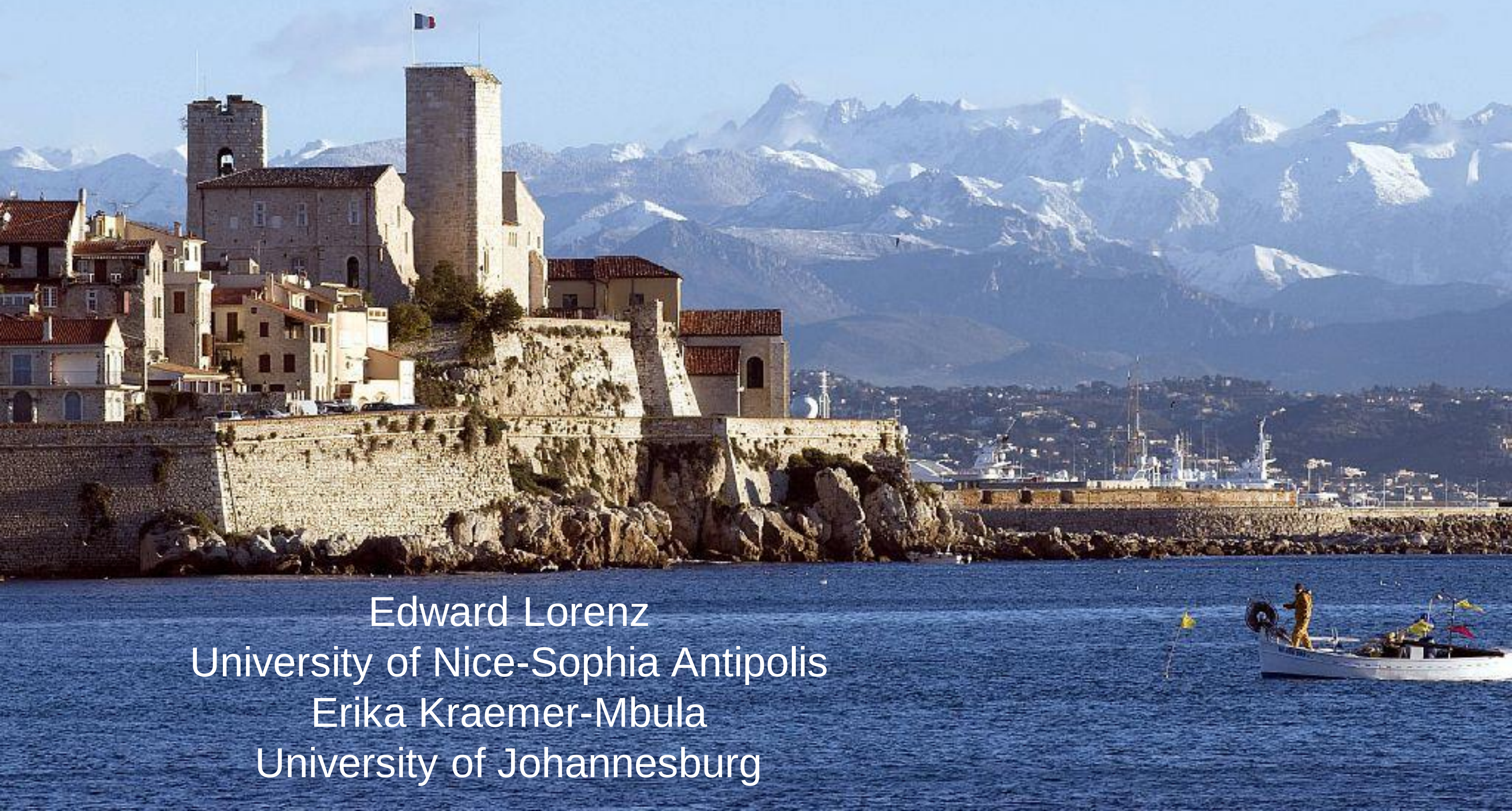
# Organizational Design, Forms of Knowledge and the Automation Debate



Edward Lorenz
University of Nice-Sophia Antipolis
Erika Kraemer-Mbula
University of Johannesburg

# Are we on the cusp of an economic singularity?

- This is sometimes asked with the question, ‘Is this time different?” If this is taken to mean, “Are we rapidly moving in a time frame of 10 to 15 years to an economy in which human labor will be entirely or largely substituted for by “robots”?”, our response would be a resounding no.
- If the question is rather taken to mean, “Are both the nature and scope of automation processes changing with important impacts on employment and skills needs?”, then our response would be in the positive.

