UNIVERSITY OF
TORONTO

ORDER-EMBEDDINGS OF IMAGES AND LANGUAGE

Ivan Vendrov, Ryan Kiros, Sanja Fidler, Raquel Urtasun

Semantic Image Search

- Given a database of images and a natural language query, identify which images it accurately describes

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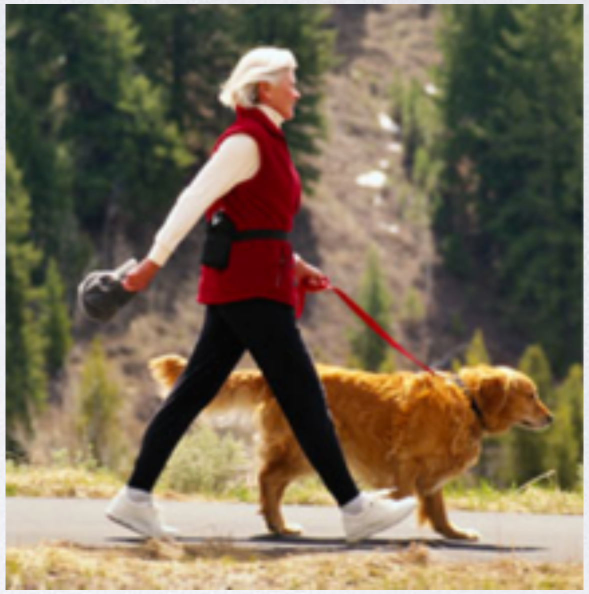

“a woman walking her dog in a park”

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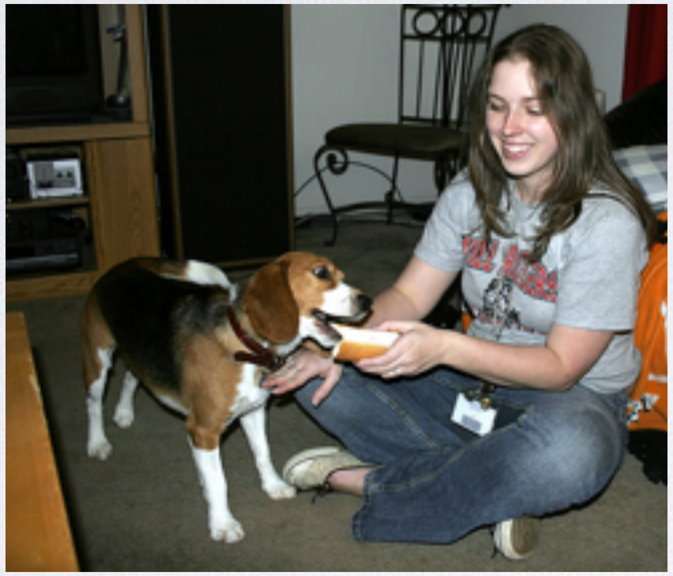

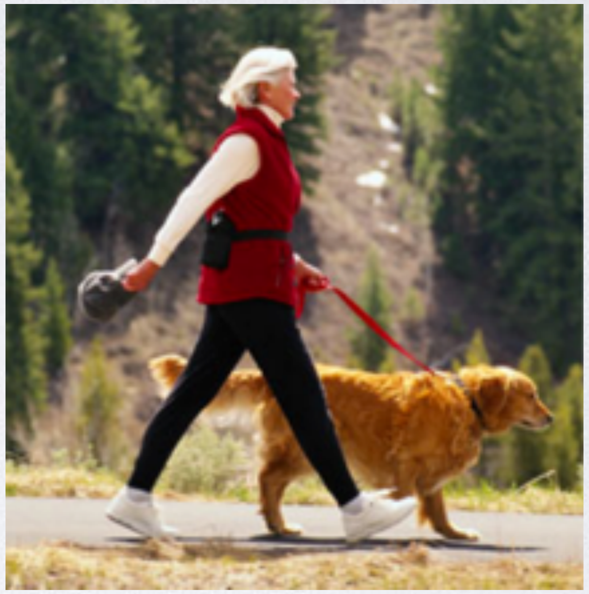

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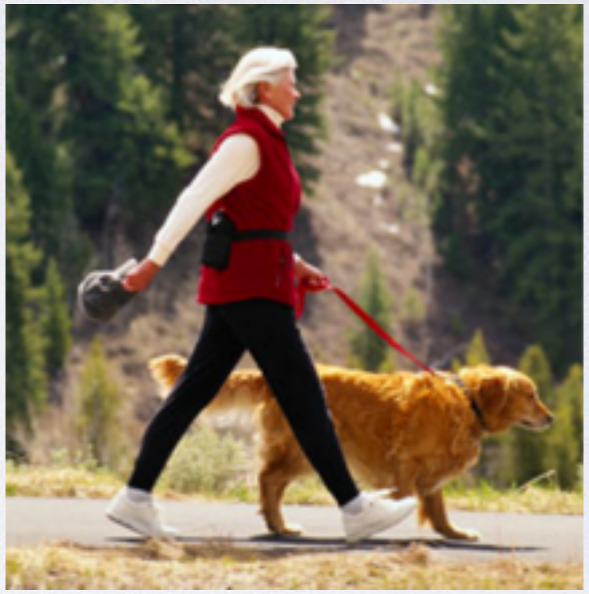
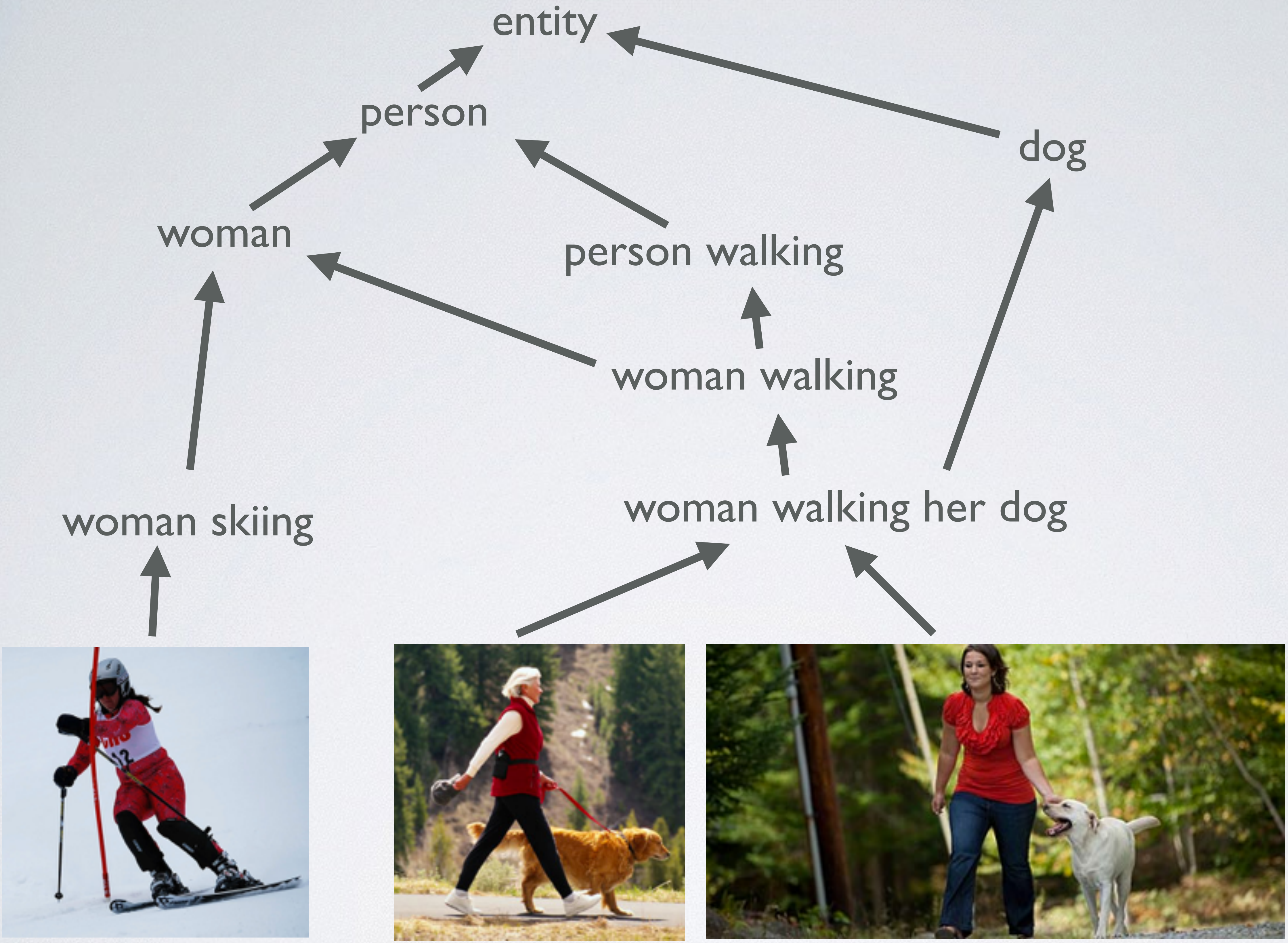


“a woman walking her dog in a park”

What is the relationship between images and the language we use to **describe** them?



entity

person

dog

woman

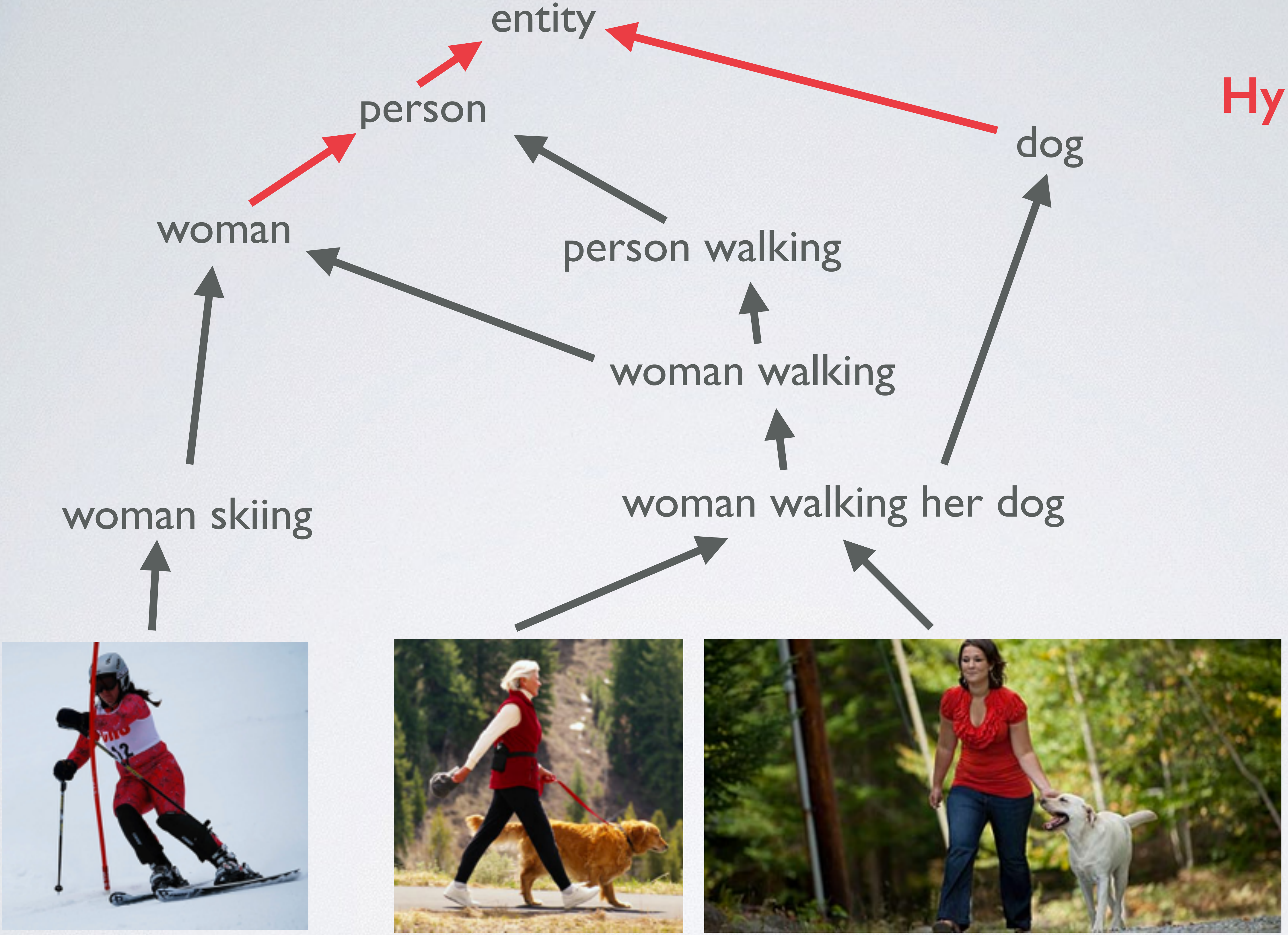
person walking

woman walking

woman skiing

woman walking her dog

Hypernymy



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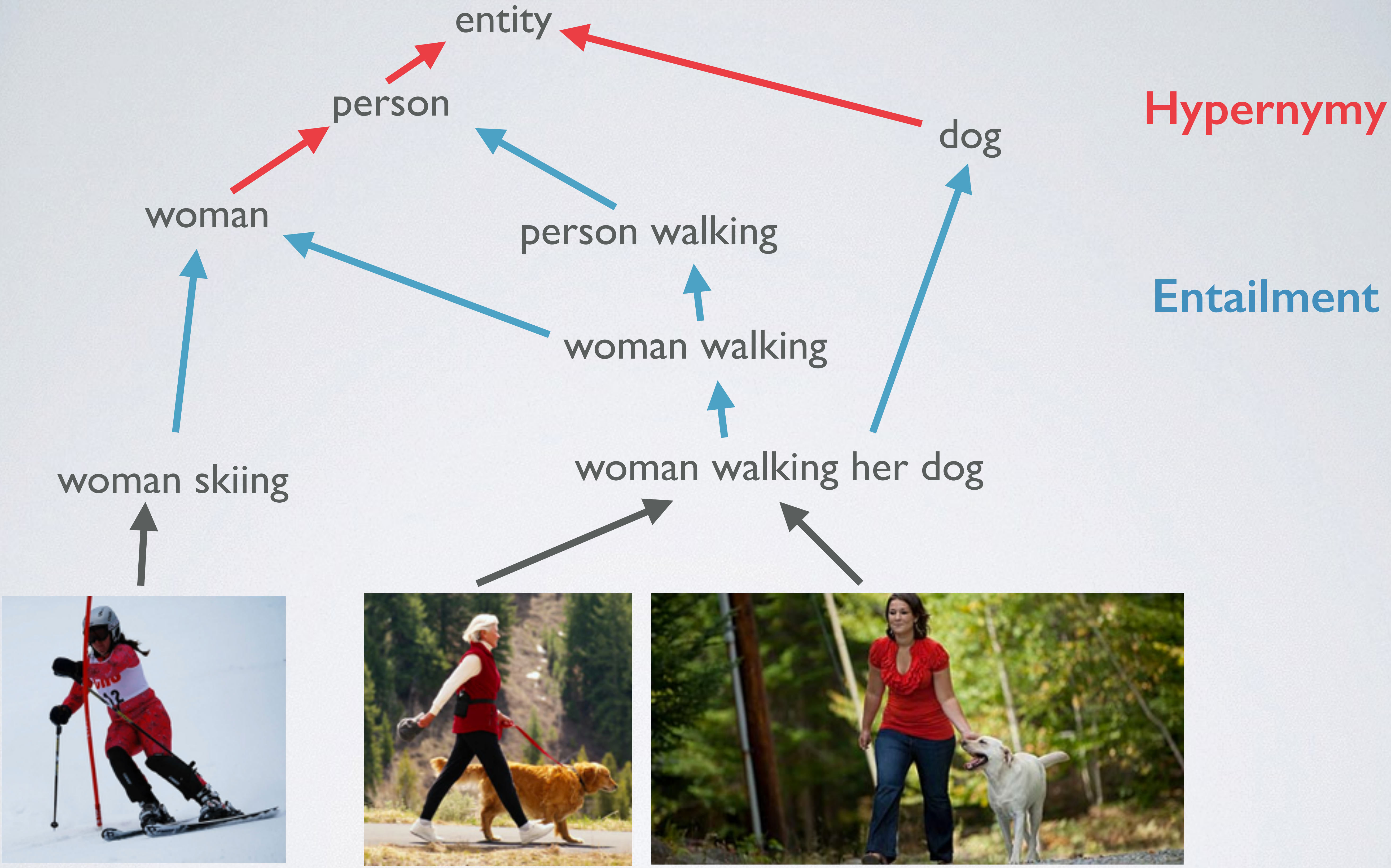

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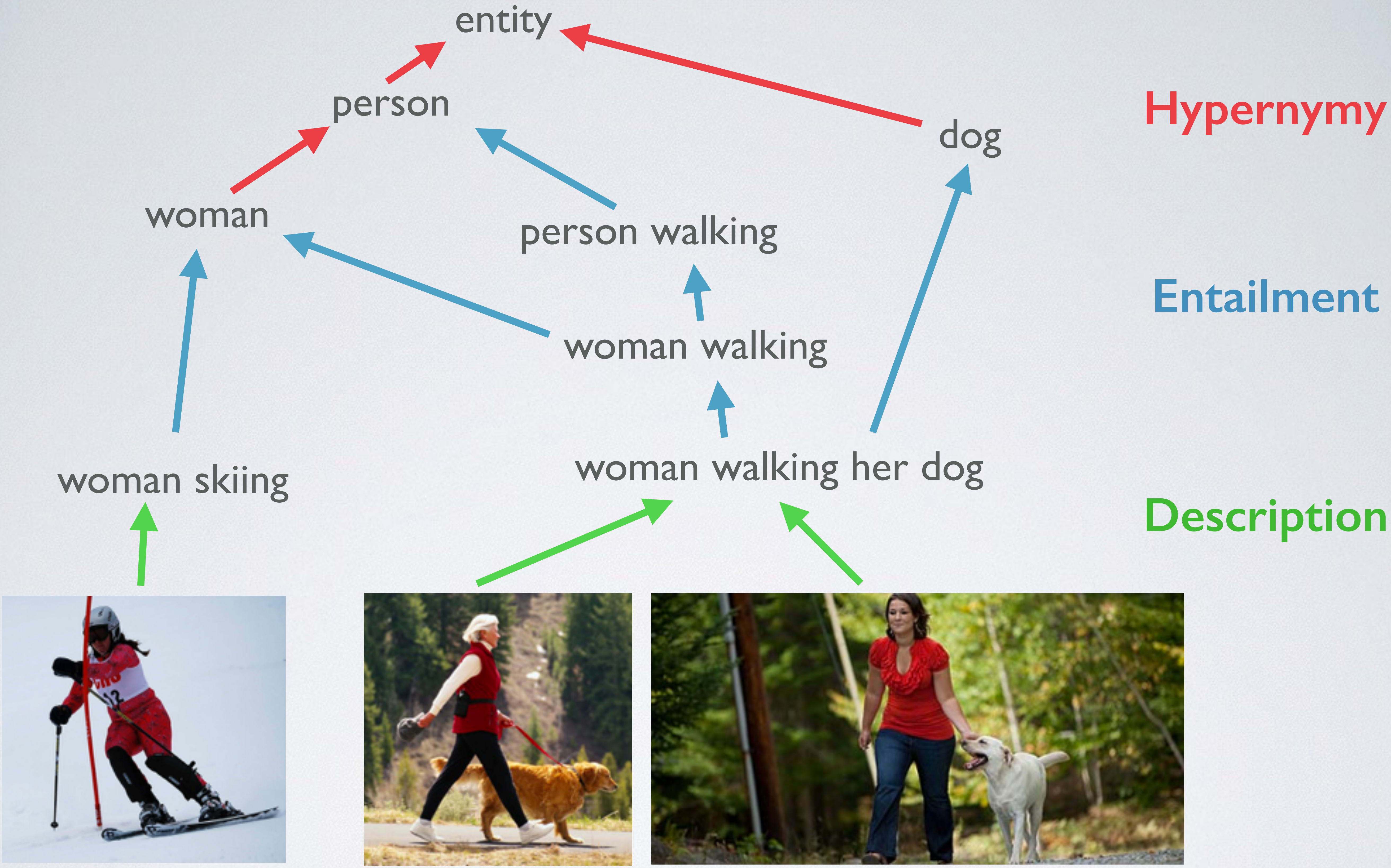

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Description

Modeling the Visual-Semantic Hierarchy

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Our approach:

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Our approach:

- Impose a partial-order prior by embedding into an **ordered** space.

