Théories de l’IA

Séance 6

Attention, context et compréhension

Jonathan Simon

programme

- 1) Qu’est-ce que l’attention ?
- 2) Rappel : vectorisations de mots
- 3) Context, mécanismes attentionnels et transformeurs
- 4) Capacités émergentes
- 5) *mais comprennent-ils*?

Qu’est-ce que l’attention?

Qu’est-ce que l’attention?

- “Everyone knows what attention is. It is the taking possession by the mind, in clear, and vivid form, of one out of what seems several simultaneously possible objects or trains of thought.” – William James

Qu’est-ce que l’attention?

- «L'attention est le contrôle flexible de ressources informatiques limitées. La raison pour laquelle ces ressources sont limitées et la meilleure façon de les contrôler varieront selon les cas d'utilisation, mais la capacité de modifier et d'acheminer dynamiquement le flux d'informations présente des avantages évidents pour la capacité d'adaptation de tout système.»
    - -- Grace Lindsay (2019)

Qu’est-ce que l’attention?

- Si un réseau neuronal est une configuration de poids et de biais, on peut considérer l'attention comme un moyen de modifier (temporairement, dynamiquement) ces poids et ces biais, en fonction de la tâche à accomplir.

Qu’est-ce que l’attention?

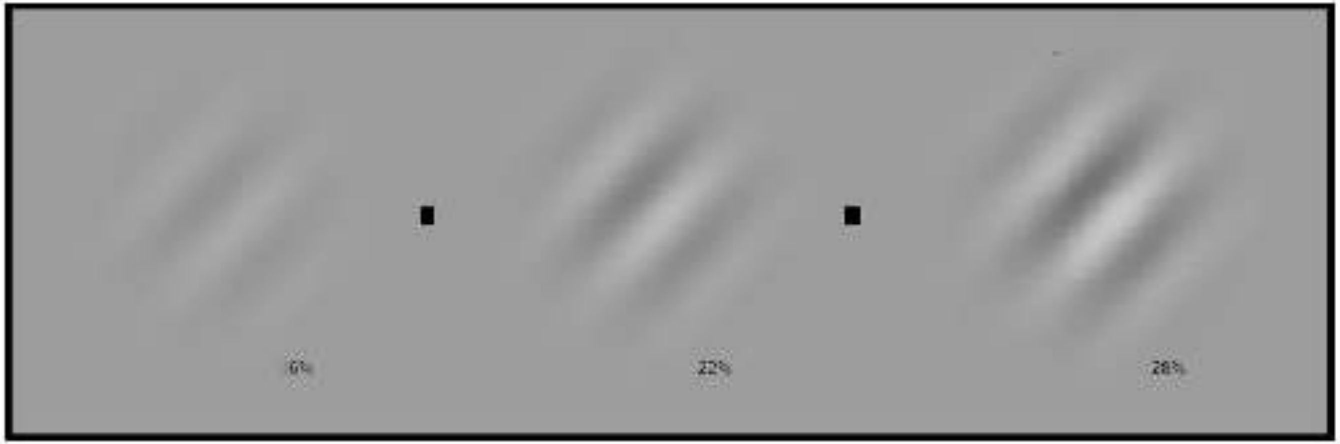
- 1) Attention diffuse (éveil) vs attention focale
- 2) Sensorielle vs éxecutive
- 3) Spatial vs Caractéristique vs Objet
- 4) Bottom-up vs Top-Down
- 5) Hard vs Soft

Qu’est-ce que l’attention?

- Quel est le lien entre l'attention et la conscience ?
- Quelle est la structure phénoménologique de l'attention ou quel est l'impact de l'attention sur la structure phénoménologique ?

Attention alters contrast appearance

Test Cued Neutral Standard Cued



Carrasco, Ling & Read
Nature Neuroscience, 2004

Vectorisation de mots (et de jetons)

Vectorisation de mots (Embeddings)

- Le vectorisation d'un mot (ou d'un jeton, en fait un phonème) est un vecteur qui exprime, sous forme compressée, des informations sur les statistiques d'apparition de ce mot ou de ce jeton dans les données de manière plus générale

Vectorisation de mots (Embeddings)

- Le résultat fascinant est qu'en utilisant cette méthode (en supposant que tu disposes d'un ensemble de textes suffisamment riche pour t'entraîner), tu arrives à des vecteurs qui capturent beaucoup de nos intuitions sémantiques sur les similitudes (sémantiques) entre les mots

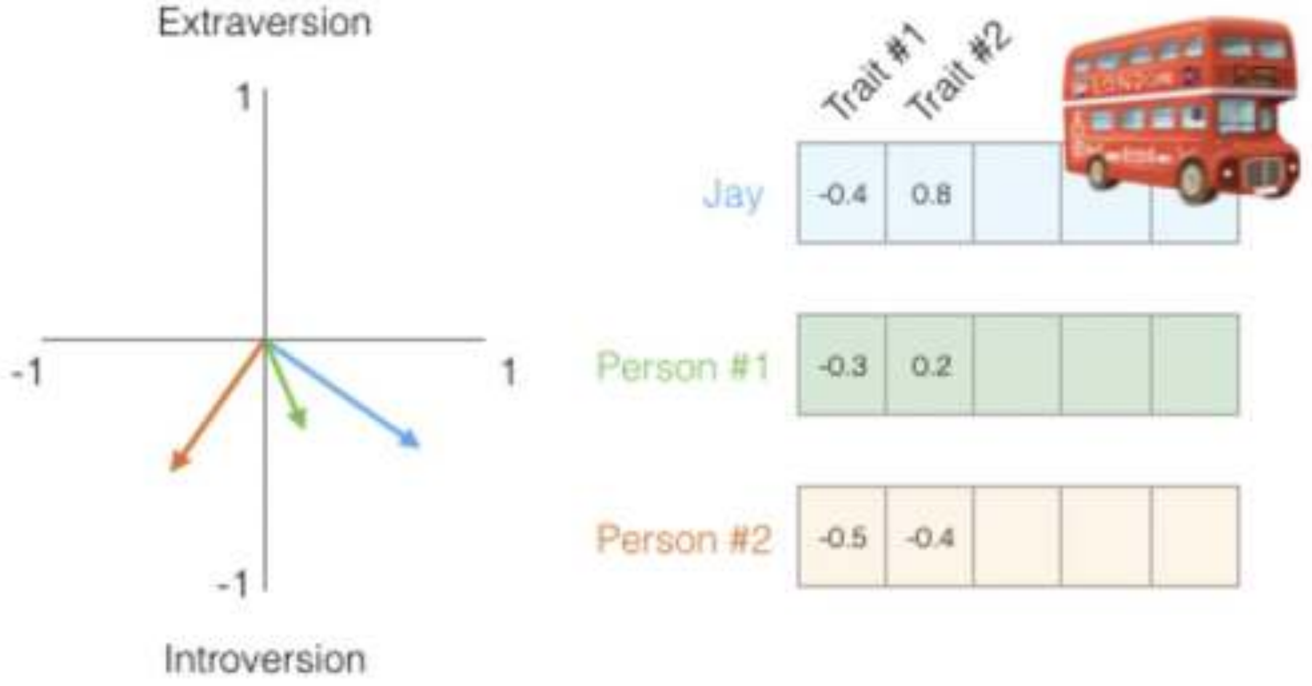
Personality Embeddings: What are you like?

> "I give you the desert chameleon, whose ability to blend itself into the background tells you all you need to know about the roots of ecology and the foundations of a personal identity" –Children of Dune

On a scale of 0 to 100, how introverted/extraverted are you (where 0 is the most introverted, and 100 is the most extraverted)? Have you ever taken a personality test like MBTI – or even better, the Big Five Personality Traits test? If you haven't, these are tests that ask you a list of questions, then score you on a number of axes, introversion/extraversion being one of them.

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

Jay Alammar

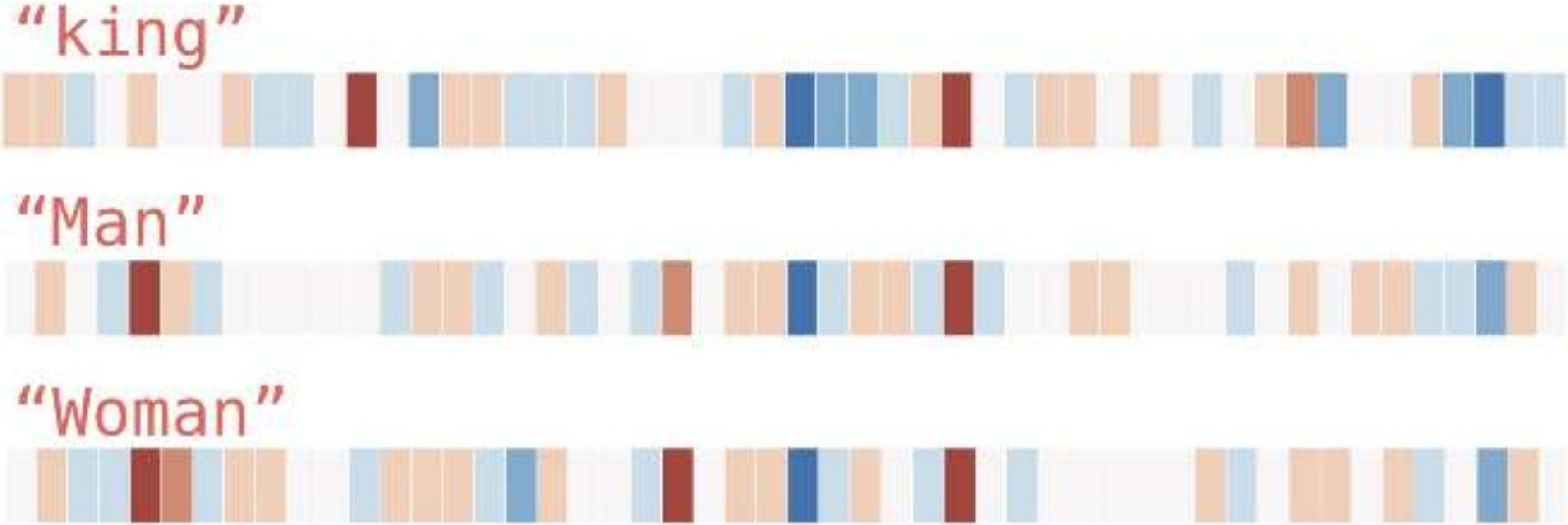


Extraversion
1
-1
1
-1
Introversion
Trait #1
Trait #2
Jay
-0.4
0.8
Person #1
-0.3
0.2
Person #2
-0.5
-0.4

Jay Alammar

	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

Jay Alammar



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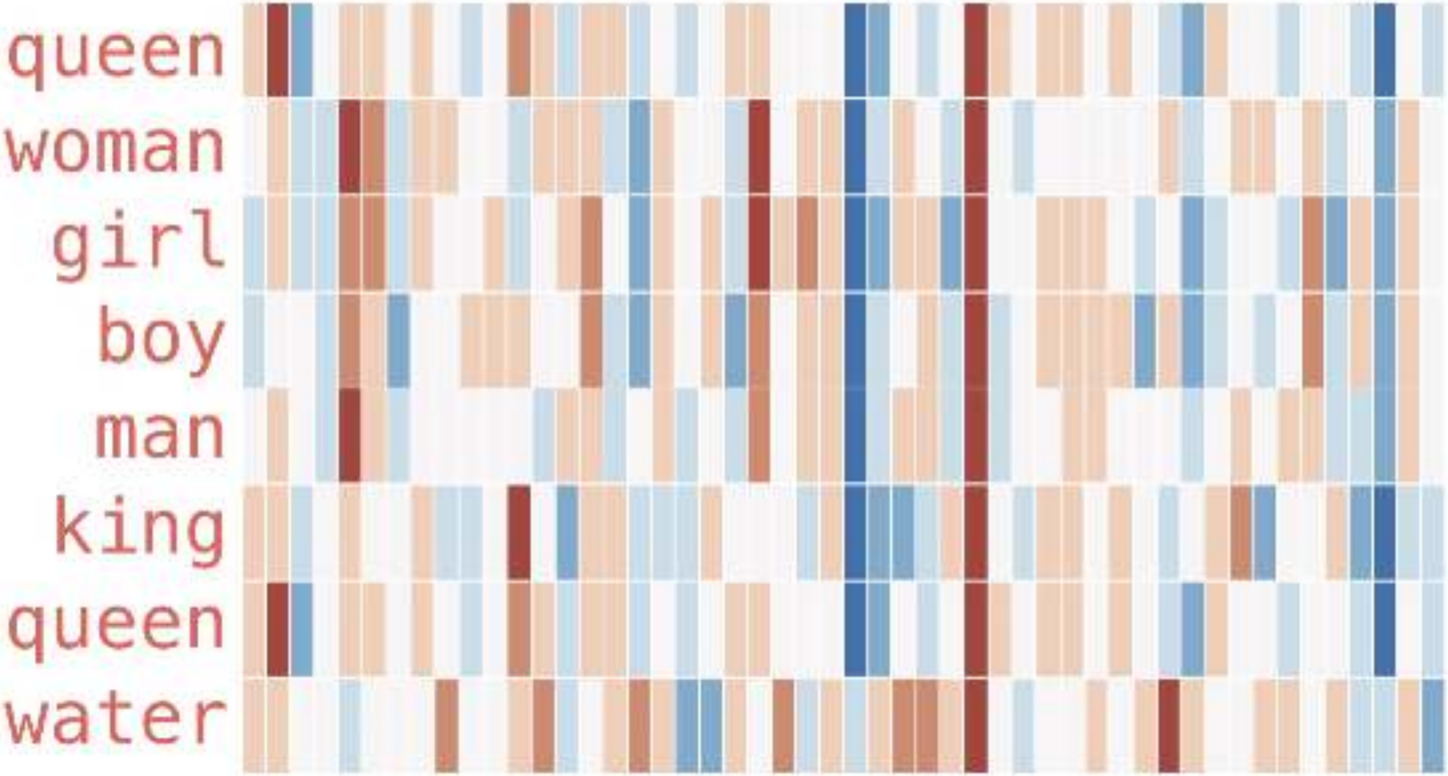

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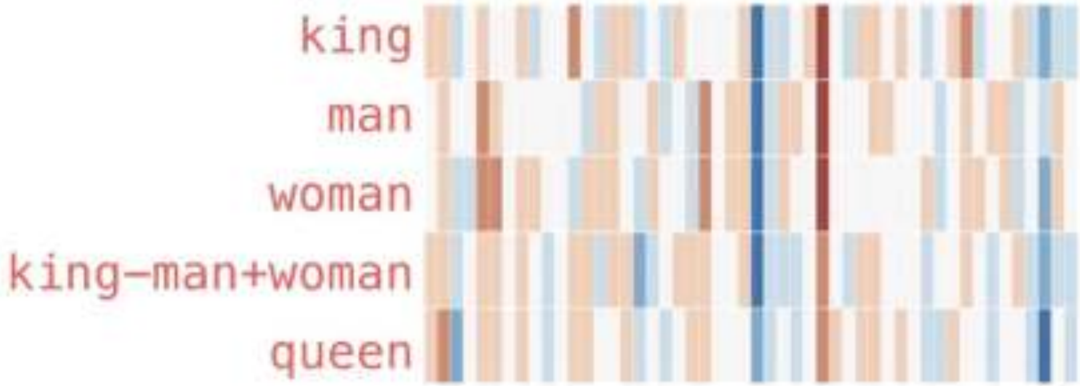
king − man + woman ~= queen



The resulting vector from "king-man+woman" doesn't exactly equal "queen", but "queen" is the closest word to it from the 400,000 word embeddings we have in this collection.

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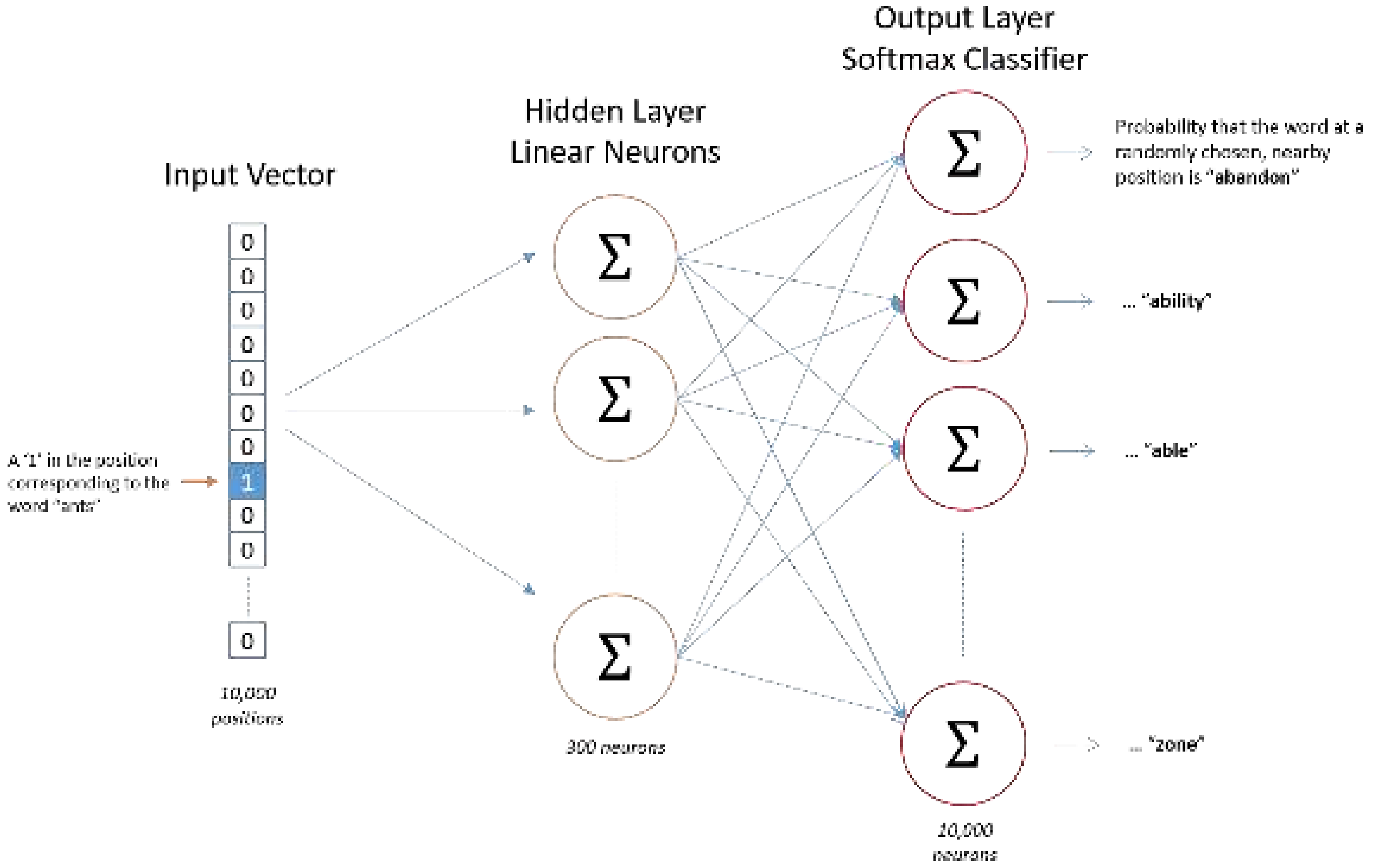
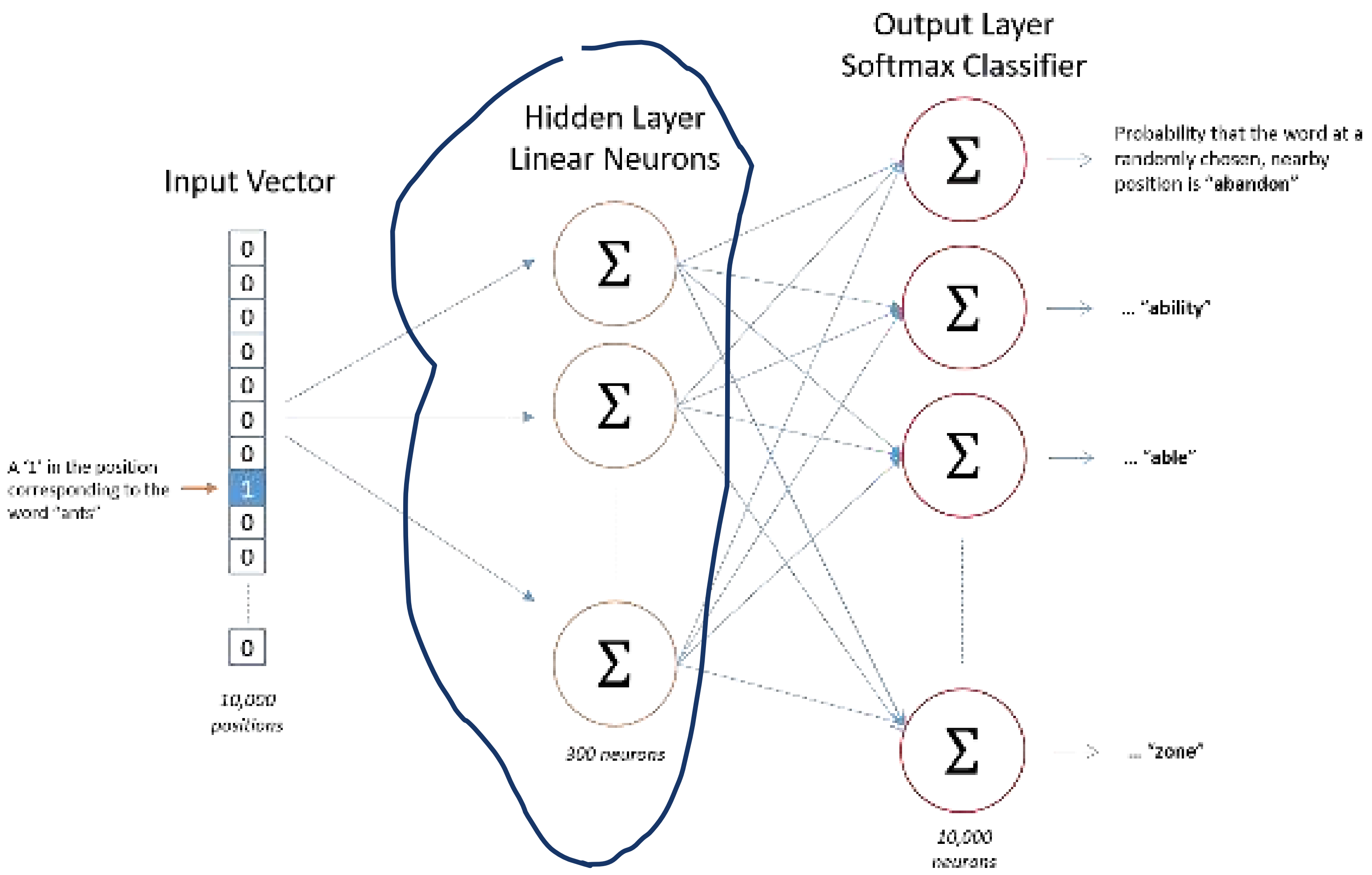
Vectorisation de mots (Embeddings)

- Comment les déduire ?
- En utilisant un autre réseau neuronal génératif :



Output Layer
Softmax Classifier
Hidden Layer
Linear Neurons
Input Vector
0
0
0
0
0
0
0
1
0
0
0
A '1' in the position corresponding to the word "ants"
10,000 positions
300 neurons
10,000 neurons
Probability that the word at a randomly chosen, nearby position is "abandon"
... "ability"
... "able"
... "zone"



Input Vector
0
0
0
0
0
0
0
1
0
0
0
10,000 positions
A '1' in the position corresponding to the word "ants"
Hidden Layer
Linear Neurons
300 neurons
Output Layer
Softmax Classifier
10,000 neurons
Probability that the word at a randomly chosen, nearby position is "abandon"
... "ability"
... "able"
... "zone"

Vectorisation de mots (Embedding)

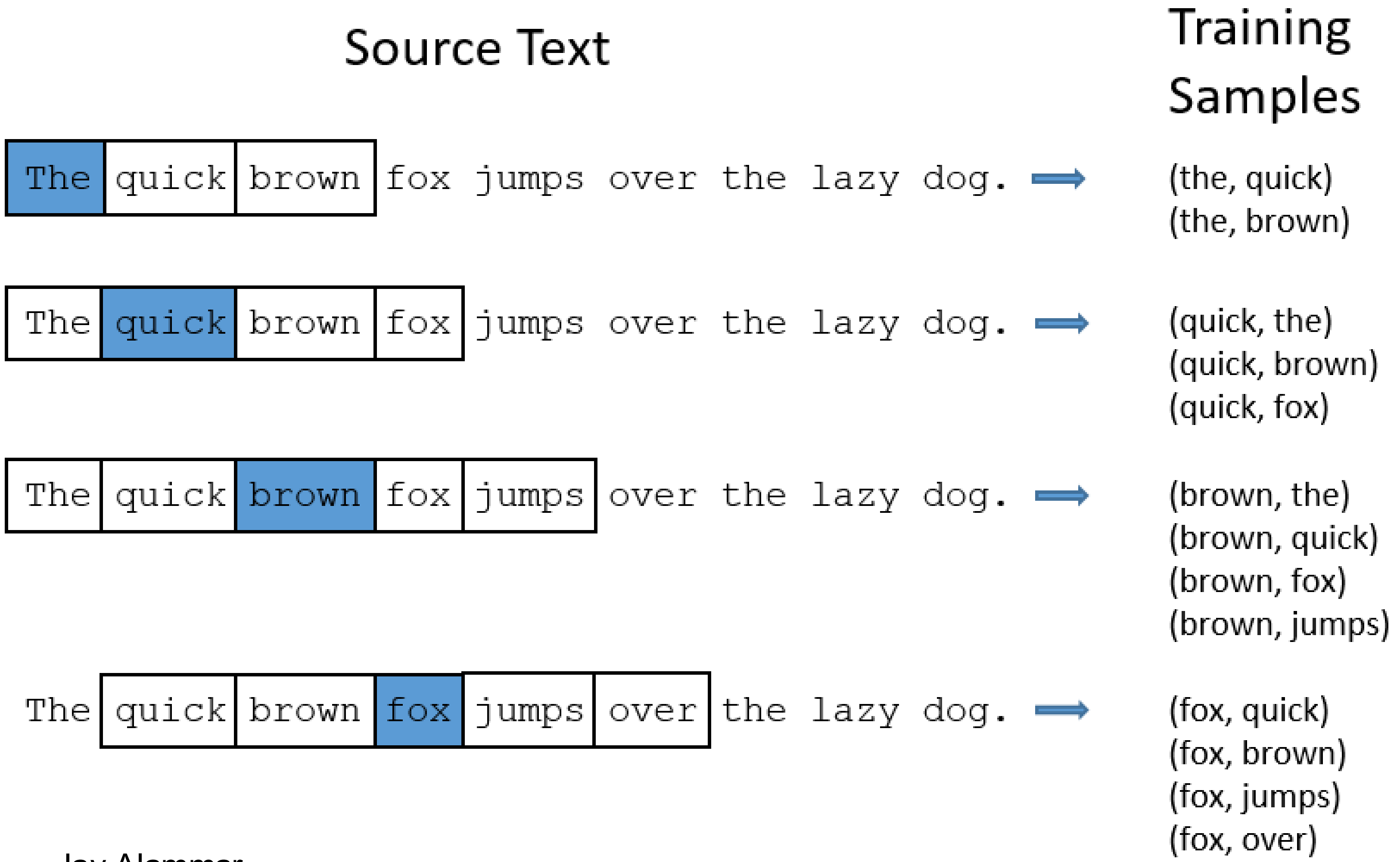
Entrée : un mot (représenté comme un vecteur "one-hot", essentiellement un index), [0,0,0,0,1,0,0...] si c'est le 5ieme mot

Sortie: une probabilité, pour tous les autres mots de l'index, de l'occurrence d'un mot à proximité.

Vectorisation de mots

<u>Données d'entraînement pour la fonction de coût :</u>

« contexts »: séquences de texte courtes, par exemple de 2 à 5 mots


Source Text
Training Samples
The quick brown fox jumps over the lazy dog.
(the, quick)
(the, brown)
The quick brown fox jumps over the lazy dog.
(quick, the)
(quick, brown)
(quick, fox)
The quick brown fox jumps over the lazy dog.
(brown, the)
(brown, quick)
(brown, fox)
(brown, jumps)
The quick brown fox jumps over the lazy dog.
(fox, quick)
(fox, brown)
(fox, jumps)
(fox, over)

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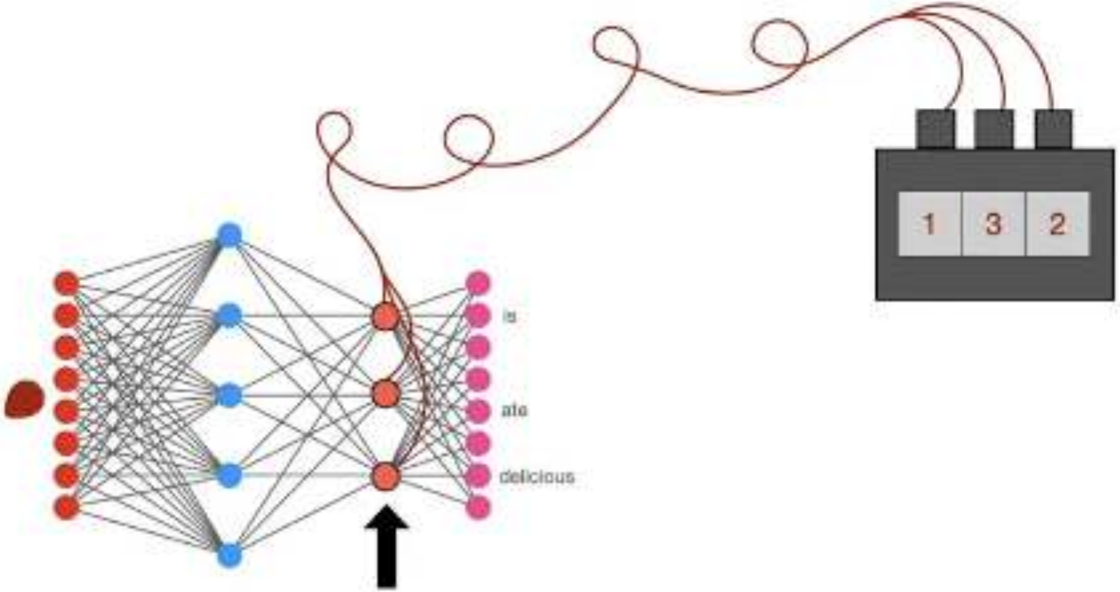
Thought experiment



Word	Numbers		
Strawberry	1	3	2
Apple	1.1	2.9	2.2

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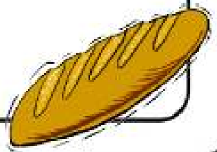
Le défi du context

Le défi du context

- Comme tout linguiste te le dira, le langage est ambigu et dépend du contexte
- Comment un ordinateur pourrait-il saisir les subtilités du contexte (cf. l'article de Landgrebe et Smith) ?

J'ai mangé une baguette avec du fromage.



La fée a jeté un sort avec sa baguette.

Baguette

Les musiciens suivent la baguette du chef d'orchestre.

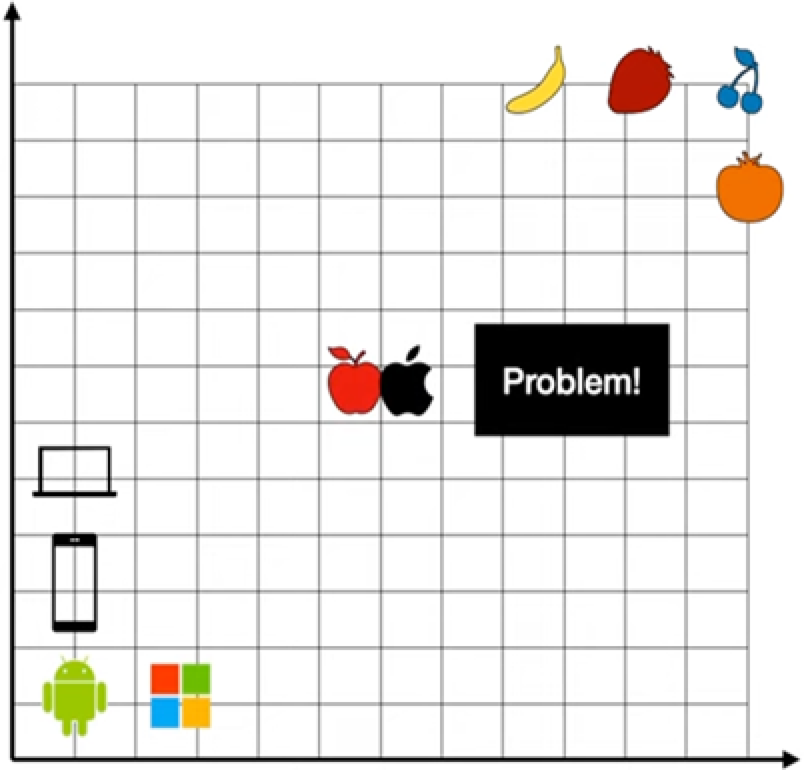
Dans la forêt, le Petit Chaperon Rouge a croisé le <u>loup</u>.

Au Carnaval, j'ai mis un <u>loup</u> pour ne pas qu'on me reconnaisse.

Loup

Le <u>loup</u> nage dans la mer.

Embeddings Quiz 2



Top right or bottom left?

Cherry

Android

Laptop

Banana

Apple?

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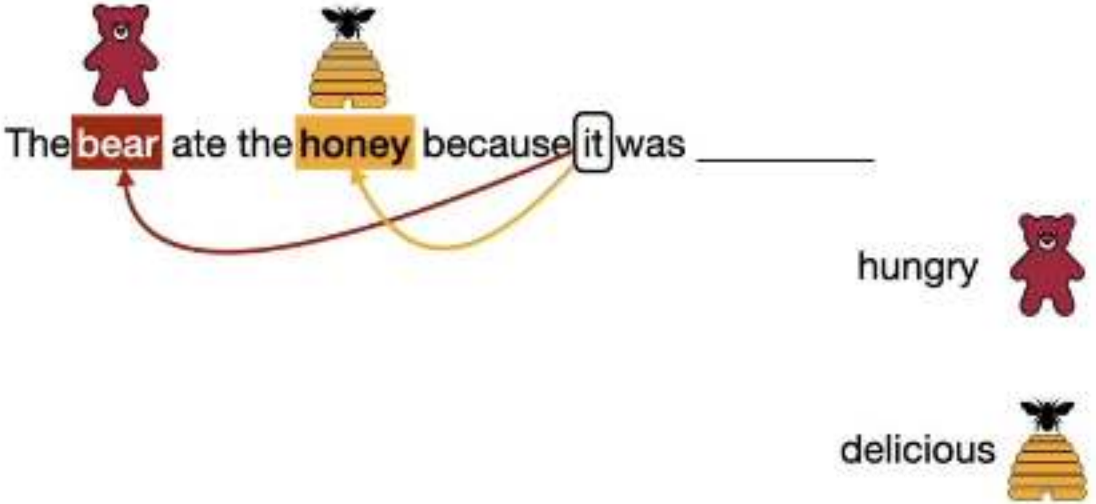
Using context



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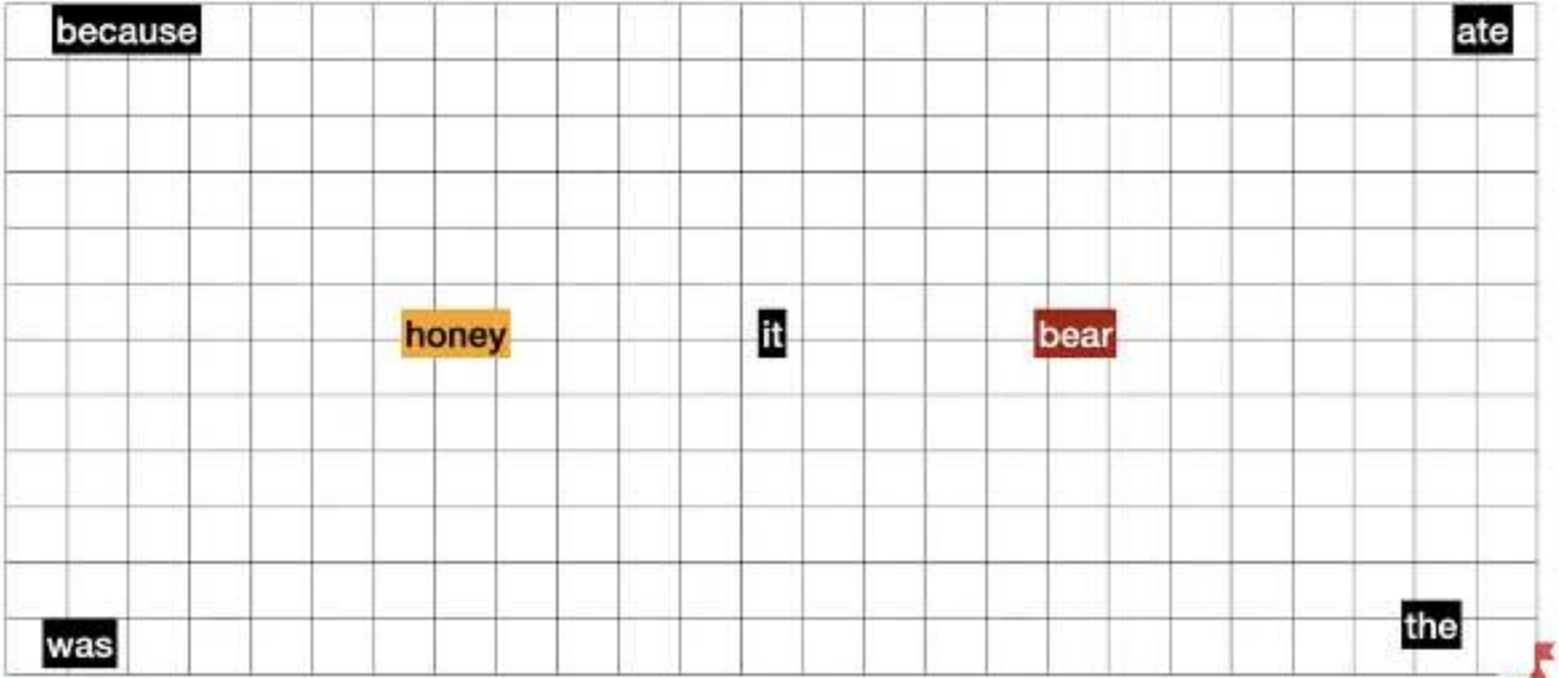
The bear ate the honey because it was _________



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Mécanismes attentionnels

Mécanismes attentionnels

- L'objectif principal des mécanismes attentionnels est de modifier "temporairement" les vectorisations des mots (pour désambiguïsation contextuelle).

