Zero-calibration BMIs for sequential tasks using error-related potentials

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JONATHAN GRIZOU

Learning from EEG error-related potentials

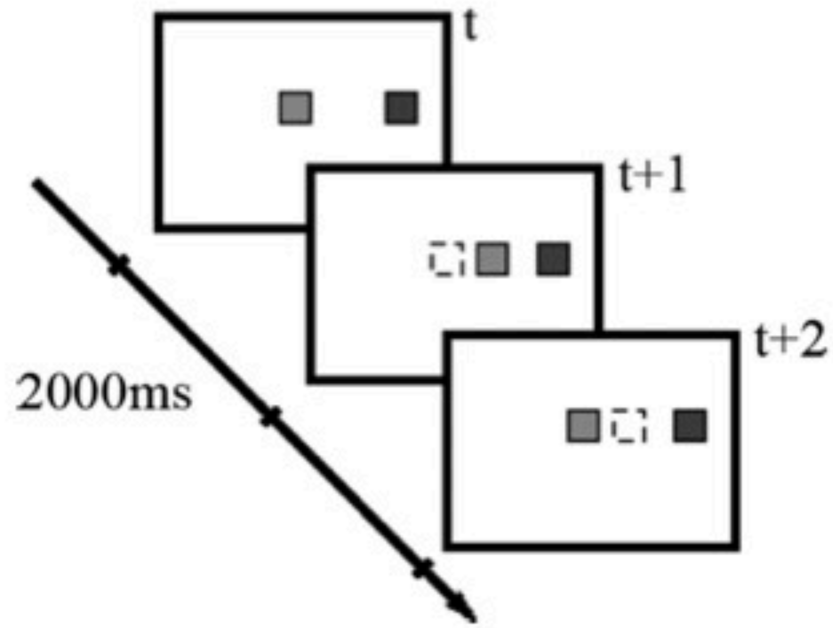
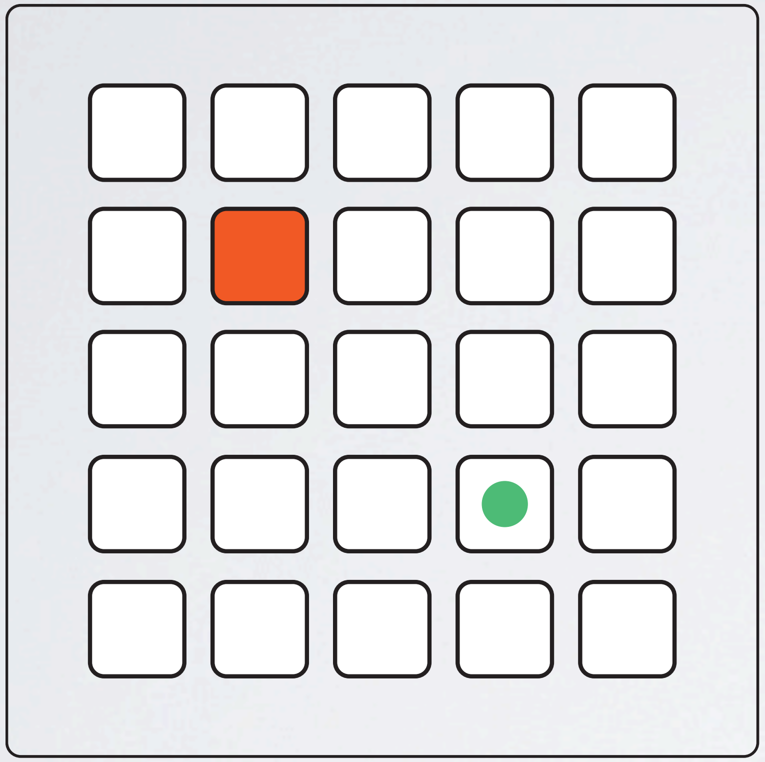


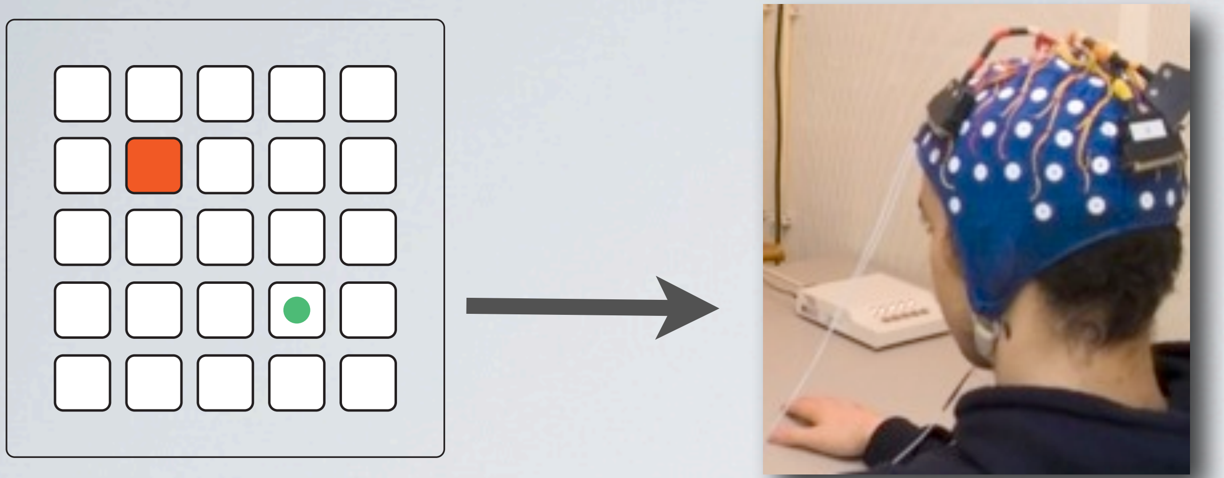
Fig. 1. Experimental protocol. *Green square*, moving cursor. *Red square*, target location. *Dotted square*, cursor location at the previous time step. Correct and erroneous movements are shown at times $t + 1$ and $t + 2$, respectively.

Chavarriaga, Ricardo, and J. del R Millán. "Learning from EEG error-related potentials in noninvasive brain-computer interfaces." *Neural Systems and Rehabilitation Engineering, IEEE Transactions on* 18.4 (2010): 381-388.

Experimental setup



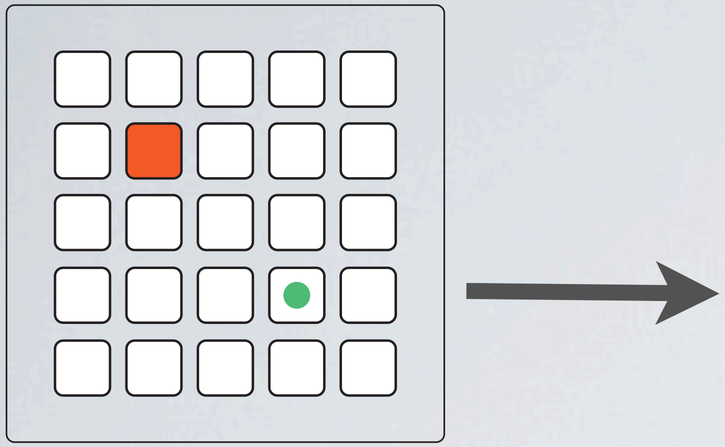
Iturrate, I., L. Montesano, and J. Minguez. "Task-dependent signal variations in EEG error-related potentials for brain–computer interfaces." *Journal of neural engineering* 10.2 (2013): 026024.

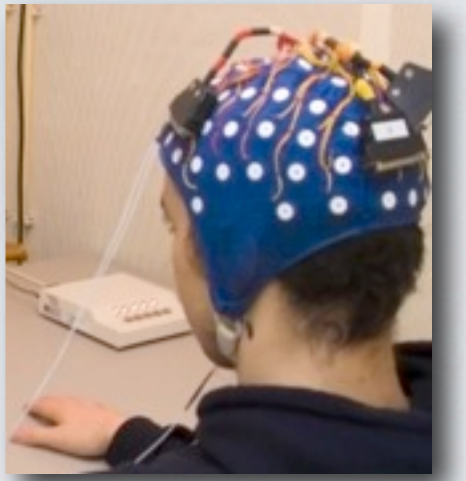


Calibration

Restricted interaction protocol,
e.g. assessing agent’s actions

Known target, i.e. known signal to
meaning relation





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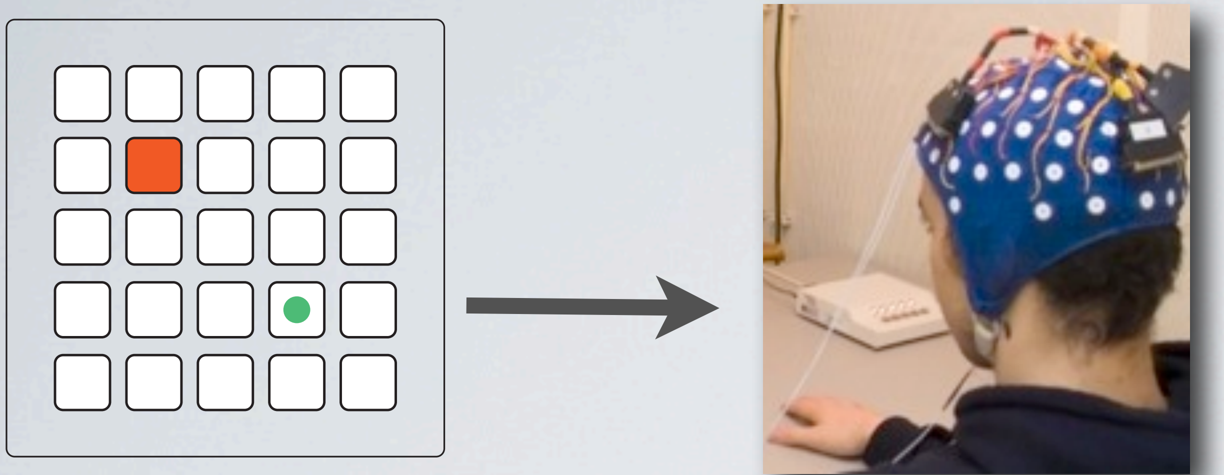
Infer signal to meaning model,
e.g. train a classifier



