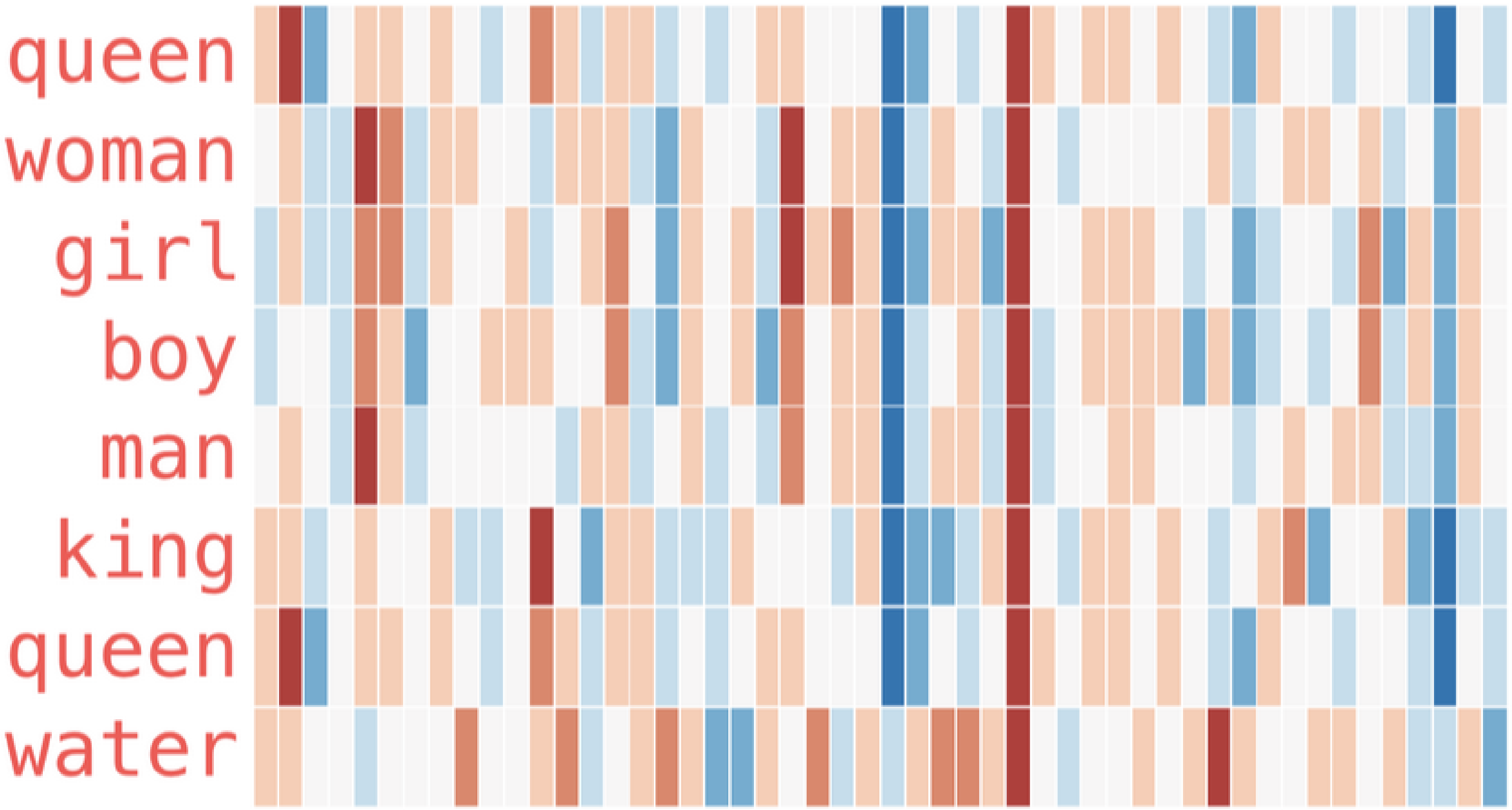
“Man”



“Woman”

