Week 1: Introduction

Matthew Caldwell

COMP0088 Introduction to Machine Learning • UCL Computer Science • Autumn 2024

Course Outline

1. Introduction

2. Linear Models
3. Non-Parametric Models
4. Linear Models Revisited
5. Neural Networks
6. More Neural Networks

→ Supervised Learning

7. Clustering & Dimensionality Reduction
8. Mixture Models & Expectation Maximisation

→ Unsupervised Learning

9. Deep Learning Applications & Pitfalls
10. Fun & Games

Prerequisites

- Linear Algebra
- Calculus
- Probability & Statistics
- Python Programming

→ NB: This is not a course in any of these subjects.

Our focus is **pragmatic**: these are tools we need to get stuff done.

Format

- Pre-recorded lectures
  → 1—2 hours in ~15 minute chunks
  - Video and slides available the previous week
  - Watch at your own pace
  - …but preferably **before** lab sessions!
- In person recap / Q&A
  → Friday, 16:00—17:00
  - Ask questions live or in advance on forum
  - Latter might get priority
- In person practical labs
  → Friday 10:00—12:00 / 12:00—14:00
  - These are the heart of the module!
  - Exercises available the previous week
- Optional drop in – “office hour”
  → Friday 15:00—16:00, Hub 4
  - One-to-one or small group
  - For “private” questions
  - Q&A session better for most topics

Assessment

- Exam (100% overall)
  - → Online
  - → 3 hours
  - → Open book
  - → Handwrite or type — you will also need to sketch some answers
  - → We will work through some practice papers towards the end of term
  - → Fair warning: the exam is not easy, but we'll do our best to make it fair

Ethos

- People learn in different ways
- You are responsible for your own engagement
  - → If you can’t stand to watch the videos, at least read the slides
  - → Whatever you do, do it before Friday!
- ML is a practical discipline mediated by programming
  - → Doing the practical exercises will really help your understanding
  - → If you shun programming you won’t get the most from ML
  - → But: there is no coding in the exam

Week 1 Recap

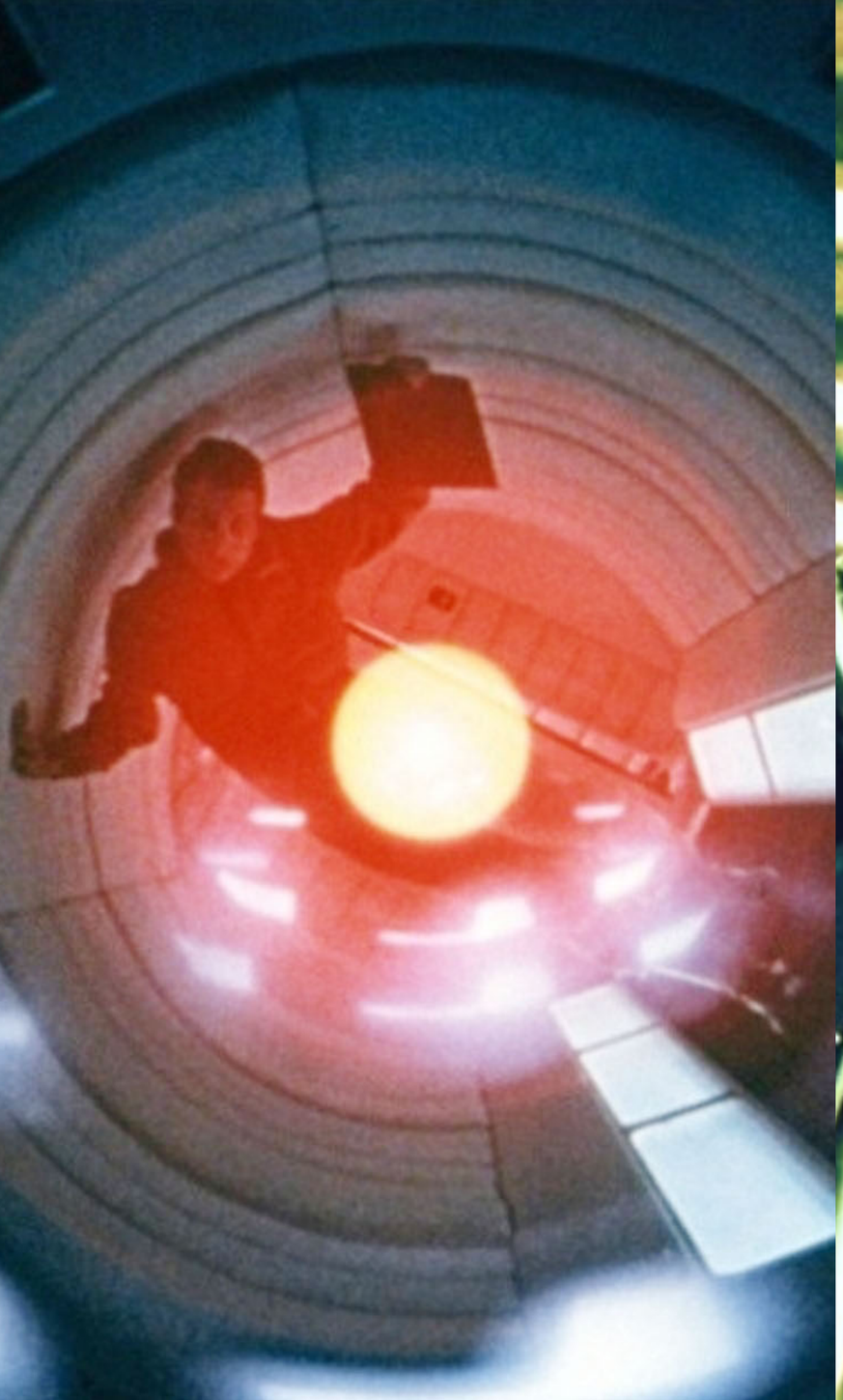
The Three Laws of Machine Learning

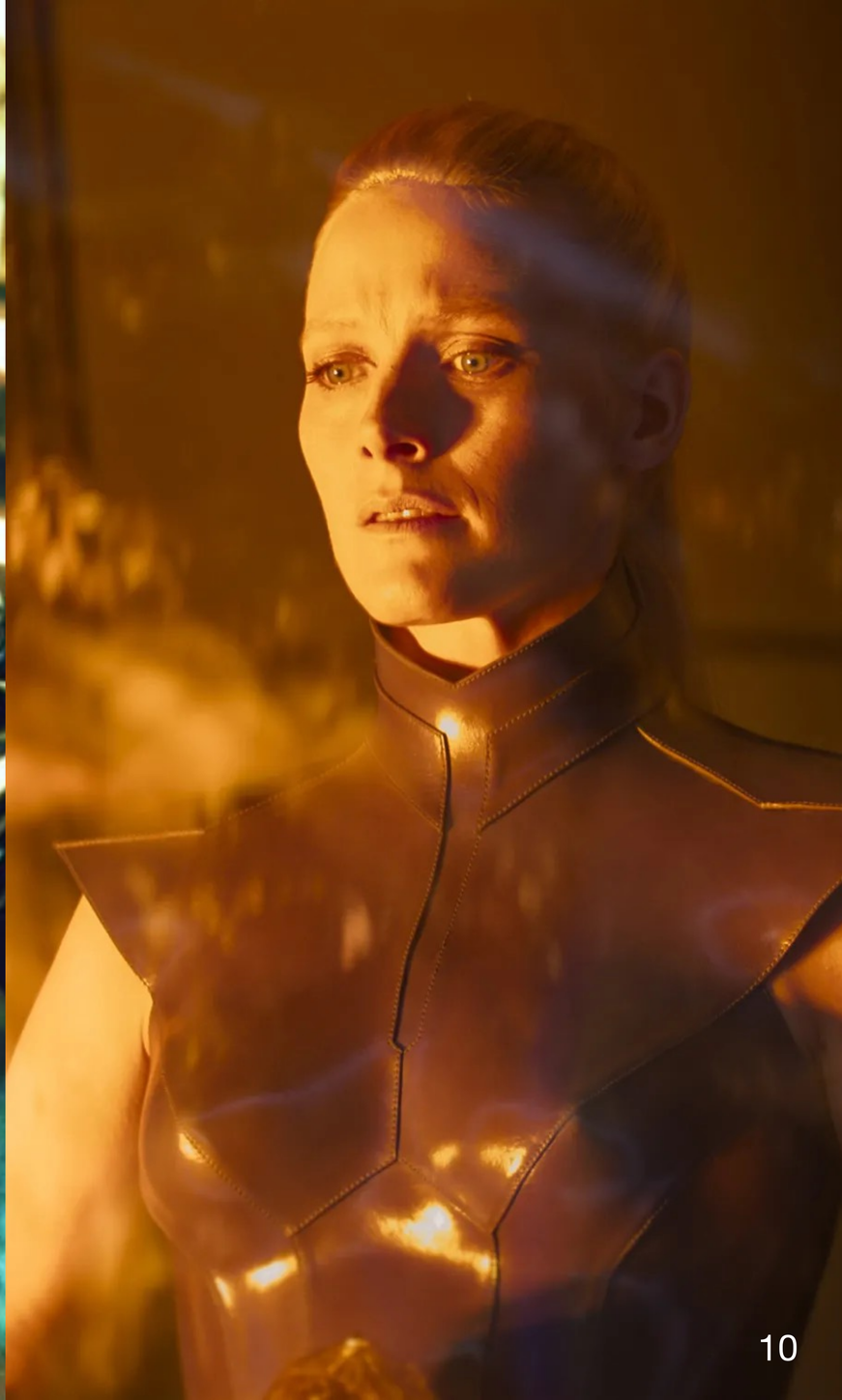
The Zeroth Law of Machine Learning

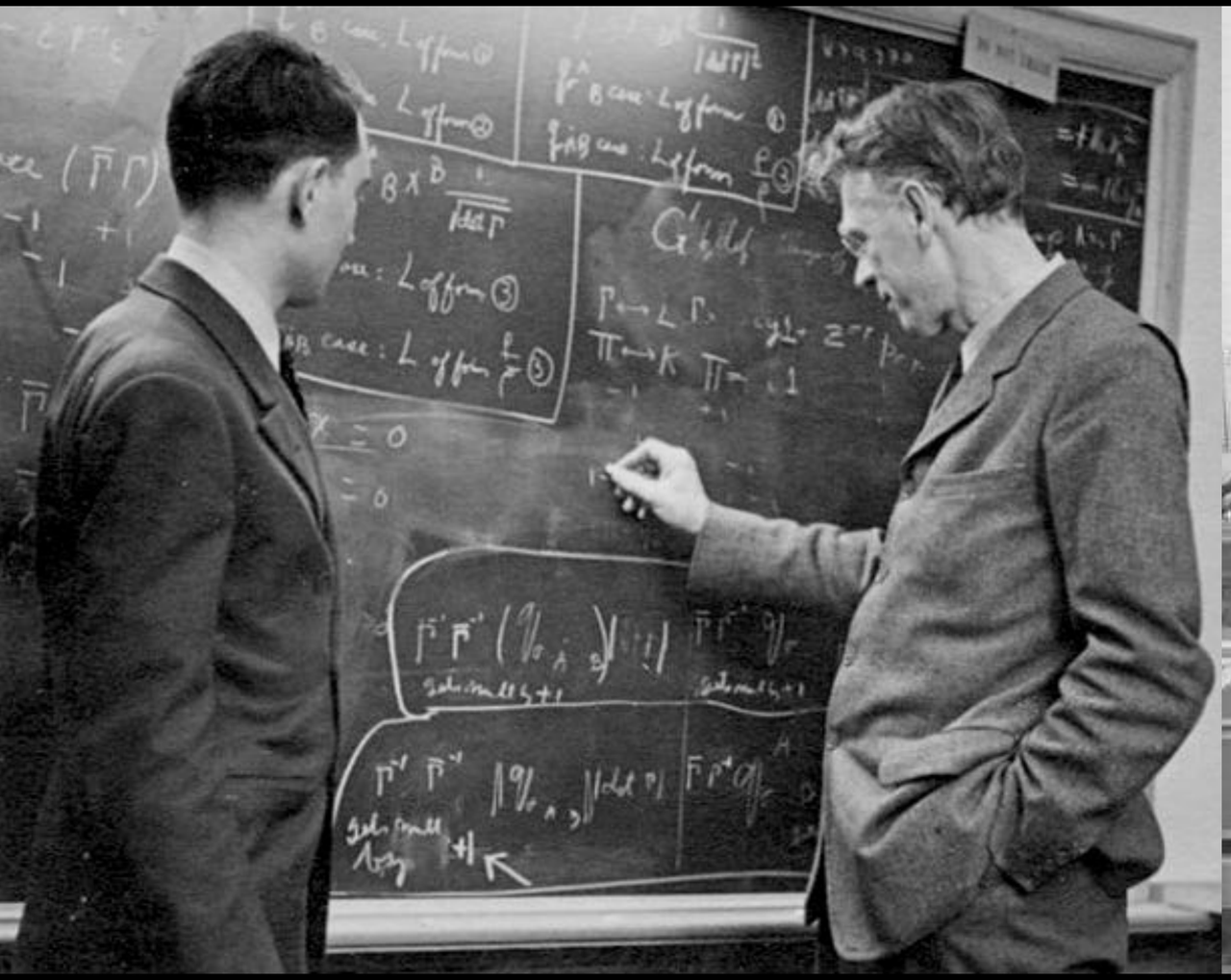
Laws are just models
and all models are wrong

The First Law of Machine Learning

Machine Learning is parameter fitting







learn | lə:n |
verb (past and past participle **learned** | lə:nt, lə:nd | or *mainly British* **learnt** | lə:nt |) *[with object]*

1 gain or acquire knowledge of or skill in (something) by study, experience, or being taught: *they'd started learning French* | *[with infinitive] : she is learning to play the piano* | *[no object] : we learn from experience*.

- commit to memory: *I'd learned too many grim poems in school*.
- become aware of (something) by information or from observation: *[with clause] : I learned that they had eaten already* | *[no object] : the trading standards office* ***learned of*** *the illegal network*.

2 *archaic or informal* teach (someone): *'That'll learn you,' he chuckled* | *[with object and infinitive] : we'll have to learn you to milk cows*.

