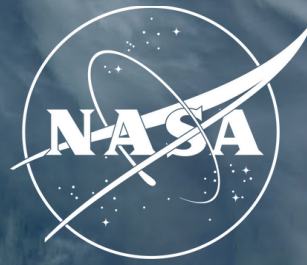




Attribution: Bayes vs. ML

Kate Marvel
NASA GISS

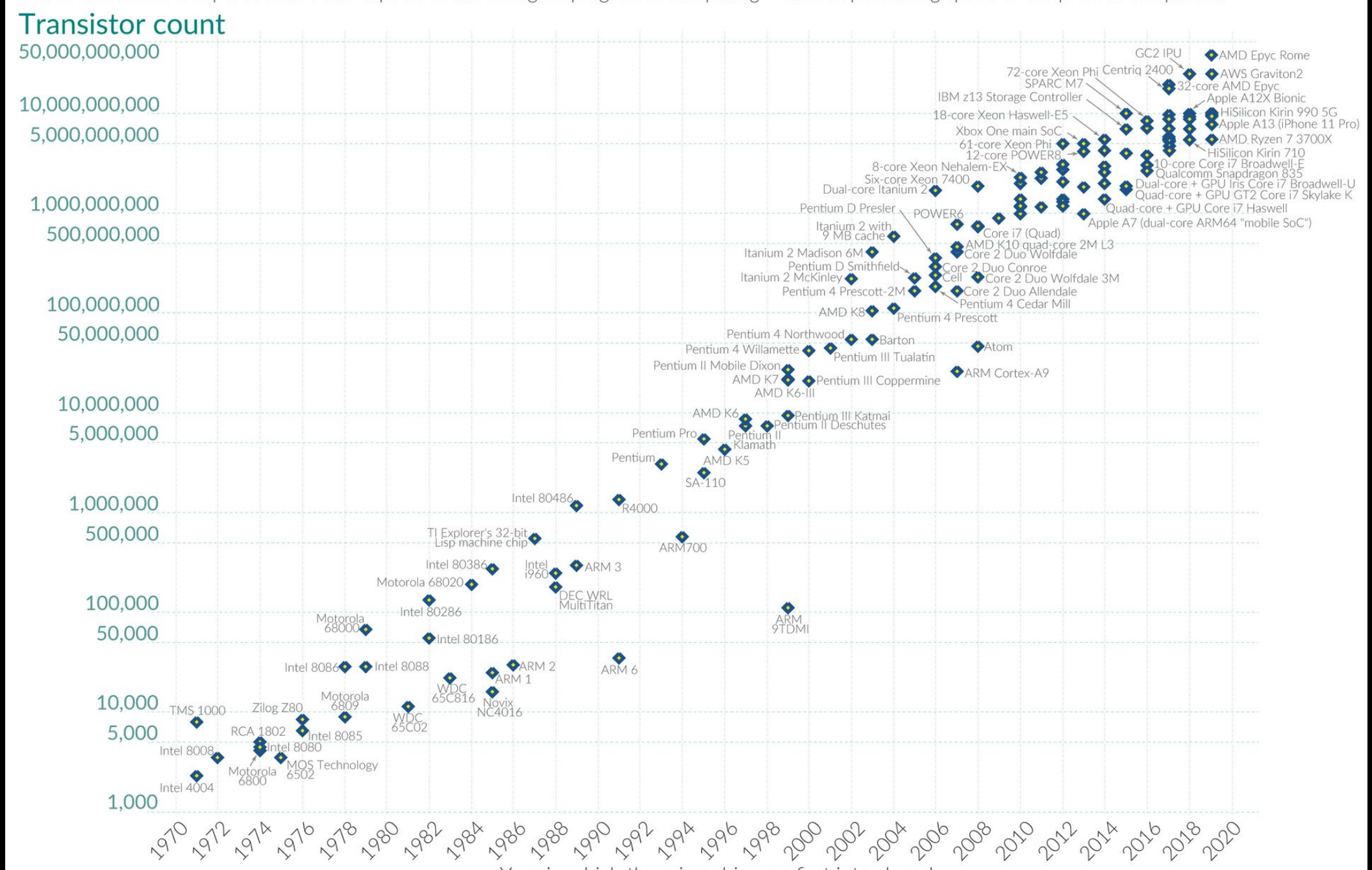
NEW APPROACHES



Moore's Law: The number of transistors on microchips doubles every two years

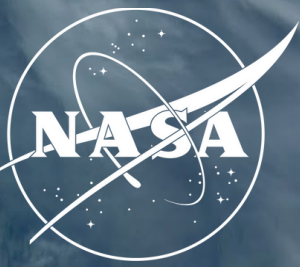


Moore's law describes the empirical regularity that the number of transistors on integrated circuits doubles approximately every two years. This advancement is important for other aspects of technological progress in computing – such as processing speed or the price of computers.



Data source: Wikipedia (wikipedia.org/wiki/Transistor_count)
 OurWorldinData.org – Research and data to make progress against the world's largest problems. Licensed under CC-BY by the authors Hannah Ritchie and Max Roser.





MACHINE LEARNING:

- Requires little knowledge of underlying structure
- Can use weak/uninformative priors
- Assumes training data are like test data
- Good in situations where
 - a) we have lots of training data
 - b) that are interchangeable with test data
 - c) we don't need full posteriors (or are OK with bootstrap estimates)

