Generalizing with overly complex representations

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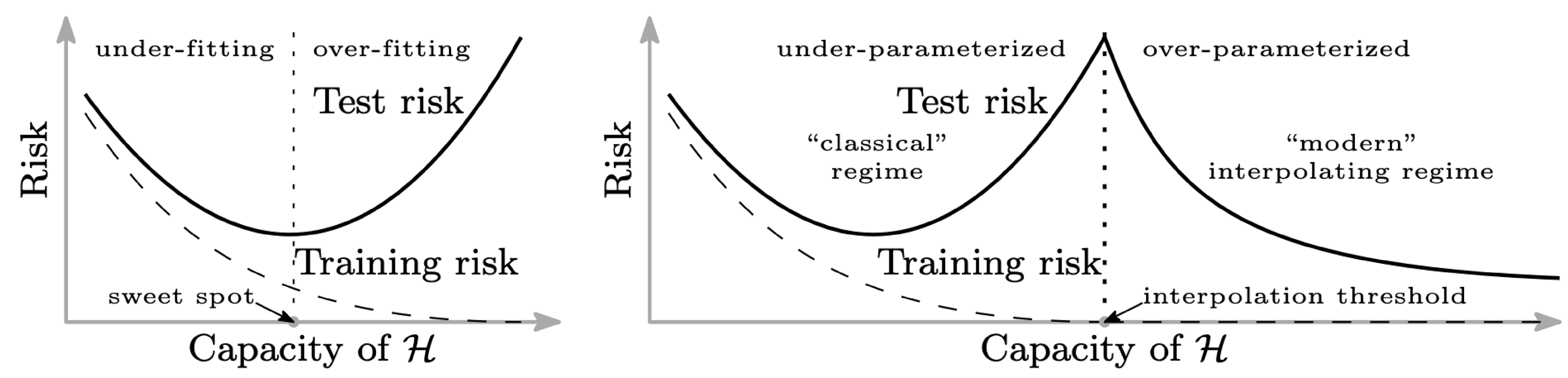
1. Simplicity as a core cognitive principle

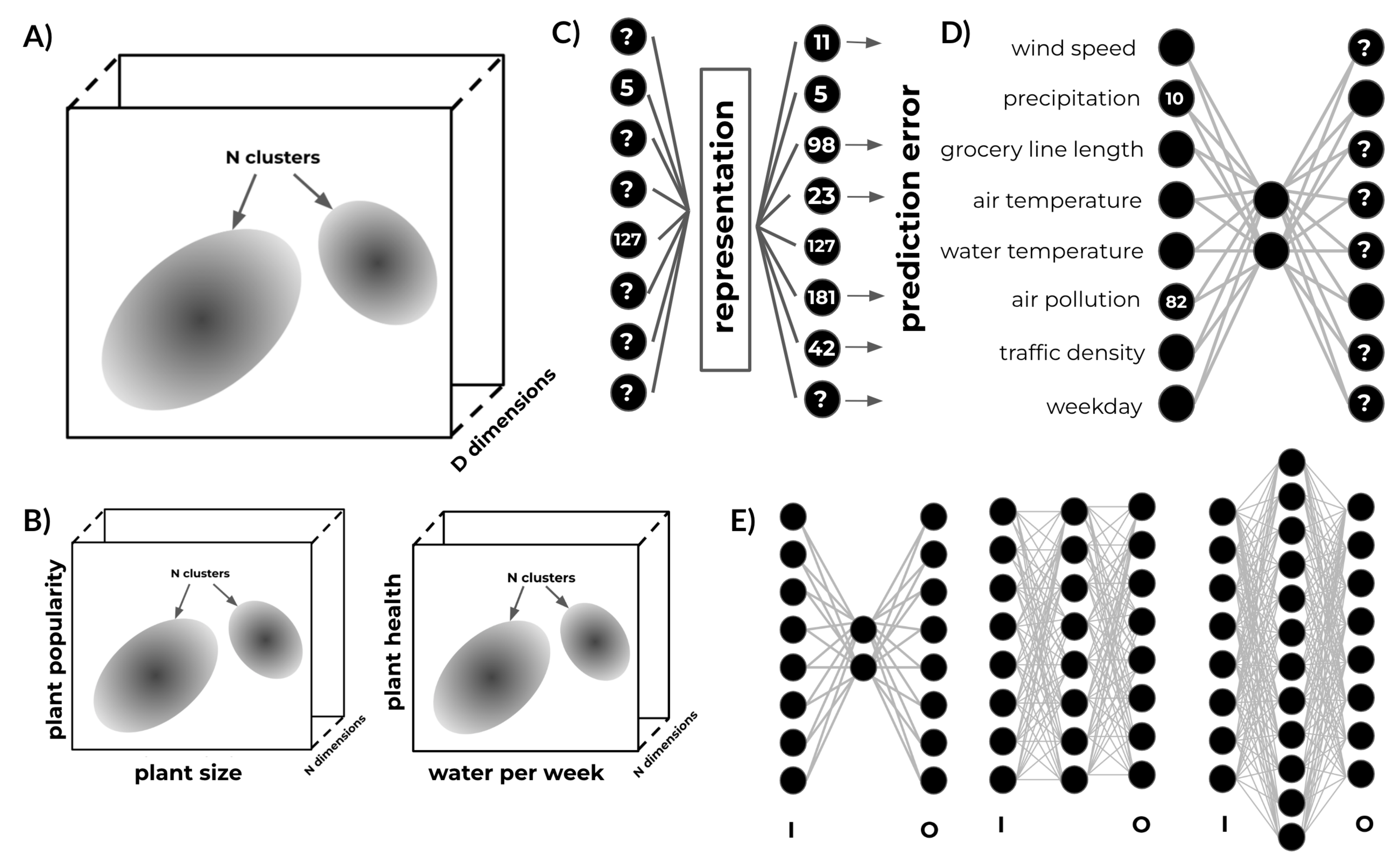
- Simple representations and algorithms are often suggested to govern robust behavior and successful perception, learning, and decision making.
- One of the key virtues of simple representations is their superior generalization: representations that "compress" the multidimensional world to the right extent are more likely to capture the essential structure in the data while eliminating the noise.
- More complex representations are notorious for overfitting the observations and amplifying the noise in them, leading to arbitrarily poor generalization performance.
- To learn and generalize well, cognitive systems should have a preference for simpler representations (see the arguments on bias-variance tradeoff, Bayesian Occam's razor, simple heuristics).

