Using neural networks to simulate brain damage: The Farah & McClelland model

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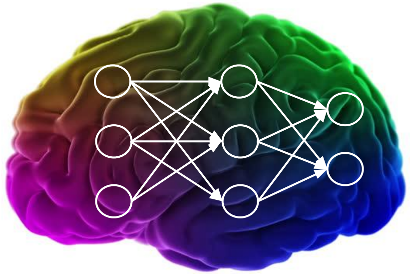
Course: Kognitive Neuropsychologie
Lecturer: Prof. Axel Mecklinger

2 February 2021



Outline

1. Introduction
2. Principles of connectionist modeling
3. A model of semantic memory impairment: Farah & McClelland (1991)
4. A (simplified) reimplementation of the Farah & McClelland model
5. Conclusion

1. Introduction

Studying cognition

Cognitive neuropsychology

→ study cognition by examining the performance of brain-damaged subjects (changed performance w.r.t. controls)

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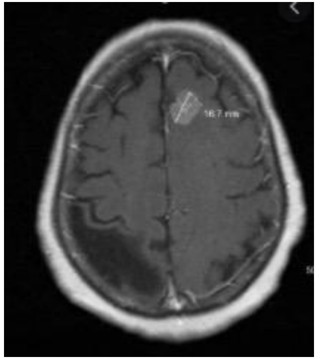

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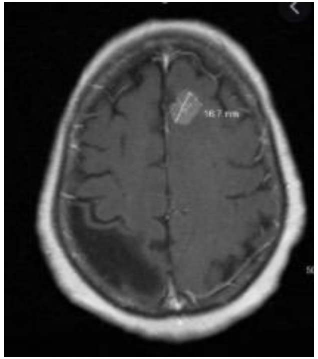

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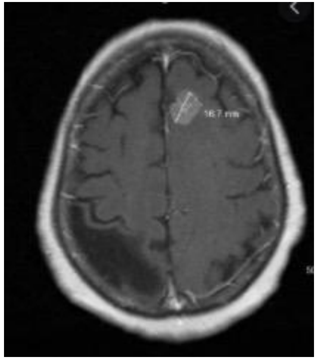

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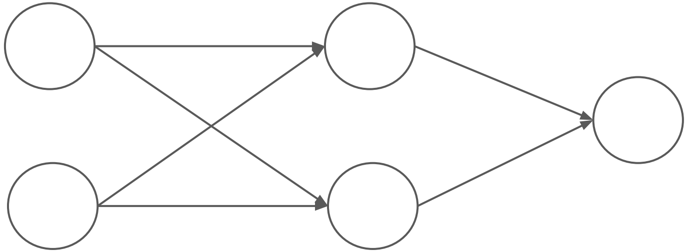

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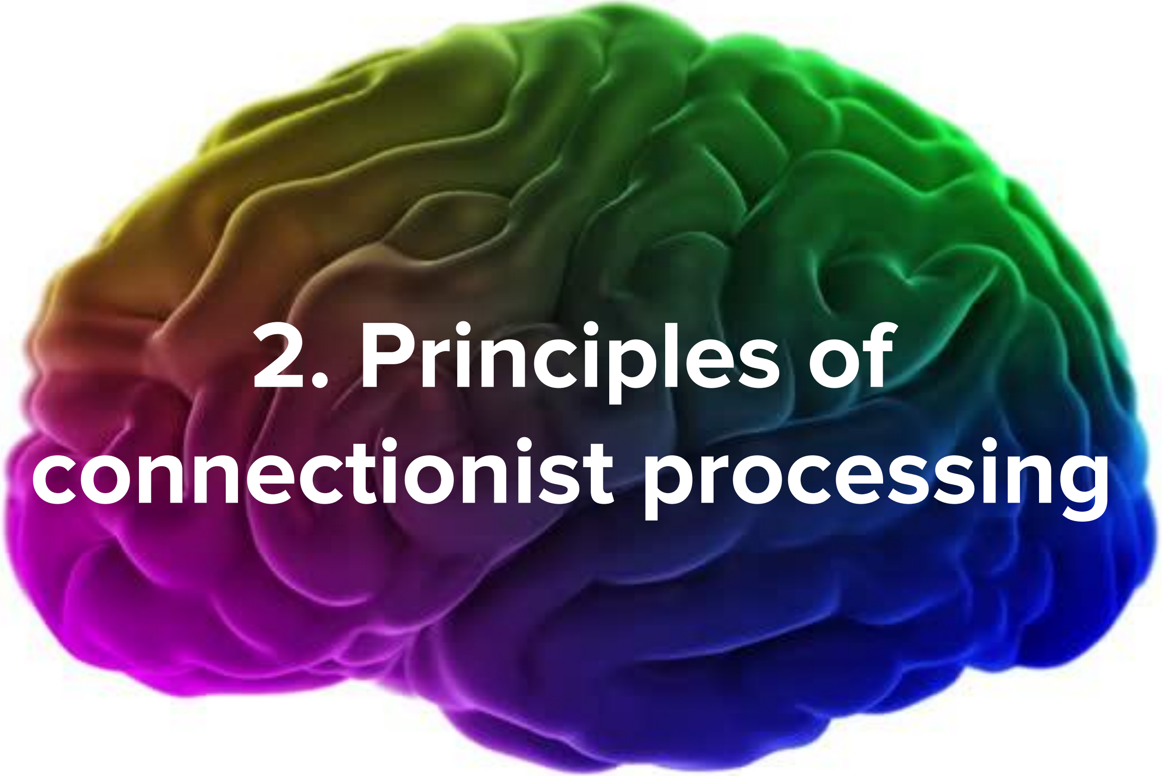
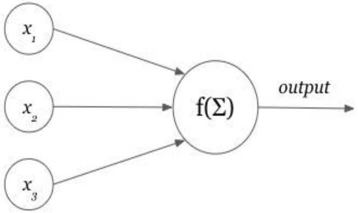
➔ Go through a (simplified) **reimplementation** of the model



2. Principles of connectionist processing

A minimal history of neural networks

- The **McCulloch & Pitts (1943) neuron**: simplest neural model



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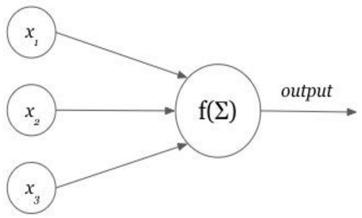

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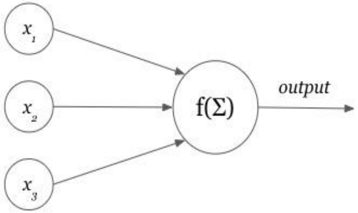

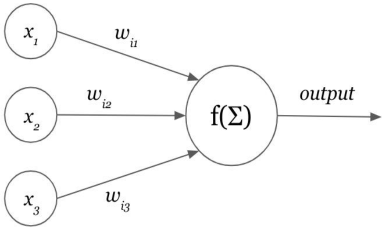

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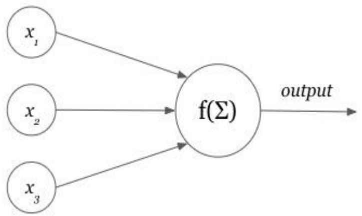

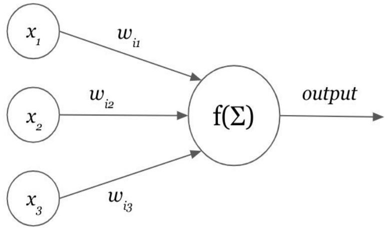

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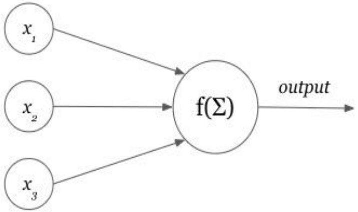

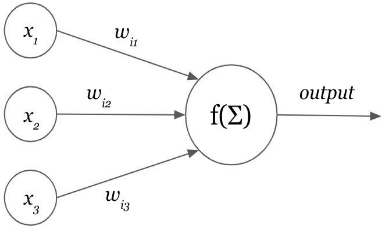

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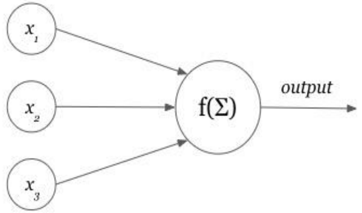
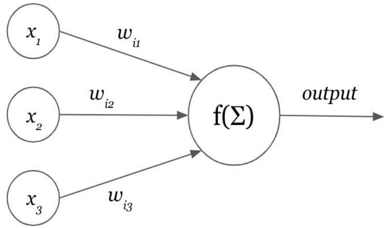
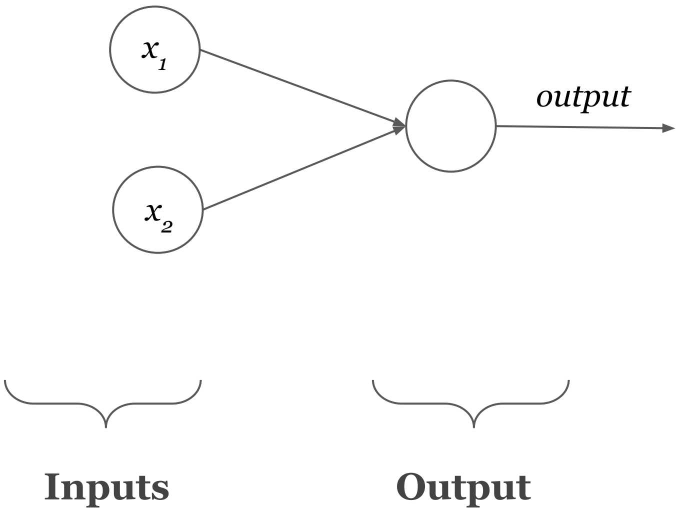
- In the past decade: huge boom of neural networks/**"deep learning"** in artificial intelligence/machine learning: Google Translate, Alexa, autocorrect, text prediction, recommendation systems like Spotify, ...





