FOUNDATIONS OF MACHINE LEARNING SYSTEMS

Robert Williamson

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machine learning
new perspectives
for science

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OPTIMIST

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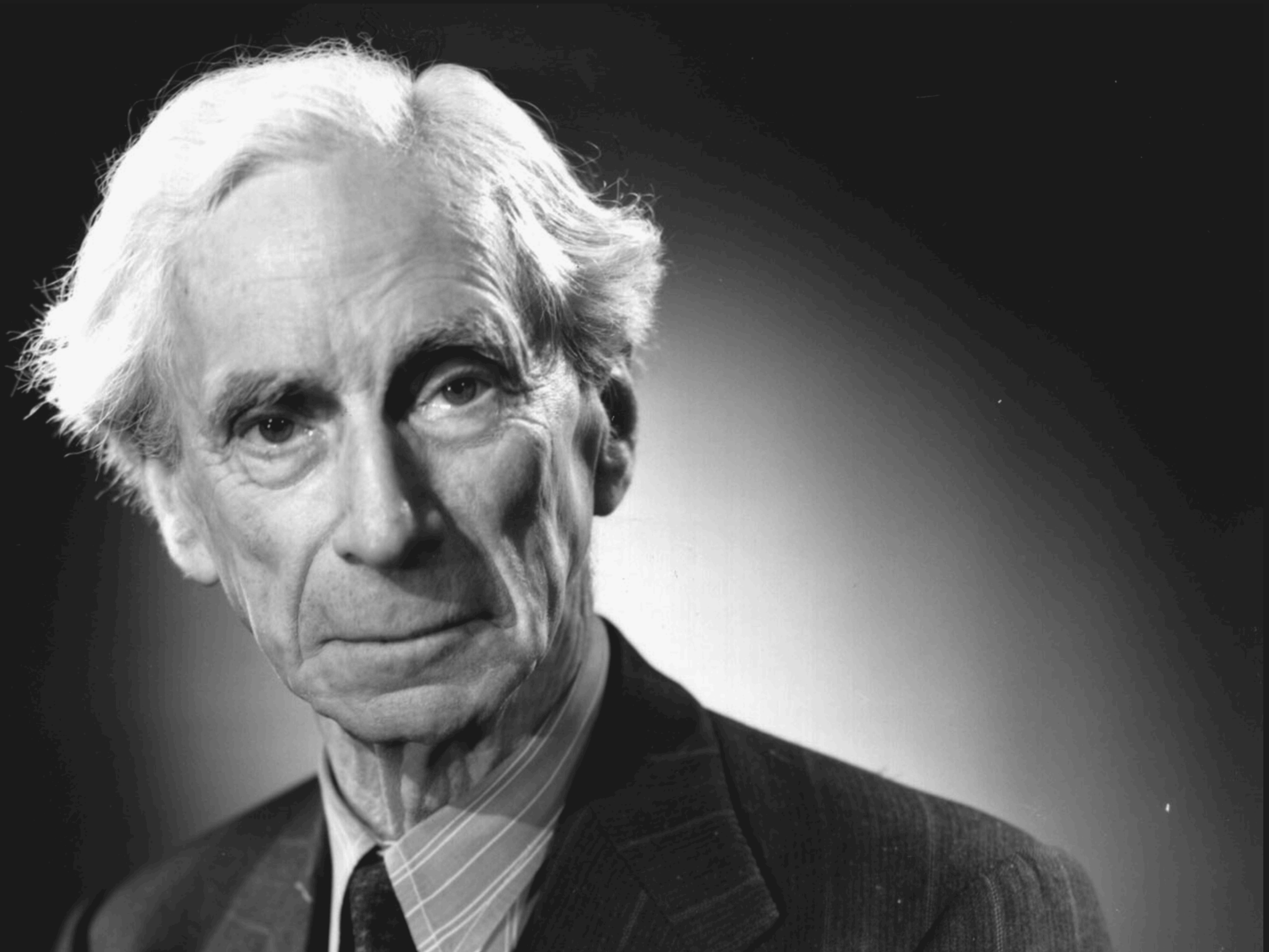
FOUNDATIONS of . . .

THE PHILOSOPHER'S VIEW



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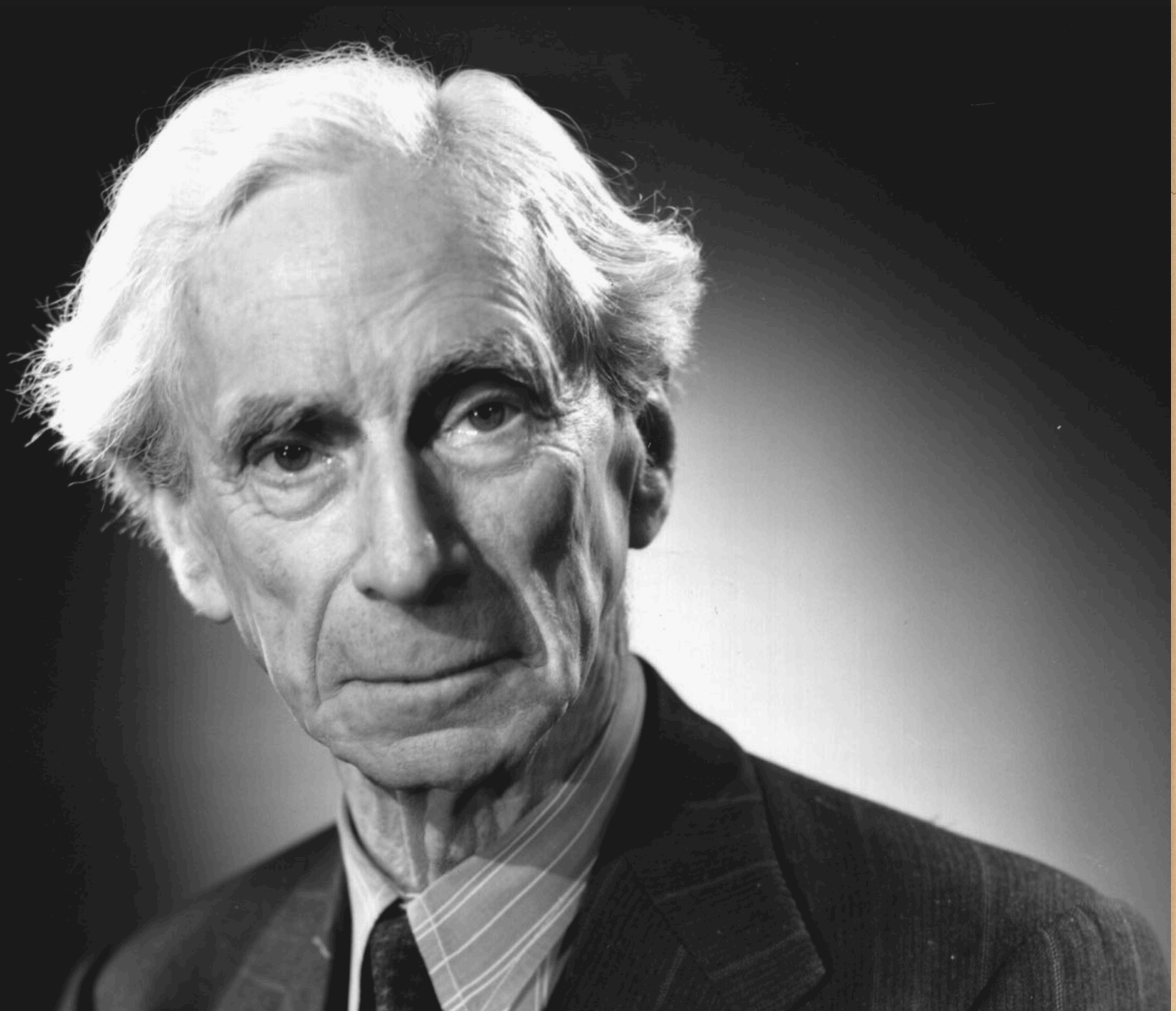

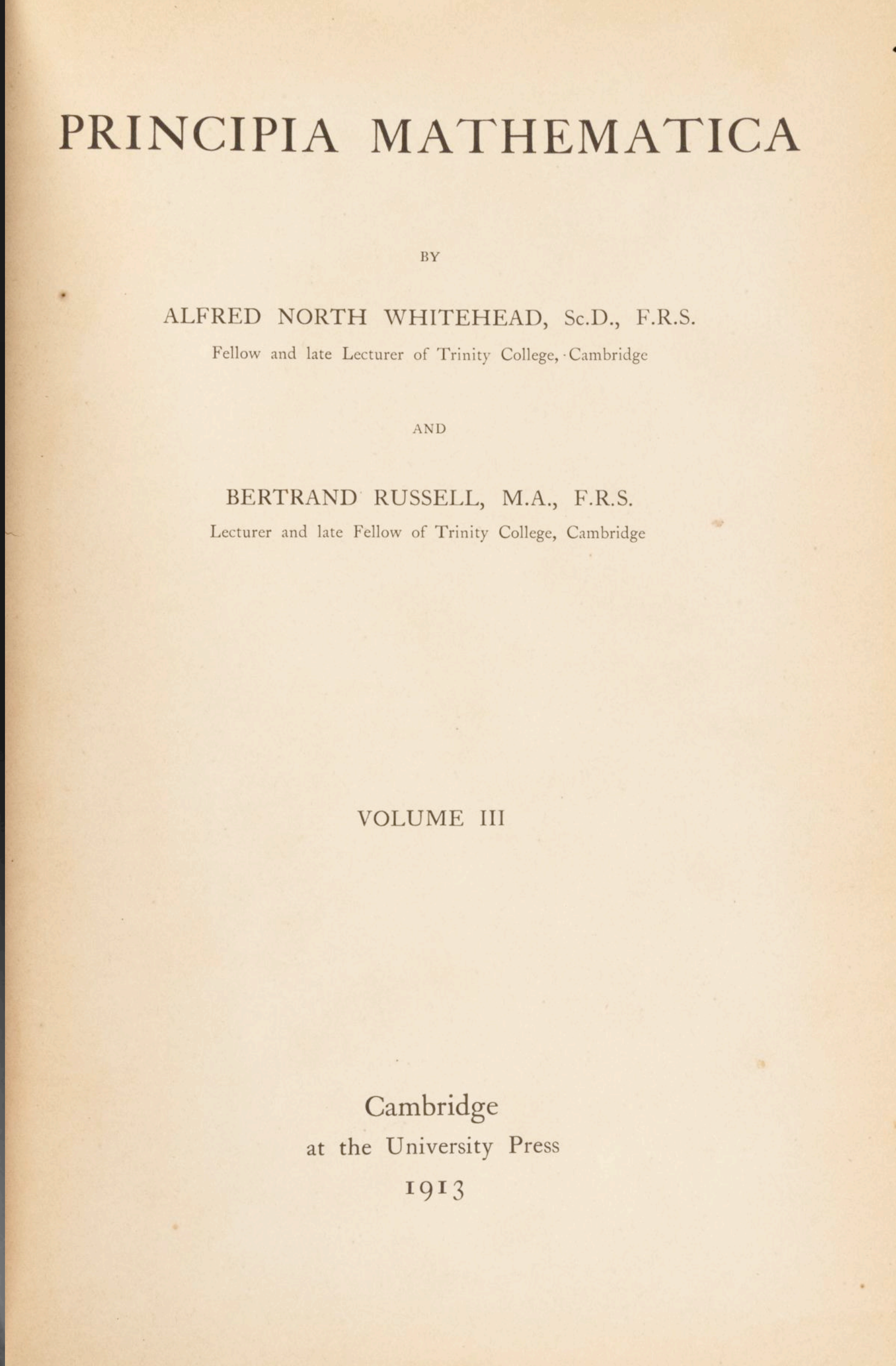

PRINCIPIA MATHEMATICA

BY

ALFRED NORTH WHITEHEAD, Sc.D., F.R.S.
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AND

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Lecturer and late Fellow of Trinity College, Cambridge

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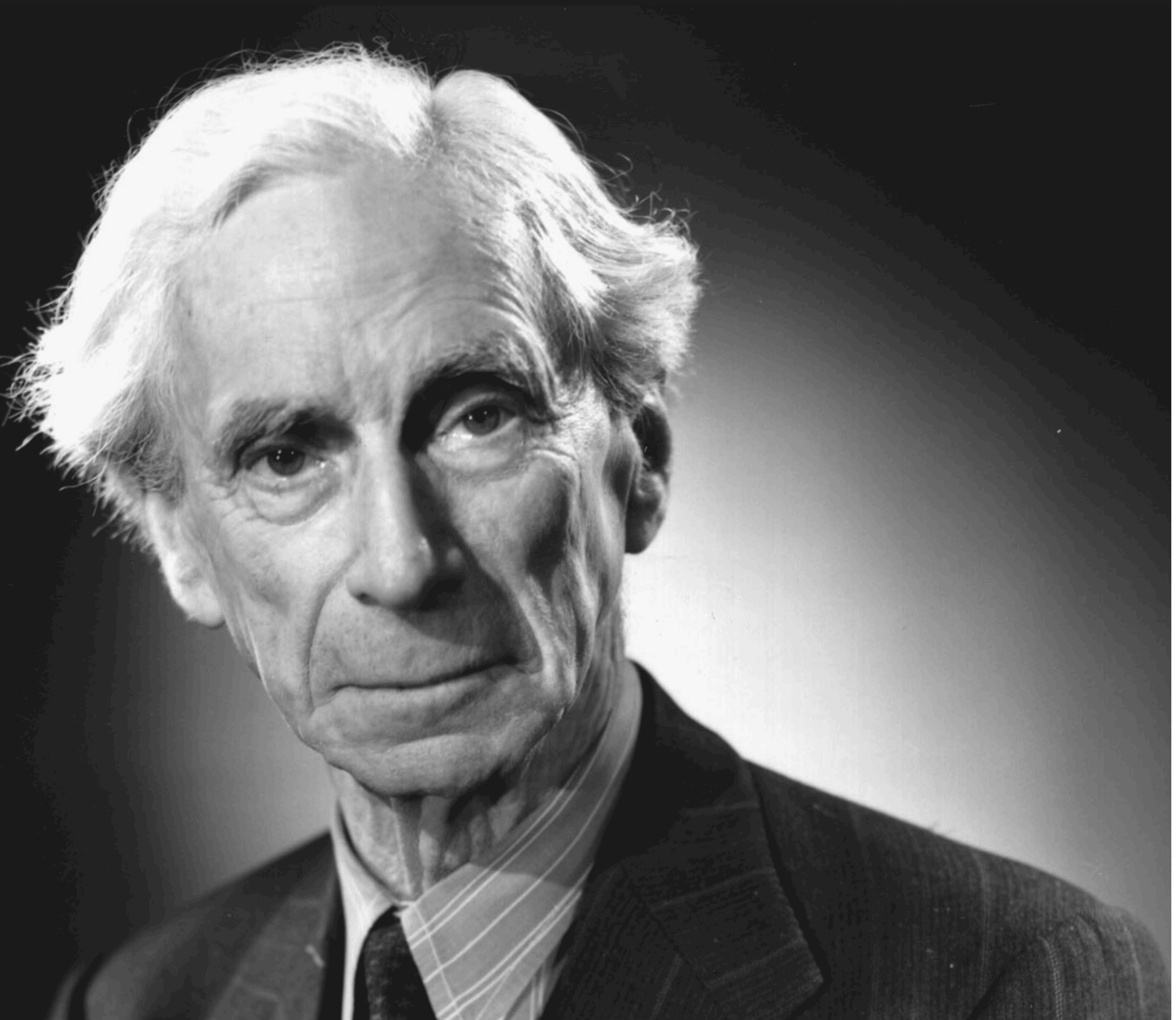

∗10·2. $\vdash :. (x) . p \lor \phi x . \equiv : p . \lor . (x) . \phi x$

Dem.

$\vdash . *10\cdot1 . *1\cdot6 . \supset \vdash :. p . \lor . (x) . \phi x : \supset . p \lor \phi y :.$

$[*10\cdot11] \quad \supset \vdash :. (y) :. p . \lor . (x) . \phi x : \supset . p \lor \phi y :.$

$[*10\cdot12] \quad \supset \vdash :. p . \lor . (x) . \phi x : \supset . (y) . p \lor \phi y \quad (1)$

$\vdash . *10\cdot12 . \quad \supset \vdash :. (y) . p \lor \phi y . \supset : p . \lor . (x) . \phi x \quad (2)$

$\vdash . (1) . (2) . \quad \supset \vdash .$ Prop.

∗10·21. $\vdash :. (x) . p \supset \phi x . \equiv : p . \supset . (x) . \phi x \quad \left[*10\cdot2 \frac{\sim p}{p}\right]$

This proposition is much more used than ∗10·2.

∗10·22. $\vdash :. (x) . \phi x . \psi x . \equiv : (x) . \phi x : (x) . \psi x$

Dem.

$\vdash . *10\cdot1 . \quad \supset \vdash : (x) . \phi x . \psi x . \supset . \phi y . \psi y . \quad (1)$

$[*3\cdot26] \quad \supset . \phi y :$

$[*10\cdot11] \quad \supset \vdash :. (y) : (x) . \phi x . \psi x . \supset . \phi y :.$

$[*10\cdot21] \quad \supset \vdash :. (x) . \phi x . \psi x . \supset . (y) . \phi y \quad (2)$

$\vdash . (1) . *3\cdot27 . \quad \supset \vdash :. (x) . \phi x . \psi x . \supset . \psi z :.$

$[*10\cdot11] \quad \supset \vdash :. (z) : (x) . \phi x . \psi x . \supset . \psi z :.$

$[*10\cdot21] \quad \supset \vdash :. (x) . \phi x . \psi x . \supset . (z) . \psi z \quad (3)$

$\vdash . (2) . (3) . \text{Comp} . \supset \vdash :. (x) . \phi x . \psi x . \supset : (y) . \phi y : (z) . \psi z \quad (4)$

$\vdash . *10\cdot14\cdot11 . \quad \supset \vdash :. (y) :. (x) . \phi x : (x) . \psi x : \supset . \phi y . \psi y :.$

$[*10\cdot21] \quad \supset \vdash :. (x) . \phi x : (x) . \psi x : \supset . (y) . \phi y . \psi y \quad (5)$

$\vdash . (4) . (5) . \quad \supset \vdash .$ Prop

The above proposition is true whenever it is significant; but, as was pointed out in connexion with ∗10·14, it is not always significant when "$(x) . \phi x : (x) . \psi x$" is significant.

∗10·221. If ϕx contains a constituent $\chi(x, y, z, \ldots)$ and ψx contains a constituent $\chi(x, u, v, \ldots)$, where χ is an elementary function and $y, z, \ldots u, v, \ldots$ are either constants or apparent variables, then $\phi\hat{x}$ and $\psi\hat{x}$ take arguments of the same type. This can be proved in each particular case, though not generally, provided that, in obtaining ϕ and ψ from χ, χ is only submitted to negations, disjunctions and generalizations. The process may be illustrated by an example. Suppose ϕx is $(y) . \chi(x, y) . \supset . \theta x$, and ψx is $fx . \supset . (y) . \chi(x, y)$. By the definitions of ∗9, ϕx is $(\exists y) . \sim \chi(x, y) \lor \theta x$, and ψx is $(y) . \sim fx \lor \chi(x, y)$. Hence since the primitive ideas $(x) . Fx$ and $(\exists x) . Fx$ only apply to functions, there are functions $\sim \chi(\hat{x}, \hat{y}) \lor \theta\hat{x}$, $\sim f\hat{x} \lor \chi(\hat{x}, \hat{y})$. Hence there is a proposition $\sim \chi(a, b) \lor \theta a$. Hence, since "$p \lor q$" and "$\sim p$" are only significant

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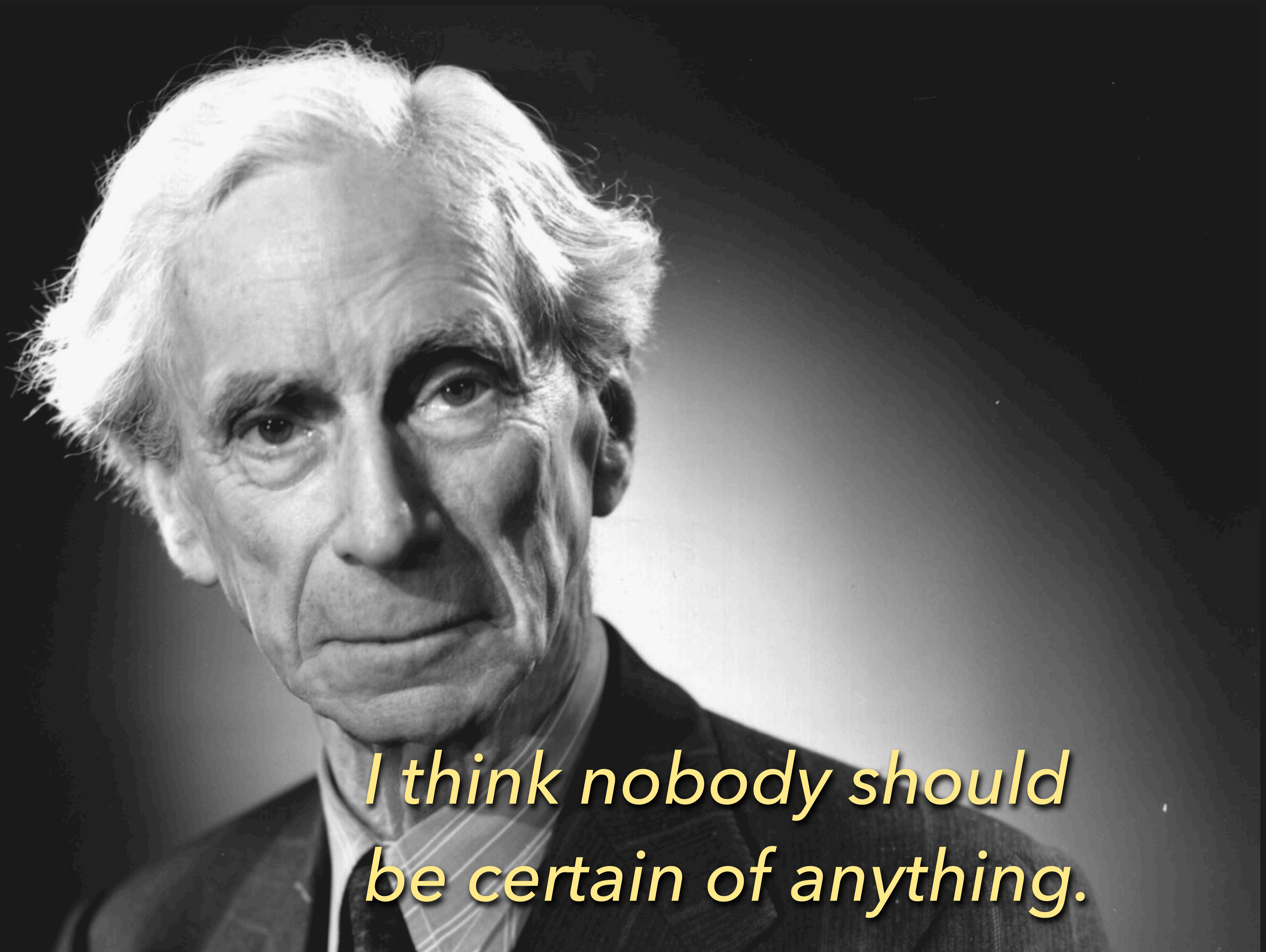

THE ENGINEER'S VIEW

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- "an element of a structure which connects it to the ground" – Wikipedia

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- "an element of a structure which connects it to the ground" – Wikipedia
- Abstracting just slightly: An Interface to the World
- And what happens if your interface does not respect the properties of the world?
    - Or if the world changes, and what was solid before no longer is…

FOUNDATIONS OF MACHINE LEARNING SYSTEMS

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- Study the *interface* of ML systems to the world

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- Pay attention to what we *assume* about the world

FOUNDATIONS OF MACHINE LEARNING SYSTEMS

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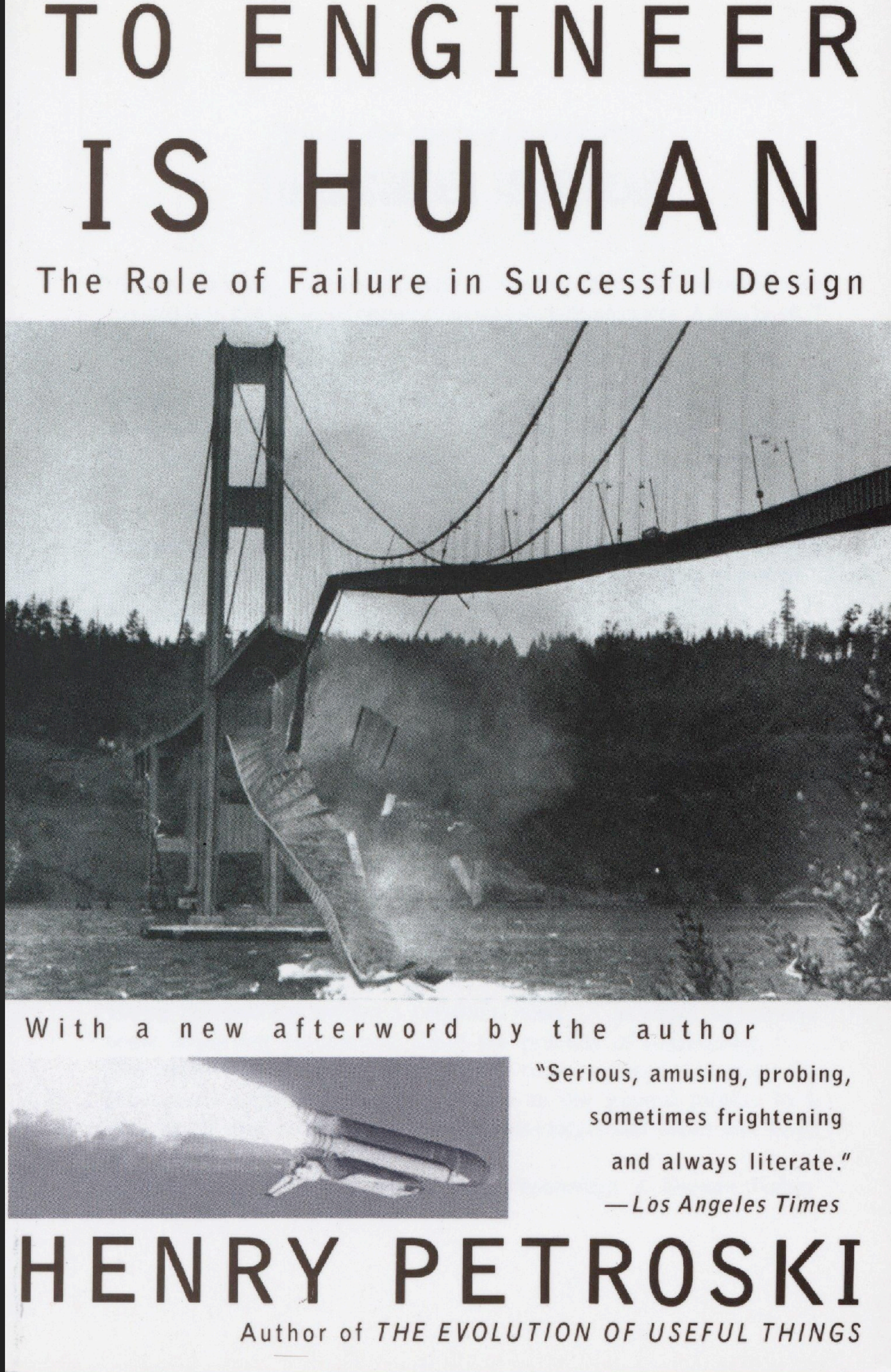
- Pay attention to what we *assume* about the world
- Like other areas of engineering, learn from *failure*

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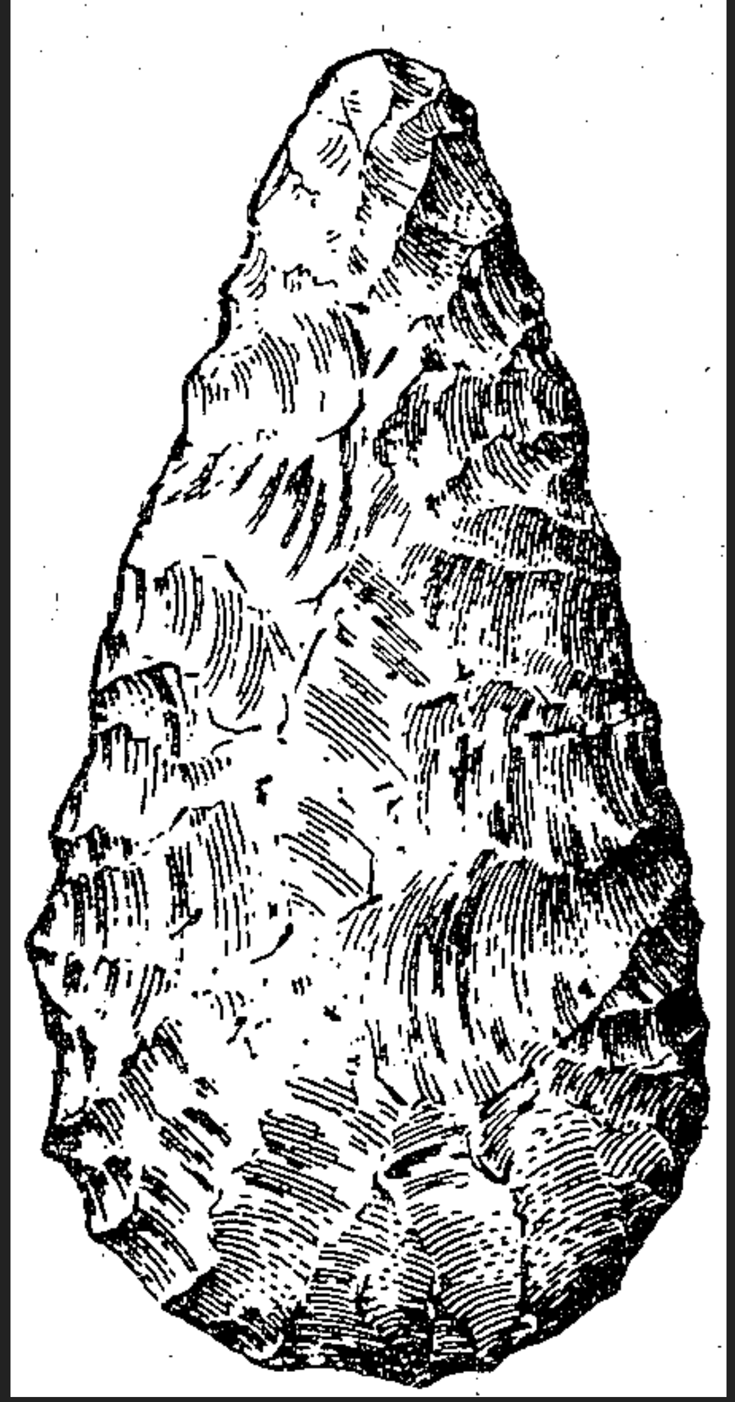

