Similarity and Contrast on Conceptual Spaces for Pertinent Description Generation

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Similarity is crucial to cognition

General (often implicit) hypothesis:

similar stimulus in *similar* context ➡ *similar* response

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Practical uses: *description generation*

proximate elements can be used as **reference** to identify a certain **target** (*object*, *situation*, etc.)

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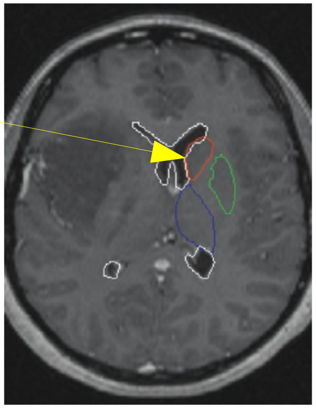
the caudate nucleus is an internal brain structure which is very close to the lateral ventricles



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- similarity is a function of a mental ***distance*** between conceptualizations [Shepard1962]

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- relies on some ***metric*** to compare inputs
- offers ***pseudo-metric*** learning methods

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geometrical model of cognition

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- similarity in human judgments does not satisfy **fundamental geometric axioms** [Tversky77]

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- approaching logical structures through geometric methods (e.g. [Distel2014])

Towards an alternative solution..

associationistic methods

conceptual spaces

symbolic methods

Overview on conceptual spaces

- Conceptual spaces stem from (continuous) perceptive spaces.

→ ***grounded***

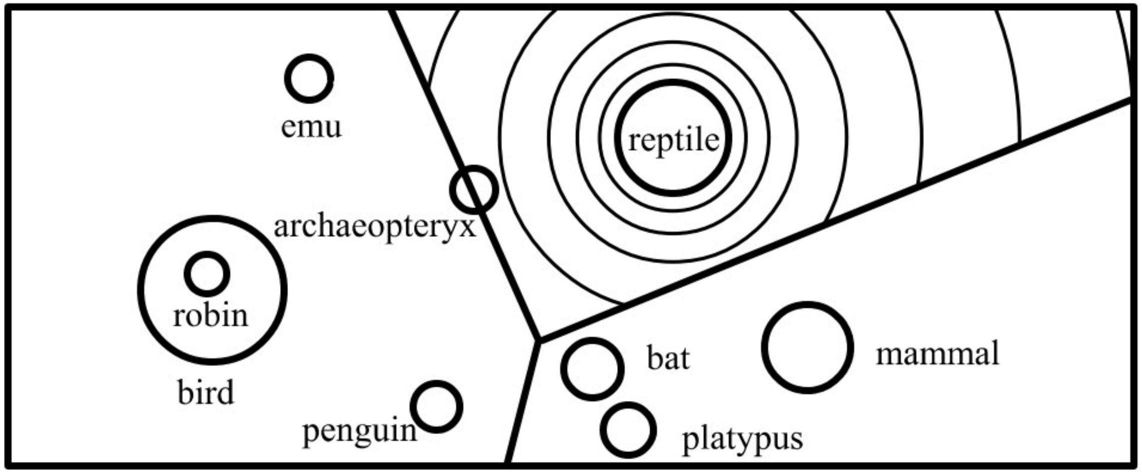
- Natural **properties** emerge as convex regions over ***integral domains*** *(e.g. color).*

- **Concepts** are combinations of properties

- **Prototypes** can be seen as centroids of convex regions (properties or concepts).

  ↔ convex regions can be seen as resulting from the competition between prototypes (forming a *Voronoi Tessellation*).

conceptual spaces



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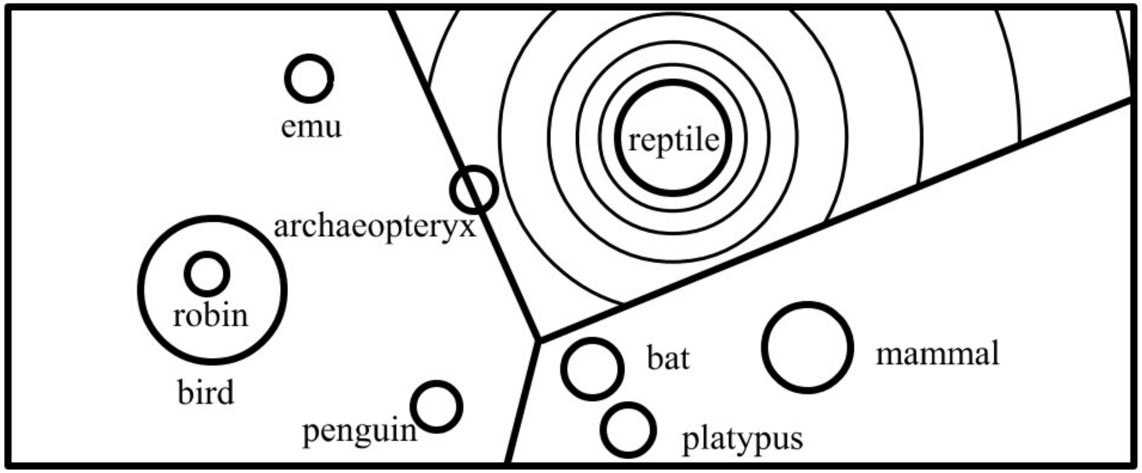

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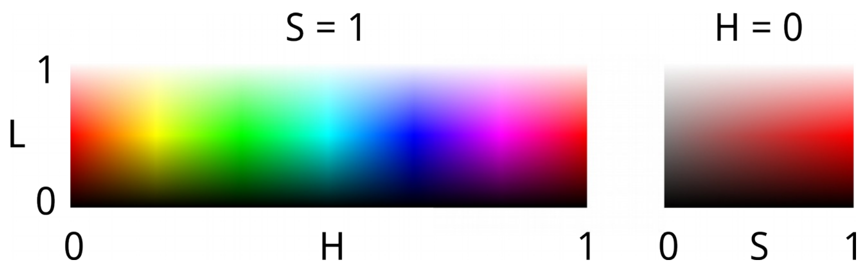

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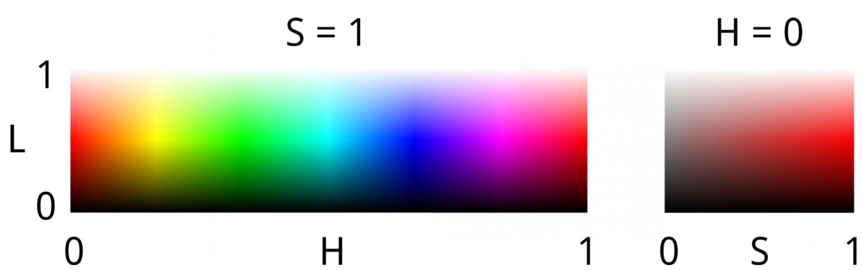