Example of a very small neural network



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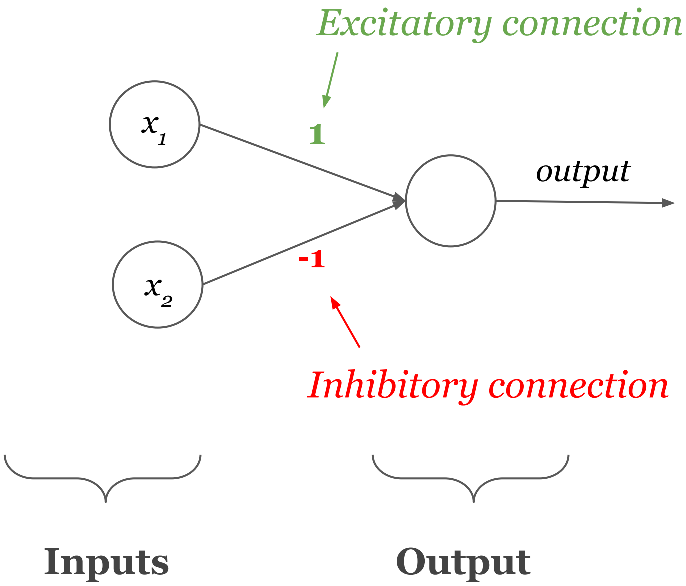

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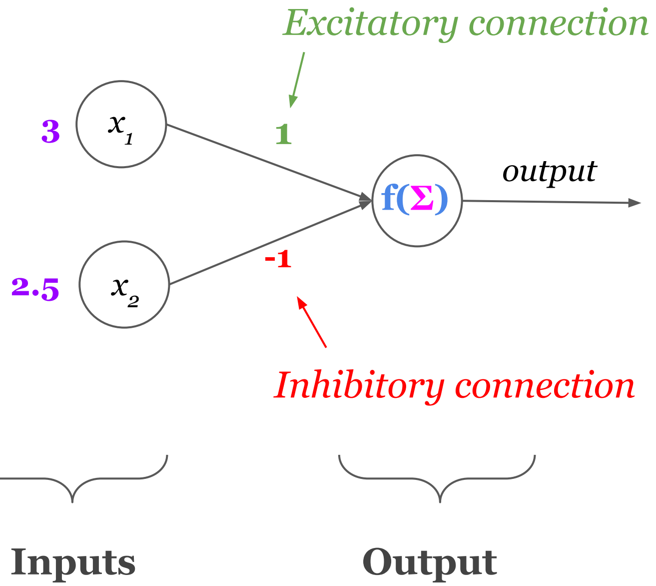

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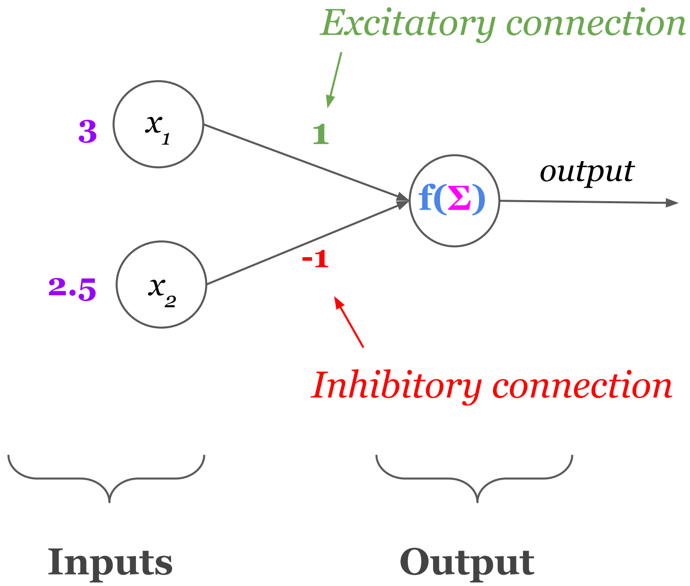
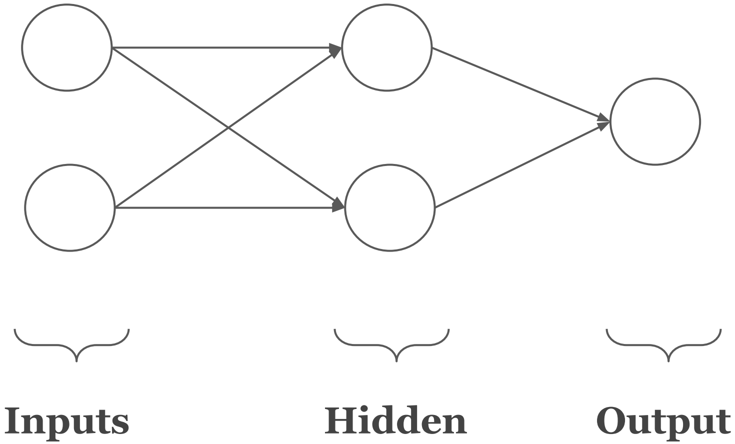


$$\Sigma = 3 * 1 + 2.5 * (-1)$$
$$= 3 - 2.5$$
$$= 0.5$$

$$f(x) = 1 \text{ if } x > 0$$
$$= 0 \text{ if } x <= 0$$

$$f(\Sigma) = f(0.5) = 1$$

A (slightly) more complex network



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- **Break down the complexity** of a model
- Make **precise, quantitative** predictions ("testable")
- Not a replacement, but a **complement** to verbal theories or box-arrow diagrams; an **additional test** for the consistency and completeness of a theory

Why make computational models of cognition?

Level 1 (computational)	Input-output behavior
Level 2 (algorithmic)	Mind-as-symbol-manipulator hypothesis vs. “brain-like” connectionist models
Level 3 (implementational)	Neurons vs. transistors in computers

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These properties “come for free”; networks not specifically trained for them.

3. The Farah & McClelland model

The double dissociation between living and non-living things

Table 1

Performance of Two Patients With Impaired Knowledge of Living Things on Various Semantic Memory Tasks

Case	Living thing	Nonliving thing
	Picture identification	
JBR	6%	90%
SBY	0%	75%
	Spoken word definition	
JBR	8%	79%
SBY	0%	52%

The double dissociation between living and non-living things

Table 2
Performance of Two Patients With Impaired Knowledge of Nonliving Things on Various Semantic Memory Tasks

Case	Category: Animal	Flower	Object
Spoken word–picture matching			
VER	86%	96%	63%
YOT	86%	86%	67%
Picture–picture matching			
YOT	100%	—	69%

The sensory-functional hypothesis

Visual and functional knowledge play different roles in the representation of living and non-living things:

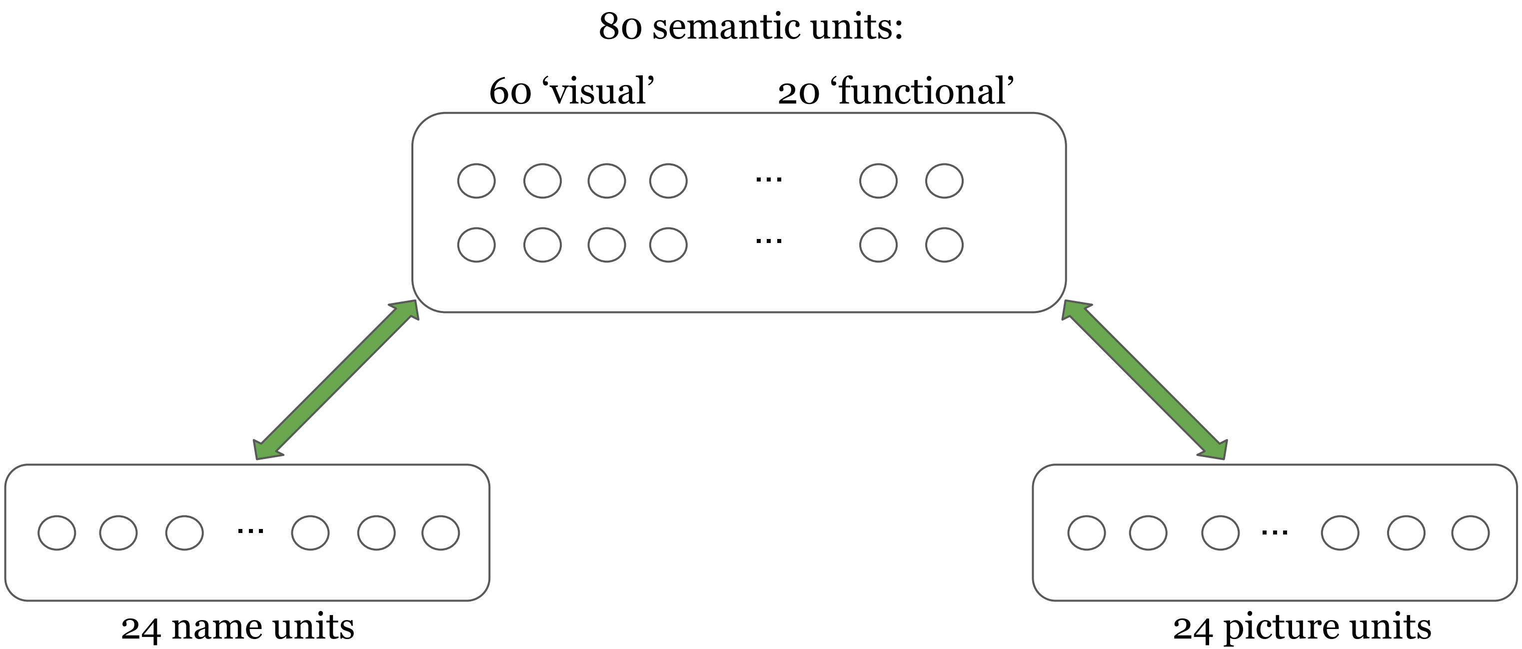
- Living things like ‘dog’ are represented as more **visual** in semantic memory
- Non-living things like ‘hammer’ are represented as more **functional** in semantic memory

Experiment 1

Visual and functional knowledge play different roles in the representation of living and non-living things:

- On average **2.68 visual** and only **0.35 functional** descriptors used to describe living things
- Vs. **1.57 visual** and **1.11 functional** descriptors used to describe non-living things

The Farah & McClelland model



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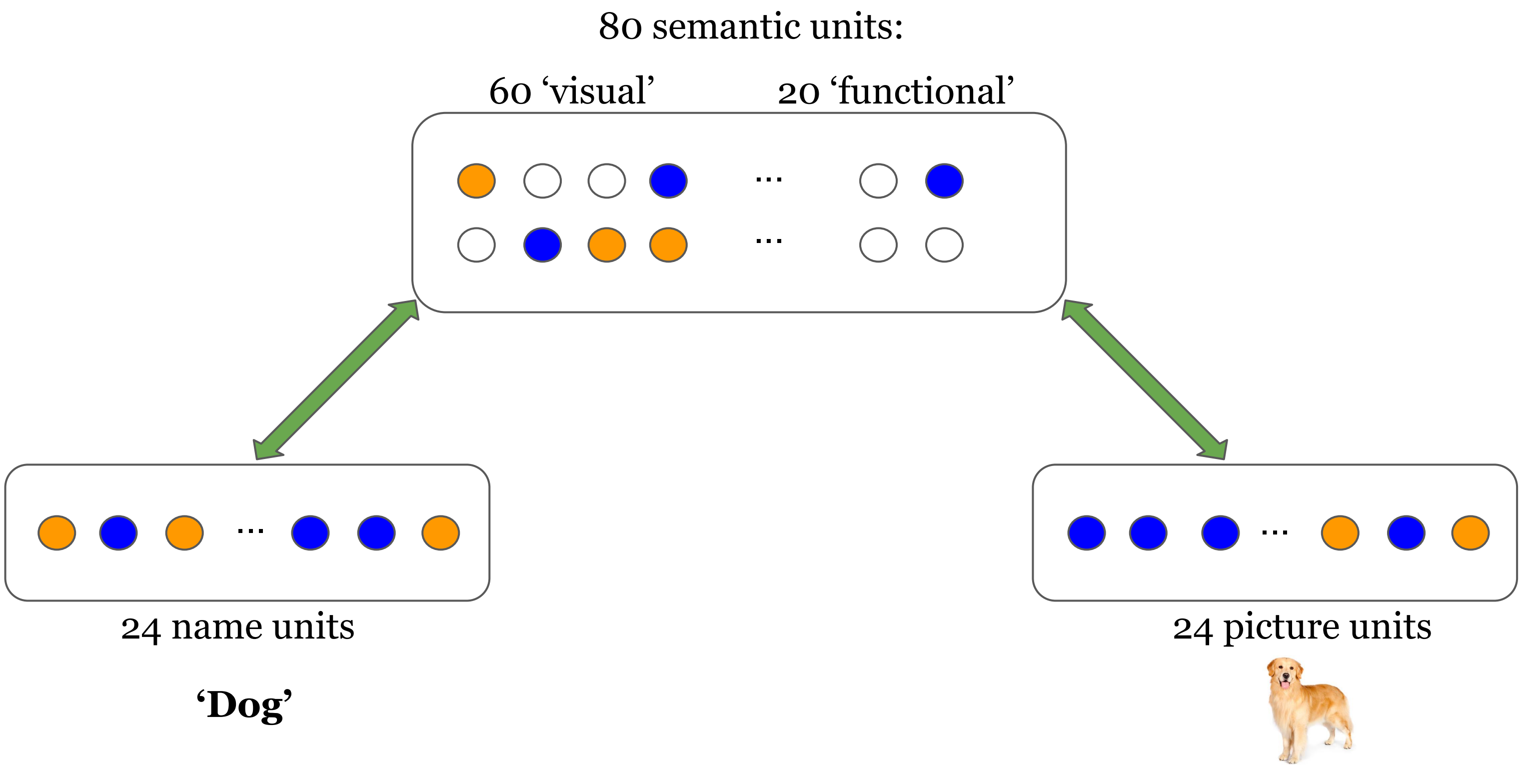