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  according to goals we (or others) set…

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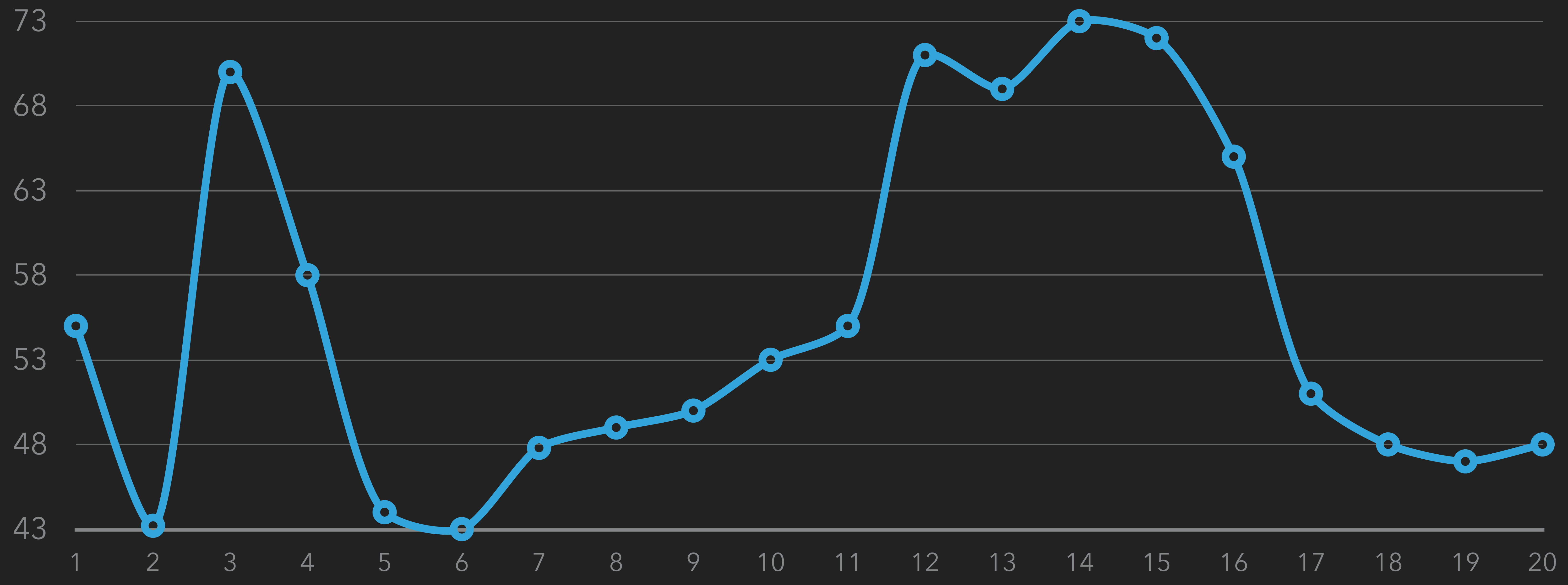

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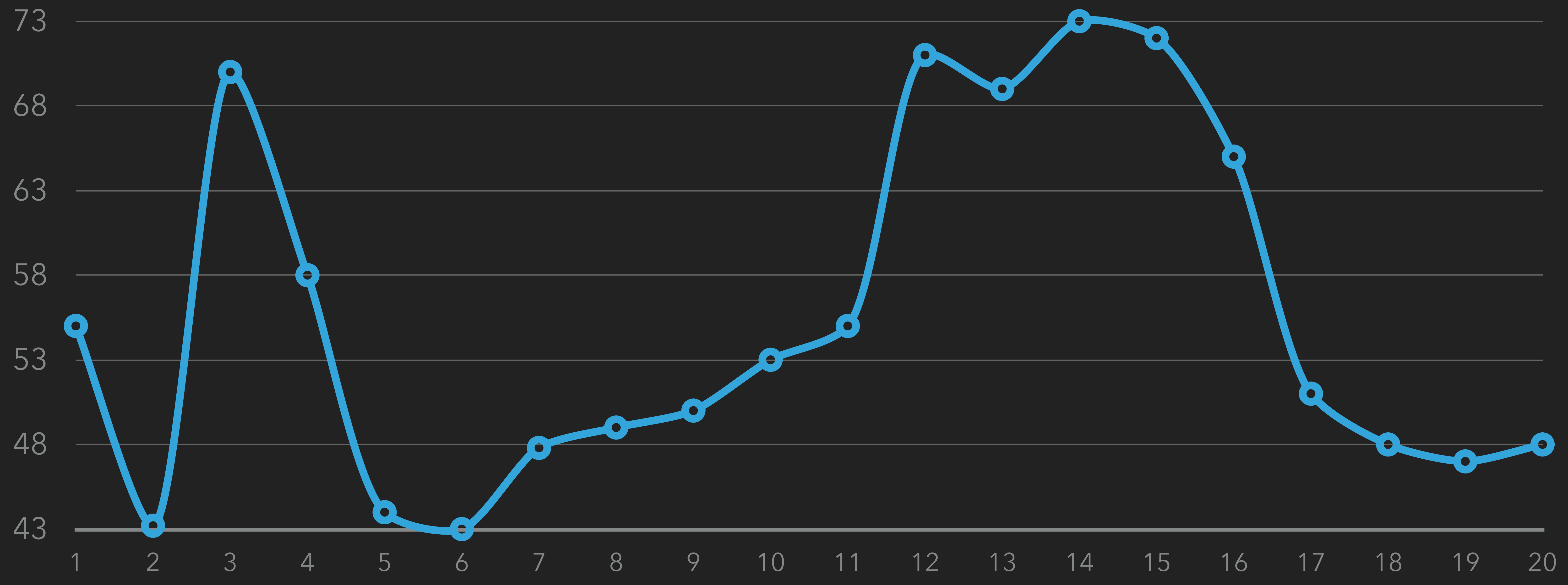

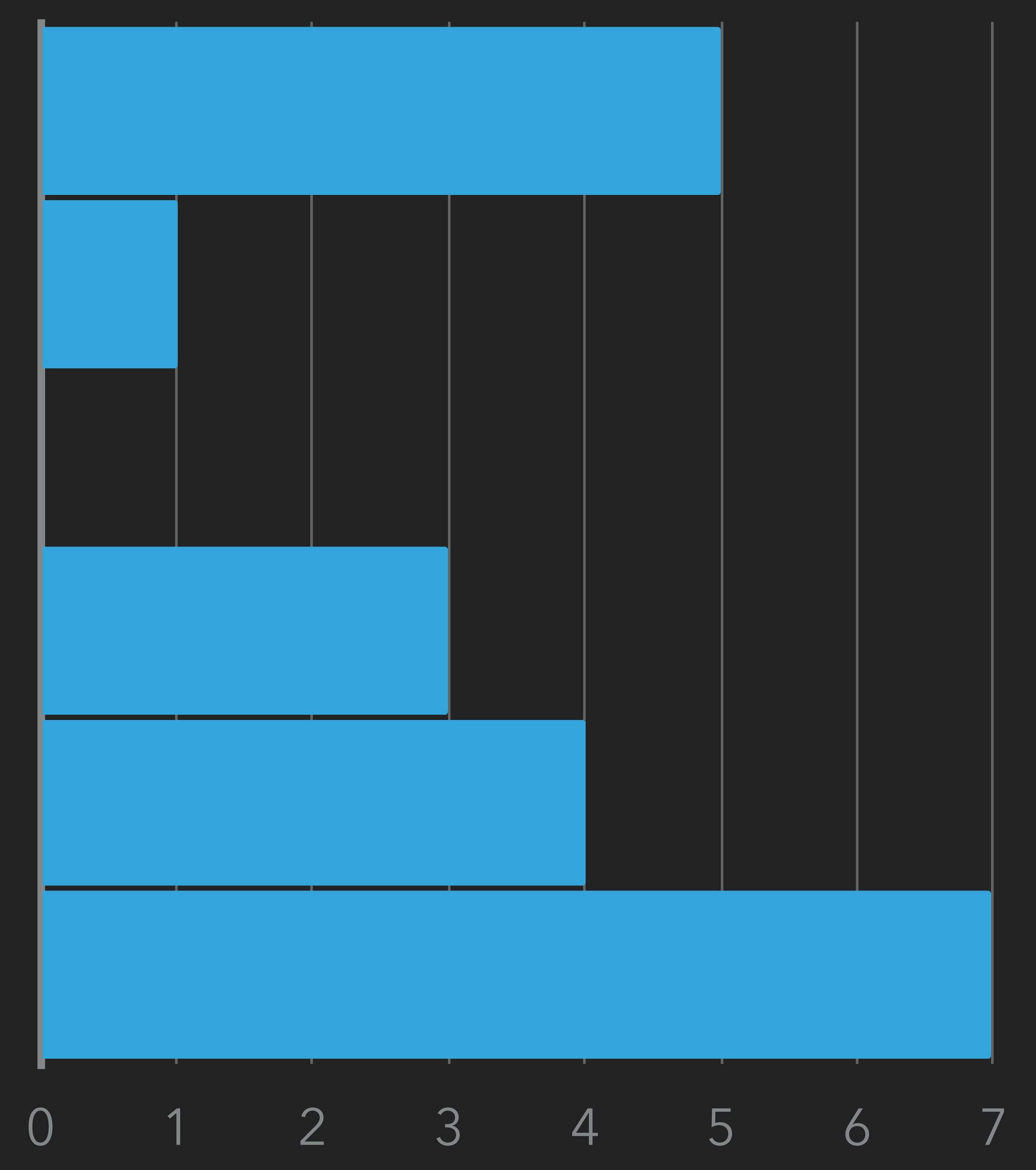

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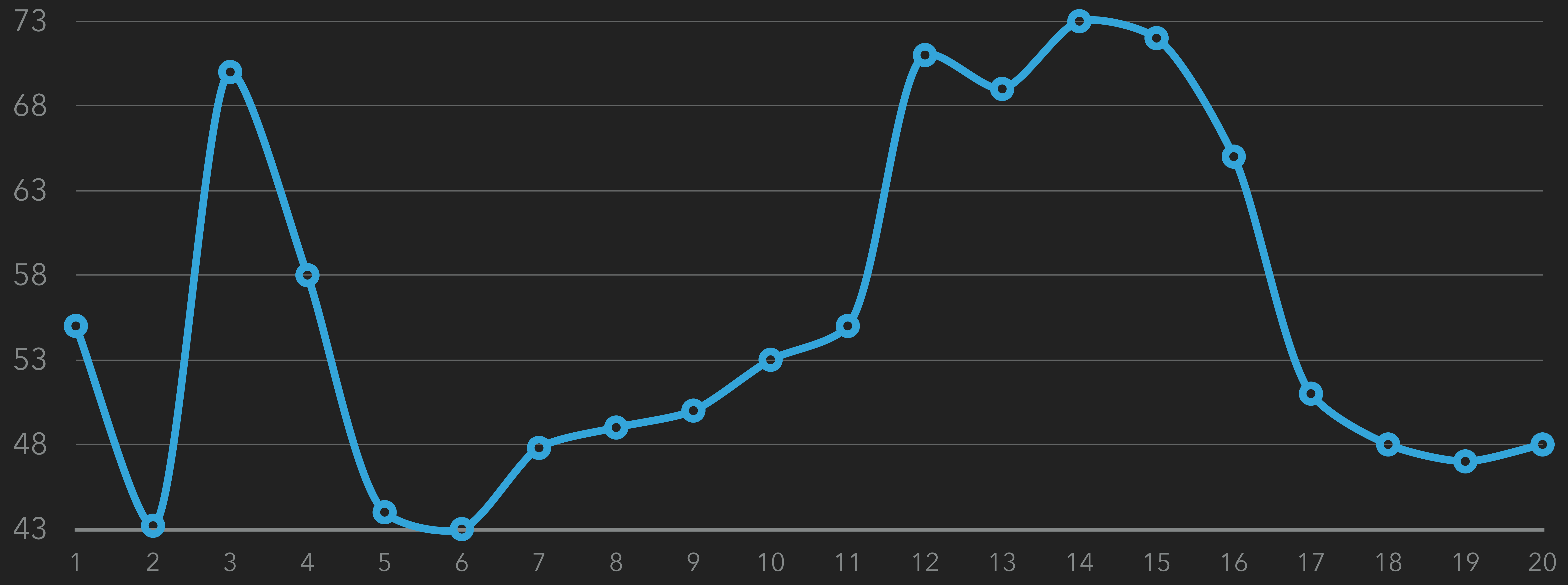

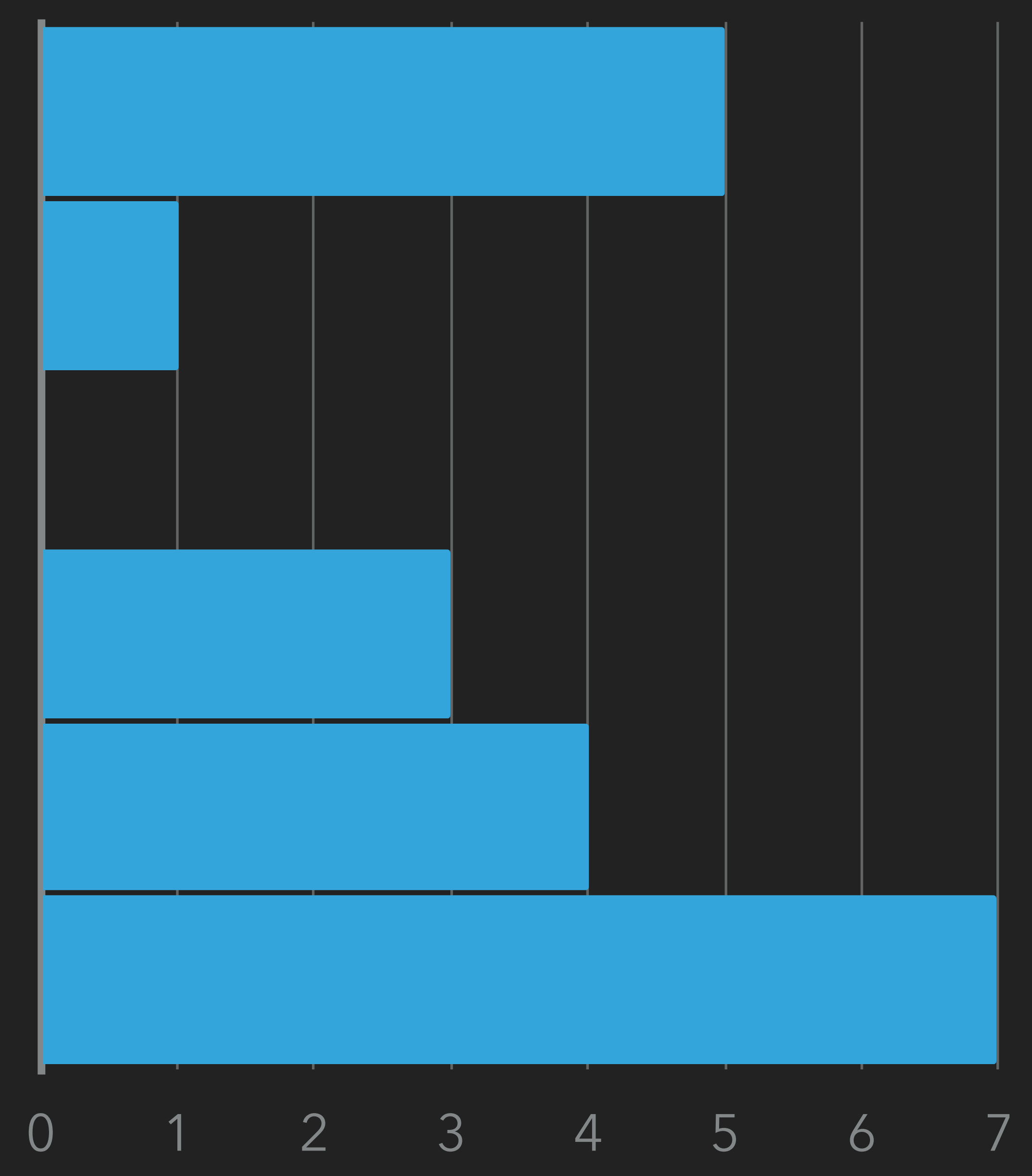

- Statistical Mechanics as an exemplar

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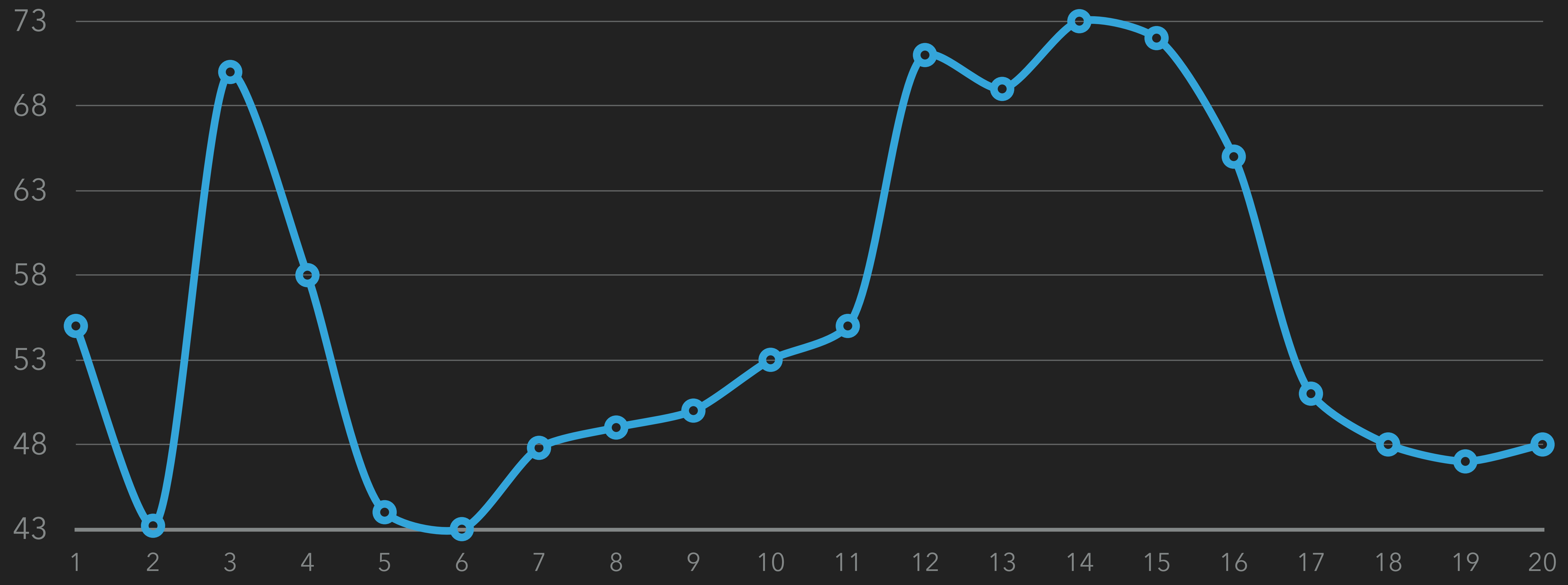

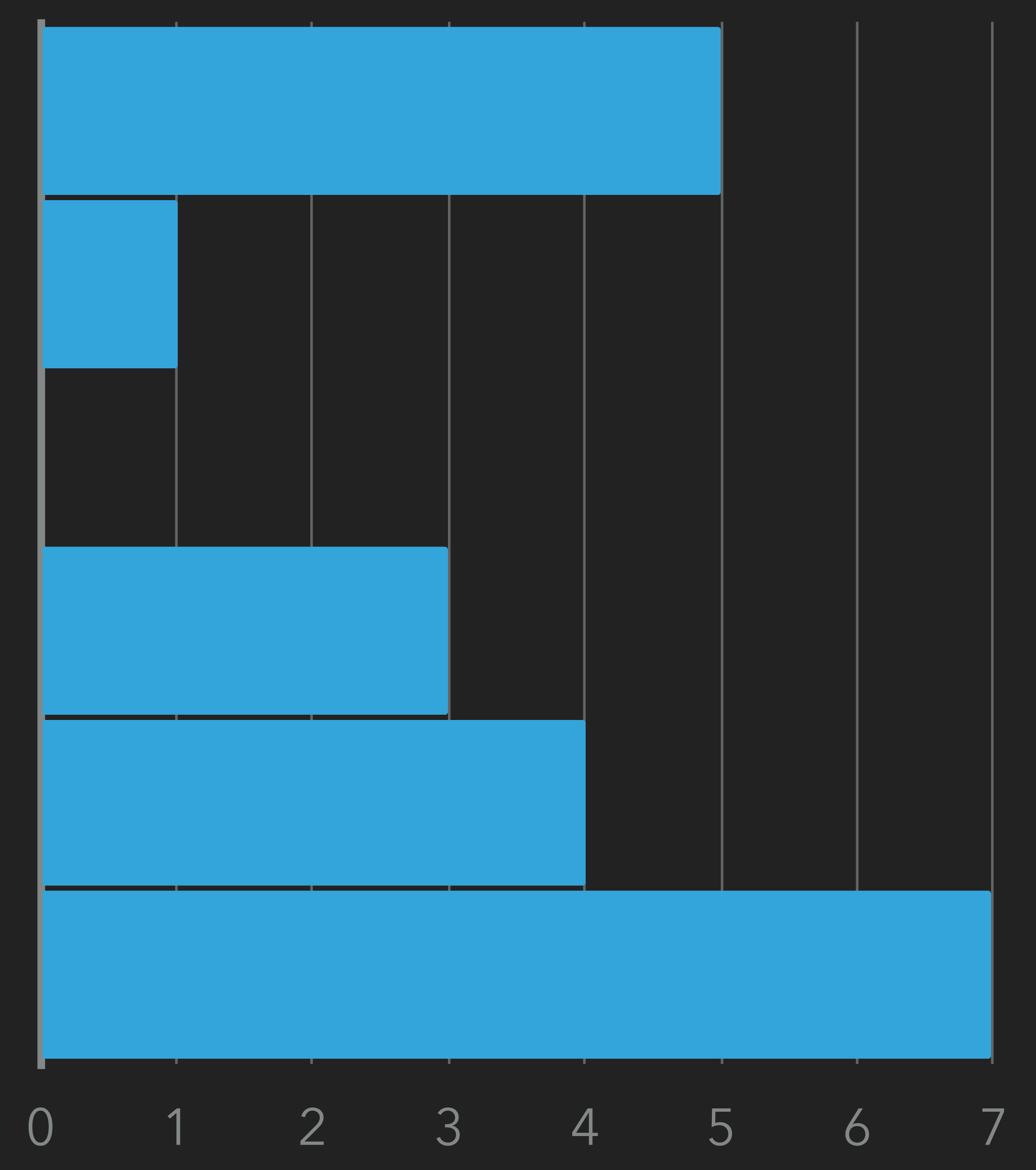

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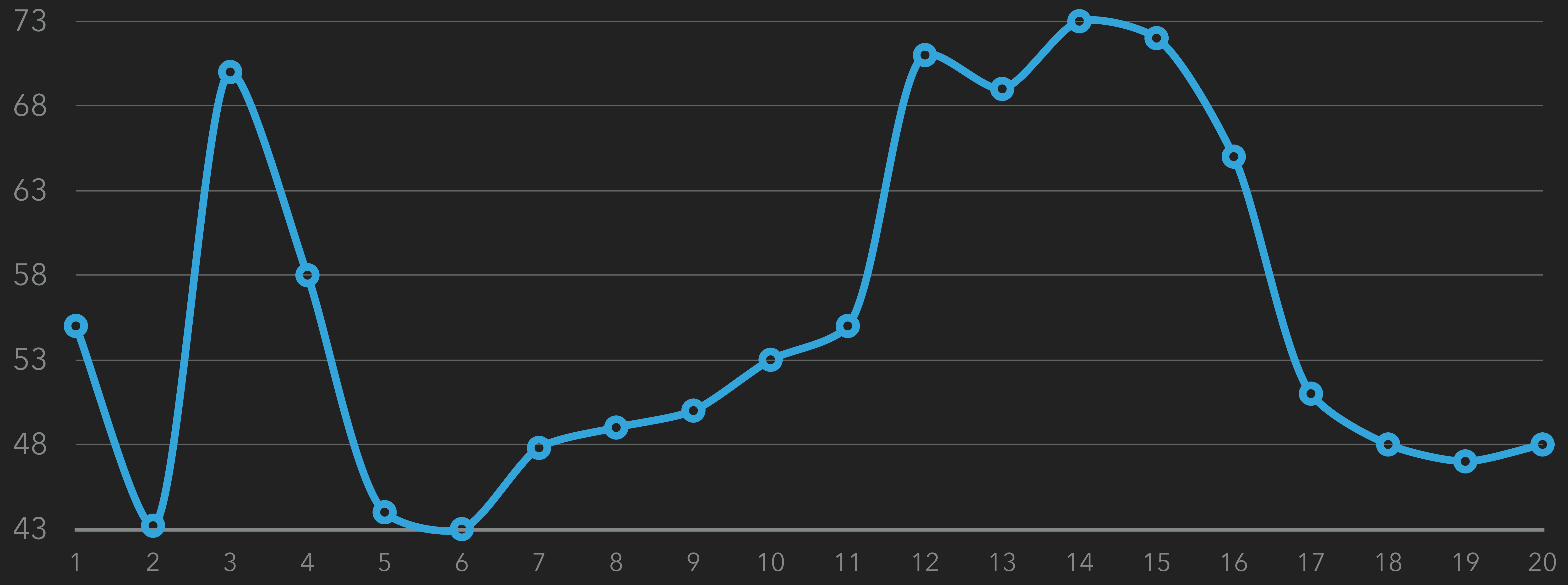

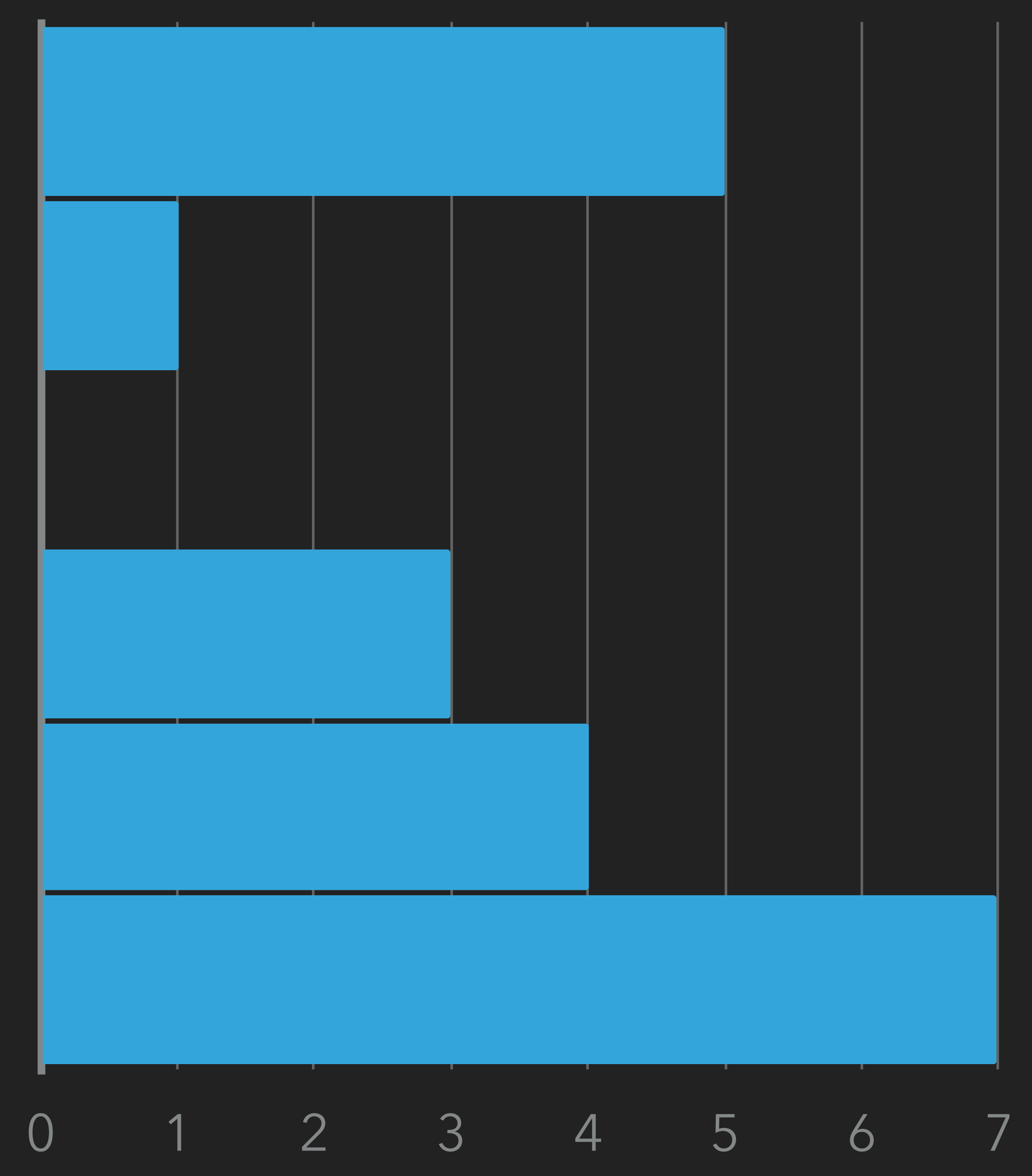

- Statistical Mechanics as an exemplar
- ML systems: an actuarial technology
  - (which means we can learn from insurance!)