2. U-curve vs. double descent of generalization error



Belkin, M., Hsu, D., Ma, S., Mandal, S. (2019). Reconciling modern machine-learning practice and the classical bias–variance trade-off. Proceedings of the National Academy of Sciences, 116(32), 15849-15854.

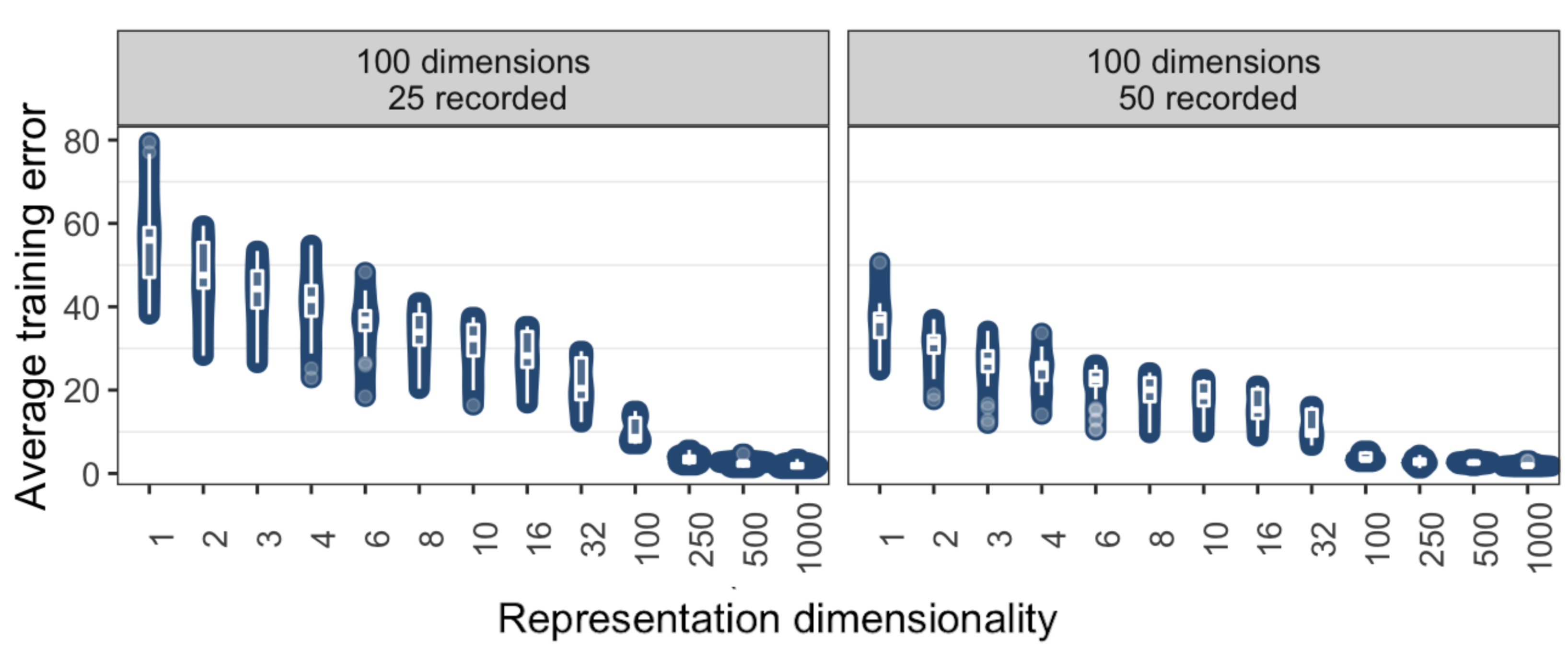
3. Task: learning predictive representations