Mécanismes attentionnels

- Compare : l'idée générale de l'attention sensorielle est d'augmenter le volume des neurones dont tu fais attention

- (rappelle que les vectorisations sont en fait définis par les poids neuronaux)

Mécanismes attentionnels

- différences possibles avec attention sensoriel:
- 1) Les mécanismes attentionnels de l’IA pour LLM agissent par paire, par exemple, ils ressemblent davantage à un champ gravitationnel, où tout agit sur tout... il est possible que l'attention sensorielle ne fonctionne pas de cette façon.

Mécanismes attentionnels

- différences possibles avec attention sensoriel:

- 1) En particulier, l'attention sensorielle met généralement en avant une chose et fait passer les autres au second plan. L'attention de l’IA (pour les LLM) ne fait que modifier la proximité des choses les unes par rapport aux autres

Mécanismes attentionnels

- différences possibles avec attention sensoriel:

- 2) L'attention sensorielle peut réellement modifier les poids neuronaux, tandis que l'attention de l'IA produit simplement une nouvelle couche pour simuler ce que la sortie aurait été si les poids avaient été modifiés

Mécanismes attentionnels

- différences possibles avec attention sensoriel:

- 3) L'attention sensorielle peut être top-down, c'est-à-dire dirigée par ce que tu penses ou ressens, plutôt que par ce que tu vois ou entends. Dans l'IA, l'attention est entièrement fonction de ce que tu « vois »

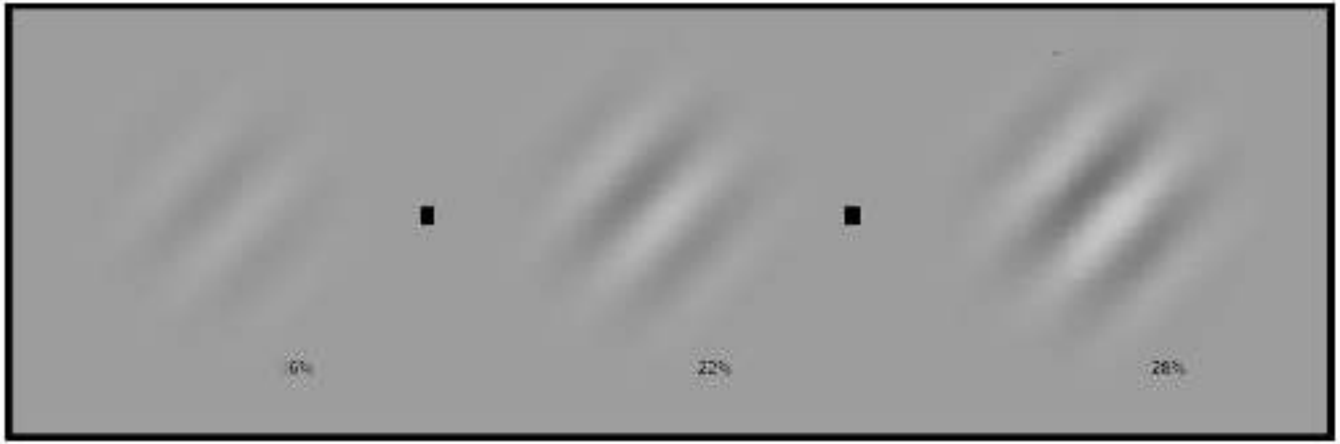
Mécanismes attentionnels

- différences possibles avec attention sensoriel:

- 4) Intuitivement, l'attention sensorielle ne modifie pas le contenu de ta représentation, elle se contente de «zoom-in» - en revanche l'attention en IA modifie la vectorisation qui donne le sens lui-même
- Mais …

Attention alters contrast appearance

Test Cued | Neutral | Standard Cued



Carrasco, Ling & Read
Nature Neuroscience, 2004

D’ici

- A partir d’ici j’utilize beaucoup des diapos tirée des videos de….

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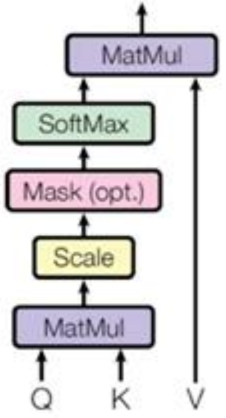
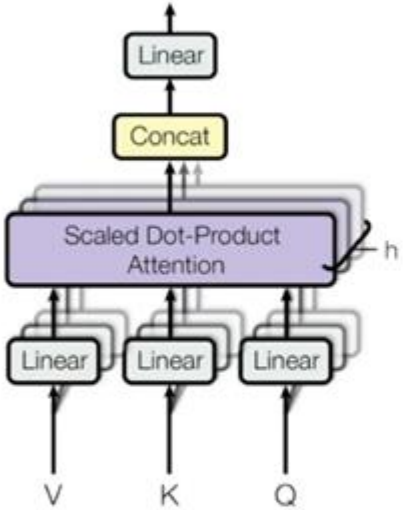
Attention

Scaled Dot-Product Attention



Multi-Head Attention

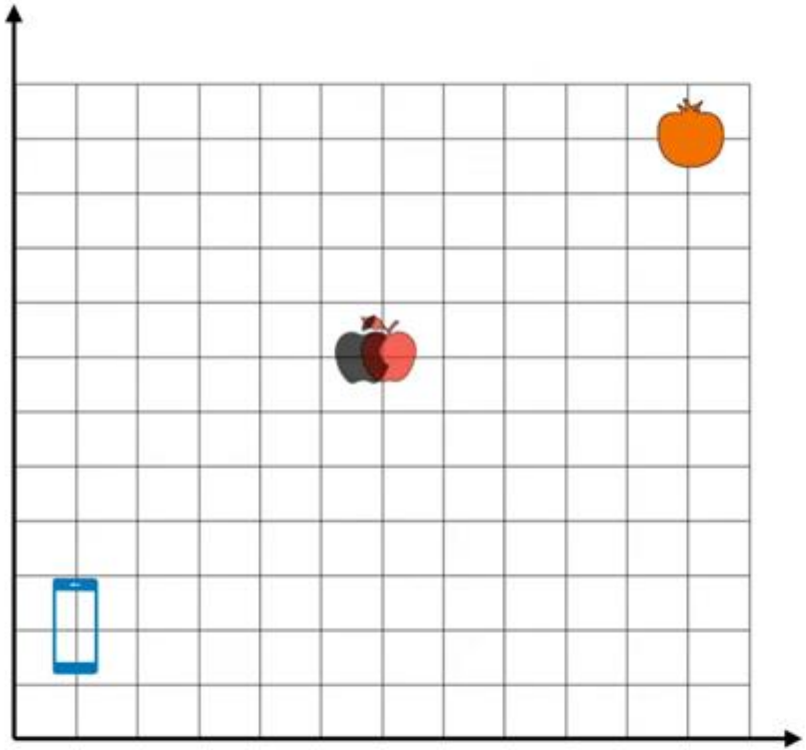


$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

$$\mathrm{MultiHead}(Q, K, V) = \mathrm{Concat}(\mathrm{head_1}, ..., \mathrm{head_h})W^O$$
$$\text{where } \mathrm{head_i} = \mathrm{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

Vaswani et al 2017

Attention



please buy an apple and an orange

apple unveiled the new phone

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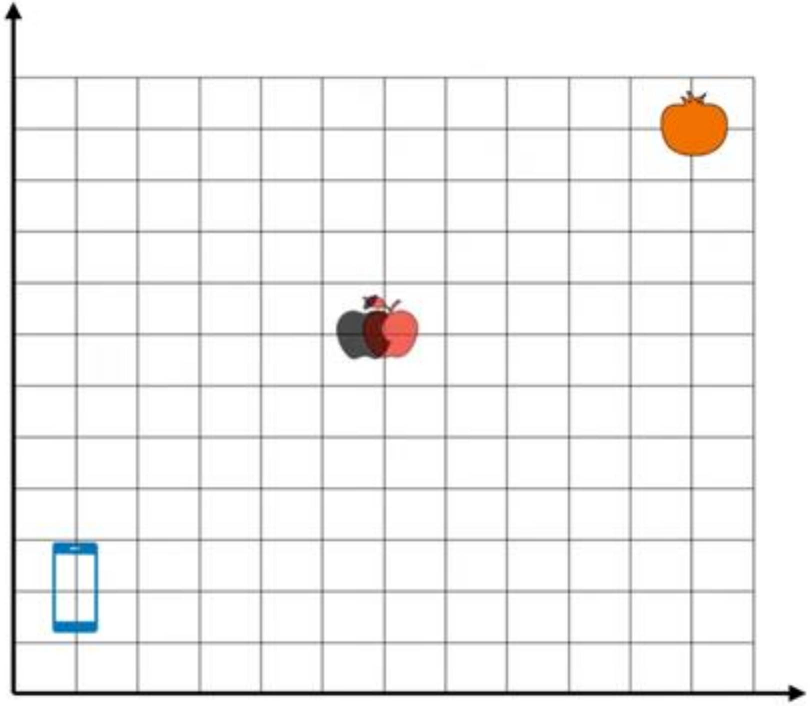
Attention

please buy an apple and an orange

apple unveiled the new phone

Attention



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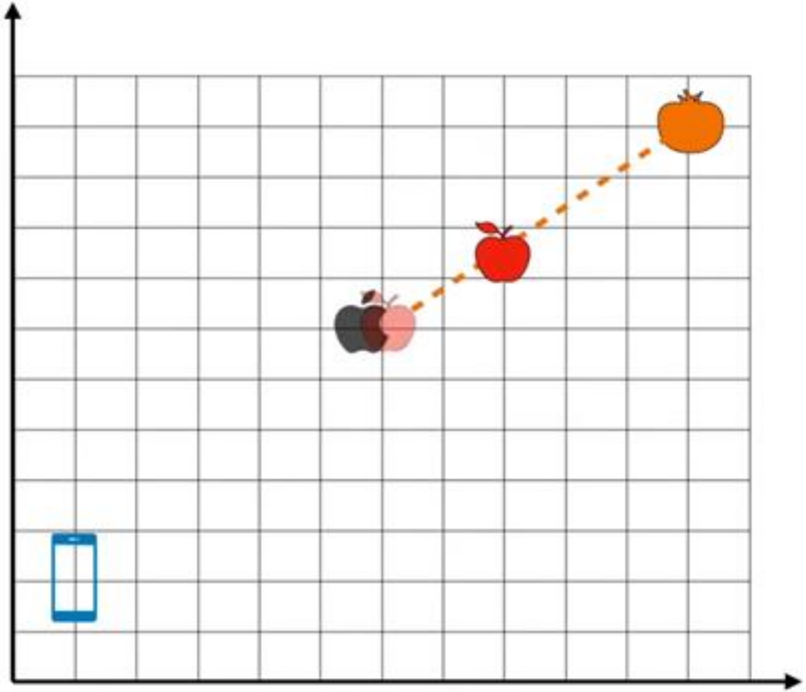
Attention



please buy an apple and an $\boxed{\text{orange}}$

apple unveiled the new phone

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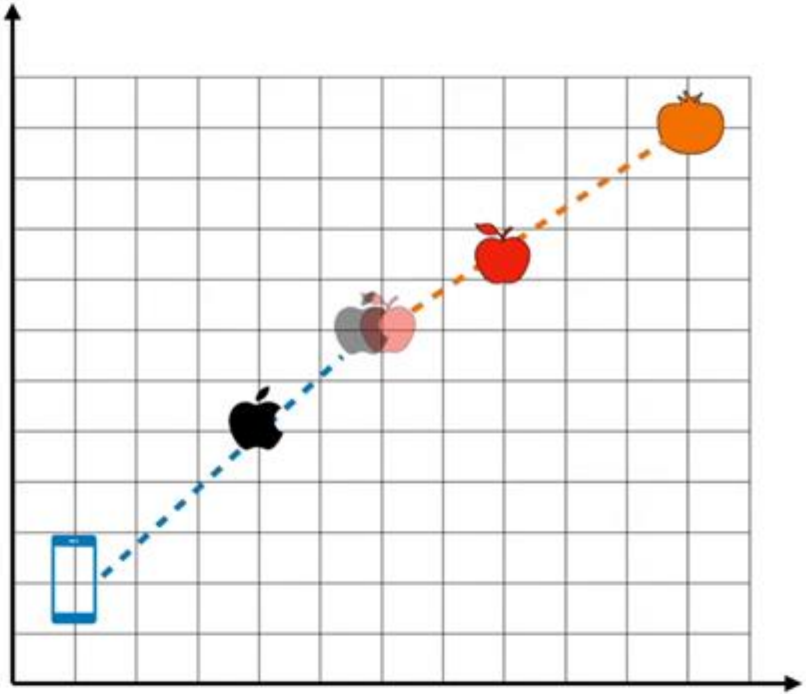
Attention

please buy an apple and an $\boxed{\text{orange}}$



apple unveiled the new $\boxed{\text{phone}}$

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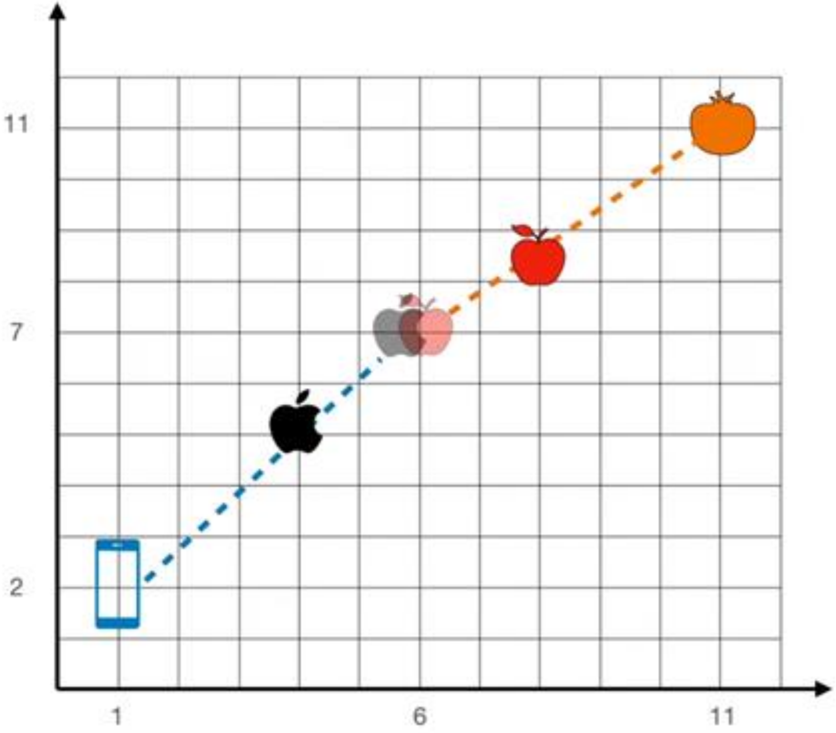
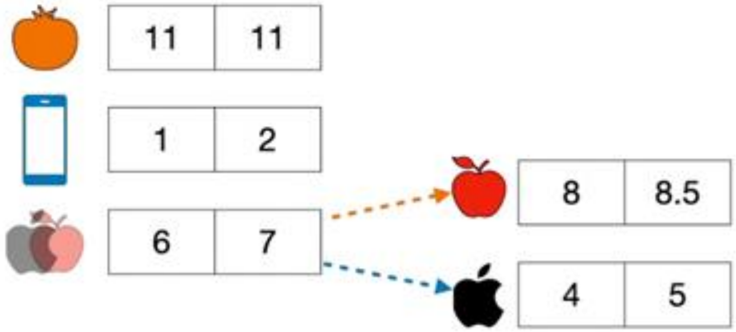
Attention

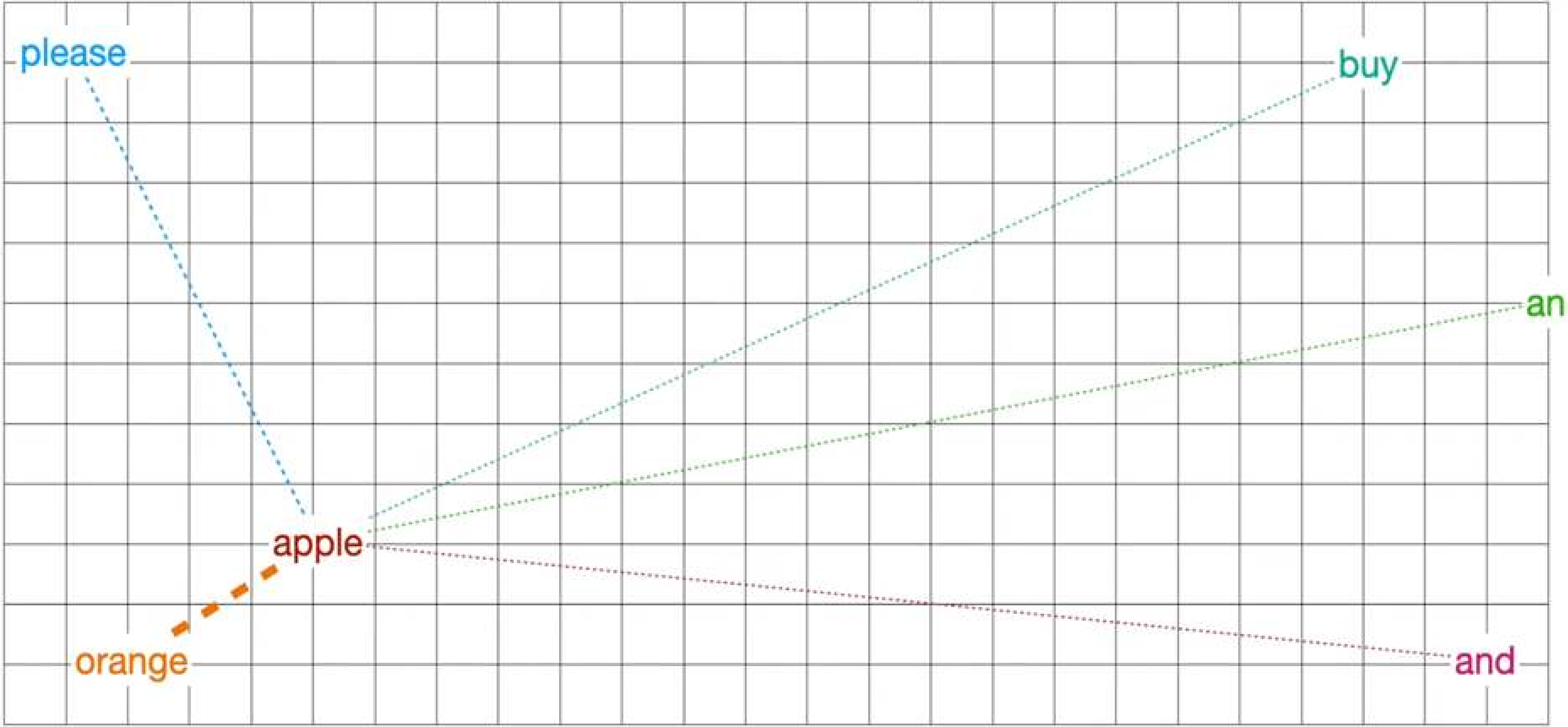
please buy an apple and an orange

apple unveiled the new phone



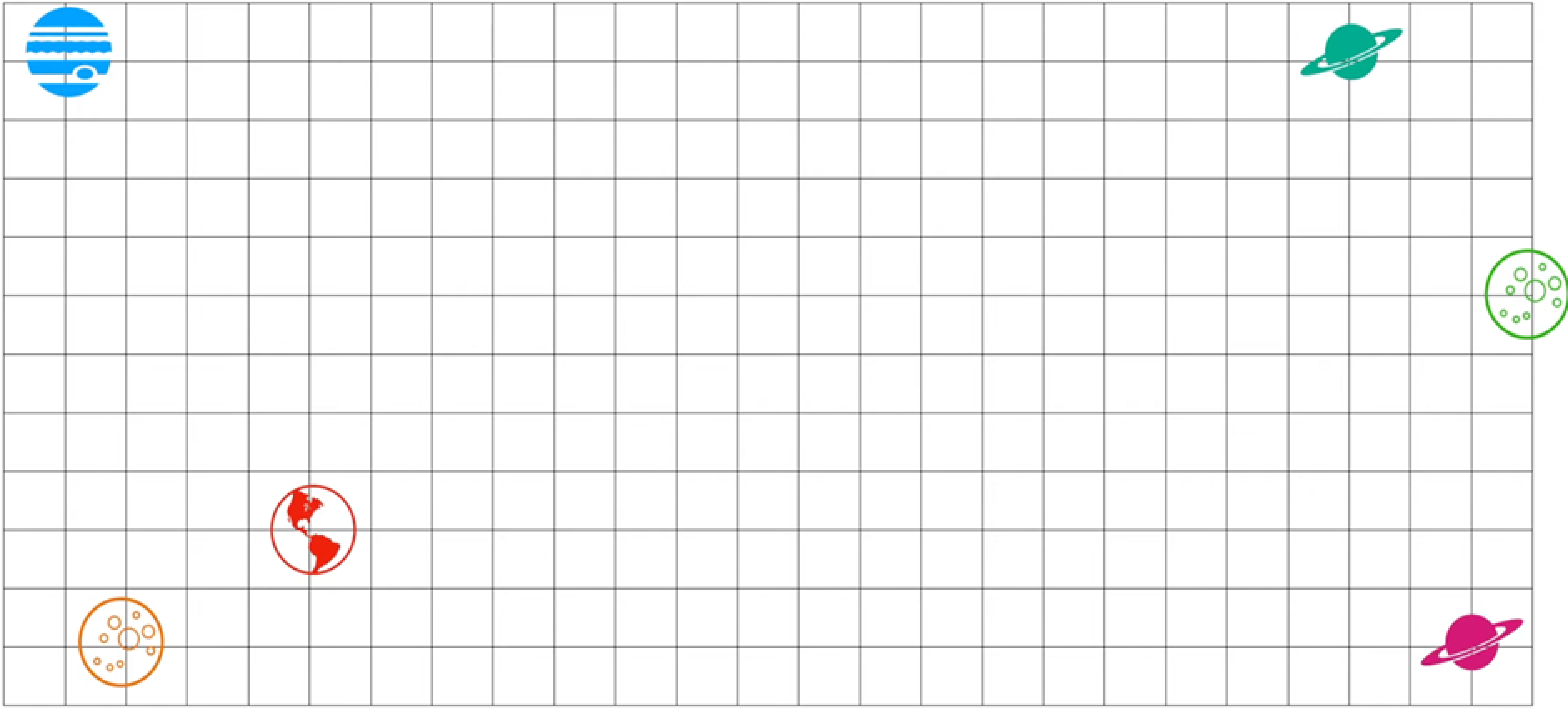


What about the other words?



please buy an apple and an orange

It’s kind of like gravity…



please buy an apple and an orange

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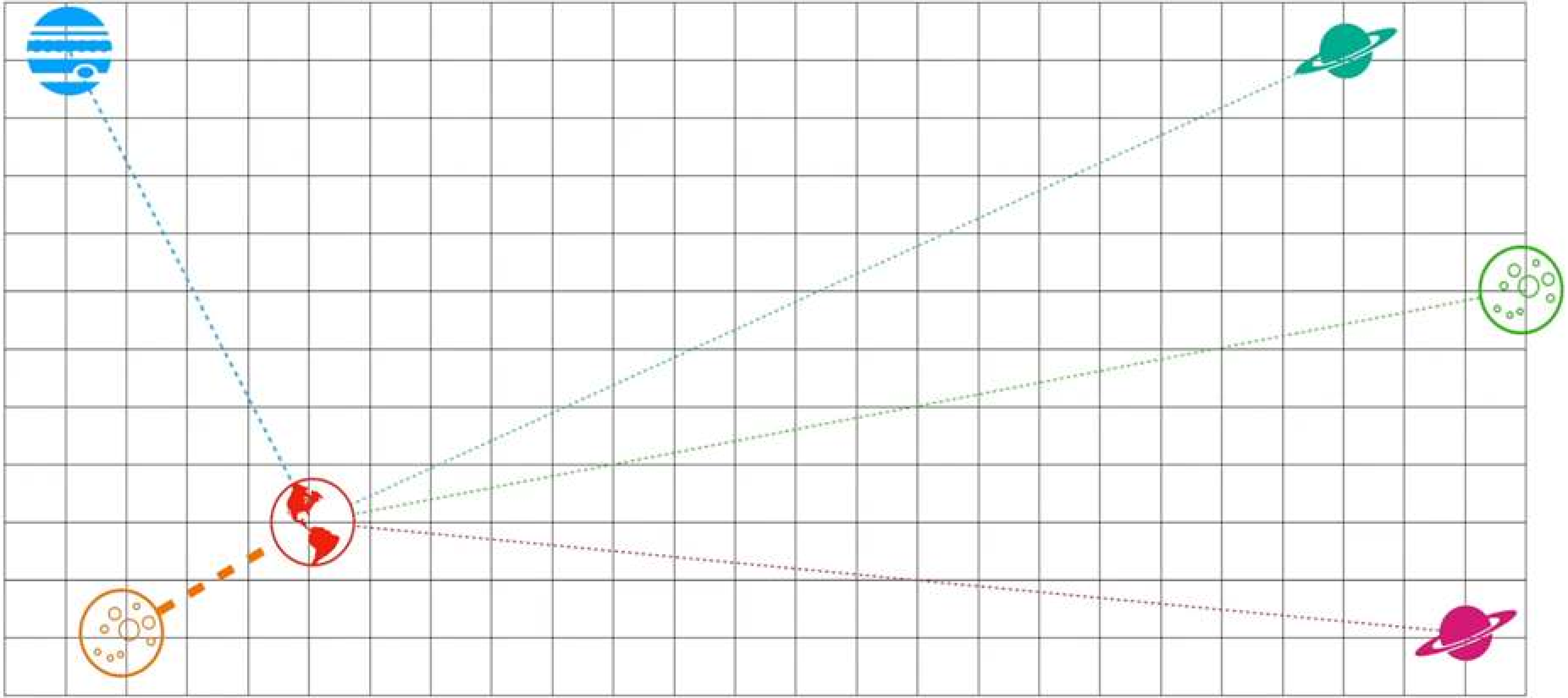

please buy an apple and an orange

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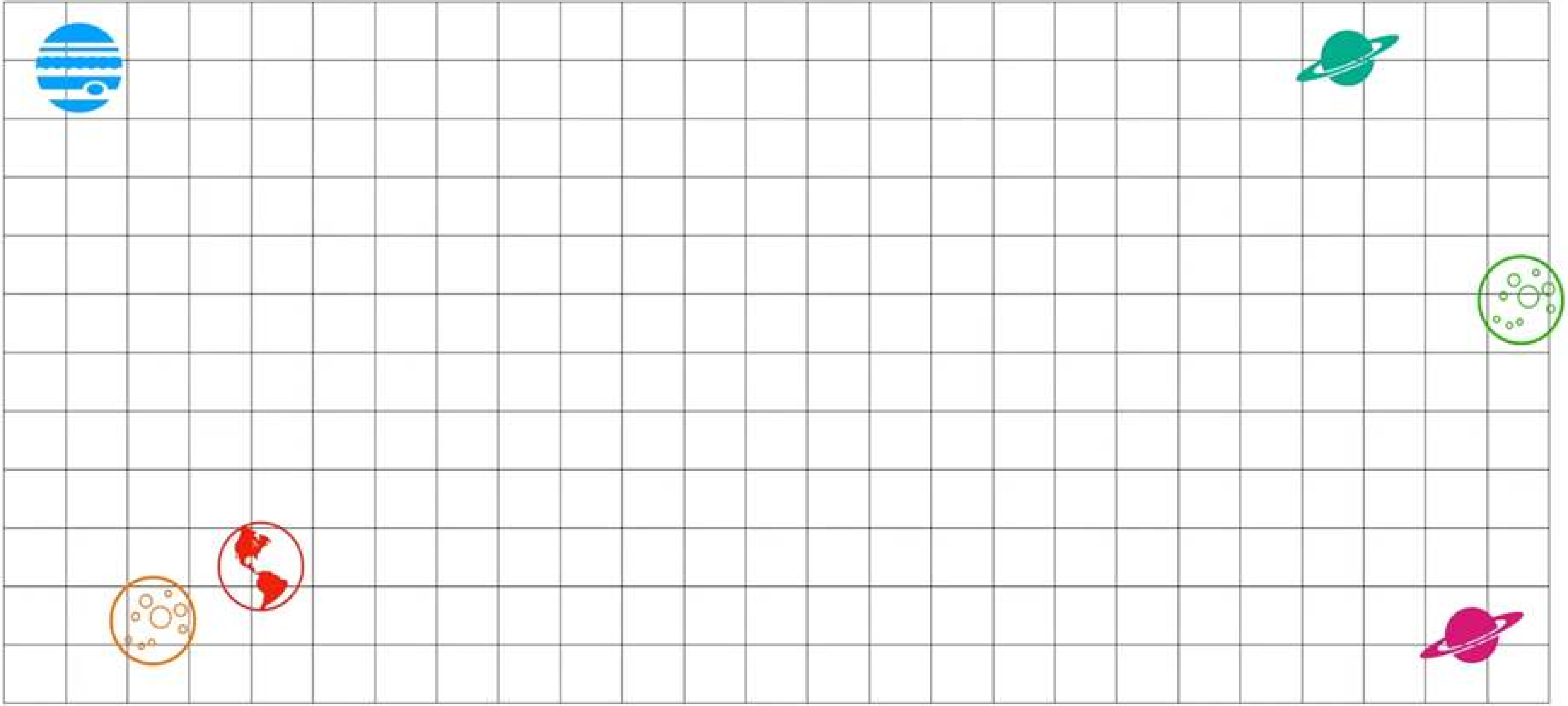
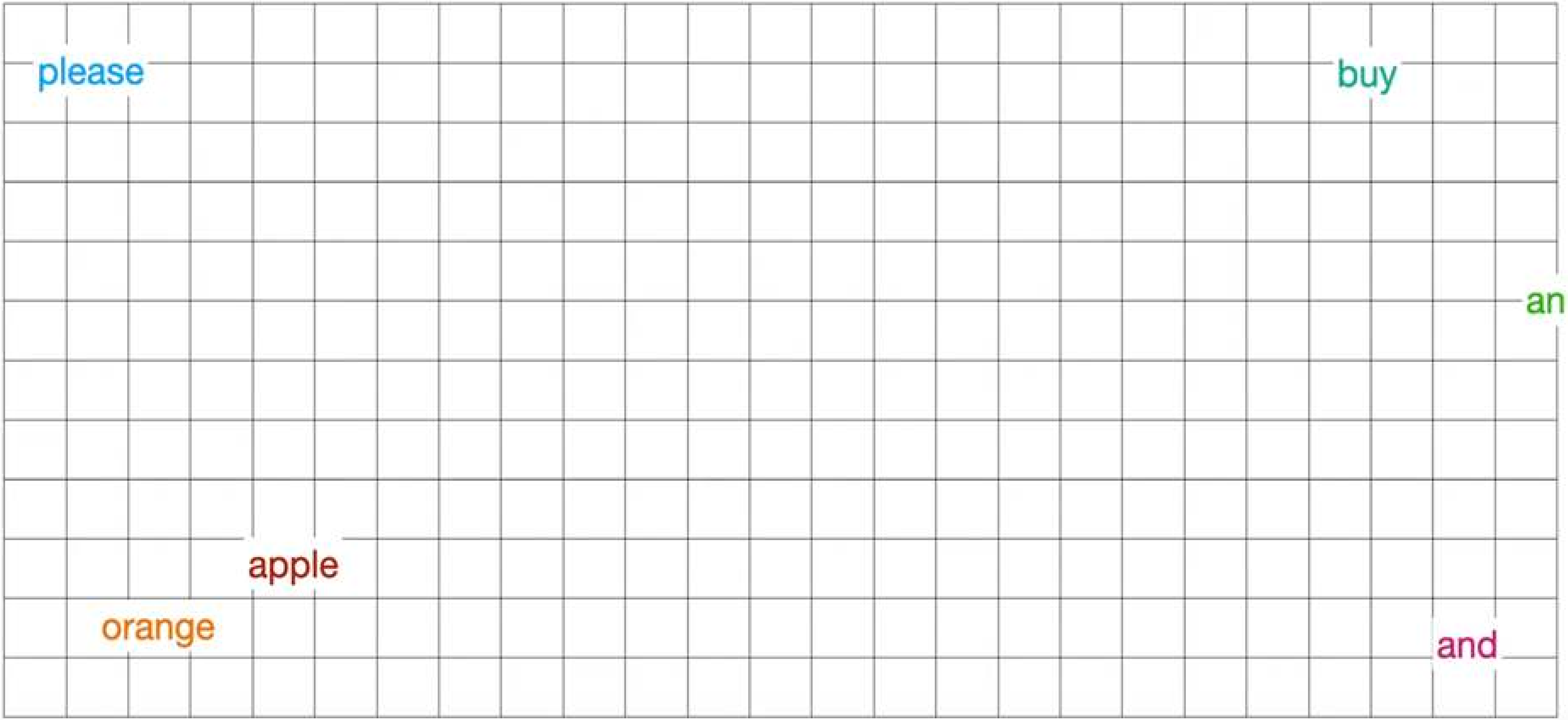