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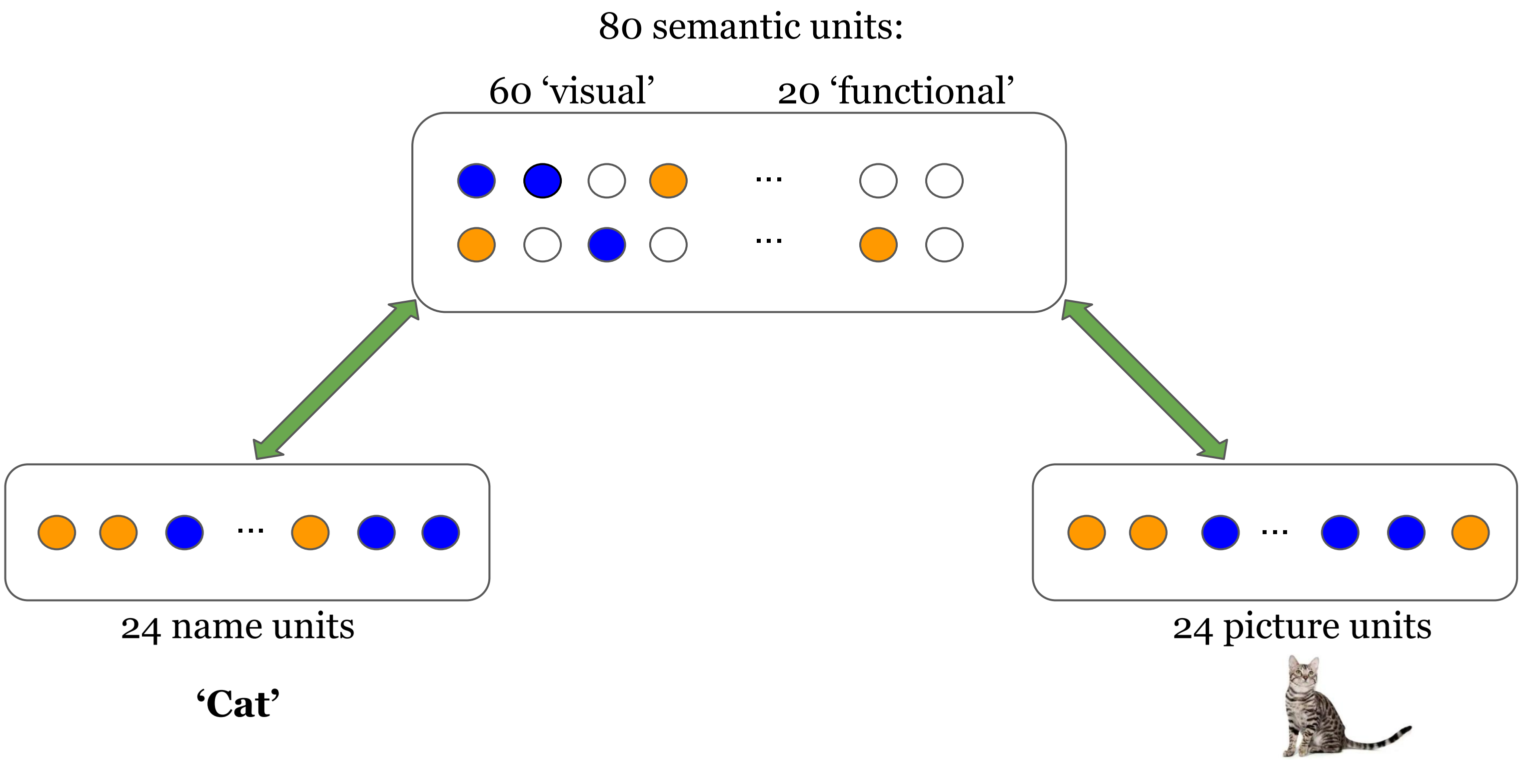

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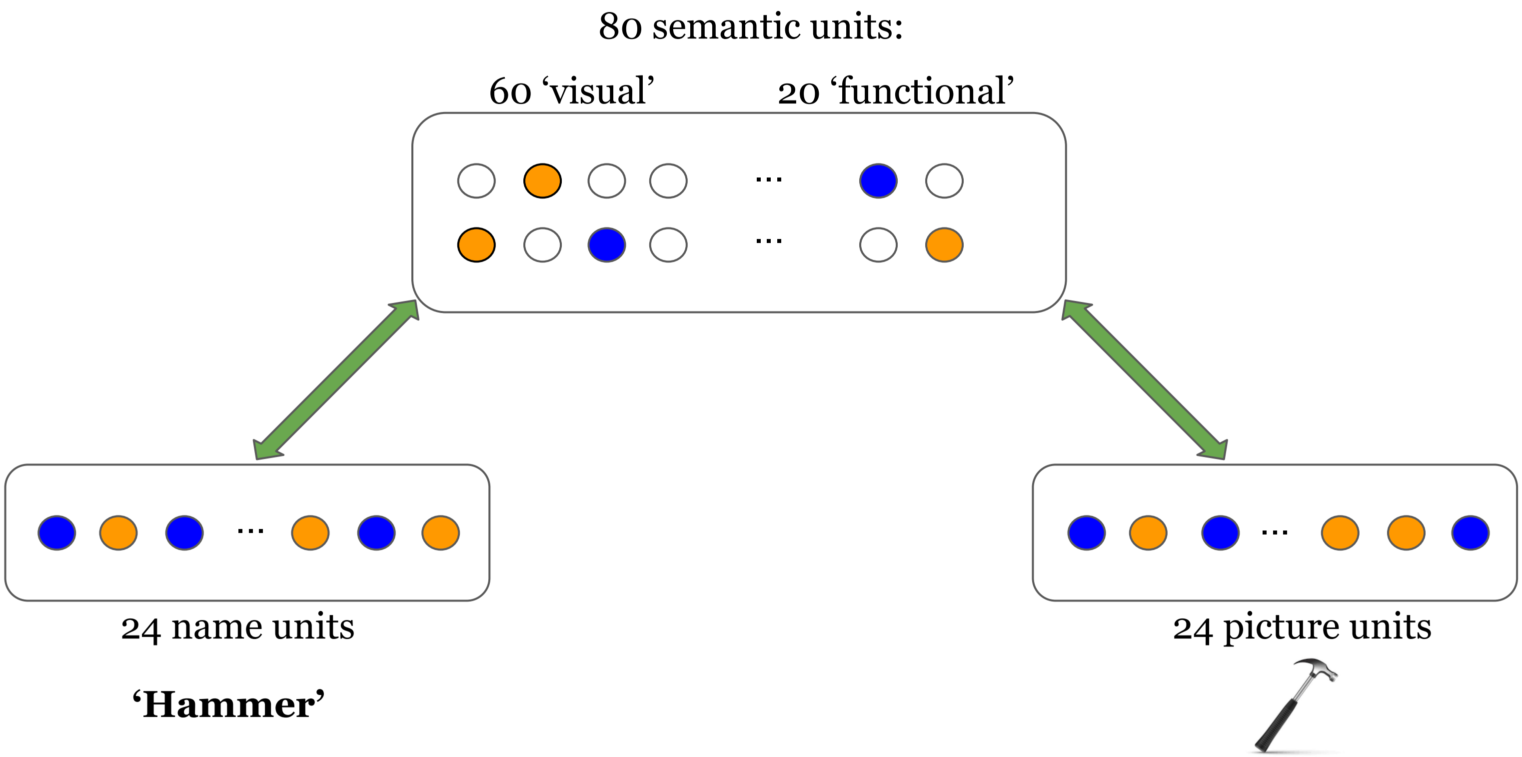

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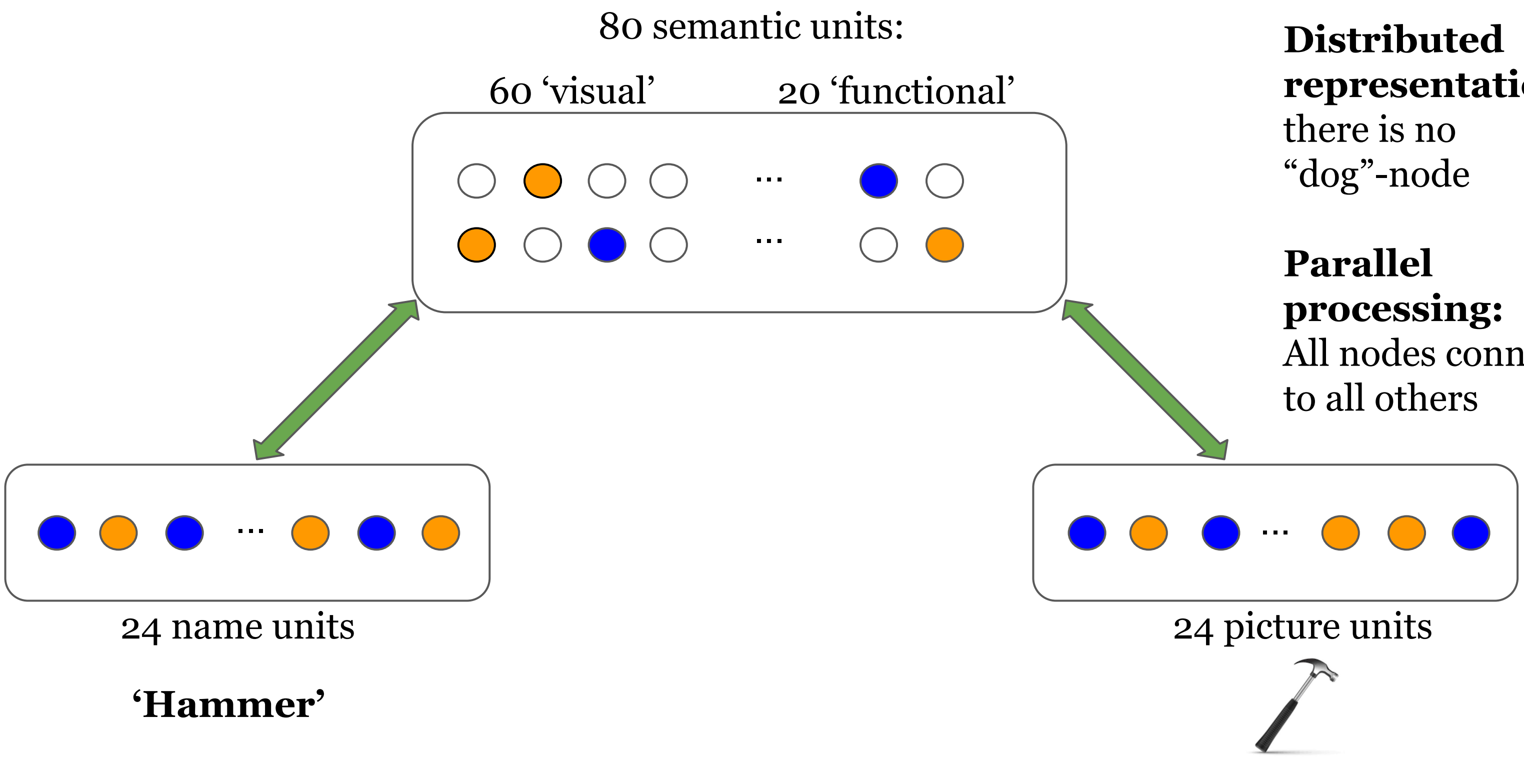
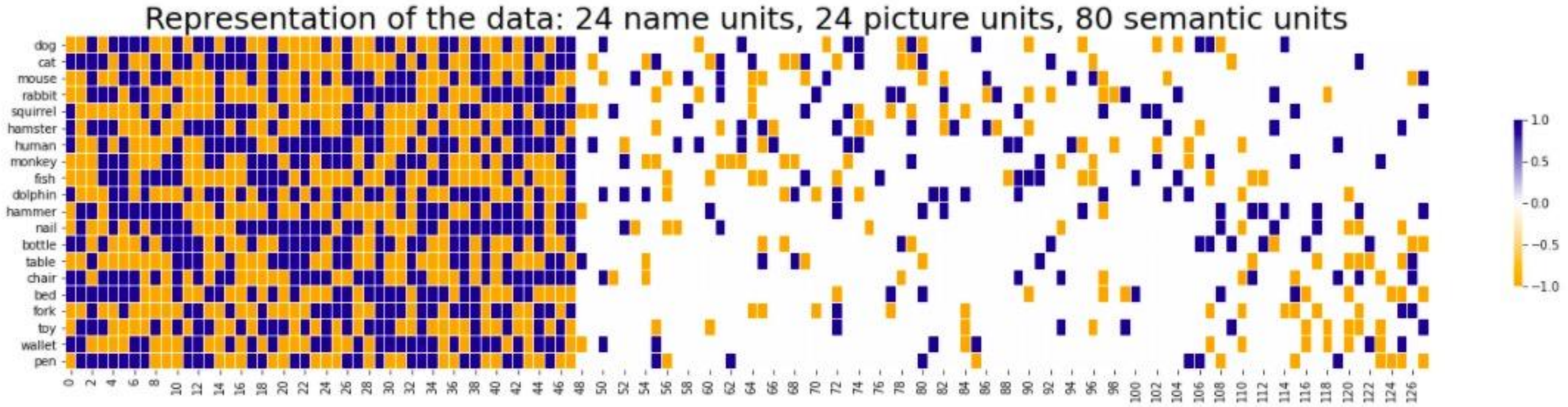