ChatGPT

Write a limerick about Jeremy Bentham

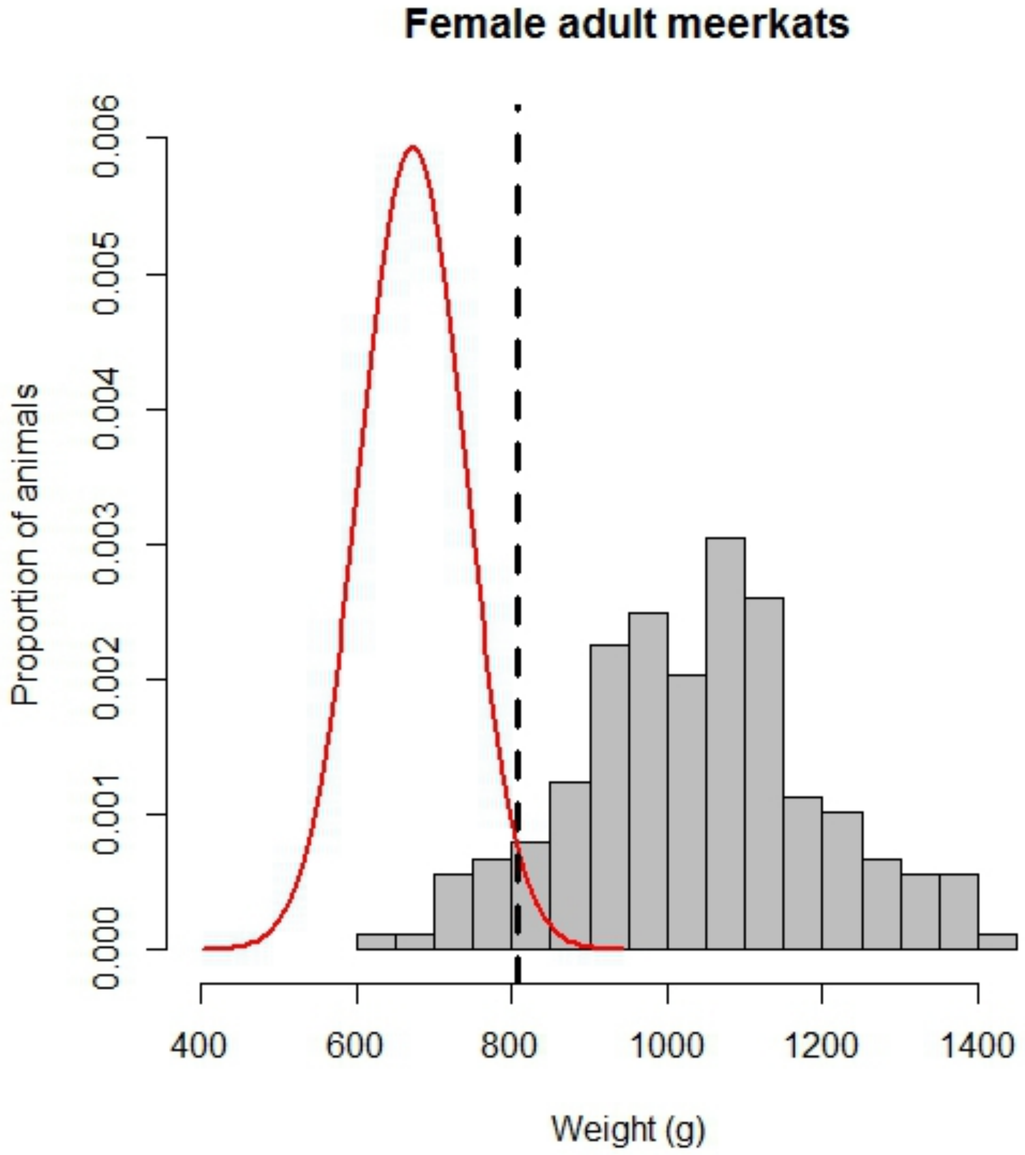
Jeremy Bentham, a thinker so bright,
In ethics, he shed a clear light.
Utilitarian he'd preach,
The greatest good within reach,
For happiness, he'd gladly fight!

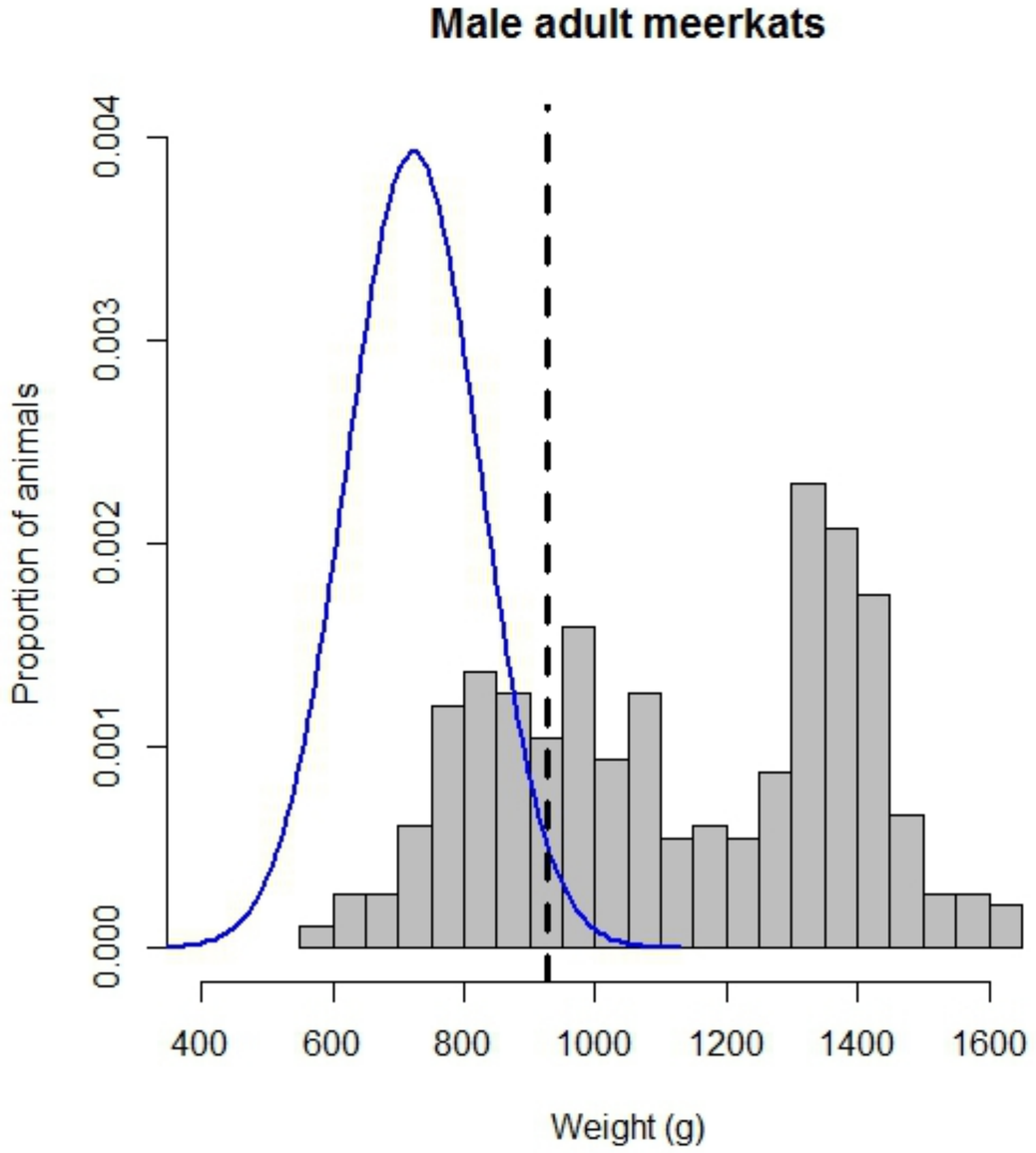
MidJourney

/imagine Boris Johnson appearing on Strictly Come Dancing after leaving politics in disgrace

The First Law of Machine Learning

Machine Learning is parameter fitting



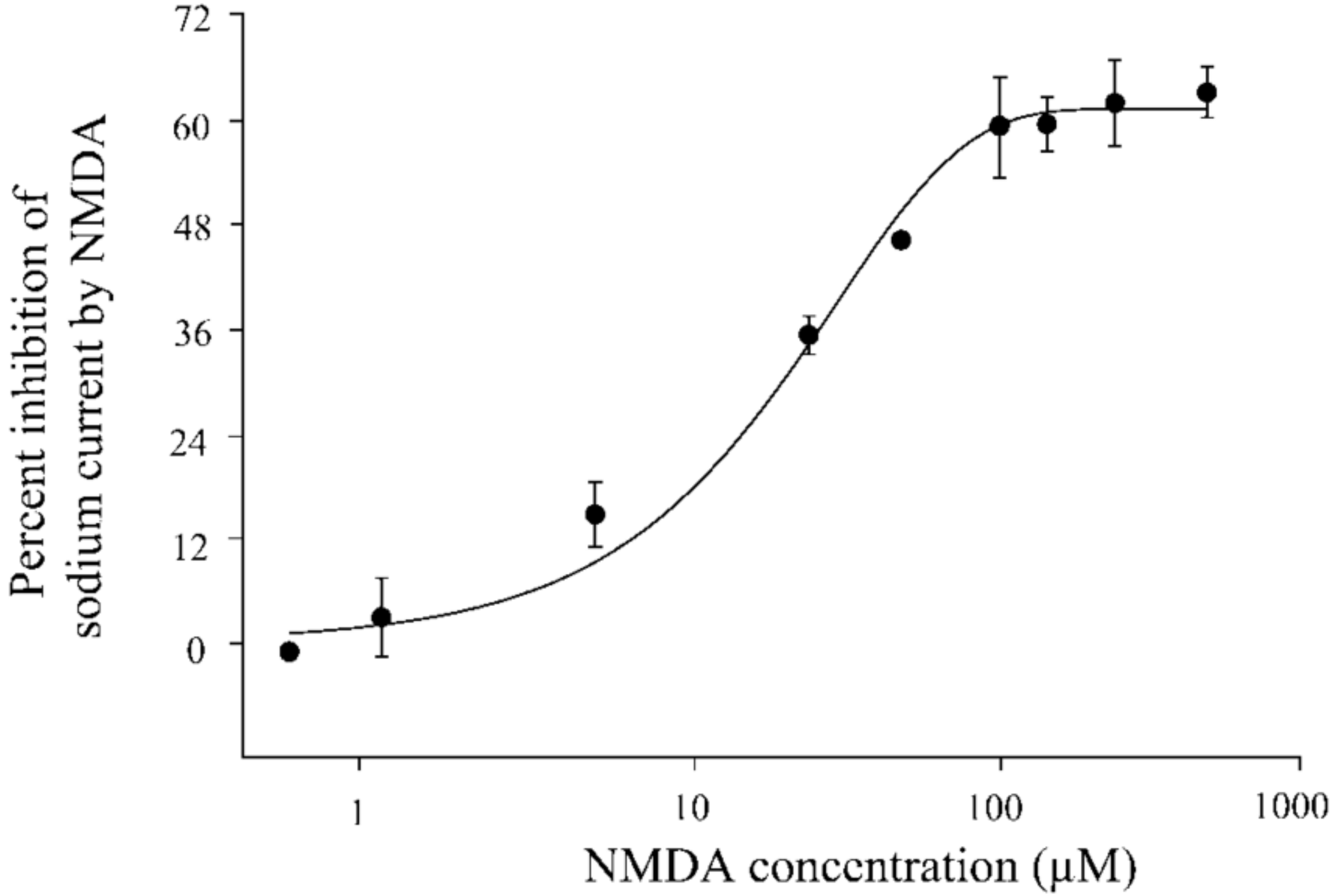


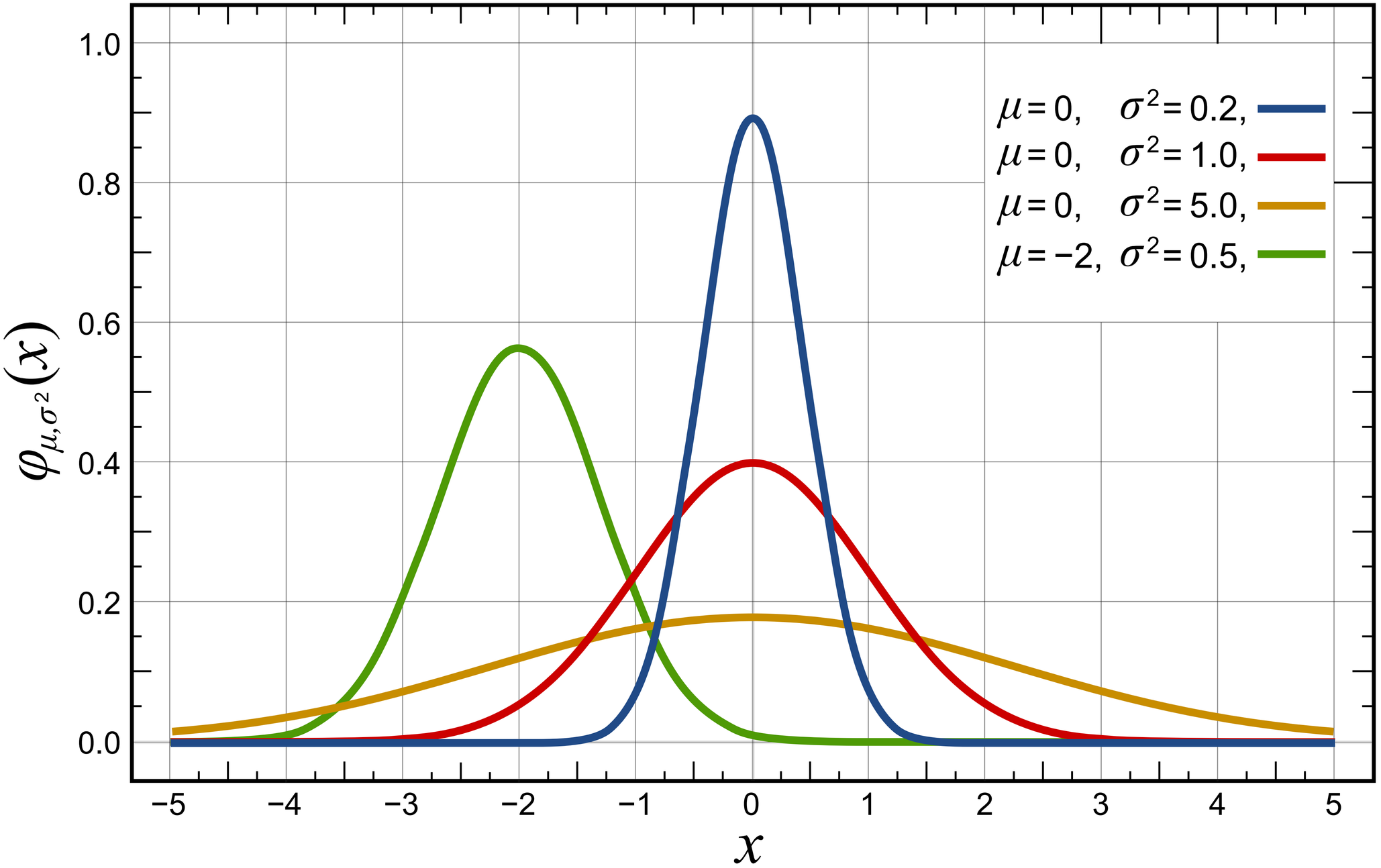
K. Scott, *Behaviour and Endocrinology of Meerkats in Zoos*, PhD Thesis, University of Essex, 2014

