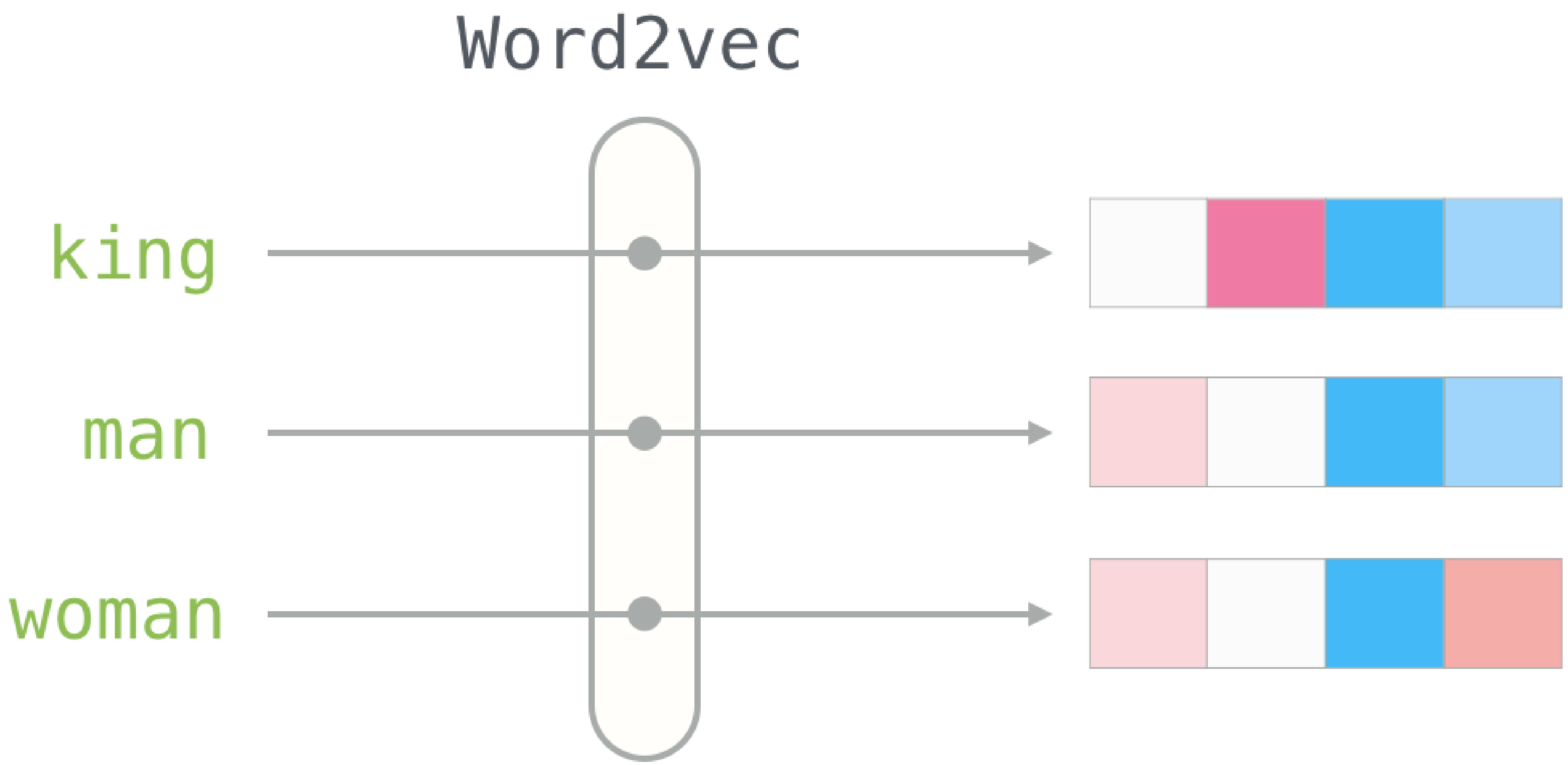
word2vec

Jay Alammar **The Illustrated Word2vec**

2020

word2vec illustrated

Word2Vec illustrated



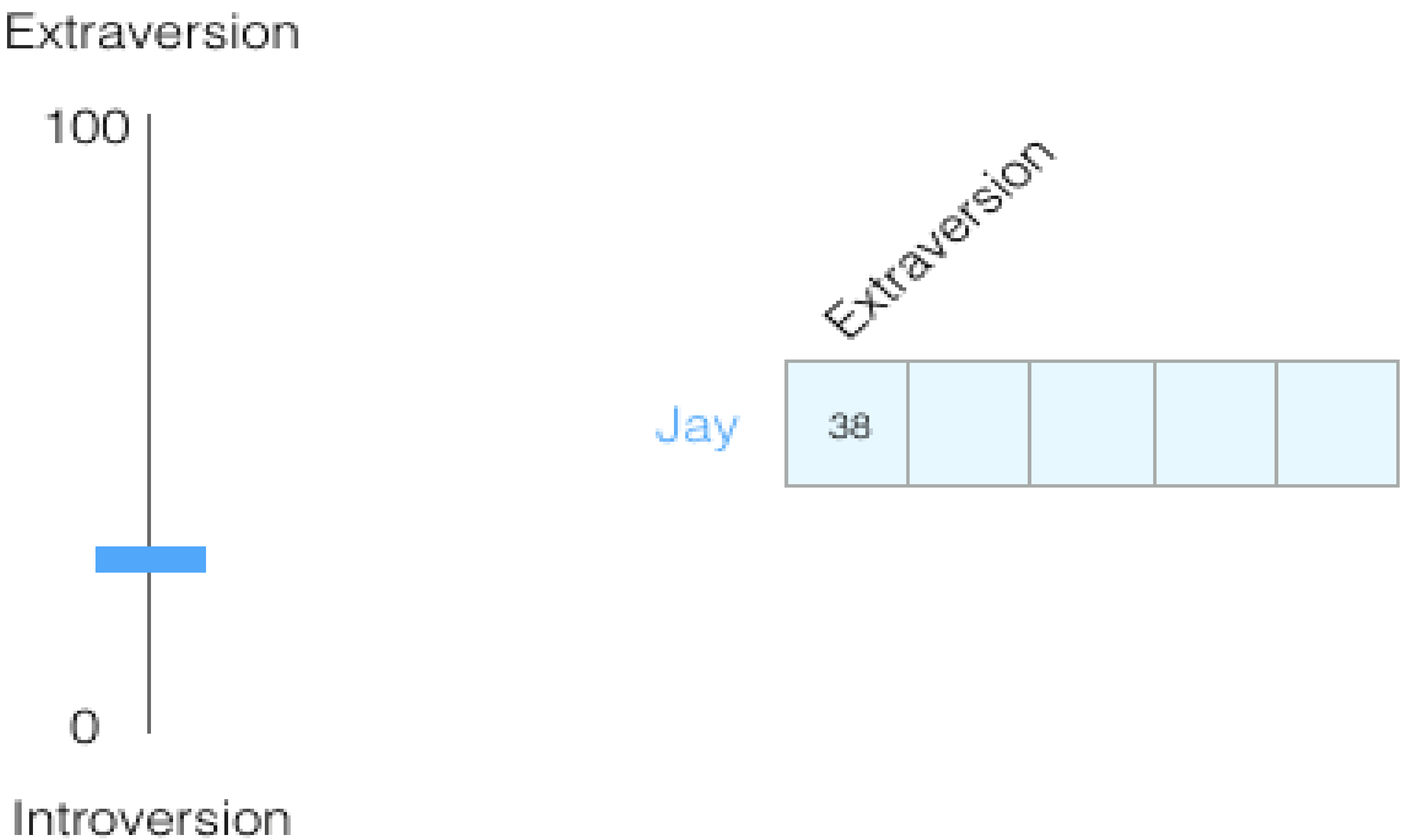
성격 임베딩: 당신의 성격은 어떠한가?

- 성격 임베딩의 예제

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

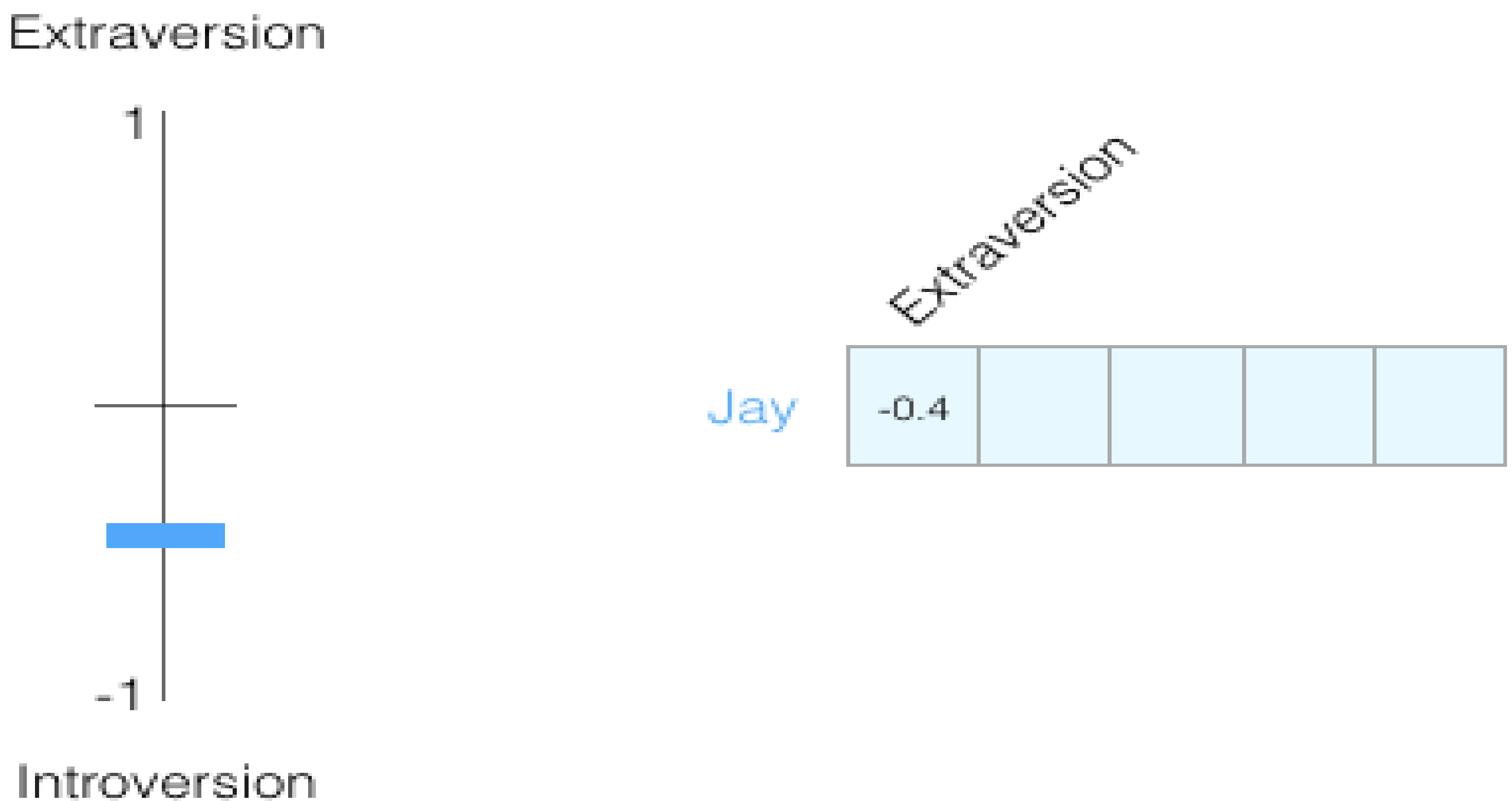
성격 임베딩: 당신의 성격은 어떠한가?

