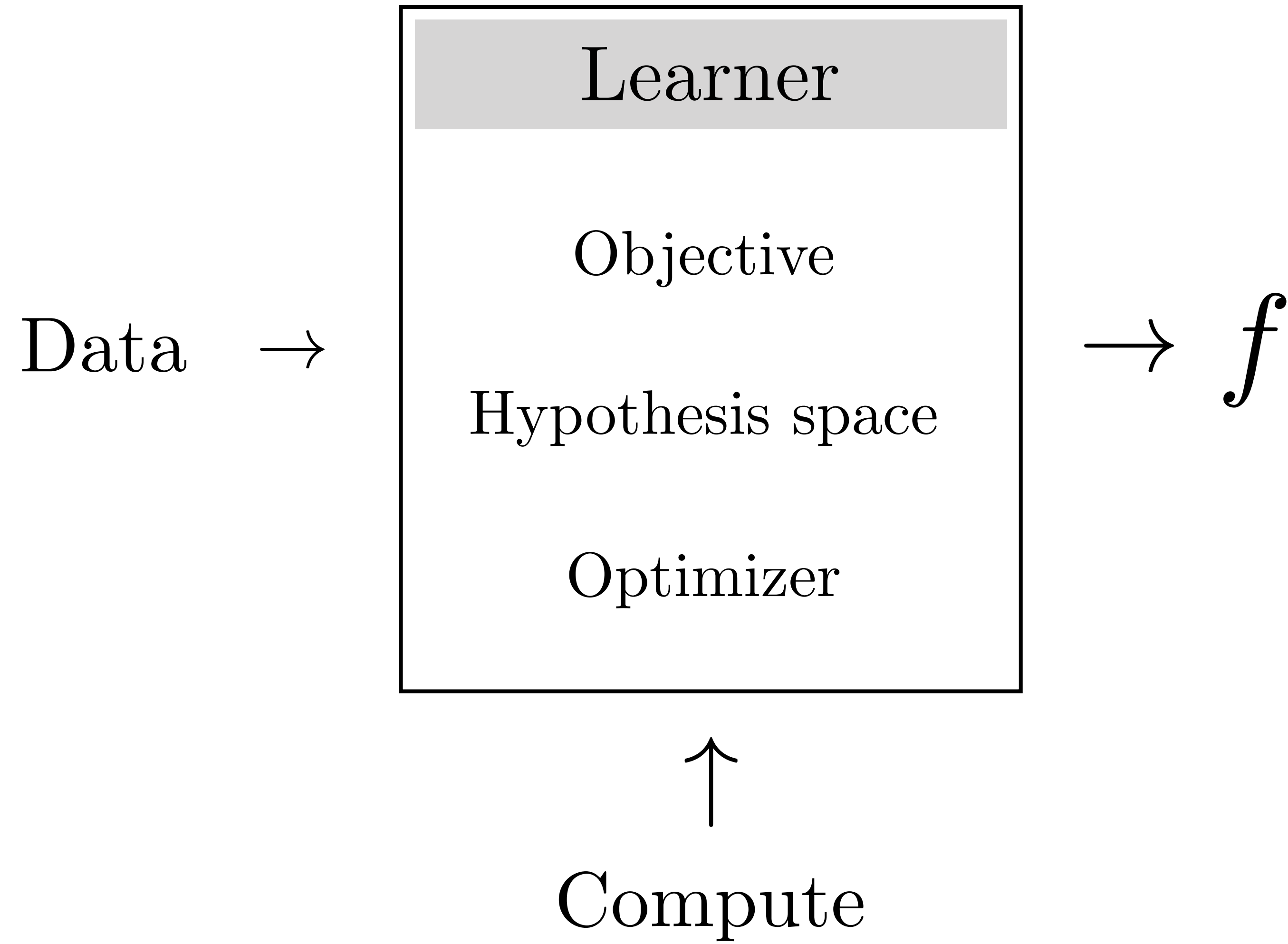
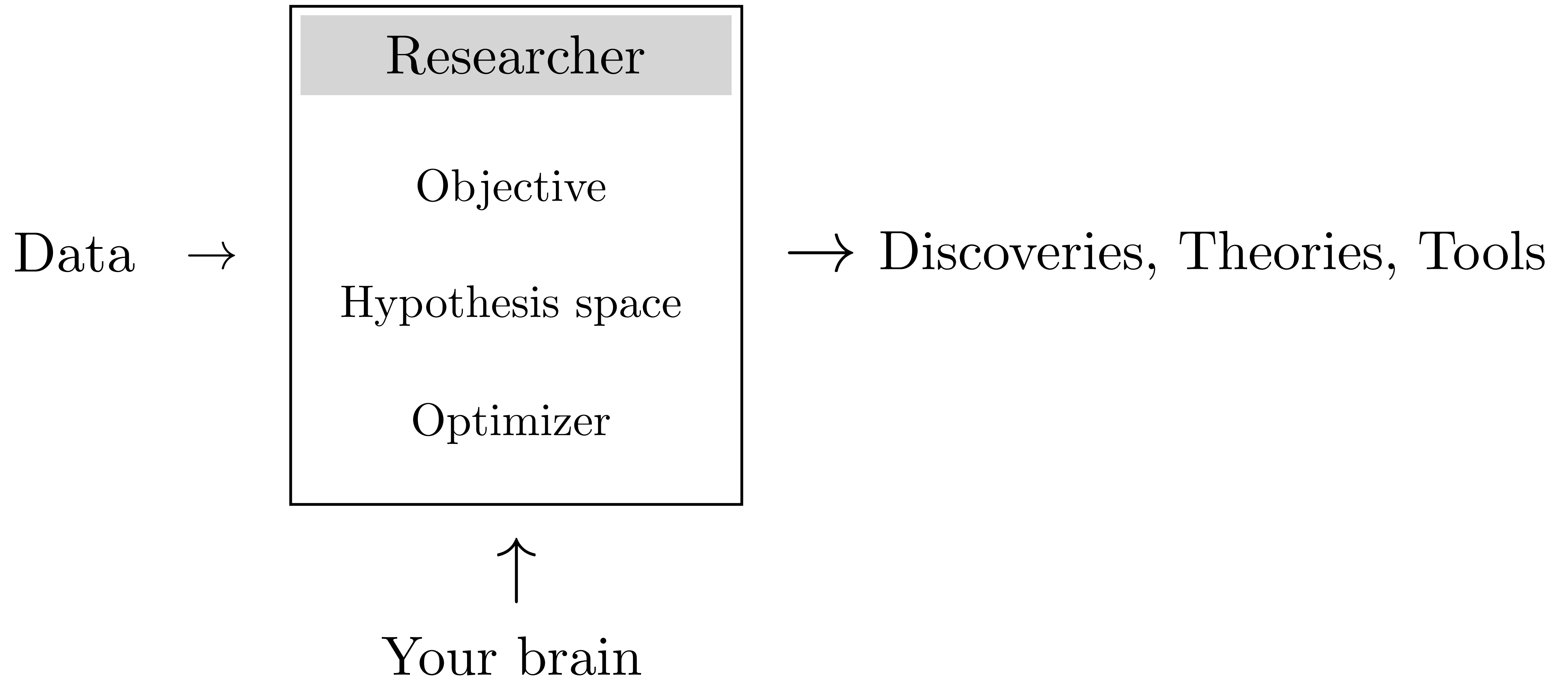


