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Frontier Talk

Memo by Marco Almada

The future of prediction. The Social Consequences of Algorithmic Forecasting

Speaker: Elena Esposito (University of Bielefeld and University of Bologna)

This event has been organised by the Technological Change and Society Interdisciplinary Research Cluster

***Elena Esposito**, the speaker, is a professor of legal sociology (systems theory) working on communication issues. Her presentation draws from work developed within an ERC Advanced grant (PREDICT—The Future of Prediction) on algorithms and prediction, in which she is the principal investigator. Esposito recently published a book on this topic, which develops a theoretical framework and applies it to the in-depth analysis of three domains: insurance, medicine, and policing.*

Algorithmic prediction promises a new way to manage the uncertainty of the future. One frequent issue in discussions about prediction is *pre-emption*: that is, prediction restricting possibilities of action. The PREDICT project focuses, instead, on a related question: prediction reduces uncertainty about the future, but uncertainty is not always a negative thing. For example, our current insurance models operate by spreading risks through insurance pooling, a movement justified by the uncertainty regarding accidents. What happens to stabilized forms of management of the future when their premise—that we live in an uncertain world where the future cannot be predicted with exactitude—is no longer valid?

With this frame, the project is the contemporary counterpart of research by scholars such as Ian Hacking. They have investigated how the introduction and development of probability calculus in the Early Modern period has had important social consequences, such as enabling the business model of insurance companies.

Another important element Prof. Esposito brought to the discussion is the ongoing debate between the machine learning and statistics communities. While these two groups of scholars and practitioners use similar tools in their work, grounded on the same fundamental theories, they are increasingly differentiated in their purposes and overall approach to problem-solving.

Oversimplifying things—but just a bit—statisticians deploy their mathematical toolset to identify explanations of the phenomenon under analysis. Machine learning practitioners, on the other hand, eschew explanations in favour of building models that can predict future outcomes.

This change in goals, and the current boom in machine learning technologies, prompts Esposito to probe algorithmic predictions in three dimensions: *individualization*, *generalization*, and *bias*. While these three dimensions are not easily separable in practice, each of the application domains studied in PREDICT puts one of them to the fore.

In **personalized insurance**, the salient issue is *individualization*. Current insurance practices rely a lot on actuarial averages. Nobody has 1.4 children, but if one looks at the behaviour of the entire population in the long run, then it makes sense to speak of an average of 1.4 children per couple. This reliance reflects the development of probability-based approaches described above, as no insurance model could account for the particularities of each singular case. Algorithmic insurance, however, promises to do just that: if you have the data, so it is claimed, you could provide a tailor-made risk profile for each individual rather than just hoping that results will average out in the long run. Accordingly, the PREDICT project looks at how the availability of individual information affects the business model and social role of insurance.

The analysis unveiled three possible consequences of the shift towards individualized prediction. The first is the *demutualization* of risks: since companies can distinguish high-risk clients from low-risk clients, they will no longer need to spread out risks toward their entire client pool. Instead, they can segment clients and increase prices—or even deny service altogether, when that is possible—to clients who are likely to require much in terms of payout. As a result, the price of insurance might increase considerably for those who need insurance the most.

Algorithmic insurance also raises the potential of *inversion of information asymmetry*. Currently, clients know more about their circumstances and history than insurance companies. The availability of big data, collected directly and indirectly from clients, might put companies in a situation where they have data to predict things that a client might not know about themselves—for example, by predicting that someone is likely to have a stress-related disease. If that is the case, companies are in a much better position to negotiate prices *vis-à-vis* individual clients.

Last but not least, algorithmic prediction might push insurance companies towards a more *proactive* model. Instead of restricting themselves to paying out clients whenever something comes up, predictive insurance could prompt clients to take action against foreseeable events. In this context, insurance companies would be akin to coaches, encouraging their clients to take action rather than disbursing cash once something happens.

The scenario is somewhat different when it comes to **precision medicine**. While individualized insurance is a rupture with current practices, individualized treatment is largely seen as positive in the medical field. Particularly in the US, there is a quite strong push away from a “one size fits all” view of medical care, and there is much expectation about what AI technologies can deliver in that sense. The main challenge, instead, is *generalization*: how can one generalize medical diagnoses from the data used for training—which necessarily refers to past events—to future cases?

The use of AI in precision medicine does not mean a move away from statistics, which are still deemed necessary. Nevertheless, it raises questions about the interfaces between good old-fashioned statistical analyses and machine learning predictions. Here, the PREDICT project captures three shifts in medical practice. First, there is a shift regarding the kind of data used: whereas statistics in medicine would produce average profiles of patients drawing from large data sets of various patients, precision medicine relies on large volumes of data referring to a single patient (prediction with n=1). The second shift refers to the evaluation of patient status: whereas the idea of a healthy patient is currently defined—explicitly or implicitly—based on statistical averages, the availability of data about individuals promises to allow healthcare professionals to make personalized decisions about patients. Finally, people currently have the right to refuse information about their medical status, but how can this “right not to know” be maintained in a context in which so much data is directly or indirectly available to describe a patient’s health status?