Ordered Embedding Space

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Space: $\mathbb{R}_{+}^{N}$

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Order: $x \preceq y$ if and only if $\forall i, x_i \geq y_i$

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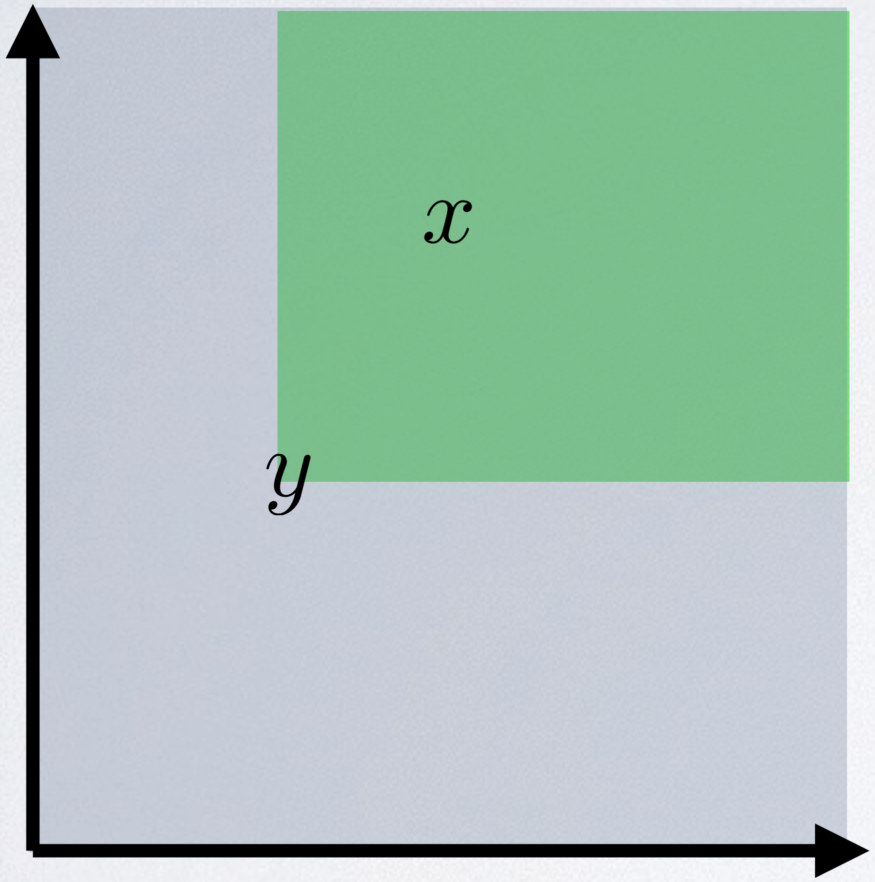

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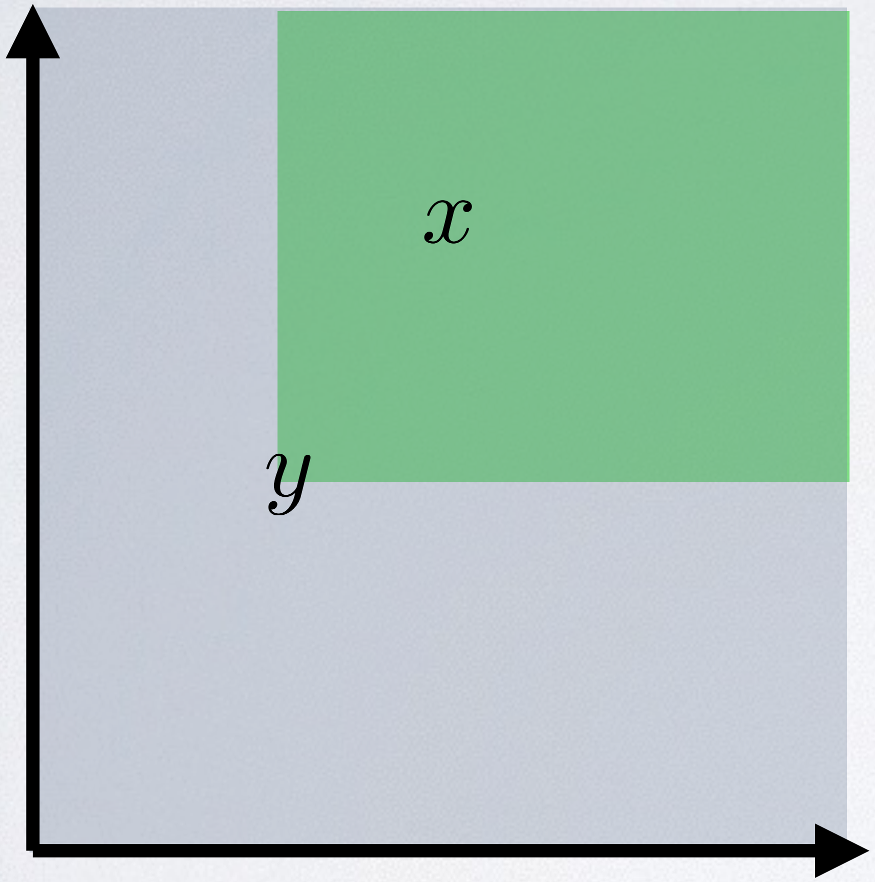
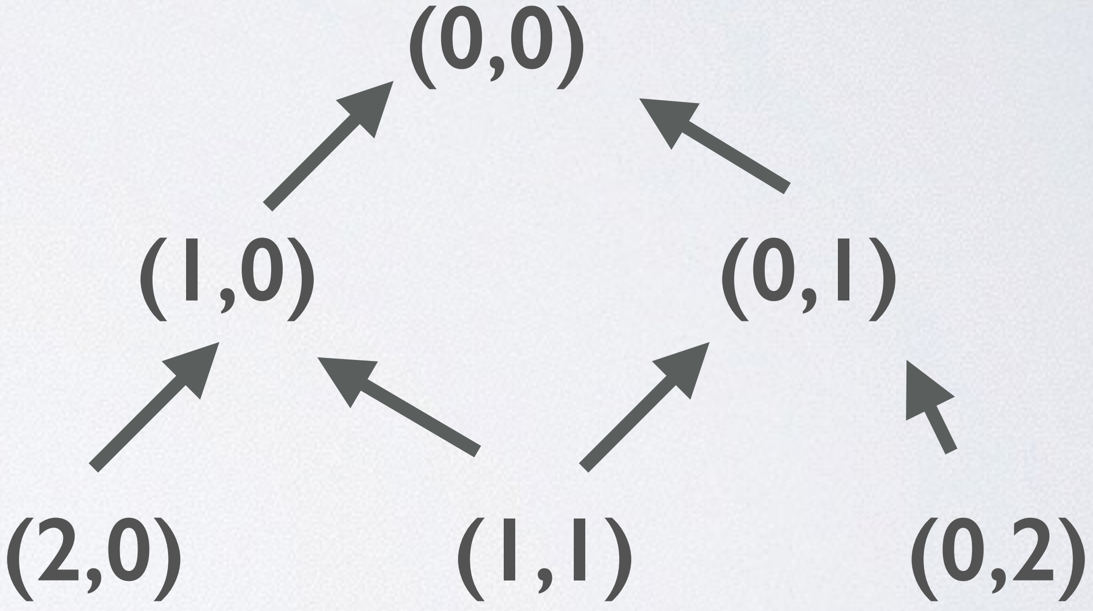



(0,0)

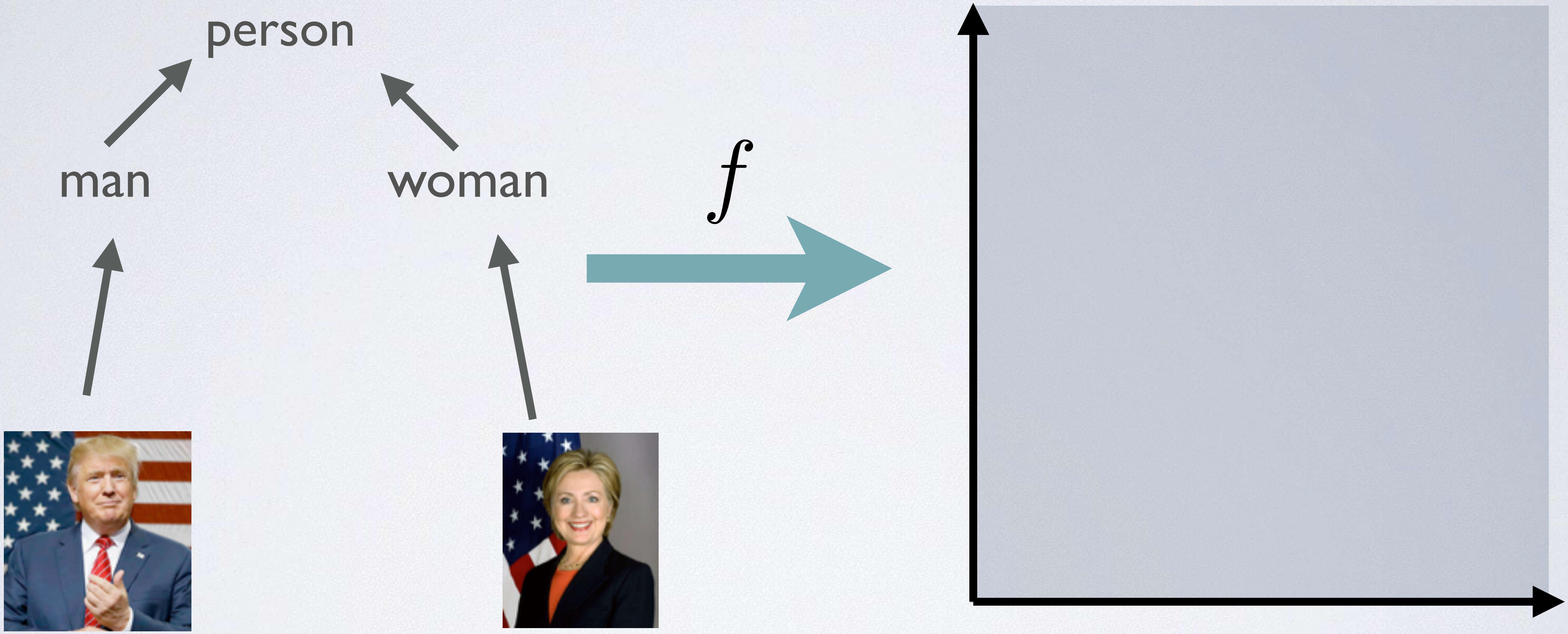
(1,0)

(0,1)

(2,0)

(1,1)

(0,2)



person

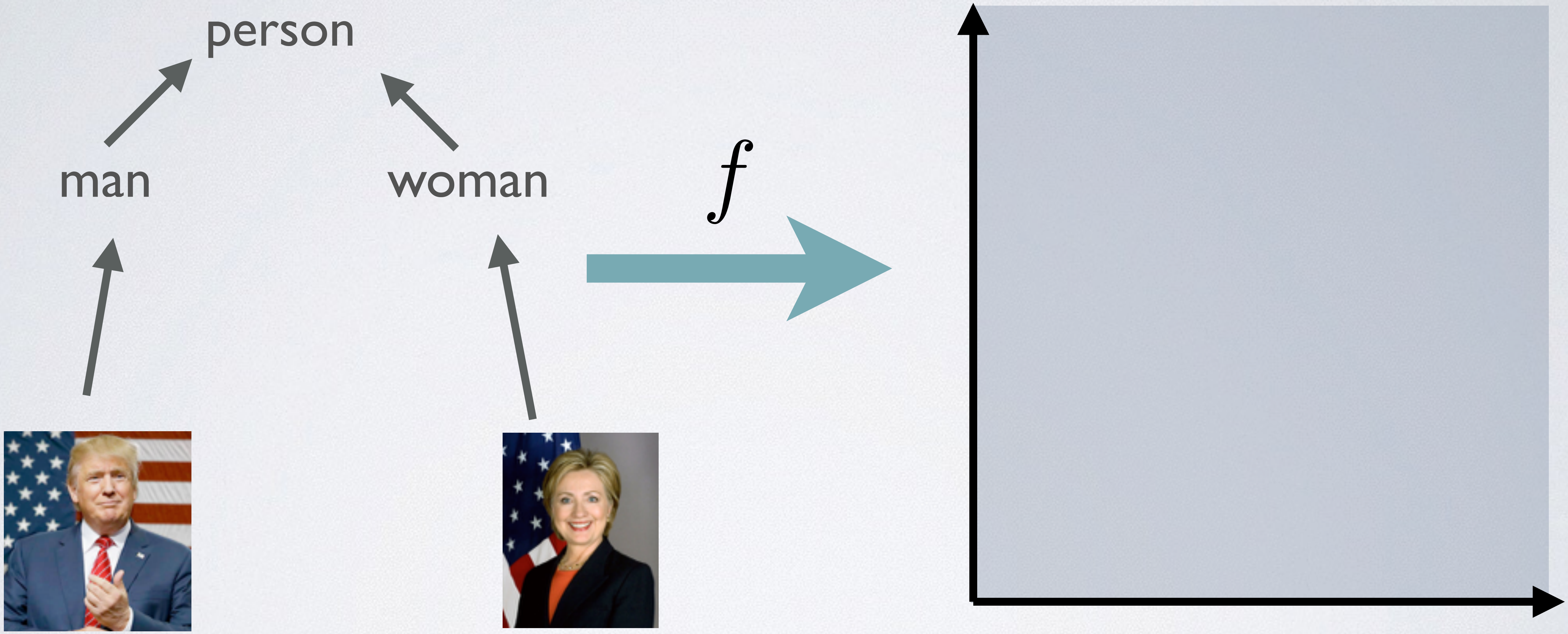
man

woman

f

f is an **order-embedding** if

$$u \preceq v \iff f(u) \preceq f(v)$$



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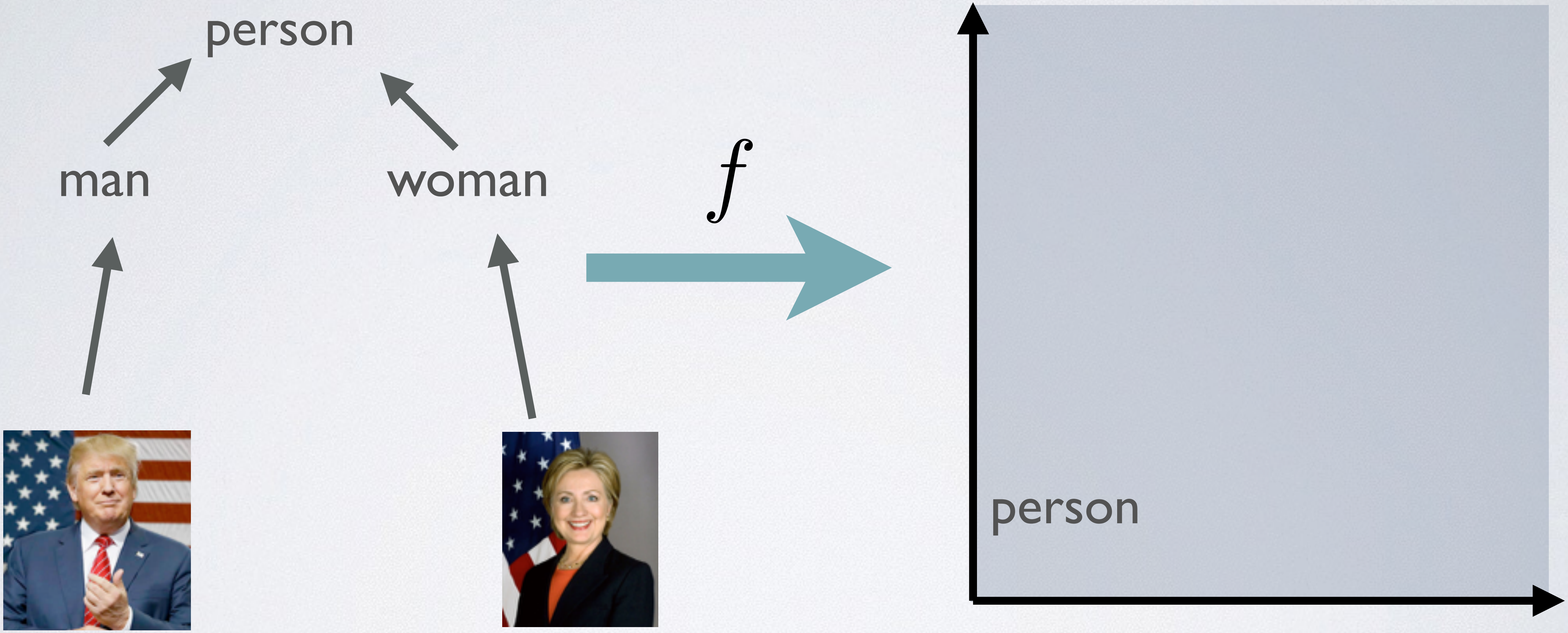