Distributed representations: there is no "dog"-node

Parallel processing: All nodes connected to all others

The training data



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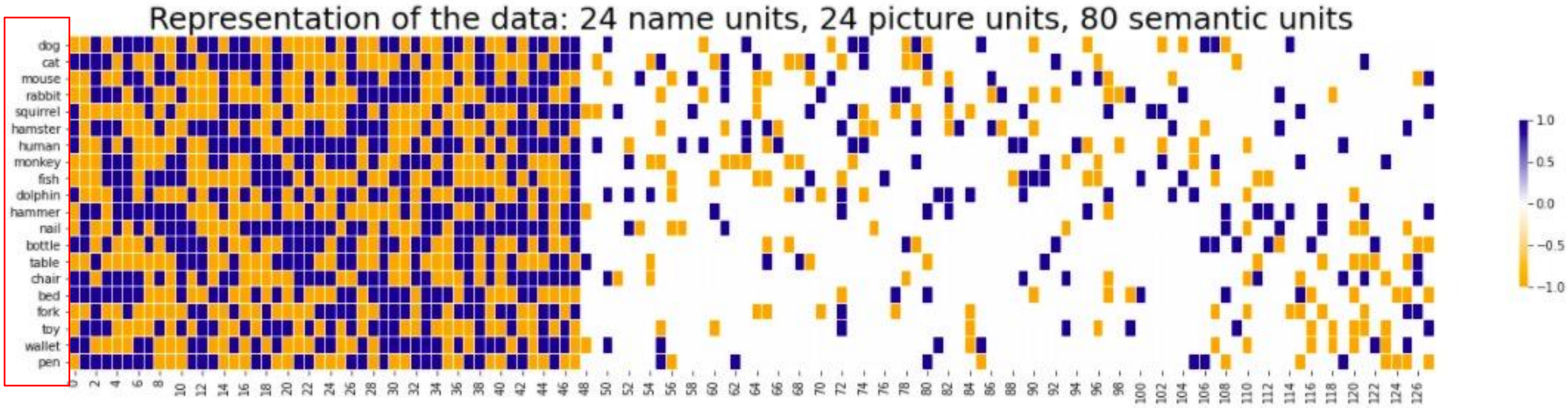

Labels

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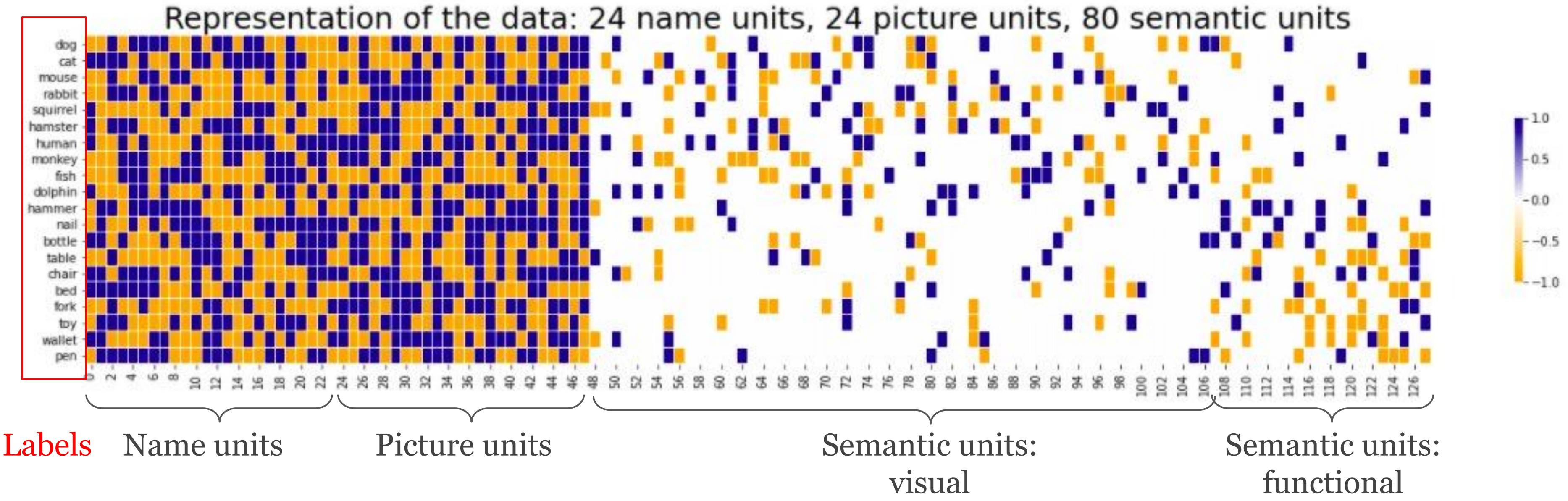

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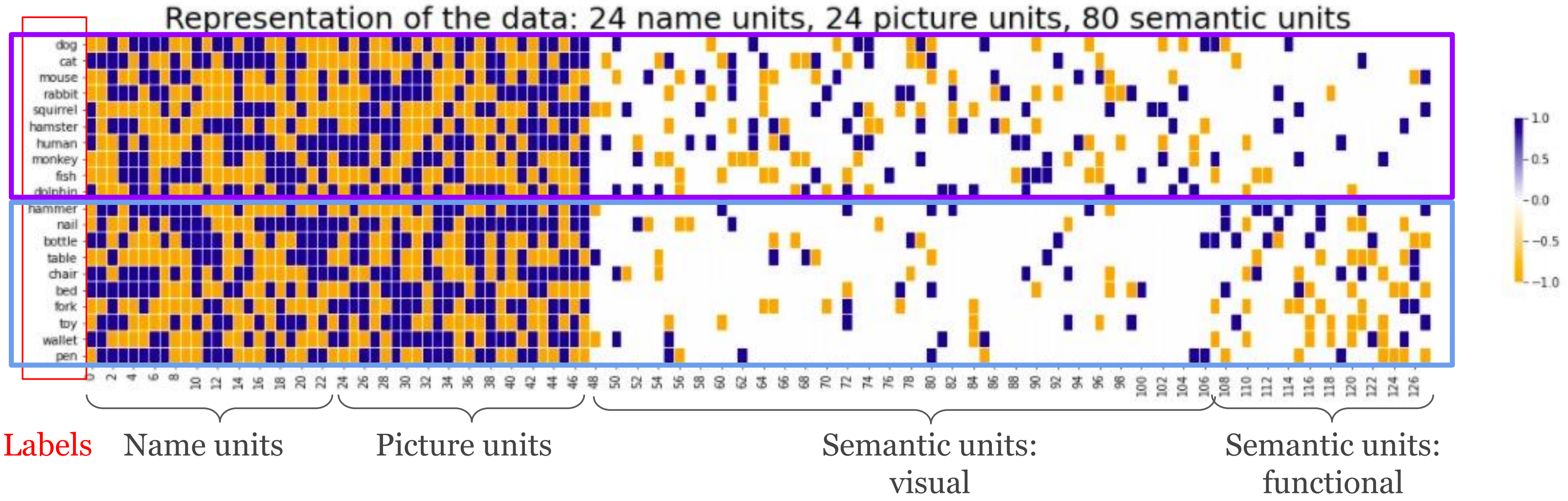

Training the model (I): name-2-picture task

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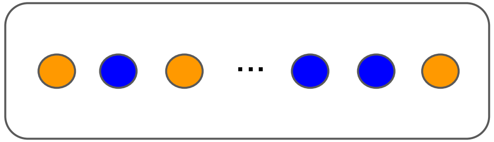

24 name units

Input: ‘Dog’

