

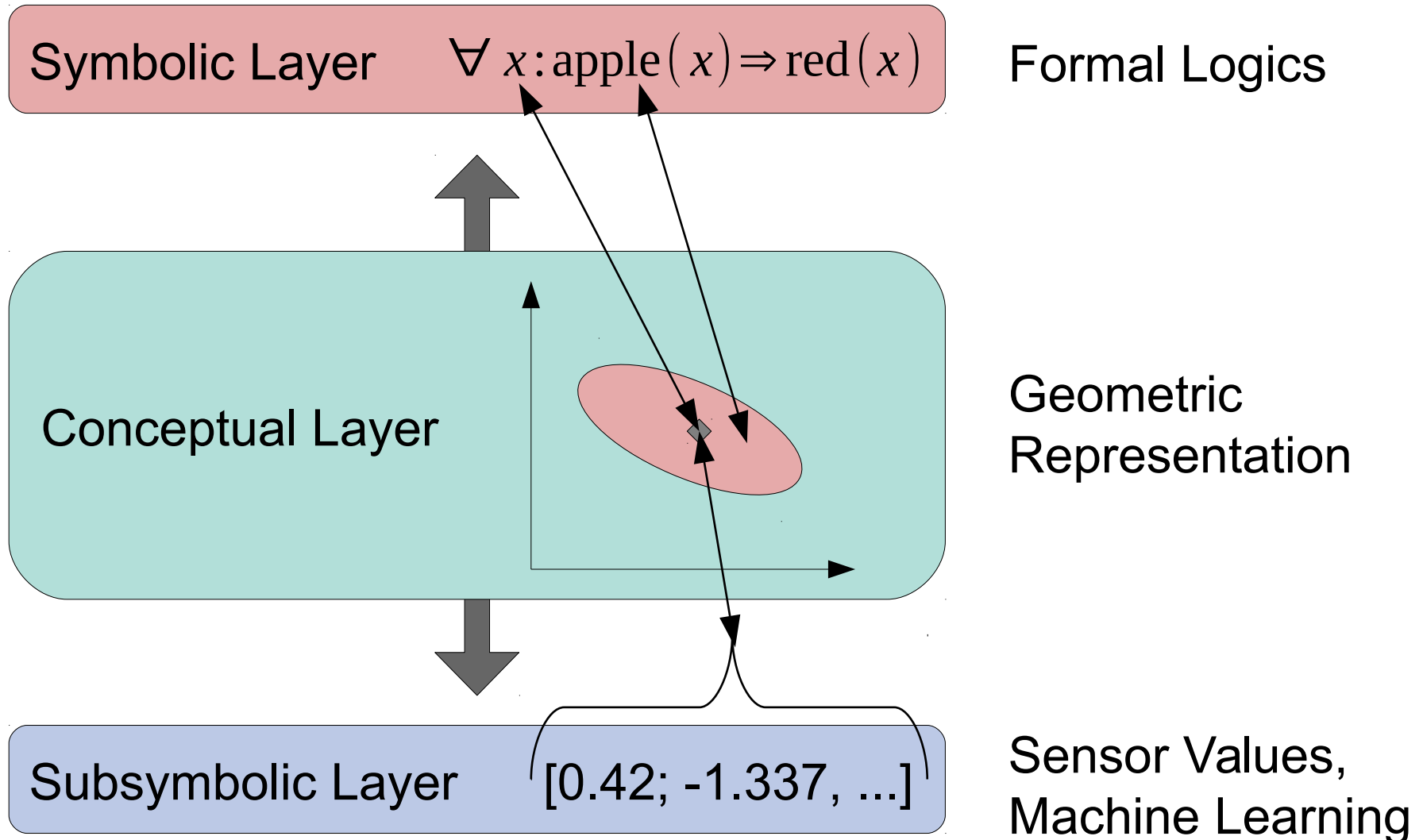
Machine Learning in Conceptual Spaces

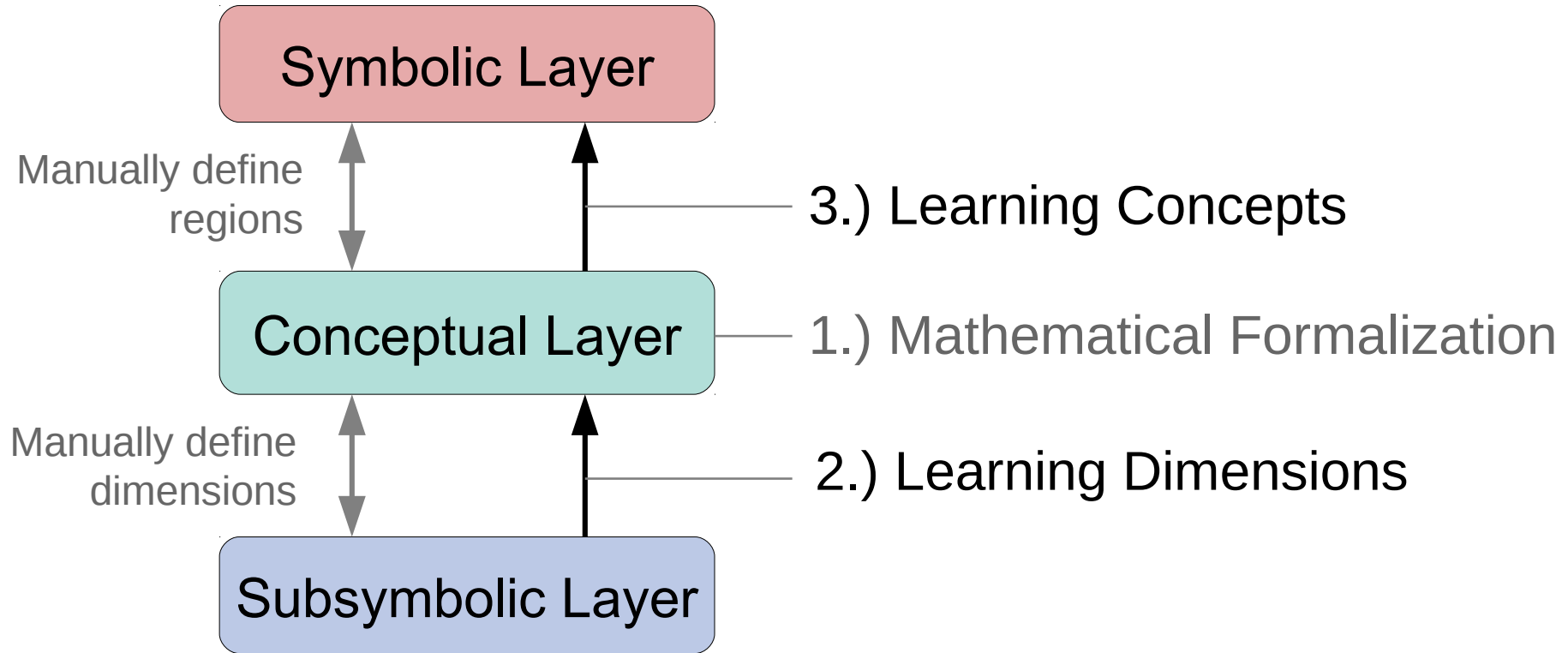
Two Learning Processes