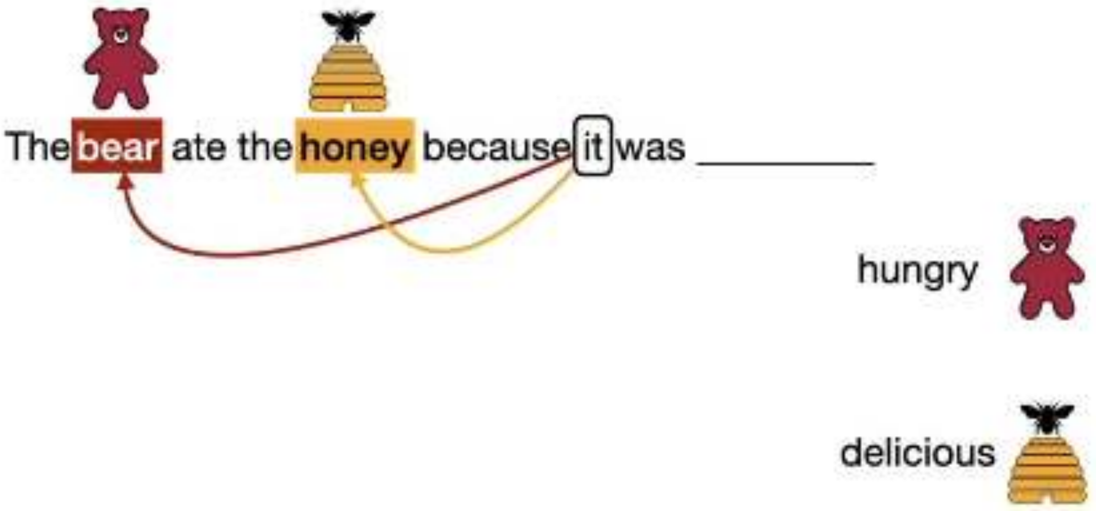
please buy an apple and an orange

You apply attention to all the words



please buy an apple and an orange

Using context



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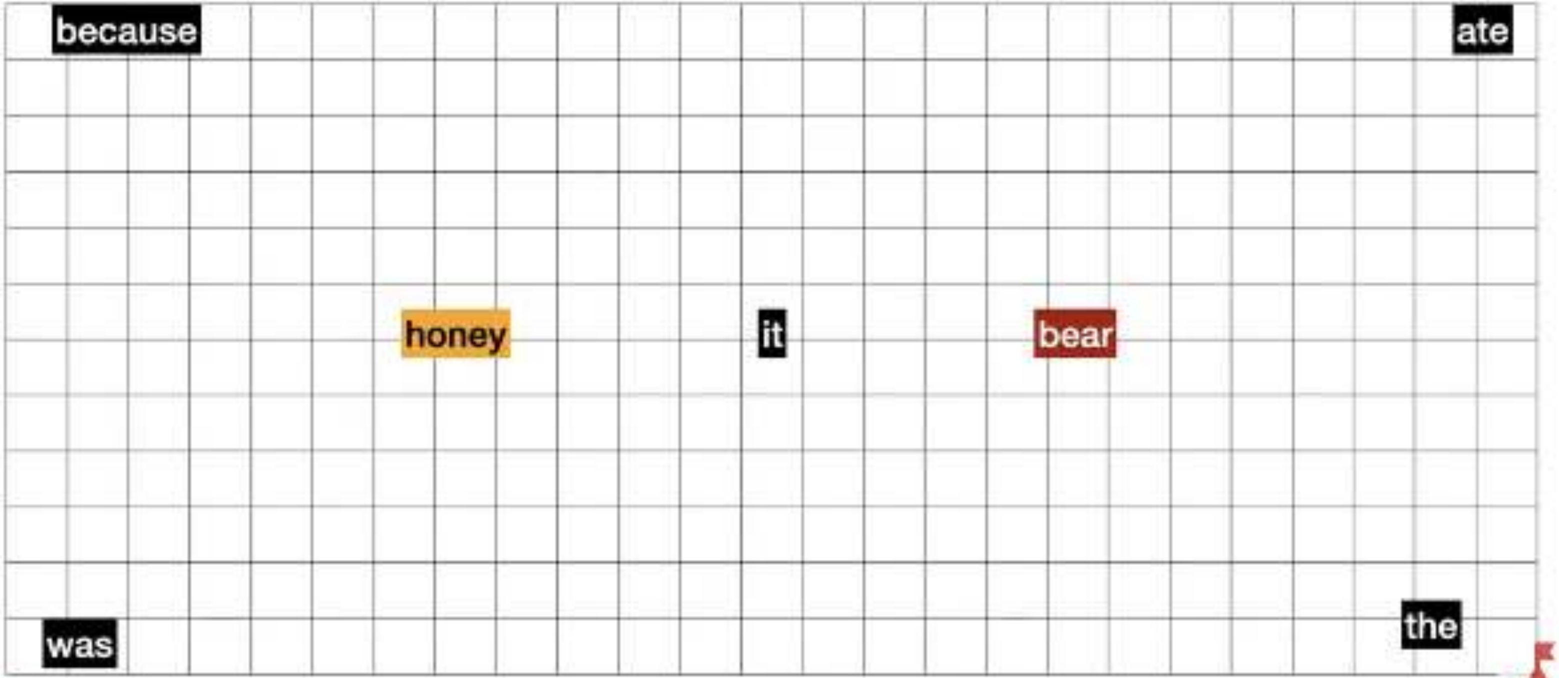
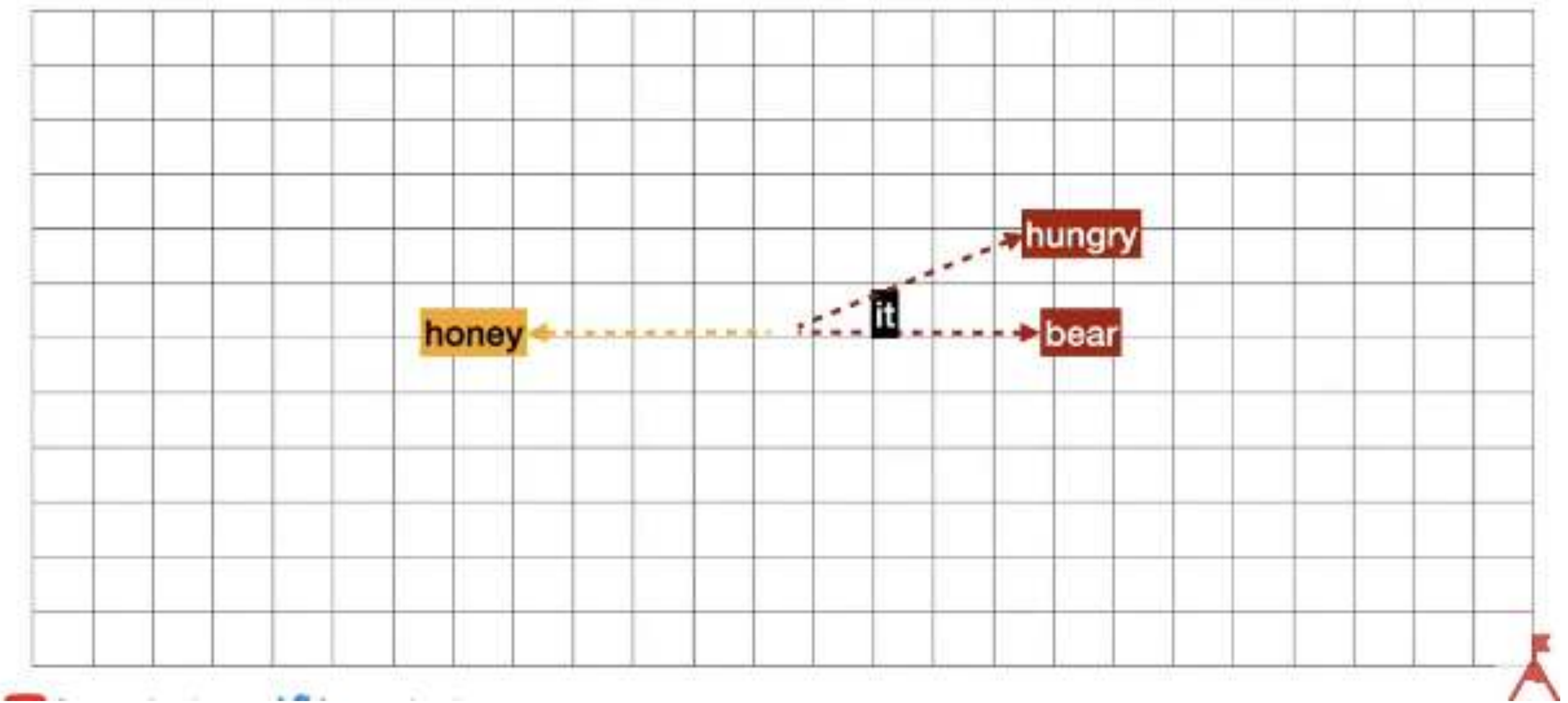
The bear ate the honey because it was _________



The bear ate the honey because it was hungry



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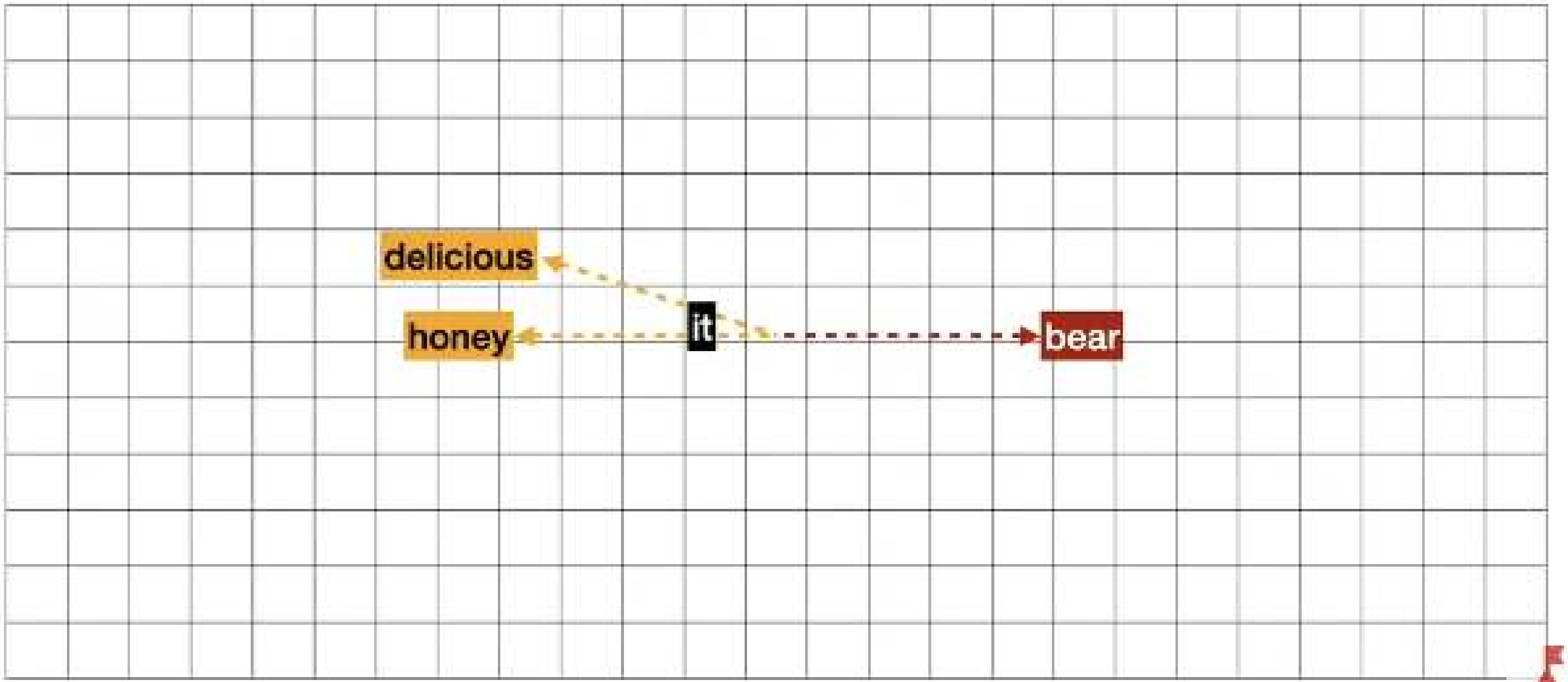
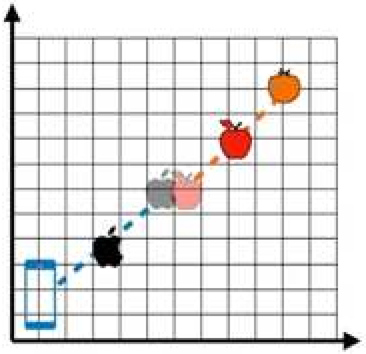
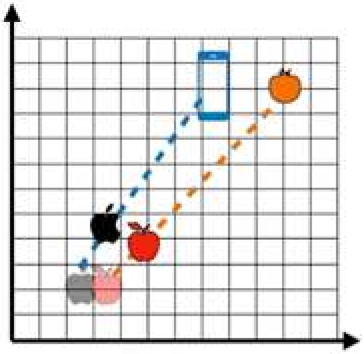
The bear ate the honey because it was delicious



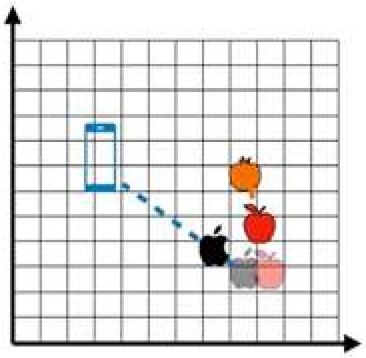
Ideally, we'd like to have lots of embeddings



Good



Bad



So-so

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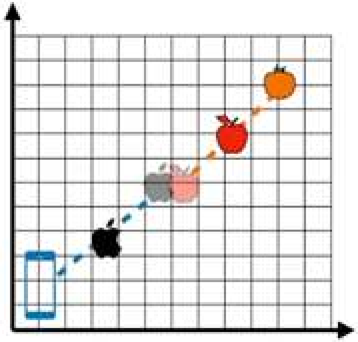
Ideally, we'd like to have lots of embeddings



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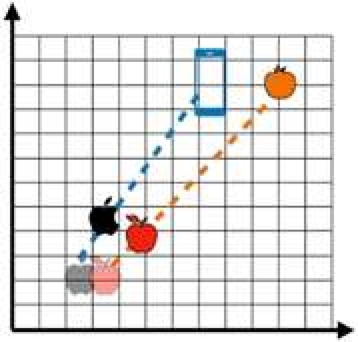

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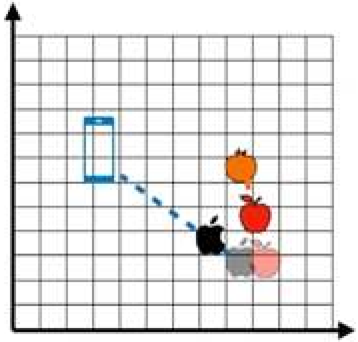

So-so

Problem: Building many embeddings is a lot of work!

Solution: We'll build embeddings by modifying existing embeddings

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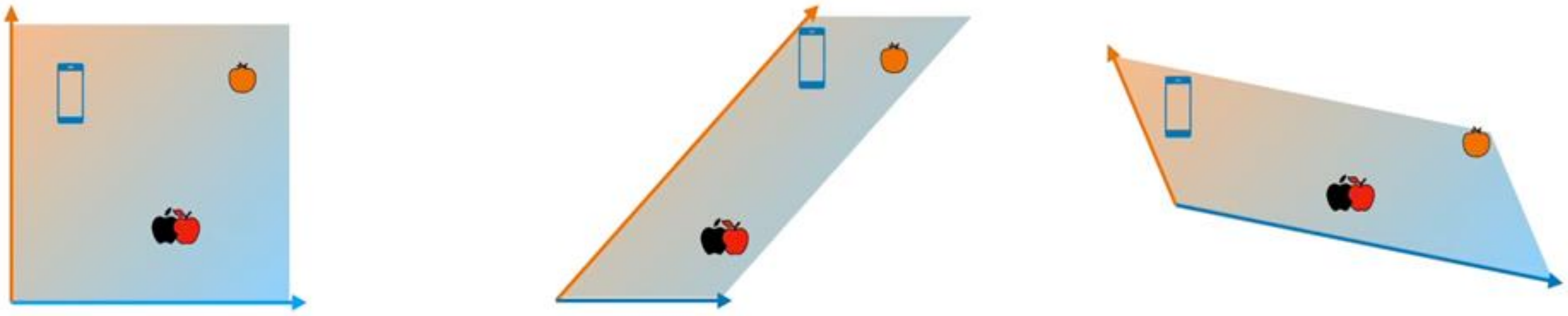
Get new embeddings from existing ones



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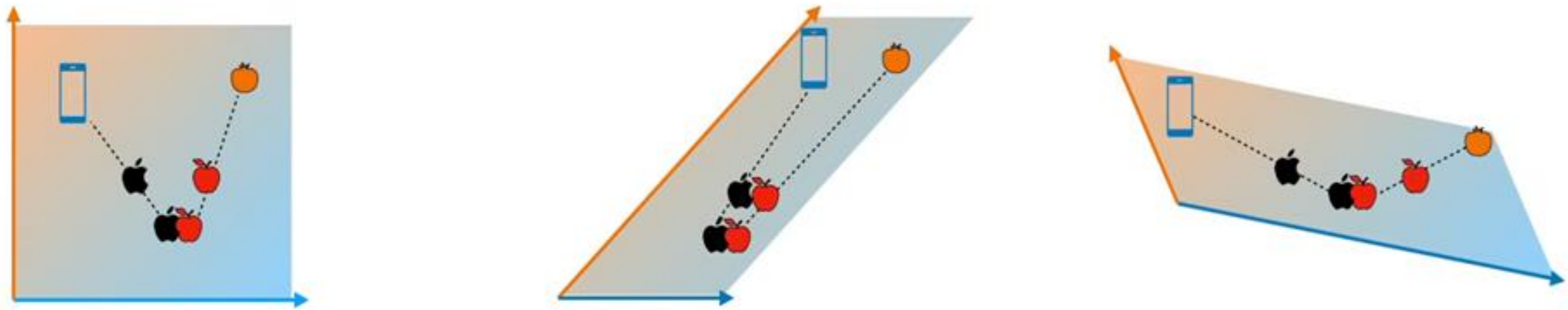
Get new embeddings from existing ones



Okay Bad Good

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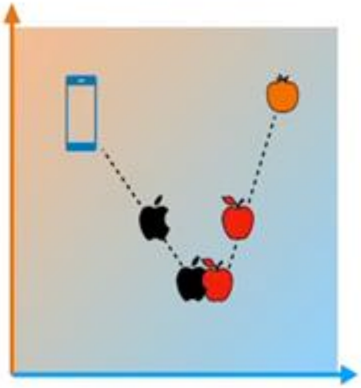
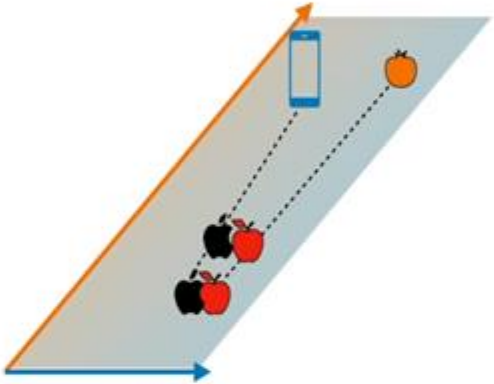
Get new embeddings from existing ones



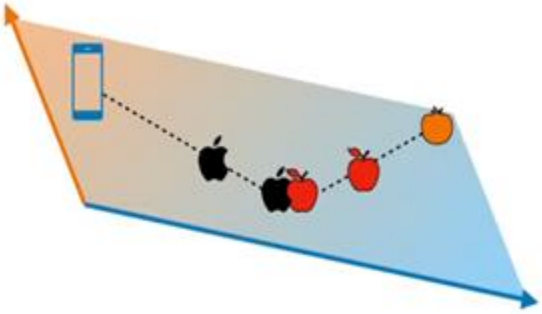
Okay

Score: 1



Bad

Score: 0.1



Good

Score: 4

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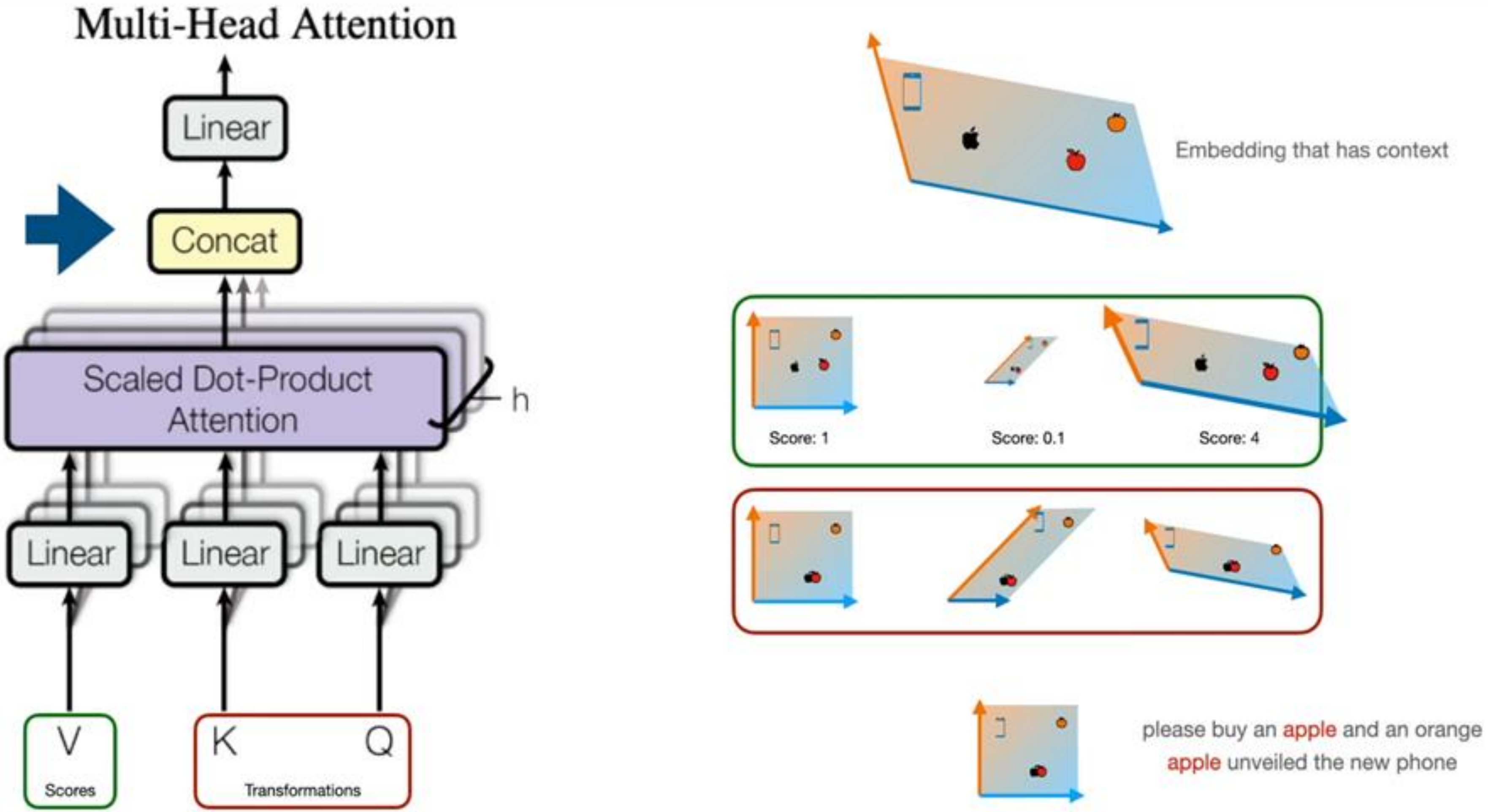

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Comment faire le calcul?

Measure 1: Dot product

Sim

🍒	1	4
🍅	0	3

Measure 1: Dot product

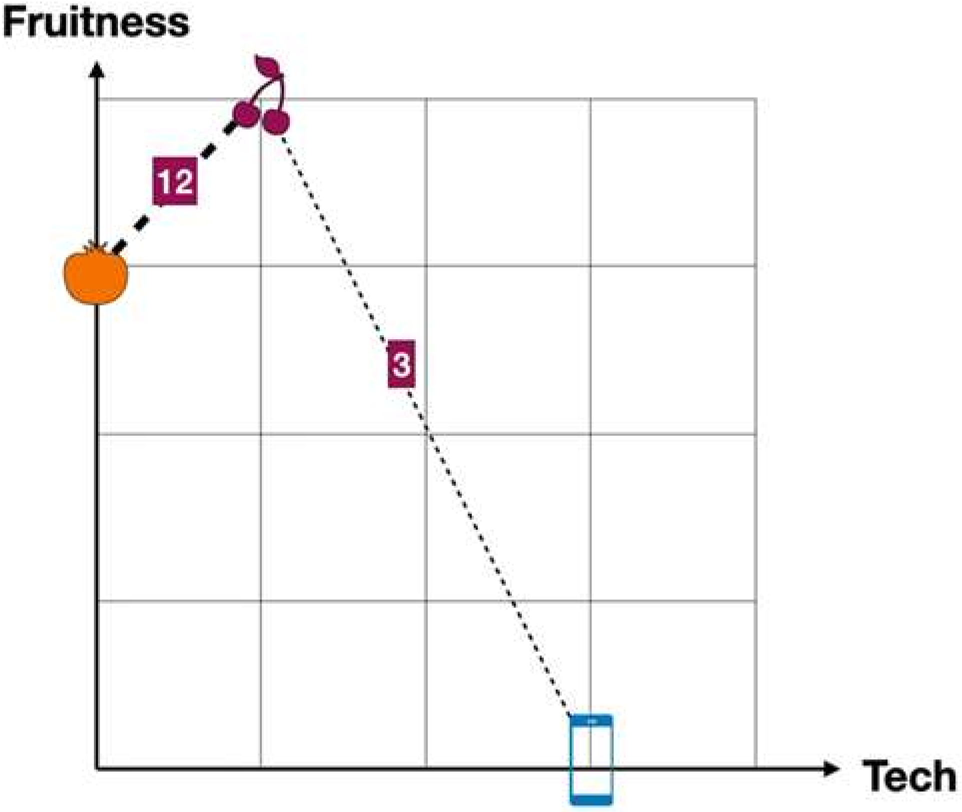
Sim

	Tech	Fruitness
	1	4
	0	3

Tech Fruitness

$$1 \cdot 0 \; + \; 4 \cdot 3 \; = 12$$

Measure 1: Dot product



Sim

Tech	Fruitness
1	4
0	3

Tech Fruitness

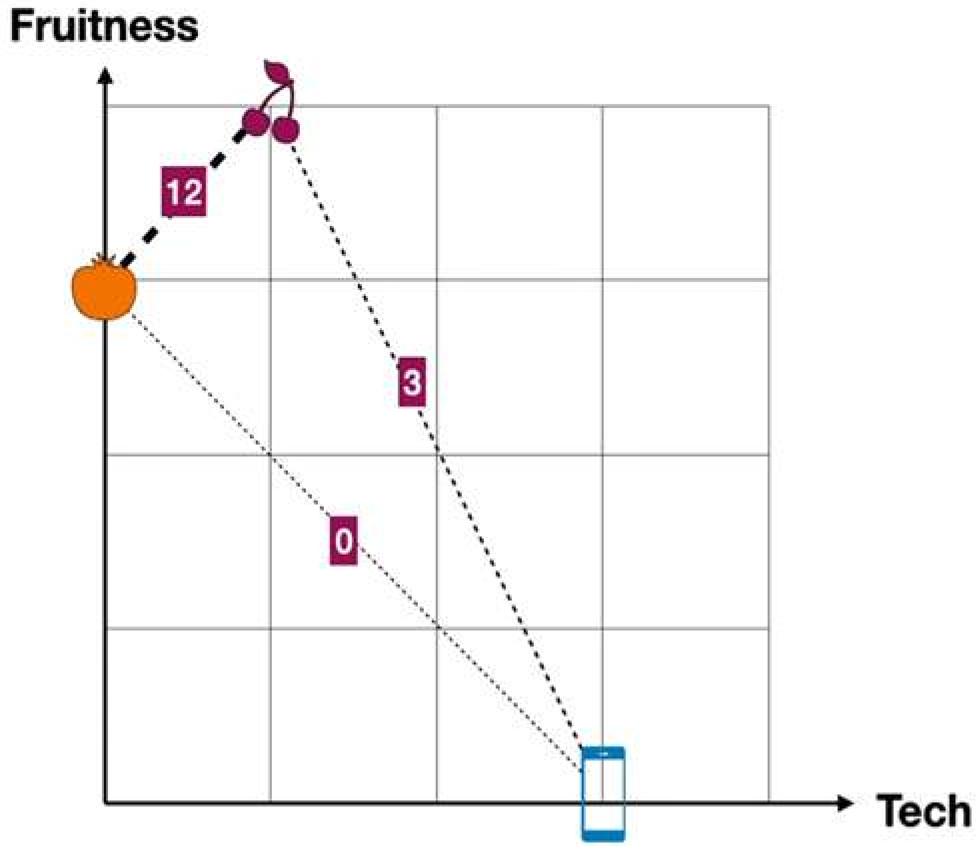
$$1 \cdot 0 \; + \; 4 \cdot 3 \; = 12$$

Sim

1	4
3	0

$$1 \cdot 3 \; + \; 4 \cdot 0 \; = 3$$

Measure 1: Dot product



Sim	Tech	Fruitness
	1	4
	0	3

$$\underset{\text{Tech}}{1 \cdot 0} + \underset{\text{Fruitness}}{4 \cdot 3} = 12$$

Sim	Tech	Fruitness
	1	4
	3	0

$$1 \cdot 3 + 4 \cdot 0 = 3$$

Sim	Tech	Fruitness
	0	3
	3	0

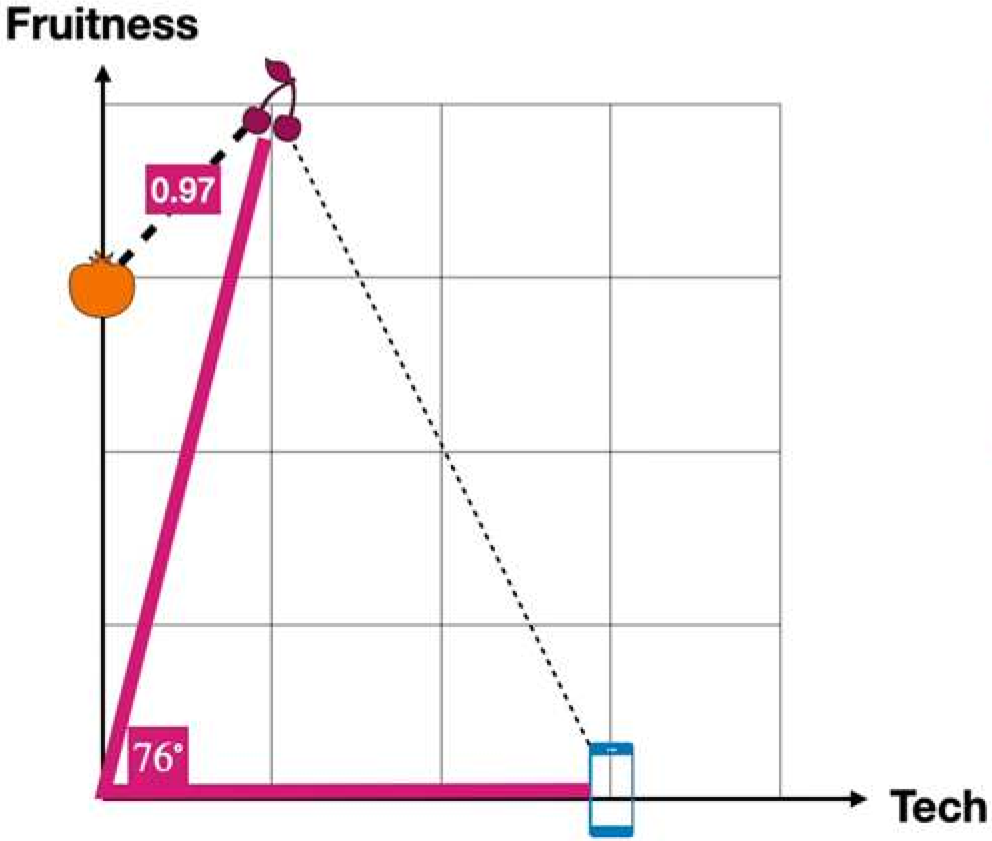
$$0 \cdot 3 + 3 \cdot 0 = 0$$

Measure 2: Cosine similarity

Measure 2: Cosine similarity

$cos(14^{\circ}) = 0.97$

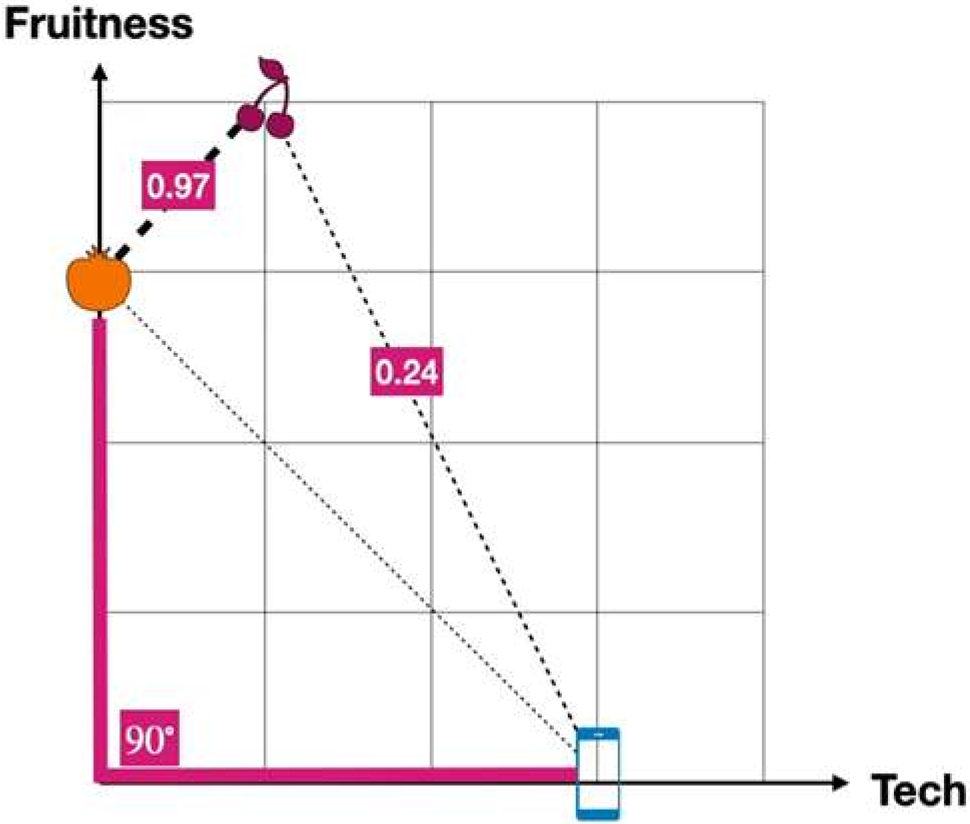
Measure 2: Cosine similarity

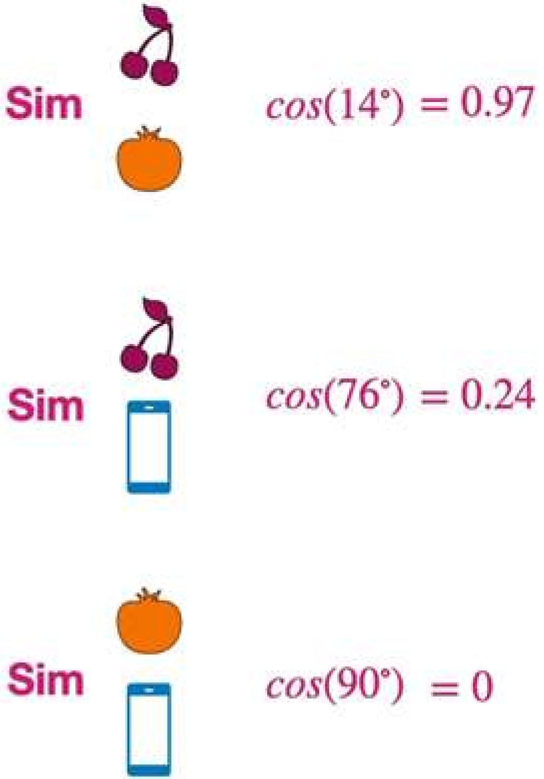


Sim  $cos(14^{\circ}) = 0.97$

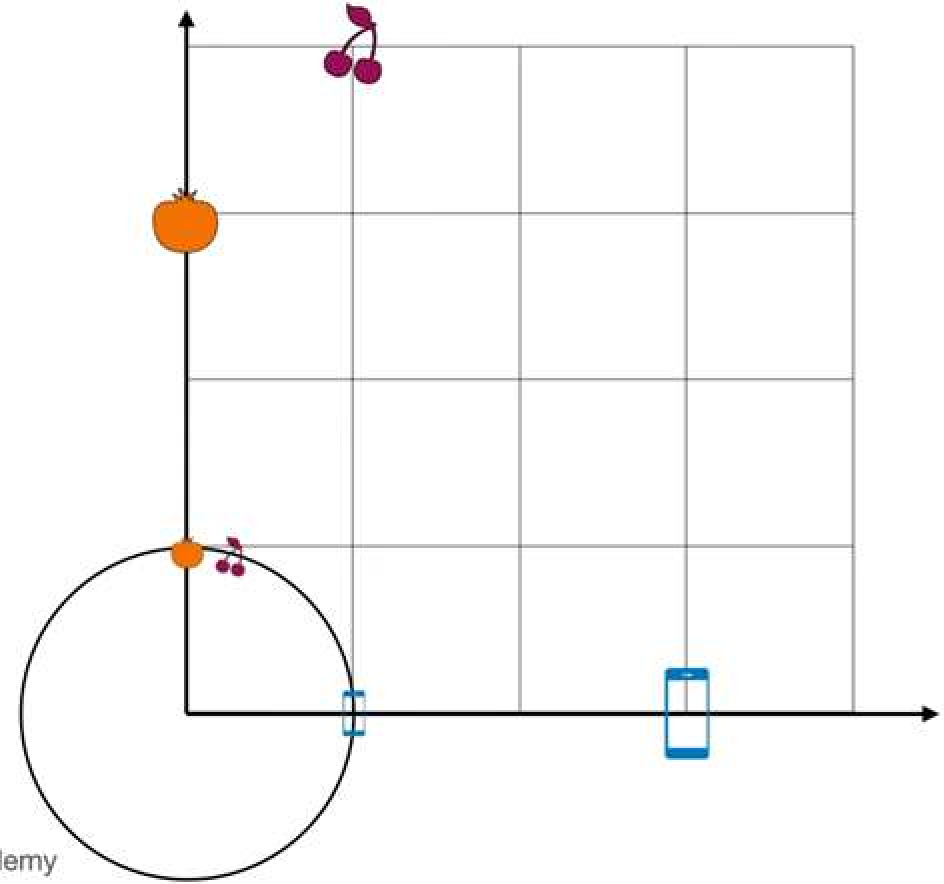
Sim  $cos(76^{\circ}) = 0.24$

Measure 2: Cosine similarity

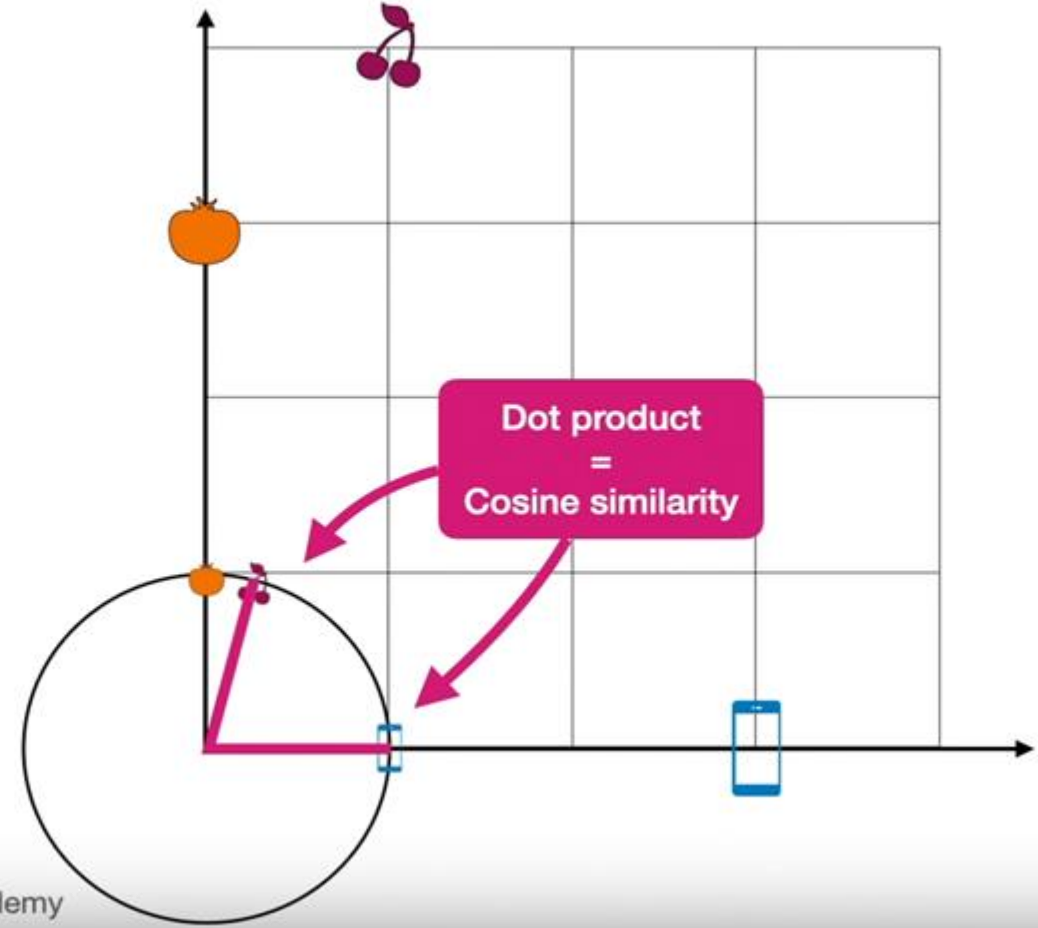




Dot product and cosine similarity



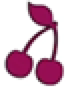
Dot product and cosine similarity



Measure 3: Scaled dot product

Dot product divided by the square root of the length of the vector

Sim



1	4

0	3

$$1 \cdot 0 + 4 \cdot 3 = 12 \longrightarrow \frac{12}{\sqrt{2}} = 8.49$$

Measure 3: Scaled dot product

Dot product divided by the square root of the length of the vector

Sim

1	4
0	3

$$1 \cdot 0 + 4 \cdot 3 = 12 \longrightarrow \frac{12}{\sqrt{2}} = 8.49$$

Sim

1	4
3	0

$$1 \cdot 3 + 4 \cdot 0 = 3 \longrightarrow \frac{3}{\sqrt{2}} = 2.12$$

Sim

0	3
3	0

$$0 \cdot 3 + 3 \cdot 0 = 0 \longrightarrow \frac{0}{\sqrt{2}} = 0$$

Measure 3: Scaled dot product

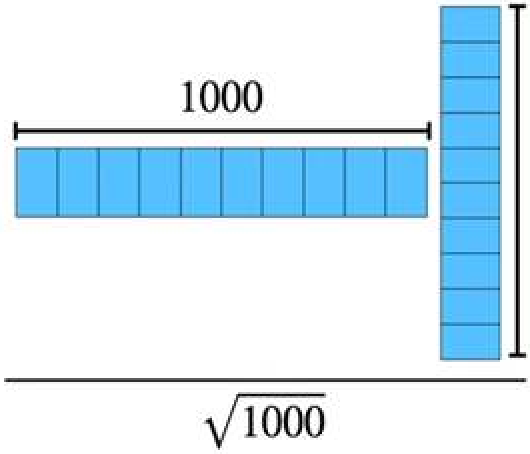
Dot product divided by the square root of the length of the vector

