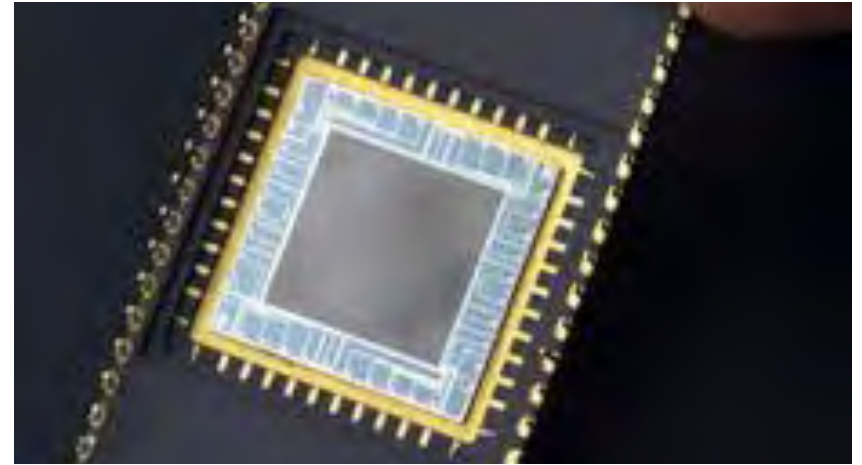
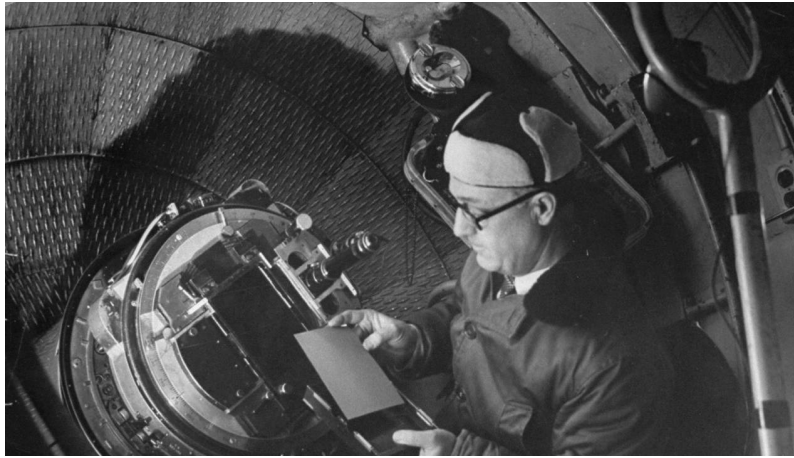




KNOWLEDGE GAIN IN THE AGE OF HPC AND BIG DATA

SUSANNE PFALZNER

SECOND BIG DATA CHALLENGE

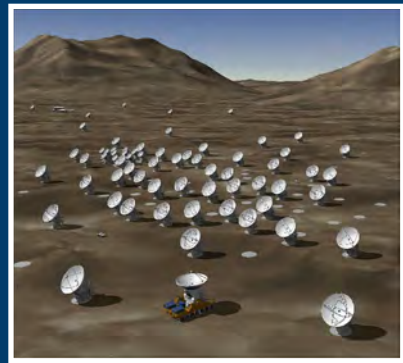


Efficiency around 1%
most of the photons lost!

- Extremely high **efficiency** at redder wavebands -- almost 100%!
- Limiting magnitudes increased by four to five magnitudes!

Output is digital

DATAWORKFLOWS



Combining
different
wavelength

Final
image



Original
data

Combining
single
telescopes

Data
reduction

e.g. Machine
learning



DATA FLOOD

Second data release of Gaia

0.9 billion individual CCD observations **per day**

•celestial positions **1.3 billion** sources

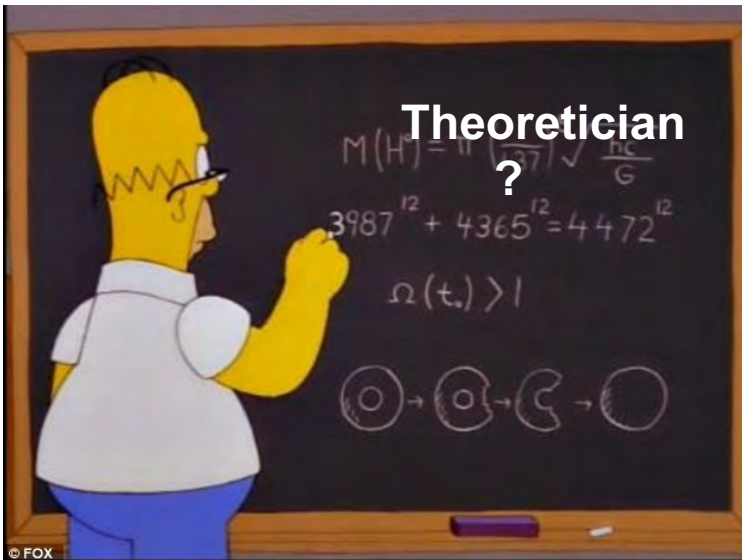
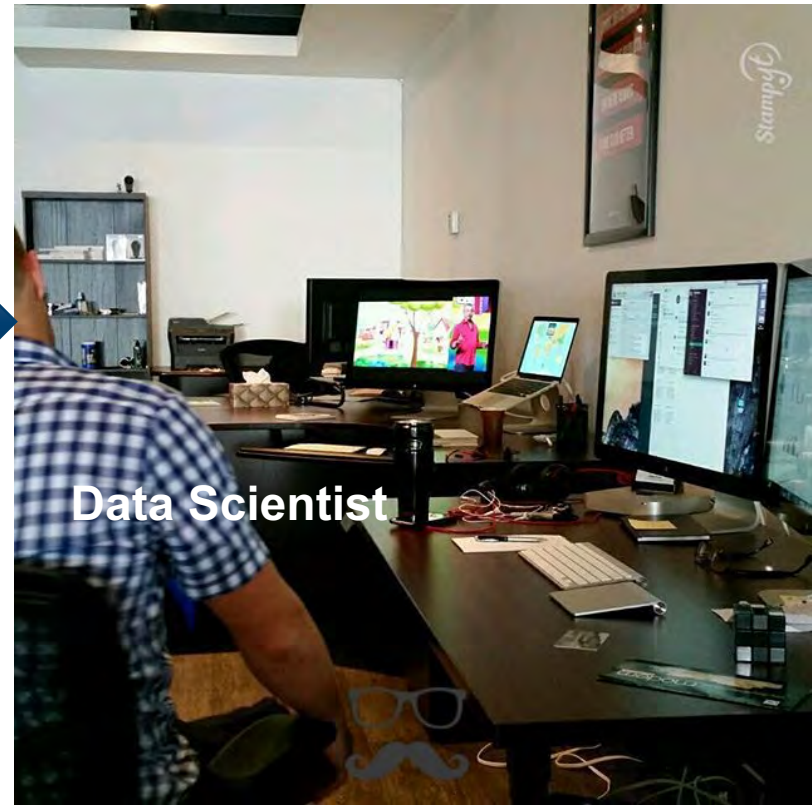
•stellar effective temperature, extinction, reddening, and radius and luminosity for **161 million** sources

Each of these needs multiple data processing

AIM:

high-value knowledge out of data is

OBSERVER



ASTROPHYSICAL SIMULATIONS

Observations provide only **snapshots** at a certain moment in time

Theory (simulation) must create **time sequence**

Several theories –
Which is the right one?