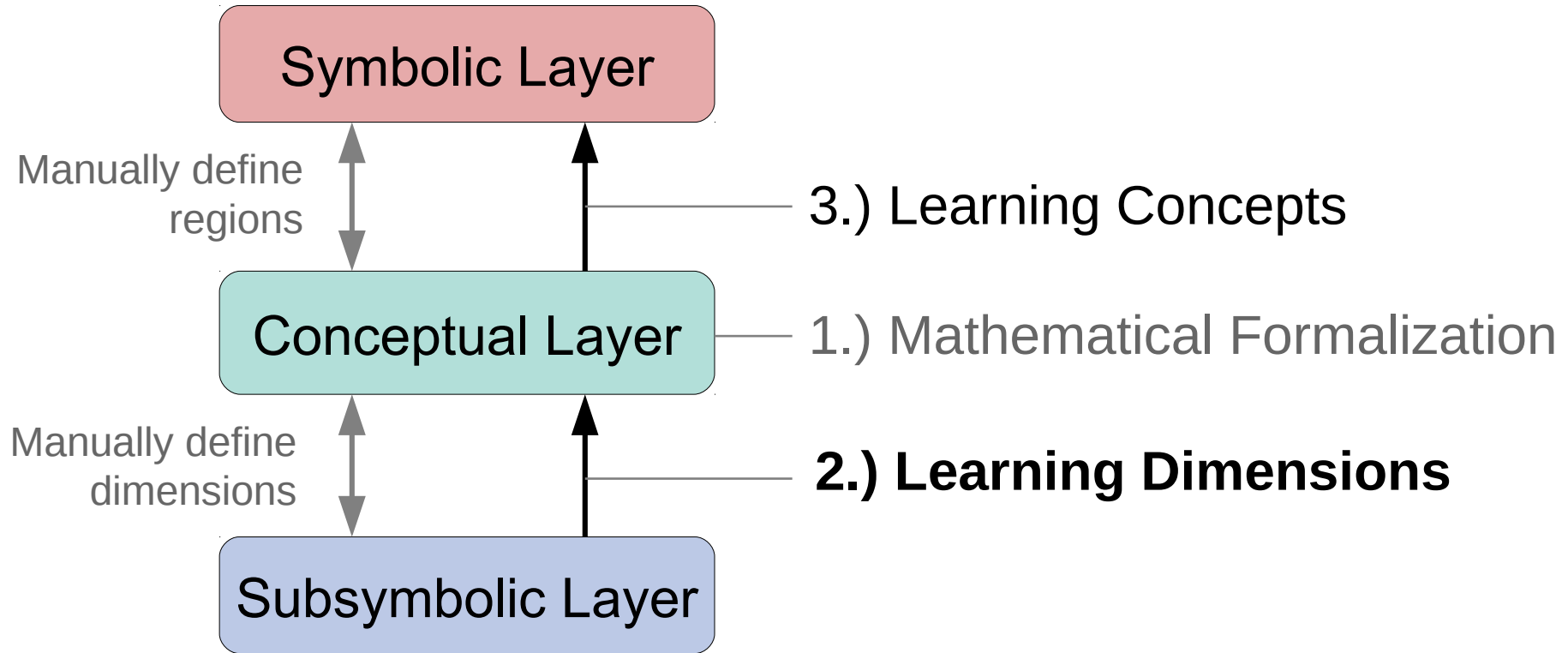
Lucas Bechberger

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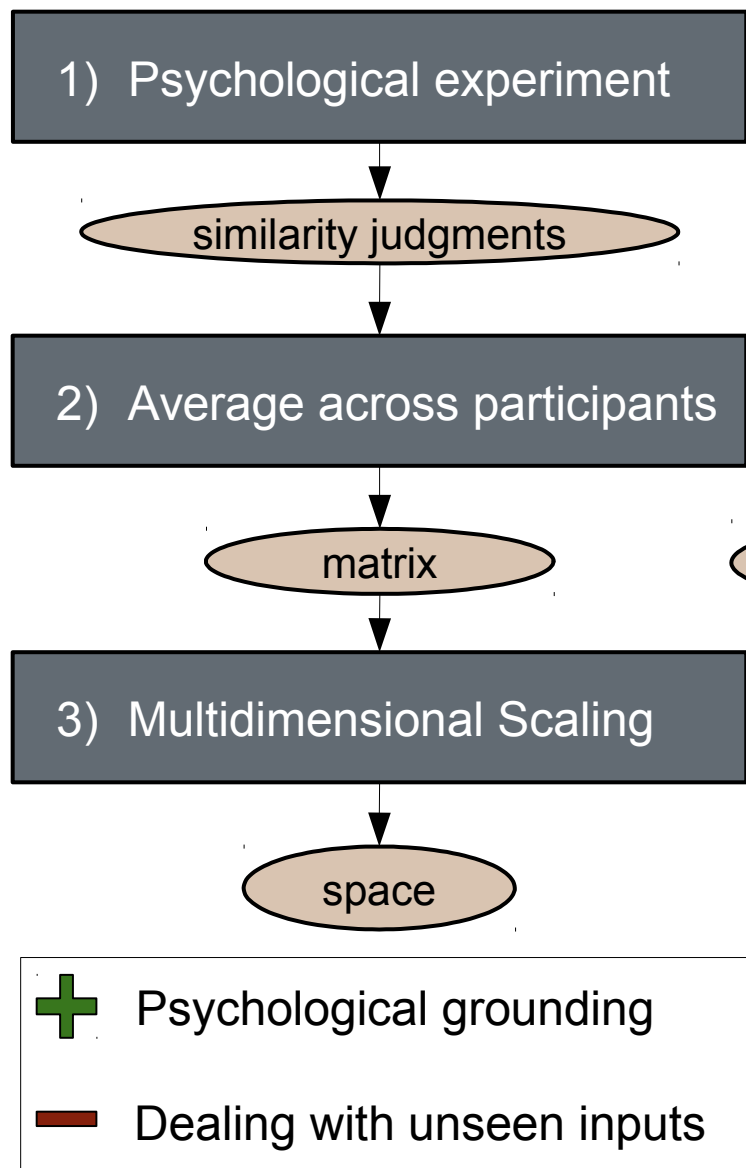




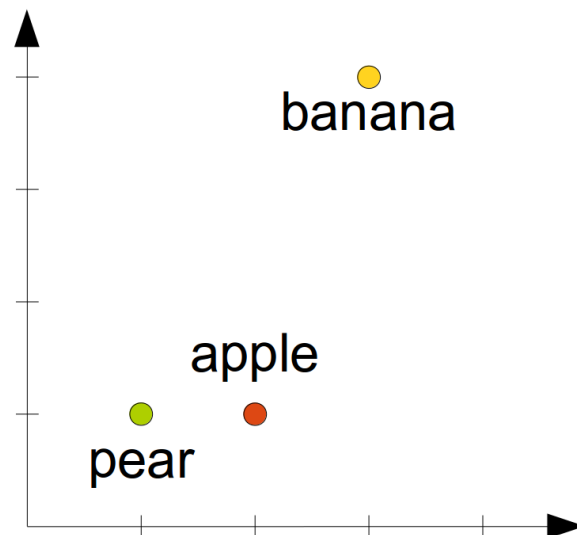


- There are (at least) three approaches:
 - Handcrafting
 - Multidimensional Scaling
 - Artificial Neural Networks
- Bonus: A Hybrid Approach

