Into the unknown:
How uncertainty guides active learning

Doug Markant
New York University

Should people control how they learn?

Active vs. passive learning

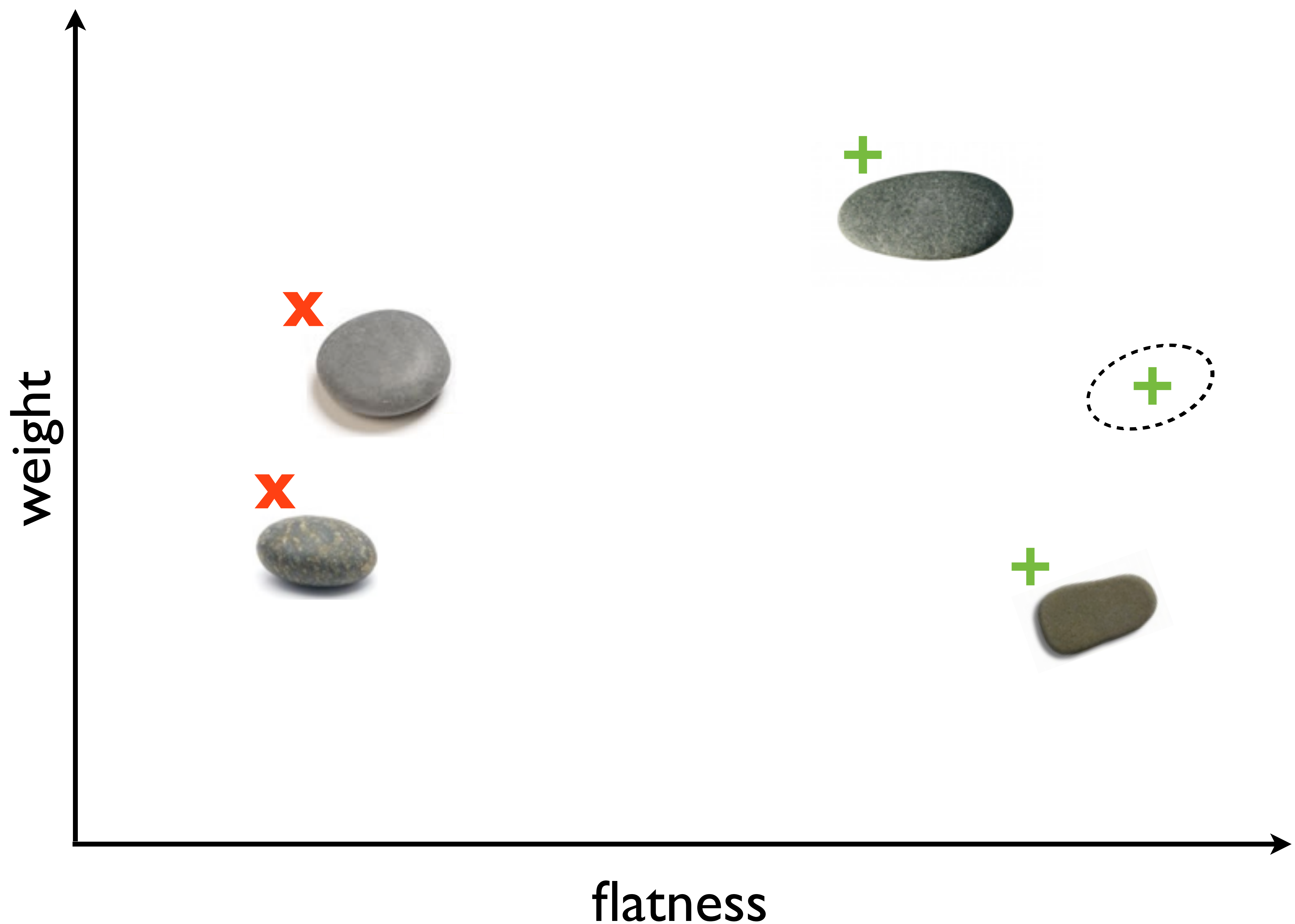
How does active control interact with basic learning processes?

- How do people evaluate what they do and don’t know?
- How do people decide what to learn about?
- Under what conditions does active control lead to more effective learning?

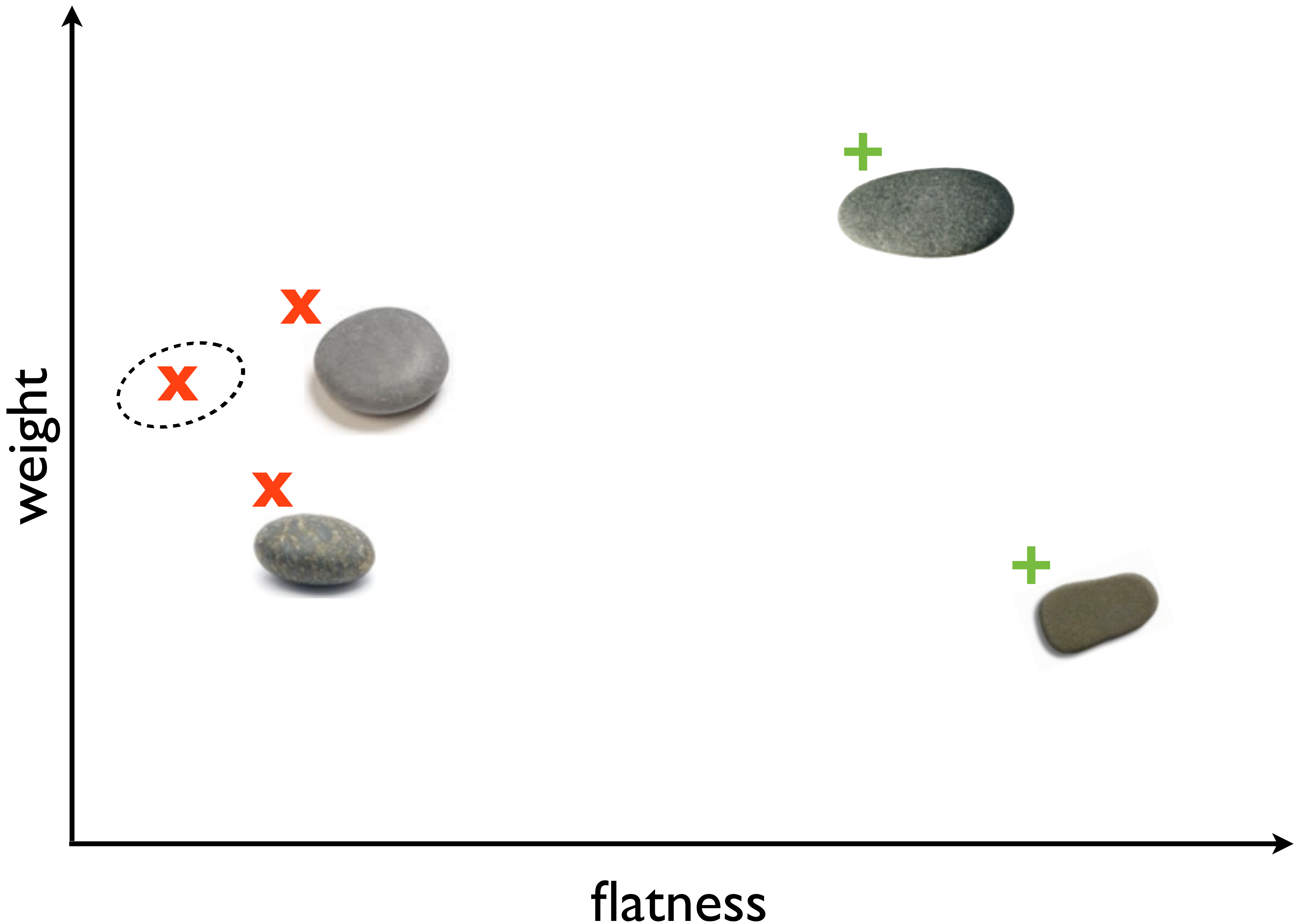
What makes a good skipping stone?

What makes a good skipping stone?

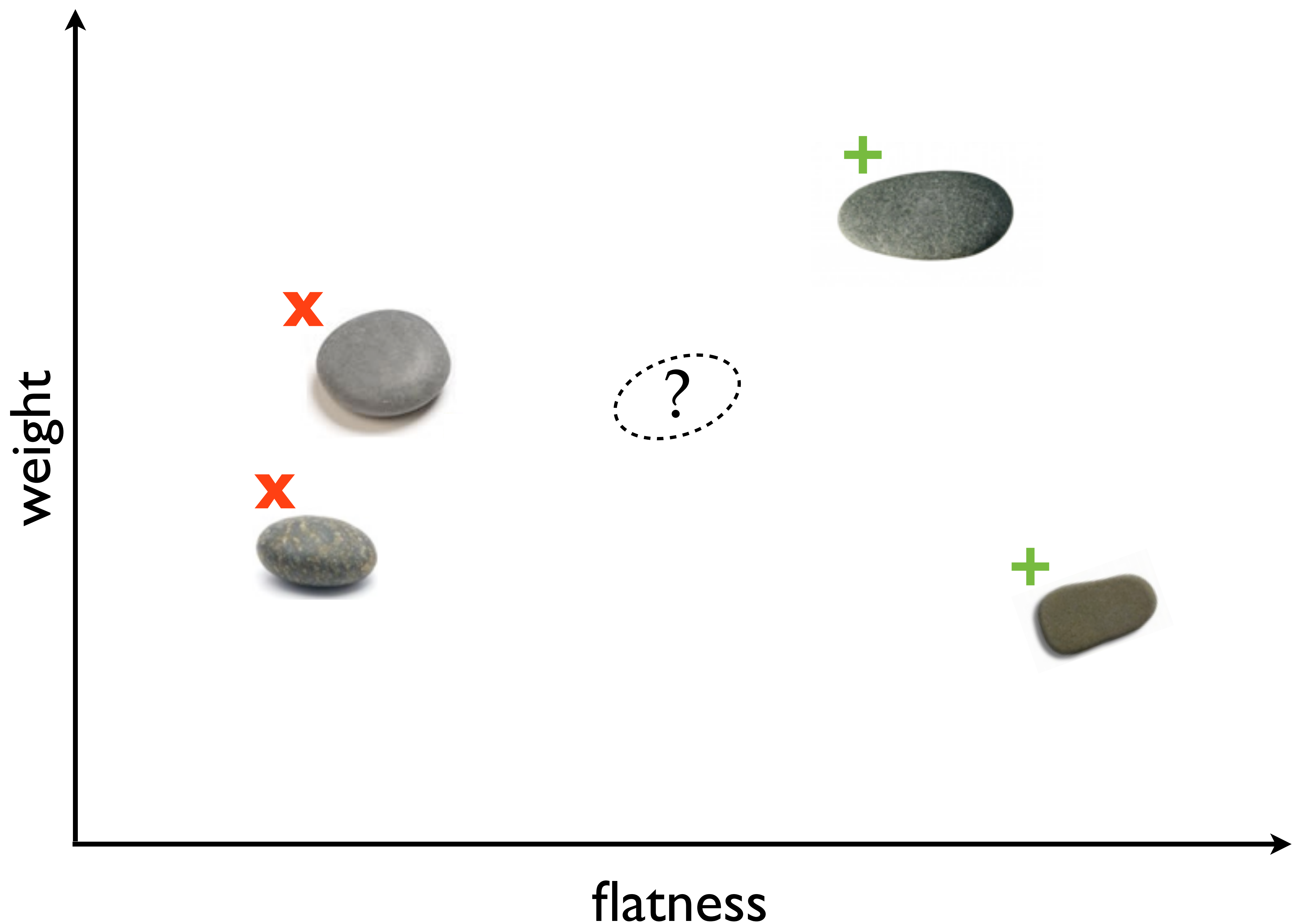
What makes a good skipping stone?



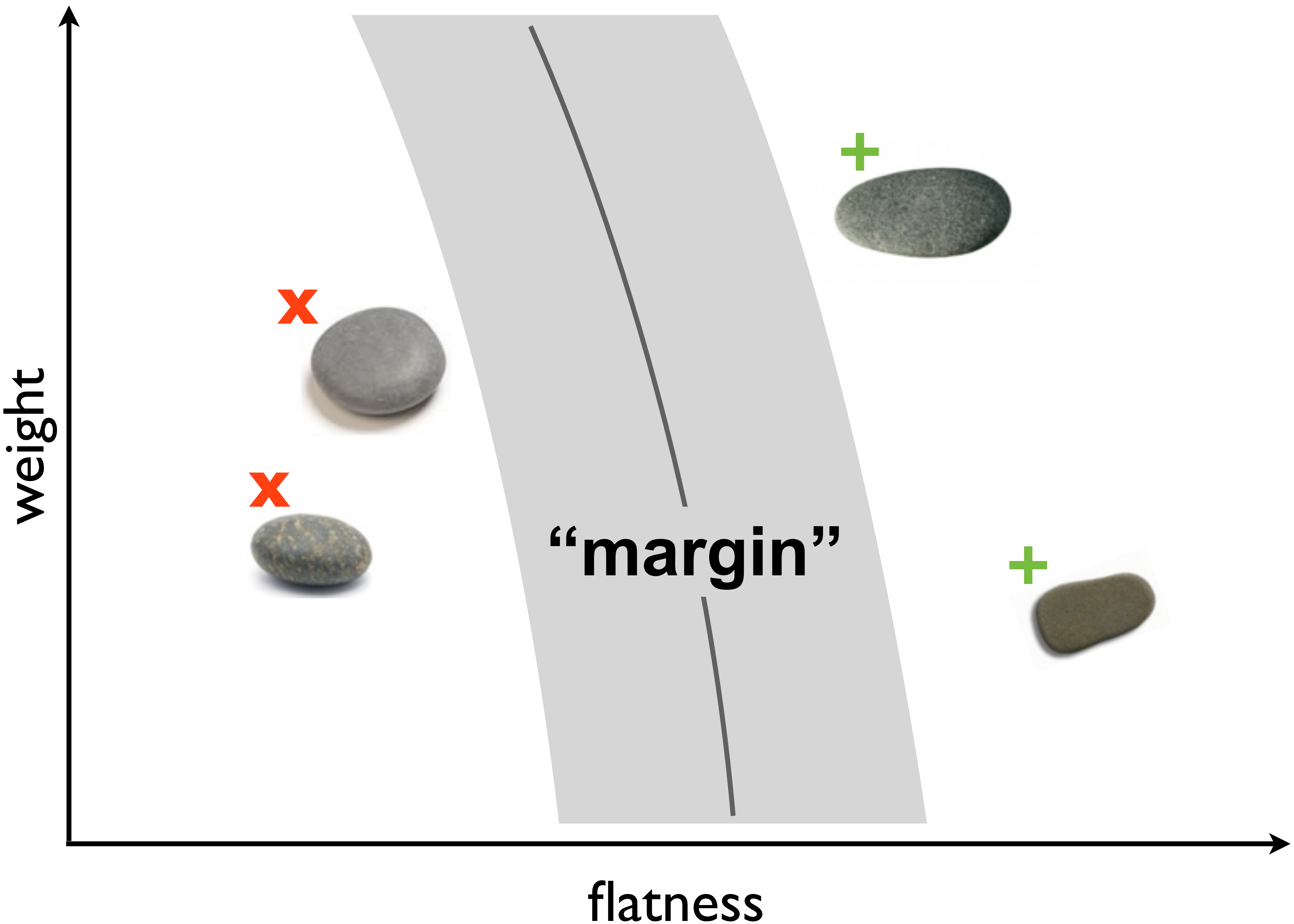
What makes a good skipping stone?



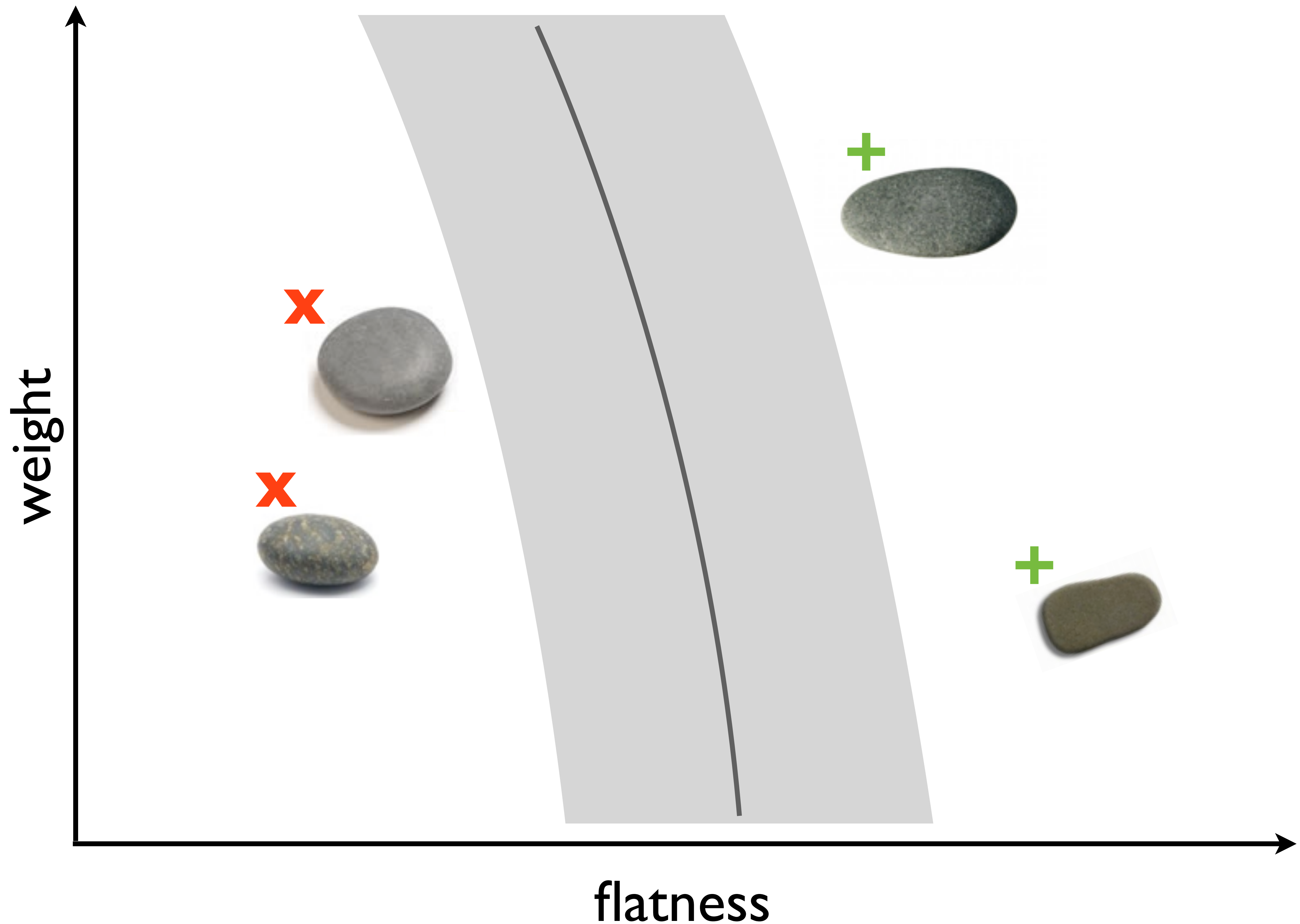
What makes a good skipping stone?



What makes a good skipping stone?

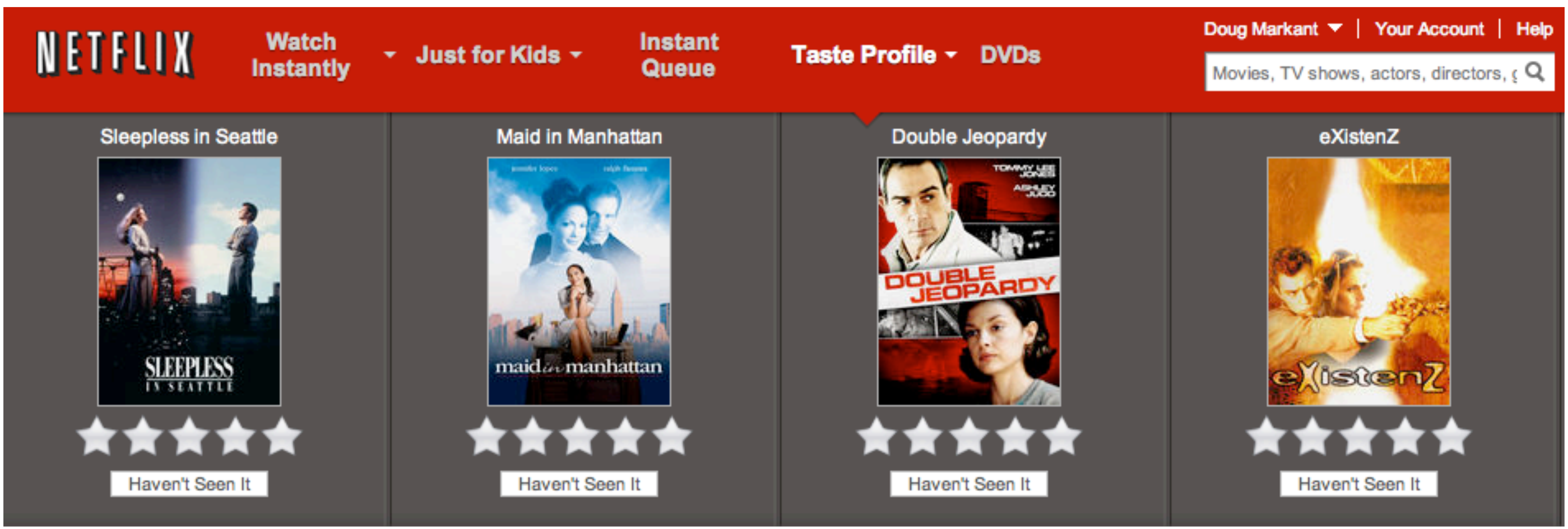


What makes a good skipping stone?