ML USE CASES

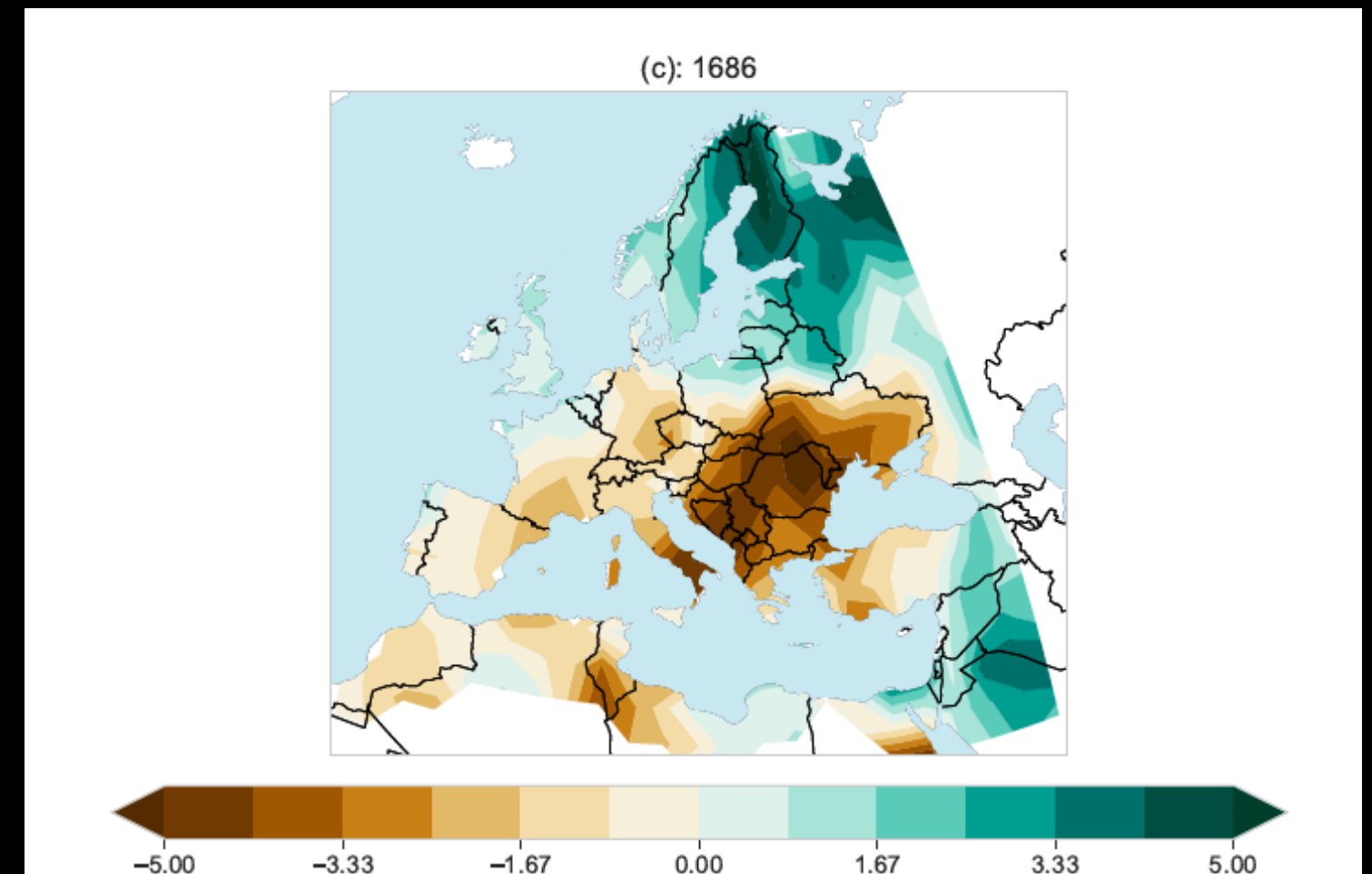
Classification

- “Is this event categorically different from others?”

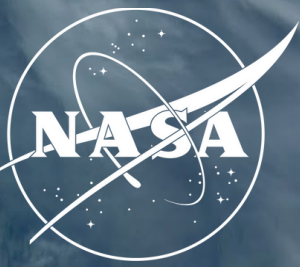
Prediction

- “Given the observed or predicted values of many variables, will there be an extreme event?”

1686 Czech Lands drought: most unusual spatial pattern in pre-industrial European history



Marvel and Cook Phil Trans A 2022



BAYESIAN INFERENCE

- Requires clearly specified underlying generative model
- Strong priors can incorporate existing knowledge
- Good in situations where
 - a) we have sparse training data
 - b) we wish to infer parameter posteriors

