Supervised Evaluation of Representations

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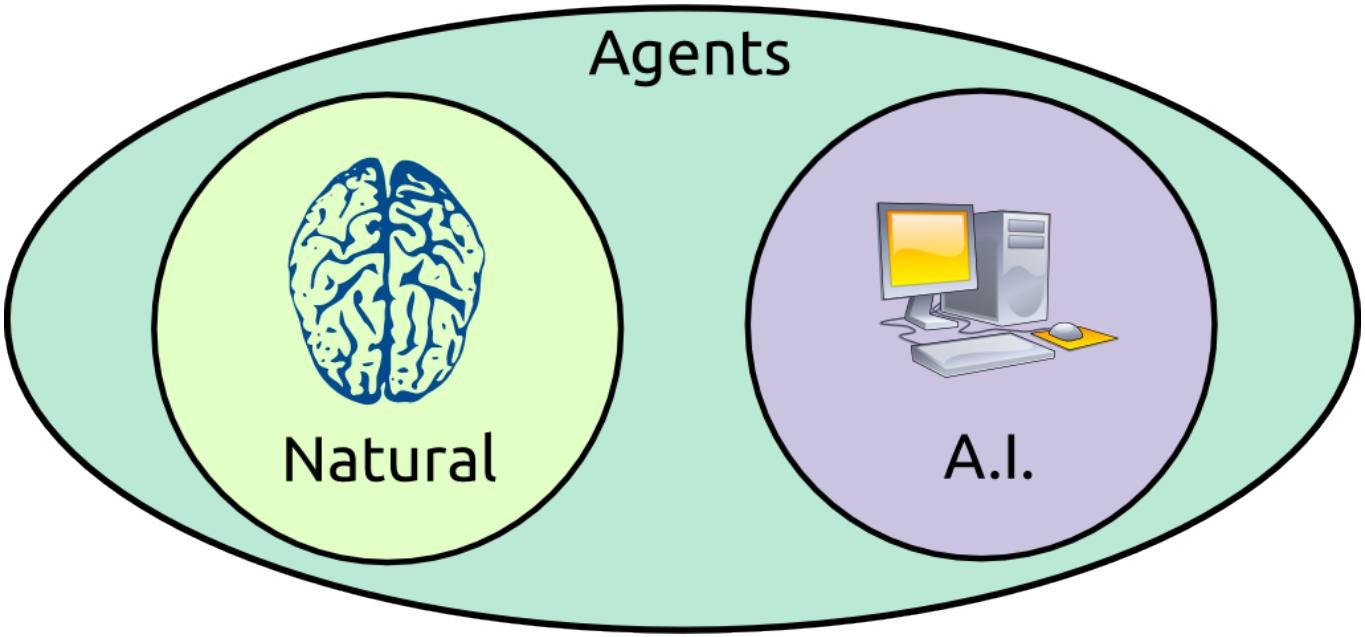
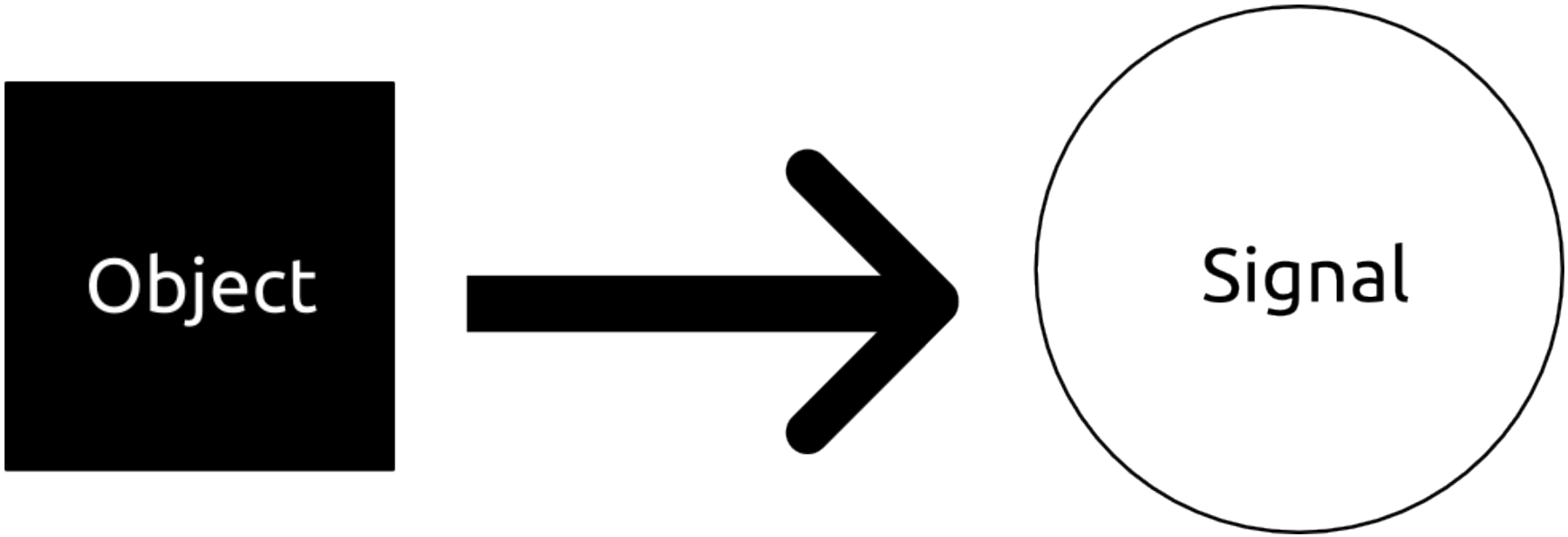
Overview