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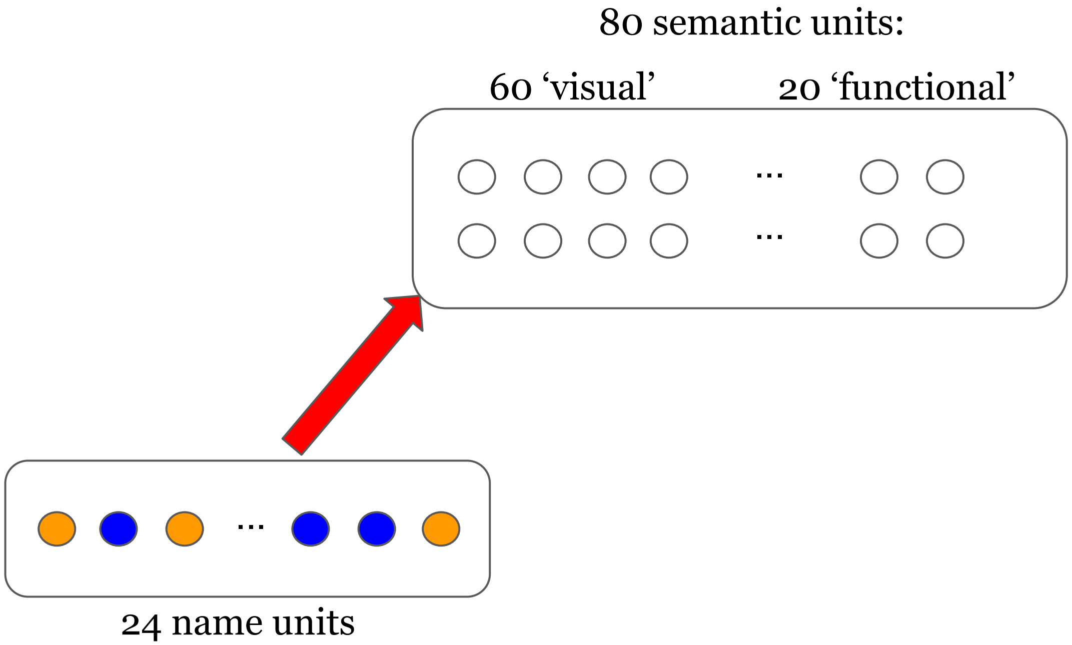

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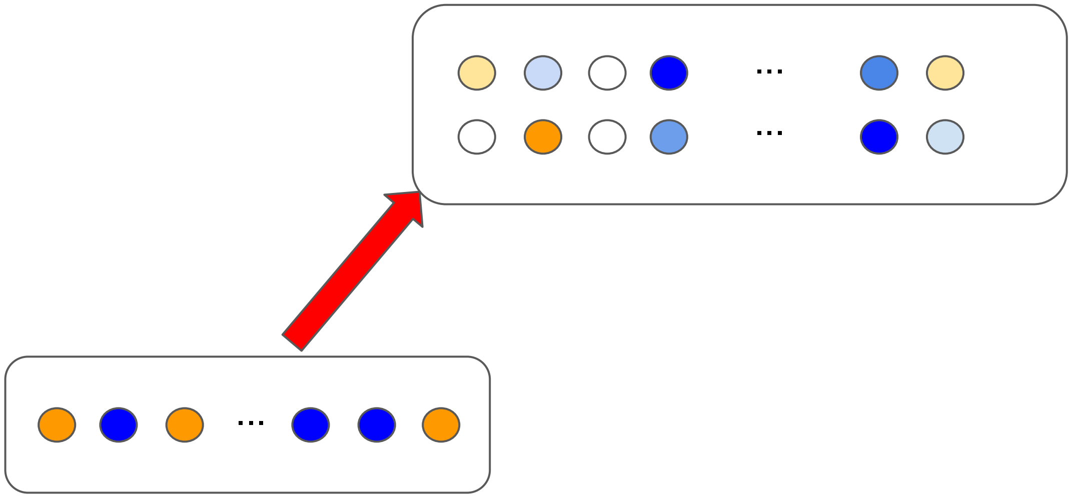

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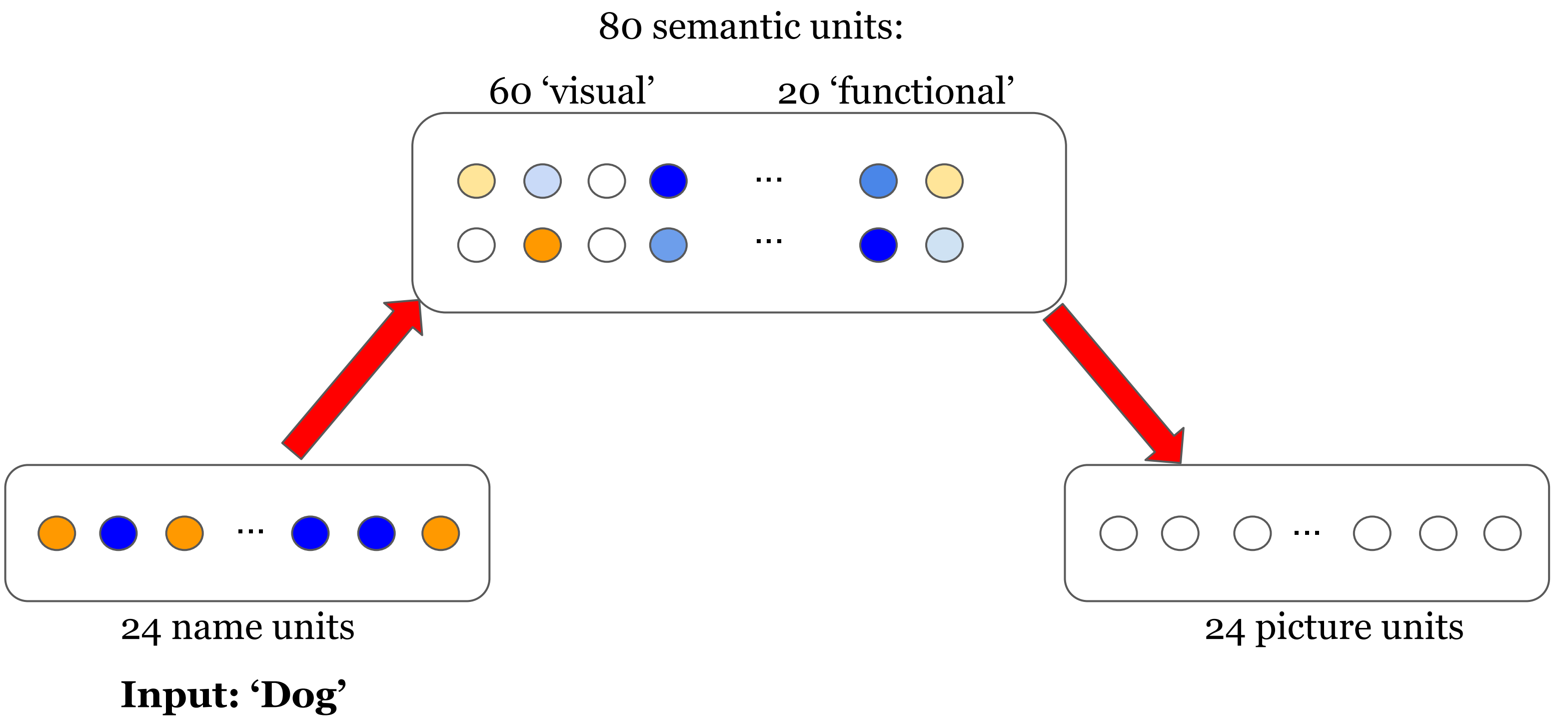

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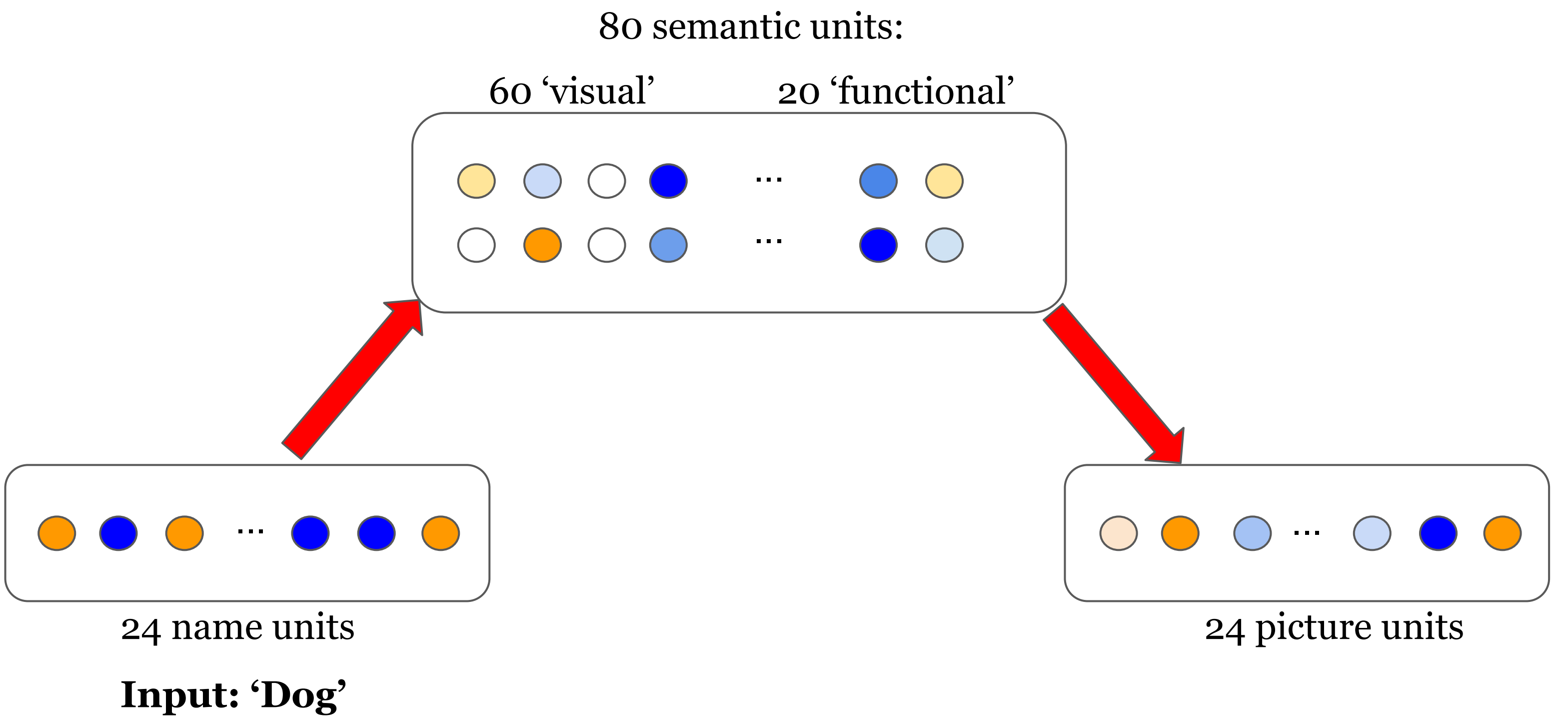

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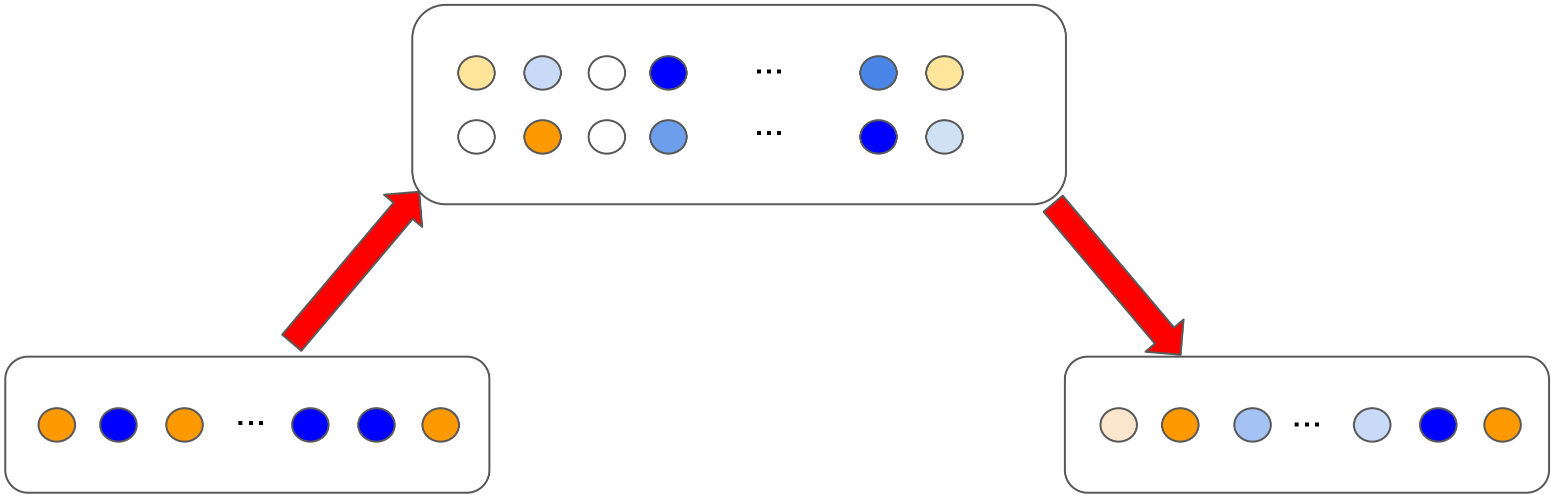
80 semantic units:

60 ‘visual’ 20 ‘functional’



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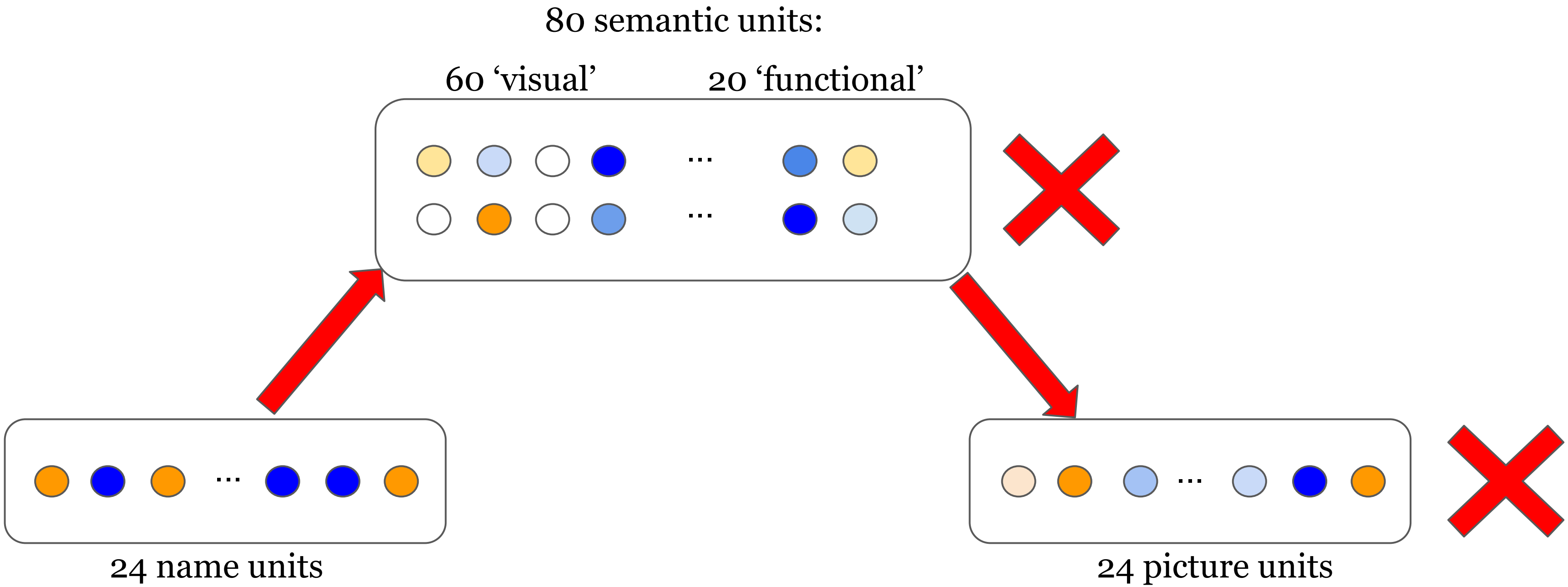

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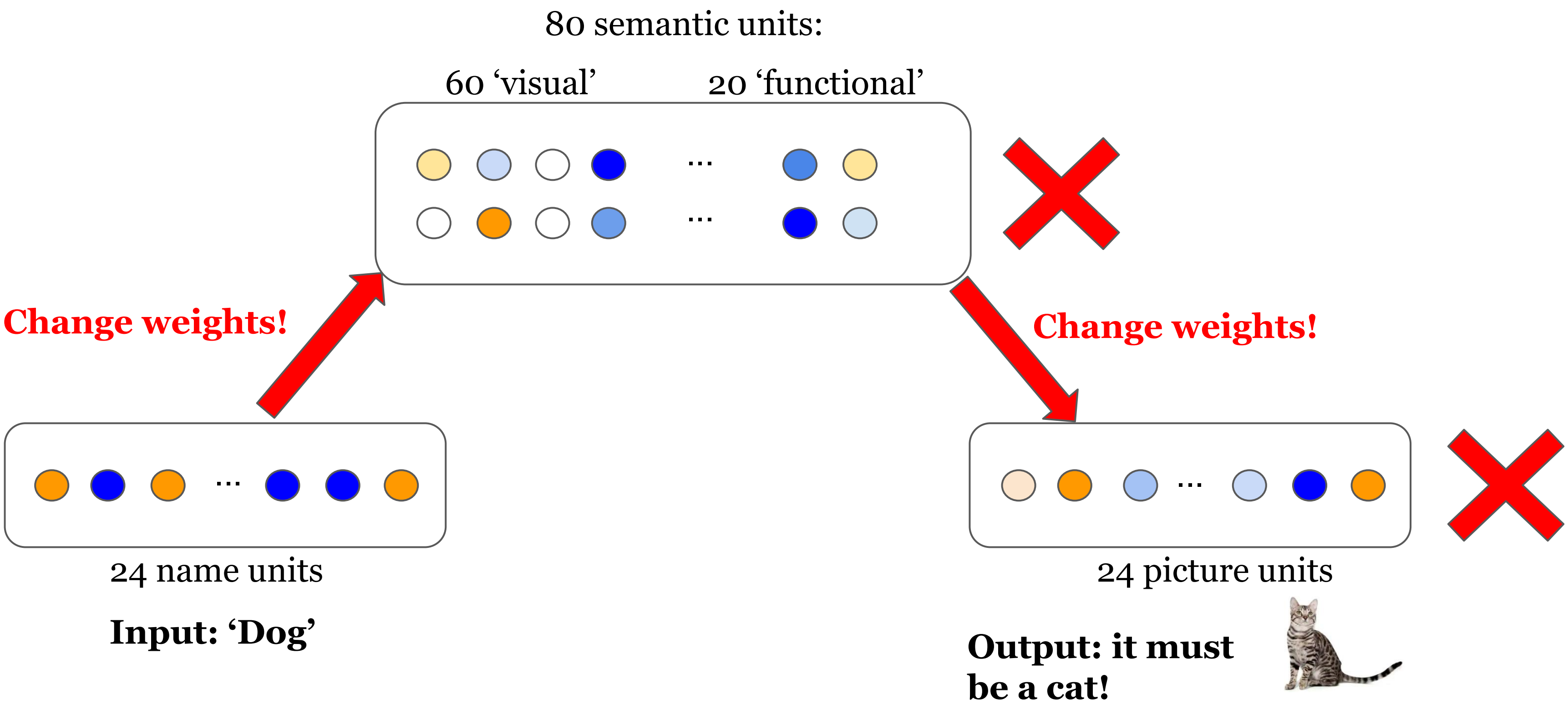

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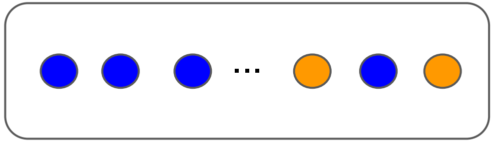

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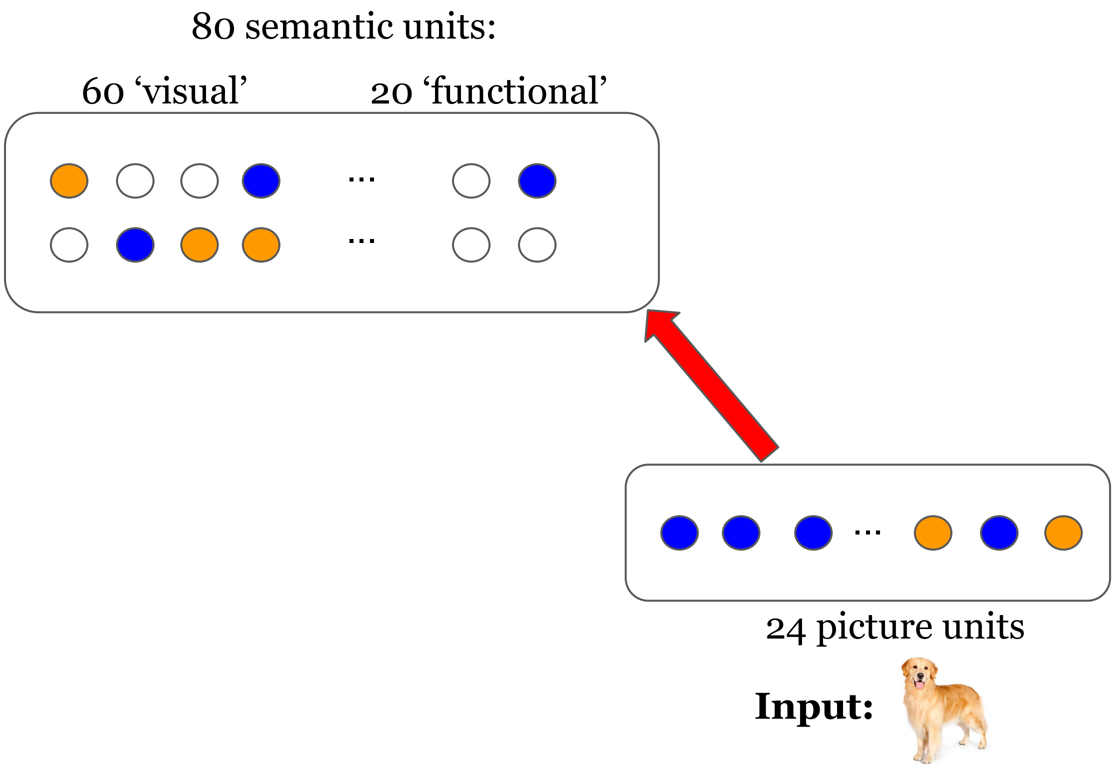