How to do research

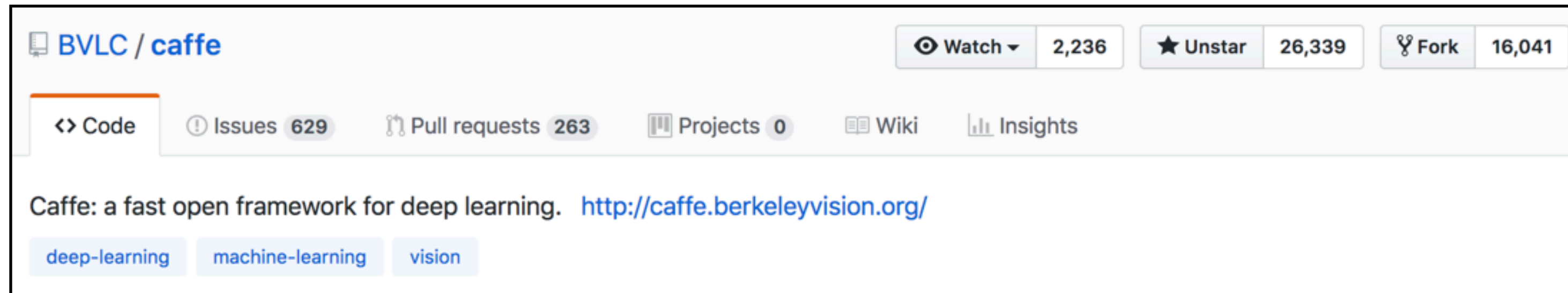
Phillip Isola, 2019



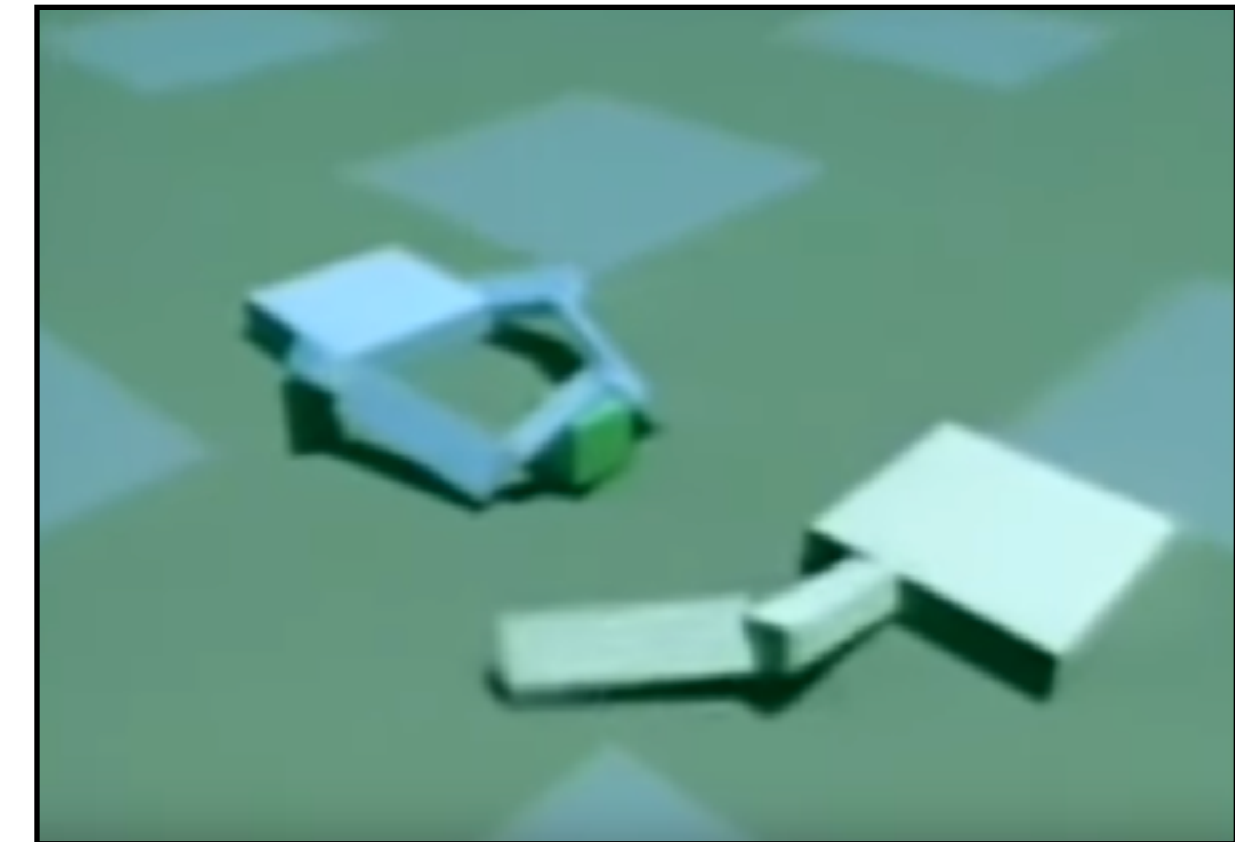


There are many ways to contribute

Tools



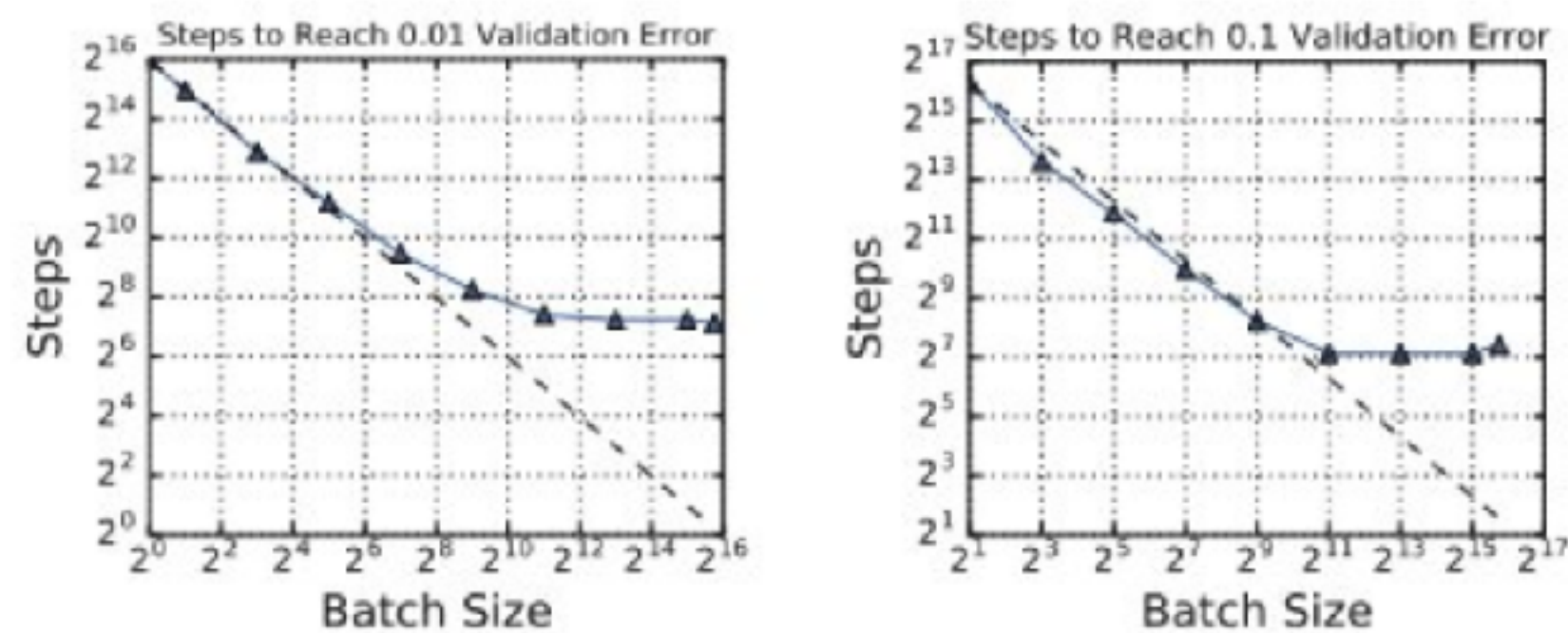
Creativity



Theory

Theorem 4. (*weak* topology*) Let $\{\mathbb{P}_n\}$ be a sequence of distributions. Considering $n \rightarrow \infty$, under mild Assumption, $\max_{\phi} M_{f_{\phi}}(\mathbb{P}_{\mathcal{X}}, \mathbb{P}_n) \rightarrow 0 \iff \mathbb{P}_n \xrightarrow{D} \mathbb{P}_{\mathcal{X}}$, where \xrightarrow{D} means converging in distribution [3].

Empiricism



(a) Simple CNN on MNIST

(b) Simple CNN on Fashion MNIST

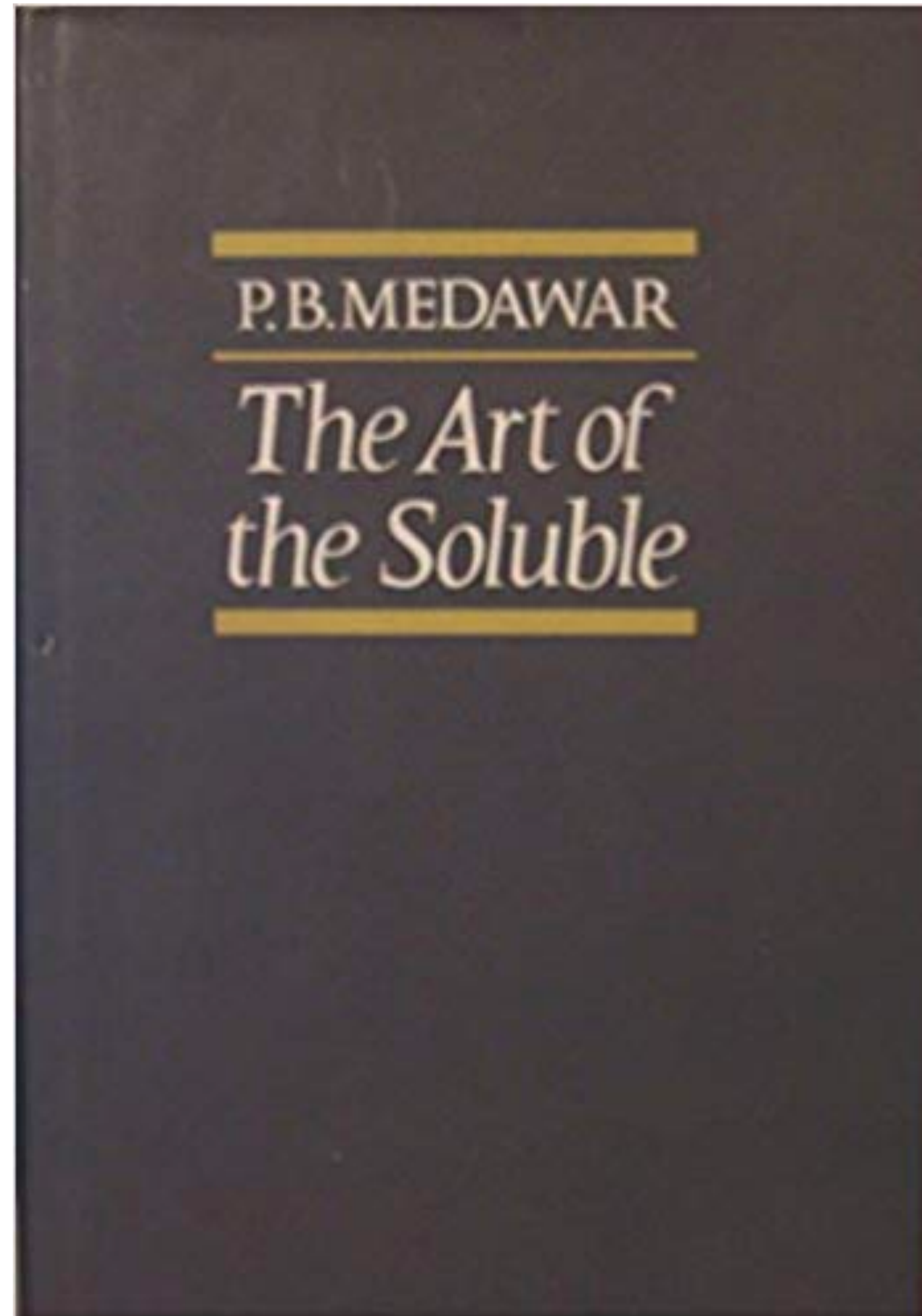
Communication



Picking a topic



Science is the “Art of the Soluble”



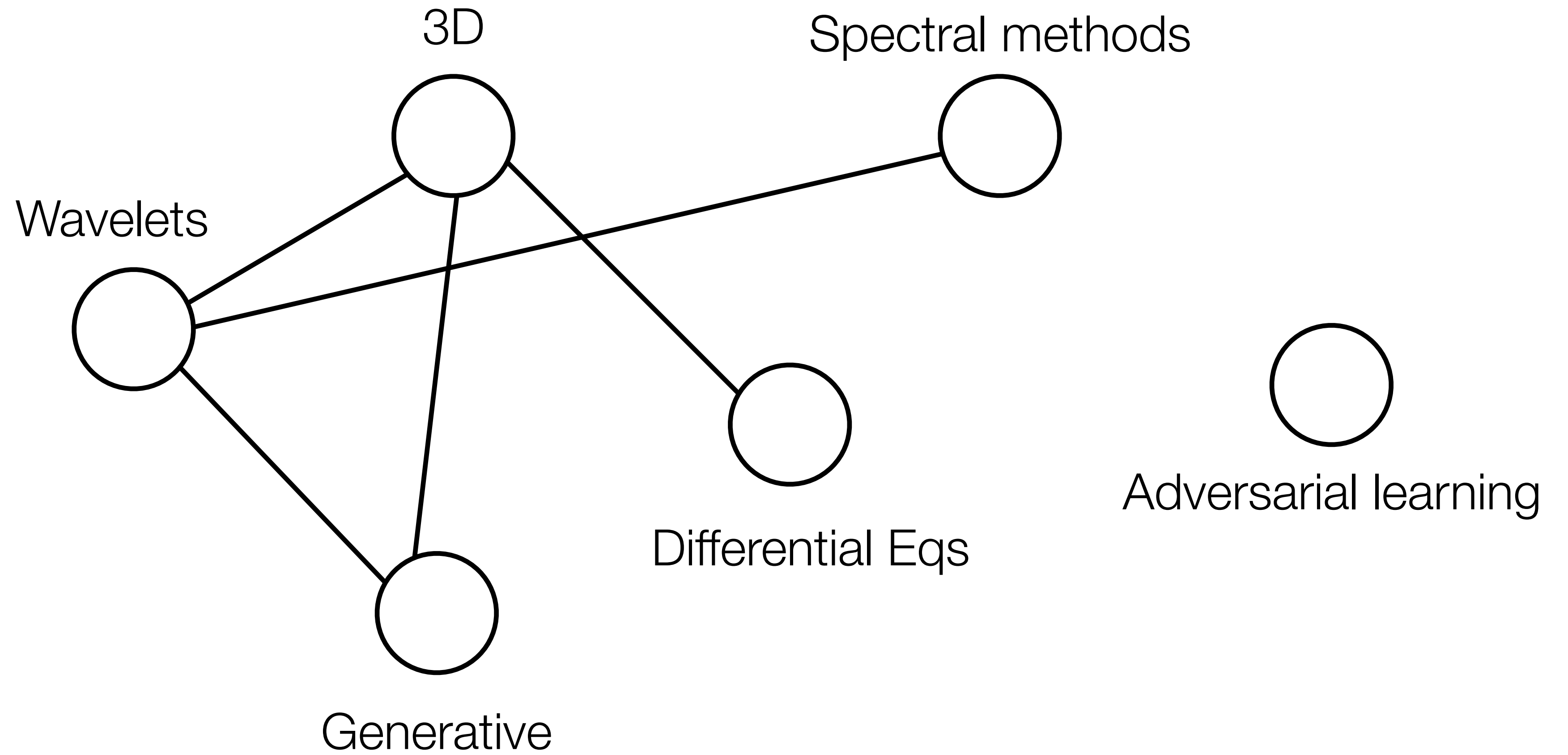
““Good scientists study the most important problems they think they can solve. It is, after all, their professional business to solve problems not to grapple with them.’ —Peter Medawar”
— Jitendra Malik