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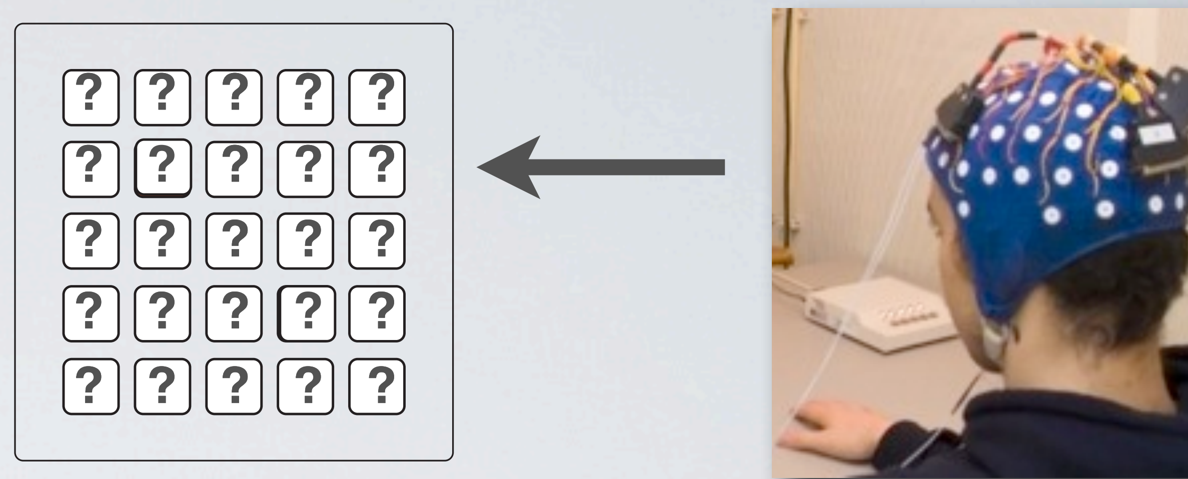
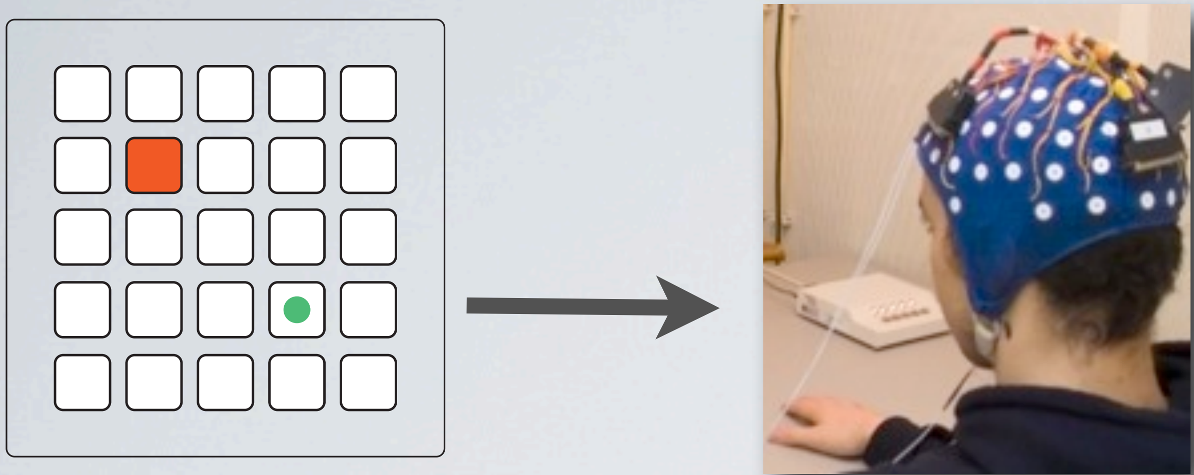


Learning

Restricted interaction protocol, e.g. assessing agent's actions

Unknown target, but target must be one of the squares

Known signal to meaning classifier



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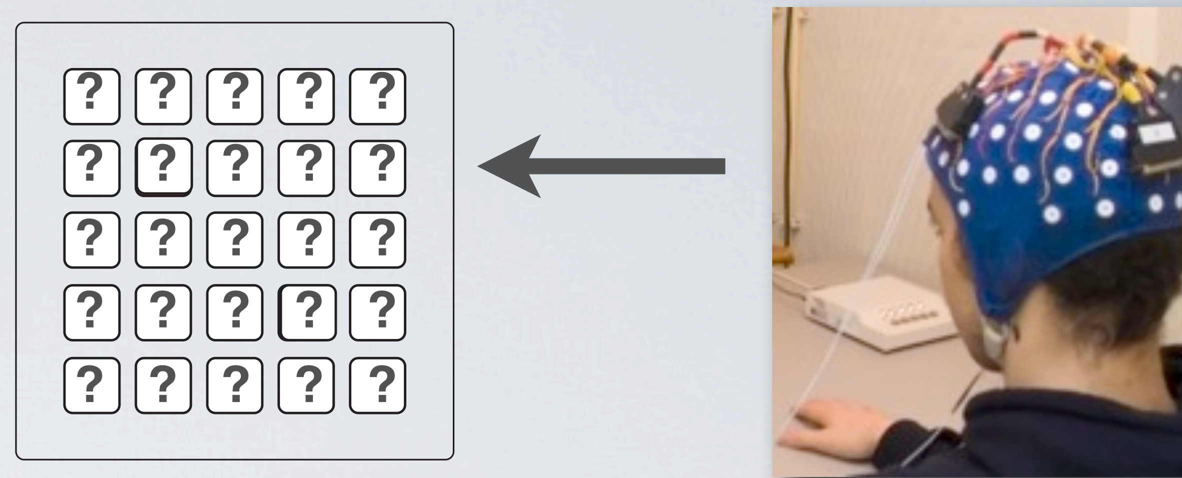

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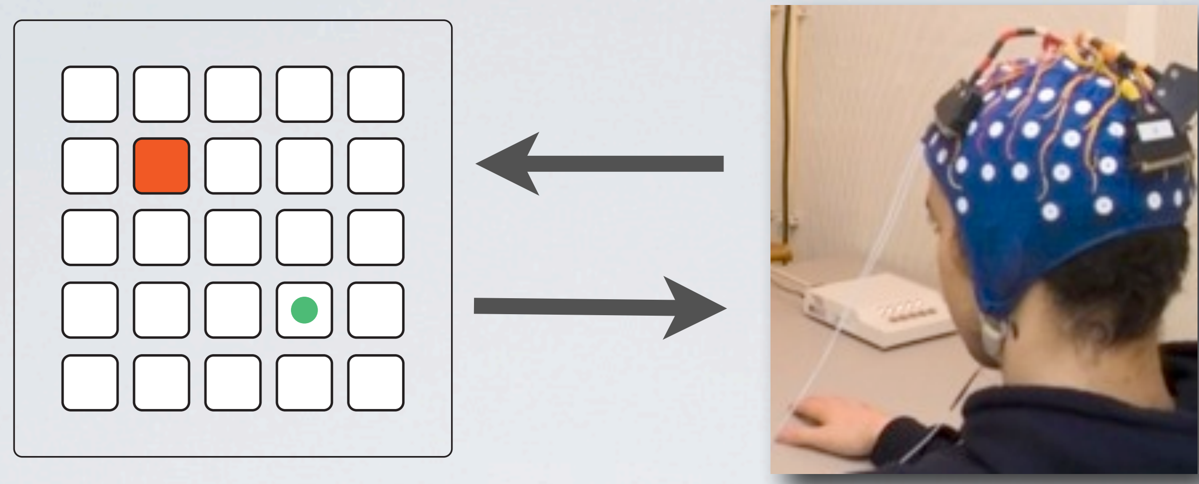
Identify the intended target



Calibration and Learning

Restricted interaction protocol, e.g. assessing agent's actions

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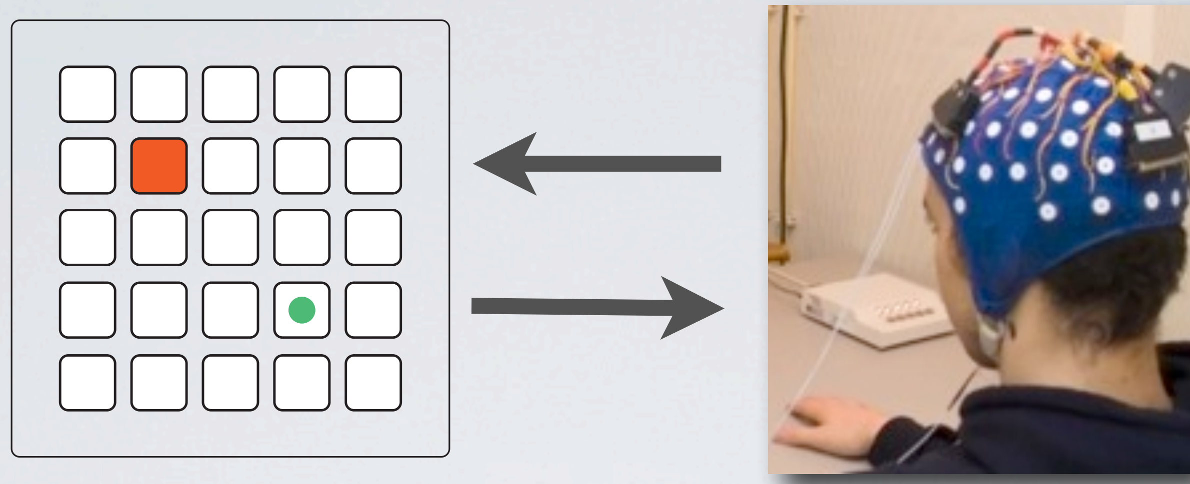

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	↓
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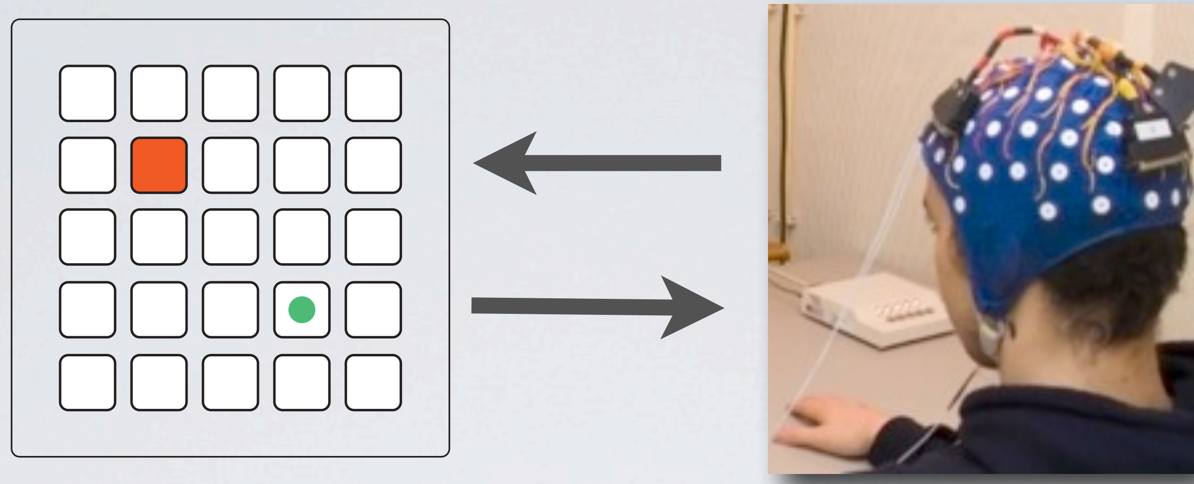