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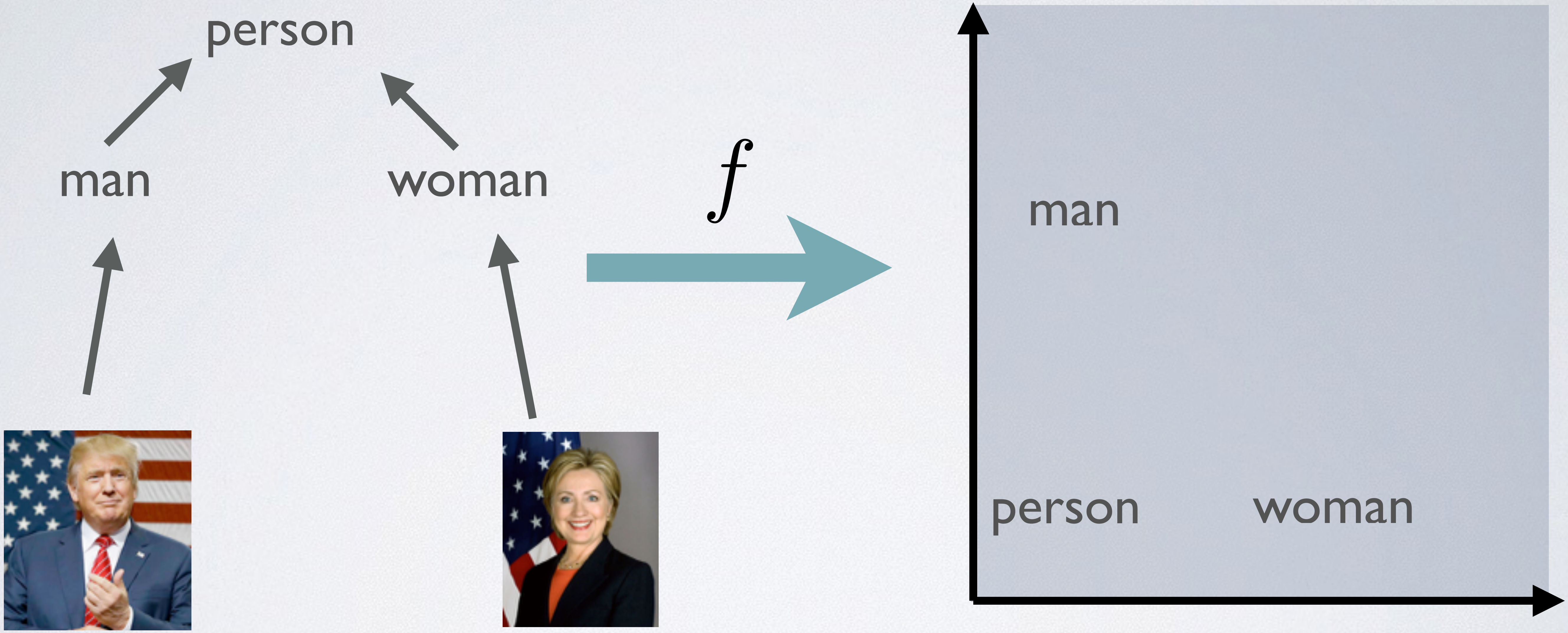

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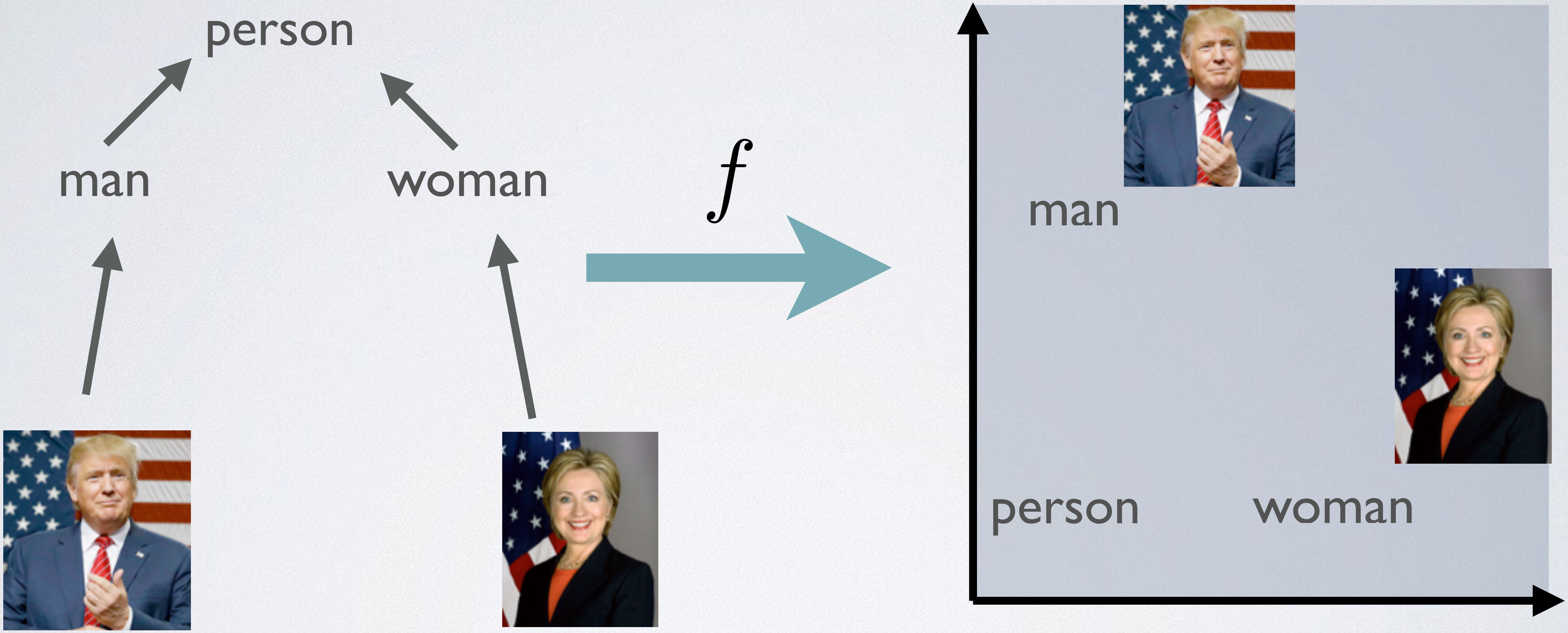

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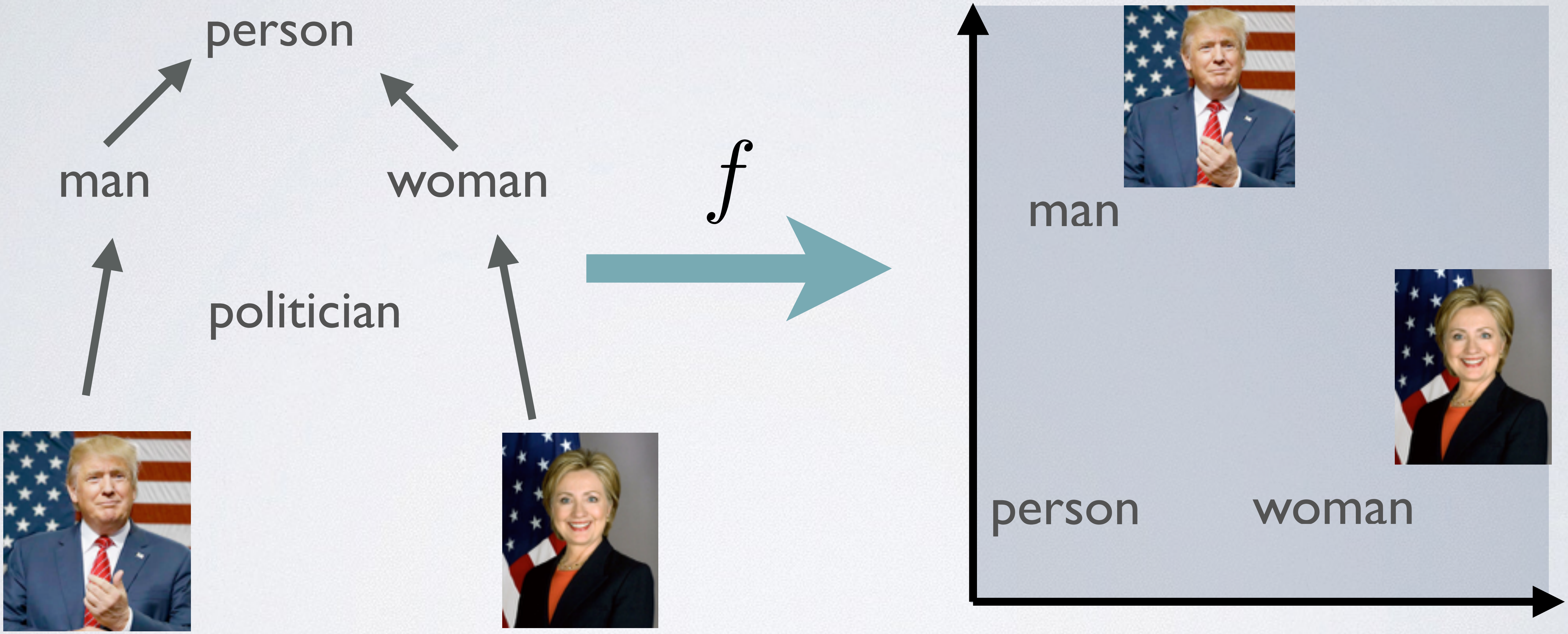

person

man

woman

politician

f

man

person

woman

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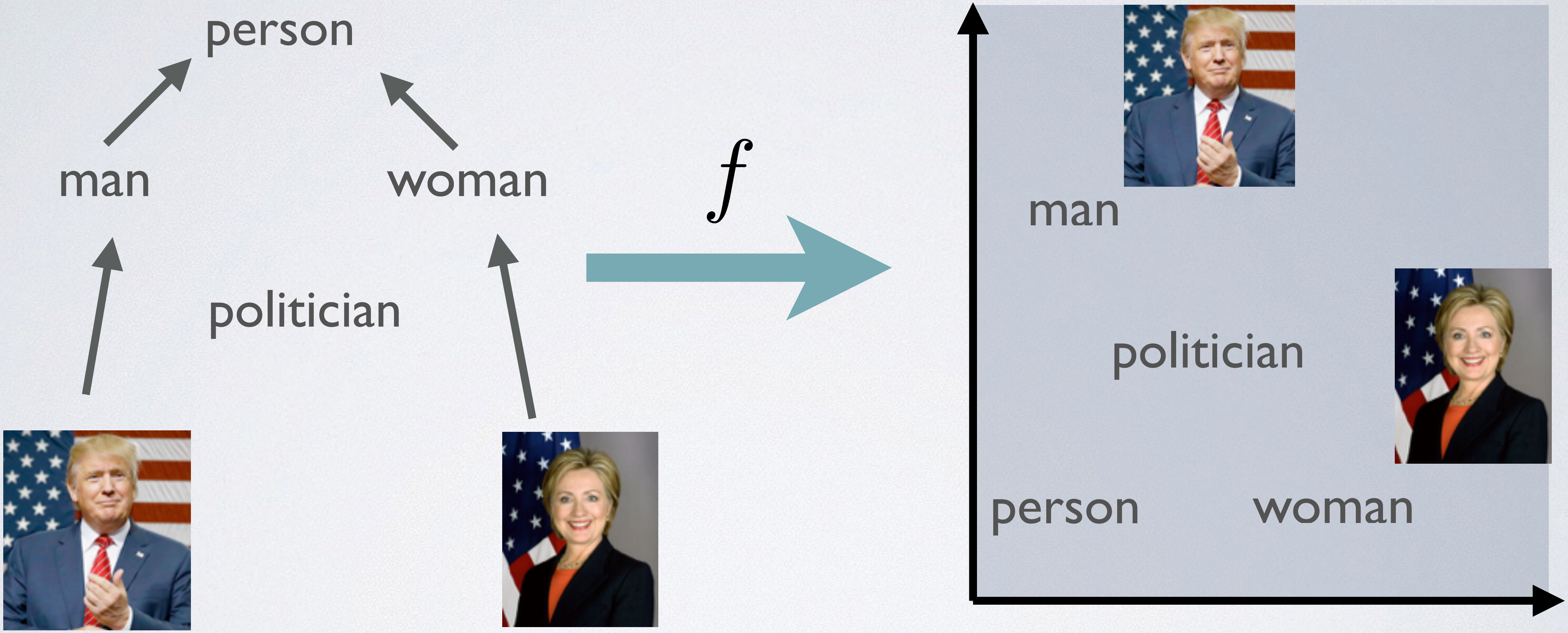

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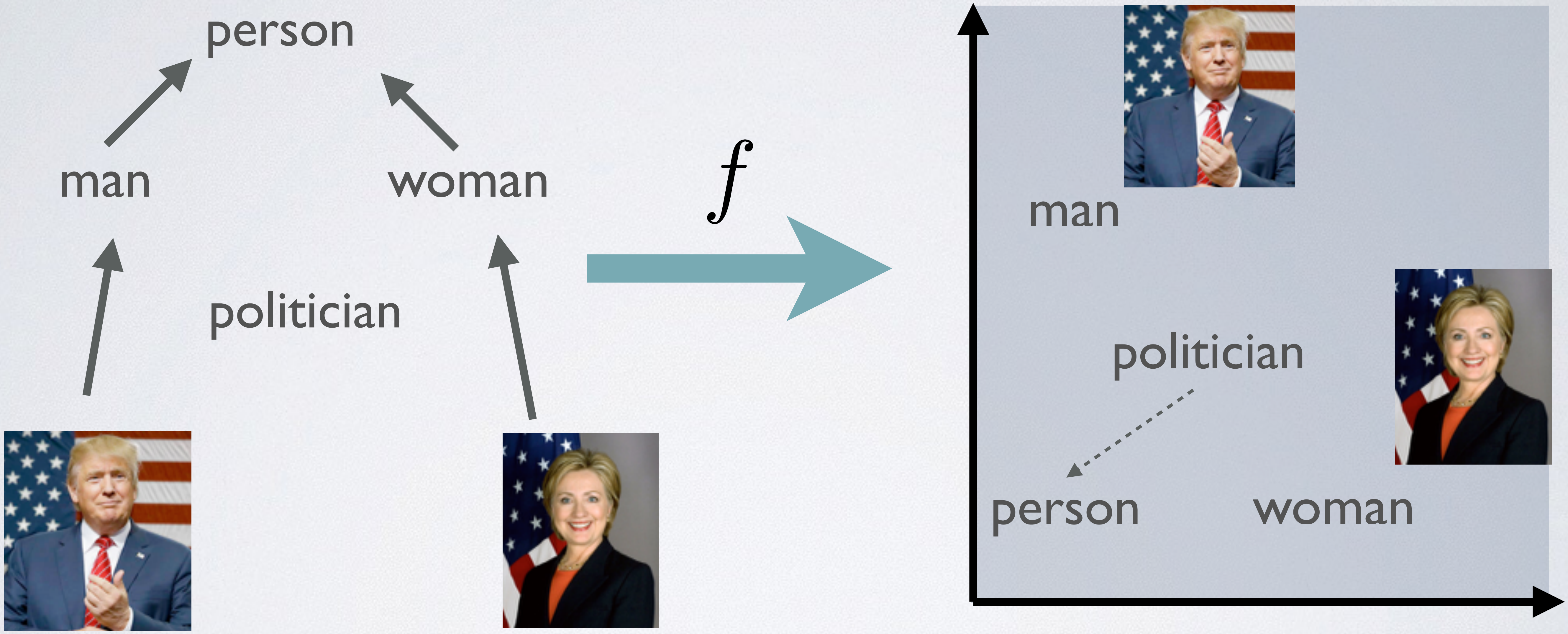

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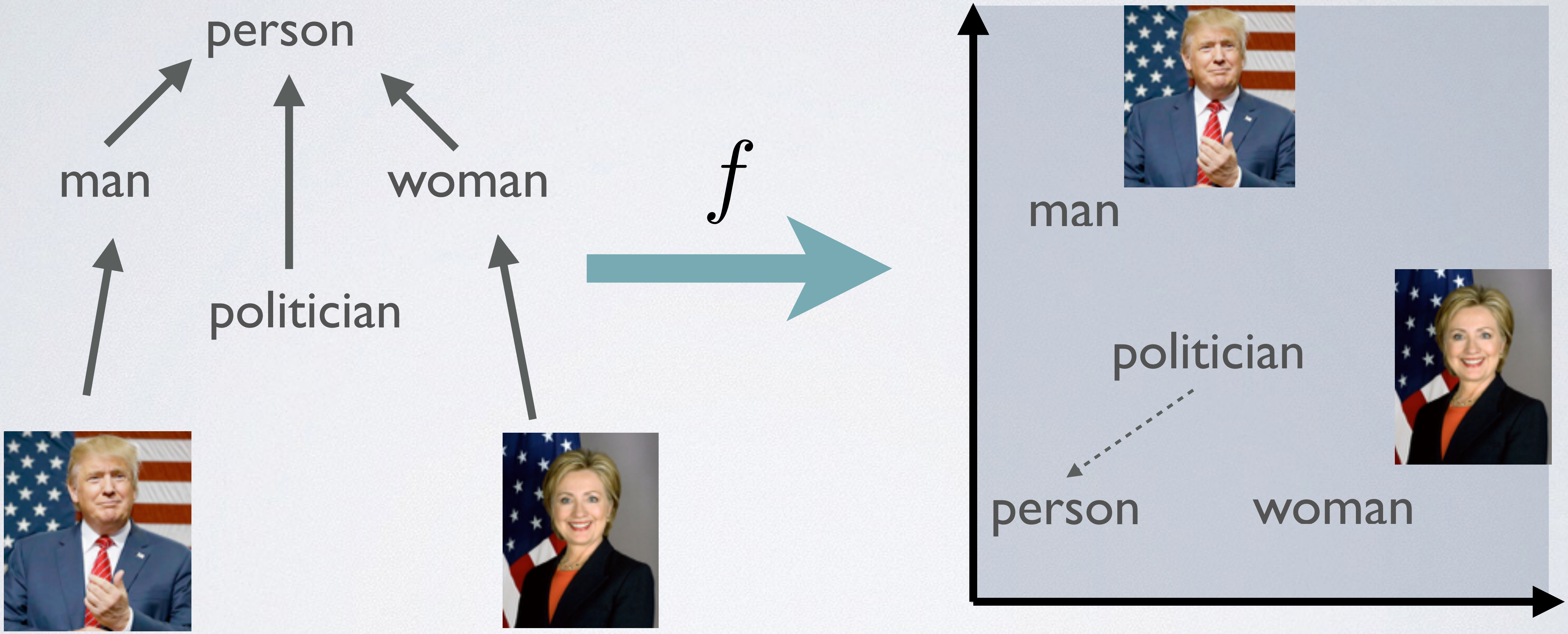