Identify limitations

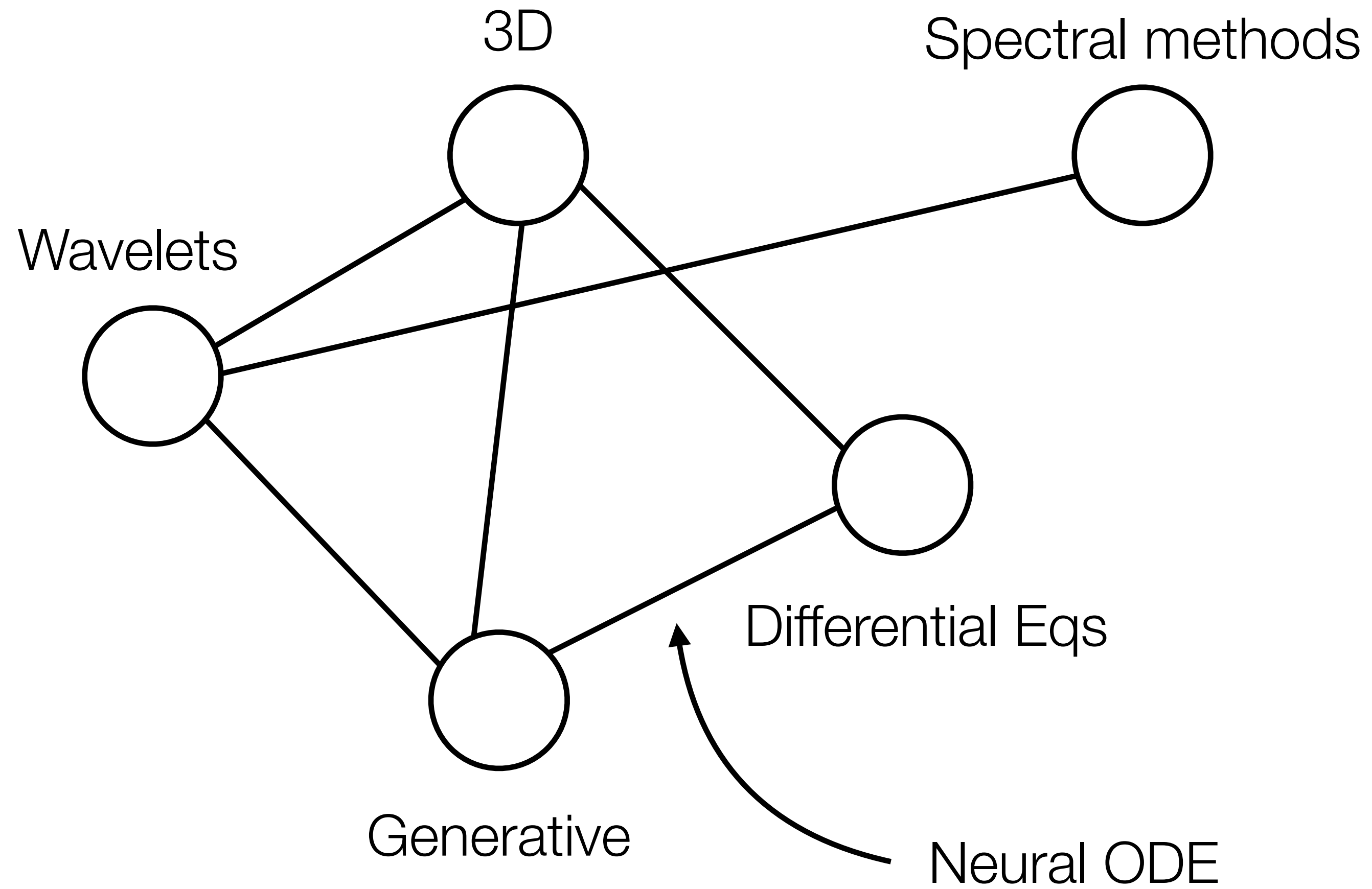
	Method	Train on data	One-pass Sampling	Exact log-likelihood	Free-form Jacobian
	Variational Autoencoders	✓	✓	✗	✓
	Generative Adversarial Nets	✓	✓	✗	✓
	Likelihood-based Autoregressive	✓	✗	✓	✗
Change of Variables	Normalizing Flows	✗	✓	✓	✗
	Reverse-NF, MAF, TAN	✓	✗	✓	✗
	NICE, Real NVP, Glow, Planar CNF	✓	✓	✓	✗
	FFJORD	✓	✓	✓	✓

Table 1: A comparison of the abilities of generative modeling approaches.

Add a node



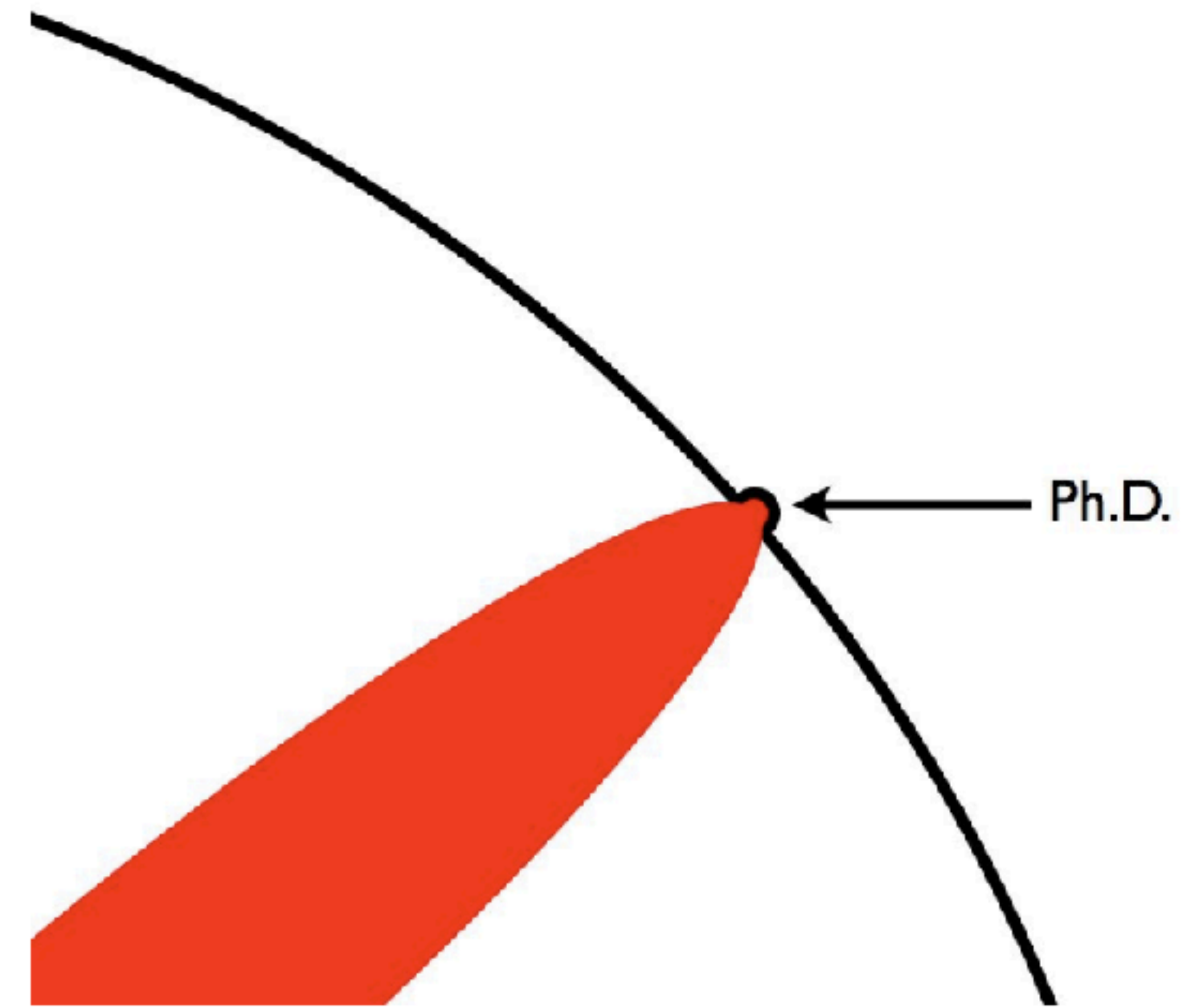
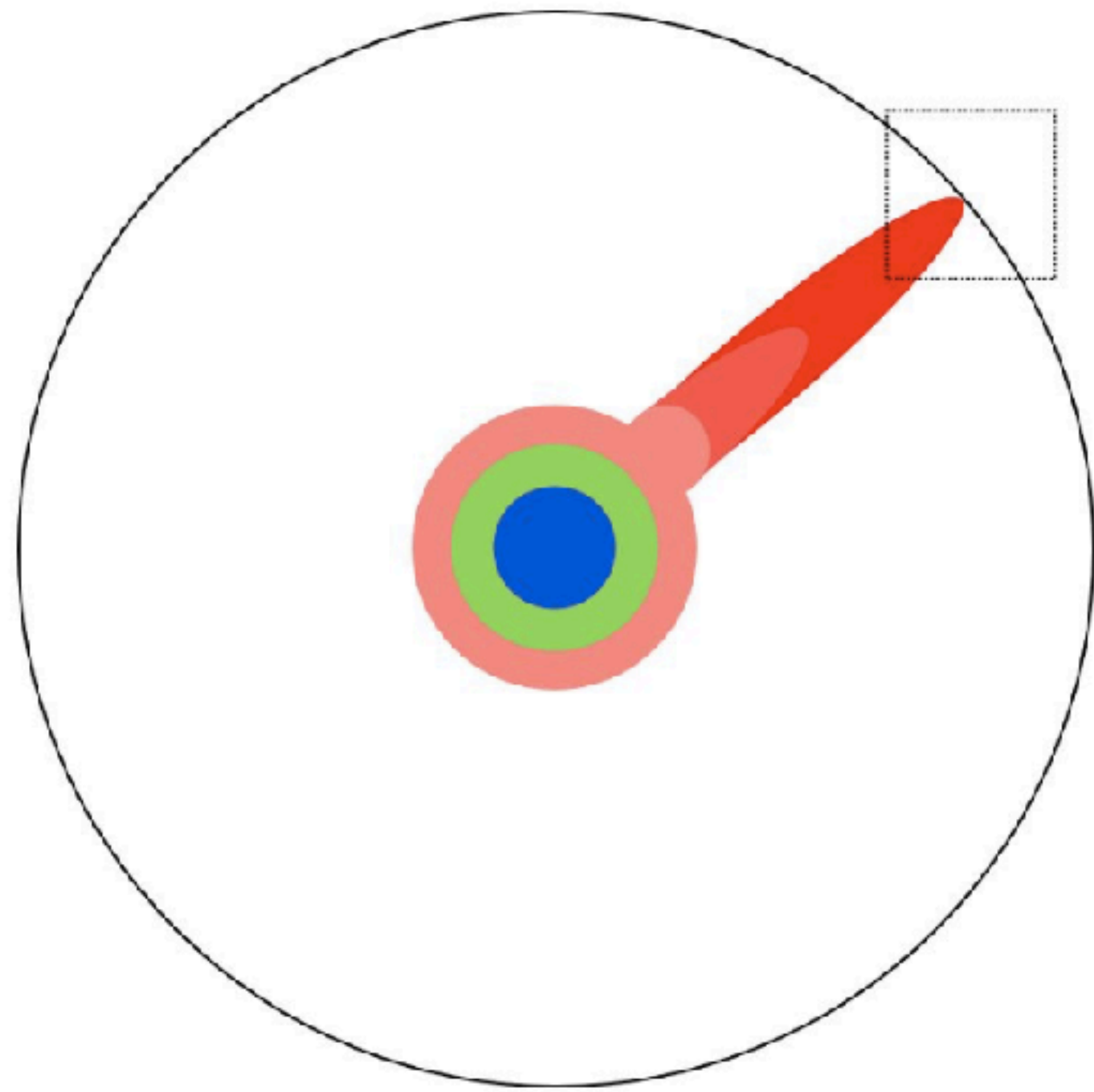
Add an edge