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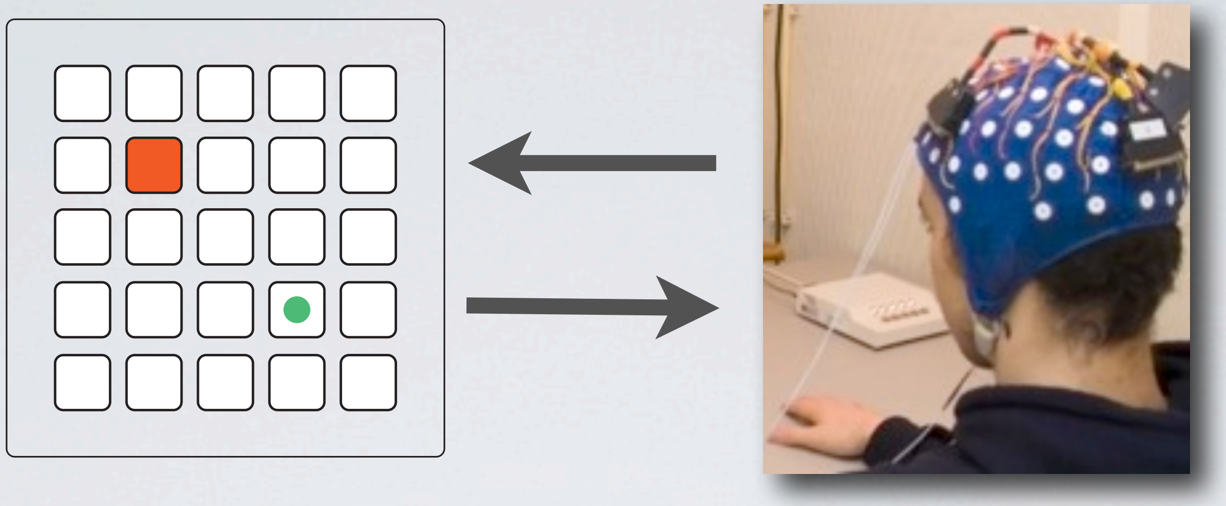
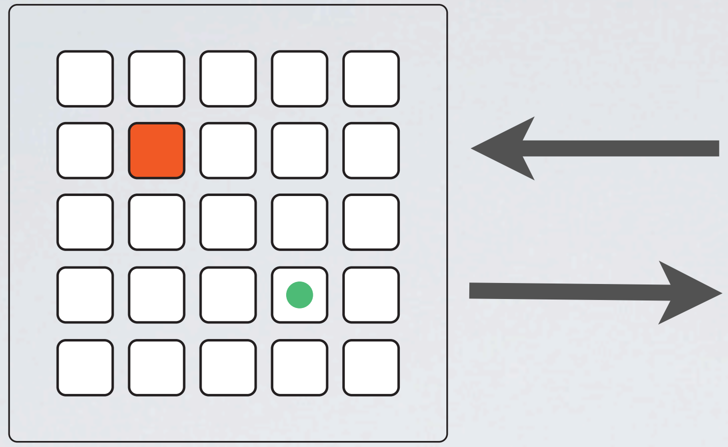


Calibration and Learning

Restricted interaction protocol,
e.g. assessing agent's actions

Known signal to meaning relation for
each hypothetic target



Calibration and Learning

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Known signal to meaning relation for
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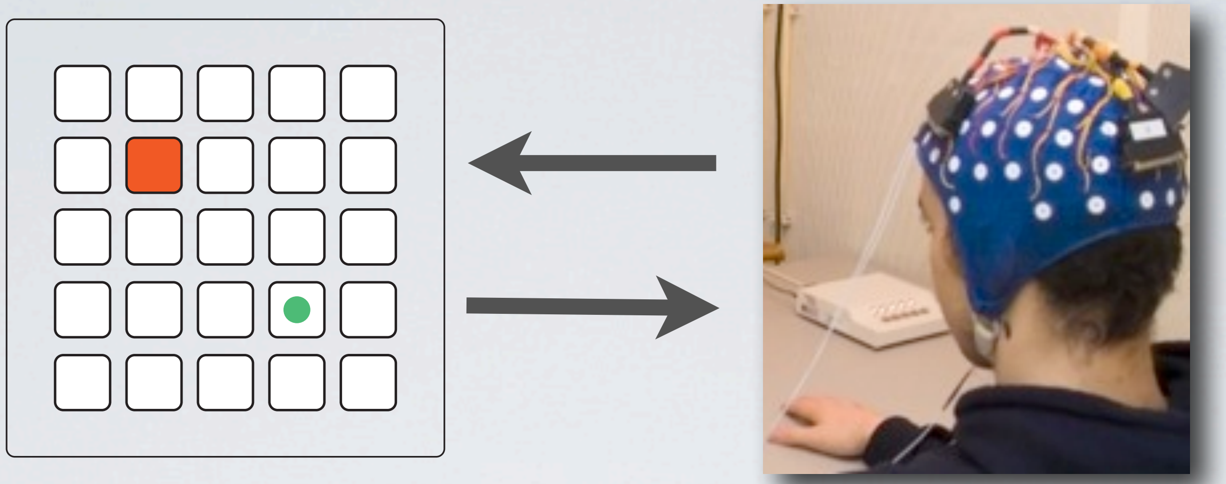
The intended hypothesis should label correctly the signals



Calibration and Learning

Restricted interaction protocol,
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Known signal to meaning relation for
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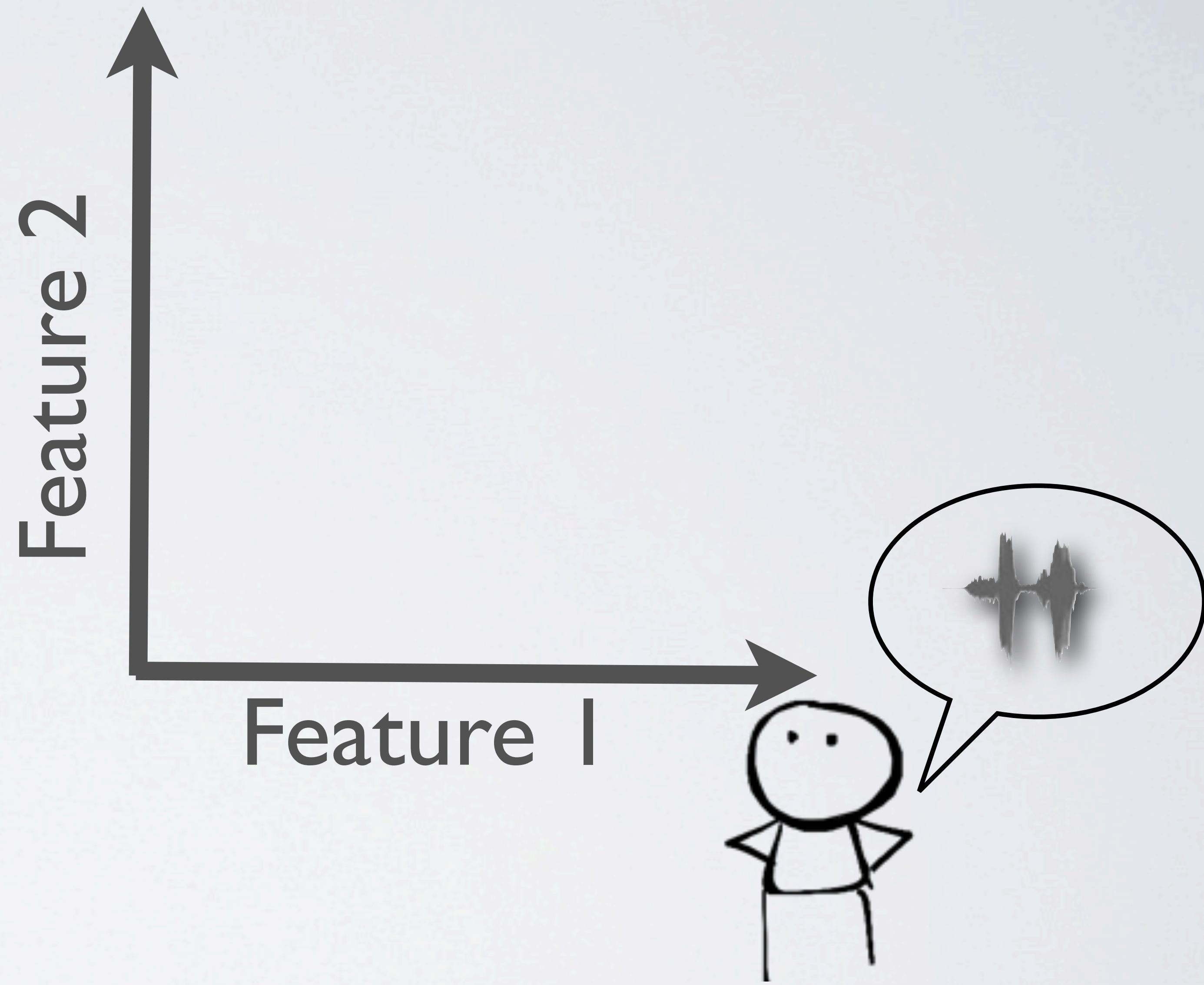
The intended hypothesis should label correctly the signals

????

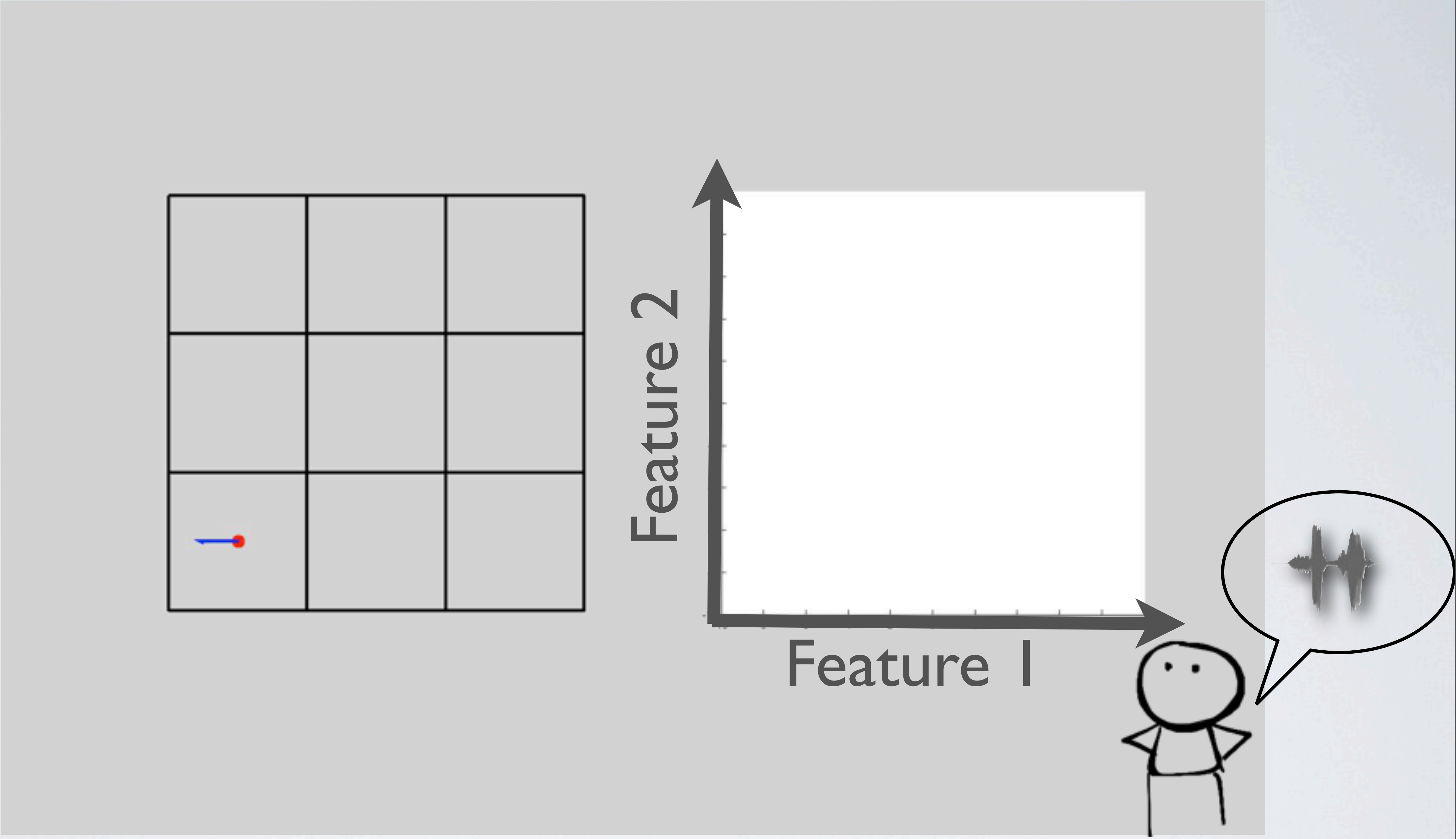
What does it means ? we do not know the ground truth!