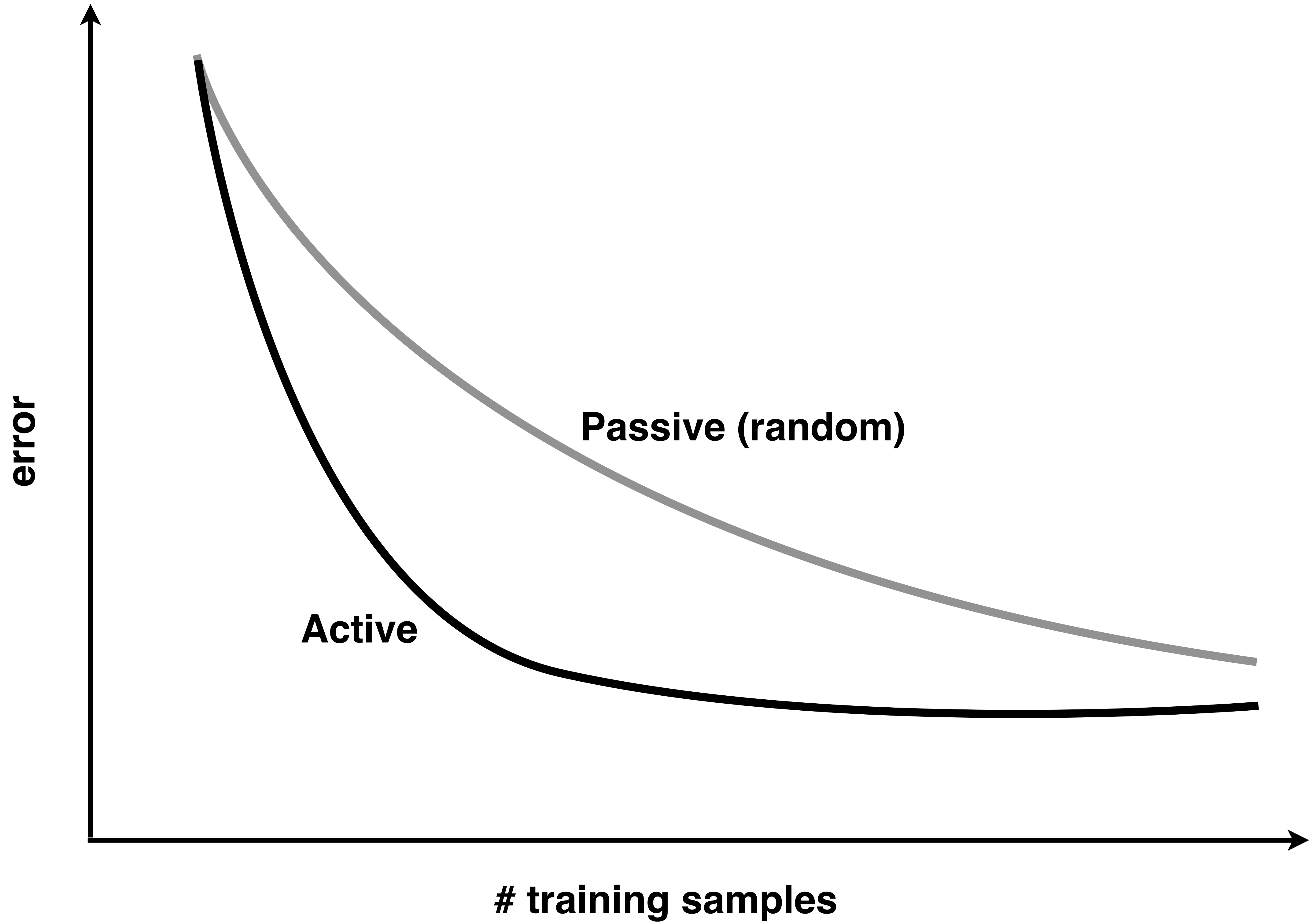


Active machine learning

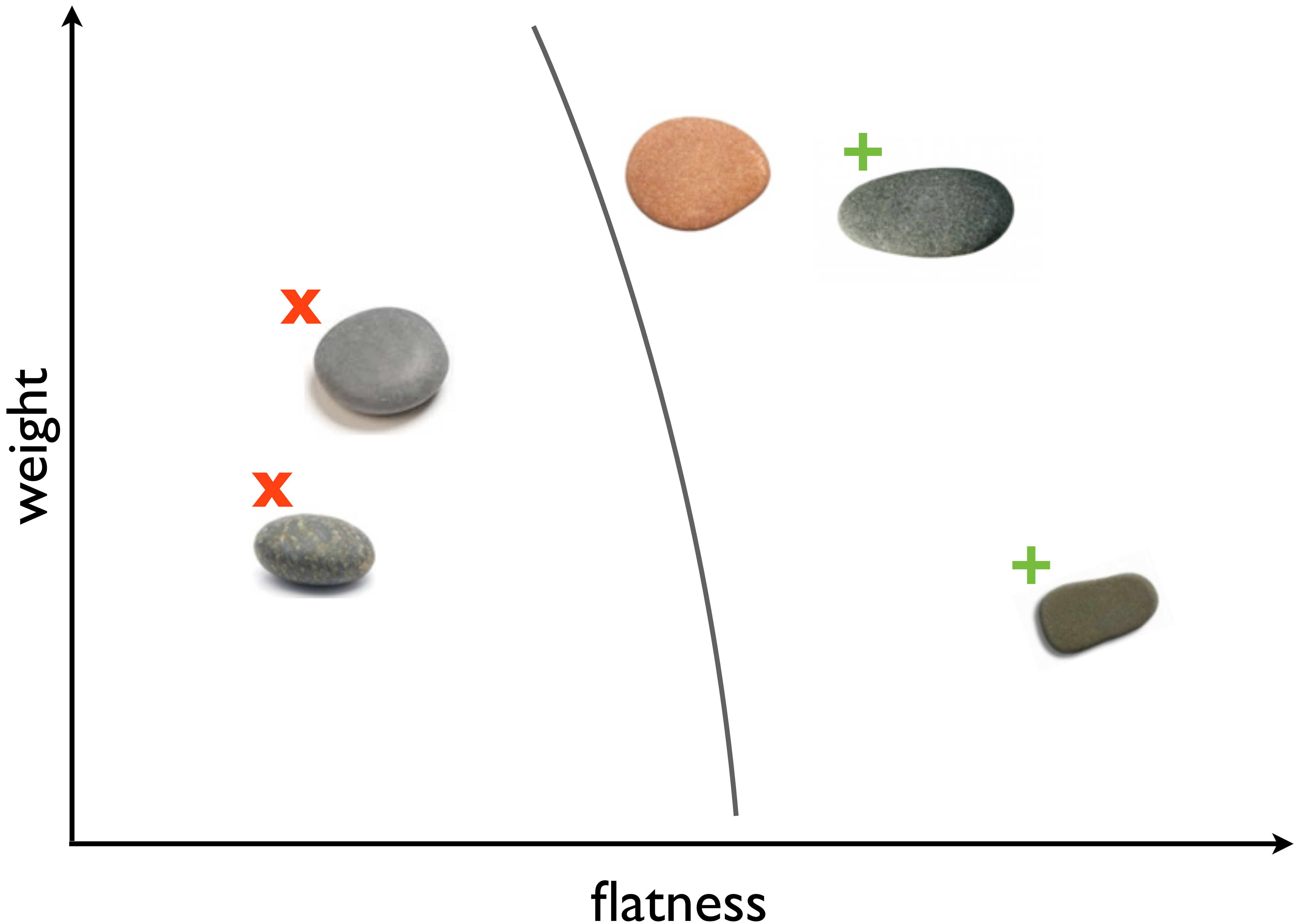
- Data is abundant, but **labels** are costly
- If human intervention is necessary to label items, only useful items should be selected
    - Recommendation engines, spam/fraud detection, scene annotation, etc.



More efficient learning

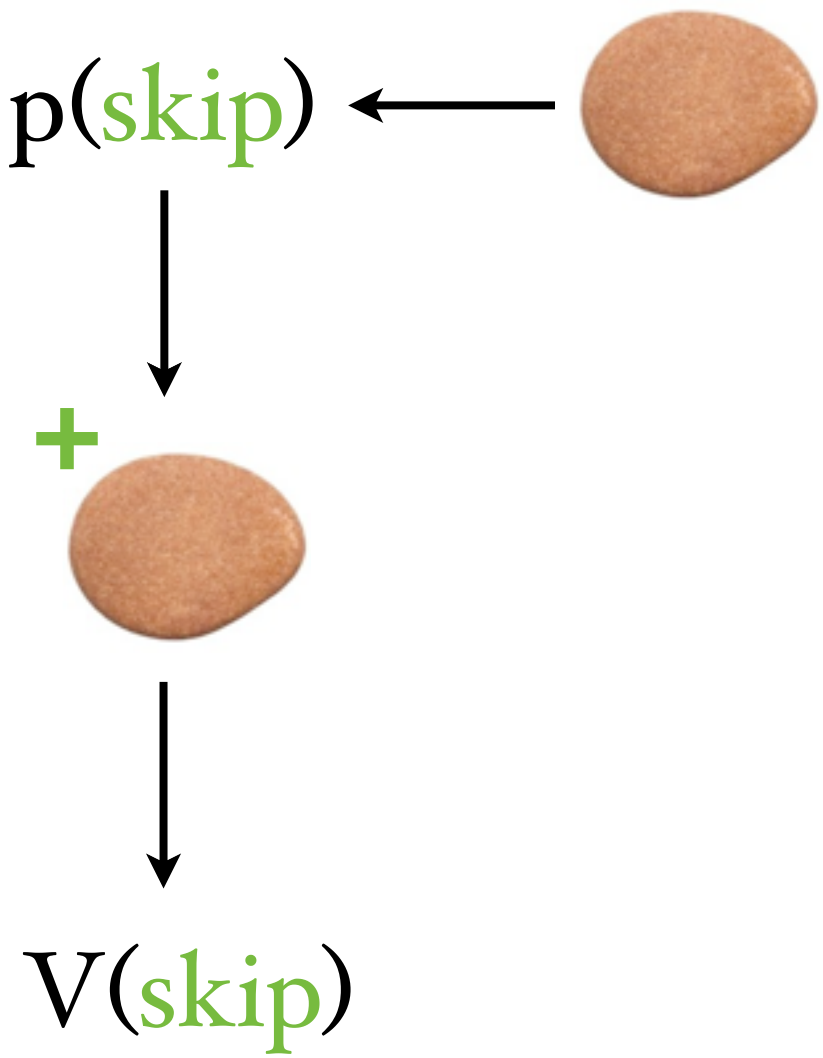


How to select new data?



How to select new data?

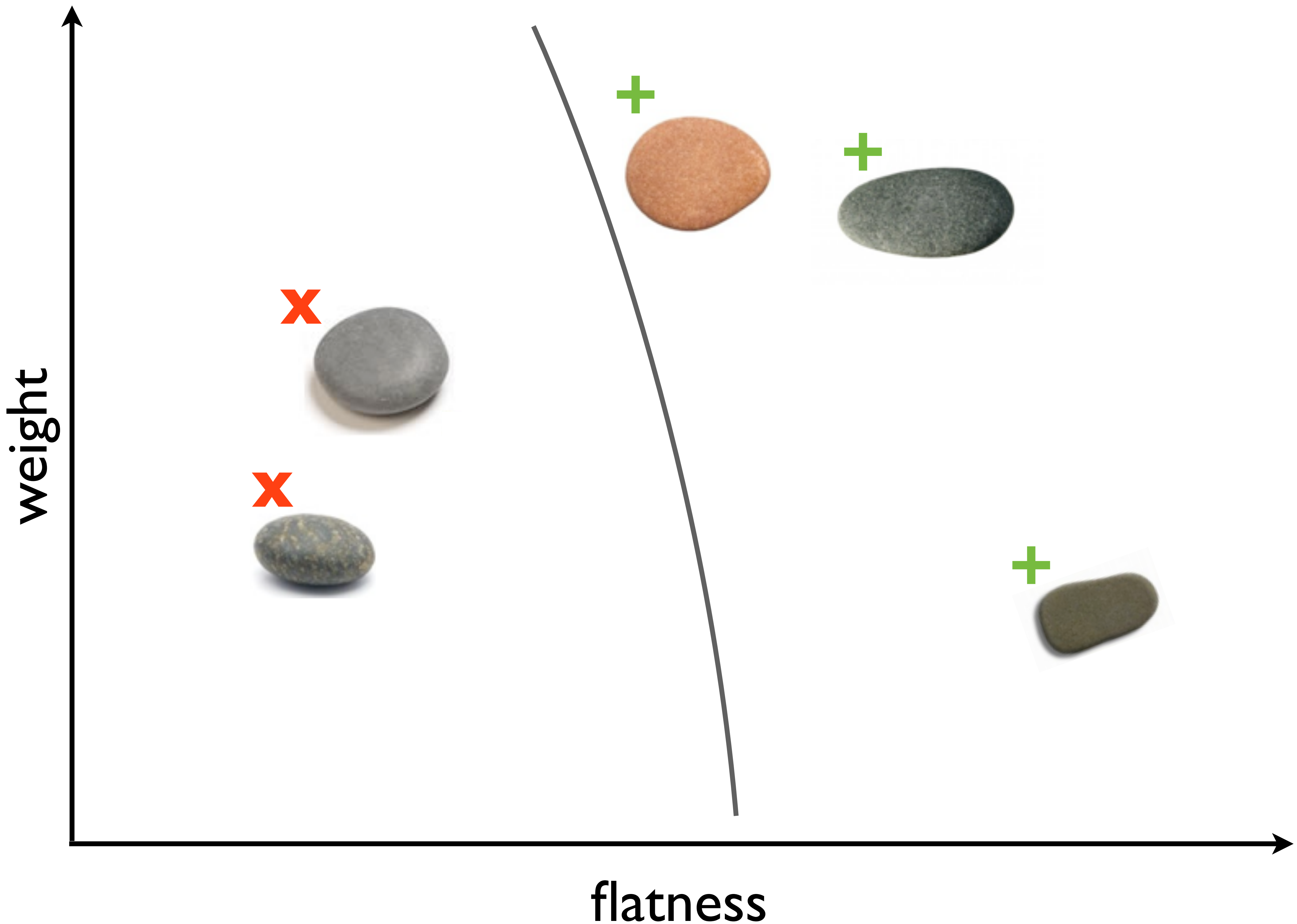
- **Expected change**: How much will the model change if re-trained with a new item?



How much did the model change?

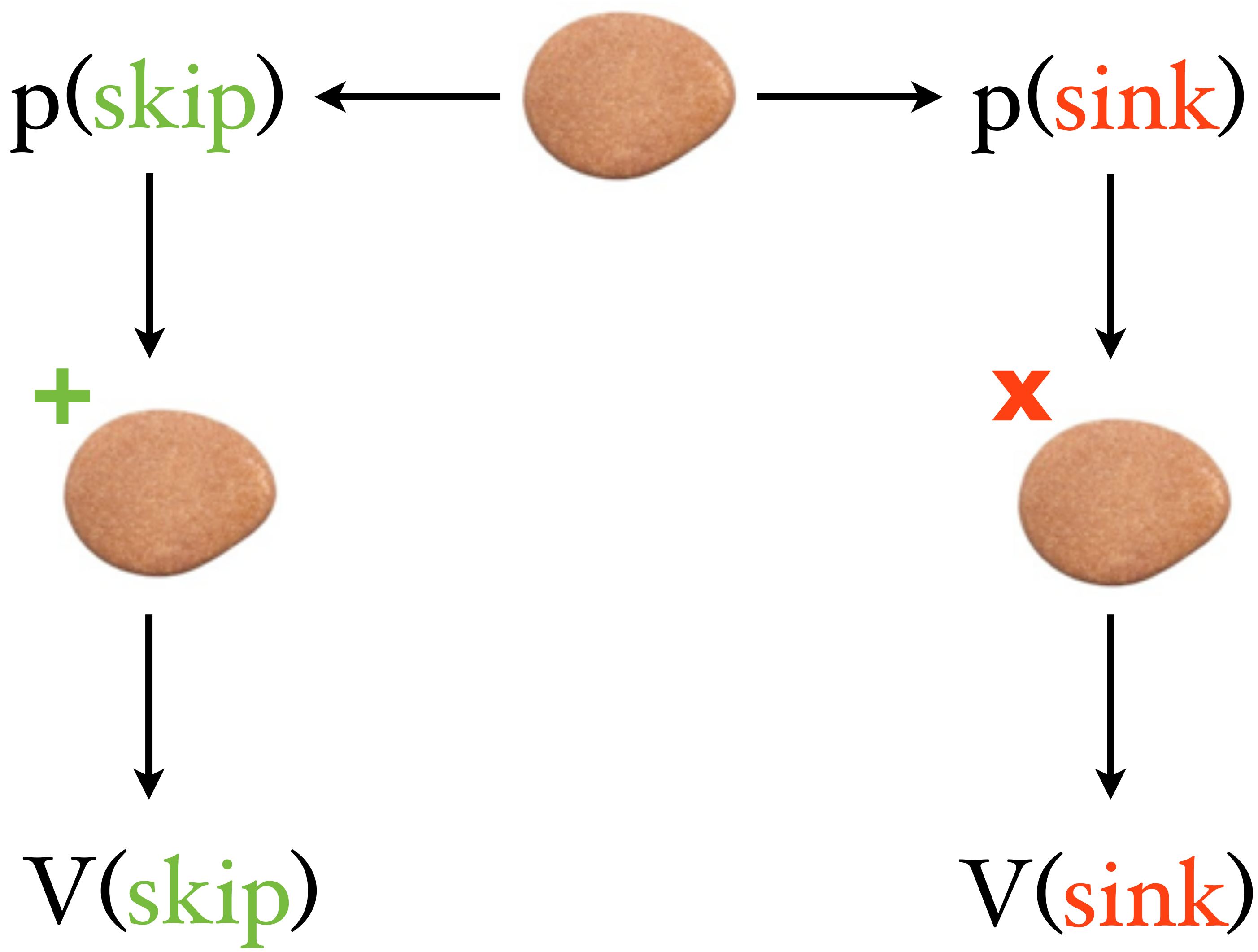
How much did the model's error decrease?

How to select new data?



How to select new data?

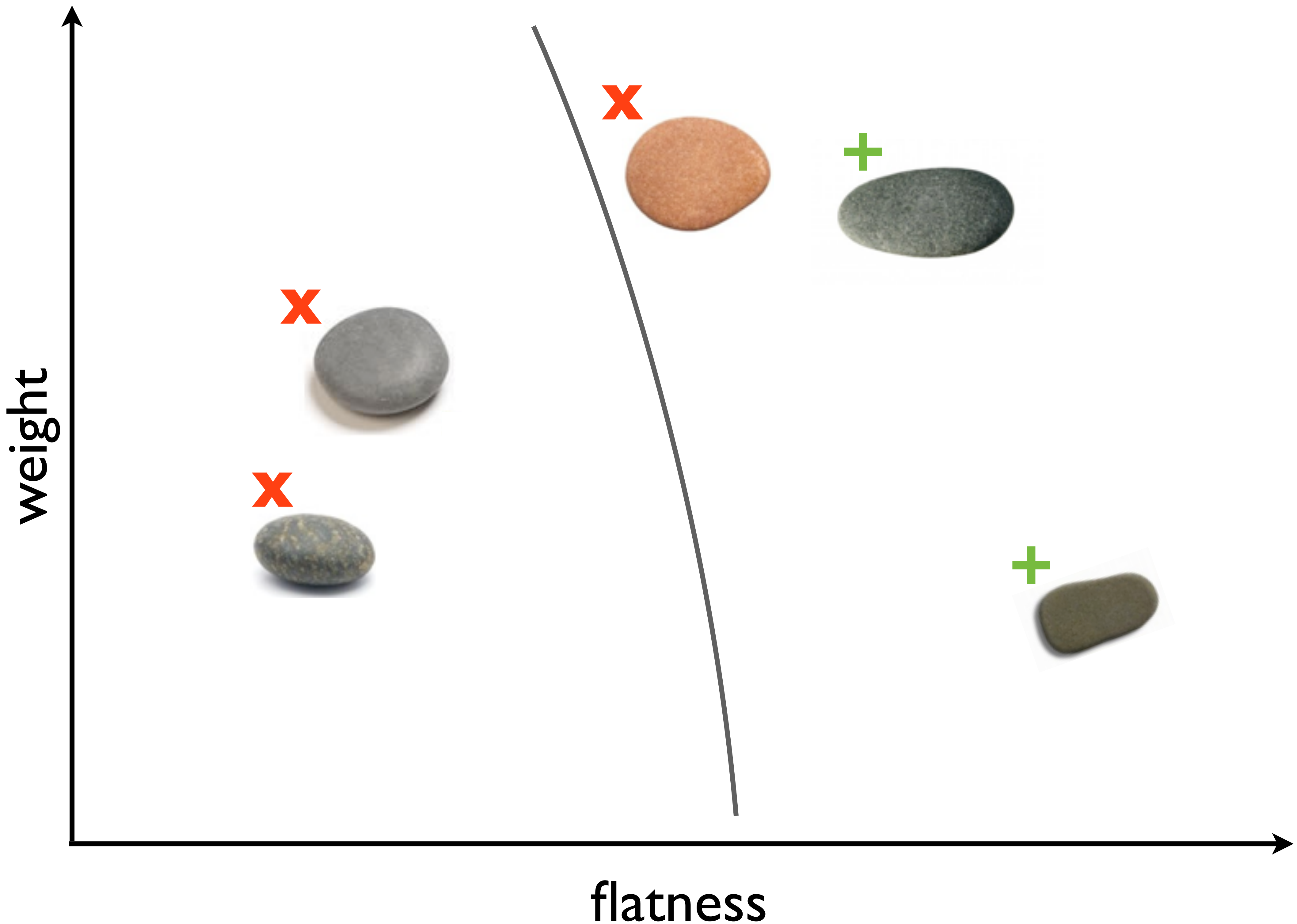
- **Expected change**: How much will the model change if re-trained with a new item?



How much did the model change?

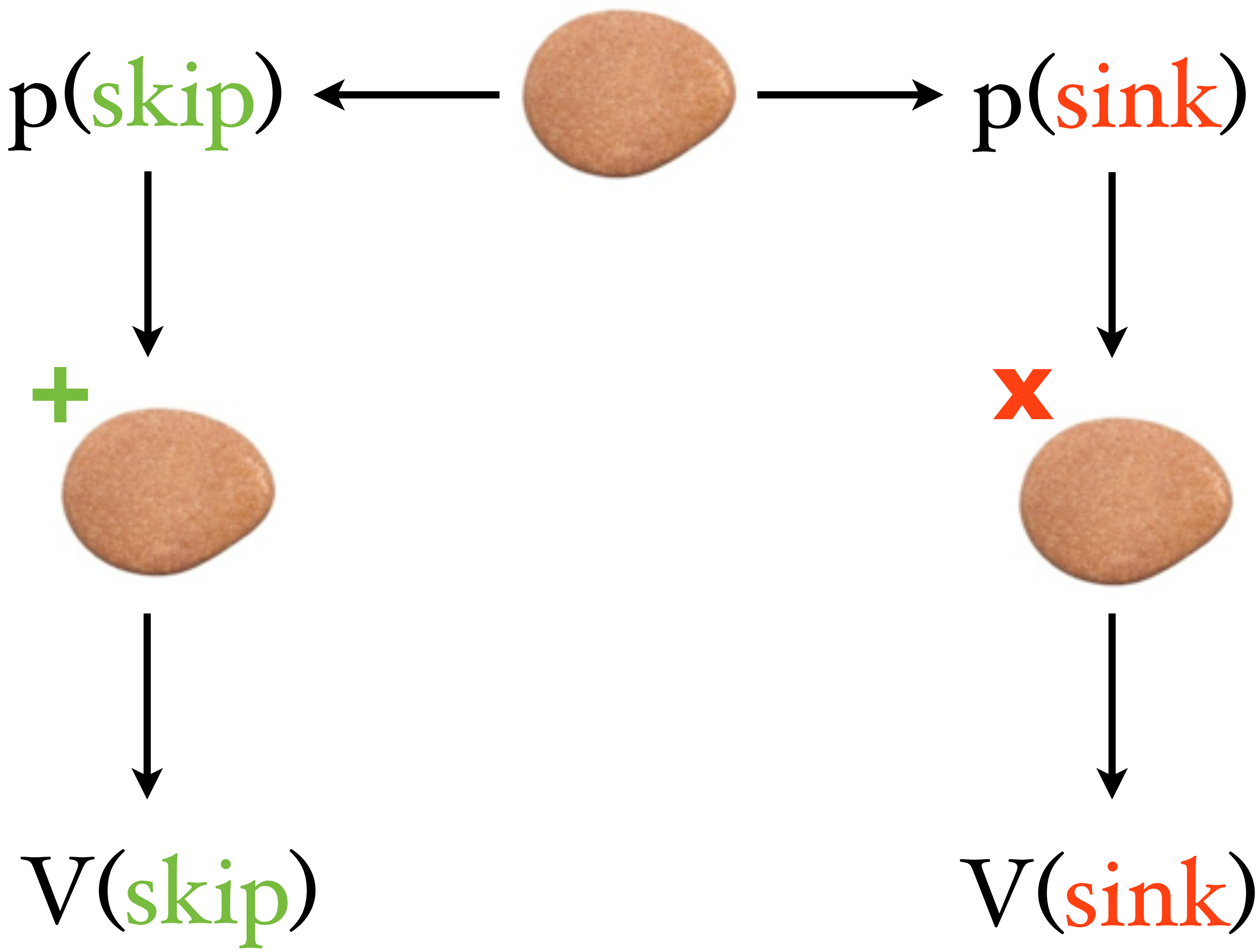
How much did the model's error decrease?

How to select new data?



How to select new data?

- **Expected change**: How much will the model change if re-trained with the new item?



$$E[V] = p(\text{skip}) * V(\text{skip}) + p(\text{sink}) * V(\text{sink})$$

How to select new data?