Why do we say “**red dogs**” even if they are actually brown?



images after Google

Predicates resulting from contrast

Alternative hypothesis [Dessalles2015]:

predicates are generated *on the fly* after an operation of ***contrast***.

$$C = O - P$$

contrastor

object
(target)

prototype
(reference)

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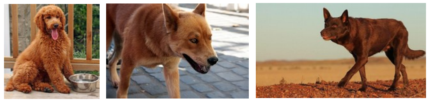
These dogs are “red dogs”: 

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Test:

- Colors of 9 common dog furs on the internet

	Hue	Luminance	Saturation
mean:	[0.10,	0.52,	0.46]
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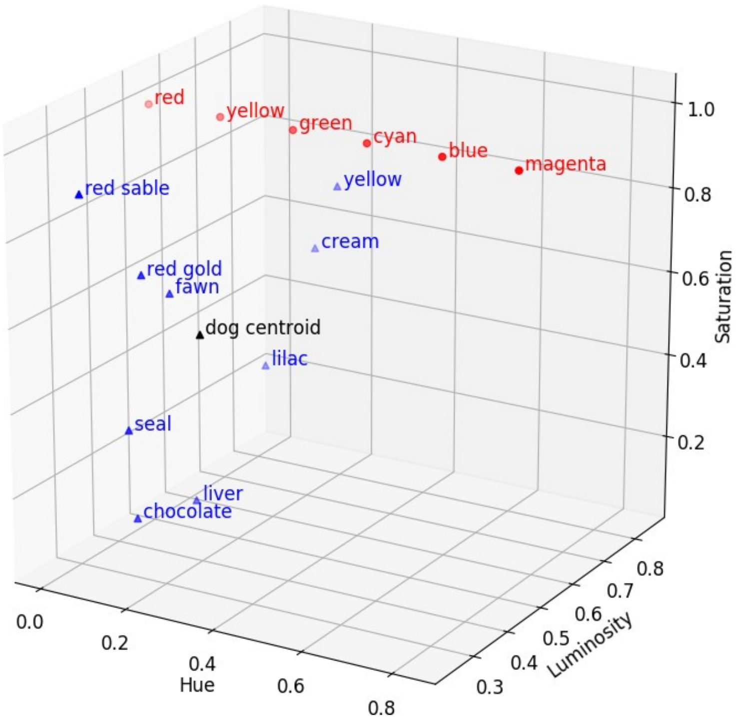

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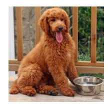
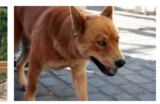
These dogs are “red dogs”:   

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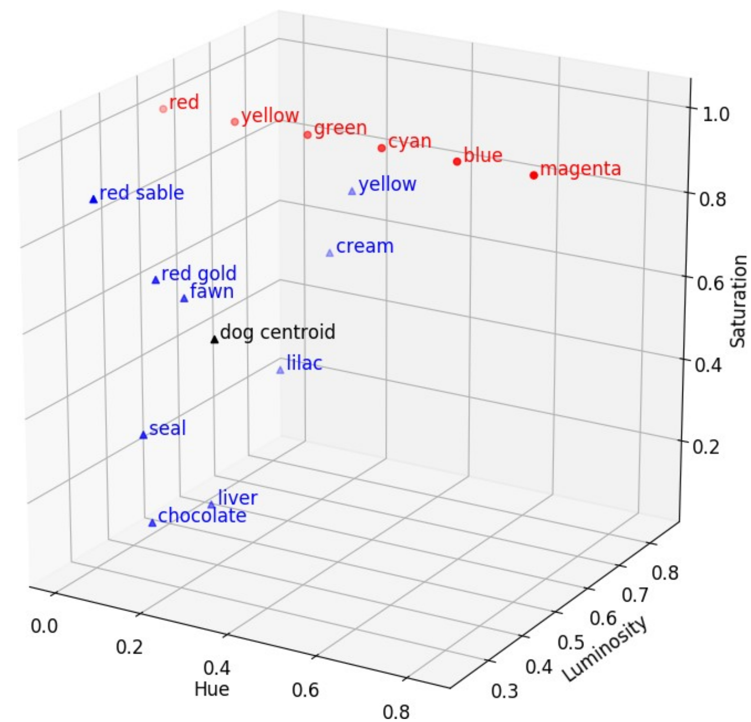
0.29 is the std dev of a uniform distribution on [0, 1]!
we neglect the dimensions approaching it.



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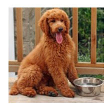
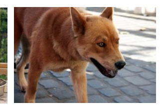
These dogs are "red dogs":   

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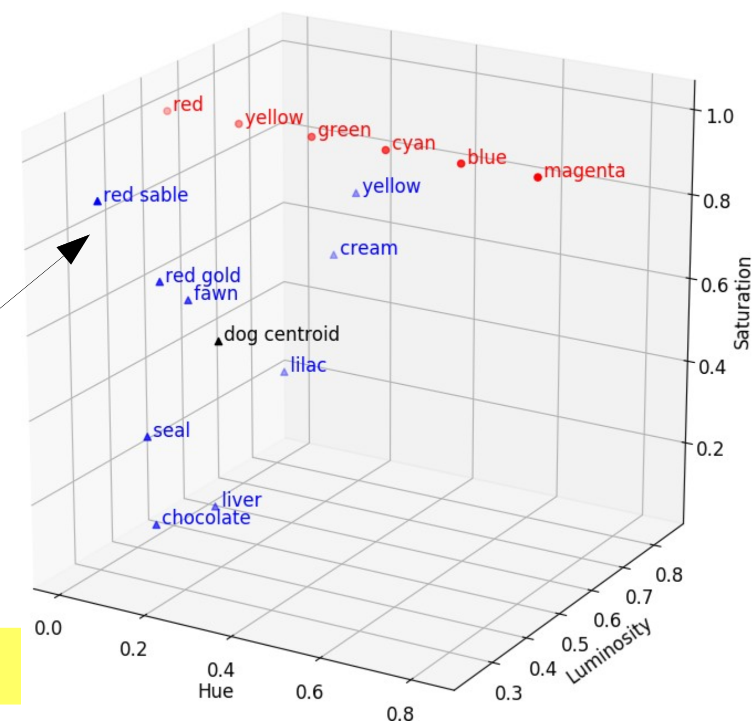