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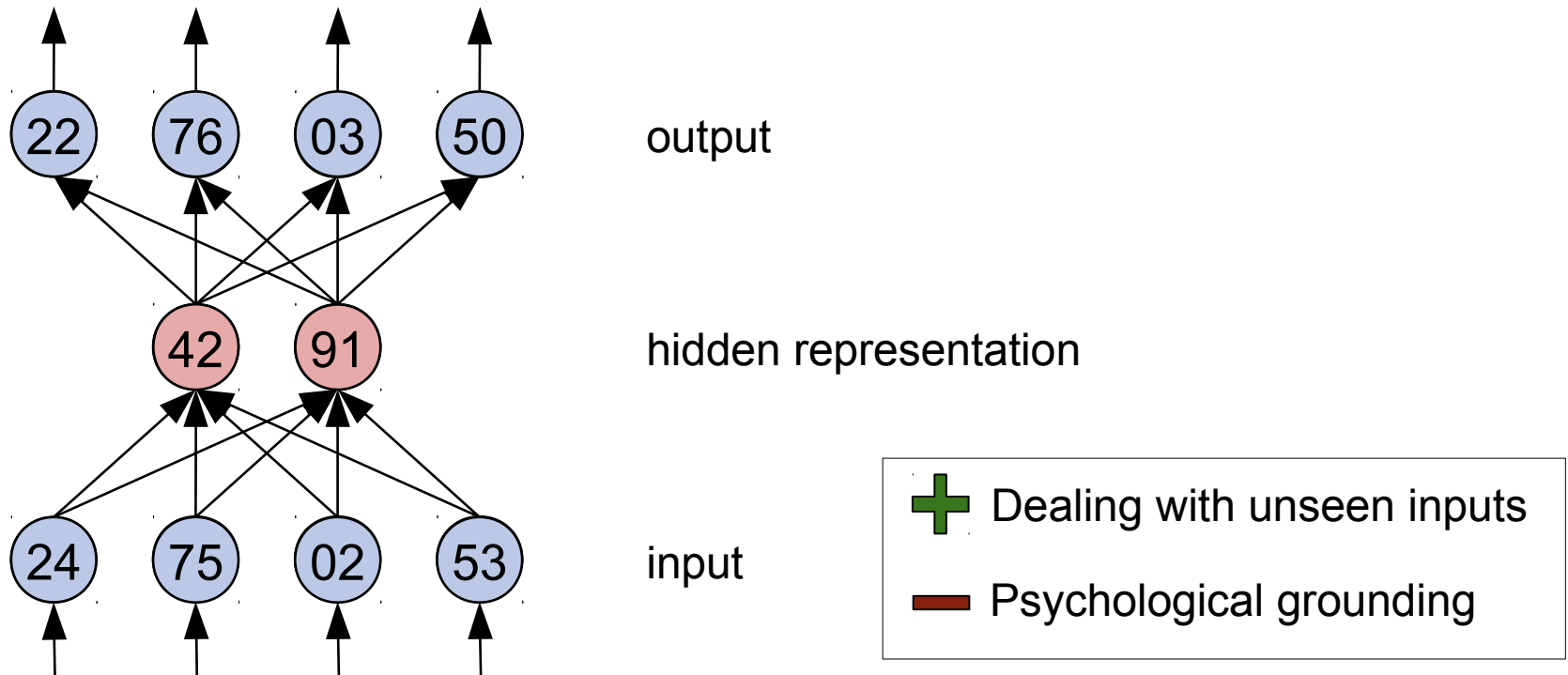
distance	apple	pear	banana
apple	0.0	1.0	3.2
pear	1.0	0.0	3.6
banana	3.2	3.6	0.0



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 - Multidimensional Scaling
 - **Artificial Neural Networks**