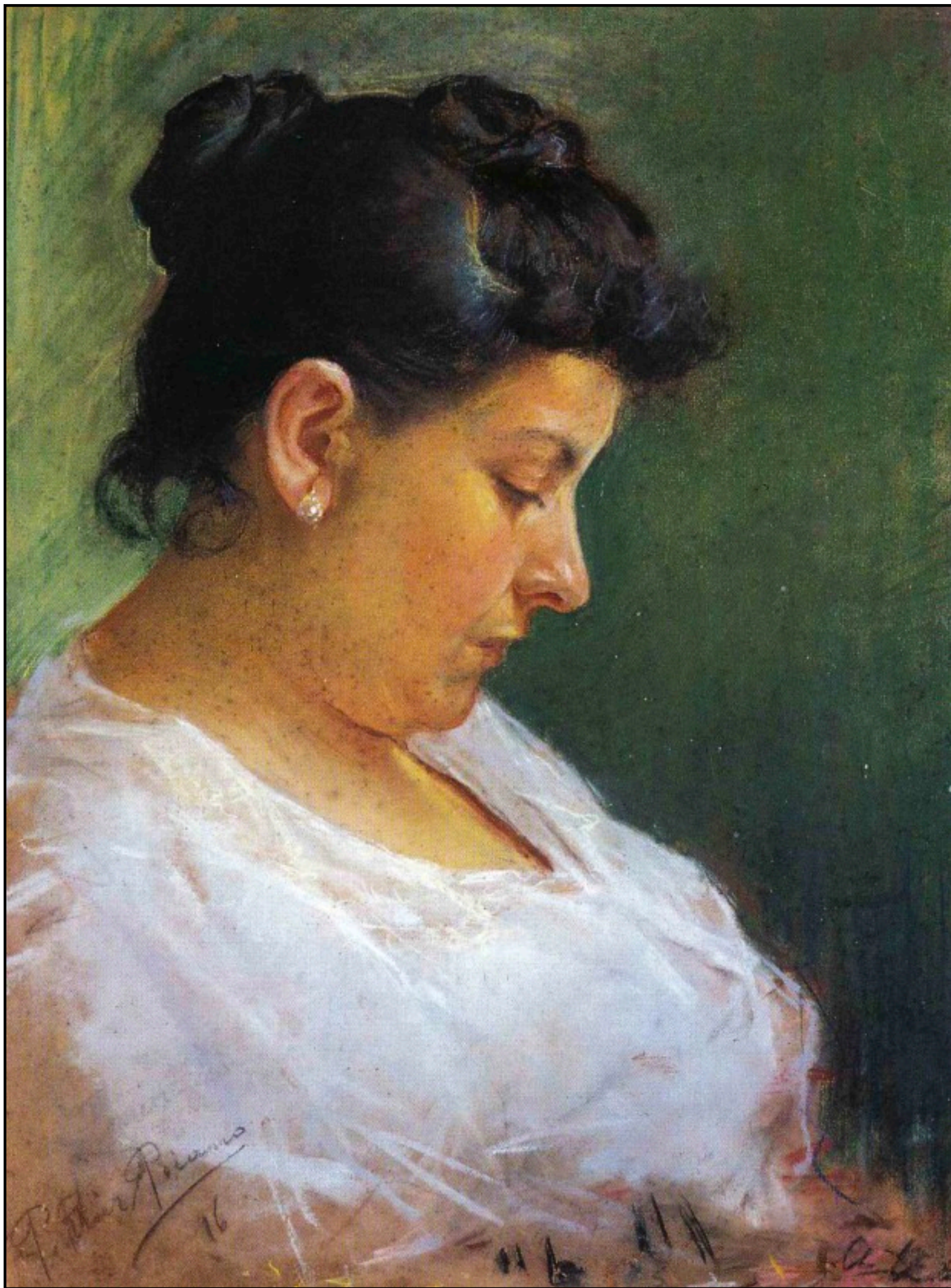


Novelty

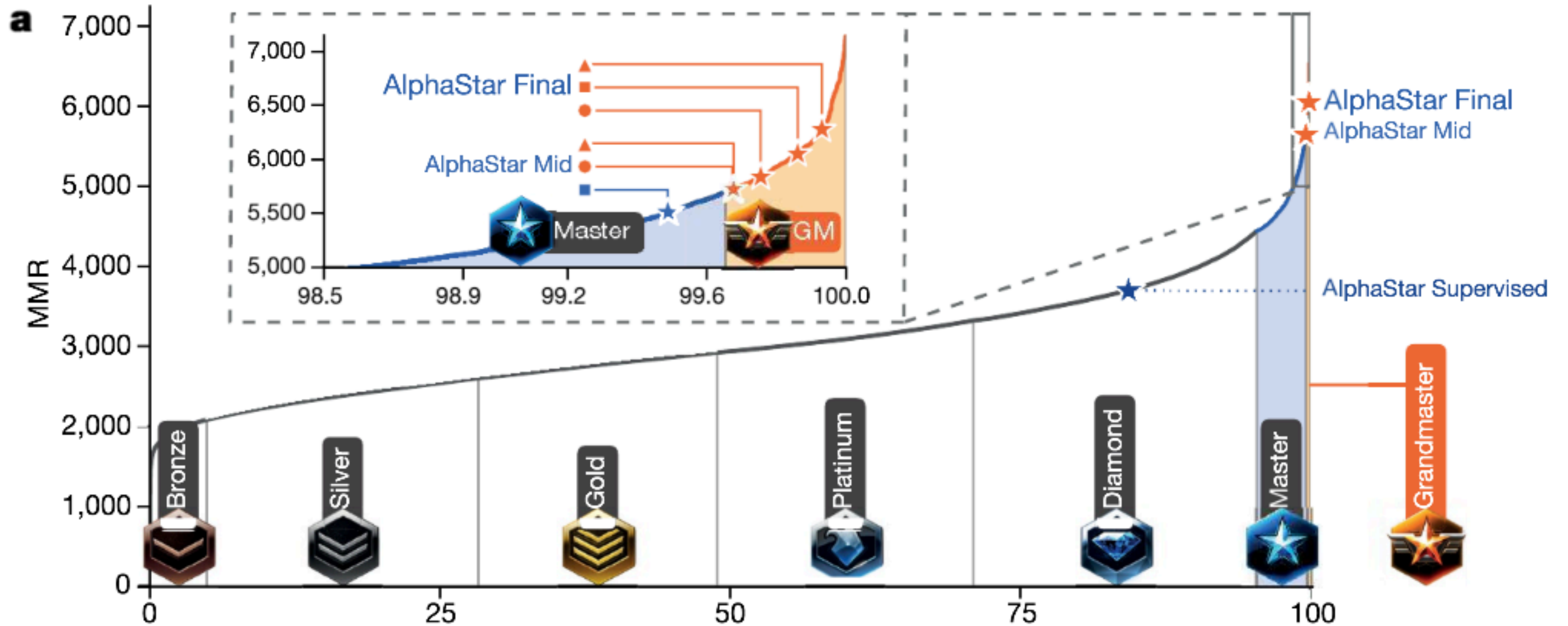
What matters is novelty w.r.t. humanity.

Very hard to achieve without knowing what has already been done.





[Picasso]



First imitates humans, then innovates

[“AlphaStar”, Vinyals et al., Nature 2019]

Know something no one else knows



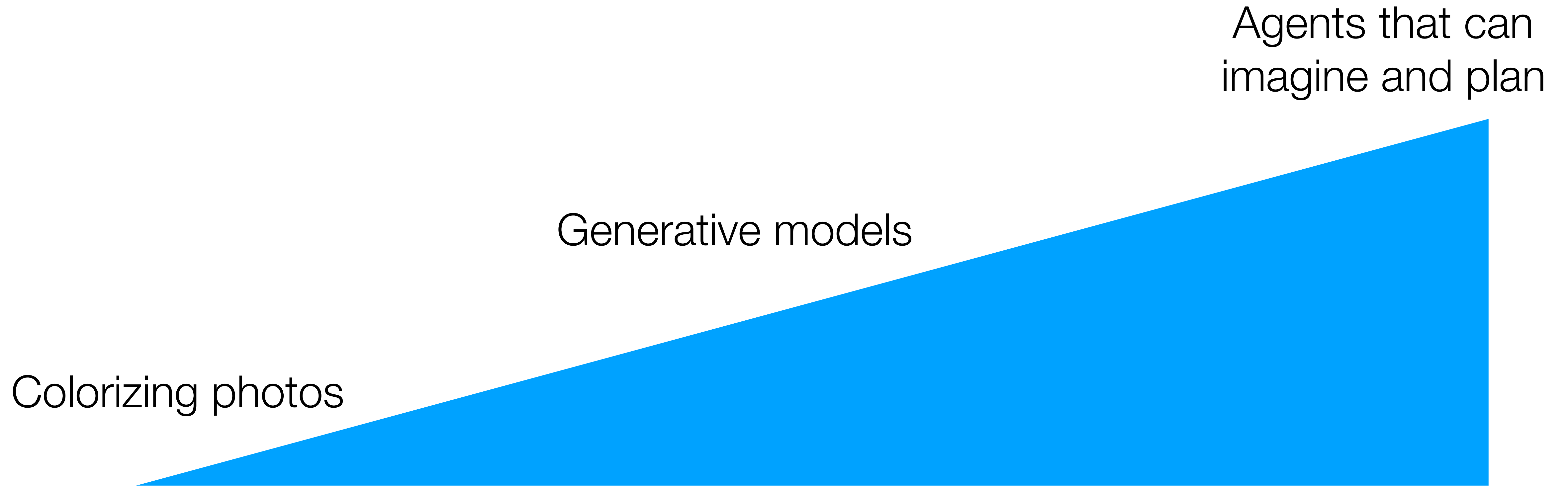
- It's necessary but not sufficient to master the core knowledge of your field

- Acquire a unique skillset

- Take difficult or unusual classes
- Read old papers
- Take on a complementary hobby
- Talk to people in other fields

“My answer to "Now What" is "here is a research problem which is unusual, perhaps significant, novel, that I can pose and probably solve because of my background in physics". The situation would not be readily identified as a problem at all by those whose background seems much more relevant than my own.”
— “Now What”, John Hopfield

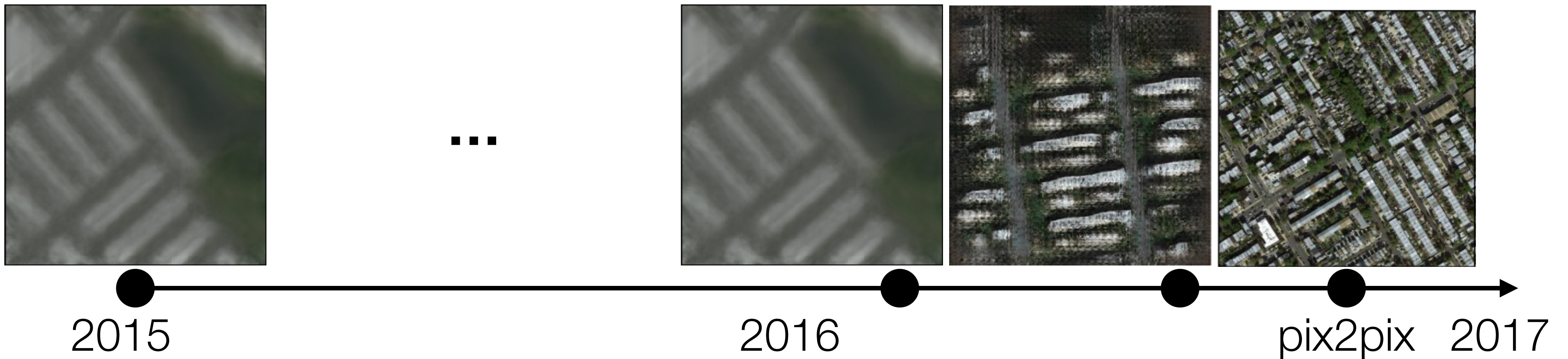
Build a ramp



“When you are famous it is hard to work on small problems. This is what did Shannon in. After information theory, what do you do for an encore? The great scientists often make this error. They fail to continue to plant the little acorns from which the mighty oak trees grow.”

— Richard Hamming, “You and Your Research”