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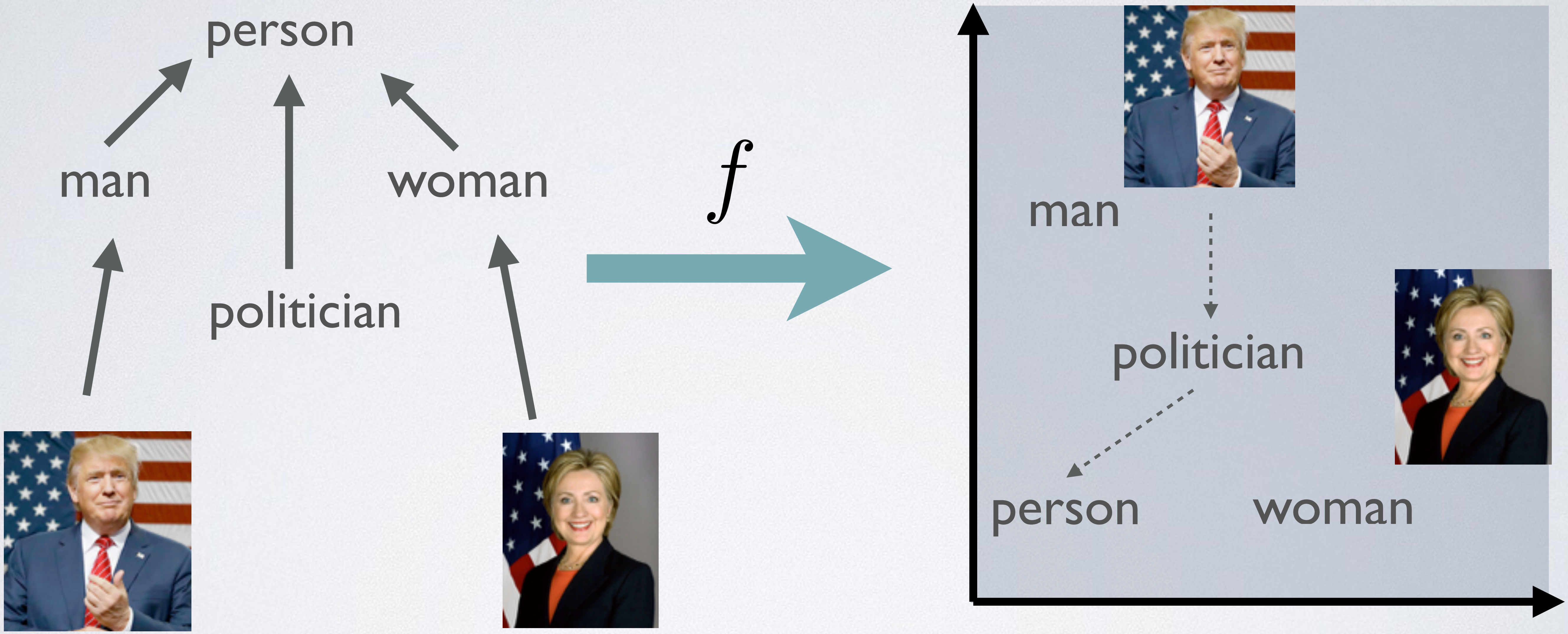

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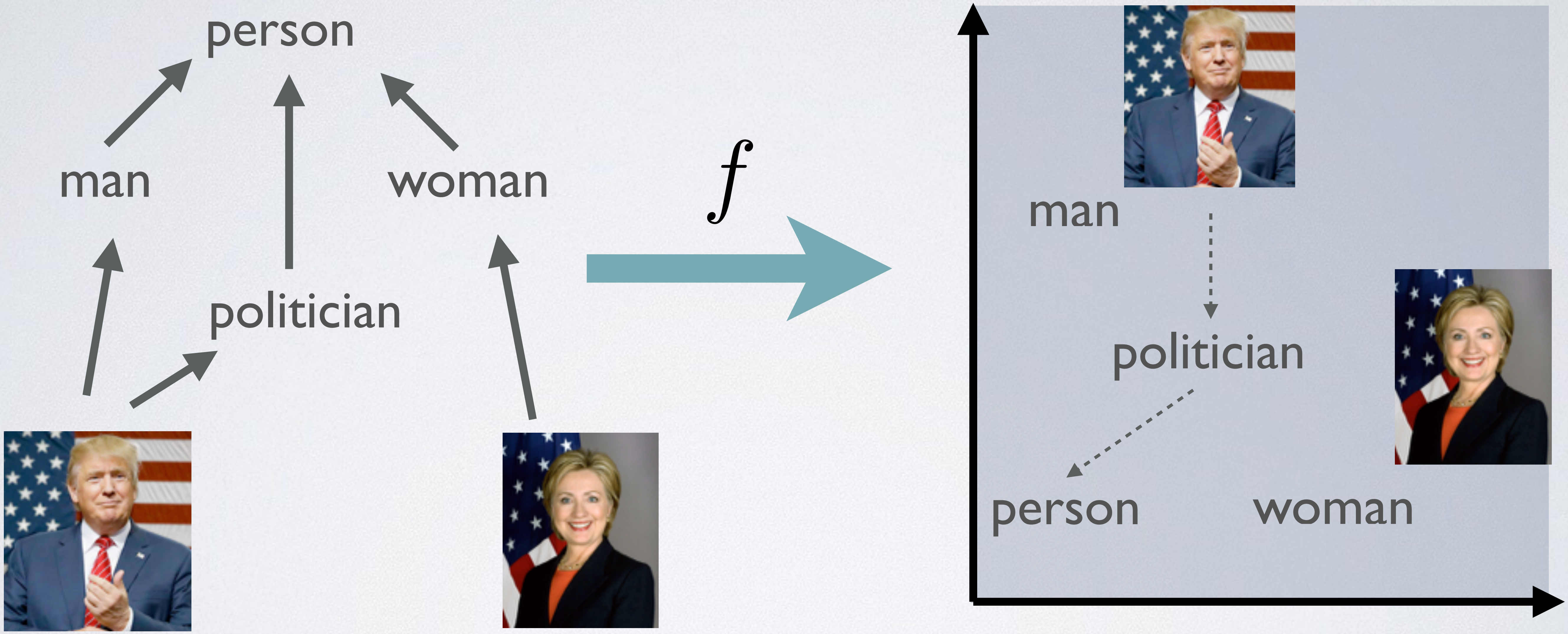

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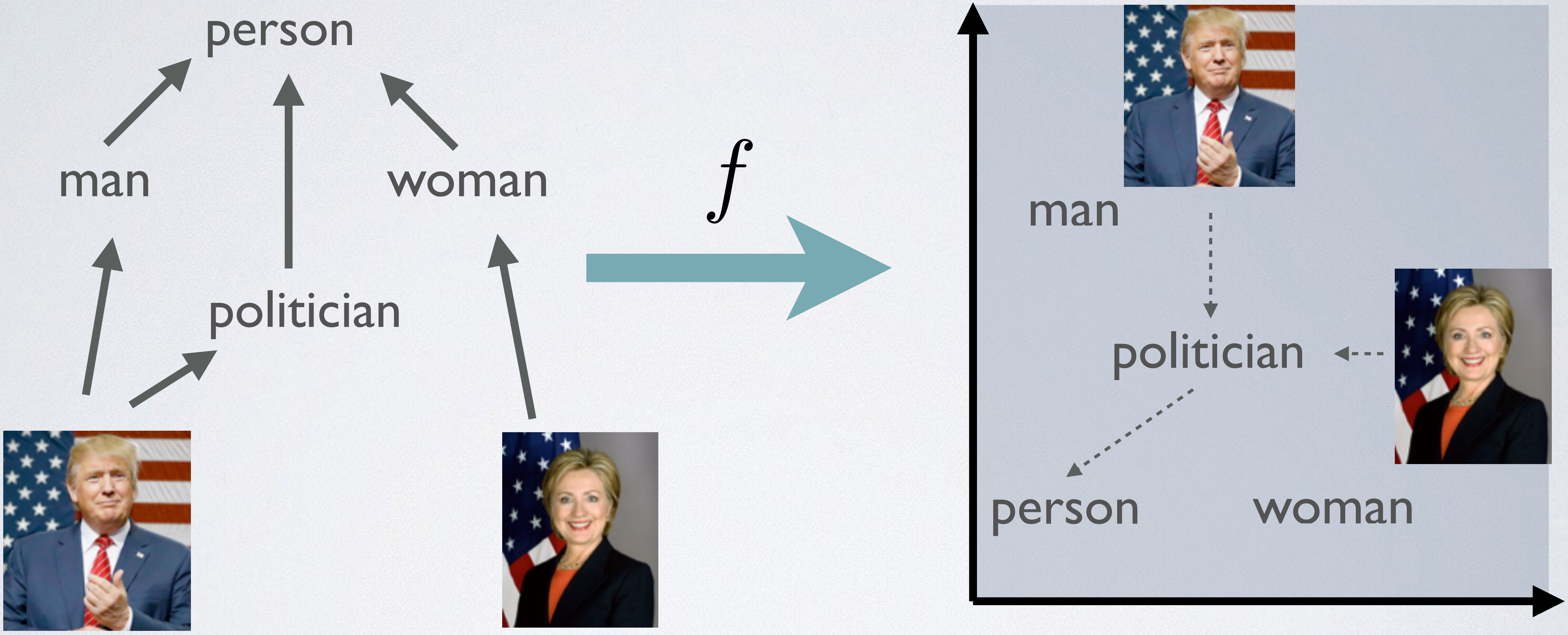

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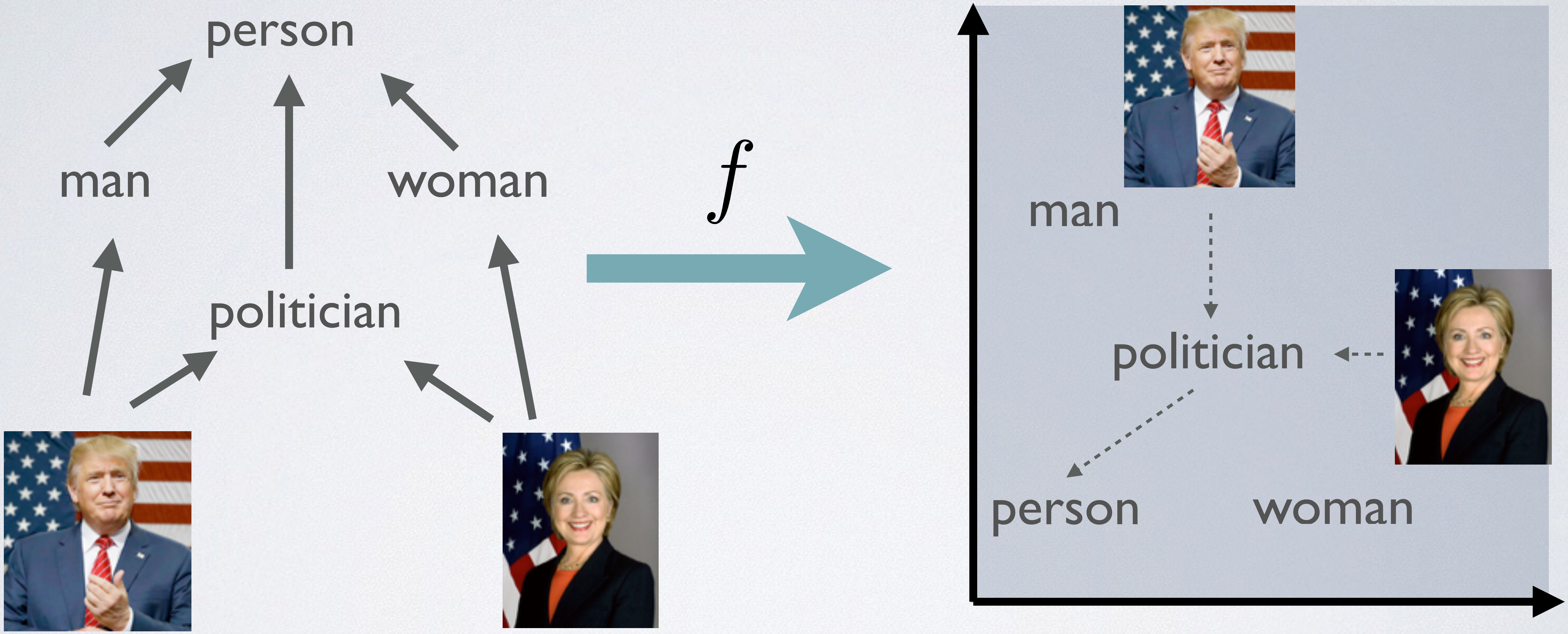

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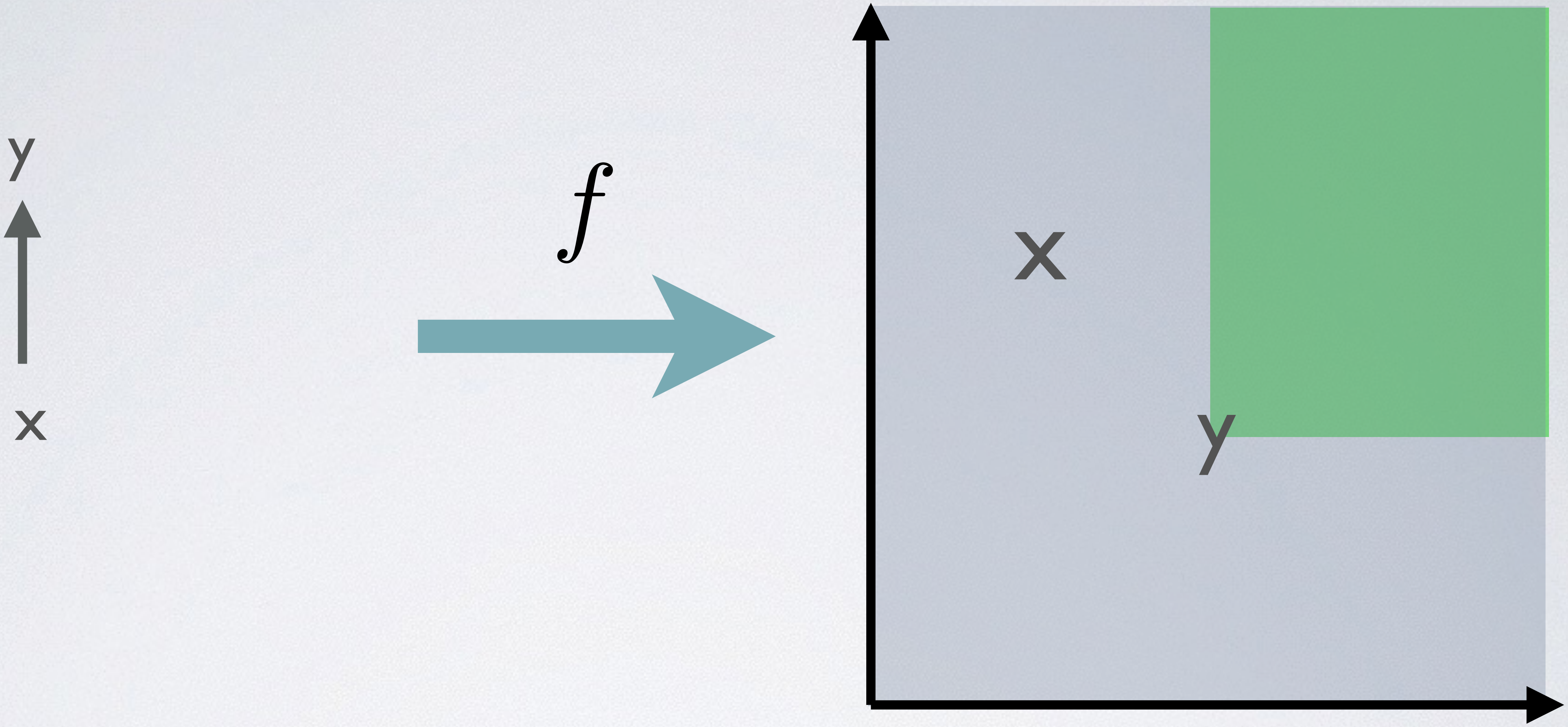
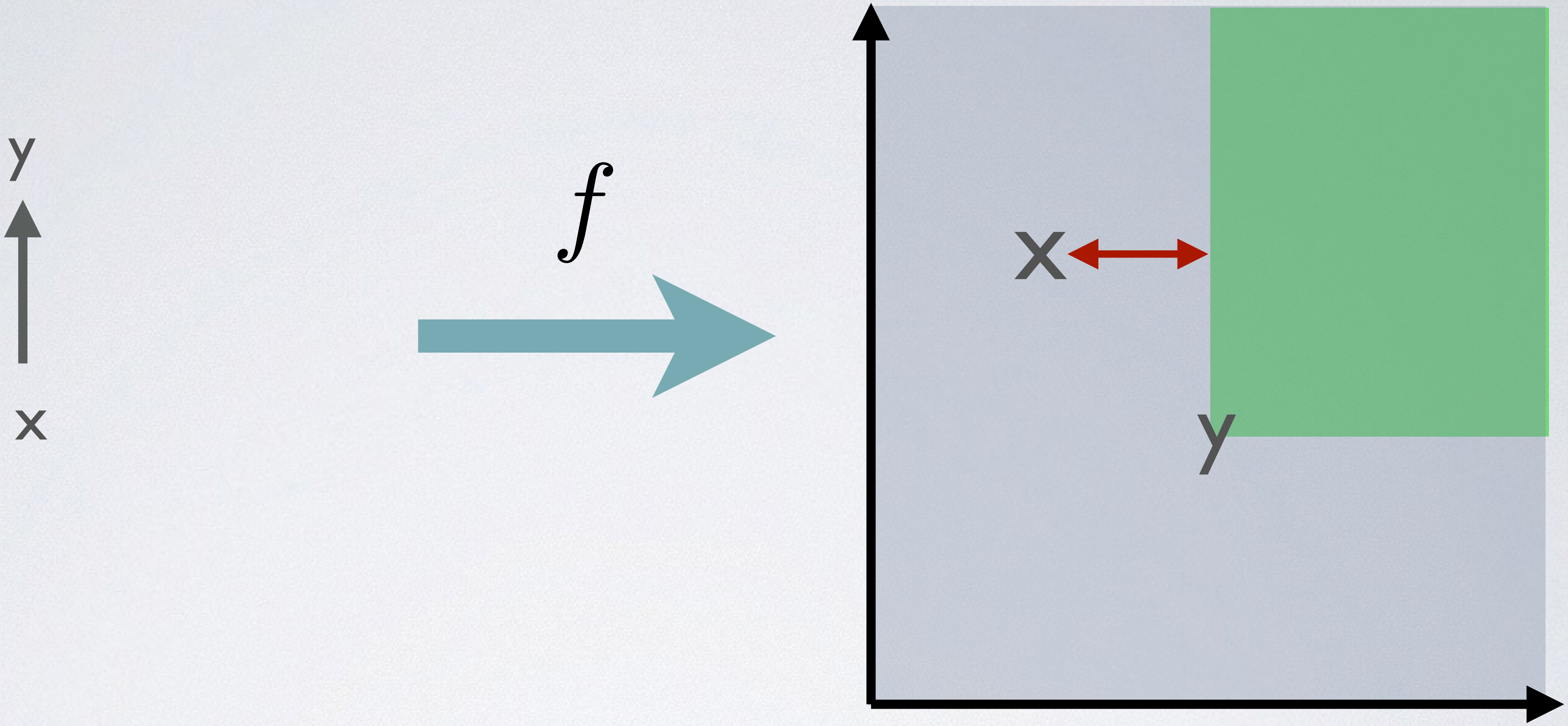