- **내성적인지 외향적인지?**



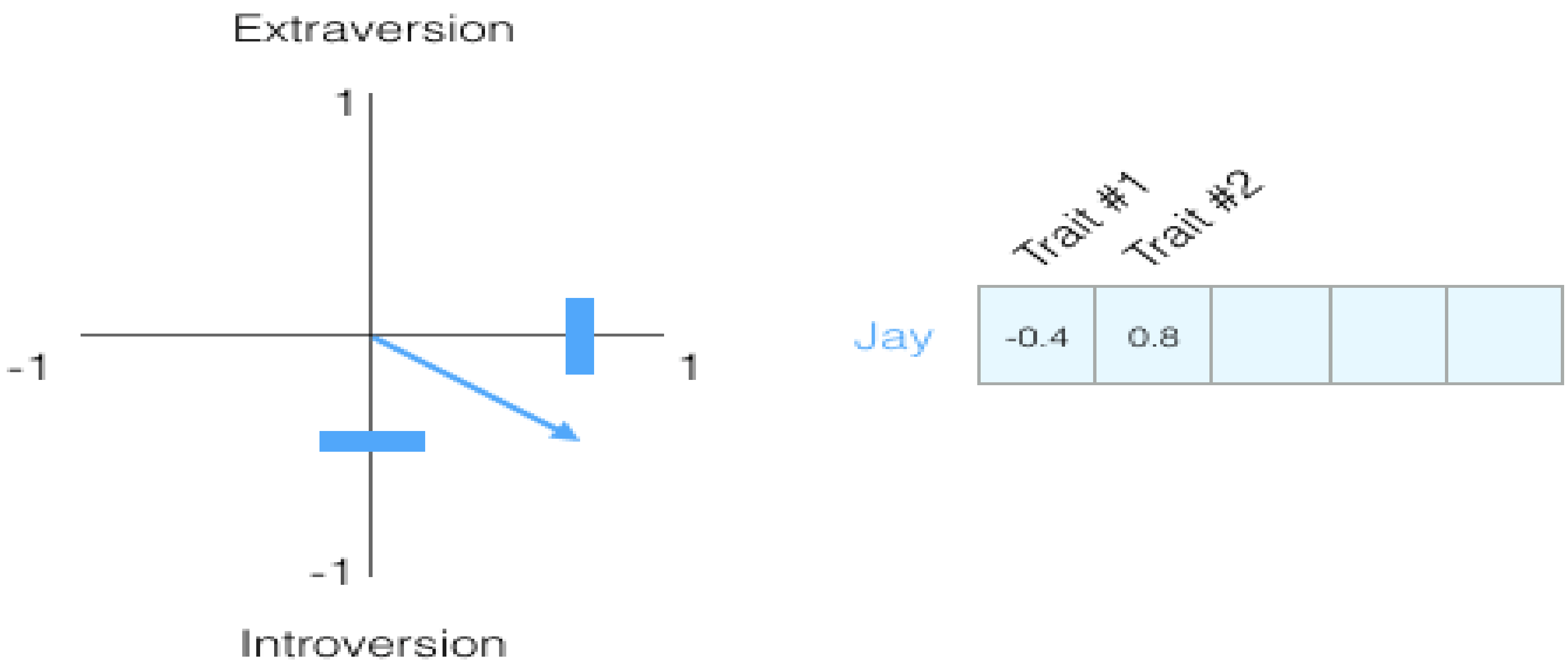
성격 임베딩: 당신의 성격은 어떠한가?

- **내성적인지 외향적인지? (표준화)**



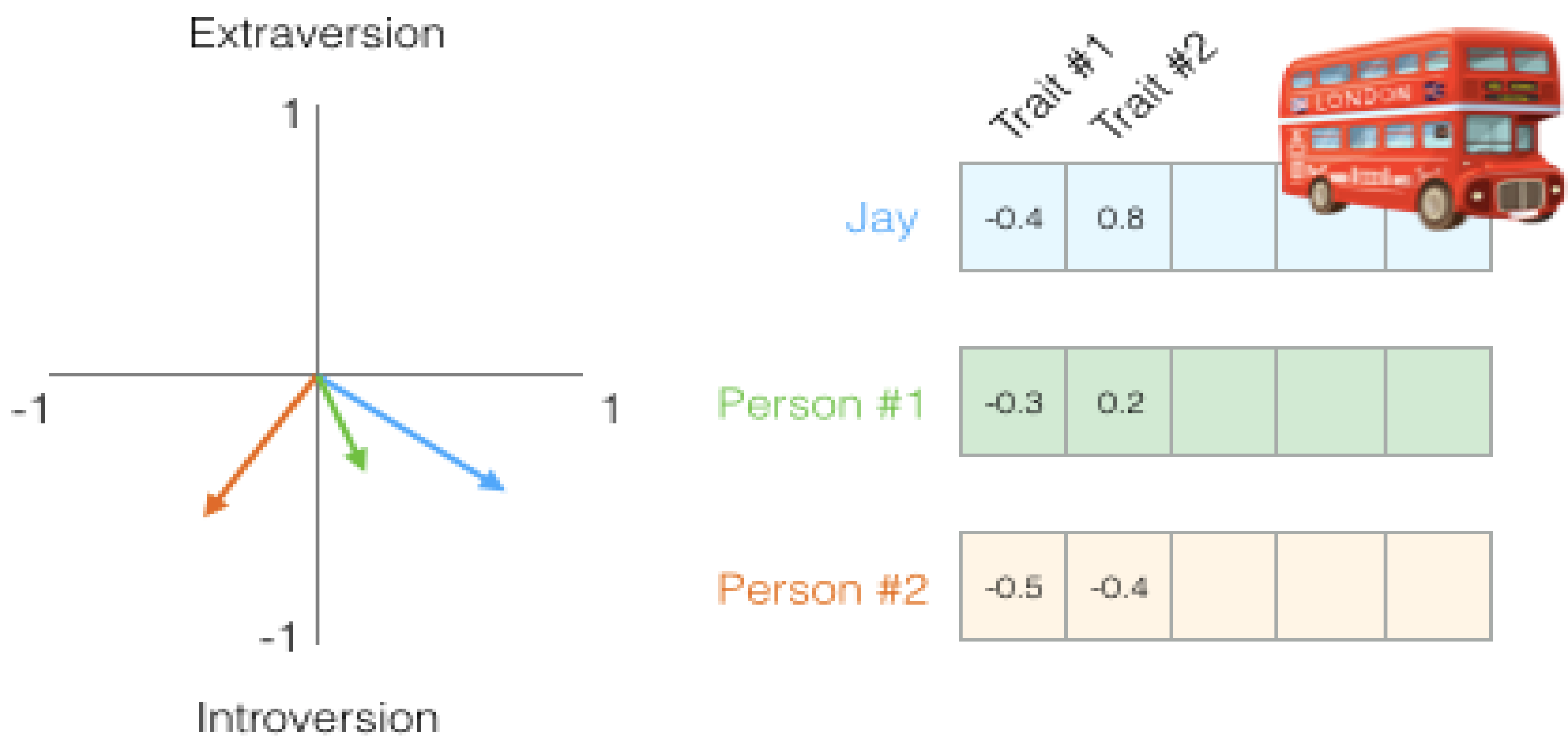
성격 임베딩: 당신의 성격은 어떠한가?

- 여러 특성이 있으면 벡터로 표시할 때 더 잘 표현할 수 있다.



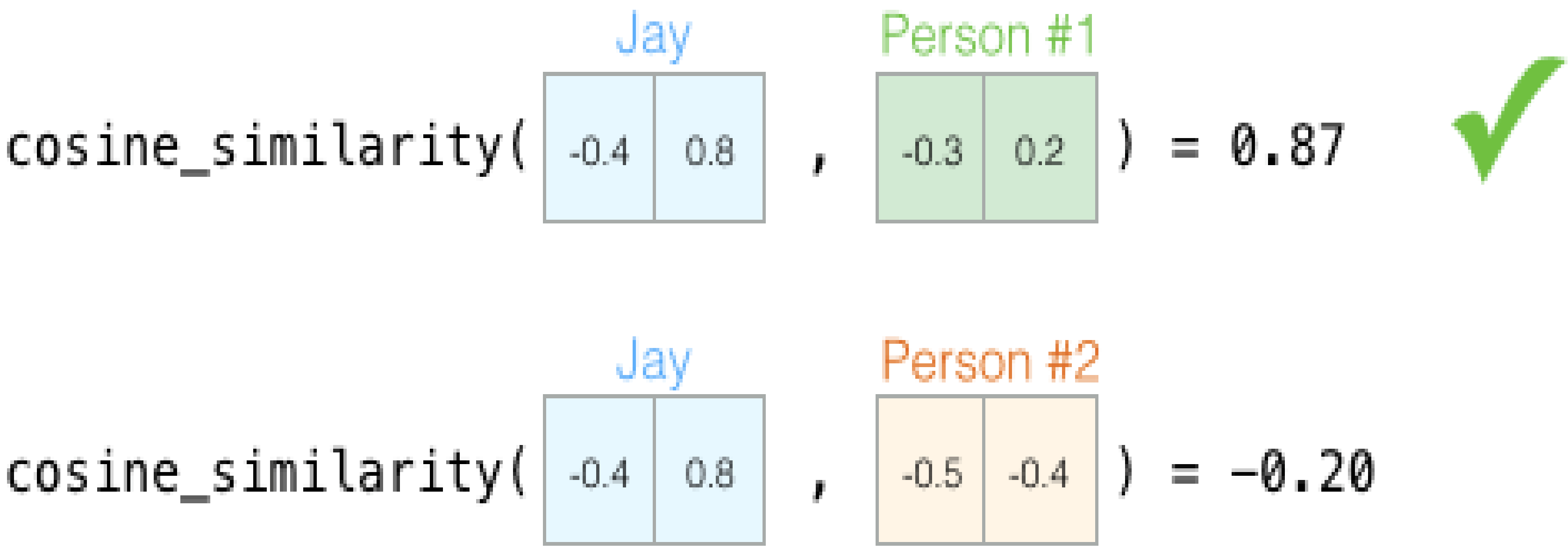
성격 임베딩: 당신의 성격은 어떠한가?

- 벡터로 표시하면 비교하기 더 쉽다.



성격 임베딩: 당신의 성격은 어떠한가?

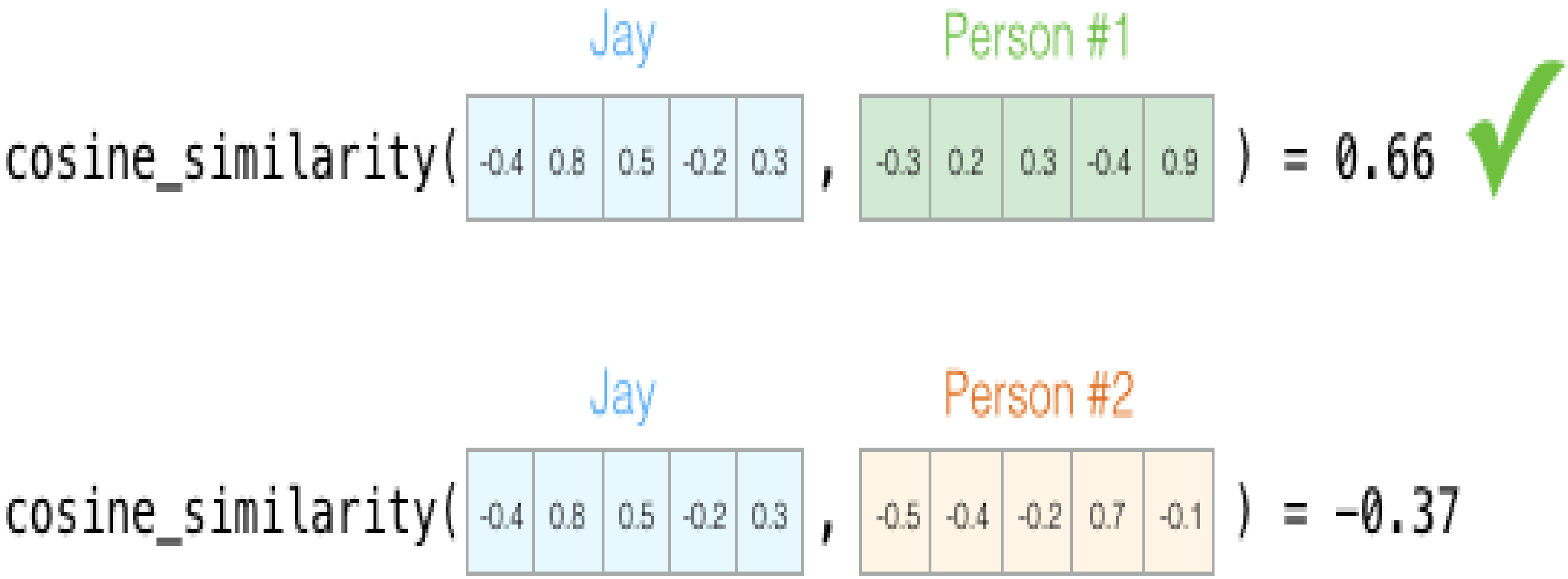
- 유사도를 구할 수 있다.



성격 임베딩: 당신의 성격은 어떠한가?

	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

성격 임베딩: 당신의 성격은 어떠한가?