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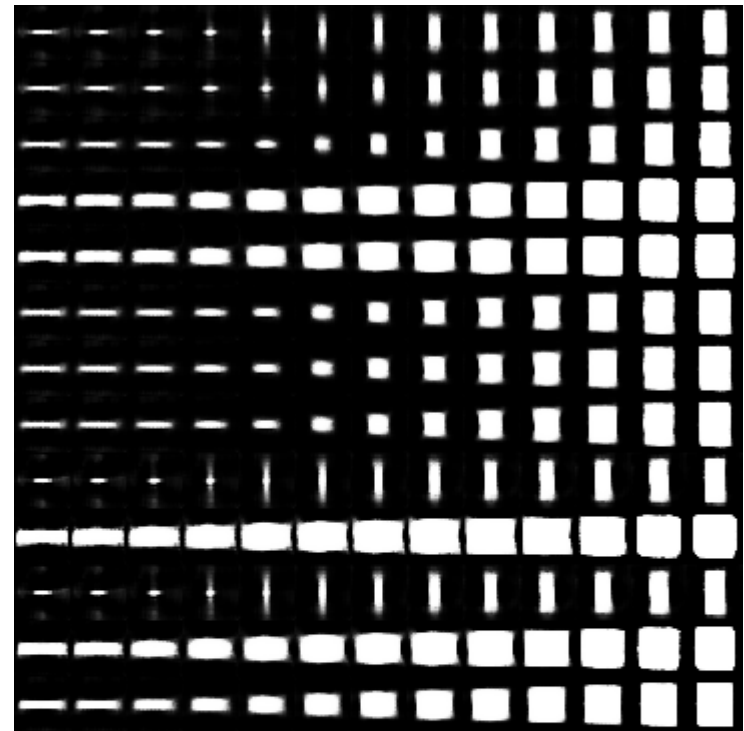
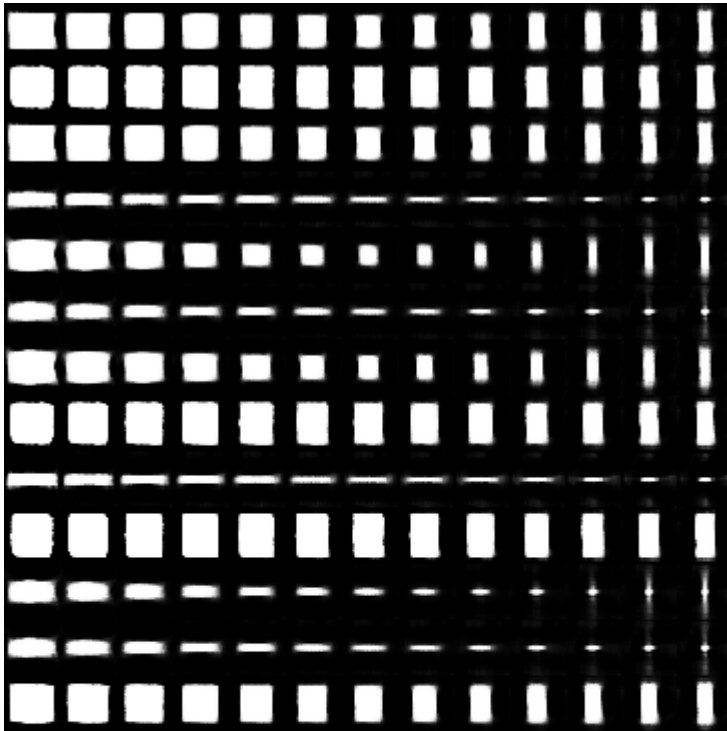
- Autoencoder (e.g., β -VAE): compress and reconstruct input



- Hidden neurons = dimensions in our conceptual space

Higgins, I.; Matthey, L.; Pal, A.; Burgess, C.; Glorot, X.; Botvinick, M.; Mohamed, S. & Lerchner, A. β -VAE: Learning Basic Visual Concepts with a Constrained Variational Framework, ICLR 2017