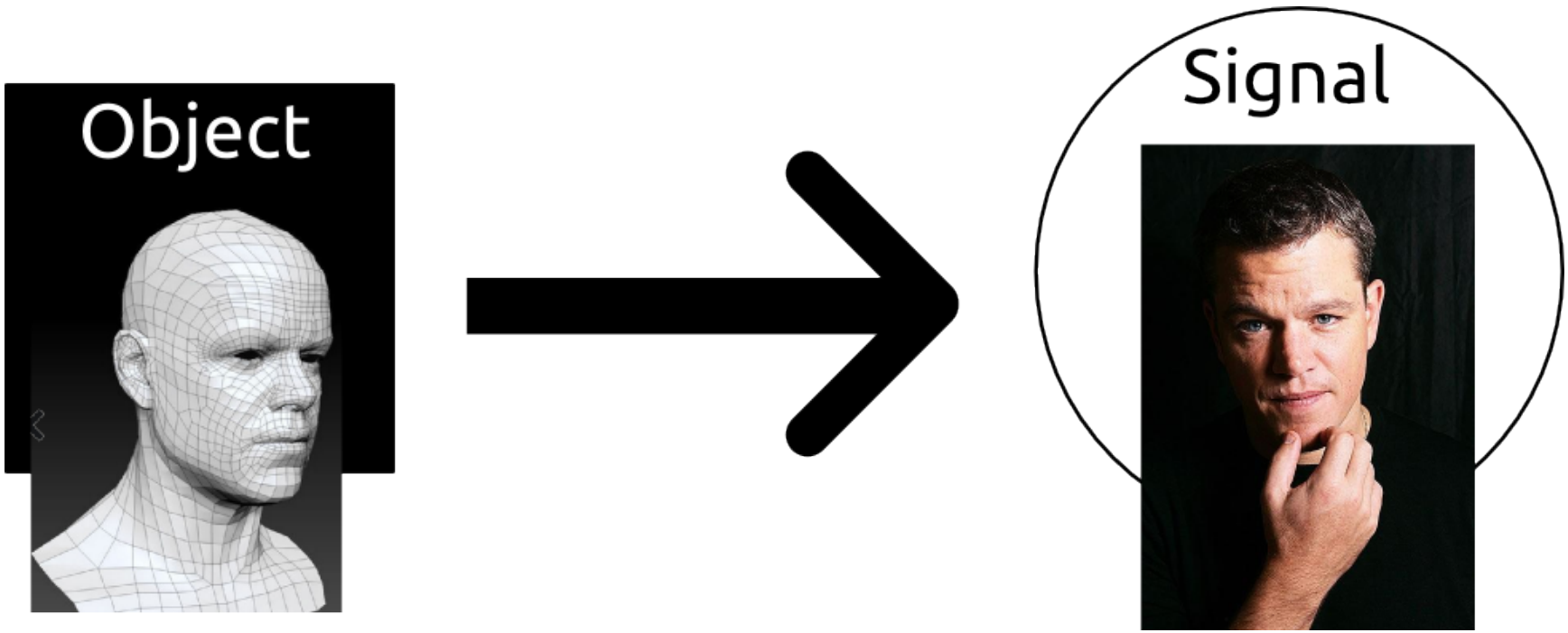
Human brains and machine learning algorithms tackle similar types of problems.

Perception

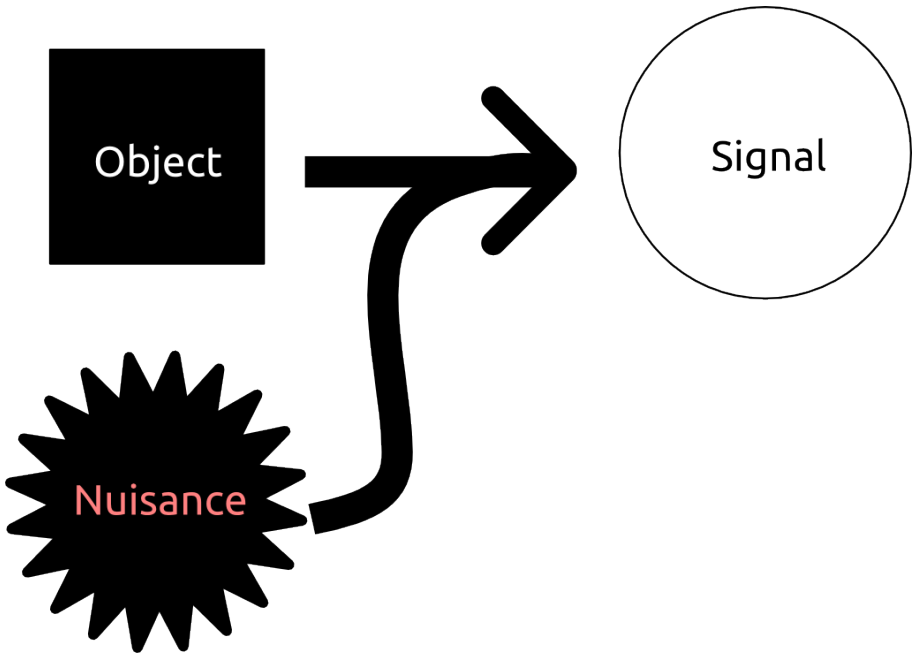


Perception: the problem of inferring *objects* in the environment given observed *signals*.