Problem:

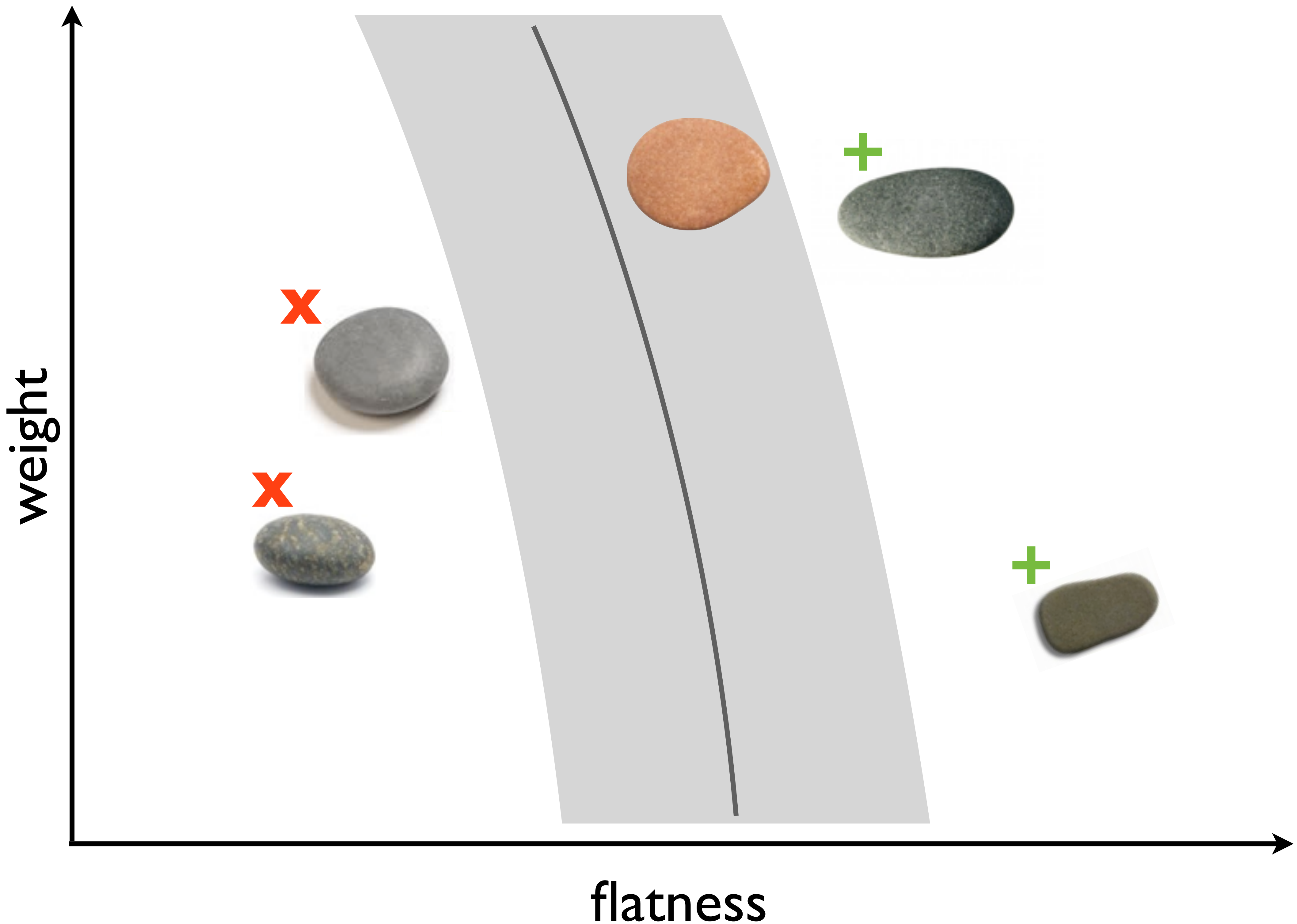
"Prospective" evaluation is computationally expensive, and in many cases intractable

How to select new data?

- **Uncertainty sampling:** Use current prediction about outcome to judge whether it will be useful to learn about

p(skip) ⟵  ⟶ p(sink)

How to select new data?



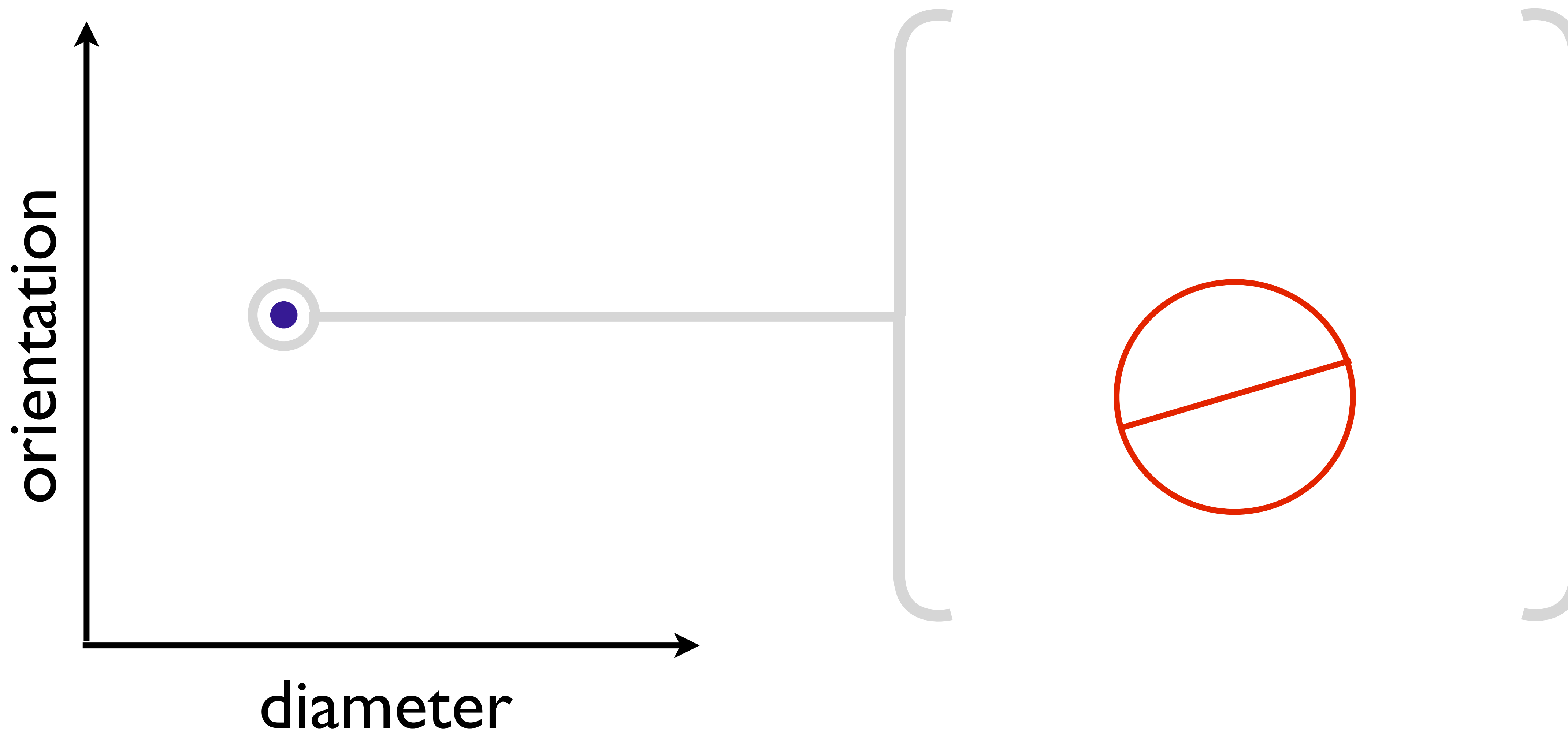
Questions

Does active control lead to more efficient learning?
(Study 1)

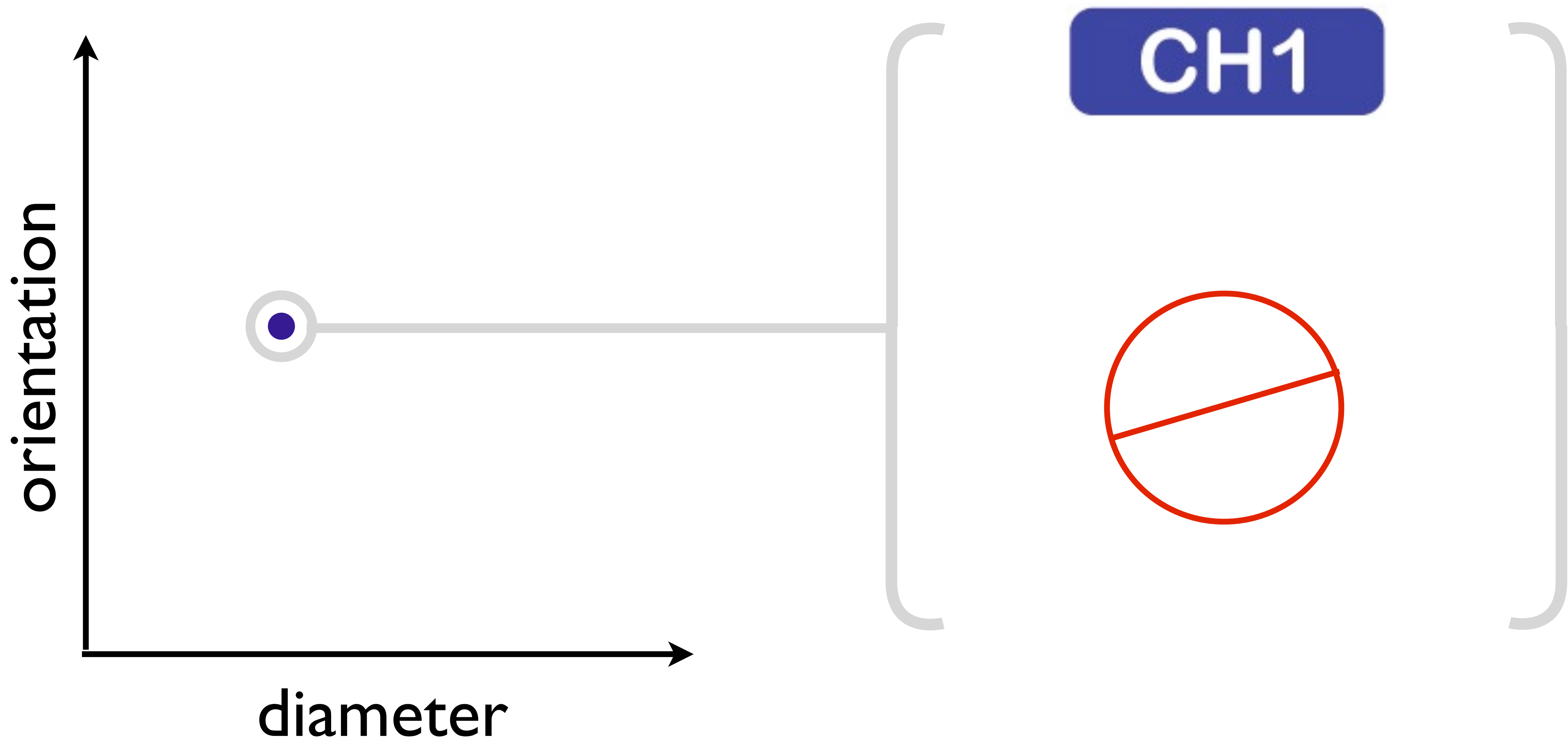
How is uncertainty used to decide what to learn about?
(Study 2)