성격 임베딩: 당신의 성격은 어떠한가?

- 사람의 성격을 벡터로 표시할 수 있고, 유사도를 구할 수 있다.

1- We can represent things
(and people) as vectors of
numbers
(Which is great for machines!)

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

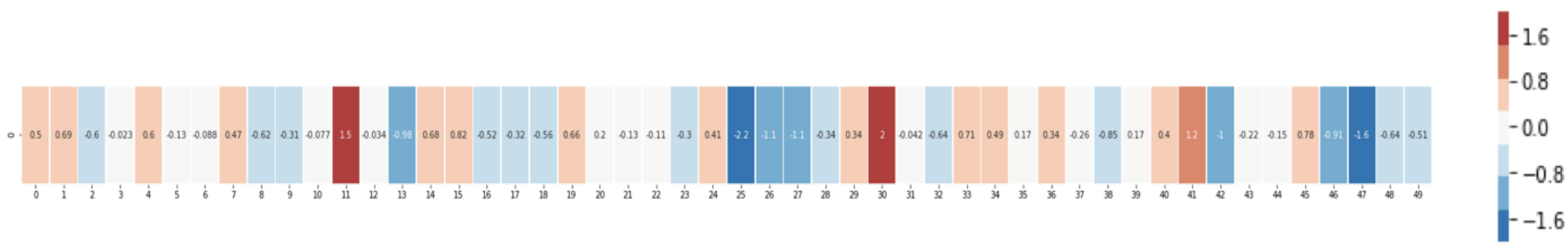
Word Embedding

● 사전학습된 word-vector 예 (word-embedding이라고도 불린다)

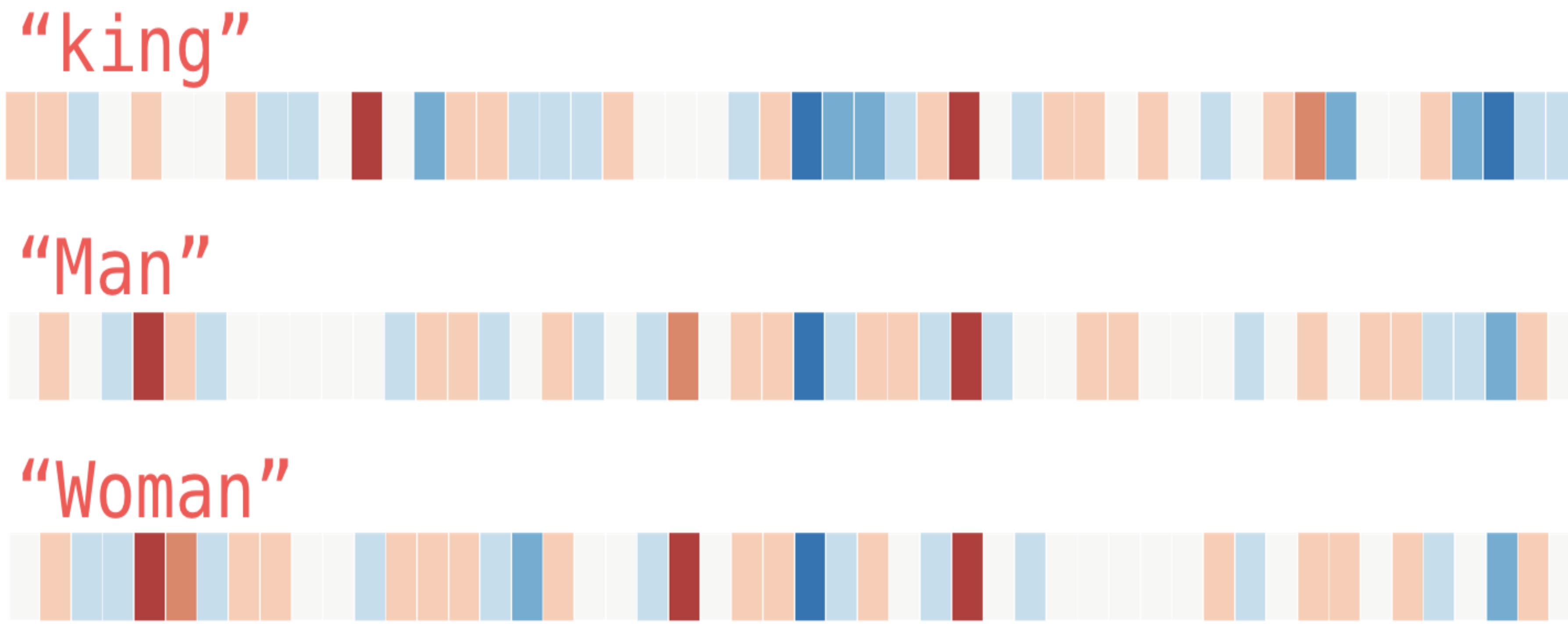
- 예를 들면 “king” (GloVe vector trained on Wikipedia)은 다음과 같이 표현된다.

[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 , -1.0137 , -0.21585 , -0.15155 , 0.78321 , -0.91241 , -1.6106 , -0.64426 , -0.51042]

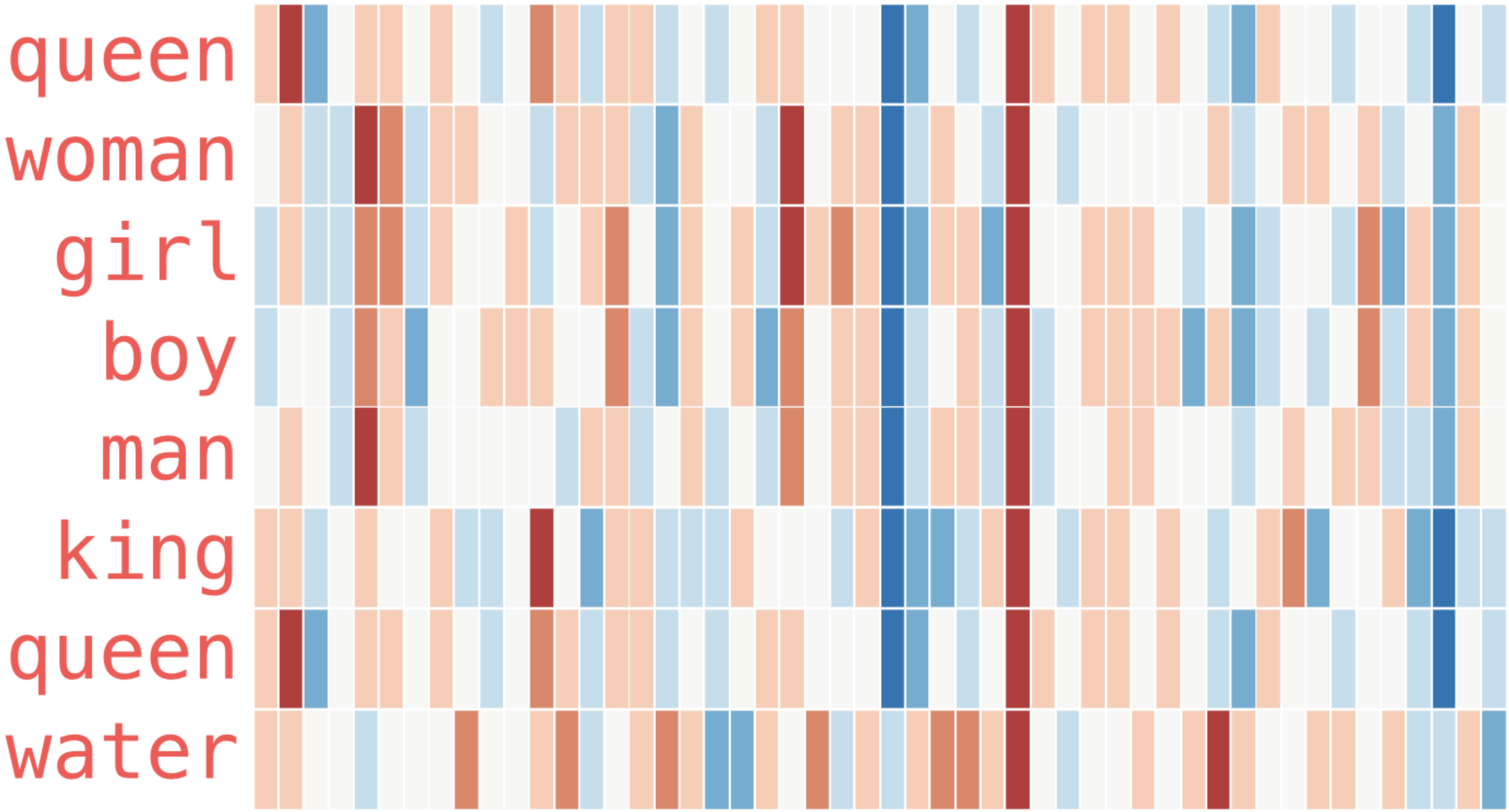
- 이는 50개의 숫자 리스트이다. 알아보기 힘들지만, 다른 단어벡터와 비교하기 위해 시각화할 수 있다.



Word Embedding



Word Embedding

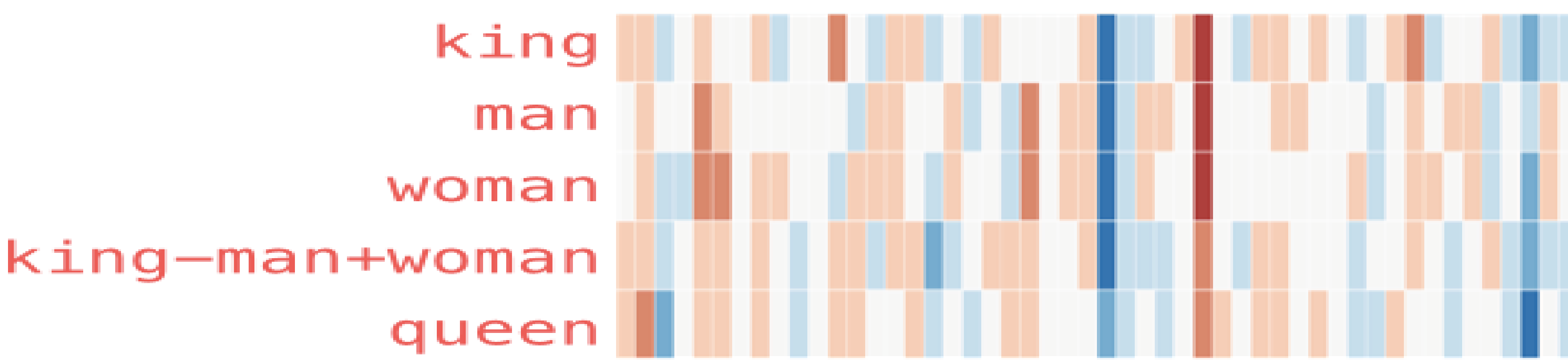


Analogies

```
model.most_similar(positive=["king","woman"], negative=["man"])
```

```
[('queen', 0.8523603677749634),
 ('throne', 0.7664335581924438),
 ('prince', 0.7592144012451172),
 ('daughter', 0.7473883032798767),
 ('elizabeth', 0.7460219860076904),
 ('princess', 0.7424570322036743),
 ('kingdom', 0.7337411642074585),
 ('monarch', 0.721449077129364),
 ('eldest', 0.7184862494468689),
 ('widow', 0.7099430561065674)]
```