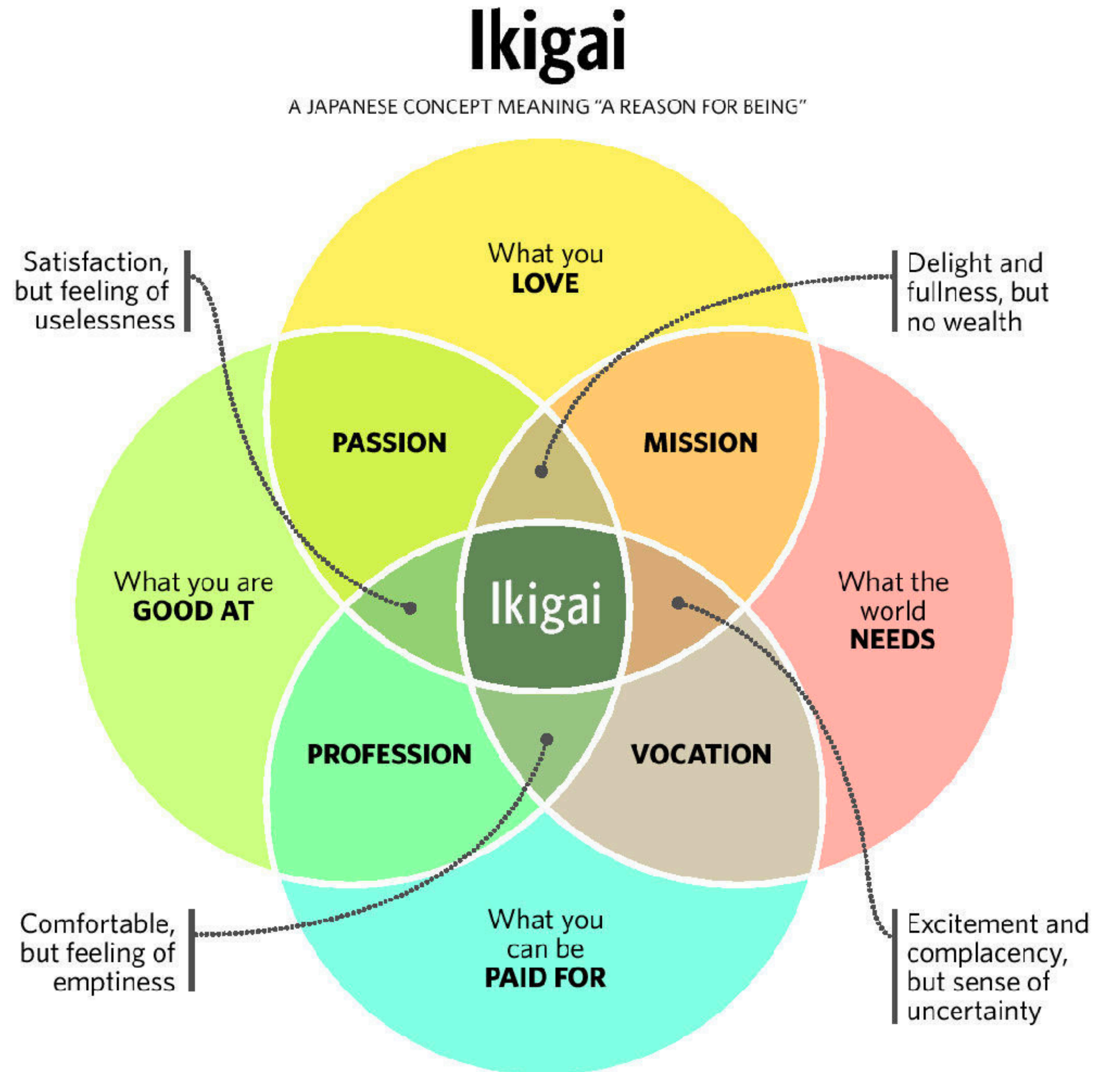
Research takes time



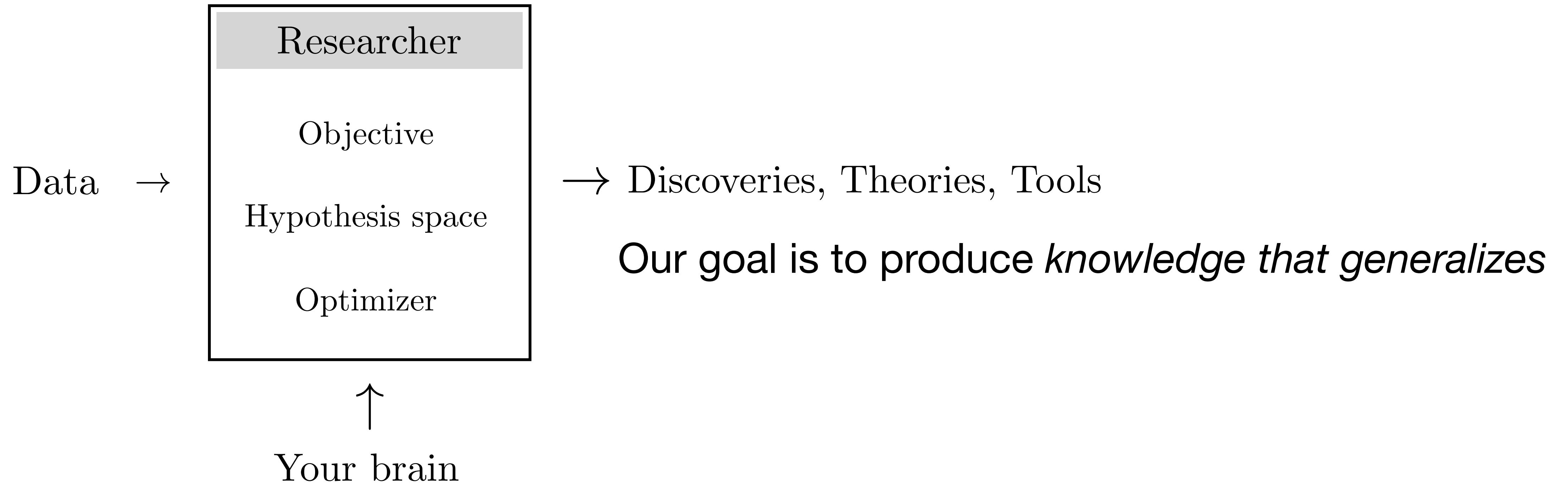
Picking a topic

Don't worry too much if a topic is unpopular

If it is important, and you do good work on it, you can *make it popular*



Doing good work on that topic



“One kind of result which probably won’t generalize is: “algorithm A works better than algorithm B.” Different application areas have their own requirements... The kind of result I believe generalizes to new situations is the nature of the tradeoffs between different approaches.”

— “Which Research Results Will Generalize?” Roger Grosse [<https://lips.cs.princeton.edu/which-research-results-will-generalize/>]

Fit the data

“Now I’m going to discuss how we would look for a new law. In general, we look for a new law by the following process. First, we guess it (audience laughter), no, don’t laugh, that’s the truth. Then we compute the consequences of the guess, to see what, if this is right, if this law we guess is right, to see what it would imply and then we compare the computation results to nature or we say compare to experiment or experience, compare it directly with observations to see if it works.

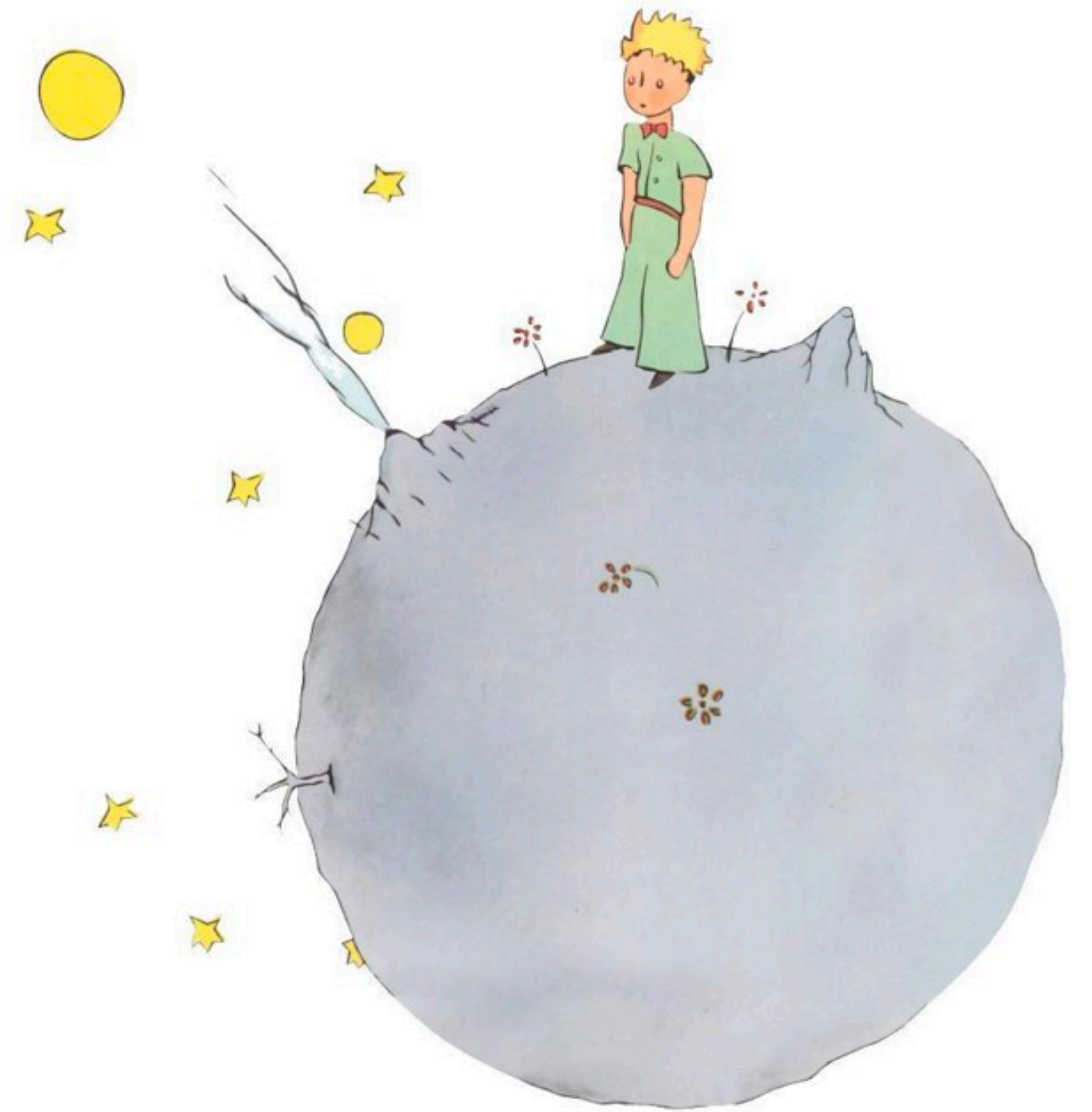
If it disagrees with experiment, it’s wrong. In that simple statement is the key to science. It doesn’t make any difference how beautiful your guess is, it doesn’t matter how smart you are who made the guess, or what his name is ... If it disagrees with experiment, it’s wrong. That’s all there is to it.”

— Richard Feynman

Omit needless bits

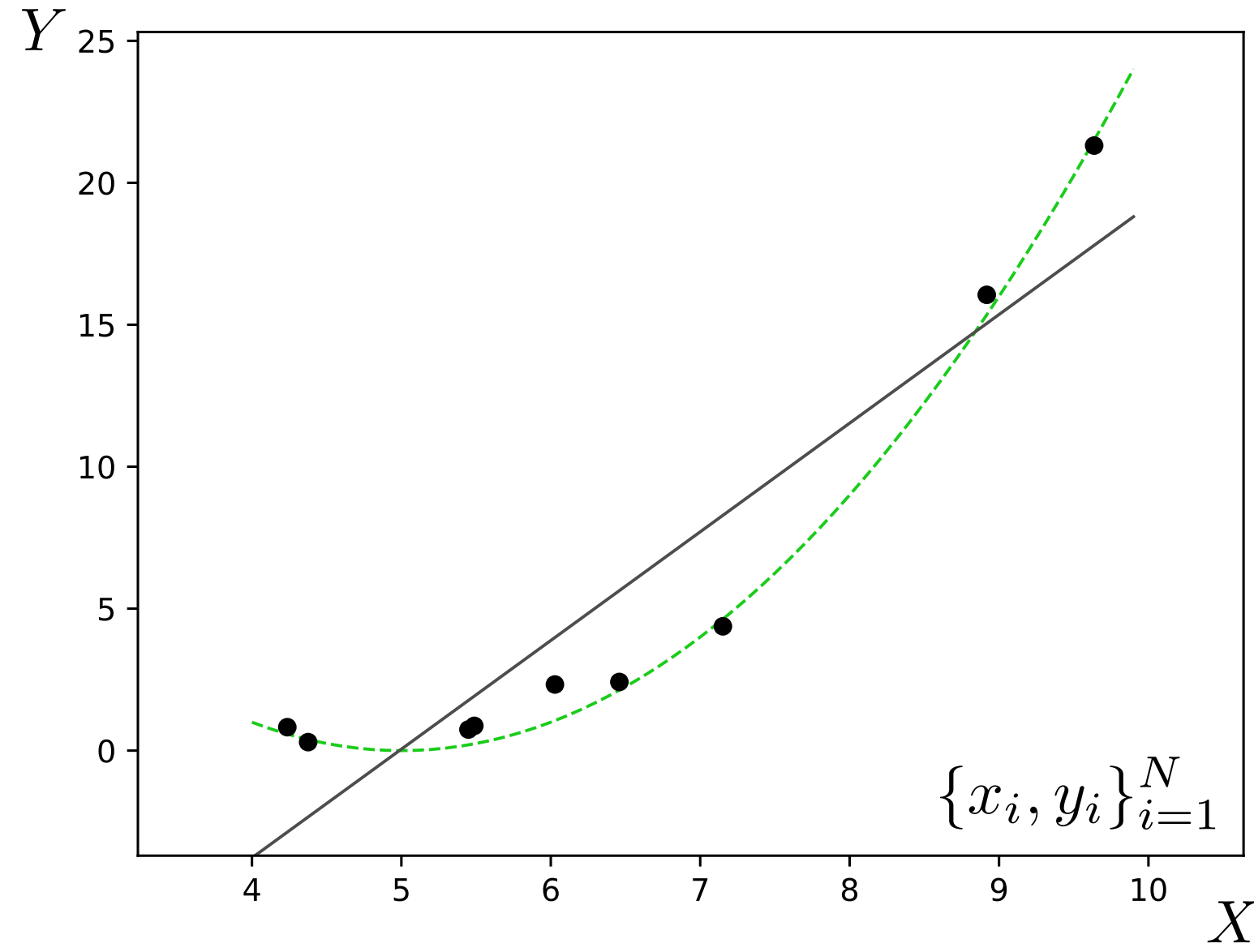
"Perfection is finally attained not when there is no longer anything to add, but when there is no longer anything to take away"

