MACHINE LEARNING in SCIENCE

BRIDGING DATA-DRIVEN & MECHANISTIC MODELLING APPROACHES

SNAPSHOTS of AI in SCIENCE

BUILDING EFFECTIVE SIMULATIONS

CONNECTING DATA to CAUSALITY

ENCODING DOMAIN KNOWLEDGE

an EMERGING RESEARCH AGENDA

the ML for SCIENCE ECOSYSTEM

AI for SCIENCE ROADMAP

THIS CONFERENCE WAS HELD at SCHLOSS DAGSTUHL 19-23 SEPTEMBER, 2022.

PARTICIPANTS' TALKS

- LEARNING from RECENT EXPERIENCES
- BUILDING EFFECTIVE SIMULATIONS
- CONNECTING DATA to CAUSALITY
- ENCODING DOMAIN KNOWLEDGE

CLICK EACH TITLE to go to PAGE

UNIVERSITY OF CAMBRIDGE

EBERHARD KARLS UNIVERSITÄT TÜBINGEN

NYU

WISCONSIN UNIVERSITY OF WISCONSIN-MADISON

REAL WORLD APPLICATIONS

EXAMPLES of MACHINE LEARNING APPLICATIONS in SCIENCE can be FOUND ACROSS a WIDE SPECTRUM of SCIENTIFIC STUDY- from ATOMIC to ASTRONOMICAL!

IN EARTH SCIENCES...

INTEGRATING OBSERVATIONAL DATA w/PHYSICS-INFORMED MODELLING- ACROSS SCALES

THIS ABILITY can HELP us BETTER UNDERSTAND the IMPLICATIONS of CLIMATE CHANGE!

HYBRID MODELS can HELP FORE-CAST the IMPACT of CLIMATE CHANGE on DIFFERENT LANDSCAPES

TOOLKITS to MAKE ICE-MELT MODELS more ACCURATE

DIFFERENT DOMAINS have SPECIFIC NEEDS from ML TOOLS!

IN PHYSICAL SCIENCES...

NEURAL NETWORKS can HELP w/COMPLEX PREDICTIONS

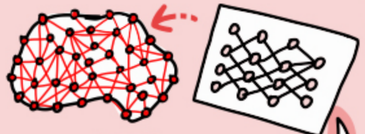
ML MODELS can HELP EXTRACT INSIGHTS from MACROSCOPIC PATTERNS in the UNIVERSE

ML TOOLS help FIND NEW APPROACHES to FIND APPROXIMATE NUMERICAL SOL. in DIFFUSION MODELING

THIS is USEFUL ACROSS MULTIPLE DOMAINS!

IN BIOLOGICAL SCIENCES...

COMBINING STATISTICAL & MECHANISTIC APPROACHES to RECONSTRUCT GENE DYNAMICS



ALLOWS RESEARCHERS to PREDICT CELL SPECIALIZATION & ASSOC. GENETIC CHANGES!

STREAMLINING the MODEL DEFINITION PROCESS to RAPIDLY DEVELOP SIMULATIONS of COMPLEX STRUCTURES like BRAINS or NERVOUS SYSTEMS

IN ENVIRONMENTAL SCIENCES...

COLLABORATING ACROSS DOMAINS & FROM FARMERS to BUILD a ROBUST SYSTEM for ANALYZING POULRY FECAL SAMPLES

REQUIRES CAREFUL CALIBRATION of INPUT SOURCES

APPLYING ML to ANALYZE MULTIPLE INPUTS to ESTIMATE # & BIOMASS of TREES

USING ML INSIGHTS from SATELLITES to MANAGE VECTOR BORNE ILLNESSES

MODELS have INHERENT ASSUMPTIONS, WHICH SHOULD be made TRANSPARENT to USER GROUPS

HOME

UNIVERSITY OF CAMBRIDGE

EBERHARD KARLS UNIVERSITÄT TÜBINGEN

NYU

WISCONSIN UNIVERSITY OF WISCONSIN-MADISON

BUILDING EFFECTIVE SIMULATIONS

HISTORICALLY, SCIENTISTS have COMPRESSED the DATA they COLLECT into NUMERICAL MATHEMATICAL MODELS...

THIS WORK RELIES on ALGORITHMS

AI for SCIENCE

OFFERS a DATA-CENTRIC APPROACH

ENABLES SOPHISTICATED SIMULATIONS of REAL-WORLD SYSTEMS

HOW do RESEARCHERS COMBINE this w/ TRADITIONAL METHODS?

"A" "B" "C"

ALLOW the SCIENTIST to INSERT & TEST VARIABLES in a MODEL

w/ ML, WE CAN do THIS in REVERSE w/ SIMULATION-BASED INFERENCE (SBI) & EXTRACT FURTHER INSIGHTS

SIMULATIONS ARE an ESTABLISHED TOOL in SCIENTIFIC DISCOVERY.

CHALLENGE: EXISTING MECHANISTIC MODELS are not SUITED to ML METHODS

NEW ML METHODS...

PROBABILISTIC NUMERICS OFFERS FLEXIBILITY of a STATISTICAL APPROACH

WE HAVE to BALANCE MODEL CHARACTERISTICS:

- PARAMETER GRANULARITY
- ROBUSTNESS

the SCIENCE COMMUNITY has CHECKS & BALANCES for SCRUTINIZING NEW KNOWLEDGE

WHAT GUARDRAILS are NEEDED to GIVE RESEARCHERS CONFIDENCE in ML ENABLED SIMULATIONS?

DIAGNOSTIC TESTS for COMPUTATIONAL FAITHFULNESS

THERE are CLEAR BENCHMARKS w/in the ML COMMUNITY as WELL

HOW do we ENSURE THESE ALIGN to DOMAIN EXPECTATIONS?

- [x] DOES the SIMULATION-GENERATED DATA MATCH the OBSERVED DATA?
- [x] DESIGN ML METHODS to be MORE CONSERVATIVE.

HOW do we MANAGE UNCERTAINTY?

WE CAN'T AFFORD OVER-CONFIDENT MODELS

CREATE a FEEDBACK LOOP:

- BUILD MODEL
- COMPUTE
- CRITIQUE
- REPEAT

THIS REQUIRES COLLABORATION

COMPUTATIONAL TOOLS MUST ALIGN to USER NEEDS

CONSTRUCTING THESE TAKES KNOW-HOW & SKILL...

USER-GUIDE w/ CASE STUDIES for DOMAIN APPLICATION

HOME

UNIVERSITY OF CAMBRIDGE

EBERHARD KARLS UNIVERSITÄT TÜBINGEN

NYU

WISCONSIN UNIVERSITY OF WISCONSIN-MADISON

CONNECTING DATA to CAUSALITY

MOST SCIENTIFIC ENDEAVORS have a CAUSAL ELEMENT.

HOW? WHY? WHAT? WHAT IF...?

ACROSS DOMAINS, SCIENTIST HAVE DIFFERENT WAYS to I.D. CAUSE & EFFECT RELATIONSHIPS

RESEARCHERS INSERT & TEST VARIABLES in CAUSAL MODELS

= "A"
= "B"
= "C"

IN CONTRAST...

ML LEARNS from DATA RATHER THAN SYSTEM RULES (like PHYSICAL LAWS)

SOMETIMES, DATA can be NOISY.

RESEARCHERS can IMPROVE AI APPLICATIONS by BEING ATTENTIVE to STRUCTURES w/in DATA!

BUT, FAILURE CAN HAVE HUGE NEGATIVE EFFECTS...

AIM in AI RESEARCH... CAUSAL INFERENCE: the ABILITY to ID CAUSE-&-EFFECT RELATIONSHIPS in DATA-

MIS-IDENTIFICATION of US vs. USSR TANKS...

INACCURATE ASSESSMENT of COLLAPSED LUNG...

AI FOUND CORRELATIONS, RATHER THAN CAUSAL PATTERNS

THESE ERRORS COME from a CORE ASSUMPTION..

DATA in the REAL WORLD DOES NOT FOLLOW IID (INDEPENDENT + IDENTICALLY DISTRIBUTED)

WE NEED AI MODELS that can MANAGE this VIOLATION

DISTINGUISH BETWEEN PATTERNS that:
- CO-OCCUR
- are CAUSAL

LOT'S of MICRO-DECISIONS to MAKE

GOOD MODEL DESIGN REQUIRES COLLABORATION

"HAND-CRAFTED" APPROACH MAY MAKE METHODS LESS ACCESSIBLE!

THERE is a TENSION BETWEEN SPECIFICATION & LEARNING

ADVANCES in CAUSAL INFERENCE can HELP ANSWER BROADER QUESTIONS on the NATURE of INTELLIGENCE!

MUST

ML MODELS that ACHIEVE this COULD...
- OPERATE w/OUT-of-DISTRIBUTION DATA
- LEARN a TASK from FEW EXAMPLES
- HELP ATTRIBUTE CREDIT for ACTIONS in DIFFERENT INTERVENTIONS
- COMMUNICATE in MULTIPLE METHODS

COMBINES the STRENGTH of STATISTICAL MODELING w/ DIFFERENTIAL EQUATIONS

a TRULY CAUSAL AI MODEL WOULD BE:
- FUNCTIONAL ACROSS VARIED ENVIRONMENTS
- ROBUST
- EFFICIENT to TRAIN

HOME

UNIVERSITY OF CAMBRIDGE

EBERHARD KARLS UNIVERSITÄT TÜBINGEN

NYU

WISCONSIN UNIVERSITY OF WISCONSIN-MADISON

ENCODING DOMAIN KNOWLEDGE

HUMANS HAVE LONG IMAGINED how AI can IMPROVE/ACCELERATE THEIR LIVES...

BUT THERE are FAILURE MODES...

- INSUFFICIENT CONTEXTUAL AWARENESS
- MISSPECIFICATION of USER NEEDS
- UNDERSTANDING of ENVIRONMENTAL DYNAMICS

it's a TWO-WAY STREET...

AI: ANALYTIC POWER & HUMAN INSIGHTS

TRADITIONAL MODELS FOLLOW WELL-DEFINED RULES.

$E=mc^2$

THIS DEMANDS INTEGRATION

- ALGORITHMIC DESIGN
- AI INTEGRATION in the LAB
- EFFECTIVE COMMUNICATION & COLLABORATION

UNDERPINNED by:

- MATHEMATICAL SYMMETRIES
- INVARIANCES
- CAUSAL UNDERSTANDING

MODELS SHOULD OBEY the LAWS of PHYSICS

OUTPUTS SHOULD be CONSTRAINED by WHAT is PHYSICALLY POSSIBLE!

the GOAL: MODELS THAT...

- PRODUCE MORE ACCURATE RESULTS
- CREATE SMALLER GENERALISATION ERRORS
- BETTER OUT-of-DISTRIBUTION GENERALISATIONS

HOW do we DEPLOY this AI in LABS?

DATA from...

MEASUREMENT DEVICES + SIMULATIONS of LAB PROCESSES + COMPUTATIONAL MODELS of OBJECTIVES

"VIRTUAL ASSISTANTS" in VIRTUAL LAB SPACES can HELP ACCELERATE the RESEARCH PROCESS!

SMART TOOLKITS PACKAGE SIMULATIONS, CAUSAL MODELLING, & ENCODED PRE-EXISTING DOMAIN INSIGHTS

NEEDED: FEEDBACK LOOP

MATCH the MODEL to USER NEED

KEEP it SIMPLE!

INTERROGATION METHODS HELP PRESSURE TEST AI SYSTEMS!

INSIGHTS SHOULD be INTERPRETABLE & ACCESSIBLE

THE RIGHT SOFTWARE is KEY for WIDER USE

SIDEKICKS ELICIT GUIDANCE & HELP DRIVE RESEARCH

LEVERAGE COGNITIVE SCIENCE, STUDIES on TEAM DECISION-MAKING to MODEL GOALS EVEN WHEN USERS CAN'T CLEARLY ARTICULATE THOSE THEMSELVES

HOME

UNIVERSITY OF CAMBRIDGE

EBERHARD KARLS UNIVERSITÄT TÜBINGEN

NYU

WISCONSIN UNIVERSITY OF WISCONSIN-MADISON

A RESEARCH AGENDA in AI for SCIENCE

'AI for SCIENCE' SITS at a NEXUS POINT of METHODS, DISCIPLINES, & COMMUNITIES

& w/a CORE SHARED INTEREST:

LEARNING from DATA!

BUILDING AI SYSTEMS for SCIENCE

THERE are GAPS in our CURRENT CAPABILITIES

AREAS of PROGRESS..

- ADVANCING METHODS & TOOLKITS
- INTEGRATE SCIENTIFIC LAWS into ML MODELS
- ADVANCE CAUSAL MACHINE LEARNING

KEY QUESTIONS to CONSIDER..

HOW can AI METHODS be MADE ROBUST & EASY to USE by DOMAIN SCIENTISTS?