Toy example



Sequential task
{state, action, instruction} interaction loop
Instructions are feedback on the robot' actions

Toy example

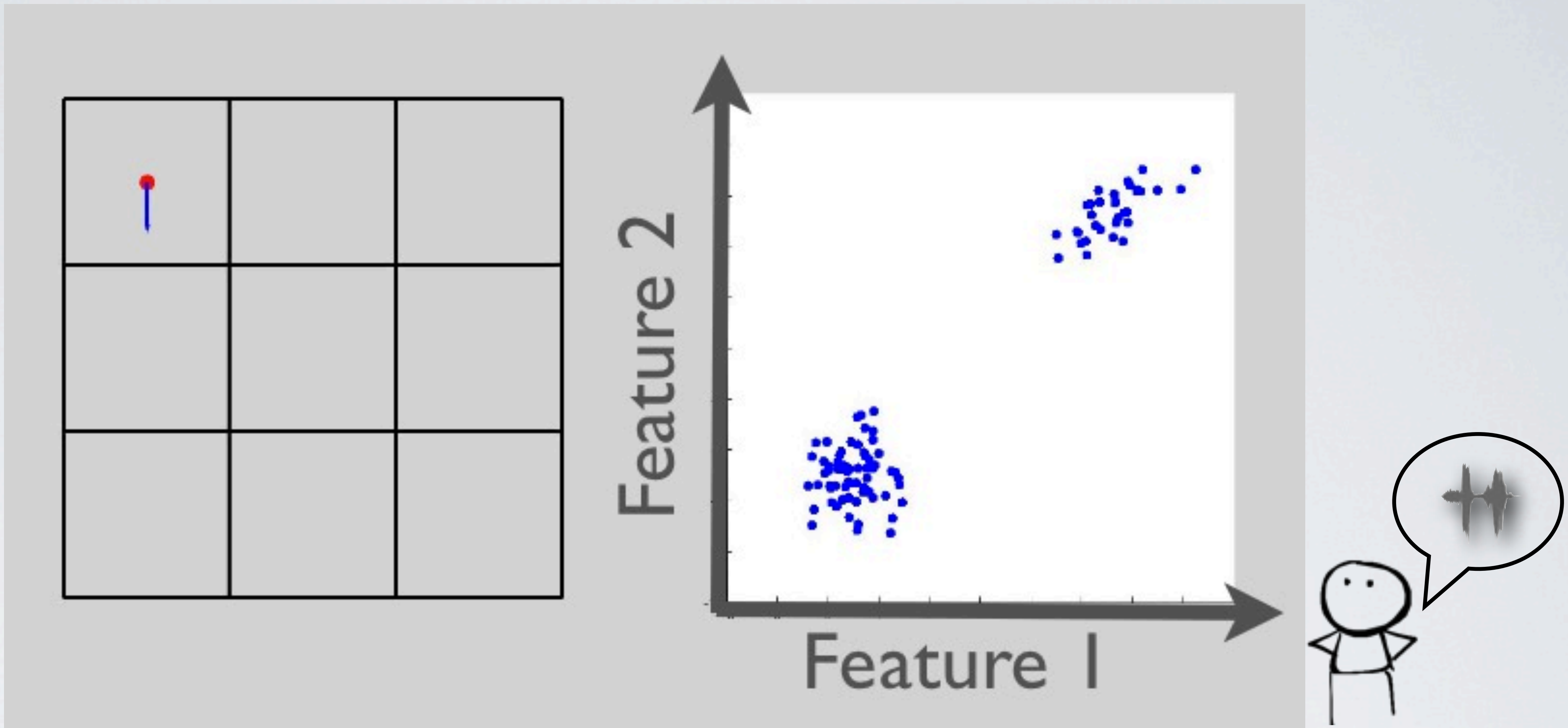


Sequential task

{state, action, instruction} interaction loop

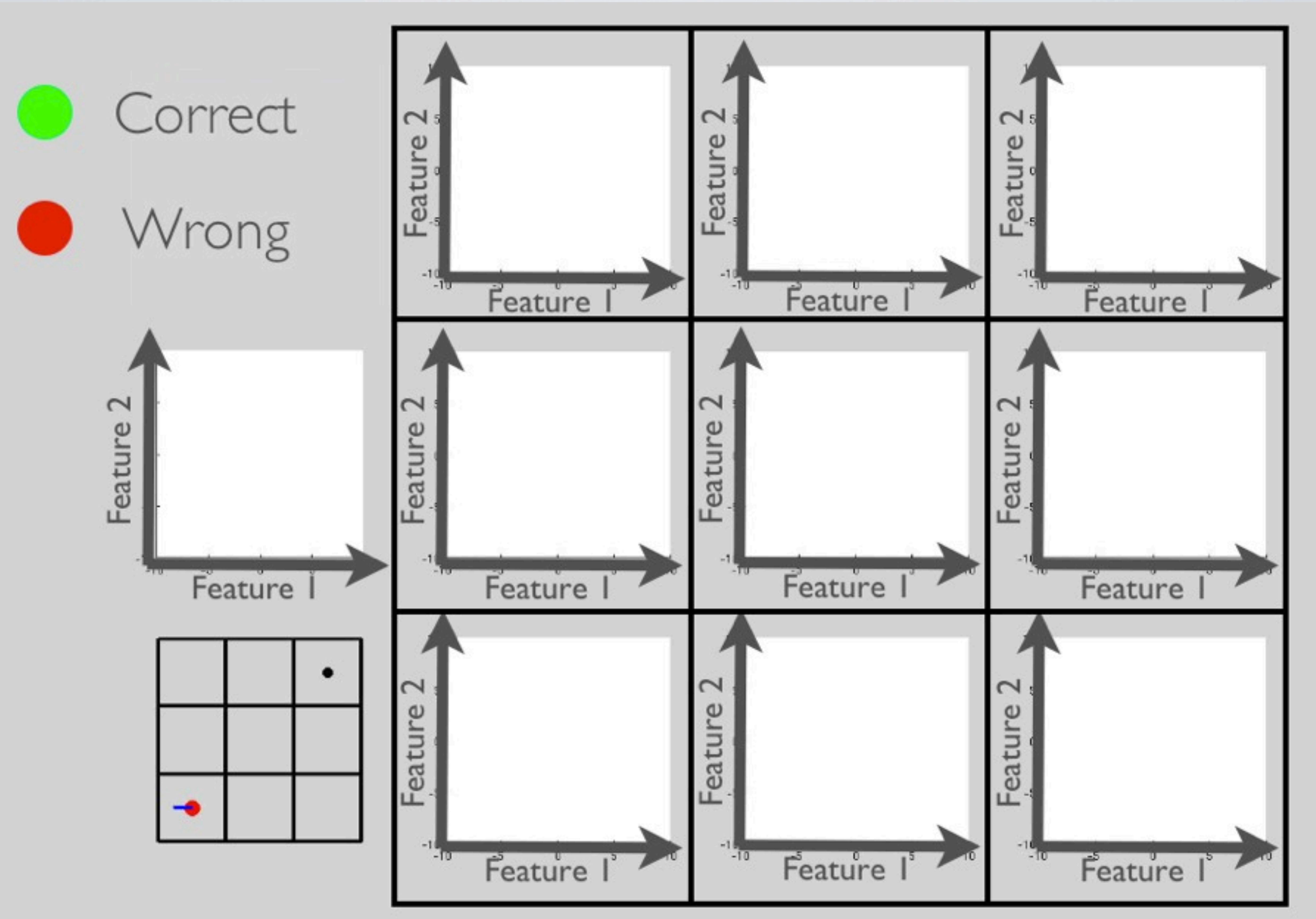
Instructions are feedback on the robot' actions

Finding the hypothesis that best explains the underlying structure of the data



1- Assigning hypothetic labels for each possible target

2- Computing the likelihoods of the resulting datasets (signal + label)