king – man + woman ~= queen



언어 모델

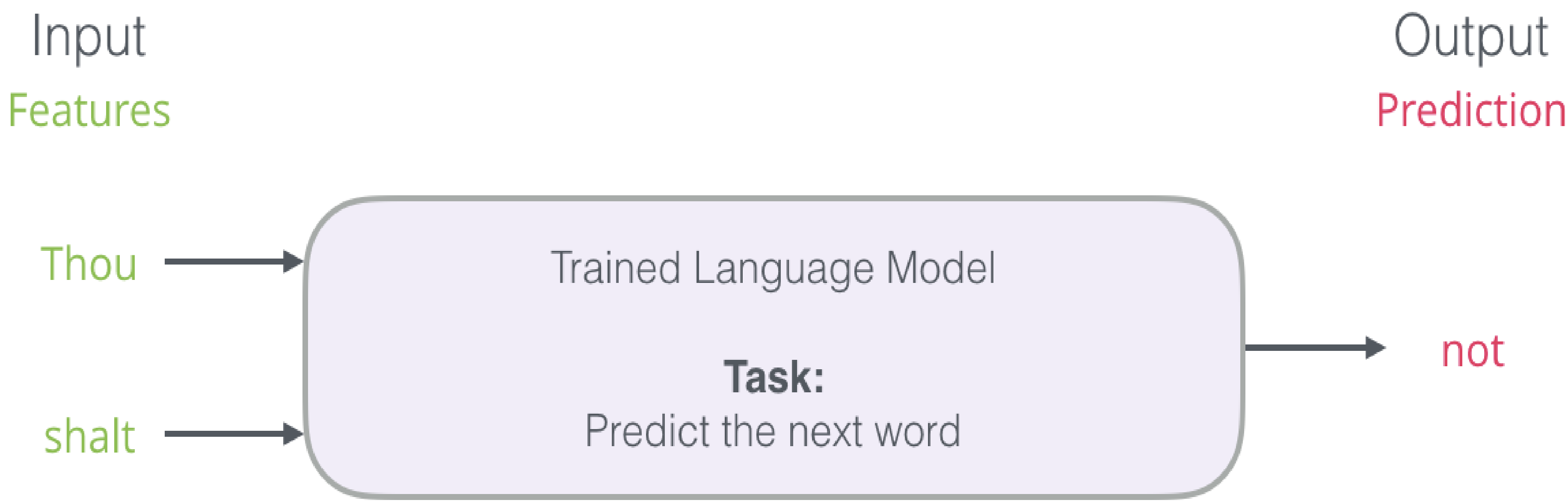
- 다음 단어 예측(Next-word prediction)

input/feature #1 | input/feature #2 | output/label

Thou shalt ________

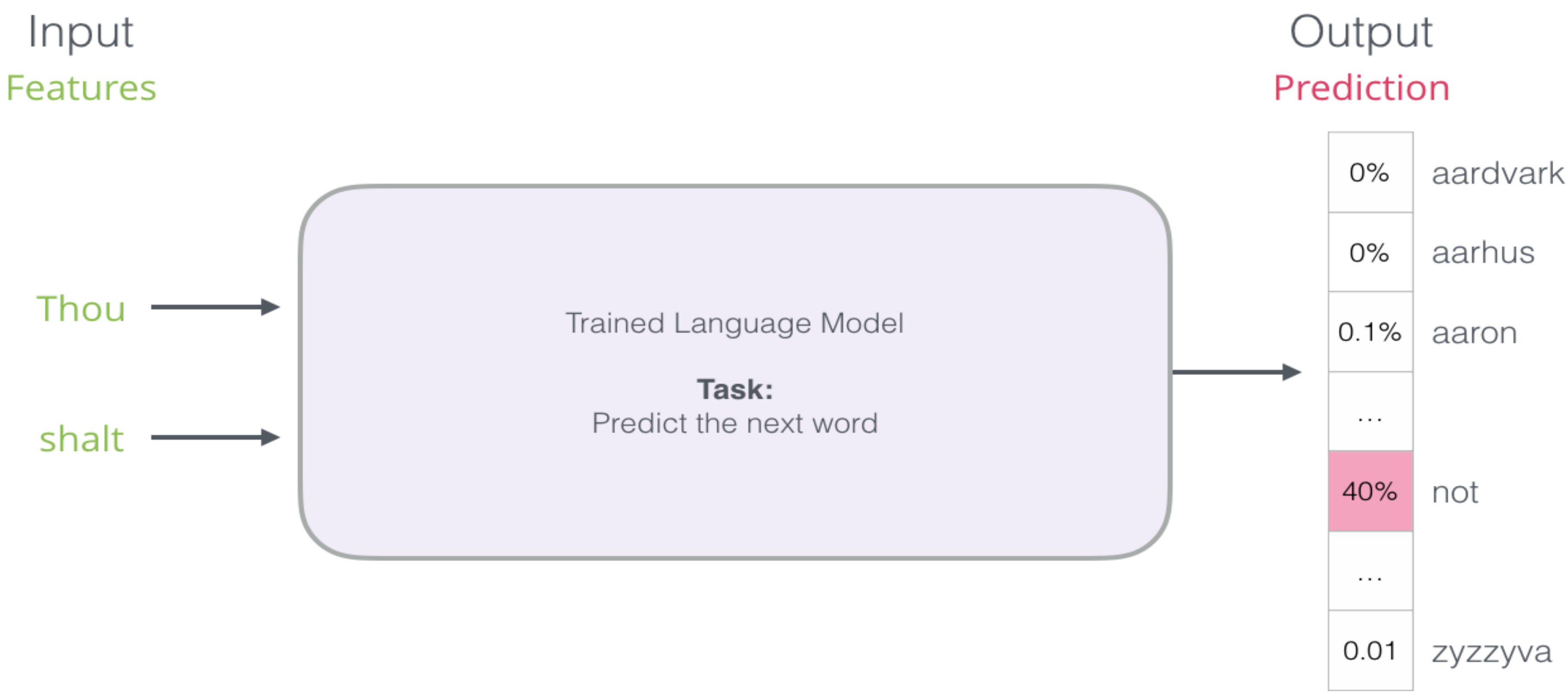
언어 모델

- 다음 단어 예측(Next-word prediction)



언어 모델

- 다음 단어 예측(Next-word prediction)



언어 모델

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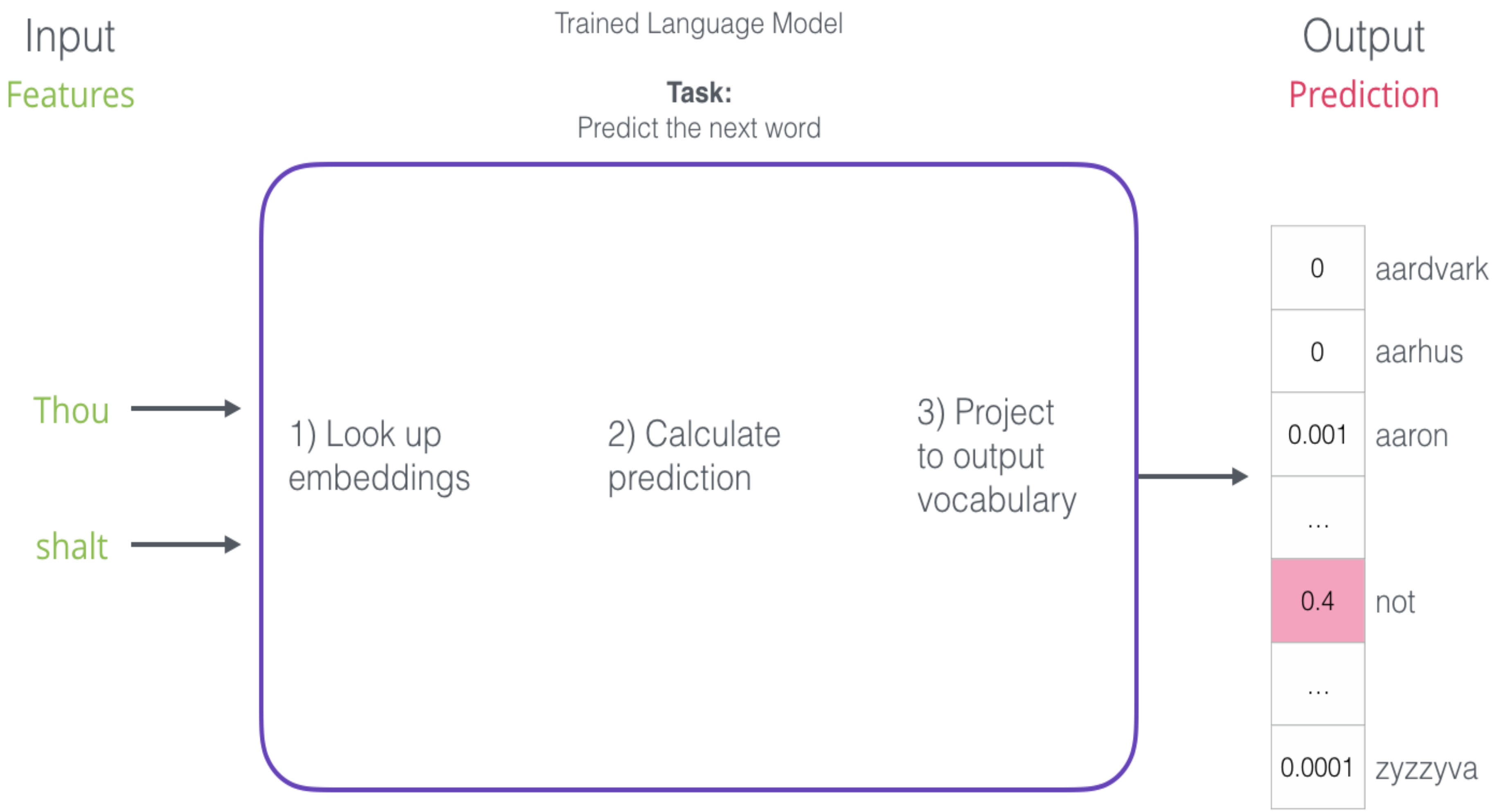
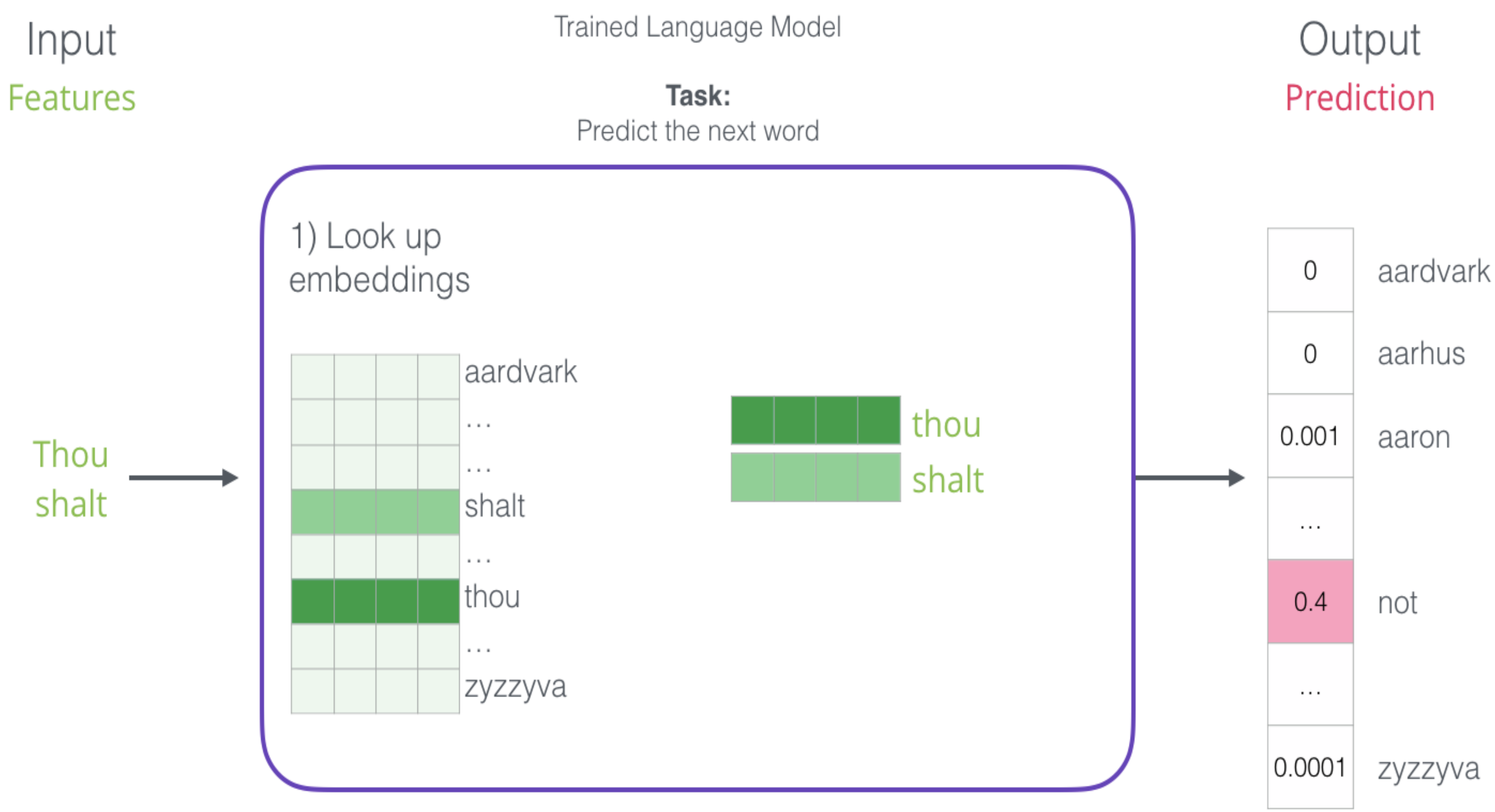