Study 1: Antenna learning

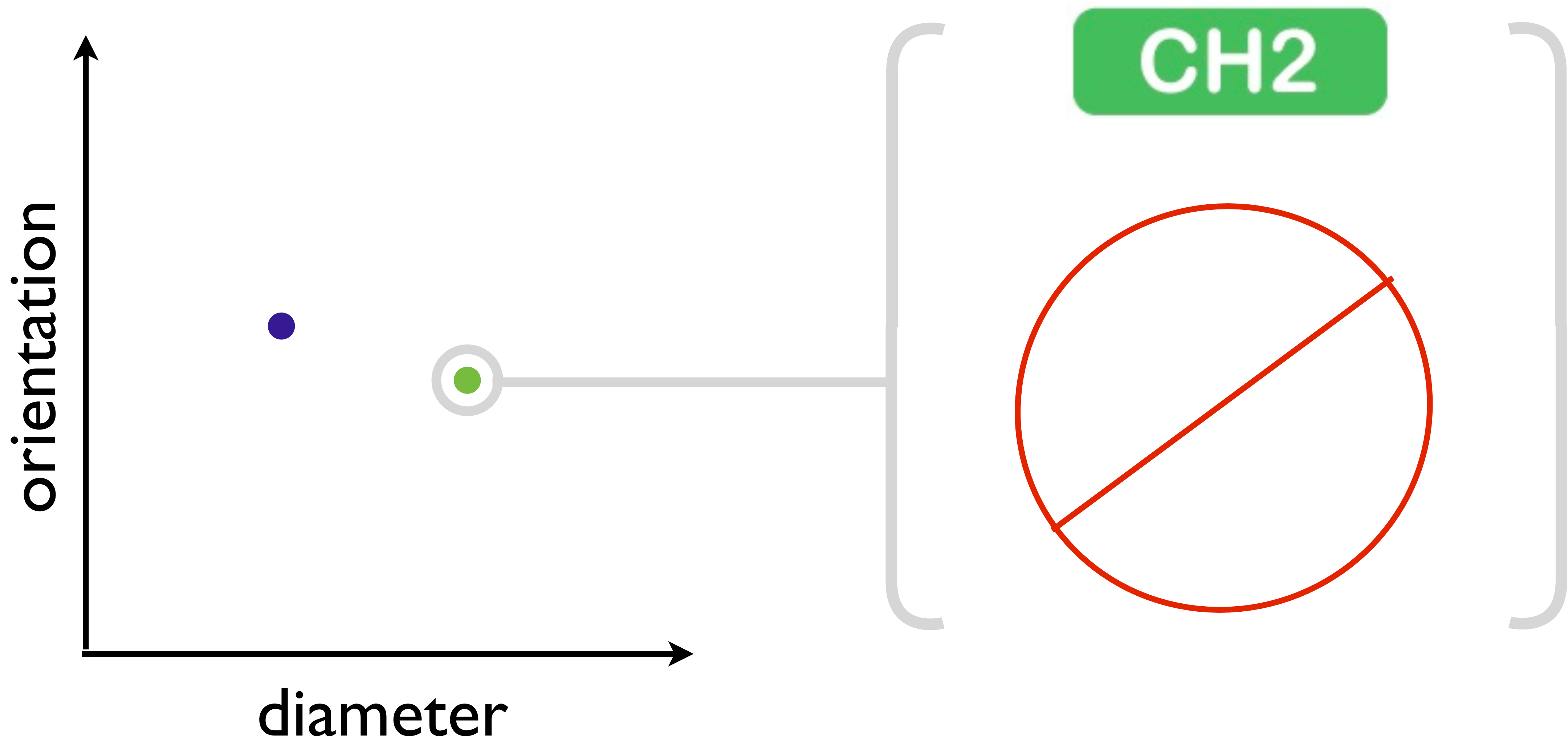
Antennas



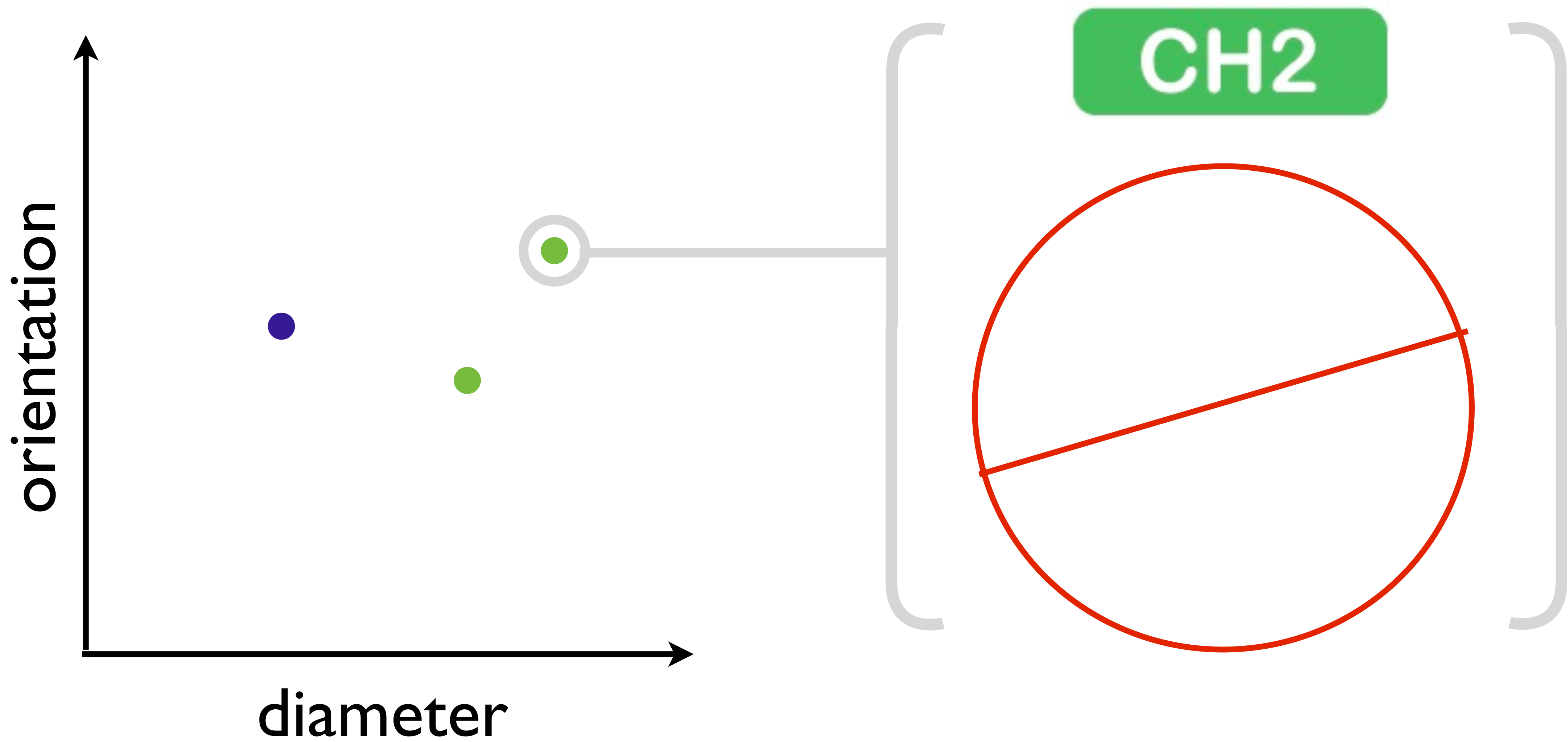
Antennas



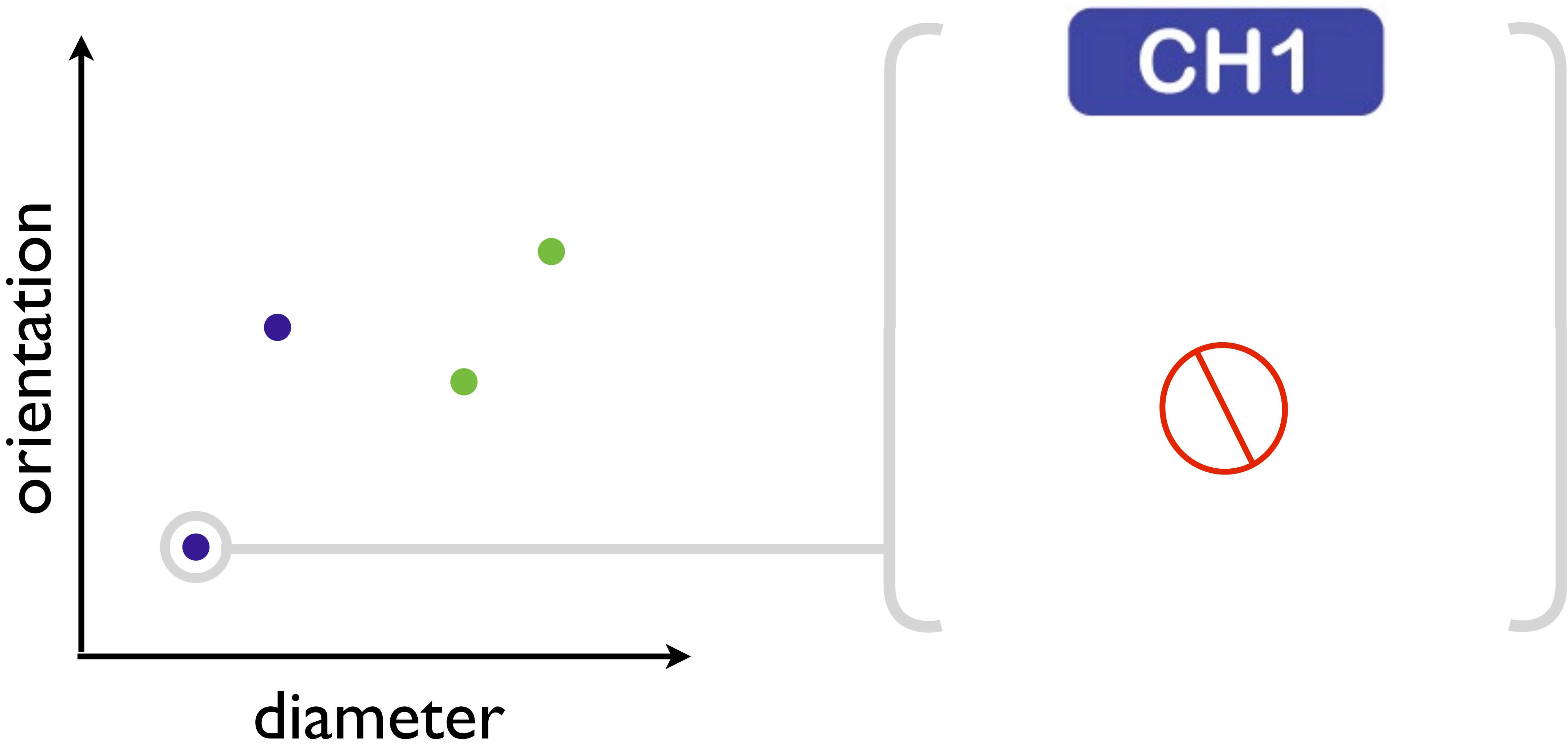
Antennas



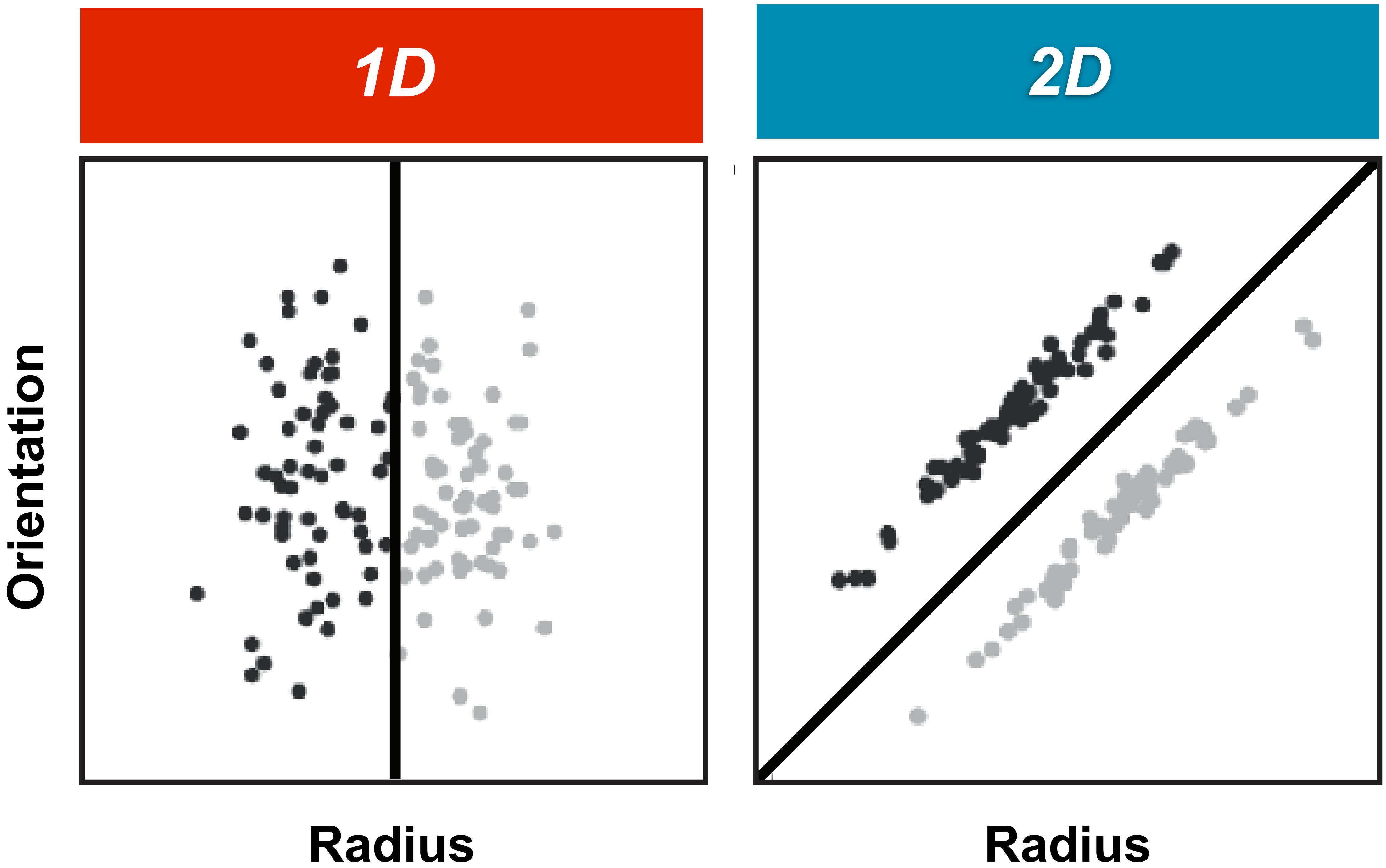
Antennas



Antennas



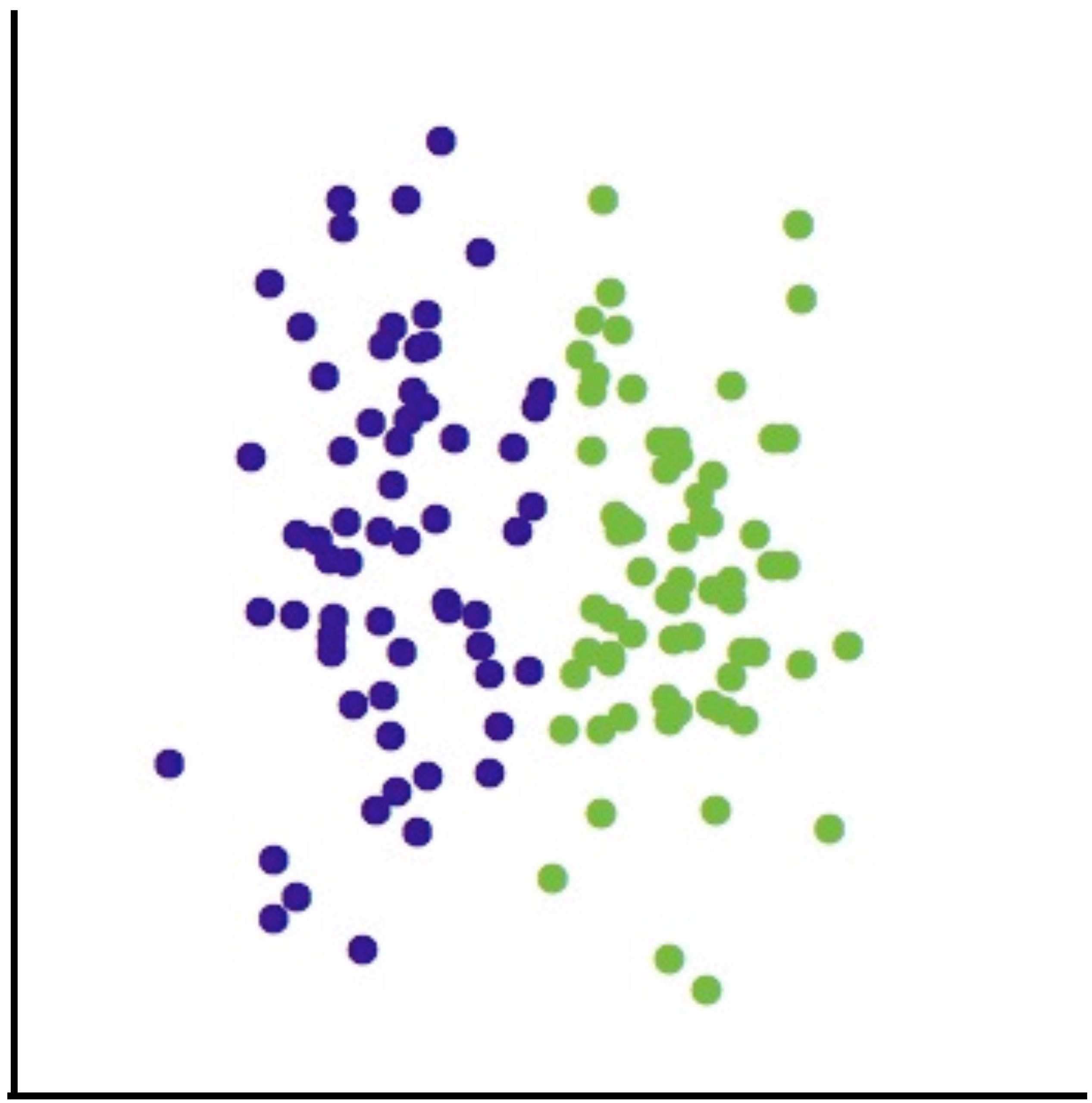
Two kinds of rules



Ashby, F.G, Maddox, W.T., and Bohil, C.J (2002), Memory & Cognition

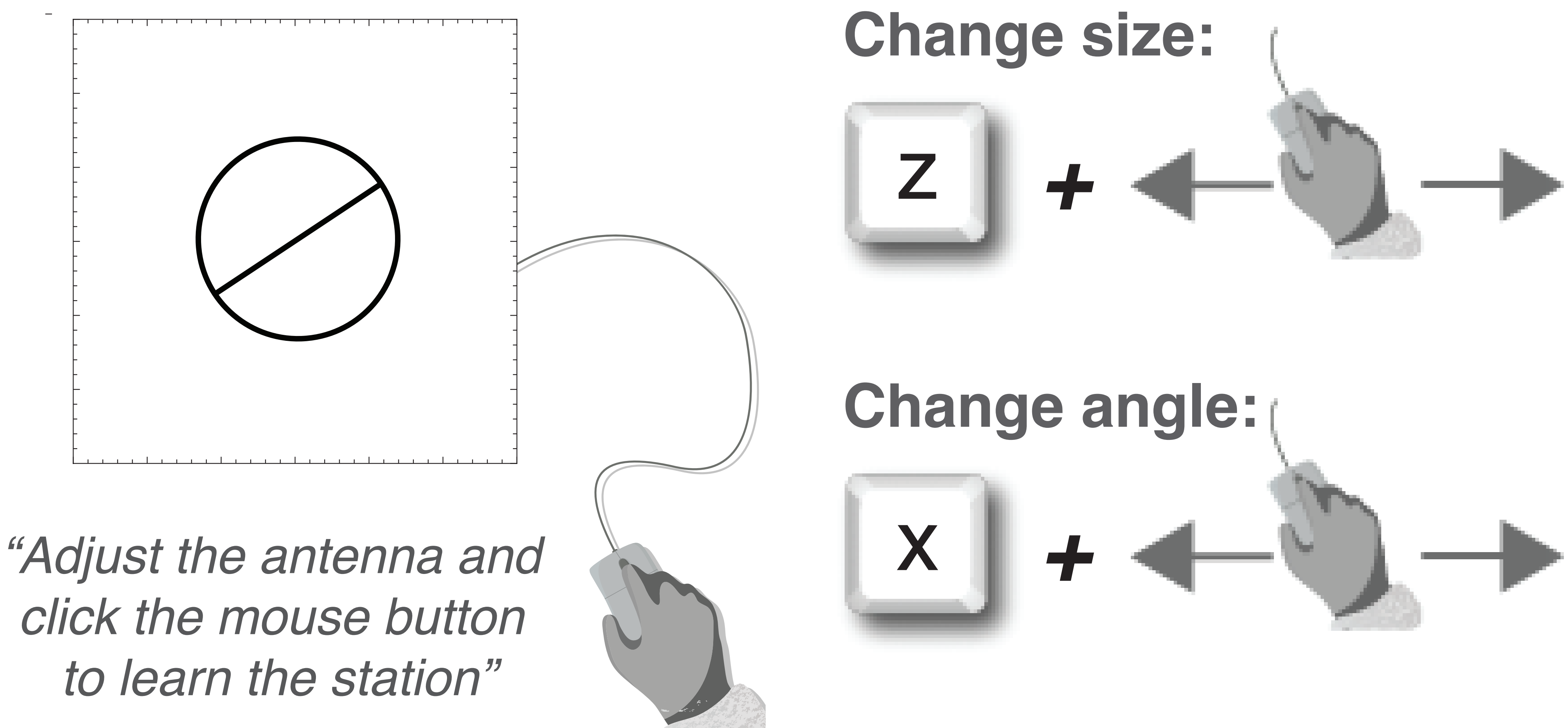
Passive "reception" condition

- Observe items sampled from category distributions



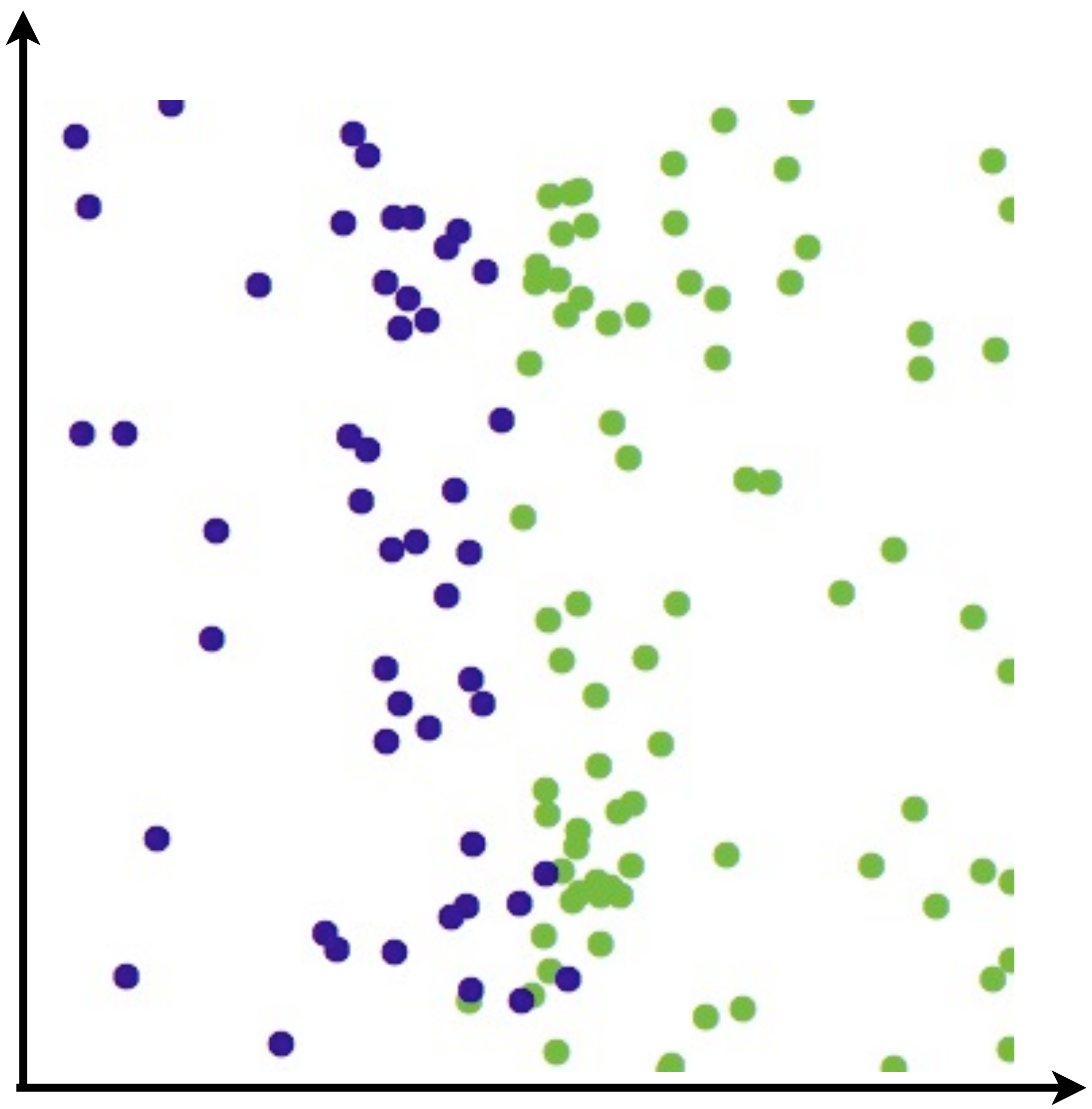
Active "selection" condition

- "Design" antennas to learn about on every trial



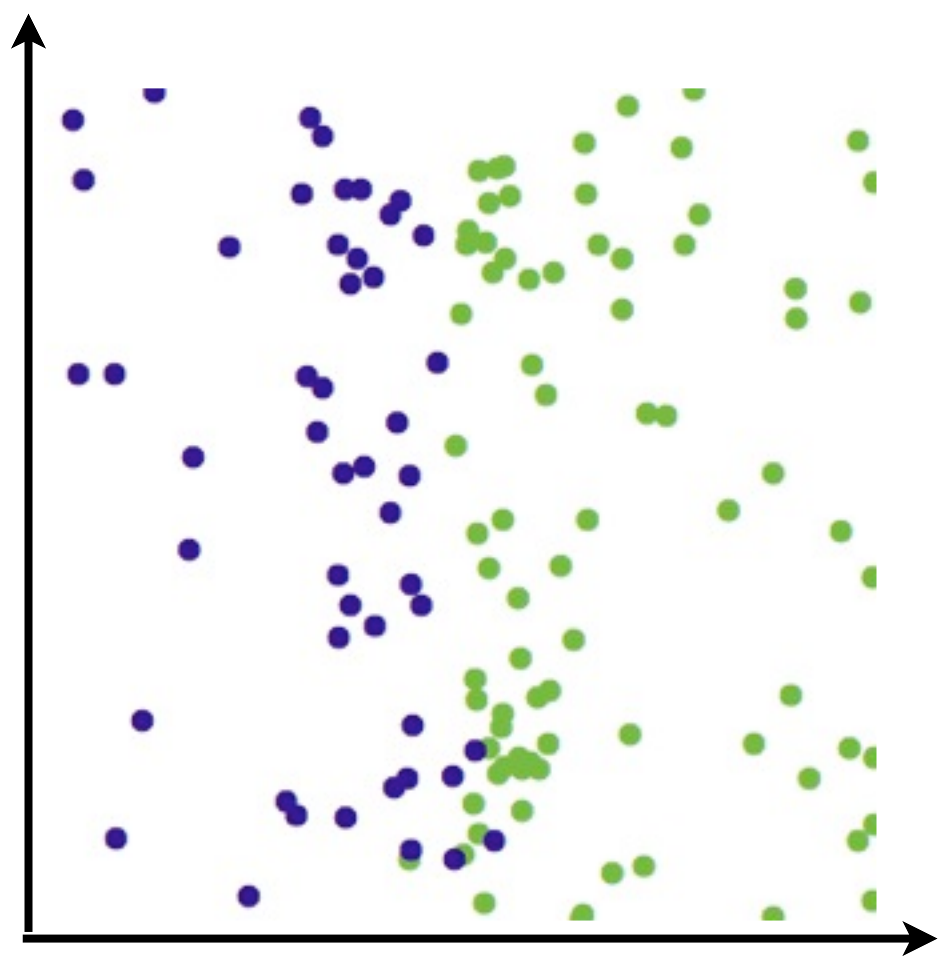
Active “selection” condition

- “Design” antennas to learn about on every trial

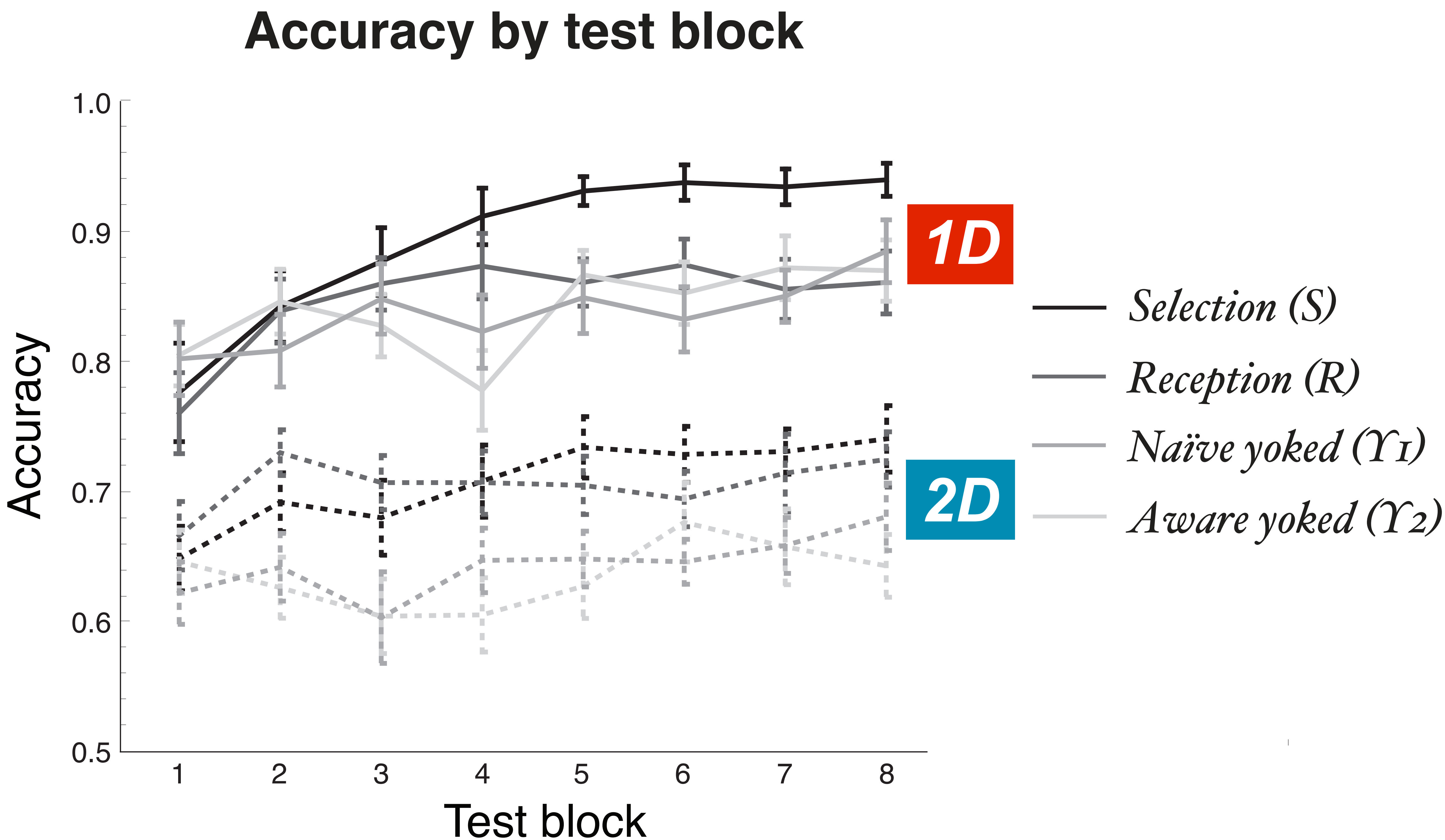


Yoked reception conditions

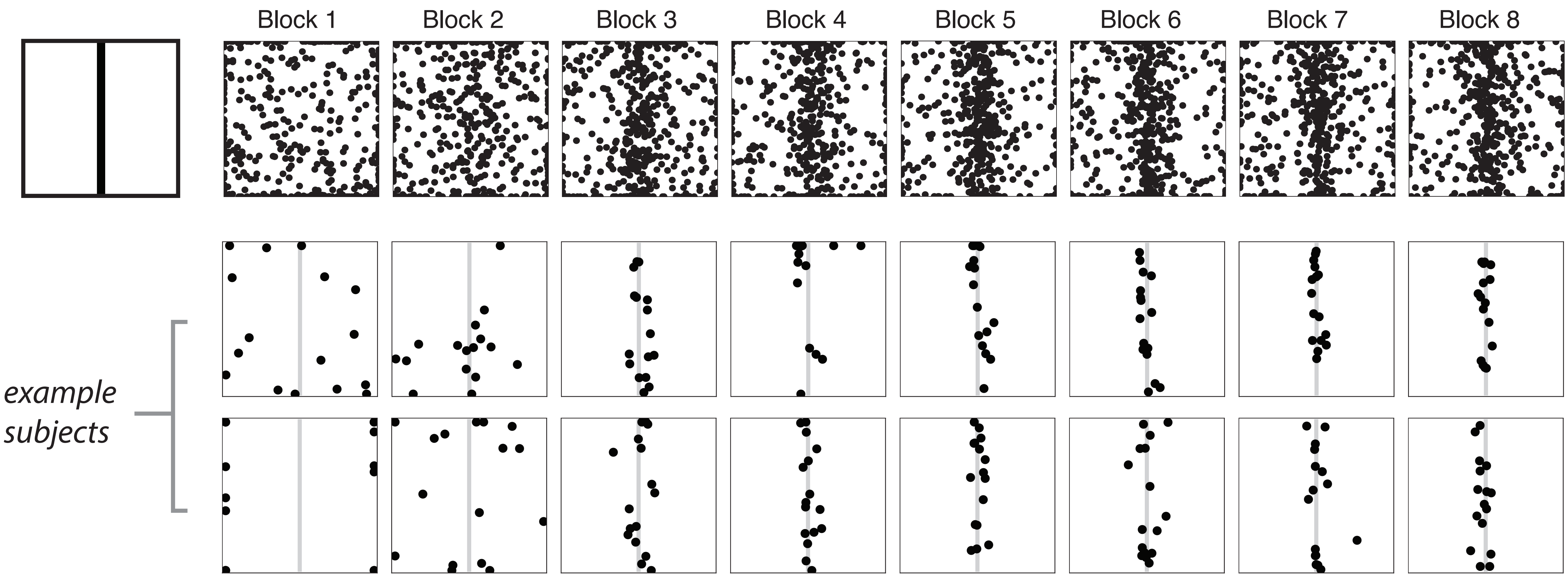
- Learn from the same sets of data generated by active participants
- **Naive yoked:** Not told about where the data came from
- **Aware yoked:** Instructed that data was generated by a previous person with the same learning goal



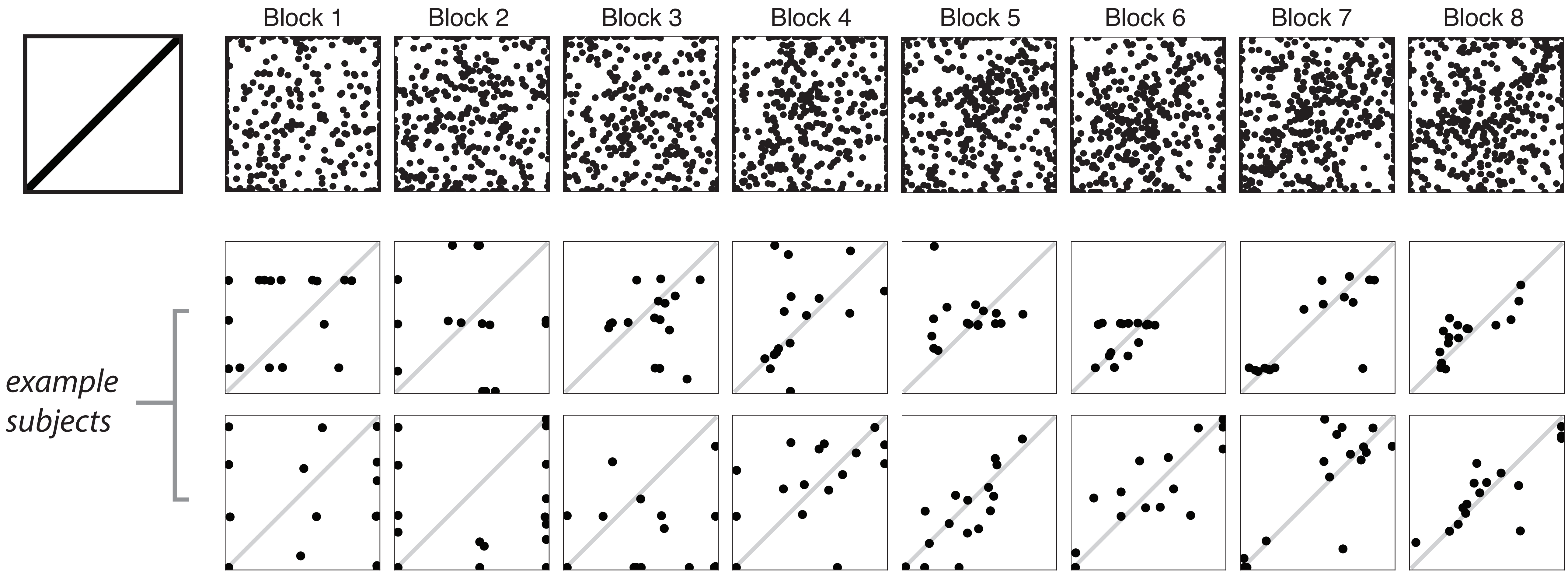
Classification performance



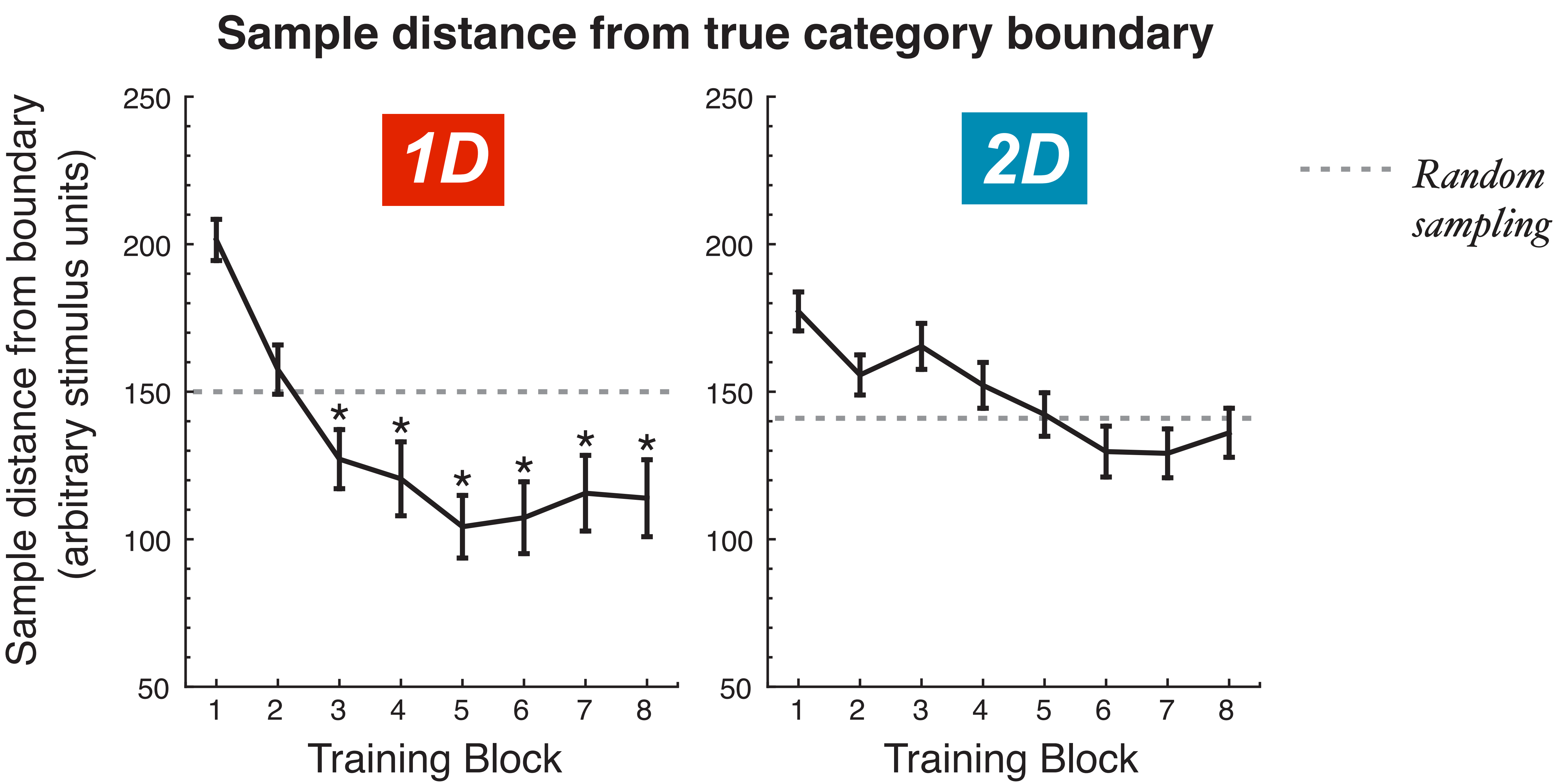
Selections (1D)