y
x
f
x
y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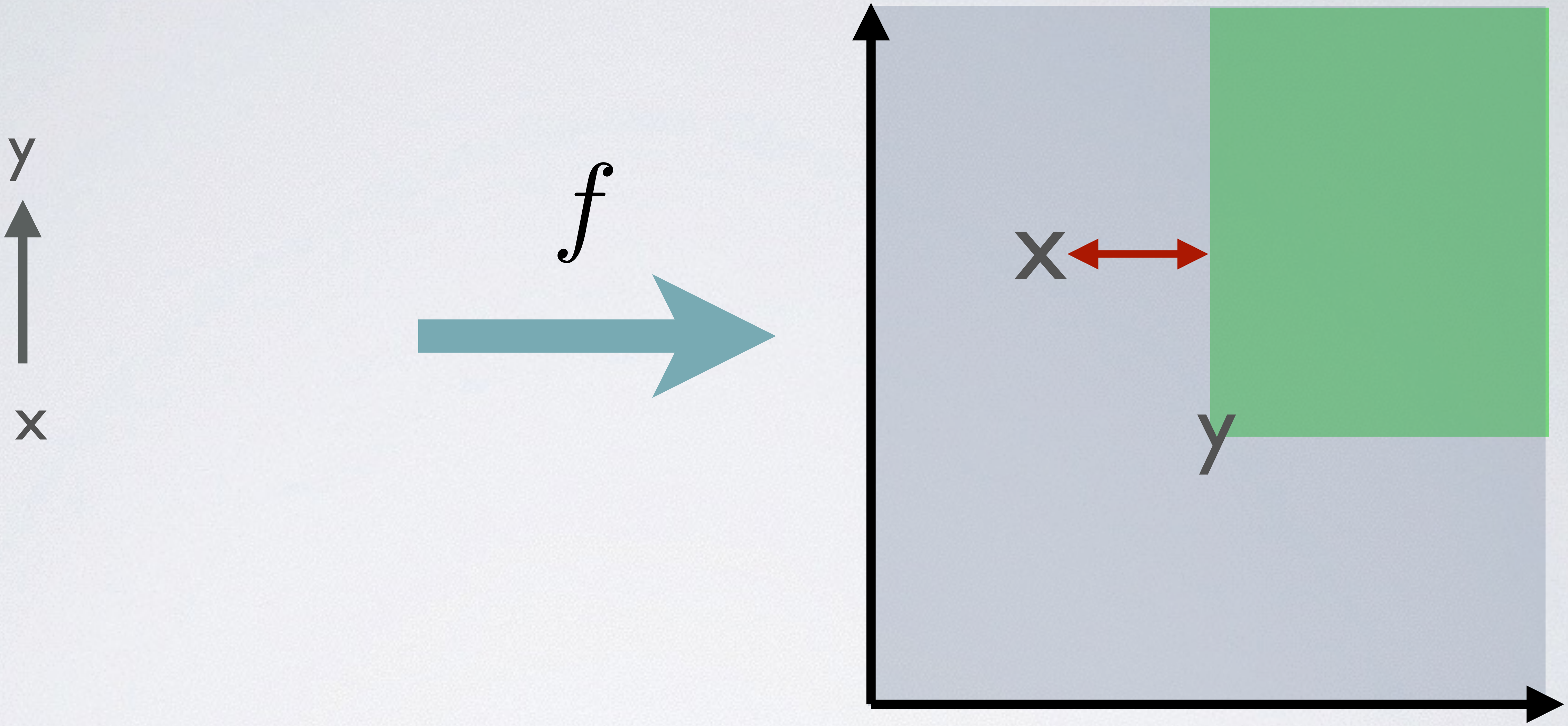
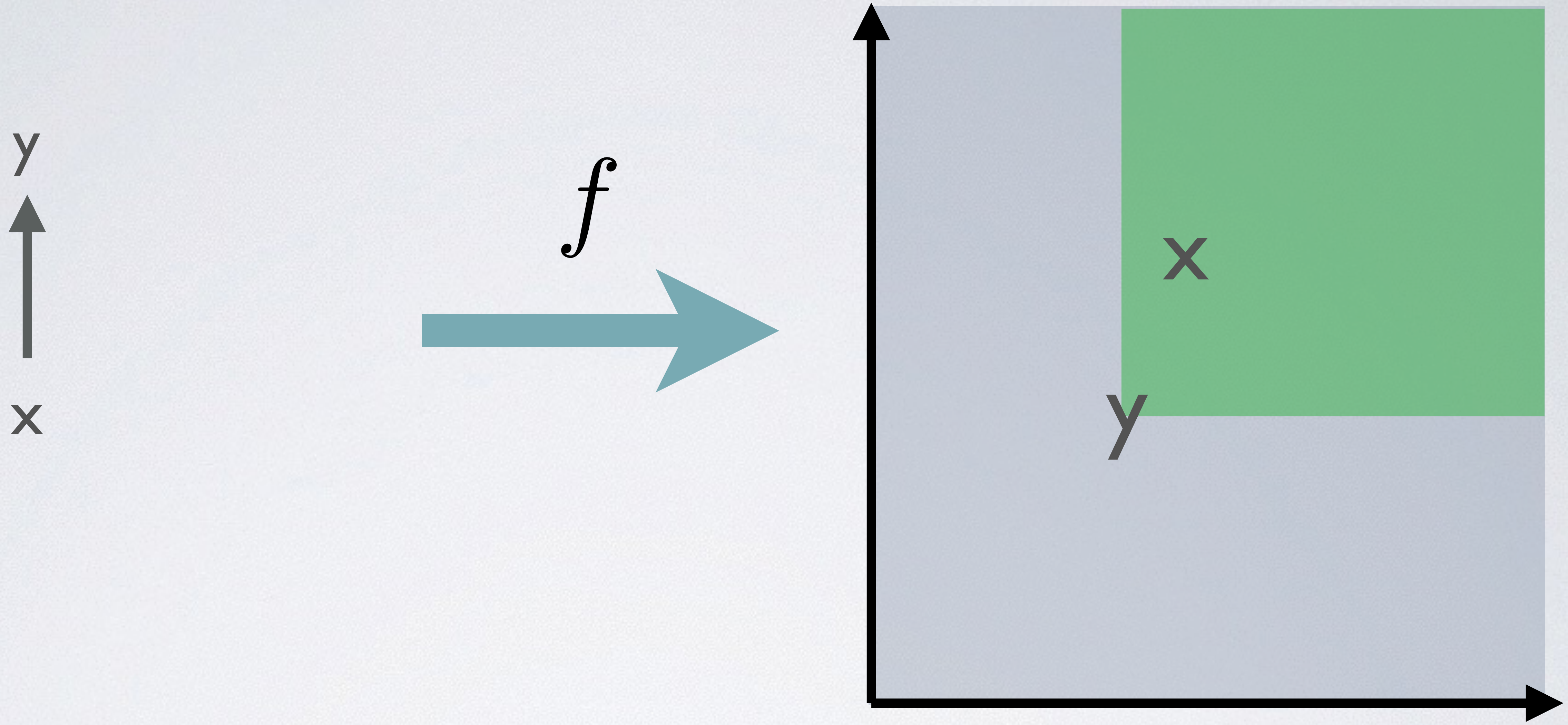


Order violation error: $E(x, y) = ||\max(0, y - x)||^2$



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Experiments

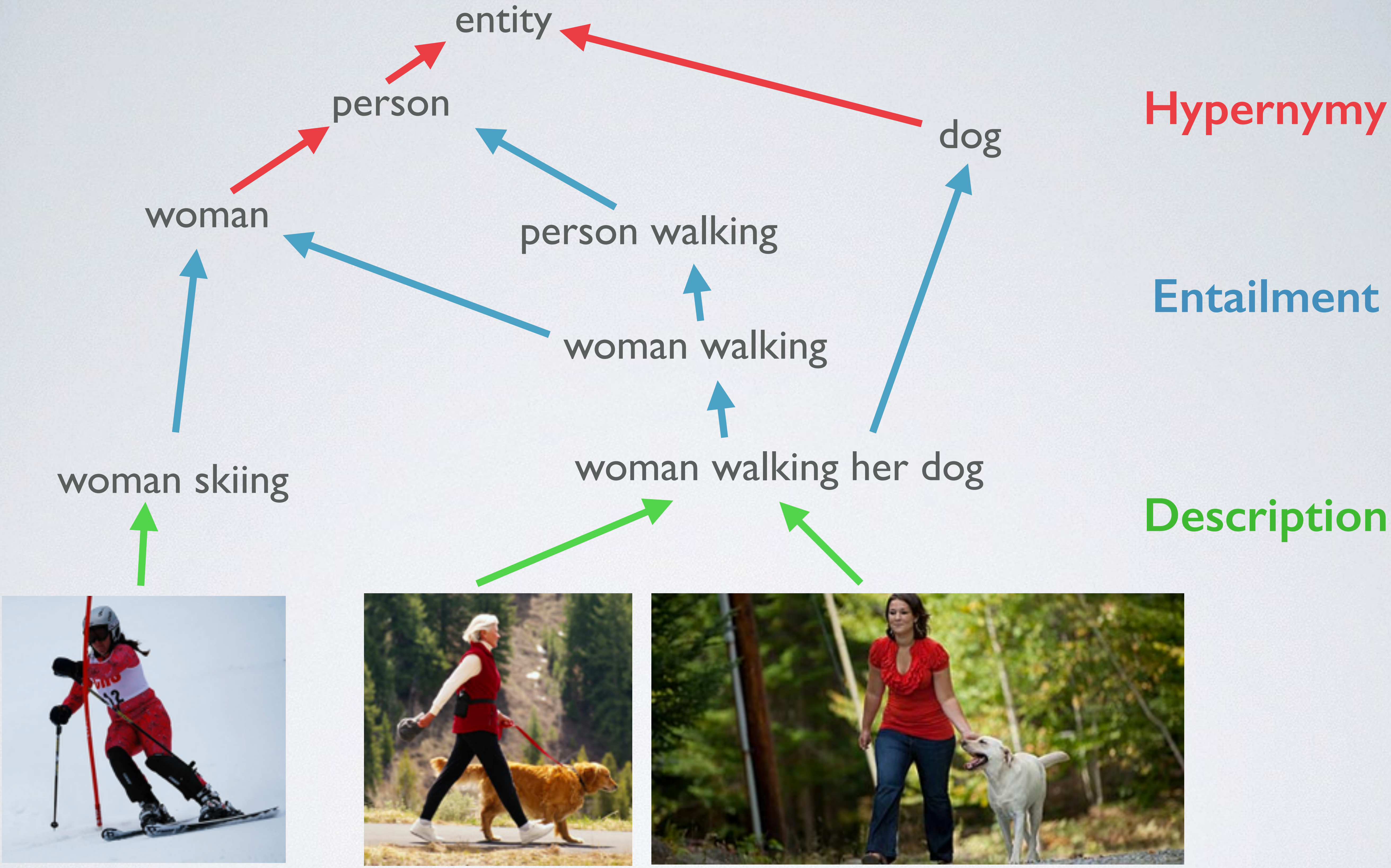

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Image Search w. Visual-Semantic Embeddings

(Kiros et al, 2014)

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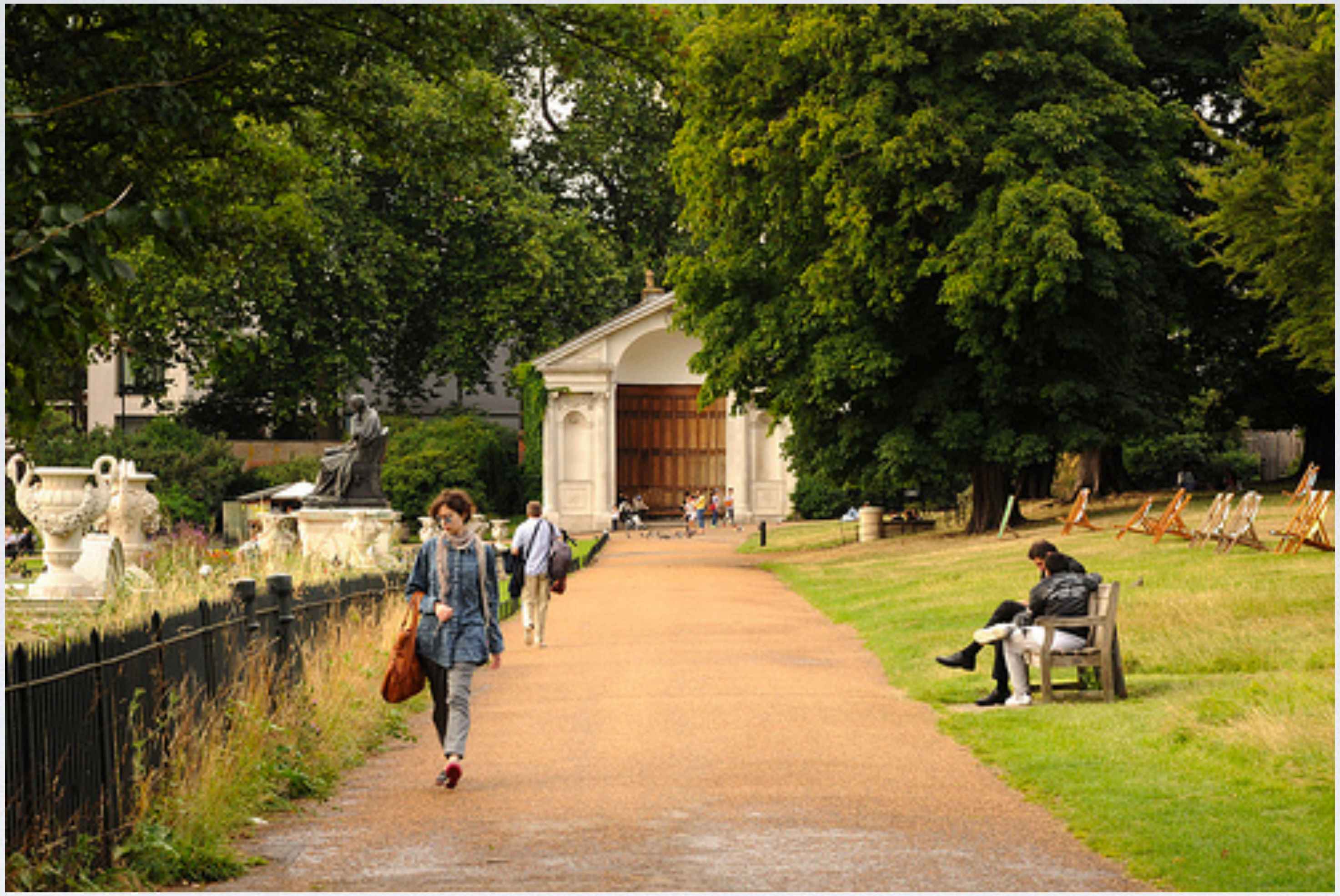
MS-COCO Ranking Benchmark

- 120k images
- Each image has 5 human-written captions.
- We use 110k images for training, 5k for validation and test.



- a group of people walking down a small walkway.
- a girl walking on a path near a person on a bench.
- young lady walking down a path on the right is a couple setting on a park bench.
- a woman with a large, brown purse walks down a path while two people sit on a bench.
- people walking and sitting along a road dividing a green park and a cemetery.