Sim

1	4

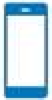
0	3

$$1 \cdot 0 + 4 \cdot 3 = 12 \longrightarrow \frac{12}{\boxed{\sqrt{2}}} = 8.49$$



Sim

1	4

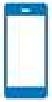


3	0

$$1 \cdot 3 + 4 \cdot 0 = 3 \longrightarrow \frac{3}{\boxed{\sqrt{2}}} = 2.12$$

Sim

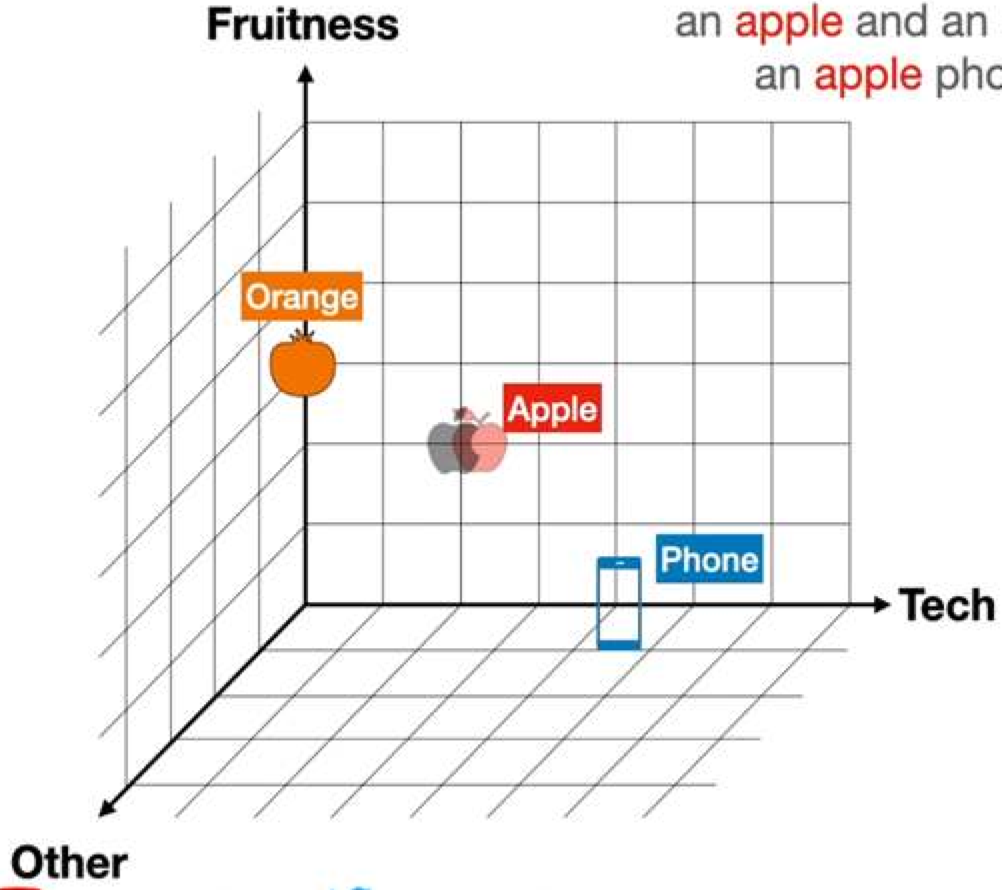
0	3



3	0

$$0 \cdot 3 + 3 \cdot 0 = 0 \longrightarrow \frac{0}{\boxed{\sqrt{2}}} = 0$$

Cosine similarity



an apple and an orange
an apple phone

	Tech	Fruitness	Other
Orange	0	3	0
Phone	4	0	0
Apple	2	2	0

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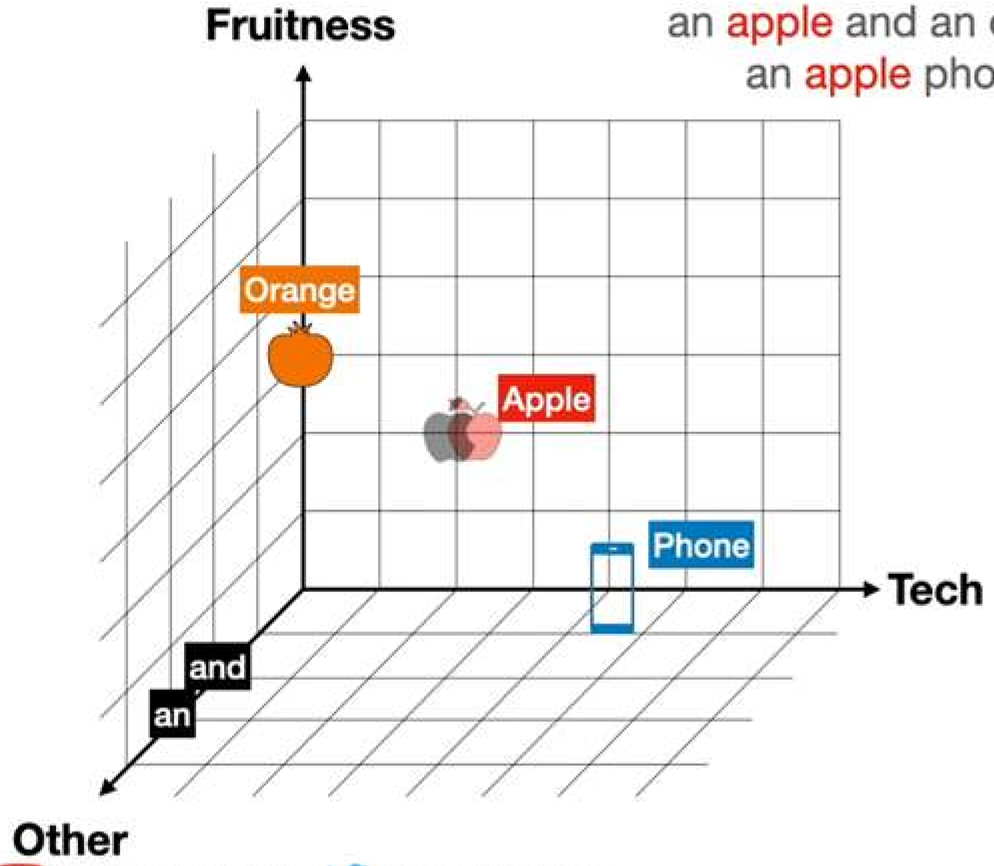
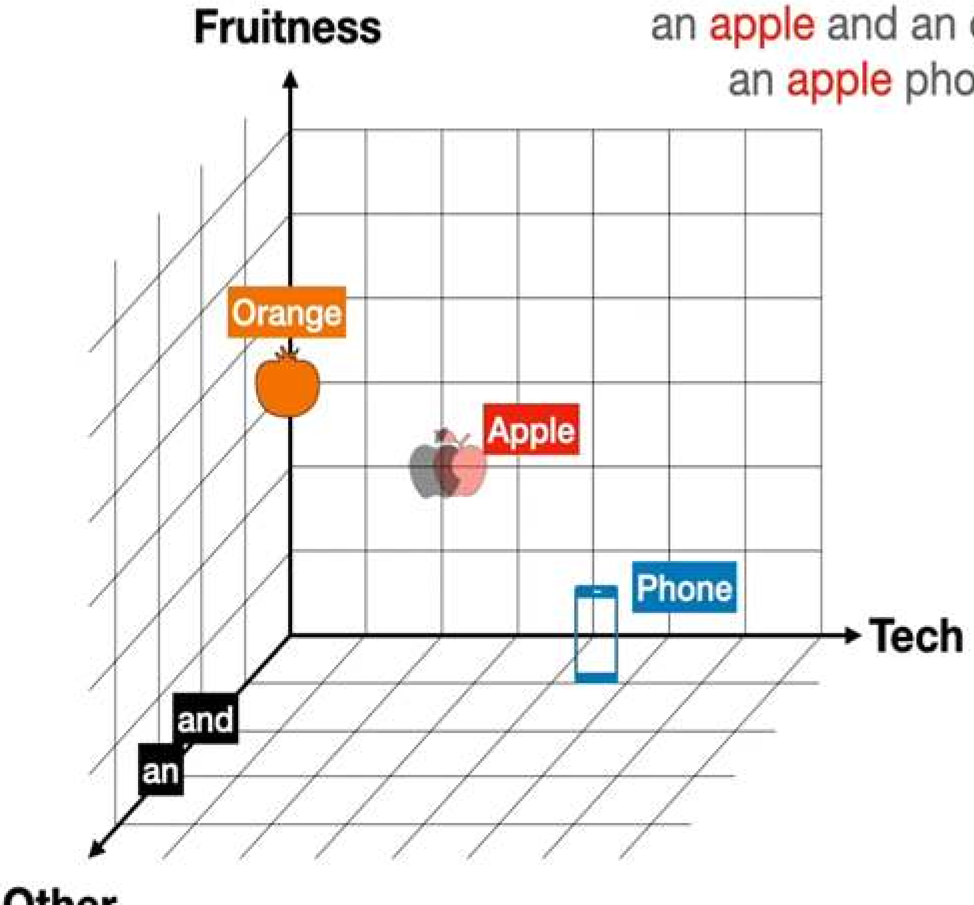
Cosine similarity



an apple and an orange
an apple phone

	Tech	Fruitness	Other
Orange	0	3	0
Phone	4	0	0
Apple	2	2	0
And	0	0	2
An	0	0	3

Cosine similarity

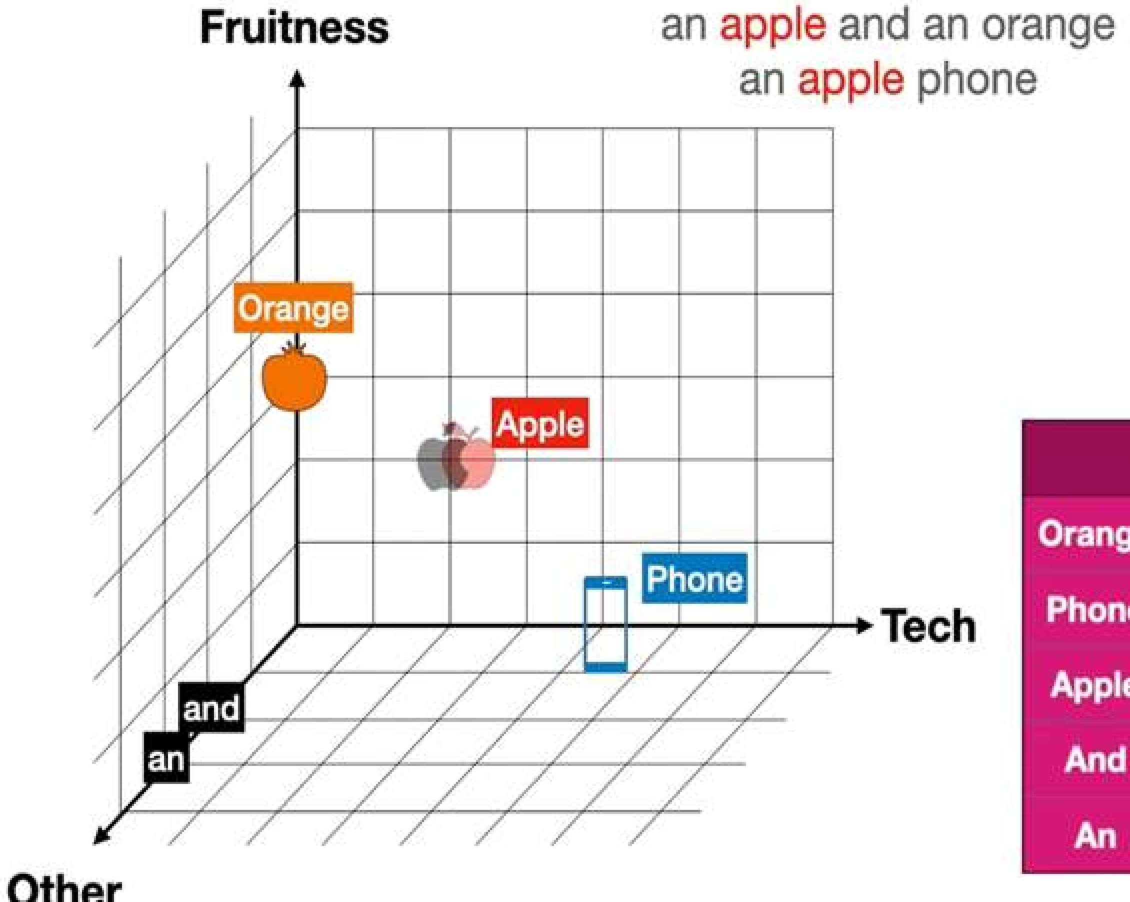


an apple and an orange
an apple phone

	Tech	Fruitness	Other
Orange	0	3	0
Phone	4	0	0
Apple	2	2	0
And	0	0	2
An	0	0	3

	Orange	Phone	Apple	And	An
Orange	1				
Phone		1			
Apple			1		
And				1	
An					1

Cosine similarity



	Tech	Fruitness	Other
Orange	0	3	0
Phone	4	0	0
Apple	2	2	0
And	0	0	2
An	0	0	3

	Orange	Phone	Apple	And	An
Orange	1	0	0.71	0	0
Phone	0	1	0.71	0	0
Apple	0.71	0.71	1	0	0
And	0	0	0	1	1
An	0	0	0	1	1

Word math

an apple and an orange

	Orange	Apple	And	An
Orange	1	0.71	0	0
Apple	0.71	1	0	0
And	0	0	1	1
An	0	0	1	1

Orange $\longrightarrow$ 1 Orange + 0.71 Apple

Apple $\longrightarrow$ 0.71 Orange

And $\longrightarrow$

An $\longrightarrow$

Word math

an apple and an orange

	Orange	Apple	And	An
Orange	1	0.71	0	0
Apple	0.71	1	0	0
And	0	0	1	1
An	0	0	1	1

Orange $\longrightarrow$ 1 Orange + 0.71 Apple

Apple $\longrightarrow$ 0.71 Orange + 1 Apple

And $\longrightarrow$

An $\longrightarrow$

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Word math

an apple and an orange

	Orange	Apple	And	An
Orange	1	0.71	0	0
Apple	0.71	1	0	0
And	0	0	1	1
An	0	0	1	1

Orange $\longrightarrow$ 1 Orange + 0.71 Apple

Apple $\longrightarrow$ 0.71 Orange + 1 Apple

And $\longrightarrow$ 1 And + 1 An

An $\longrightarrow$

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Word math

an apple and an orange

	Orange	Apple	And	An
Orange	1	0.71	0	0
Apple	0.71	1	0	0
And	0	0	1	1
An	0	0	1	1

Orange $\longrightarrow$ 1 Orange + 0.71 Apple

Apple $\longrightarrow$ 0.71 Orange + 1 Apple

And $\longrightarrow$ 1 And + 1 An

An $\longrightarrow$ 1 An

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Word math

an apple phone

	Phone	Apple	An
Phone	1	0.71	0
Apple	0.71	1	0
An	0	0	1

Phone $\longrightarrow$ 1 Phone + 0.71 Apple

Apple $\longrightarrow$ 0.71 Phone + 1 Apple

An $\longrightarrow$ 1 An

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Normalization

Want coefficients to add to 1

$$\text{Orange} \longrightarrow 1\ \text{Orange} + 0.71\ \text{Apple}$$

Normalization

Want coefficients to add to 1

$$\text{Orange} \longrightarrow \frac{1\ \text{Orange} + 0.71\ \text{Apple}}{1+0.71} = 0.58\ \text{Orange} + 0.42\ \text{Apple}$$

Normalization

Want coefficients to add to 1

$$\text{Orange} \longrightarrow \frac{1\ \text{Orange} + 0.71\ \text{Apple}}{1 + 0.71} = 0.58\ \text{Orange} + 0.42\ \text{Apple}$$

Need coefficients to be positive

!

$$\text{Orange} \longrightarrow \frac{1\ \text{Orange} - 1\ \text{Motorcycle}}{1 - 1} =$$

Normalization

Want coefficients to add to 1

$$\text{Orange} \longrightarrow \frac{1\ \text{Orange} + 0.71\ \text{Apple}}{1 + 0.71} = 0.58\ \text{Orange} + 0.42\ \text{Apple}$$

Need coefficients to be positive

$$\text{Orange} \longrightarrow \frac{1\ \text{Orange} - 1\ \text{Motorcycle}}{1 - 1} =$$

Solution? $x \longrightarrow e^{x}$

Softmax

$$x \longrightarrow e^x$$

$$\text{Orange} \longrightarrow \frac{e^1\ \text{Orange} + e^{0.71}\ \text{Apple}}{e^1 + e^{0.71}} = 0.58\ \text{Orange} + 0.42\ \text{Apple}$$

$$\text{Orange} \longrightarrow \frac{1\ \text{Orange} - 1\ \text{Motorcycle}}{1 - 1} =$$

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Softmax

$$x \longrightarrow e^{x}$$

$$\text{Orange} \longrightarrow \frac{e^{1}\,\text{Orange} + e^{0.71}\,\text{Apple}}{e^{1} + e^{0.71}} = 0.57\,\text{Orange} + 0.43\,\text{Apple}$$

$$\text{Orange} \longrightarrow \frac{1\,\text{Orange} - 1\,\text{Motorcycle}}{1 - 1} =$$

Softmax

$$x \longrightarrow e^{x}$$

$$\text{Orange} \longrightarrow \frac{e^{1}\,\text{Orange} + e^{0.71}\,\text{Apple}}{e^{1} + e^{0.71}} = 0.57\,\text{Orange} + 0.43\,\text{Apple}$$

$$\text{Orange} \longrightarrow \frac{e^{1}\,\text{Orange} + e^{-1}\,\text{Motorcycle}}{e^{1} + e^{-1}} = 0.88\,\text{Orange} + 0.12\,\text{Motorcycle}$$

an apple and an orange

	Orange	Apple	And	An
Orange	1	0.71	0	0
Apple	0.71	1	0	0
And	0	0	1	1
An	0	0	1	1

Orange $\longrightarrow$ 0.57 Orange + 0.43 Apple

Apple $\longrightarrow$ 0.43 Orange + 0.57 Apple

And $\longrightarrow$ 0.5 And + 0.5 An

An $\longrightarrow$ 0.5 An + 0.5 And

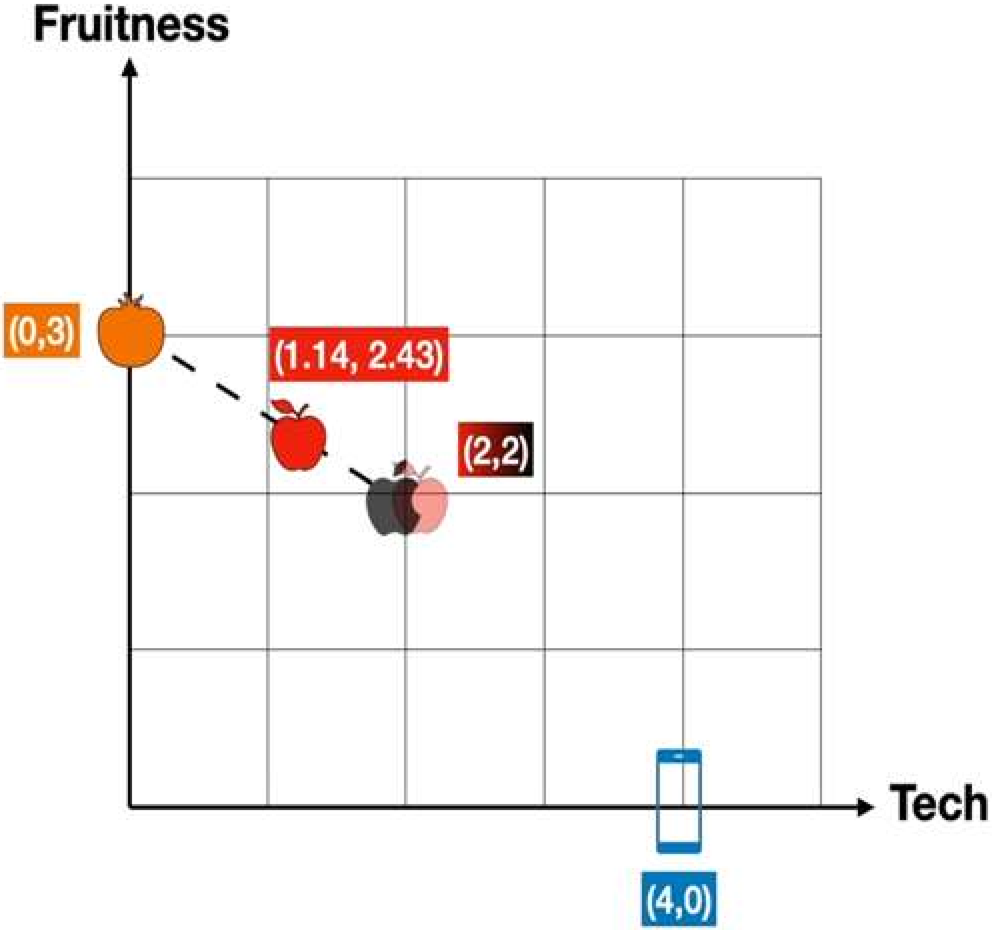
an apple phone

	Phone	Apple	An
Phone	1	0.71	0
Apple	0.71	1	0
An	0	0	1

Phone $\longrightarrow$ 0.57 Phone + 0.43 Apple

Apple $\longrightarrow$ 0.43 Phone + 0.57 Apple

An $\longrightarrow$ 1 An



an apple and an orange

Apple $\longrightarrow$ 0.43 Orange + 0.57 Apple

an apple phone

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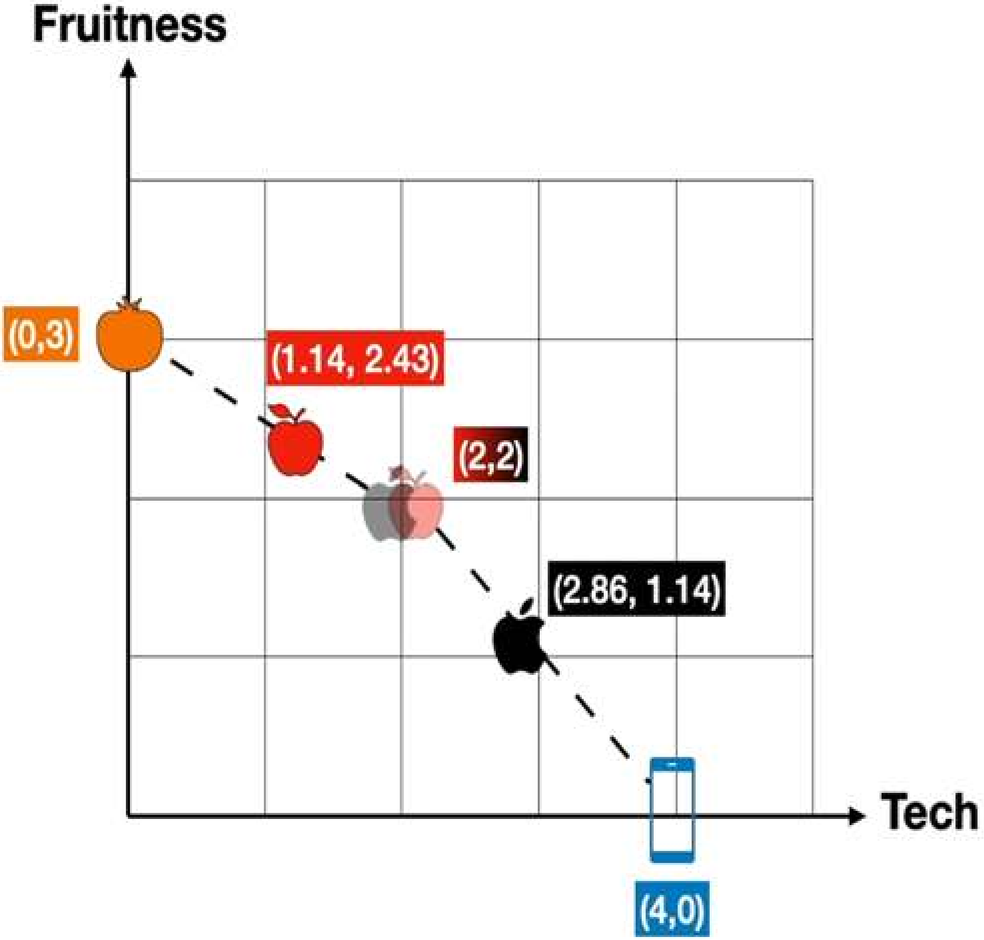

an apple and an orange

Apple $\longrightarrow$ 0.43 Orange + 0.57 Apple

an apple phone

Apple $\longrightarrow$ 0.43 Phone + 0.57 Apple

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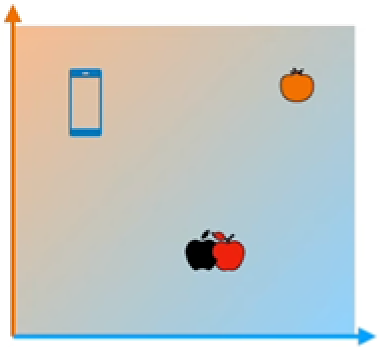
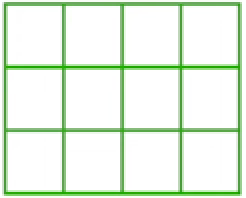
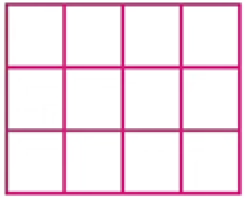
Get new embeddings from existing ones



Keys



Queries



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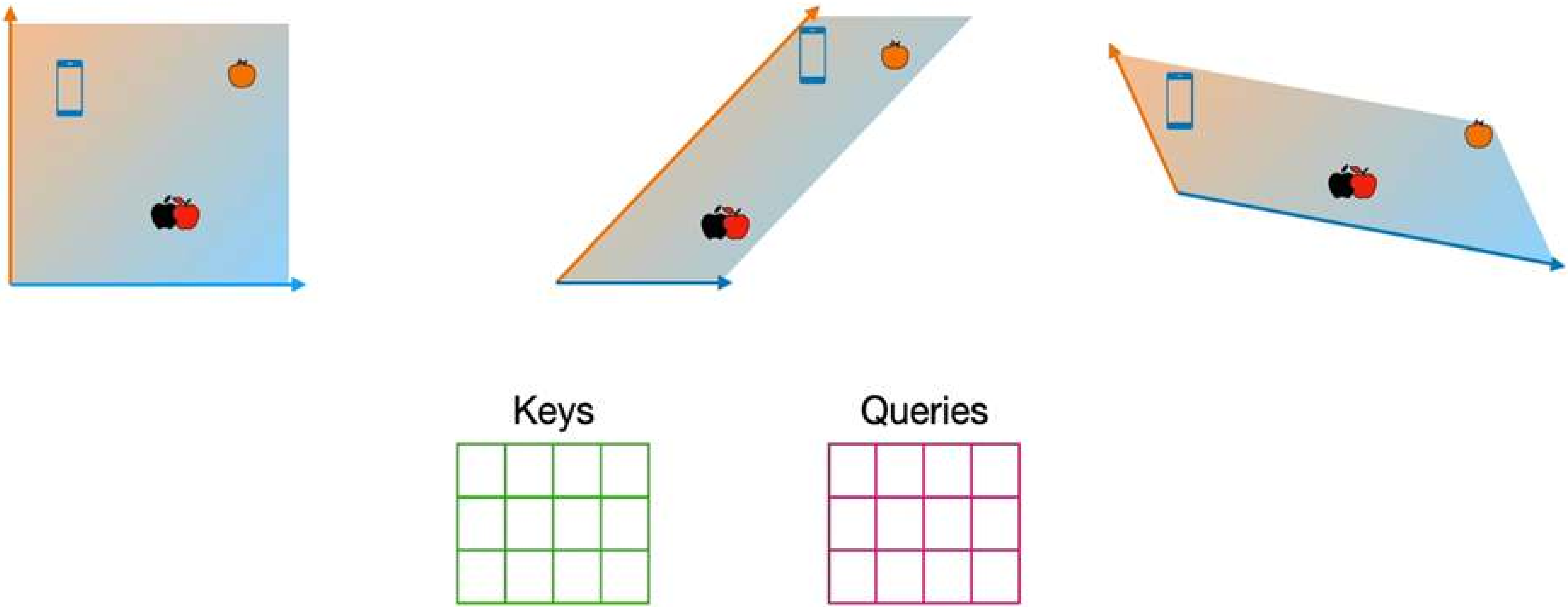
Get new embeddings from existing ones



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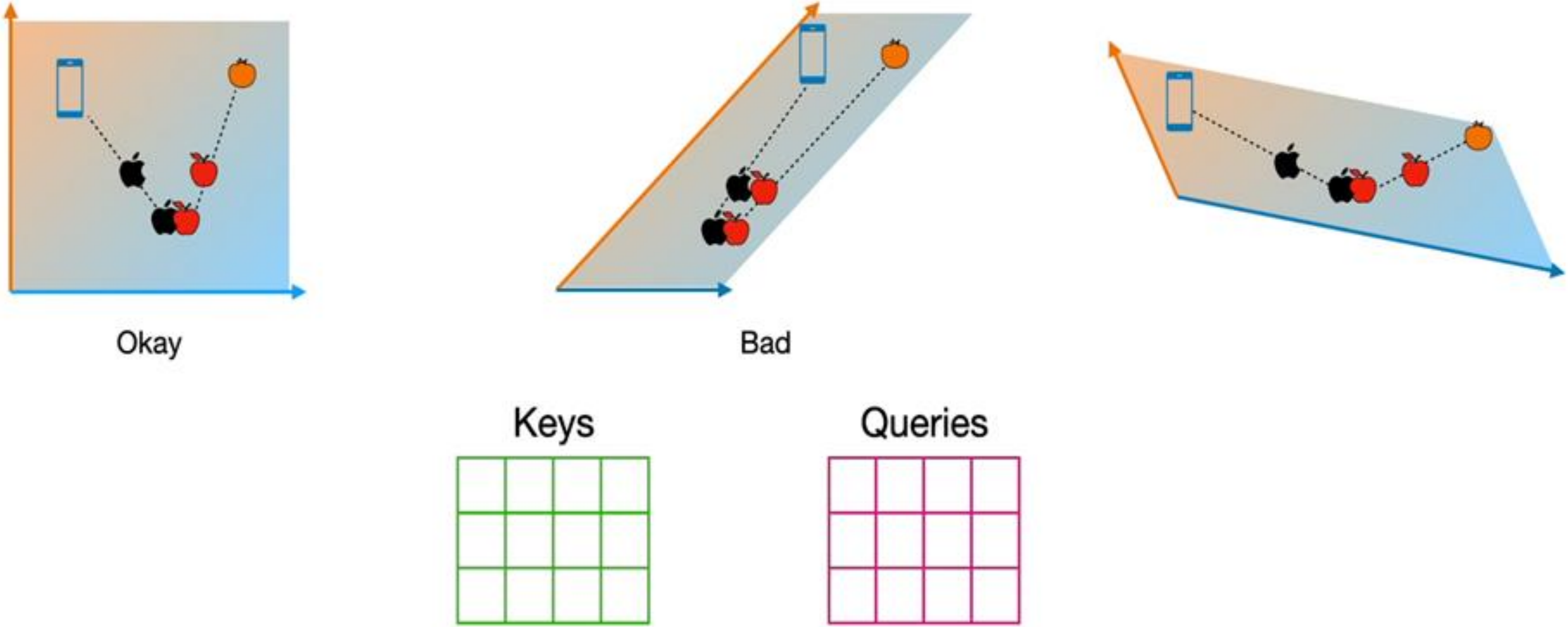
Get new embeddings from existing ones