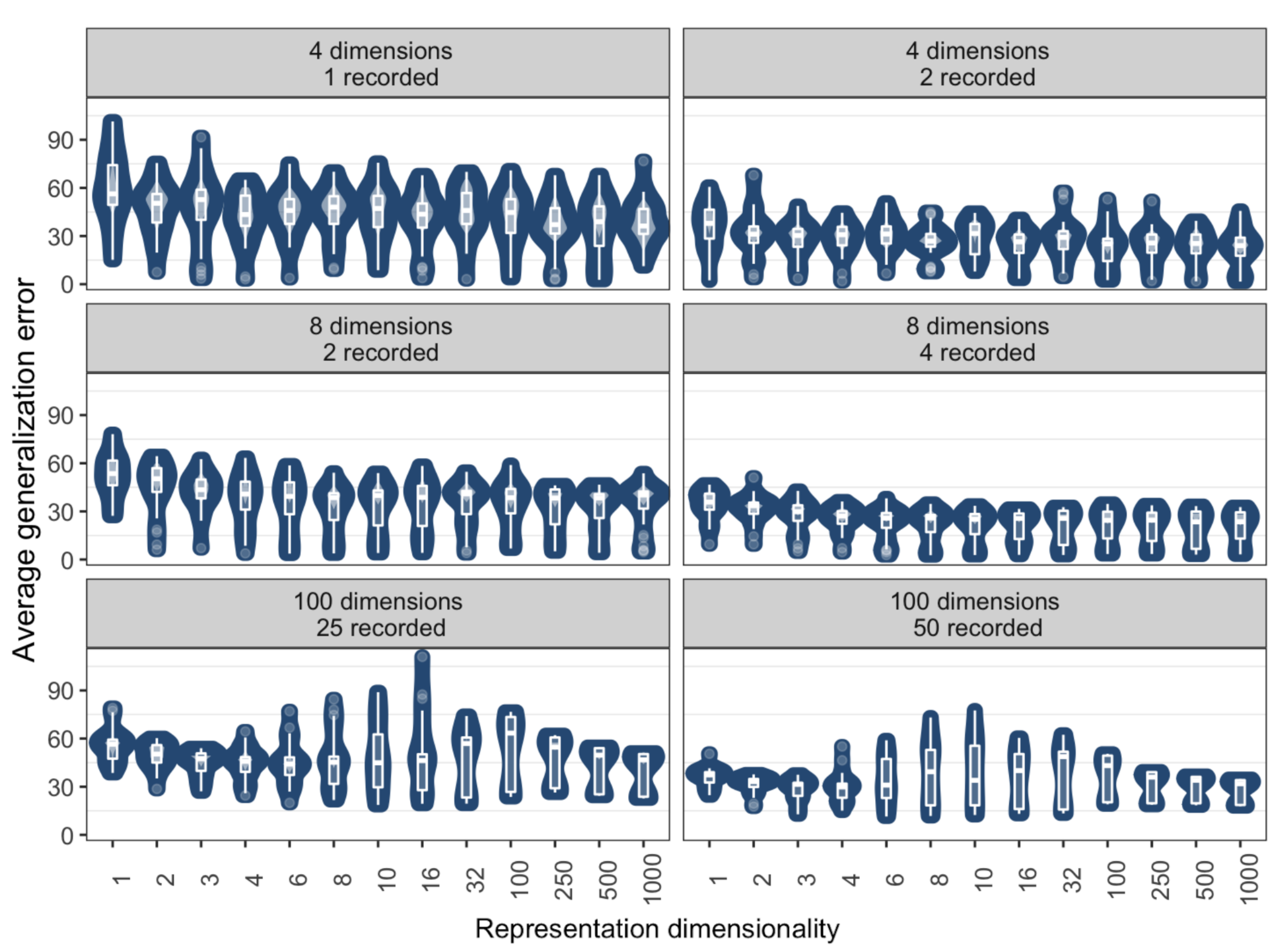
4. Simulation parameters

Dimensionality of the representation	1 2 3 4 6 8 10 16 32 100 250 500 1000
Dimensionality of the world (D)	4 8 100
N of dimensions to predict	¾ D ½ D
N of clusters in the world	1 10 100