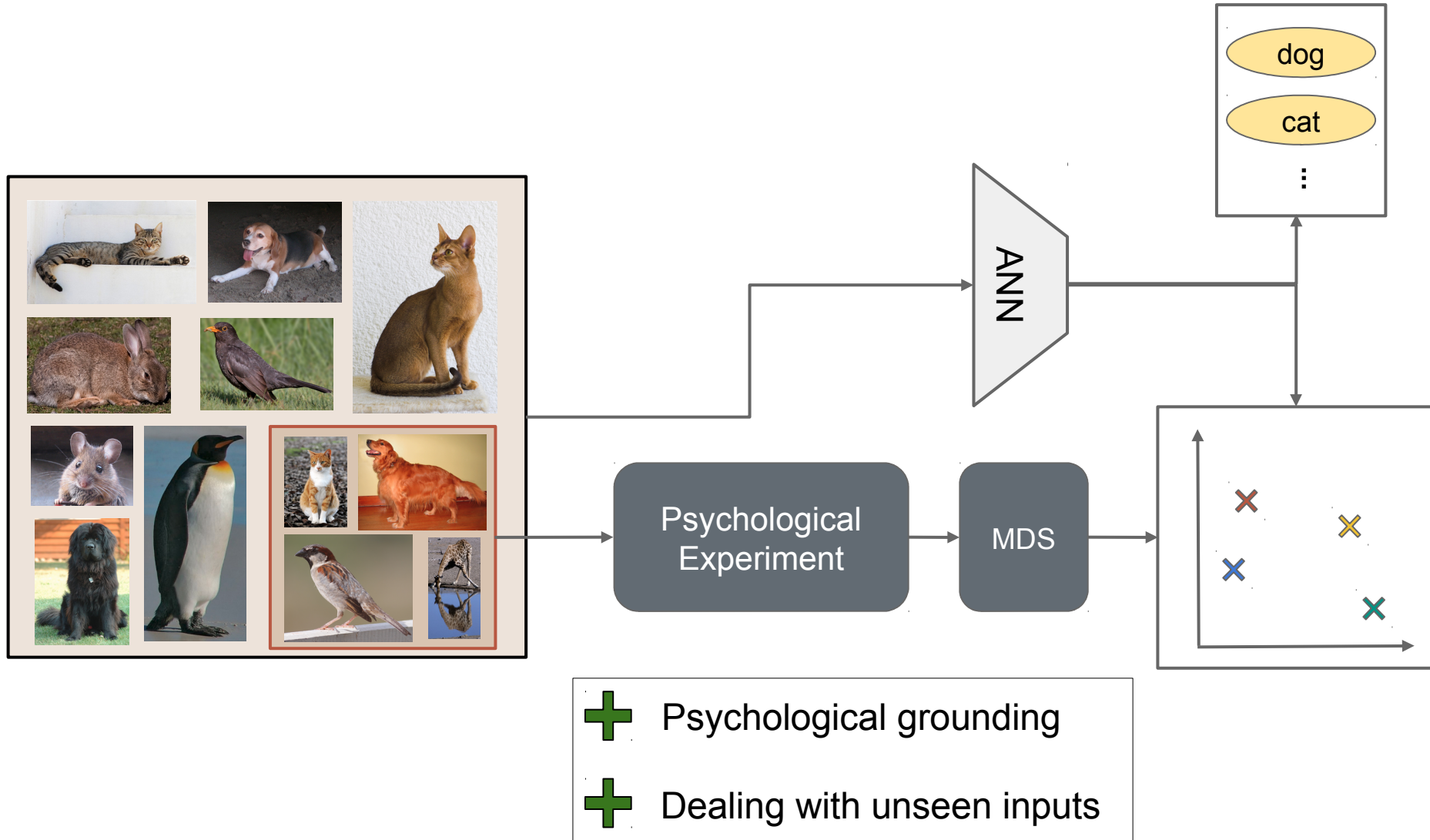
- Centered, unrotated rectangles
 - Differing only with respect to width and height
- Use InfoGAN to learn interpretable dimensions



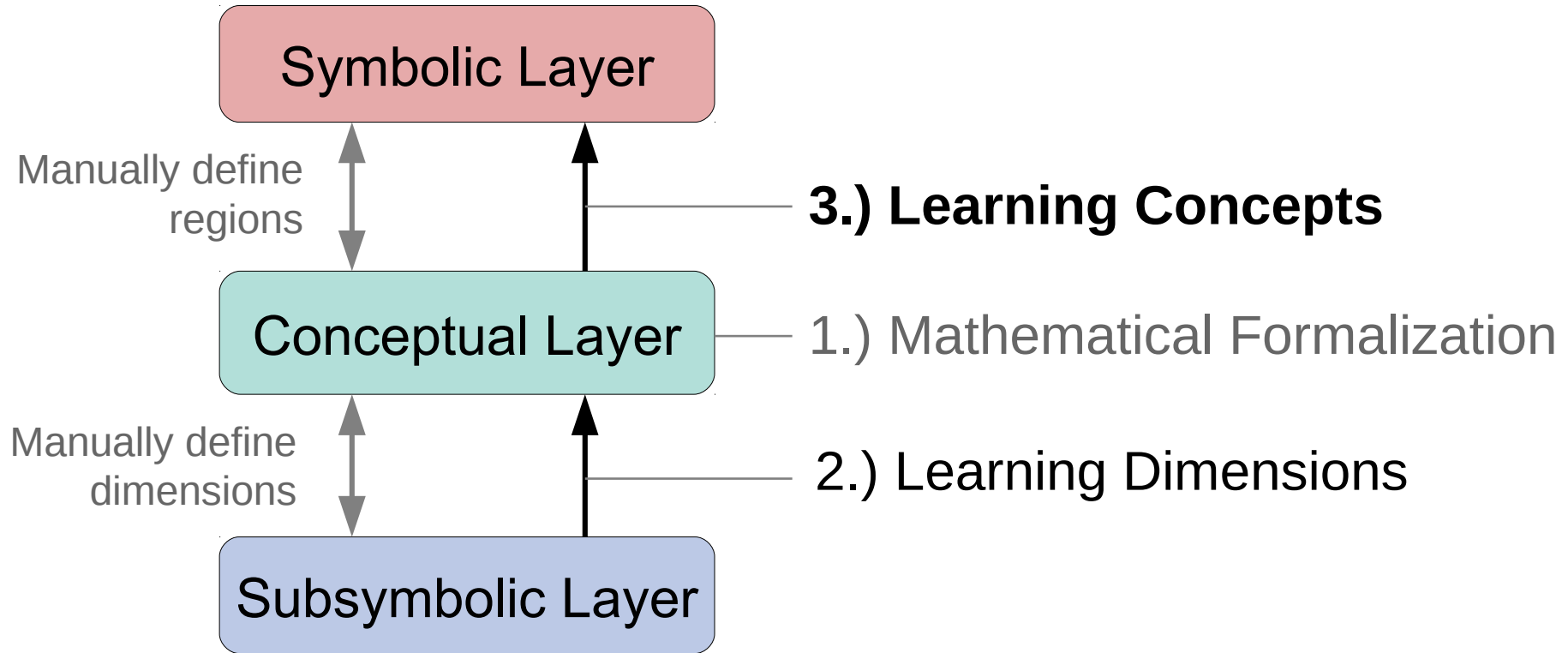
Chen, X.; Duan, Y.; Houthoofd, R.; Schulman, J.; Sutskever, I. & Abbeel, P. InfoGAN: Interpretable Representation Learning by Information Maximizing Generative Adversarial Nets Advances in Neural Information Processing Systems, 2016