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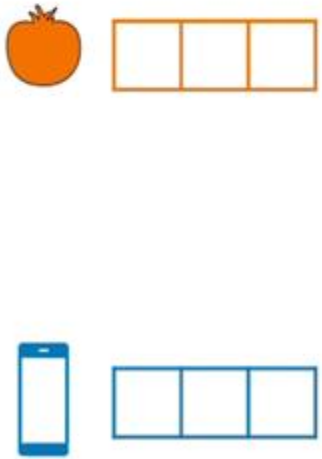
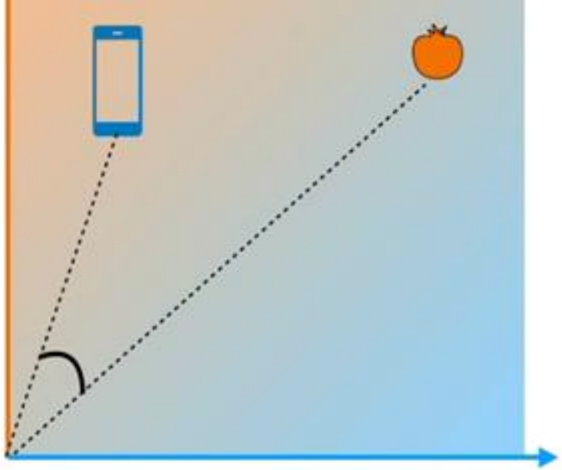
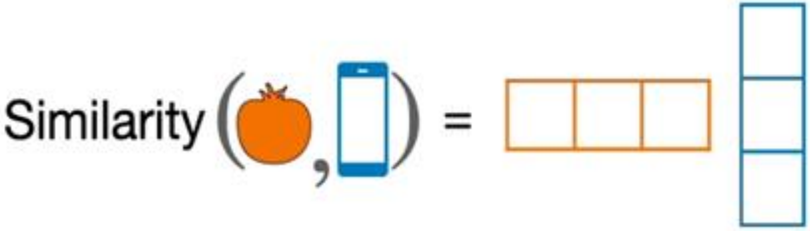
Similarity







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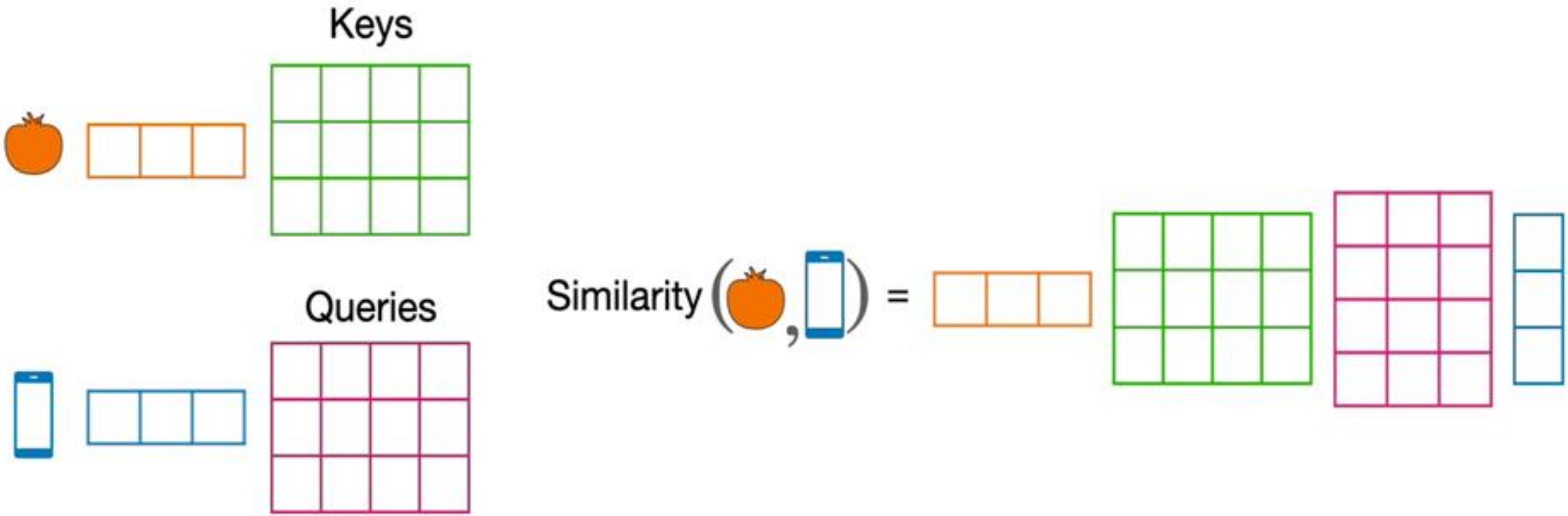
Keys and Queries Matrices



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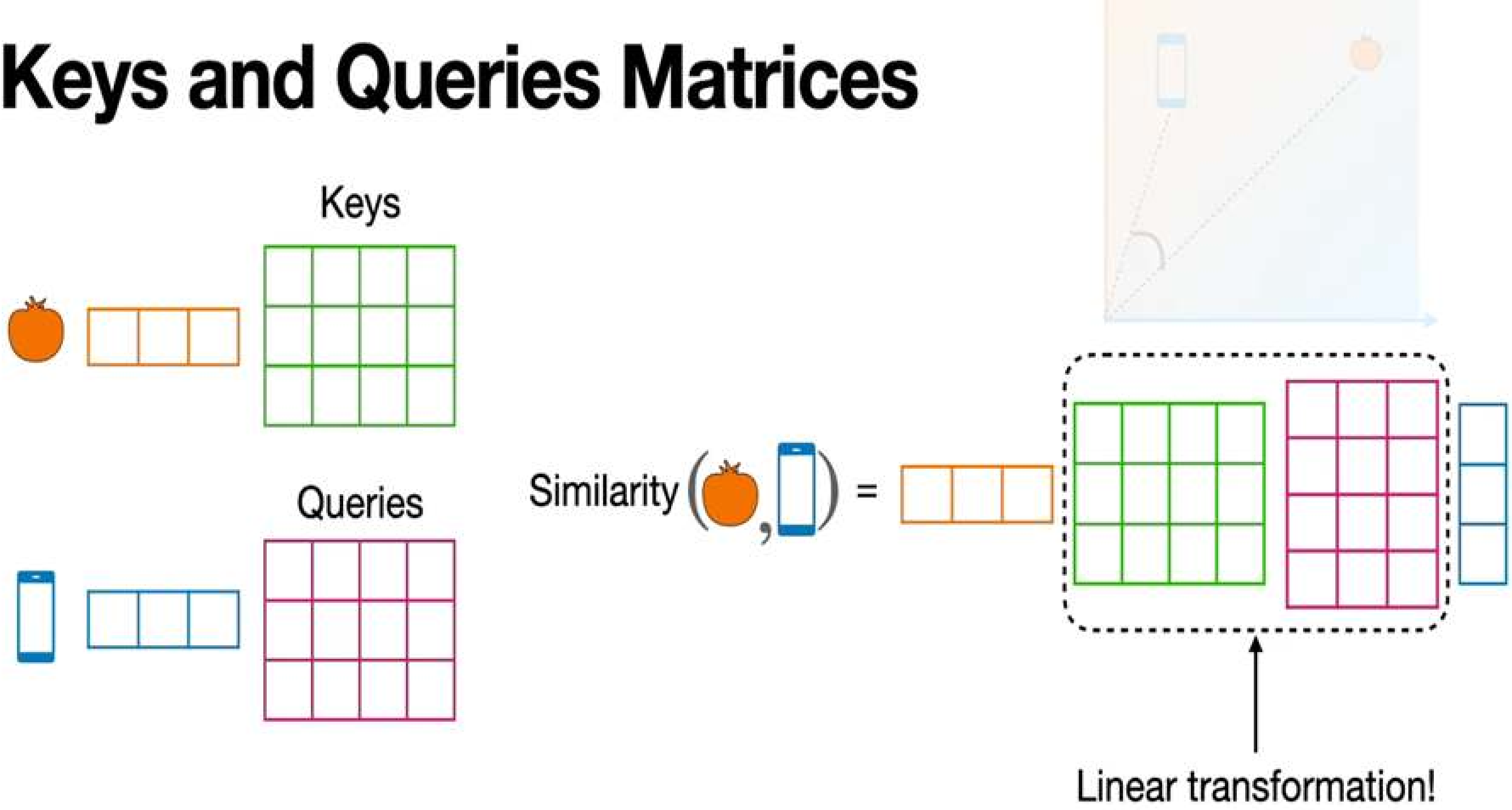
Keys and Queries Matrices



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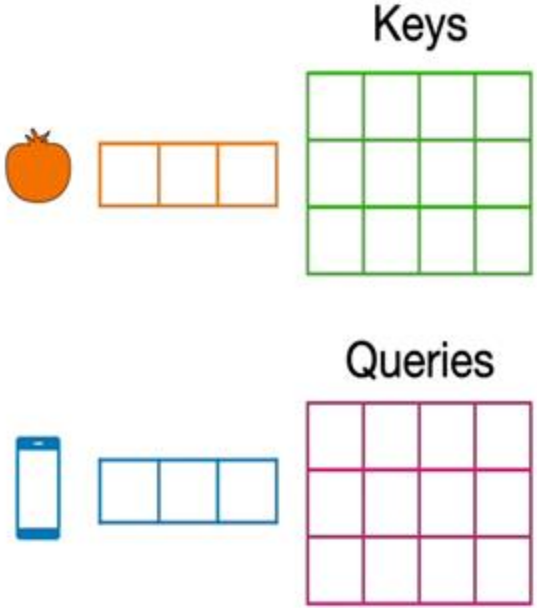
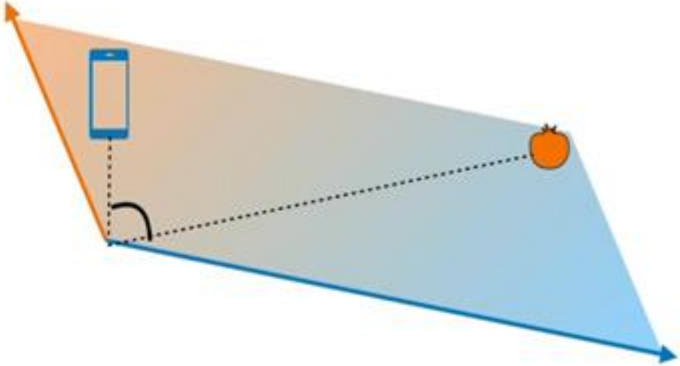
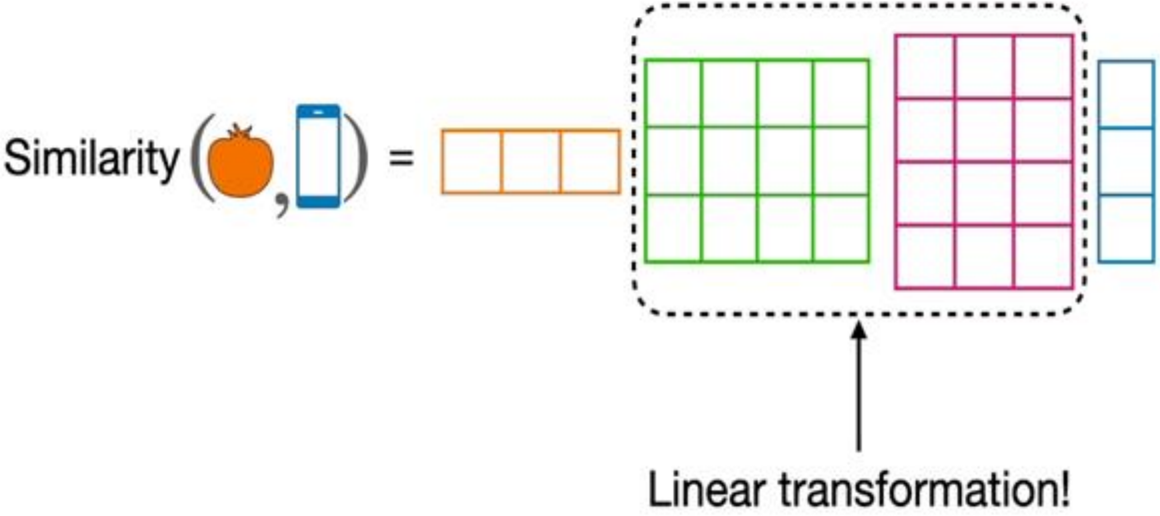
Keys and Queries Matrices







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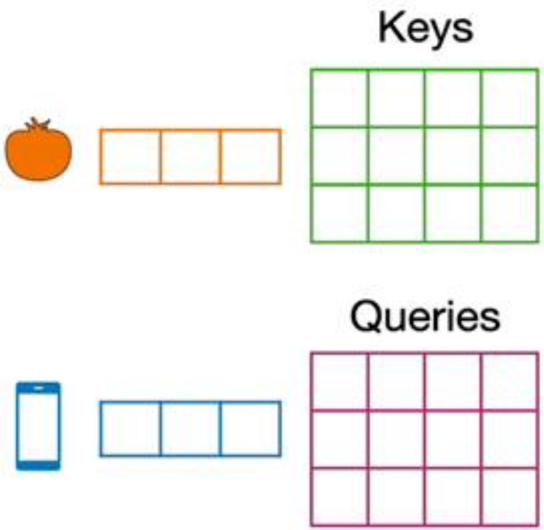
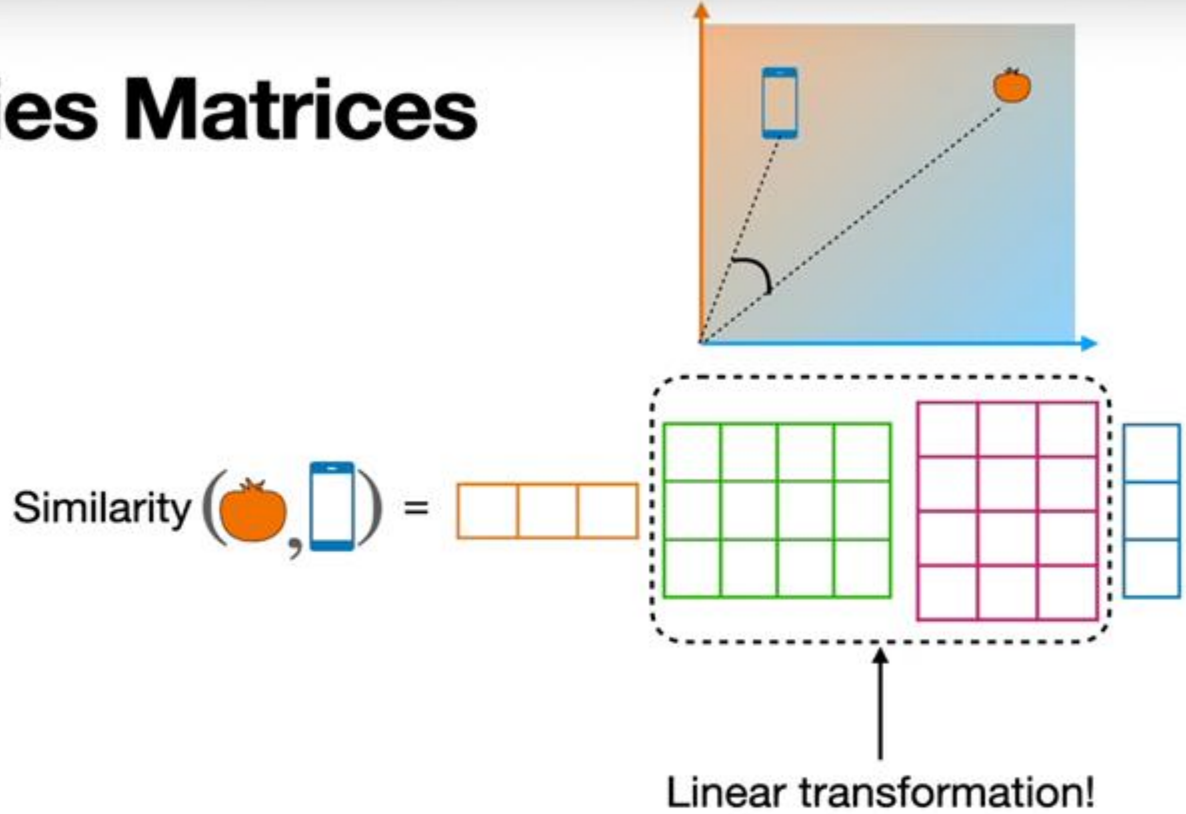
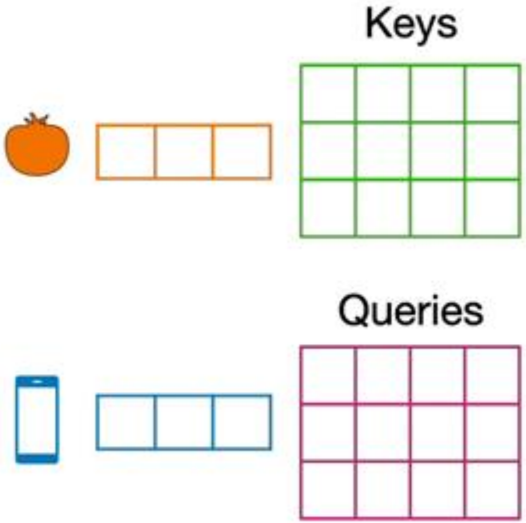
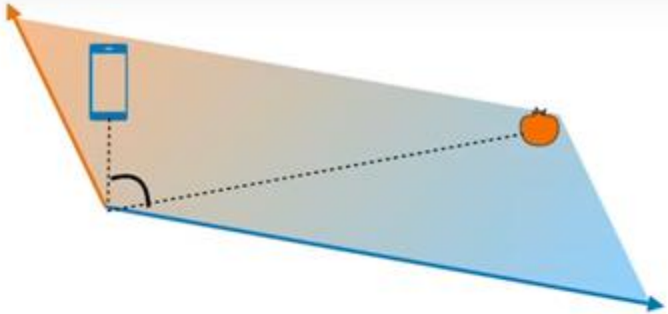
Keys and Queries Matrices

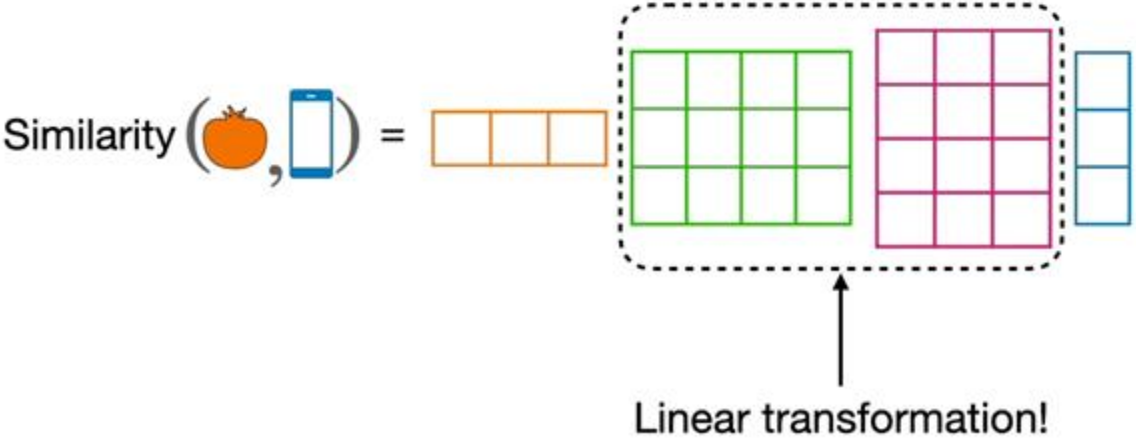




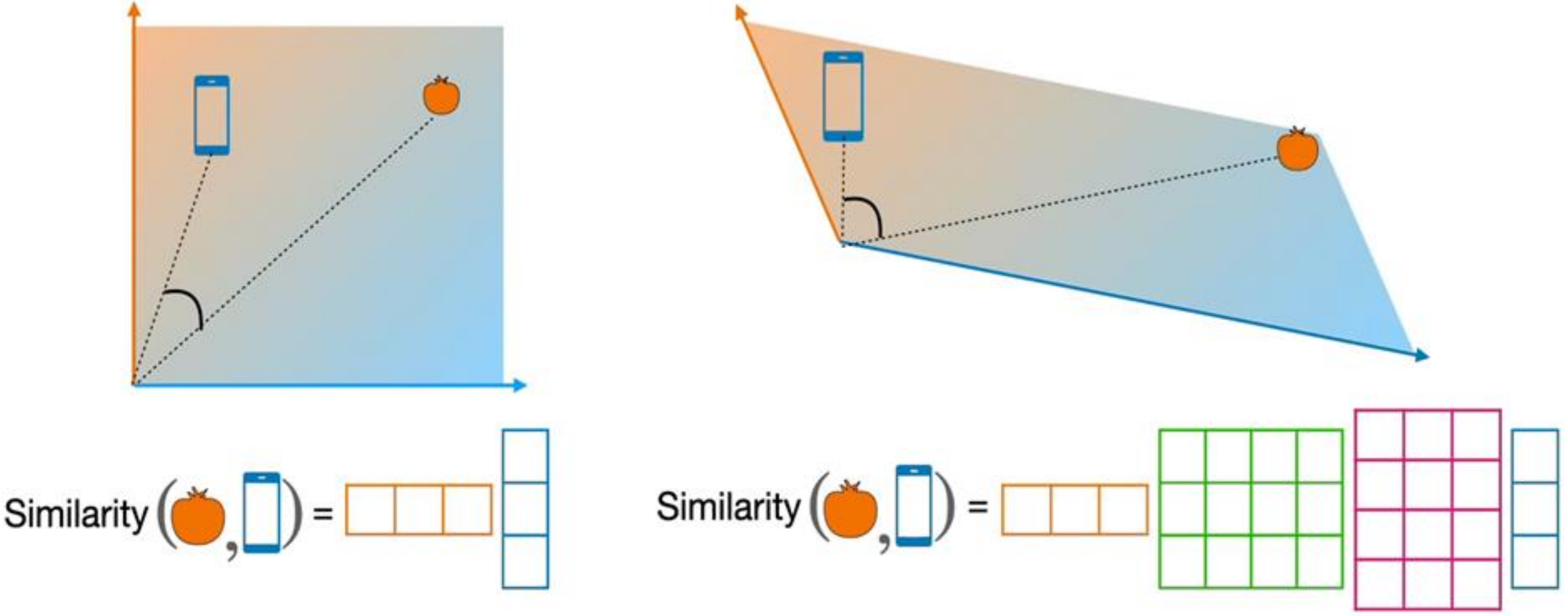
Keys and Queries Matrices







Similarity on a transformed embedding



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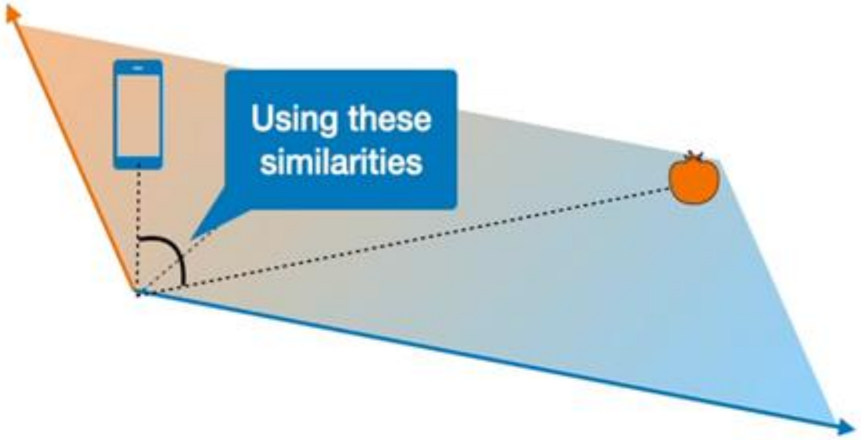
Values matrix



Best embedding for finding similarities

Best embedding for finding the next word

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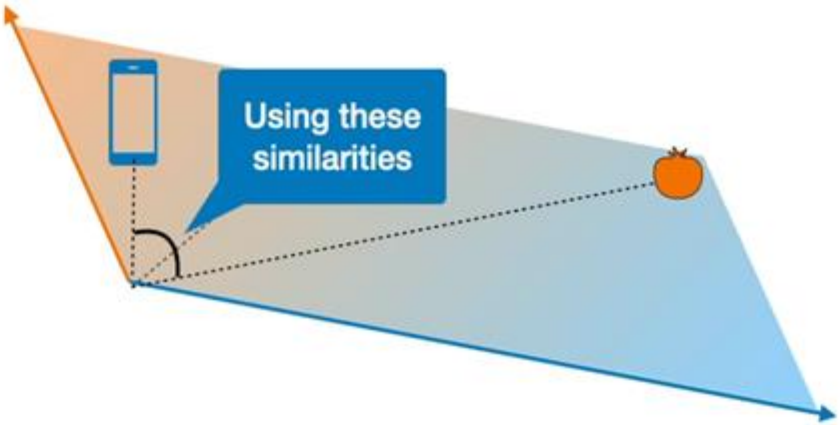
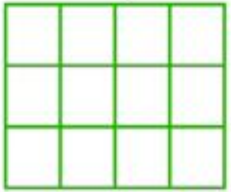
Values matrix

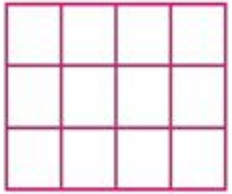


Best embedding for finding similarities

Keys

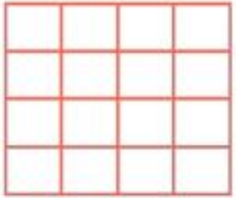


Queries

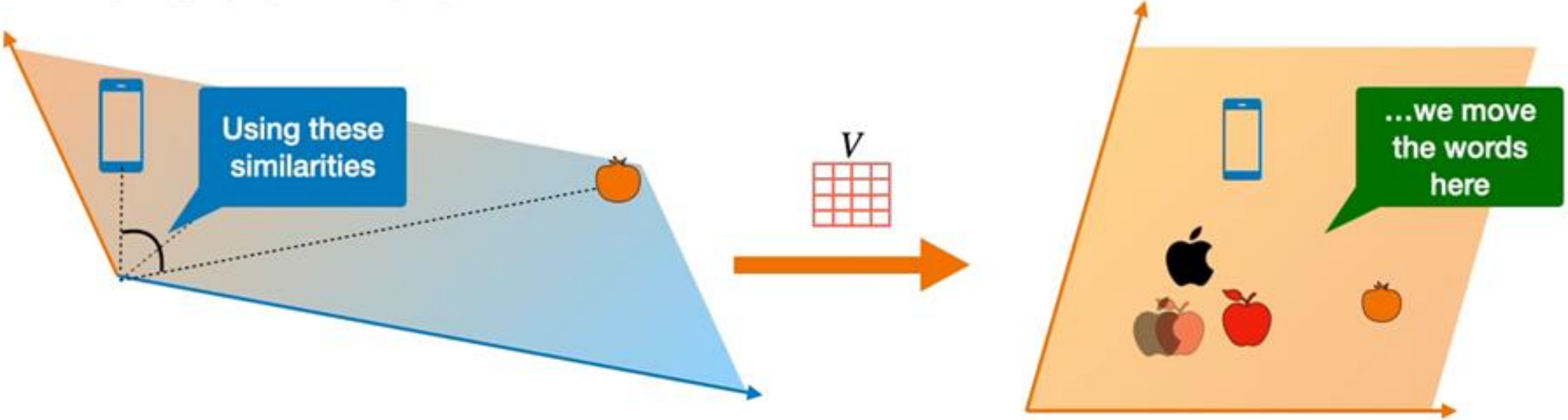


Best embedding for finding the next word

Values



Values matrix



Best embedding for finding similarities

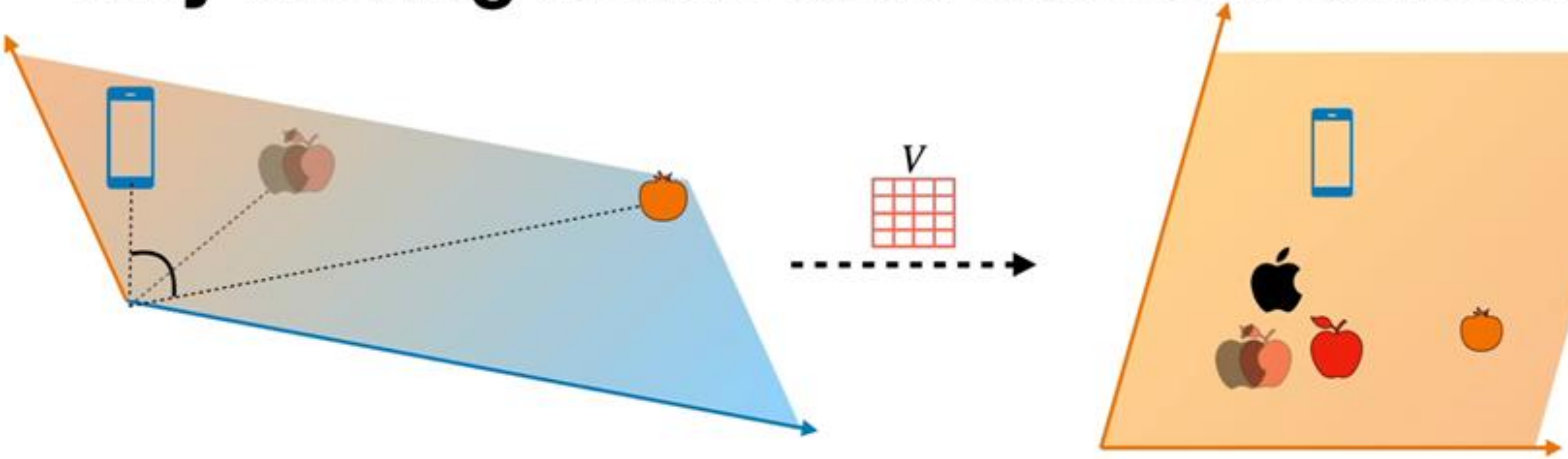
Best embedding for finding the next word

Keys

Queries

Values

Why moving words on a different embedding?



Best embedding for finding similarities

Best embedding for finding the next word

This embedding(s) know features of the words

- Color
- Size
- Fruitness
- Technology

This embedding knows when two words could appear in the same context

I want to buy a _____

- car
- apple
- phone

Value matrix

an apple and an orange

	Orange	Apple	And	An
Orange	0.4	0.3	0.15	0.15
Apple	0.3	0.4	0.15	0.15
And	0.15	0.15	0.5	0.5
An	0.15	0.15	0.5	0.5

Value matrix

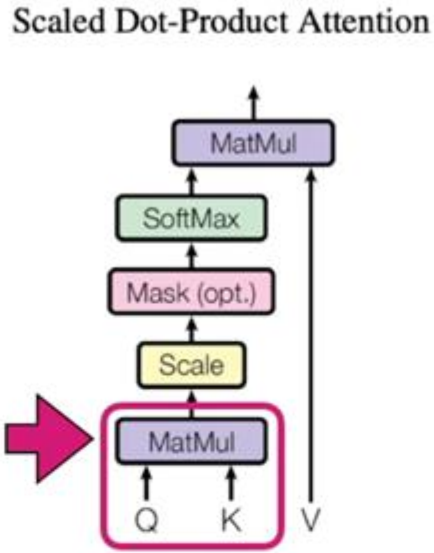
=

	Orange	Apple	And	An
Orange	v_{11}	v_{12}	v_{13}	v_{14}
Apple	v_{21}	v_{22}	v_{23}	v_{24}
And	v_{31}	v_{32}	v_{33}	v_{34}
An	v_{41}	v_{42}	v_{43}	v_{44}

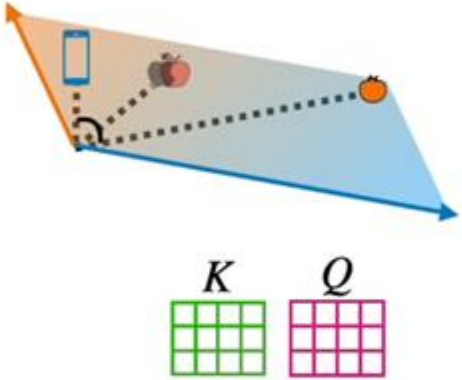
apple $\longrightarrow$ $0.3 \cdot$ orange
$+0.4 \cdot$ apple
$+0.15 \cdot$ and
$+0.15 \cdot$ an

apple $\longrightarrow$ $v_{21} \cdot$ orange
$+v_{22} \cdot$ apple
$+v_{23} \cdot$ and
$+v_{24} \cdot$ an

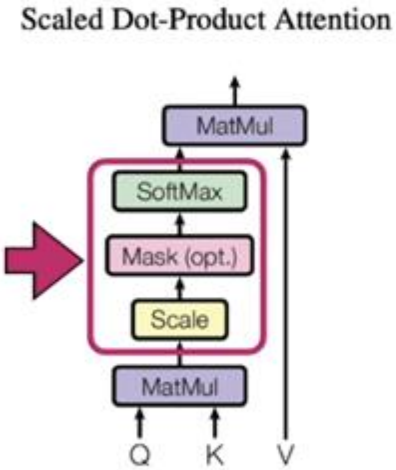
Self-attention



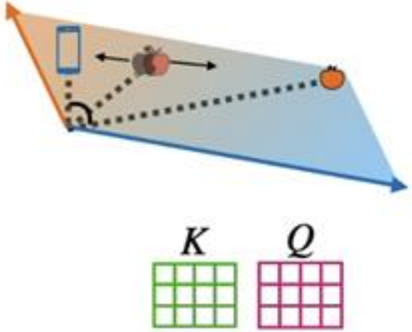
$$\mathrm{Attention}(Q,K,V) = \mathrm{softmax}\left(\boxed{\frac{QK^T}{\sqrt{d_k}}}\right)V$$



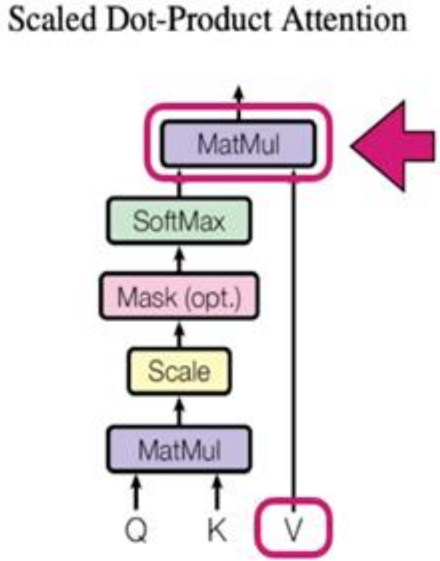
Self-attention



$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$



Self-attention



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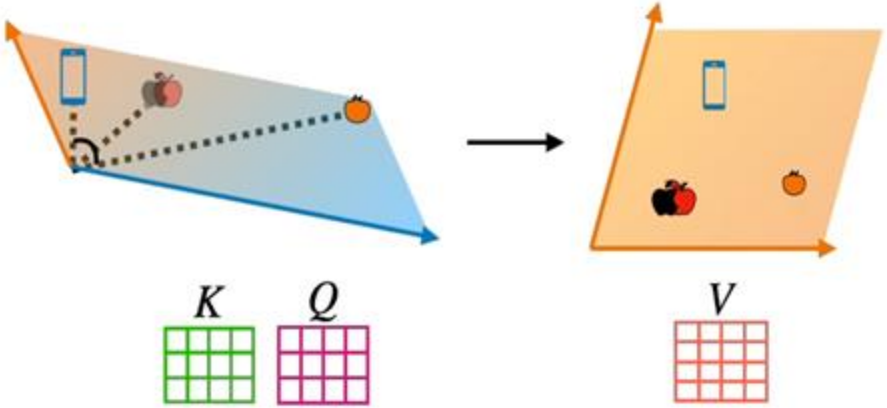
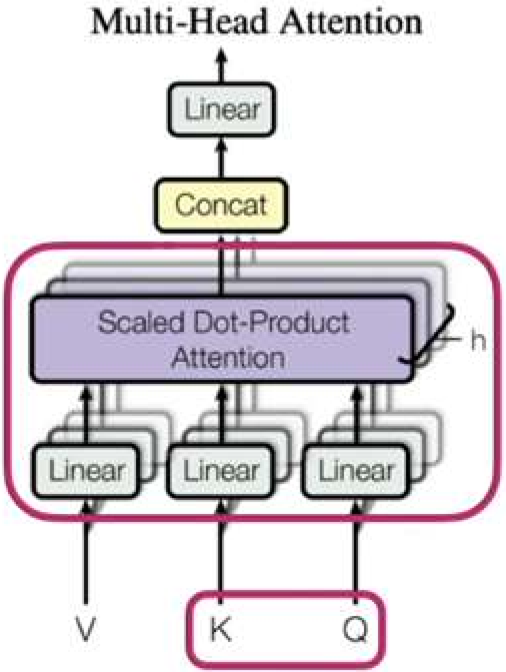
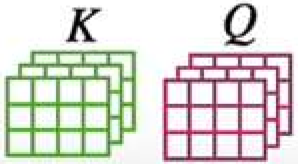


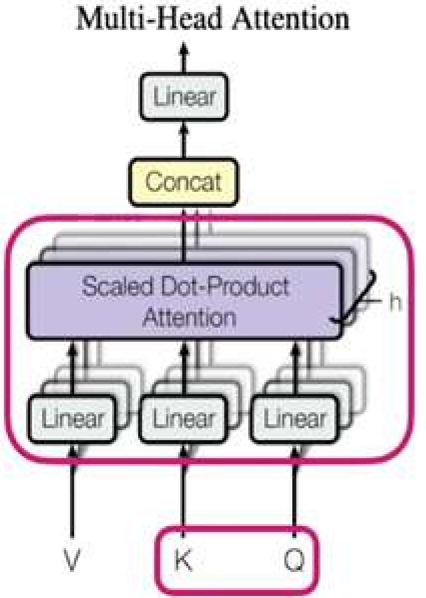
Multi-head attention



$$\mathrm{MultiHead}(Q, K, V) = \mathrm{Concat}(\mathrm{head_1}, ..., \mathrm{head_h})W^O$$
$$\text{where } \mathrm{head_i} = \mathrm{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$