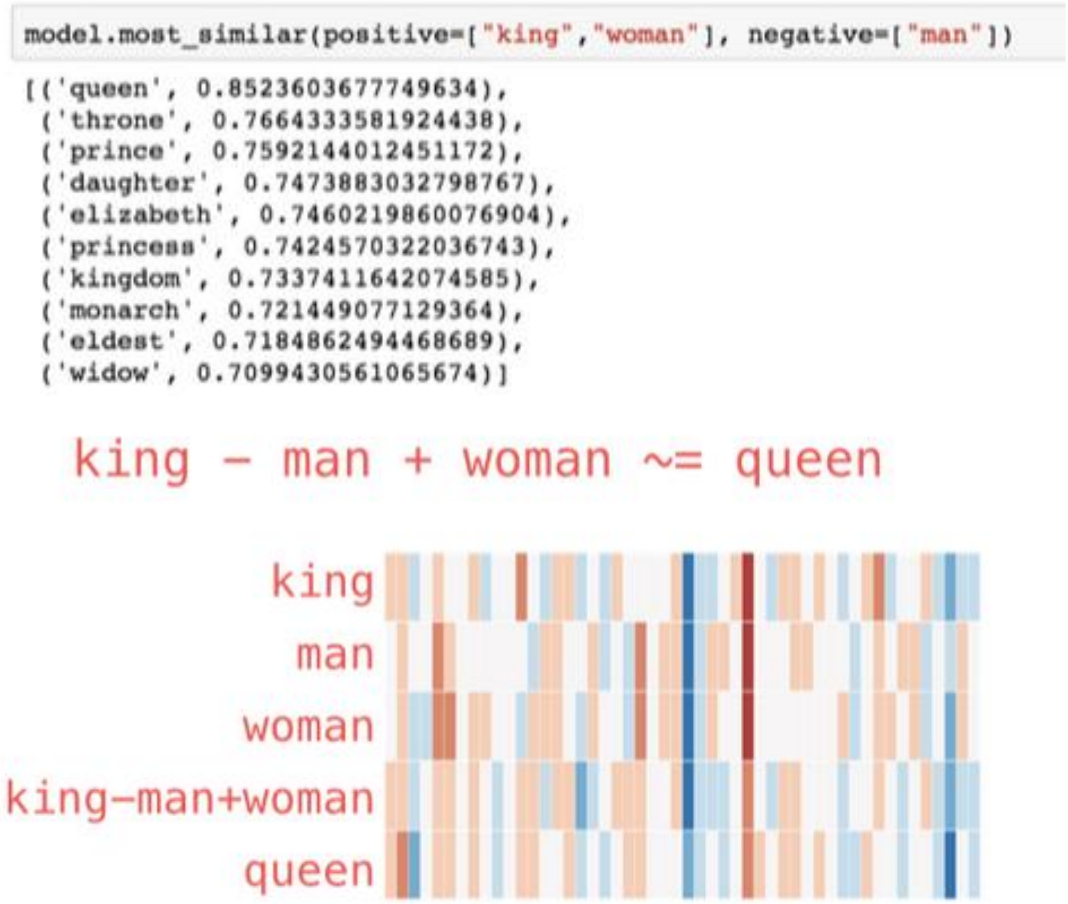


Word Embeddings



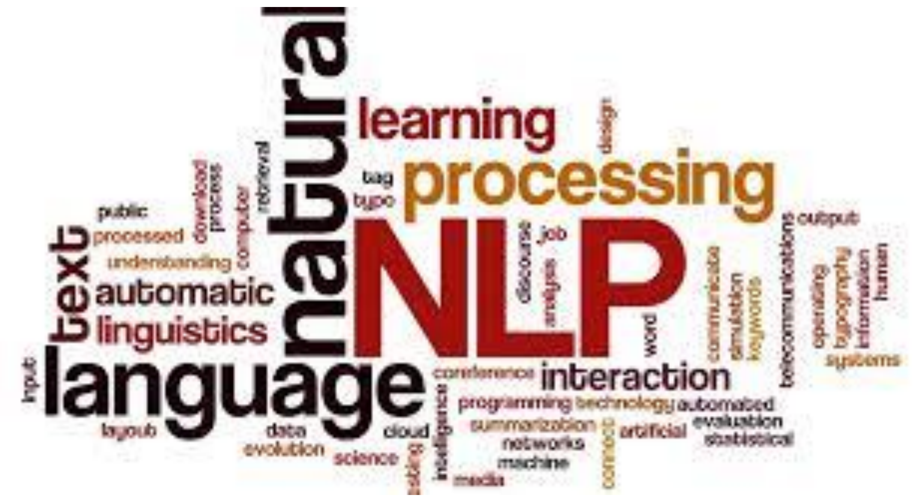
Word Embeddings

- **Word Embedding Analogies**: Demonstrates how word embeddings capture semantic relationships.
- **Famous Example**: "king" - "man" + "woman" ≈ "queen".
- **Key Insight**: Embeddings encode meaning in a way that allows vector arithmetic to reflect real-world relationships.
- **Implication**: Shows how models learn contextual and relational information beyond individual words.



Language Modeling

A **language model** is a statistical or probabilistic model that learns the likelihood of word sequences. It is used to predict the next word in a sentence or generate text based on learned patterns.