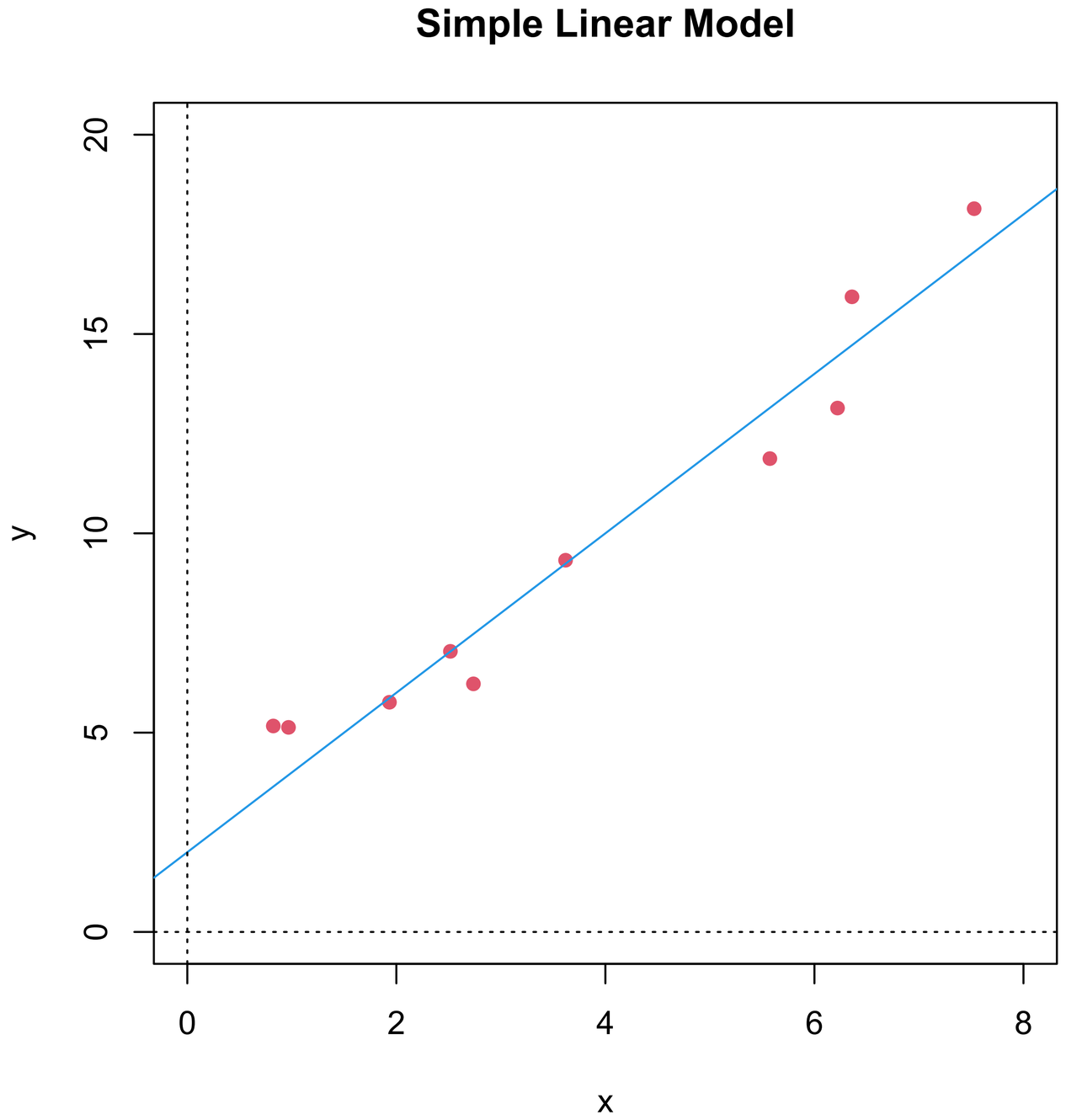
Higher average incomes are associated with higher life expectancy

Relationship between life expectancy and net household income for men and women, by neighbourhood: England, 2016–20

Sources: Health Foundation analysis of Office for National Statistics, Income Estimates for Small Areas, England & Wales, 2017/18;, Life expectancy at birth and age 65 by sex for Middle Layer Super Output Areas (MSOAs), England: 2016–20


Percent inhibition of sodium current by NMDA
72
60
48
36
24
12
0
1
10
100
1000
NMDA concentration (μM)

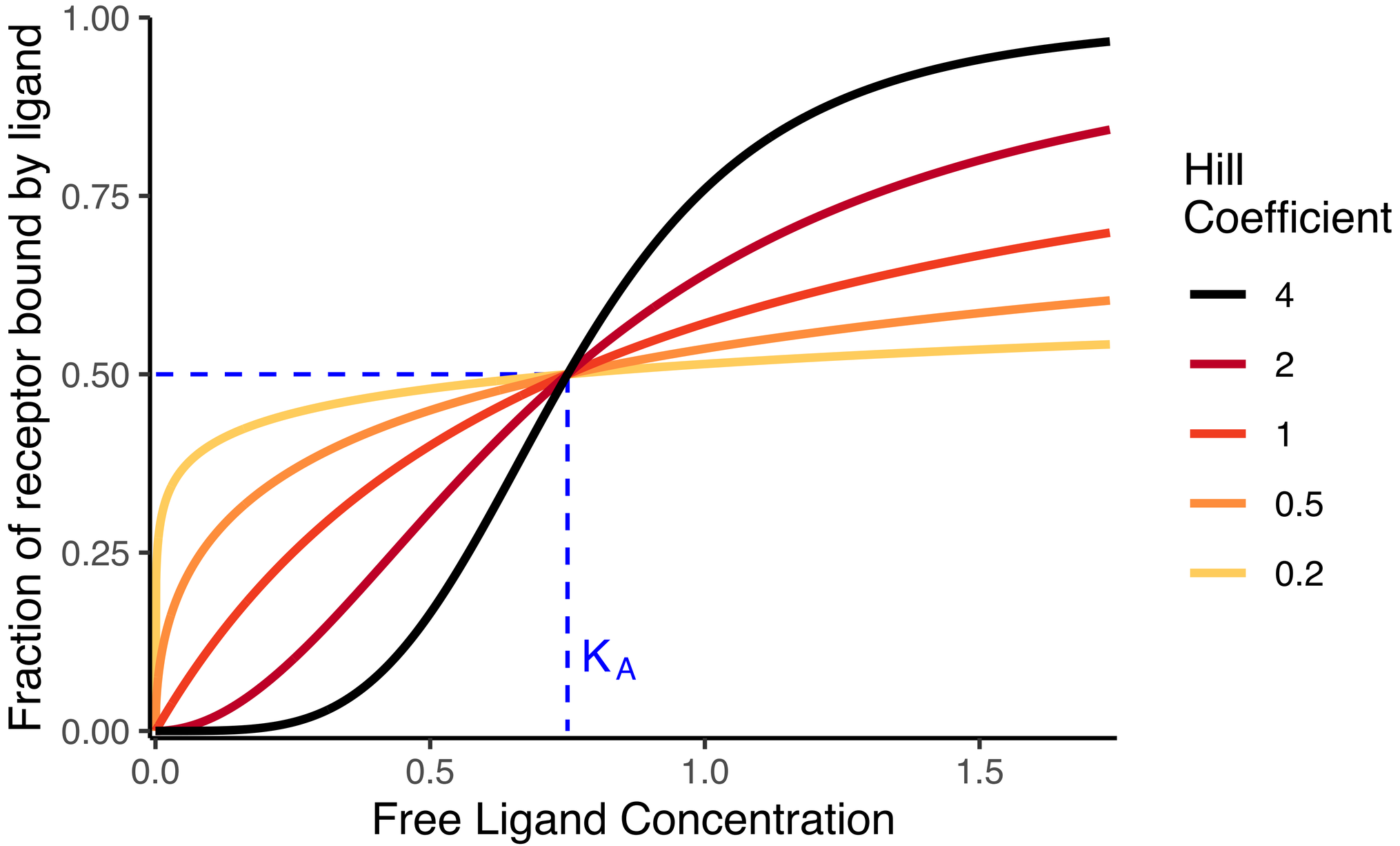

$\mu = 0, \quad \sigma^2 = 0.2,$
$\mu = 0, \quad \sigma^2 = 1.0,$
$\mu = 0, \quad \sigma^2 = 5.0,$
$\mu = -2, \quad \sigma^2 = 0.5,$
$\varphi_{\mu,\sigma^2}(x)$
x
1.0
0.8
0.6
0.4
0.2
0.0
−5
−4
−3
−2
−1
0
1
2
3
4
5



$y = ax + b$

$a \rightarrow$ slope

$b \rightarrow$ intercept

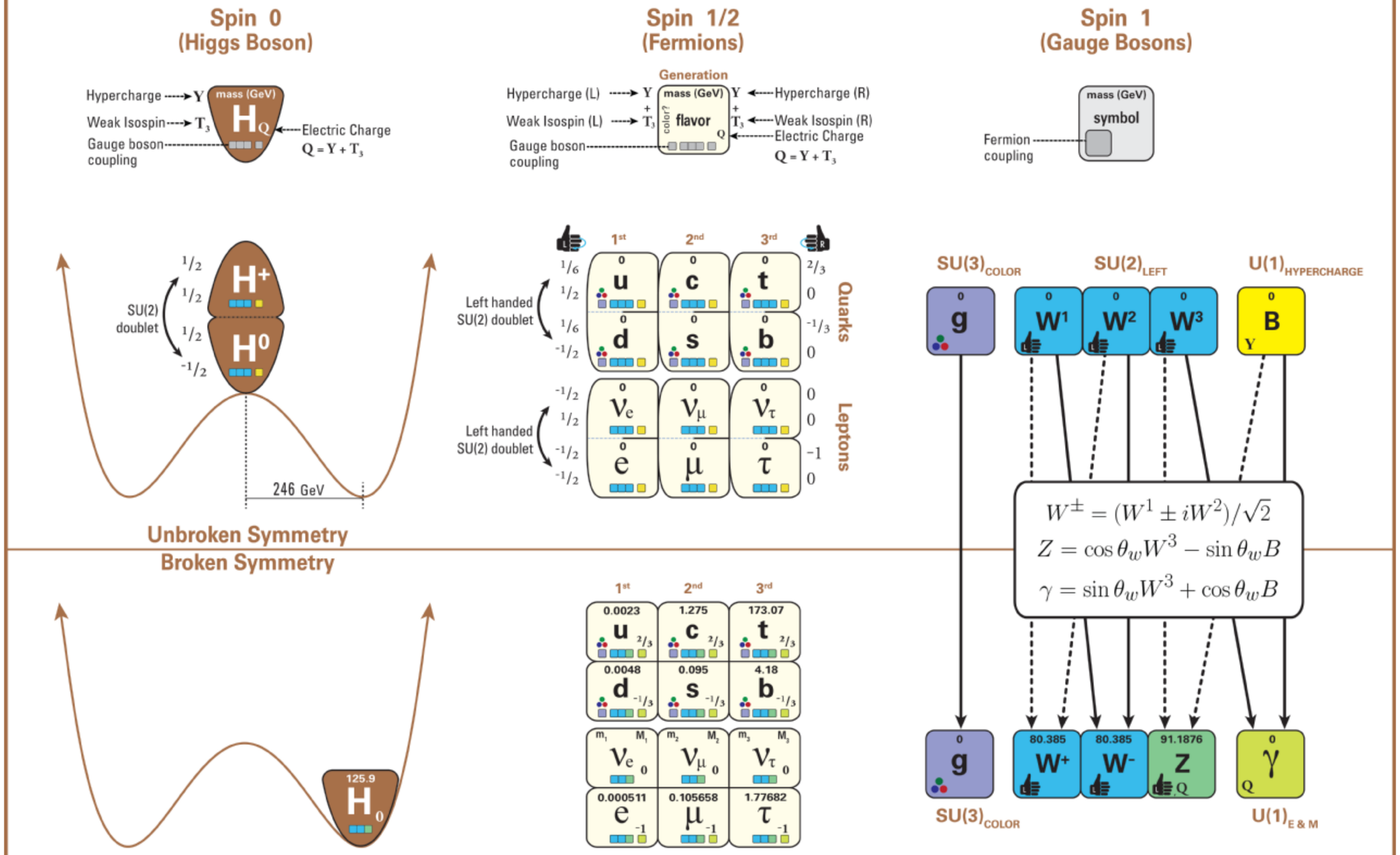

Fraction of receptor bound by ligand
1.00
0.75
0.50
0.25
0.00
0.0
0.5
1.0
1.5
Free Ligand Concentration
K_A
Hill Coefficient
4
2
1
0.5
0.2

$$C(S_t, t) = N(d_+)S_t - N(d_-)Ke^{-r(T-t)}$$

$$d_+ = \frac{1}{\sigma\sqrt{T-t}}\left[\ln\left(\frac{S_t}{K}\right) + \left(r + \frac{\sigma^2}{2}\right)(T-t)\right]$$