HOW can ADVANCES in SIMULATION METHODS be APPLIED in DOMAINS WHERE the SYSTEM at HAND is LESS EASILY DESCRIBED by EQUATIONS?

WHAT is the COMPUTATIONAL COST of COMPLEXITY, & WHAT METHODS can HELP MANAGE THIS?

HOW can 'DIGITAL SIBLINGS' be USED to EXPLORE the IMPACT of DIFFERENT INTERVENTIONS on COMPLEX SYSTEMS?

WHAT DOES it MEAN to UNDERSTAND a MODEL? HOW can RESEARCHERS COMBINE EXPLAINABILITY w/ COMPLEXITY

HOW can AI RESEARCHERS BUILD MEANINGFUL MODELS from DATA to ACCURATELY REPRESENT CAUSAL MECH. in a SYSTEM of STUDY?

COMBINING HUMAN & MACHINE INTELLIGENCE

WHICH INSIGHTS are RELEVANT, how to BEST COMMUNICATE them, & the CULTURAL ENVIRONMENT of the SCIENCE CONDUCTED!

EFFECTIVE DEPLOYMENT REQUIRES CLEAR INTERACTIONS BETWEEN:

- ☐ HUMAN
- ☐ DOMAIN
- ☐ ML

INTELLIGENCE!

AREAS of PROGRESS..

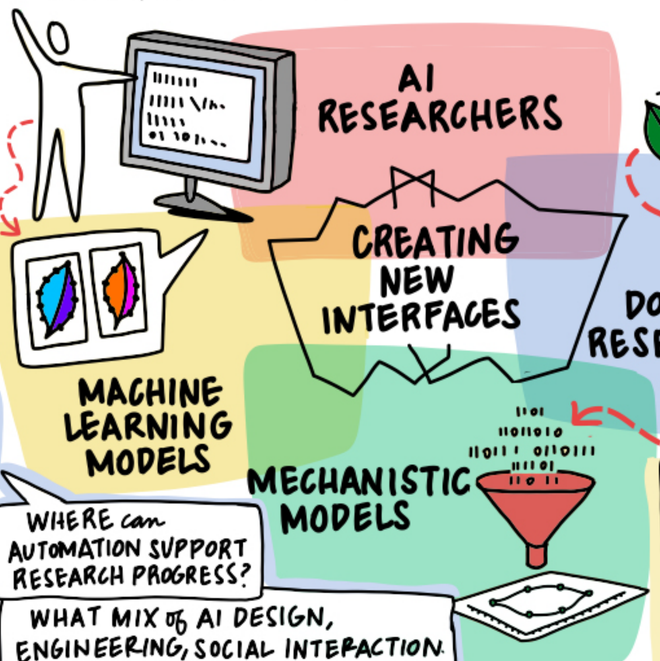
- DESIGNING PRECISE INTERFACES
- BUILDING MECHANISMS to INTERROGATE AI SYSTEMS
- ACCELERATING PACE of KNOWLEDGE CREATION & USE

HOW can AI CAPTURE the QUALITATIVE UNDERSTANDING that RESEARCHERS have in THEIR DOMAIN to APPLY in a SYSTEM?

HOW can OUTPUTS of AI SYSTEMS be MADE INTERPRETABLE for SCIENTIFIC USERS?

WHERE can AUTOMATION SUPPORT RESEARCH PROGRESS?

WHAT MIX of AI DESIGN, ENGINEERING, SOCIAL INTERACTION & EDUCATION can MAKE EFFECTIVE INTERFACES for RESEARCHERS & AI SCIENTISTS?



INFLUENCING PRACTICE & ADOPTION

WE MUST PROMOTE UPTAKE & PROGRESS for this WORK!

AREAS of PROGRESS..

- PROMOTE INTER-DISCIPLINARY COLLABORATIONS
- DEVELOP TOOLKITS & USER GUIDES to HELP RESEARCHER APPLY APPROPRIATE AI TOOLS

WHAT are the CRAFT SKILLS in AI for SCIENCE? WHAT 'KNOW-HOW is NECESSARY to MAKE AI WORK EFFECTIVELY in PRACTICE?

HOW has MACHINE LEARNING BEEN USED MOST EFFECTIVELY for RESEARCH & INNOVATION? WHAT BEST PRACTICES can EXISTING EFFORTS OFFER?

WHICH AI TOOLS are SUITABLE for WHICH PURPOSES, DISCIPLINES, or EXPERIMENTAL DESIGNS? IS IT POSSIBLE to CREATE a TAXONOMY for SCIENCE?

HOW do we BRING AI TOOLS out of the AI COMMUNITY & INTO "the LAB"?

HOME

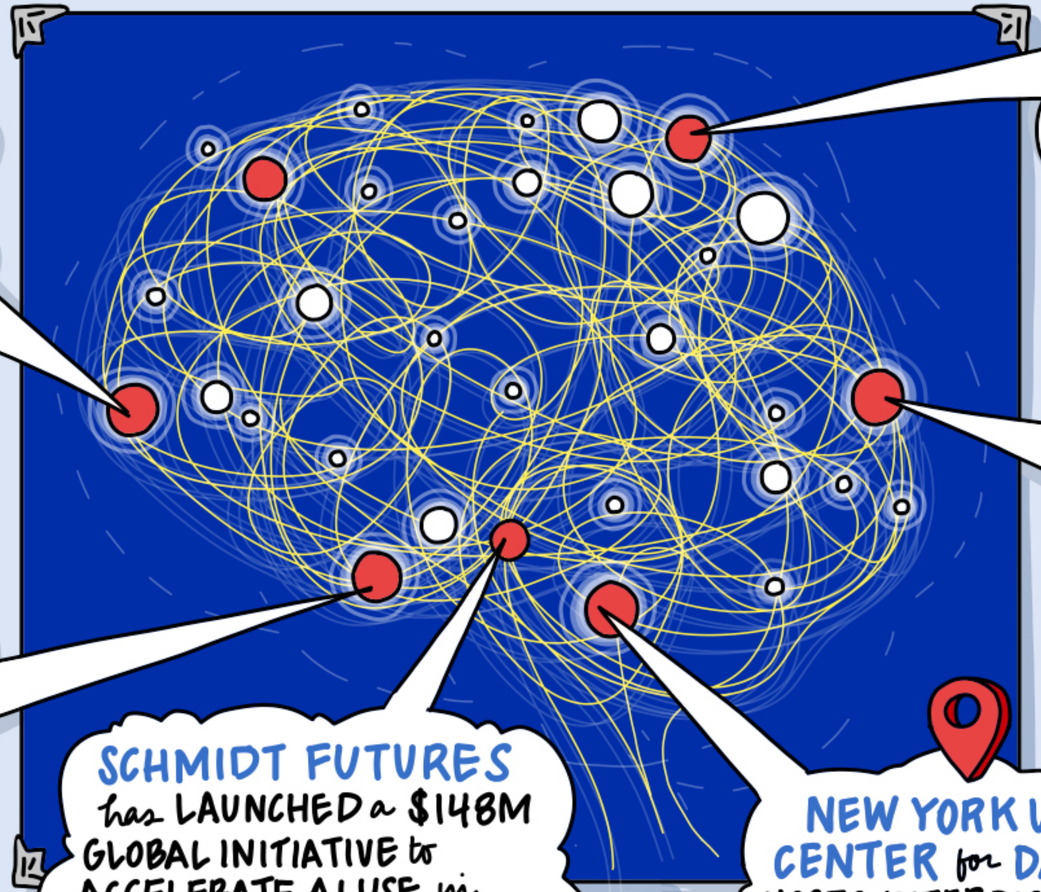
UNIVERSITY OF CAMBRIDGE

EBERHARD KARLS UNIVERSITÄT TÜBINGEN

NYU

WISCONSIN UNIVERSITY OF WISCONSIN-MADISON

ML for SCIENCE ECOSYSTEM



UNIVERSITY of CAMBRIDGE: the **ACCELERATE PROGRAMME for SCIENTIFIC DISCOVERY** is BUILDING BRIDGES ACROSS DISCIPLINES, CREATING a COMMUNITY PASSIONATE ABOUT OPPORTUNITIES for AI in SCIENCE.

UNIVERSITY of TÜBINGEN: the **ML LEARNING for SCIENCE CLUSTER** is LEVERAGING LOCAL STRENGTHS in AI to DRIVE WIDER PROGRESS in RESEARCH & INNOVATION.

UNIVERSITY of WISCONSIN-MADISON: AMERICAN FAMILY INSURANCE DATA SCIENCE INSTITUTE is DEVELOPING STRATEGIC PARTNERSHIPS to ACCELERATE the USE of DATA SCIENCE in RESEARCH.

UNIVERSITY of COPENHAGEN: SCIENCE AI CENTRE PROVIDES a FOCAL POINT AI RESEARCH & EDUCATION in it's FACULTY for SCIENCE.

SCHMIDT FUTURES has LAUNCHED a $148M GLOBAL INITIATIVE to ACCELERATE AI USE in POSTDOCTORAL RESEARCH. CLICK to LEARN MORE ABOUT the 1st COHORT of SCHOOLS.

NEW YORK UNIVERSITY: CENTER for DATA SCIENCE HOSTS INTERDISCIPLINARY FACULTY PURSUING INNOVATIVE RESEARCH & EDUCATION.

THIS MAP is INTERACTIVE. CLICK EACH BUBBLE to VISIT EXTERNAL LINKS of INTEREST

HOME

UNIVERSITY OF CAMBRIDGE

EBERHARD KARLS UNIVERSITÄT TÜBINGEN

NYU

WISCONSIN UNIVERSITY OF WISCONSIN-MADISON

AI for SCIENCE ROADMAP

INVEST in TOOLS & TOOLKITS

MAKE KNOW-HOW ACCESSIBLE!

WE MUST CHART a PATH BETWEEN the STATISTICIAN & the MATHEMATICIAN

INVEST in TOOLKITS that SUPPORT GENERALISATION of EFFECTIVE APPROACHES

→ "OFF-the-SHELF" SOLUTIONS

→ CLEAN, EASY-to-USE INTERFACE for USER!

DEVELOP PIPELINES for DATA MGMT

- BEST PRACTICES
- FRAMEWORKS

DEVELOP BEST PRACTICES in SOFTWARE ENGINEERING & USER-GUIDES for NON-EXPERTS

BUILD CAPABILITY across DISCIPLINES

NEEDED

RESEARCHERS, ENGINEERS, & CONVENERS w/a PASSION for ADVANCING SCIENCES THROUGH AI.

PROVIDE ACCESS to LEARNING & DEVELOPMENT ACTIVITIES in ML

- → TRAINING
- → TUTORIALS
- → USER GUIDES
- → BUILD CAPABILITIES in COMMUNICATION, ORGANISATION, & CONVENING.

CREATE INSTITUTIONAL INCENTIVES

→ RECOGNIZE & REWARD SUCCESSES

AI for SCIENCE is a RENDEZVOUS POINT

IT'S NEXT WAVE of DEVELOPMENT will COME from the STRENGTH of it's DIVERSE COMMUNITY!

GROW COMMUNITIES of RESEARCH & PRACTICE

COMMUNITIES of RESEARCH & PRACTICE are the BACKDROP of this EFFORT!

AI!

CREATE NEW COMMUNICATION CHANNELS

- → FORUMS
- → NEWSLETTERS
- → RESEARCH SYMPOSIA

AN OUTLET to PUBLISH & RECOGNIZE NEW IDEAS

DEVELOP "AI for SCIENCE" JOURNALS

ESTABLISH MEMBERSHIP ORGANISATIONS to FOSTER COMMUNITY & SUPPORT CAREER DEV.