Finally, the questions about **predictive policing** gravitate around **bias**. She says that *Minority Report* might not be a great movie, but it provides a strong illustration of the ideal of predictive policing: identifying crimes and relevant factors to act on before anything actually happens. While this description might sound like something out of science fiction, it has been realized to a large extent, and predictive policing technologies have been in use in the US for at least one decade. These algorithms rely on data from various sources, which might differ in quality and levels of accuracy due to various factors: biases in the data gathering procedure, differences in sensors, and so on. The PREDICT project focuses on systemic biases, such as confirmation biases.

There are various tools currently in use for predictive policing. PredPol is perhaps the most used of them. On its website, PredPol claims its goal is not merely to predict crime but to prevent it.

Accordingly, the first question investigated by PREDICT is what is the difference between predictive effectiveness and preventive effectiveness. But measuring effectiveness is, in itself, a difficult task. For example, the predictive algorithms used by the Chicago police have been subject to much scrutiny. Nonetheless, there is much disagreement about their effectiveness: while some dismiss them by pointing out that crime actually rose after the adoption of predictive algorithms, these algorithms still have proponents claiming their effectiveness. The task is further complicated by the fact that policing activities themselves are transformed by the inputs obtained from algorithmic prediction: one might indeed find more crimes happening where the algorithm has pointed out but is this a successful prediction or the result of increased police attention?

The second question PREDICT asks about predictive policing concerns its transparency. These systems can be opaque, partly because they are complex technical objects and partly because they are surrounded by secrecy. In the context of policing, the actions based on the data provided by these opaque systems must nevertheless be explained to the public in a democratic society. The project thus investigates how the communication between users and the public operates in law enforcement contexts.

A EUI Professor opened the **Q&A** with a high-level question. He's often puzzled by the tension between, on the one hand, the promise of measurement and forecasting enabled by technology, and, on the other hand, the enormous uncertainty we live in our societies. Are we living in a world with more uncertainty, less uncertainty? More specifically to the project, is there a common trend unifying the chosen fields in terms of uncertainty?

Prof. Esposito responds on two levels. First, these algorithms already operate in our society, and they are taken (with or without grounds for that) as predictors of the future, and the project seeks to understand how these systems are used and how that is different from previous practices in these fields. At a second level, the belief in the predictive capabilities of algorithms is widespread, and this changes the forms we, as a society, deal with uncertainty—the future starts to be seen as closed and not as open.

A cluster member asks whether there are any procedures to distinguish between forecasts that prevent things from happening from those who are successful divinations of what comes to pass. Prof. Esposito points out that this is a crucial question. Good prevention destroys the very elements that could be used to judge it, as one cannot simply compare what happened with the worlds in which the prediction did not happen. Prof. Esposito thus highlights the performative dimensions of forecasting as a social practice.

A EUI Professor points out the feedback loop from predictions to actual human behaviour and to machine learning in turn. He asks about how these feedback loops come up in the project. Prof. Esposito highlights how these feedback loops are built into machine systems from their very beginning. The Professor follows up on how this eliminates a positive source of uncertainty by generating endogenous worlds in which everything ends up being determined by past behaviour with no source of change. Prof. Esposito agrees that this, not the dangers of runaway AI, is what is really problematic about AI—how algorithms allow for new forms of epistemic and social closure, closing possibilities for unplanned diversity.

Another EUI Professor adds that predictions can be made conditional on human behaviour. Prof. Esposito connects this comment with the idea of prediction as a performative practice.

A member of the audience pointed out that all three cases covered in PREDICT have a similar structure in terms of agents. In each of them, one of the actors has little agency and power, while the other party has much of both elements: the insurance buyer and the insurance company, the patient and 'big medicine', the would-be criminal and police. How does this similarity impact the results? Esposito acknowledges this similarity but emphasizes that each case involves different kinds of data and issues, being thus difficult to lump together.

A participant asked whether the project considers how the three questions—individualization, generalization, and bias—interplay with the legal system and the way we perceive the future of law. Prof. Esposito responded that she looks at these issues from a sociological perspective. Addressing these normative angles, she argues, would broaden what is already a quite broad field. The question remains interesting, it is just that it exceeds Prof. Esposito's competence horizons, and she would be inclined to see how legal scholars engage with this point. The project itself is not legal research. Nevertheless, it becomes important to see how the legal way of engaging with those themes produces social effects.

A EUI Professor and Prof. Esposito discuss how algorithmic prediction eliminates room for changing human behaviour. A lazy student who is predicted to do badly might have a change of mind and become a better student, a convicted felon might give up on the life of crime, and so on (though this might be less of an issue for health predictions). Such changes would not be encouraged—or even seen—by social systems that rely on prediction as a mode of knowing for these matters.