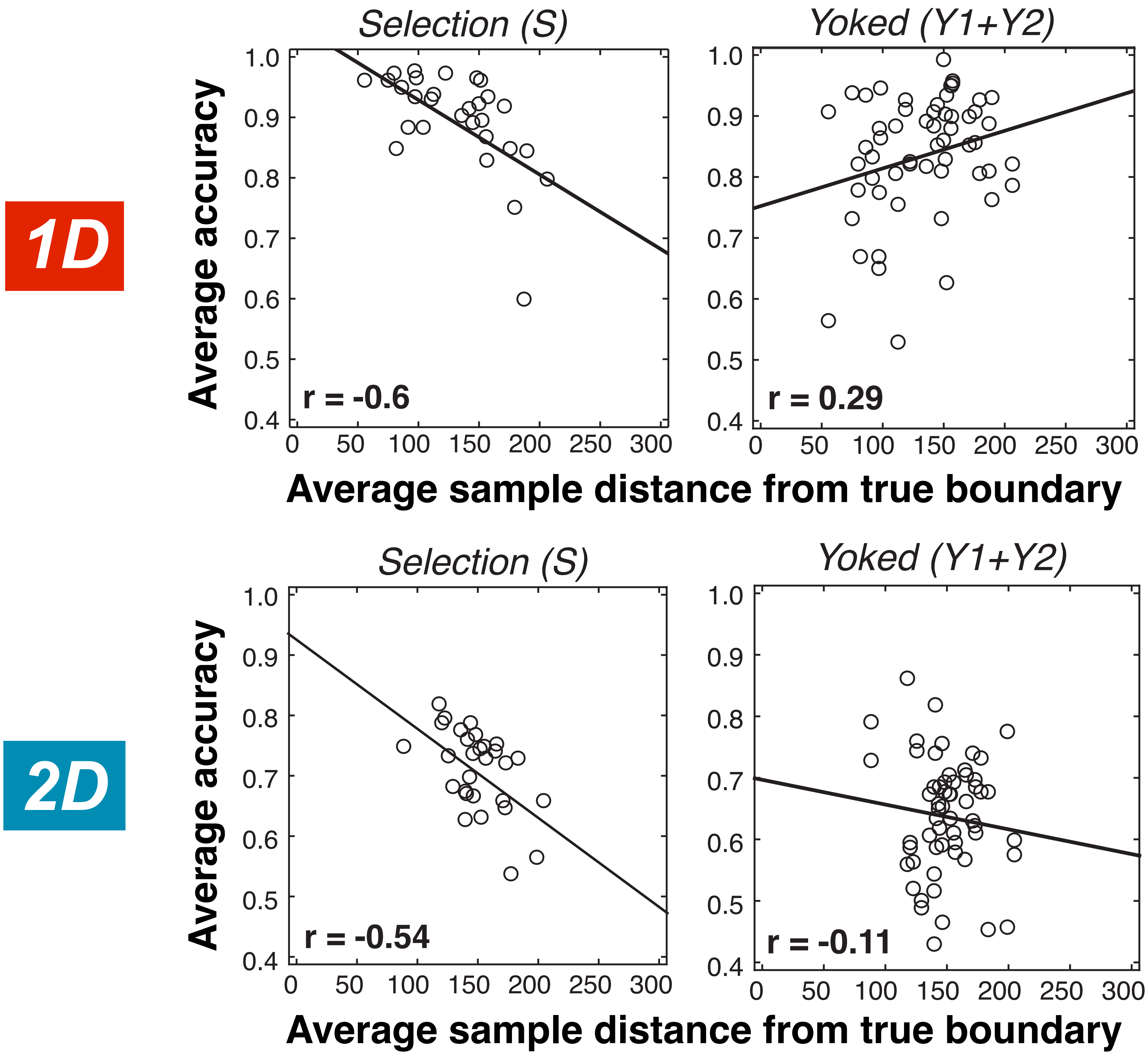
Selections (2D)