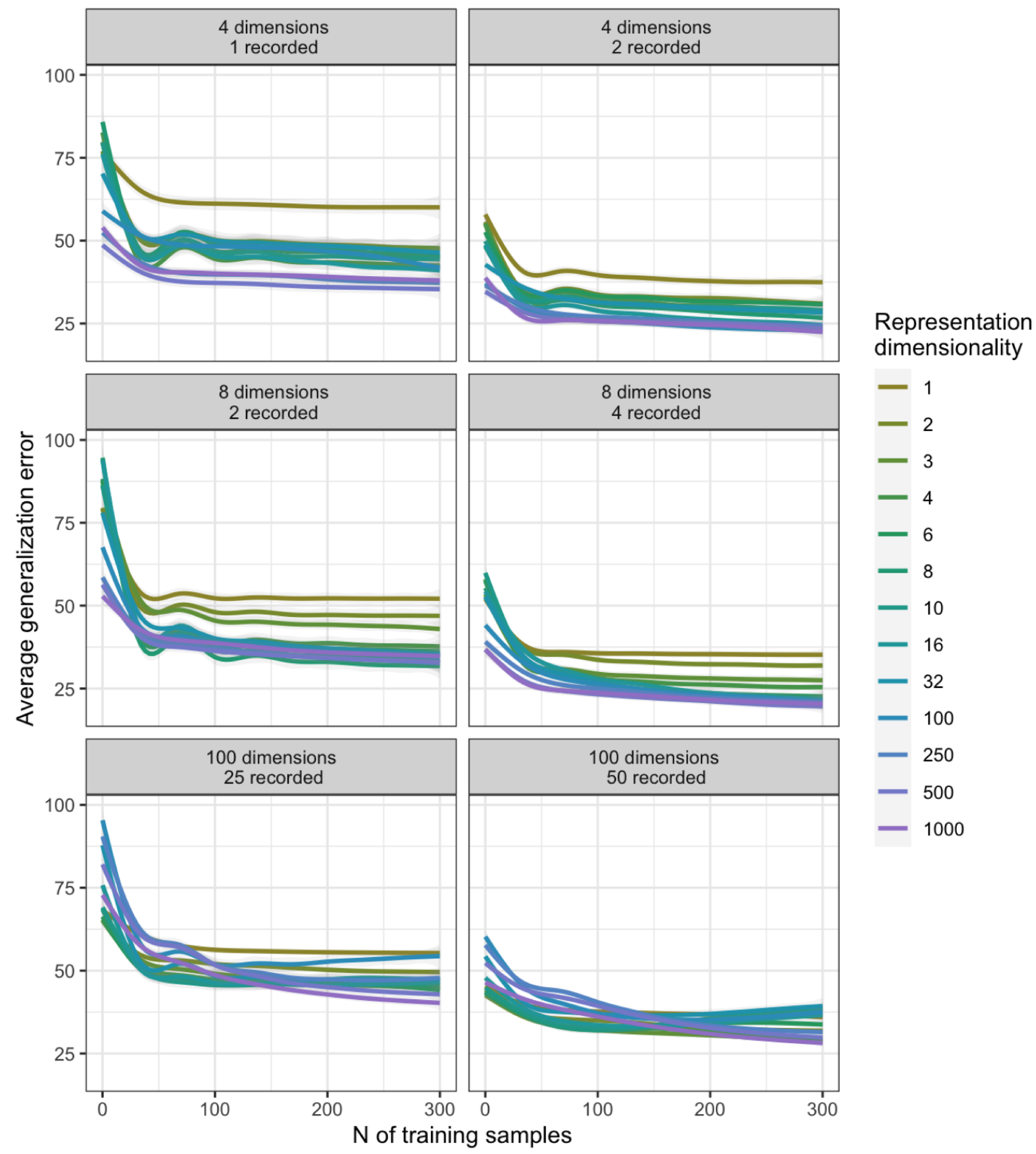
5. Training error



6. Generalization (testing) error



7. Generalization (testing) error over time



8. Double-descent of generalization error is replicated in simple predictive representation learning task

- Overfitting (fitting training data exactly) does not (always) hurt generalization
- Representations that compress information do not (always) lead to better generalization
- Overly complex representations can generalize relatively well, even better than the representations which compress information or match the complexity of the world
- Overly complex representations show reliable generalization after certain degree of complexity

9. Limitations & future directions

- More nuanced articulation of complexity of the task and representation
- Other reasons to prefer simpler representations (e.g. interpretability, memorability, communicability)
- Simplicity preference at the level of implementation, algorithm or computation
- Different goals of a representation (prediction, explanation, control)
- Interpolation vs. extrapolation

10. What does it mean for cognitive science? (for discussion)

- Cognitive systems that generalize well do not have to compress information or learn simple representations of complex data
- Successful representation learning might require a "complexity", rather than simplicity, bias