Example: face recognition

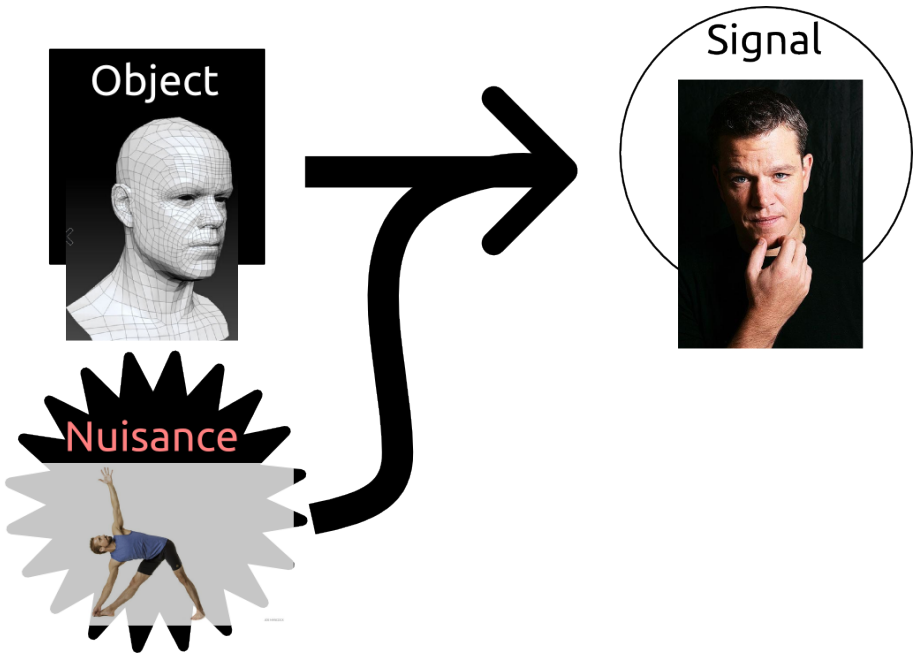


Perception



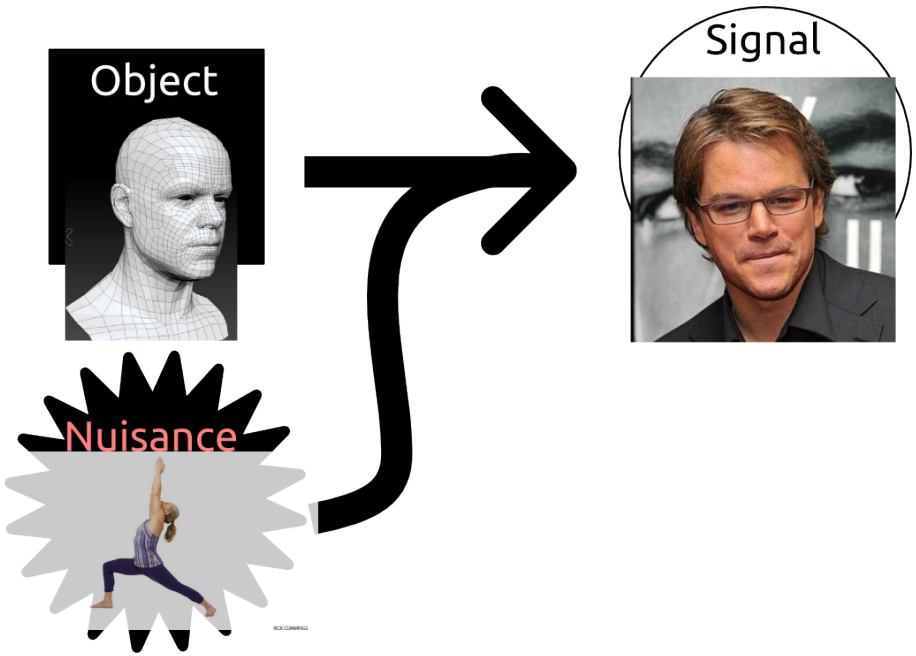
The problem is complicated because there exist some *nuisance parameters*, so the mapping from object to signal is not one-to-one.