Predictions from theory **tested by observations**



The Orion Nebula and Trapezium Cluster
(VLT ANTU + ISAAC)

ASTROPHYSICAL SIMULATIONS

Challenges

- steep spatial gradients, complex geometries, etc.
(1 AU – 20 000 000 AU)

But also,

- often very different time scales
years – several million years (Myr)
- No direct comparison with experiment

SIM AND DATA LAB ASTRO

search item



DEUTSCH | ENGLISH

Institutes

Institute for Advanced Simulation (IAS)
Jülich Supercomputing Centre (JSC)



NEWS

RESEARCH

EXPERTISE

CAREER

ABOUT US

JSC

About us

Organization

Division Computational Science

Simulation Laboratories

SL Astrophysics

ABOUT US

Simulation Laboratories

SL Biology

SL Plasma Physics

SL Molecular Systems

SL Climate Science

SL Highly Scalable Fluids and Solids Engineering

SL Quantum Materials

SL Nuclear and Particle Physics

SL Terrestrial Systems

SL Neuroscience

SL Astrophysics

Simulation and Data Science Laboratory Astrophysics

The Sim Data Lab Astrophysics is a targeted research and support structure that provides an interface between the Supercomputer facilities in Jülich and the Astrophysics research communities.

Purpose

Our tasks include the support of Data Science Projects and High Performance Computing Simulations for the Astrophysics Community. We support users in their research by

- advising code choices for their scientific applications,
- supporting the development and application of scalable methods,
- development of an integrated application infrastructure for high performance computational astrophysics (HPCA),
- supporting the development of data analysis tools,
- initiation of collaborative projects for advancing high performance computational astrophysics and data science,
- visualization of the obtained results

In addition, we host repositories of commonly used codes and data bases and offer workshops in above mentioned areas.

OBSERVATIONS VS. SIMULATIONS

Comparison between **TWO SIMULATIONS**

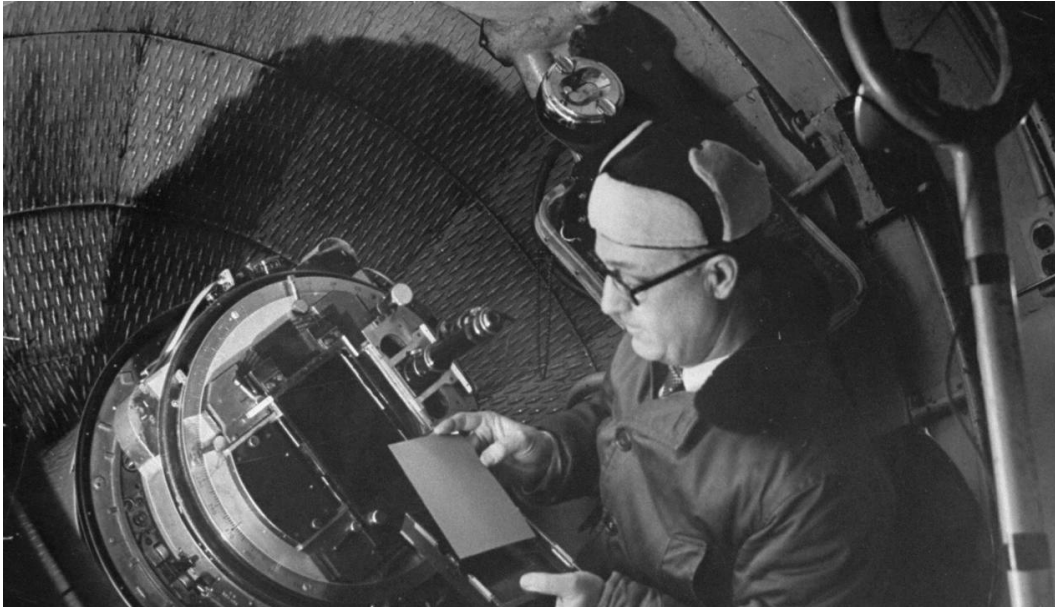
observational data

theoretical models

„It looks the same“, is not enough!

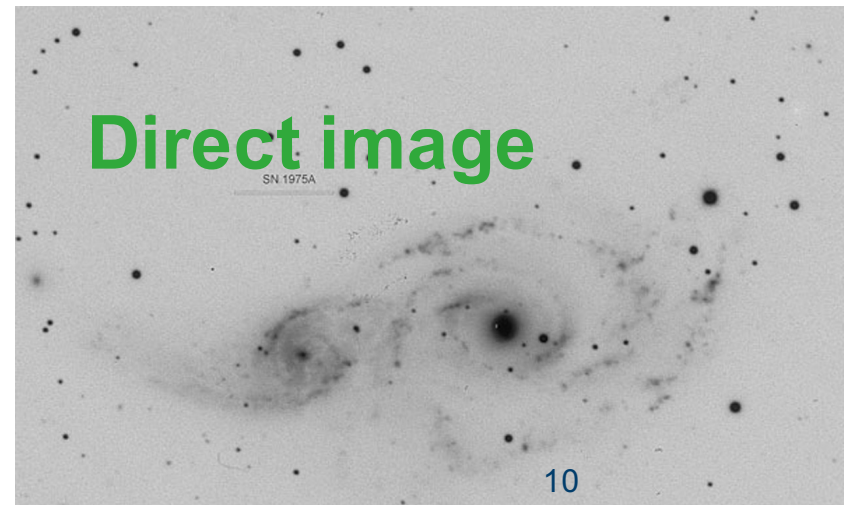


FIRST BIG DATA CHALLENGE



Photographic plates

First objective, permanent record of astronomical phenomena



FIRST COMPUTERS



...the amount of astronomical data was surpassing the capacity of the Observatories to process it

Pickering and his Computers standing in front of Building C at the Harvard College Observatory, 13 May 1913

BEYOND PROCESSING DATA ...



Antonia Maury
First spectroscopic binary star



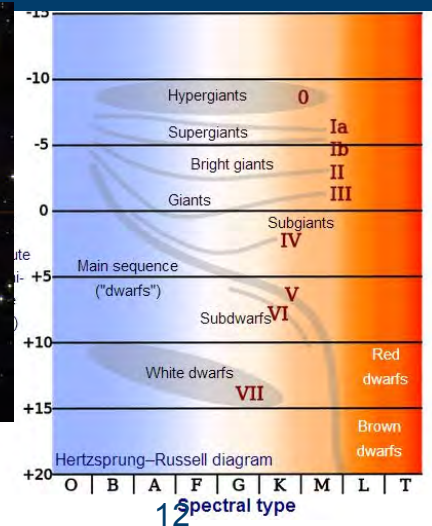
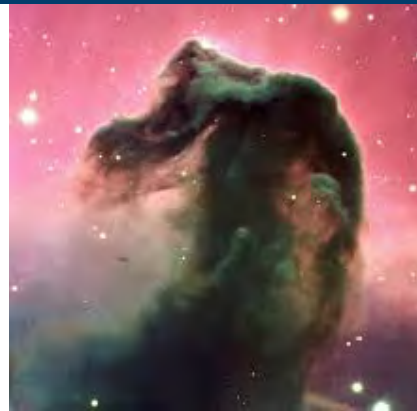
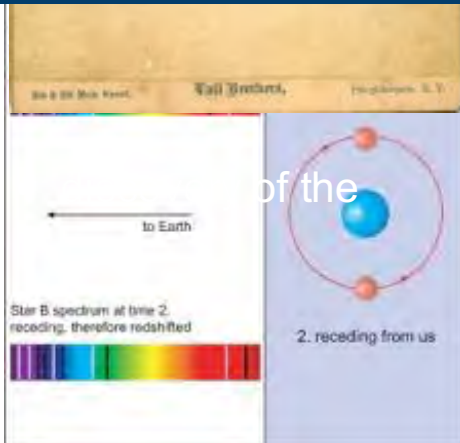
Williamina Fleming
Horseshoe Nebula