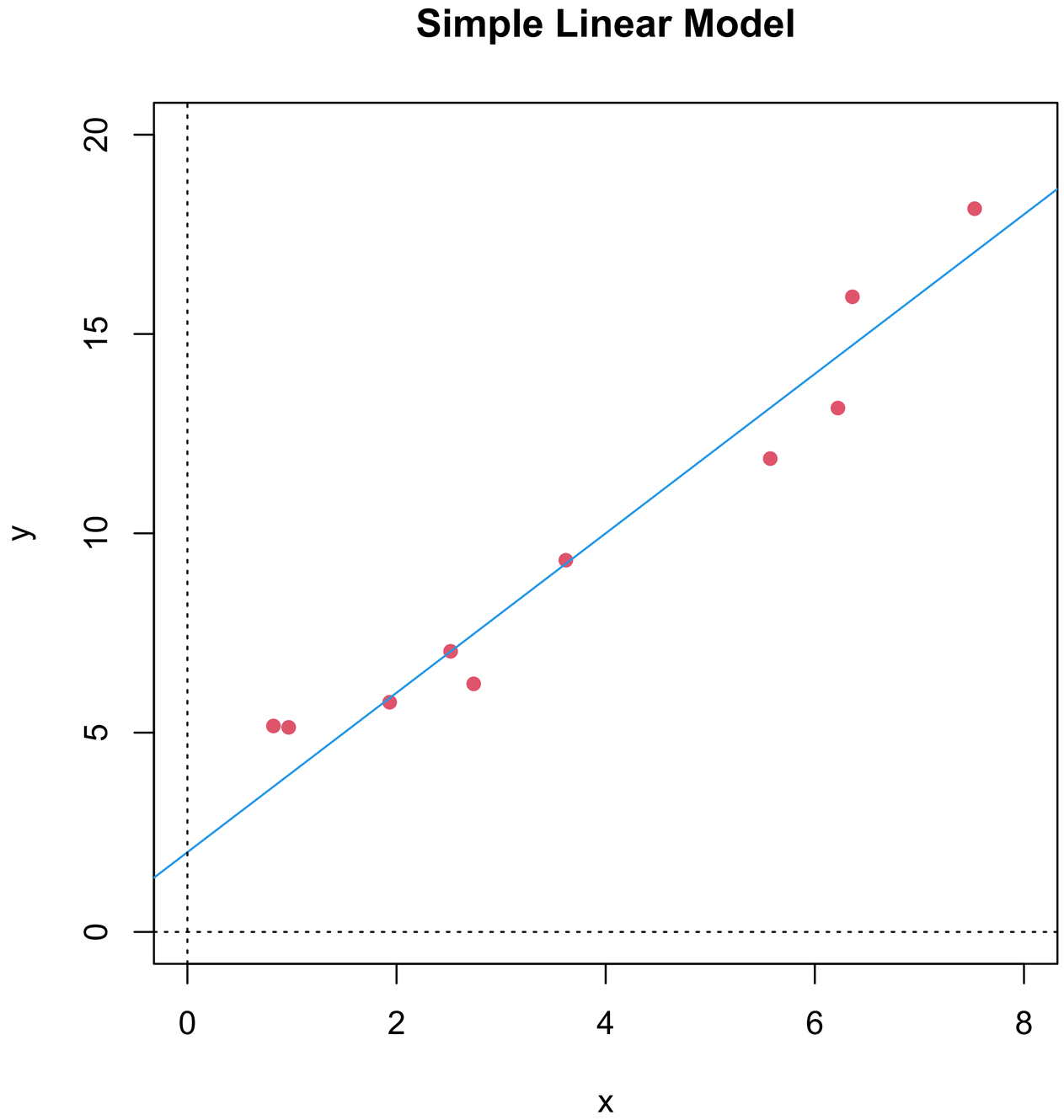
$$d_- = d_+ - \sigma\sqrt{T-t}$$

The Standard Model of Particle Physics



ChatGPT: billions of parameters

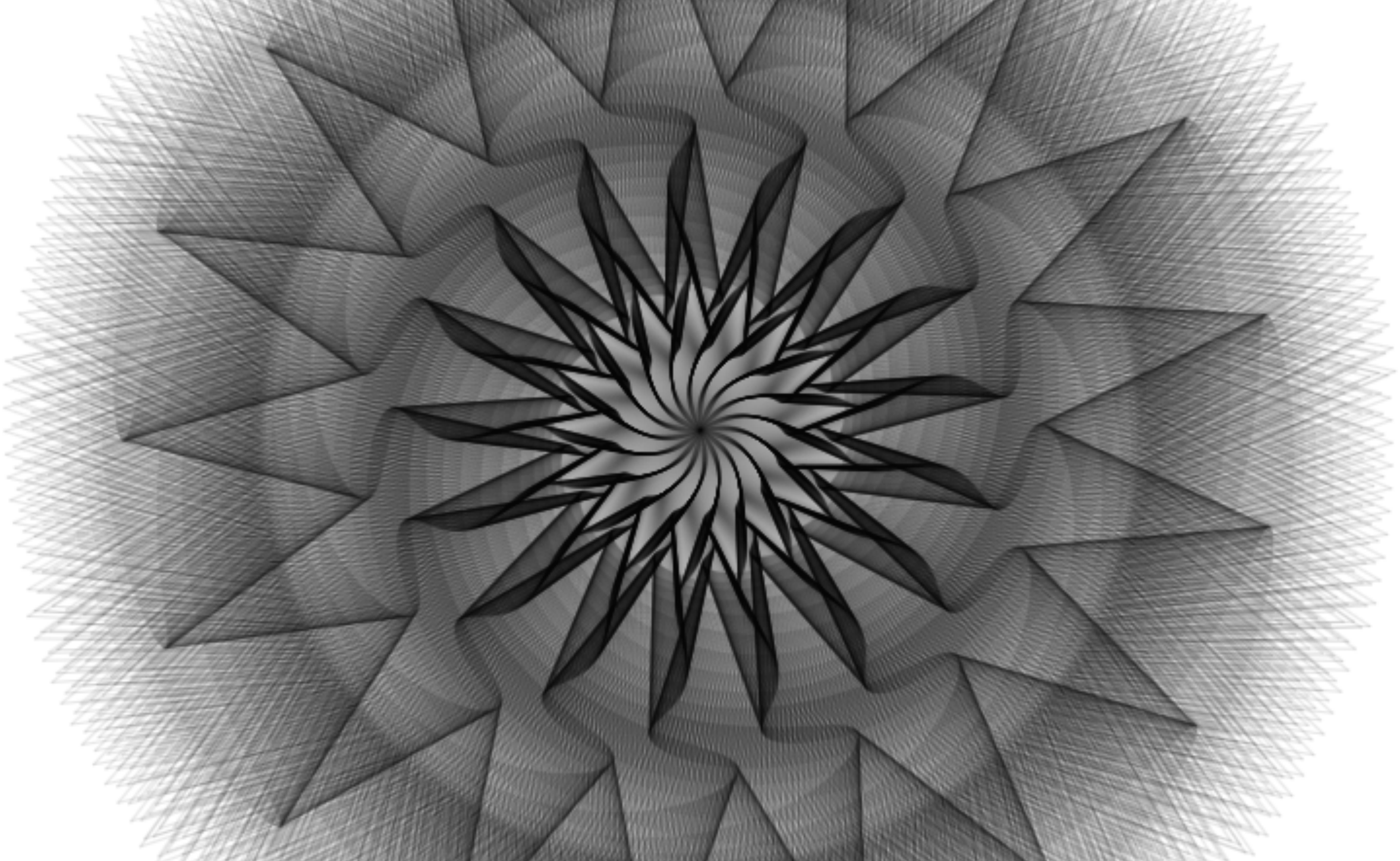
MidJourney: 10^8 – 10^{11}

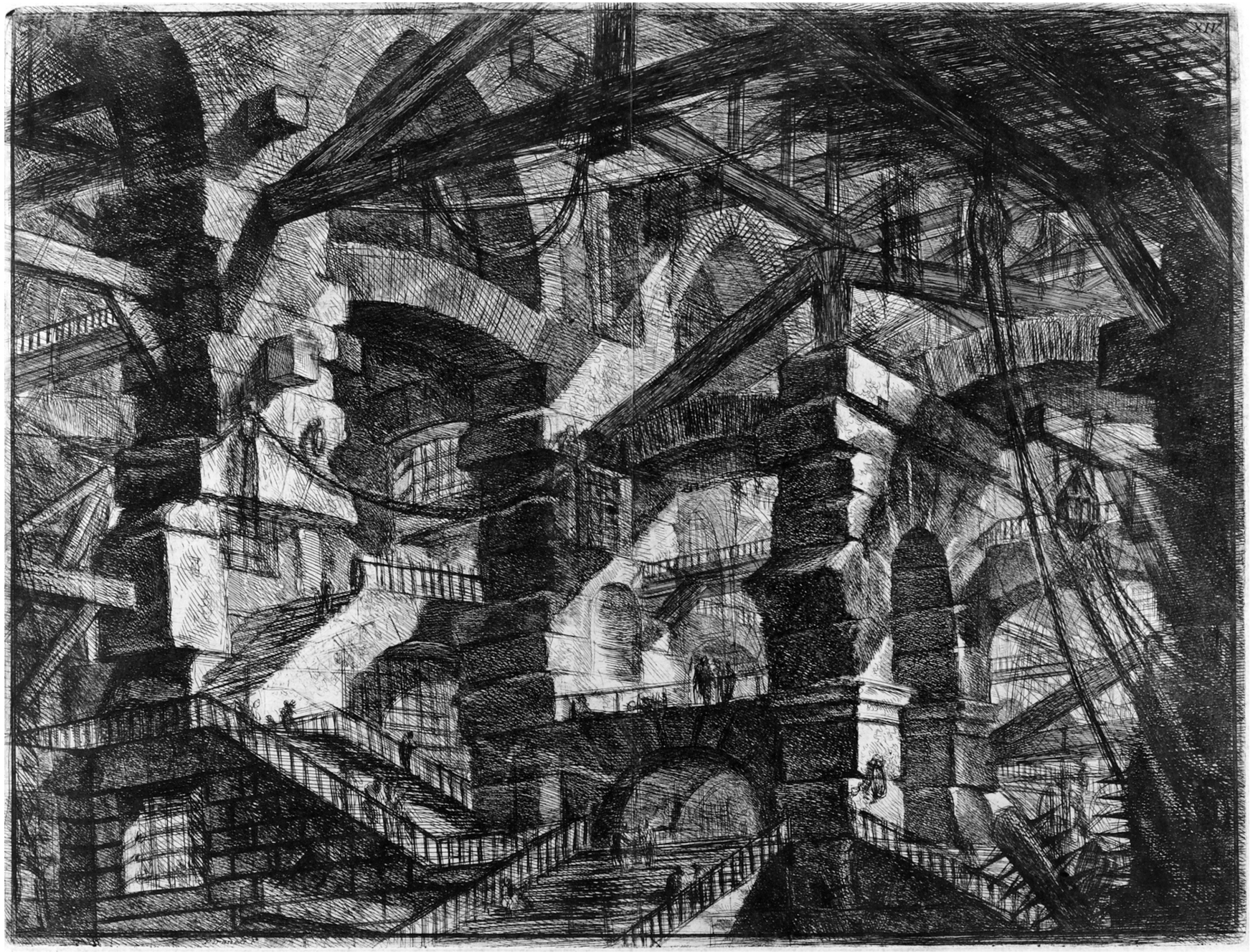


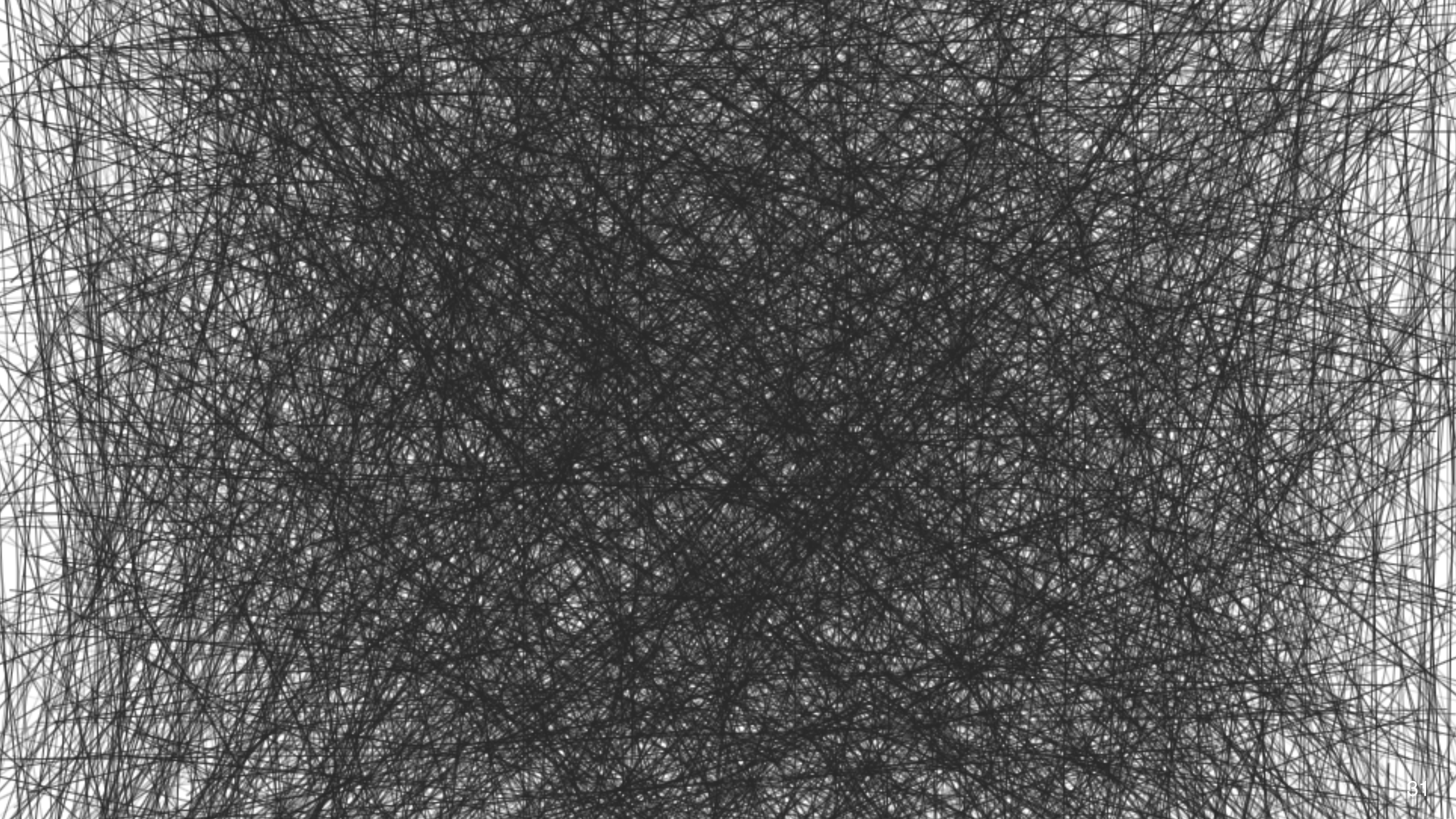
$y = ax + b$

$a \rightarrow$ slope

$b \rightarrow$ intercept







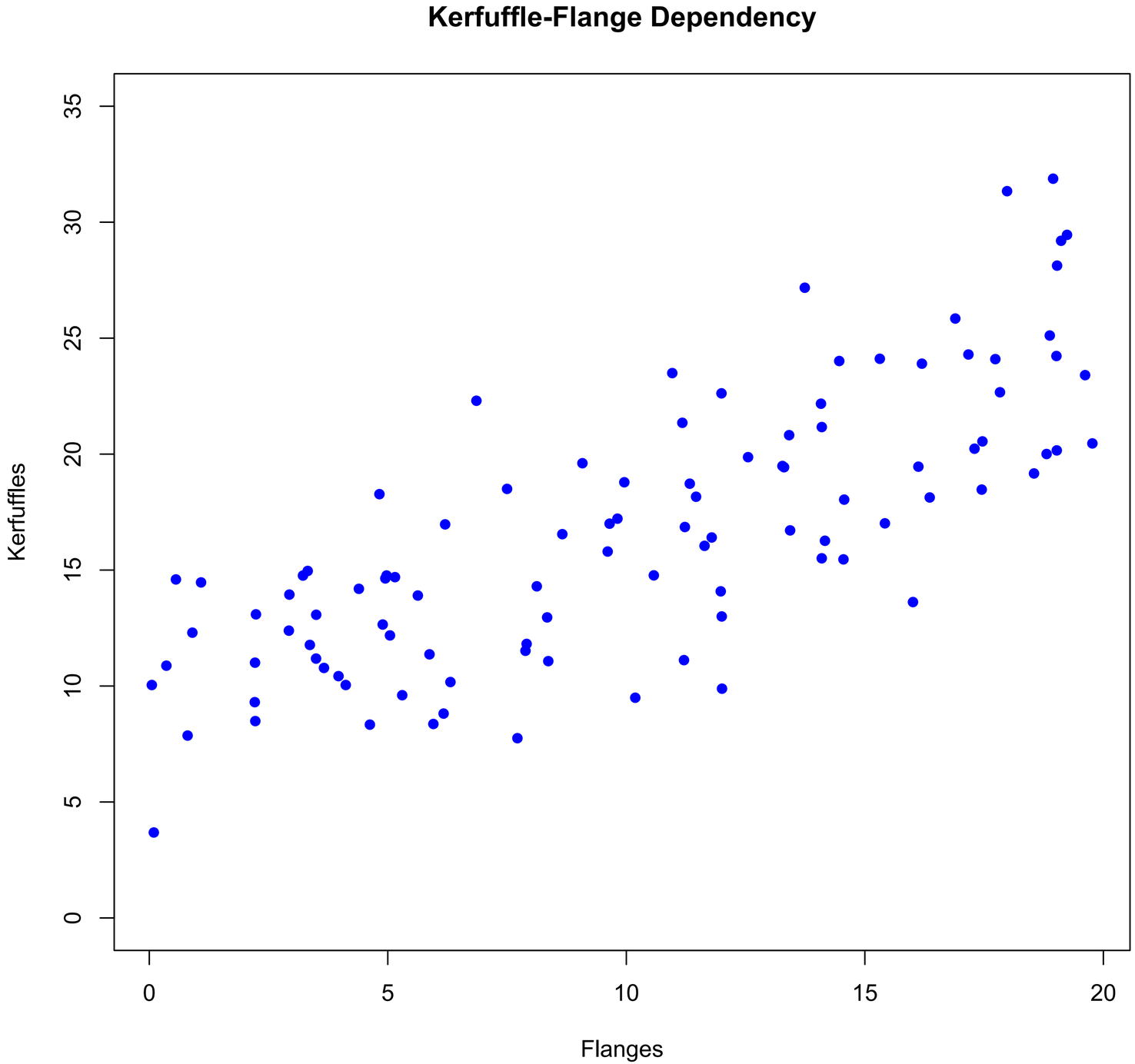
With four parameters I can fit an elephant, and with five I can make him wiggle his trunk

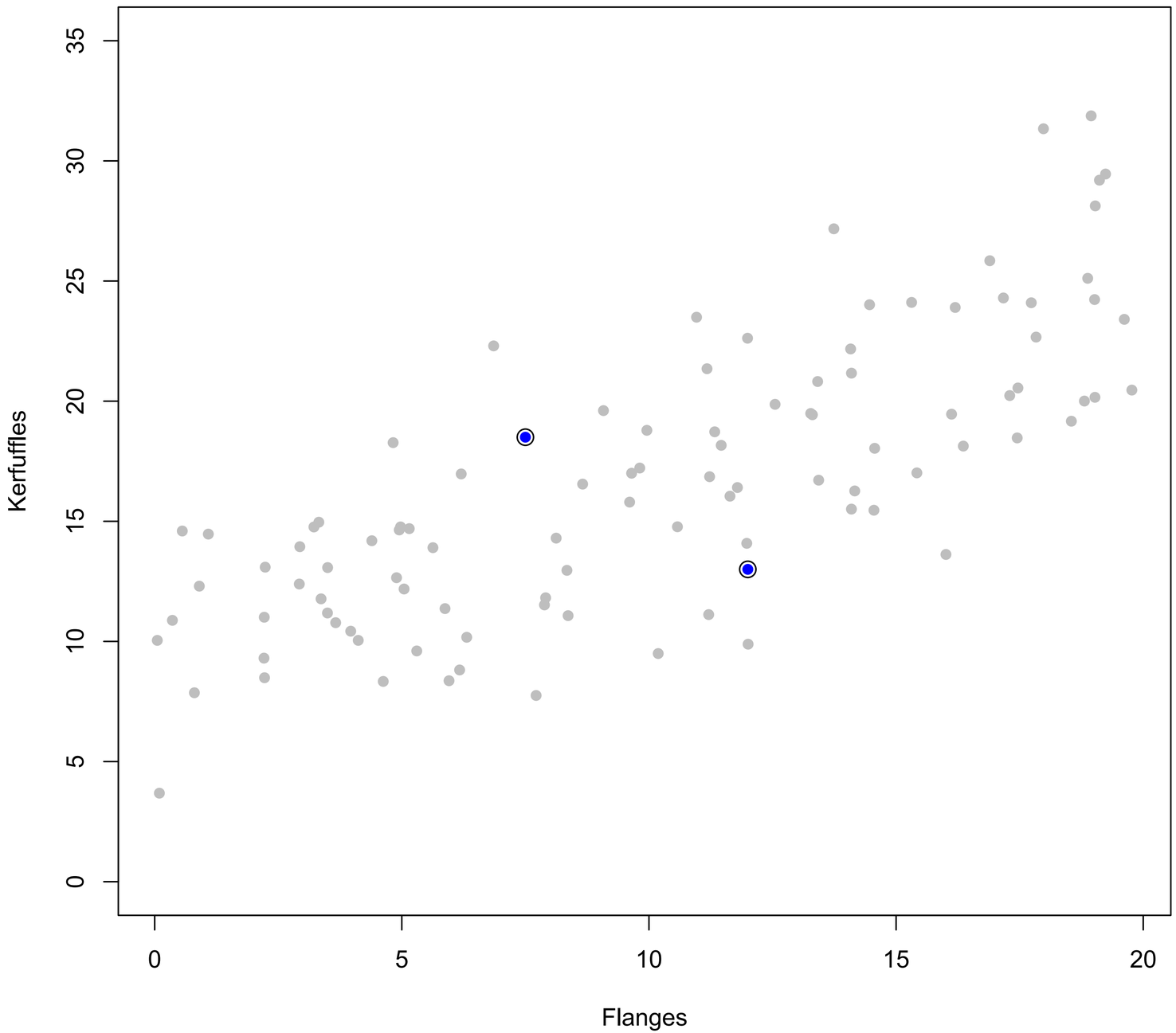
— John Von Neumann

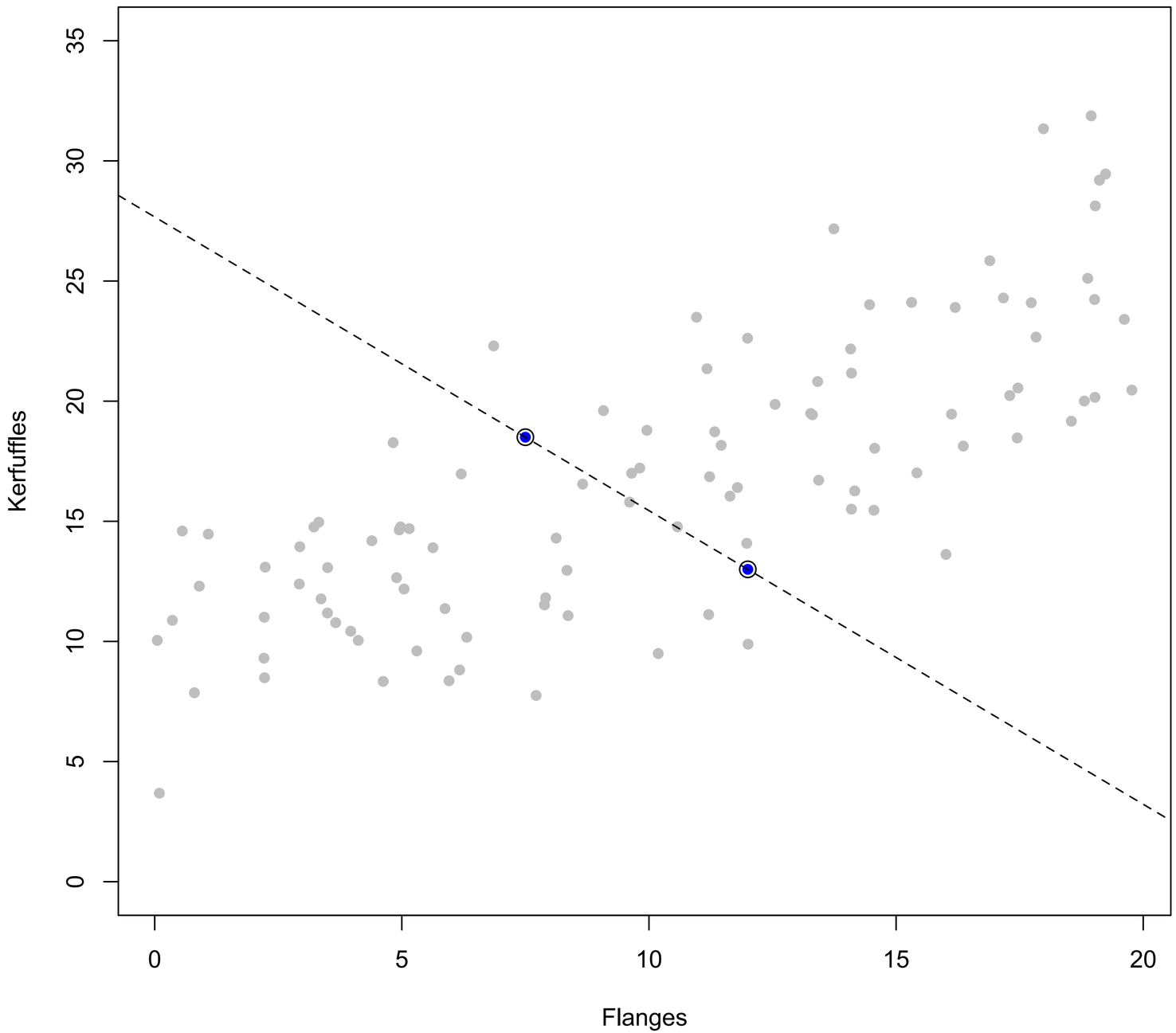
WHAT IS GOING ON??

Is it learning what you *think* it's learning?

Is it learning what you *want*?

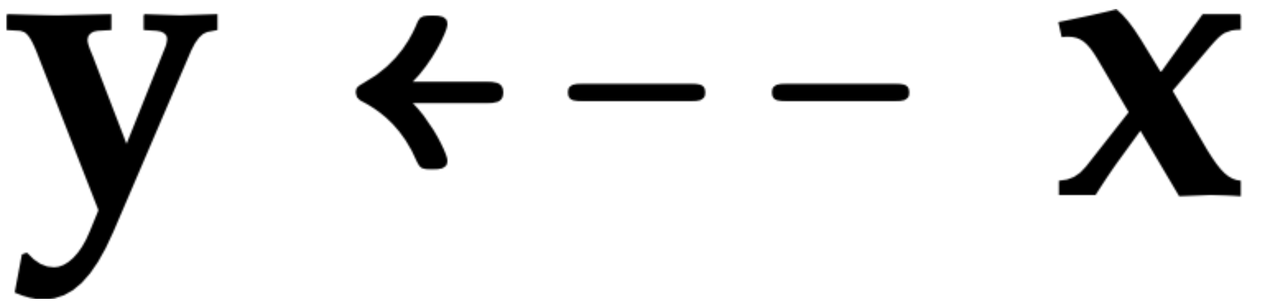

Kerfuffle-Flange Dependency
Kerfuffles
0
5
10
15
20
25
30
35
0
5
10
15
20
Flanges


Kerfuffle-Flange Dependency
Kerfuffles
Flanges
0
5
10
15
20
25
30
35
0
5
10
15
20


Kerfuffle-Flange Dependency
Kerfuffles
Flanges
0
5
10
15
20
25
30
35
0
5
10
15
20

The Second Law of Machine Learning

Generalisation is everything