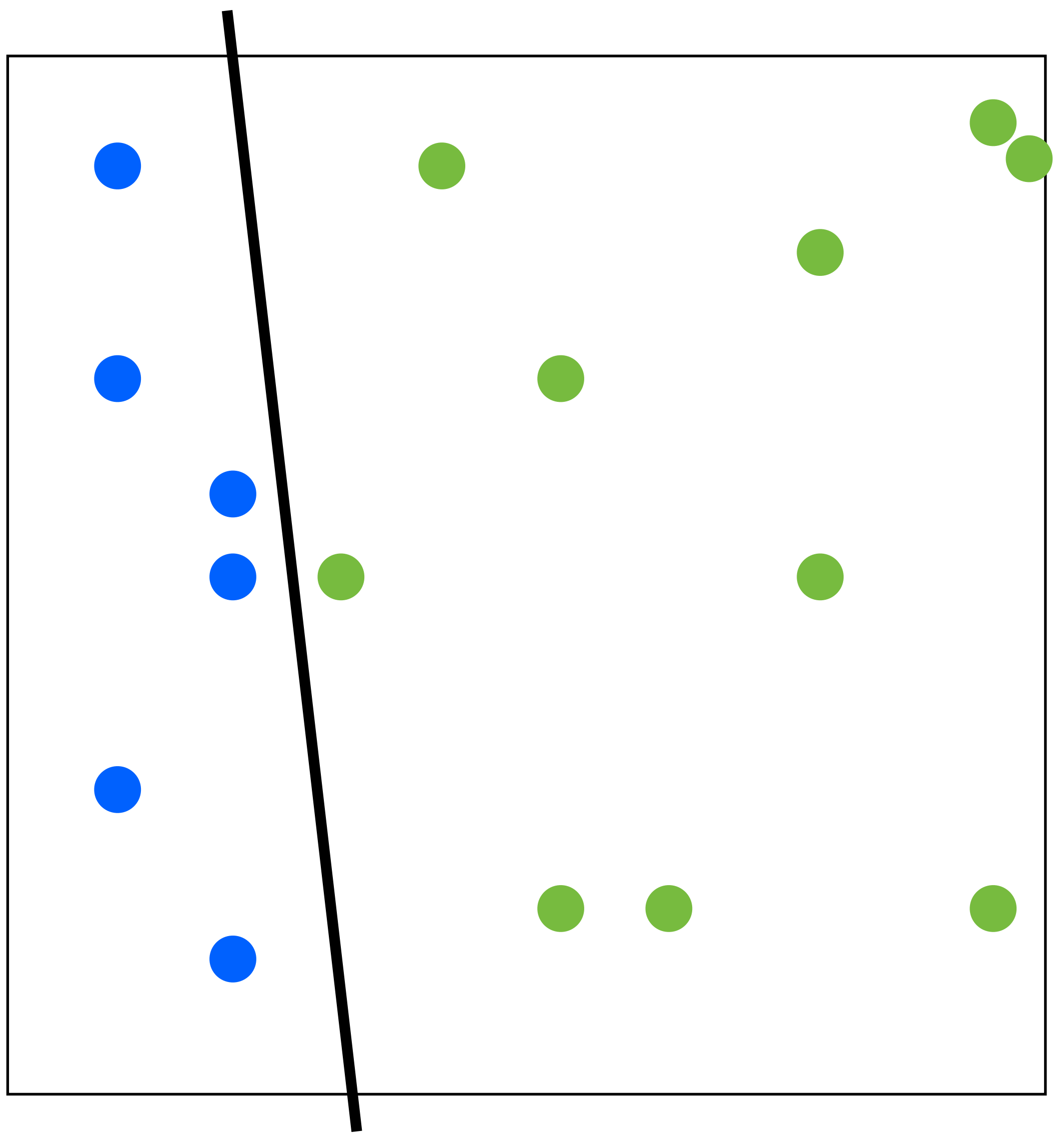
Sampling behavior

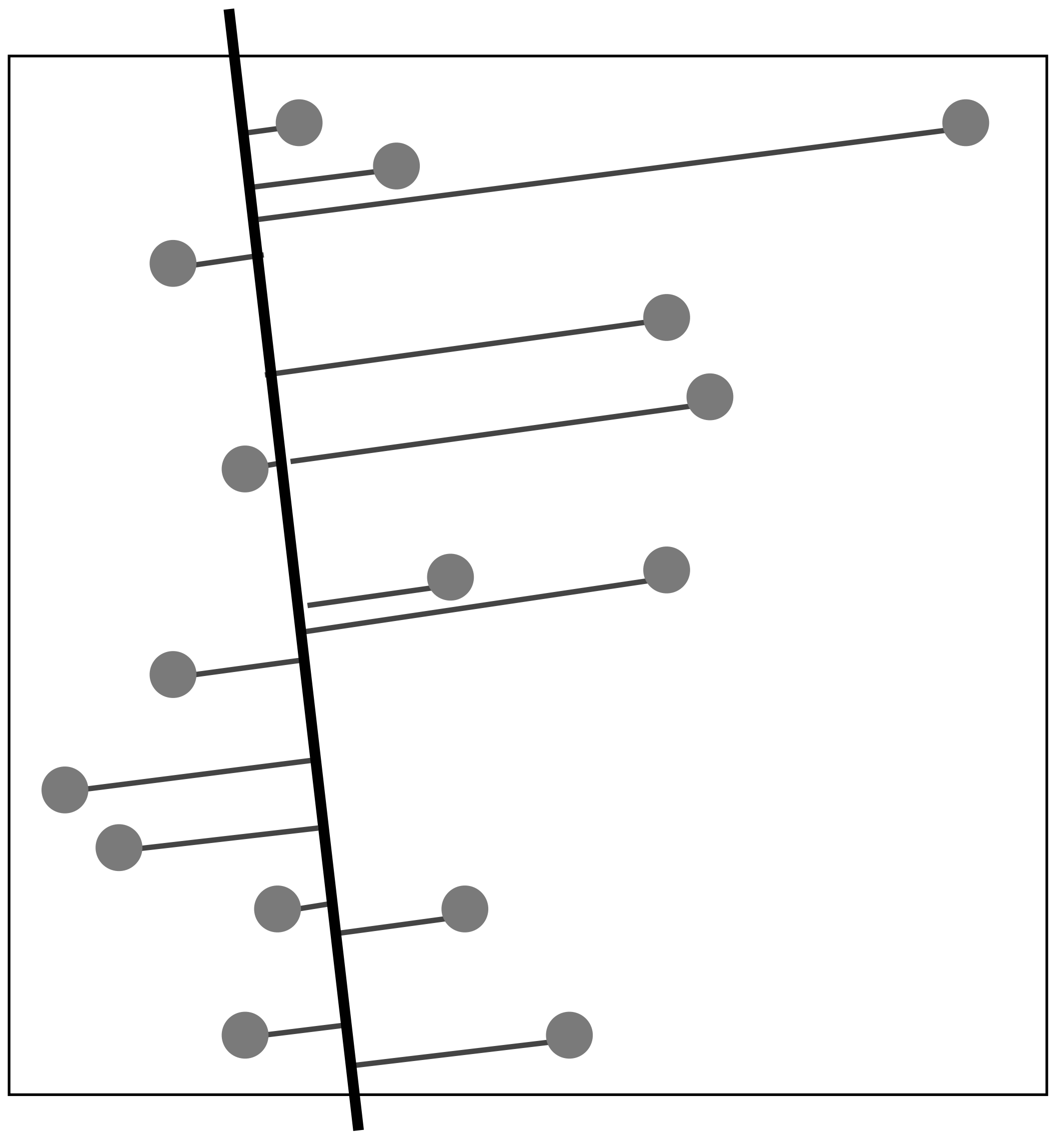


Relating selections to learning

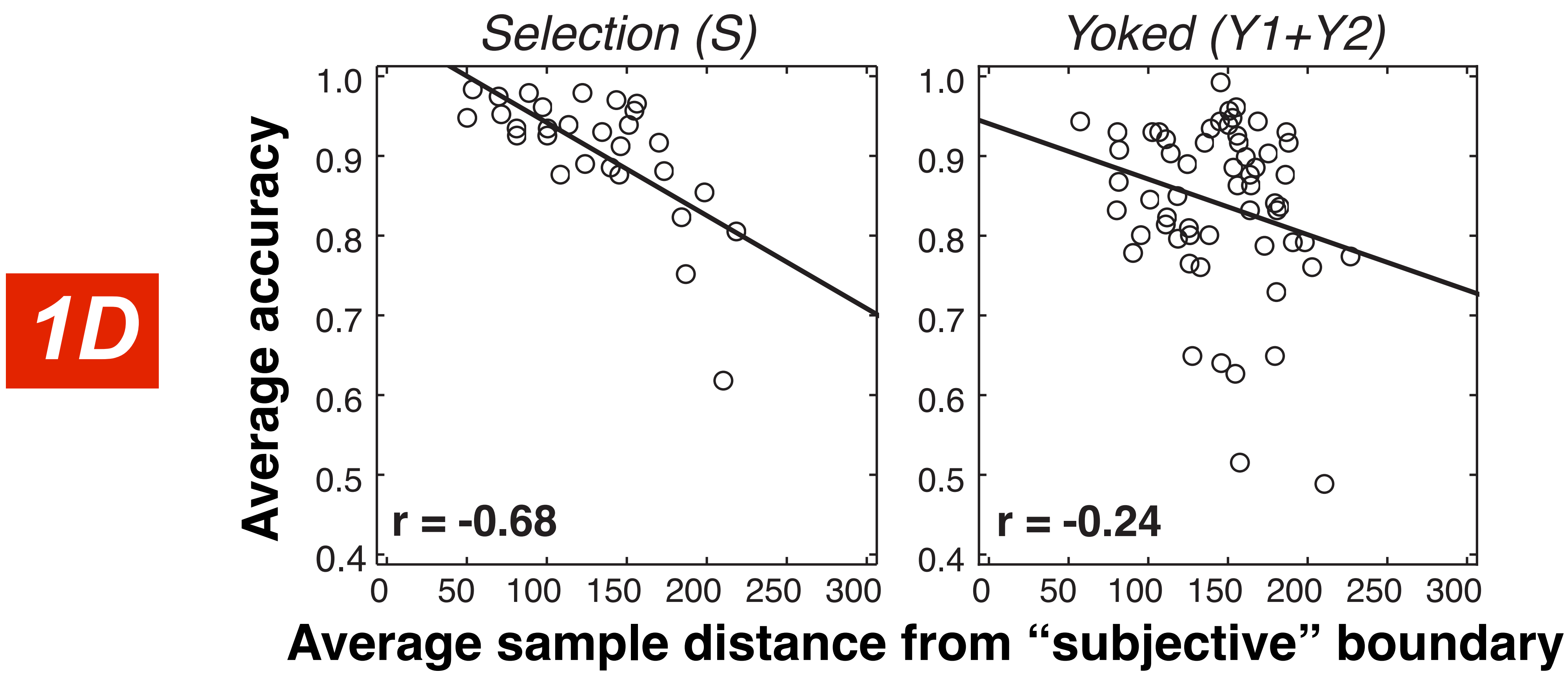


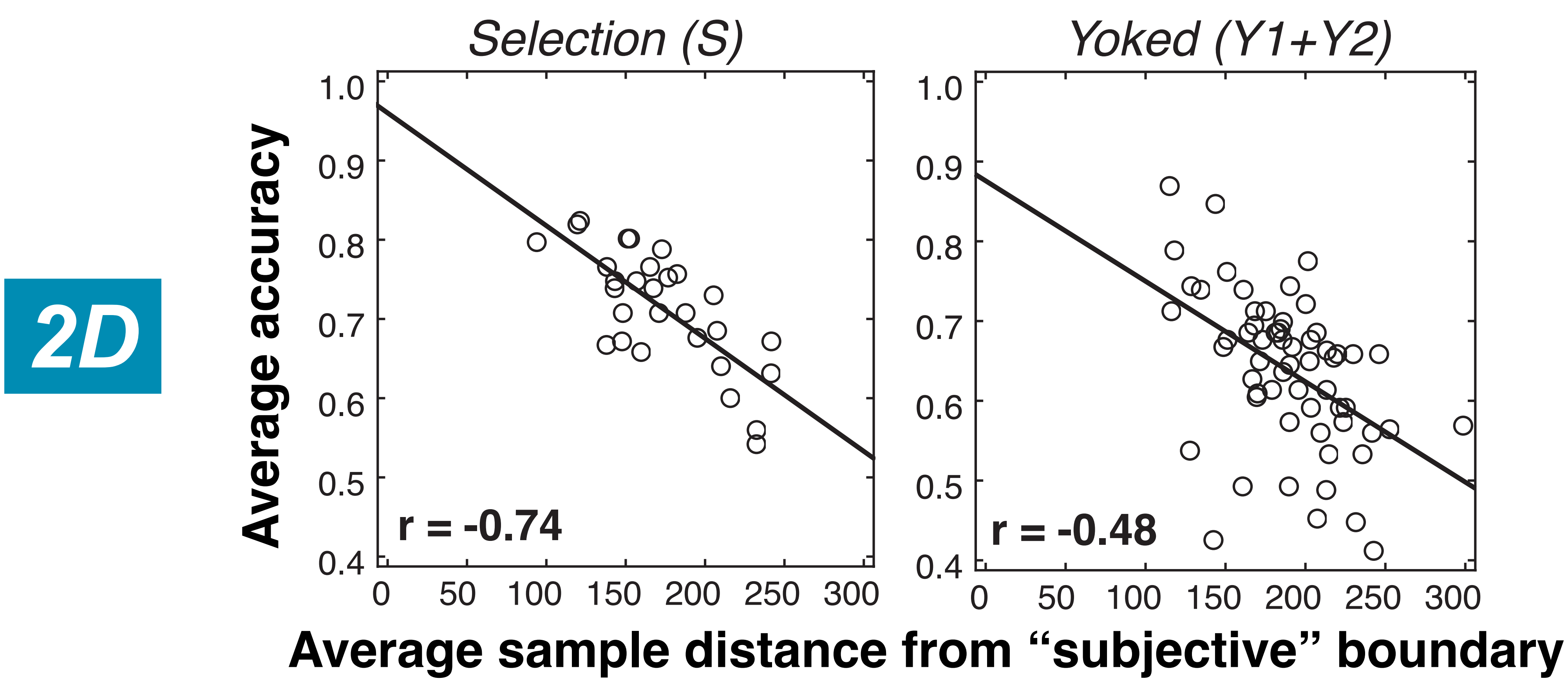
"Subjective" sample distance





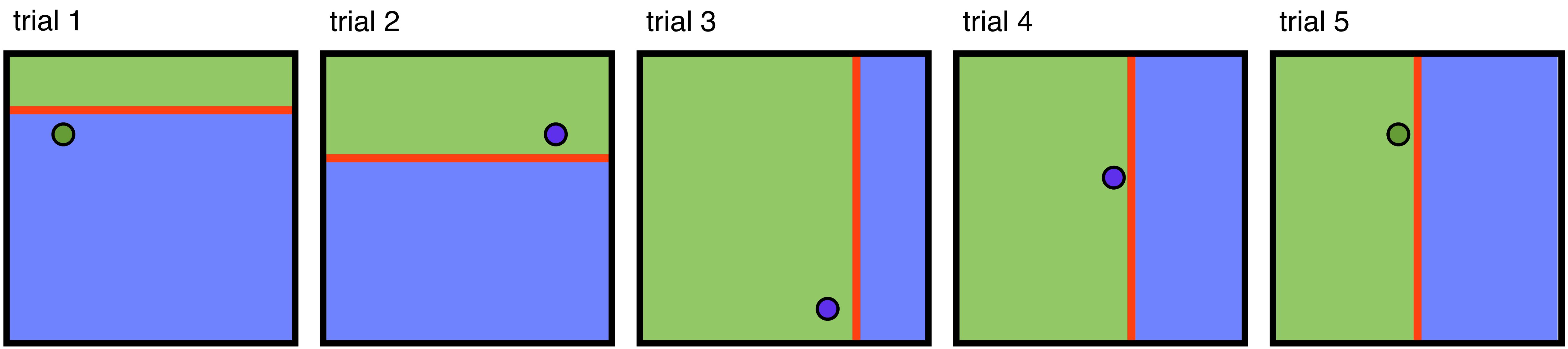
"Subjective" sample distance



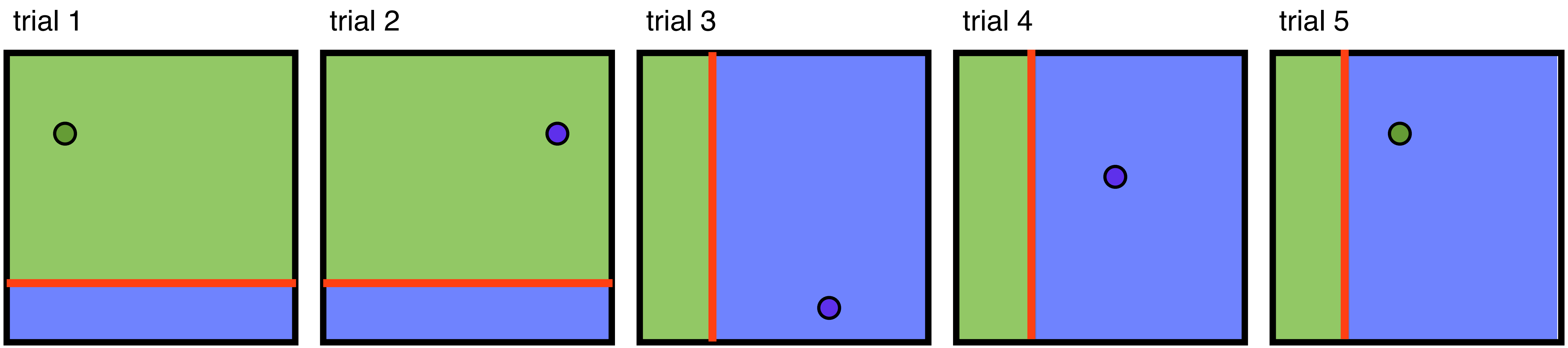


Hypothesis-dependent uncertainty sampling

Active selection participant



Yoked participant



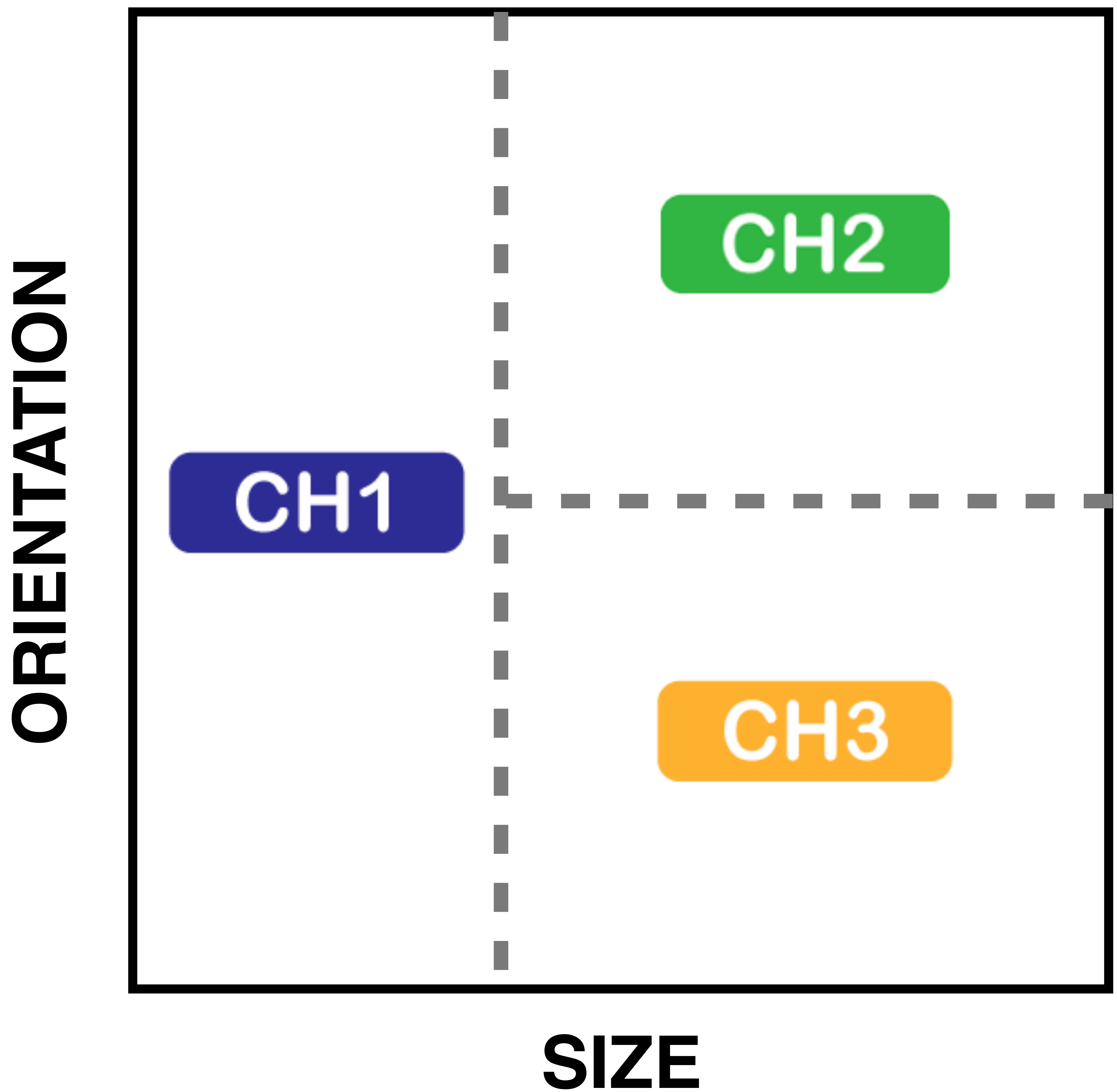
Study 1: Summary

- Active selection leads to more efficient learning for 1D task, but not 2D task, relative to typical passive condition
- Within the active condition, performance is tied to the data generated by the participant, with items closer to the boundary associated with higher performance
- Despite learning from the same data, yoked learners perform worse than their selection partners in both tasks.
- *Hypothesis-dependent uncertainty sampling* can account for the relative performance, without assuming any additional differences between conditions

Study 2

How do information selection decisions relate to the learner's uncertainty?

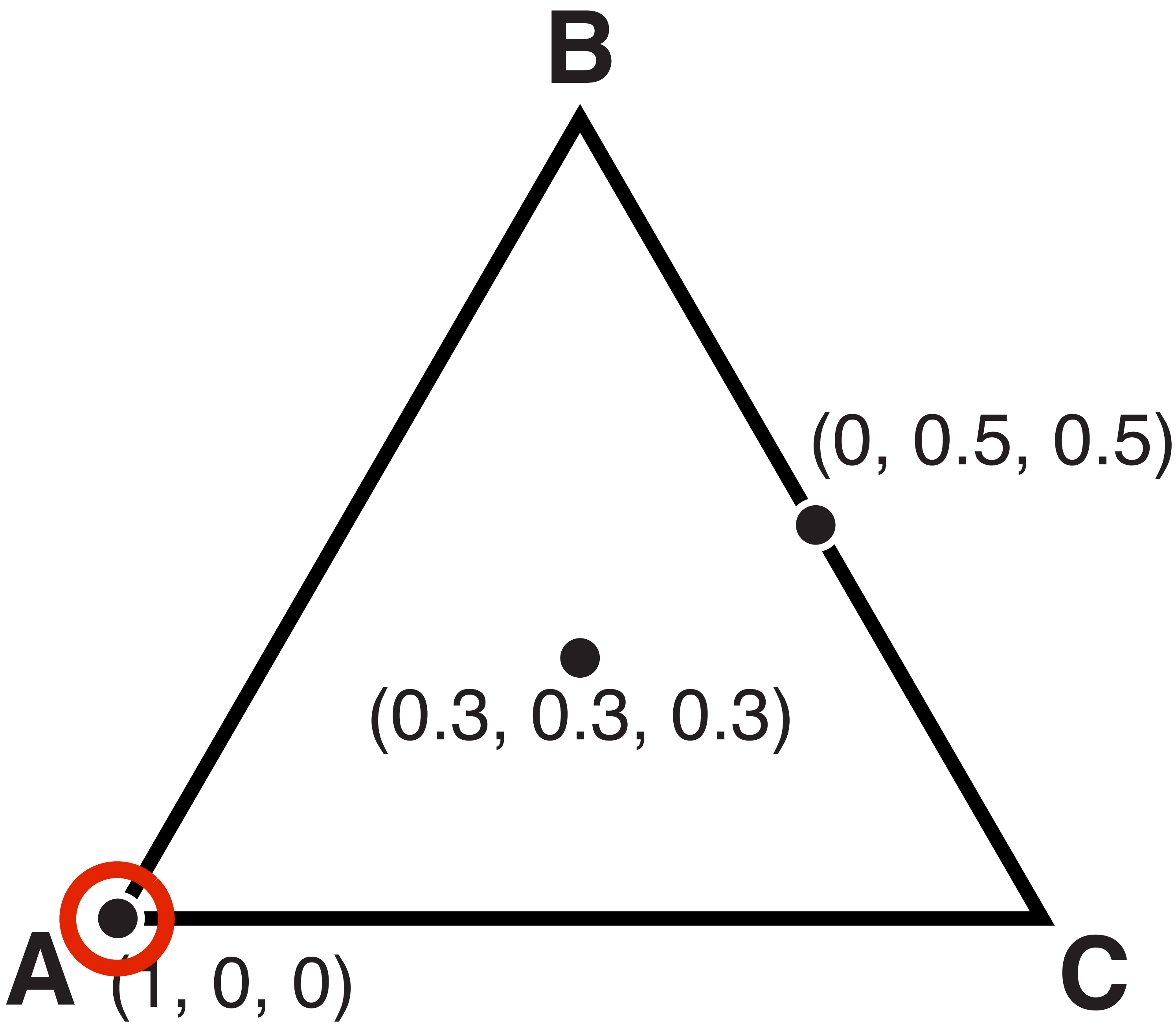
3-category rule



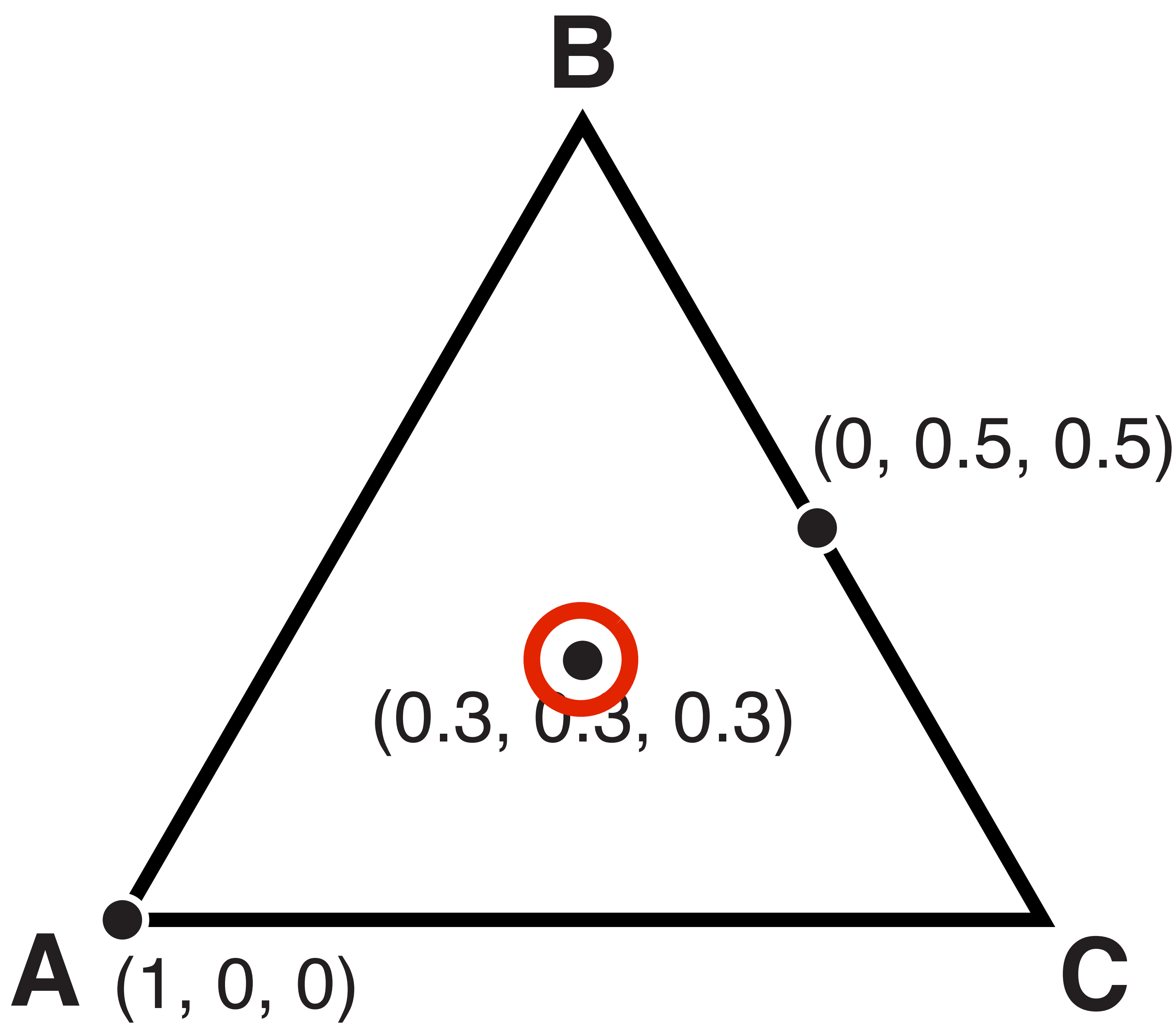
Three models

- **Least certain:** Items are preferred when there is high overall uncertainty, with no single category being especially likely
  - Maximizing "global" uncertainty across all categories
- **Label margin:** Items are preferred when two possible categories are considered equally likely
  - Finding "local", pairwise uncertainty
- **Most certain:** Items are preferred when there is **low** overall uncertainty, with one category considered especially likely
  - Sticking to what you already know