HOME

UNIVERSITY OF CAMBRIDGE

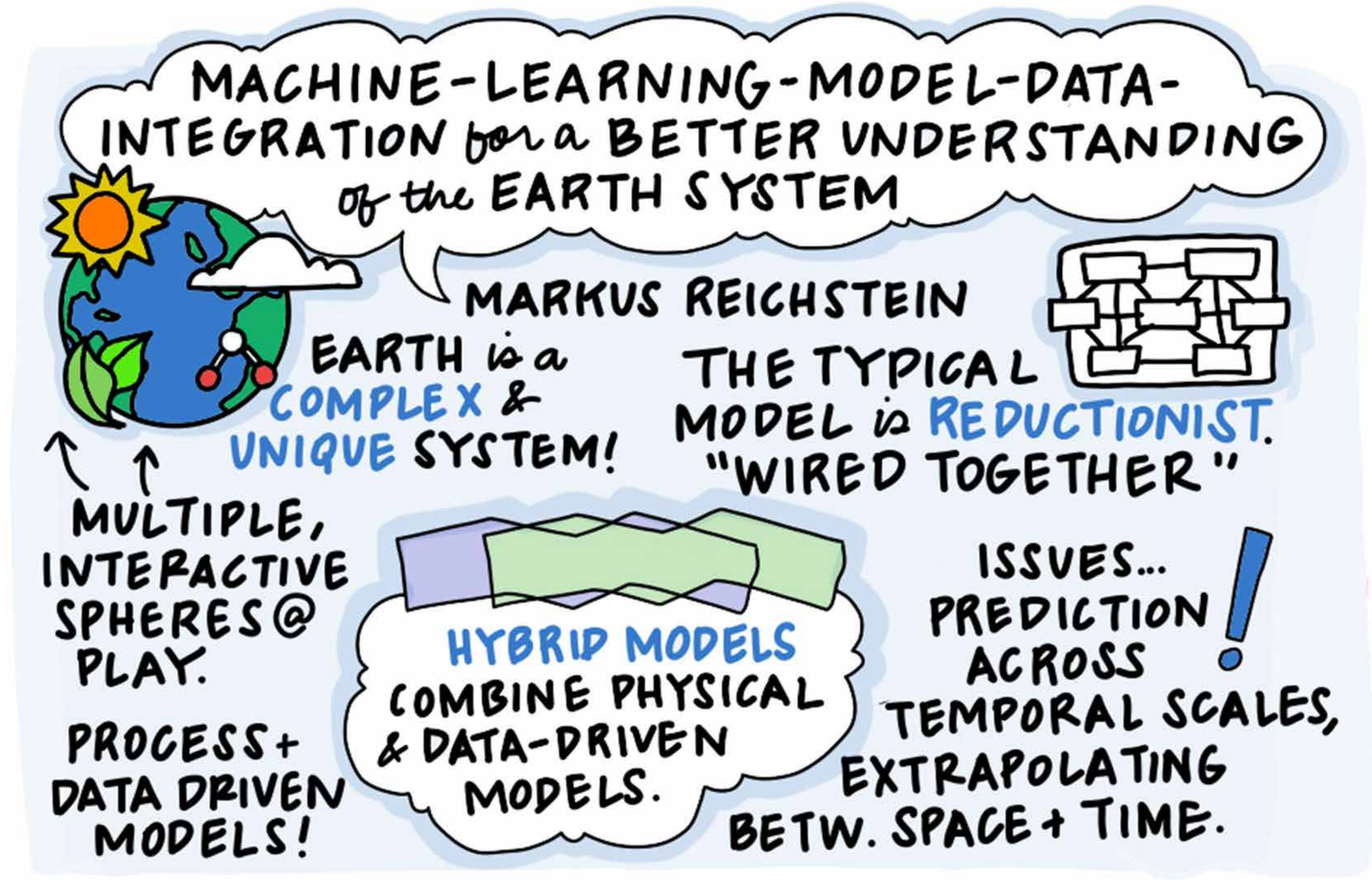
EBERHARD KARLS UNIVERSITÄT TÜBINGEN

NYU

WISCONSIN UNIVERSITY OF WISCONSIN-MADISON

Machine - Learning - Model - Data - Integration for a Better Understanding of the Earth's System

Markus Reichstein
MPI für Biogeochemistry
Max Planck Institute
Jena, DE



HOME

UNIVERSITY OF CAMBRIDGE

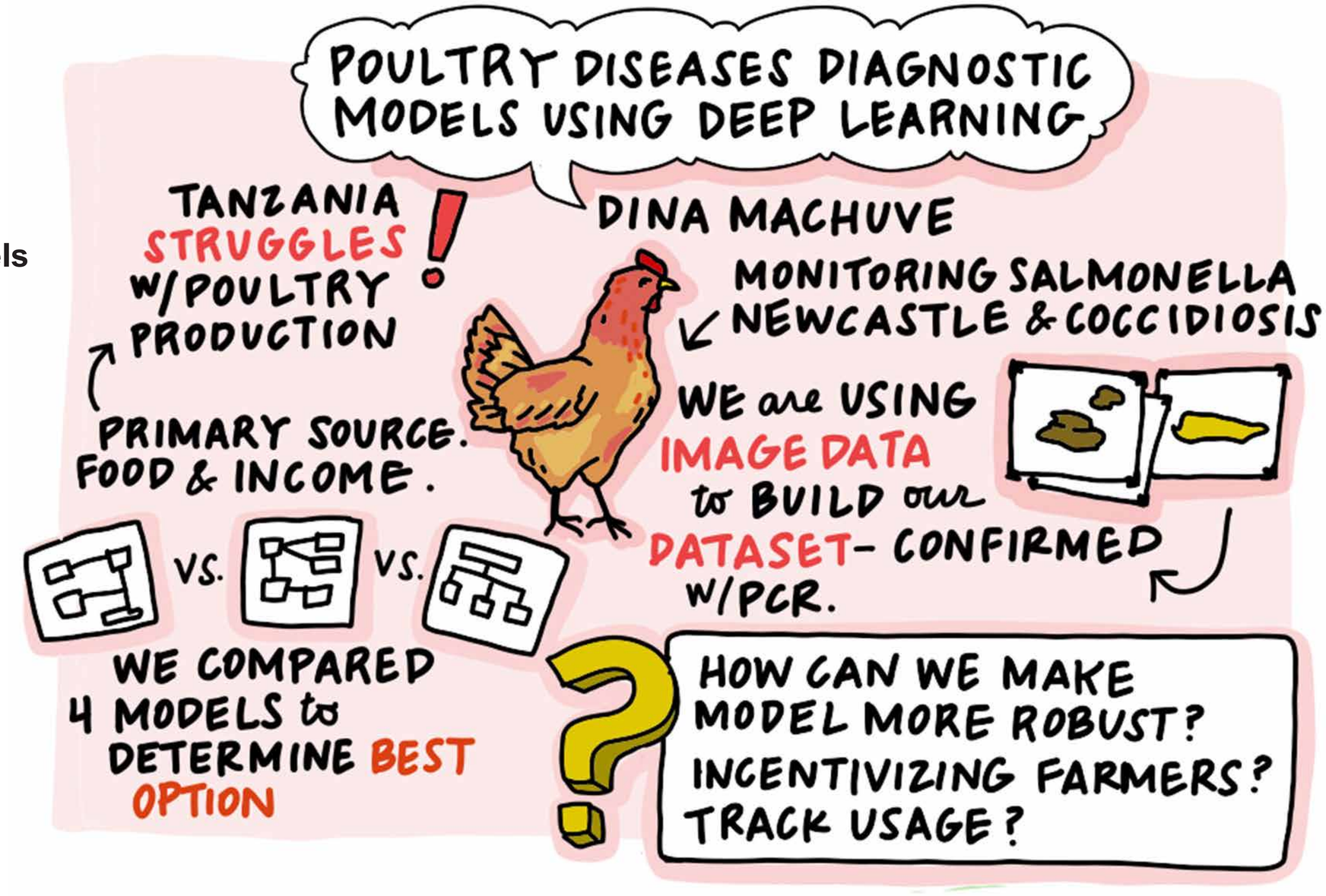
EBERHARD KARLS UNIVERSITÄT TÜBINGEN

NYU

WISCONSIN UNIVERSITY OF WISCONSIN–MADISON

Poultry Diseases Diagnostics Models using Deep Learning

Dina Machuve
DevData Analytics
Arusha, TZ



HOME

UNIVERSITY OF CAMBRIDGE

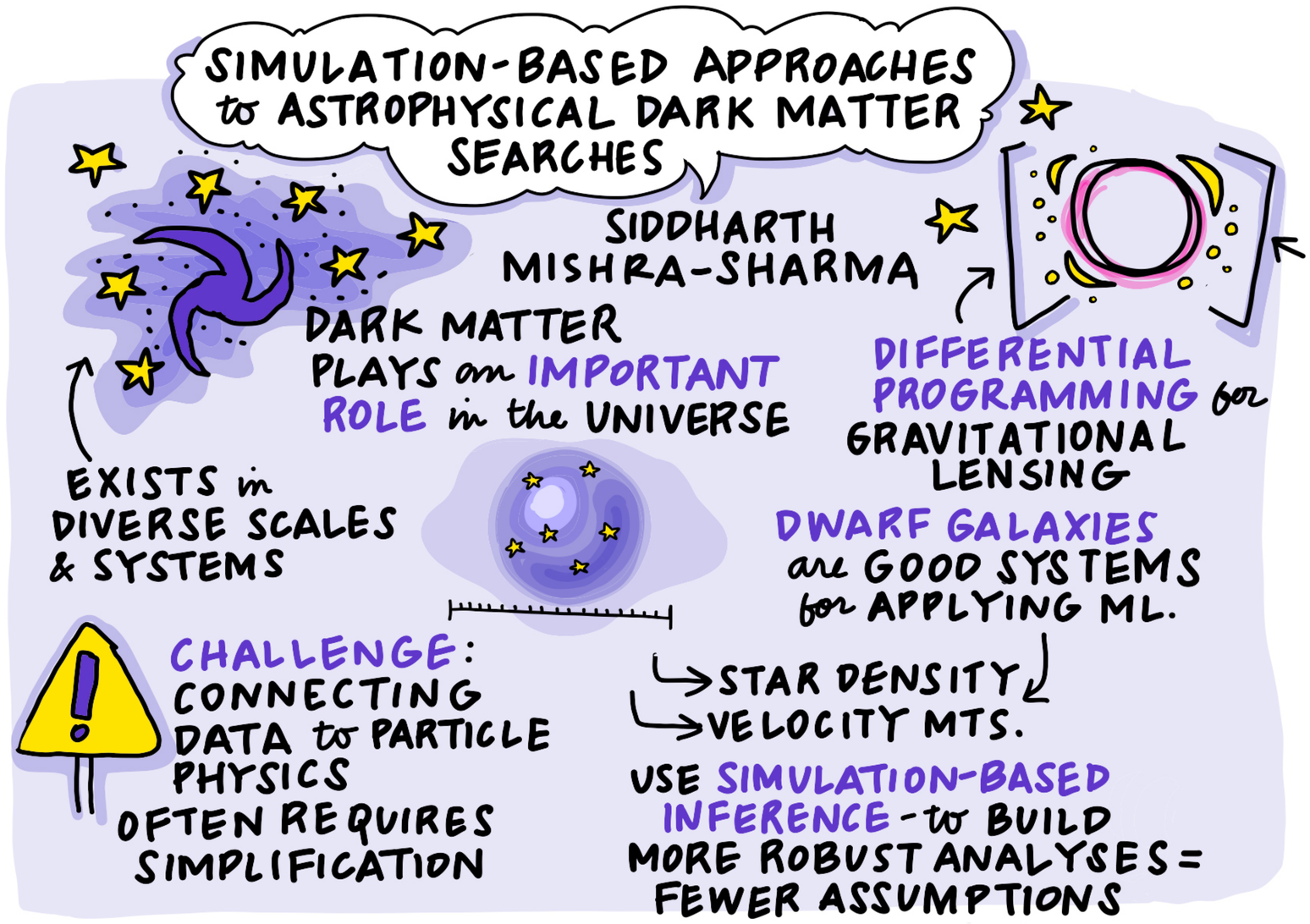
EBERHARD KARLS UNIVERSITÄT TÜBINGEN

NYU

WISCONSIN UNIVERSITY OF WISCONSIN-MADISON

Finding new physics: Simulation-based Approaches to Astrophysical Dark Matter Searches