y ← – – x

$$\mathbf{y} == \mathbf{f}(\mathbf{x})$$

$$\mathbf{y} == \mathbf{f}(\mathbf{x}, \boldsymbol{\theta})$$

$$L(\mathbf{y}, \mathbf{f}(\mathbf{x}, \boldsymbol{\theta}))$$

$$L(\mathbf{f}, \boldsymbol{\theta}, \mathbf{x}, \mathbf{y})$$

$$L(\mathbf{f}, \boldsymbol{\theta}, \{\mathbf{X}[, \mathbf{Y}]\})$$

$$\underset{\boldsymbol{\theta}}{\operatorname{argmin}}\ L(\mathbf{f}, \boldsymbol{\theta}, \{\mathbf{X}\,[, \mathbf{Y}]\})$$

$$\boldsymbol{\theta}^{\star} = \underset{\boldsymbol{\theta}}{\operatorname{argmin}}\, L\left(\mathbf{f}, \boldsymbol{\theta}, \{\mathbf{X}[, \mathbf{Y}]\}\right)$$

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$$\boldsymbol{\theta}^{\star} = \underset{\boldsymbol{\theta}}{\operatorname{argmin}}\, L(\mathbf{f}, \boldsymbol{\theta}, \{\mathbf{X}[, \mathbf{Y}]\})$$

$$\boldsymbol{\theta} > \{\mathbf{X}[,\mathbf{Y}]\}$$

$$\boldsymbol{\theta}^{\star} = \underset{\boldsymbol{\theta}}{\operatorname{argmin}}\, L\left(\mathbf{f}, \boldsymbol{\theta}, \{\mathbf{X}[, \mathbf{Y}]\}\right)$$