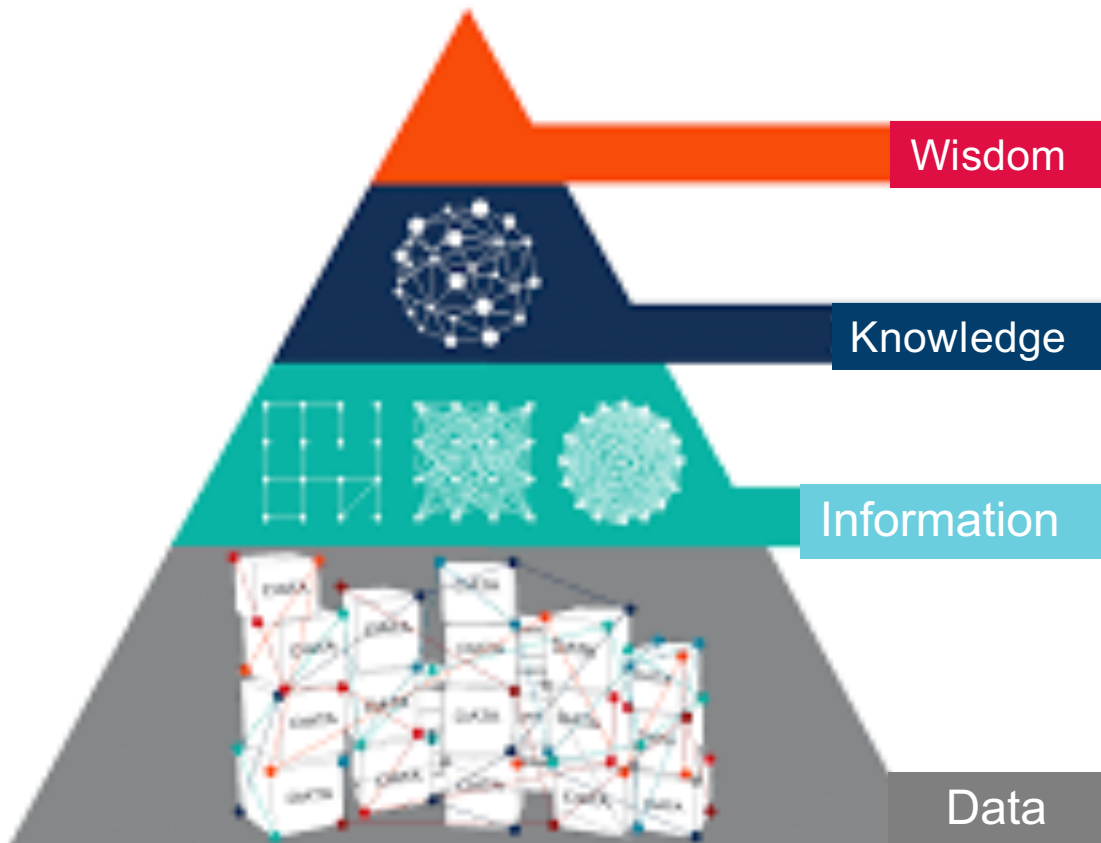
Henrietta Swan Leavitt
Luminosity in Cepheids