Multi-head attention



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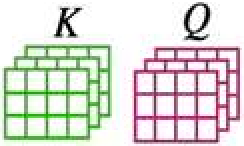
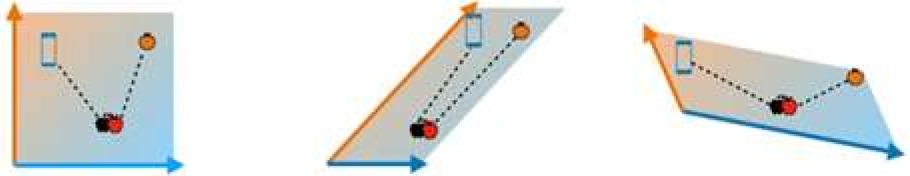
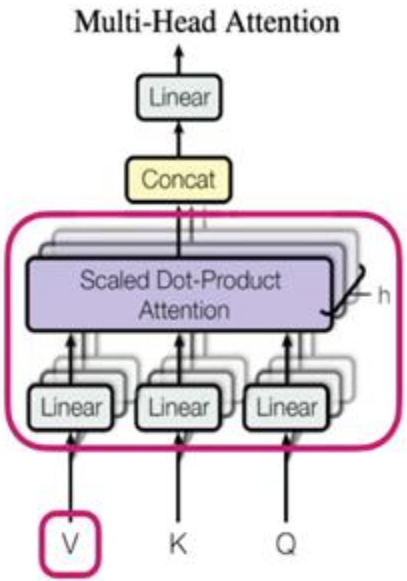




Multi-head attention



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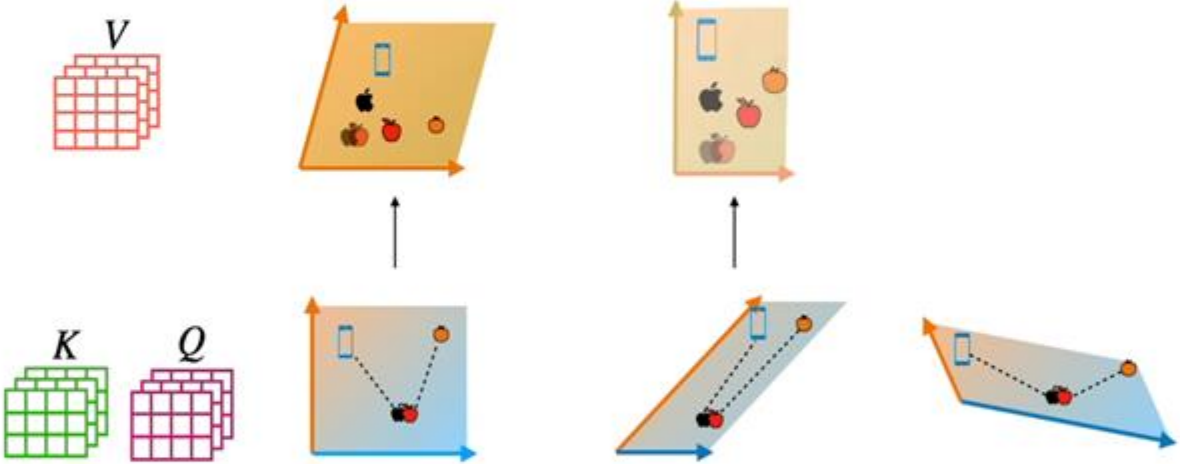
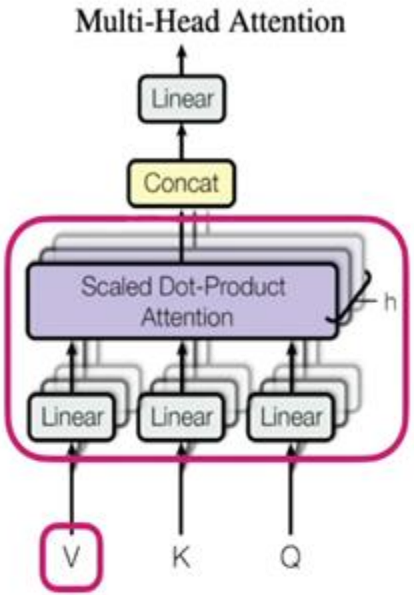


Multi-head attention



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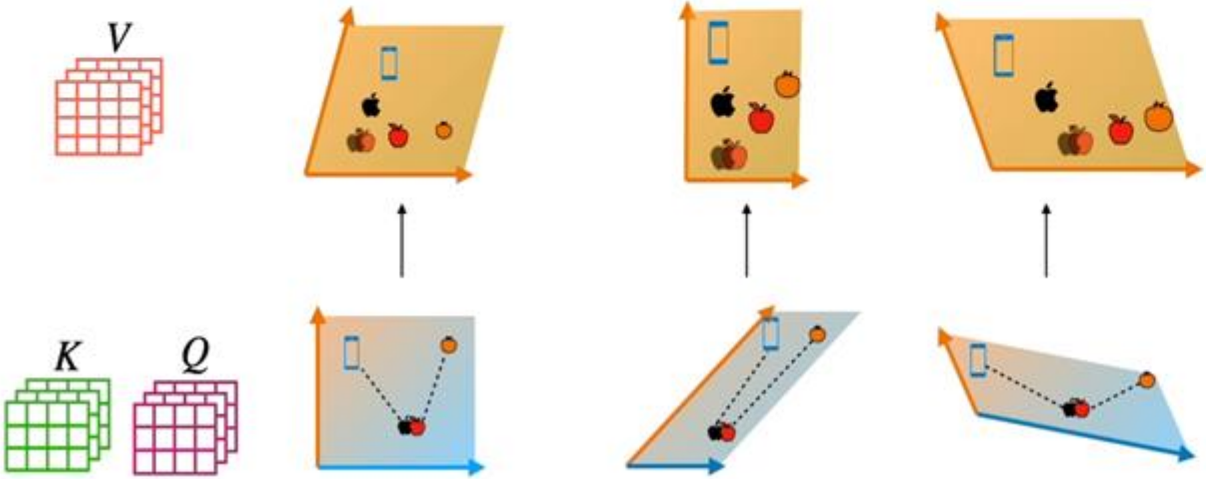
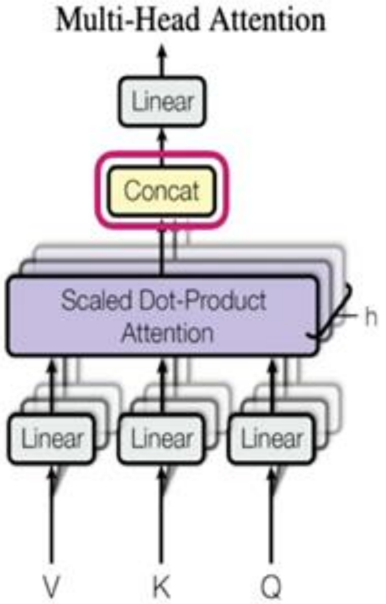


Multi-head attention



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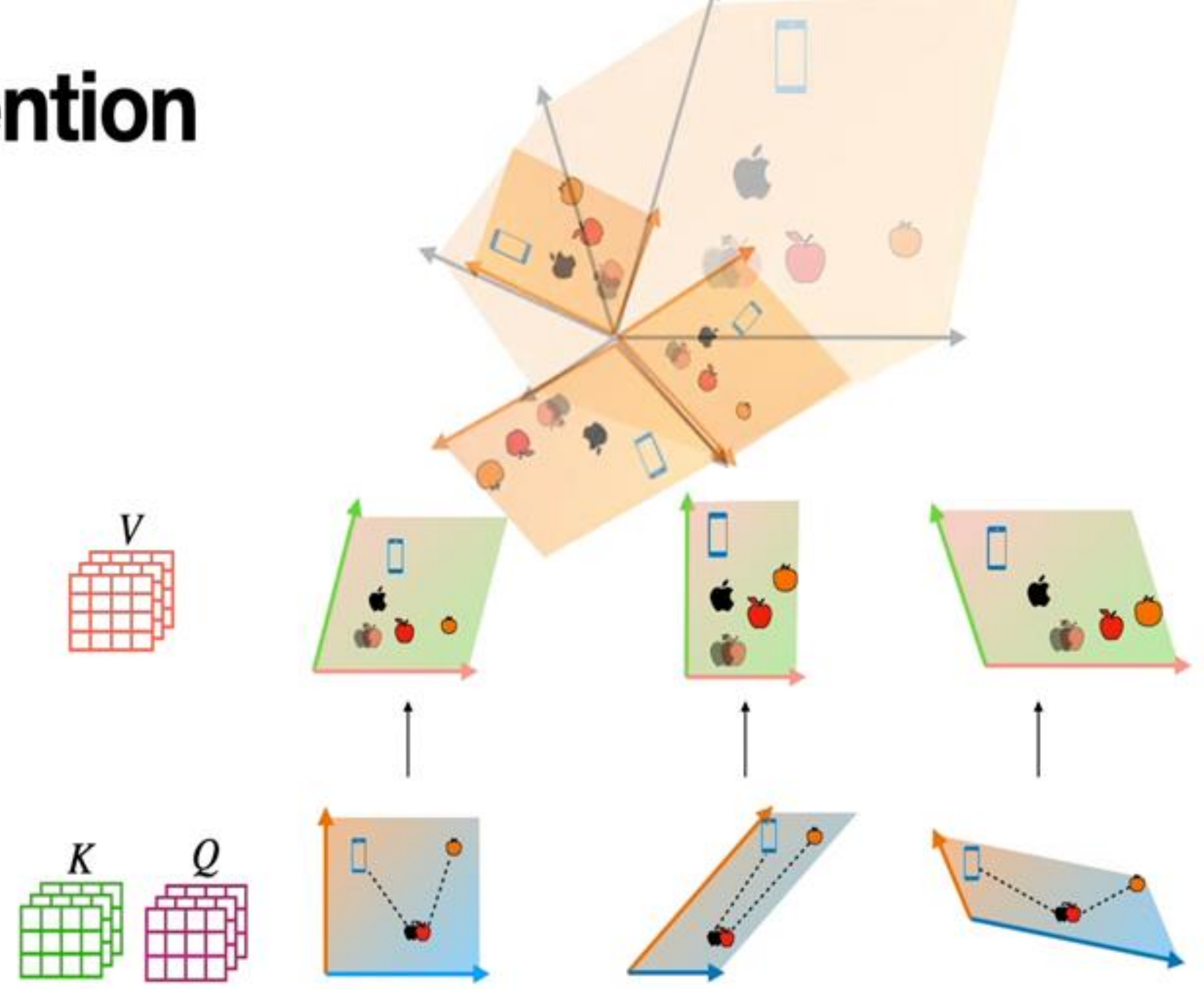
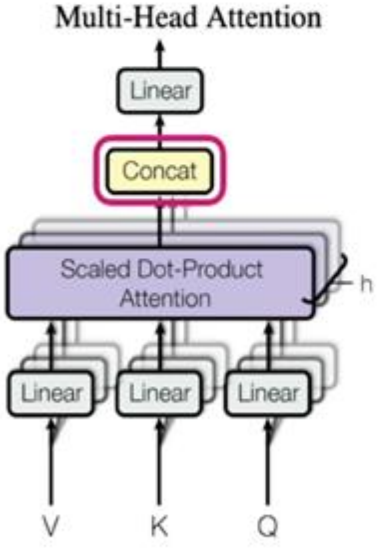


Multi-head attention



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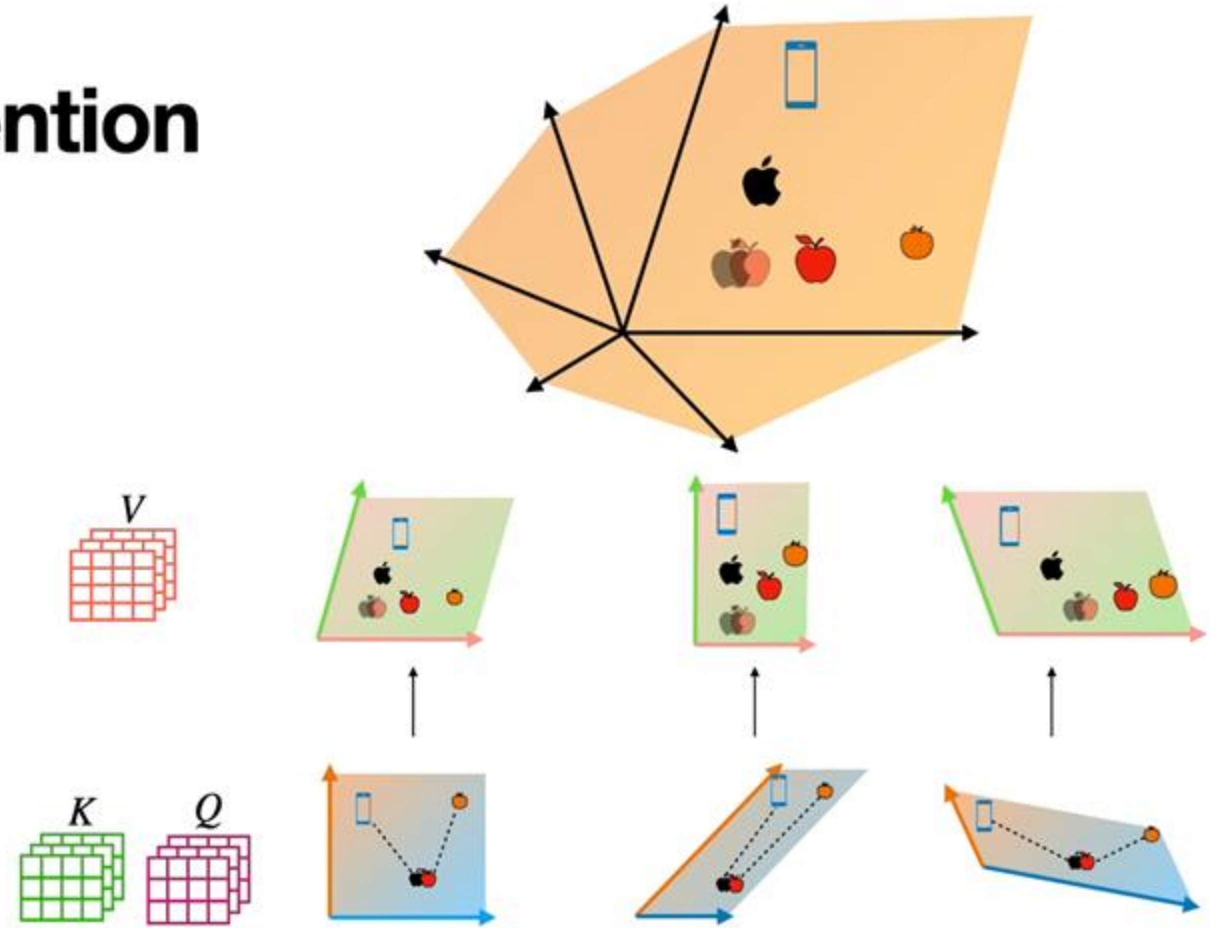
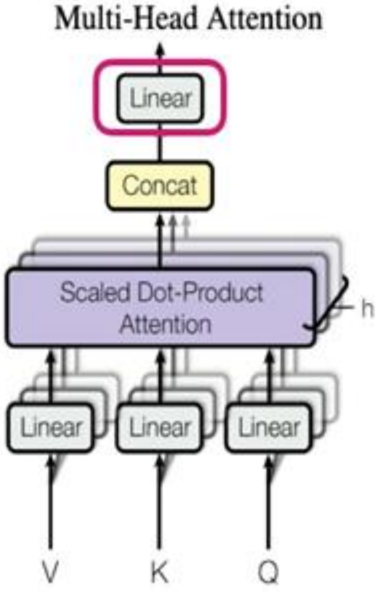


Multi-head attention



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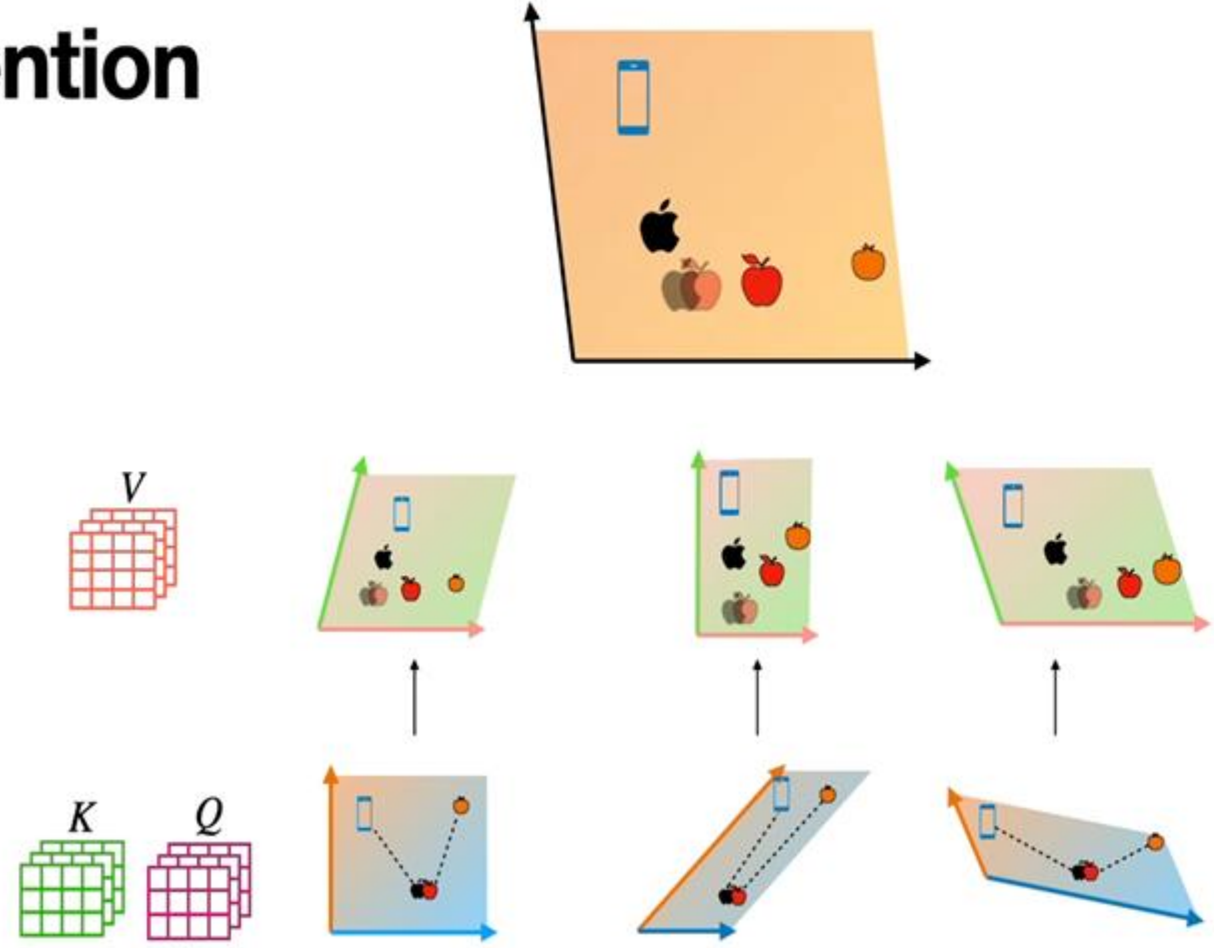
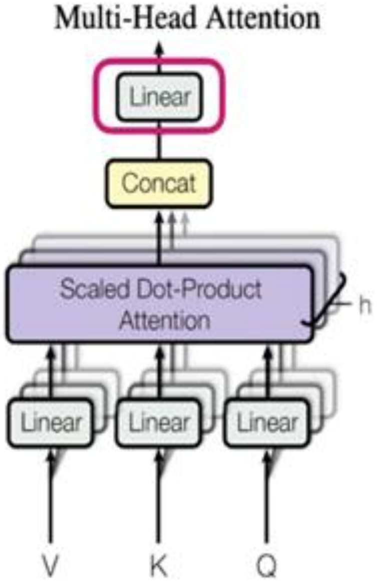


Multi-head attention



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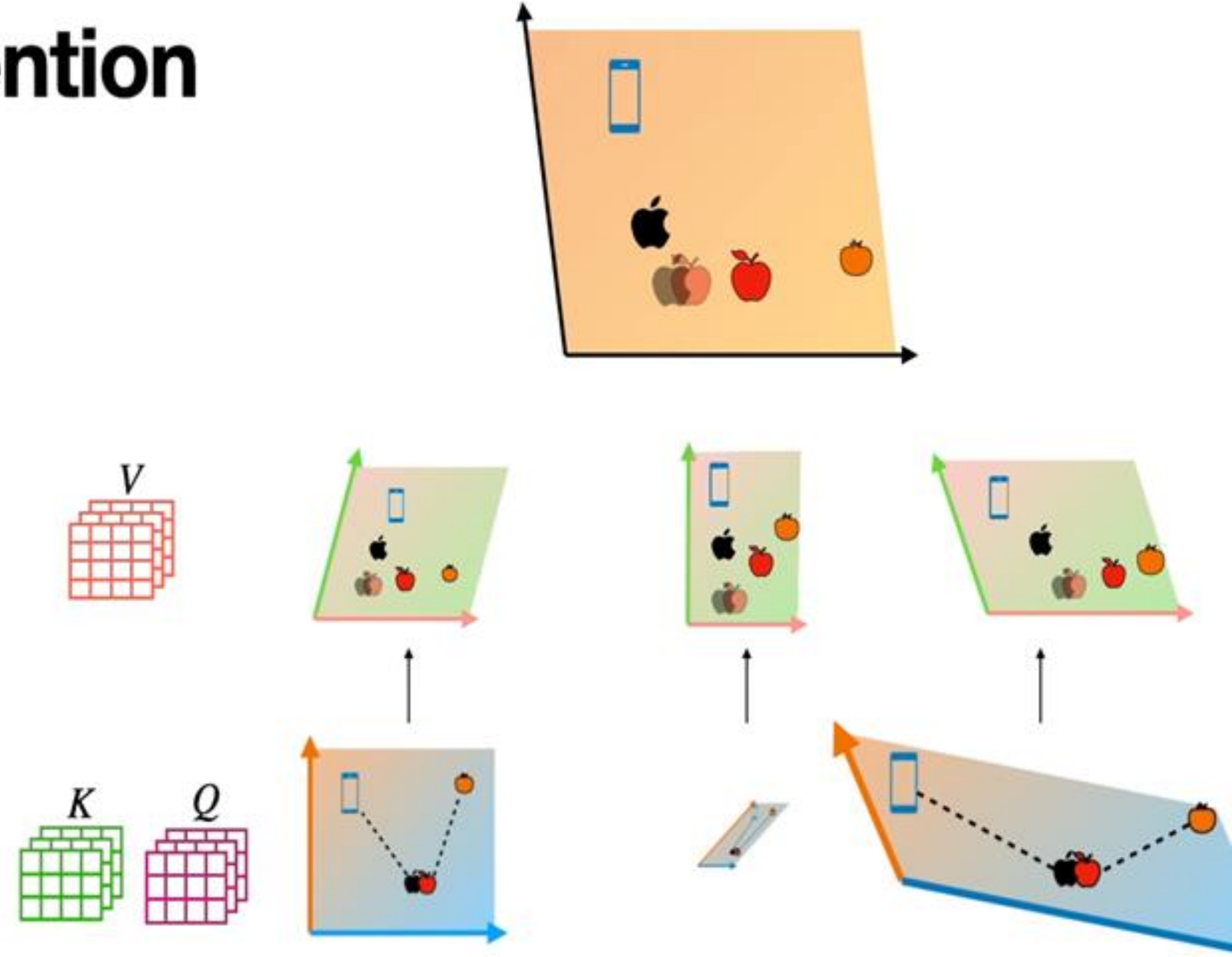
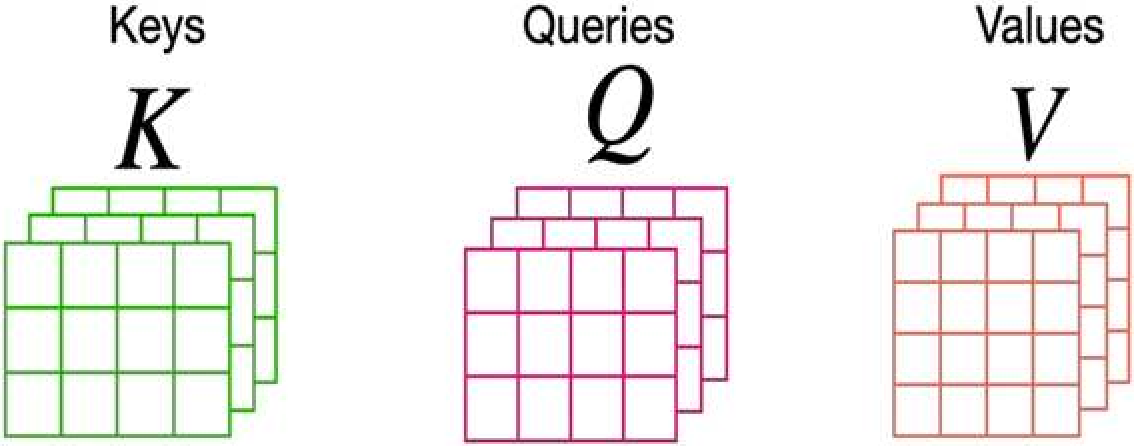
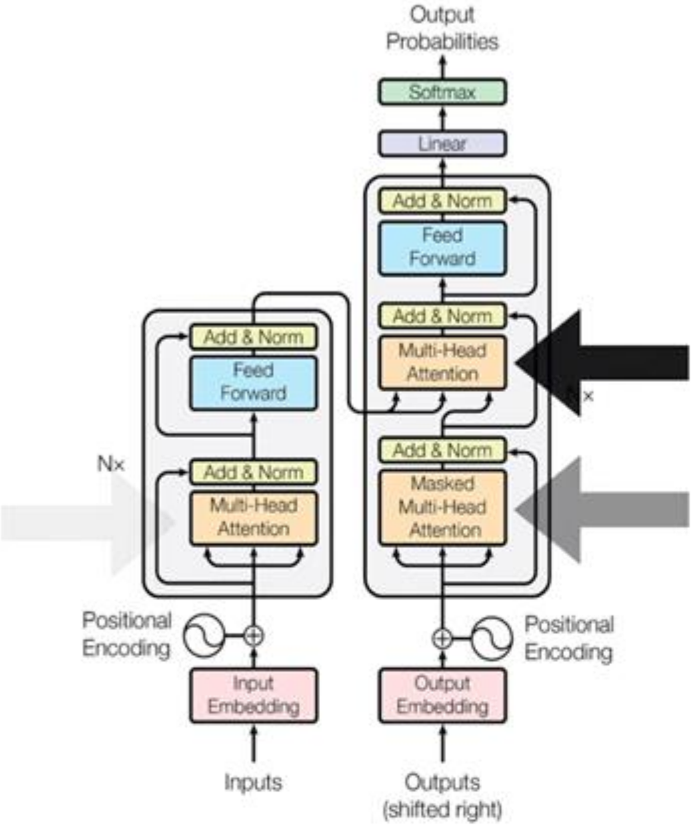


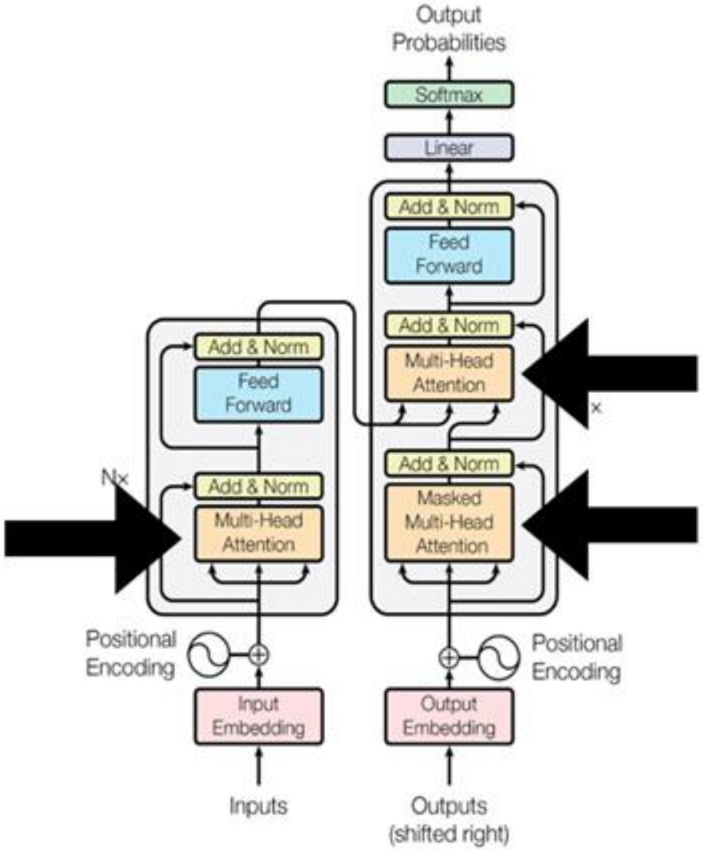
How to get these matrices?



Weights get trained with the transformer model

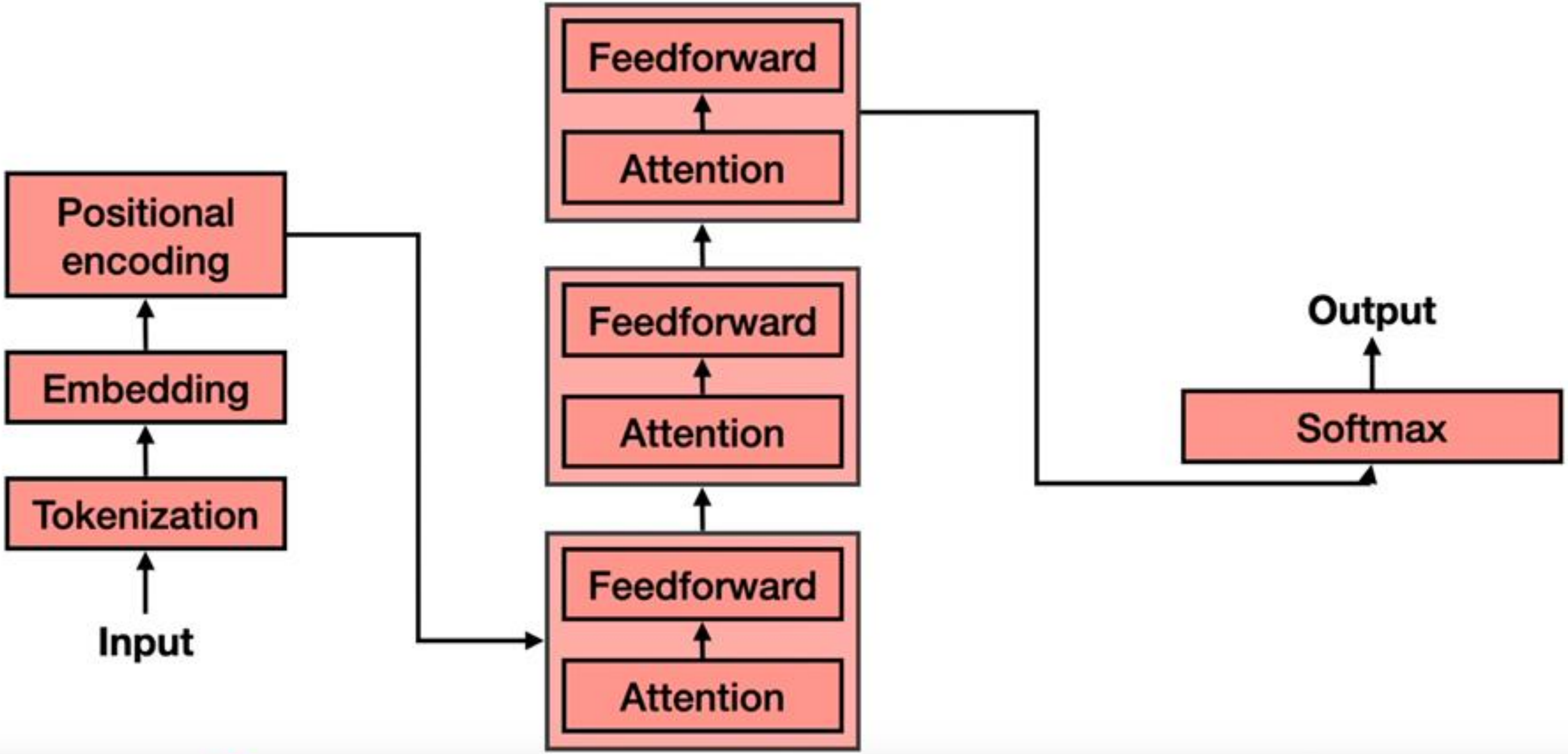


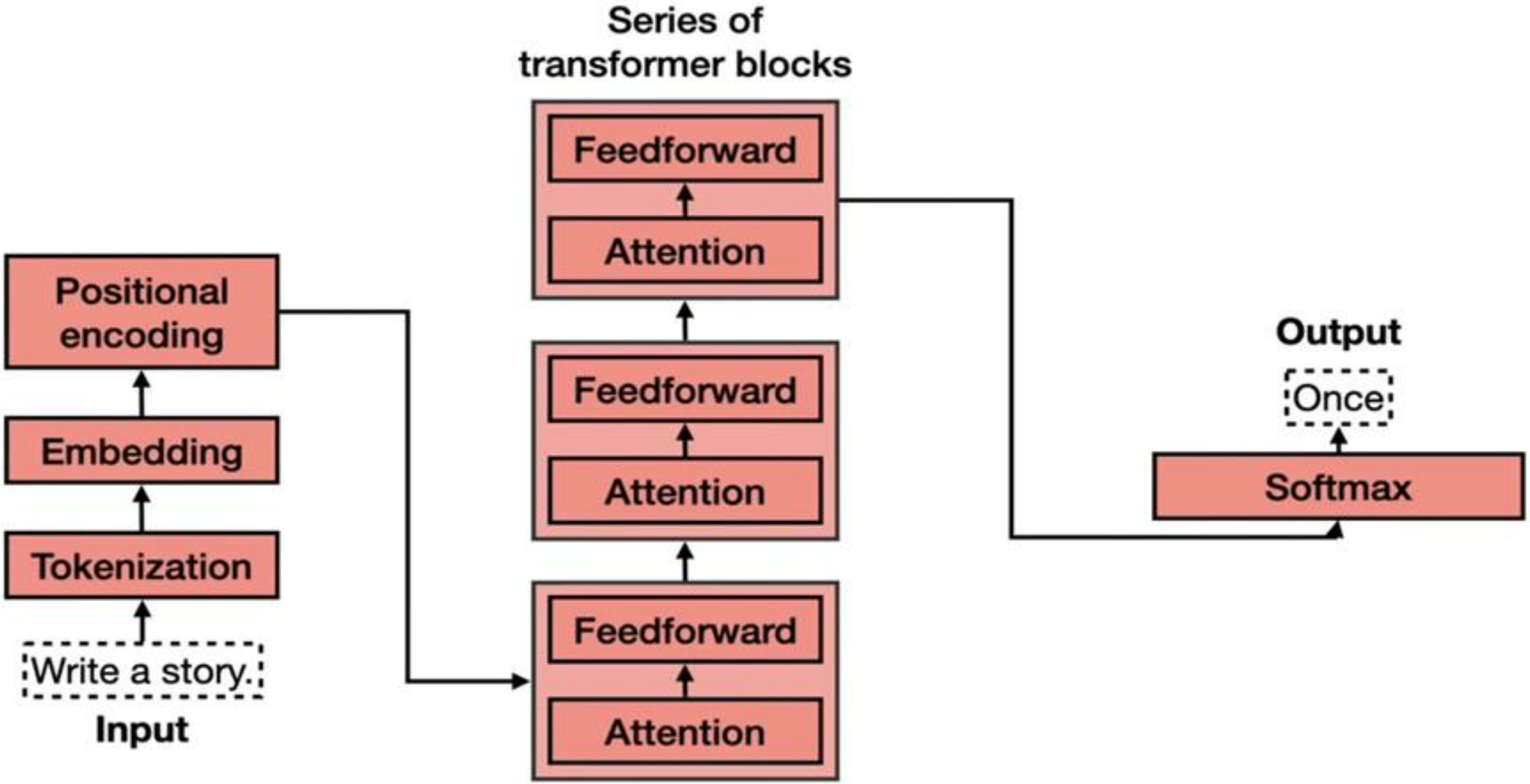
Weights get trained with the transformer model



Transformeurs

Weights get trained with the transformer model




Series of
transformer blocks
Feedforward
Attention
Feedforward
Attention
Feedforward
Attention
Positional
encoding
Embedding
Tokenization
Write a story.
Input
Output
Once
Softmax

Transformeurs

- 1) Tokenization
- 2) Encastrement
- 3) Encodage positionnel
- 4) Mécanismes d'attention
- 5) Softmax vers la sortie
- 6) Rince et répète *pour chaque mot*

1) Tokenization

- Word2vec permet de trouver des encastrements au niveau des mots. D'autres algorithmes d'intégration les trouvent à un niveau plus fin, pour les segments de mots, la ponctuation, etc. (cette méthode est plus générale, il est difficile de traiter la ponctuation par le biais des intégrations de mots).