BAYES USE CASES

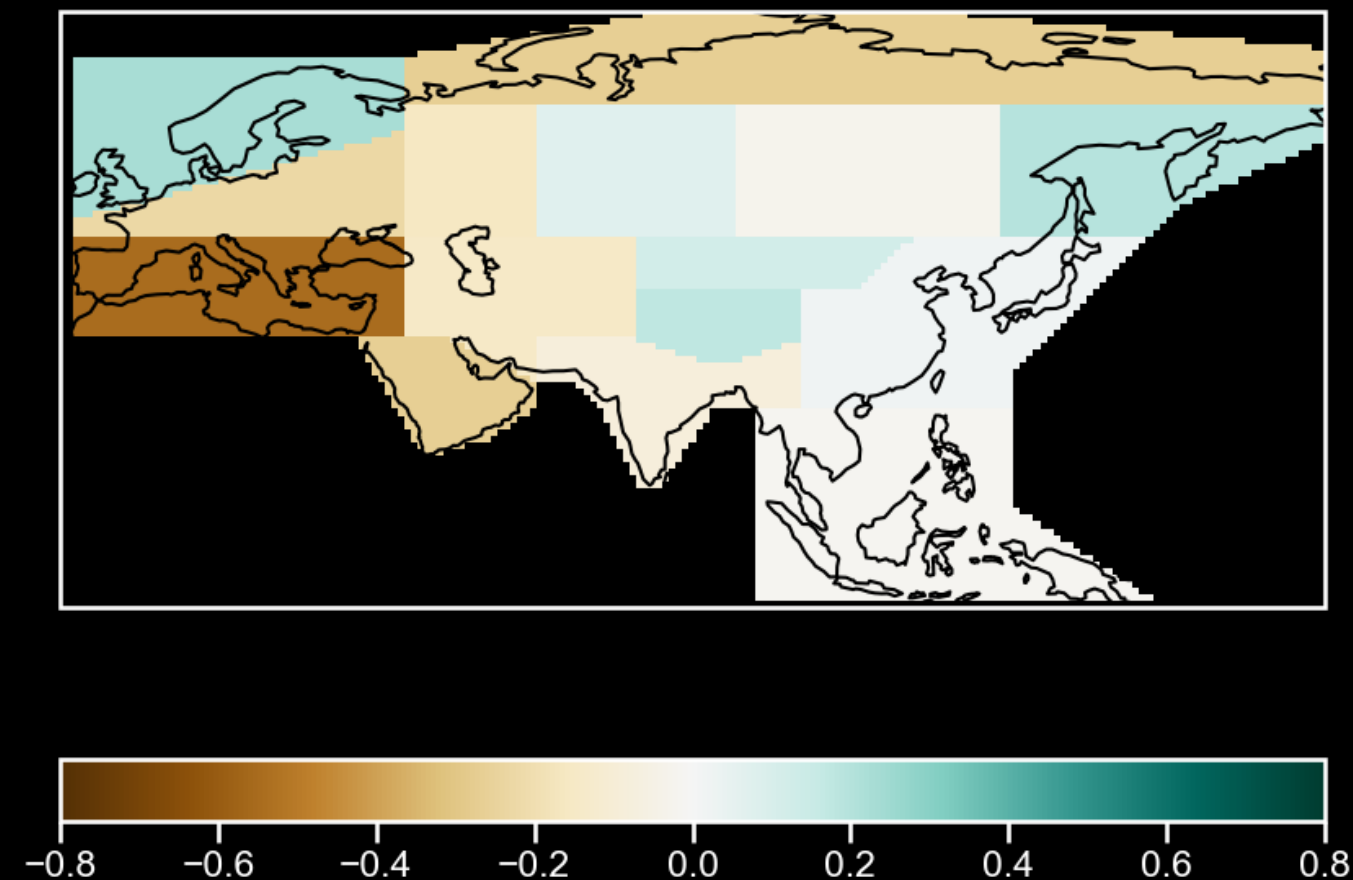
Parameter inference

- “What is forced response and what is internal variability?”

Inversion

- “Given known physical relationships, what underlying (unobserved) drivers contributed most to an observed extreme event?”

“Fingerprint” of external forcing on European/Asian drought risk (MAP value)

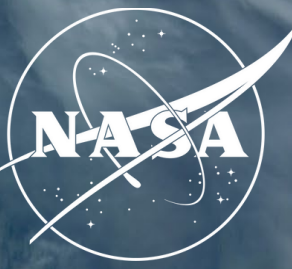


Marvel et al, *AGU Adv.* 2025

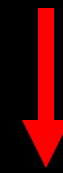
MODEL DEPENDENCE



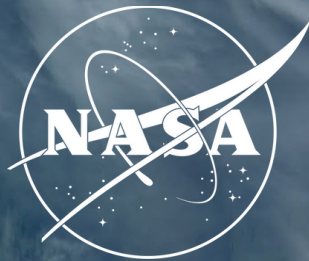
MODEL DEPENDENCE



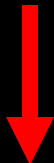
Likelihood



MODEL DEPENDENCE



Likelihood



Linear regression

Internal variability

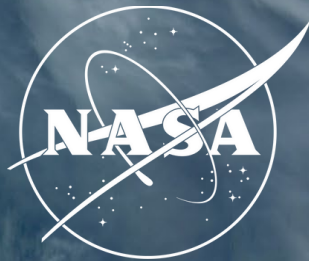


Scaling factors

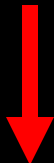
Fingerprint



MODEL DEPENDENCE



Likelihood



Internal variability

Internal variability



Every attribution statement is implicitly a model evaluation statement

How well does the model fit the observed data?

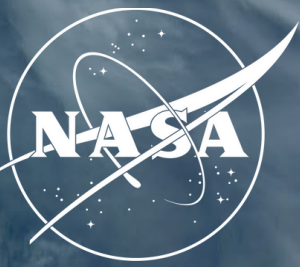
Occam's razor: penalized for more parameters
(unless we have good prior knowledge of what they are)
(OR they're very useful in generating D)

Every attribution statement requires unavoidable choices about different models

Calculate from data

Specify as prior

SUMMARY



MACHINE LEARNING

- Use in cases where it's not necessary or possible to write down the underlying generative model
- Requires abundant training data
- Requires known connection between test and training data
- Good for outlier detection, prediction
- Like all statistical methods, relies on parameters and models (mostly implicit)

BAYESIAN INFERENCE

- Use in cases where we want the model/priors to do most of the work
- Good for sparse data
- Requires the analyst to be explicit about models and prior knowledge
- Useful tools for model criticism and evaluation