Annie Jump Cannon
Stellar Classification

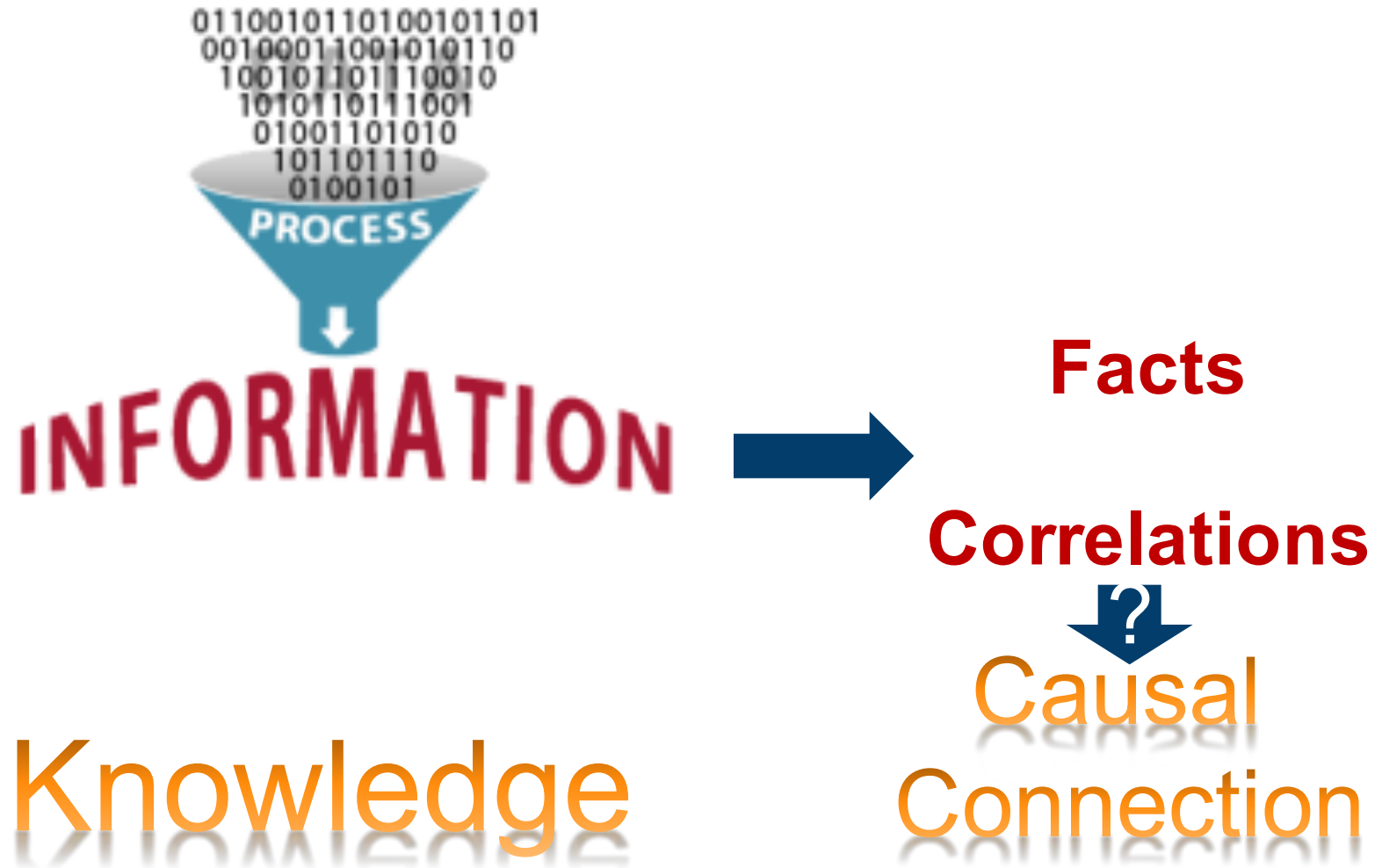


THE STEEP CLIMB TO KNOWLEDGE

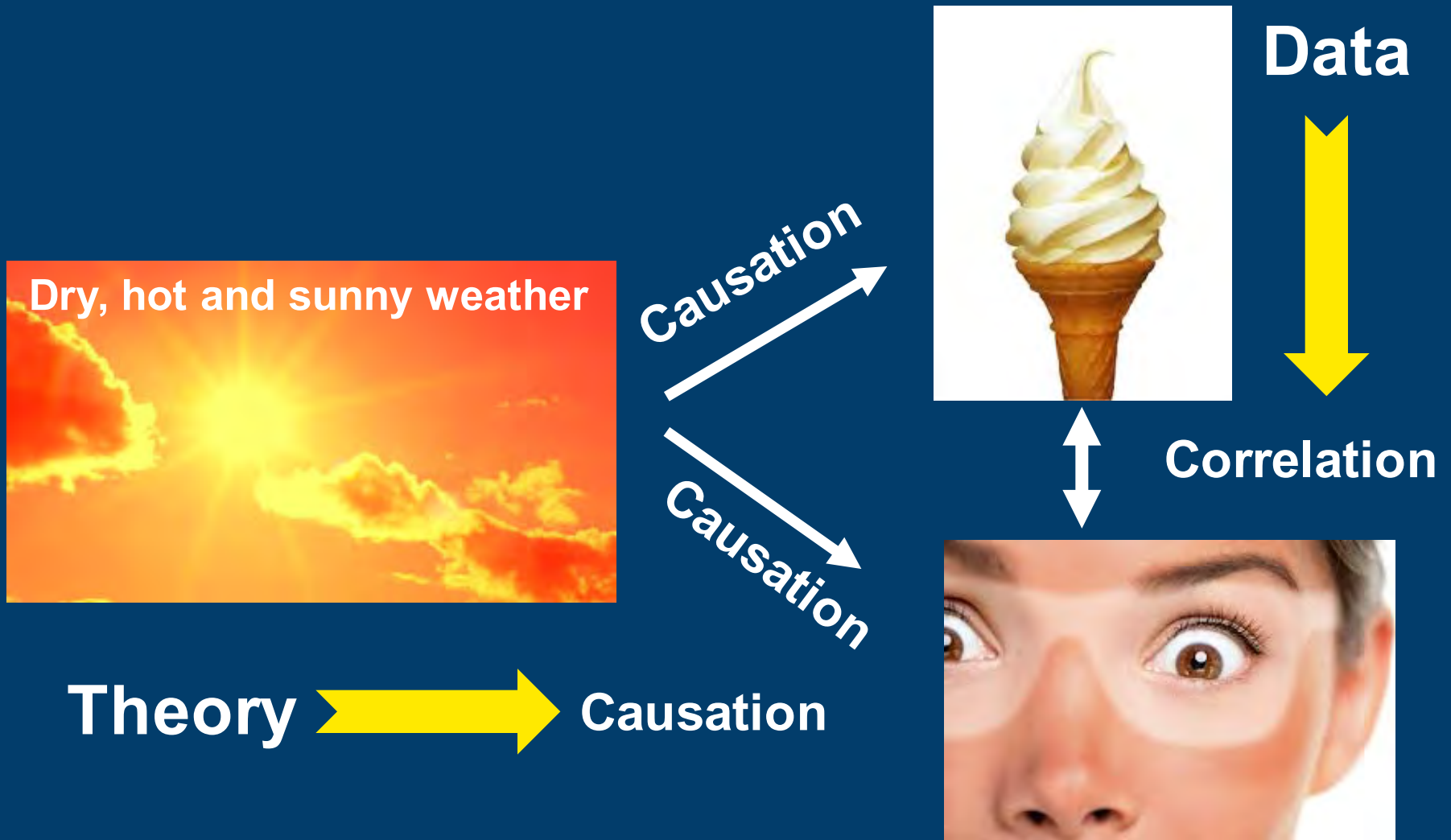


Each step up
the pyramid
answers
questions
about and
adds value
to the initial data

IT IS ALL IN THE DATA, IS IT REALLY?