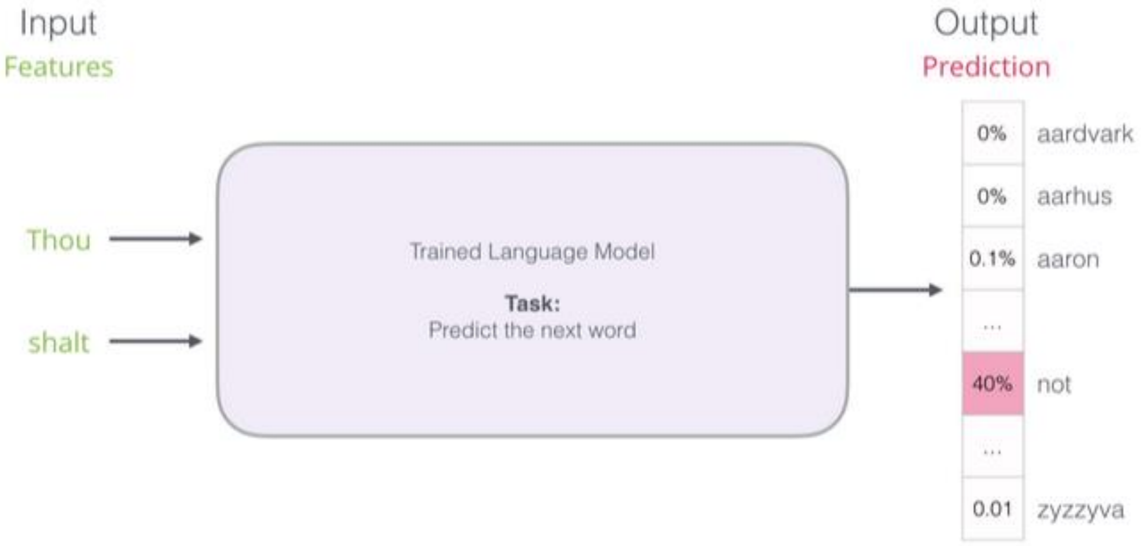


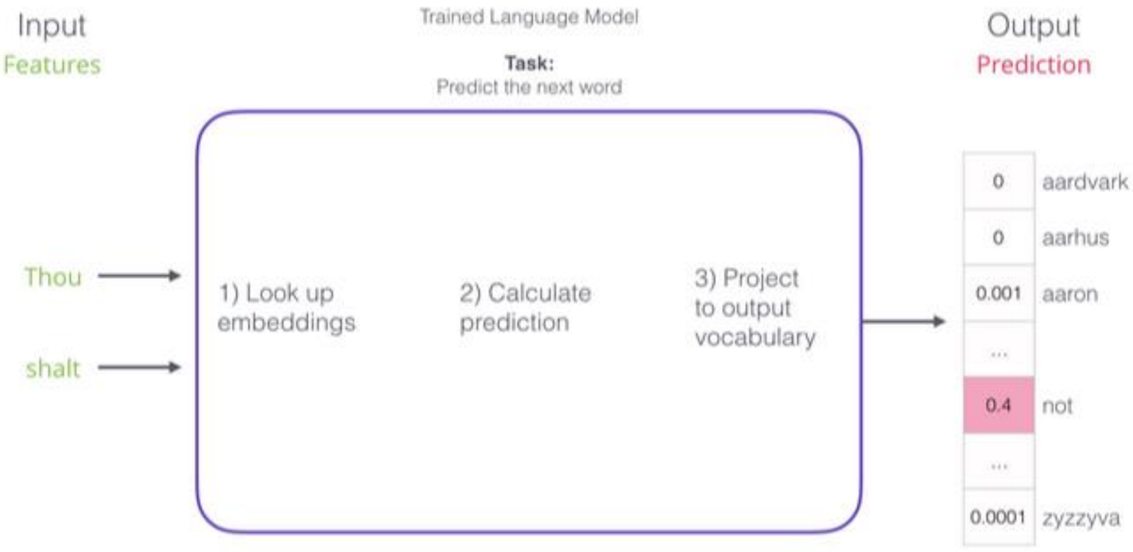
Limitations of Traditional Language Models