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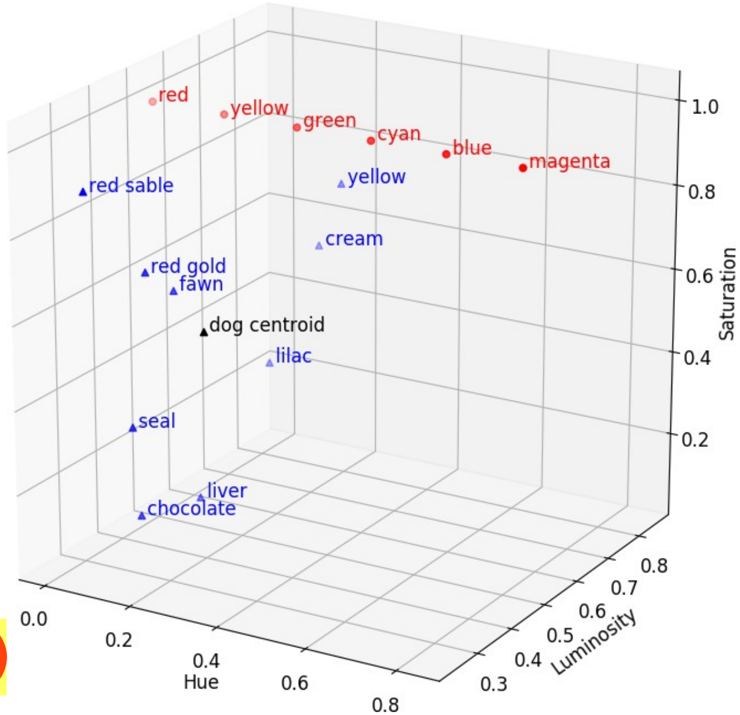
C =	[-0.16,	0.24,	0.92]	↝ **“red”**

Still in the gravitation of red, but not brown!



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we don't say
“the table is below the apple.”
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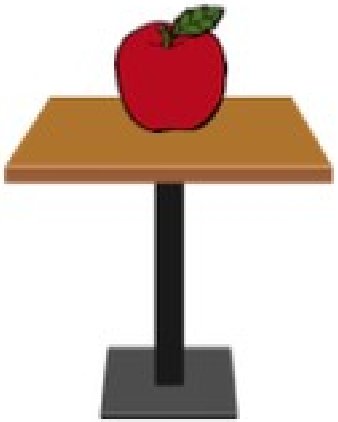

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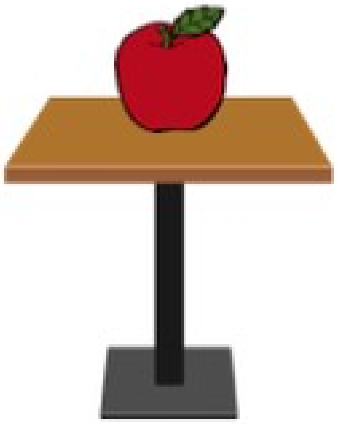
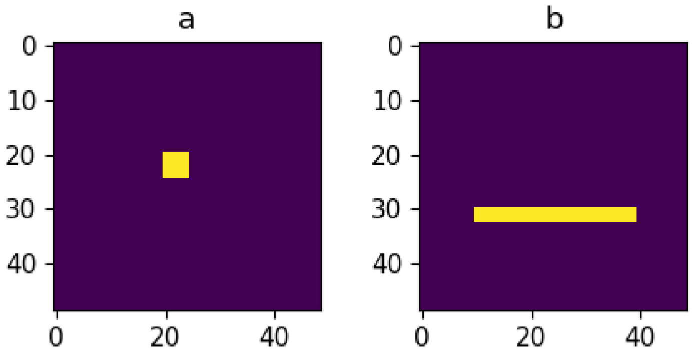


If our hypothesis is correct, $C = A - B$ ↝ "above"

Before we handled points, here we have extended objects.
→ *mathematical morphology* methods

Predicates are generated on the fly

We considered an existing method [Bloch2006] used in image processing to compute directional relative positions of visual entities (e.g. of biomedical images).



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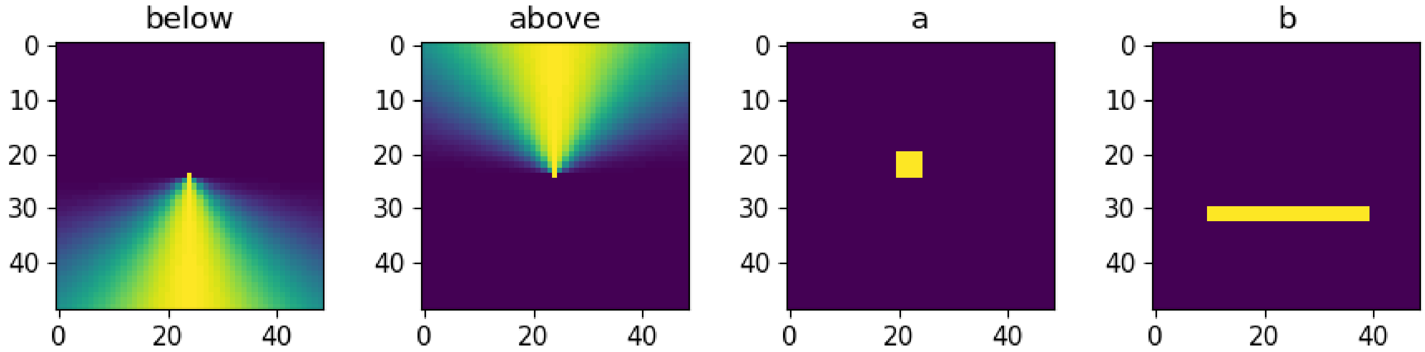

models of relations
for a point centered
in the origin

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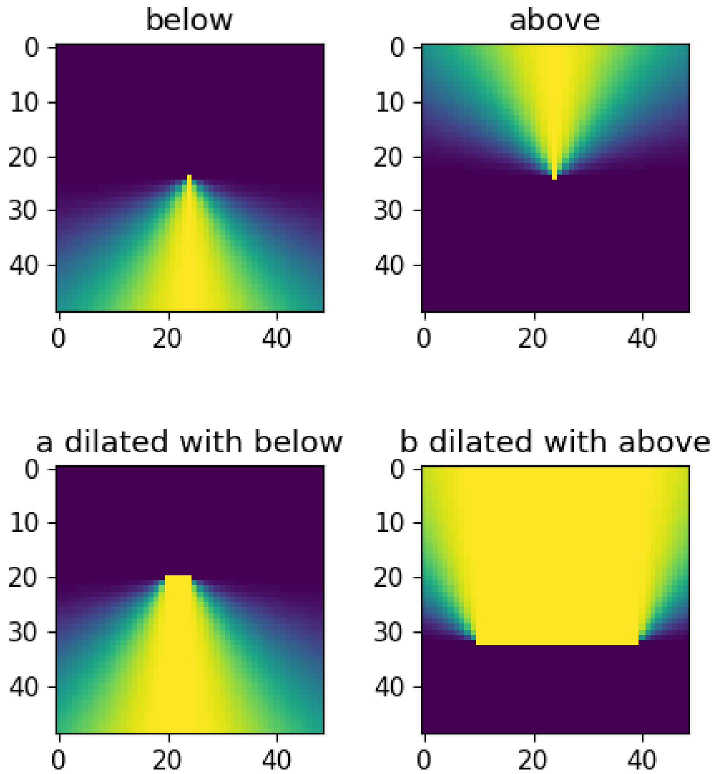