Insights From Insurance for Fair Machine Learning: Responsibility, Performativity and Aggregates

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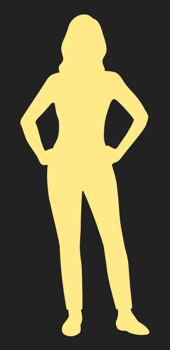

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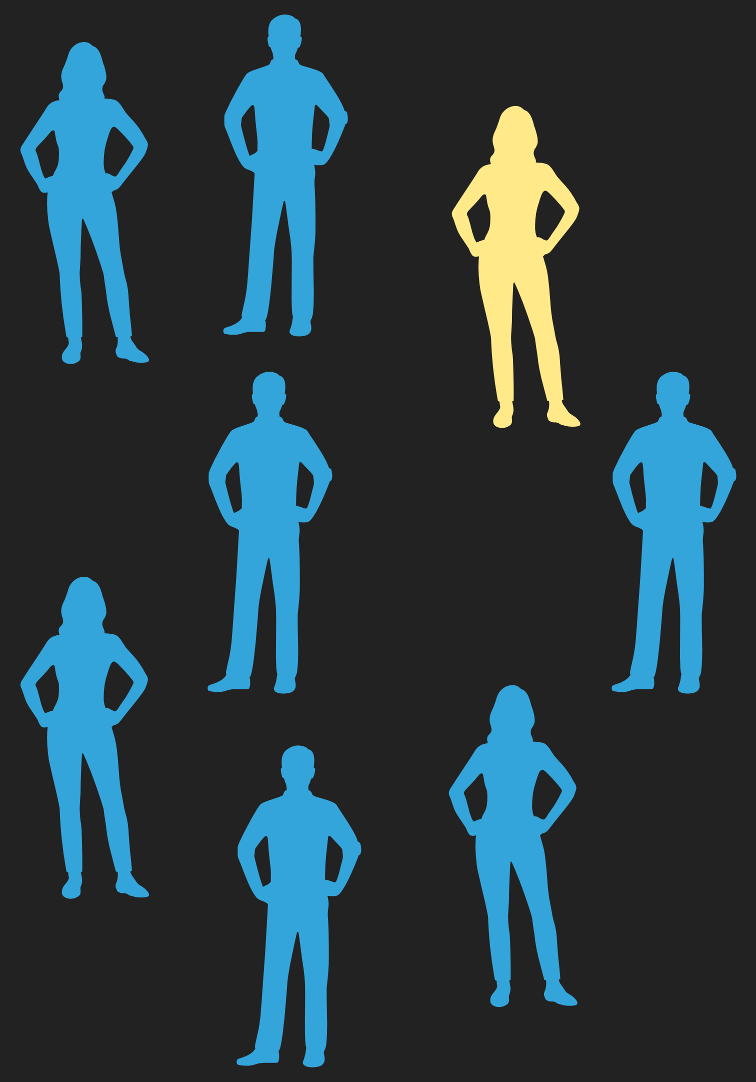

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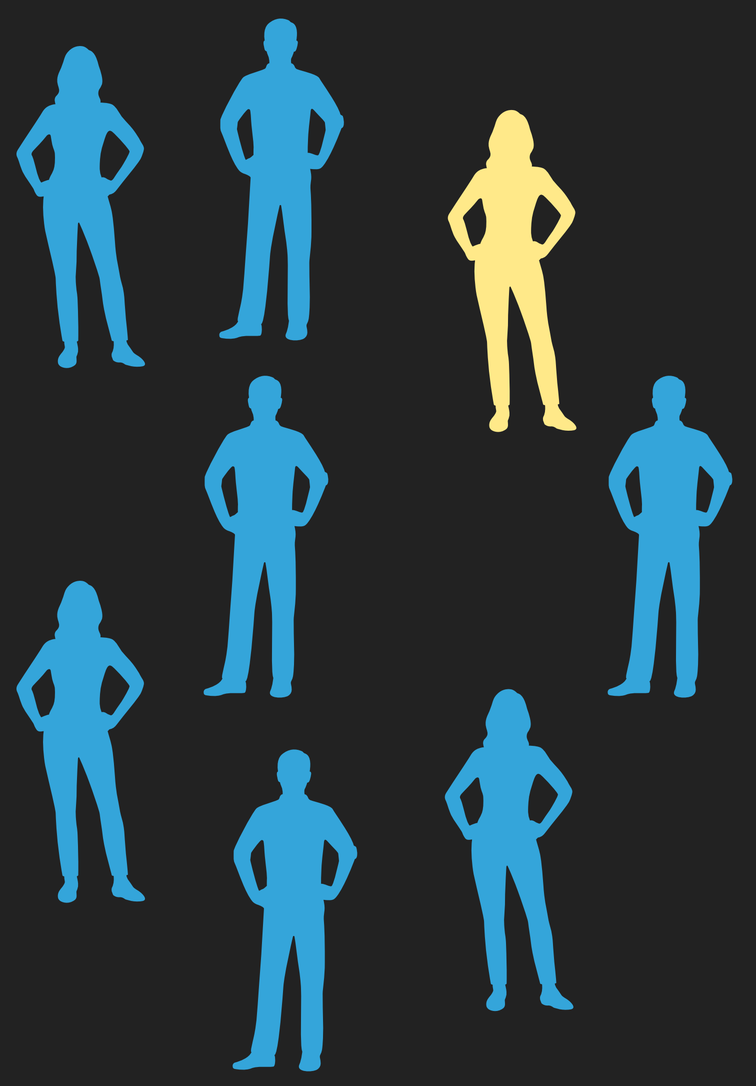

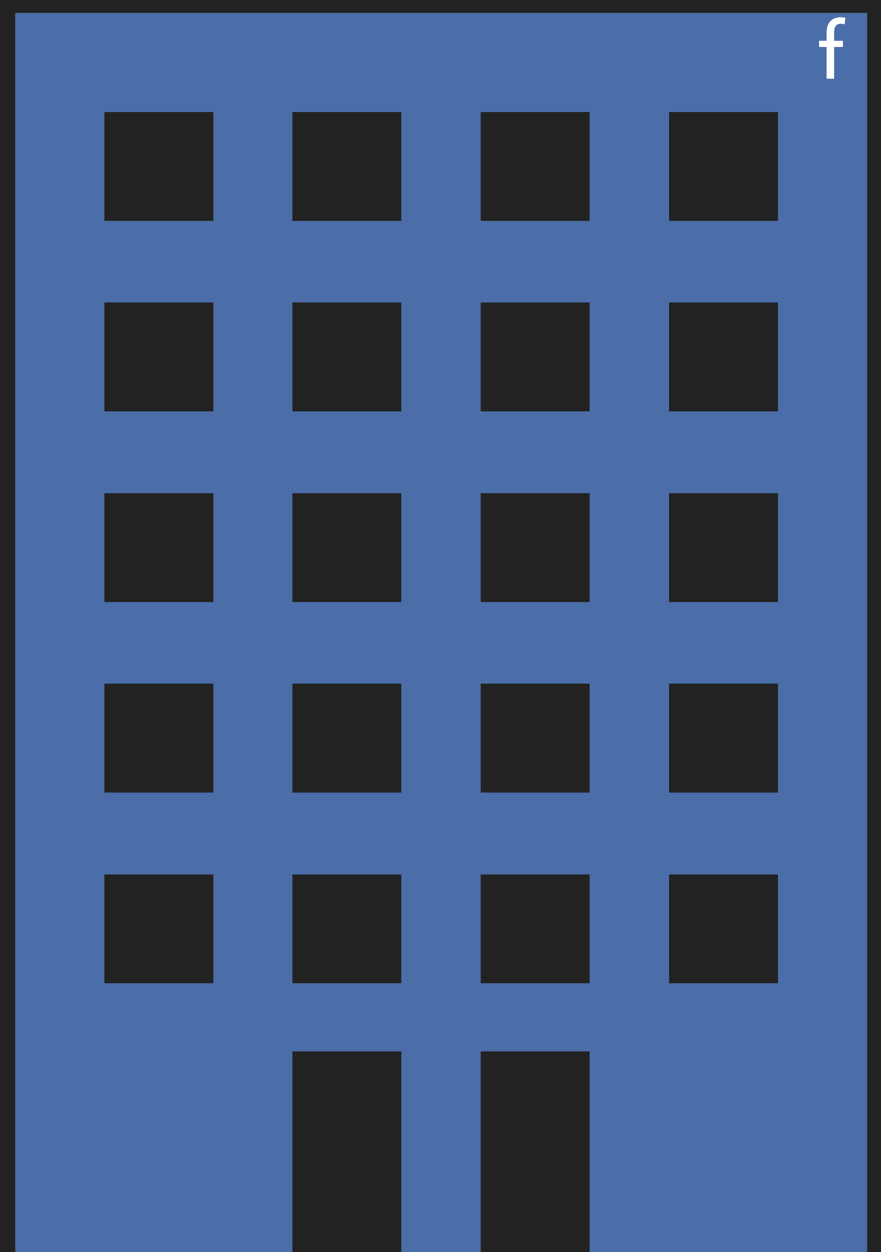

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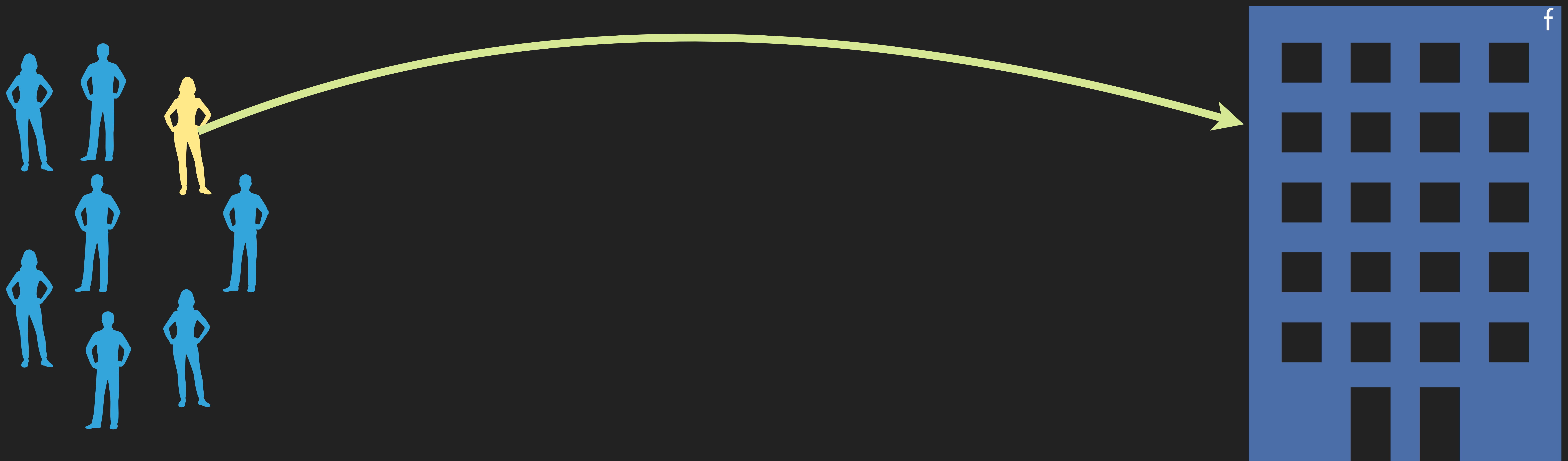

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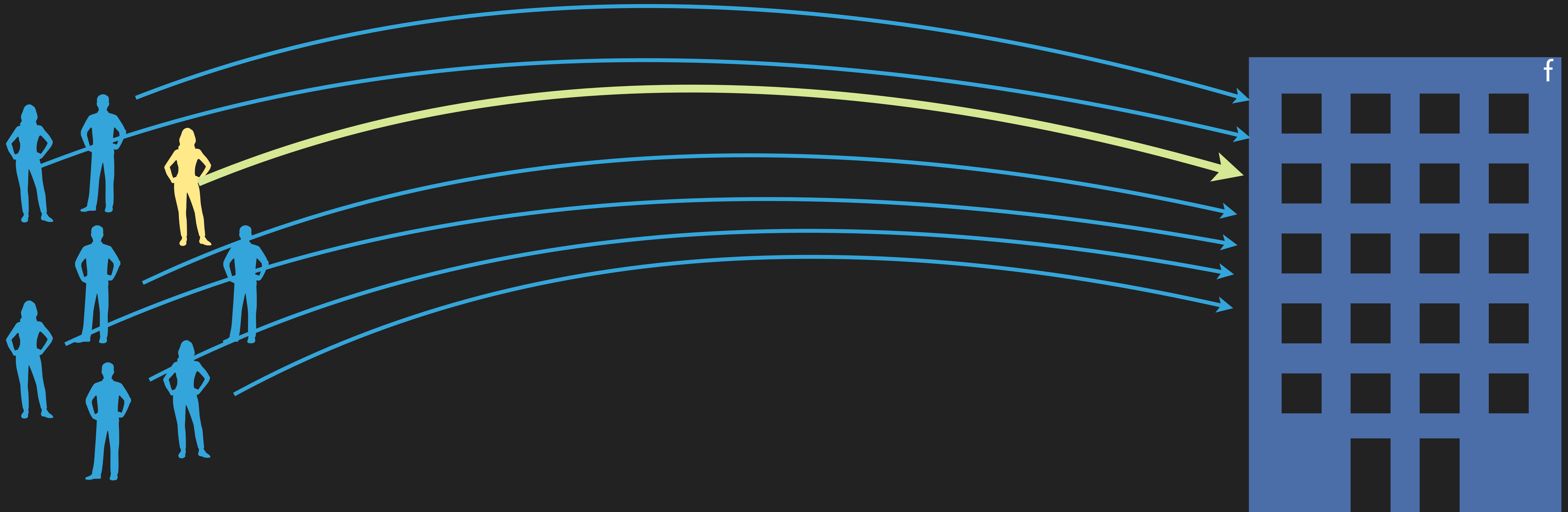

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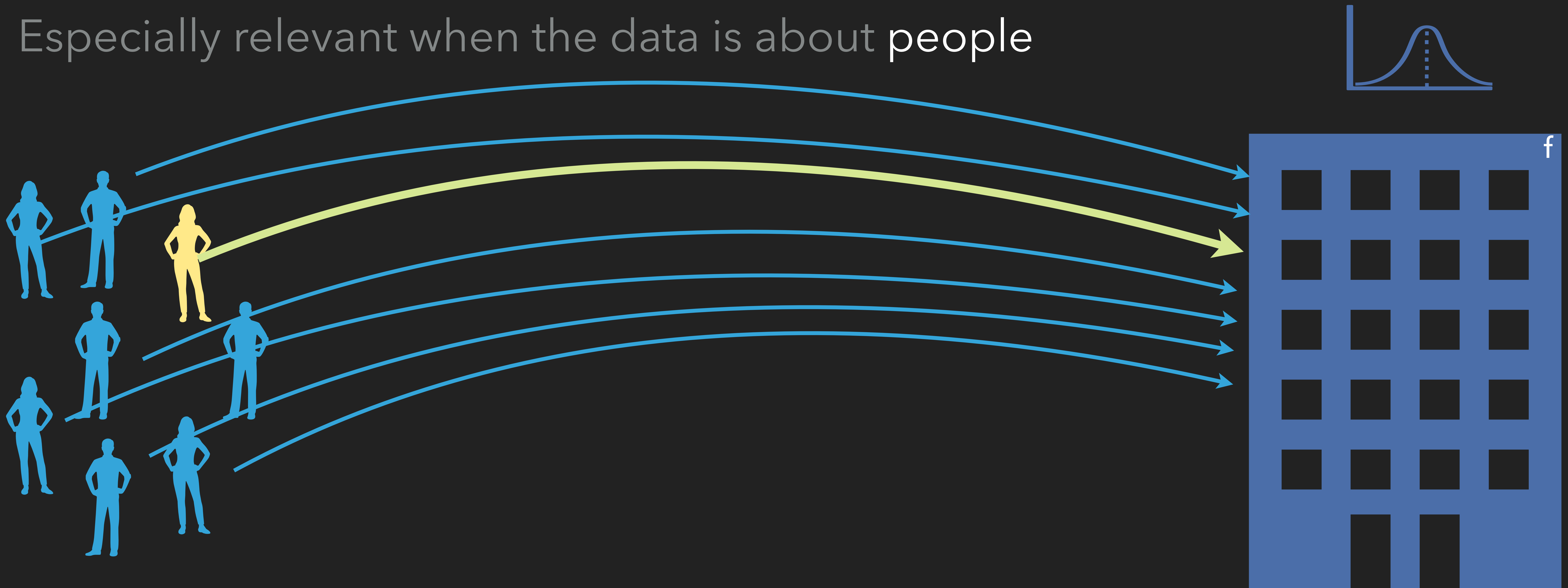

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$$Y \quad h(X)$$

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P_{XY} Y $h(X)$

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- Specific goal: find the h that minimises the average loss

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$$\underset{h \in \mathcal{Y}^{\mathcal{X}}}{\arg\min} \; \mathbb{E}_{P_{XY}} \, \ell(Y, h(X))$$

- Specific goal: find the h that minimises the average loss
  - where h is a function $\mathcal{X} \to \mathcal{Y}$
- Actually lower our sights; fix a hypothesis class $\mathcal{H}$ and consider…

$$\underset{h \in \mathcal{H}}{\arg\min} \; \mathbb{E} \, \ell(Y, h(X))$$

WHAT TO STUDY?

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The geometry and calculus of losses

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BEYOND


BEYOND
Data, Information, Probability, Independence, Expectations


BENEATH

BEYOND DATA: BENIGN AND MALIGNANT CORRUPTION

Considering what happens when we do not take data for granted

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- Open question: how to model selection bias?

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When posing problems in probability calculus, it should be required to indicate for which events the probabilities are assumed to exist

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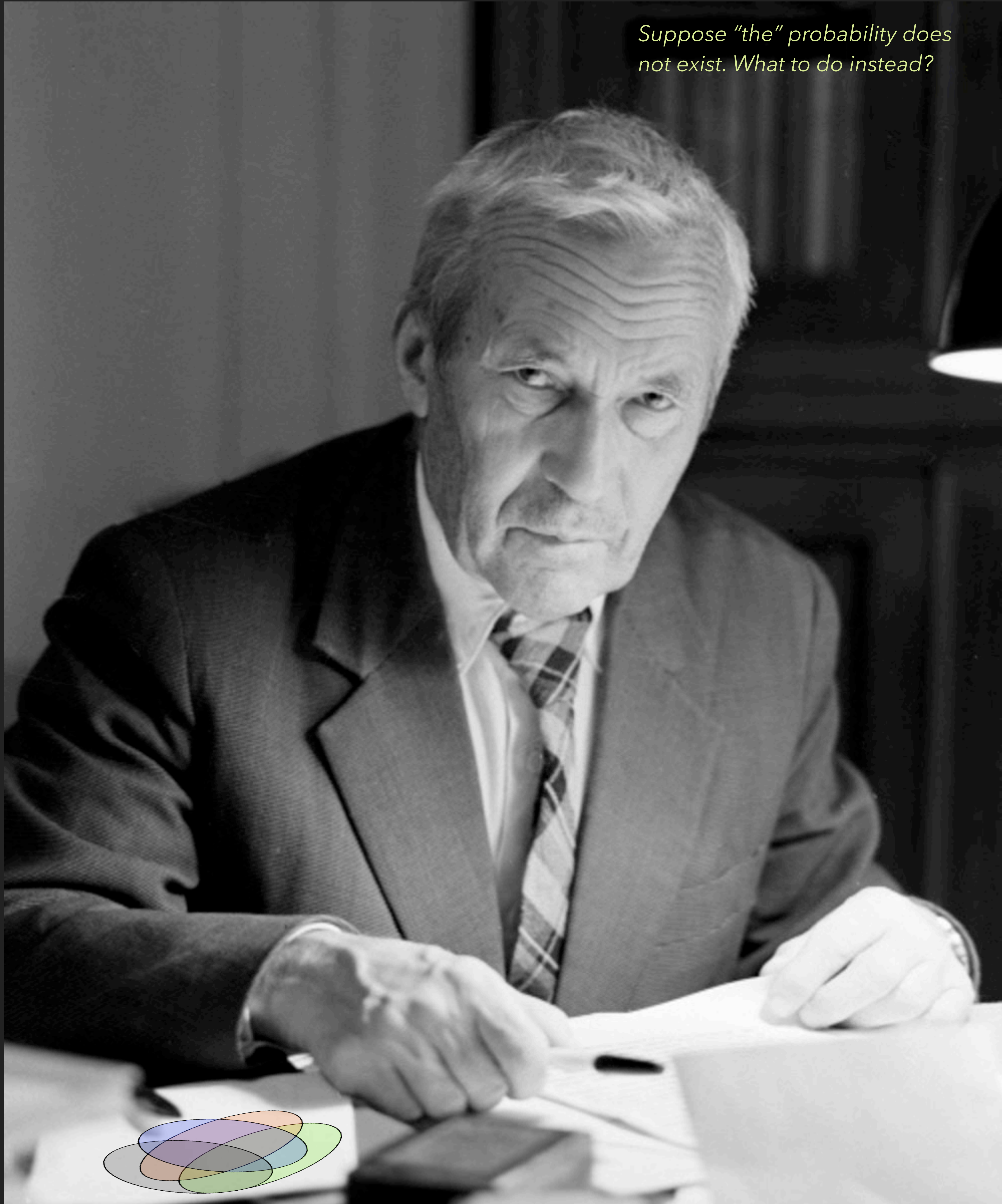

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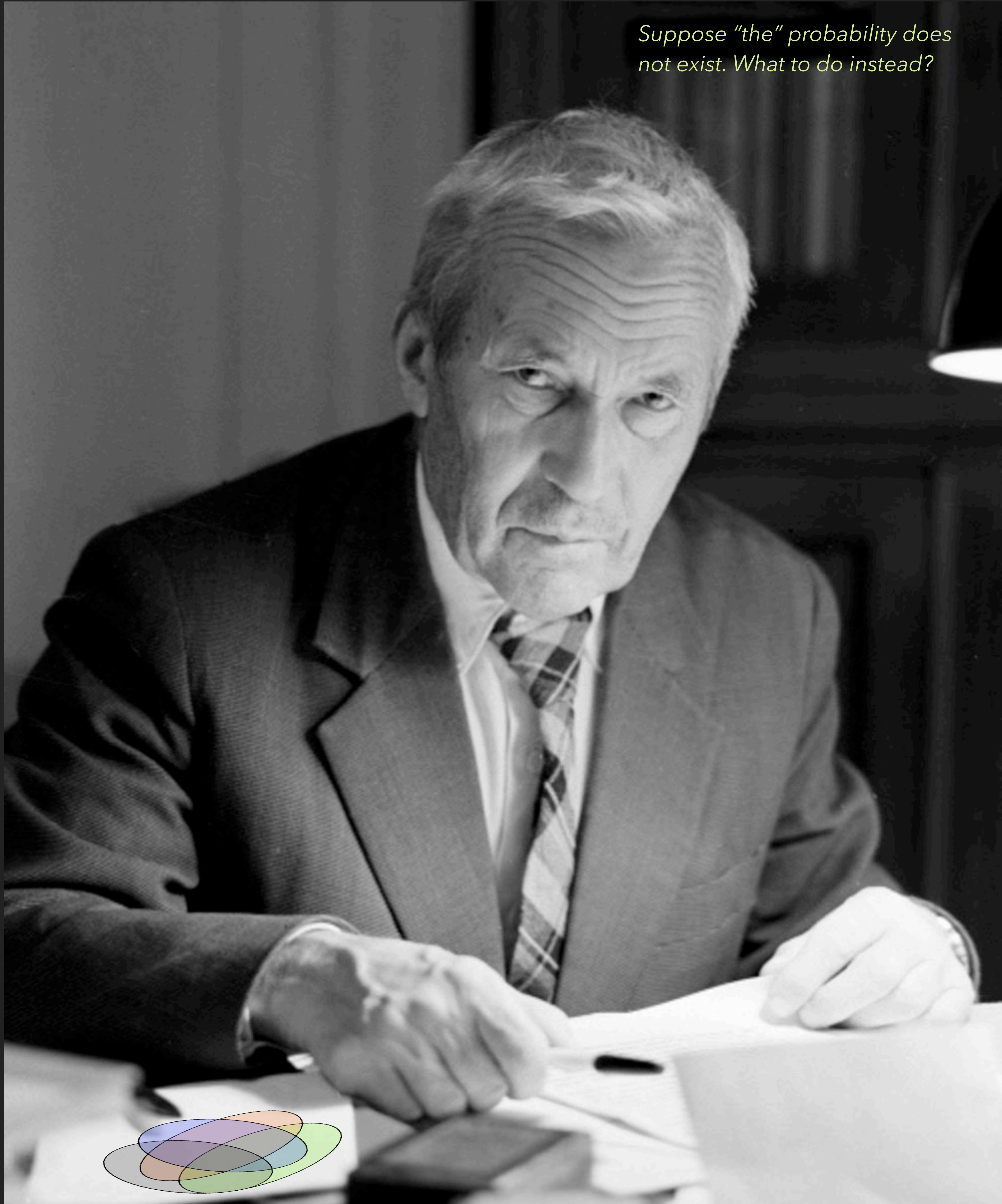

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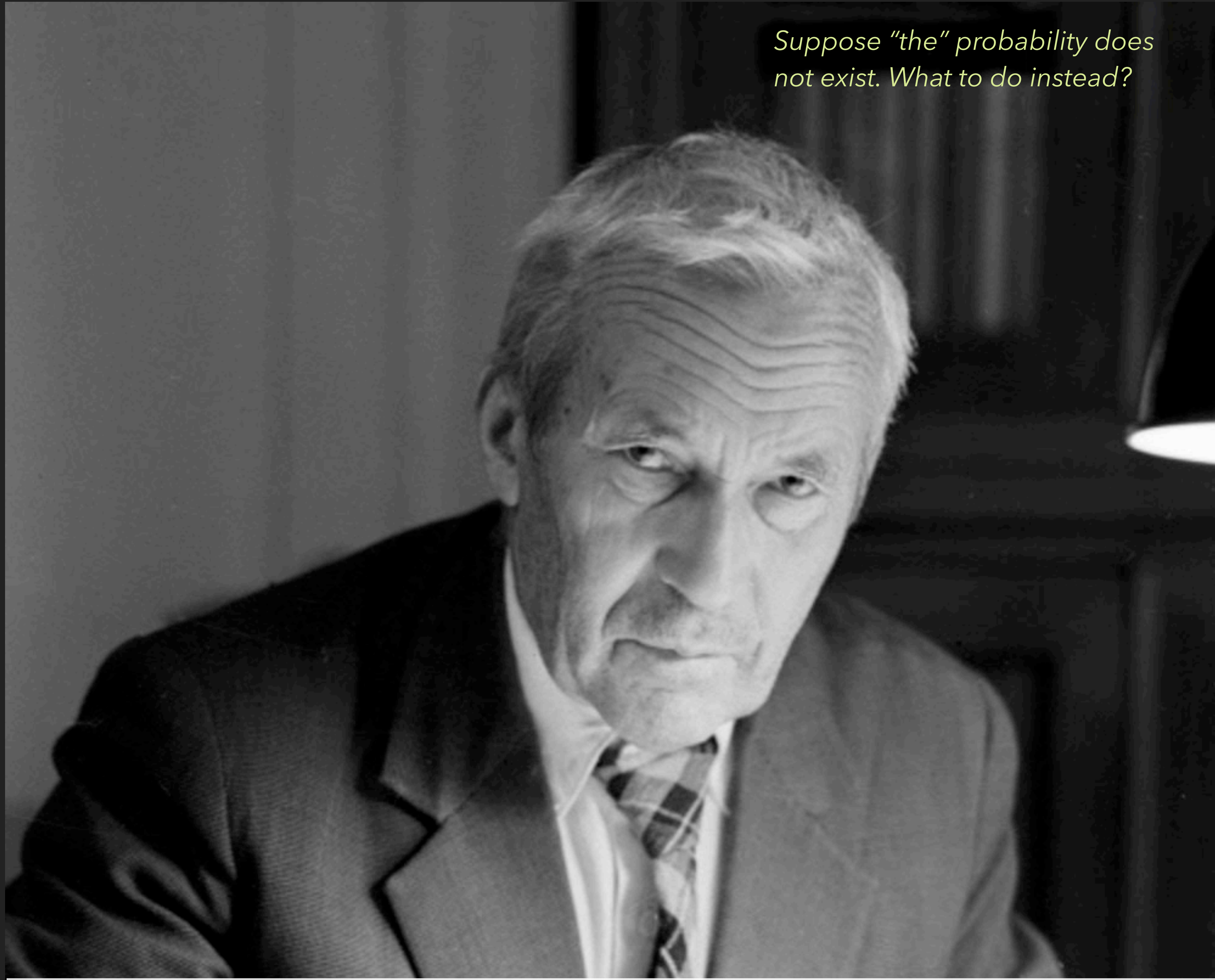

ON LOGICAL FOUNDATIONS OF PROBABILITY THEORY*) 1984

A.N.KOLMOGOROV

In everyday language we call random these phenomena where we cannot find a regularity allowing us to predict precisely their results. Generally speaking there is no ground to believe that a random phenomenon should possess any definite probability. Therefore, we should have distinguished between randomness proper (as absence of any regularity) and stochastic randomness (which is the subject of the probability theory).