Correct
Wrong
Feature 2
Feature 1
Feature 2
Feature 1
Feature 2
Feature 1
Feature 2
Feature 1
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Feature 1
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Feature 1
Feature 2
Feature 1
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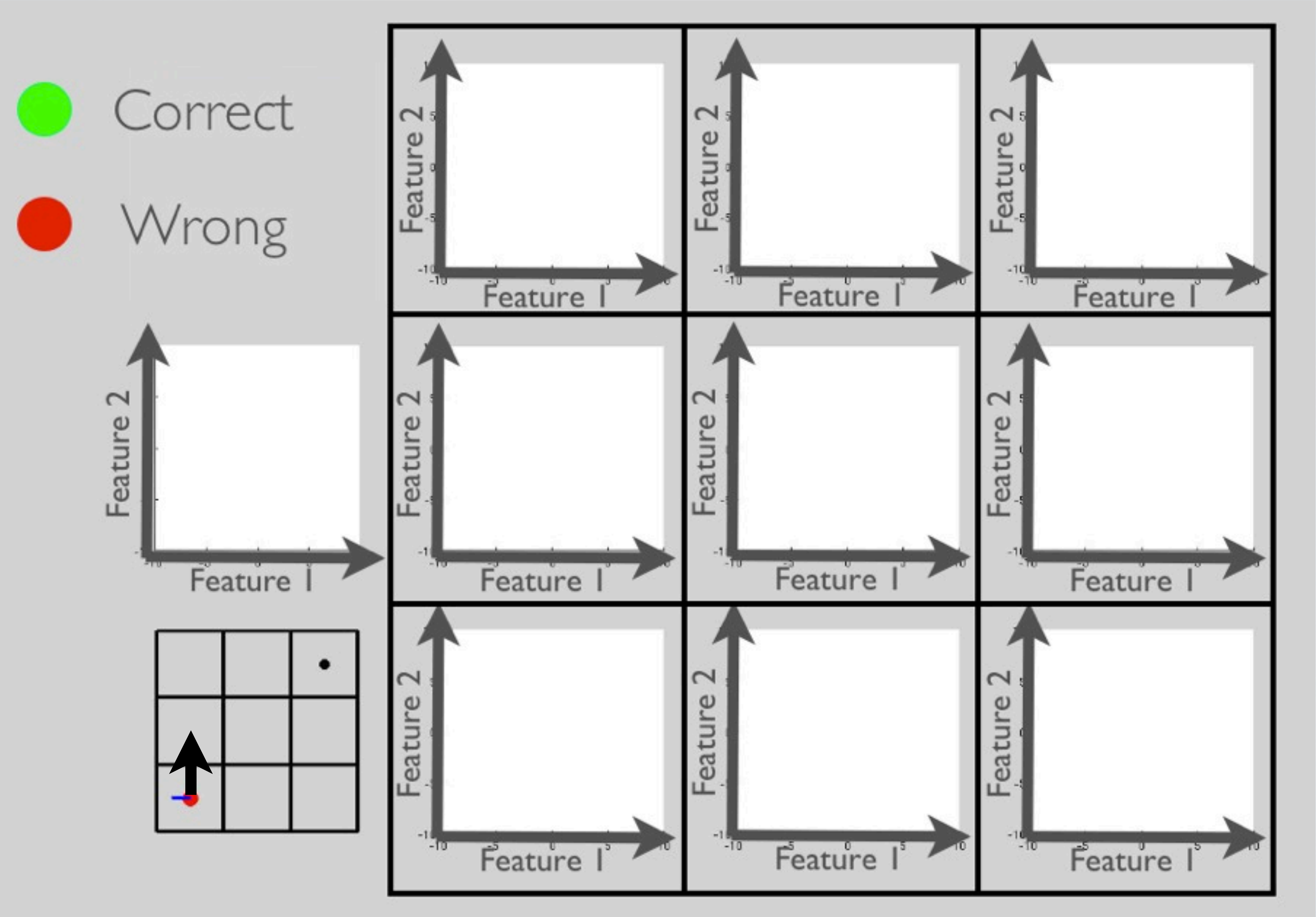
Feature 1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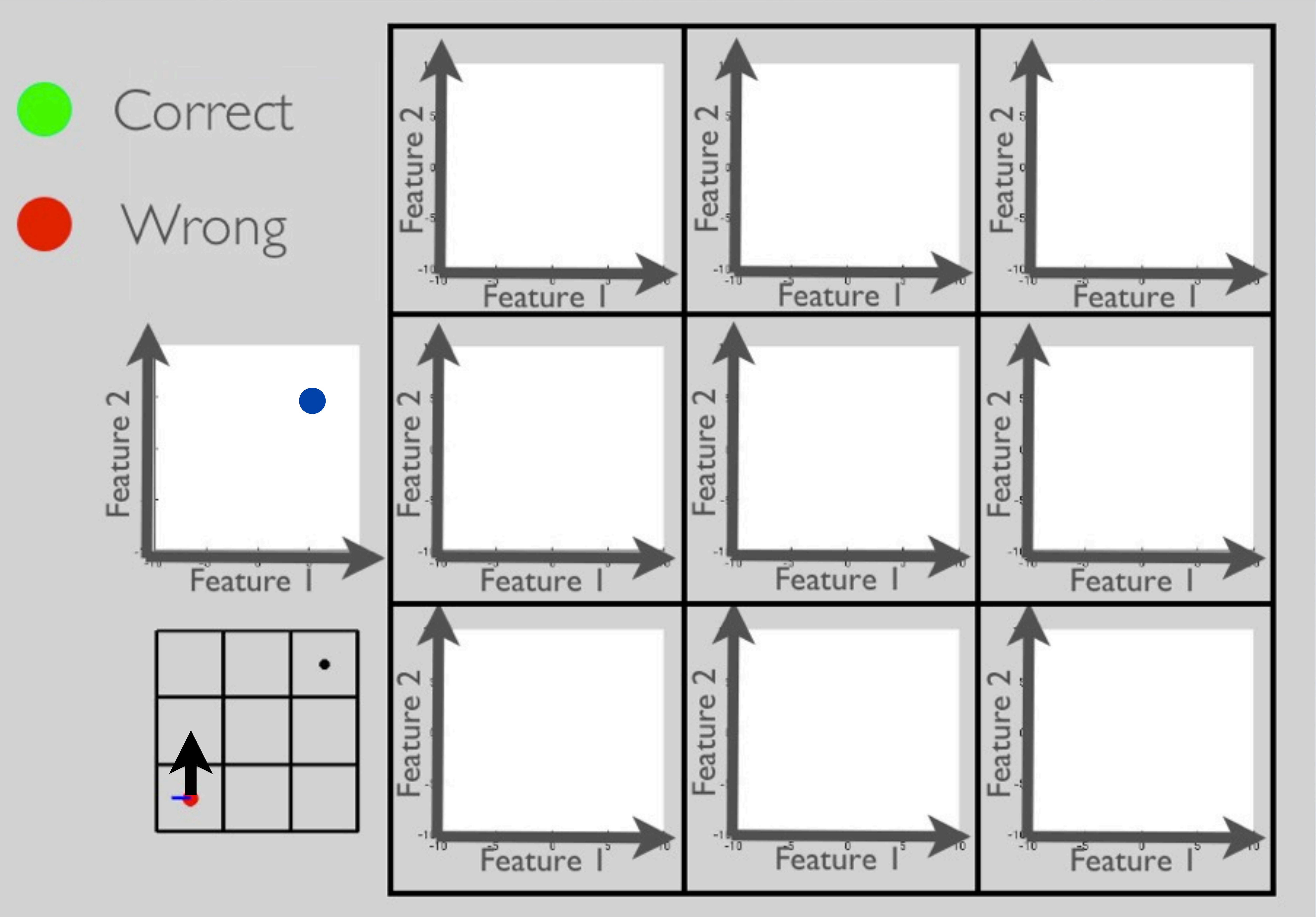

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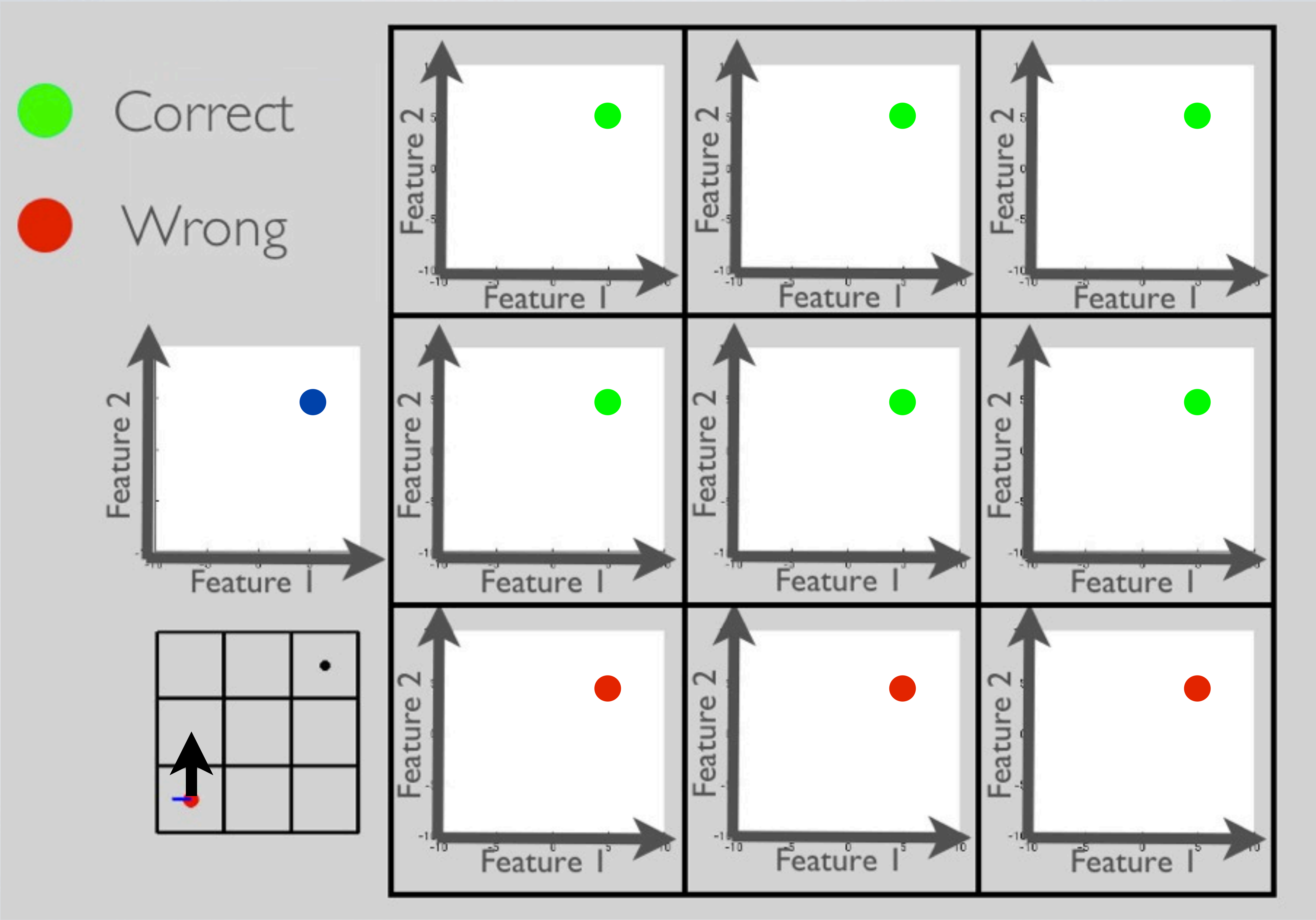