“below a” “above b”

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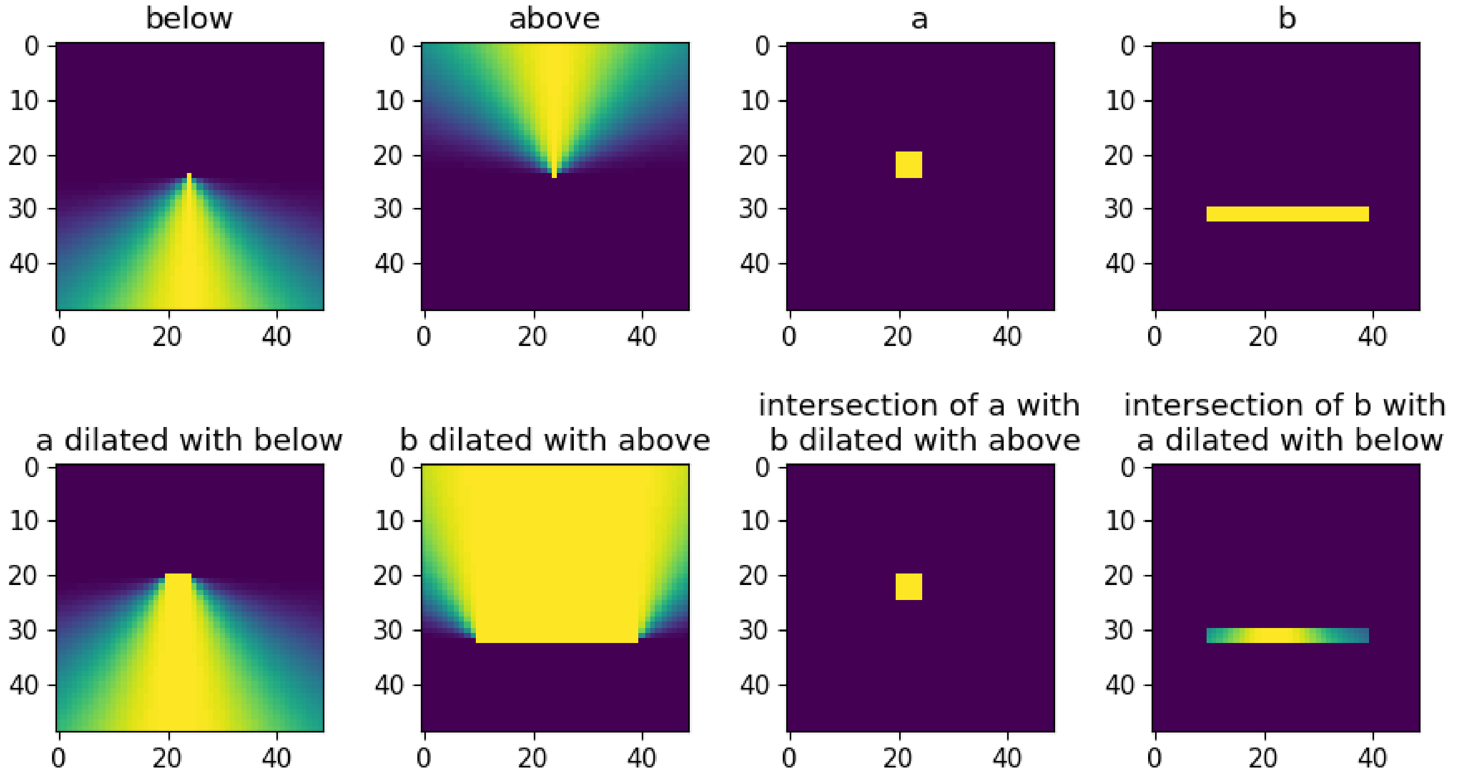

“below a” “above b” how much a is (in) “above b” how much b is (in) “below a”

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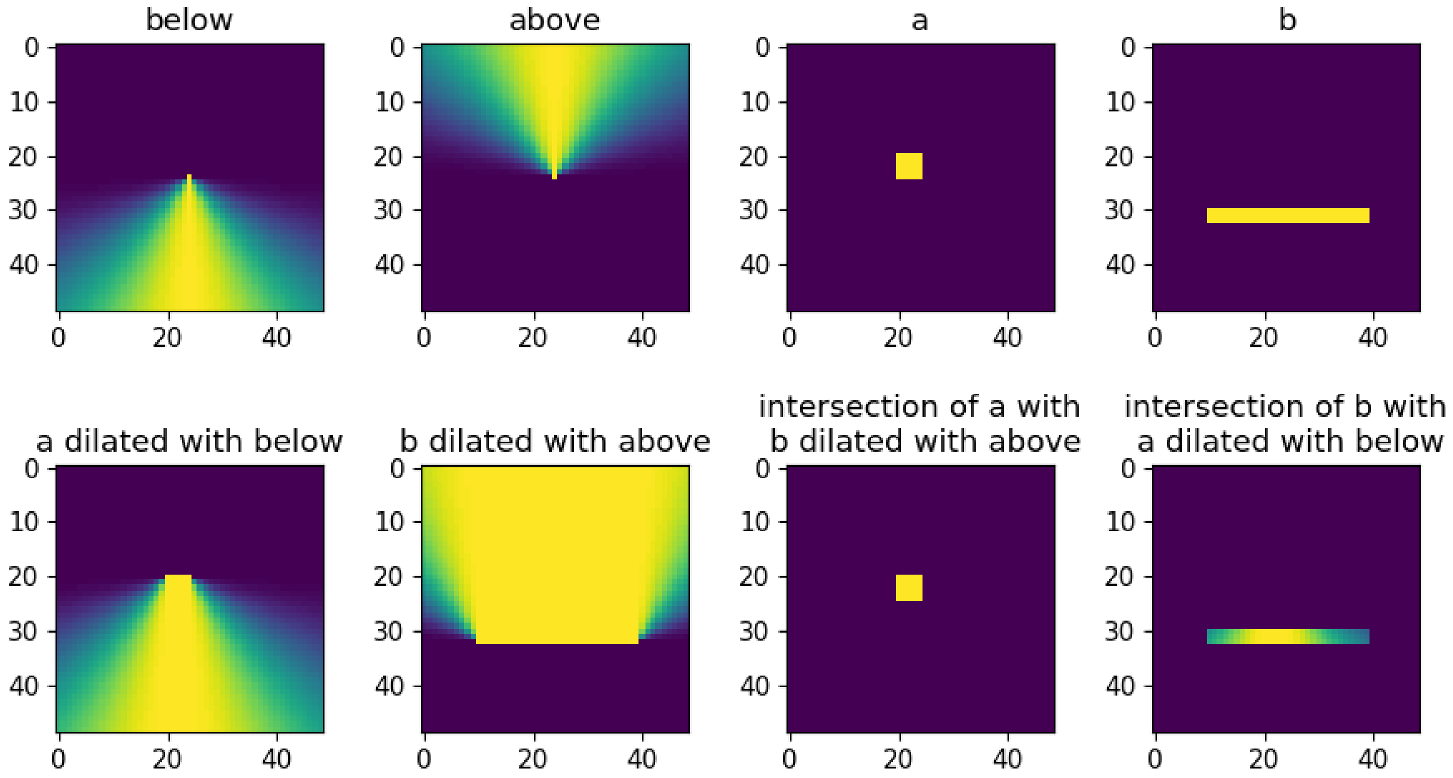