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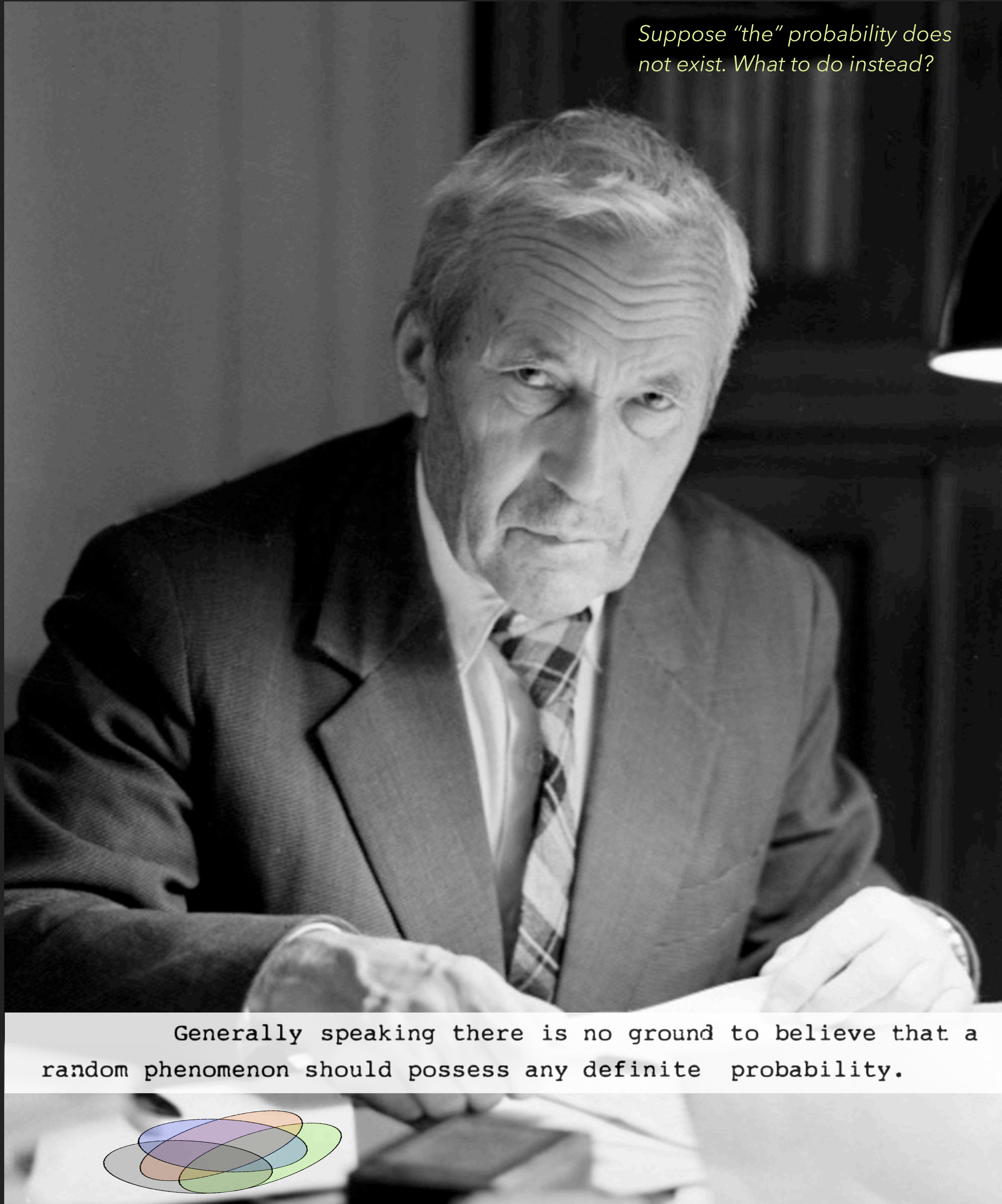

PROBABILITY AVERAGES AND LAWS

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3, 1, 3, 2, 2, 1, 2, 3, 2, 1, 3, 2, 3, 3, 2, 3, 3, 1, 1, 3, 1, 1, 3, 2, 2, 3, 3, 3, 3, 3, 1, 3, 3, 1, 1
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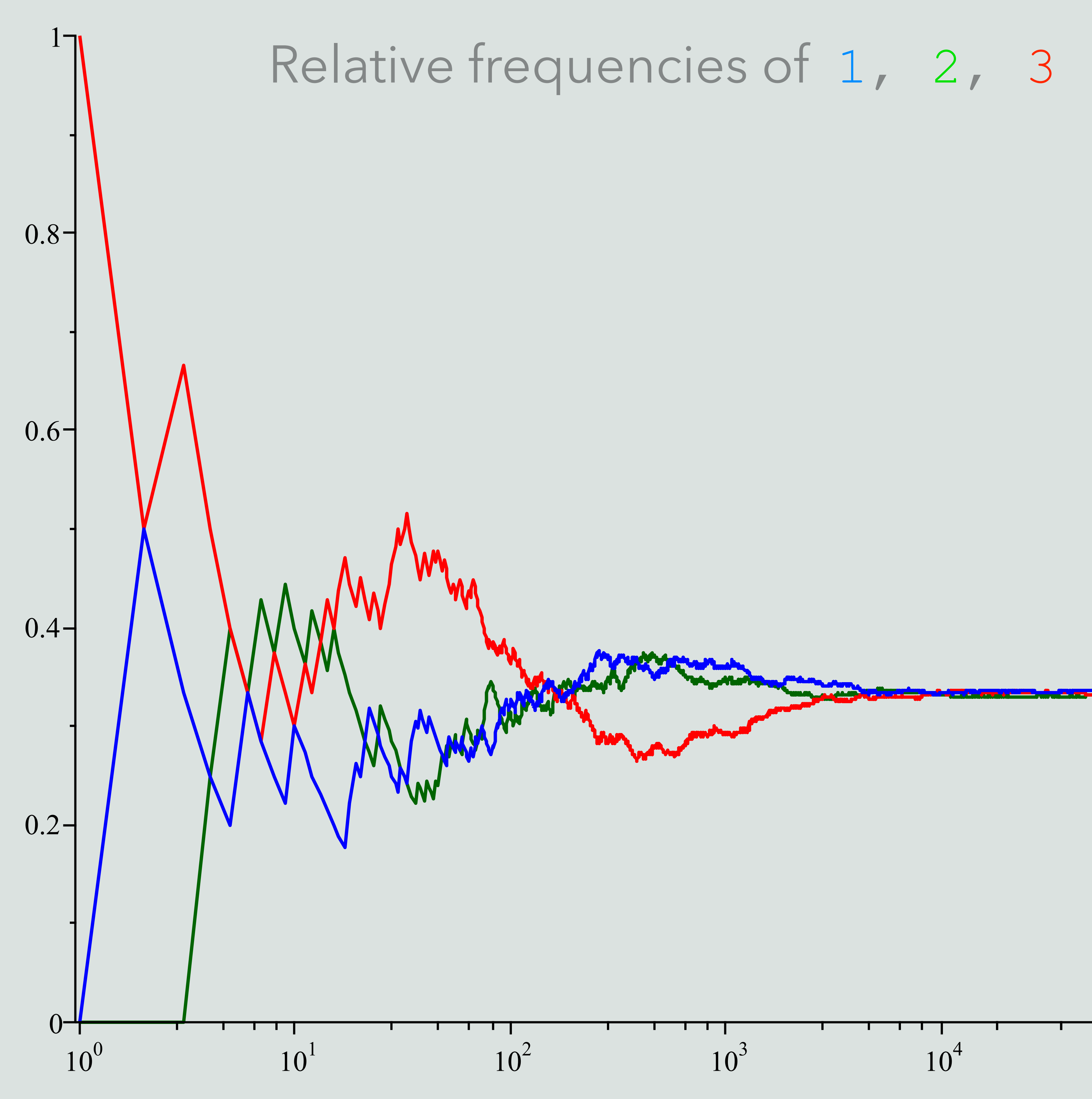
PROBABILITY AVERAGES AND LAWS

- The relative frequencies converge to $\left(\frac{1}{3}, \frac{1}{3}, \frac{1}{3}\right)$



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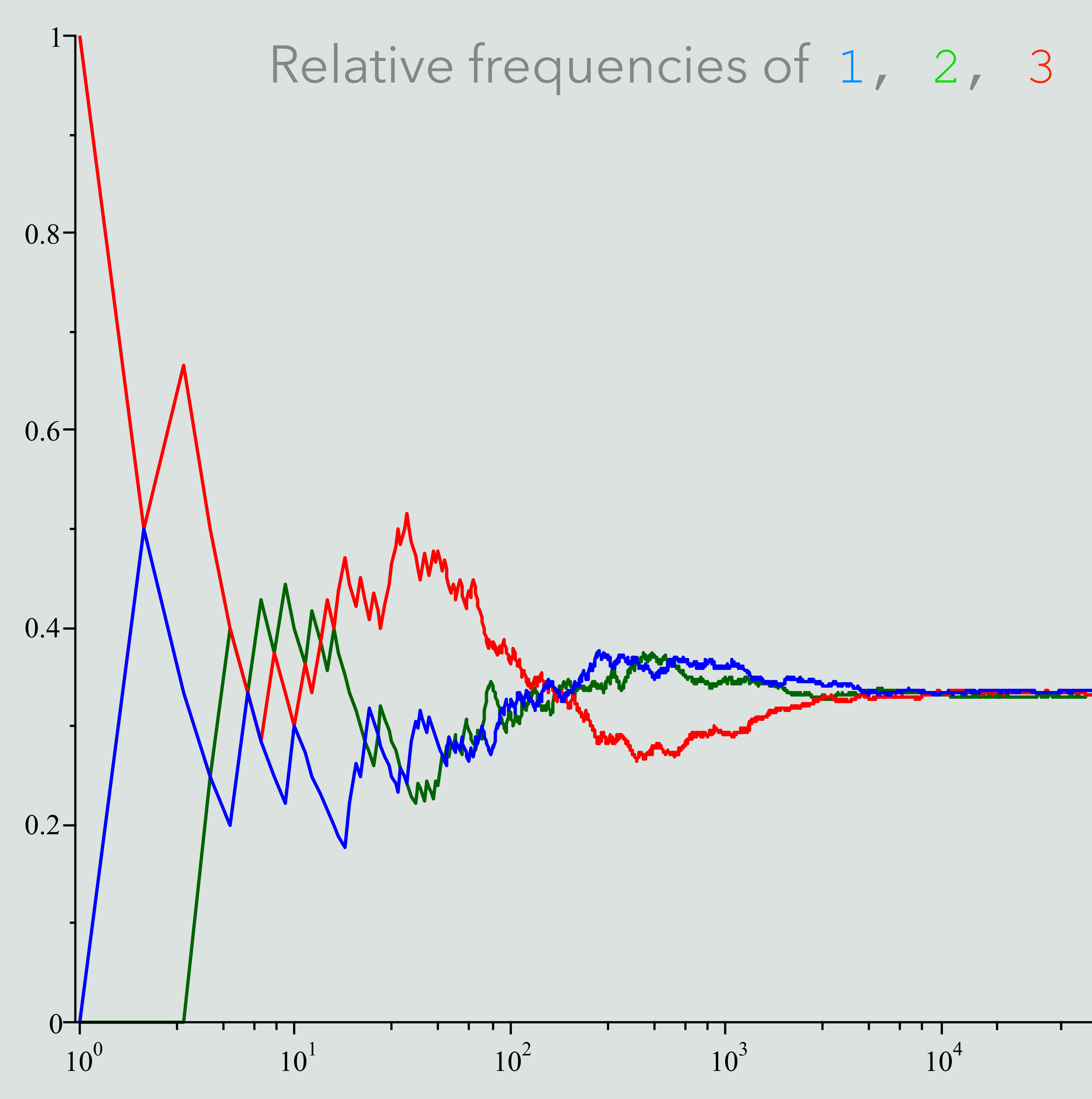

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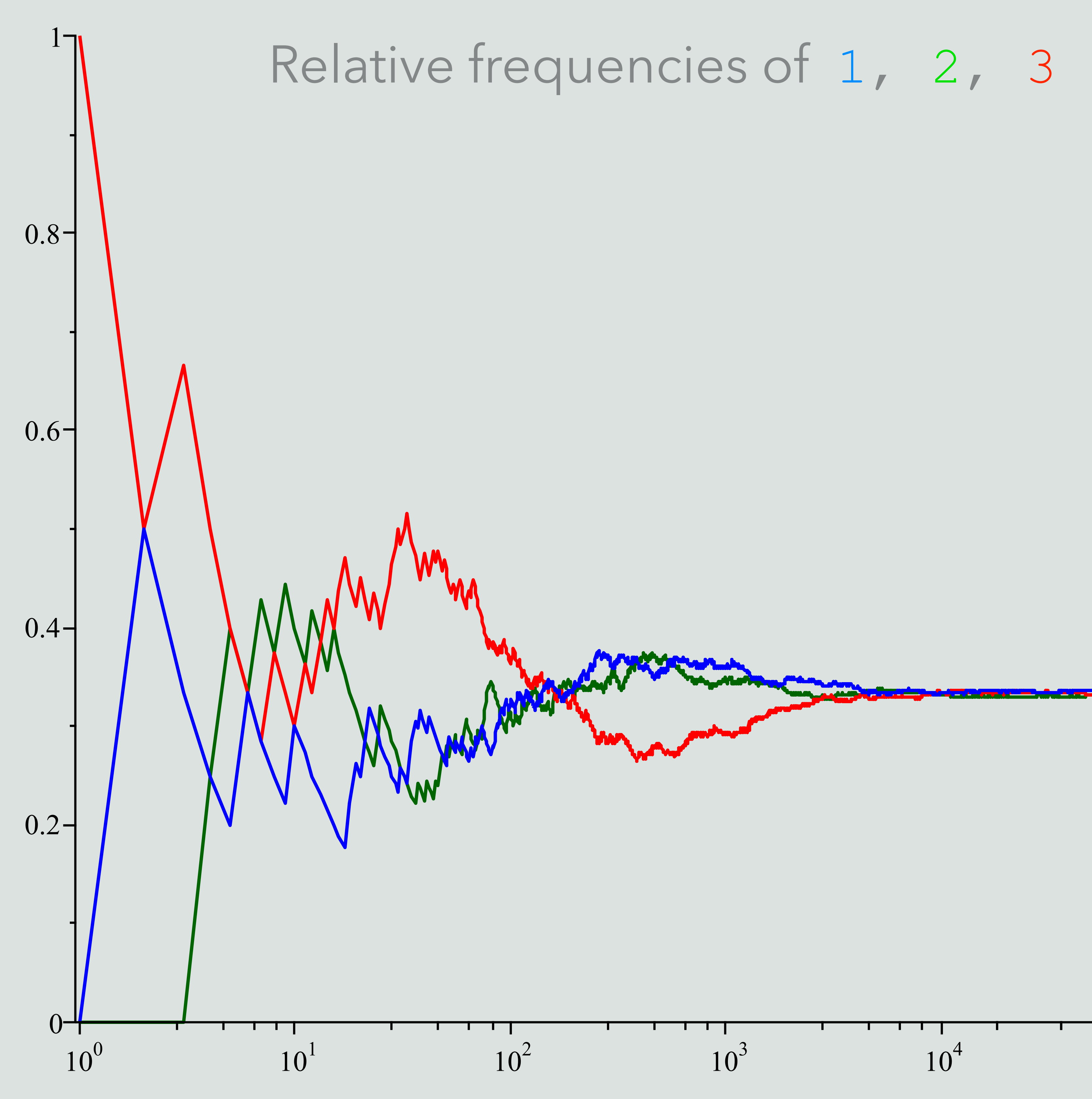

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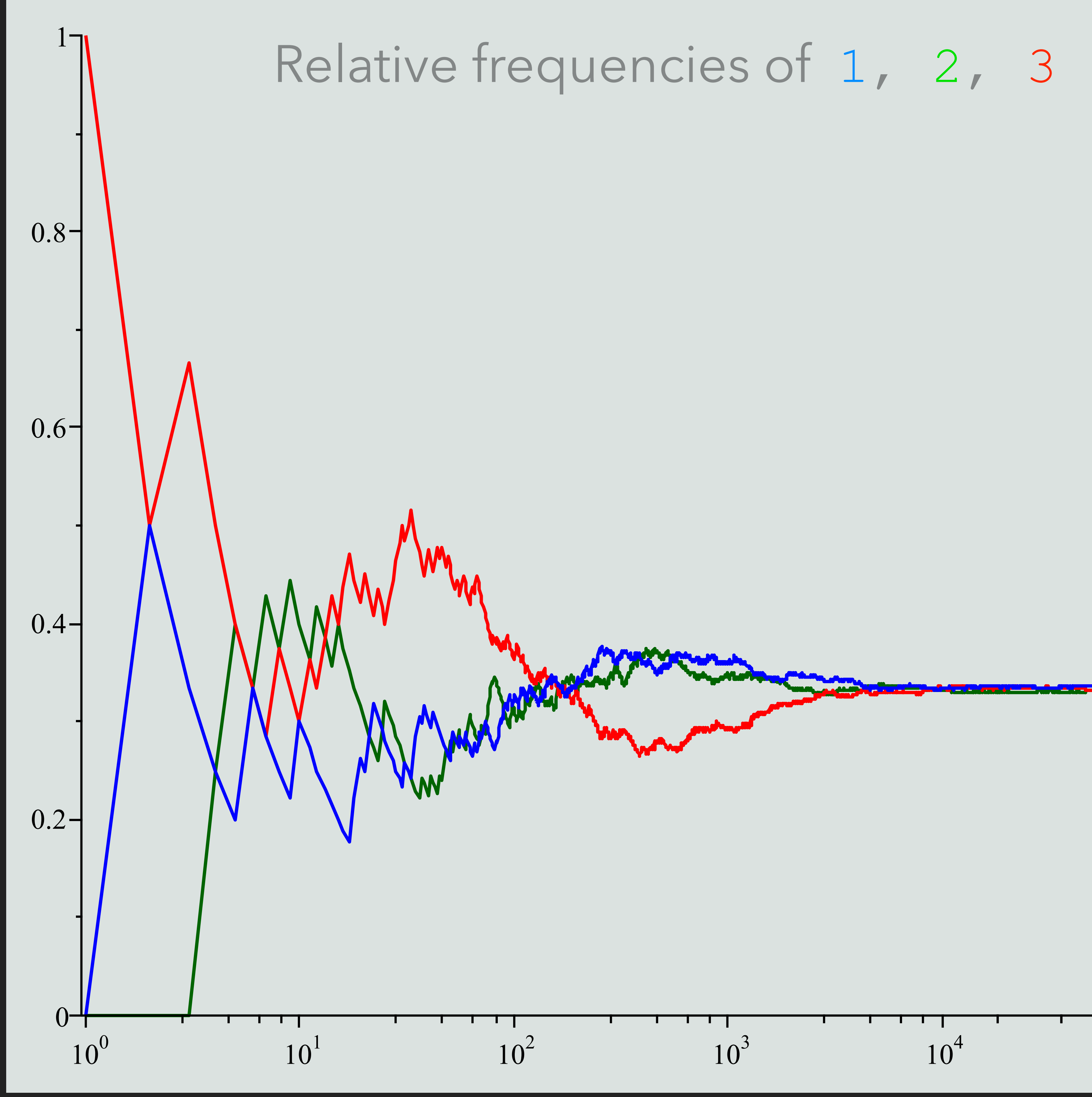

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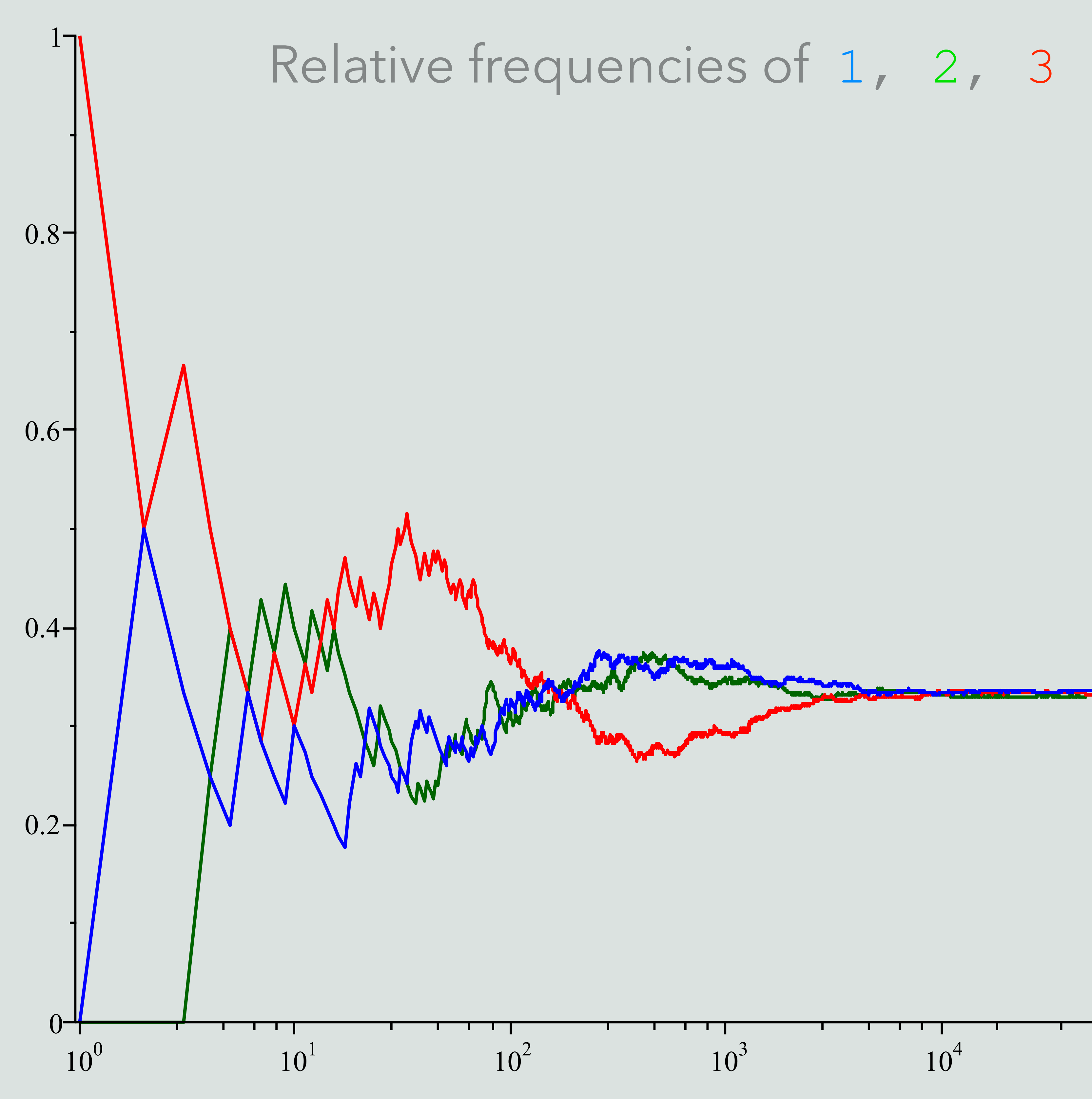

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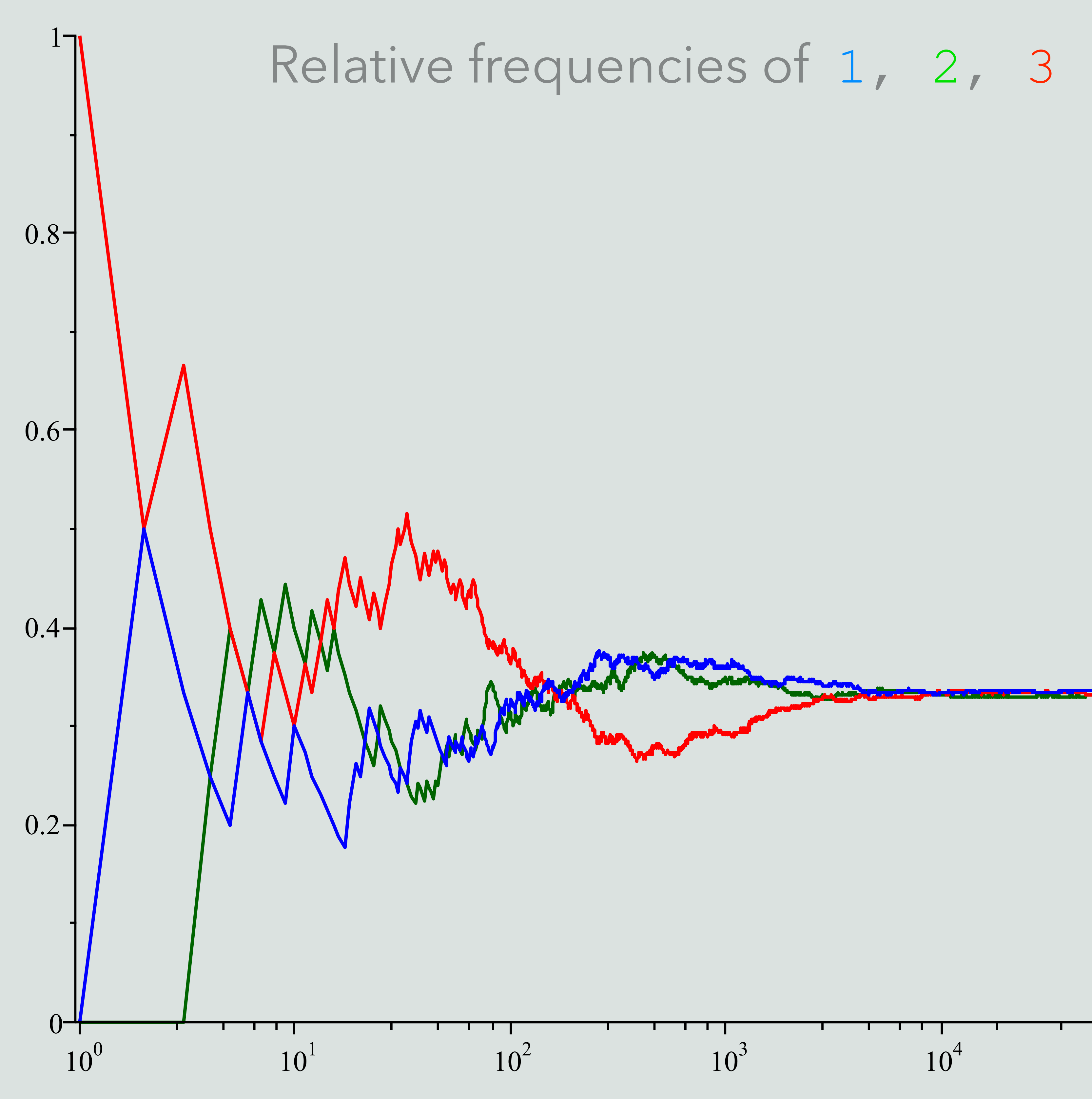

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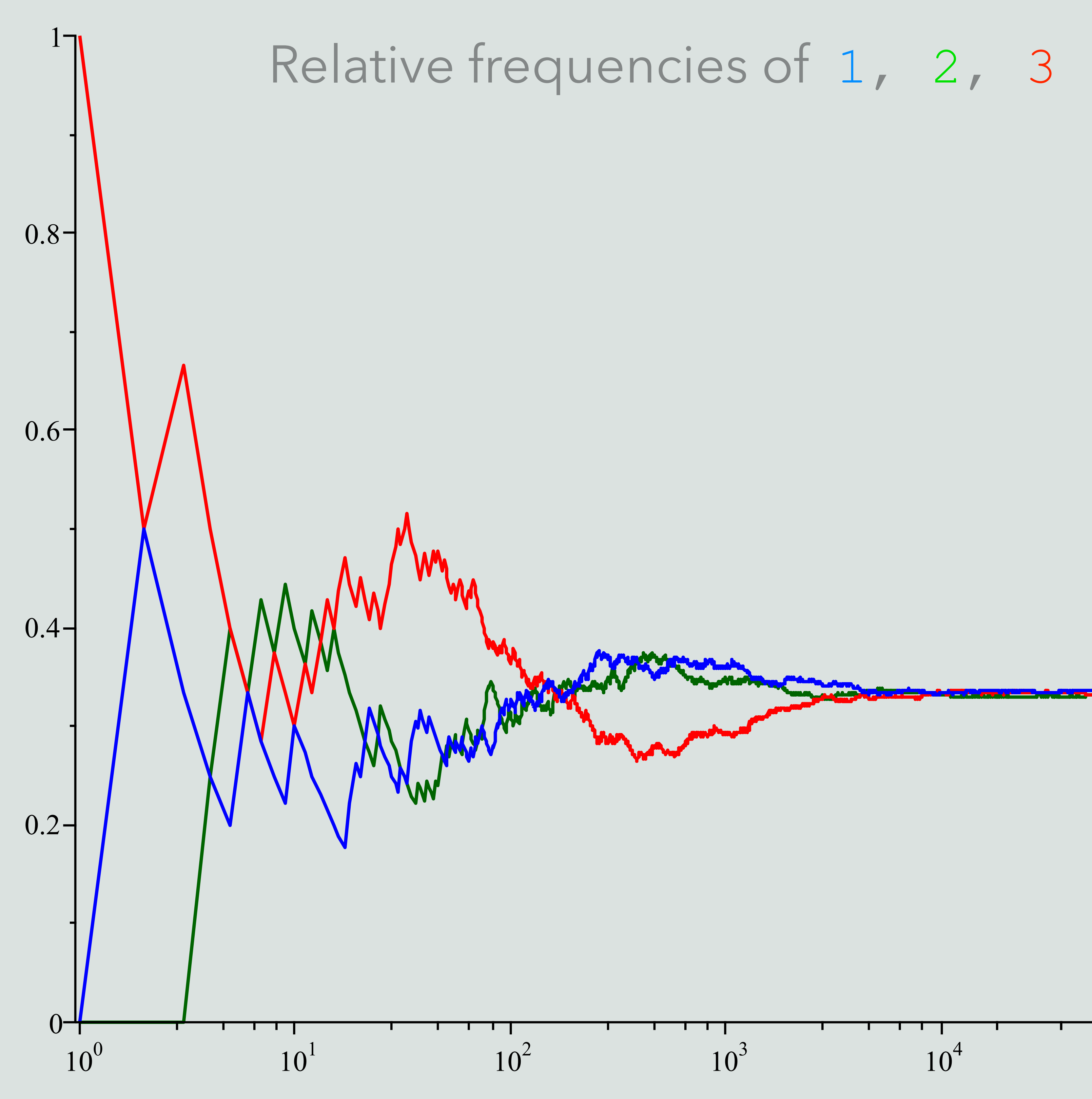