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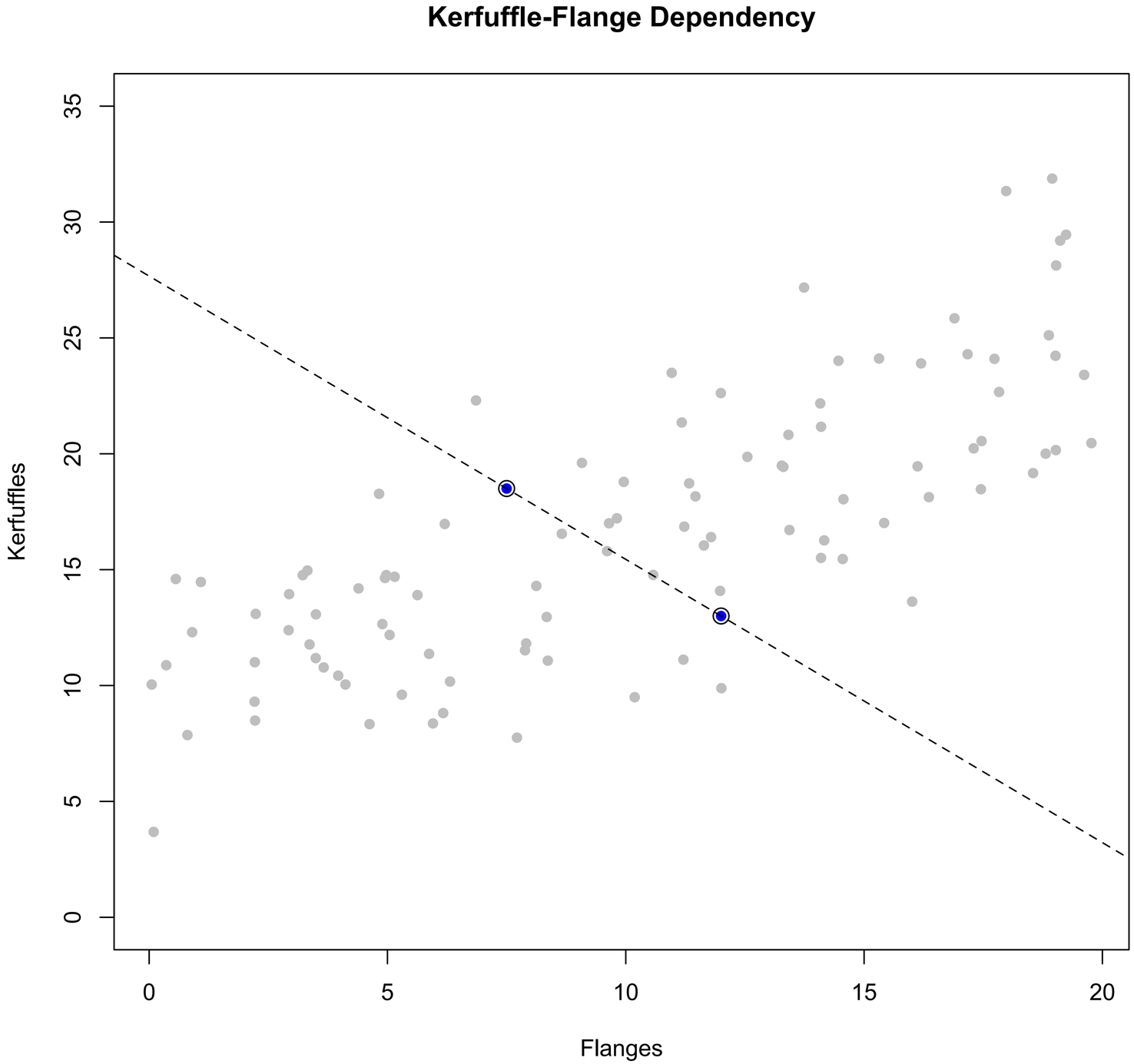
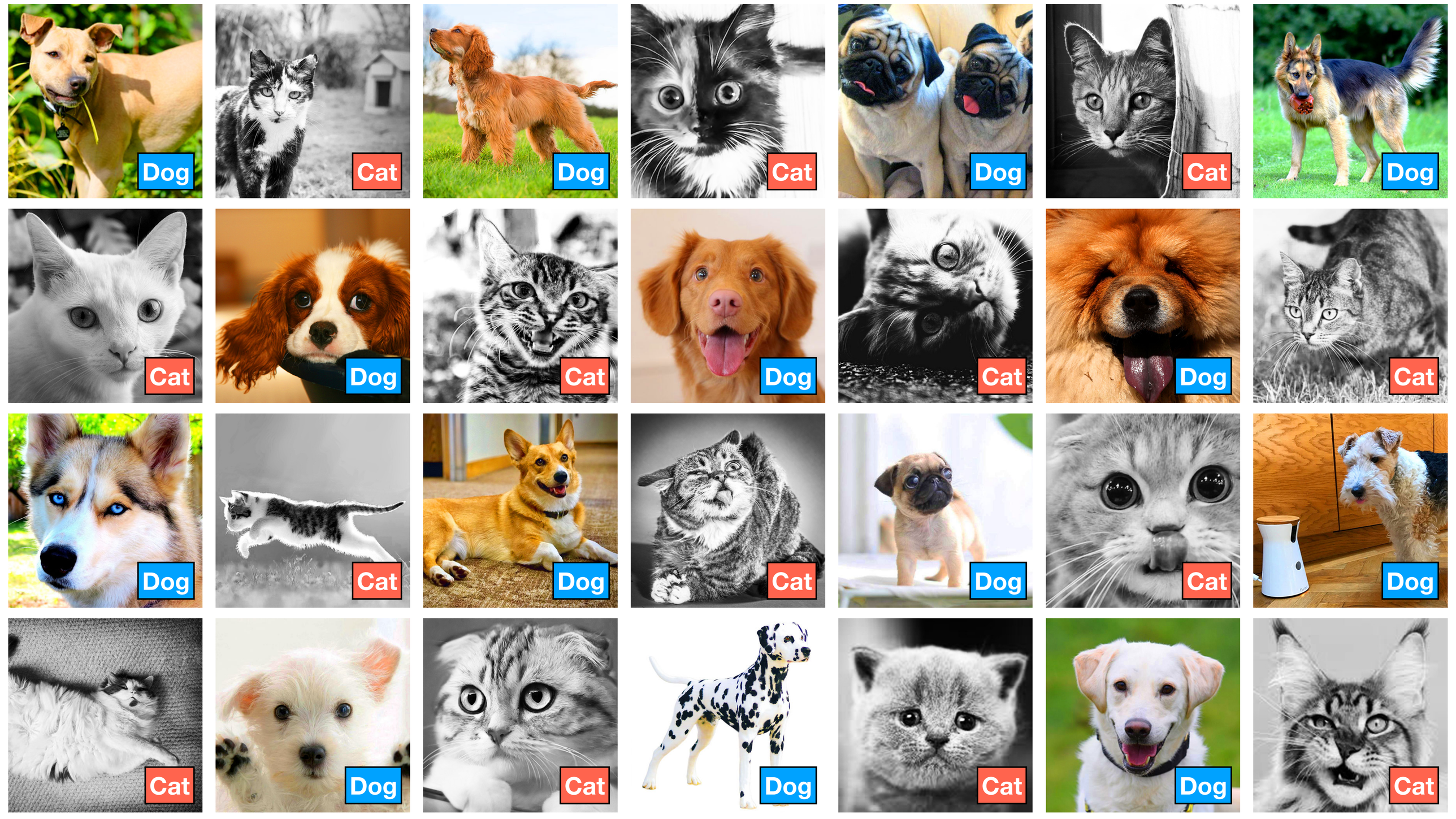

Kerfuffle-Flange Dependency
Kerfuffles
Flanges
0
5
10
15
20
25
30
35
0
5
10
15
20


Dog
Cat
Dog
Cat
Dog
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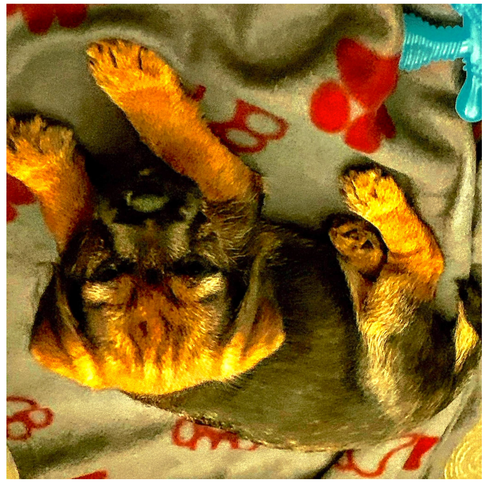
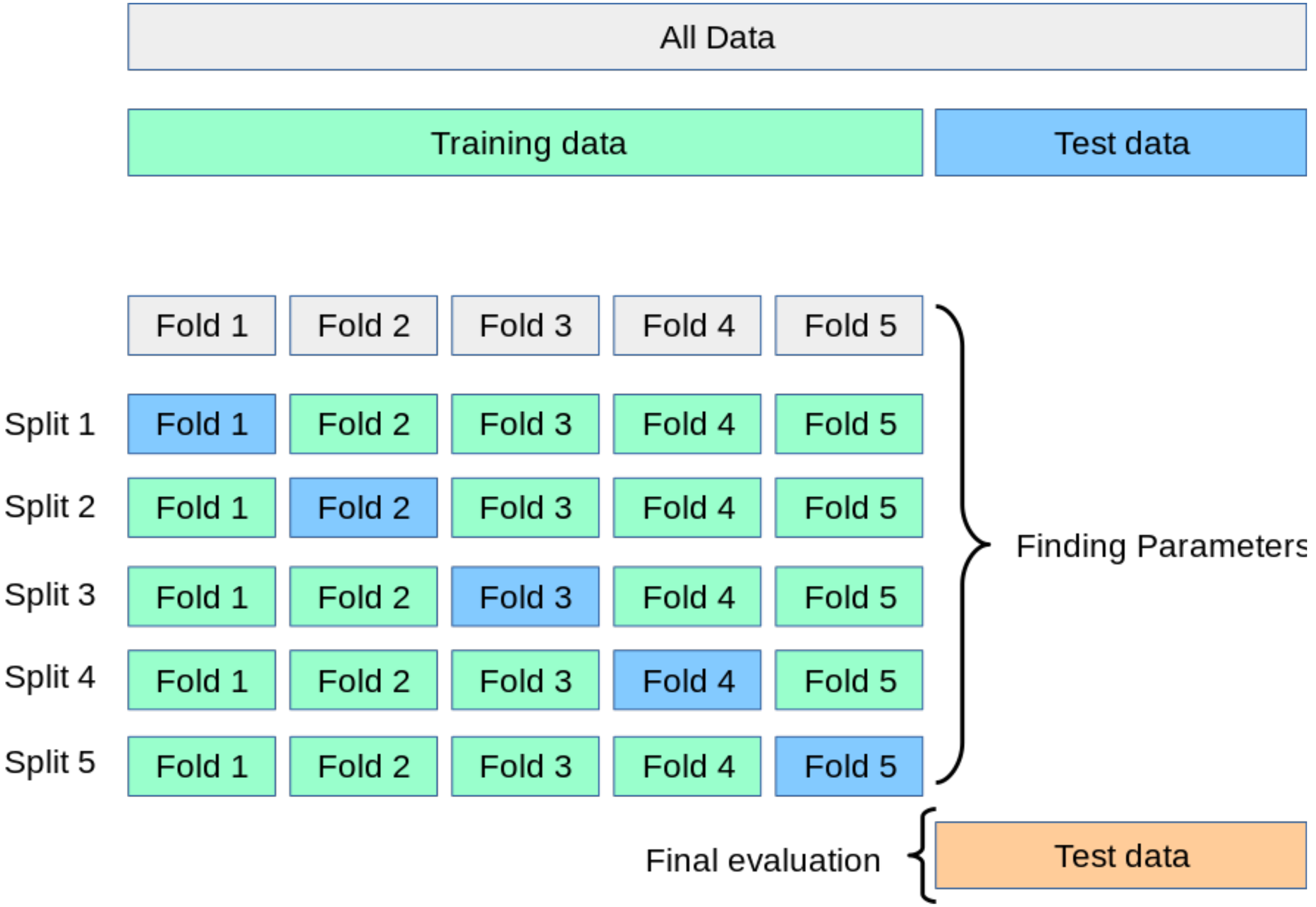
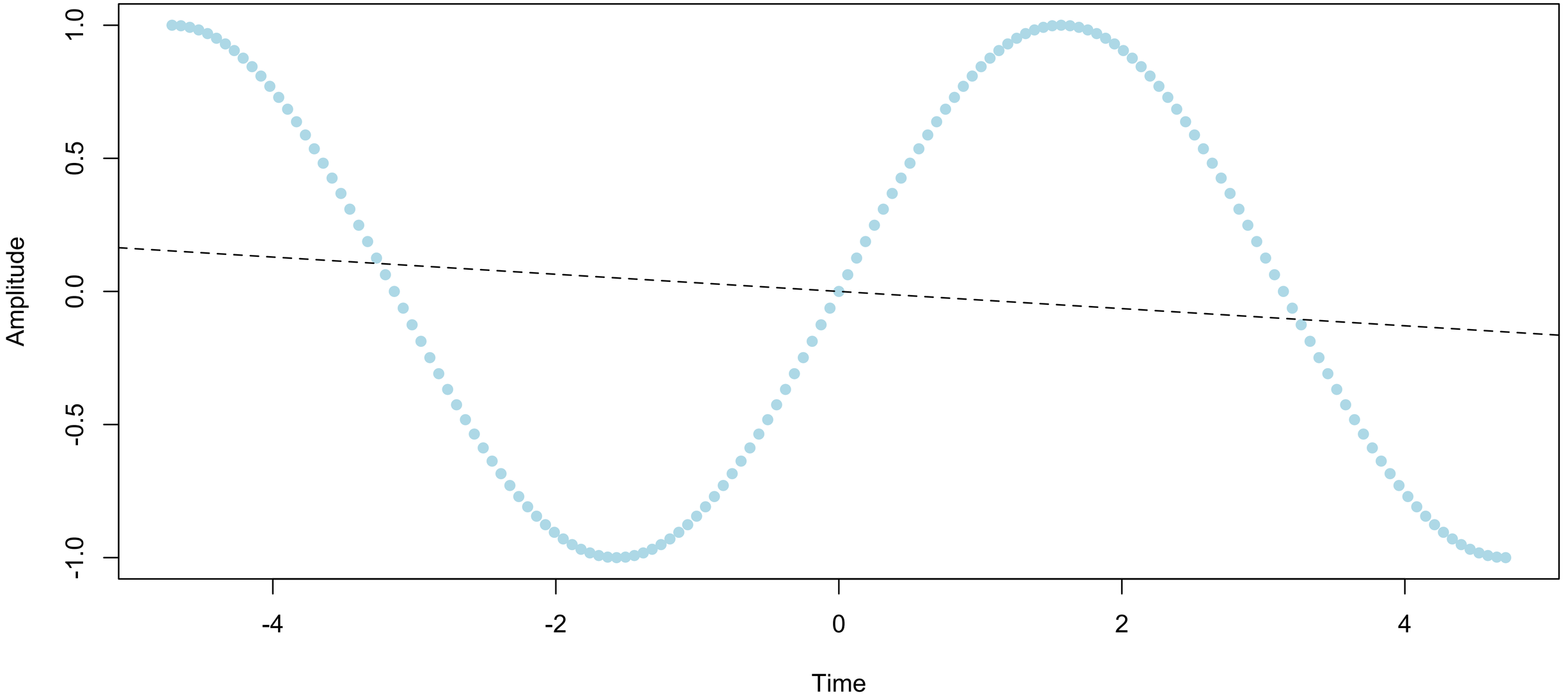
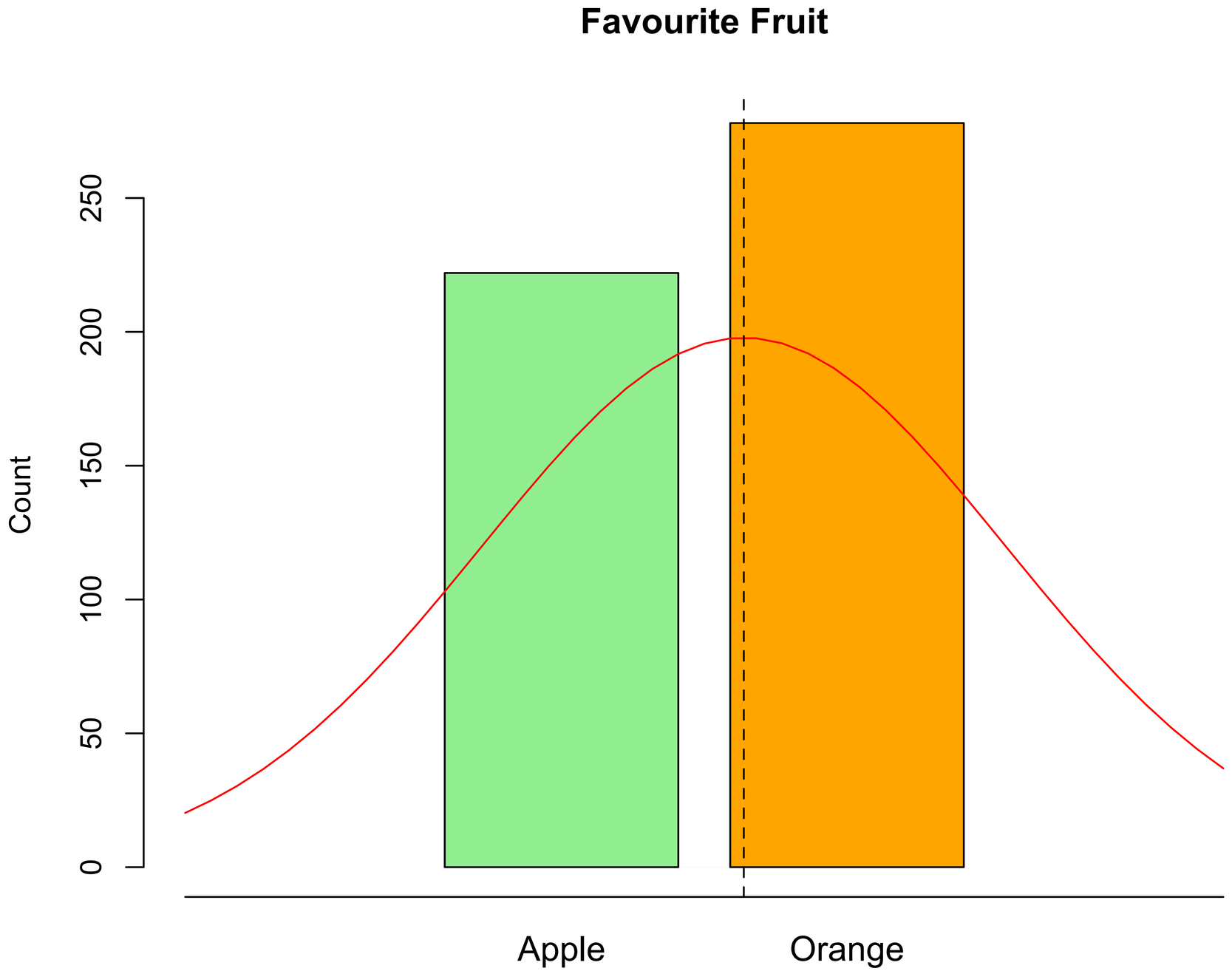
Dog
Cat