Example: face recognition



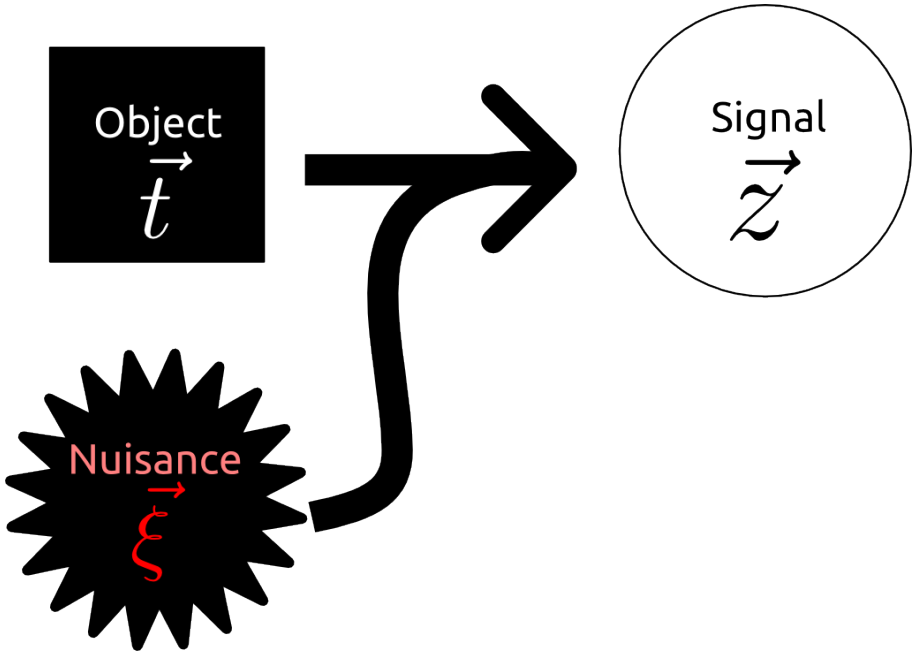
In face recognition, the *pose* (including hairstyle) and *lighting* are nuisance parameters.

Example: face recognition



The same object can map to multiple signals.

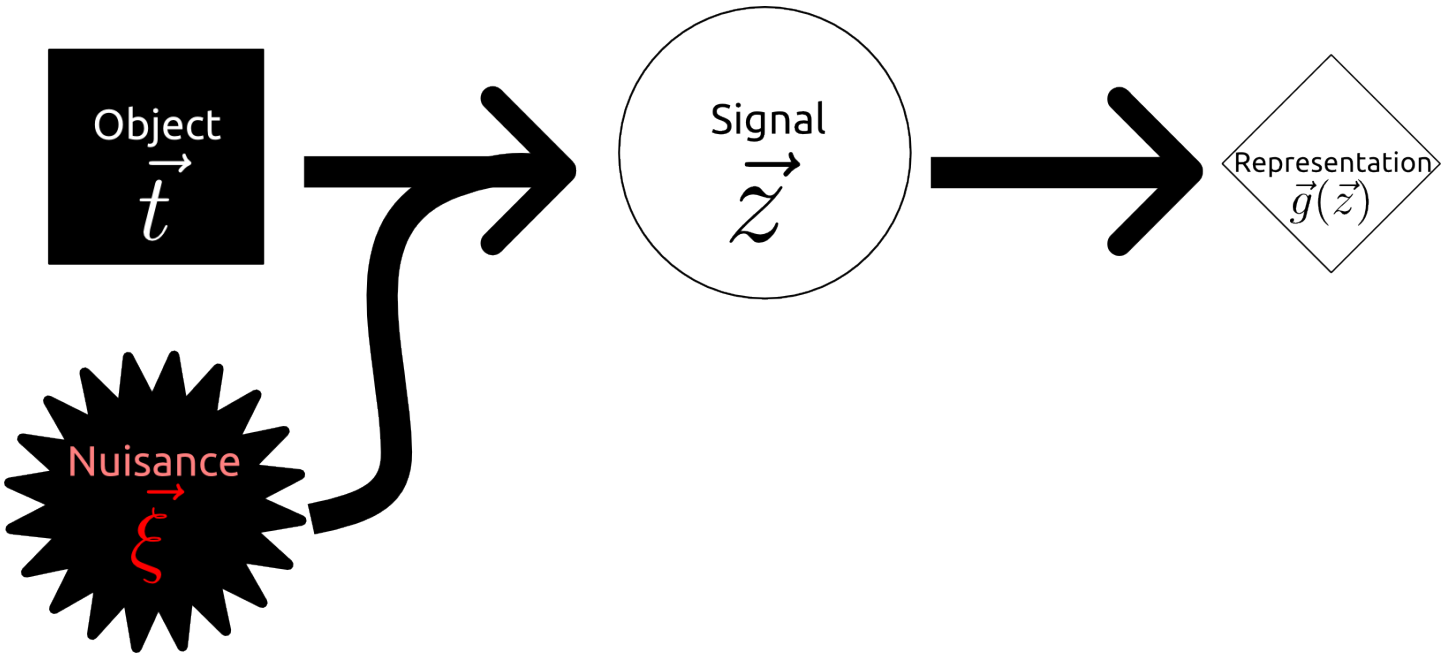
Perception



Assume there exists a function ψ that maps objects and nuisance parameters to signals:

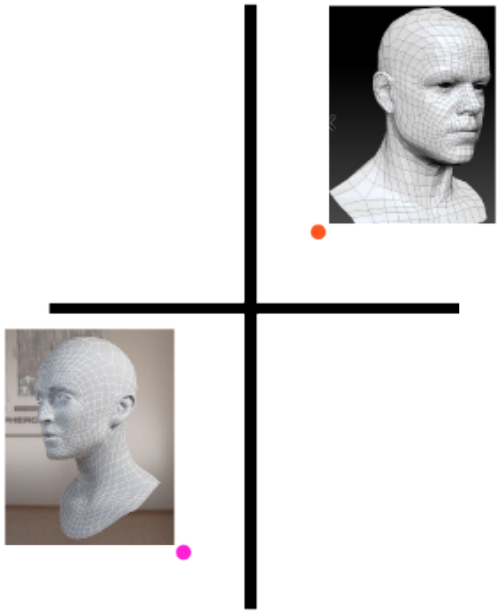
$$\vec{z} = \psi(\vec{t}, \vec{\xi}).$$

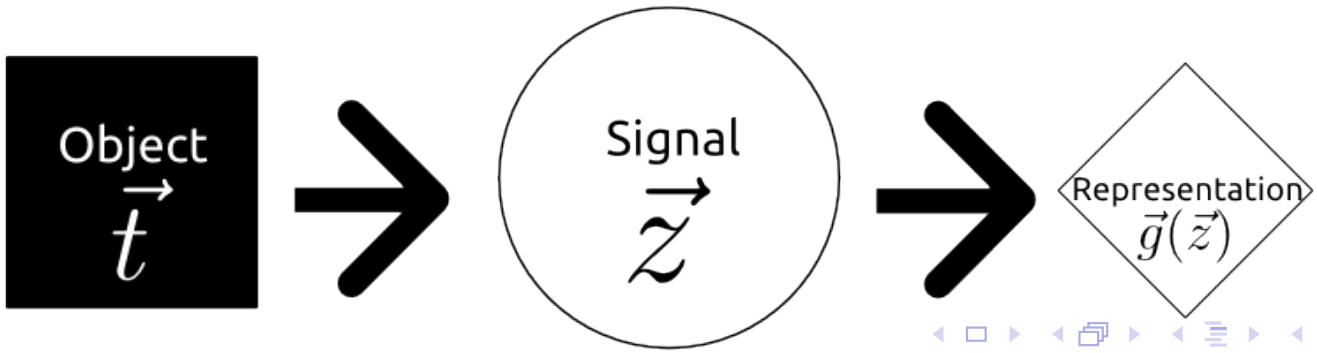
What is a representation?



A dimensionality-reducing mapping $\vec{g}$ of the signal.

A good representation...





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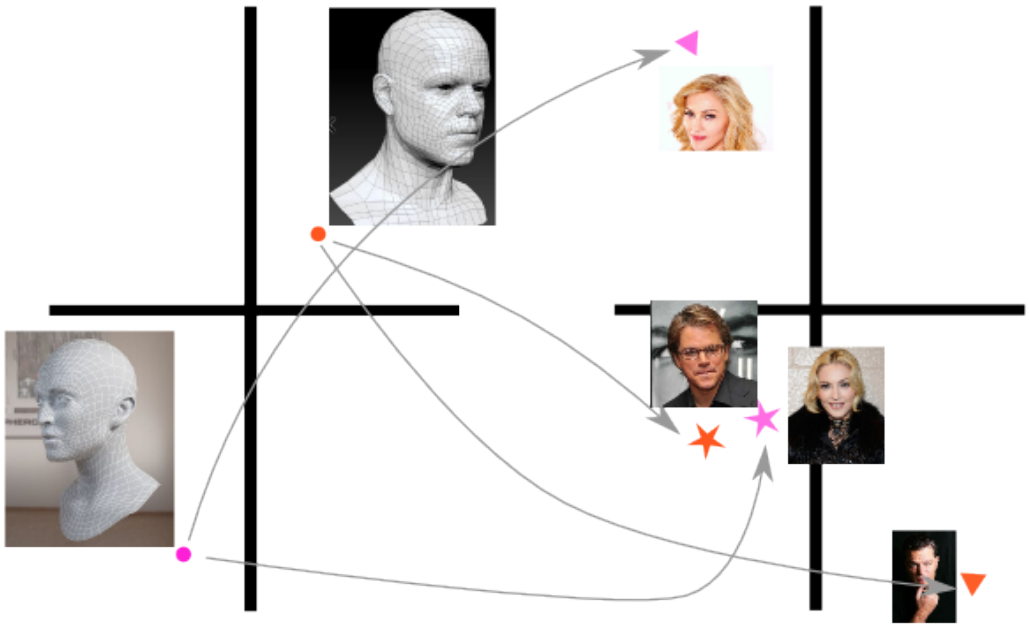