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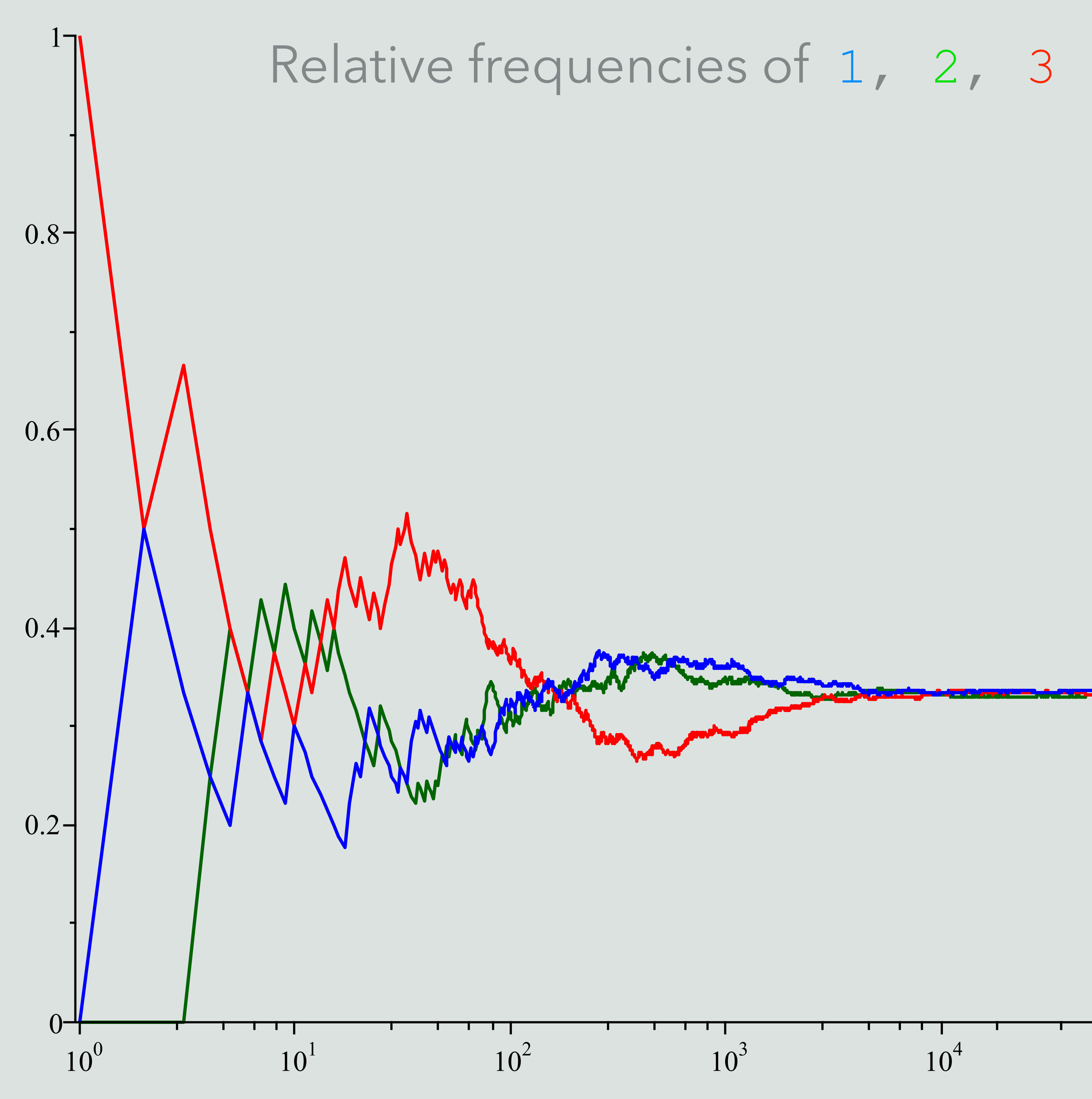

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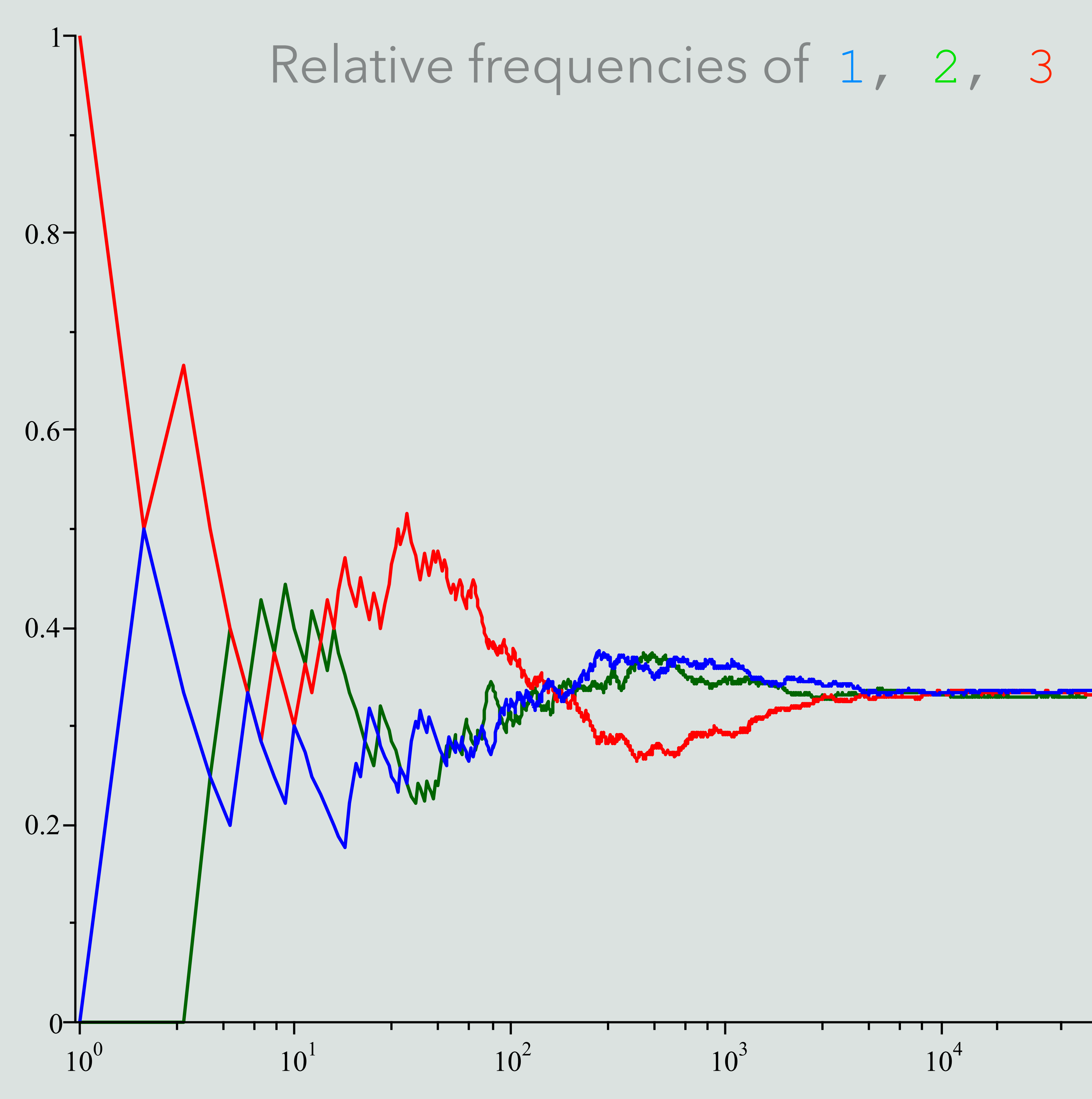

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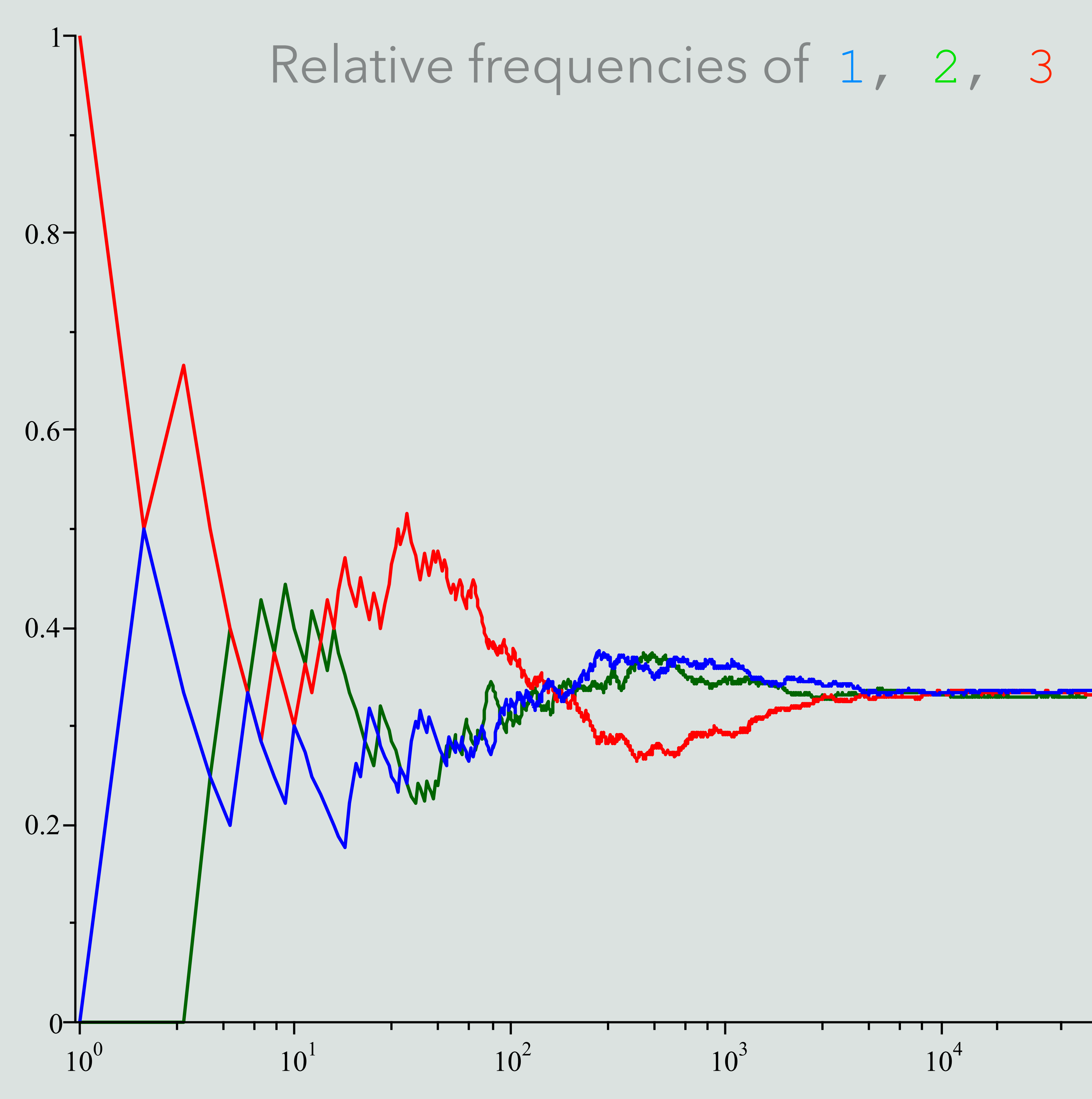

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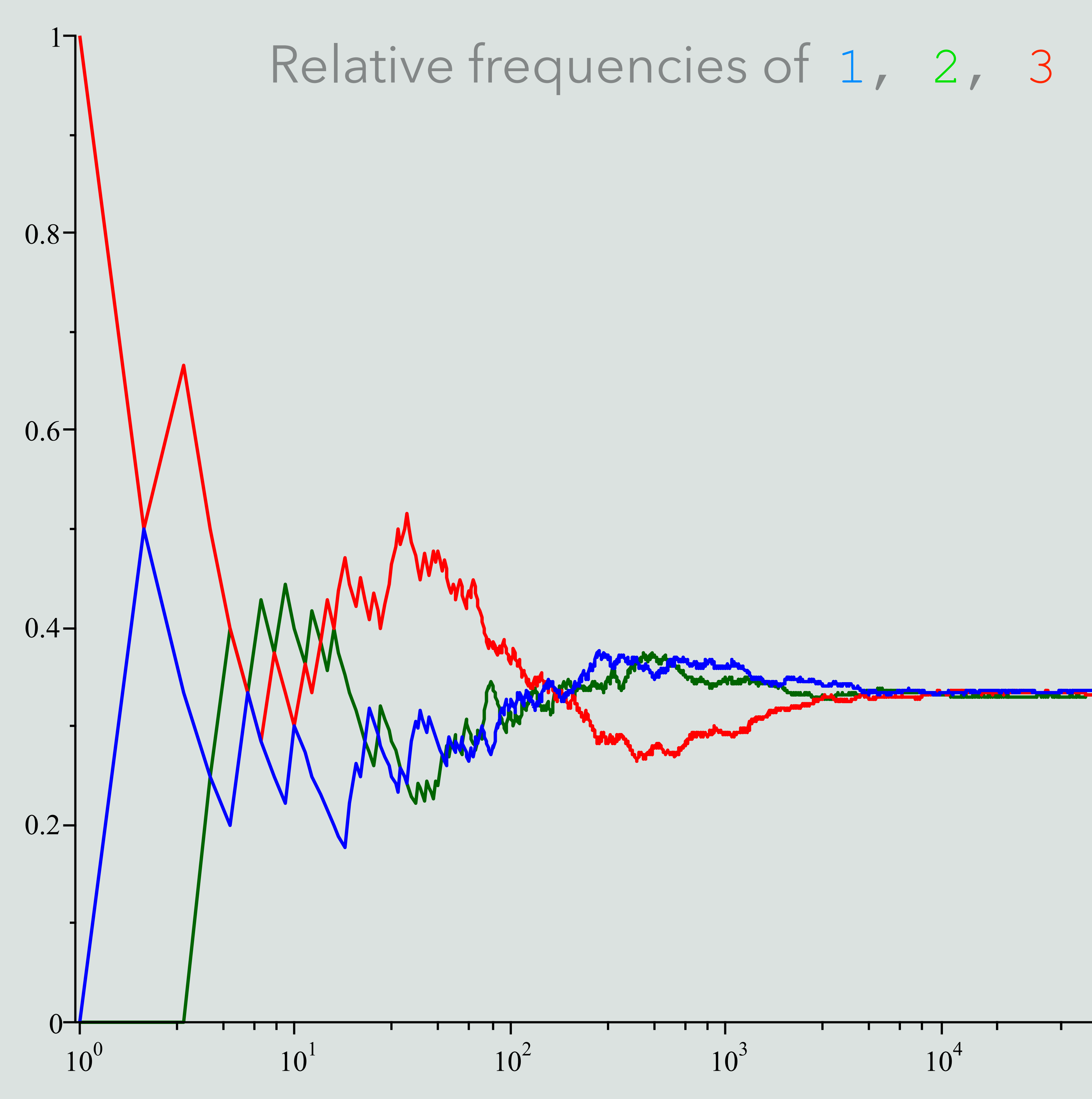
Strictly Frequentist Imprecise Probability

PROBABILITY AVERAGES AND LAWS



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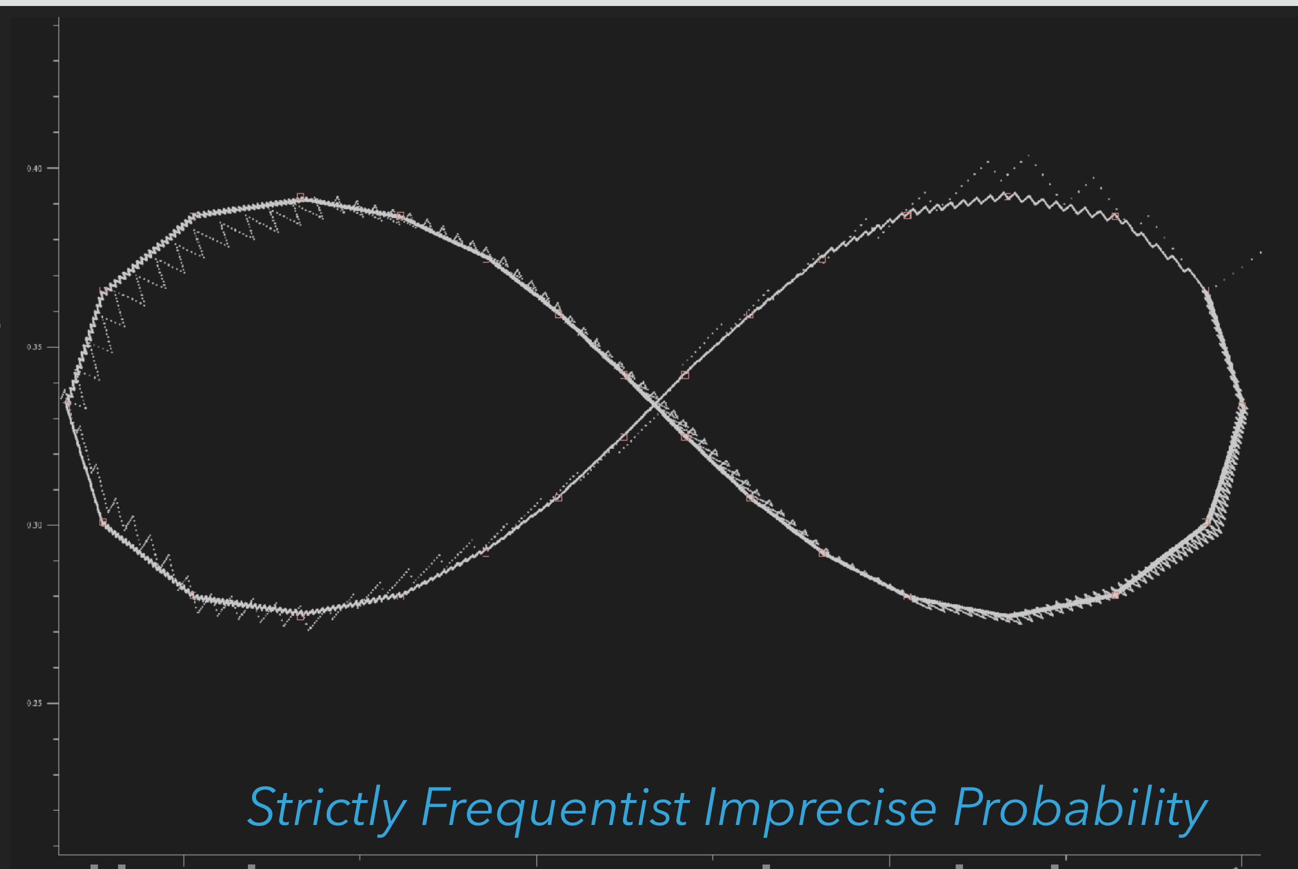
- *Most interesting stuff is not stable (non-equilibrium)*. Life, Society, Almost Everything!



MASS PHENOMENA

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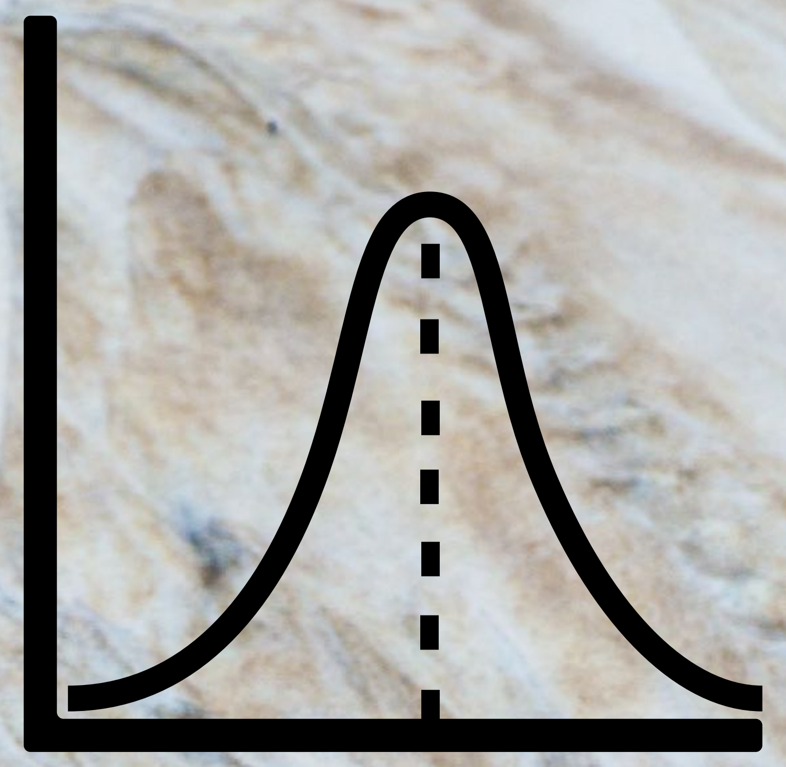

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Ralph Alger Bagnold size-grading of sand by wind, Proc. R. Soc. Lond. **A163**, 250–264, 1937

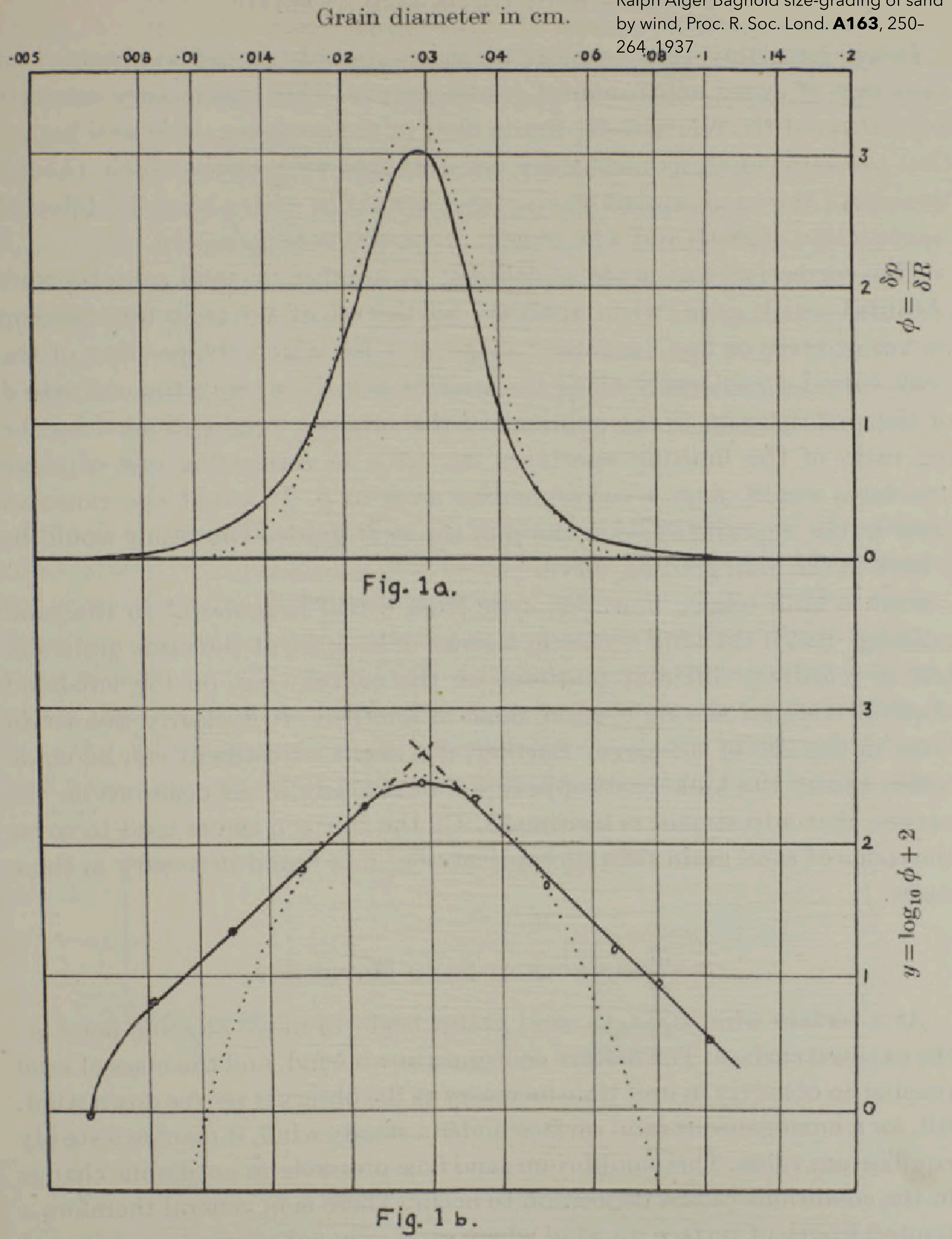

FIG. 1—Comparison of sand-grading curve (heavy line) with probability curve (dotted). *a*, ordinates on usual linear scale; *b*, ordinates on log scale.