All Data
Training data
Test data
Fold 1
Fold 2
Fold 3
Fold 4
Fold 5
Split 1
Split 2
Split 3
Split 4
Split 5
Finding Parameters
Final evaluation
Test data

$$\boldsymbol{\theta}^{\star} = \underset{\boldsymbol{\theta}}{\operatorname{argmin}}\, L(\mathbf{f}, \boldsymbol{\theta}, \{\mathbf{X}[, \mathbf{Y}]\})$$


Amplitude
1.0
0.5
0.0
-0.5
-1.0
-4
-2
0
2
4
Time


Favourite Fruit
Count
0
50
100
150
200
250
Apple
Orange

What's Your Personality Type?

Use the questions on the outside of the chart to determine the four letters of your Myers-Briggs type.
For each pair of letters, choose the side that seems most natural to you, even if you don't agree with every description.

1. Are you outwardly or inwardly focused? If you:

- Could be described as talkative, outgoing
- Like to be in a fast-paced environment
- Tend to work out ideas with others, think out loud
- Enjoy being the center of attention

then you prefer

E
Extraversion

- Could be described as reserved, private
- Prefer a slower pace with time for contemplation
- Tend to think things through inside your head
- Would rather observe than be the center of attention

then you prefer

I
Introversion

2. How do you prefer to take in information? If you:

- Focus on the reality of how things are
- Pay attention to concrete facts and details
- Prefer ideas that have practical applications
- Like to describe things in a specific, literal way

then you prefer

S
Sensing

- Imagine the possibilities of how things could be
- Notice the big picture, see how everything connects
- Enjoy ideas and concepts for their own sake
- Like to describe things in a figurative, poetic way

then you prefer

N
Intuition

ISTJ Responsible, sincere, analytical, reserved, realistic, systematic. Hardworking and trustworthy with sound practical judgment.	**ISFJ** Warm, considerate, gentle, responsible, pragmatic, thorough. Devoted caretakers who enjoy being helpful to others.	**INFJ** Idealistic, organized, insightful, dependable, compassionate, gentle. Seek harmony and cooperation, enjoy intellectual stimulation.	**INTJ** Innovative, independent, strategic, logical, reserved, insightful. Driven by their own original ideas to achieve improvements.
ISTP Action-oriented, logical, analytical, spontaneous, reserved, independent. Enjoy adventure, skilled at understanding how mechanical things work.	**ISFP** Gentle, sensitive, nurturing, helpful, flexible, realistic. Seek to create a personal environment that is both beautiful and practical.	**INFP** Sensitive, creative, idealistic, perceptive, caring, loyal. Value inner harmony and personal growth, focus on dreams and possibilities.	**INTP** Intellectual, logical, precise, reserved, flexible, imaginative. Original thinkers who enjoy speculation and creative problem solving.
ESTP Outgoing, realistic, action-oriented, curious, versatile, spontaneous. Pragmatic problem solvers and skillful negotiators.	**ESFP** Playful, enthusiastic, friendly, spontaneous, tactful, flexible. Have strong common sense, enjoy helping people in tangible ways.	**ENFP** Enthusiastic, creative, spontaneous, optimistic, supportive, playful. Value inspiration, enjoy starting new projects, see potential in others.	**ENTP** Inventive, enthusiastic, strategic, enterprising, inquisitive, versatile. Enjoy new ideas and challenges, value inspiration.
ESTJ Efficient, outgoing, analytical, systematic, dependable, realistic. Like to run the show and get things done in an orderly fashion.	**ESFJ** Friendly, outgoing, reliable, conscientious, organized, practical. Seek to be helpful and please others, enjoy being active and productive.	**ENFJ** Caring, enthusiastic, idealistic, organized, diplomatic, responsible. Skilled communicators who value connection with people.	**ENTJ** Strategic, logical, efficient, outgoing, ambitious, independent. Effective organizers of people and long-range planners.

3. How do you prefer to make decisions? If you:

- Make decisions in an impersonal way, using logical reasoning
- Value justice, fairness
- Enjoy finding the flaws in an argument
- Could be described as reasonable, level-headed

then you prefer

T
Thinking

- Base your decisions on personal values and how your actions affect others
- Value harmony, forgiveness
- Like to please others and point out the best in people
- Could be described as warm, empathetic

then you prefer

F
Feeling

4. How do you prefer to live your outer life? If you:

- Prefer to have matters settled
- Think rules and deadlines should be respected
- Prefer to have detailed, step-by-step instructions
- Make plans, want to know what you're getting into