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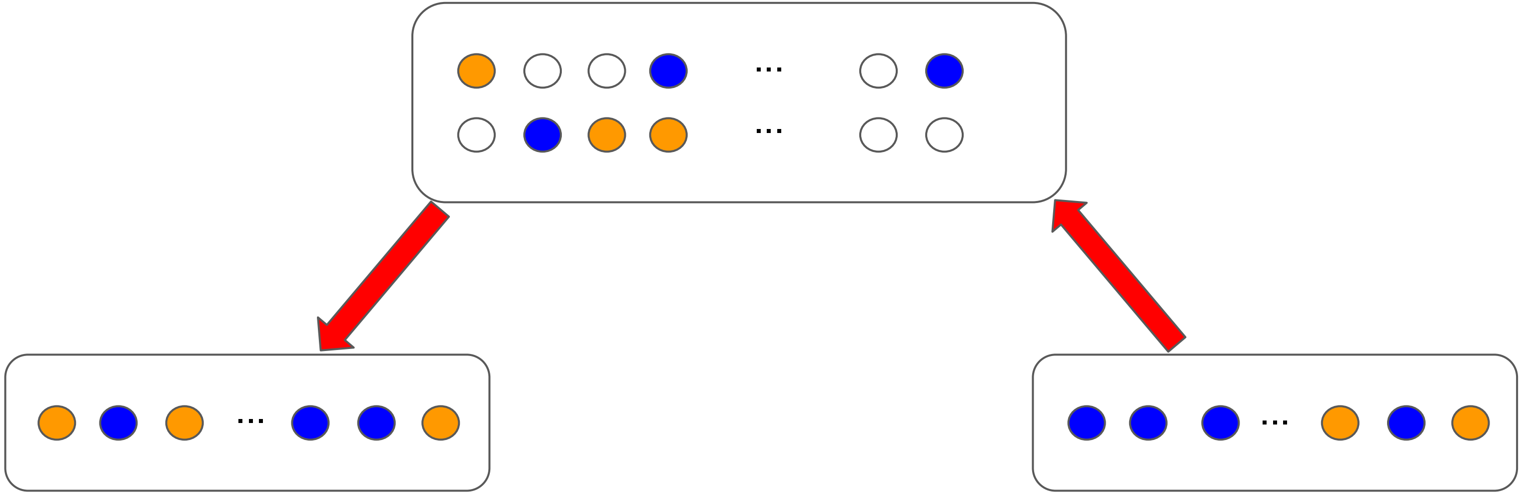


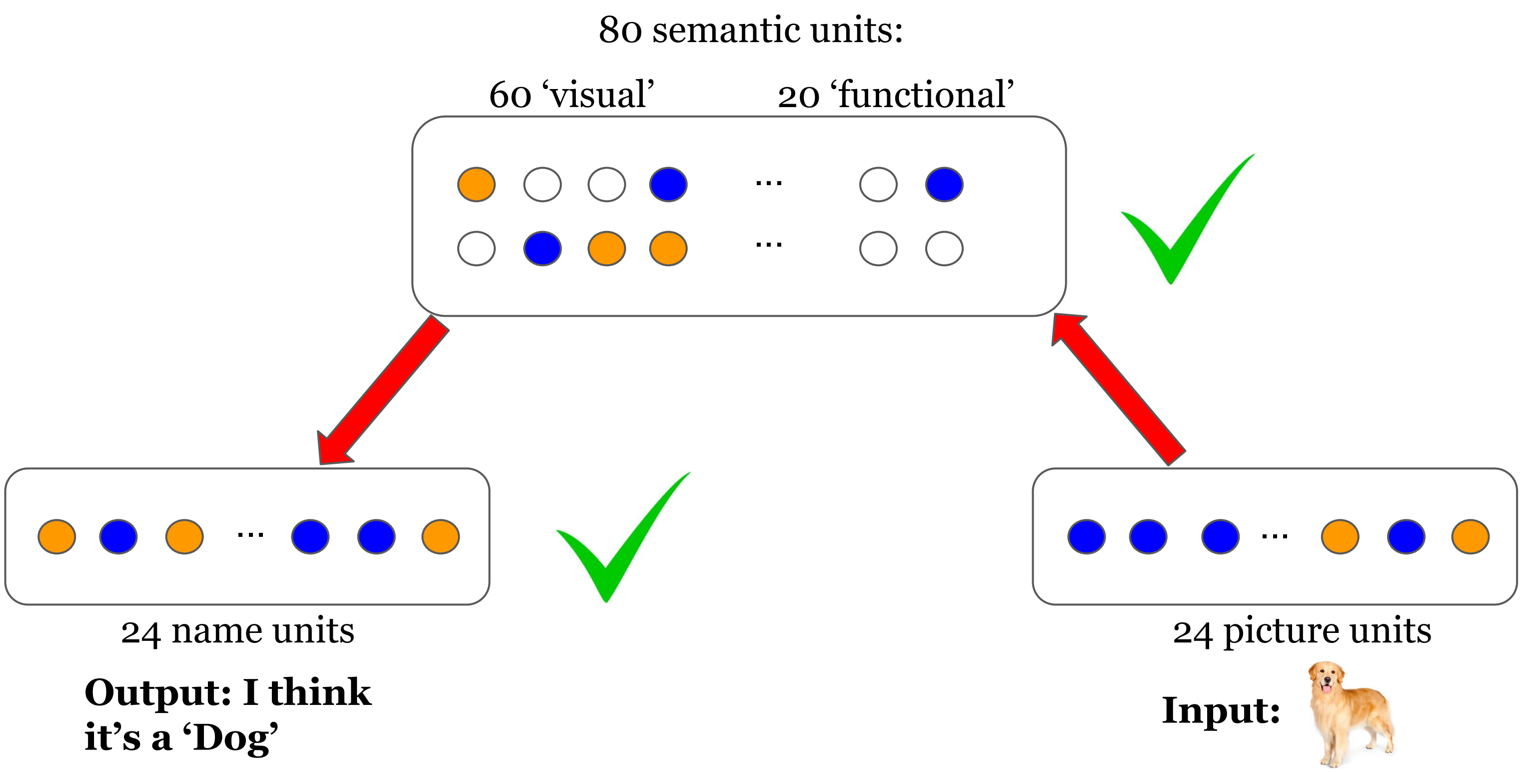
24 name units

24 picture units

Output: I think it’s a ‘Dog’

Input:

Training the model (II): picture-naming task



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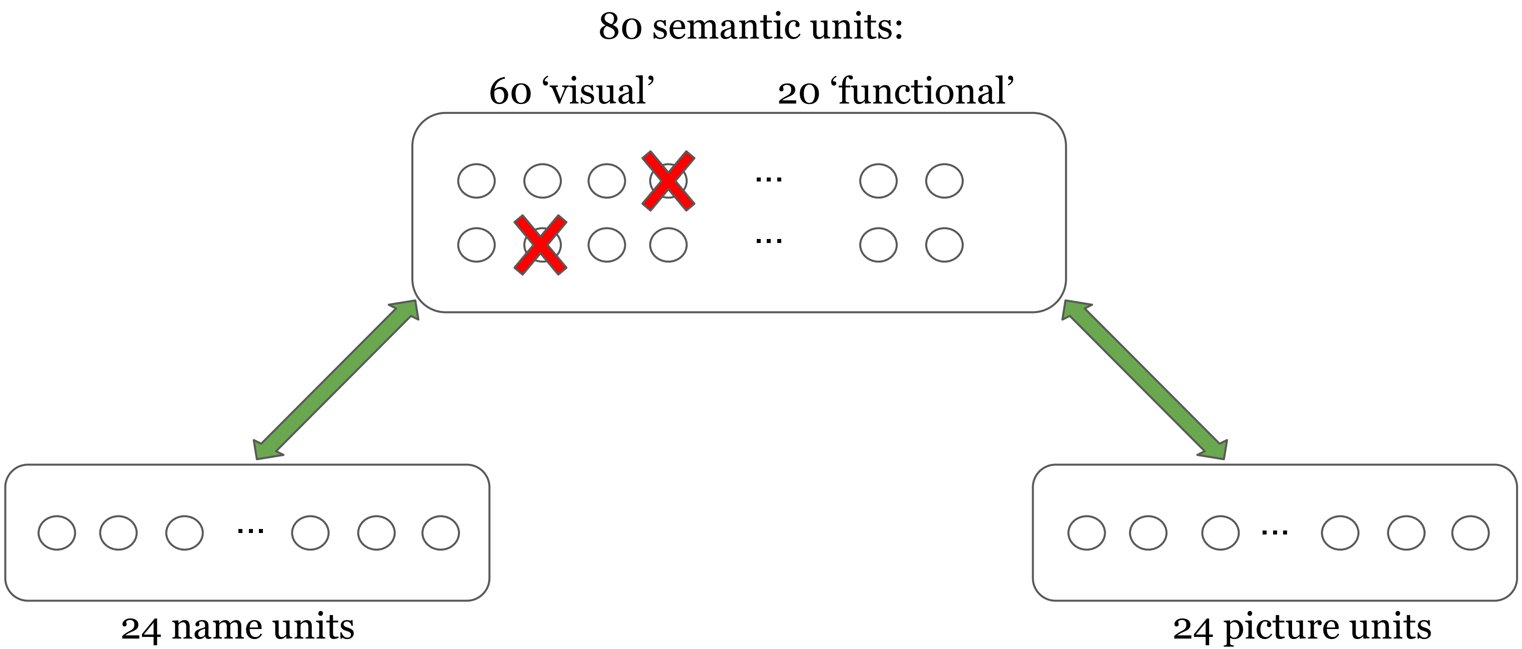
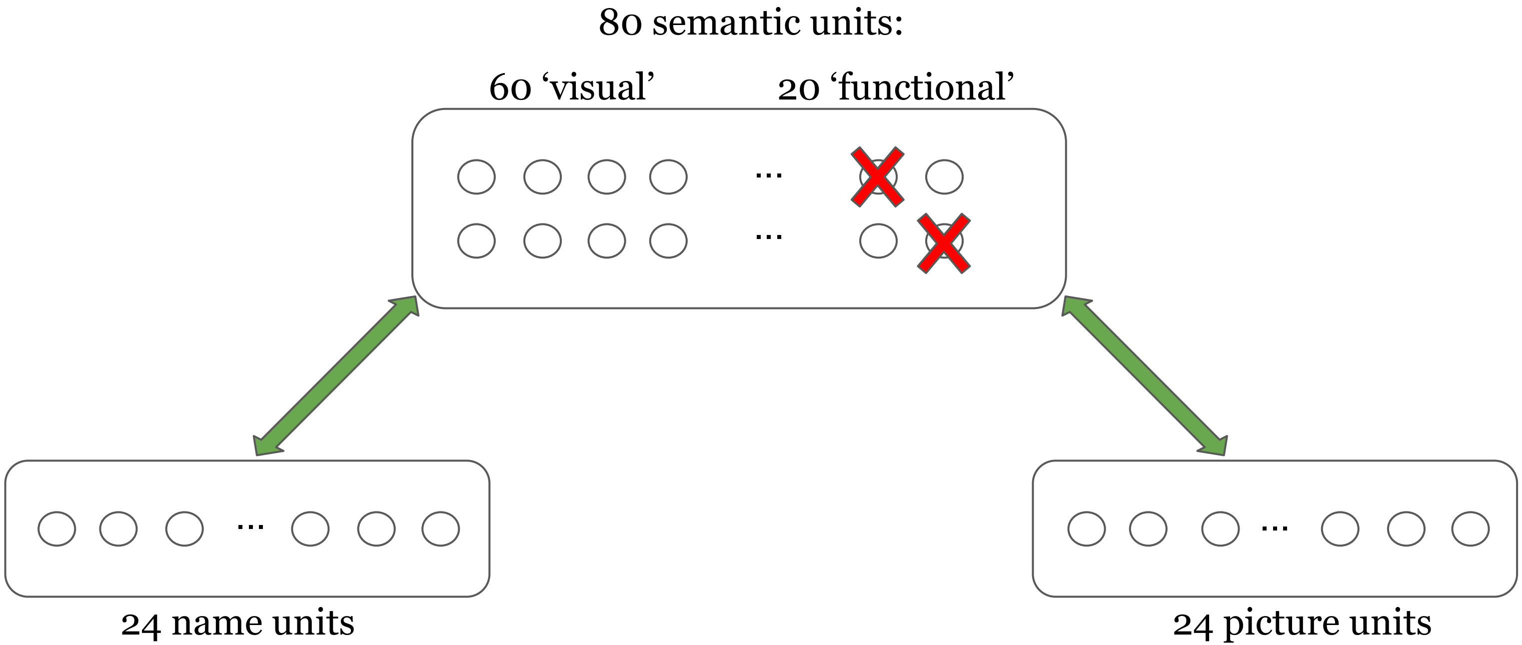
- The final, trained model has perfect accuracy in both tasks!