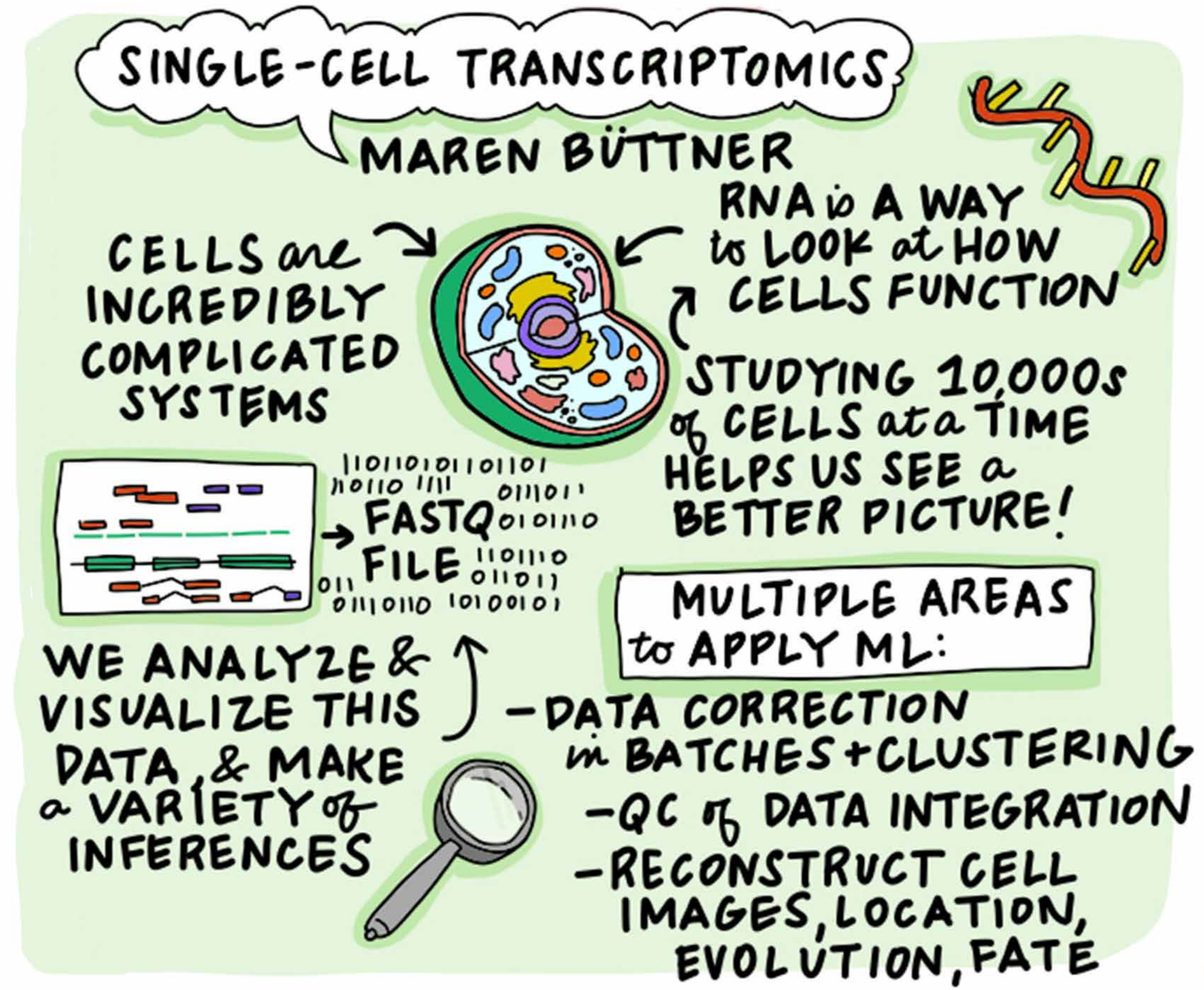
Siddharth Mishra-Sharma
MIT
Cambridge, US



HOME

Single-cell Transcriptomics

Maren Büttner
Helmholtz Zentrum München &
Universität Bonn
München, Bonn, DE



HOME

UNIVERSITY OF CAMBRIDGE

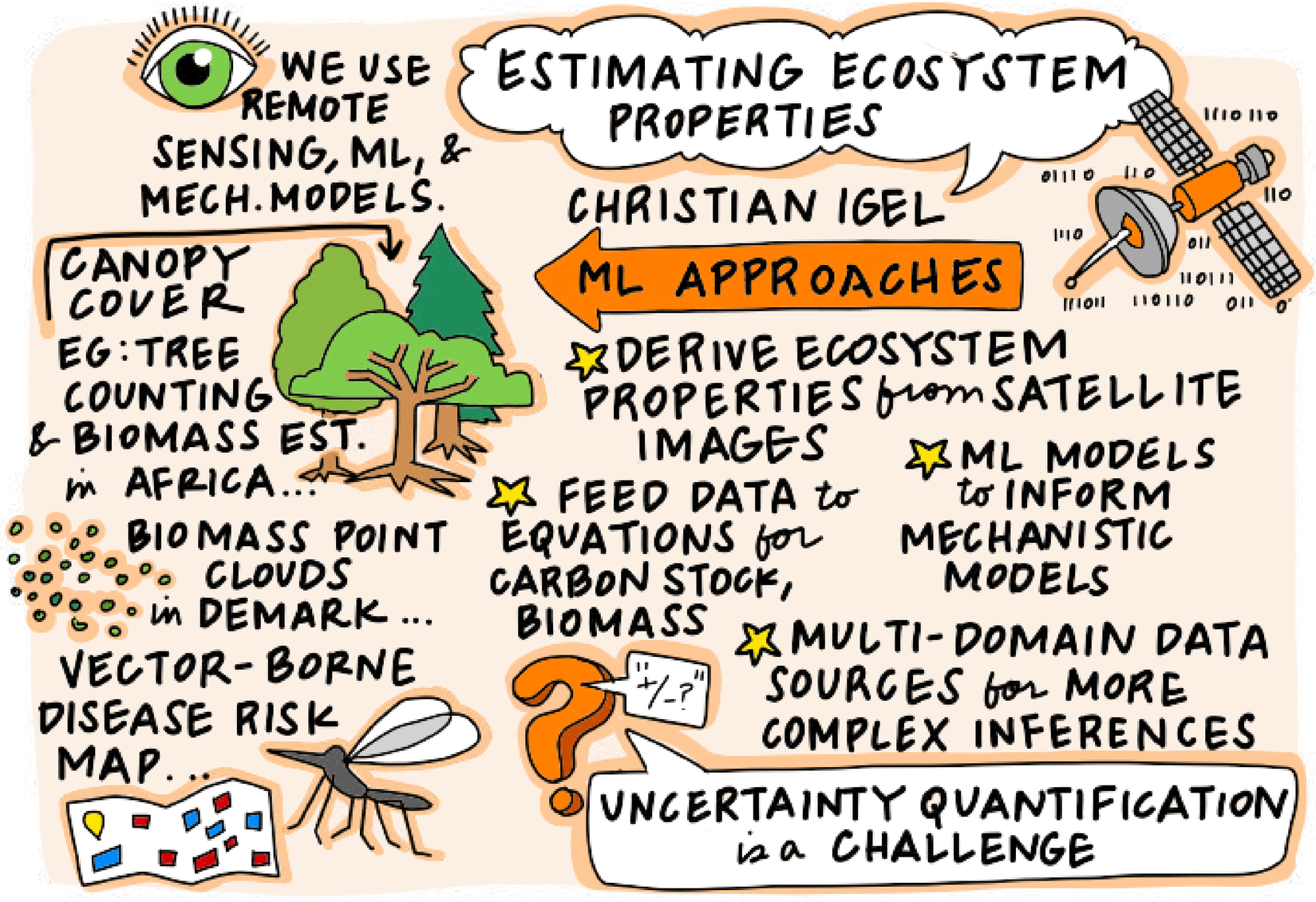
EBERHARD KARLS UNIVERSITÄT TÜBINGEN

NYU

WISCONSIN UNIVERSITY OF WISCONSIN-MADISON

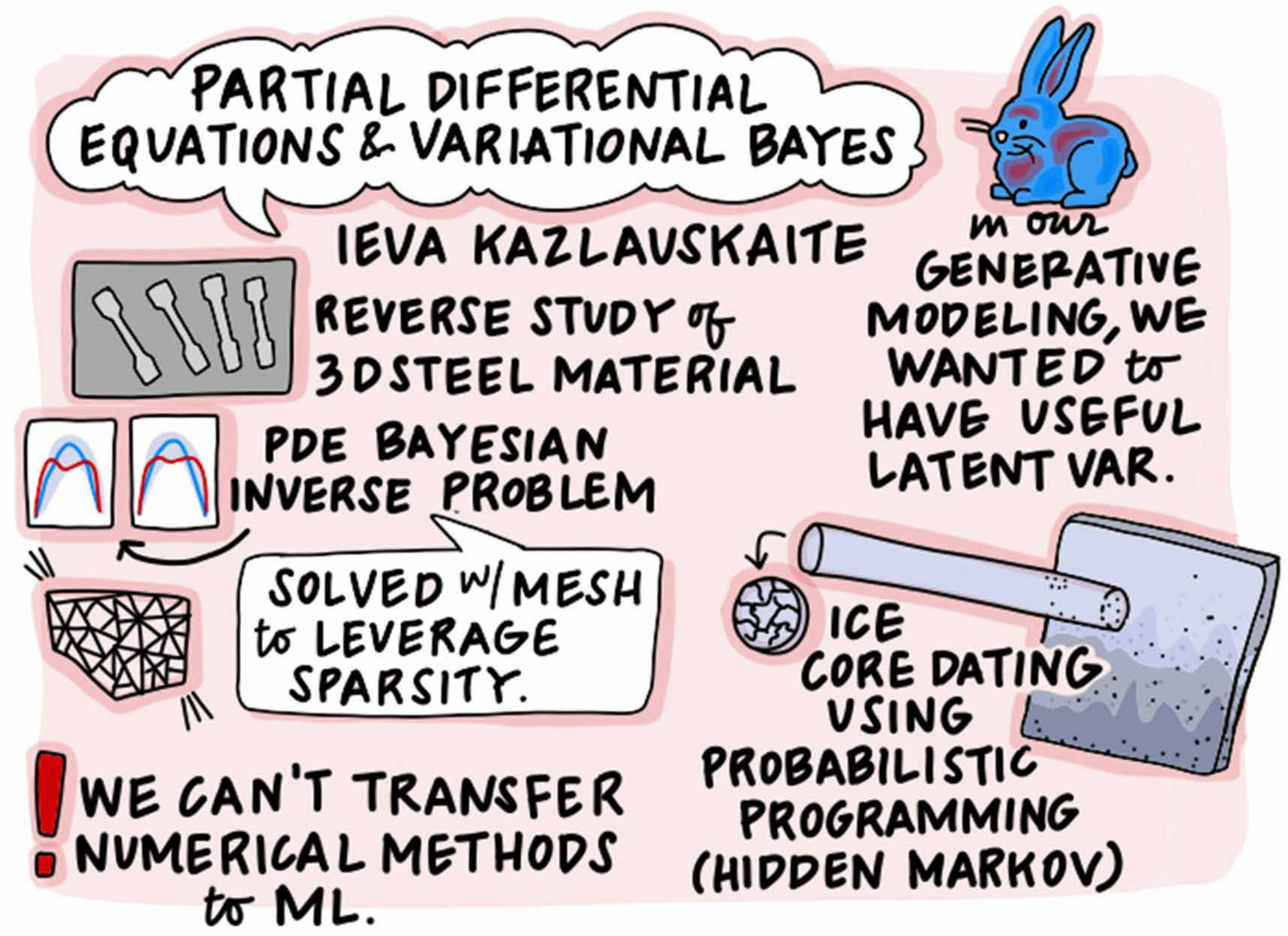
Estimating Ecosystem Properties

Christian Igel
University of Copenhagen
Copenhagen, DK



Partial Differential Equations and Variational Bayes

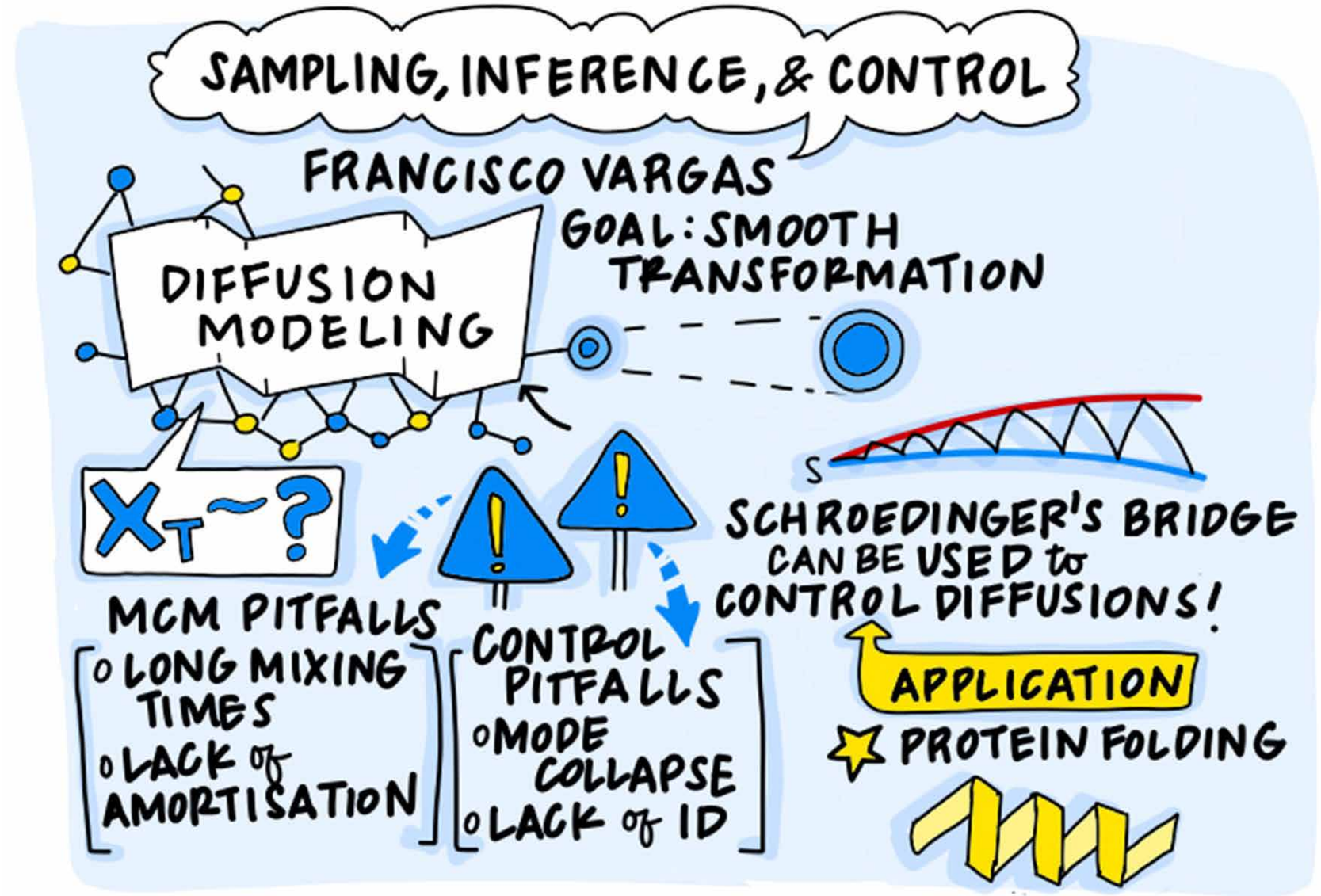
Ieva Kazlauskaite
University of Cambridge
Cambridge, GB