# Background : the task-based approach and automation predictions

- Frey and Osborne are highly cited for their prediction in 2013 that 47% of jobs in the US are at high risk of automation over a period of a decade or two.
- No enterprise-level data to base estimates on. Only the distribution of occupations and sectors.
- Assumes that the task characteristics of individual occupations are identical across firms in the same sector.
- No consideration of the possible need to unbundle tasks that are susceptible to automation from those that aren’t

# Our underlying argument

- Industrial automation, regardless of whether it is based on rules codified in a computer program or is data driven and based on prediction through deep learning (ML), depends on a degree of standardization of organizational knowledge and work.
- Where work in the area of the firm’s core competence is non-standard and is organized to promote employee learning and problem-solving, there will be less use of automation technologies and they will tend to be used in ways that complement or **augment** workers rather than simply **substituting** for them.

# Standardization, scale and robots in industrial manufacturing

- There is a very little firm level data on the use of industrial robots in manufacturing.
- The only available firm-level data on robot use is the EMS survey data collected by a private consortium of academic institutions headed by Fraunhofer ISI.
- The published results show not only a positive relation between the size of the enterprise and the adoption of robots, but also a statistically significant positive relation with batch-size.

# Example of the automotive sector

- The reasons for the positive relation between robots and batch size has more to do with the integration costs of using industrial robots or systems of robots than the cost of the robot itself. These integration costs include the costs of dedicated fixtures, tooling, programming and safety features which can be over half the total costs in robot automaton.
- These costs can only be amortized with high volumes of standard component production.

# The use of cobots

- There is evidence that some manufactures are are increasing their use of cobots in preference to industrial robots that operate behind cages at a distance from the operator.
- Cobots are flexible, suitable for small-batch production, and are easily (re)programmed by the operator drawing on tacit experience-based knowledge.
- The use of cobots points to an element of choice in the use of new automation technologies. Cobots complement or augment workers.

# Standardization and deep learning (ML)

- By deep learning I am referring to supervised learning with neural nets (e.g. convolutional nets for image classification)
- These machine learning models with several layers incorporate a loss function and back propagation and on this basis improve their predictive performance based on ‘experience’.
- This requires large amounts of human-annotated data.

# Standardization, scale and deep learning (ML)

- In the field of management and economics probably the person that has worked the most on what kinds of tasks can be automated with ML is Brynjolfsson (2018). In a 21-item rubric he refers to following:
- ***The task is highly routine and repeated frequently.***
- ***Each instance, completion, or execution of the task is similar to the other instances in how it is done and these actions can be measured.***

# 'Big data' and scale

- The problem of scale in ML is evident in the need for "big data" and the problems that are often encountered by firms in getting access to the large quantities of data needed for training the ML. Of course, some applications are generic and access to the necessary data is not limited by the scale of the establishment's activity.
- Others are more or less firm-specific and require labelling large quantities of unstructured data specific to the firm.

# Data management and labelling

- In describing the work of data engineers there is often reference to the the so-called “**80/20 rule**” :
  80 **percent** of a **data** engineer’s valuable time is spent simply finding, cleansing, and organizing **data**, leaving only 20 **percent** to actually perform analysis.
- While labelling data sets for training computer vision systems can be outsourced to on-line companies like CloudFactory or DataPure, in applications in the field of medicine, or in the case of predictive coding for e-discovery in legal work, there will be a need for expert labelling.

# Organisational design and forms of knowledge

- I want to now link this discussion into a taxonomy developed by Alice Lam (2000) of the 'dominant' form of knowledge used by an organization.
- The taxonomy distinguishes between the knowledge agent (individual or organization) and the degree of standardization of work and knowledge.
- We associate the idea of a dominant form of kwowledge with the firm's core competence

**Knowledge Agent**

| Standardization of work and knowledge | **Individual** (occupation-specific skills) | **Organization** (firm-specific skills) |
|---|---|---|
| **High** | **Professional Bureaucracy**<br><br>**Embrained Knowledge**<br>**(explicit and individual)** | **Machine Bureaucracy**<br><br>**Encoded Knowledge**<br>**(explicit and collective)** |
| **Low** | **Operating Adhocracy**<br><br>**Embodied Knowledge**<br>**(tacit and individual)** | **J-Form**<br><br>**Embedded Knowledge**<br>(tacit and collective) |

Source: Lam (2000).

