BIG DATA AND THE EMERGENCE OF ZEMBLANITY AND SELF-FULFILLING PROPHECIES

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Serendipity, zemblanity, and self-fulfilling prophecy

The term "zemblanity" was coined as the antonym of both defining aspects of serendipity: while the latter refers to a fortunate and unexpected discovery, the former refers to an unfortunate and expected finding:

> [...] serendipity, the faculty of making happy and unexpected discoveries by accident. [...] zemblanity, the opposite of serendipity, the faculty of making unhappy, unlucky and expected discoveries by design (BOYD, 1998, p. 234-235).

Serendipity is a random (unpredictable or irreducibly novel) discovery that happens to be fortunate. This notion encompasses both the sense of it being achieved (to a certain extent) by chance and the sense of it being valuable (either subjectively or relative to a specific problem), because a serendipitous event solves (or presents the means or opportunity to solve) a previously stated problem, introduces a new and promising hypothesis or line of investigation, or even "[...] becomes the occasion for developing a new theory or for extending an existing theory [...]" (MERTON, 1948a, p. 506).

Zemblanity, on the other hand, is an unfortunate finding, though not in the sense of being brought by bad luck, for it does not involve chance at all, and also not in the sense of being merely worthless, but undesirable. A zemblanitous finding reveals an underlying problem or issue, a negative side-effect or consequence, etc.

From the point of view of the initial motivations underlying Hilbert's Consistency Program, the forthcoming proofs of incompleteness results may be interpreted as a case of zemblanitous finding in formal mathematical theories. Under the same formalism and assumptions of the intended power of formal axiomatic systems in mathematics, one can obtain a proof of a meta-theorem that asserts the impossibility of certain mathematical proofs. However, incompleteness only comes as a negative side effect of formal theories for such finiteness and mechanistic aspirations of the Consistency Program. Incompleteness in mathematics actually underpins the emergence of algorithmic information in mathematical formalizations of complex systems (ABRAHAO et al., 2020; ABRAHAO and ZENIL, 2022).

Not exclusive to deterministic processes, zemblanitous discoveries may also happen in stochastic processes that generate large amounts of data. One example of this phenomenon in Big Data is the occurrence of spurious patterns (SMITH, 2020; CALUDE and LONGO, 2017). For sufficiently large amounts of random data, one can always find patterns that are spurious, i.e., patterns that are already expected to occur even if the underlying data generating process is random, i.e, free of any redundancy or governing structure. Spurious patterns can be deceptive and can be interpreted as an issue or negative effect because they can mislead an observer into thinking a statistically significant pattern was discovered, even though this pattern would have occurred anyway, and thus it gives no useful information about distinctive features of the underlying data generating process.

In addition, the presence of zemblanity in Big Data may be also more fundamental than finding spurious patterns. In general, no formal theory is capable of ruling out the possibility of the very theory being deceived into assigning more predictive powers to itself than it actually has, should the amount of available data from which the formal theory is conceived in first place, and upon which the predictions of the theory are corroborated, be sufficiently large in comparison to the complexity of the respective formal theory (ABRAHAO et al., 2021).

Serendipity is defined upon the occurrence of unexpected events, and as such it requires not only the sense of being surprising but also the sense of being unpredictable. Whether it solves a problem different than the one the researcher was concerned with, or the exact problem the researcher was dedicated to, but in an unexpected way, or even if the researcher was not targeting a specific problem when it appears, a serendipitous discovery is always contingent.

Zemblanity, by its turn, is either expected or predictable, depending on how informed the researcher is. This is why it is not a discovery at all, but rather a necessary finding one will eventually and inevitably arrive at when dealing with a certain problem or subject matter.

A serendipitous discovery happens “[...] at the intersection of chance and wisdom [...]” (COPELAND, 2019, p. 2386), or is made by accident and sagacity, as Walpole (2011) puts it. This means that, while it is triggered by a random event, only a skilled and attentive observer will be able to detect it. A zemblanitous finding is in no way the product of chance, for it happens, as Boyd (1998) states, by design; in other words, it is a feature, not a bug.

Consequently, only the unskilled and negligent will not be prepared for its appearance.

Self-fulfilling prophecy, by its turn,

> […] is, in the beginning, a false definition of the situation evoking a new behavior which makes the originally false conception come true. The specious validity of the self-fulfilling prophecy perpetuates a reign of error. For the prophet will cite the actual course of events as proof that he was right from the very beginning (MERTON, 1948b, p. 195).

In this paper, we argue that both zemblanity and self-fulfilling prophecy may emerge from the application of Big Data models in society due to the presence of feedback loops.

Zemblanity and self-fulfilling prophecy in Big Data

PredPol, one of the many predictive policing models currently in use in the United States, processes historical crime data and calculates, hour by hour, where crimes are most likely to occur; its algorithm "[...] looks at a crime in one area, incorporates it into historical patterns, and predicts when and where it might occur next." (O'NEIL, 2016, p. 88). Not focusing on individuals, PredPol would supposedly not be influenced by racial biases.