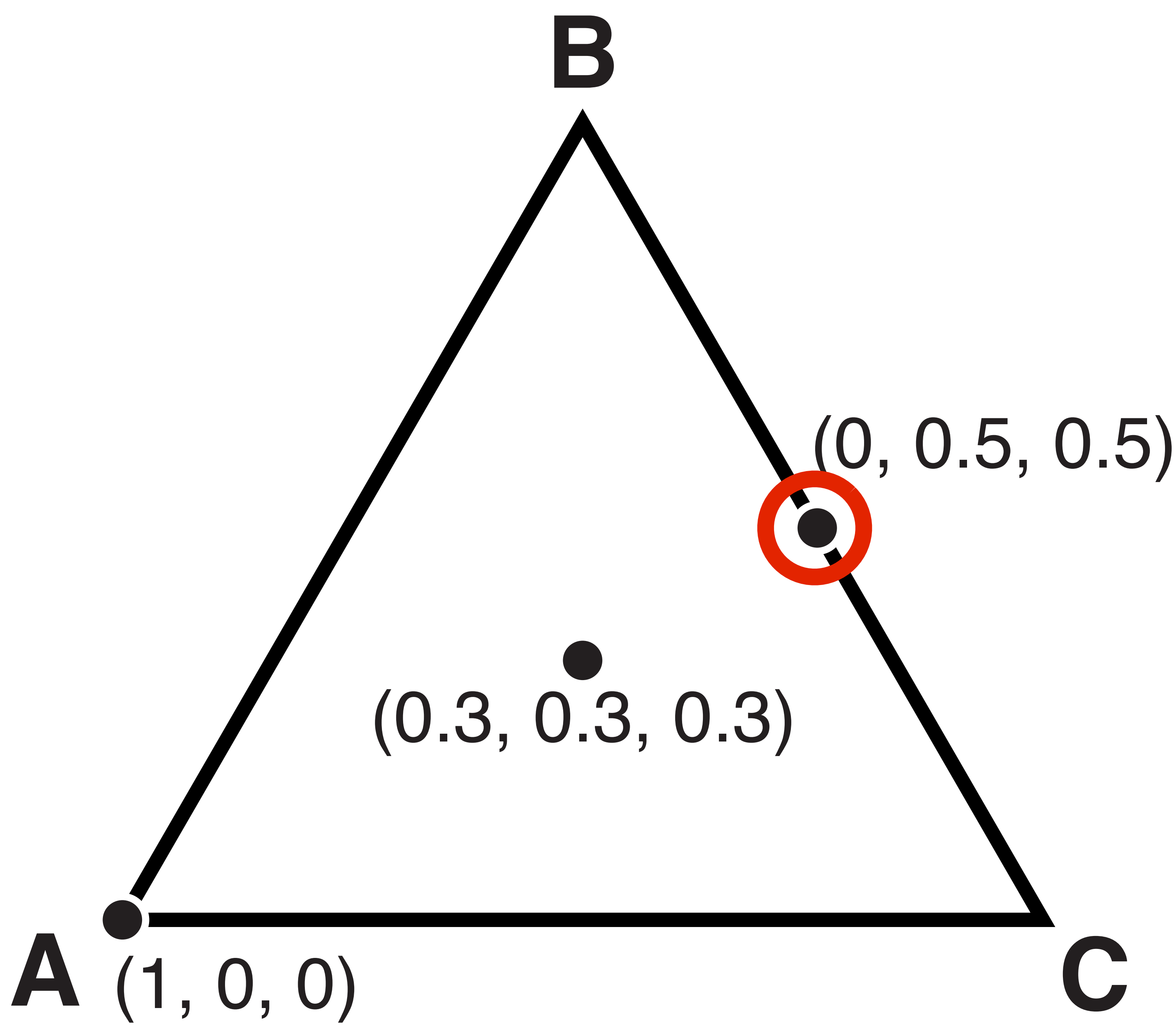
Visualizing uncertainty judgments



Visualizing uncertainty judgments

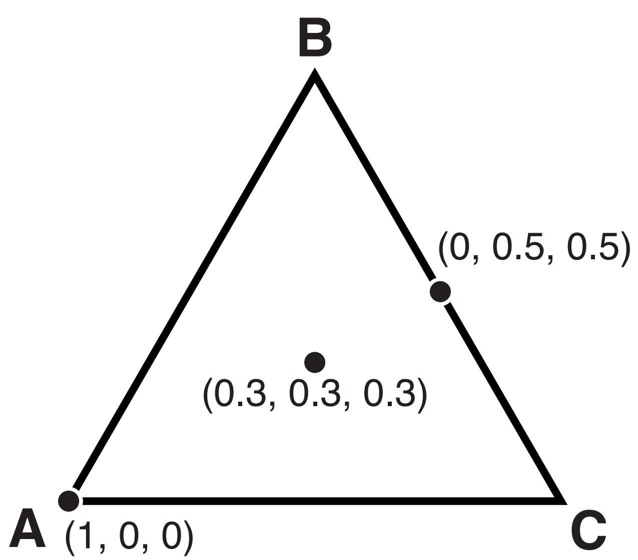


Visualizing uncertainty judgments

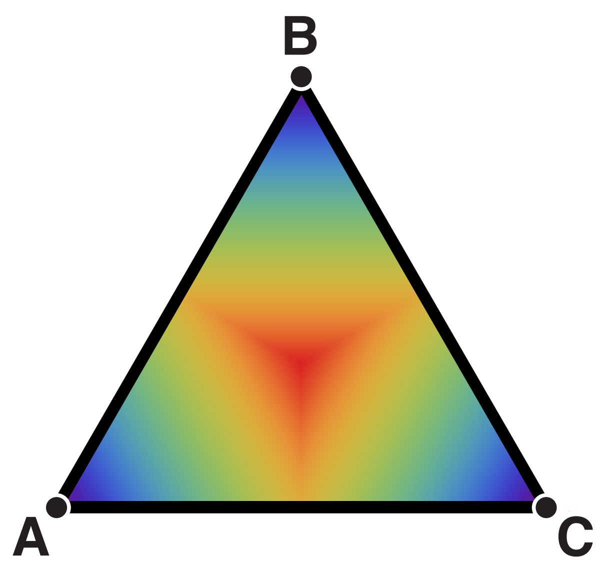


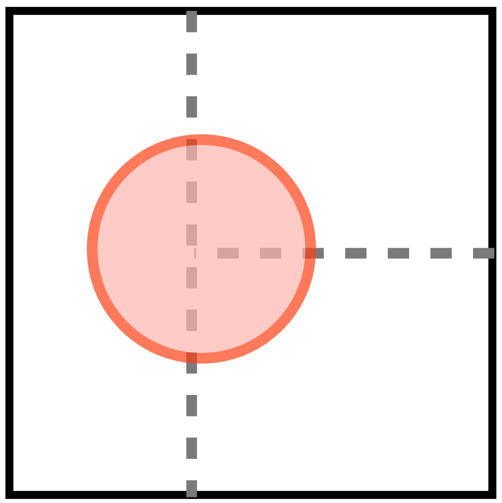
Model predictions

Space of uncertainty judgments



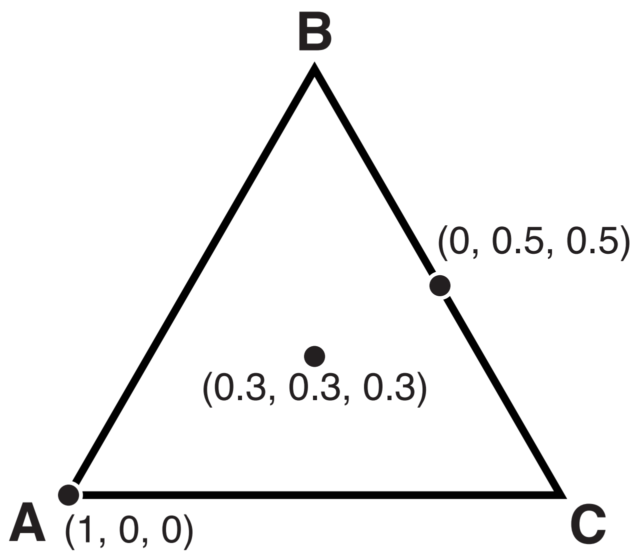
Least certain



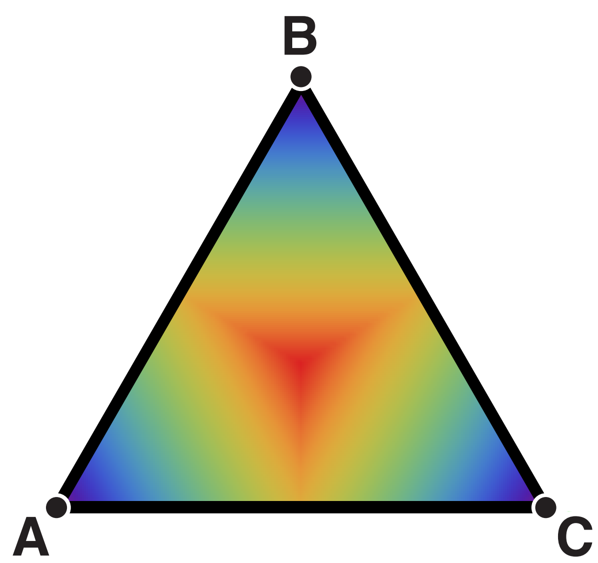


Model predictions

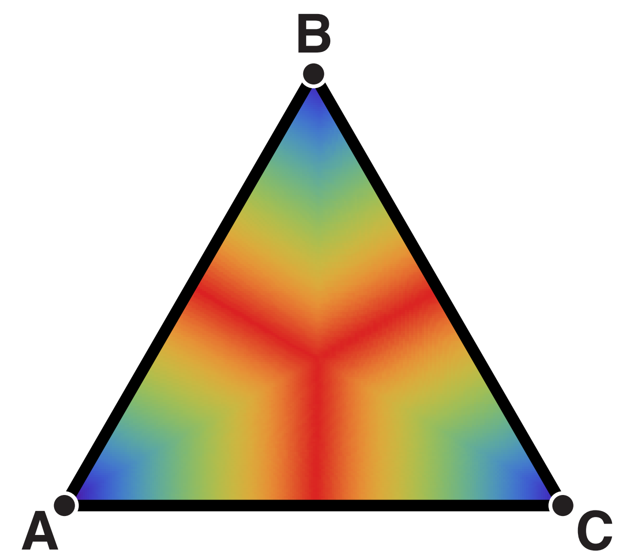
Space of uncertainty judgments

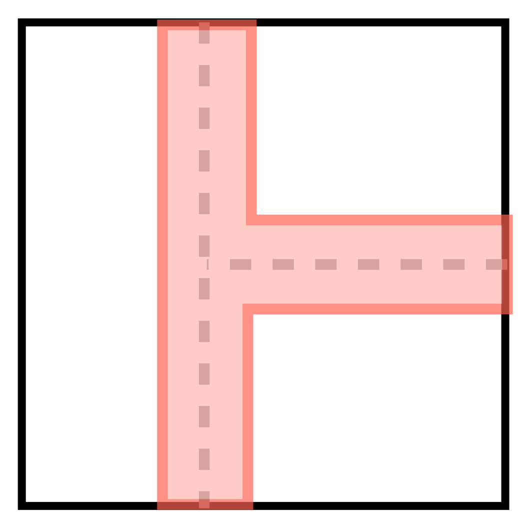


Least certain



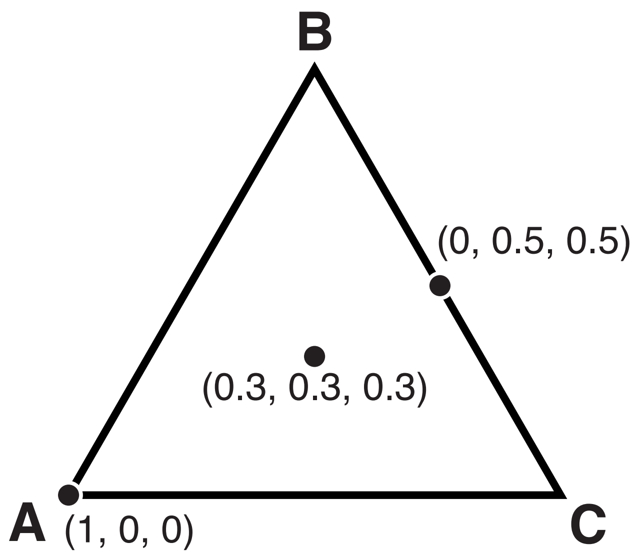
Label margin



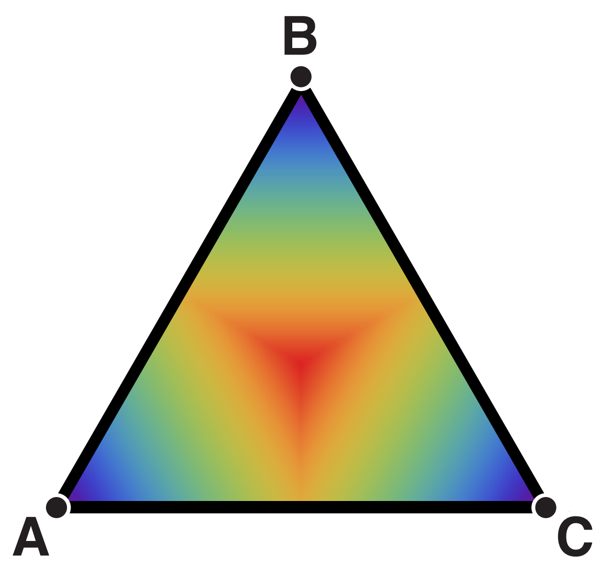


Model predictions

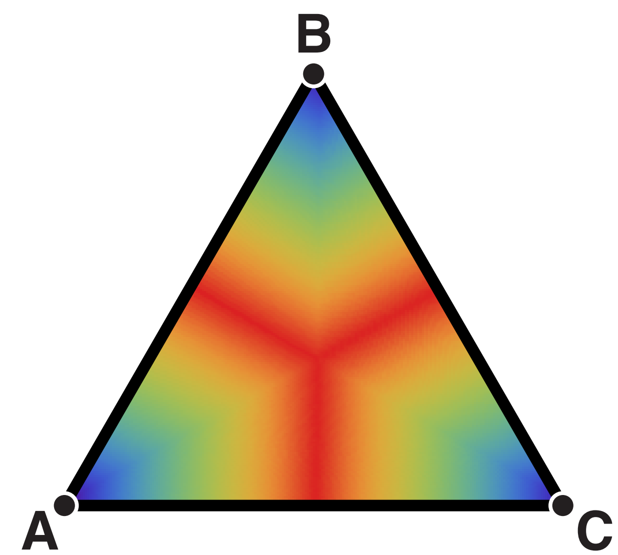
Space of uncertainty judgments



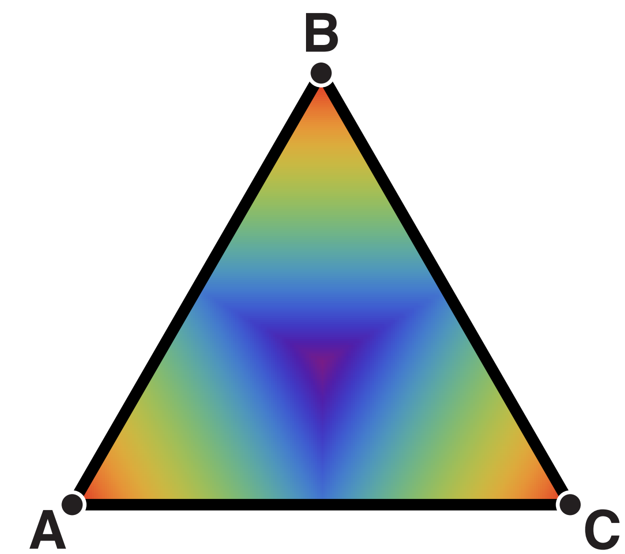
Least certain

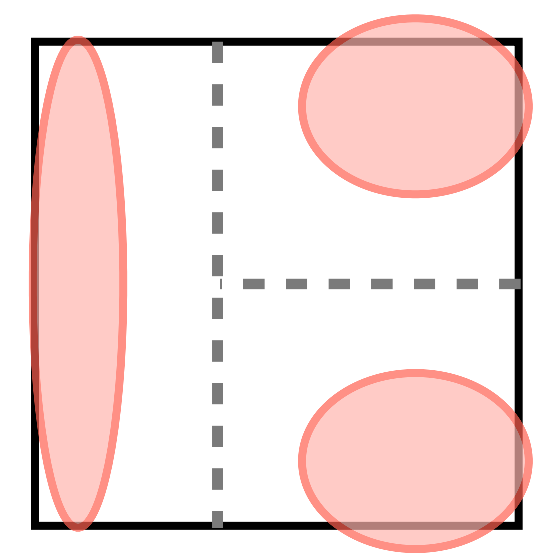


Label margin

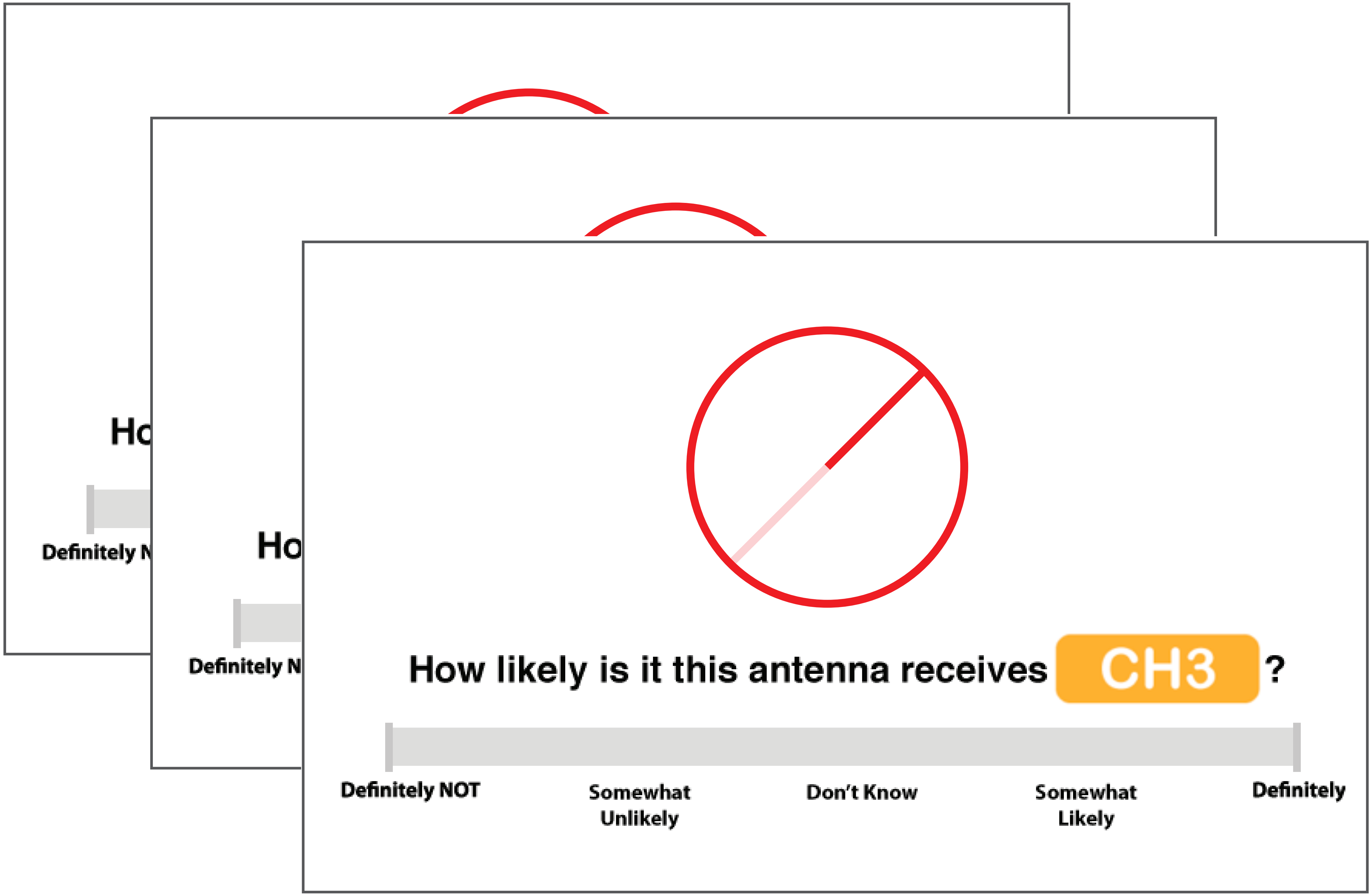


Most certain

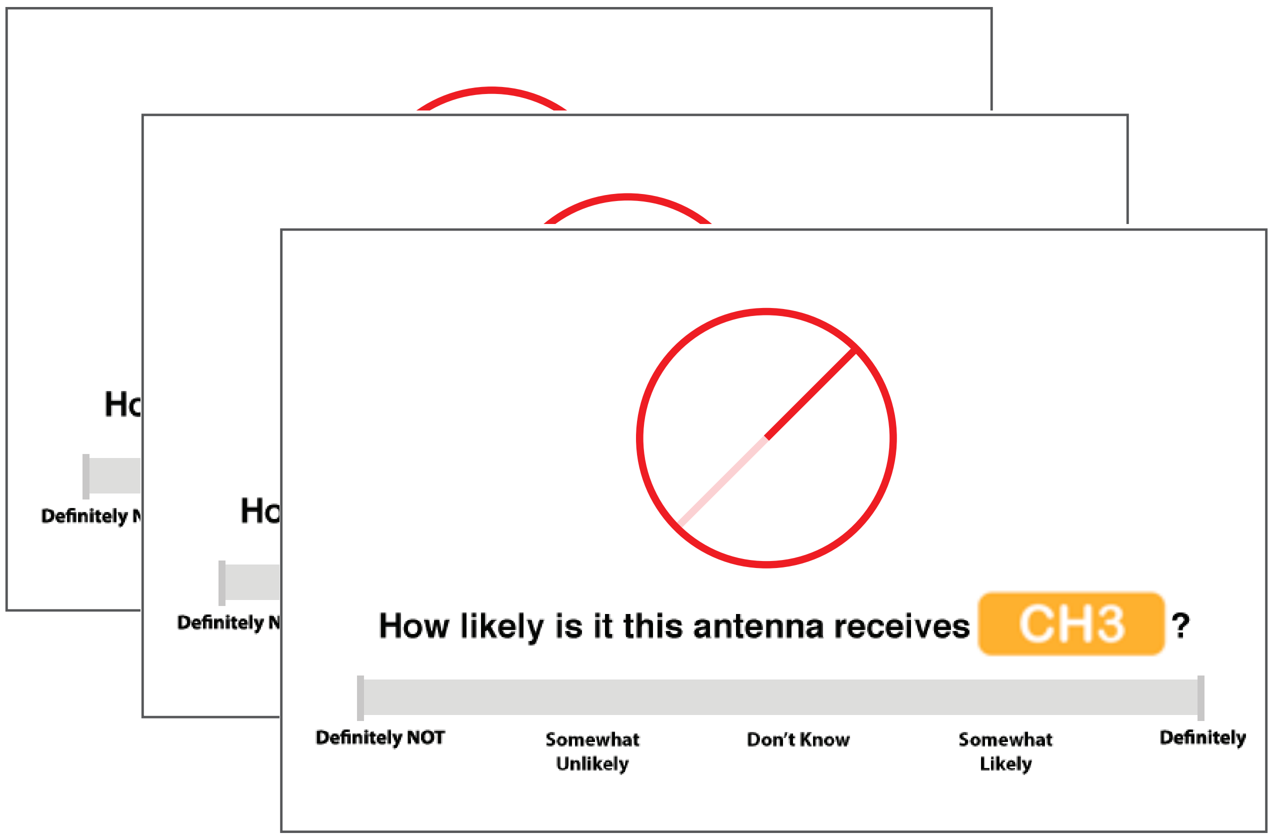




Uncertainty judgments

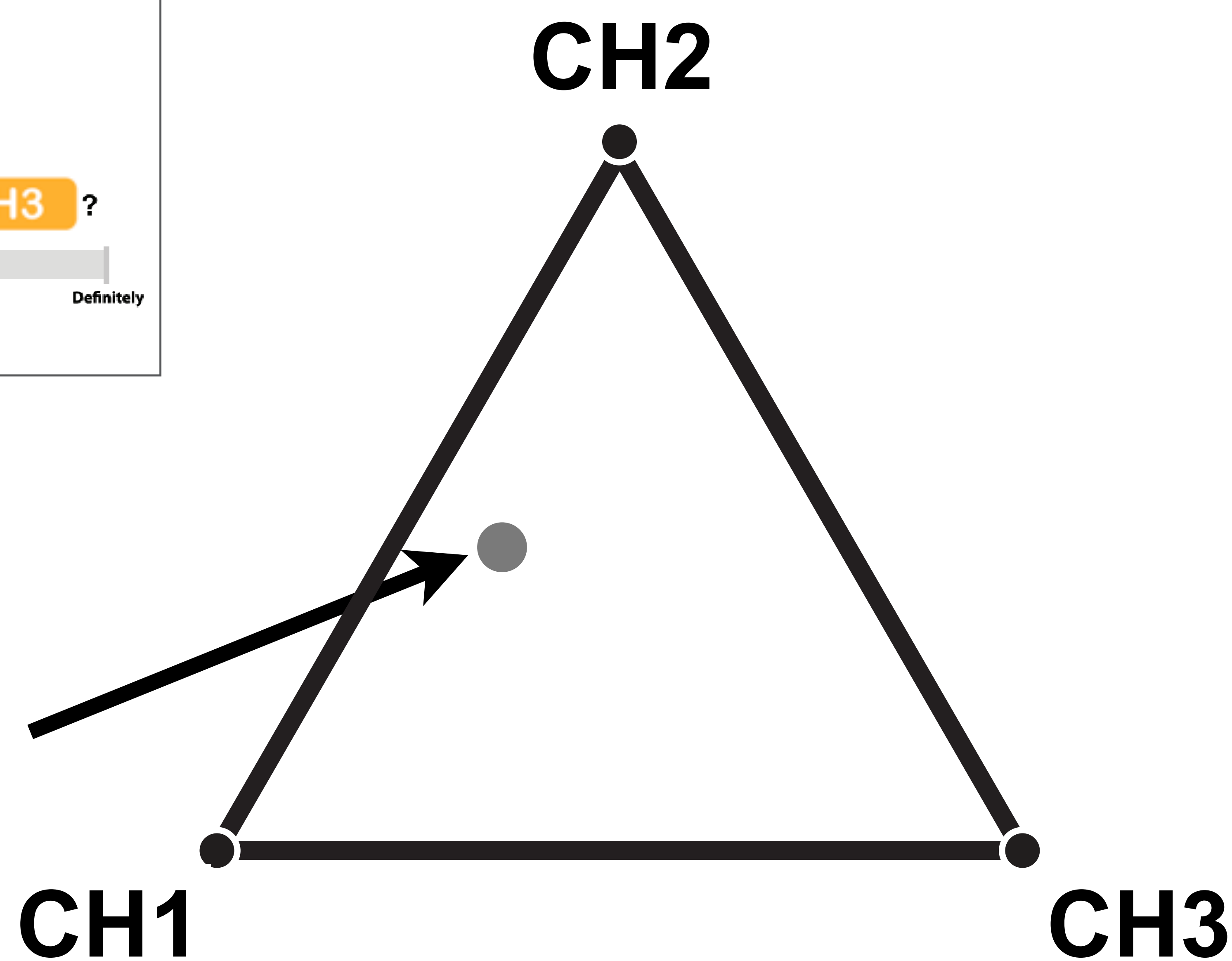


Uncertainty judgments

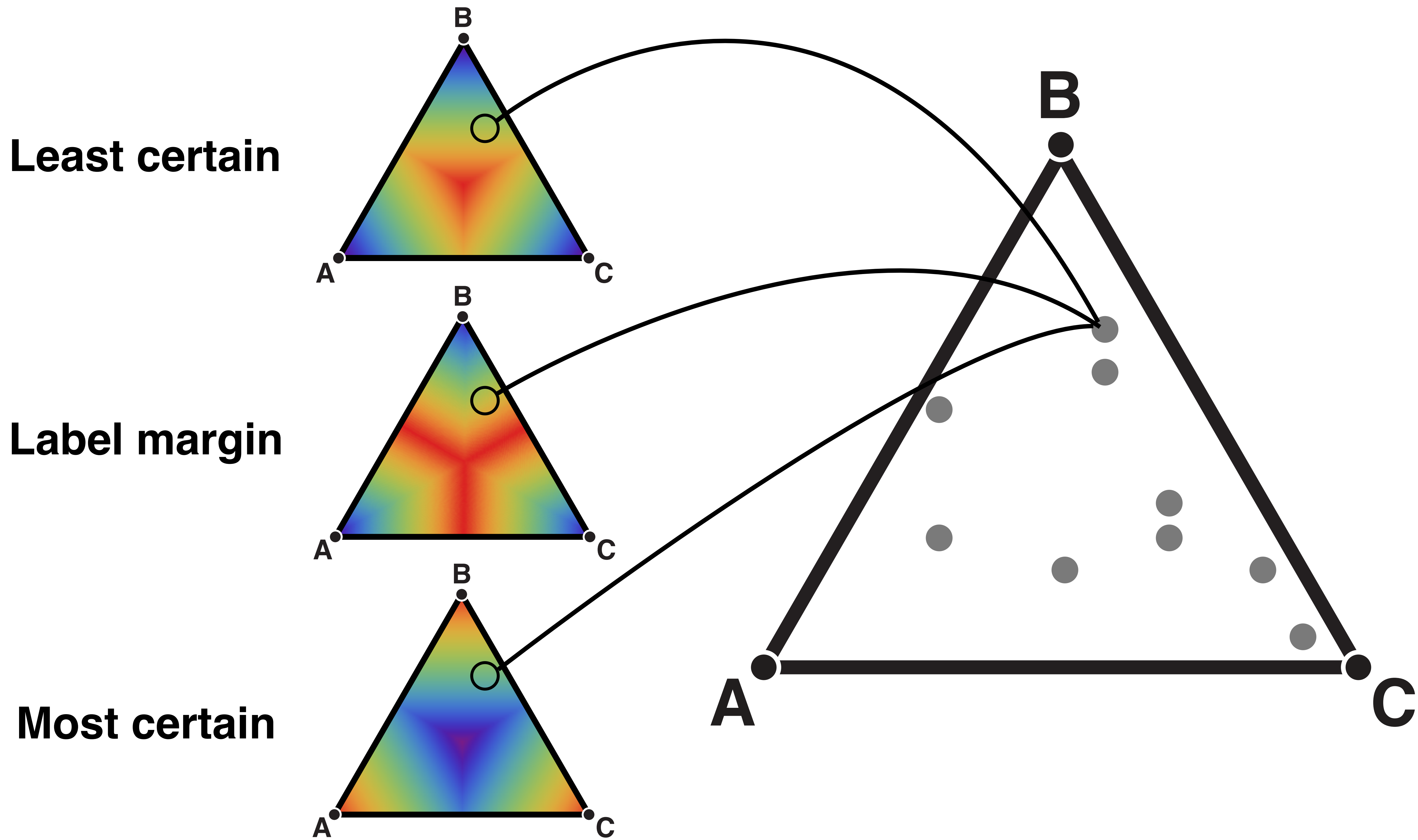


normalize

CH1	CH2	CH3
(0.4,	0.4,	0.2)

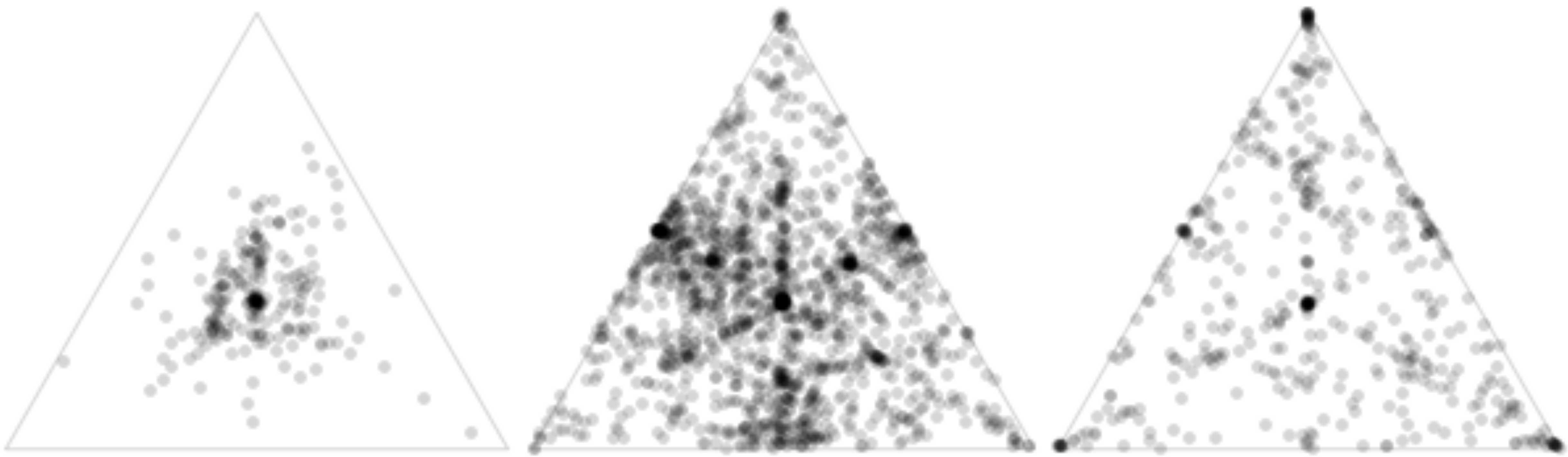


Uncertainty judgments



Most participants best-fit by margin sampling

Uncertainty judgments
(by best-fitting model)