HOME

The Schrödinger Bridge Problem

Francisco Vargas
University of Cambridge Cambridge, GB



HOME

UNIVERSITY OF CAMBRIDGE

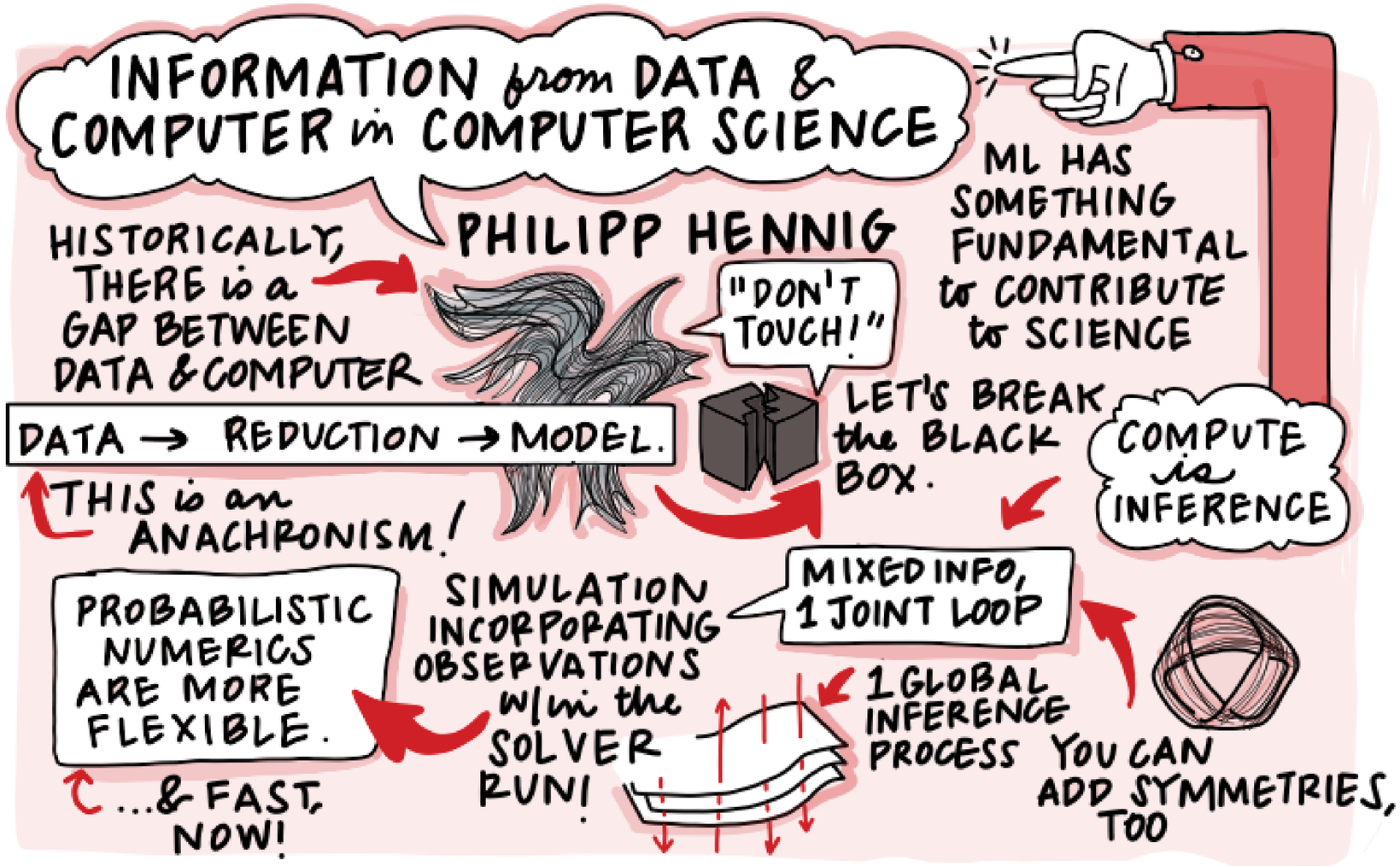
EBERHARD KARLS UNIVERSITÄT TÜBINGEN

NYU

WISCONSIN UNIVERSITY OF WISCONSIN–MADISON

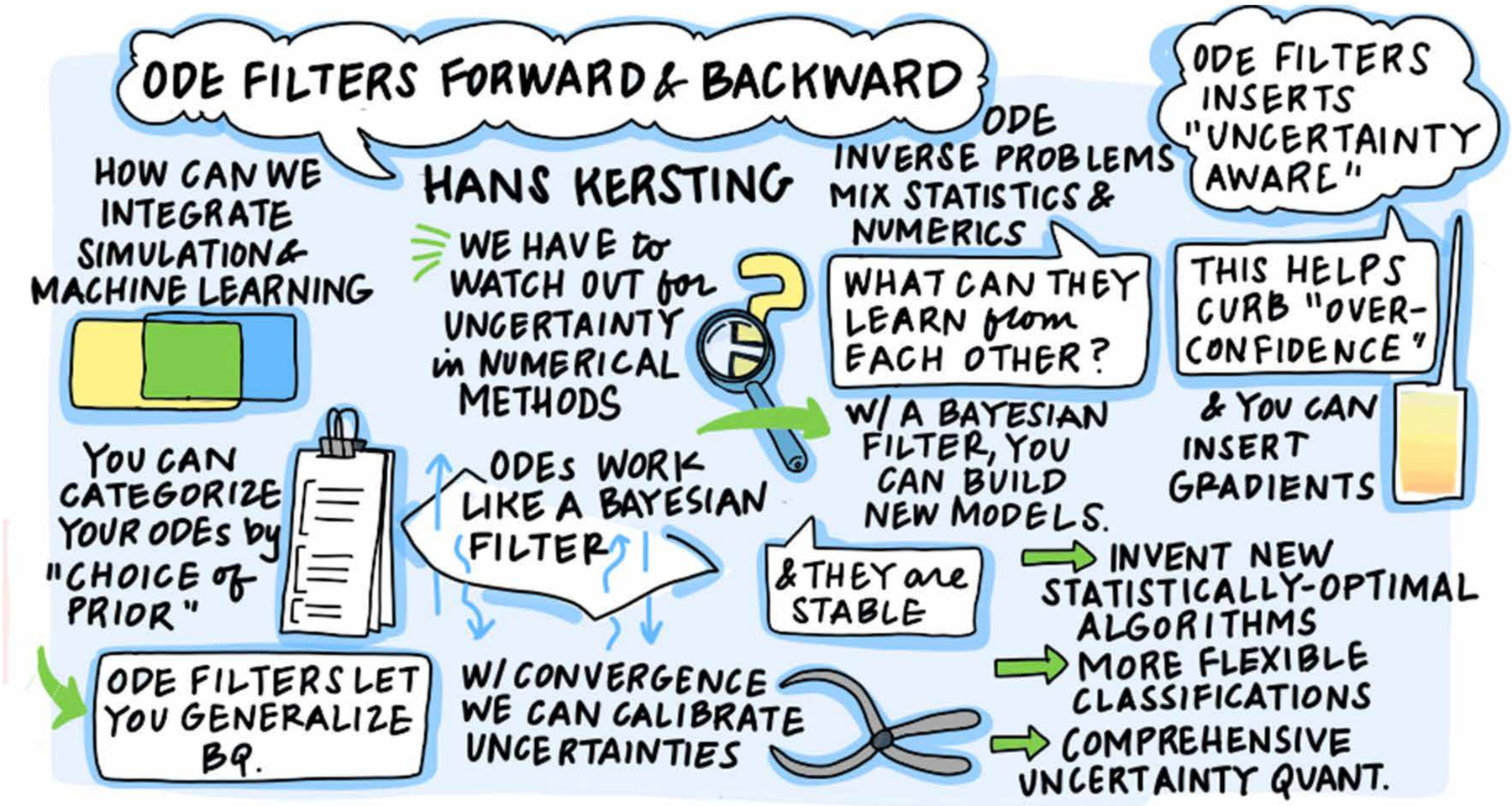
Simulation and Scientific Computing

Philipp Hennig
Universität Tübingen
Tübingen, DE



ODE Filters and Smoothers: Probabilistic Numerics for Mechanistic Modelling

Hans Kersting
INRIA
Paris, FR



HOME

UNIVERSITY OF CAMBRIDGE

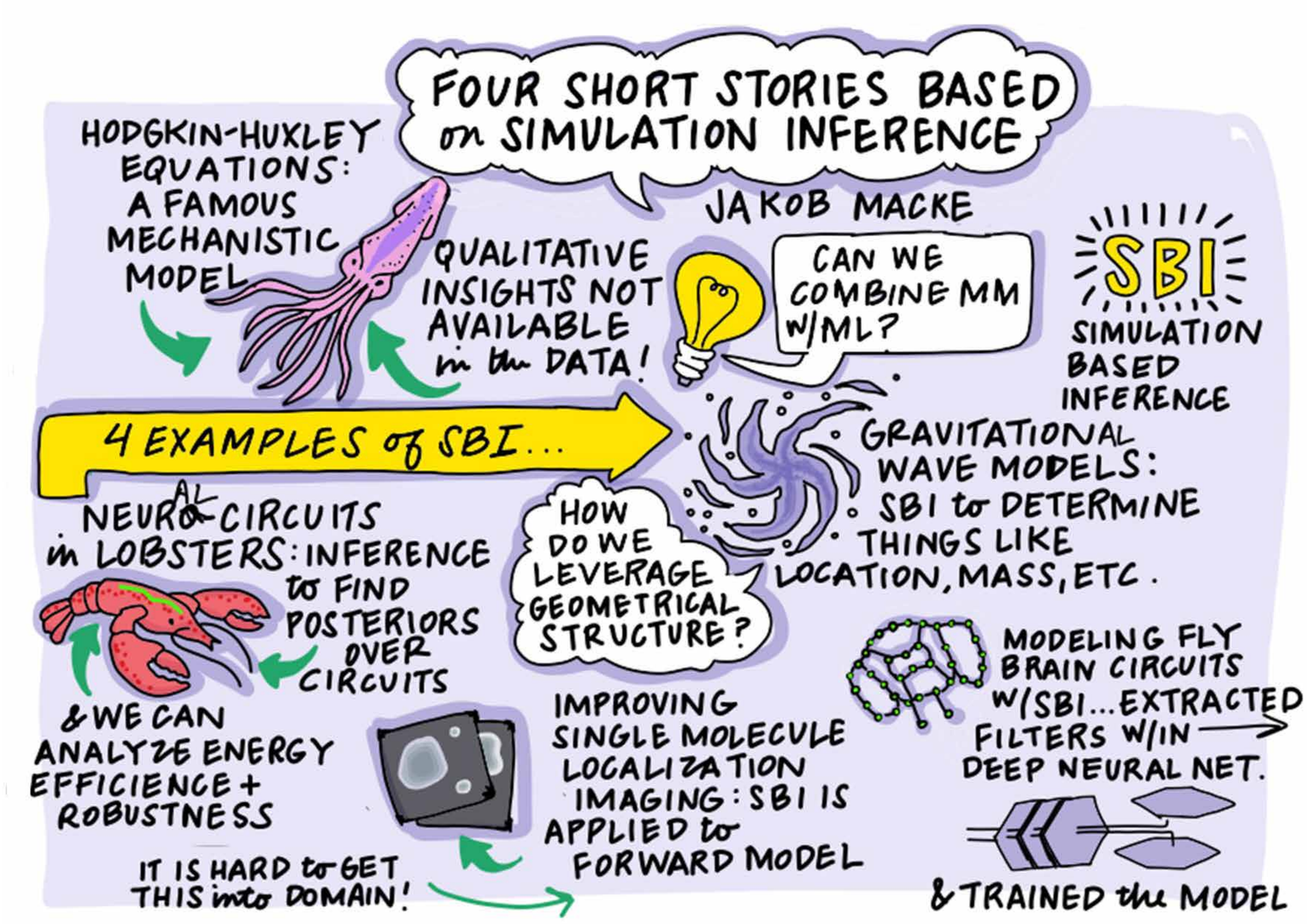
EBERHARD KARLS UNIVERSITÄT TÜBINGEN

NYU

WISCONSIN UNIVERSITY OF WISCONSIN-MADISON