CORRELATIONS VS CAUSAL CONNECTION



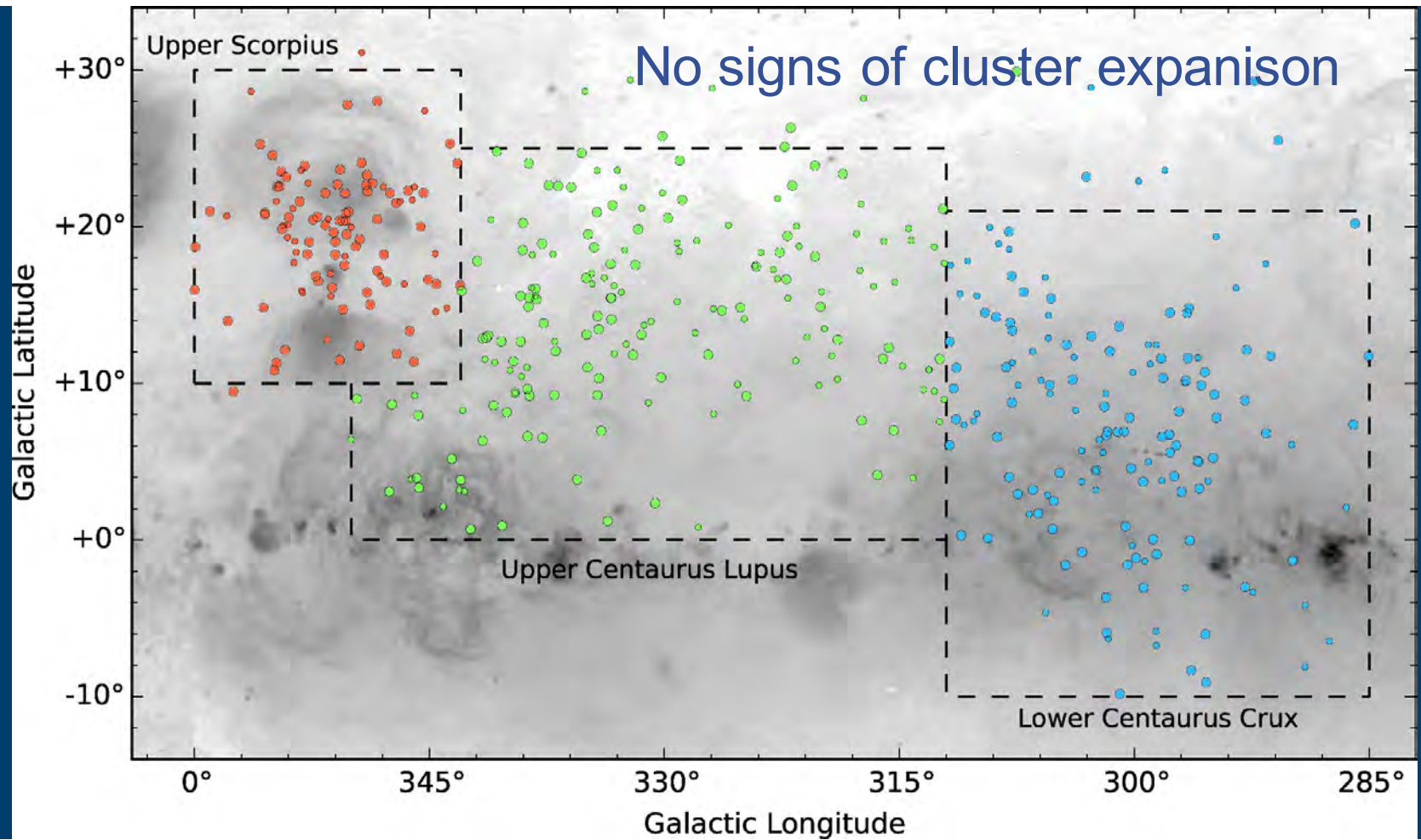
EXAMPLE: DATA ANALYSIS

EXAMPLE: STAR CLUSTER FORMATION

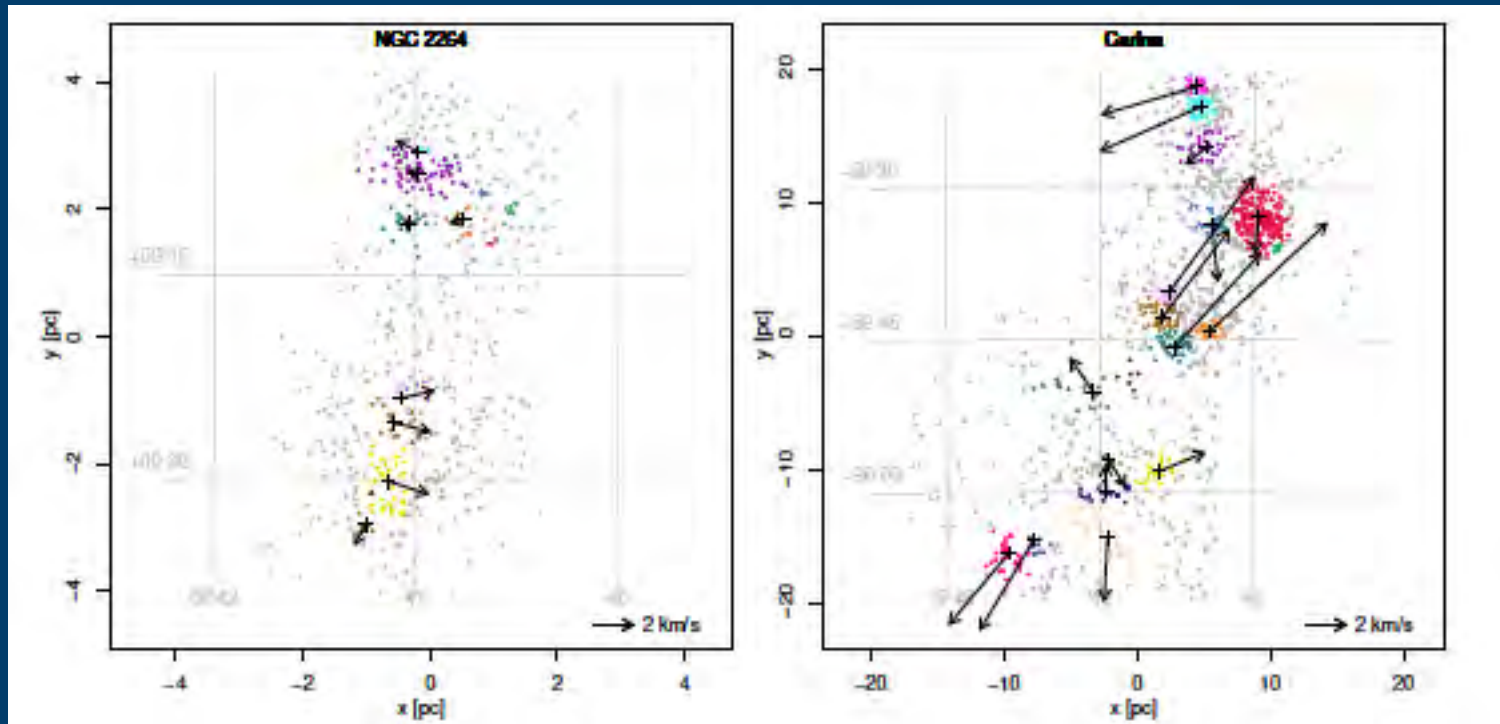
- Distribution of subclusters that merge
- Clusters form, no dynamics afterwards
- Formation as single entity, expands after gas expulsion

The Orion Nebula and Trapezium Cluster
(VLT ANTU + ISAAC)