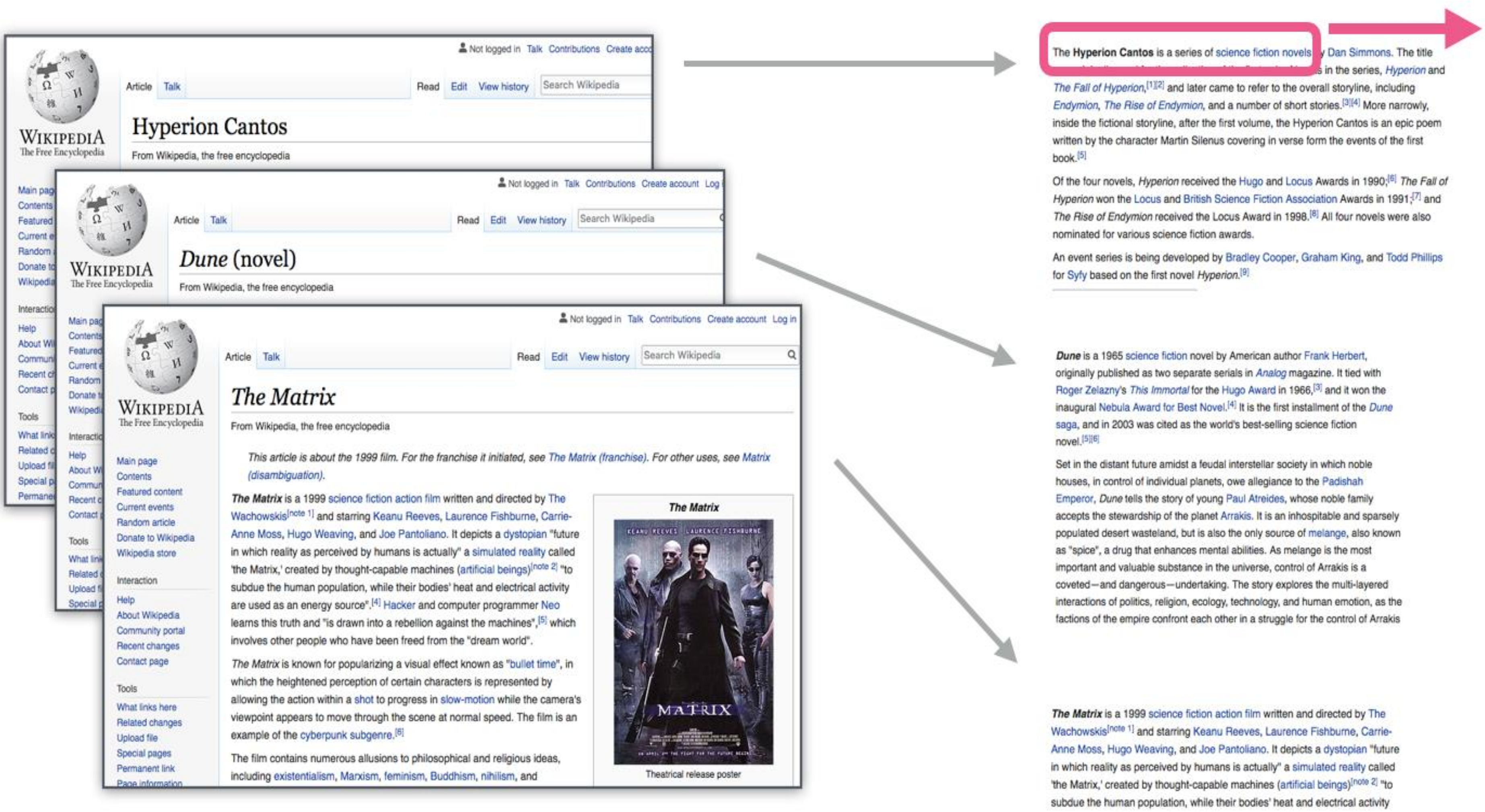
언어 모델

- 다음 단어 예측(Next-word prediction)



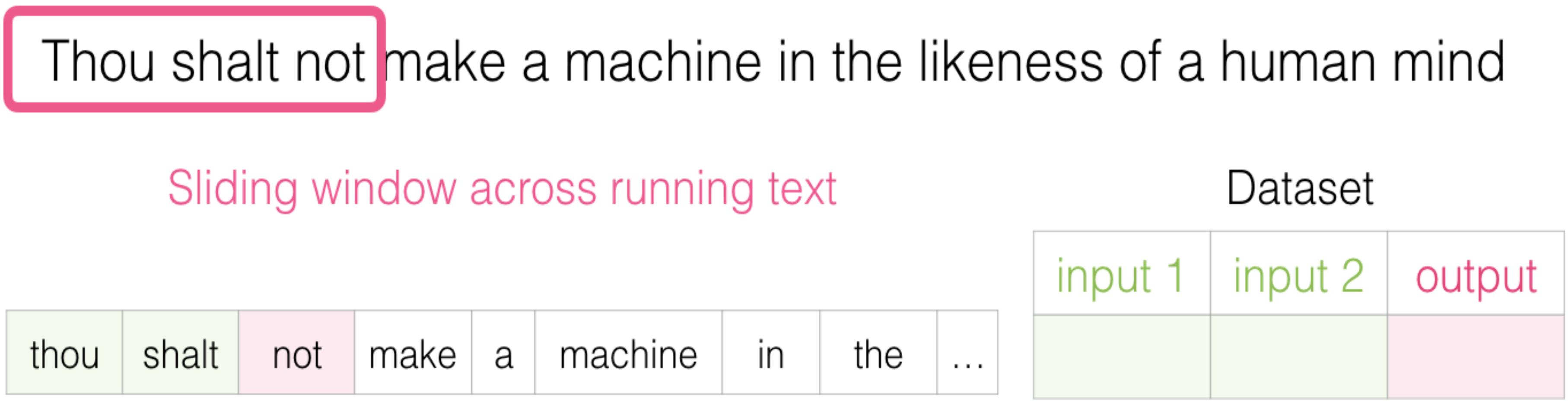
언어 모델 학습

- 다음 단어 예측(Next-word prediction)



언어모델 학습

- 다음 단어 예측(Next-word prediction)



언어모델 학습

- 다음 단어 예측(Next-word prediction)

Thou shalt not make a machine in the likeness of a human mind

Sliding window across running text

thou	shalt	not	make	a	machine	in	the	…

Dataset

input 1	input 2	output
thou	shalt	not

언어모델 학습

- 다음 단어 예측(Next-word prediction)

Thou $\boxed{\text{shalt not make}}$ a machine in the likeness of a human mind

Sliding window across running text

thou	shalt	not	make	a	machine	in	the	…
thou	shalt	not	make	a	machine	in	the	

Dataset

input 1	input 2	output
thou	shalt	not
shalt	not	make

언어모델 학습

- 다음 단어 예측(Next-word prediction)

Thou shalt not make a machine in the likeness of a human mind

Sliding window across running text

thou	shalt	not	make	a	machine	in	the	…
thou	shalt	not	make	a	machine	in	the	
thou	shalt	not	make	a	machine	in	the	
thou	shalt	not	make	a	machine	in	the	
thou	shalt	not	make	a	machine	in	the	

Dataset

input 1	input 2	output
thou	shalt	not
shalt	not	make
not	make	a
make	a	machine
a	machine	in

언어모델 학습

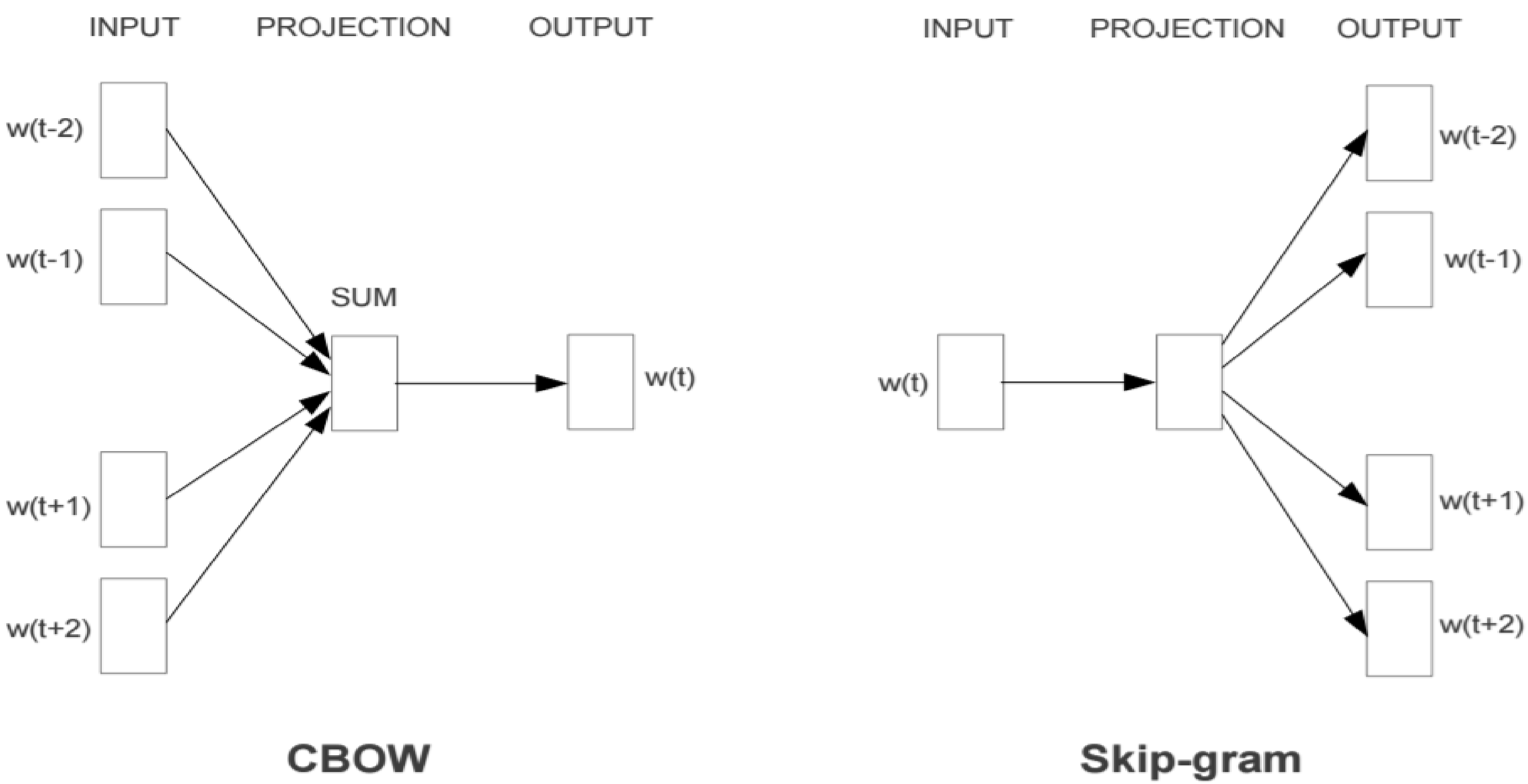
- **양방향으로 볼 필요가 있다. (Look both ways)**

Jay was hit by a ______

Jay was hit by a ______ bus

언어모델 학습

- 양방향으로 볼 필요가 있다. (Look both ways)



언어모델 학습

- 연속 단어주머니 (CBOW: Continuous Bag of Words) :이전 두 단어만 보는 것이 아니라 다음 두 단어도 본다.

Jay was hit by a ______ bus in...

by	a	red	bus	in

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

언어모델 학습

- **스킵 그램 학습 Skip gram**

Jay was hit by a red bus in...

Jay was hit by a red bus in...

by	a	red	bus	in

input	output
red	by
red	a
red	bus
red	in

- 녹색이 입력 핑크색이 출력이다.