Simulation Based Inference for Scientific Discovery: Opportunities & Challenges

Jakob Macke
Universität Tübingen
Tübingen, DE



HOME

UNIVERSITY OF CAMBRIDGE

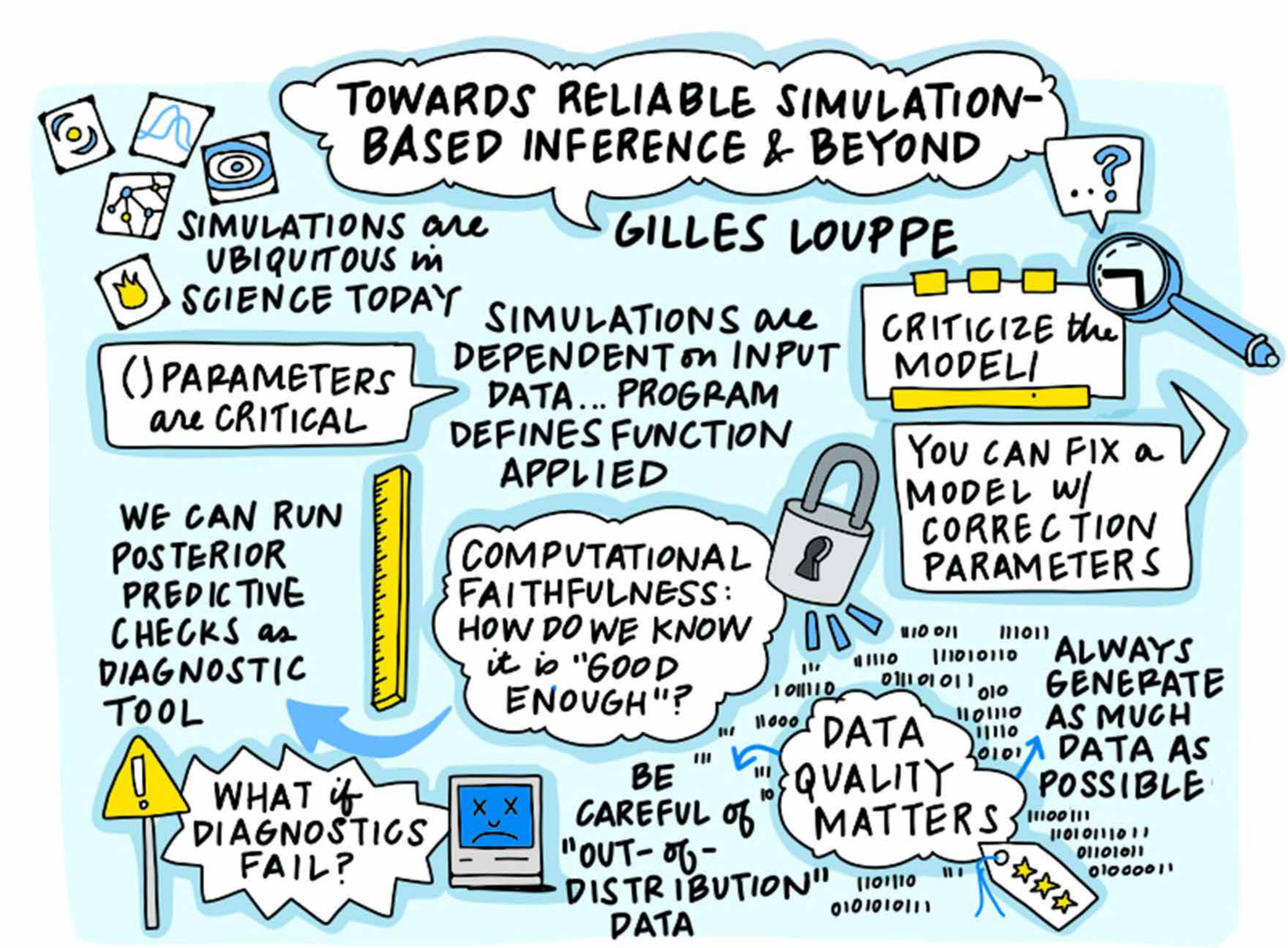
EBERHARD KARLS UNIVERSITÄT TÜBINGEN

NYU

WISCONSIN UNIVERSITY OF WISCONSIN-MADISON

Towards Reliable Simulation-based Inference

Gilles Louppe
University of Liège, BE



HOME

UNIVERSITY OF CAMBRIDGE

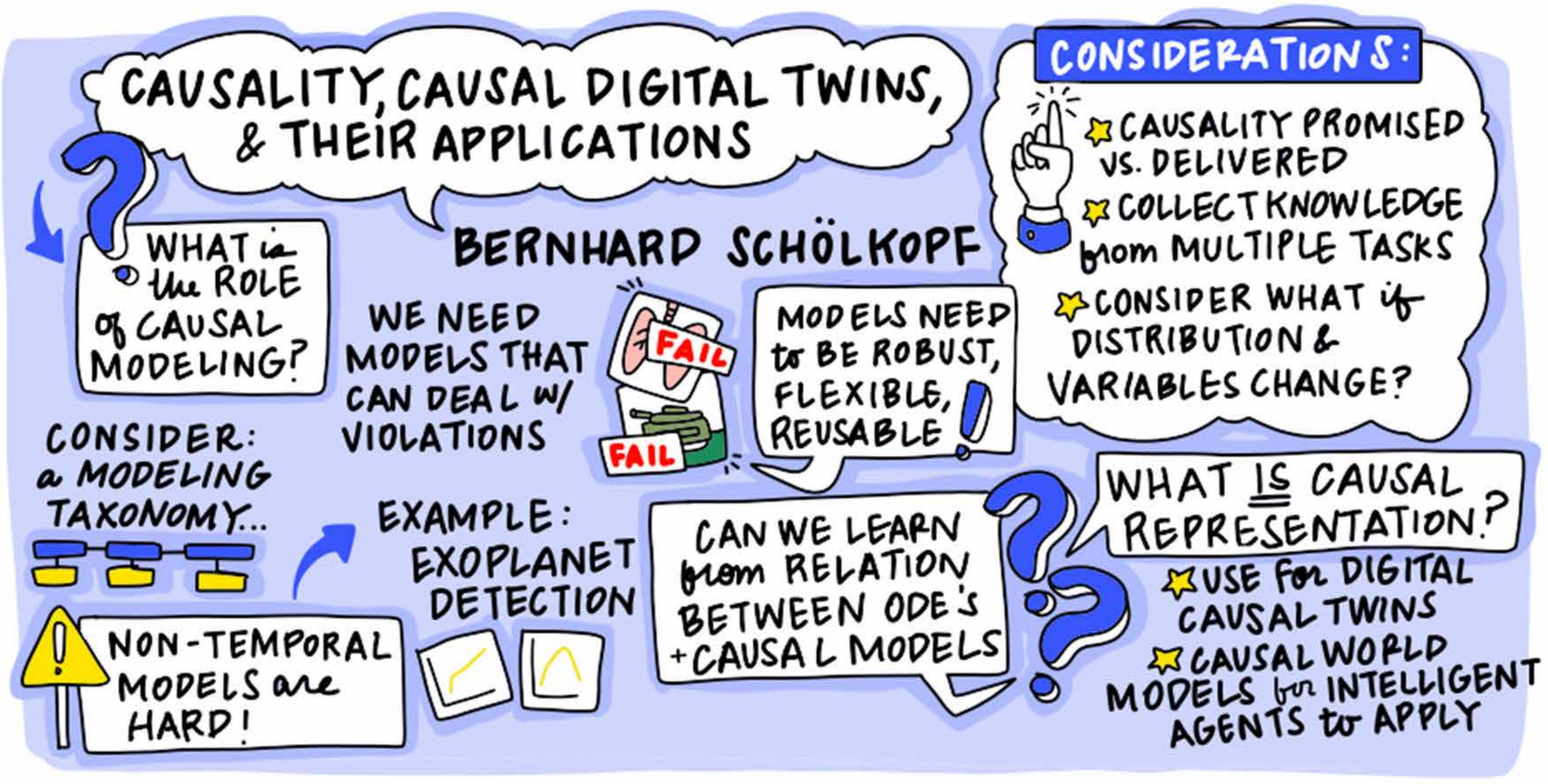
EBERHARD KARLS UNIVERSITÄT TÜBINGEN

NYU

WISCONSIN UNIVERSITY OF WISCONSIN-MADISON

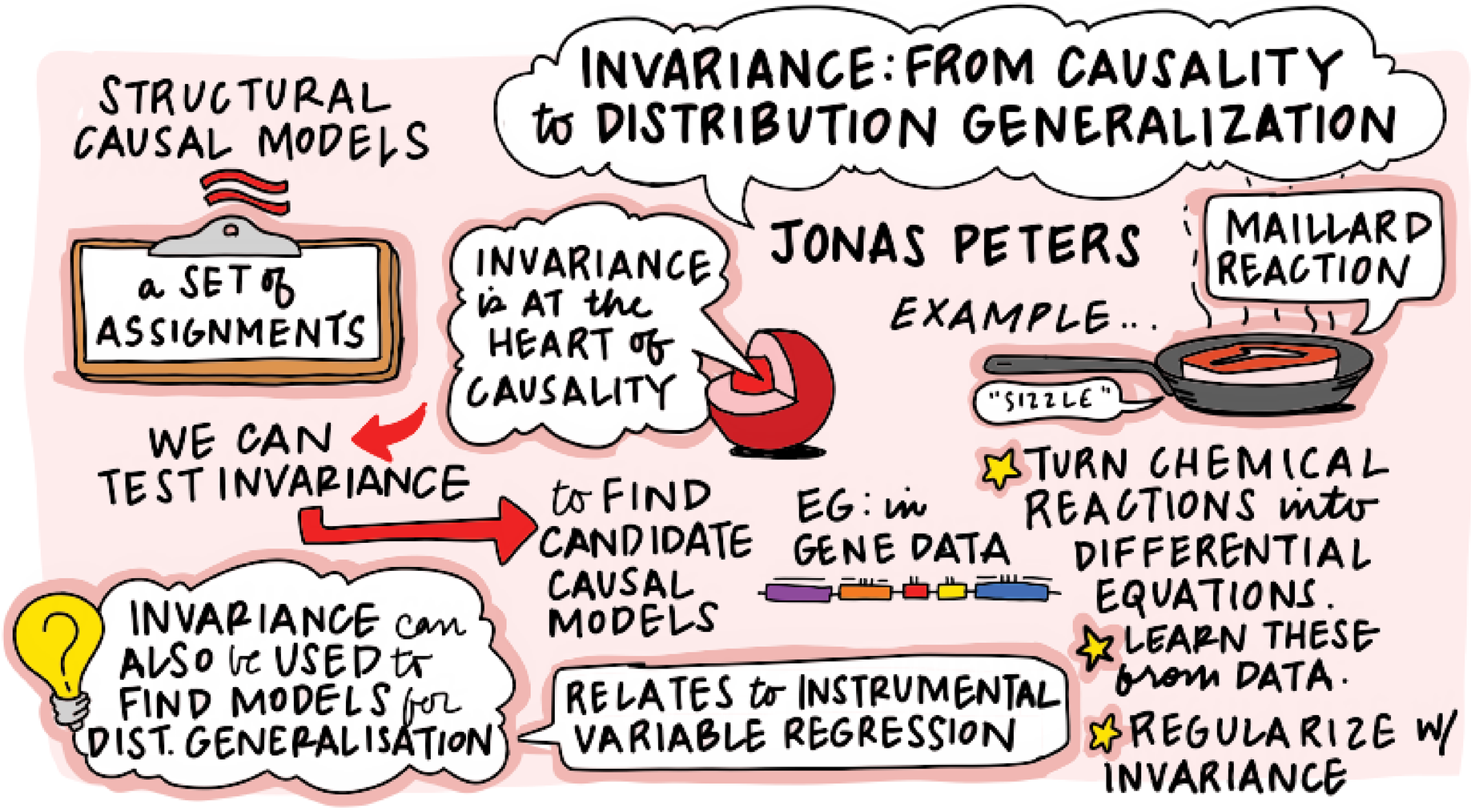
Causality, Causal Digital Twins, and their Applications