However, directed by zero-tolerance policies, stop-and-frisk practices, and productivity quotas, police departments feed PredPol not only with violent crime data but also and mostly with data on minor crimes, like illicit drug use. A study (LUM, ISAAC, 2016) has shown that the data on drug use produced by the police is by far not representative of the reality of drug use, being reported mainly in impoverished neighborhoods, where the majority of the population is African-American or Hispanic. When that data is fed to the algorithm of PredPol, it directs the police to those neighborhoods, concentrating crime-reporting on those areas, generating a feedback loop, which not only reinforces the biases already present on the data but also corroborates the biased results, granting them an aura of scientificity. Fed by data itself helps create, PredPol behaves as a self-fulfilling prophecy:

> PredPol will announce that a crime is to take place in a specific area of the city. Off the policeman goes to respond to the situation. One of two things will happen: either a crime takes place as planned and the policeman stops the offender [...] or no offence occurs. But this is probably linked to the on-the-spot presence of the policeman (DUPUY, 2018, p. 160).

For Benslimane (2014), Predpol ignores the various sociological factors that lead to criminality and the biases in policing to create a simplified, apparently objective representation according to which there are more crimes in certain areas of a city. It fails to accurately represent the actual presence of criminality in a city because the data it is fed with does not represent the totality of crimes that occur in that city (or even a random sample, but an arbitrary one), nor is the model informed by theories about the reason why certain crimes are more likely in certain areas than in others. Additionally, it is subject to a pernicious feedback loop.

The COMPAS model, designed to assess potential recidivism risk, is being used in the United States to inform judges' decisions. A study (LARSON et al., 2016) has shown that in that model, whose rate of success is of merely approximately sixty percent, African-American defendants are frequently wrongly classified with a higher risk of recidivism, while Caucasian defendants are frequently wrongly classified with a lower risk of recidivism. A subsequent study (FLORES et al., 2016) argued that the study by Larson et al. did not accurately represent the reality of the COMPAS results; however, even though the differences between the failure rates are smaller than Larson et al. claim they are, they are still there. Flores et al. also fail to account for the racial biases in policing and for the feedback loop that a higher rate of incarceration of African-Americans creates on the rate of recidivism.

Also fed with biased data produced by the police and by the judicial system, the COMPAS model does not successfully approximate the totality of the instances of the phenomena it aims to model. Differently than the PredPol model, it is allegedly grounded in theory – various criminal theories are cited in the official guide to the use of the platform (NORTHPOINTE, 2015, p. 5-6); however, in the questionnaire that feeds the system with data from the defendants there are questions like “How many of your friends/acquaintances are taking drugs illegally?” and “How often did you get in fights while at school?”. The questionnaire also asks people to agree or disagree with statements such as “A hungry person has a right to steal” (ANGWIN et al. 2016), among other questions of a highly subjective character. Thus, the model does not seem to be grounded in scientific theories that take sociological factors into account, nor is it concerned with what causes recidivism.

Thus, both models fail to accurately represent, respectively, the reality of geographical crime distribution and of potential recidivism, but their failure can be represented as success since their use increases certain indicators, their errors are not easily identifiable, they can behave as self-fulfilling prophecies, and especially since they reproduce prejudices and misconceptions already present in our society and seen as factual.

Such models generate zemblanitous findings: their results present racially biased patterns that an individual informed by the relevant theories would rightfully expect to encounter, but which nonetheless are not accounted for by the model. Their results do not deviate much from the already established practices, and thus their value lies not in the new insights they generate, but in how they corroborate and justify those practices to the public. However, their employment is not innocuous: the algorithms strengthen and naturalize the existent biases.

Self-fulfilling prophecies via feedback loops in Big Data

A feedback loop in data-driven or algorithm-driven policy making occurs when the data, whether true or false, dictate the policy, and such policy's effects feed the model back with biased data (AUERBACH, 2014). Such kind of bad circularity may generate patent errors when there is something the dataset can be compared to, such as when Google Flu Trends grossly overestimated the cases of the flu later confirmed by the CDC; but it may also generate an apparent success of the model, when there is nothing to compare its results to, thus turning it into a self-fulfilling prophecy. Thus, unlike a feedforward process (which would be desirable in this case), a model may have its dataset altered by its own application, if the population affected by the model and the population who feeds the model with data are the same, which frequently happens in the context of Big Data.

The fact that the prophet is an agent in the system that induces or triggers a novel behavior (which would otherwise be different or opposite without the agent's action) through such a collective interplay between the data-driven algorithm and the interaction of the system's components (in the above example, society) may render the occurrence of self-fulfilling prophecies a very hard effect to predict in general, therefore demanding much more attention from the complex systems scientists and philosophers. This is because it may fall under a case of emergently biased behavior defined as secondary self-organization (ALFREDO et al (eds), 2018). In addition to the feedback loop inducing a stabilization of the collective behavior in the form of an increasing bias, this self-organization occurs due to an irreducibly emergent, or creative, process with respect to the system's constituents. Thus, if the resulting self-organization of the prophet's actions is a secondary self-organization, formal theories may be in principle uncapable of predicting the presence of such prophets (ABRAHAO and ZENIL, 2022) in the system.

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