ANALYSIS OF GAIA DATA



OVER-COMING ONE'S OWN EXPECTATION

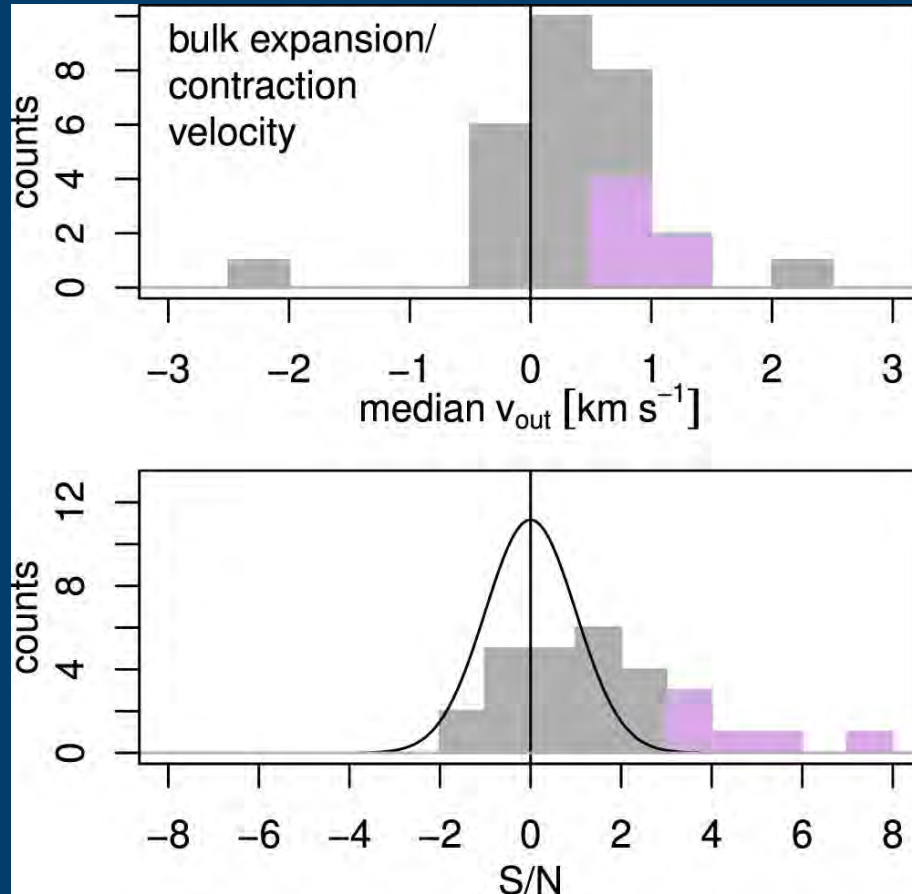


No signs of subcluster merging

Kuhn et al. arXiv:1807.06085

Mitglied der Helmholtz-Gemeinschaft

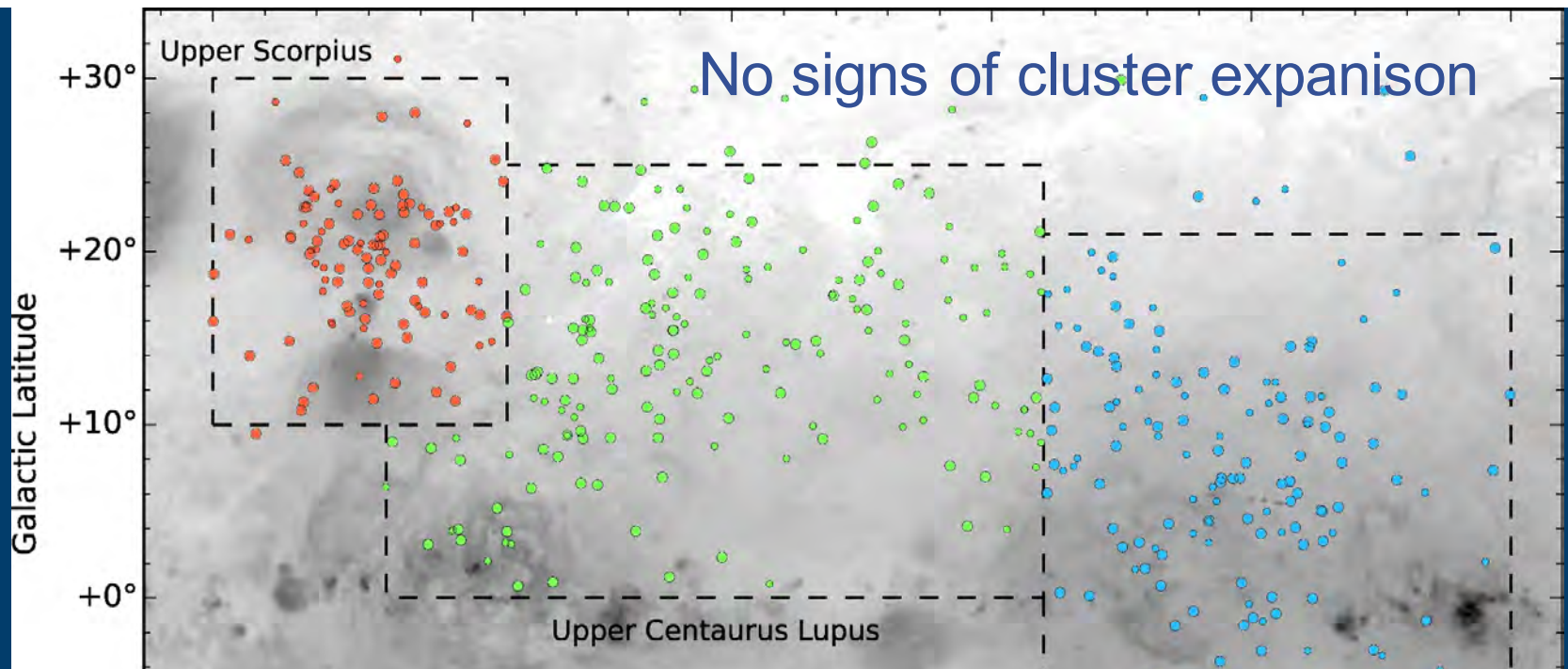
OVER-COMING ONE'S OWN EXPECTATION



velocity dispersion
in the individual
clusters shows
they expand

Kuhn, M. et al. 2019

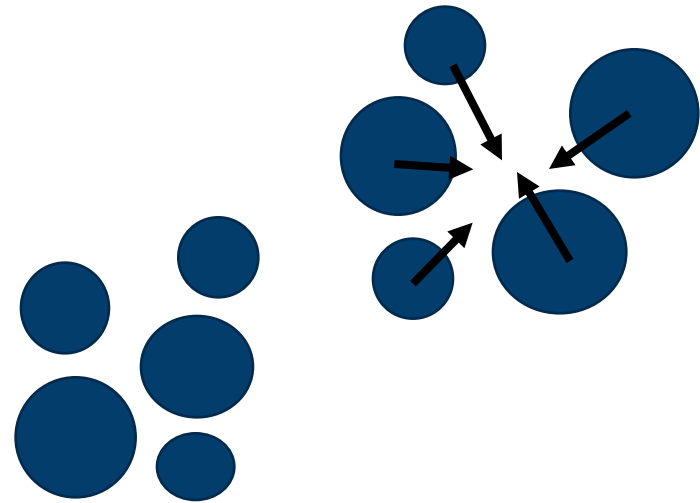
Mitglied der Helmholtz-Gemeinschaft



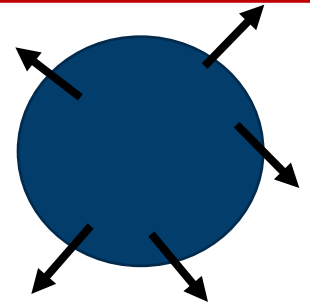
PROBLEM: MODEL ASSUMPTIONS IN DATA ANALYSIS

EXAMPLE: STAR CLUSTER FORMATION

- Distribution of subclusters that merge
- Clusters form,
no dynamics afterwards



- Formation as single entity,
expands after gas expulsion



LESSON 1:

**MACHINE LEARNING DOES NOT AVOID
HUMAN MISTAKES, BUT CAN HARDWIRES THEM**

**MODEL ASSUMPTIONS
CAN CORRUPT DATA ANALYSIS**

**DATA CHALLENGE REQUIRES
LEARNING FROM OUR MISTAKES NOW**

OVERCOMING ONES PREJUDICES PAYS

POTENTIAL PROBLEMS IN CREATING THE DATA

- Model assumption transferred to data analysis
- Progress limited to more of the same
- Correlation vs causation

- Extremely energy consuming

Today data farming
No option for the future

Needed: intelligent algorithms

BEYOND PROCESSING DATA ...



Antonia Maury
First spectroscopic binary star



Williamina Fleming
Horseshoe Nebula



Henrietta Swan Leavitt
Luminosity in Cepheids



Annie Jump Cannon
Stellar Classification

Unlike human computers, digital computers are (still) unable to

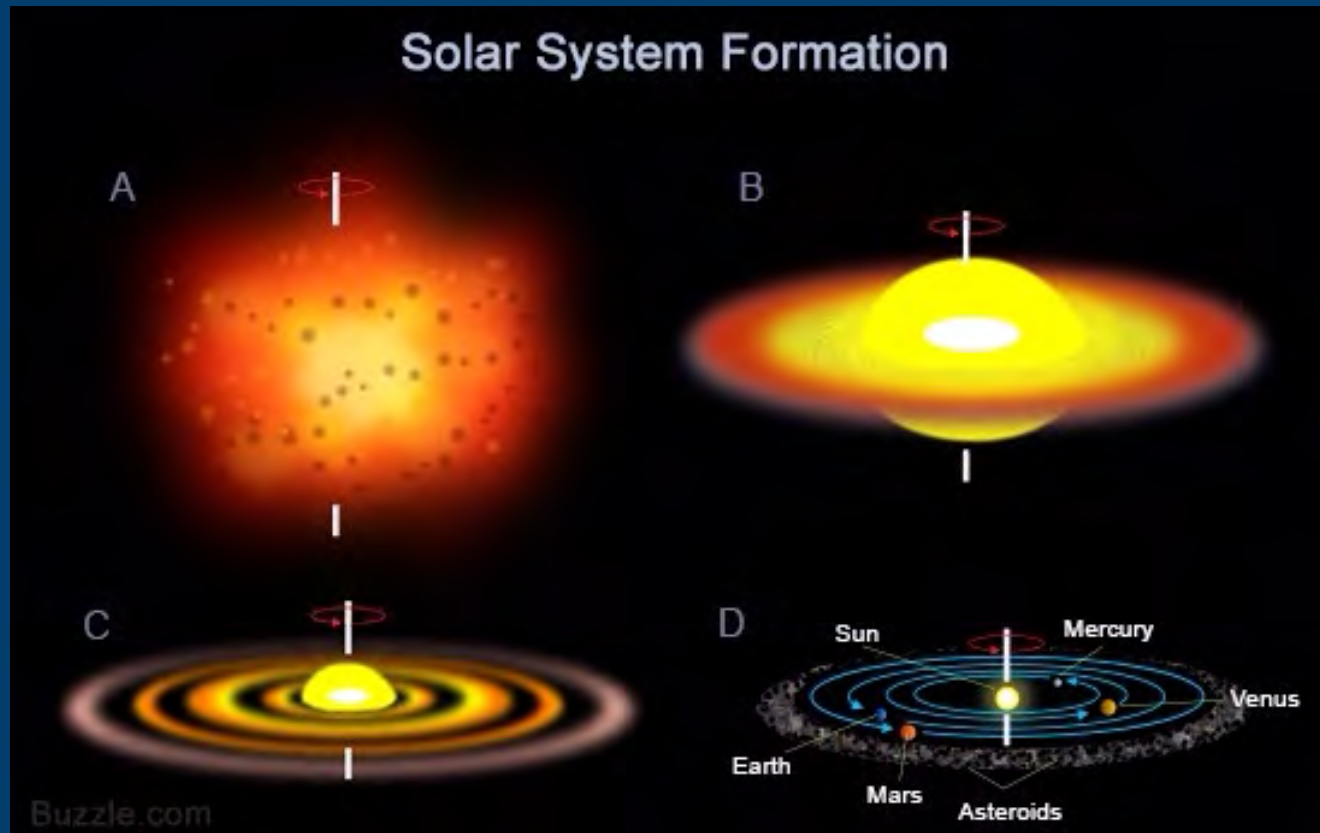
- ask for causation \longrightarrow No model development
- see the unexpected \longrightarrow Risk: more of the same