Bernhard Schölkopf
MPI für Intelligente Systeme
Universität Tübingen
Tübingen, DE



Invariance: From Causality to Distribution Generalization

Jonas Peters
University of Copenhagen
Copenhagen, DK



HOME

UNIVERSITY OF CAMBRIDGE

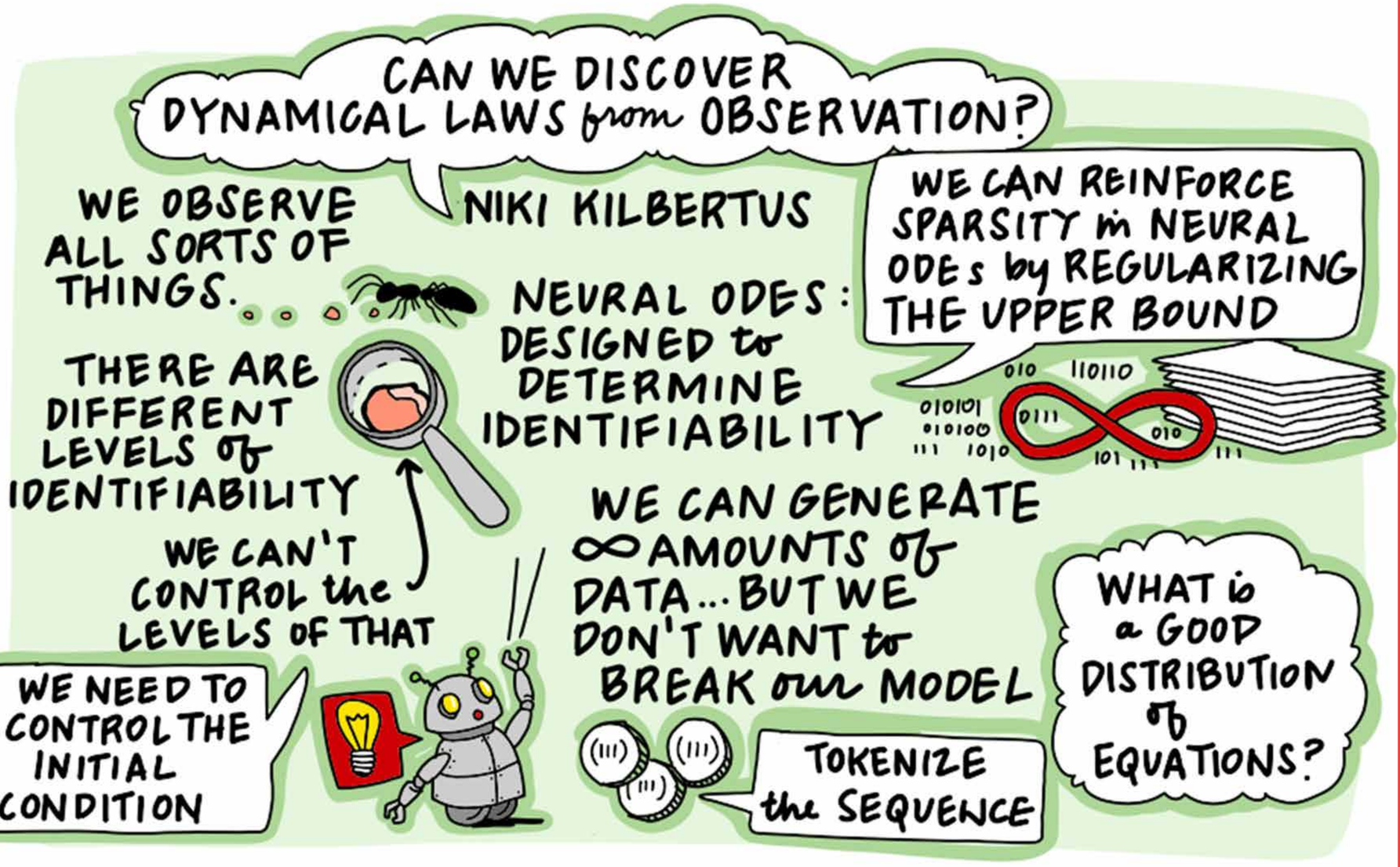
EBERHARD KARLS UNIVERSITÄT TÜBINGEN

NYU

WISCONSIN UNIVERSITY OF WISCONSIN-MADISON

Can we discover Dynamical Laws from Observation?