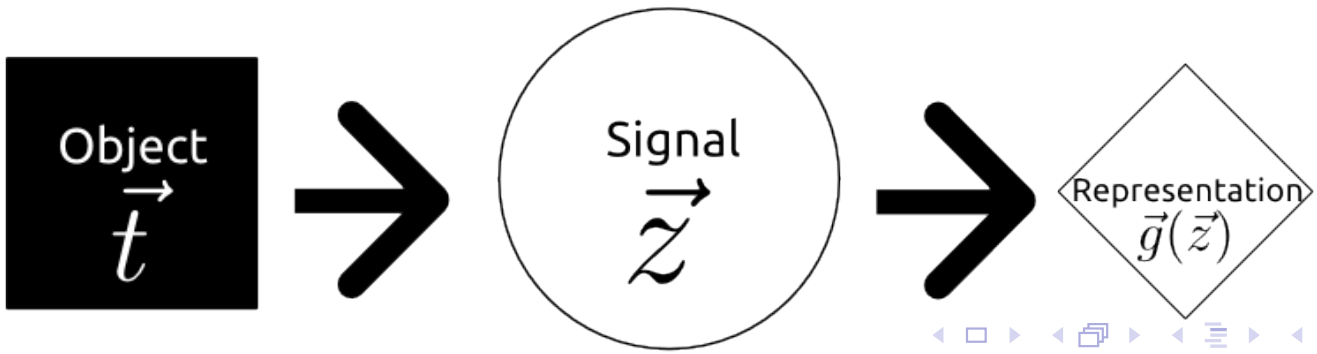

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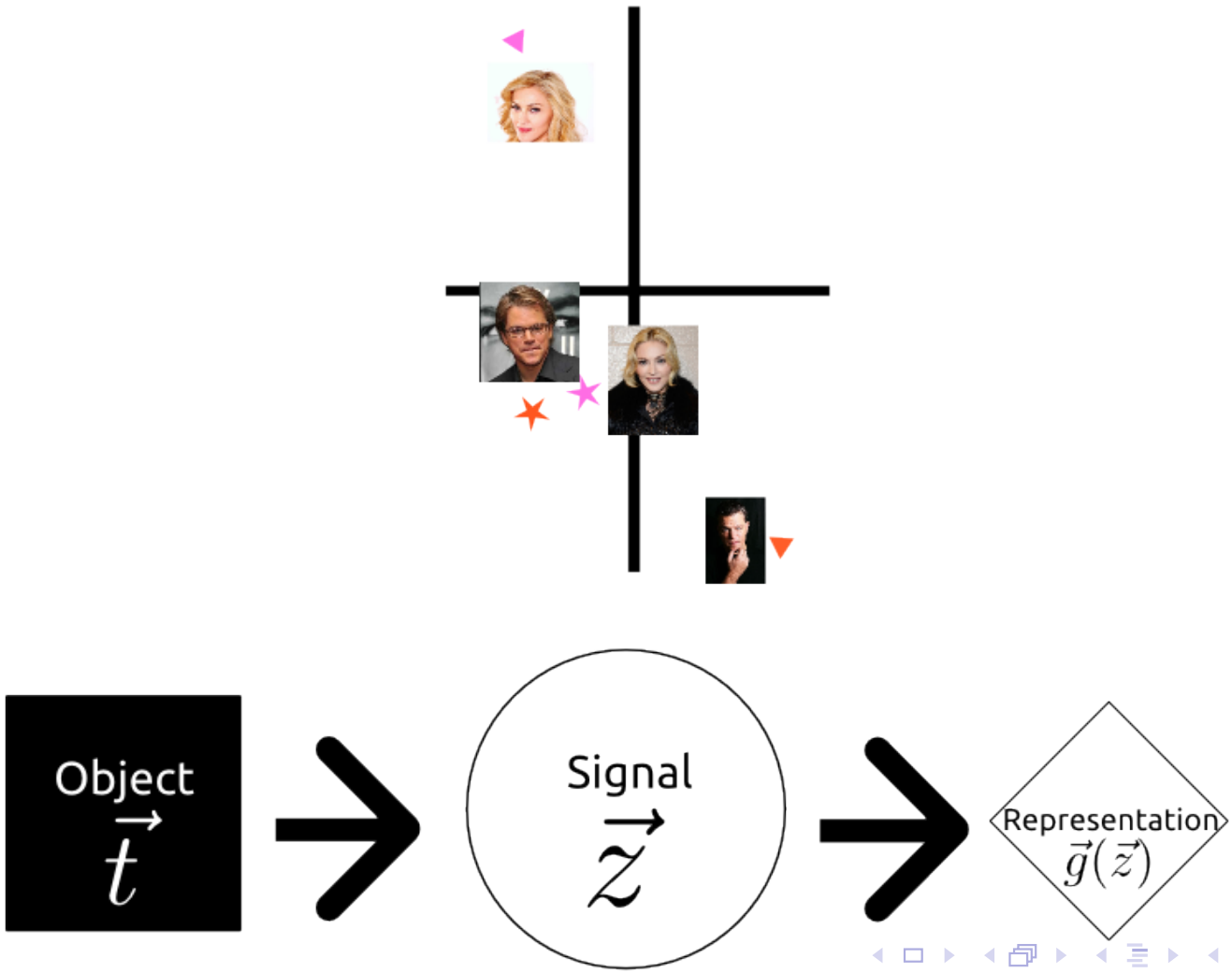
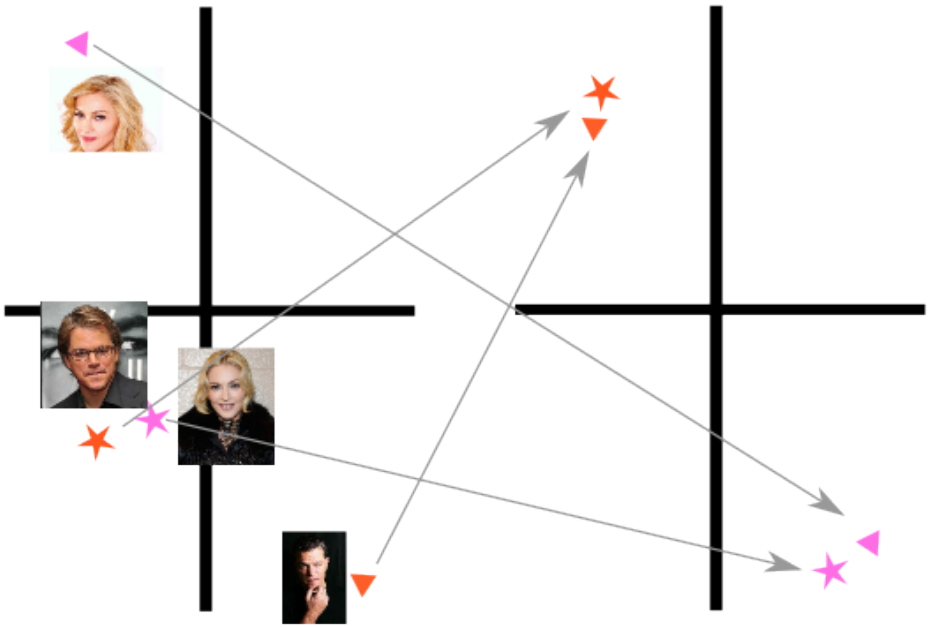
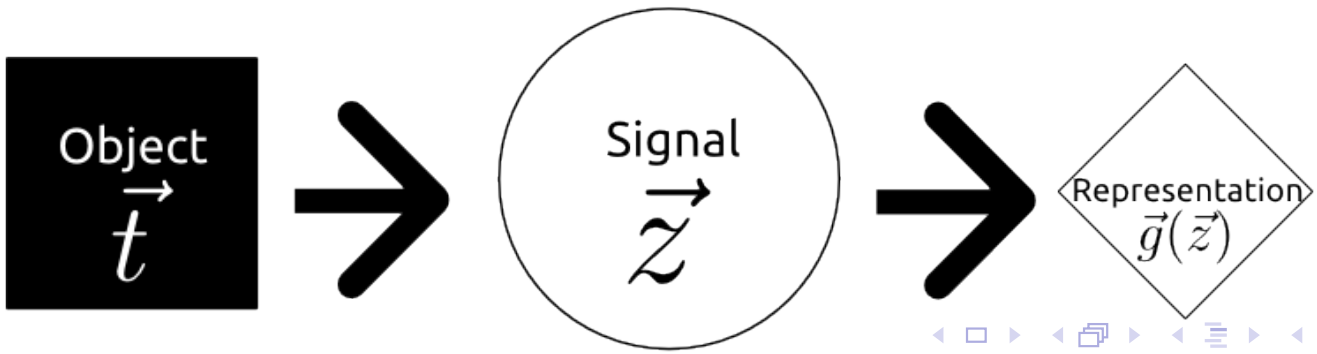