EXAMPLE: SIMULATIONS

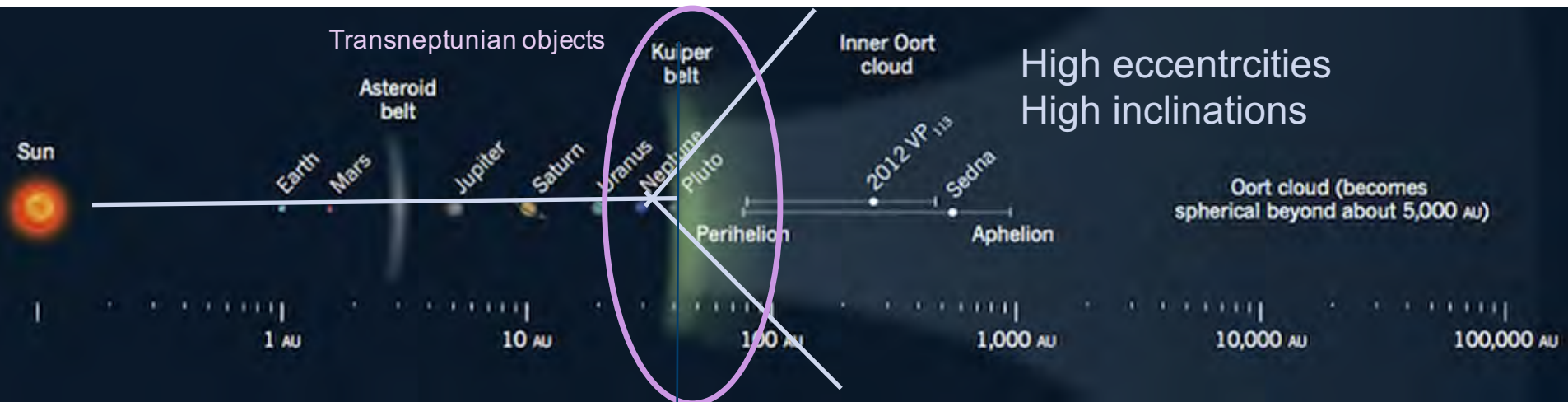
CHARACTERISTICS OF A GOOD ANALYTICAL MODEL

- Matches observation
- Reproducible
- Simple
- Fit into the general theory
- Falsifiable
- Makes prediction

FORMATION OF THE SOLAR SYSTEM



EXAMPLE: SOLAR SYSTEM FORMATION

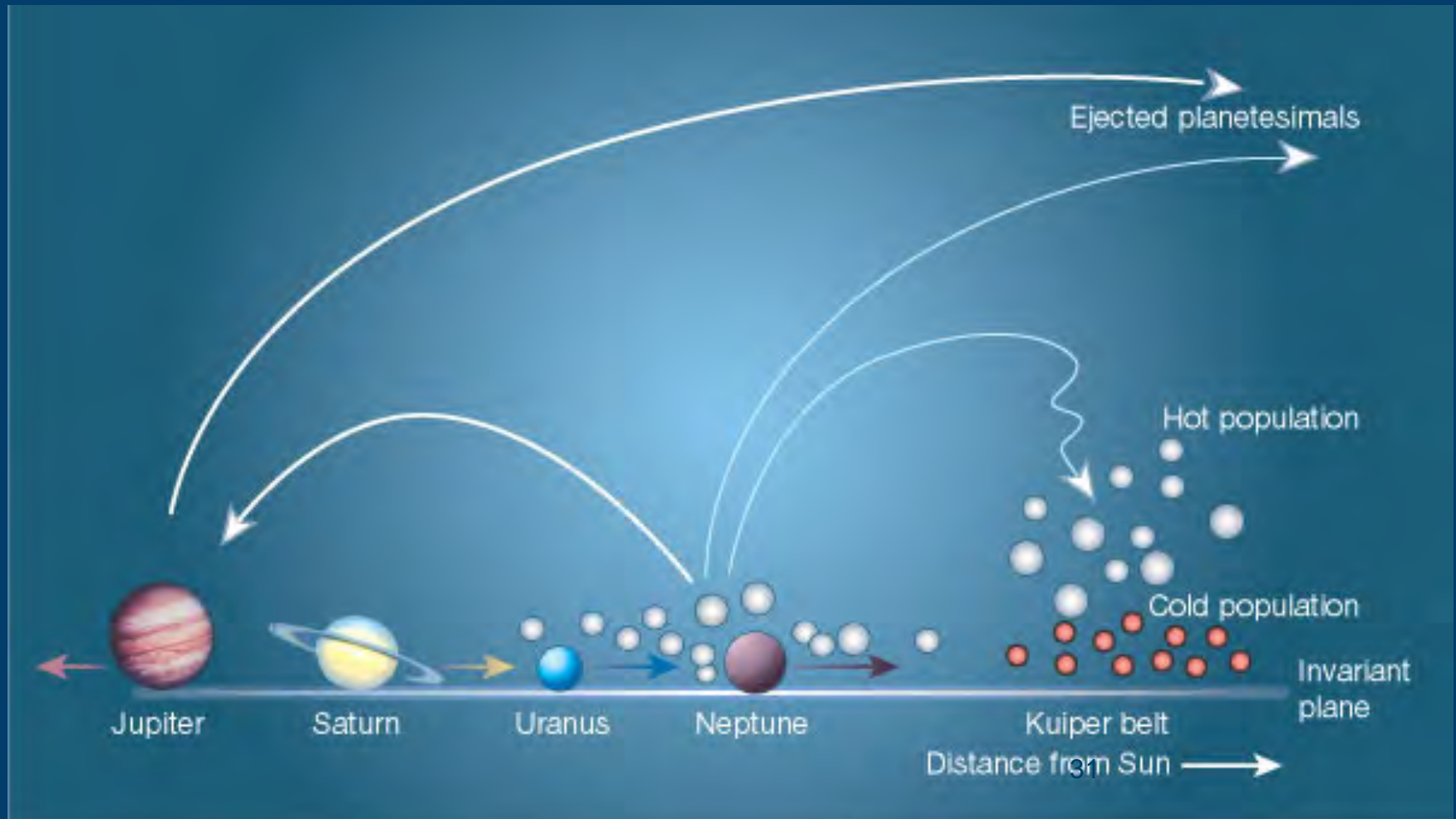


..., BUT BEYOND NEPTUNE THINGS ARE DIFFERENT

- Cut-off in mass beyond Neptune: 1000 fewer objects than expected
- Most objects have high inclinations, eccentric orbits

POPULAR EXPLANATION: NICE MODEL

- TNOs were originally between Saturn and Neptune
- Scattered outwards due to movement of planets



NICE MODEL CAN EXPLAIN

1. Late-Heavy bombardment
2. Hot Kuiper belt (90%) very well,
3. Families of Asteroids
4. Low mass of Mars
5. etc.

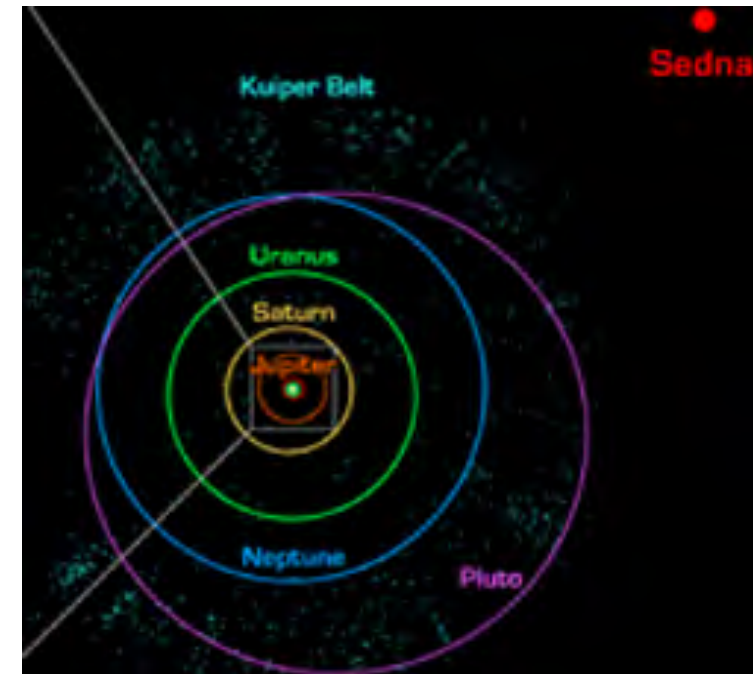
..., SOME ARE EXTREME

	Sedna	2012 VP ₁₁₃
Perhelion:	76 AU	80 AU
Apelion:	937 AU	446 AU
Period:	11400 yr	4274 yr
Eccentricity:	0.8527	0.694

High eccentricity NOT caused by planets
(Gaidos et al. 2005)

Not predicted by Nice model

Planet Nine?