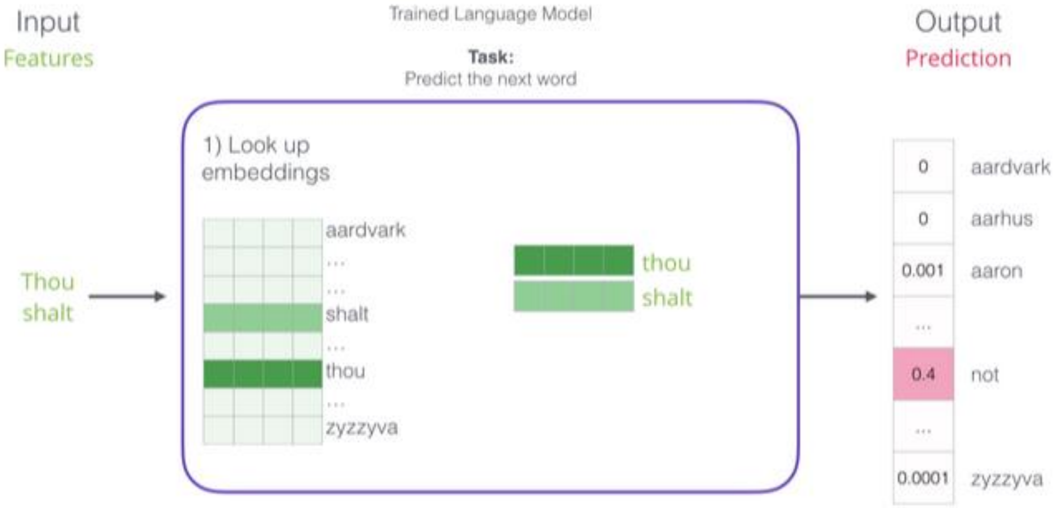
- Traditional models process text **linearly**, which may fail to capture deeper, multi-dimensional word relationships.
- Example from *God Emperor of Dune*: Language imposes a **linear structure**, but meaning can be **non-linear and contextual.**

This is not a mechanical universe. The linear progression of events is imposed by the observer. Cause and effect? That's not it at all. ***The prophet utters fateful words.*** *You glimpse a thing "destined to occur." But the prophetic instant releases something of infinite portent and power. The universe undergoes a ghostly shift." ~God Emperor of Dune*