...captures the object space geometry





Why do we care?

- 1) Neuroscience. The brain is hypothesized to use representations for cognitive purposes

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- 2) Machine learning. Representations turn out to be useful for many Machine Learning tasks!

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- Method 1: *Ground truth*. If we happen to know the object parameters $\vec{t}$ (e.g. we simulated the data).

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- Method 1: *Ground truth*. If we happen to know the object parameters $\vec{t}$ (e.g. we simulated the data).
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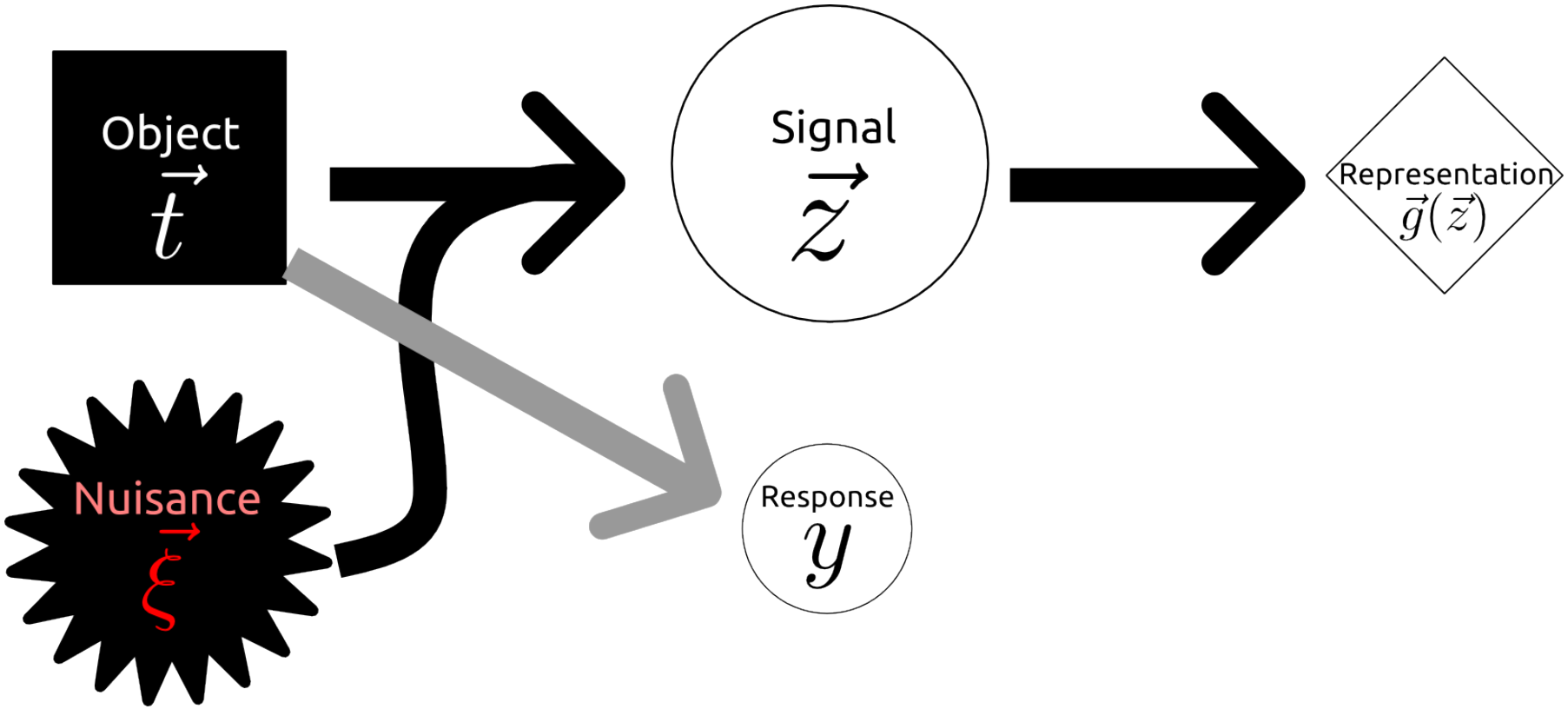
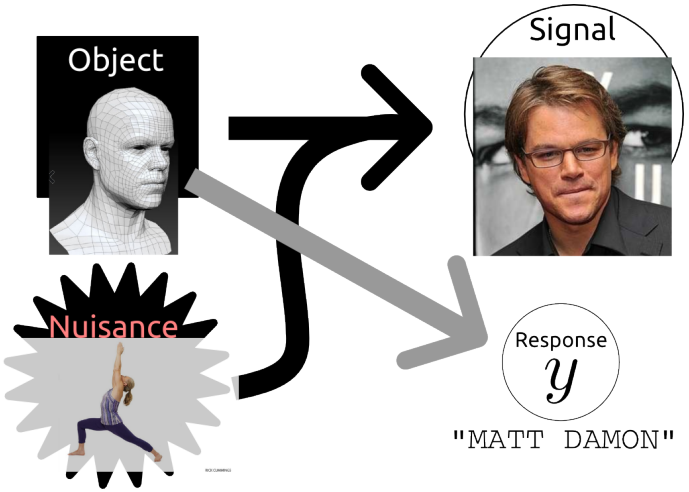
- Method 3: *Supervised*. If we have a *response variable* Y which can be used to infer distances in $\vec{t}$.