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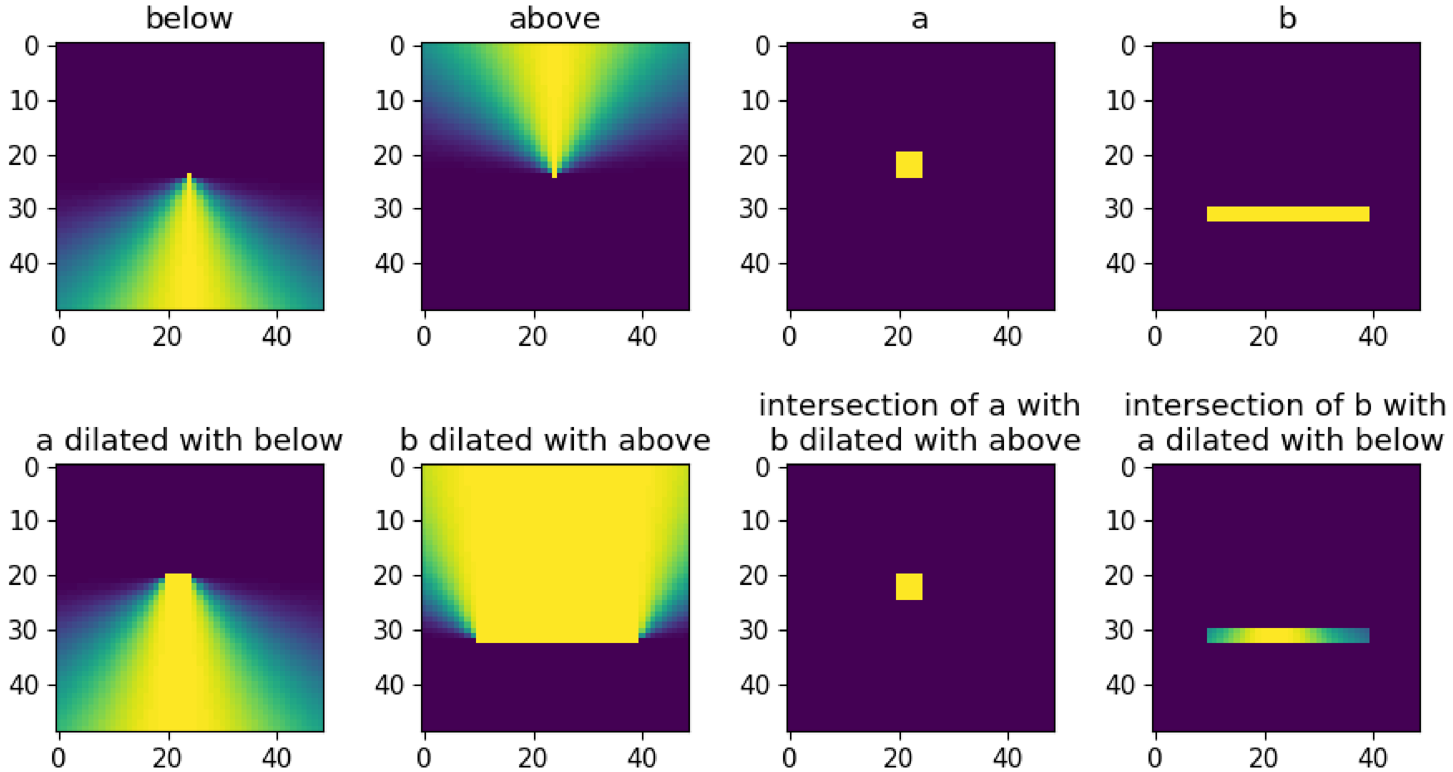