- There are (at least) three approaches:
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Learning Dimensions: Hybrid



Bechberger, L. & Kypridemou, E. Mapping Images to Psychological Similarity Spaces Using Neural Networks. AIC 2018



Learning Concepts

Give me a big data set of labeled examples!

I'll train a neural network for a bunch of epochs to find a nice decision boundary.

It's just a standard ML problem!

That's too complicated for now.



Machine Learning Engineer

Wait a second, that's cognitively implausible!

In real life, we have more unlabeled than labeled examples.

Plus: Humans don't learn via batch processing.



Cognitive Science Researcher

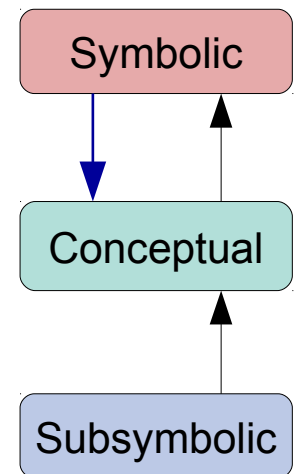
- Fuzzy Logic

- Degree of membership between 0 and 1

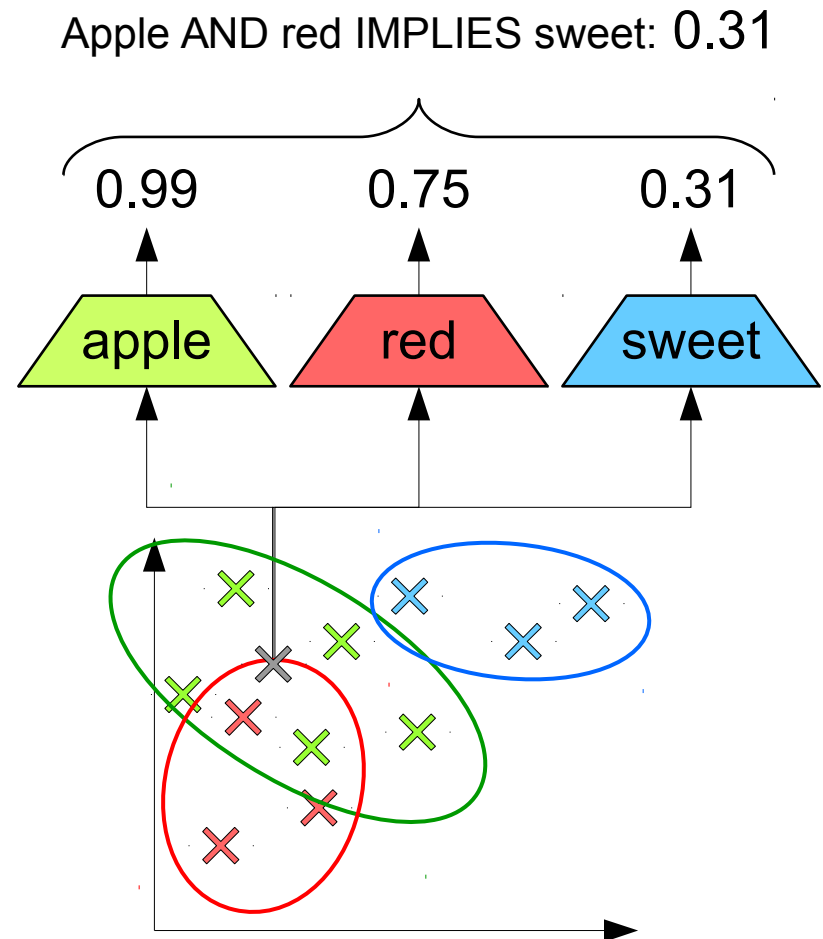


apple:	1.0
red:	0.9
round:	0.7
banana:	0.0

- One can generalize logical operators:
 - apple AND red = $\min(\text{apple}, \text{red})$
 - We can express **rules** over these fuzzy sets