Thou shalt not make a machine in the likeness of a human mind

thou	shalt	not	make	a	machine	in	the	…

input word	target word

언어모델 학습

- **스킵 그램 학습 Skip gram**

Thou shalt not make a machine in the likeness of a human mind

thou	shalt	not	make	a	machine	in	the	…

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

언어모델 학습

- **스킵 그램 학습 Skip gram**

Thou shalt not make a machine in the likeness of a human mind

thou	shalt	not	make	a	machine	in	the	…

thou	shalt	not	make	a	machine	in	the	…

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

언어모델 학습

- **스킵 그램 학습 Skip gram**

Thou shalt not make a machine in the likeness of a human mind

thou	shalt	not	make	a	machine	in	the	…

thou	shalt	not	make	a	machine	in	the	…

thou	shalt	not	make	a	machine	in	the	…

thou	shalt	not	make	a	machine	in	the	…

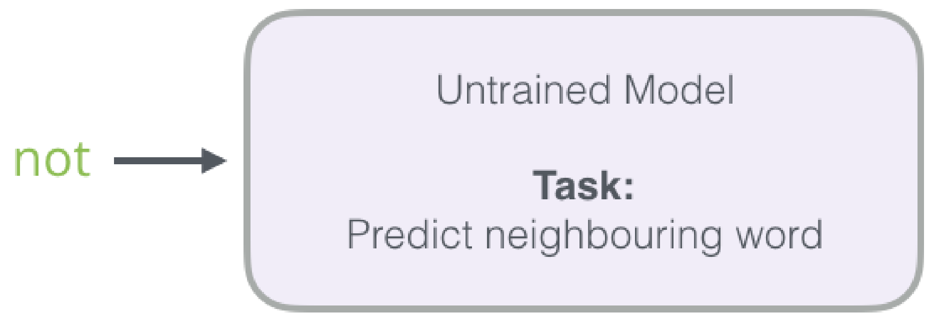
thou	shalt	not	make	a	machine	in	the	…

input word	target word
not	thou
not	shalt
not	make
not	a
make	shalt
make	not
make	a
make	machine
a	not
a	make
a	machine
a	in
machine	make
machine	a
machine	in
machine	the
in	a
in	machine
in	the
in	likeness

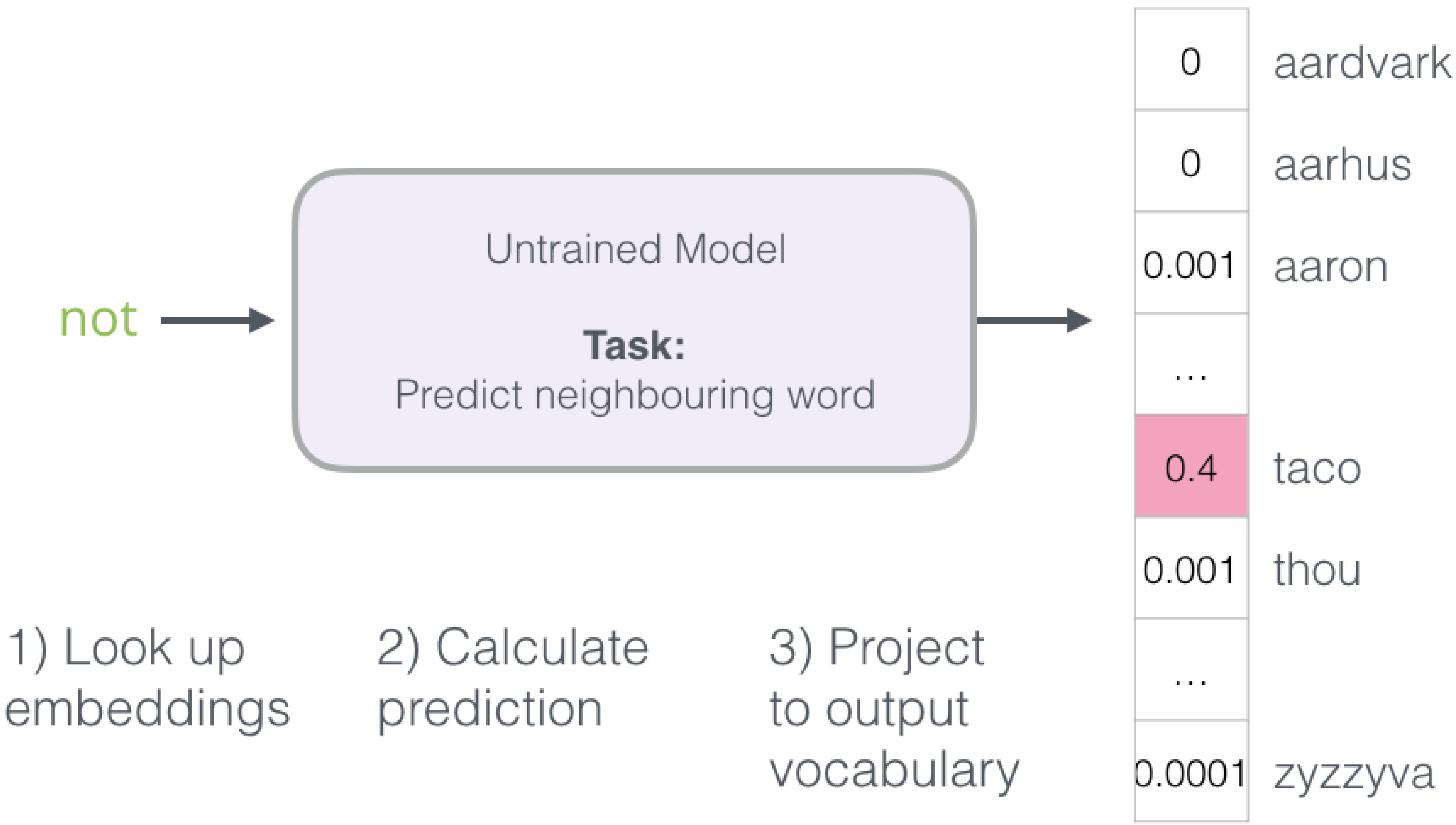
학습 프로세스

- **스킵 그램 학습 Skip gram**

input word	target word
not	thou
not	shalt
not	make
not	a
make	shalt
make	not
make	a
make	machine
a	not
a	make
a	machine
a	in
machine	make
machine	a
machine	in
machine	the
in	a
in	machine
in	the
in	likeness



학습 프로세스



not
Untrained Model
Task:
Predict neighbouring word
0
aardvark
0
aarhus
0.001
aaron
...
0.4
taco
0.001
thou
...
0.0001
zyzzyva
1) Look up embeddings
2) Calculate prediction
3) Project to output vocabulary

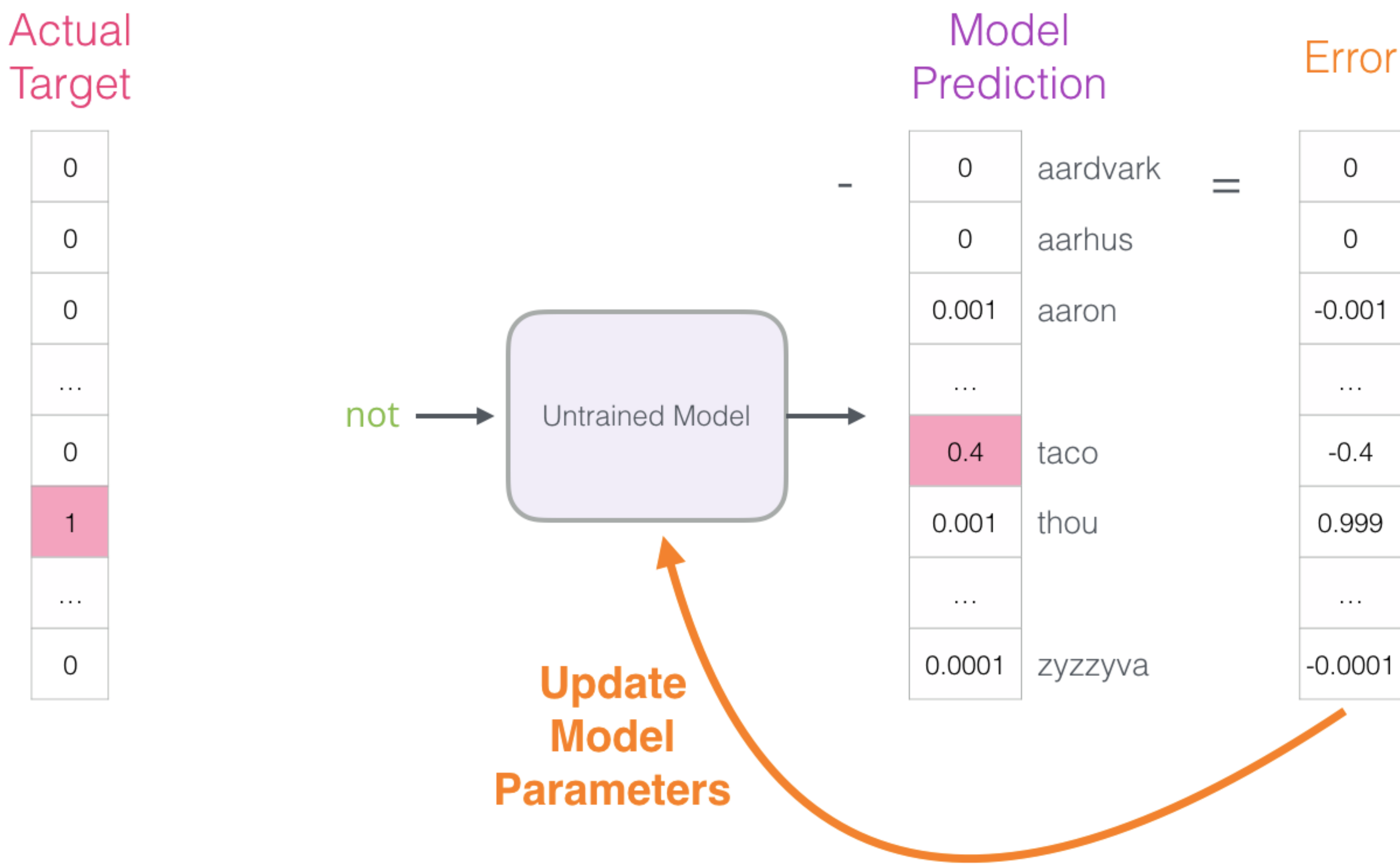
학습 프로세스

Actual Target		Model Prediction	
0		0	aardvark
0		0	aarhus
0		0.001	aaron
...	−	...	
0		0.4	taco
1		0.001	thou
...		...	
0		0.0001	zyzzyva

학습 프로세스

Actual Target		Model Prediction			Error
0		0	aardvark		0
0		0	aarhus		0
0		0.001	aaron		-0.001
…	-	…		=	…
0		0.4	taco		-0.4
1		0.001	thou		0.999
…		…			…
0		0.0001	zyzzyva		-0.0001