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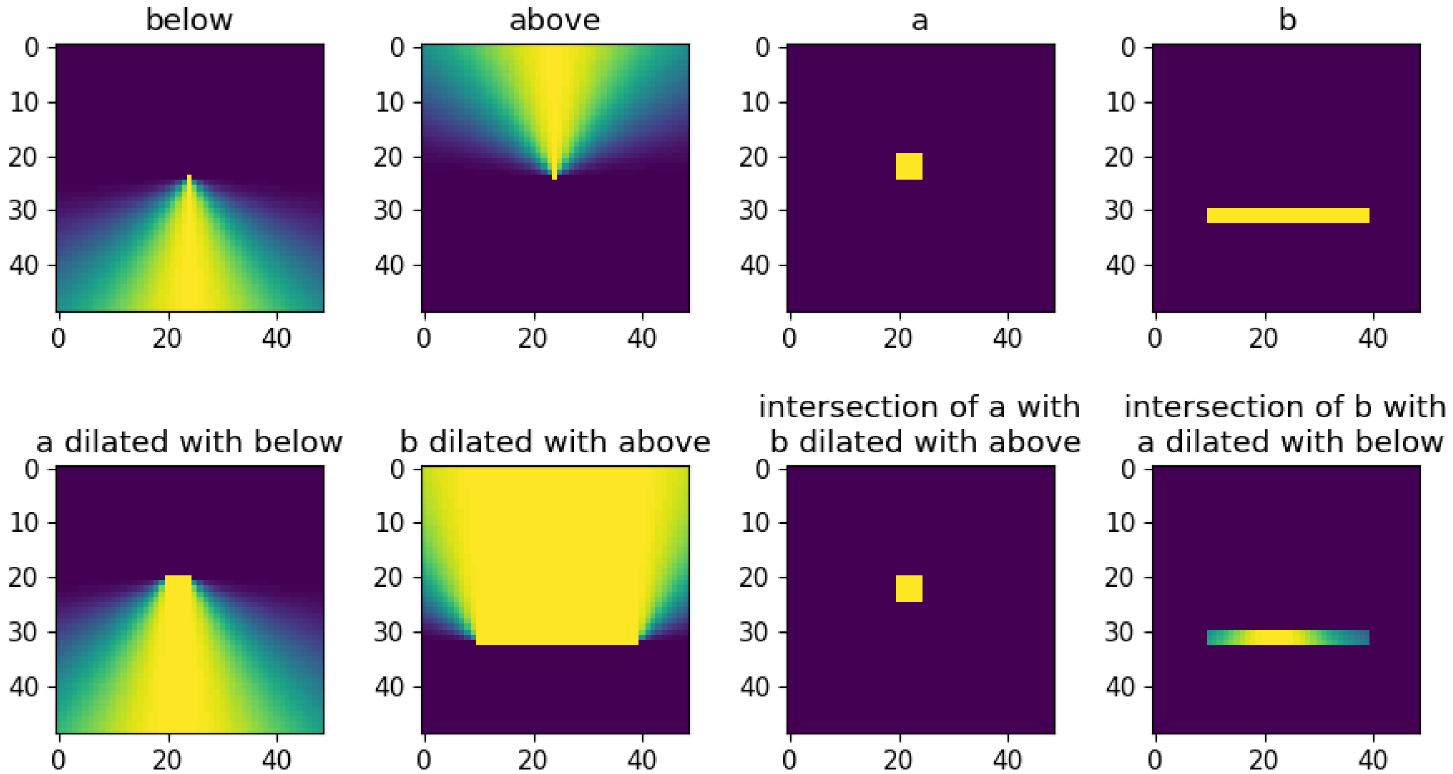

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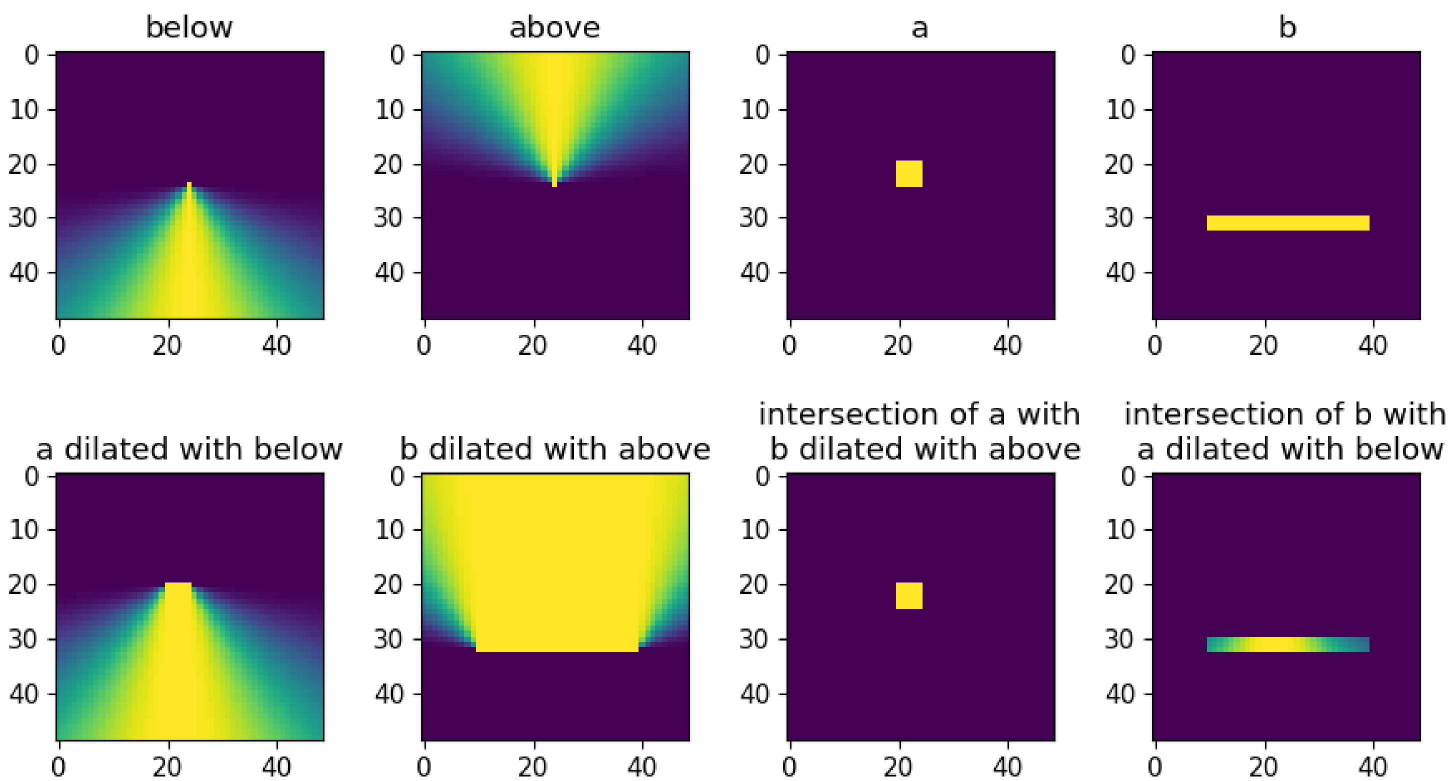

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cf. with $o - p \leadsto \text{"red"}$

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From contrast to concept similarity

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- *But what about concept (i.e. multi-dimensional) similarity?*

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“she is strong.”

this person − prototype person ↝ *“strong”*

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Concept similarity is a sequential, multi-layered computation

psychology **machine learning**

geometrical model of cognition

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basis of feature-based models

but.. **feature selection?**

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Our explanation: **changing of reference activates different features**