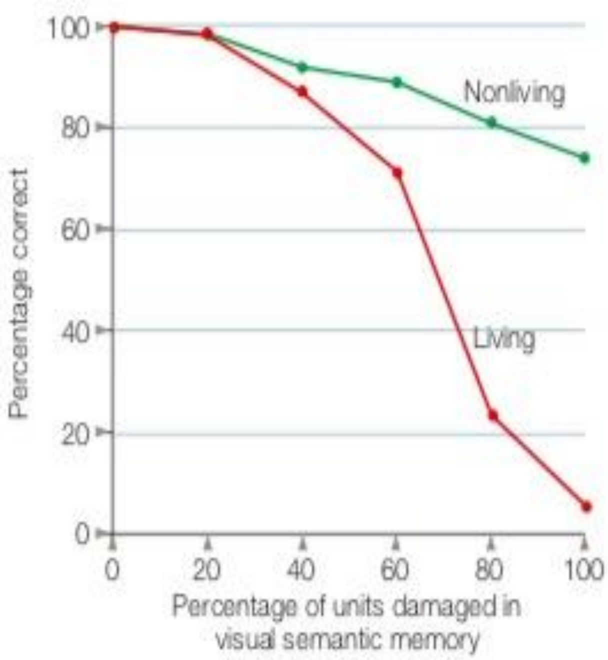
Lesioning the model (I): damage visual memory



Lesioning the model (II): damage funct. memory



Farah & McClelland lesioning results



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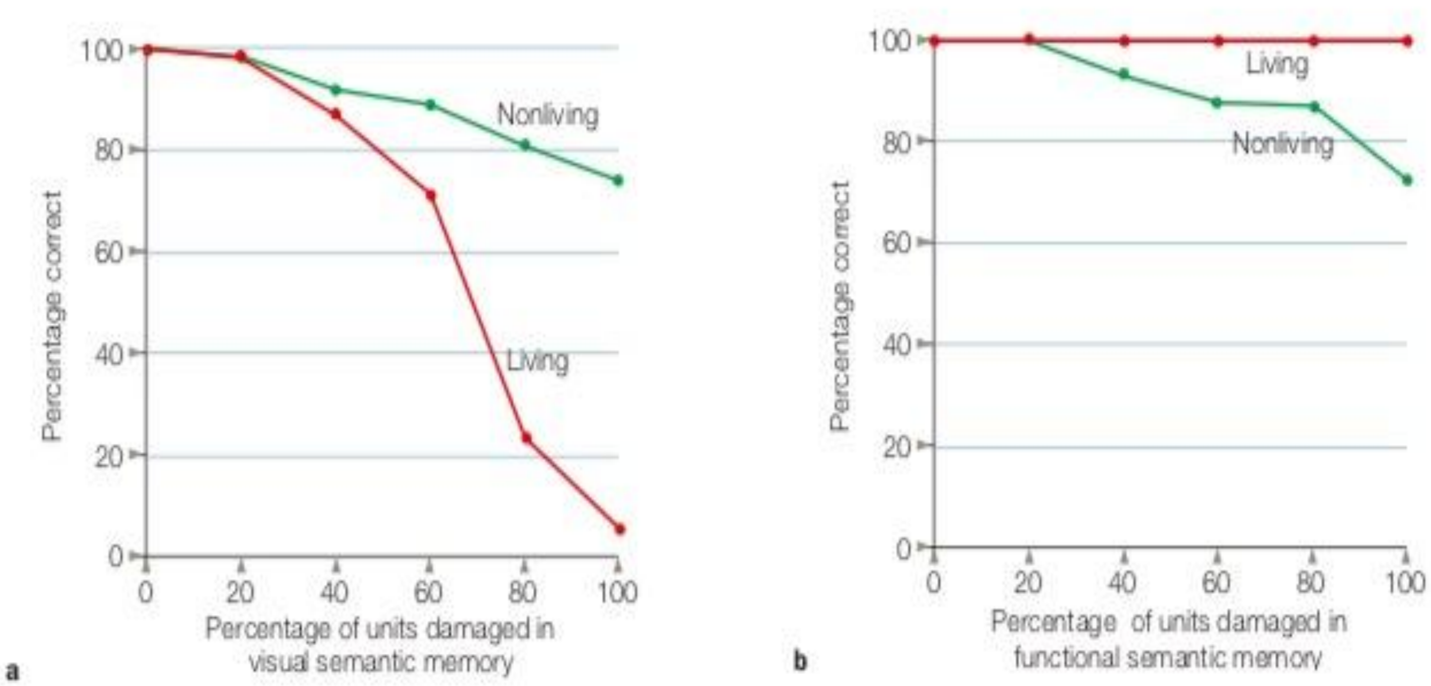

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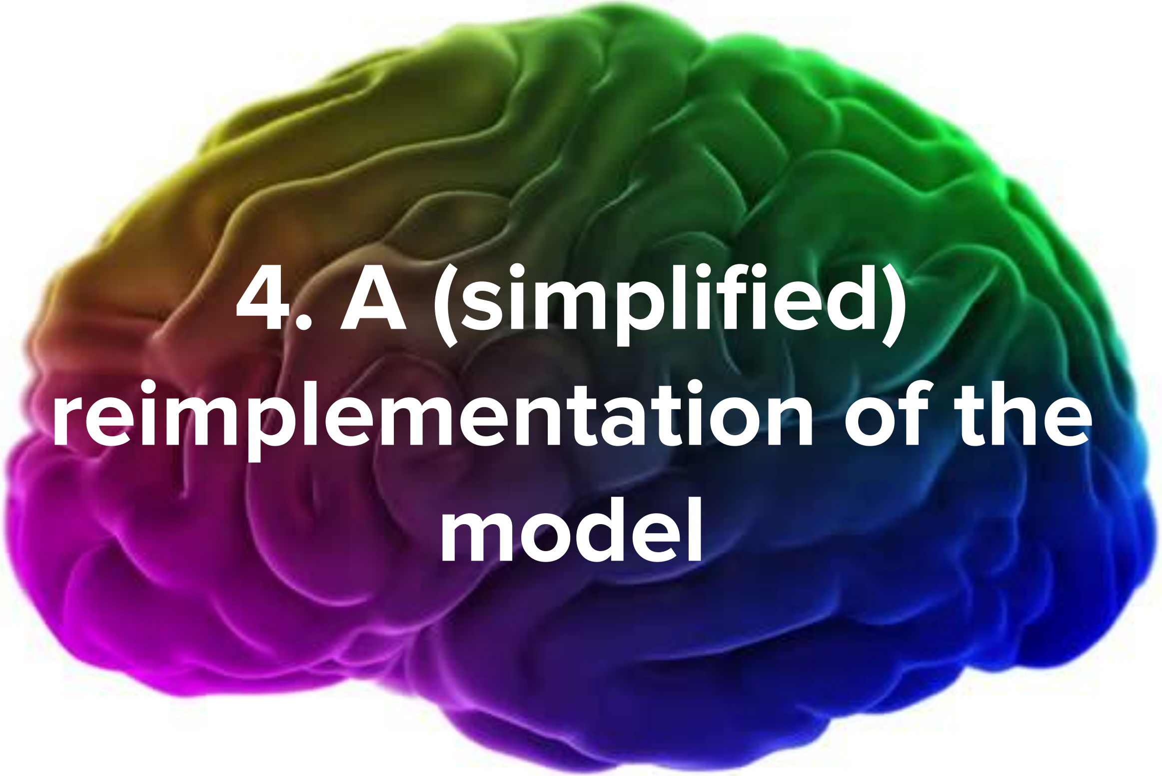
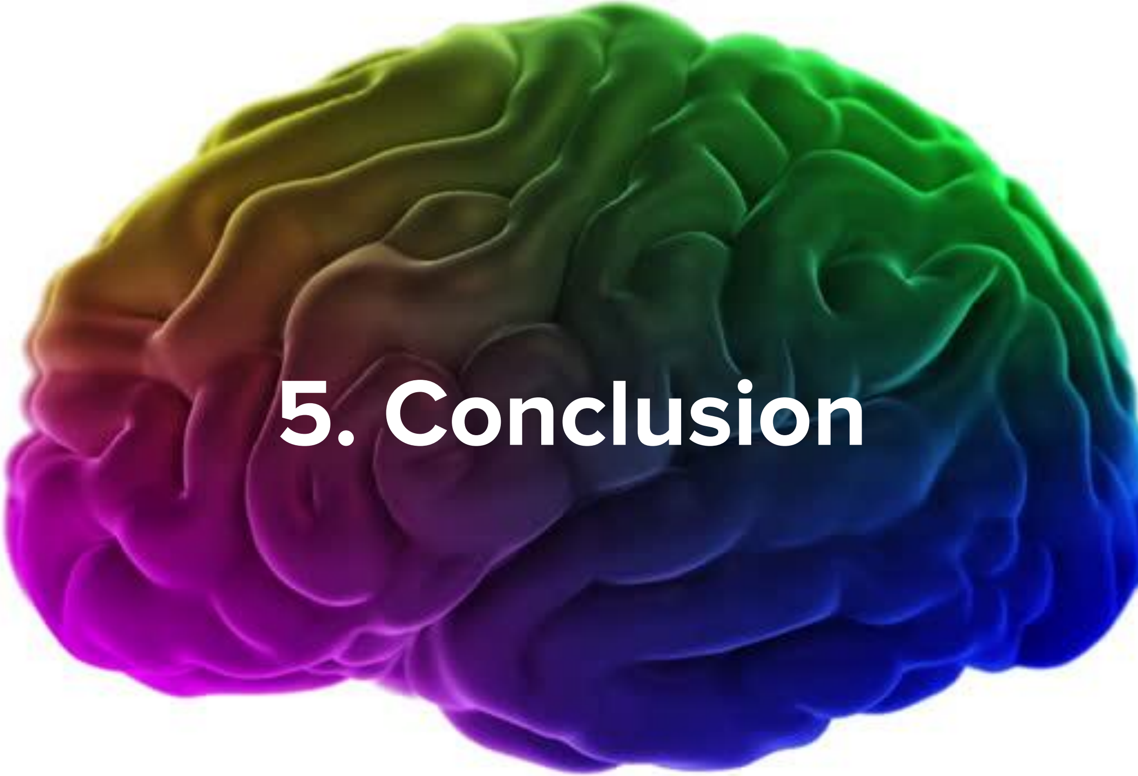


https://github.com/miriamschulz/KNP_project

5. Conclusion



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Discussion / Conclusions

- ➔ Complex behavior can be modeled with a relatively simple connectionist model
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- ➔ Implications: use such models as **proof-of-theory** and **complement** for neuropsychological theories?

Discussion / Conclusions

➔ **Symbolic** vs. **distributed** representations

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Discussion / Conclusions

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- No need for a separate semantic memory system for living vs. non-living things
- But: recent evidence of specific cells in large deep neural networks that reply to very specific concepts! (see e.g. Bowers, 2017)

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Questions & Discussion