Niki Kilbertus
TU & Helmholtz AI
München, DE



HOME

UNIVERSITY OF CAMBRIDGE

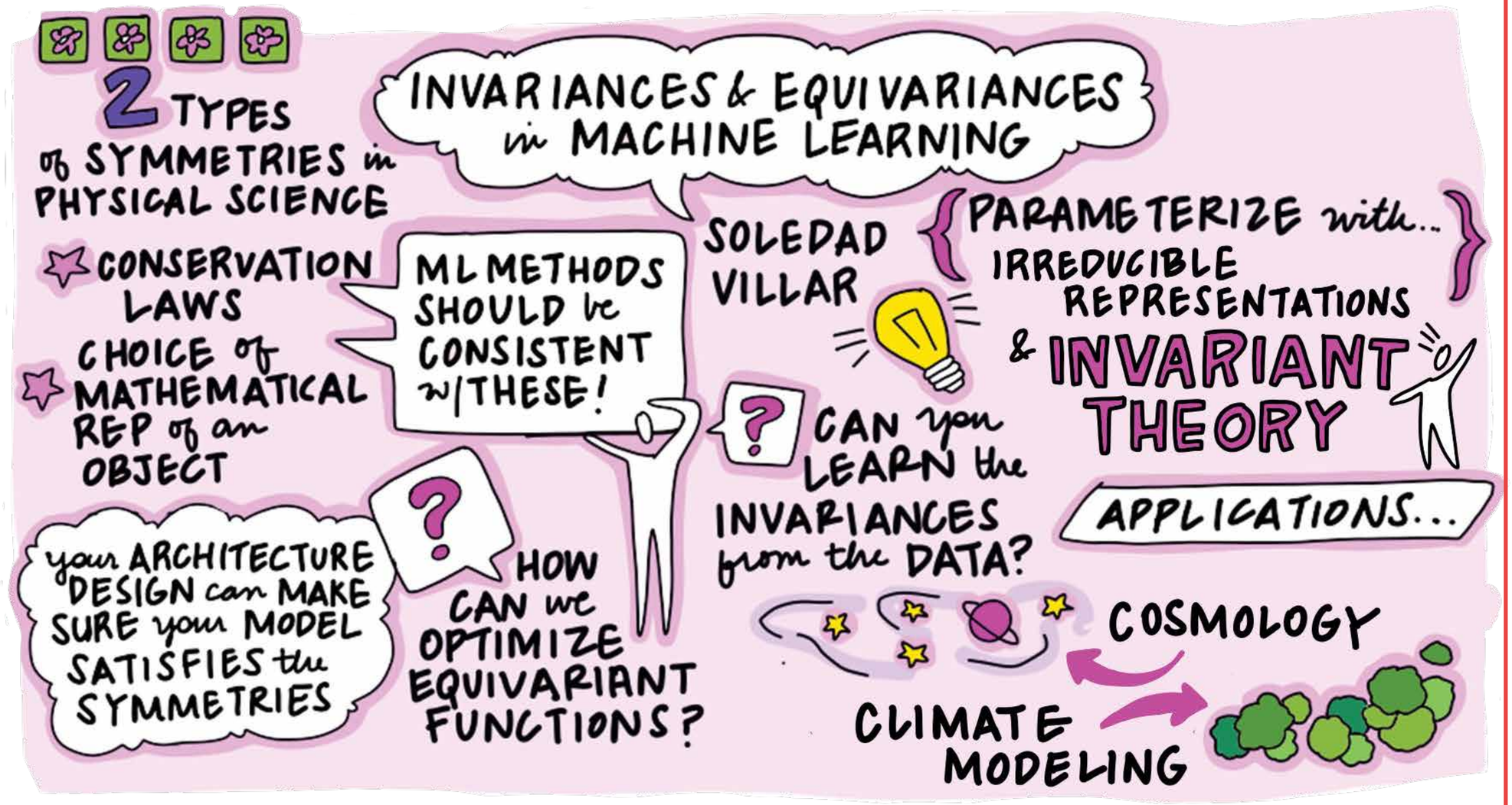
EBERHARD KARLS UNIVERSITÄT TÜBINGEN

NYU

WISCONSIN UNIVERSITY OF WISCONSIN–MADISON

Invariances and Equivariances in Machine Learning

Soledad Villar
Johns Hopkins University
Baltimore, US



HOME

UNIVERSITY OF CAMBRIDGE

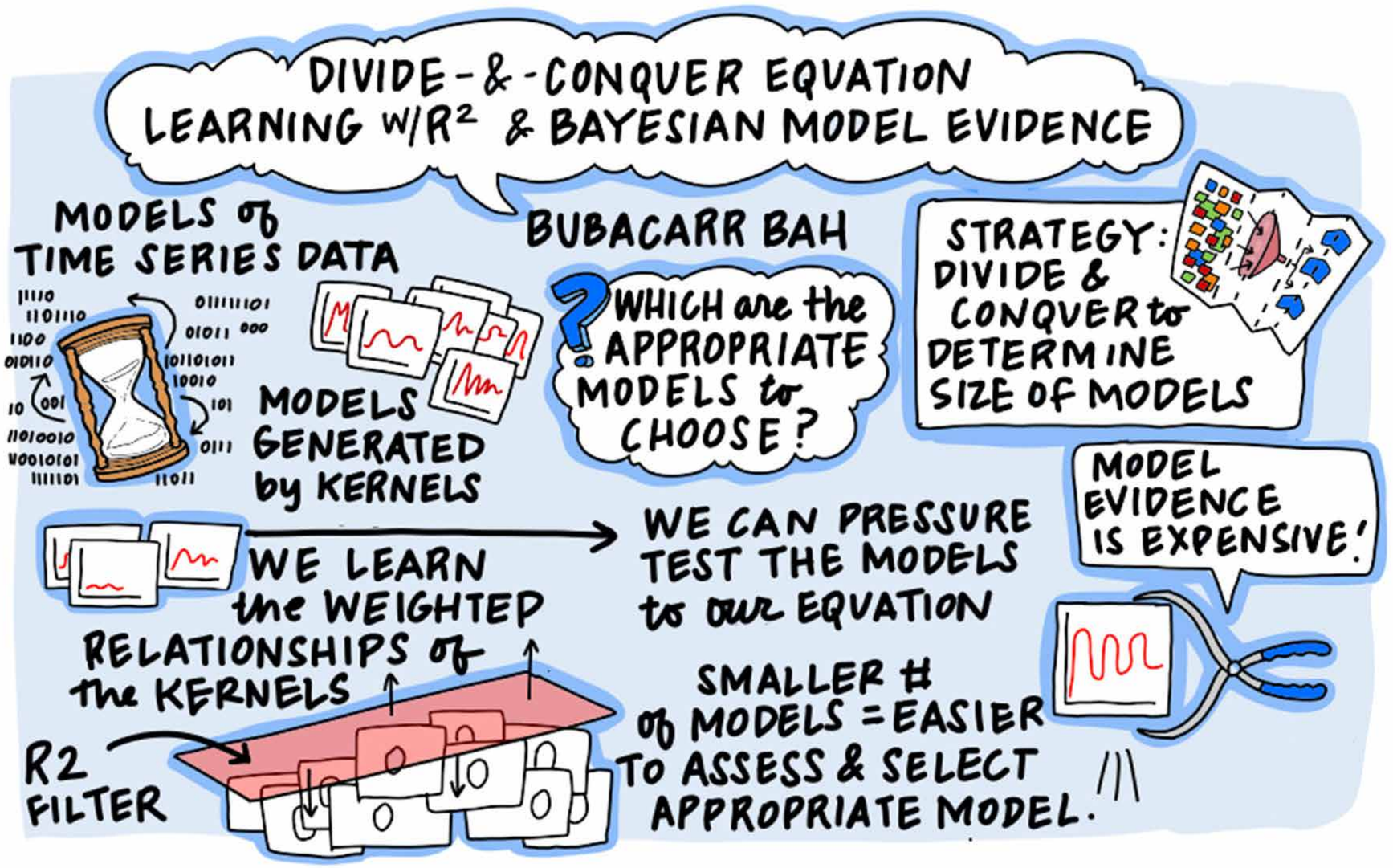
EBERHARD KARLS UNIVERSITÄT TÜBINGEN

NYU

WISCONSIN UNIVERSITY OF WISCONSIN–MADISON

Divide-and-Conquer Equation Learning with R2 and Bayesian Model Evidence

Bubacarr Bah
AIMS South Africa
Cape Town, ZA



HOME

UNIVERSITY OF CAMBRIDGE

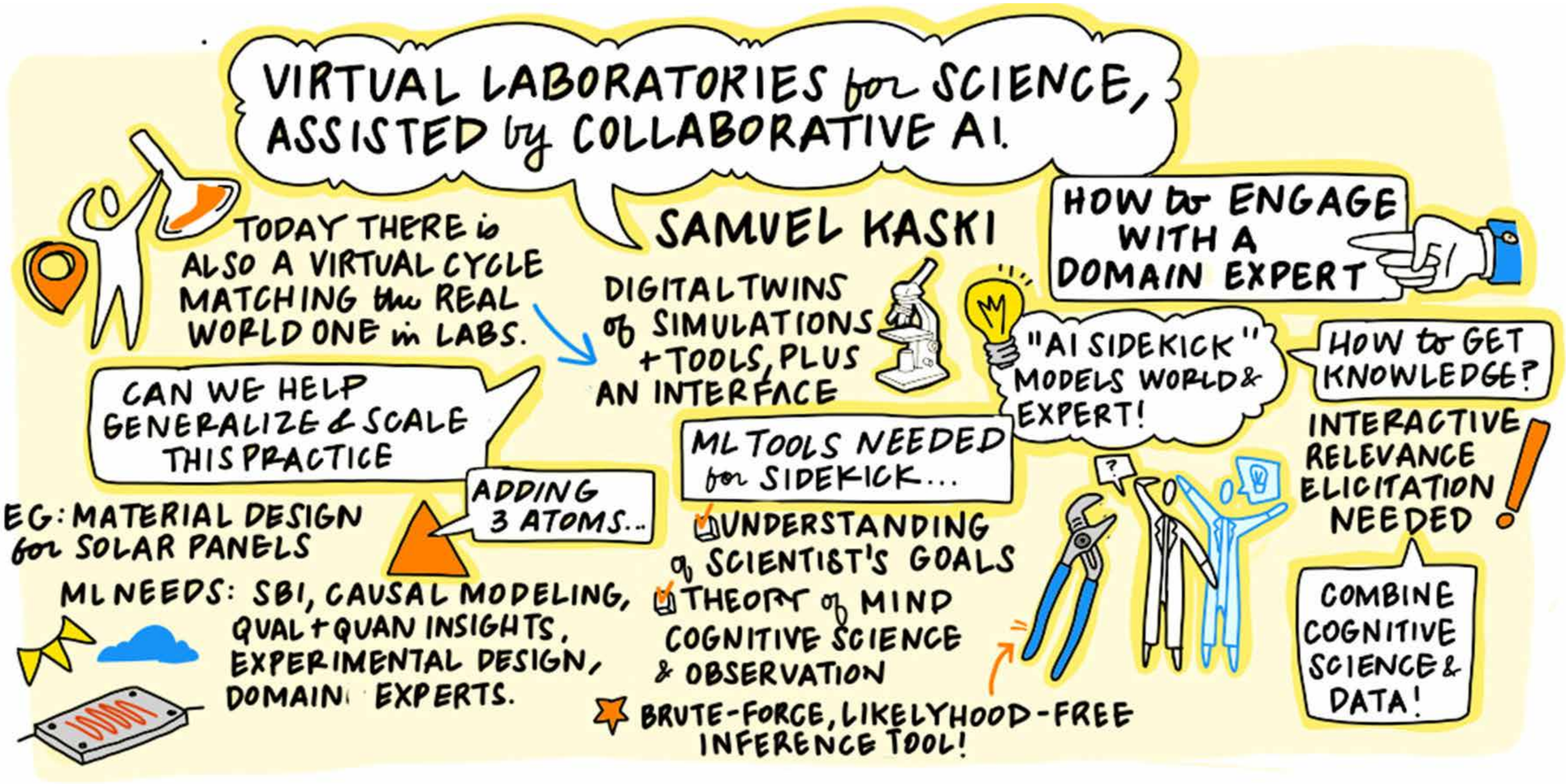
EBERHARD KARLS UNIVERSITÄT TÜBINGEN

NYU

WISCONSIN UNIVERSITY OF WISCONSIN-MADISON

Virtual Laboratories for Science, Assisted by Collaborative AI

Samuel Kaski
Aalto University
Helsinki, FI
University of Manchester
Manchester UK



HOME

UNIVERSITY OF CAMBRIDGE

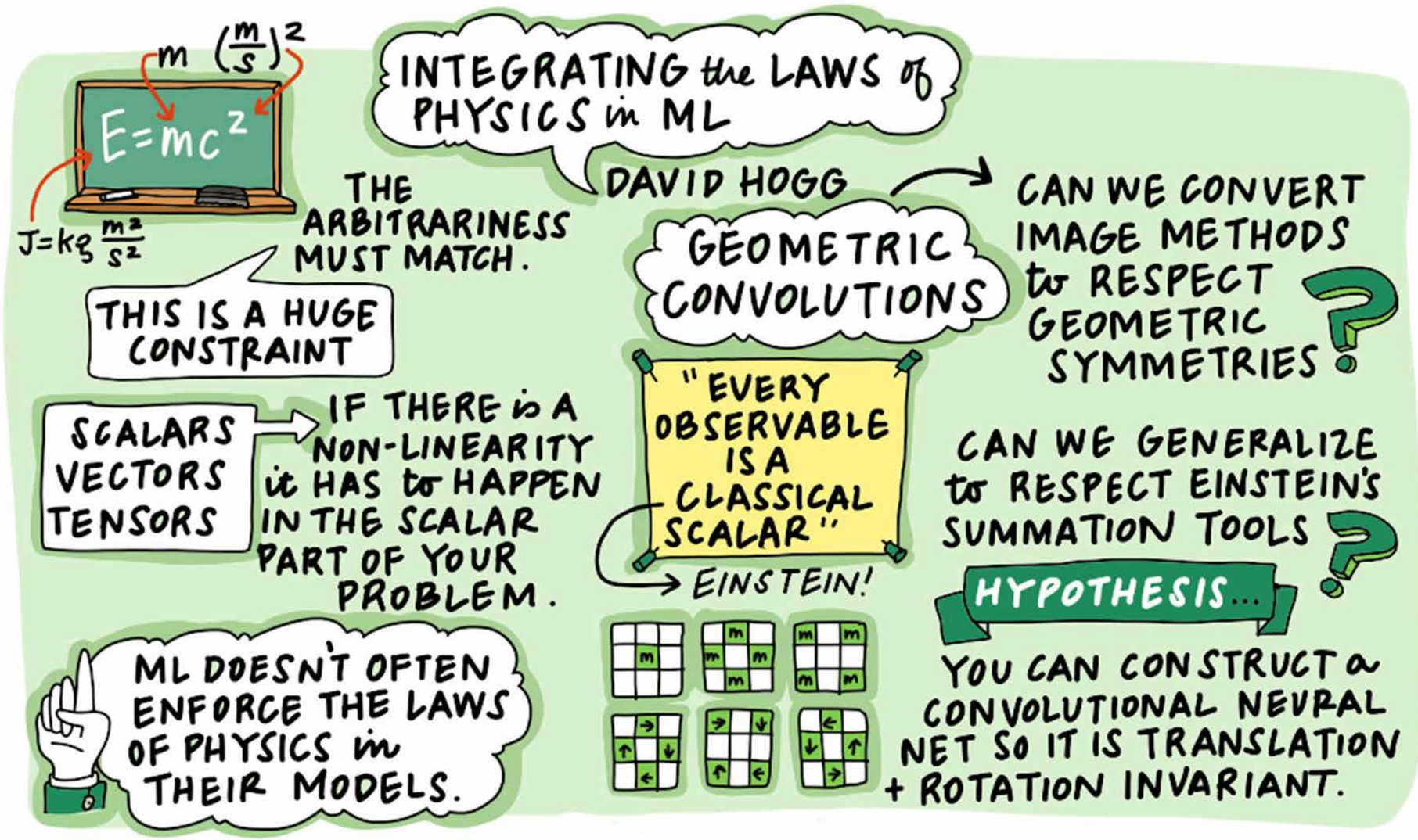
EBERHARD KARLS UNIVERSITÄT TÜBINGEN

NYU

WISCONSIN UNIVERSITY OF WISCONSIN-MADISON

Integrating the laws of Physics in ML

David W. Hogg
New York University
NYC, US



HOME

UNIVERSITY OF CAMBRIDGE

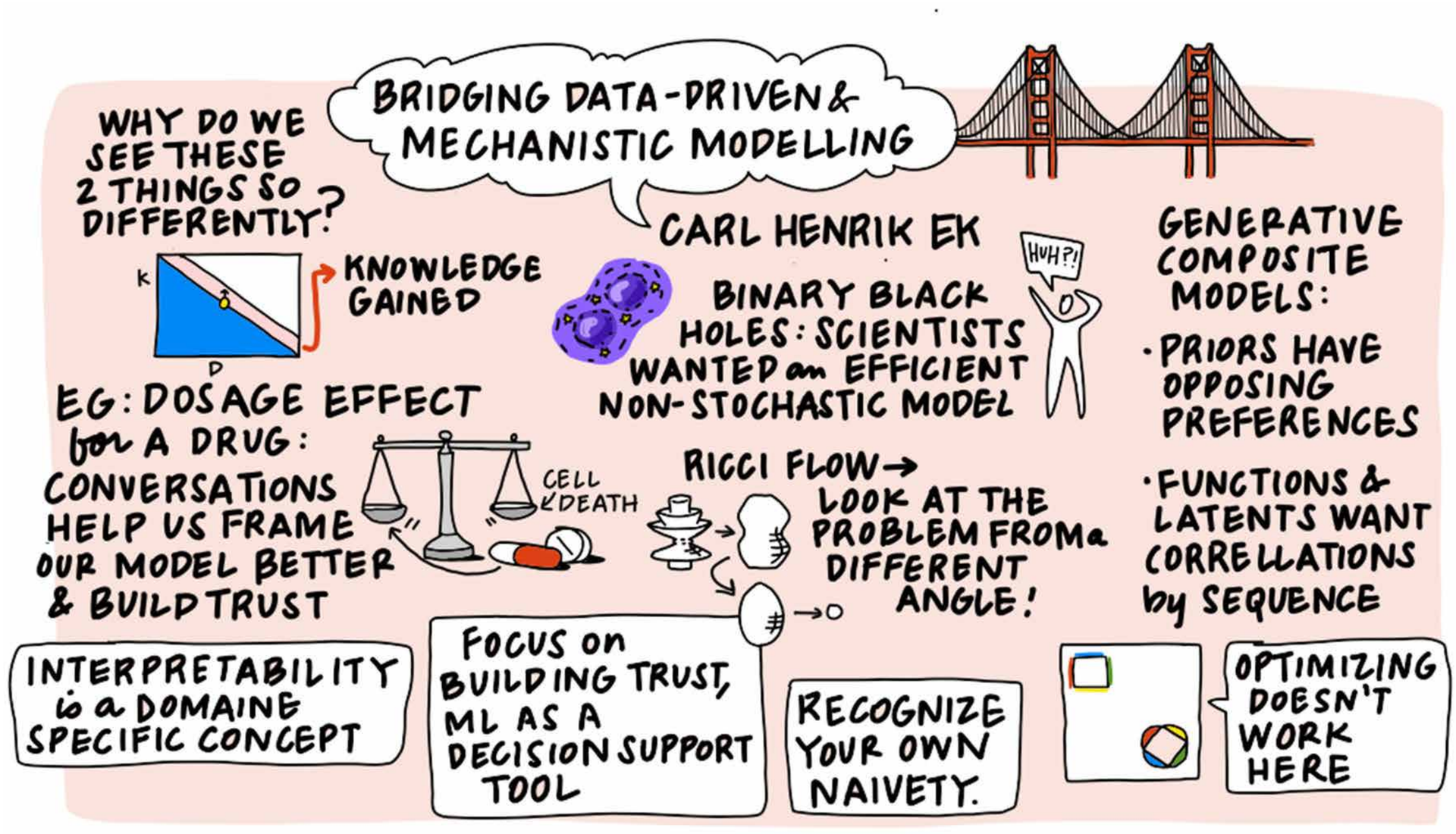
EBERHARD KARLS UNIVERSITÄT TÜBINGEN

NYU

WISCONSIN UNIVERSITY OF WISCONSIN–MADISON

Translating Mechanistic Understandings to Stochastic Models

Carl Henrik Ek
University of Cambridge
Cambridge, GB



HOME

UNIVERSITY OF CAMBRIDGE

EBERHARD KARLS UNIVERSITÄT TÜBINGEN

NYU

WISCONSIN UNIVERSITY OF WISCONSIN-MADISON