Next word prediction

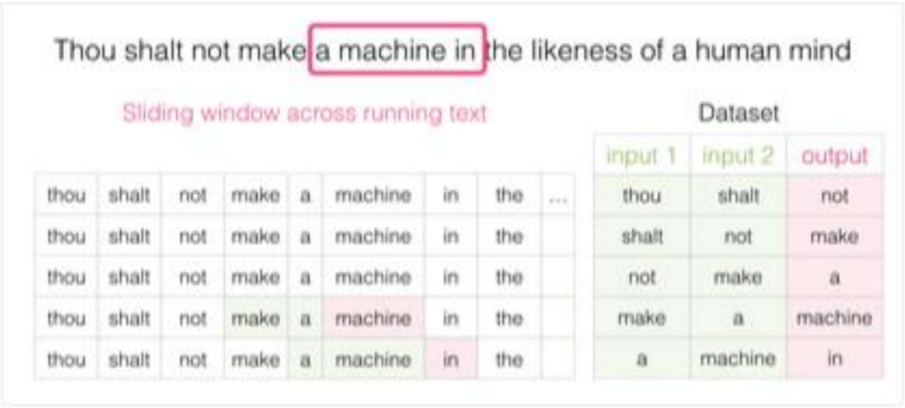


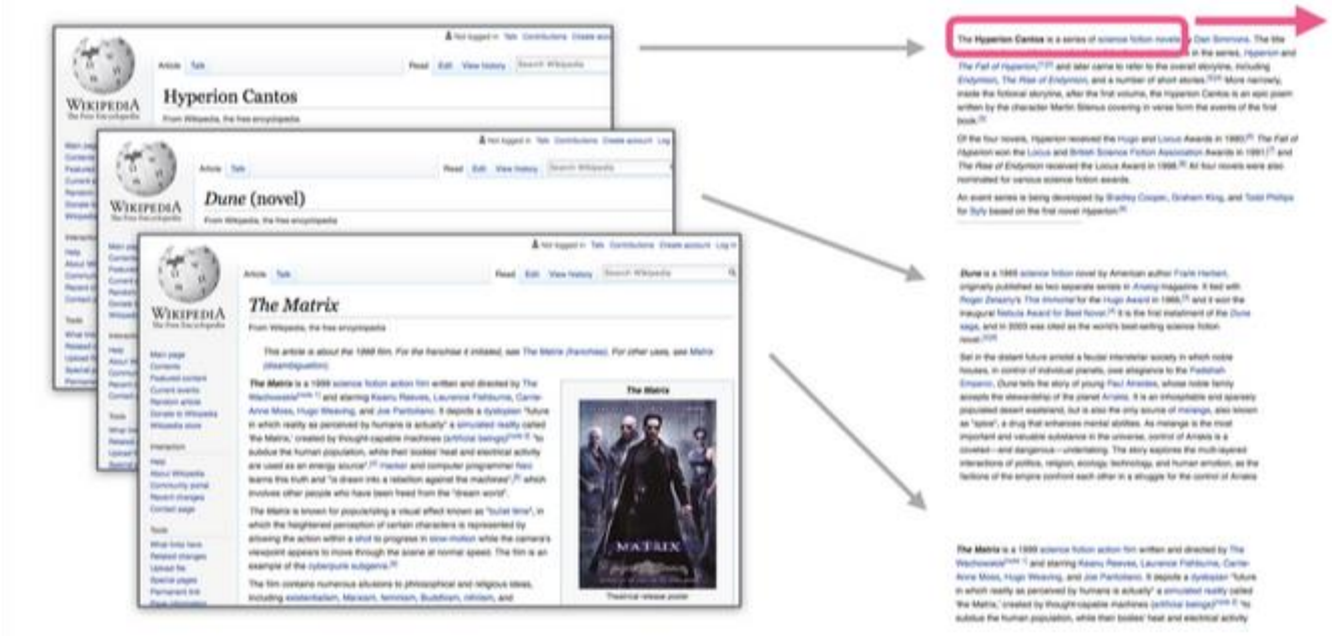




Language Model Training

- Learn the context in which a particular word appears
- Words that appear in similar contexts have similar embeddings
- Unlike other applications, in Language Models we have a lot of text to train





Continuos Bag of Words

Jay was hit by a ______   Jay was hit by a ______ bus

- Instead of only looking two words before the target word, we can also look at two words after it.

Jay was hit by a ______ bus in...

by	a	red	bus	in

- If we do this, the dataset we're virtually building and training the model against would look like this:

input 1	input 2	input 3	input 4	output