— Antoine de Saint Exupéry



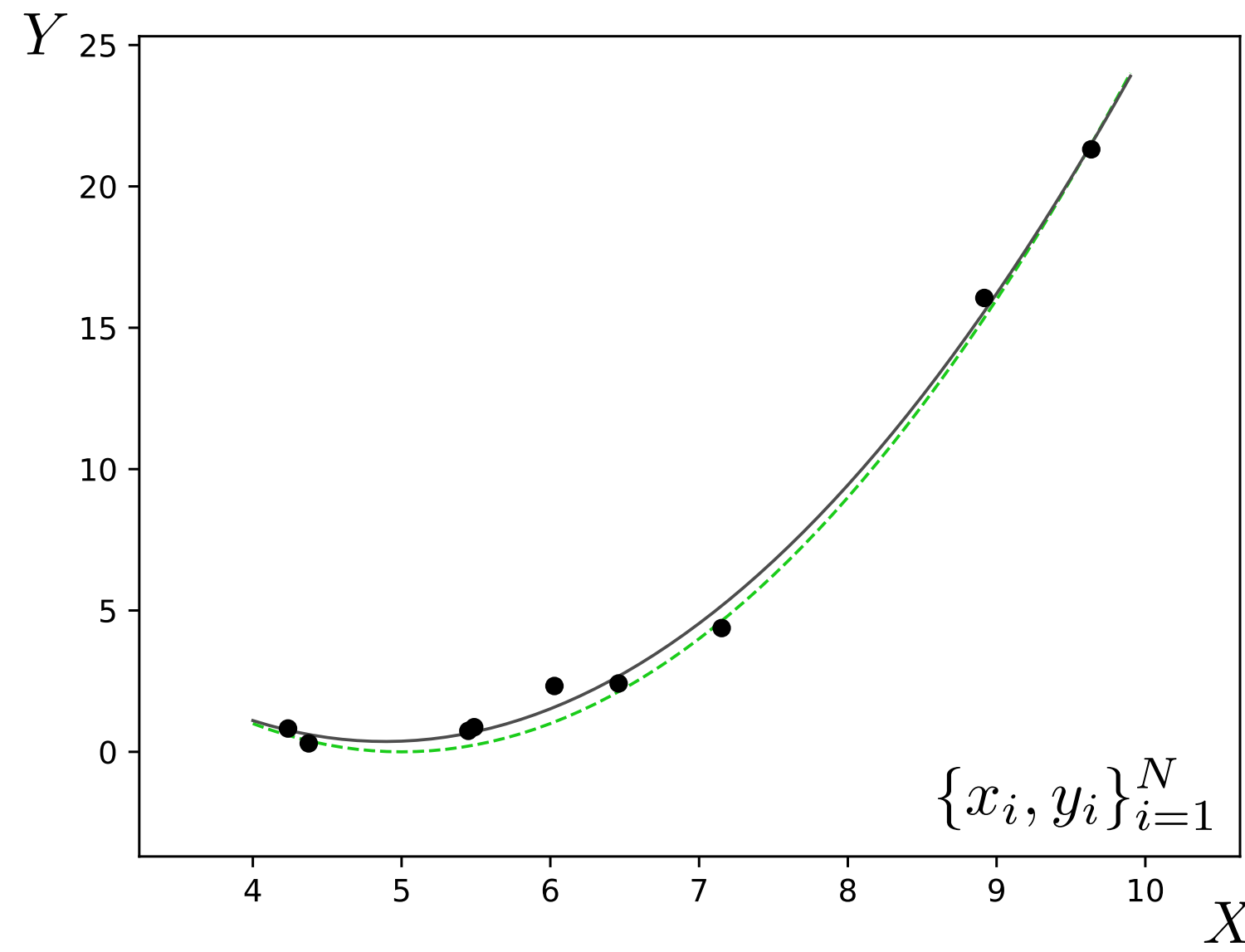
Underfitting

$$K = 1$$



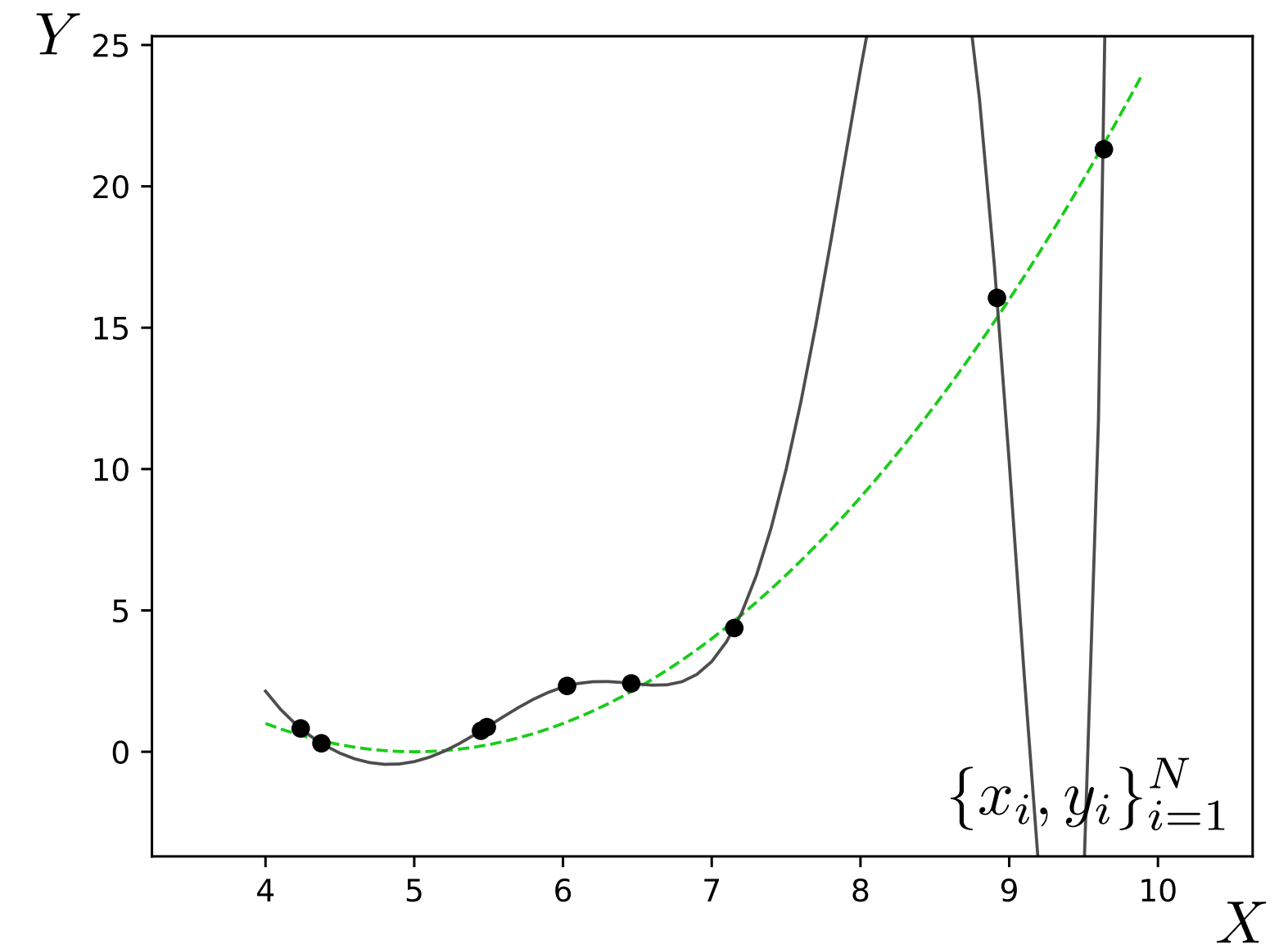
Appropriate model

$$K = 2$$

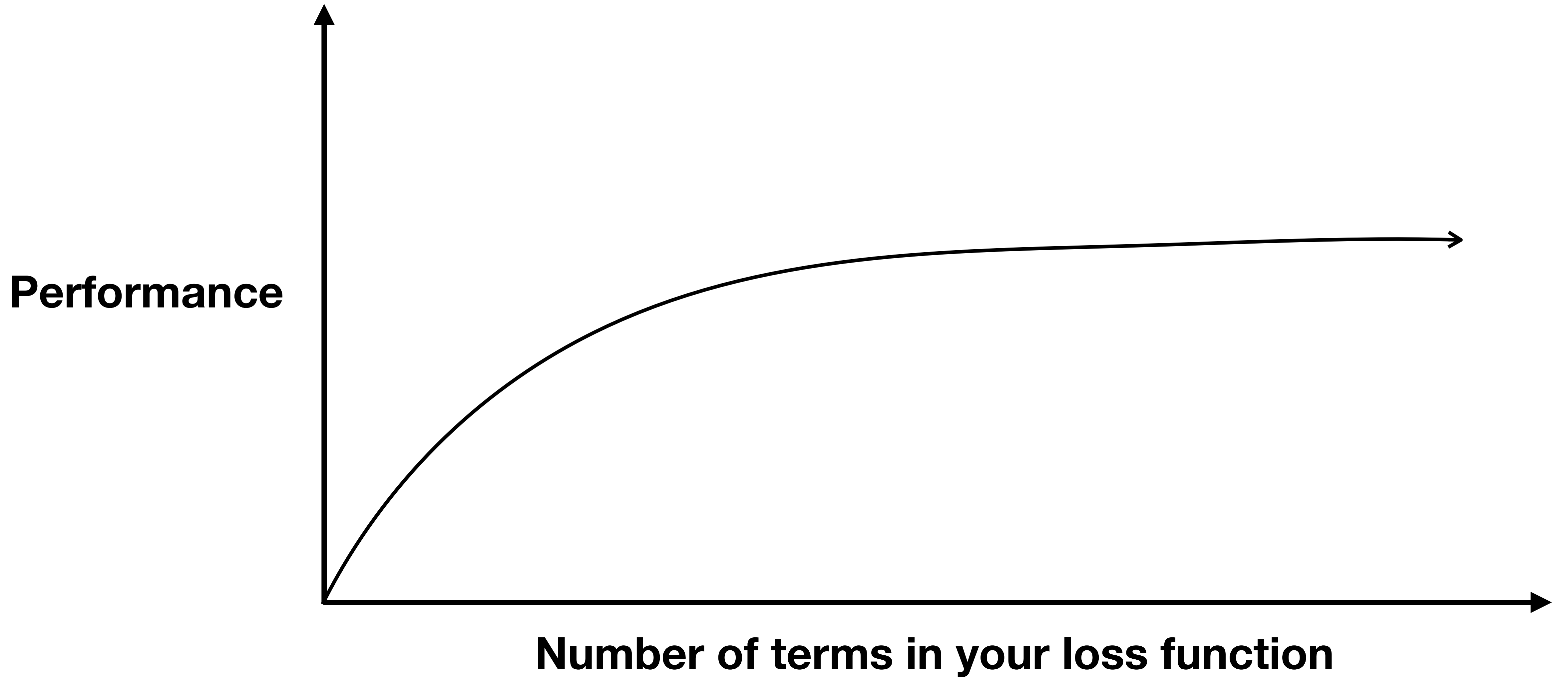


Overfitting

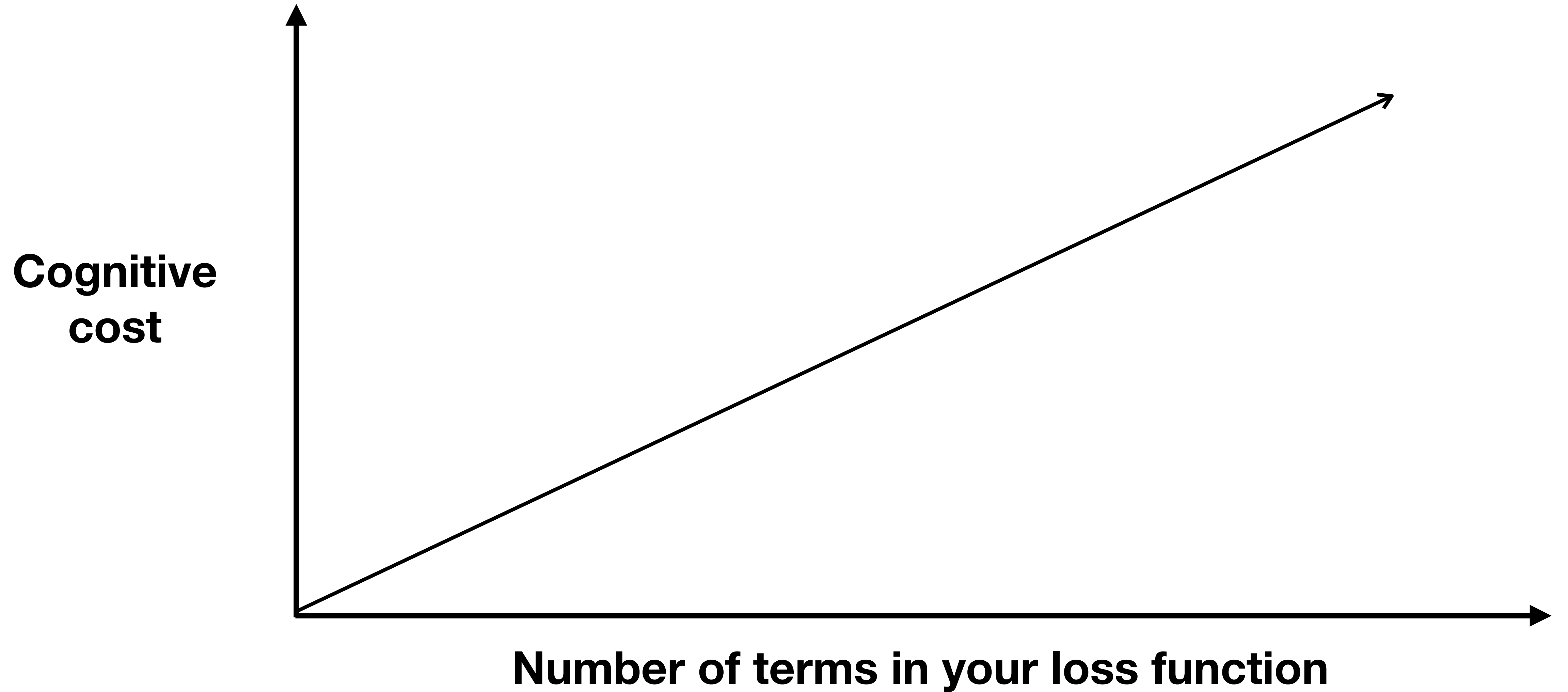
$$K = 10$$



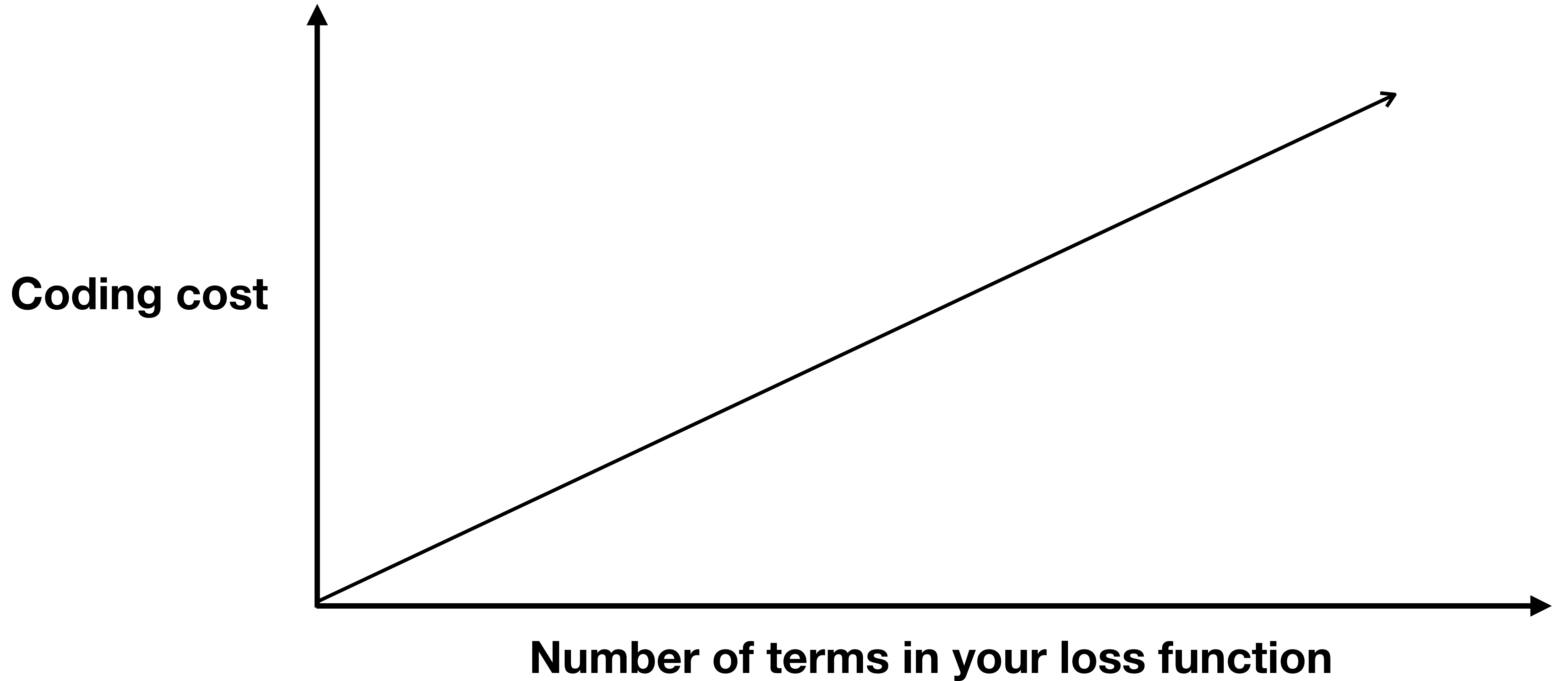
Information creep



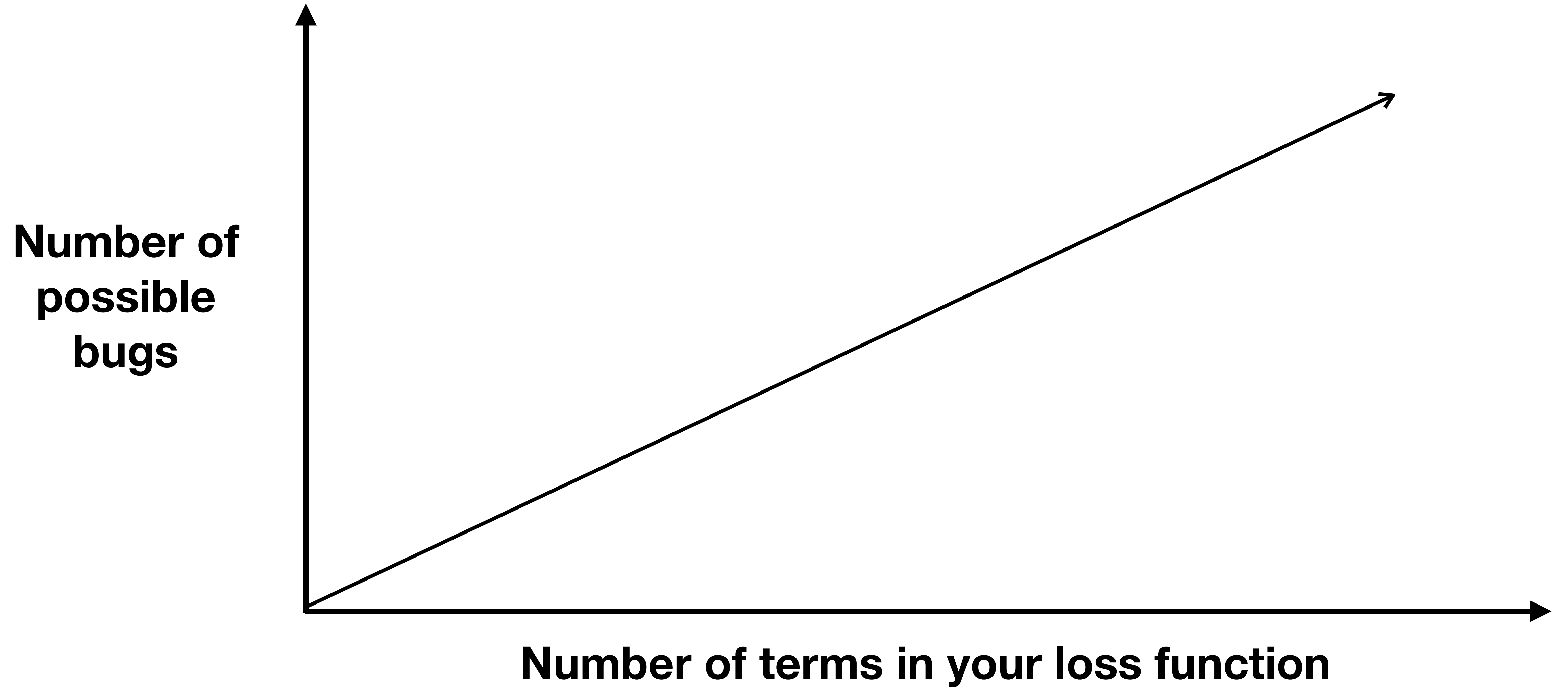
Information creep



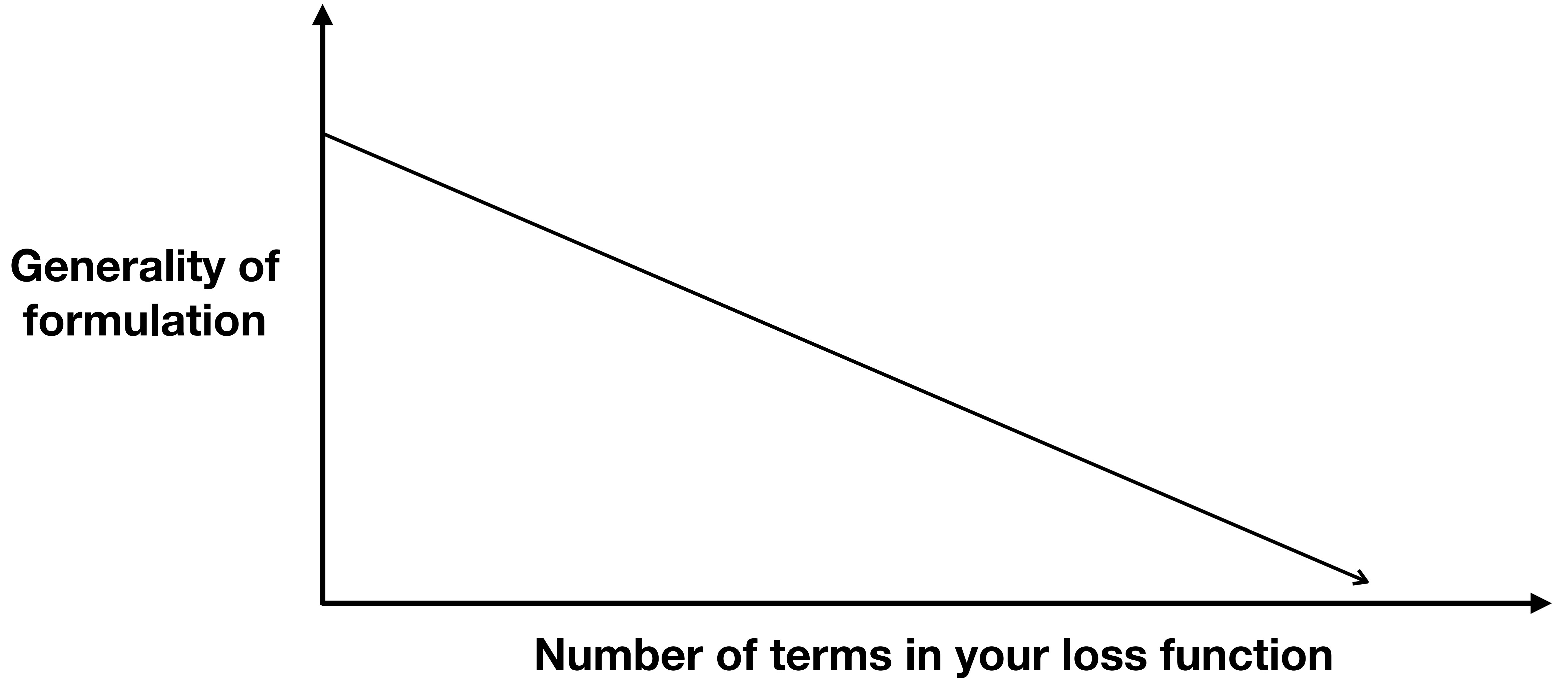
Information creep



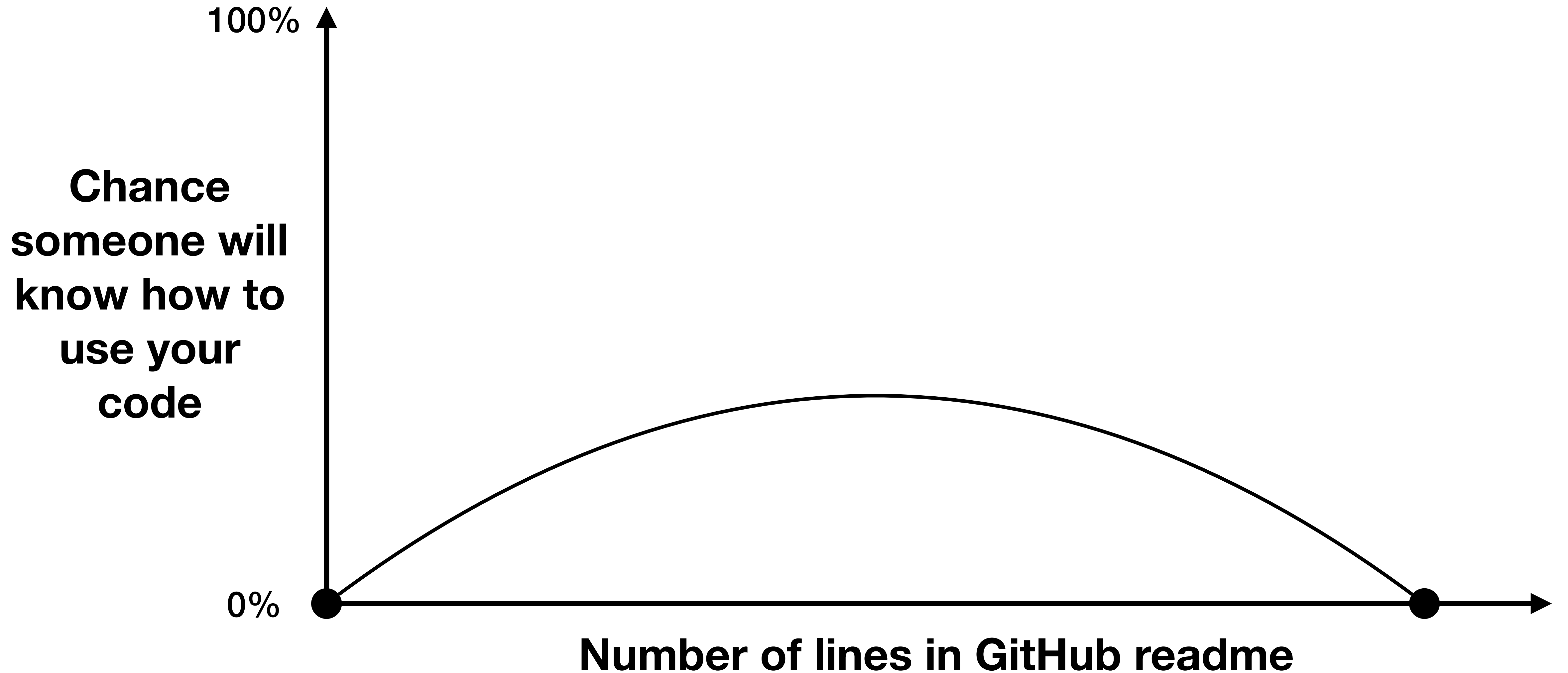
Information creep



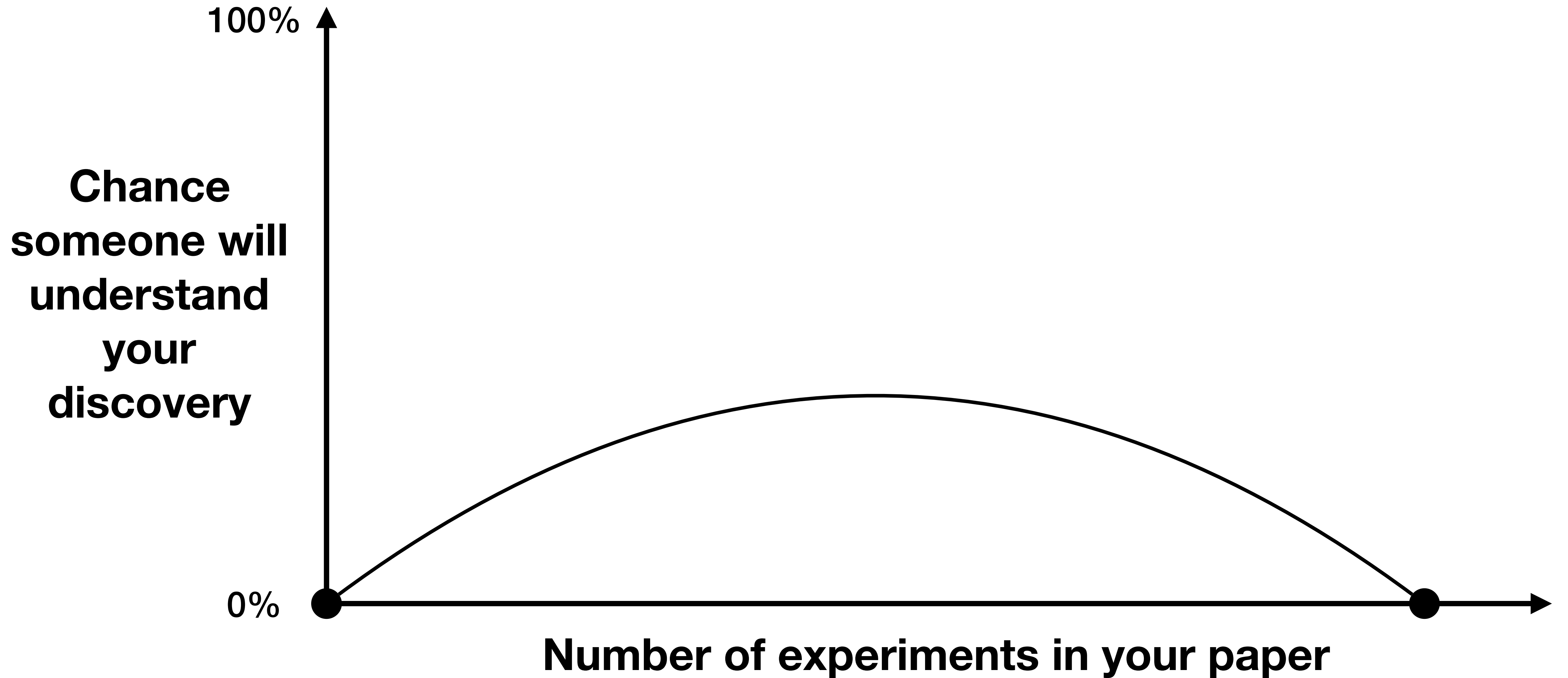
Information creep



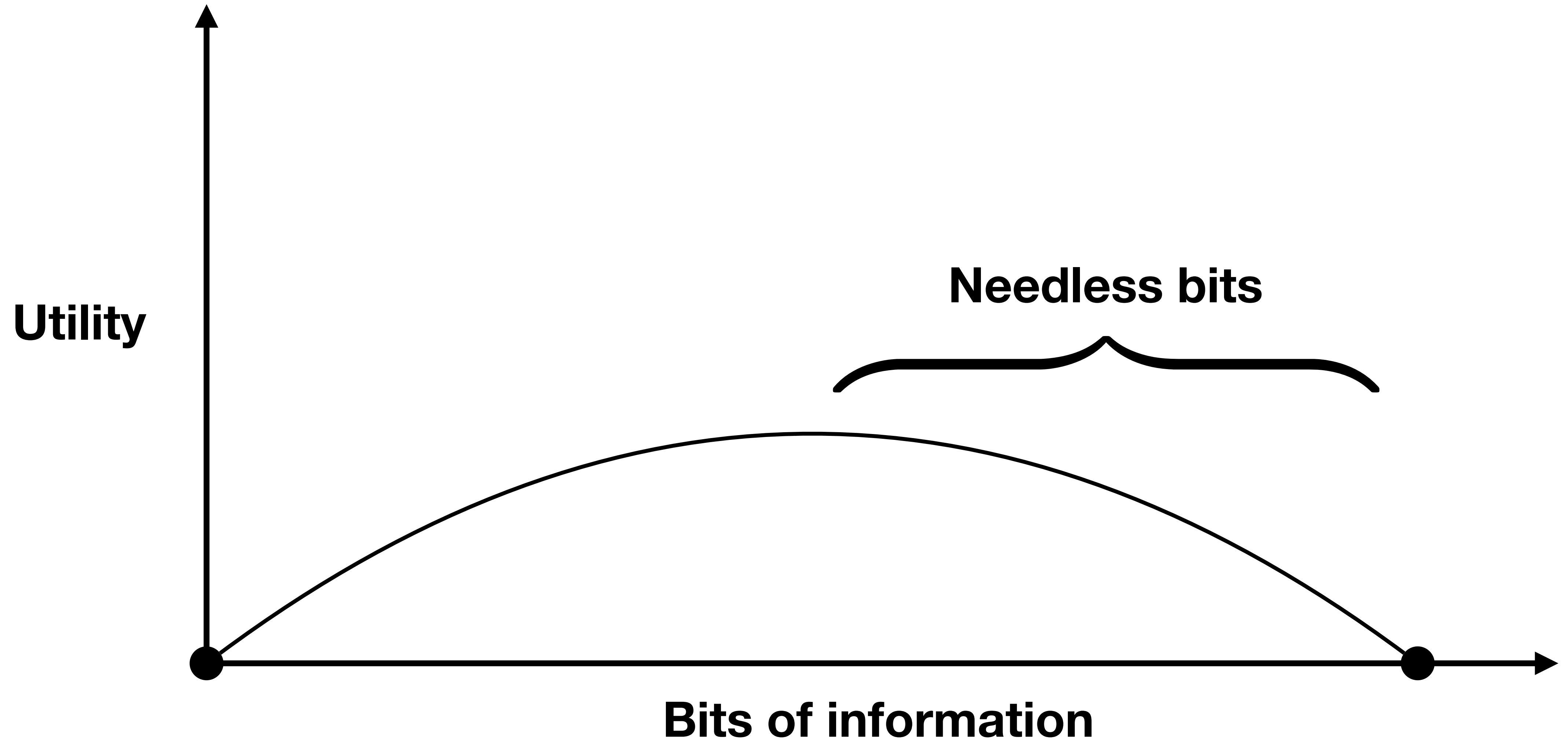
Information creep



Information creep



Information creep



Do the most, with the least

Products

Discoveries
Explanations
Results
Tools
...



=

Metric for research

Costs

Words
Equations
Concepts
Lines of code