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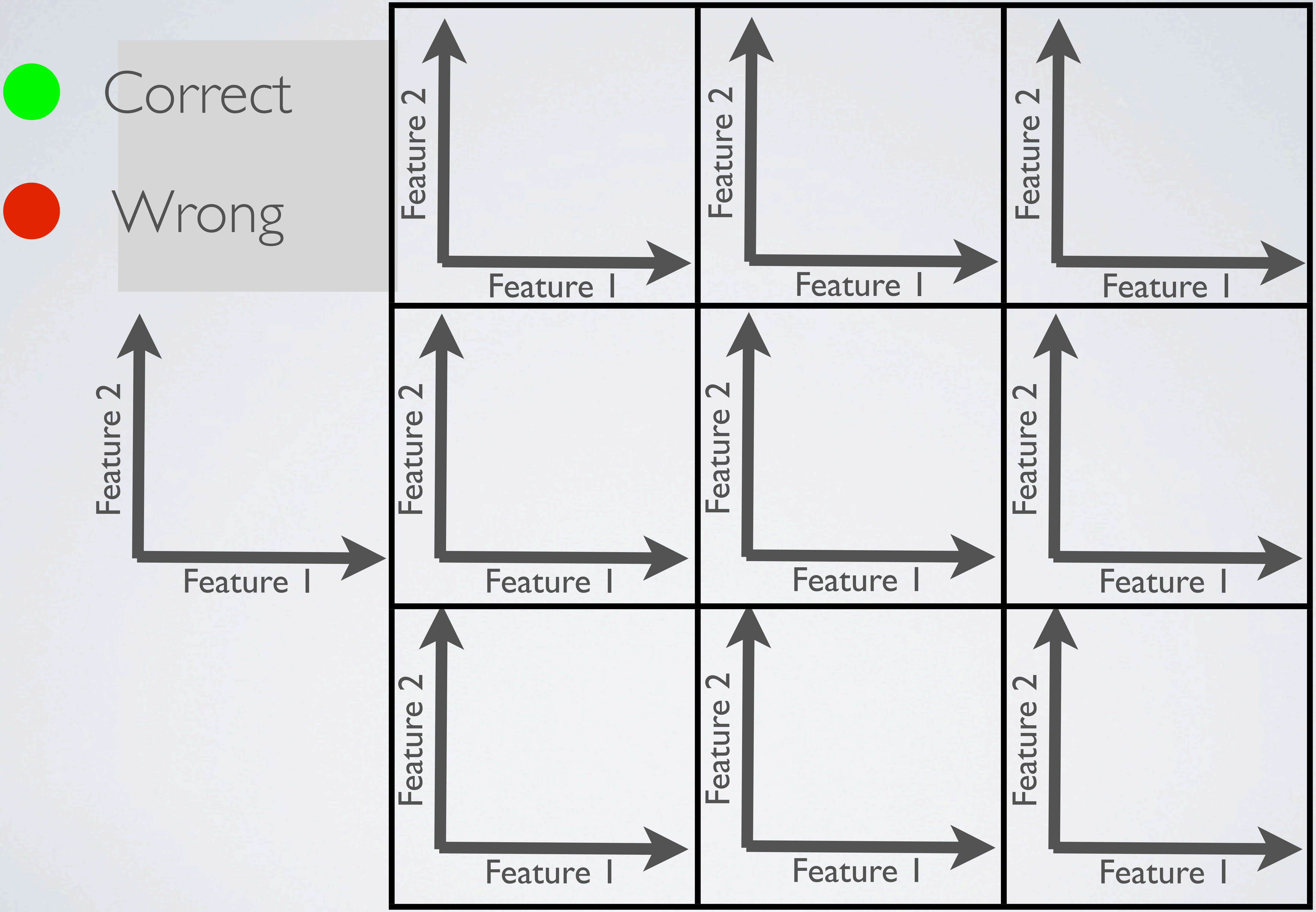
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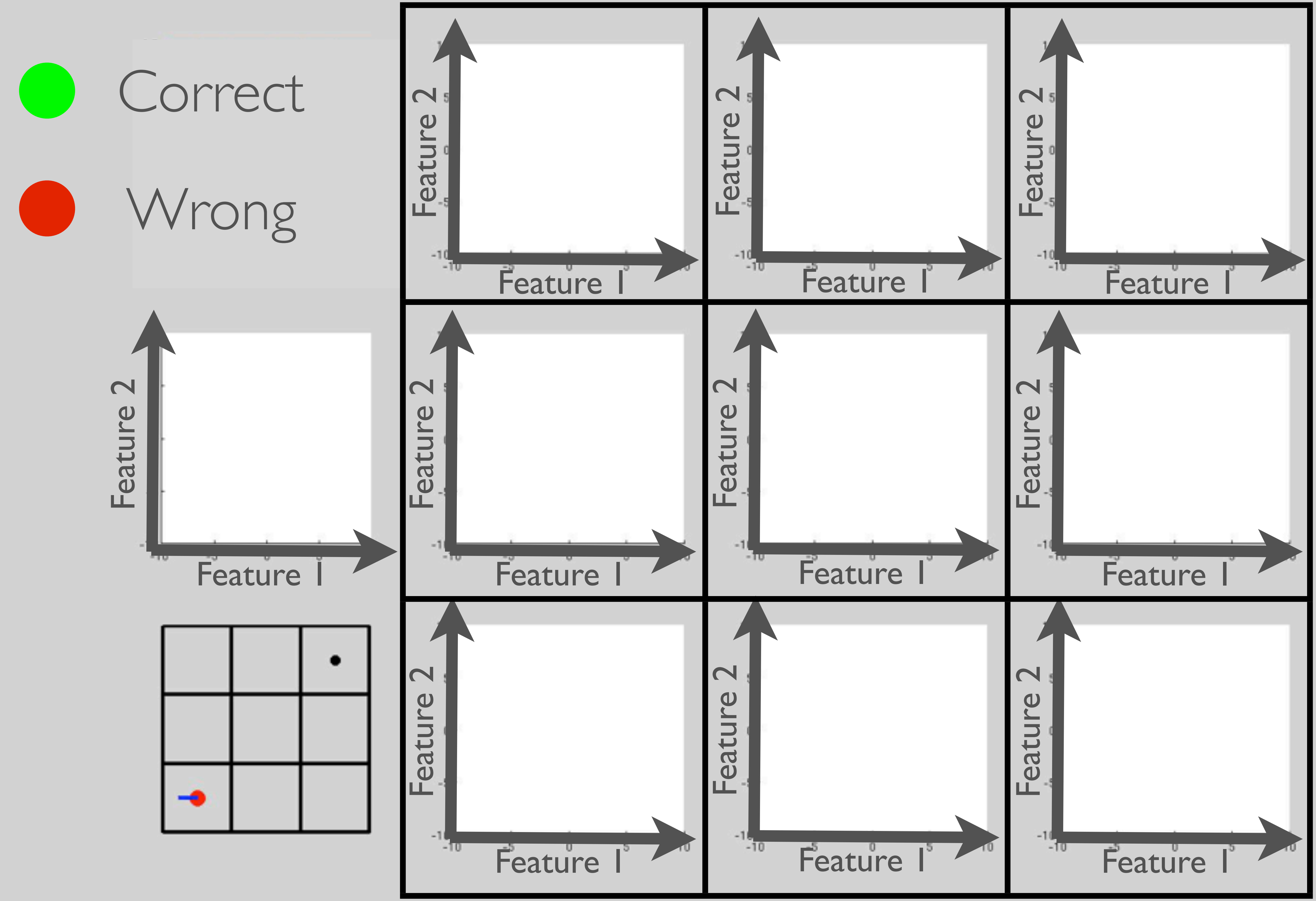
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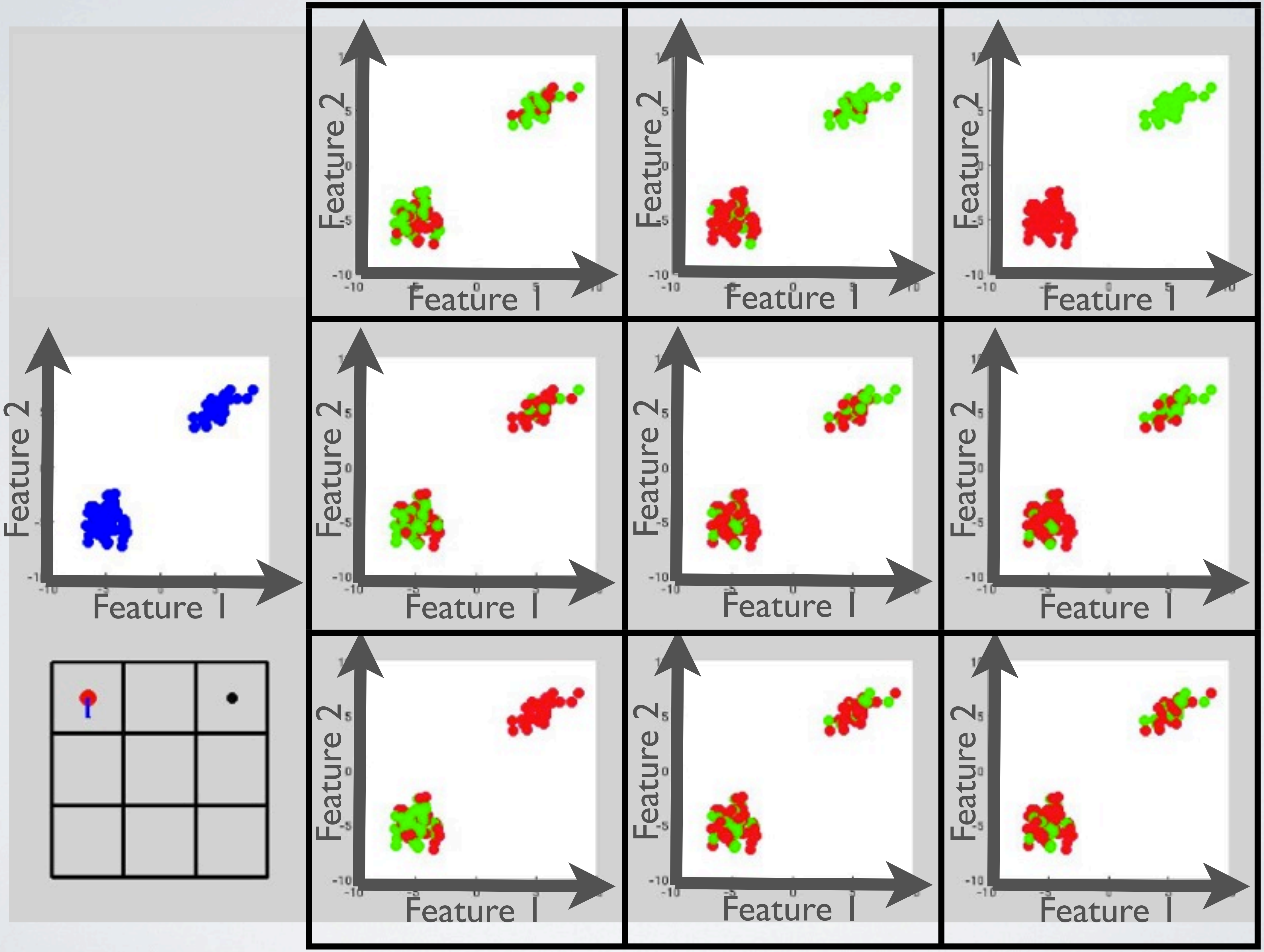
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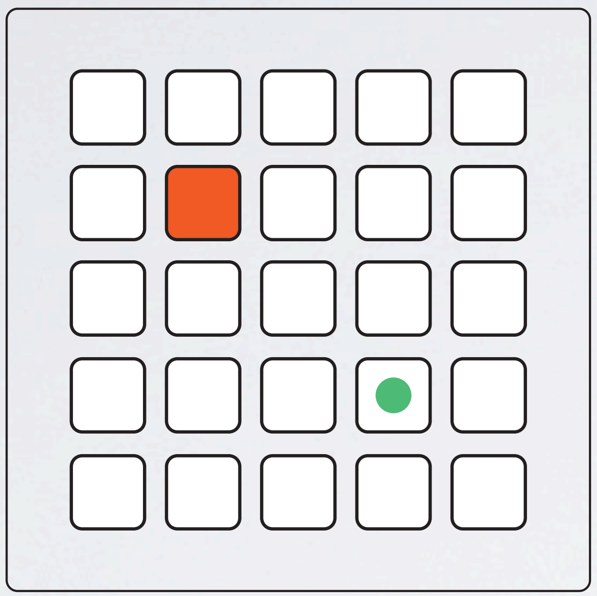
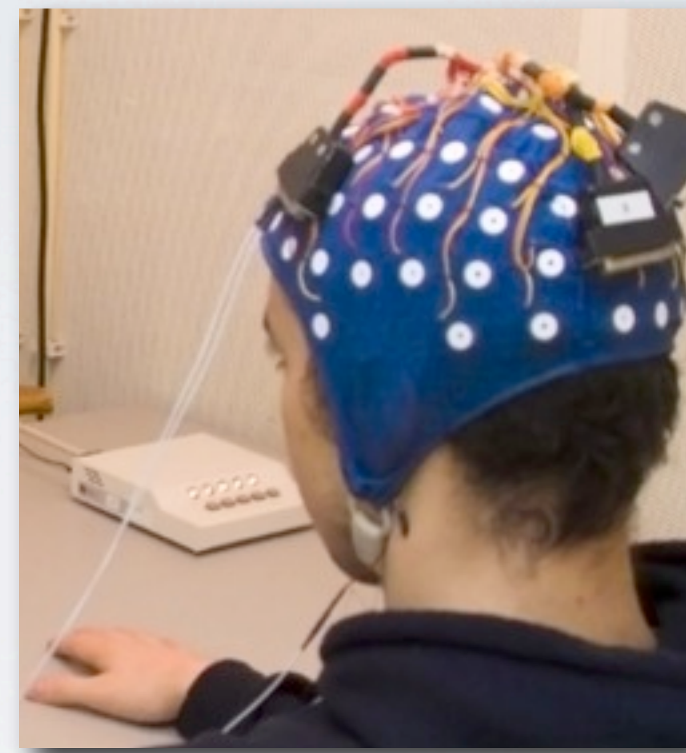
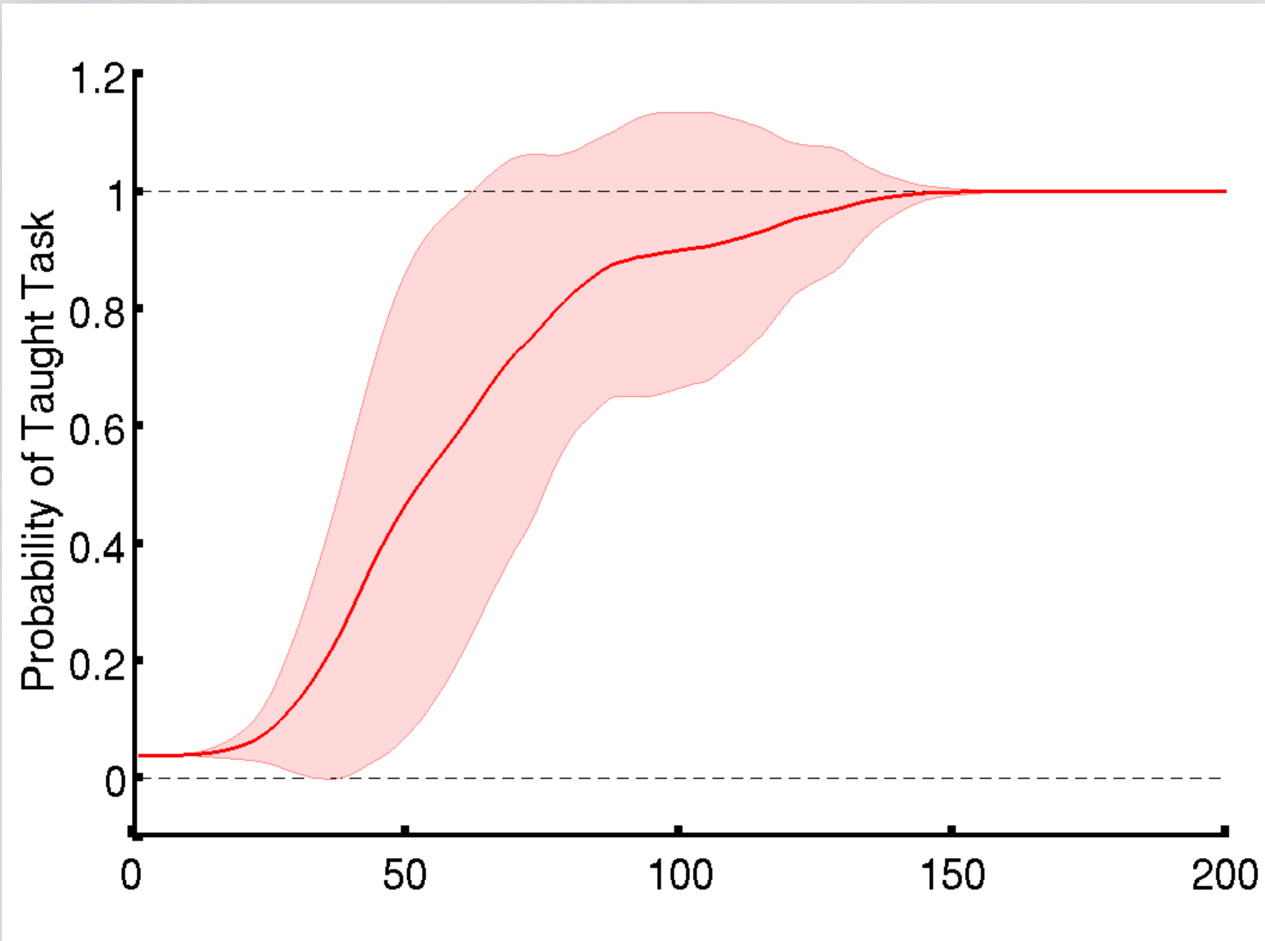
Experimental setup