Supervised evaluation of representations



Example: face recognition



- The ID of the individual is an appropriate *response* variable...

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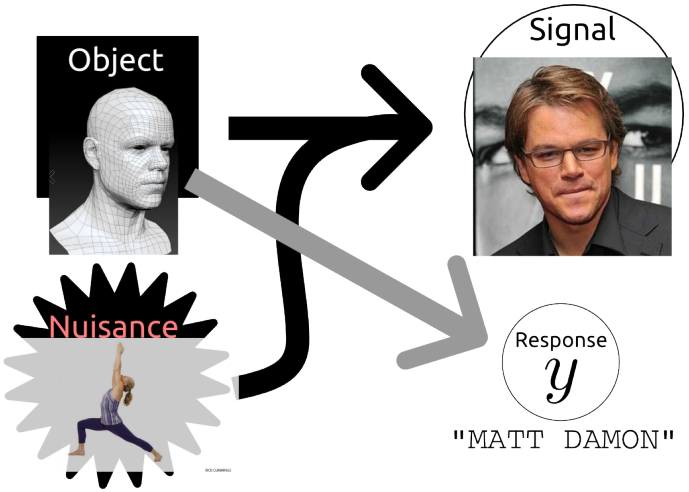

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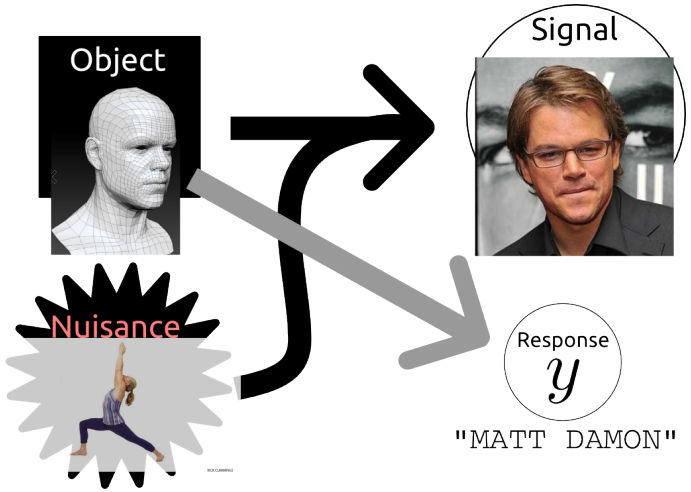


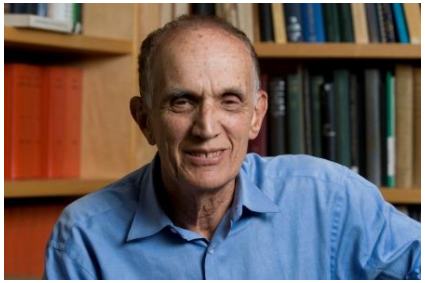
- The ID of the individual is an appropriate *response* variable...
- ...because two photos labeled with the same ID must belong to the same object $\vec{t}$
- That is, for $d(y, y')$ being the zero-one distance,

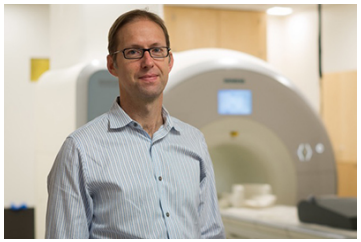
$$d(y, y') = 0 \Leftrightarrow d(\vec{t}, \vec{t}') = 0.$$

Section 2

Acknowledgements


CHALLENGER



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Section 3

The end