Evaluation (Image Search)

- Take each caption from the test set, and rank all test images by decreasing S(c,i) (i.e. increasing order-violation error E)

Recall@k: % of captions for which the GT image was in the first **k**
Mean r: mean rank of first ground-truth image
Med r: median rank of first ground-truth image

Quantitative Results

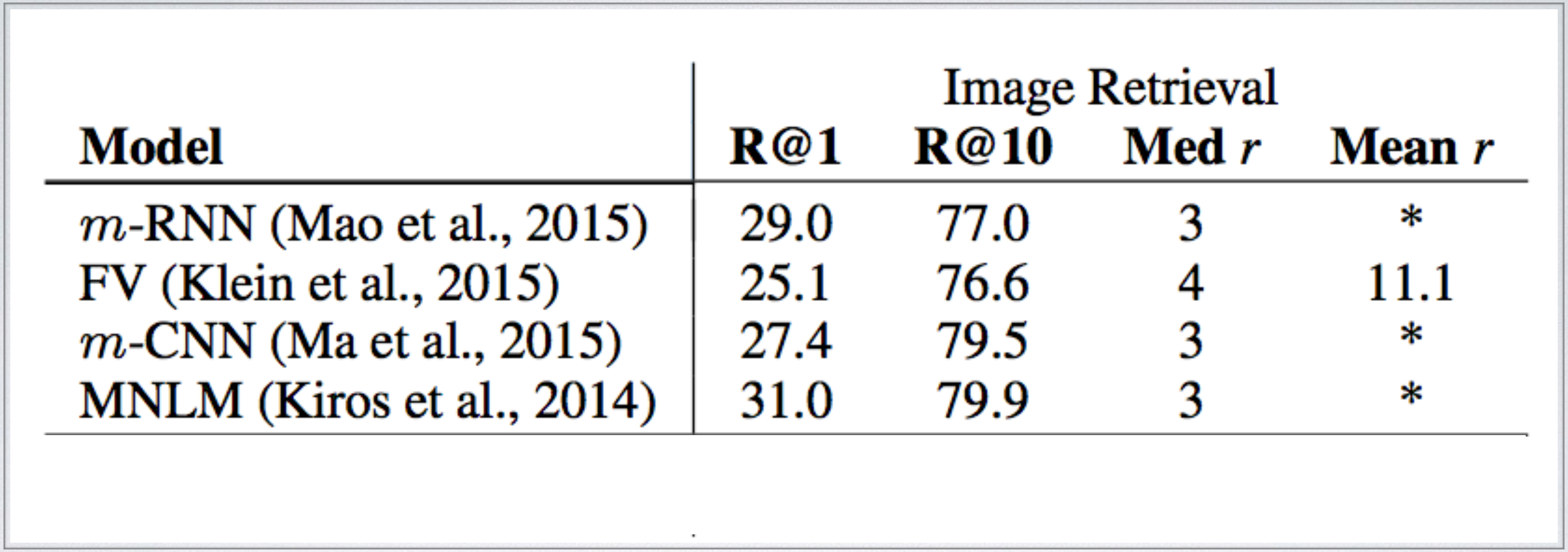


	Image Retrieval			
Model	**R@1**	**R@10**	**Med *r***	**Mean *r***
m-RNN (Mao et al., 2015)	29.0	77.0	3	*
FV (Klein et al., 2015)	25.1	76.6	4	11.1
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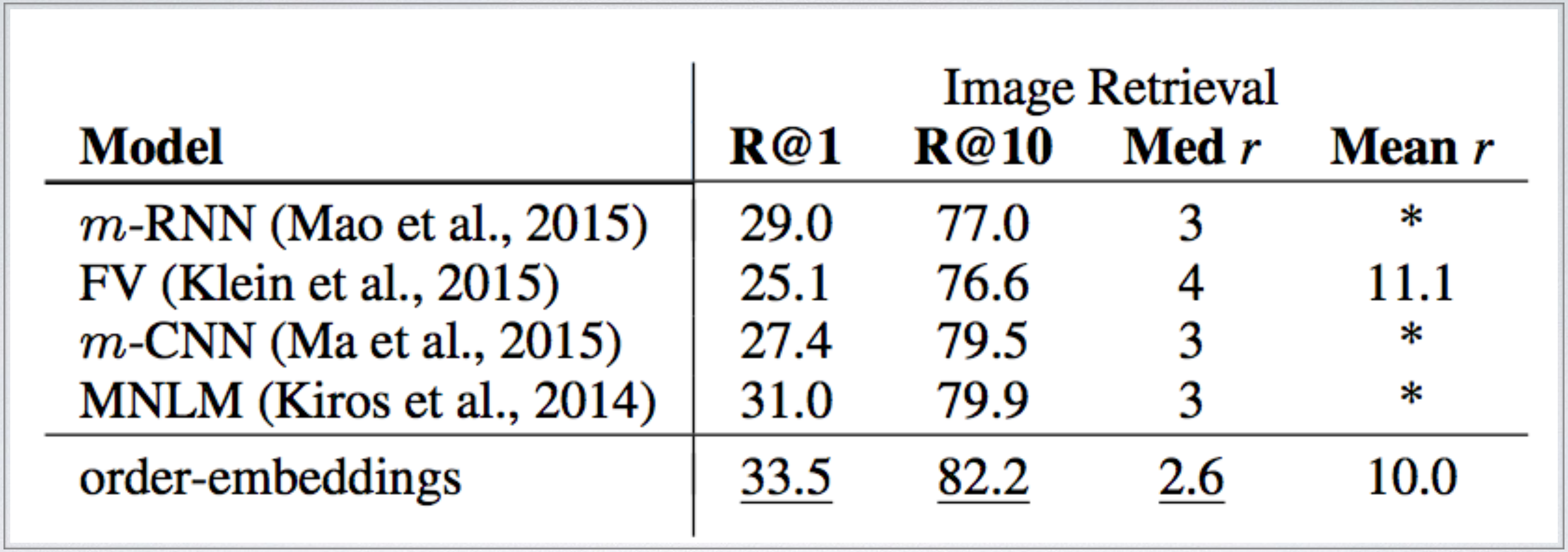
MNLM (Kiros et al., 2014)	31.0	79.9	3	*

Table 1: Results on COCO test with test set of1k images.

Quantitative Results



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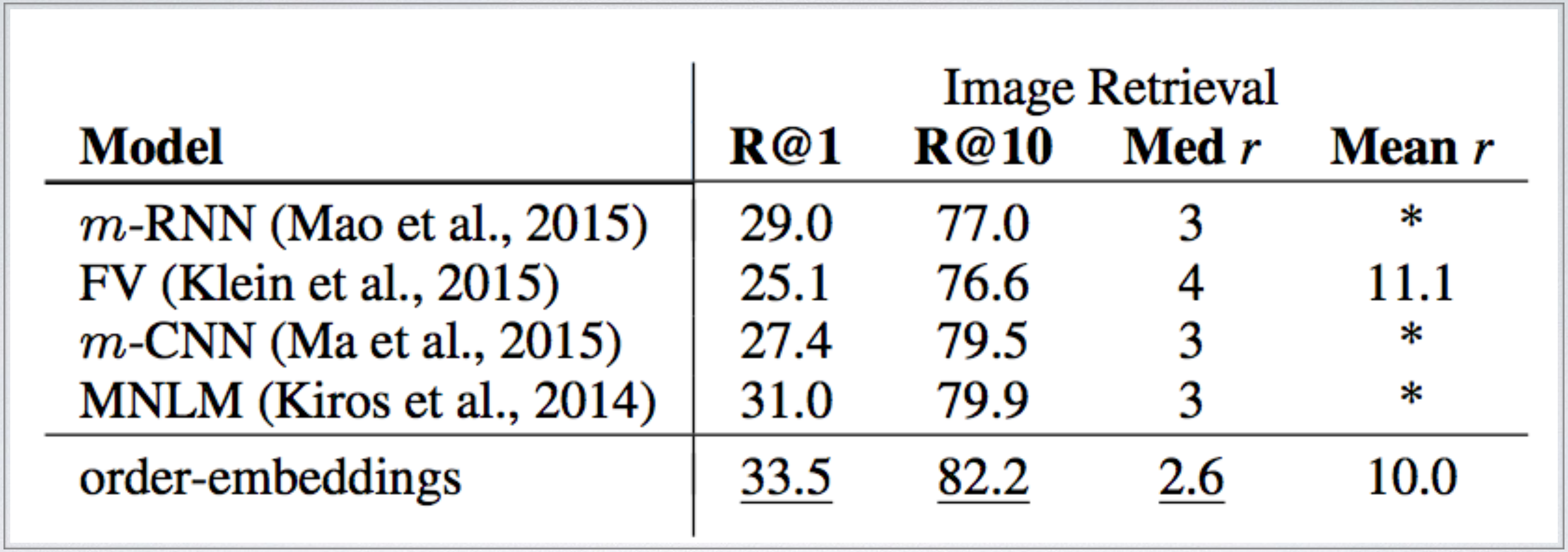

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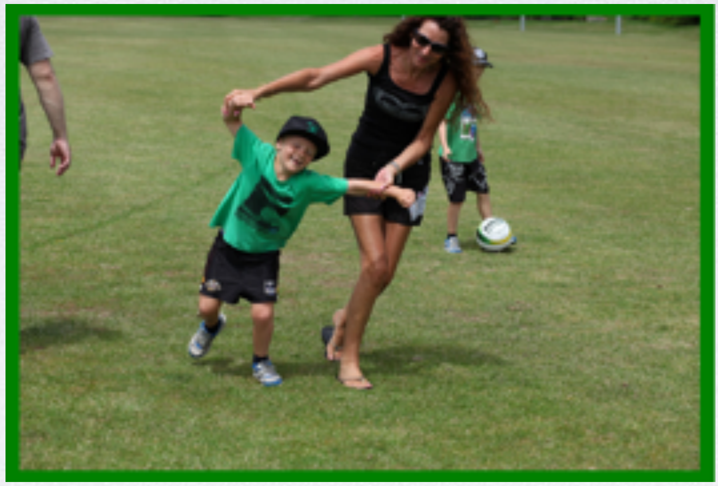
(See our paper for full results)

Image Search Examples: Success

Query

Top Images

"a woman and little boy are walking and holding arms on a soccer field"



"a man in a mask is holding an umbrella"

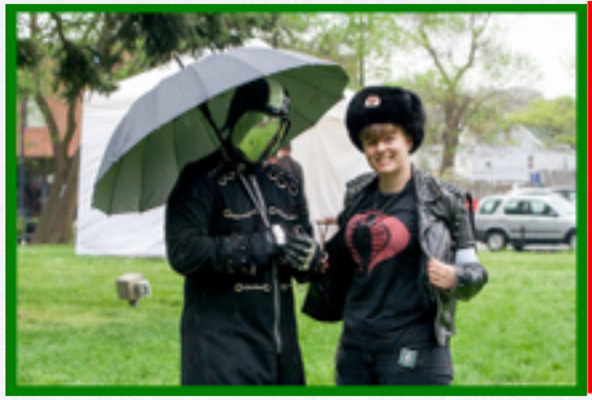


Image Search Example: Failure

Query

"the man is trying to eat three hot dogs are the same time"

Top Images

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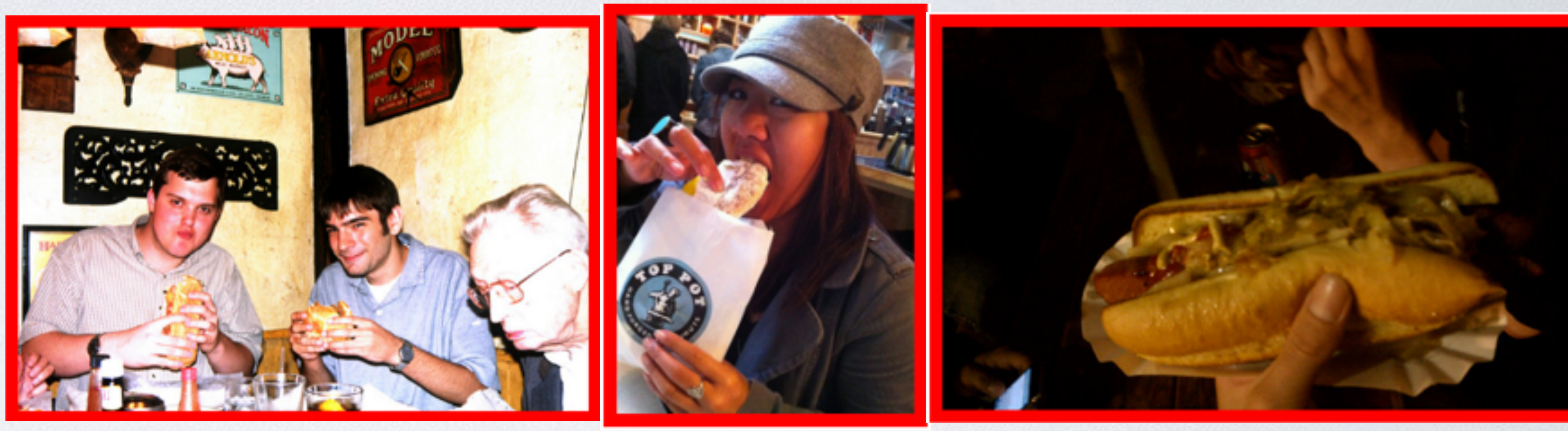
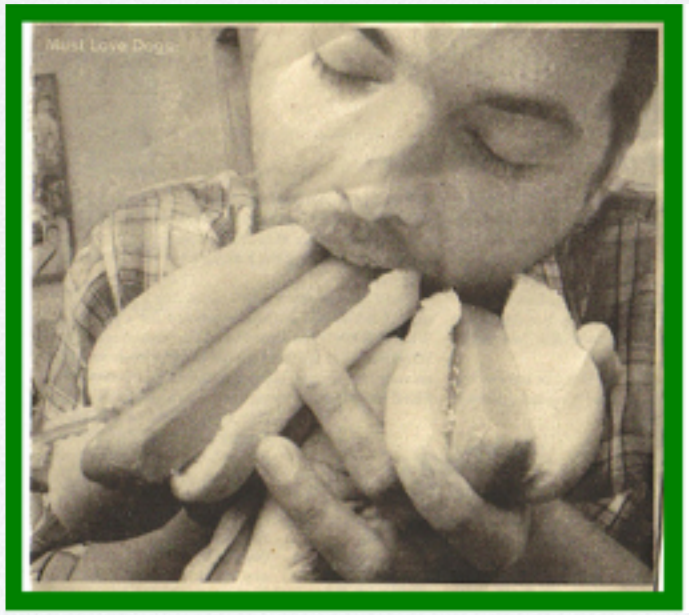
Top Images



GT Image:



Multimodal Regularities

Multimodal Regularities

“king” - “man” + “woman” ~ queen

Multimodal Regularities

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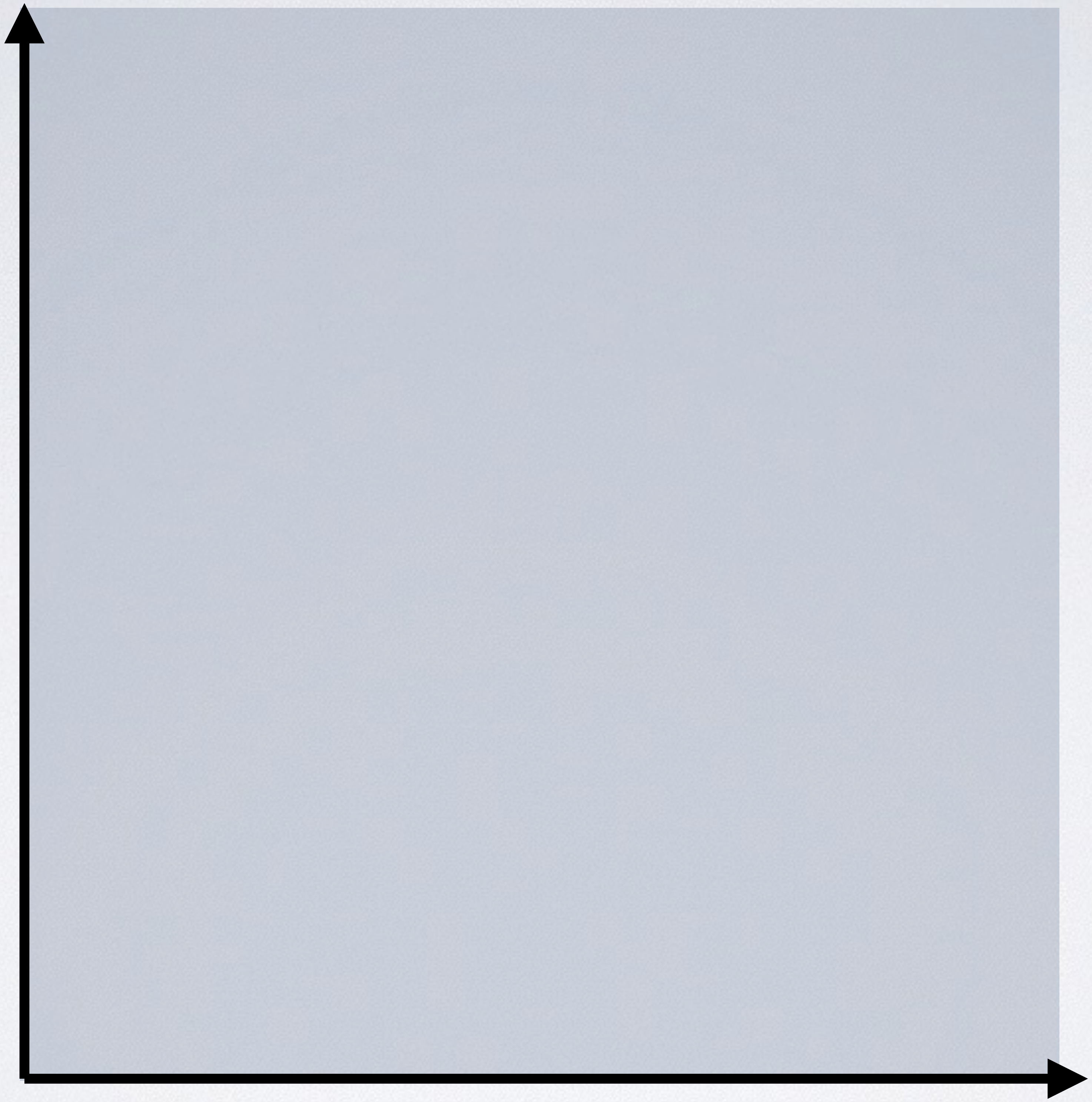
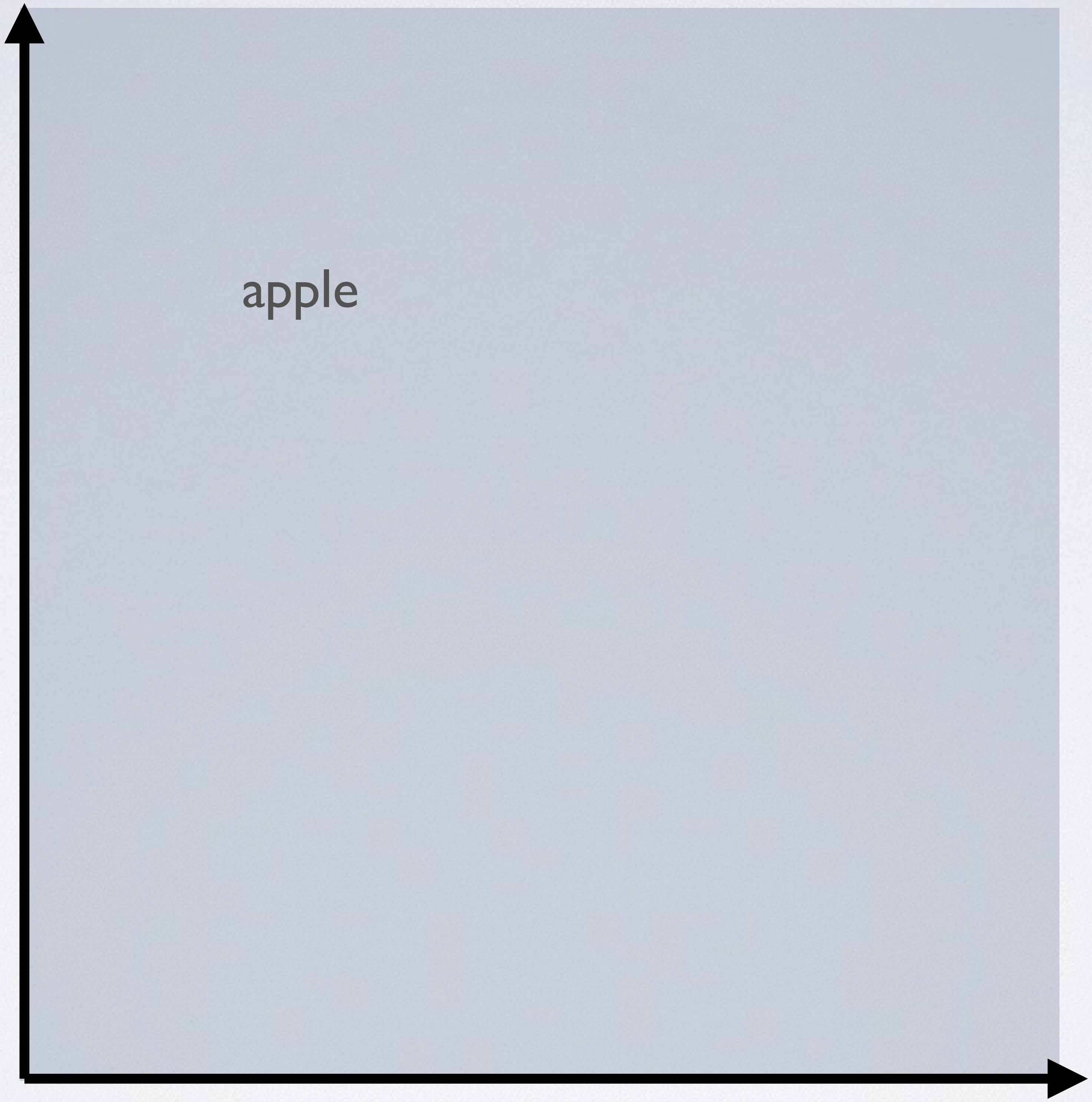
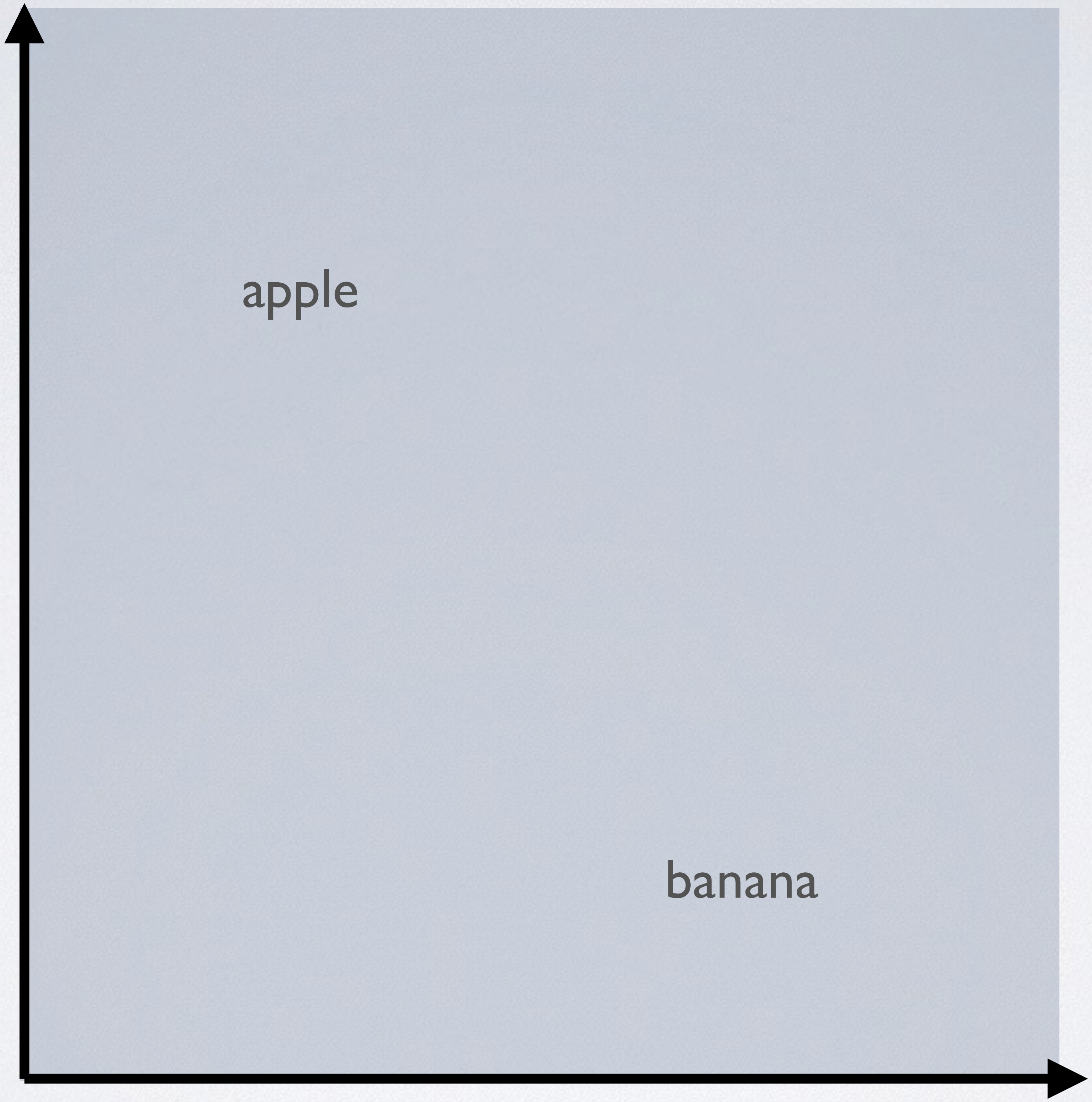