by	a	bus	in	red

Continuos Bag of Words - CBoW

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Skipgram

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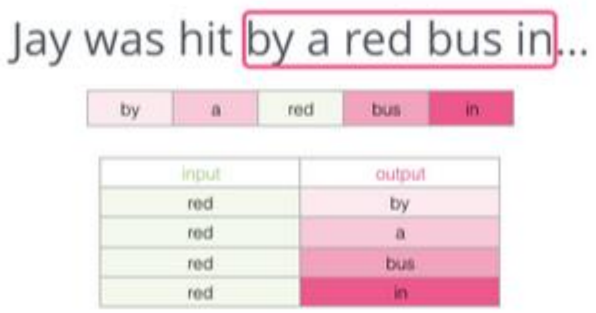
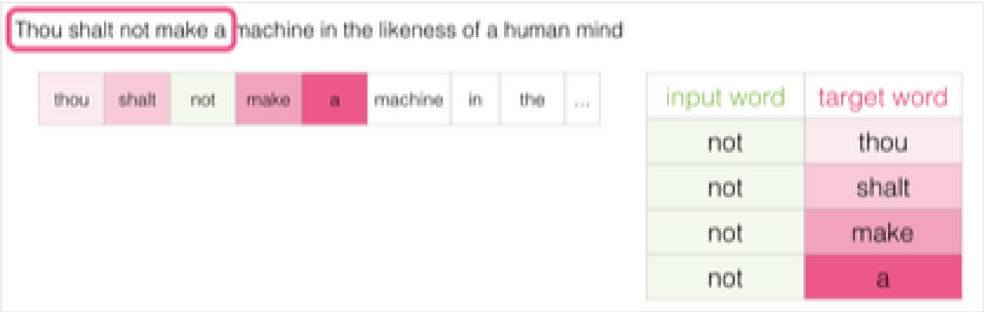
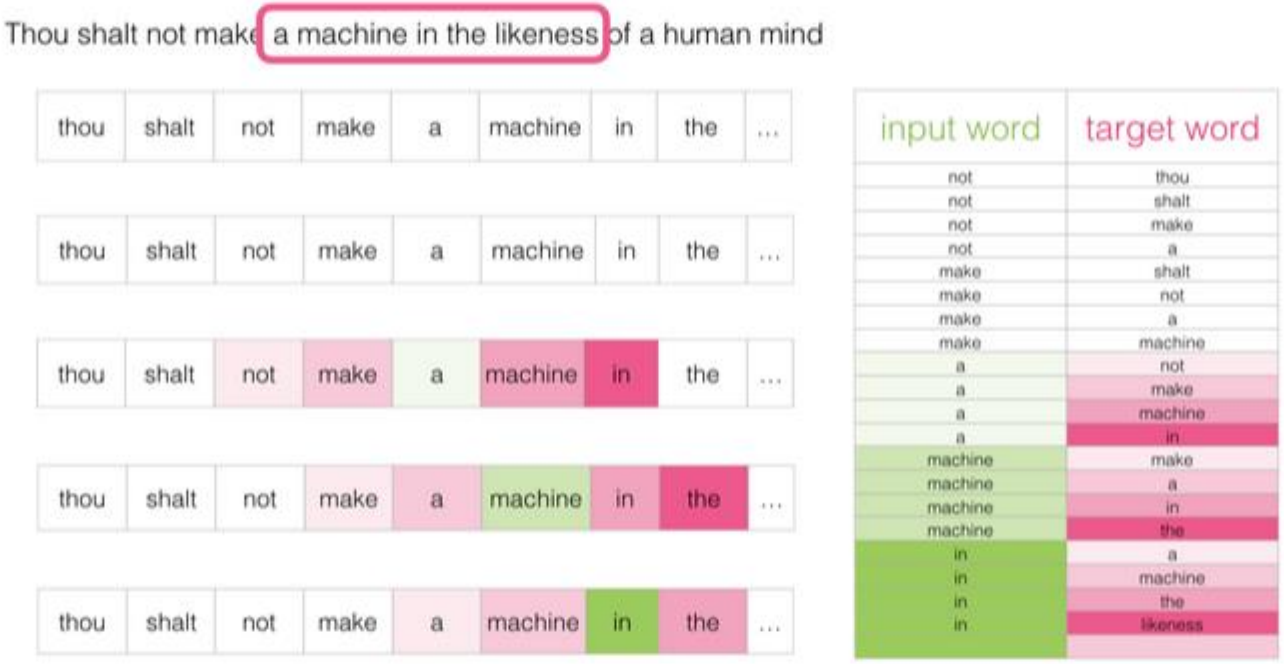
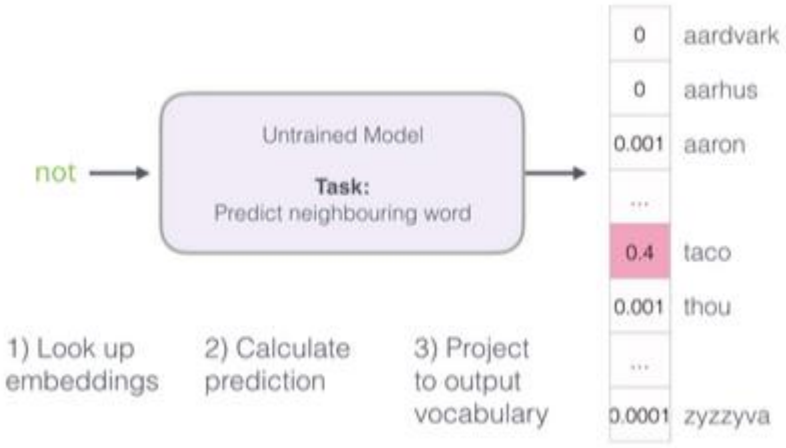
- **Skip-Gram Architecture**: Instead of predicting a word based on its context, Skip-Gram predicts **neighboring words** given a **target word**.
- **Sliding Window Approach**: The model moves through the text, learning which words frequently appear around others.
- **Key Benefit**: Works well with **smaller datasets** and captures rare word relationships.