1) Tokenization

- Aujourd'hui, les principaux modèles utilisent des enchâssements de jetons, par exemple, « doesn’t » sera composé de deux jetons, « does » et « n’t ».
- «.» sera son propre jeton, etc

2) Vectorisation

- Nous commençons par des représentations simples de chaque token, par exemple des vecteurs «one-hot» (un vecteur de la forme [0,0,0,0,1,0,0,00], avec un emplacement pour chaque token du vocabulaire).

- Nous appliquons ensuite un algorithme de vectorisation (déjà entraîné) pour rappeler le vectorisation de ce jeton.

- Nous allons maintenant commencer à modifier le vectorisation de défaut pour gérer le contexte

3) Encodage positionnel

- Tout d'abord, nous devons saisir le fait que l'ordre a de l'importance.

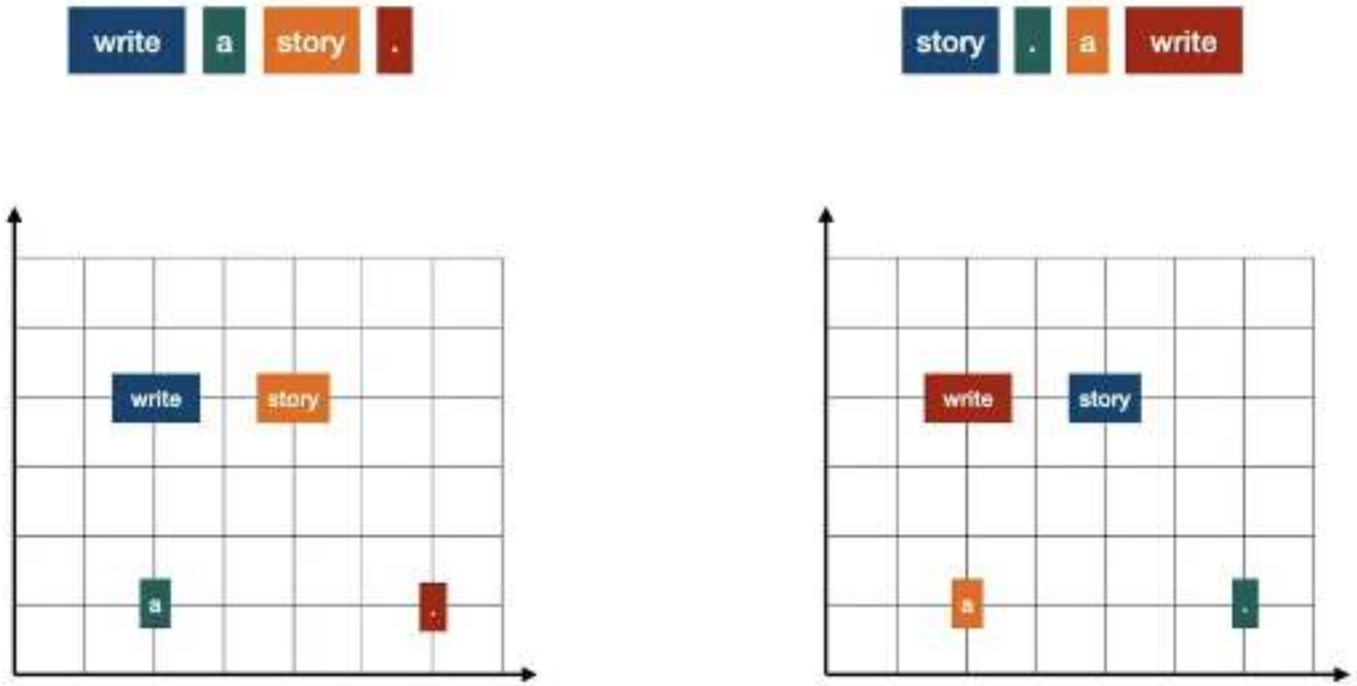
- Les réseaux neuronaux récurrents disposent d'un mécanisme pour ce faire (mais il s'est avéré moins efficace pour les séquences plus longues)

- Les transformateurs utilisent le codage positionnel : en fait, ils indexent chaque élément de la séquence avec un numéro, par exemple 1) j’ 2) ai 3) faim, qui sera différent de 1) faim 2) ai 3) je

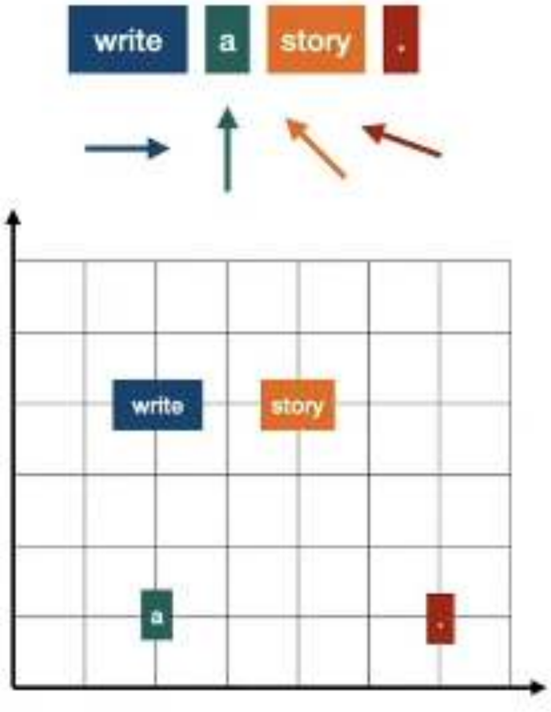
3) Encodage positionnel

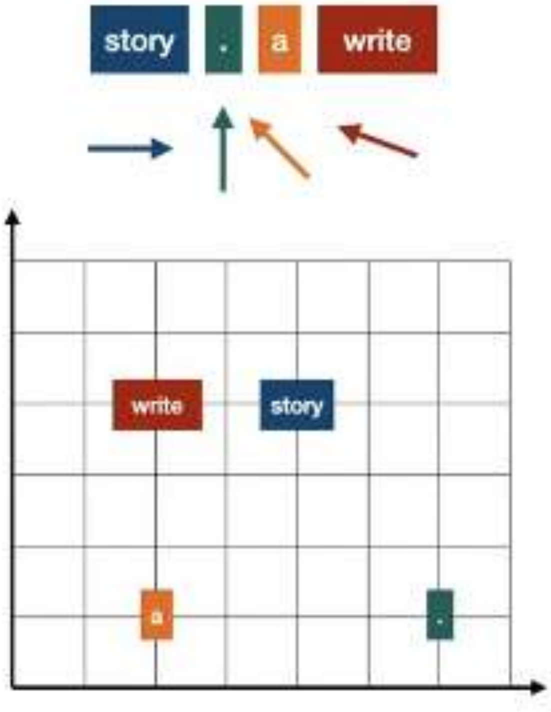
- En fait, tu le fais par une première modification de l'intégration : au lieu d'un index avec des nombres, il s'agit d'un index avec des directions.

Positional encoding



Positional encoding





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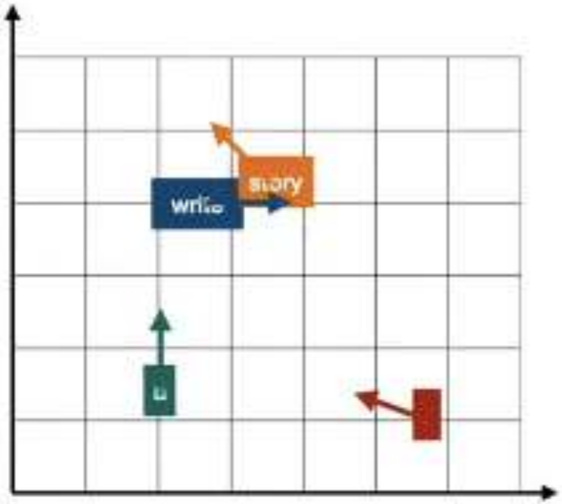
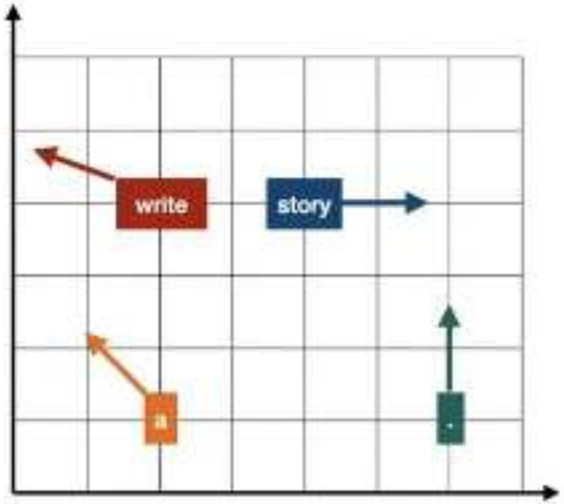
Positional encoding

write a story .

story . a write





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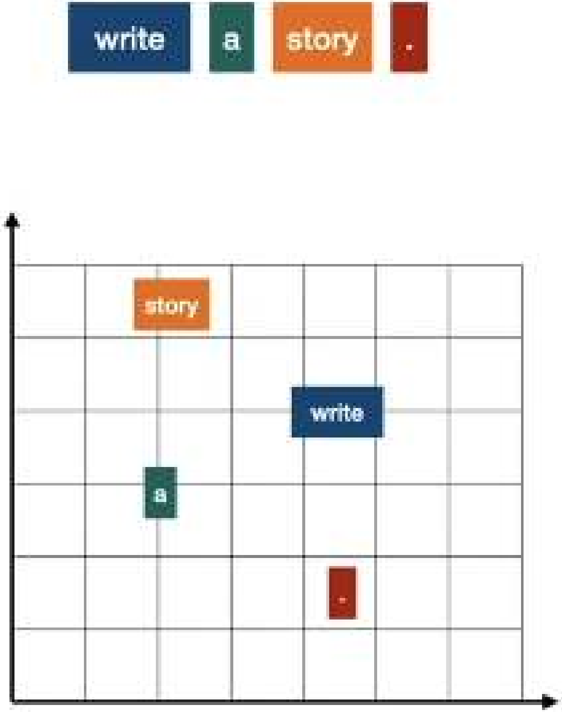
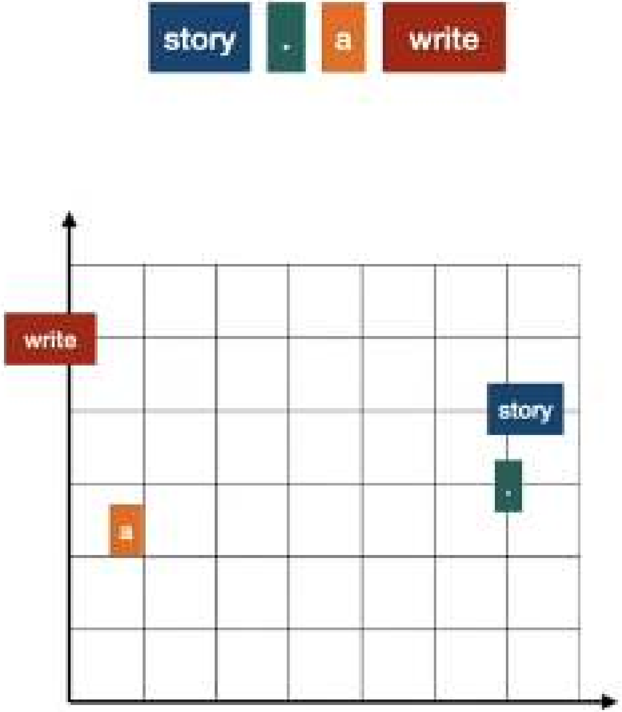
Positional encoding





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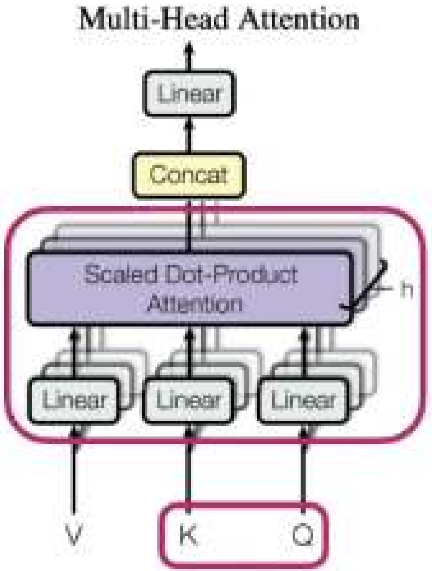
4) Attention

- Ainsi, lorsque le mécanisme attentionnel reçoit l'entrée, les enregistrements ont déjà été modifiés...
- Le mécanisme agit ensuite sur ces encastrements modifiés en position, comme nous l'avons vu plus haut.
- Le processus peut être itéré : imagine plusieurs pas de temps d'un système dans un champ gravitationnel.

Multi-head attention



$$\mathrm{MultiHead}(Q,K,V) = \mathrm{Concat}(\mathrm{head}_1, ..., \mathrm{head}_h)W^O$$
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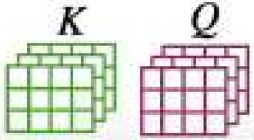
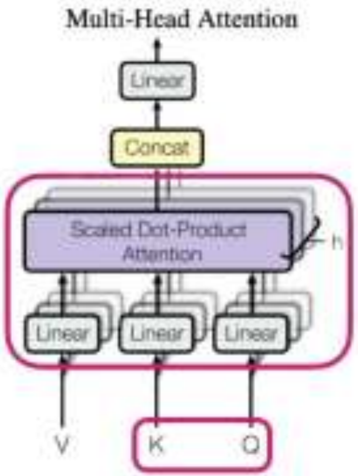


Multi-head attention



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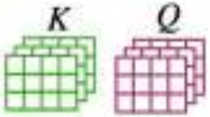

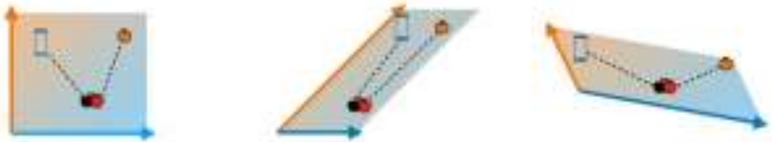

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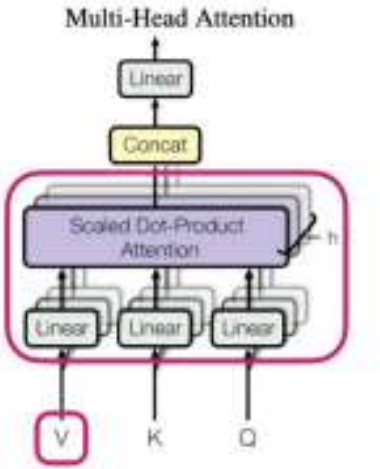
Multi-head attention



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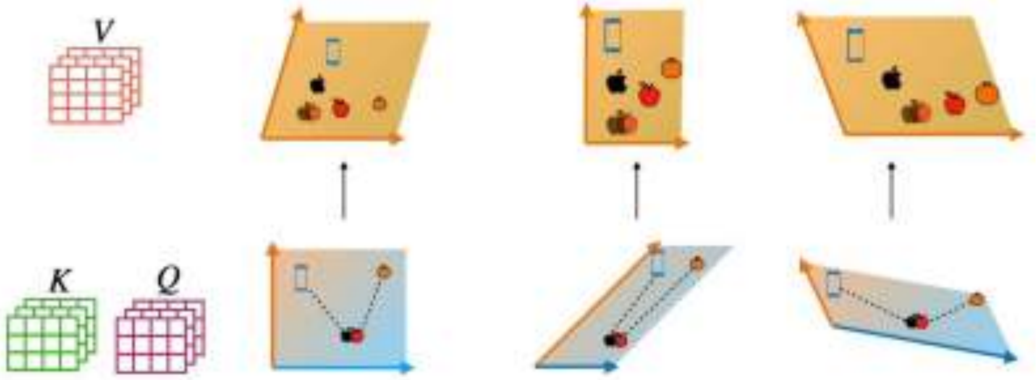

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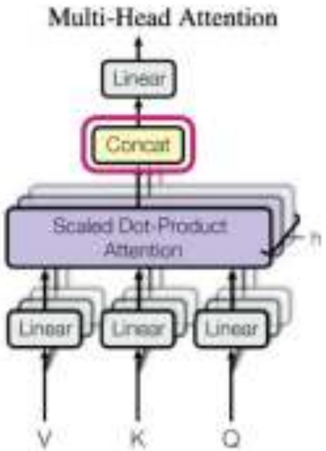
Multi-head attention



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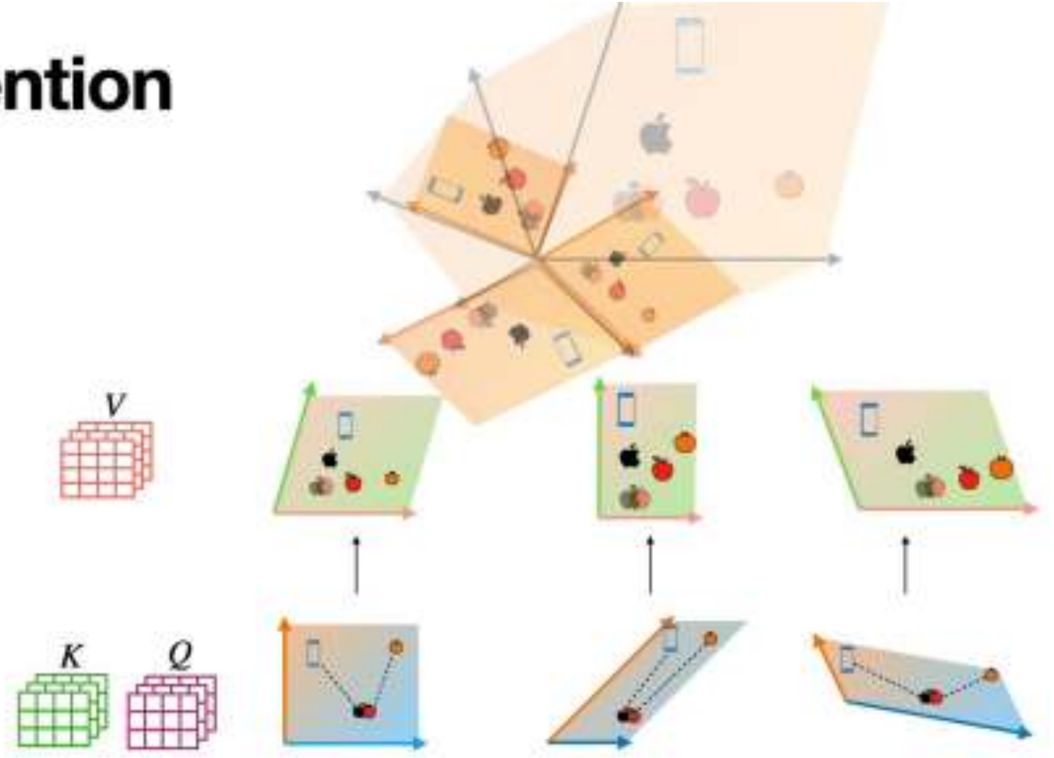

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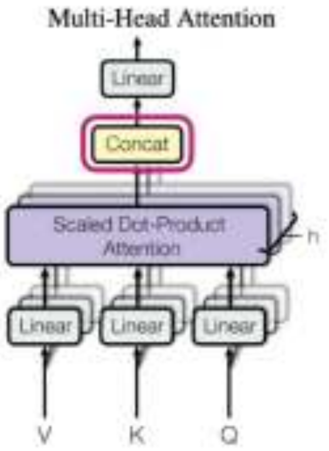
Multi-head attention



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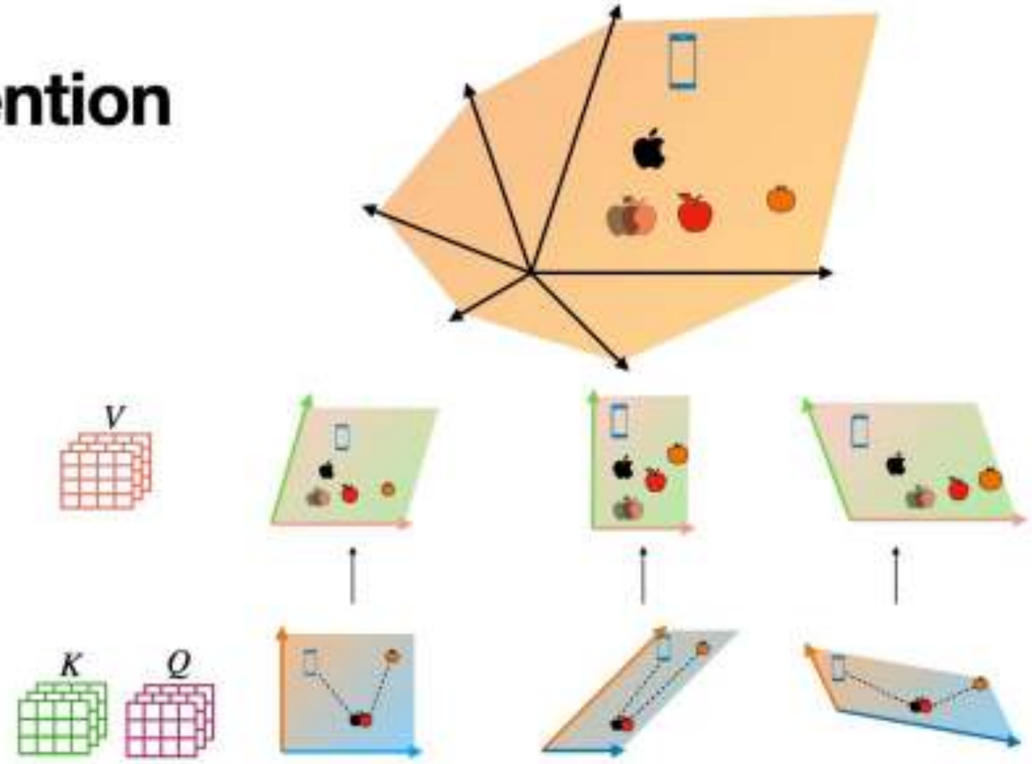
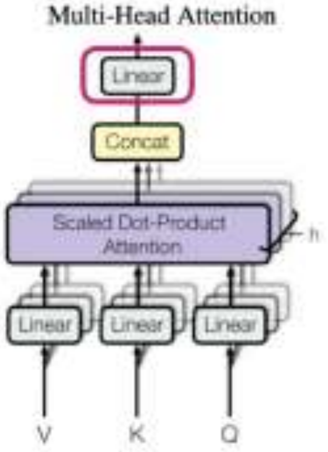


Multi-head attention



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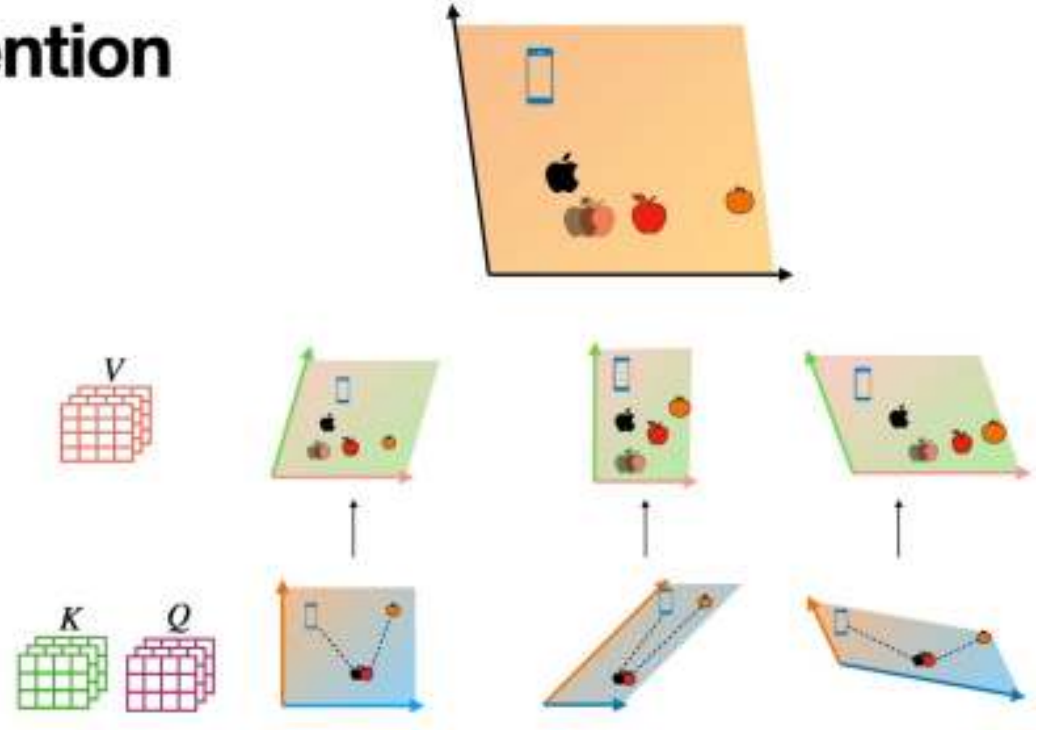

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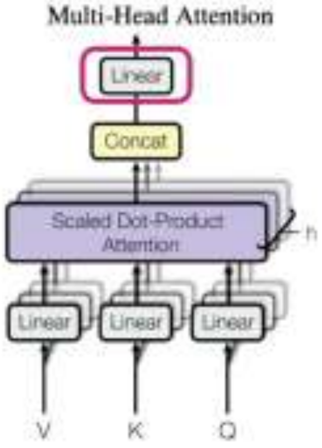
Multi-head attention



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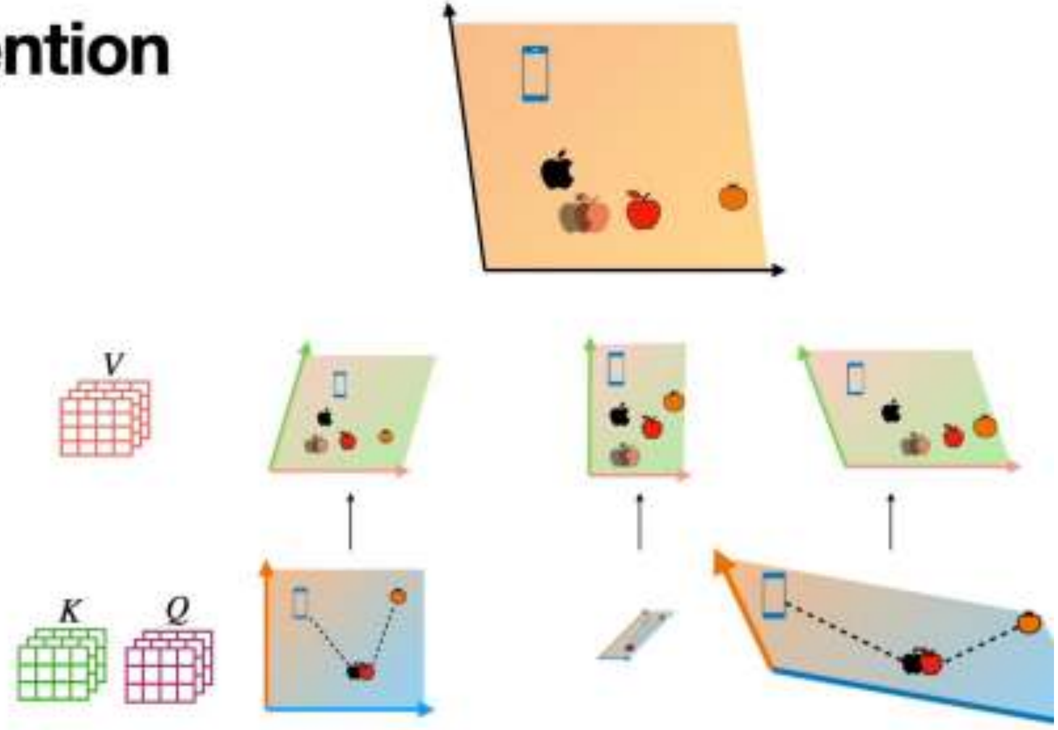

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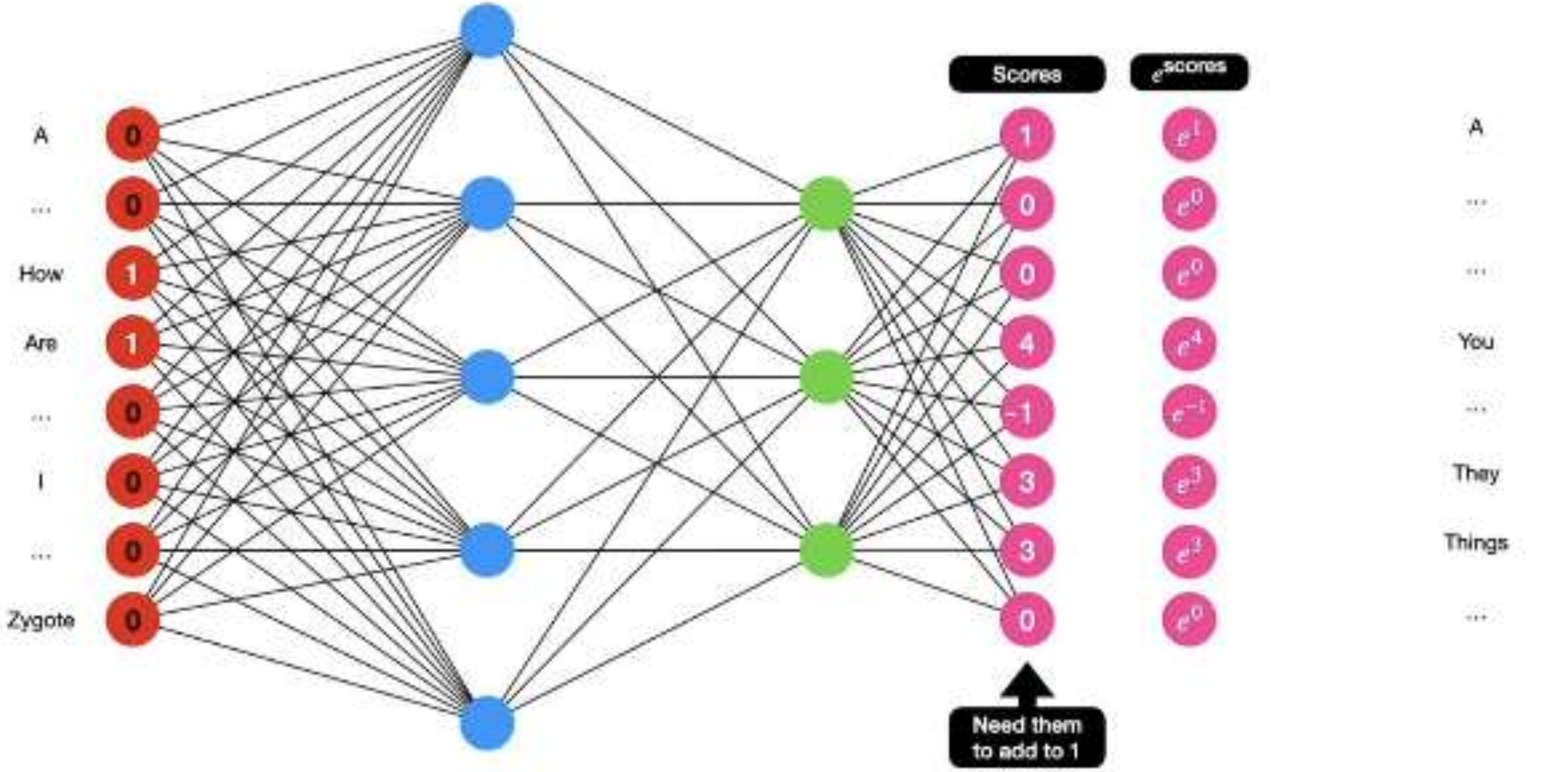
5) Softmax

- Enfin, le système émettra des scores, plus il est positif plus il pense que ce mot est approprié, plus il est négatif plus il pense que ce mot est inapproprié
- Tu veux normaliser ces données en probabilités : softmax est un bon moyen de le faire.