MASS PHENOMENA

- Probability "mass"…
- Imagined to be like sand
- Data on people:
  treat people like sand…

```
462  % The true underlying data generating distribution
463  \newcommand{\pdata}{p_{\rm{data}}}
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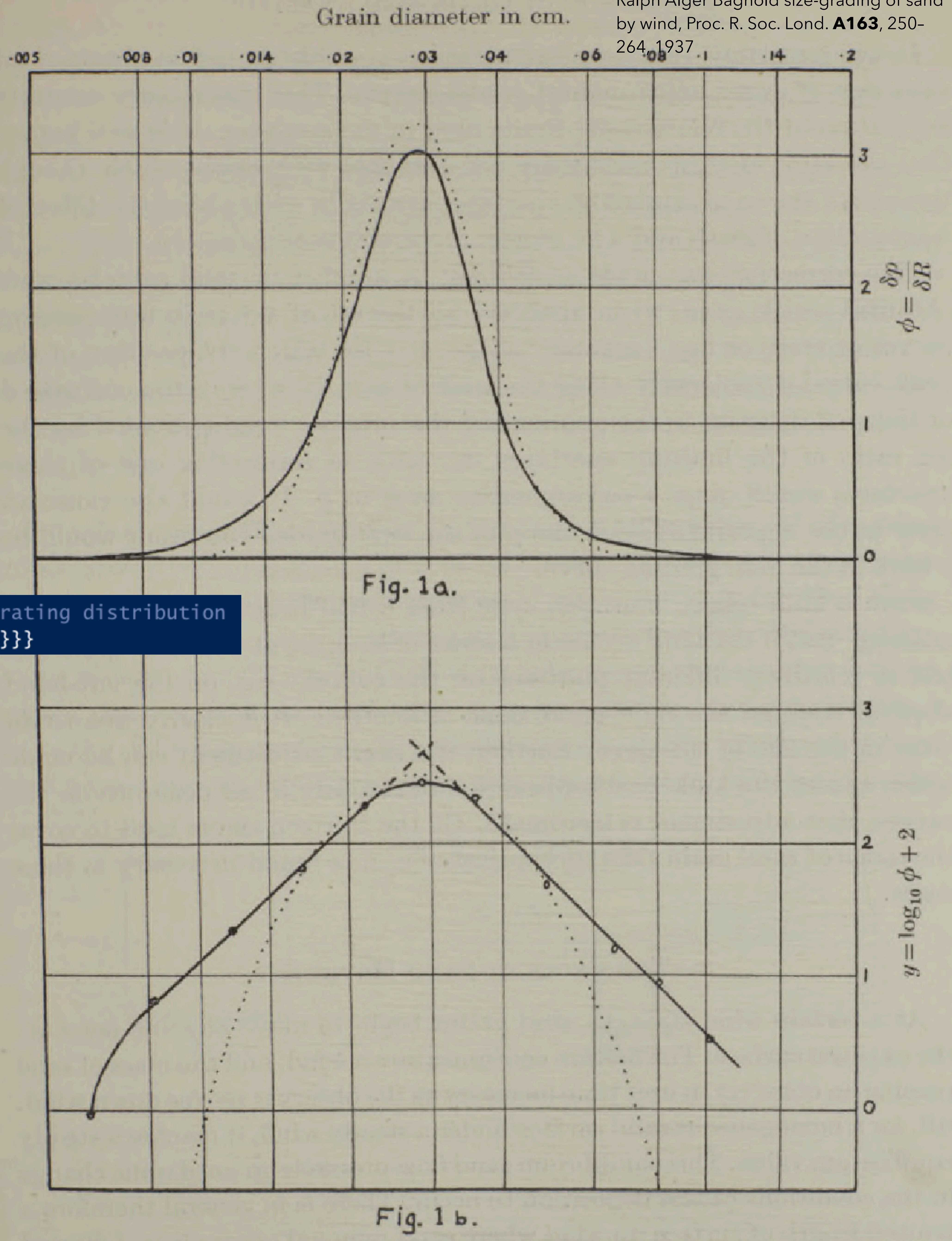

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MASS PHENOMEN

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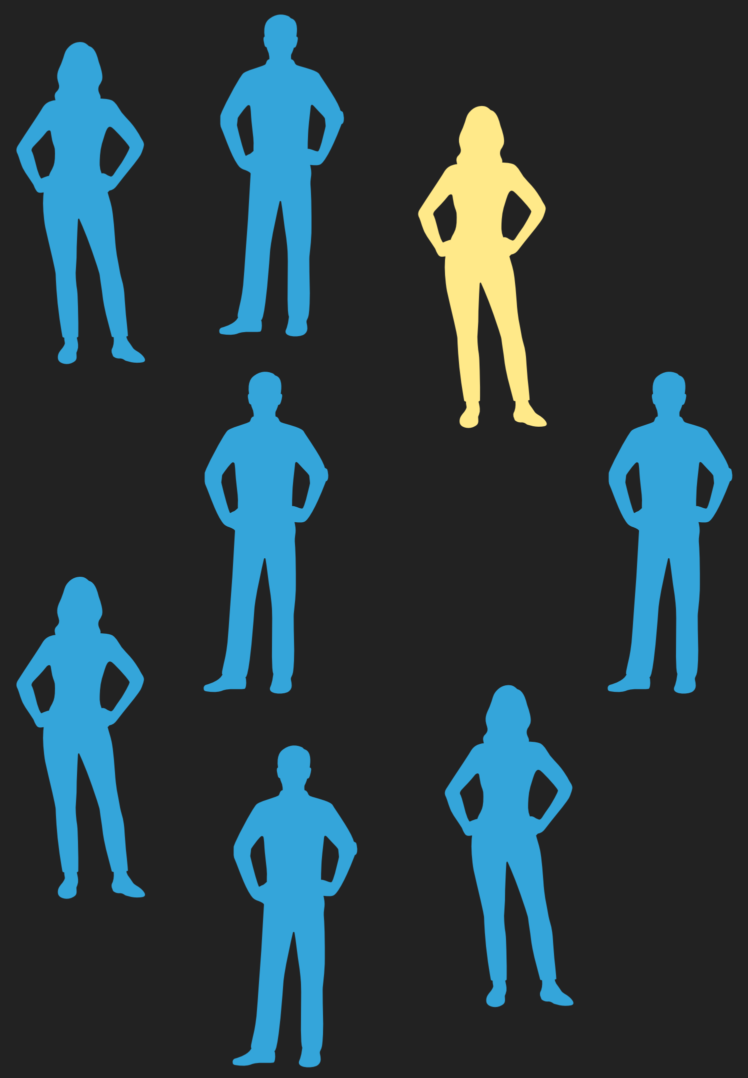
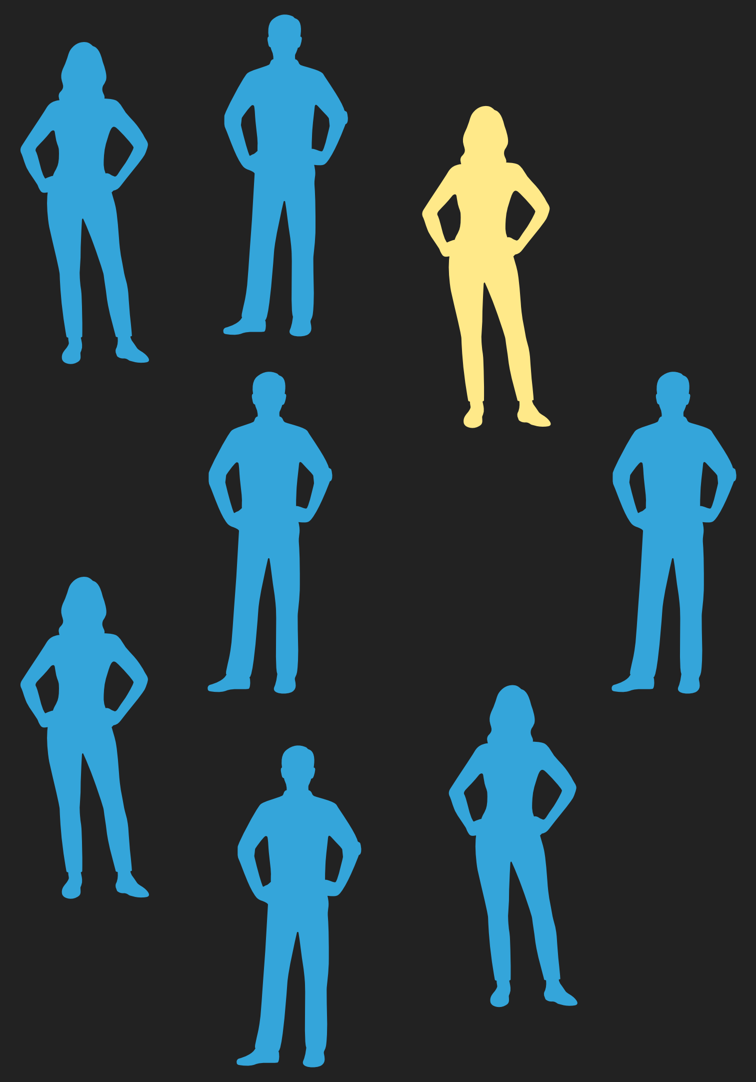
-
-
-
-
- What would a theory of mass phenomena that took account of individuals actually look like?

THE INDIVIDUAL AND THE AGGREGATE



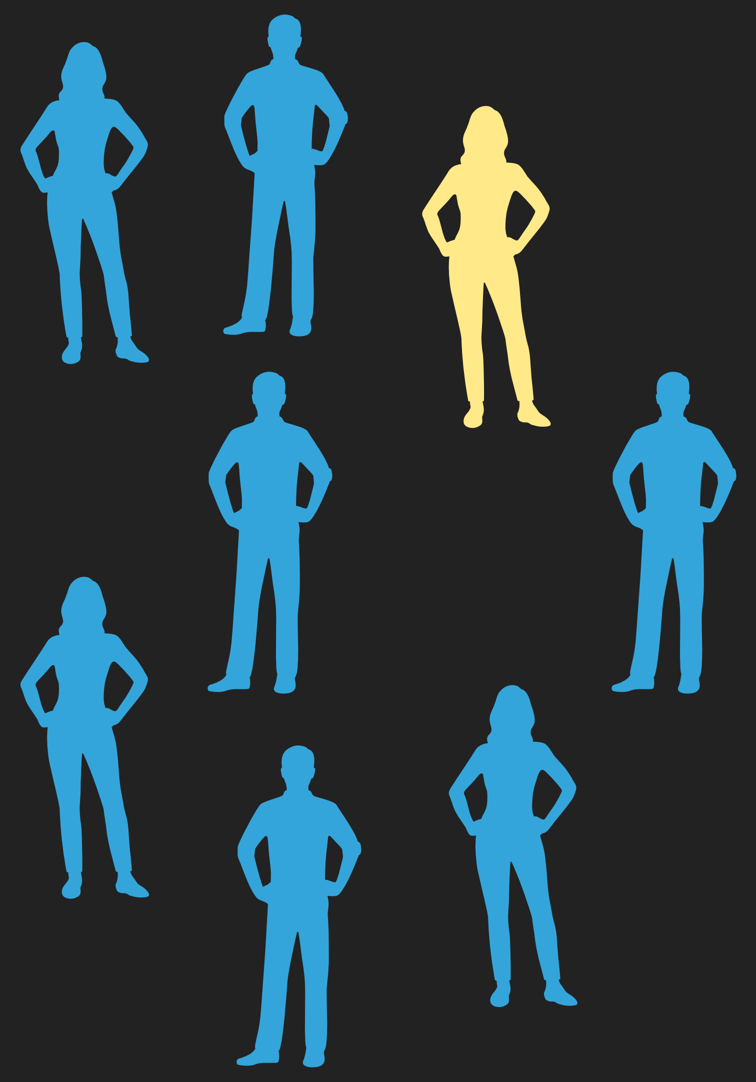
THE INDIVIDUAL AND THE AGGREGATE

- Starting with the data gives new insight into when something like probability exists



THE INDIVIDUAL AND THE AGGREGATE

- Starting with the data gives new insight into when something like probability exists
- But it does not answer the trickier question: what is the relationship between an individual and a probability?



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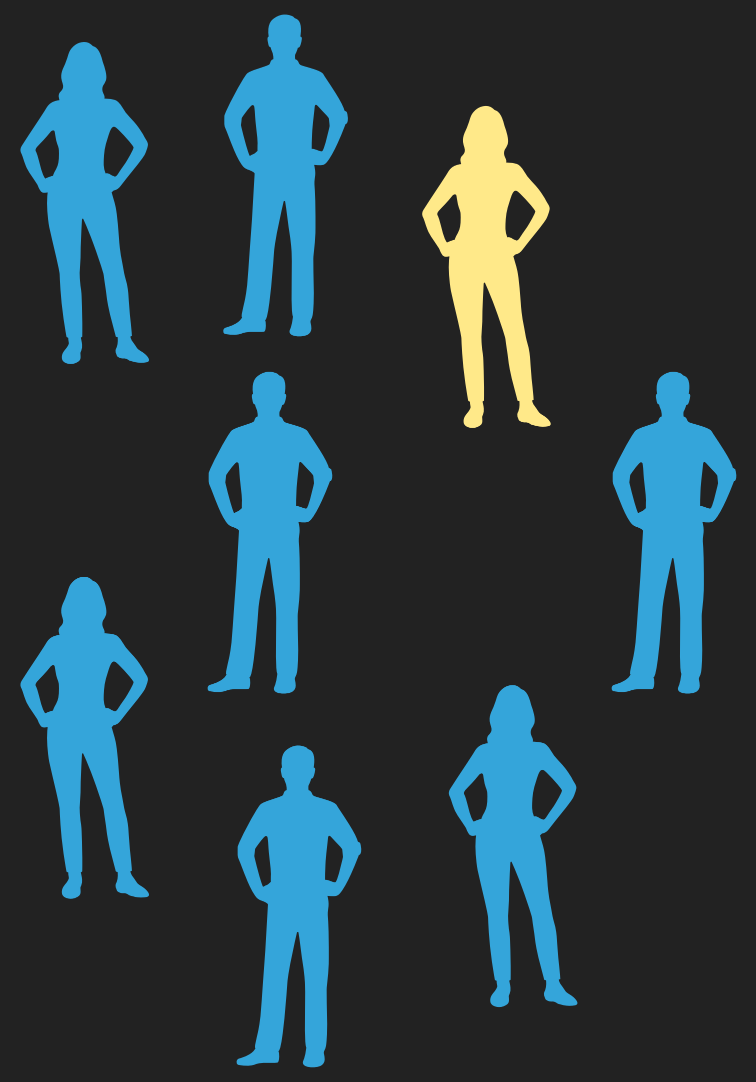

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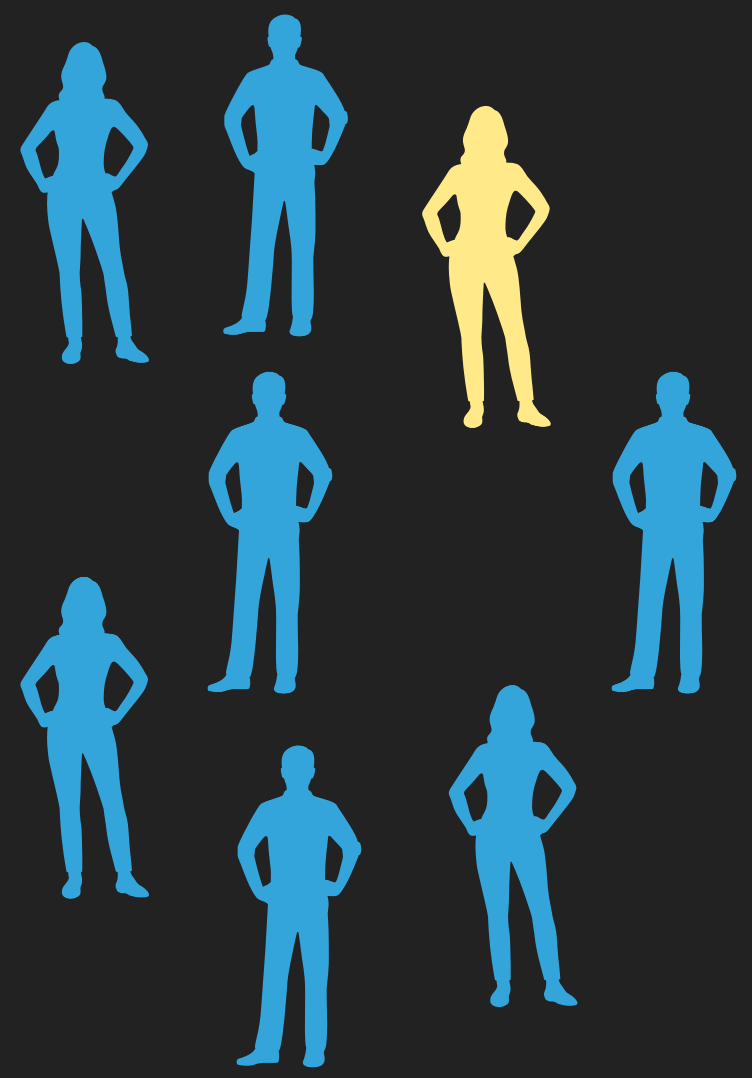

- Because statistics deals with aggregates, and ethics concerns the individual…

BEYOND EXPECTATIONS

Aggregating data in ways other than the average, and the connection to the earlier points

Risk Measures and Upper Probabilities: Coherence and Stratification

Tailoring to the Tails: Risk Measures for Fine-Grained Tail Sensitivity

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And they have already been used in ML (e.g. SVM via CVaR

The upshot: multiple compelling reasons to go "beyond expectations"

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RHETORIC

THE RHETORIC OF MACHINE LEARNING

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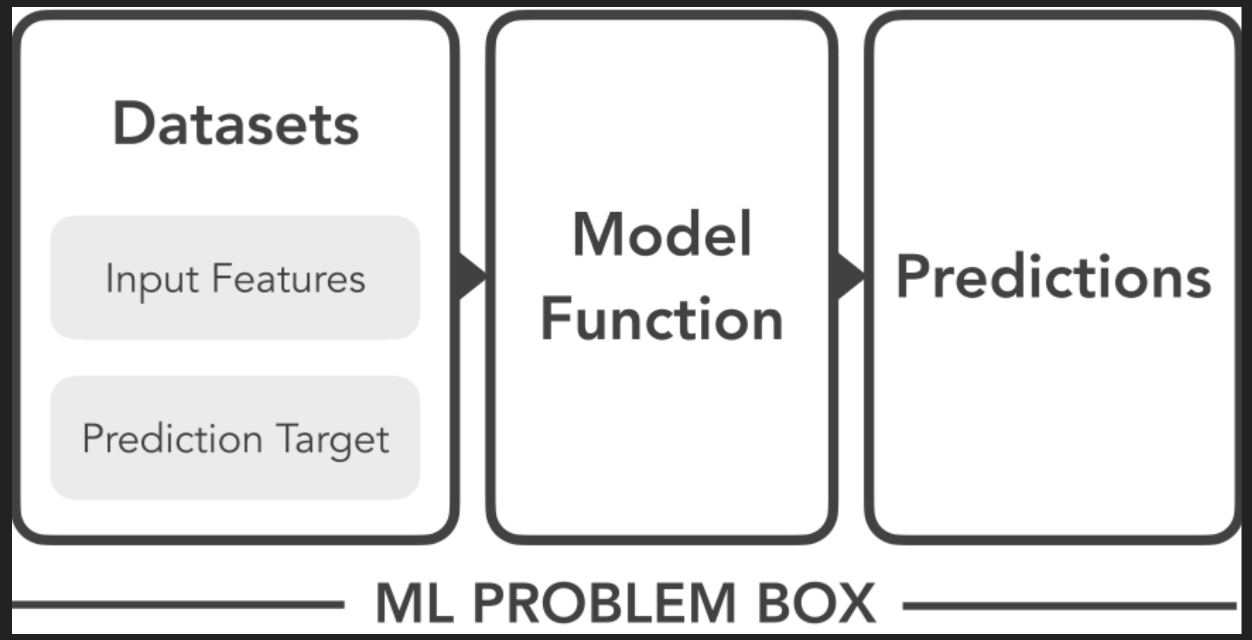

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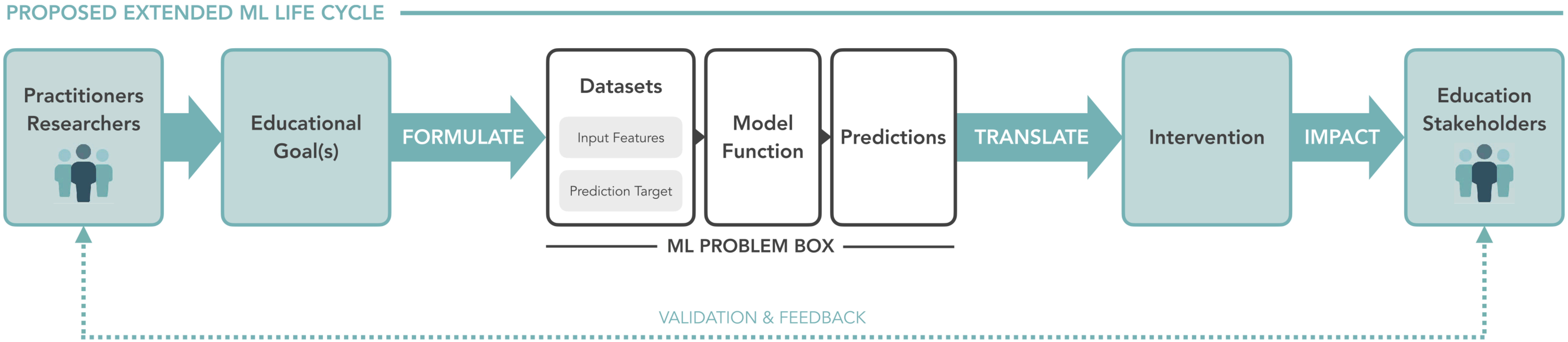

Fig. 1. An extended ML life cycle diagram. The inner "ML Problem Box" represents the typical aspects of the ML problem detailed in the surveyed ML research papers. Our interview findings reveal the need to consider an extended version of the ML life cycle in ML research, including the initial problem formulation stage by practitioners and researchers and the translation from predictions to interventions that eventually impact stakeholders.

Liu, L.T., Wang, S., Britton, T. and Abebe, R., 2023. Reimagining the machine learning life cycle to improve educational outcomes of students. Proceedings of the National Academy of Sciences, 120(9), p.e2204781120.


LOOKING AHEAD

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- A professor's largest legacy is in people – so focus upon helping them grow

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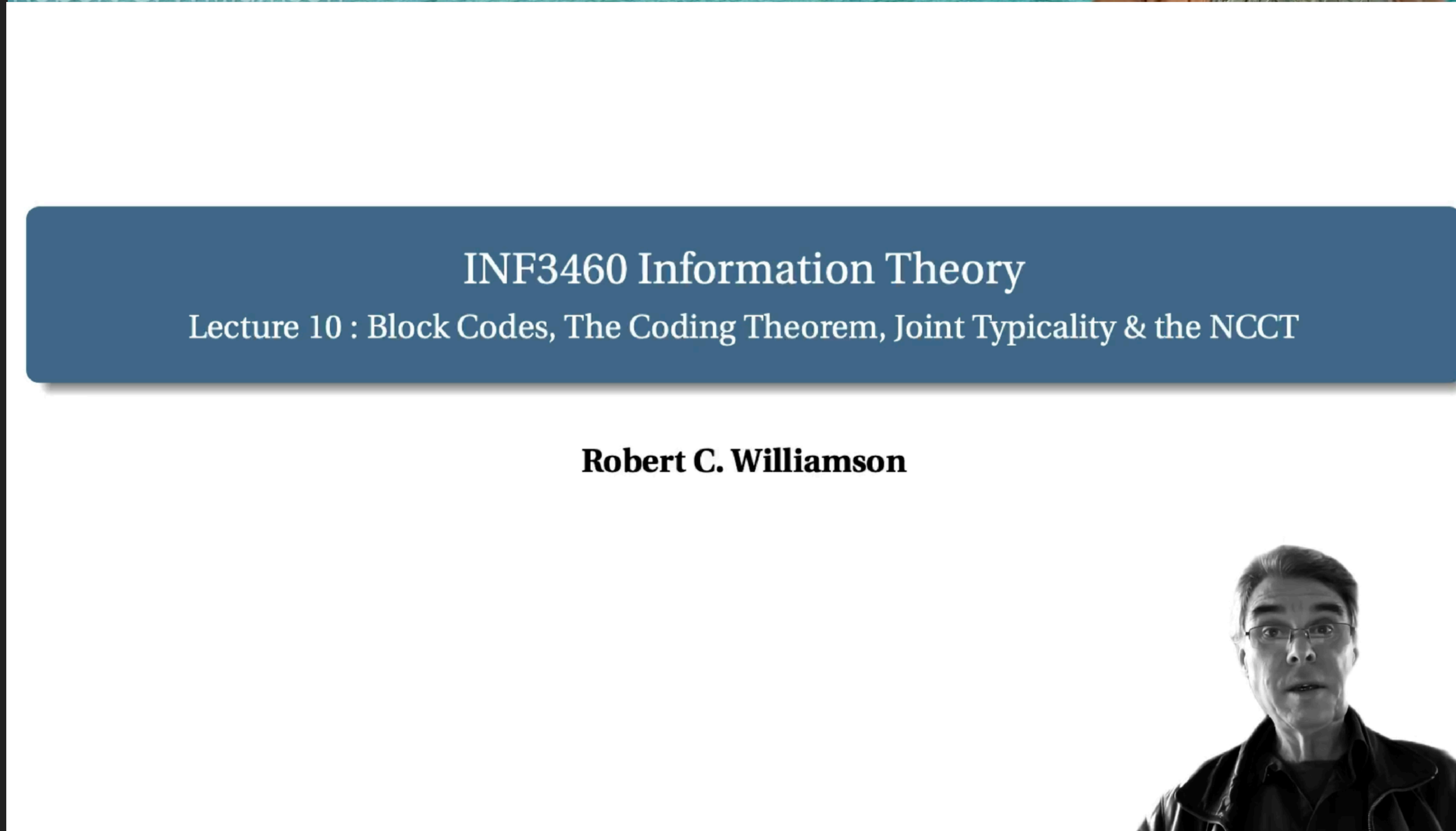

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KYLIE CATCHPOLE AND ROBERT WILLIAMSON

BEING A SCIENTIST

INF3460 Information Theory

Lecture 10 : Block Codes, The Coding Theorem, Joint Typicality & the NCCT

Robert C. Williamson

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- ML is *not rhetorical*; it is *objective* (it is "data driven" … and data is *fact*)


fm.ls

SPARE SLIDES

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- Nowadays: "benchmark data sets" ; but what gets lost in this view of data?

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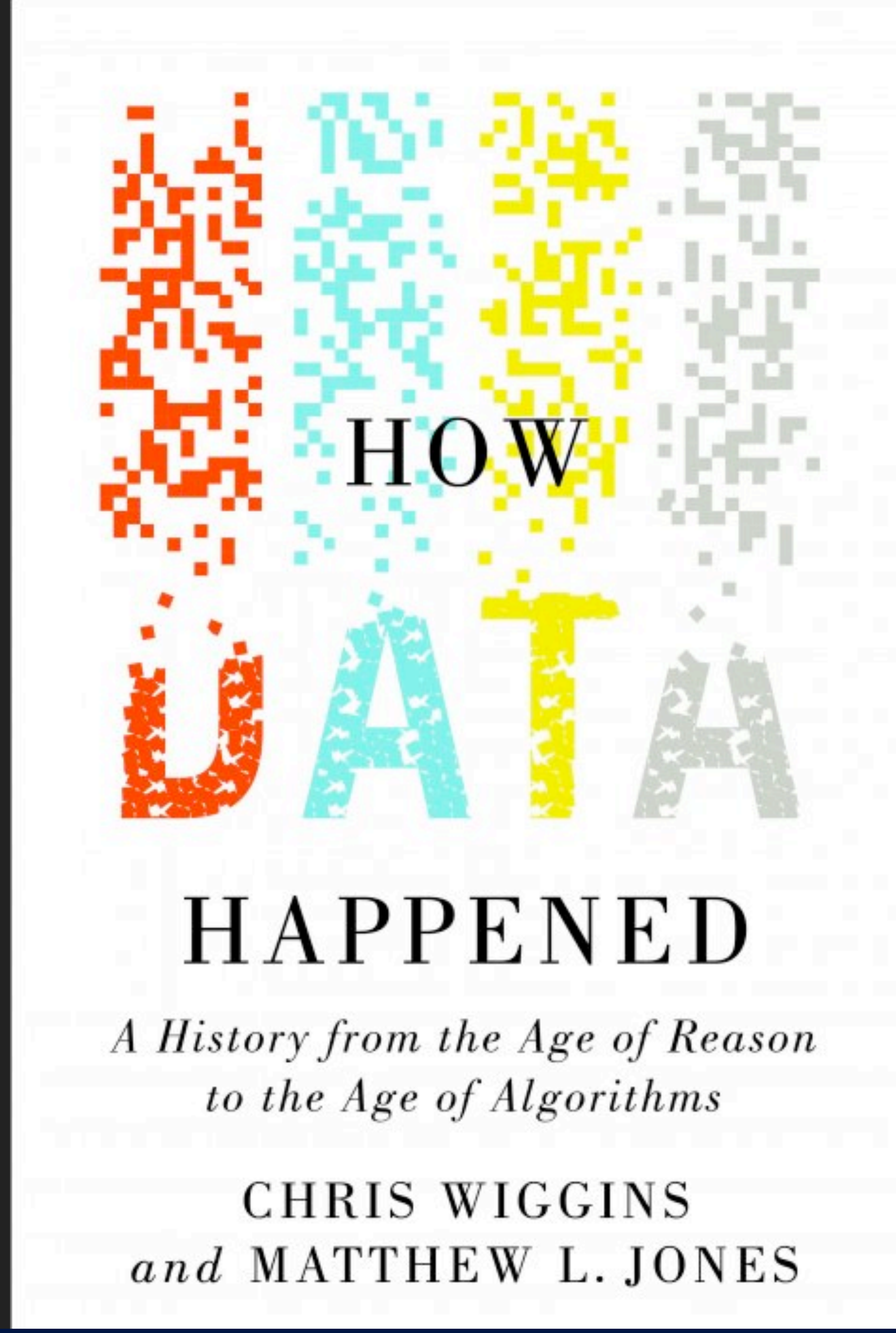

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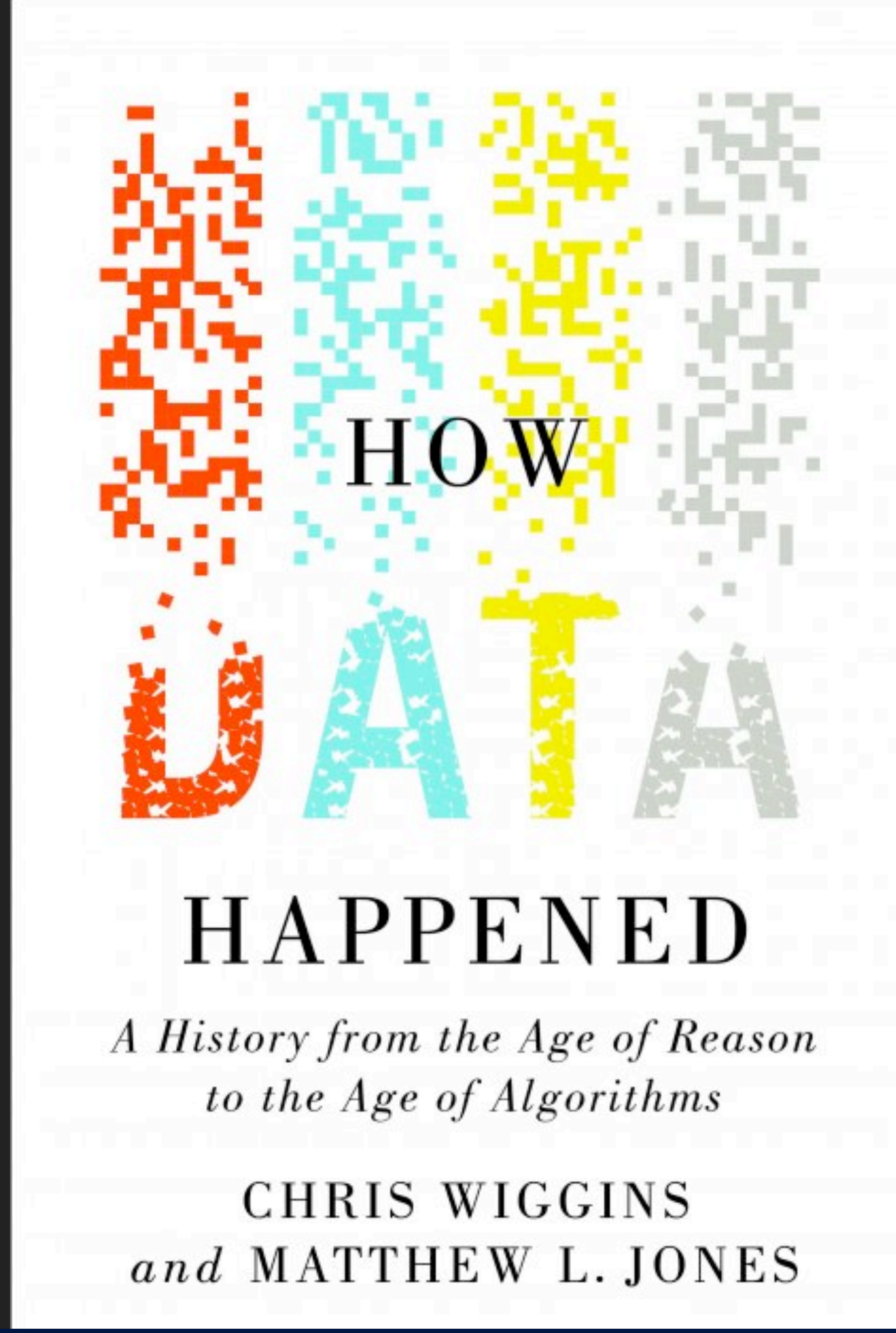

JOHN VENN

- Grouping into "natural kinds" underpins statistical regularity (cf. the "reference class problem"!)

"Such regularity as we trace in nature is owing, much more than is often suspected, to the arrangement of things in natural kinds, each of them containing a large number of individuals.

…

A large number of objects in the class, together with that general similarity which entitles the objects to be fairly comprised in one class, seem to be important conditions for the applicability of the theory of Probability to any phenomenon."

John Venn, *The logic of chance* (3rd edition), MacMillan and Co., 1888, pages 55-56

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  - What does this say about an individual?

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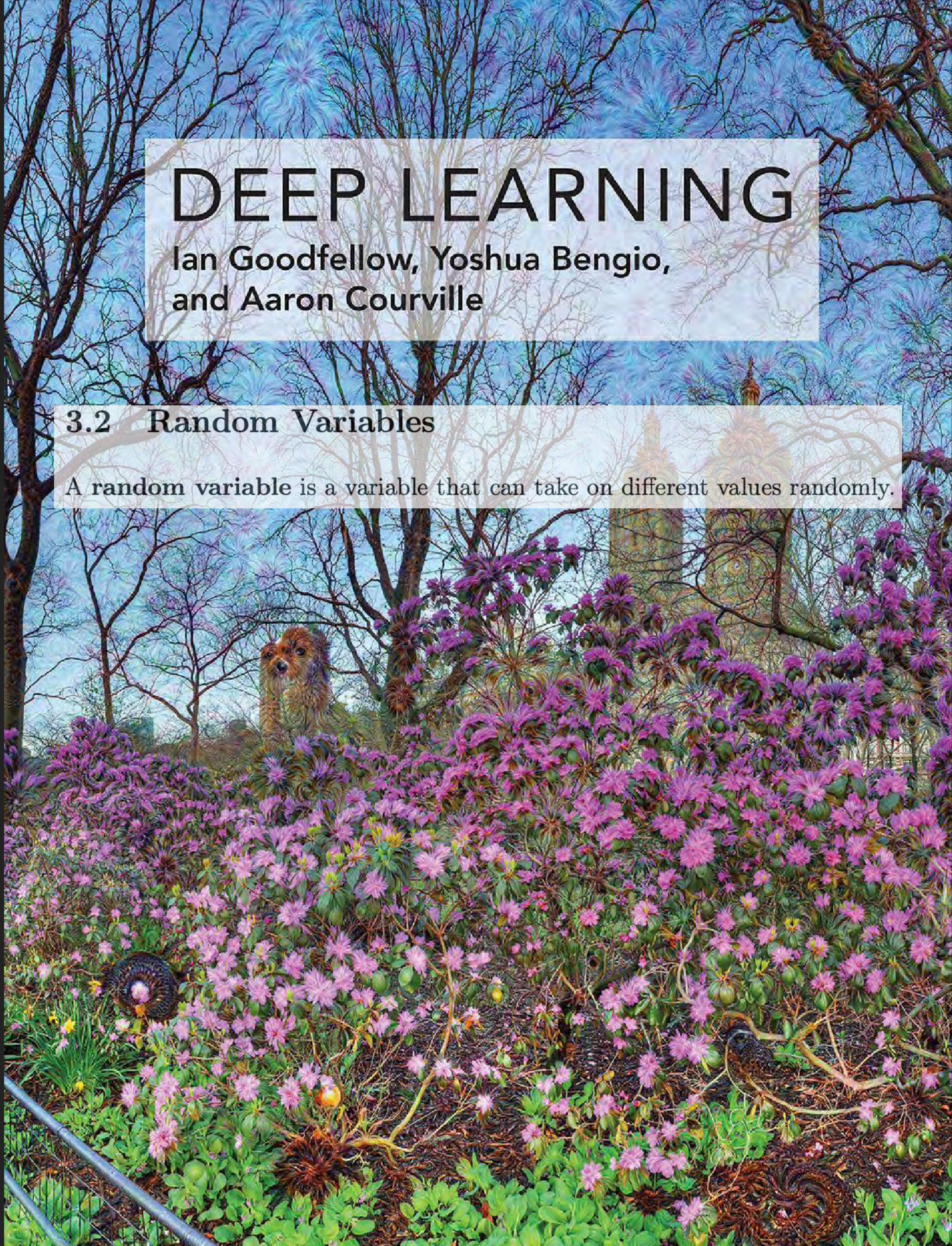

DATA AS "RANDOM VARIABLES"

- The canonical model of "data"