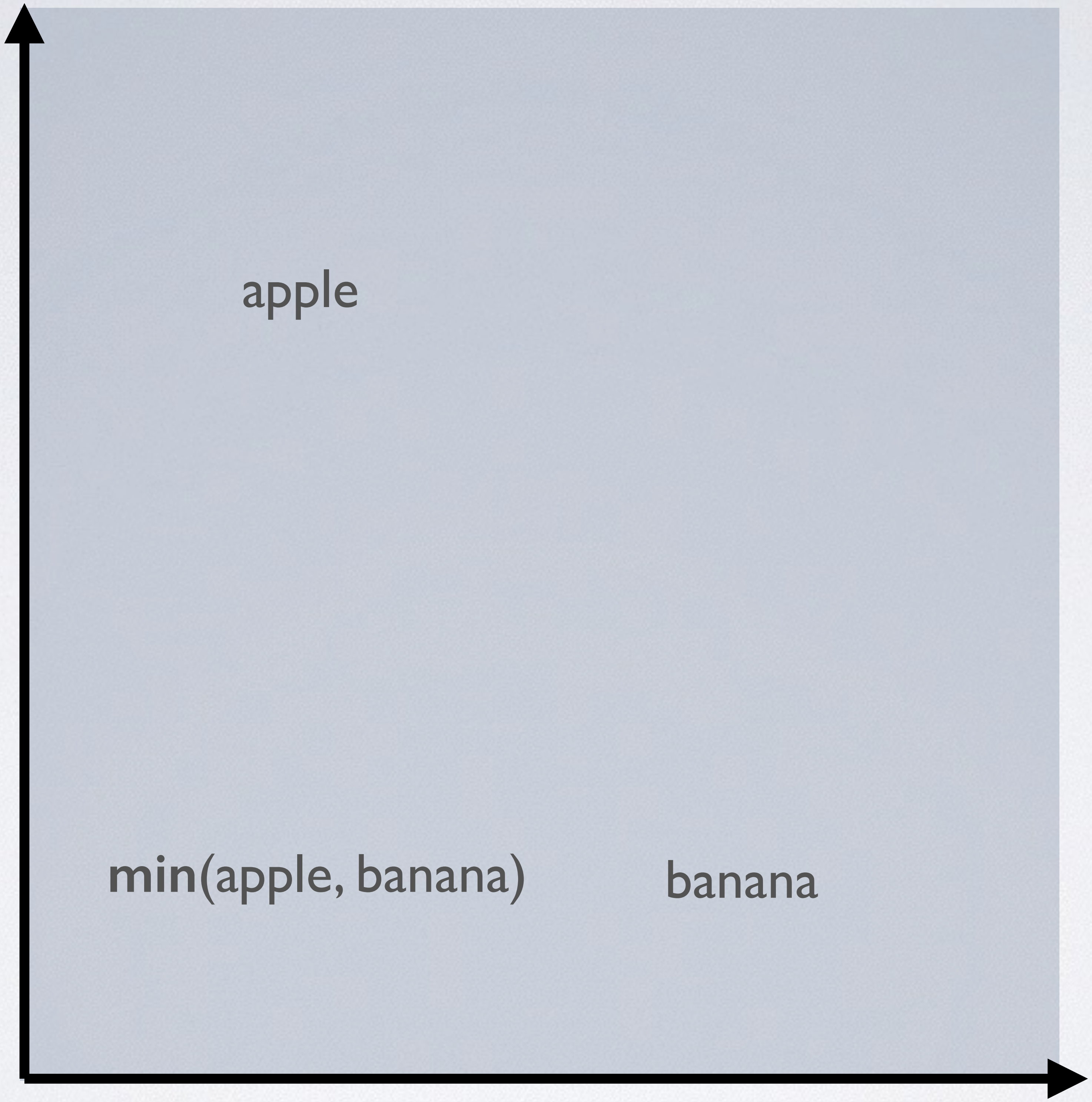
Multimodal Regularities



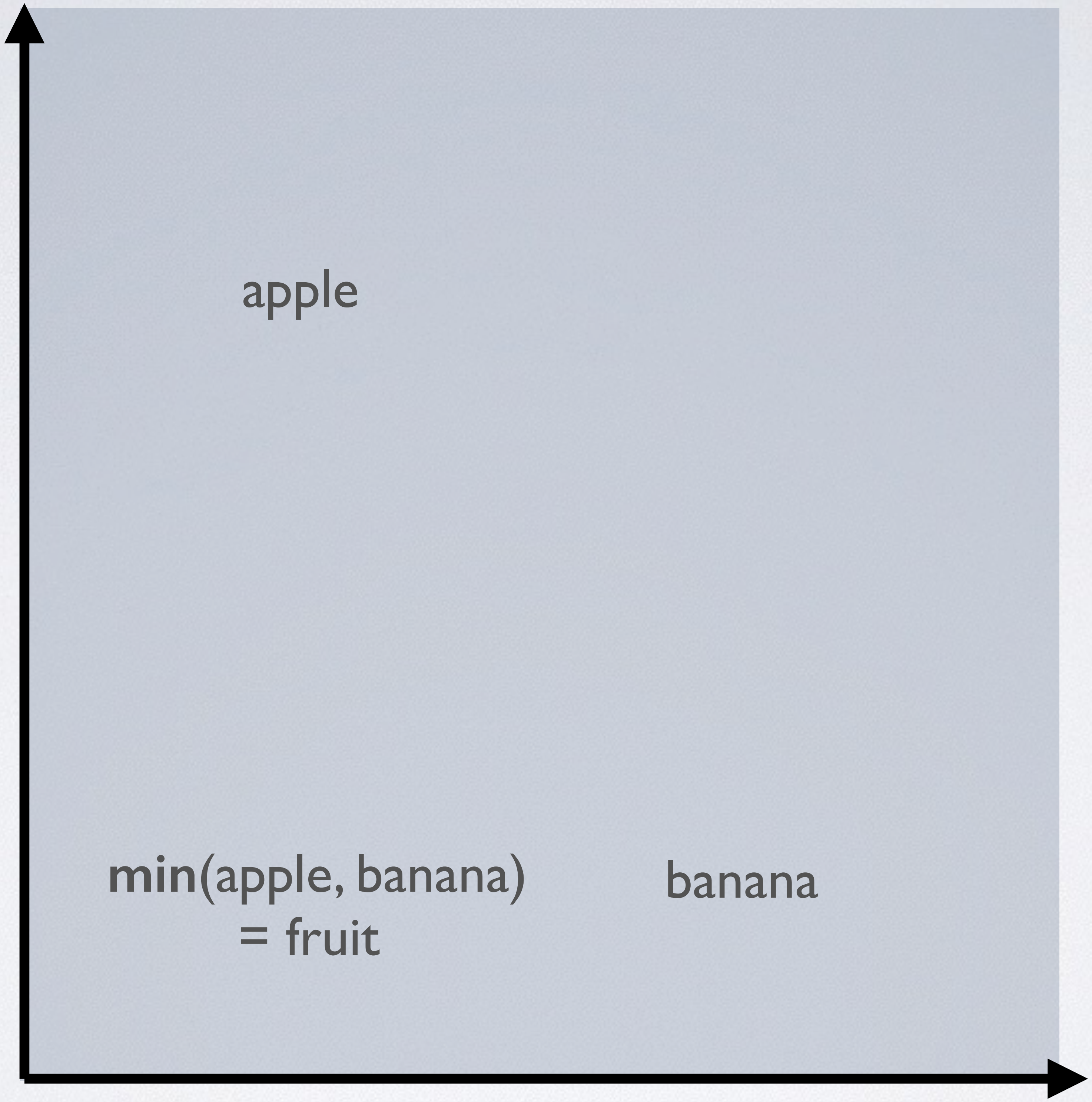
Multimodal Regularities



Multimodal Regularities



Multimodal Regularities

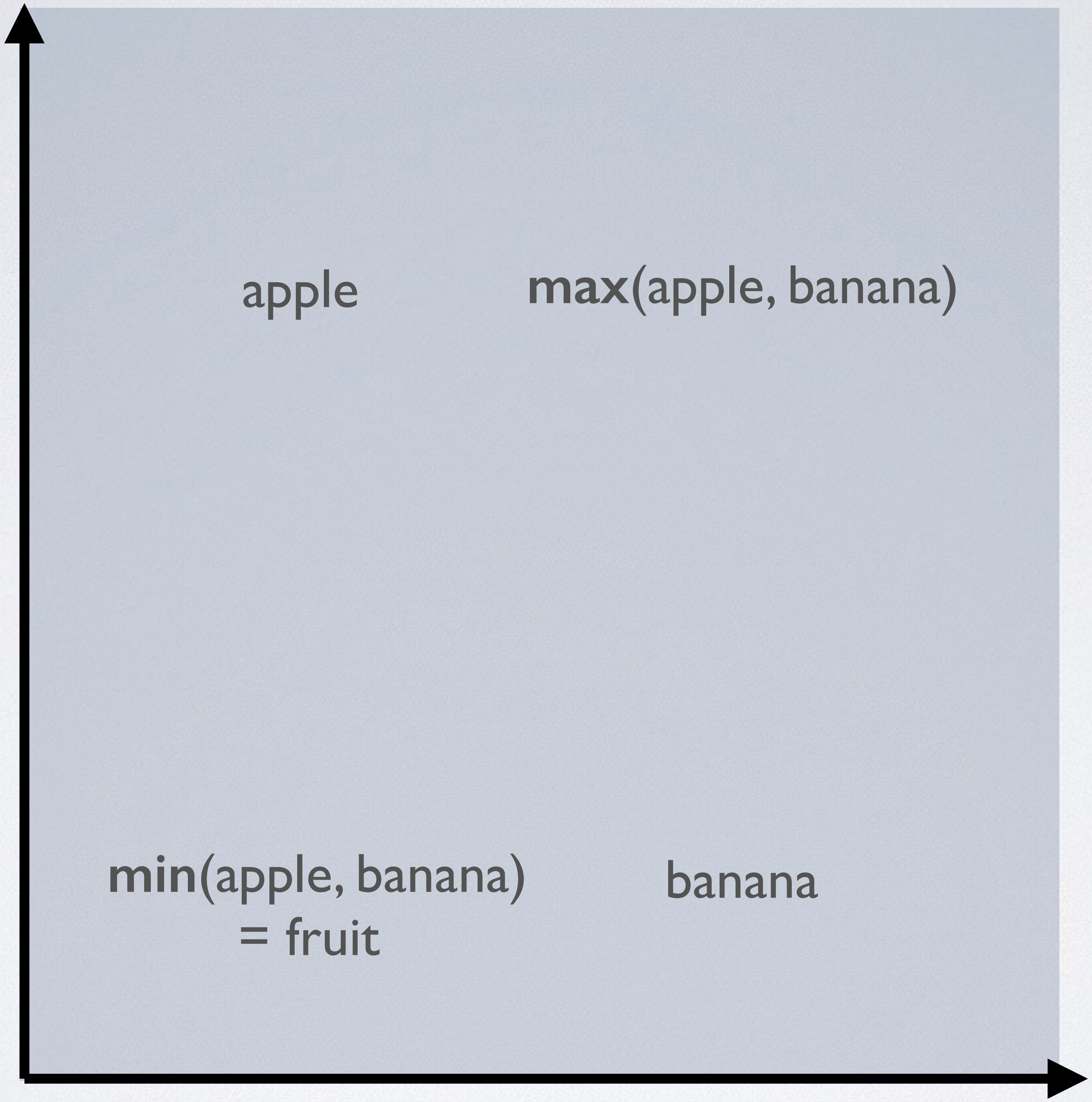


apple

min(apple, banana)
= fruit

banana

Multimodal Regularities



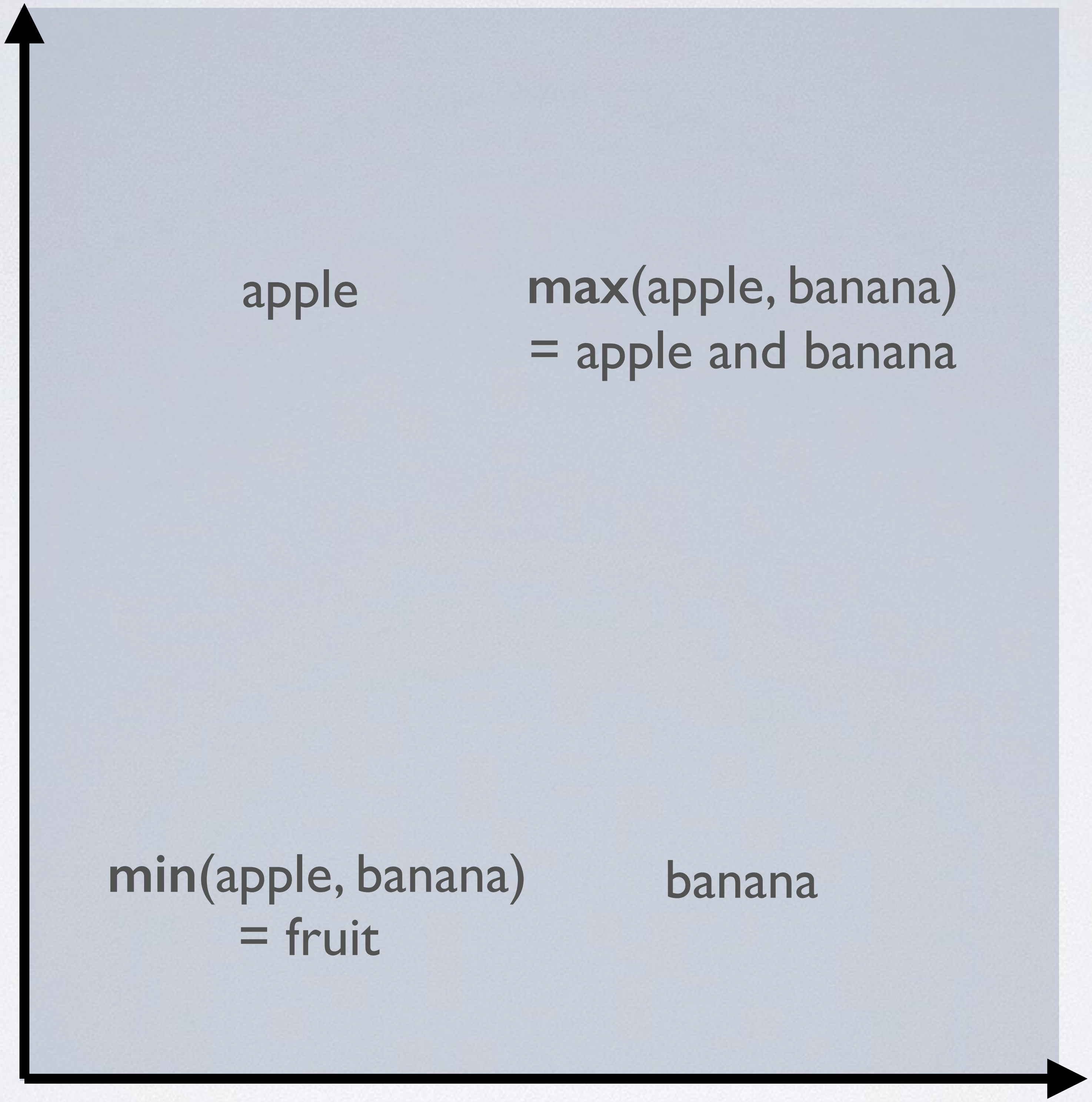
apple

max(apple, banana)

min(apple, banana)
= fruit

banana

Multimodal Regularities



apple

max(apple, banana)
= apple and banana

min(apple, banana)
= fruit

banana

Query

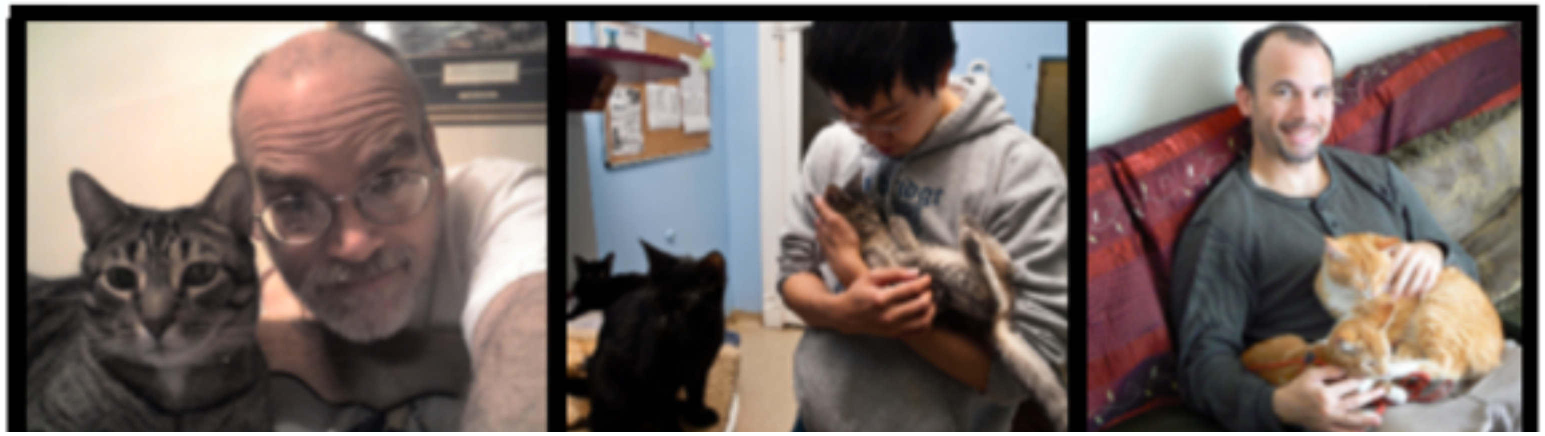
Nearest non-query images in COCO train

max(“man”, “cat”)

Query

max(“man”, “cat”)

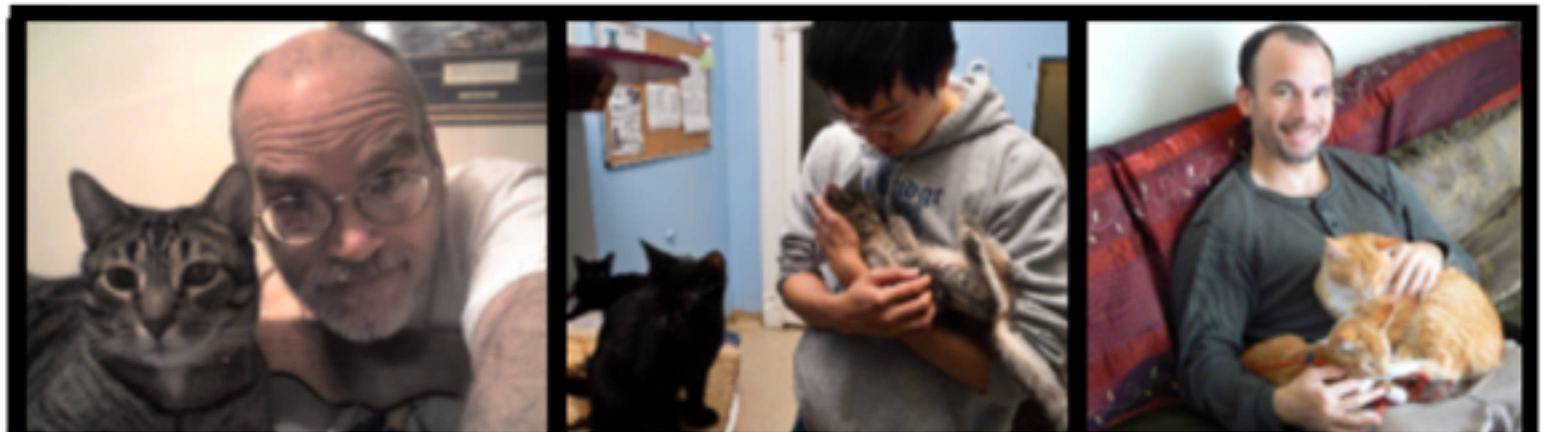
Nearest non-query images in COCO train



Query

Nearest non-query images in COCO train

max(“man”, “cat”)

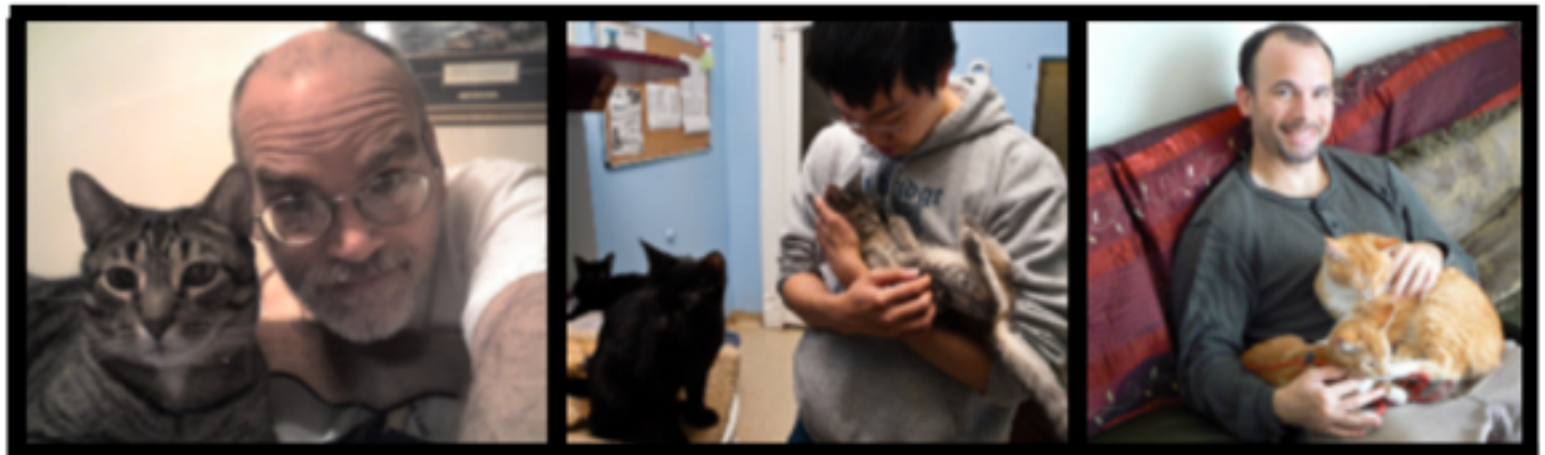


max(“black dog”, “park”)

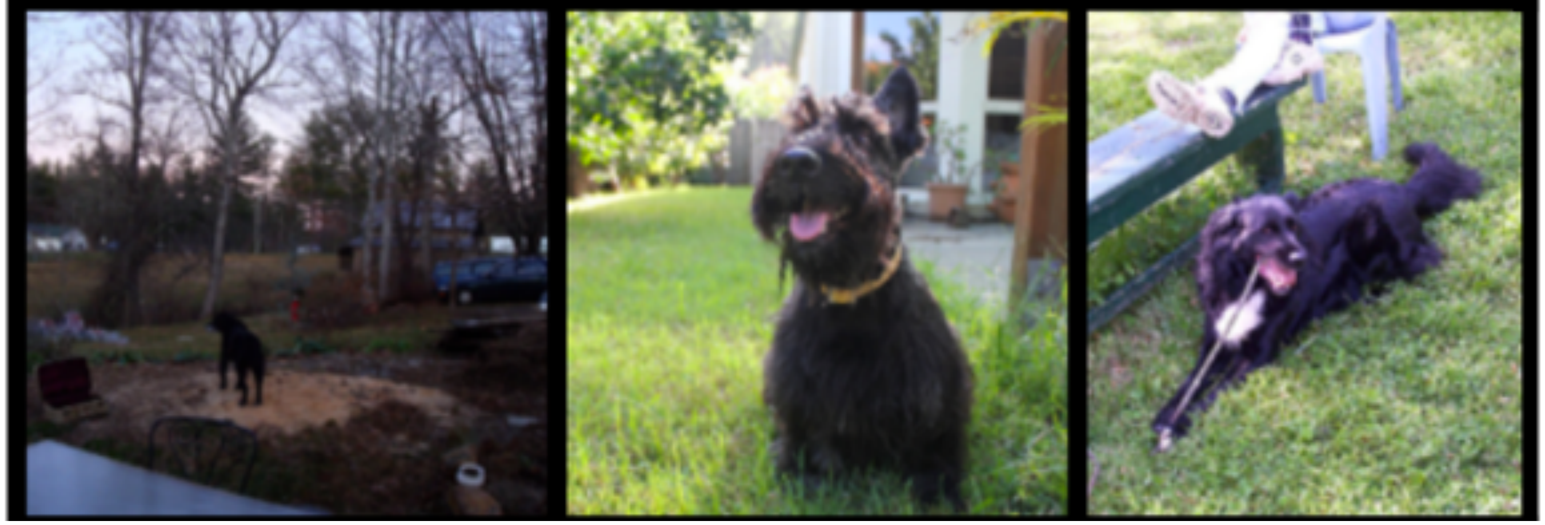
Query

Nearest non-query images in COCO train

max("man", "cat")



max("black dog", "park")



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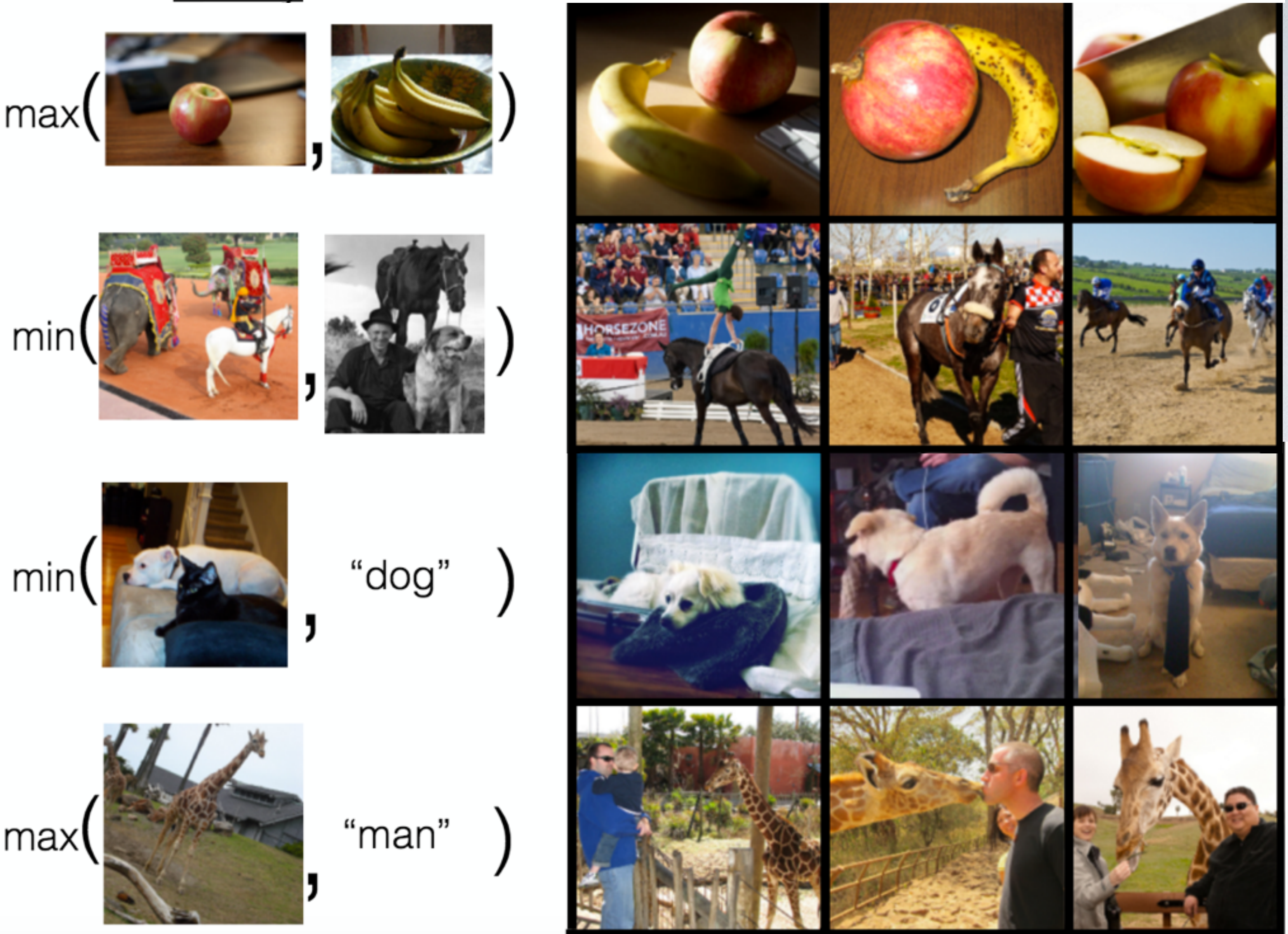

Conclusions

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Code available at github.com/ivendrov/order-embedding