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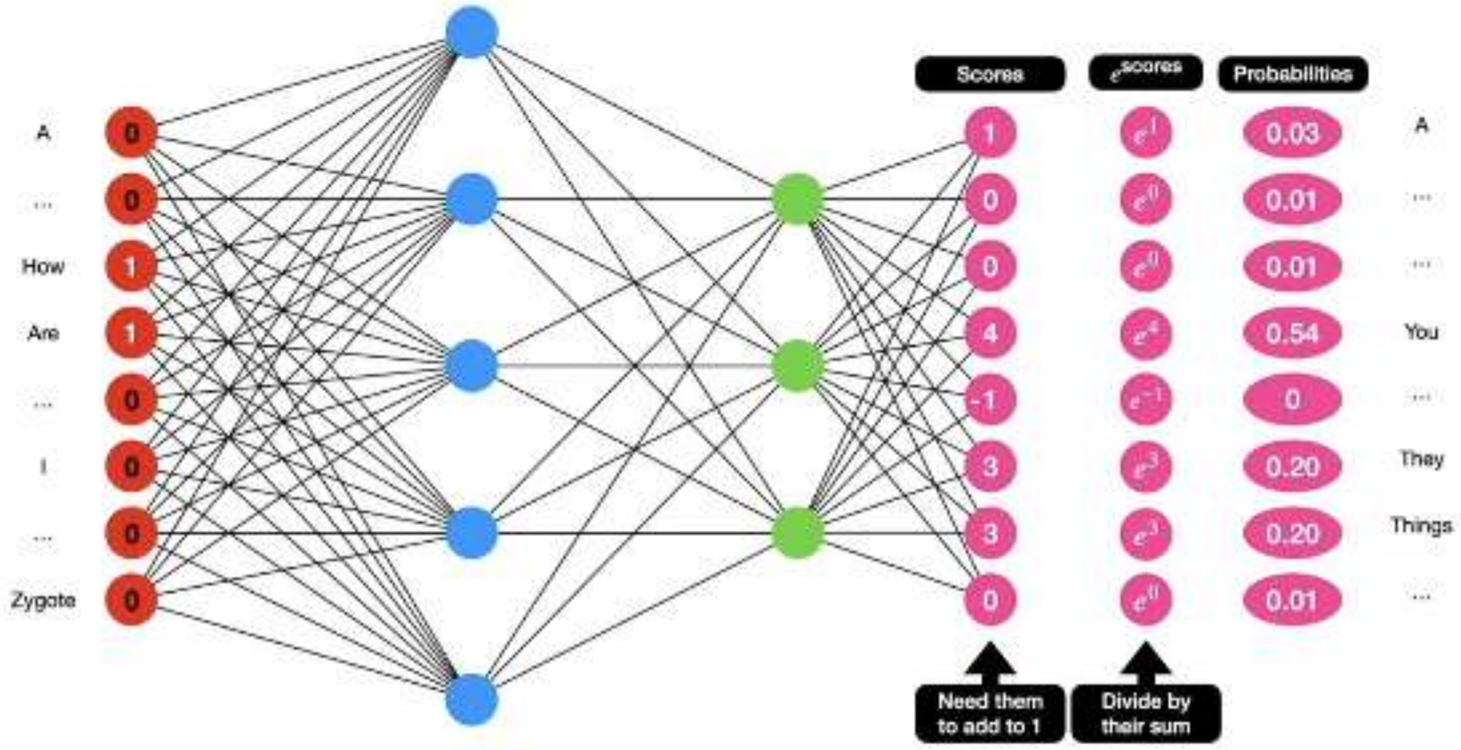

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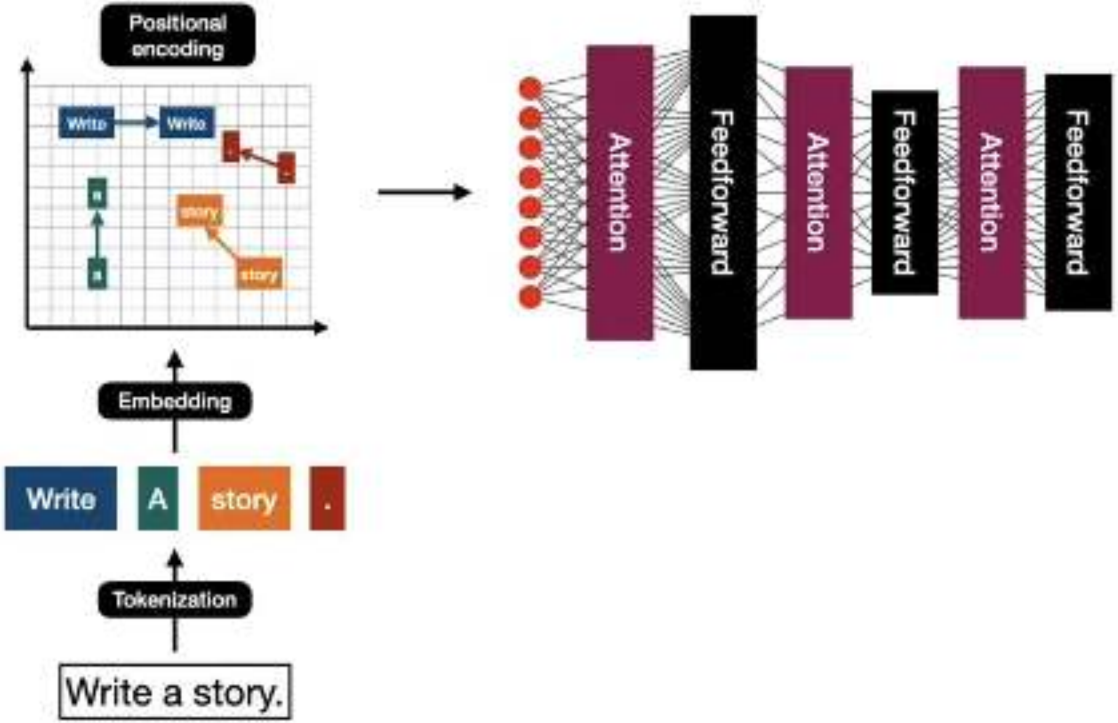
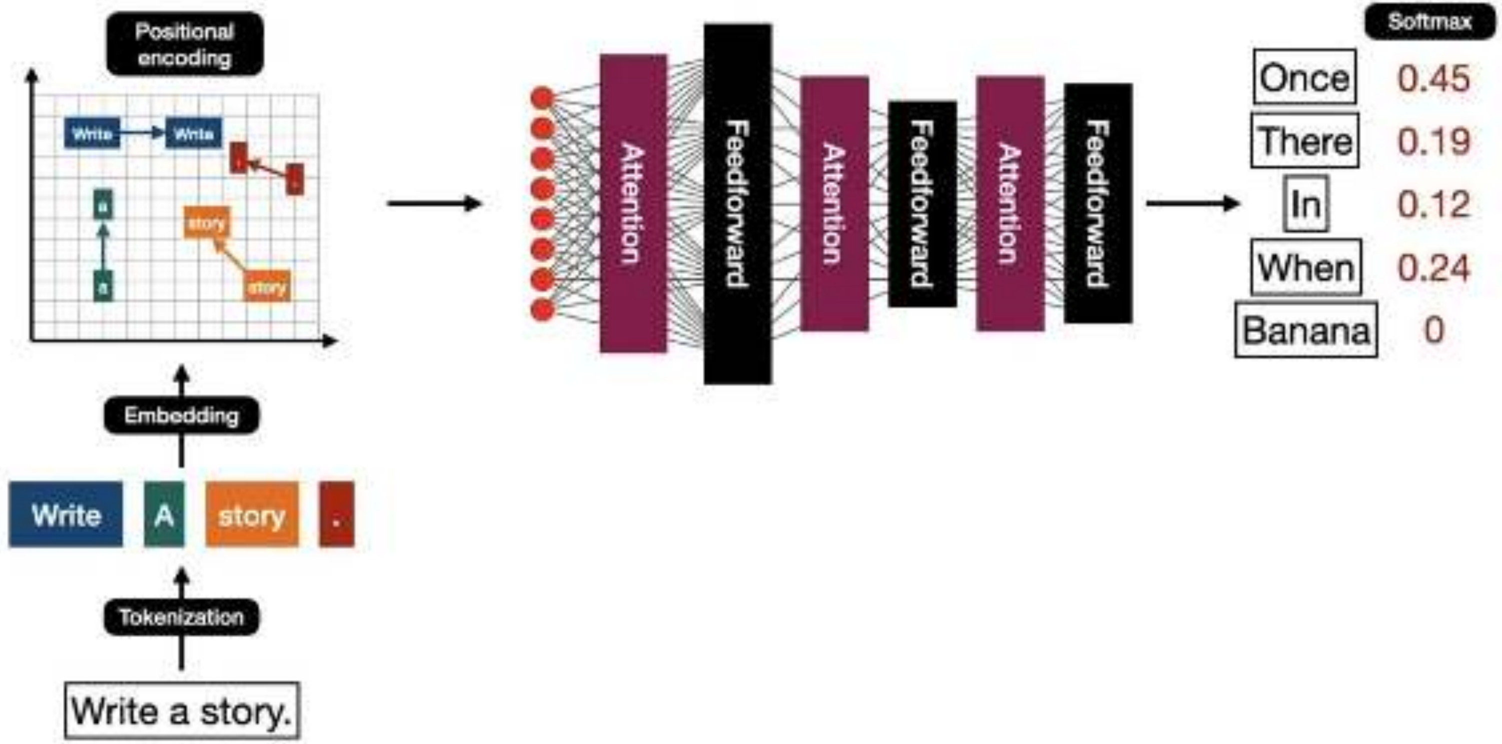
Tout ensemble:


Positional encoding
Write
Write
story
story
Embedding
Write
A
story
.
Tokenization
Write a story.
Attention
Feedforward
Attention
Feedforward
Attention
Feedforward



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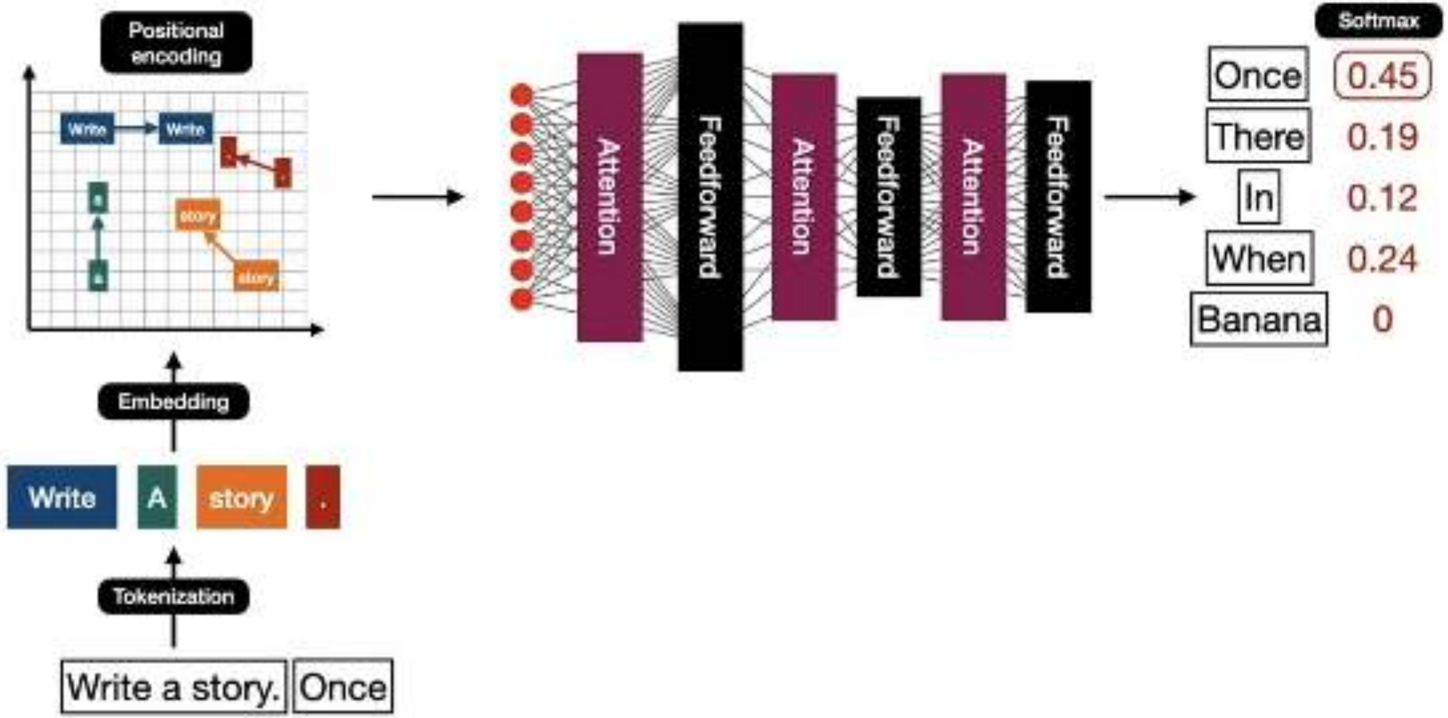

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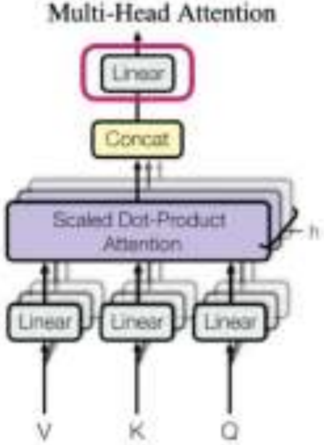
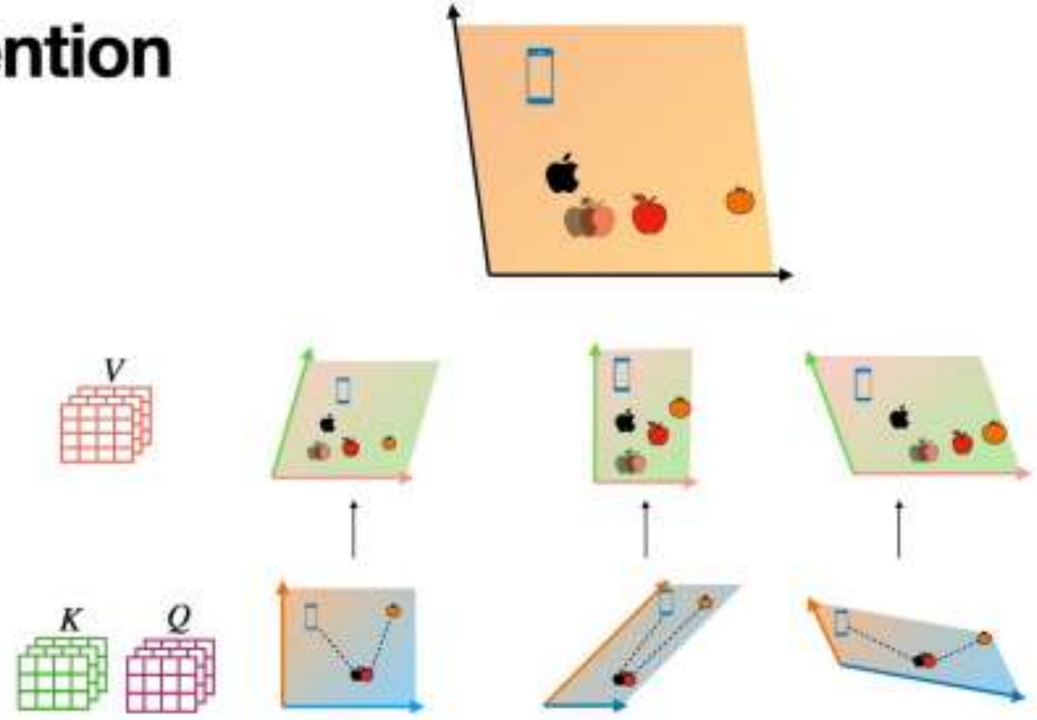
Entrainement / Apprentissage

- 1) Pre-training (la parti génératif)

Multi-head attention



$$\mathrm{MultiHead}(Q,K,V) = \mathrm{Concat}(\mathrm{head}_1, \ldots, \mathrm{head}_h)W^O$$
$$\text{where } \mathrm{head}_i = \mathrm{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$



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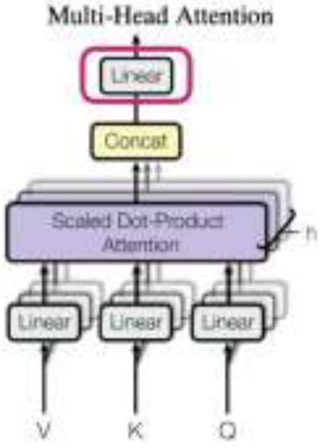
Multi-head attention



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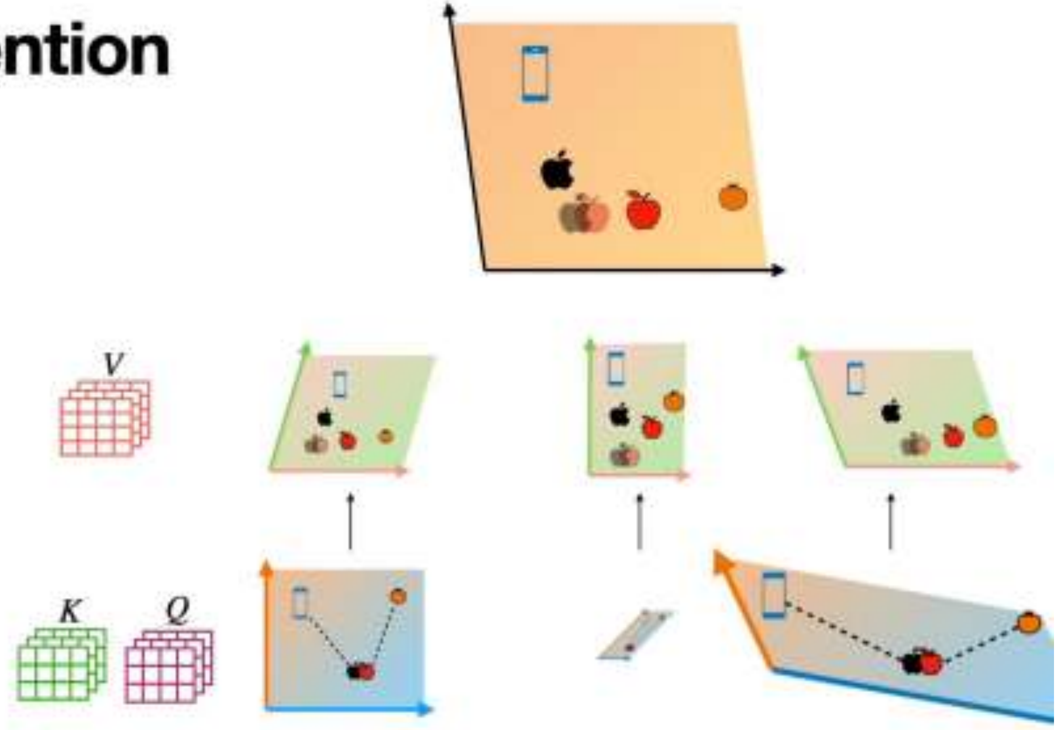


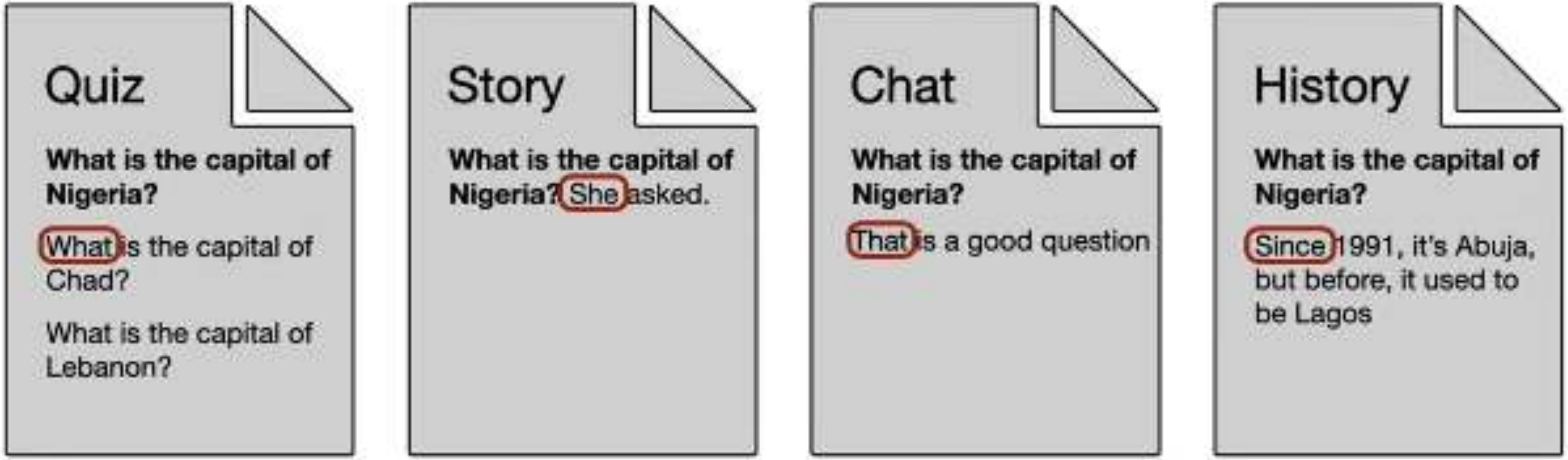
Luis Serrano

Entrainement / Apprentissage

- 2) Fine-tuning (étapes d'apprentissage supervisé ou par renforcement après pre-training

The internet is not a question/answer repository

What is the capital of Nigeria? Abuja



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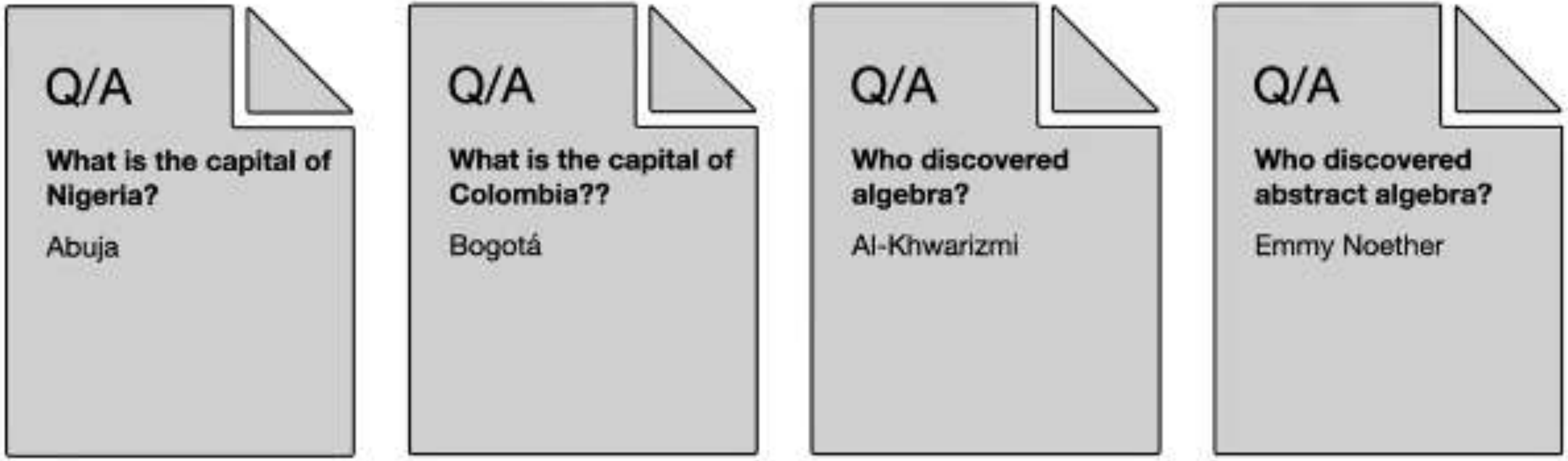
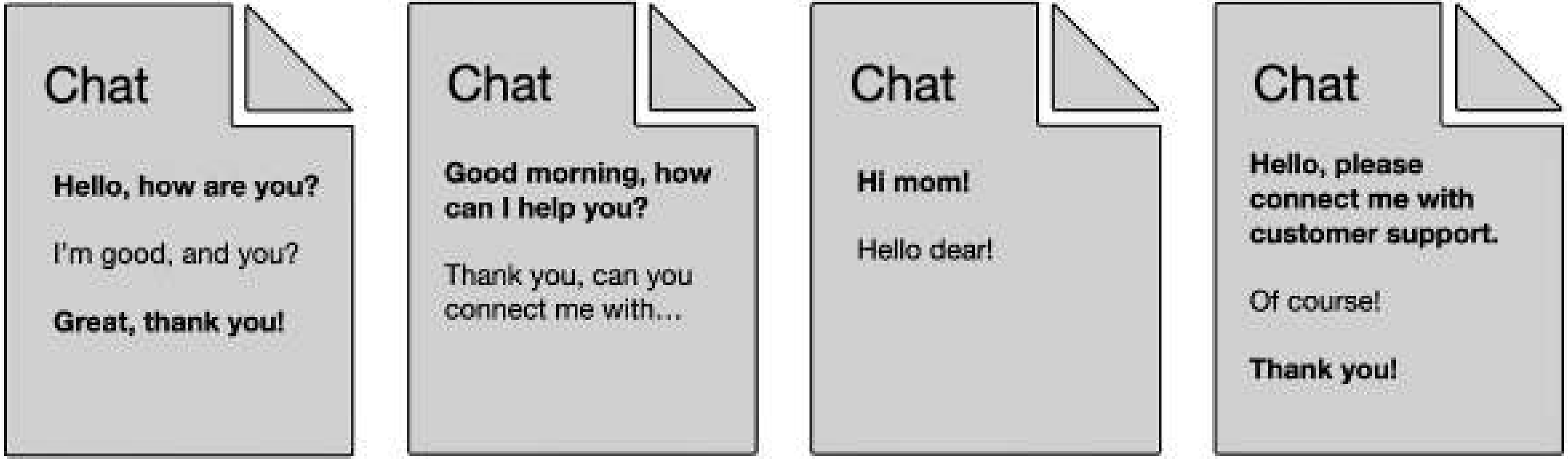
Solution: Post-train it with Q/A datasets

What is the capital of Nigeria? Abuja



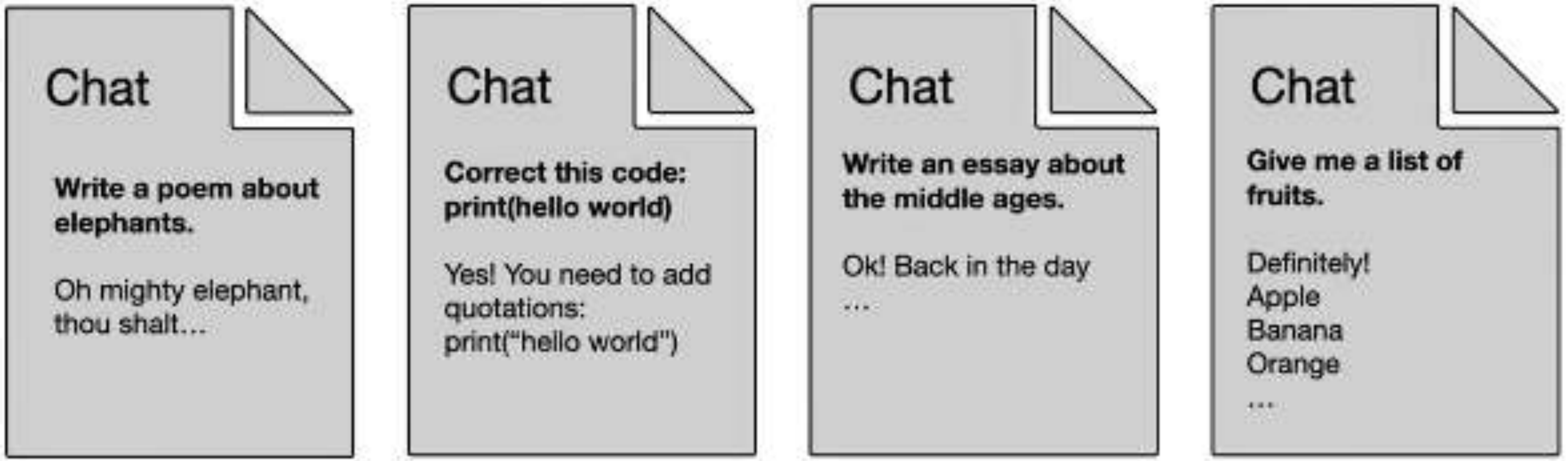
For chat: Post-train it with chats

Hello, how are you?
Good, and you?
...



For commands: Post-train it with command/action pairs

Do this!
Ok, boss!



Capacités émergentes

- **Neurons responding to specific words which are split into multiple tokens:** "Bank|ing", "word|ing", "Ch|olesterol", "Libert|arian", "Civil|ian", "Sh|anghai", "Not|withstanding"...
- **Neurons responding to the names of famous people:** "Martin| Luther| King", "Donald| Trump", "Lyndon| Johnson", "George| Orwell", "Ernest| Hemingway", "Muhammad| Ali", "Oprah| Winfrey"... (cf. [17])
- **Neurons responding to other nouns:** "Human| Rights| Watch", "International| Monetary| Fund", "Hurricane| Matthew", "Real| Madrid"...
- **Neurons responding to compound words:** "book| club", "social| security", "computer| vision", "organized| crime", "birthday| party", "heart| attack"...
- **Neurons responding to LaTeX "\" commands:** "\|left", "\|frac|{", "\|begin"...

Elhage et al 2022

A huge variety of interesting neurons can be found in these layers. Some common categories we observed include:

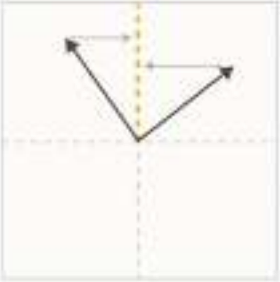
- **Neurons which fire on particular types of descriptive clauses:** a neuron which fires on a clause describing a sound, a neuron for clauses describing clothing, a neuron for musical descriptive clauses (e.g. "in the key of C major"), a neuron for clauses describing text written on an object, ...
- **Neurons which respond to discourse markers:** a neuron which responds to markers emphasizing the importance of something (e.g. "the amazing thing is"), a neuron which responds to hedging (e.g. "it seems to me that..."), ...
- **Neurons which disambiguate a special interpretation of a token:** a neuron which responds to A/B/C/D when used as grades, a neuron which responds to the "day" portion of a date, a neuron which responds to numbers when they're a quantity in a recipe, a neuron which responds to C-style format specifiers (e.g. "%s" or "%d") in strings, ...

Elhage et al 2022

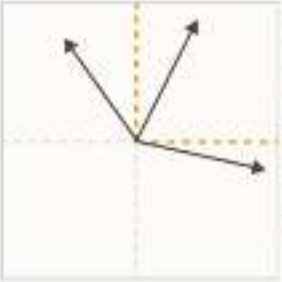
3.4 The Superposition Hypothesis

Roughly, the idea behind the superposition hypothesis is that neural networks "want to represent more features than they have neurons," so they exploit a property of high-dimensional spaces to simulate a model with many more neurons. (Note that as a matter of terminology we use "polysemanticity" to refer to the empirical phenomenon of neurons responding to multiple features, and "superposition" to refer to the hypothesis described here.)

If true, the superposition hypothesis means there is *no basis* in which activations are interpretable: searching for an interpretable basis is fundamentally the wrong framing. Especially important features might get dedicated neurons, but most features don't align with neurons because they need to share and *can't* have a dedicated one.



Polysemanticity is what we'd expect to observe if features were not aligned with a neuron, despite incentives to align with the privileged basis.



In the **superposition hypothesis**, features can't align with the basis because the model embeds more features than there are neurons. Polysemanticity is inevitable if this happens.

Elhage et al 2022

Mais comprennent-ils ?

… mais comprennent-ils?

- (1) Les arguments de Landgrebe et Smith
- (2) La pieuvre encore (Bender et Koller)

… mais comprennent-ils?

- (1) Les arguments de Landgrebe et Smith

- (A) Un mauvais argument
- (B) Un Meilleur argument
- (C) Réponse de Sogaard

… mais comprennent-ils?

- (1) Les arguments de Landgrebe et Smith
- (A) Un mauvais argument

- (P1) La compréhension du langage nécessite une sensibilité au contexte
- (P2) Les modèles d'IA ne sont pas sensibles au contexte ;
- (C) Par conséquent, ils ne comprennent pas le langage

… mais comprennent-ils?

- (1) Les arguments de Landgrebe et Smith
- (B) Un meilleur argument (?)

- (P1) Nos mots ont un sens parce que nous avons des intentions
- (P2) Avoir des intentions nécessite (a) d'avoir des états mentaux et (b) d'avoir un corps ou des représentations non linguistiques *ou quelque chose (?)*
- (P3) Les LLM n'ont pas d'états mentaux, de corps *ou quoi que ce soit (?)*
- (C) Donc, les mots des LLM n’ont pas de sens

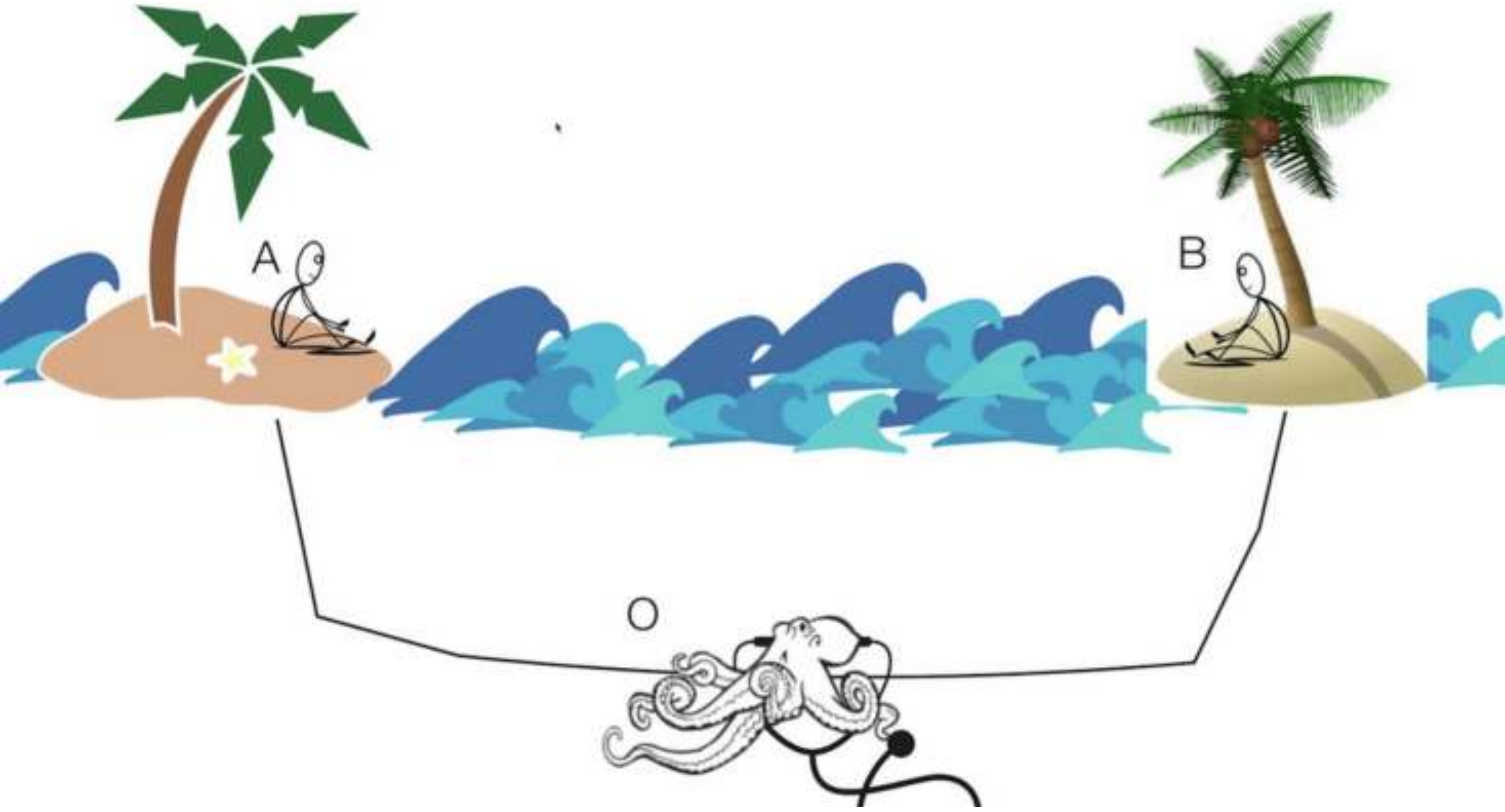
… mais comprennent-ils?

- (1) Les arguments de Landgrebe et Smith
- (C) Réponse de Sogaard

- .. Le *but* des mécanismes attentionnels est de gérer le contexte
- Parce que l'hypothèse distributionnelle est vraie, la structure de leur sémantique inférentielle est isomorphe à la structure qu'un ensemble de représentations mentalistes, incarnées et fondées sur le réel pourrait avoir...

Ancrage sensoriel

- Bender et Koller 2020:

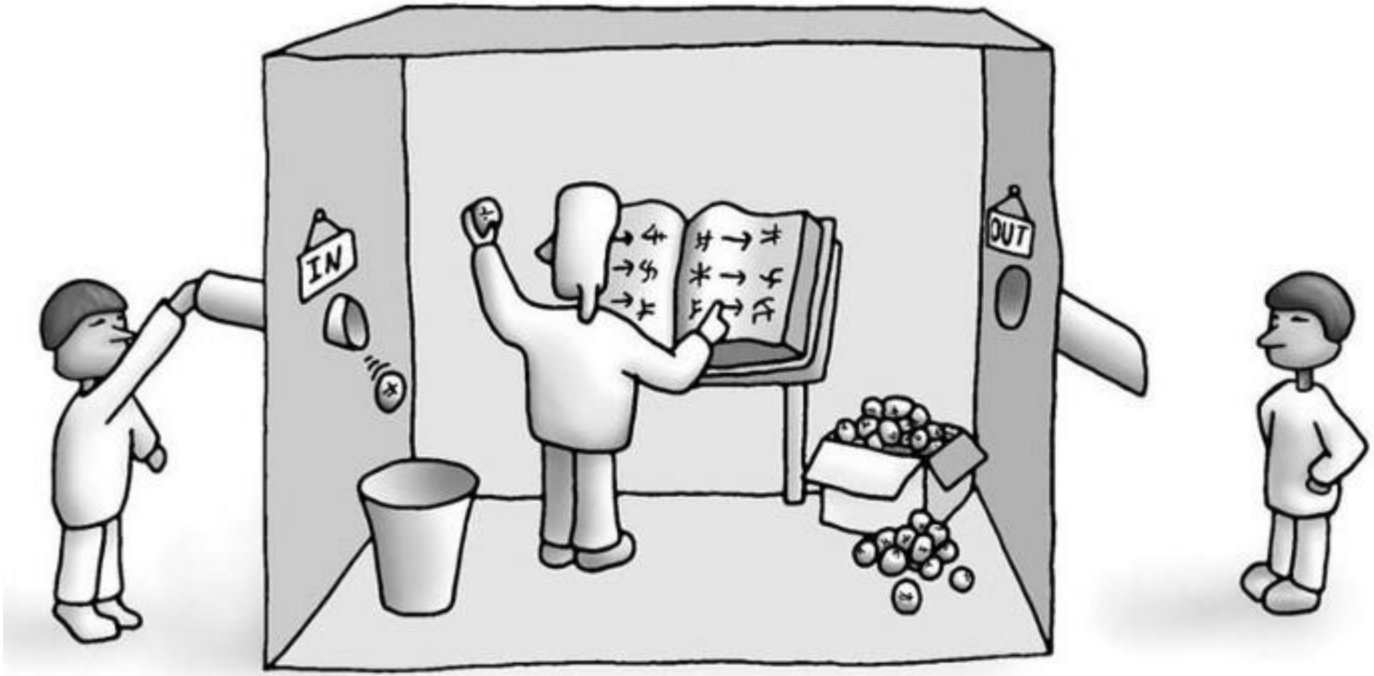

A
B
O

La pieuvre

- (P1) La pieuvre peut mettre en œuvre le même algorithme qu'un LLM
- (P2) Si (1), alors si le LLM comprend ce qu'il dit, la pieuvre le comprend aussi
- (P3) La pieuvre ne comprend pas ce qu'elle dit
- (C) Par conséquent, le LLM ne comprend pas ce qu'il dit

Ancrage sensoriel

- À comparer avec Searle (1980):


IN
OUT

Searle vs La Pieuvre

- Notez que l'argument de la pieuvre peut être plus fort - la réponse des systèmes concède que Searle ne comprend pas, mais après tout, il n'est que le CPU - la question est de savoir si l'ordinateur comprend, et non si le CPU comprend. Cette réponse ne peut pas être tirée ici.

Searle vs La Pieuvre

- Cela dit, la réponse que je préfère à celle de Searle est différente. Elle dit : être un fonctionnaliste computationnel, c'est admettre que la compréhension de Searle peut s'expliquer par un processus algorithmique qu'il met en œuvre. Cependant, tout ce qui émule ce processus ne le met pas nécessairement en œuvre (cf., un émulateur Windows sur un Mac, ou quelque chose qui émule le tri à bulles via le tri par fusion).

- ... Mais pour que cela fonctionne pour la pieuvre, il faut que le processus inclut plus que l'algorithme du Transformer + les poids, mais aussi d'autres détails sur le matériel (hardware)...