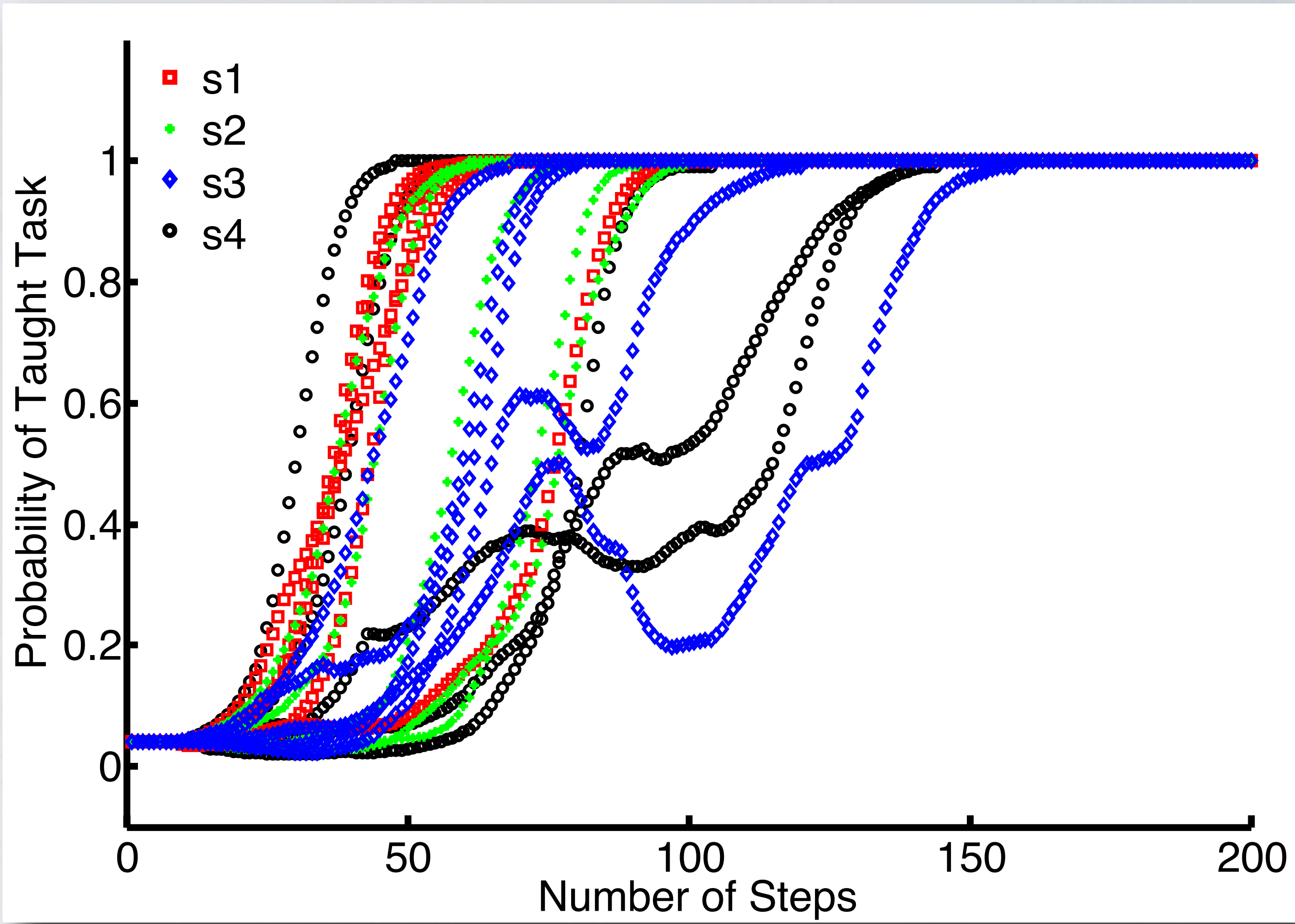




- 34 features, high amount of noise
- 25 possible targets (5x5 grid world)