# Work standardization and automation in the Machine and Professional Bureaucracy

- The machine bureaucracy refers to the typical organizational structure of a mass producers based on Taylorism with a high degree of standardization of tasks based on formal rules for how work should be carried out.
- This lends itself to conventional automation which as Autor (2003) in his discussion of the automation of ‘routine’ tasks with computer programming is limited to tasks which can be described in terms of rules that are sufficiently well understood to be specified in computer code.

# Work standardization and automation in the Machine and Professional Bureaucracy

- A distinctive feature of the Professional Bureaucracy is knowledge is held in individual people. The standardization of work is determined outside the boundaries of the firm and is closely linked to the forms of professional education and certification that legitimize the expertise of professionals.
- As Mintzberg (1980) emphasizes, unlike the Machine Bureaucracy which must design its own standards, in the case of the Professional Bureaucracy, "*no time is lost and no scale of operations is required to establish standards.*"

# Automation in the Professional Bureaucracy

- The fact that many of the most discussed applications are in professional service areas such as medicine and finance can in part be explained by the standardization of knowledge at the level of the profession or occupation.
- With some important qualifications, this means that the large quantities of possibly unstructured data that are needed for purposes of training and testing the ML may be available independently of the firm's scale of operations.
  - Small amounts of site specificity may reduce the performance of a general or 'global' ML in medical image analysis. (See Litjens et al., 2017 for a survey.)

# The limits to automation in the J-Form organization

- The core competence of the J-Form is achieving continuous improvements in product quality and productivity through the  experience-based learning and the practical problem-solving skills that teams of employees acquire through their daily work activity.
- High levels of automation with industrial robots will be antithetical to the principle of continuous employee learning and improvement and will tends to result in organizational rigidity and a lack of flexibility.

# Augmenting workers skills with cobots in the auto industry

- Of course firms like Toyota and ‘diversified quality producers’ like Mercedes and BMW do use industrial robots and this may appear to go against this conclusion.`
- There is evidence that auto producers valuing customization and continuous improvement are pulling back from high level of the automaton. The recent trend is to adopt cobots which work alongside the operator and draw on the operator’s experience and tacit knowledge as a basis for programming for small batch production

# Use of cobots at Mercedes

- The head of production at Mercedes was recently quoted as reporting to Bloomsberg that,

  “*We’re moving away from trying to maximize automation with people taking a bigger part in industrial processes again. We need to be flexible. The variety is too much to take on for the machines. They can’t work with all the different options and keep pace with changes*.”

# The operating adhocracy: augmentation or substitution

- Companies such as IBM which arguably fit in the category of an operating adhocracy, are actively developing and marketing ML applications. Some of these focus on business services in areas such as finance, and health which fit under the heading of the operating bureaucracy. The perhaps obvious point is that the development of ML products by firms like IBM depends on their use of highly skilled human workers: data scientists and engineers.

# The promise of ML?

- This arguably misses the point that ML may provide results that are useful for the innovative activities of skilled knowledge workers. One area where this would appear to be the case is ML applications by pharmaceutical companies for screening compounds in the early stage of the drug discovery process.
- An obstacle here is the opacity of ML. Ching et al. (2018, p. 34) in their survey concluded that at present deep learning, “has not transformed the study of human disease” and that this will only be achieved when it is possible to, “generate interpretable models that lead scientists to ask questions they did not know how to ask.”

# François Chollet from Google: ML as a game change and ML as hype.

- "Here's what you should remember: the only real success of deep learning so far has been the ability to map space X to space Y using a continuous geometric transform, given large amounts of human-annotated data. Doing this well is a game-changer for essentially every industry, but it's still a long way from human-level AI."

# François Chollet from Google on ML

- “As a machine-learning practitioner, always be mindful of this, never fall into the trap of believing that neural networks understand the task they perform—they don’t, at least not in a way that would make sense to us. They were trained on a different, far narrower task than the one we wanted to teach them: that of mapping training inputs to training targets, point by point. Show them anything that deviates from their training data, and they will break in absurd ways.”