GPUs
People, Time, Money
...

Avoid fallacies of conspicuous consumption

- This paper is really great, it used thousands of GPUs!
- The equations in this paper are so hard to decipher, I bet it is really powerful stuff
- “We present a simple but effective approach”
- The human brain is so fantastically complex we cannot hope to match it with today’s basic algorithms

Alpern’s razor (via Ted Adelson):

“Among competing hypotheses, the most boring is the most likely to be true.”

The regularizing force of human fallibility

- The vast majority of information at any given academic conference is forgotten — that's a good thing
- We tend to forget all but the simplest and starkest discoveries
- Complex and subtle discoveries are usually either overfit or unimportant

[\[https://www.youtube.com/watch?v=mrw4KIP5en0\]](https://www.youtube.com/watch?v=mrw4KIP5en0)

The sociotechnical forces
against overfitting

Moritz Hardt
UC Berkeley

Reviews

Review of “Generative Adversarial Networks”, Goodfellow et al. 2014:

“The theoretical work is primitive, and the experiments are pretty basic.”

Neural Networks for Machine Learning

Lecture 6e

rmsprop: Divide the gradient by a running average
of its recent magnitude

Geoffrey Hinton
with
Nitish Srivastava
Kevin Swersky

Dropout

Srivastava, Nitish, et al. “Dropout: A simple way to prevent neural networks from overfitting.” *The Journal of Machine Learning Research* 15:1 (2014): 1929-1958.

- Srivastava’s Master’s(!) thesis.
- Training scheme that randomly masks neurons at every step.
- Usually gives a small performance boost.
- Mysterious.

This paper was rejected from NIPS in 2012, and propagated solely as a preprint on arxiv.