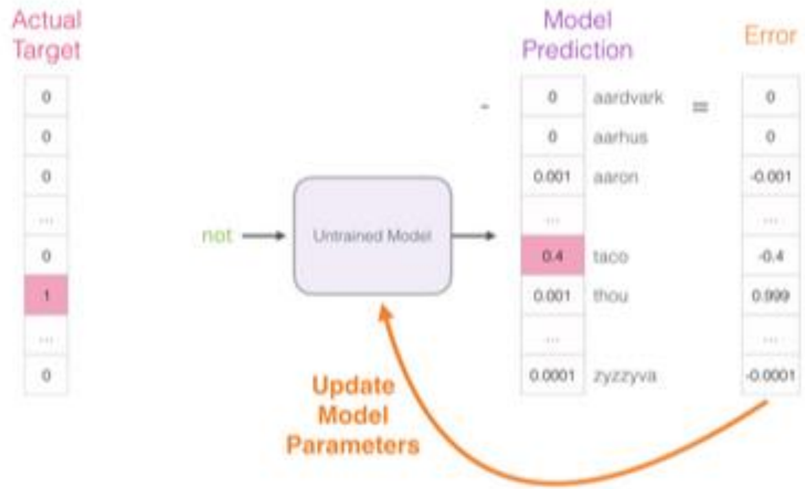






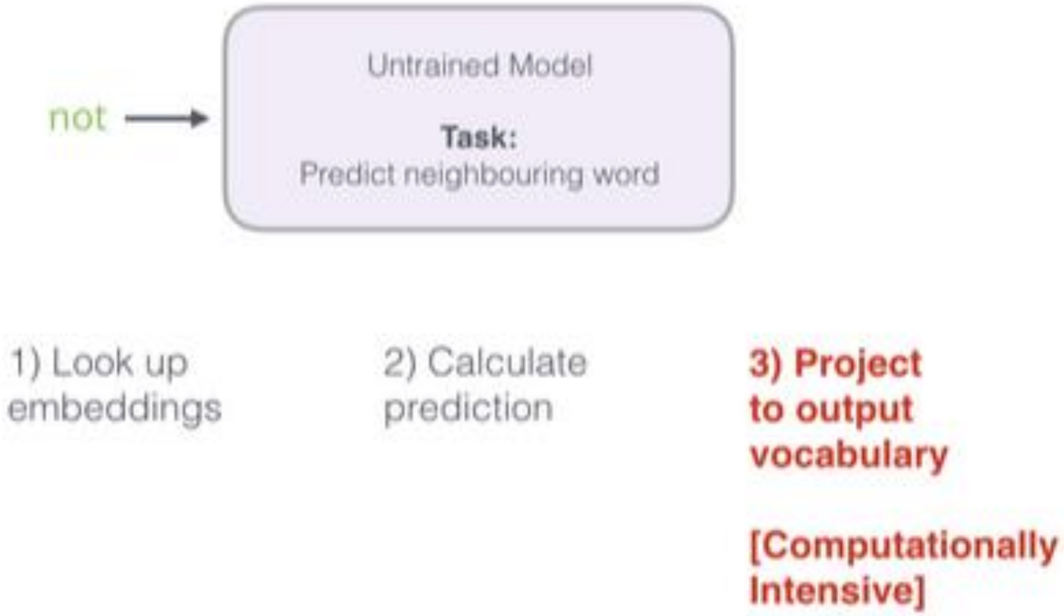
Trainig process





Negative sampling

- Recall the three steps of how this neural language model calculates its prediction:



- The third step is computationally expensive due to the size of the vocabulary

1. Generate high-quality word embeddings (Don't worry about next-word prediction).
2. Use these high-quality embeddings to train a language model (to do next-word prediction).

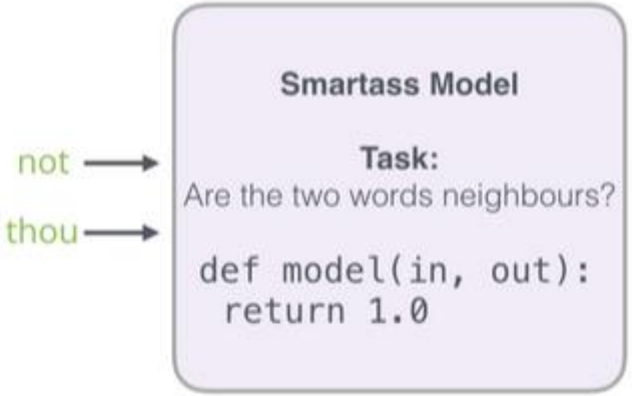
We'll focus on step 1.

From:

To:

Negative sampling

- We need to introduce *negative samples* to our dataset – samples of words that are not neighbors.
- We use random words from our vocabulary



input word	target word
not	thou
not	shalt
not	make
not	a
make	shalt
make	not
make	a
make	machine

input word	output word	target
not	thou	1
not	shalt	1
not	make	1
not	a	1
make	shalt	1
make	not	1
make	a	1
make	machine	1

Pick randomly from vocabulary (random sampling)

input word	output word	target
not	thou	1
not	aaron	0
not	taco	0
not	shalt	1
not	make	1

Skipgram with negative sampling

Skipgram

shalt	not	make	a	machine

input	output
make	shalt
make	not
make	a
make	machine

Negative Sampling

input word	output word	target
make	shalt	1
make	aaron	0
make	taco	0

Noise-contrastive estimation: A new estimation principle for unnormalized statistical models

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Word2vec training process

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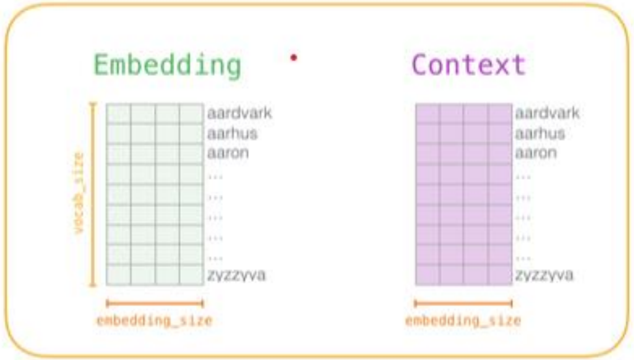
- We create two matrices – an Embedding matrix and a Context matrix. These two matrices have an embedding for each word in our vocabulary. At the start of the training process we initialize both matrices randomly.