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  - They are not "random" ; they do not "vary"
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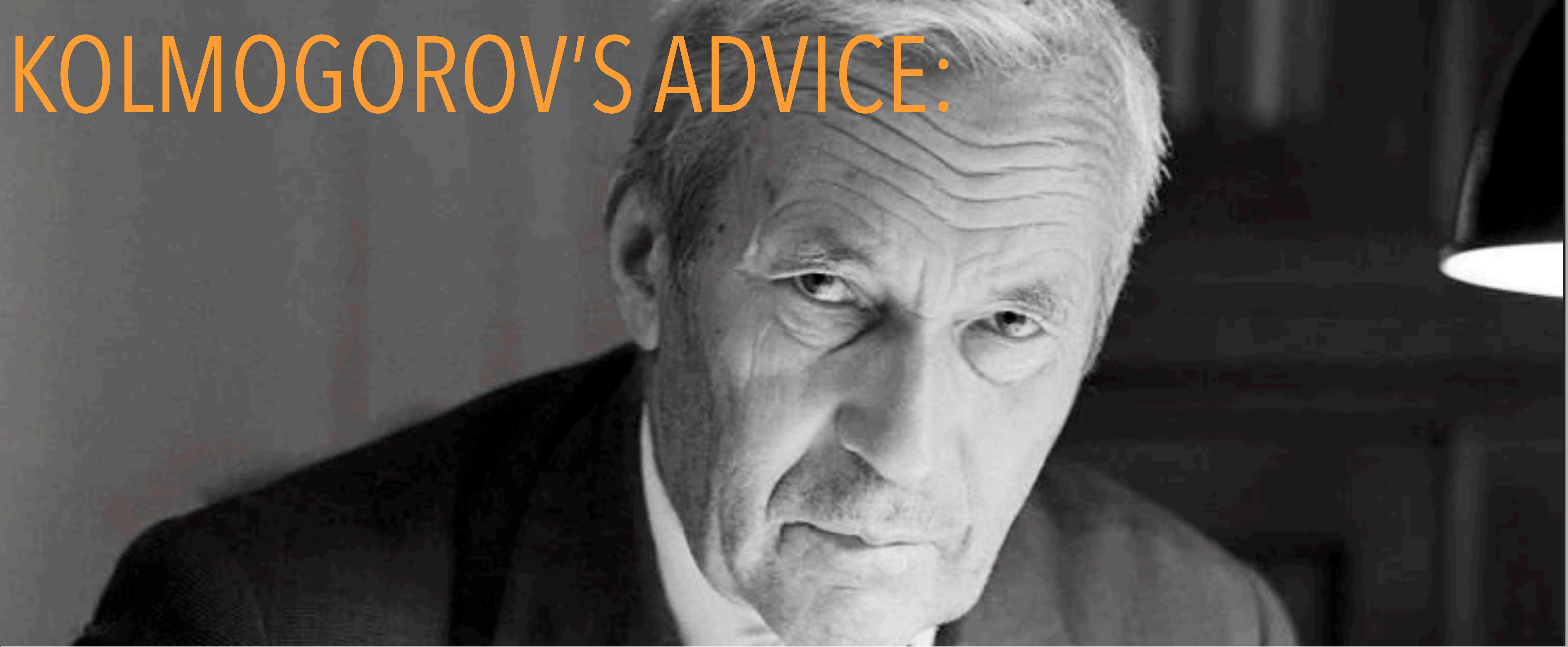
- Indeed! Based upon the Kolmogorov's axiomatisation. So what does he have to say?

KOLMOGOROV'S ADVICE:



FOUNDATIONS
OF THE
THEORY OF PROBABILITY

BY

A.N. KOLMOGOROV

Second English Edition

TRANSLATION EDITED BY
NATHAN MORRISON

WITH AN ADDED BIBLIOGRPAHY BY
A.T. BHARUCHA-REID

UNIVERSITY OF OREGON

CHELSEA PUBLISHING COMPANY
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§ 2. The Relation to Experimental Data[1]

[1] The reader who is interested in the purely mathematical development of the theory only, need not read this section, since the work following it is based only upon the axioms in § 1 and makes no use of the present discussion. Here we limit ourselves to a simple explanation of how the axioms of the theory of probability arose and disregard the deep philosophical dissertations on the concept of probability in the experimental world. In establishing the premises necessary for the applicability of the theory of probability to the world of actual events, the author has used, in large measure, the work of R. v. Mises, [1] pp. 21-27.

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  - Seek to understand the effects; not to just "fix" the problem

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- Can this give analogous insights in situations where distributions are not stable (non-equilibrium)?

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WILLIAM KRUSKAL*

Journal of the American Statistical Association
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The primary theme of this address is cautionary: Statistical independence is far too often assumed casually, without serious concern for how common is dependence and how difficult it can be to achieve independence (or related structures). After

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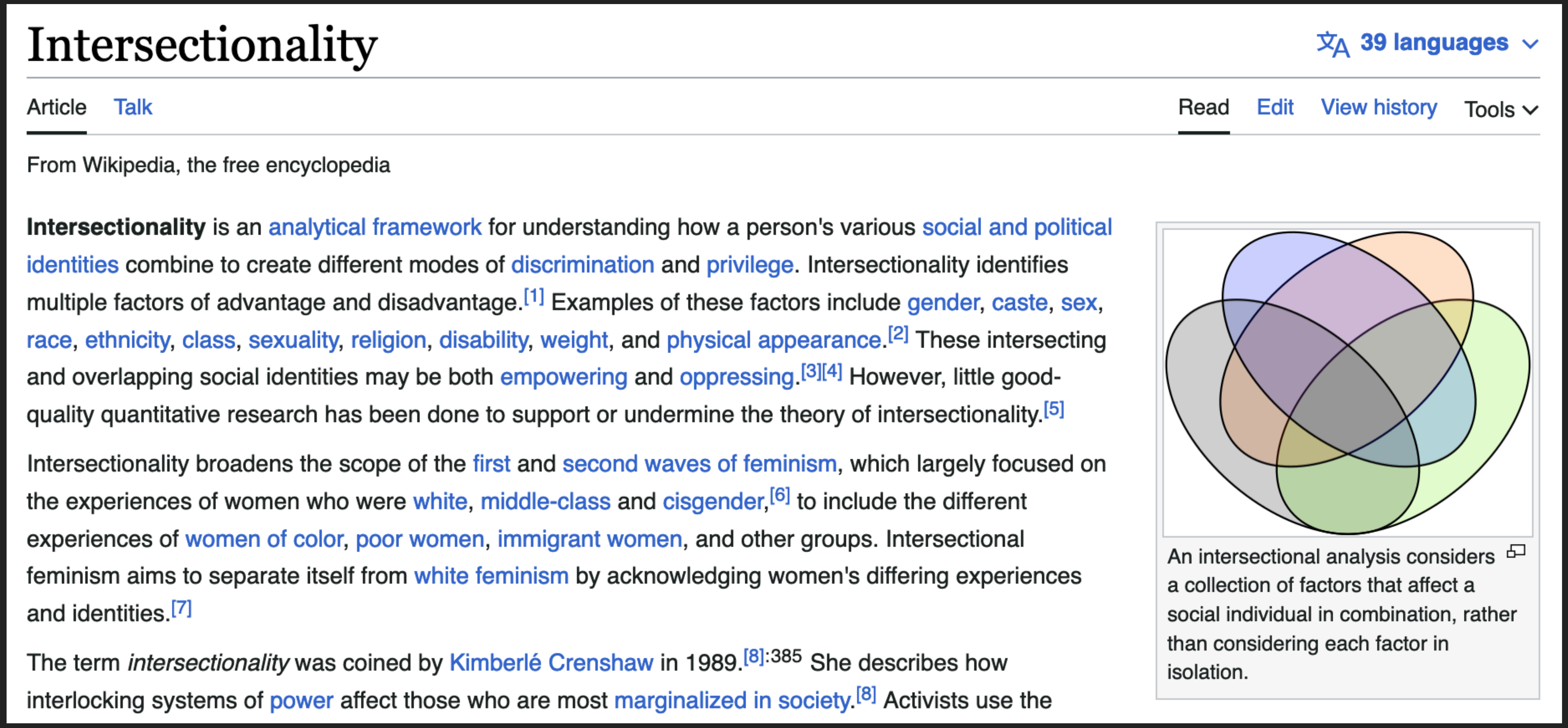
- What if not all events have a probability?
  - "Intersectionality"
- Recall $A \perp B \Leftrightarrow P(A \cap B) = P(A) \times P(B)$



Intersectionality

39 languages

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Intersectionality is an analytical framework for understanding how a person's various social and political identities combine to create different modes of discrimination and privilege. Intersectionality identifies multiple factors of advantage and disadvantage.[1] Examples of these factors include gender, caste, sex, race, ethnicity, class, sexuality, religion, disability, weight, and physical appearance.[2] These intersecting and overlapping social identities may be both empowering and oppressing.[3][4] However, little good-quality quantitative research has been done to support or undermine the theory of intersectionality.[5]

Intersectionality broadens the scope of the first and second waves of feminism, which largely focused on the experiences of women who were white, middle-class and cisgender,[6] to include the different experiences of women of color, poor women, immigrant women, and other groups. Intersectional feminism aims to separate itself from white feminism by acknowledging women's differing experiences and identities.[7]

The term *intersectionality* was coined by Kimberlé Crenshaw in 1989.[8]:385 She describes how interlocking systems of power affect those who are most marginalized in society.[8] Activists use the

An intersectional analysis considers a collection of factors that affect a social individual in combination, rather than considering each factor in isolation.

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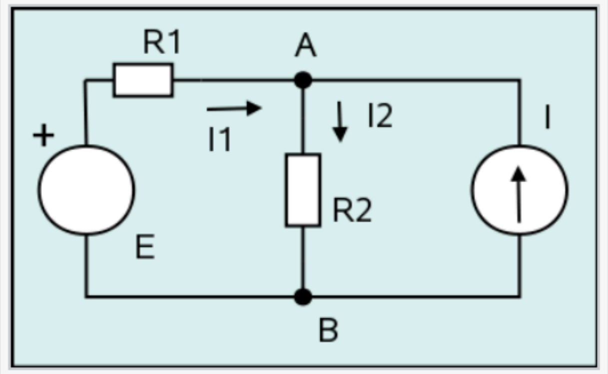
Hypergraph drawing [edit]

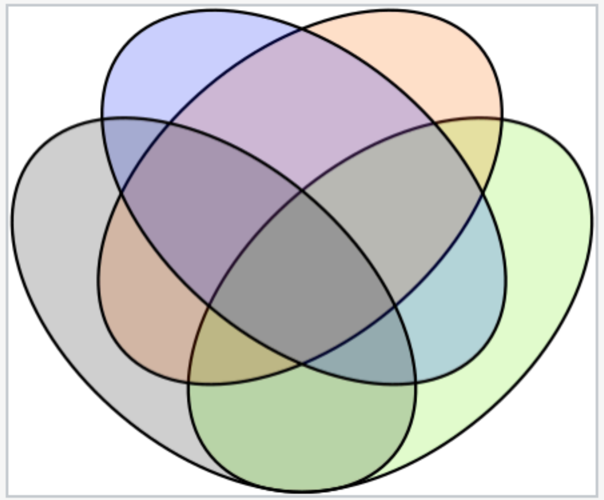
Although hypergraphs are more difficult to draw on paper than graphs, several researchers have studied methods for the visualization of hypergraphs.

In one possible visual representation for hypergraphs, similar to the standard graph drawing style in which curves in the plane are used to depict graph edges, a hypergraph's vertices are depicted as points, disks, or boxes, and its hyperedges are depicted as trees that have the vertices as their leaves.[19][20] If the vertices are represented as points, the hyperedges may also be shown as smooth curves that connect sets of points, or as simple closed curves that enclose sets of points.[21][22][23]



This circuit diagram can be interpreted as a drawing of a hypergraph in which four vertices (depicted as white rectangles and disks) are connected by three hyperedges drawn as trees.