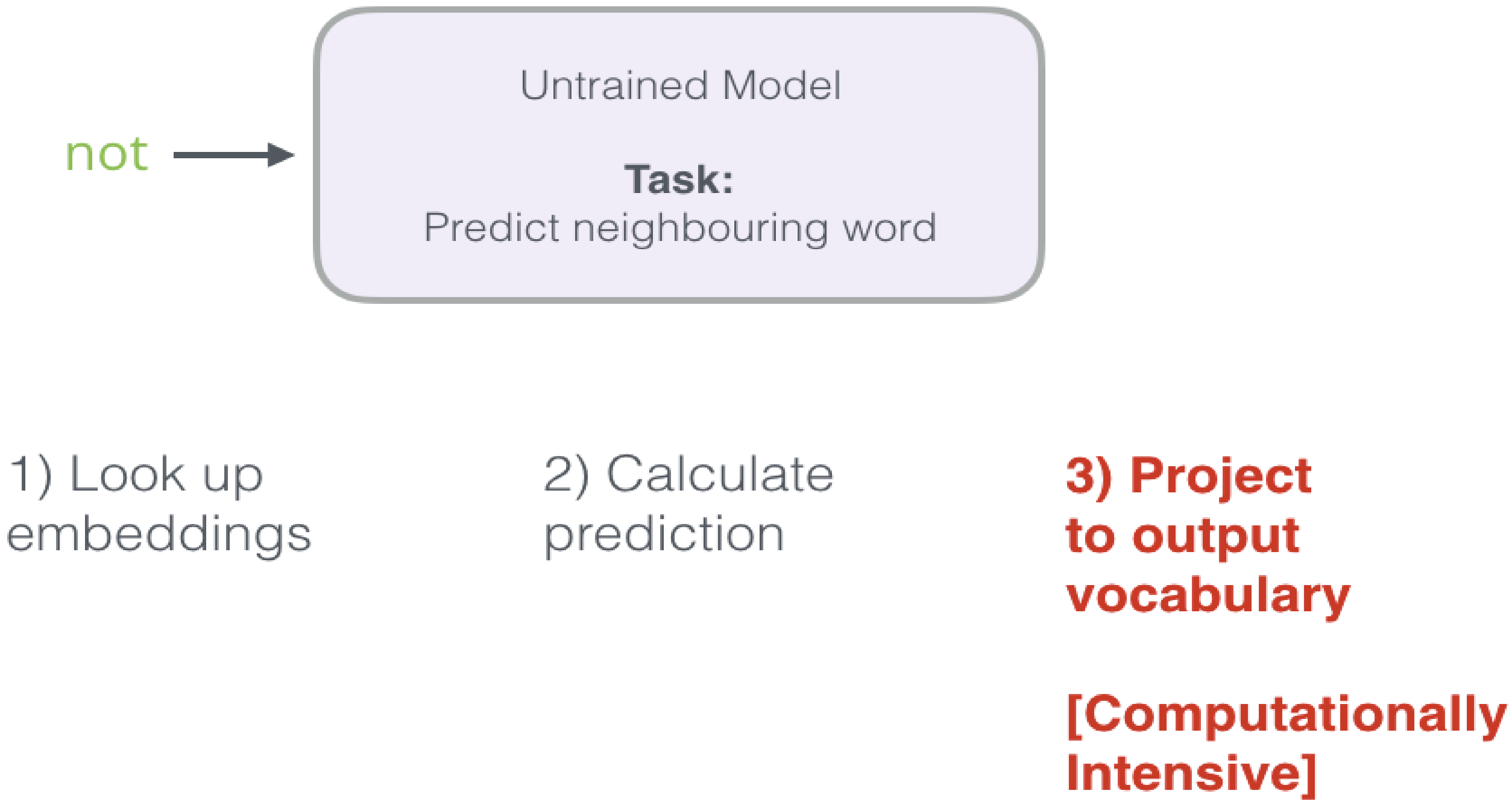
학습 프로세스



Actual
Target
0
0
0
...
0
1
...
0
not
Untrained Model
Model
Prediction
-
0
aardvark
=
0
0
aarhus
0
0.001
aaron
-0.001
...
...
0.4
taco
-0.4
0.001
thou
0.999
...
...
0.0001
zyzzyva
-0.0001
Error
Update
Model
Parameters

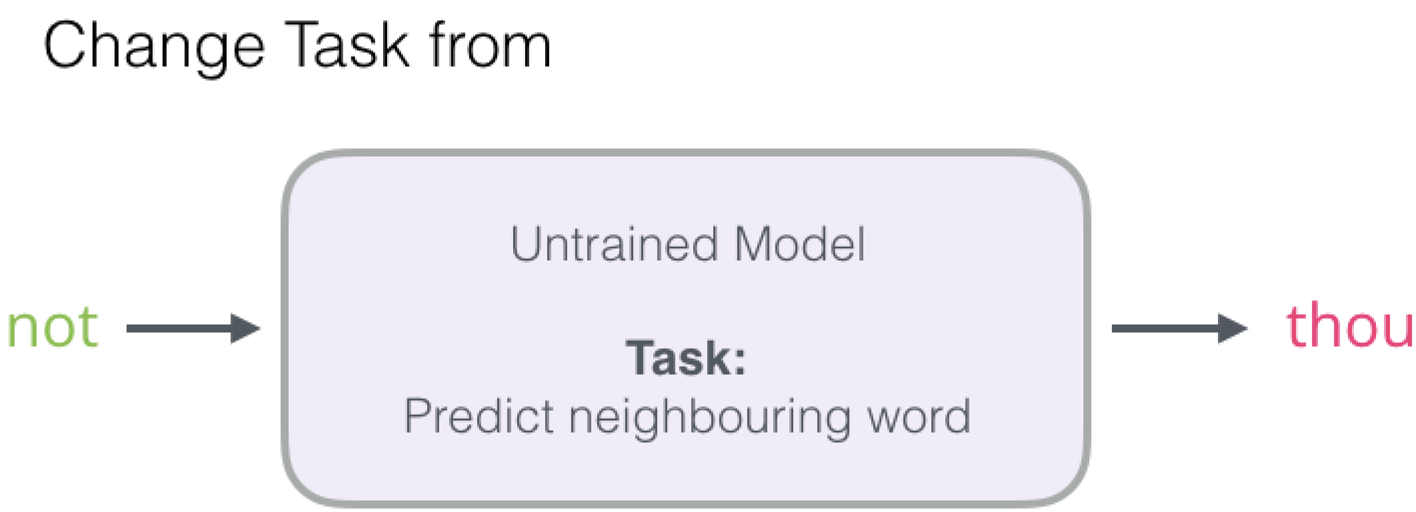
부정 샘플링 (Negative Sampling)

- 단어집의 모든 단어에 대해서 오차를 계산해야 하는 이 방식은 계산비용이 큼



부정 샘플링 (Negative Sampling)

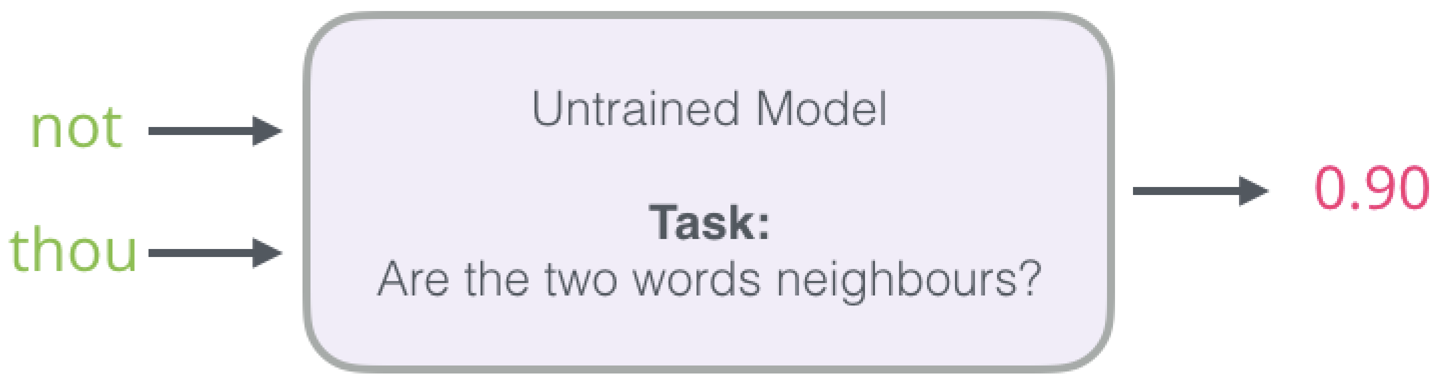
- 작업을 좀 바꿔보자: 신경망 -> 로지스틱 회귀로



부정 샘플링 (Negative Sampling)

- 작업을 좀 바꿔보자: 신경망 -> 로지스틱 회귀로

To:



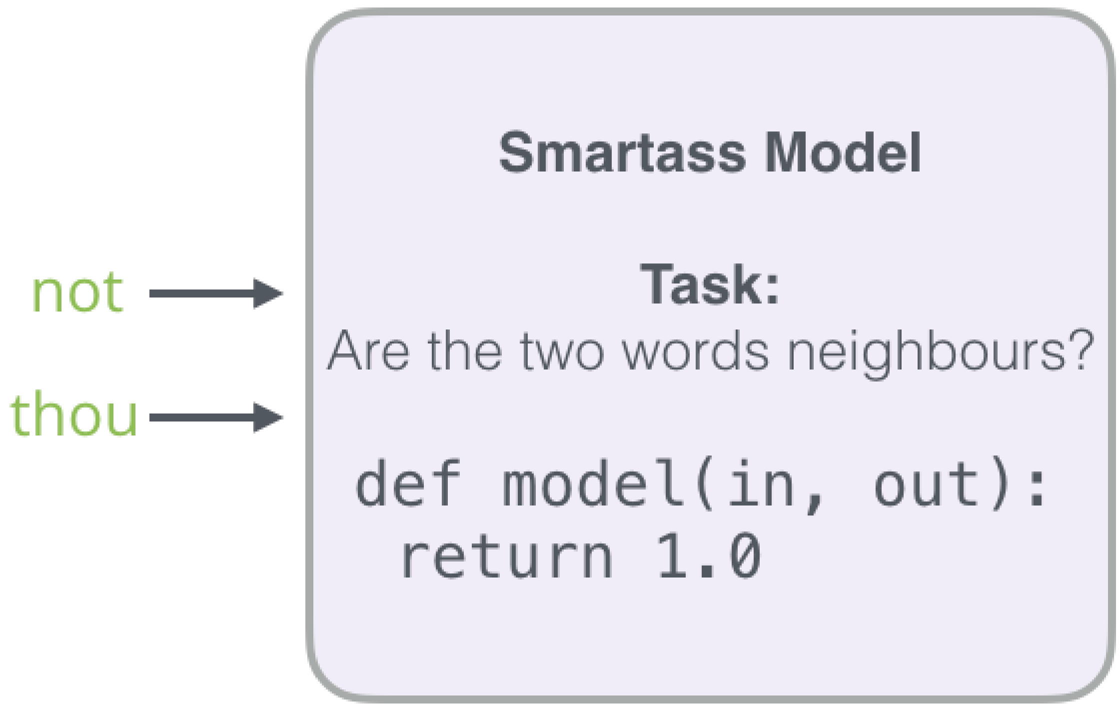
부정 샘플링 (Negative Sampling)

- 이웃에 있는 단어에 대해서 1

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

부정 샘플링 (Negative Sampling)



부정 샘플링 (Negative Sampling)

- 이웃이 아닌 단어에 대해서 0를 할당

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

Negative examples

부정 샘플링 (Negative Sampling)

- 이웃이 아닌 단어에 대해서 0를 할당

\- 이웃이 아닌 단어를 단어집에서 랜덤추출

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

Word	Count	Probability
aardvark		
aarhus		
aaron		
taco		
thou		
zyzzyva		

부정 샘플링 (Negative Sampling) Skipgram (SGNS)