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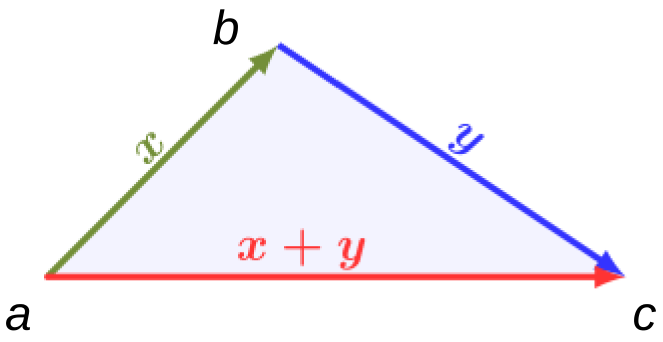
$$d(a,b) + d(b,c) \geq d(a,c)$$



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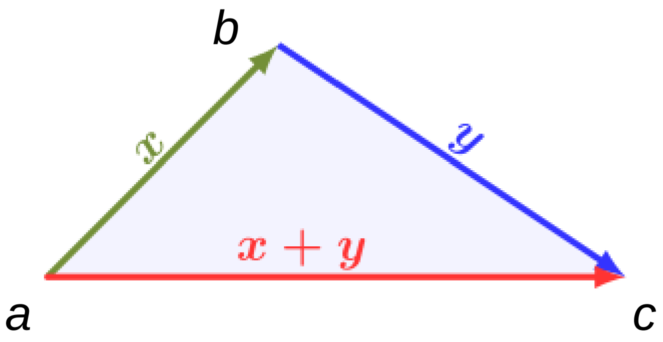
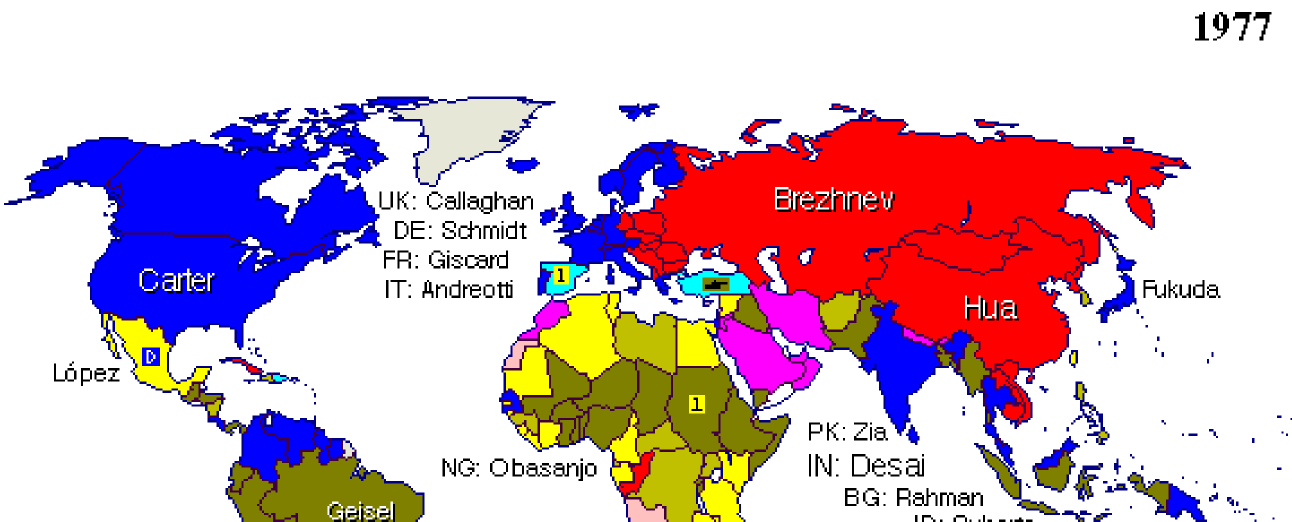


However,

Jamaica is similar to Cuba

Cuba is similar to Russia

Jamaica is ***not*** similar to Russia.



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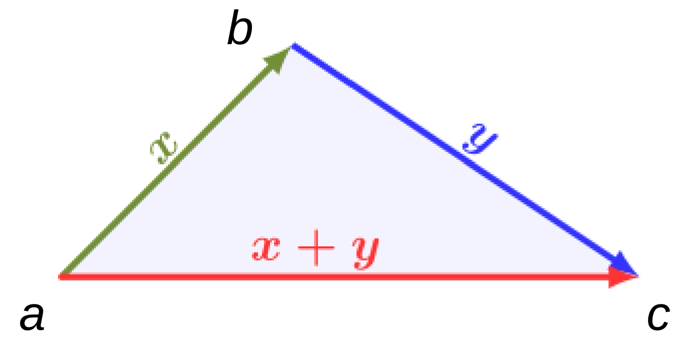

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1977

Our explanation: **different/no *comparison grounds* after contrast**

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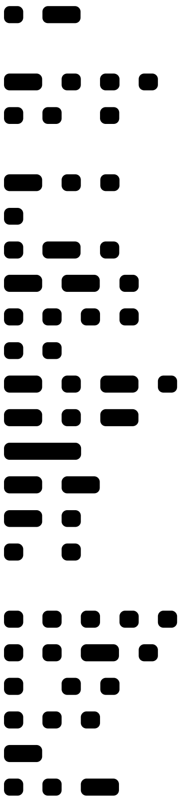

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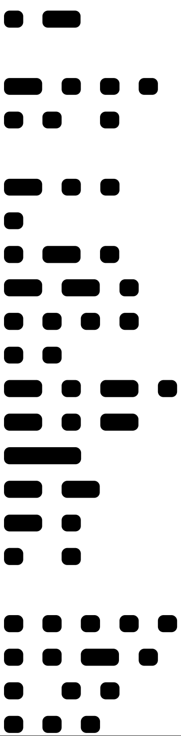

Our explanation: **sequential nature of similarity assessment.**

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However,

– when people were asked for the country most similar to a reference amongst a given group of countries, they changed answers depending on the group.