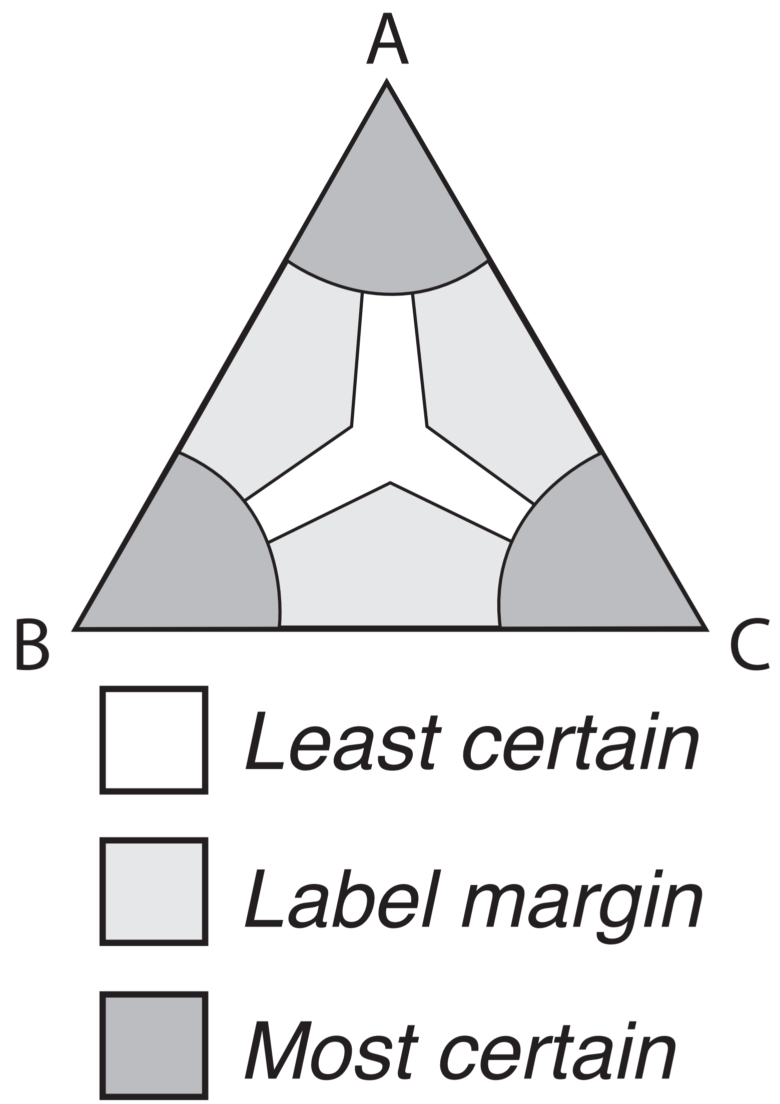
least certain *(6 participants)*

label margin *(40 participants)*

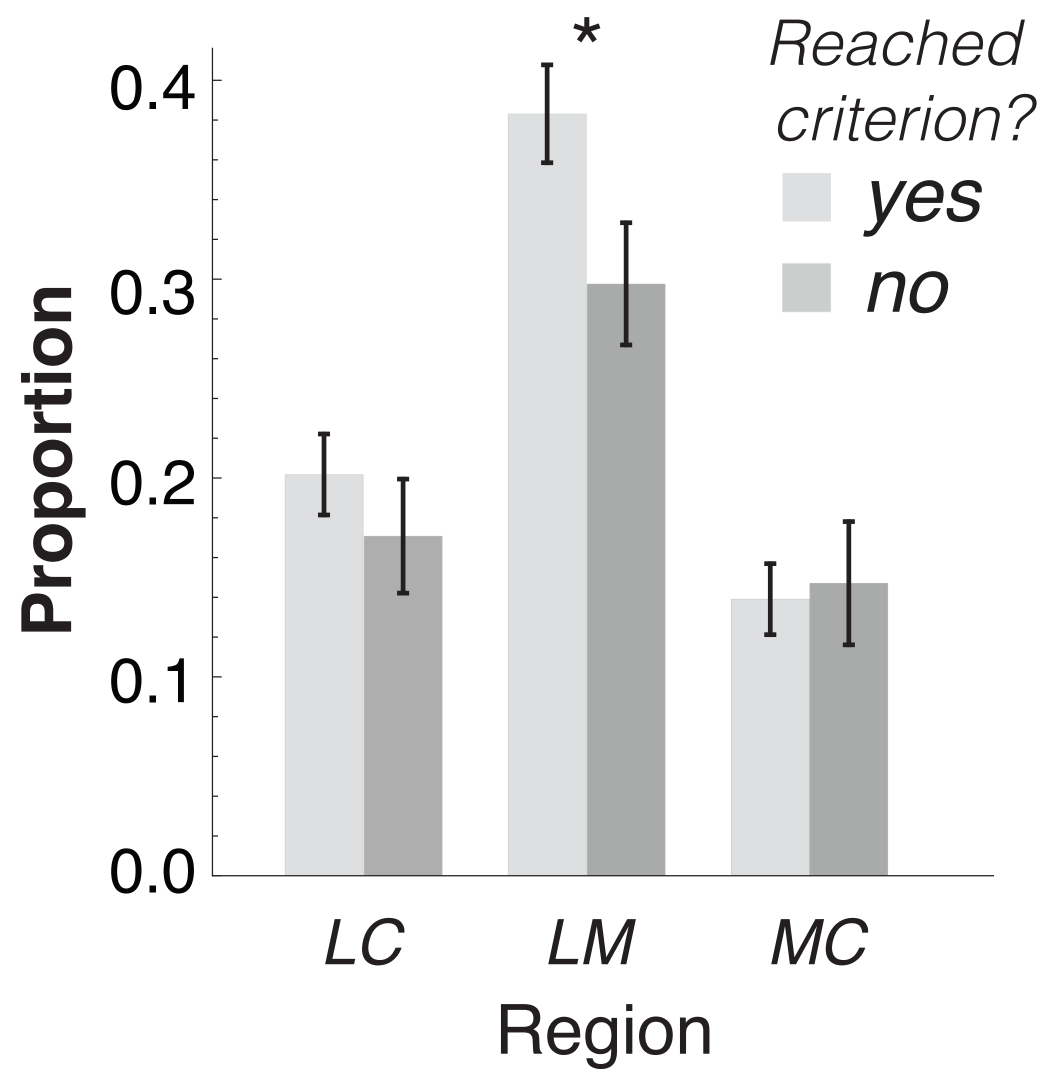
most certain *(11 participants)*

More margin sampling among fast learners

Regions



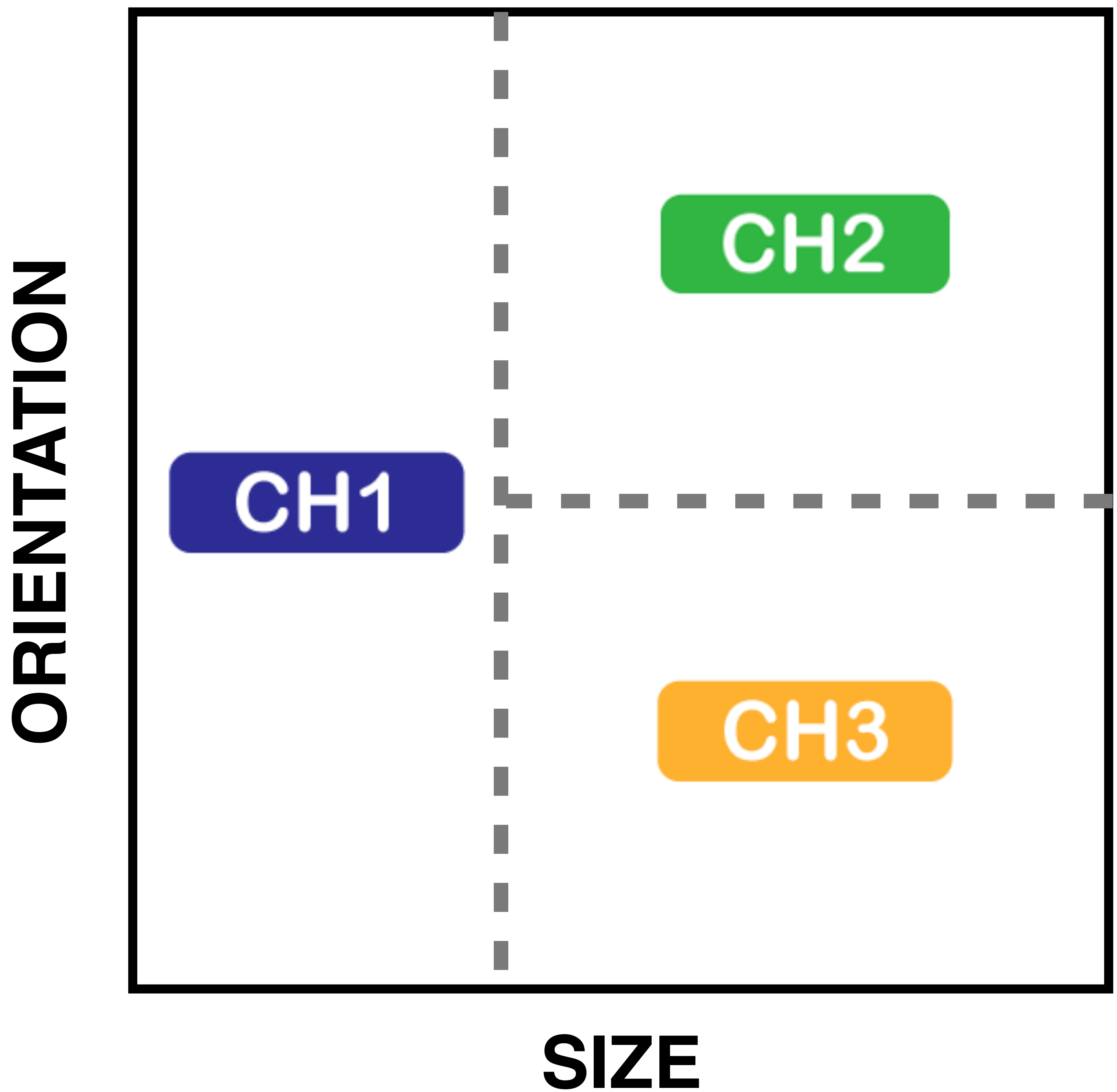
Overall proportion of samples by region



Study 2: Summary

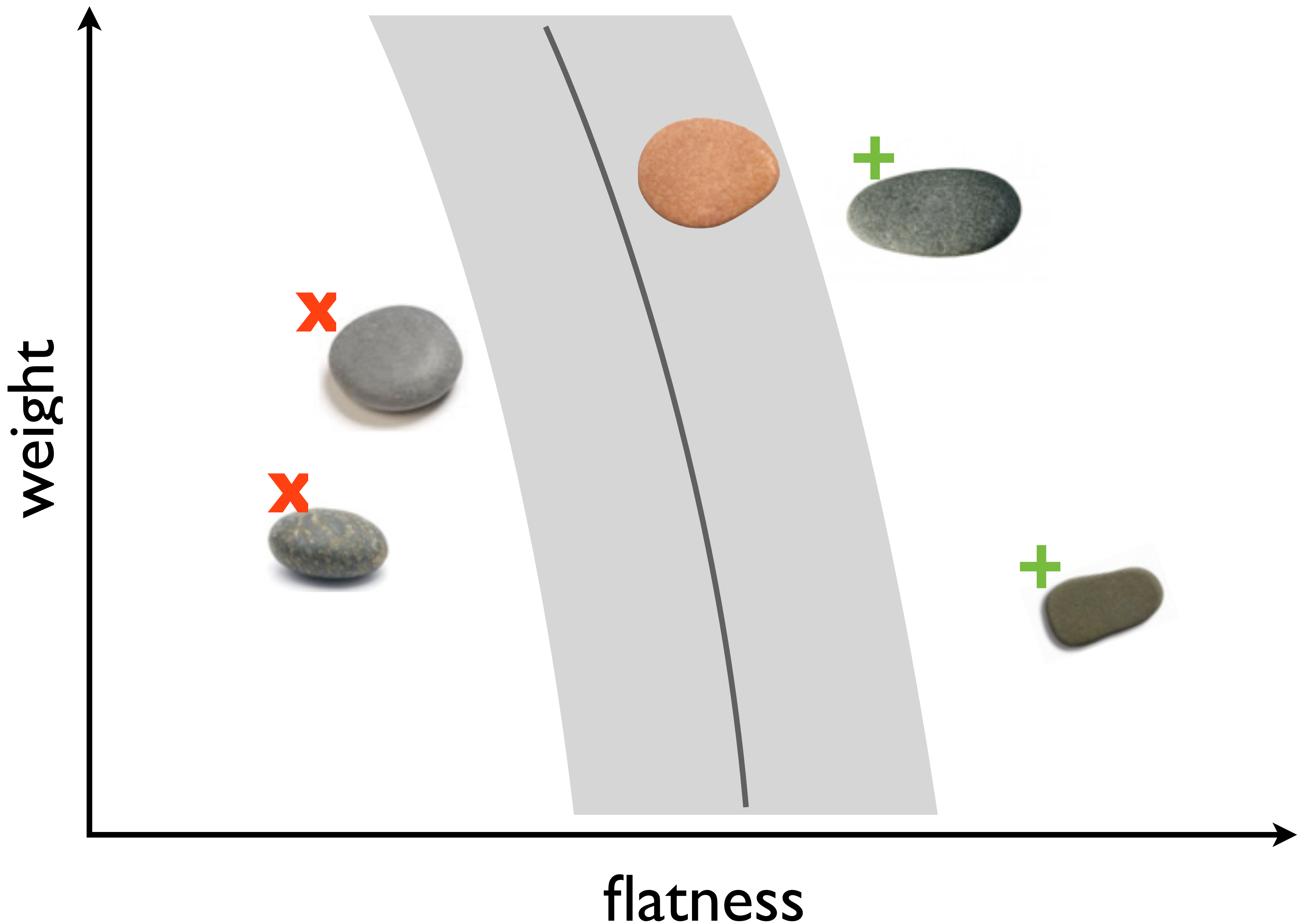
- Based on their own uncertainty judgments, most people are best accounted for by **label margin,** even though it ignores information about a third category
- The rate of sampling in the margin was higher for those participants that reached the learning criterion

Study 2: Summary



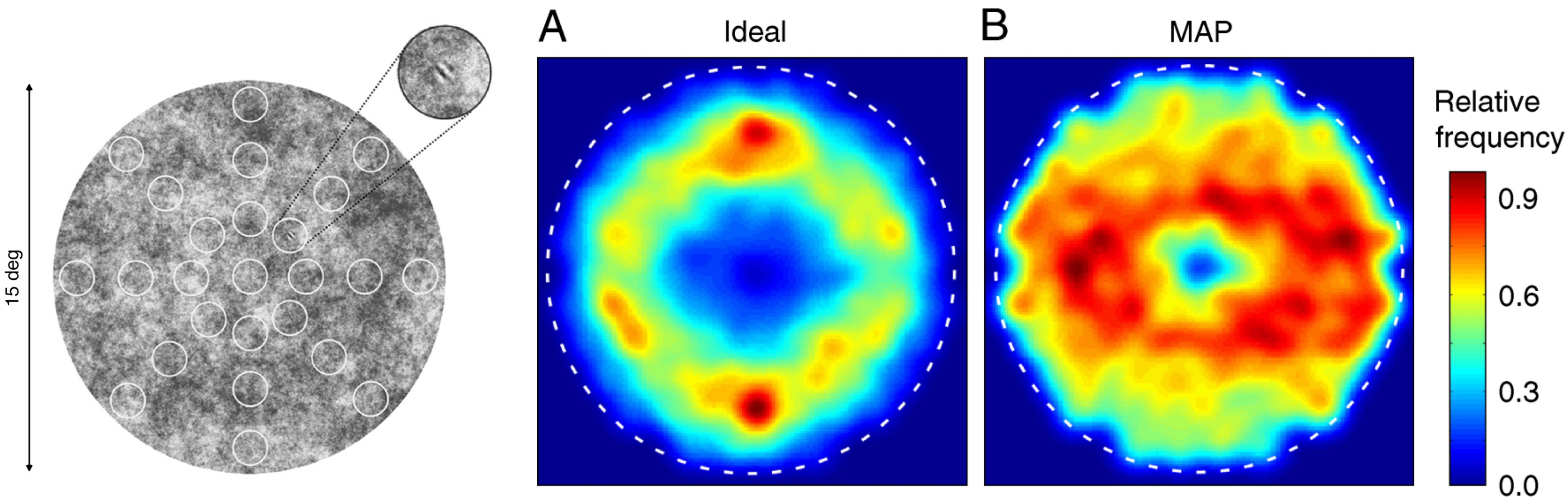
Wrap-up: Active learning across domains

Category learning



Wrap-up: Active learning across domains

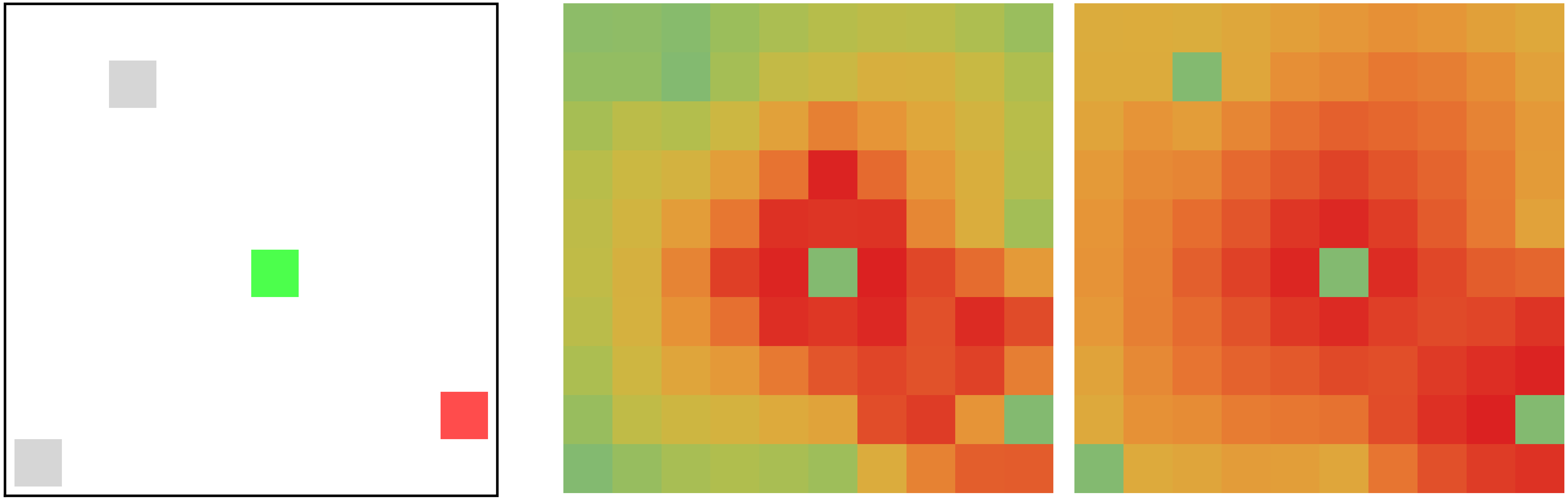
Visual search



Najemnik & Geisler, 2008

Wrap-up: Active learning across domains

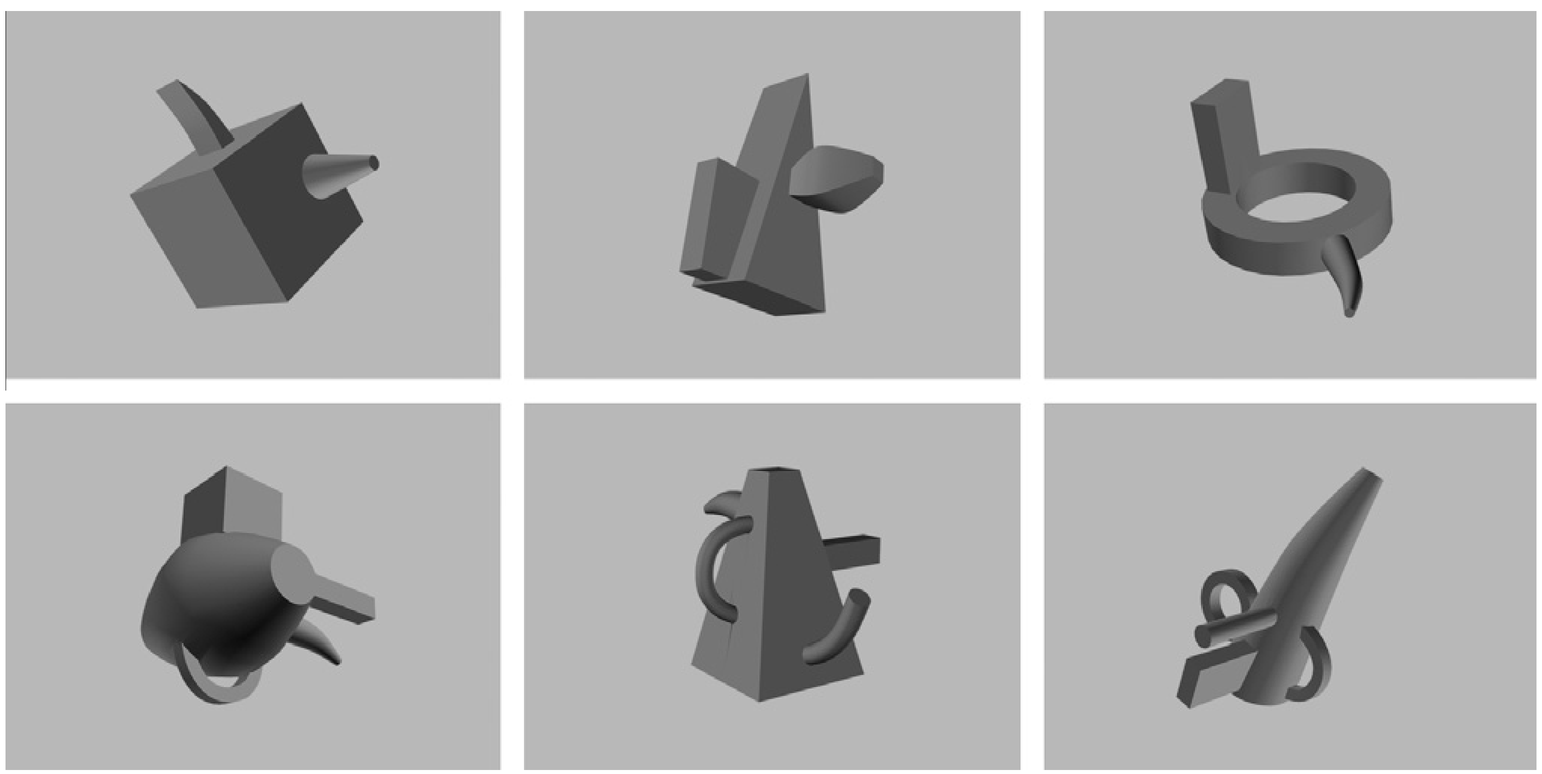
"Battleship"



Markant and Gureckis (2012) CogSci Proceedings

Wrap-up: Active learning across domains

Memory for 3D objects/faces

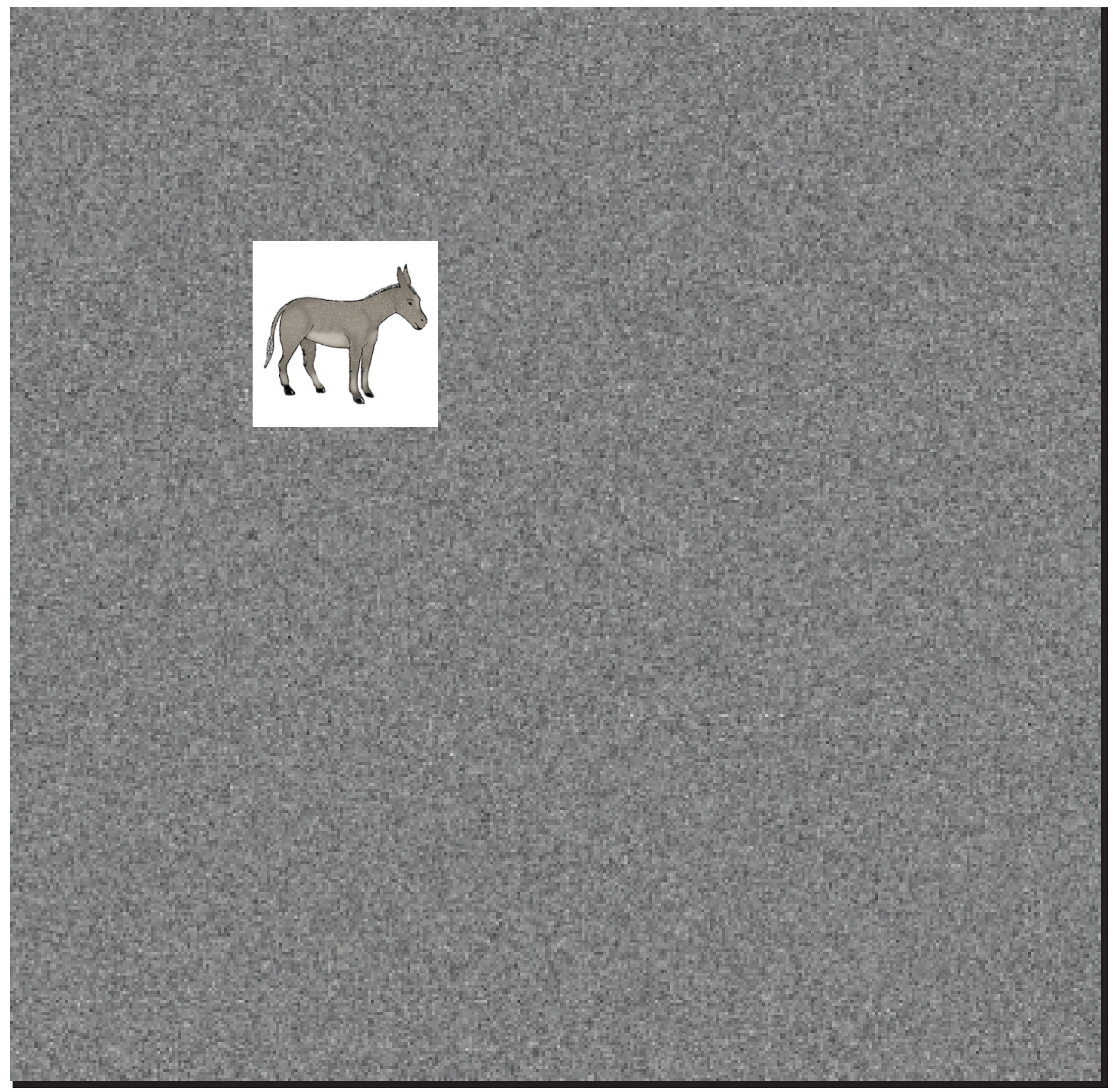


Liu., C.H., Ward, J., and Markall, H. (2007), JEP:HPP

Meijer, F. and Van der Lubbe, R. H. J. (2011), Vision Research

Wrap-up: Active learning across domains

Recognition memory



Markant, D., Dubrow, S., Davachi, L., Gureckis, T. (submitted). Deconstructing the effect of self-directed study on episodic memory.

Wrap-up: Active learning across domains

THANKS!