- 부정 샘플링 + 스킵그램

Skipgram

shalt	not	make	a	machine

input	output
make	shalt
make	not
make	a
make	machine

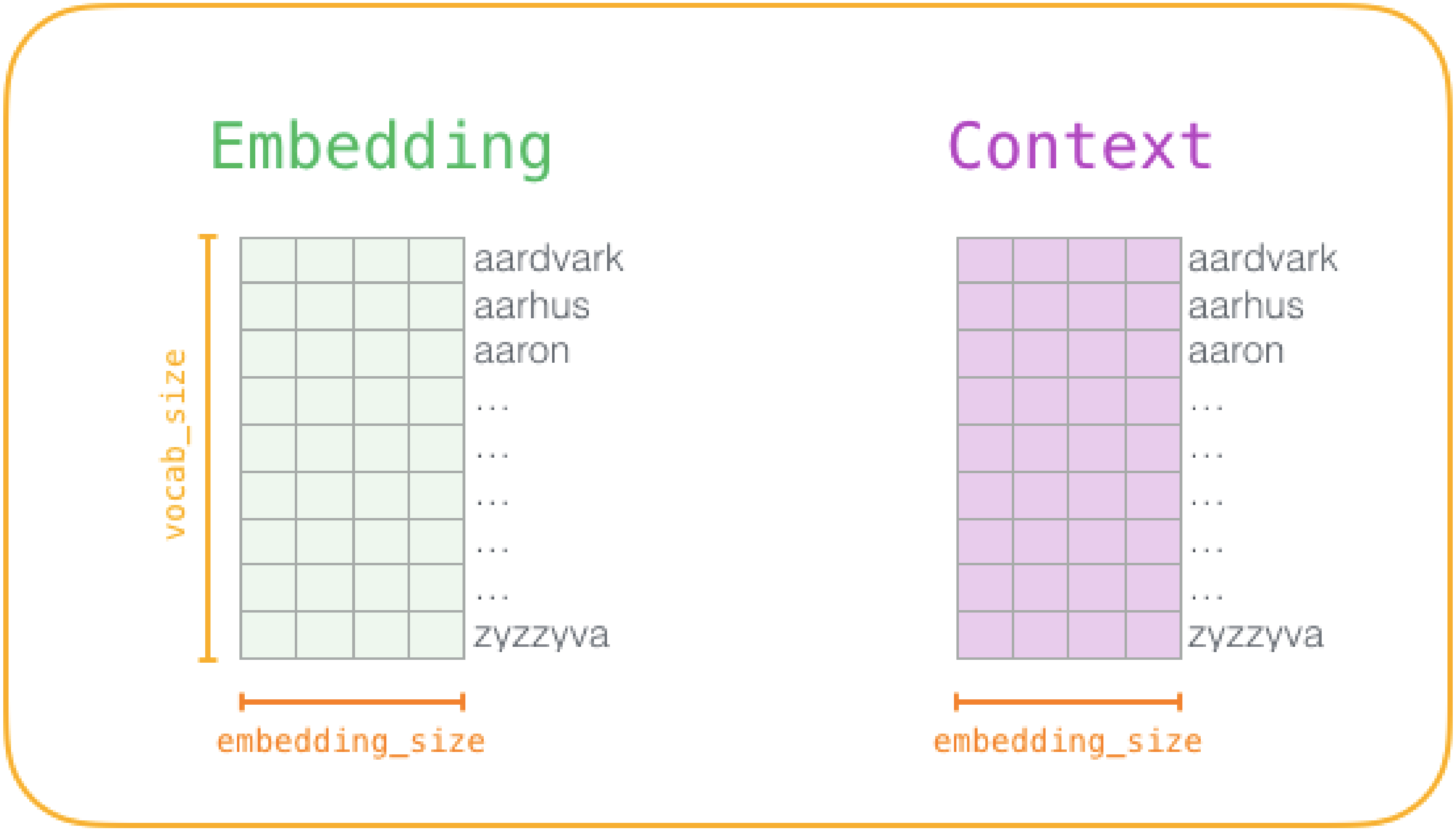
Negative Sampling

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

word2vec

Word2Vec 학습 프로세스

- 2개의 임베딩 행렬을 생성한다. embedding_size는 일반적으로 300



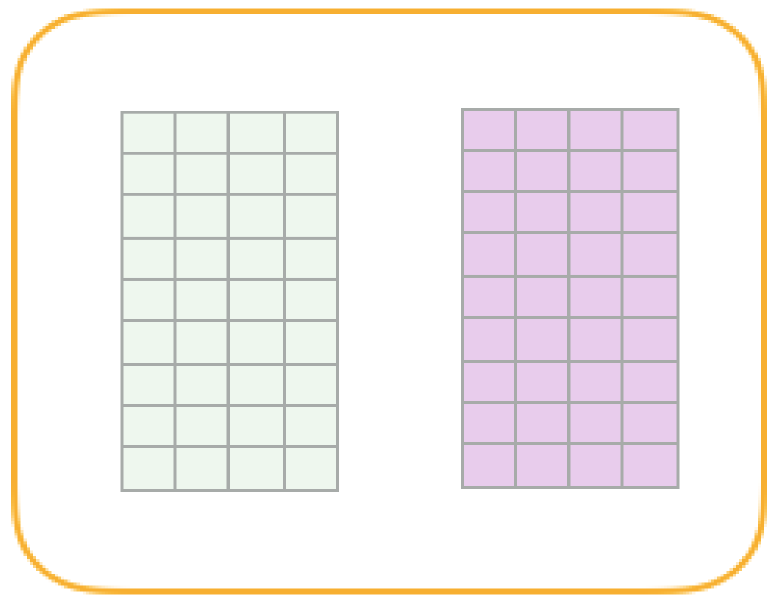
Word2Vec 학습 프로세스

- 시작은 랜덤넘버로 시작

dataset

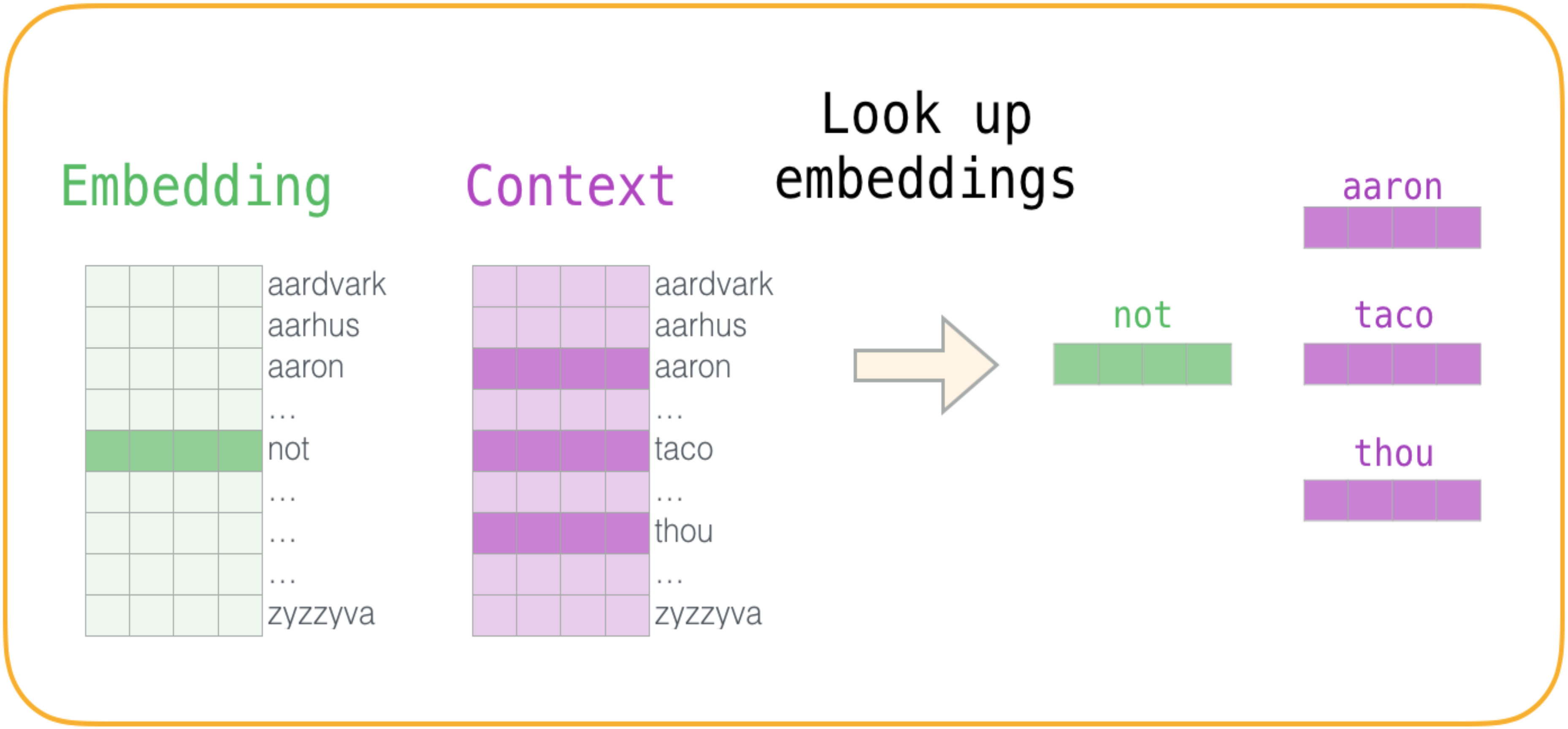
input word	output word	target
not	thou	1
not	aaron	0
not	taco	0
not	shalt	1
not	mango	0
not	finglonger	0
not	make	1
not	plumbus	0
...	...	...

model



Word2Vec 학습프로세스

- 임베딩 행렬에서 입력단어 1개, 콘텍스트 행렬에서 타겟단어 3개 추출



Word2Vec 학습 프로세스

- 유사도를 측정하기 위해 점곱을 계산 (코사인유사도를 상기하라.)

input word	output word	target	input • output
not	thou	1	0.2
not	aaron	0	-1.11
not	taco	0	0.74

Word2Vec 학습 프로세스

- 유사도 결과에 시그모이드를 적용해 확률을 계산하고, 다음 오차를 계산한다.

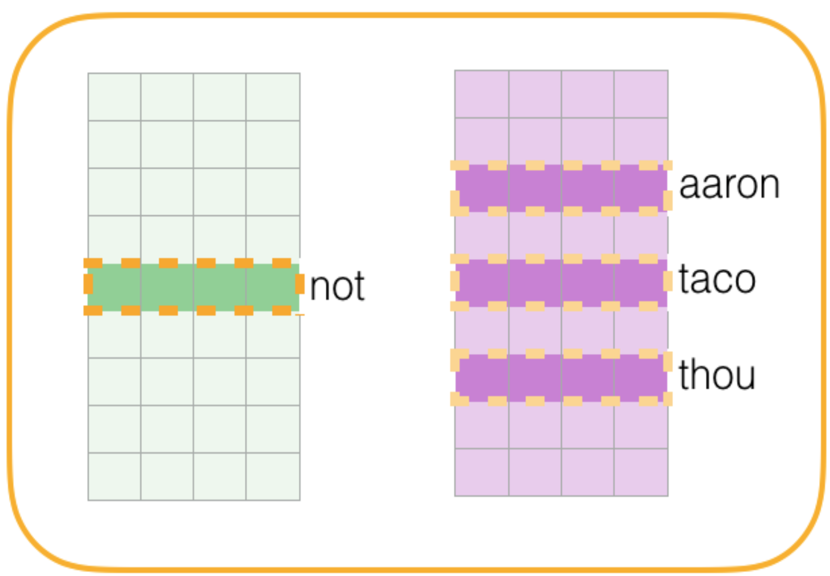
\- 오차는 타겟 – 시그모이드이다.

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

Word2Vec 학습 프로세스

- 오차를 최소화하기 위해 선택된 단어들의 임베딩을 조정한다.

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



Update Model Parameters

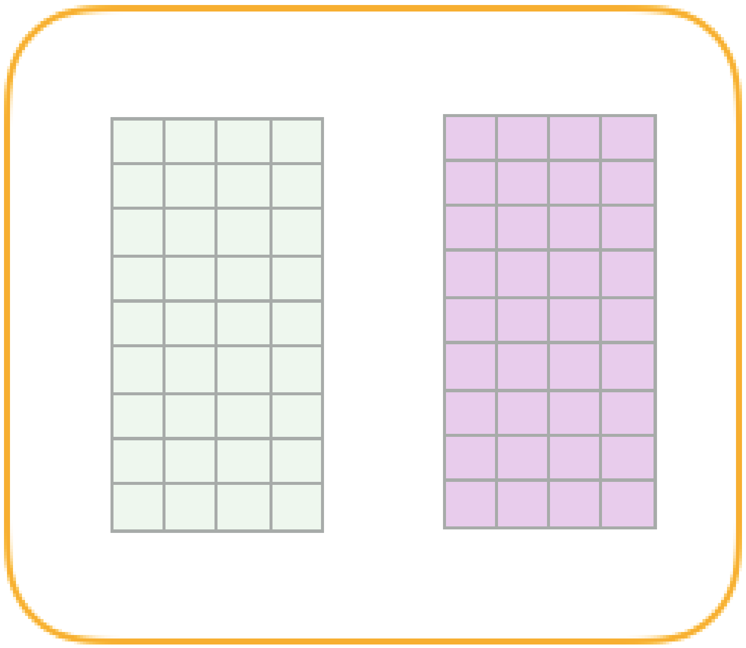
Word2Vec 학습 프로세스

- 다음 단어셋(not shalt mango, finglonger)에 대해서 이 프로세스를 반복한다.

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



윈도우 크기와 부정 샘플링 갯수

- 중요한 하이퍼 파라미터가 윈도우크기와 부정 샘플링 갯수이다.

- 윈도우 크기 (5-15) 15-50도 사용하지만, 젠심은 5을 기본으로 한다.
  윈도우 크기가 작으면 인접 단어가 교환가능한 단어(동의어 뿐 아니라 반대말도) 찾게 되며, 큰 윈도우는 관련언어를 찾게 된다.

위도우 크기와 부정 샘플링 갯수

- 부정 샘플링 갯수 (5-20) 하지만 2-5도 나쁘지 않으며 Gensim은 5를 기본으로 한다.

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

참고문헌

- Distributed Representations of Words and Phrases and their Compositionality [pdf]

- Efficient Estimation of Word Representations in Vector Space [pdf]

- A Neural Probabilistic Language Model [pdf]

- Speech and Language Processing by Dan Jurafsky and James H. Martin is a leading resource for NLP. Word2vec is tackled in Chapter 6.

- Neural Network Methods in Natural Language Processing by Yoav Goldberg is a great read for neural NLP topics.

- Chris McCormick has written some great blog posts about Word2vec. He also just released The Inner Workings of word2vec, an E-book focused on the internals of word2vec.

- Want to read the code? Here are two options:

  - Gensim's python implementation of word2vec

  - Mikolov's original implementation in C – better yet, this version with detailed comments from Chris McCormick.

- Evaluating distributional models of compositional semantics

- On word embeddings, part 2

- Dune