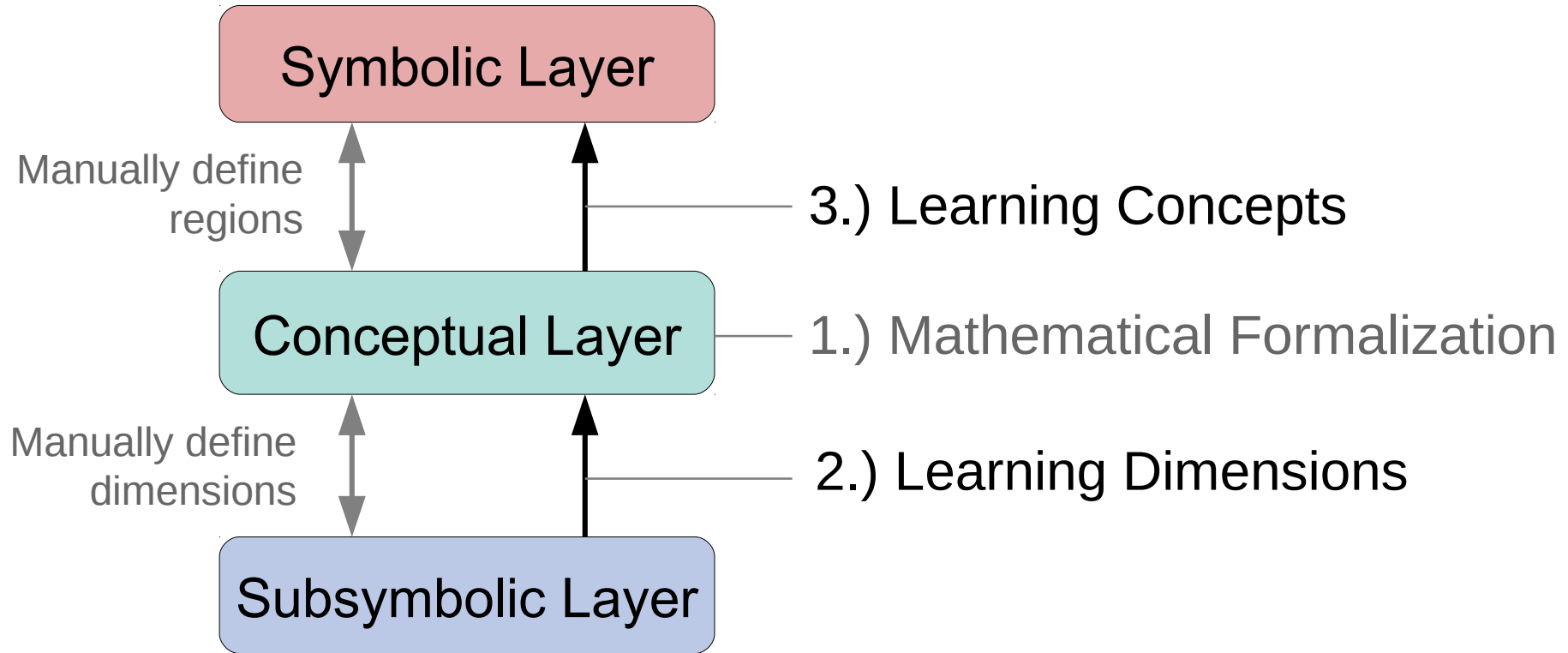


- Use neural networks to learn membership functions
- Constraints:
 - Labels
 - Rules
- Tune NN weights such that all constraints are fulfilled



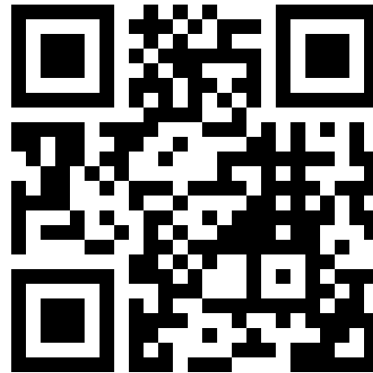
- Conceptual space of movies from Derrac and Schockaert
 - Extracted conceptual space from movie reviews
 - 15.000 data points, labeled with one or more of 23 genres
- Use LTN to learn genres in that space
 - Compare to kNN with respect to classification performance
 - Compare to simple counting with respect to rule extraction
- Long run: align LTN with conceptual spaces theory
 - Convexity, domain structure, ...

Joaquín Derrac and Steven Schockaert. Inducing semantic relations from conceptual spaces: a data-driven approach to commonsense reasoning, Artificial Intelligence, vol. 228, pages 66-94, 2015



Thank you for your attention!

Questions? Comments? Discussions?



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