AI as statistical methods for imperfect theories

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Abstract

Science has progressed by reasoning on what models could not predict because they were missing important ingredients. And yet without correct models, standard statistical methods for scientific evidence are not sound. Here I argue that machine-learning methodology provides solutions to ground reasoning about empirically evidence more on models' predictions, and less on their ingredients.

How can scientists reason about observations without binding the validity of their conclusions too much to the validity of a theoretical framework?

1 Science has progressed by refining the relevant constructs

1.1 Observing motions of bodies, working out laws of physics

Early scientists, such as Aristotle, did not conceive mechanics in terms of acceleration, mass, and forces but thought in terms of natural motion of objects, proportional to their weight. The notion of force made his way, as discussed by Ibn Sīnā, but motion was seen as proportional to external forces. The Copernican revolution motivated the importance of acceleration. Increasingly precise astronomical observations led to formulate planetary motion as elliptical trajectories and invariants. Scientists such as Kepler were seeking simple phenomenological rules, "harmonies" in his words, to explain the observations, *eg* that across the different planets the square of the period is proportional to the cube of the major diameter of the orbit. By introducing differential calculus, Newton was able to propose laws of mechanics that explained observations of both celestial and earthly motion.

The birth of Newtonian mechanics illustrates how better *observations* and *statistical models* lead to better theories, even when starting *without the right theoretical framework*. It shows how *new ingredients* may be needs, such as introducing the construct of acceleration. It shows that progress is driven by seeking theories that *generalize* across many settings. The importance of acceleration was revealed by uniting motion of bodies on Earth and in astronomy. Indeed, as friction is ubiquitous on Earth, applying a force to an object often leads to a velocity roughly proportional to this force.

Better observations called for new frameworks, quantum or relativistic. Irregularities in the orbit of Mercury were first explained by adding a planet to the solar system, Vulcan. But observations of this planet turned out to be flawed, and the irregularities in Mercury's orbit are now understood as relativistic corrections. The Vulcan hypothesis illustrates how theoretical frameworks shape the interpretations of empirical results: theory-laden observations [Boyd and Bogen, 2021].

Today, the fundamental laws of physics are incredible precise. Are phenomenological models still important for their empirical validation? From a statistical perspective, the Neyman-Pearson lemma tells us that optimal comparison between models builds on their likelihood van Dyk [2014]. Indeed, particle physics has long polished probabilistic models, minute stochastic description of observations

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built from first principles Sjöstrand et al. [2001], Aaltonen et al. [2008]. And yet recent statistical analysis of Higgs bosons is powered by black-box machine learning models –such as boosted decision trees– as they capture best background sensor noise Aaltonen et al. [2009], Radovic et al. [2018].

1.2 Cognitive neuroscience: uncovering the functional units of human vision

Cognitive neuroscience strives to explain cognitive functions from neural activity. Which ingredients to include in such a model is a more open-ended question in than in physics. Breaking down high-level functions into units of investigation is particularly challenging. This endeavor has made much progress for the specific problem of vision.

Studying early visual cortex response to specially-crafted stimuli, Hubel and Wiesel [1959] showed that groups of neurons formed localized edge detectors. Slightly more complex shapes isolated other brain units [**?**]. These findings are tied to the stimuli presented. Indeed, cognitive-psychology theories build upon decompositions of mental processes. Marr [1982] decomposed visual processing in successive operations tuned to specific aspects of the stimuli.

Their empirical neuroscience validation is bound to this decomposition. Building such an decomposition on invalid ingredients, such as "alimentiveness" or "philoprogenitiveness" put forward by 19th century phrenologists, would lead to a statistically-valid brain mapping even with modern measurements [Poldrack, 2010].

Many variants of hierarchical visual-processing models have been put forward, based on different principles [Riesenhuber and Poggio, 1999, **?**, **?**]. How to choose one for valid brain mapping?

Dimarco's papers have compared a bunch of these models [**?**]. Point is: difficult to craft these models, as the investigation into each function units are crafted in isolation.

Face vs place

Switching to low-dimensional statistical modeling to high-dimensional predictions: more ingredients jointly

2 How do statistical tools fit in scientific progress

2.1 Reasoning with statistical tools

Baiocchi and Rodu [2021]

2.2 Well documented epistemological challenges

Validity theory

Realism Center of gravity

Incommensurable theories and epistemological closures Taxonomical incommensurability versus methodological incommensurability

3 Grounding more statistical reasoning on output rather than models

3.1 For statistical validity

Counter-factual reasoning

3.2 For domain validity

4 Conclusion

Empirical validation of theory by its ingredient leads to self-fulfilling prophecies. Yet, this is what most of inferential statistics bring to the table. Science needs statistical reasoning based more on model predictions. Machine learning will provide the building blocks.

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