then you prefer

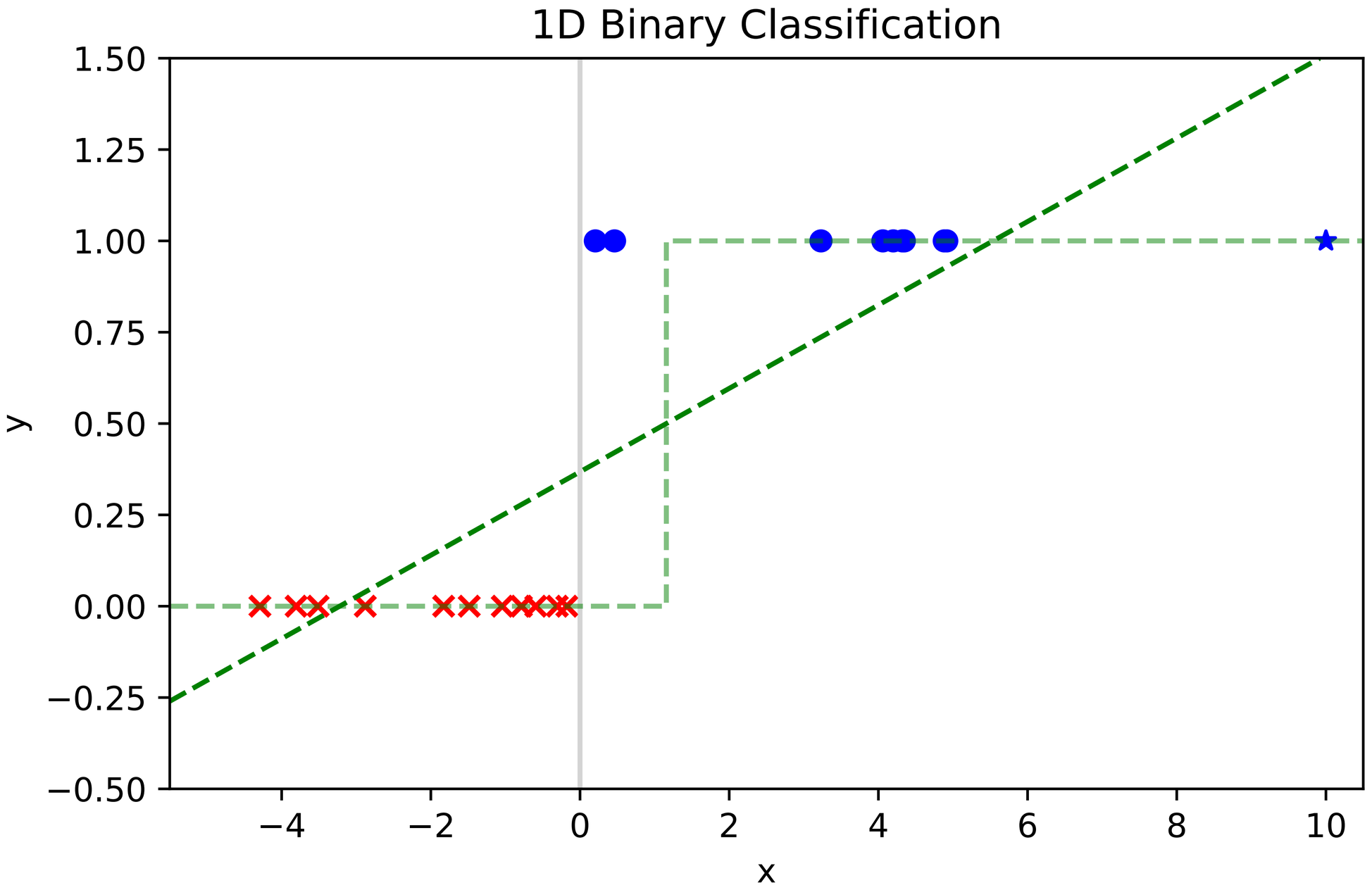
J
Judging

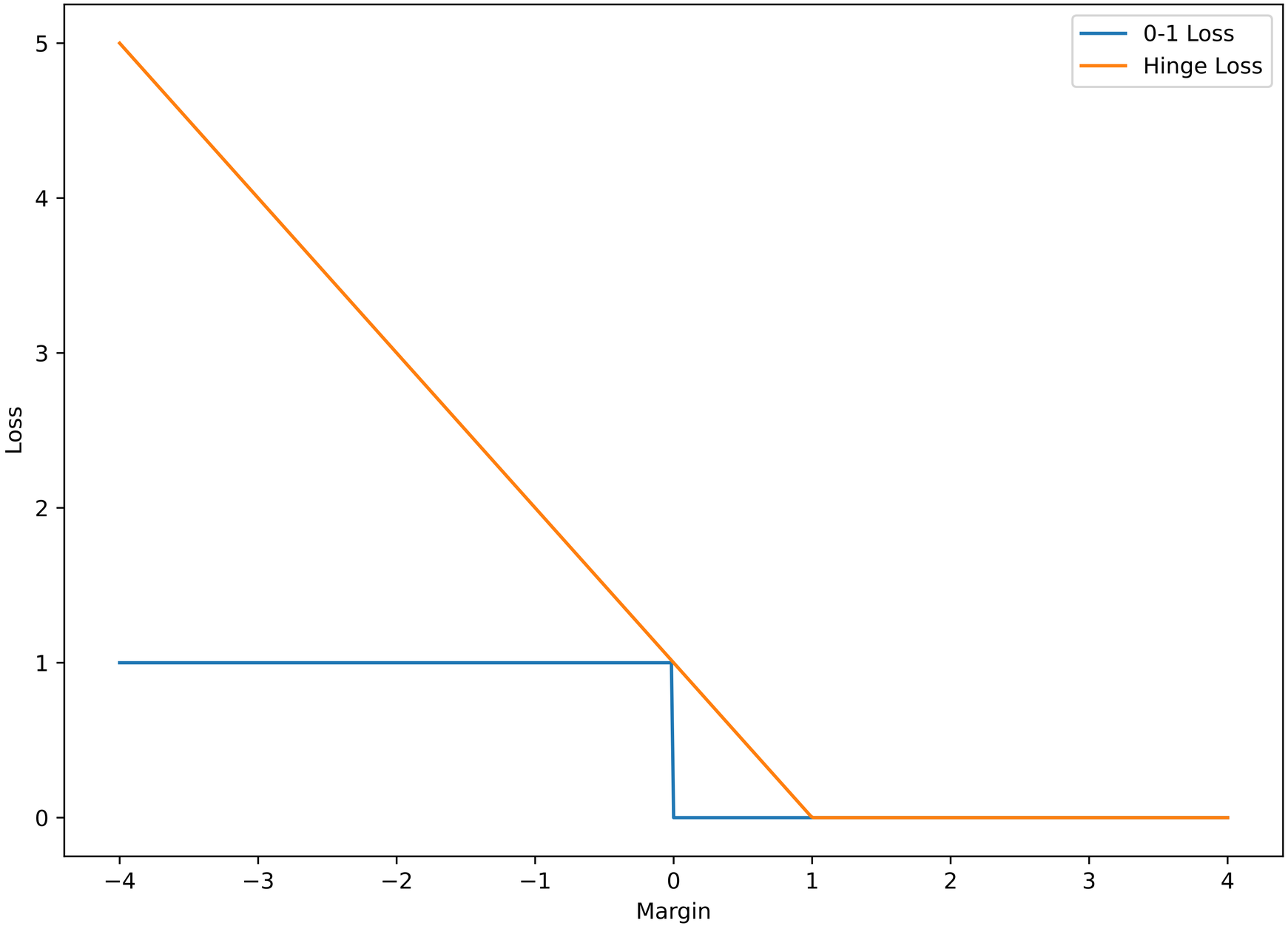
- Prefer to leave your options open
- See rules and deadlines as flexible
- Like to improvise and make things up as you go
- Are spontaneous, enjoy surprises and new situations

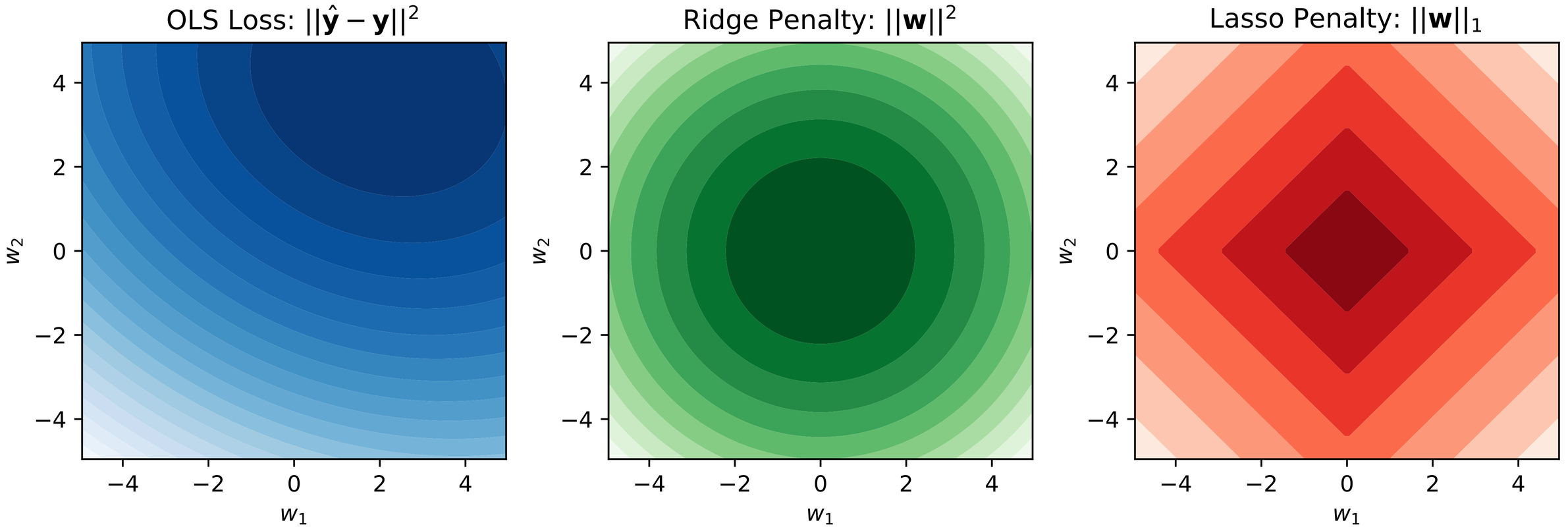
then you prefer

P
Perceiving

$$\boldsymbol{\theta}^{\star} = \underset{\boldsymbol{\theta}}{\operatorname{argmin}}\, L(\mathbf{f}, \boldsymbol{\theta}, \{\mathbf{X}[, \mathbf{Y}]\})$$

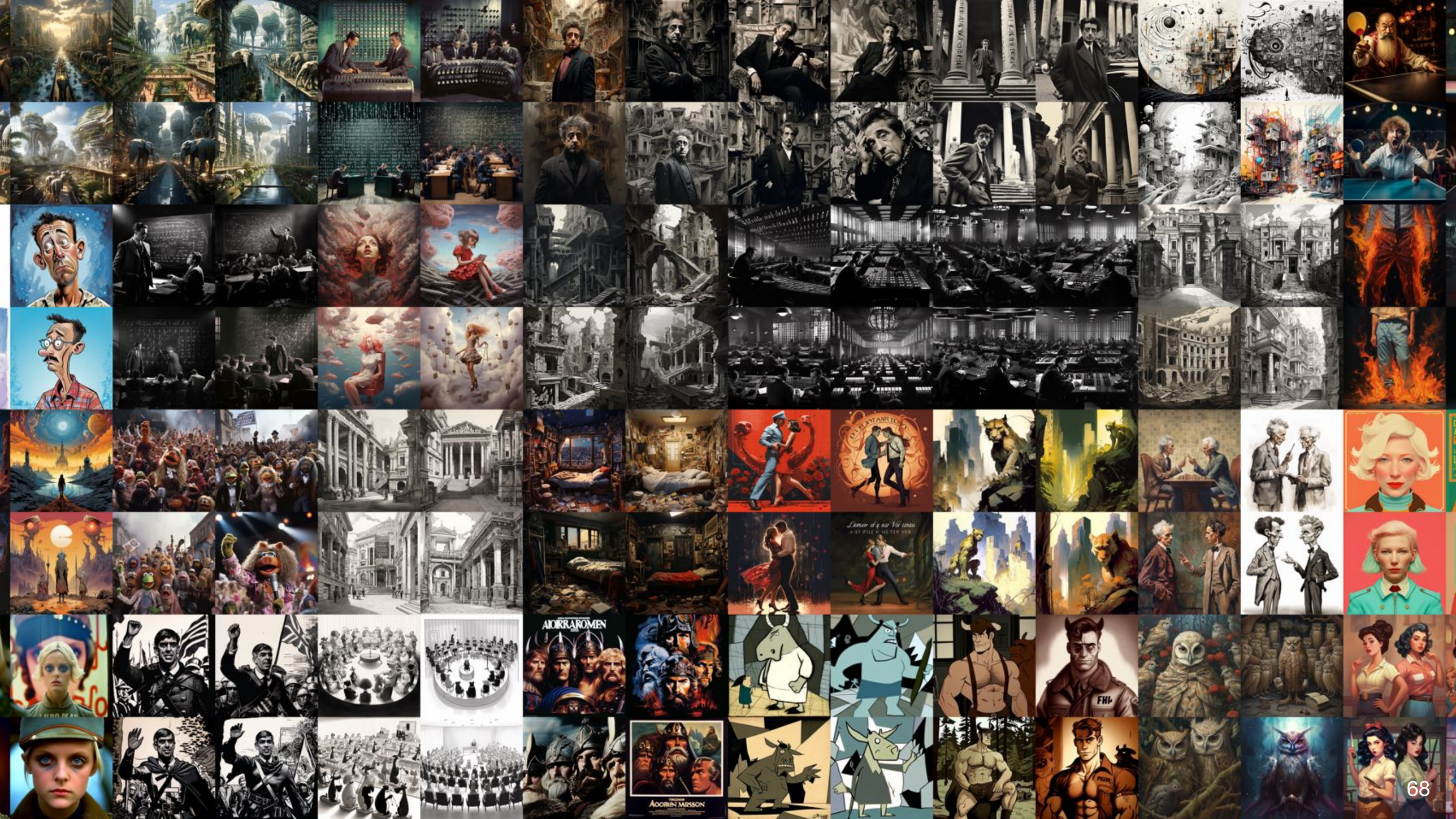

1D Binary Classification
1.50
1.25
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
y
−4
−2
0
2
4
6
8
10
x

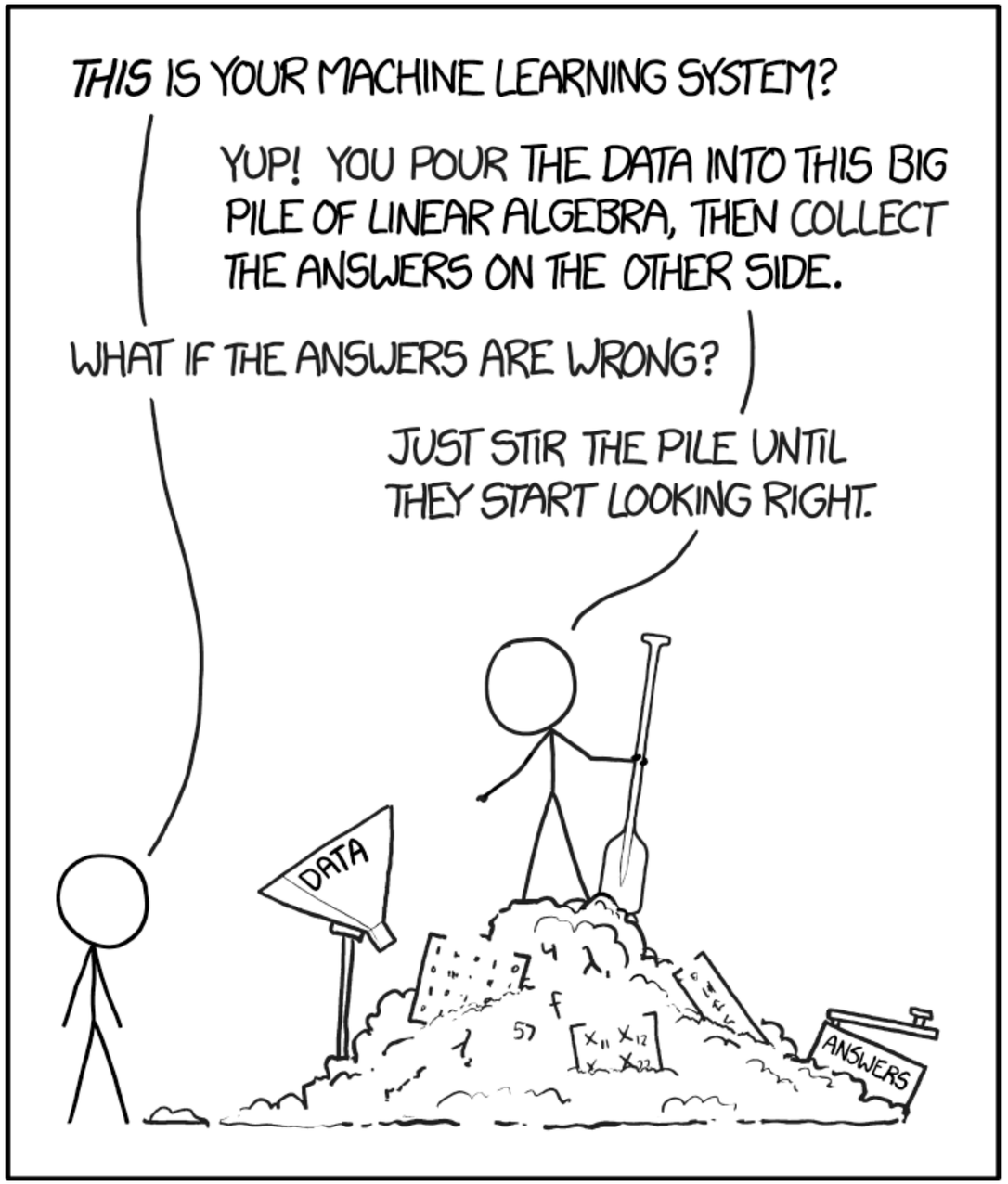

0-1 Loss
Hinge Loss
Loss
Margin
5
4
3
2
1
0
−4
−3
−2
−1
0
1
2
3
4


OLS Loss: $||\hat{\mathbf{y}} - \mathbf{y}||^2$
Ridge Penalty: $||\mathbf{w}||^2$
Lasso Penalty: $||\mathbf{w}||_1$
w_1
w_2
4
2
0
−2
−4

The Third Law of Machine Learning

Machine Learning is not magic


AIORRAROMEN
AOORRIN MRSSON


THIS IS YOUR MACHINE LEARNING SYSTEM?
YUP! YOU POUR THE DATA INTO THIS BIG PILE OF LINEAR ALGEBRA, THEN COLLECT THE ANSWERS ON THE OTHER SIDE.
WHAT IF THE ANSWERS ARE WRONG?
JUST STIR THE PILE UNTIL THEY START LOOKING RIGHT.
DATA
ANSWERS

Questions?

Next week: Linear Models