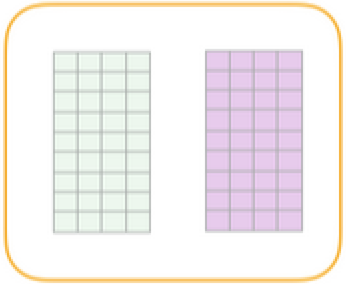
vocab_size = 10.000
embedding_size = 300

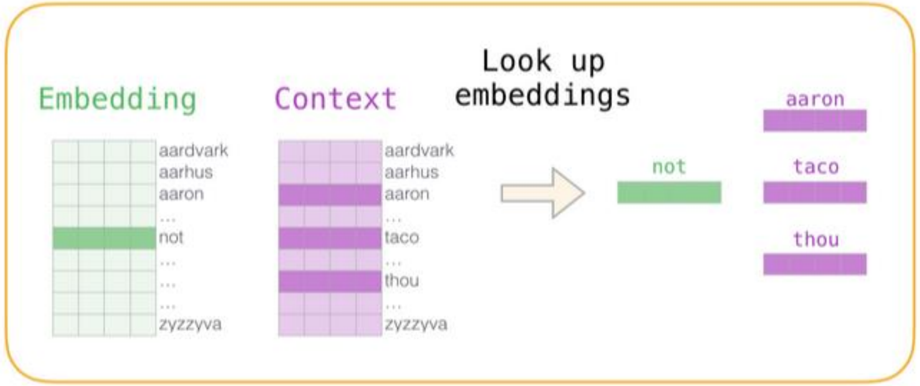
- In each training step, we take one positive example and its associated negative examples.

dataset

input word	output word	target
not	thou	1
not	aaron	0
not	taco	0
not	shalt	1
not	mango	0
not	finglonger	0
not	make	1
not	plumbus	0
...	...	...

model





Word2vec training process

- **Compute Similarity**: Take the **dot product** between the input word embedding and each context word embedding.
- **Apply Sigmoid Function**: Convert similarity scores into **probabilities** between **0 and 1**.
- **Compare with Target**: Measure how well the model's predictions match the **actual context words**.
- **Compute Error**: Calculate **error = target - sigmoid_scores** for each word.
- **Update Embeddings**: Adjust the embeddings using the error to improve **word representation**.
- **Repeat Process**: Move to the **next training sample** and perform the same steps.

input word	output word	target	input • output	sigmoid()	Error
not	thou	1	0.2	0.55	0.45
not	aaron	0	-1.11	0.25	-0.25
not	taco	0	0.74	0.68	-0.68

Word2vec cost function

- **For each positive (correct) word pair**, the model should output a probability **close to 1**.
- **For each negative (randomly sampled) word pair**, the model should output a probability **close to 0**.

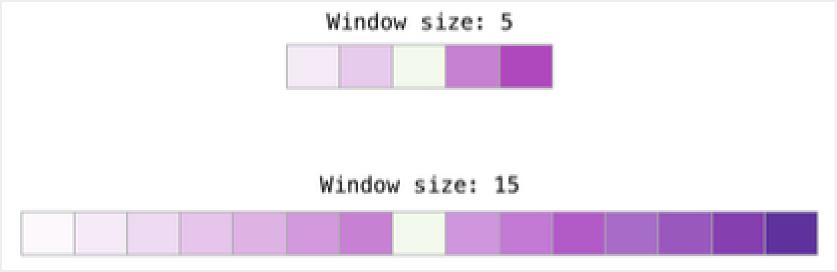
The loss function for a single word pair is:

$$L = -\sum_{(c,w)\in D} \left[y \log \sigma(\mathbf{v}_c \cdot \mathbf{v}_w) + (1-y)\log(1-\sigma(\mathbf{v}_c \cdot \mathbf{v}_w)) \right]$$

$$\sigma(x) = \frac{1}{1+e^{-x}}$$

- y is **1** for positive (real) word-context pairs and **0** for negative (random) pairs.
- σ(x) is the **sigmoid function**, ensuring outputs are between **0 and 1**.

Parameters



Negative samples: 2

input word	output word	target
make	shalt	1
make	aaron	0
make	taco	0

Negative samples: 5

input word	output word	target
make	shalt	1
make	aaron	0
make	taco	0
make	finglonger	0
make	plumbus	0
make	mango	0

- **Window Size in Word2Vec**: Determines how many words before and after the target word are considered.
- **Small Window (2-15 words)**: Produces embeddings where **high similarity means interchangeability** (e.g., "good" and "bad" may appear in similar contexts).
- **Large Window (15-50+ words)**: Captures **relatedness** rather than interchangeability (e.g., "car" and "road" are related but not interchangeable).
- **Annotation Matters**: The choice of window size depends on the task and may require manual tuning.
- **Gensim Default**: Uses a window size of **5** (five words before and after the target word).