THE PROBLEM WITH THE NICE MODEL

- ~~1. Late Heavy bombardment~~
2. Hot Kuiper belt (90%) very well,
3. Families of Asteroids
4. Low mass of Mars
5. etc.

Match to observations not self-consistent

Each “match“ for different initial condition and subset of simulations

No predictions

Not falsifiable

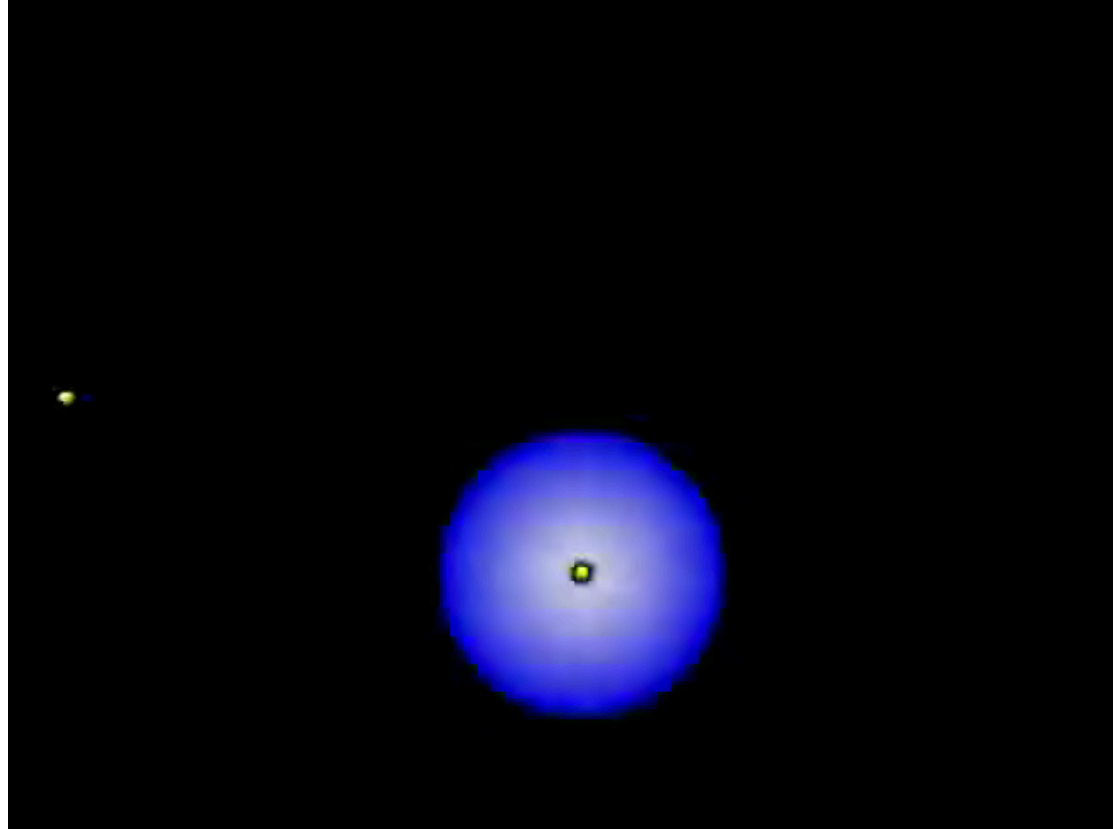
ALTERNATIVE: CLOSE STELLAR FLYBY

First suggested by
Kobayashi & Ida (2001)
Kenyon & Bromley (2004)

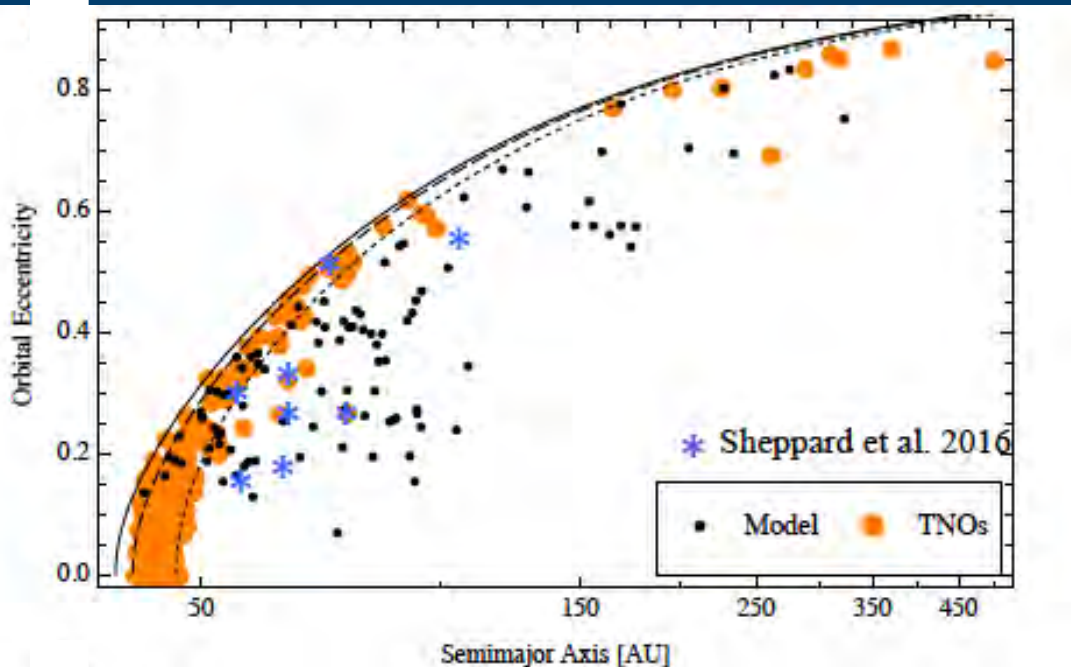
Simulated some specific
cases and found that
**inclined, eccentric orbits
can be obtained by flyby**

But did not get

- Sednoids
- cold Kuiper belt
- Resolution was too low
- Too small initial disc



FLY-BY REPRODUCES TRANSPENTUNIAN OBJECTS



Fly-by of star with

Mass: 0.5
 M_{sun}
Perihelion distance: 100 AU
Inclination: 60°
Solar disc: > 100 AU

reproduces

- 30 AU drop
- Kuiper belt
- Sednoids

LESSON 2:

**LOOKING AT PHENOMENA IN
ISOLATION IS DANGEROUS**

MODELS HAVE TO BE FALSIFIABLE

**MODEL PREDICTIONS ARE
ESSENTIAL**

CHARACTERISTICS OF A GOOD ANALYTICAL MODEL

- Matches observation
- Reproducible
- Simple
- Fit into the general theory
- Falsifiable
- Makes prediction

Criteria should be fulfilled by any model

FIRST DATA CHALLENGE