In another style of hypergraph visualization, the subdivision model of hypergraph drawing,[24] the plane is subdivided into regions, each of which represents a single vertex of the hypergraph. The hyperedges of the hypergraph are represented by contiguous subsets of these regions, which may be indicated by coloring, by drawing outlines around them, or both. An order-n Venn diagram, for instance, may be viewed as a subdivision drawing of a hypergraph with n hyperedges (the curves defining the diagram) and $2^n - 1$ vertices (represented by the regions into which these curves subdivide the plane). In contrast with the polynomial-time recognition of planar graphs, it is NP-complete to determine whether a hypergraph has a planar subdivision drawing,[25] but the existence of a drawing of this type may be tested efficiently when the adjacency pattern of the regions is constrained to be a path, cycle, or tree.[26]



An order-4 Venn diagram, which can be interpreted as a subdivision drawing of a hypergraph with 15 vertices (the 15 colored regions) and 4 hyperedges (the 4 ellipses).

An alternative representation of the hypergraph called PAOH[1] is shown in the figure on top of this article. Edges are vertical lines connecting vertices. Vertices are aligned on the left. The legend on the right shows the names of the edges. It has been designed for dynamic hypergraphs but can be used for simple hypergraphs as well.

Hypergraph coloring [edit]

Classic hypergraph coloring is assigning one of the colors from set $\{1, 2, 3, \ldots, \lambda\}$ to every vertex of a hypergraph in such a way that each hyperedge contains at least two vertices of distinct colors. In other words, there must be no monochromatic hyperedge with cardinality at least 2. In this sense it is a direct generalization of graph coloring. Minimum number of used distinct colors over all colorings is called the chromatic number of a hypergraph.

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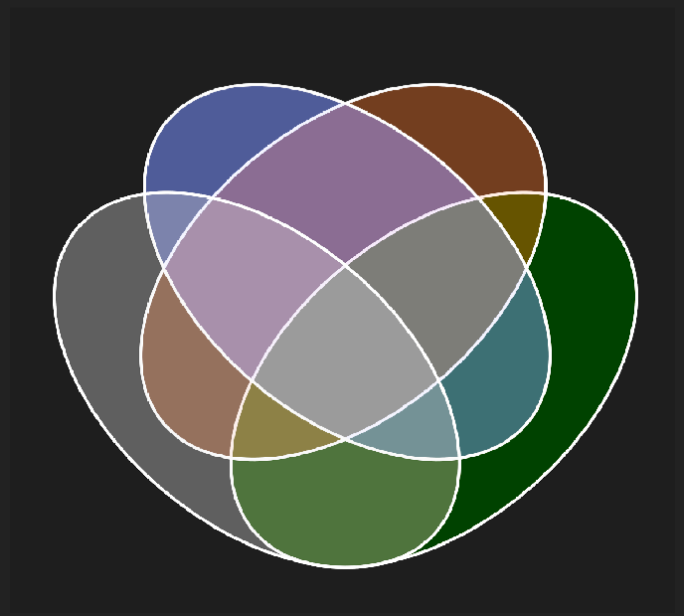
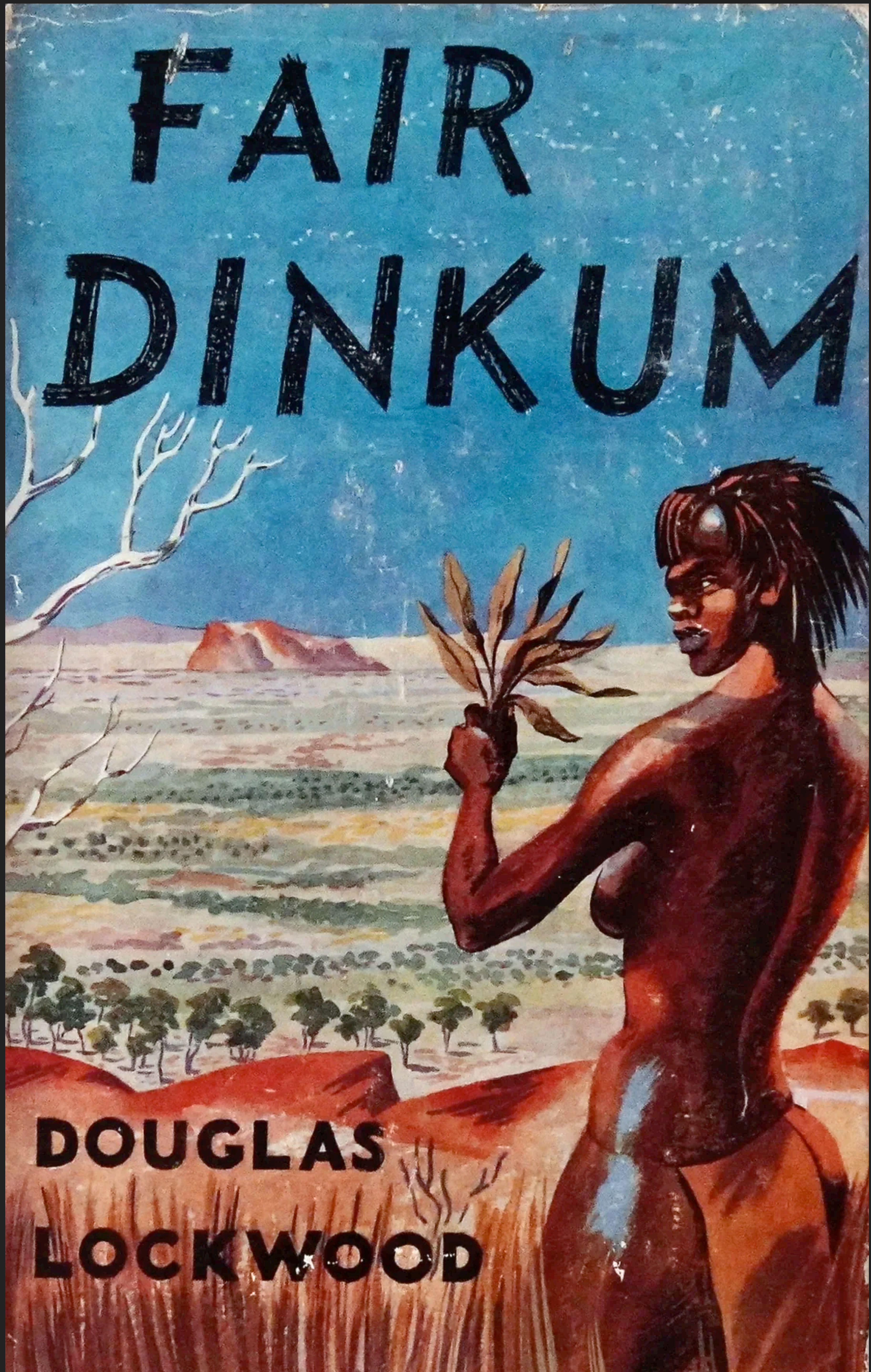
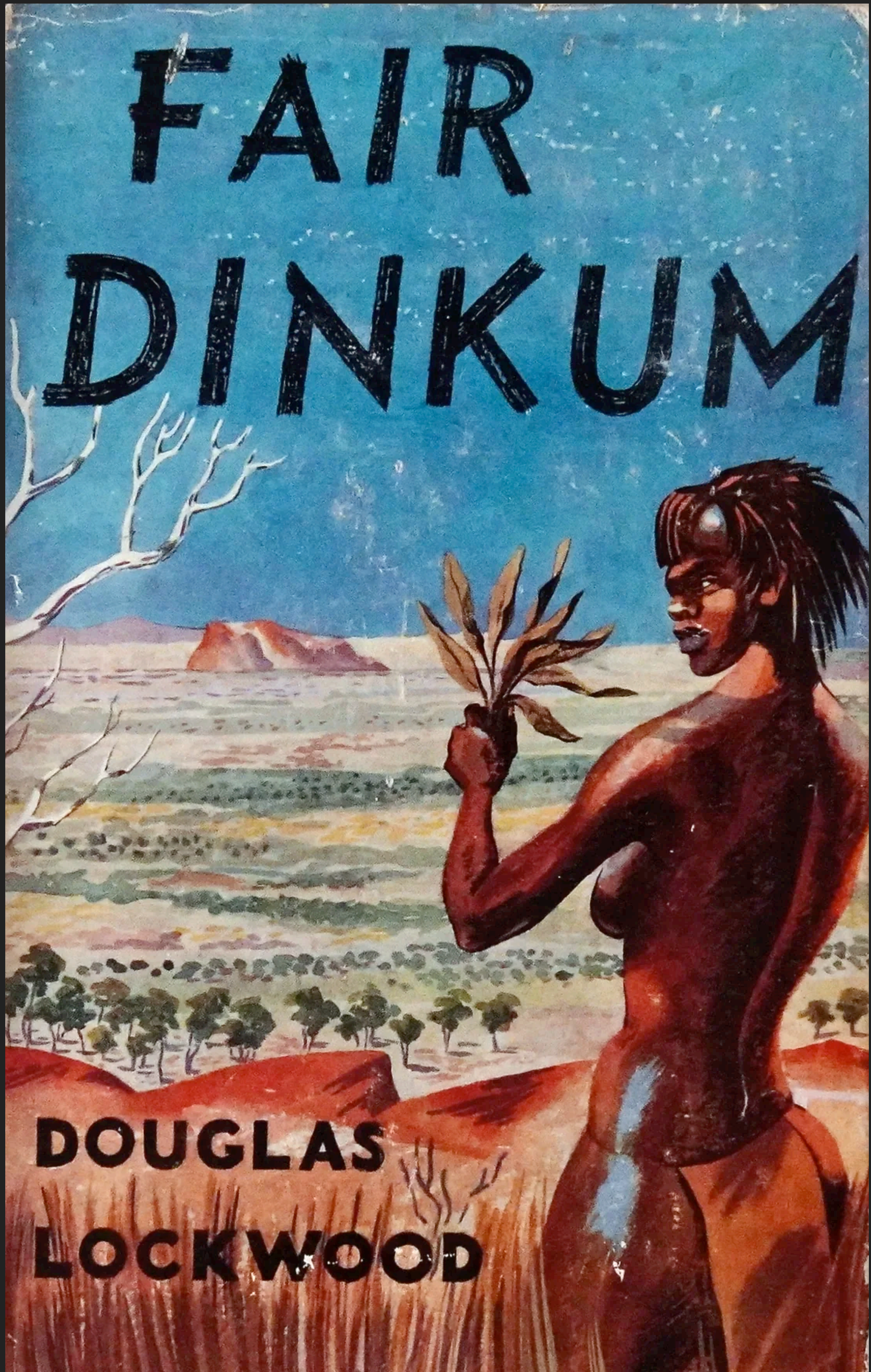


FAIR DYNKIN!



FAIR DYNKIN!

- Fairness as an actuarial problem



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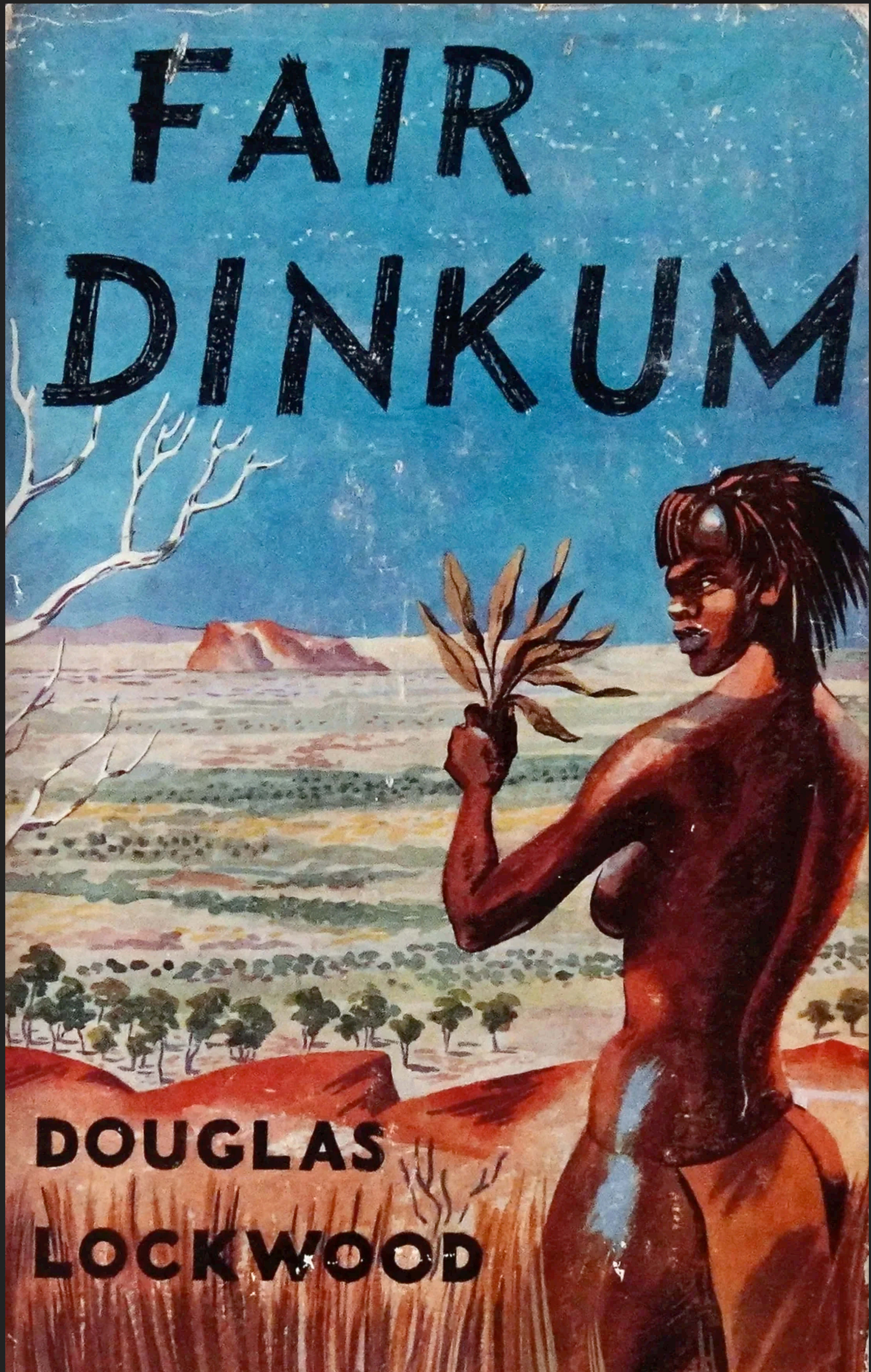

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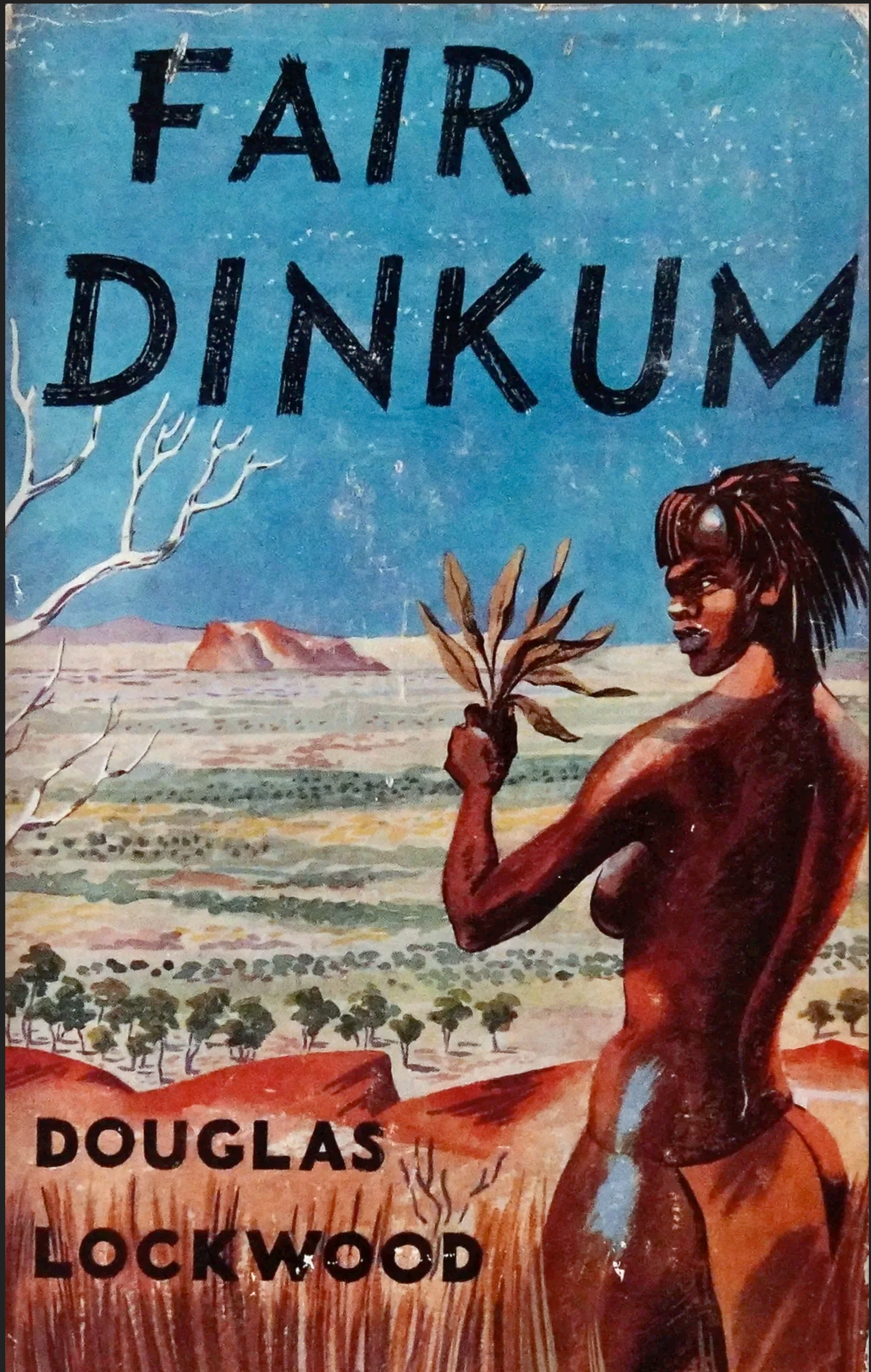

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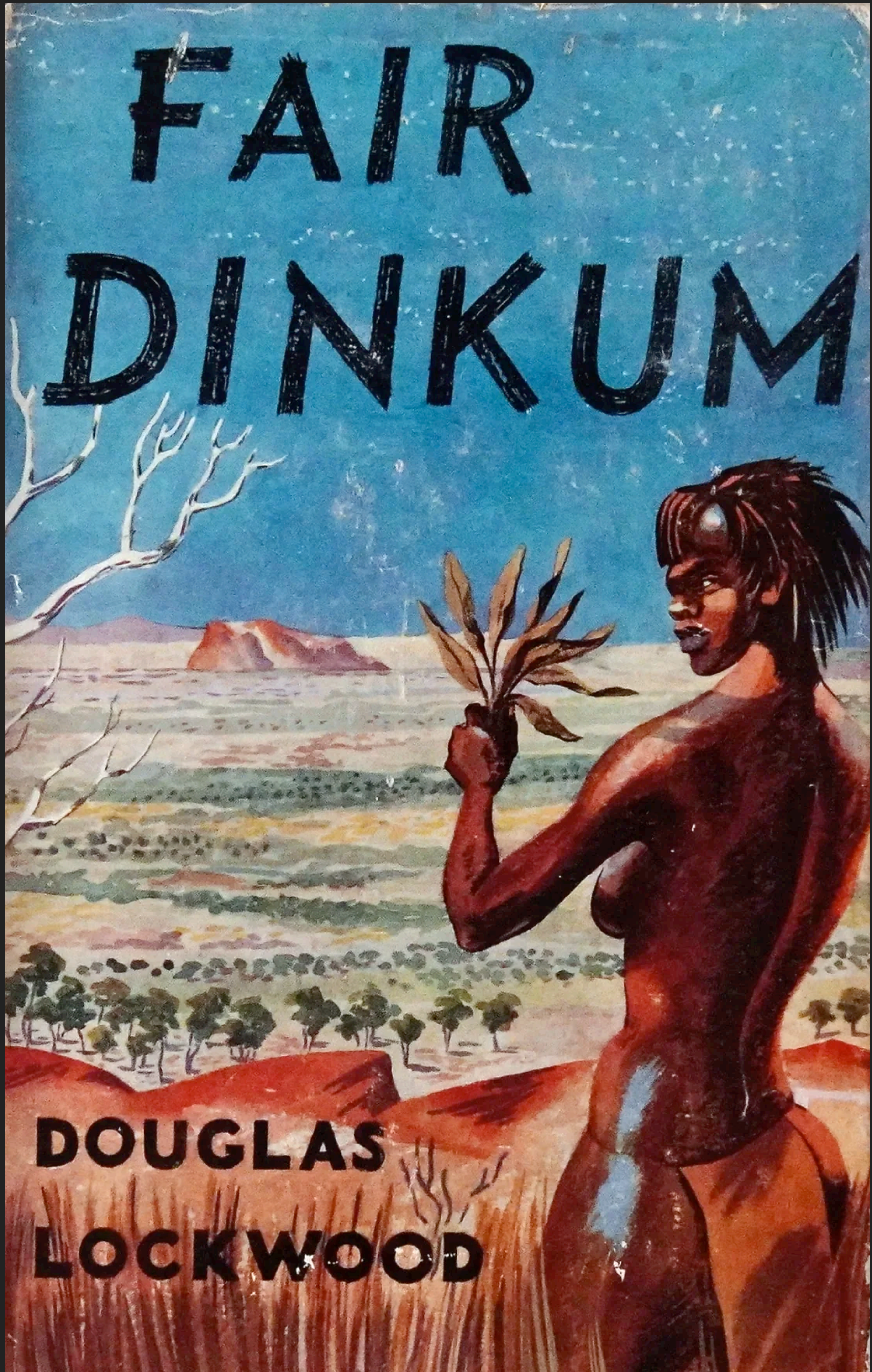

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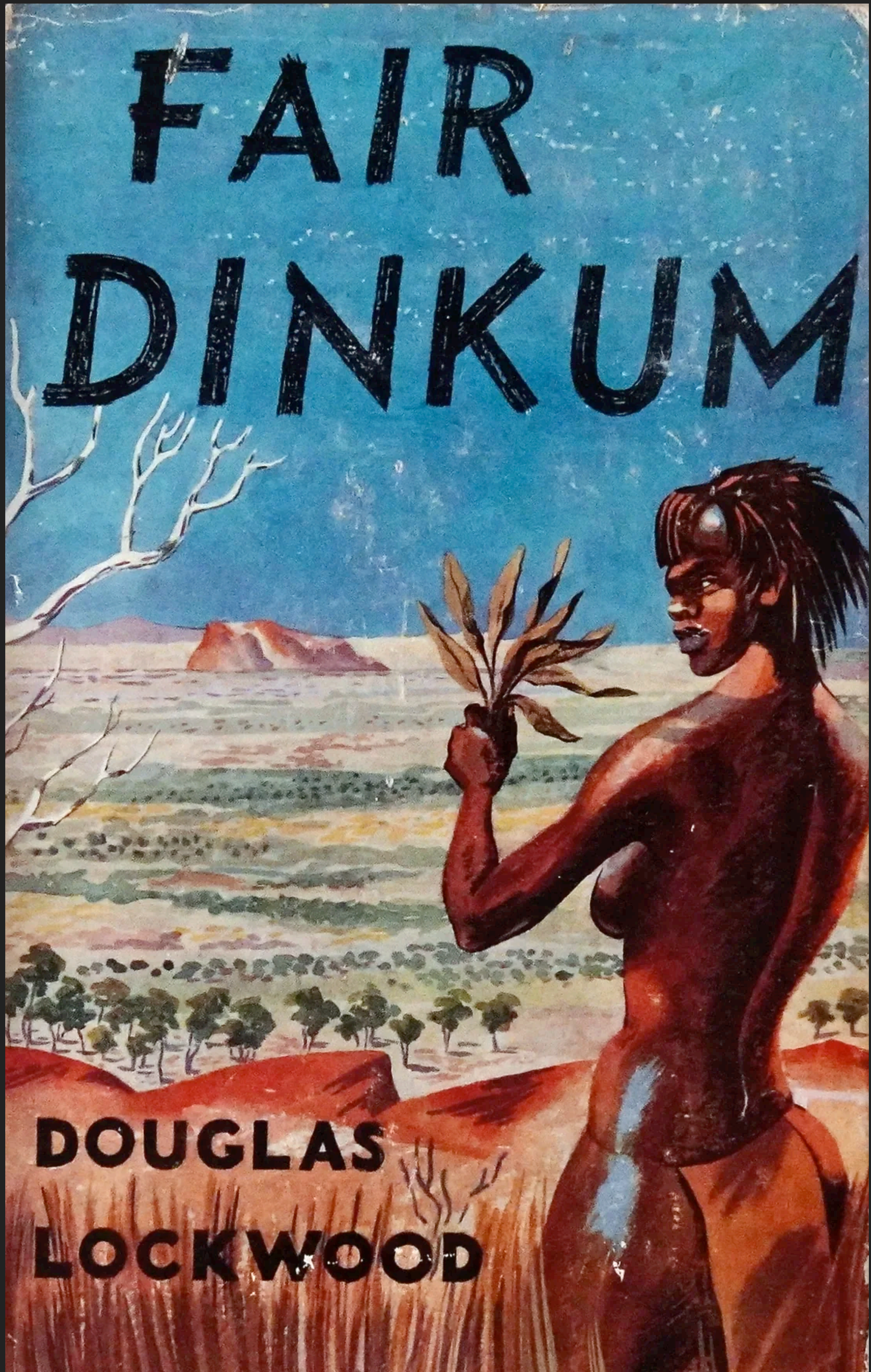

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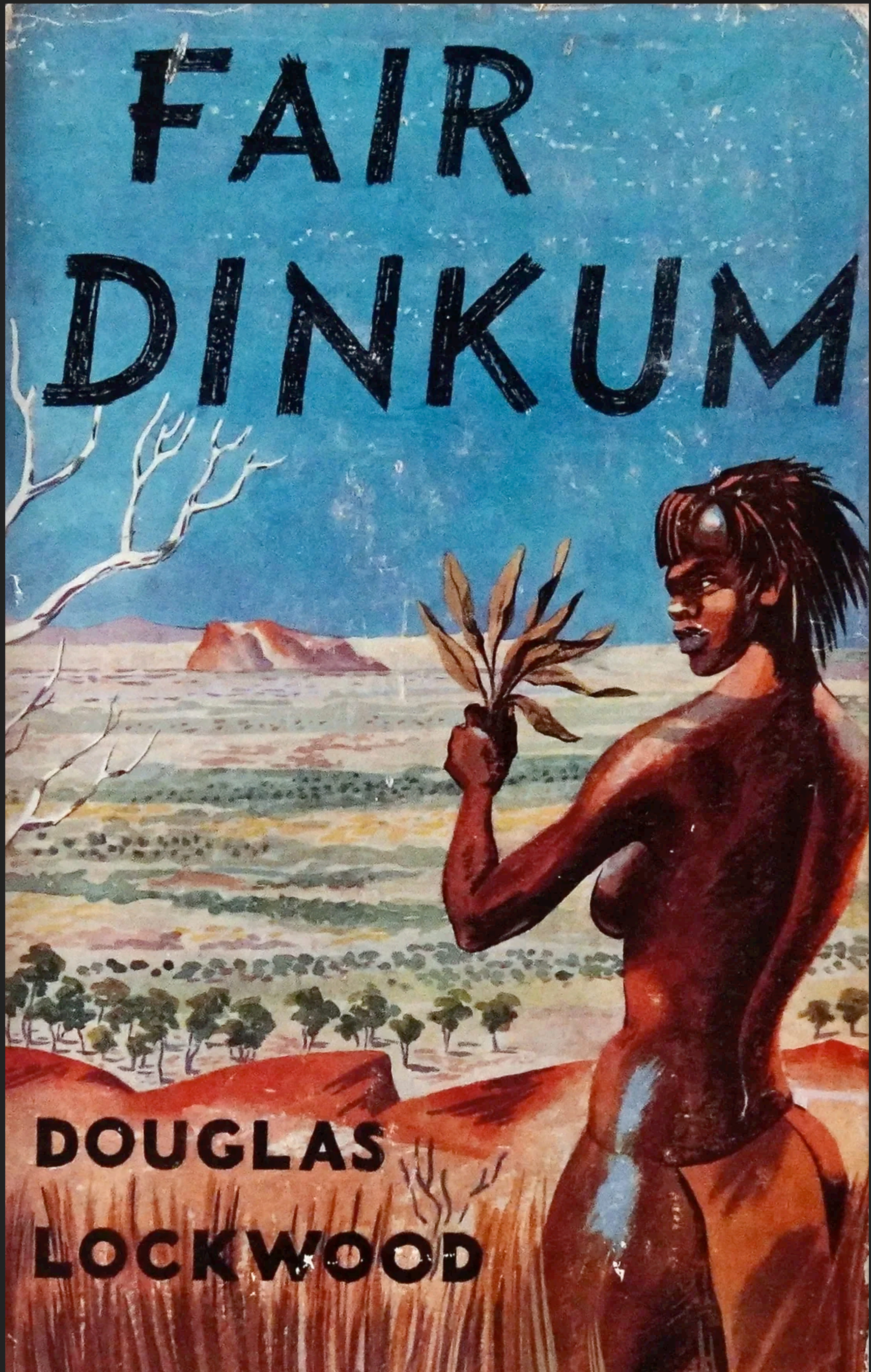

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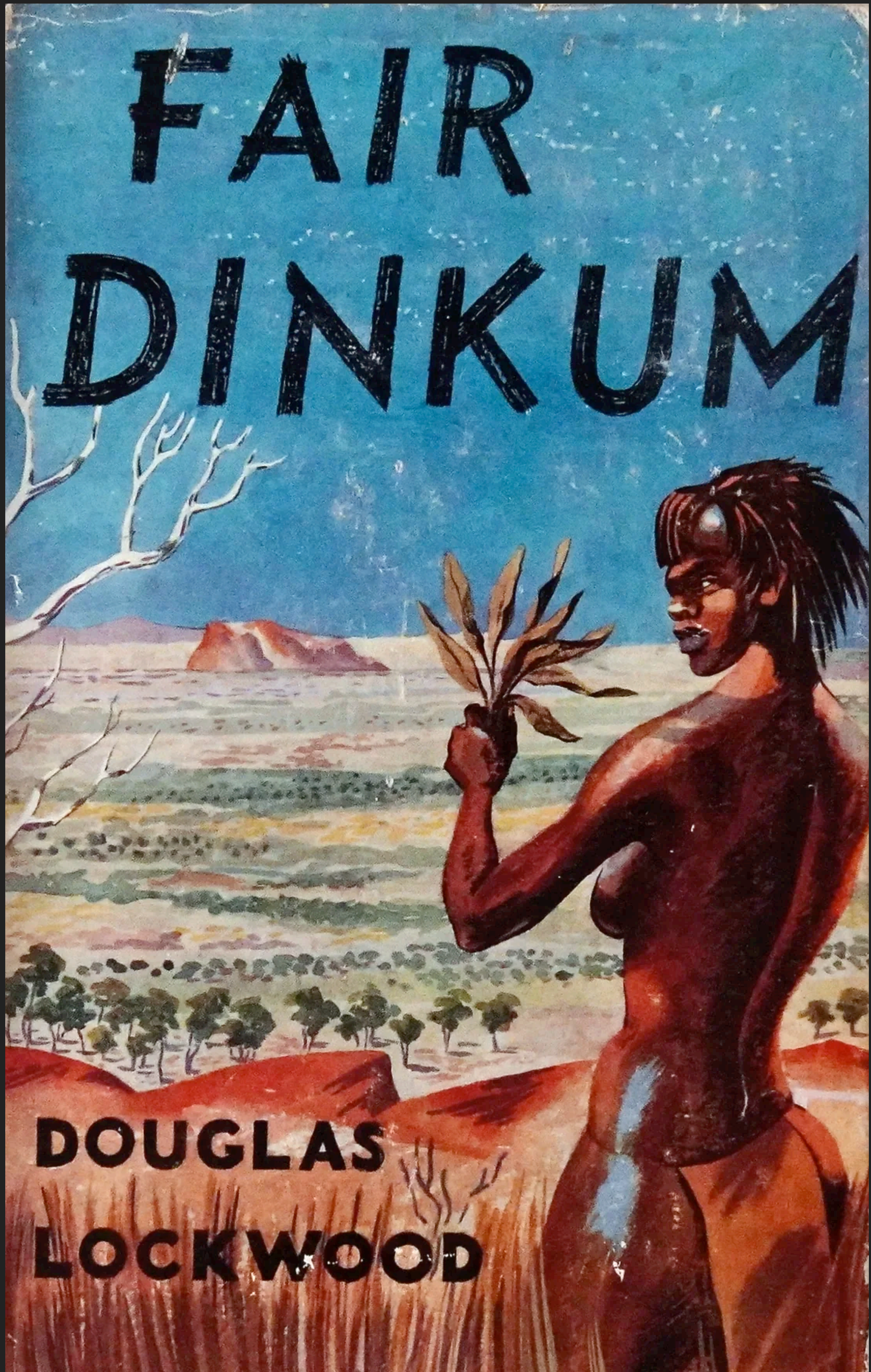

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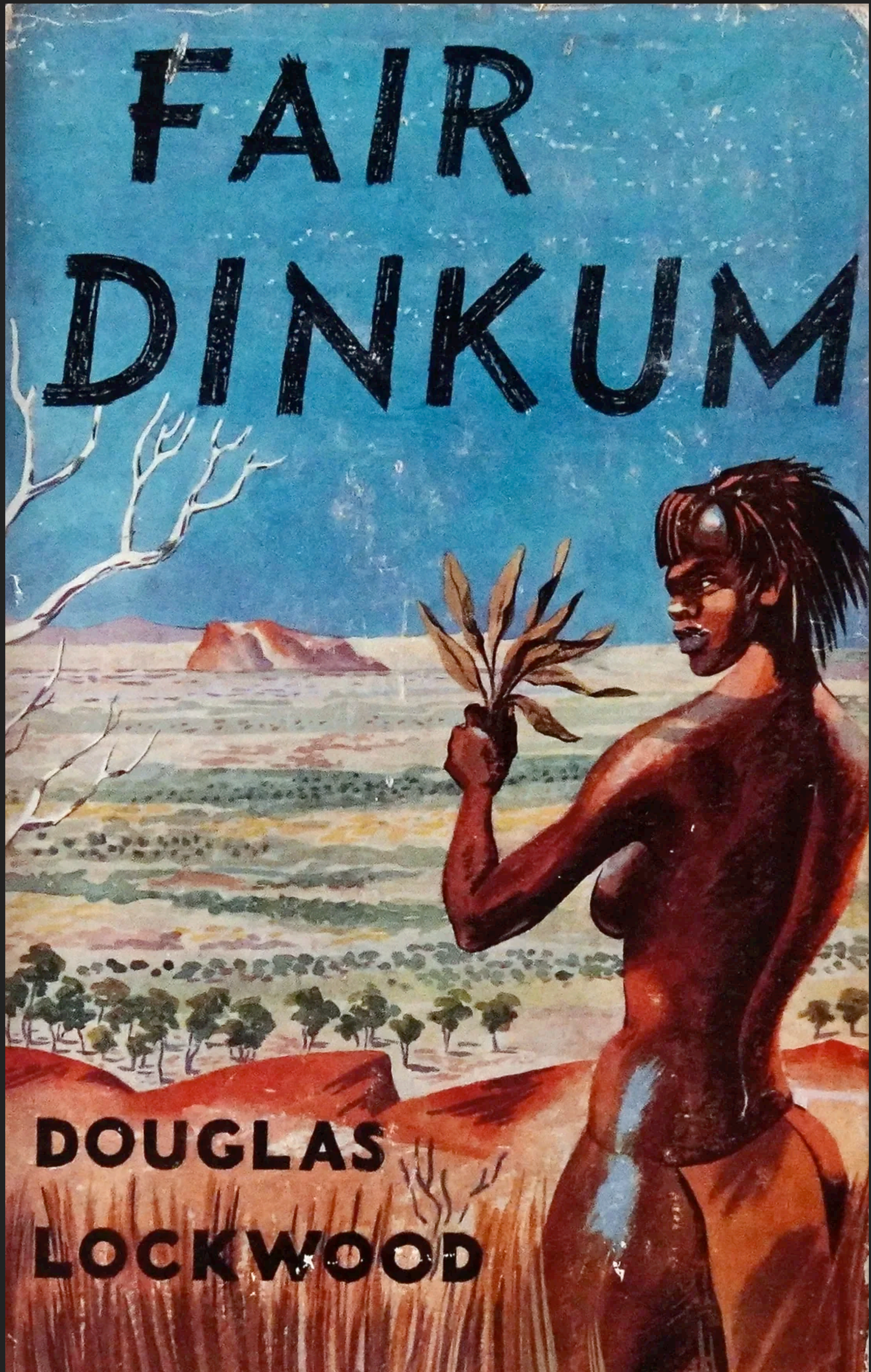
- Thus too for fairness (no surprise there really)



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- But a crucial part of one's modelling of the world

A COMMON STORY – SECTION 2, LINE 1…

arXiv > cs > arXiv:2101.02703

Computer Science > Machine Learning

[Submitted on 7 Jan 2021 (v1), last revised 4 Aug 2021 (this version, v3)]

Distribution-Free, Risk-Controlling Prediction Sets

Stephen Bates, Anastasios Angelopoulos, Lihua Lei, Jitendra Malik, Michael I. Jordan

1 Introduction

Black-box predictive algorithms have begun to be deployed in many real-world decision-making settings. Problematically, however, these algorithms are rarely accompanied by reliable uncertainty quantification. Algorithm developers often depend on the standard training/validation/test paradigm to make assertions of accuracy, stopping short of any further attempt to indicate that an algorithm's predictions should be treated with skepticism. Thus, prediction failures will often be silent ones, which is particularly alarming in high-consequence settings.

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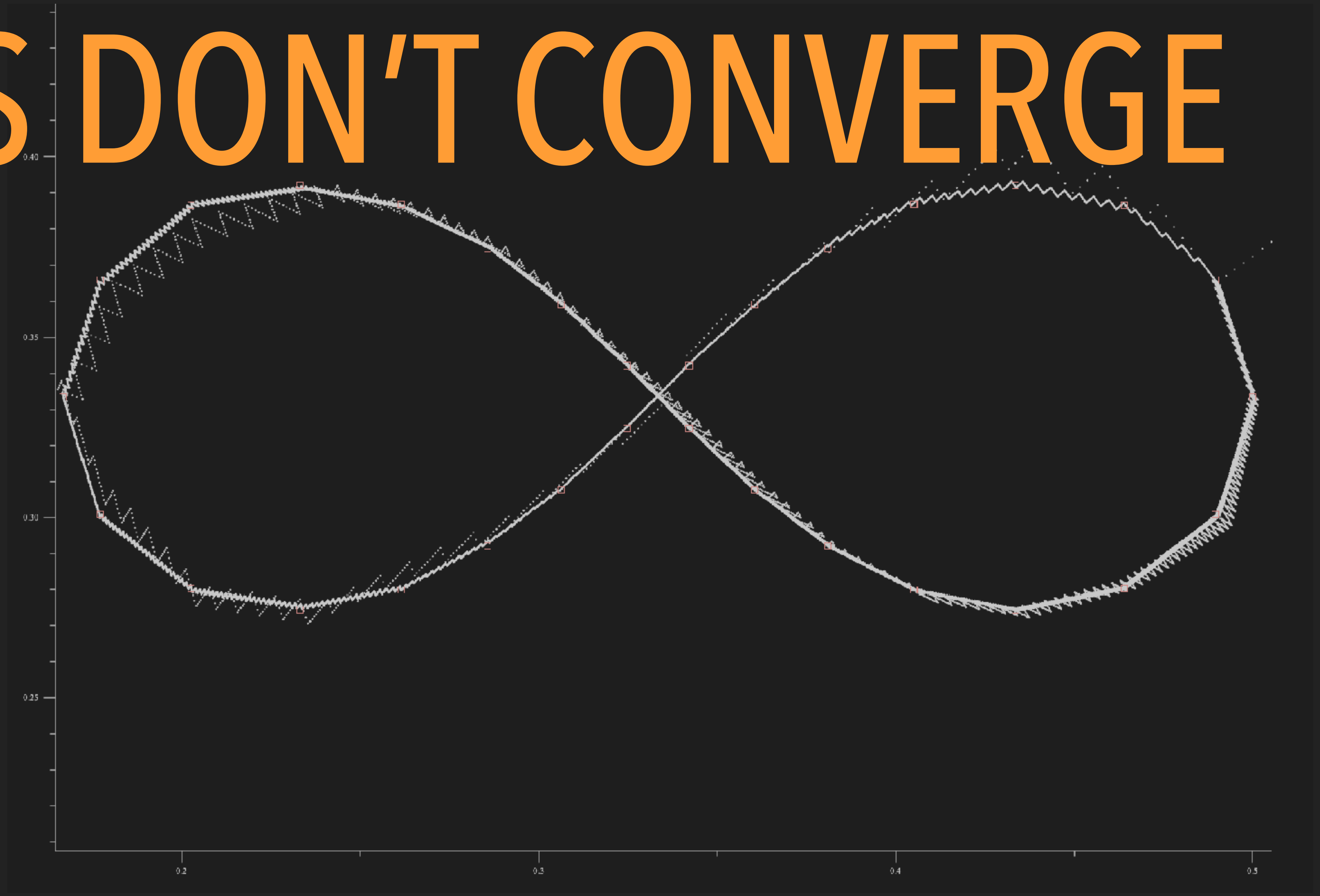

- "Non-stochastic randomness"
- Start with sequences (the data)
- Compute relative frequencies
- Von Mises assumes they converge to a limit – "the" probability
- What happens when they don't? (And no, there is no "law" that says they do)
- Multiple "cluster points" – generalisation of the mathematical limit
- *Every* sequence generates a sequence of relative frequencies with a set of cluster points
- *Any* connected set is the set of cluster points of the relative frequencies of some sequence