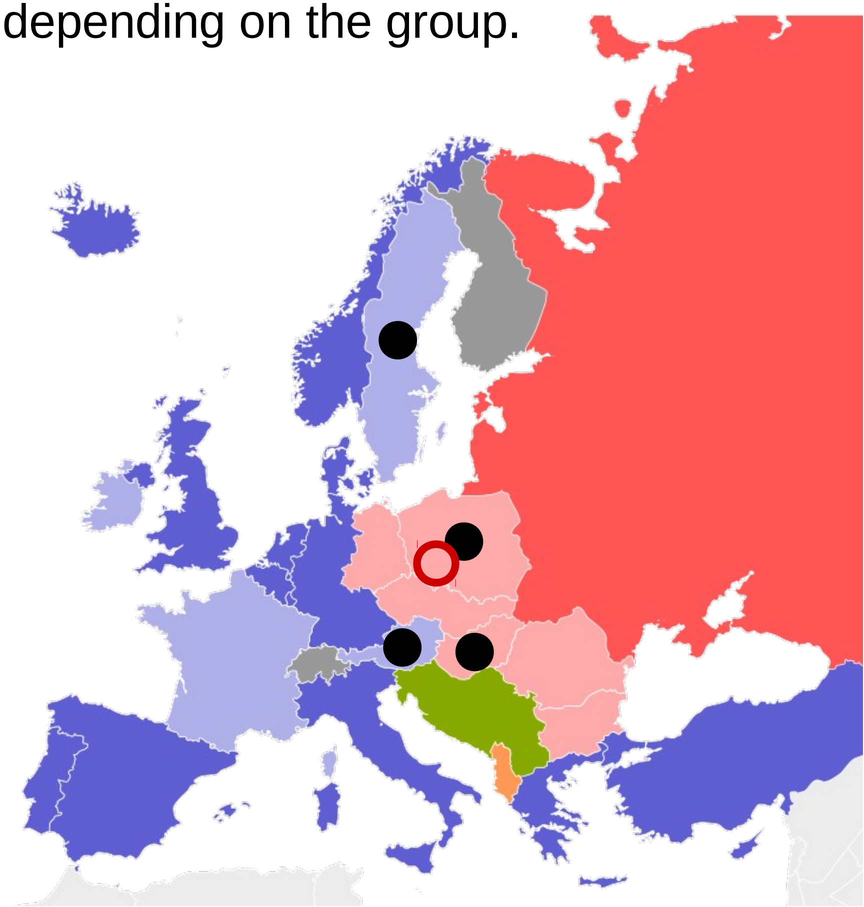
Austria

most similar to

Hungary

Poland

Sweden



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- *The distance between two points in a set should not change when changing the set.*

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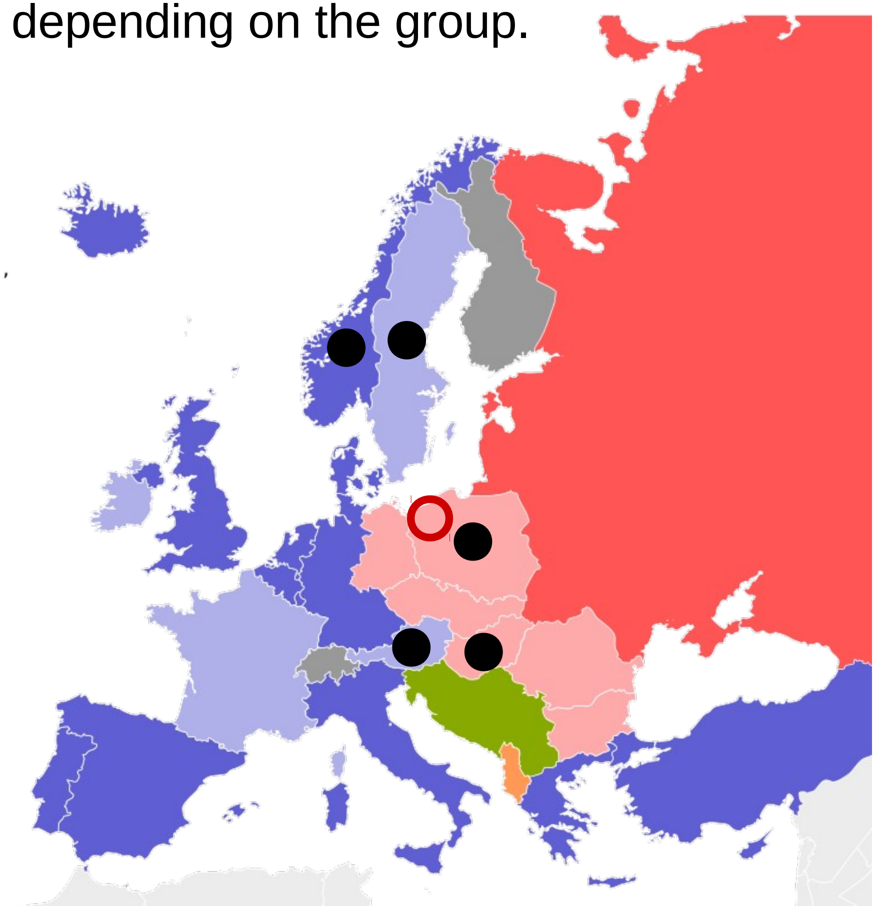

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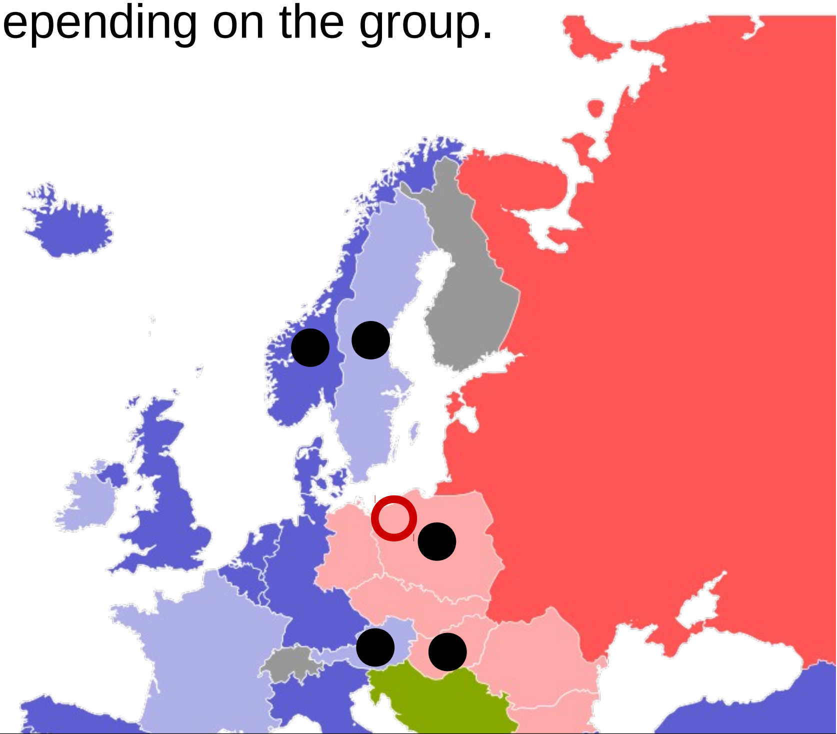

Our explanation: effect due to the **change of group prototype**

Conclusions

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- This hypothesis provides simple explanations to empirical experiences manifesting non-metrical properties, yet maintaining a geometric infrastructure.
- Future investigations: normalizing effects, contrast with regions, non-descriptive pertinence.