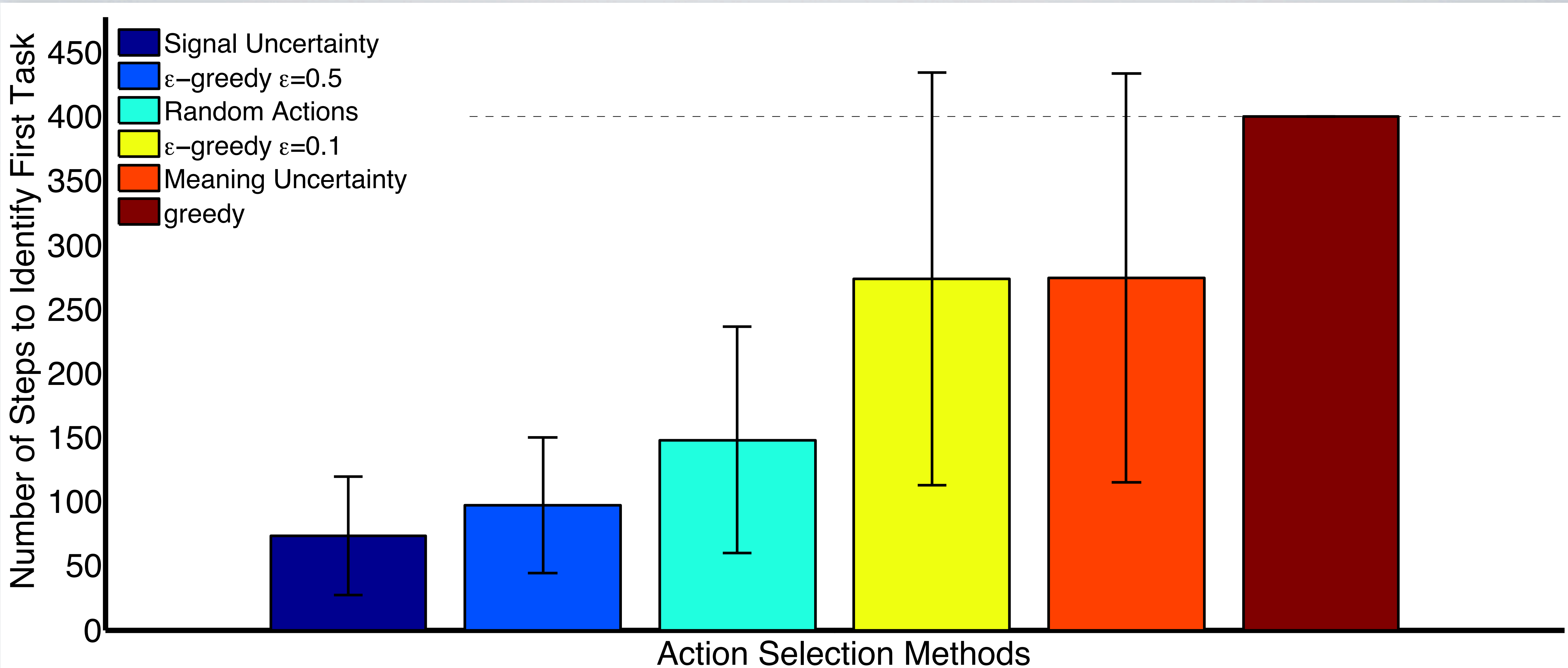
Online experiments





Standard calibration procedure : ~ 400 steps

Planning



Number of Steps to Identify First Task
0
50
100
150
200
250
300
350
400
450
Signal Uncertainty
ε–greedy ε=0.5
Random Actions
ε–greedy ε=0.1
Meaning Uncertainty
greedy
Action Selection Methods

Requirements

Hypothesis (a finite and reasonable number for now).

Pre-defined interaction frame to interpret the signals wrt. an objective, e.g. feedback, guidance, object naming...

Useful feature space to project signals.

A unifying framework ?

Calibration procedure: Reducing the number of hypothesis to one.

Language games: Several objects, one is named.

...

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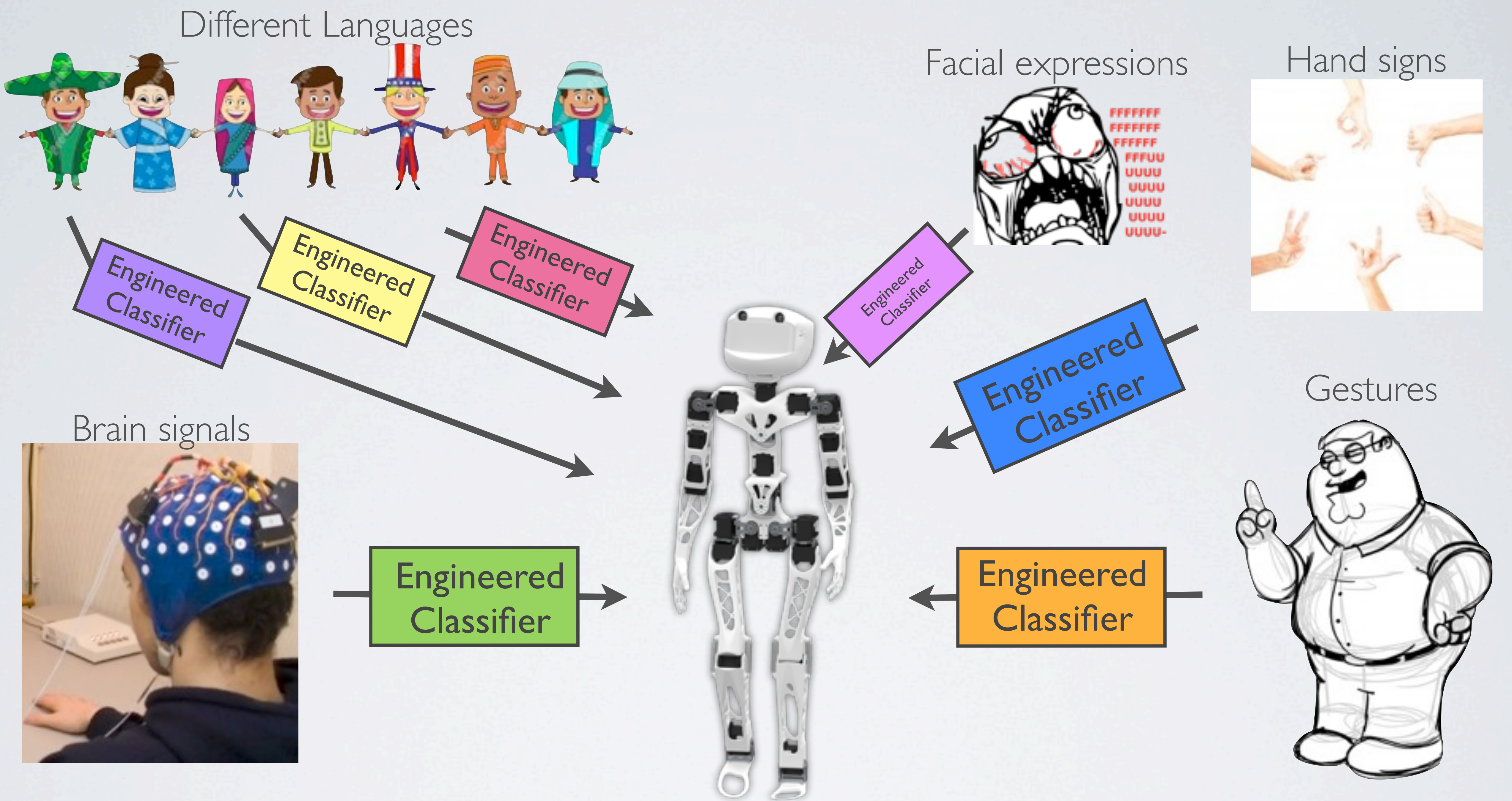
Which open new perspectives

Perspectives

Different people, with their own preferences, skills, and limitations.



Requires to build a personalized database for each user and modality

Perspectives

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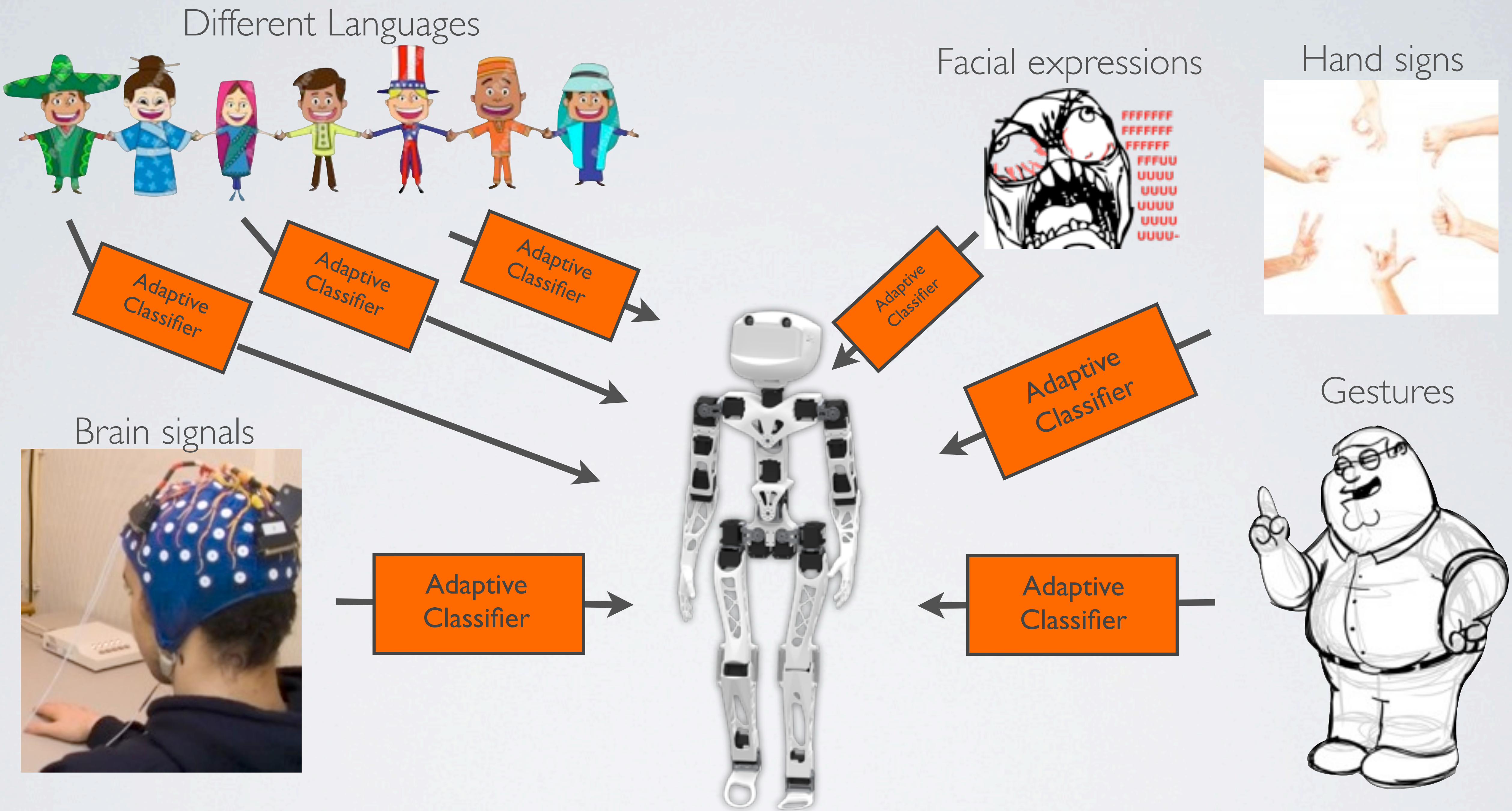

Adapt <u>automatically and online</u>
to each user's own preferred teaching signals.

Of interest

- Learn a task from unlabeled signals

- Reuse acquired knowledge.

- Use standard classification technics.

- Signal expressed as feature vector in R^N (can encode facial expression, gesture, speech, EEG ...).

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Limitations

- Non differentiable signals: as other technics but we can't test it

- Computationally expensive, but highly parallelisable

- Symmetric hypothesis

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Short-term applications

- Cases requiring an expert to calibrate <u>and re-calibrate</u> devices due to frequent signal variations.

- Example of suitable scenario: grasping an object on a table.

Thank you for your attention

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Jonathan Grizou, Manuel Lopes, and Pierre-Yves Oudeyer. "Robot learning simultaneously a task and how to interpret human instructions." *Joint IEEE International Conference on Development and Learning an on Epigenetic Robotics (ICDL-EpiRob)*. 2013.