Our mission

We are interested in understanding how knowledge moves, grows, and decays, from teams to nations, and from the past to the future.

We study how technology, geography, and culture impact the growth and diffusion of knowledge using machine learning and data science tools.
Who we are

The Center for Collective Learning (CCL) is a multidisciplinary research center with offices at the Artificial and Natural Intelligence Institute (ANITI) of the University of Toulouse and at the Corvinus Institute of Advanced Studies (CIAS) at Corvinus University.

The CCL is internationally recognized for its work on economic complexity, economic geography, and data visualization.
What are we known for?

**Economic Complexity:**
For nearly 20 years we have pioneered the use of machine learning and network science tools to study economic development. This includes seminal concepts, such as the product space, the network of related economic activities used to anticipate and strategize industrial diversification strategies, and the economic complexity index (ECI), a popular international development statistics explaining international variations in future economic growth, inequality, and emissions.

**Digital Democracy:**
We have developed digital democracy platforms to scale nuanced deliberation and expand the boundaries of social choice theory.

**Urban Perception:**
We pioneered the use of crowdsourcing and machine learning methods to map and understand urban perception and physical urban change.

**Data Visualization:**
We have built dozens of data visualization platforms and experiences.

**Collective Memory:**
We have explored the role of languages, technology, and time on collective memory.

**Perception of AI:**
We have explored people's perception of AI in dozens of controlled experiments.
Who supports us

Our support comes from several European and National research projects.

Support for CCL at Corvinus University comes from the European Research Executive Agency (ERA) Chair. Support for CCL at the University of Toulouse comes from an ANITI Chair provides by the national french research agency (ANR) and from the European Lighthouse of AI for sustainability (ELIAS) Horizon project and Obs4Sea (Horizon) project.
A large & growing multidisciplinary team

4 postdocs, 2 PhD Students, 2 Assistant Professors, 1 Engineer, 1 Designer, 1 External Visiting Professor, 4 graduate students, 1 executive director, 1 director
Our impact includes the creation, inspiration, and development of dozens of public data observatories around the world, visited by millions of people every month.
Our Impact,
Includes multiple well-cited books and academic papers
What did we do between 2019 and 2023?
Institutional building:

Went from 1 person and 1 project in 2019, to over a dozen people in two universities with several funded projects in 2023.
Academic Publications
one billion USD and have a population of at least one million. Likewise, it is common to disregard products with small export volumes (for instance, <0.5 million in global exports at the four-digit level). These tricks of the trade are important to perform meaningful comparisons and are used in all data types (including products, patents or industries).
The amenity mix of urban neighborhoods

César A. Hidalgo, Elisa Castañer, Andres Sevtsuk

(a) Node Color Amenity type
- Green: Food & Drinks
- Blue: Services
- Pink: Shopping
- Orange: Transportation
- Red: Education
- Gray: Other
- Yellow: Government
- Purple: Entertainment

(b) Node Size Number of Amenities
- 1k
- 20k
- 100k
- Total number of amenities

(c) 3D representation of amenity distribution in Boston

(b) Intra-city Scale
- Size (total number of amenities)
- Composition (type of amenities in cluster)

*** difference in Bayesian Information Criterion is larger than 1000
Spillovers across industries and regions in China’s regional economic diversification

Jian Gao\textsuperscript{a} \textsuperscript{,} Bogang Jun\textsuperscript{b} \textsuperscript{,} Alex ‘Sandy’ Pentland\textsuperscript{c} \textsuperscript{,} Tao Zhou\textsuperscript{d} \textsuperscript{,} and César A. Hidalgo\textsuperscript{e} \textsuperscript{,} \textsuperscript{f}

\textbf{ABSTRACT}\nIndustrial diversification depends on spillovers from related industries and nearby regions, yet their interaction remains largely unclear. We study economic diversification in China during the period 1990–2015 and present supportive evidence on both spillover channels. We add to the literature by showing that these two channels behave as substitutes when explaining new entries and exits, and by using acceleration campaigns of high-speed rail to address some endogeneity concerns with regional spillovers. Our findings confirm the role of relatedness and geographical distance in the diffusion of economic capabilities and support the idea that improvements in transportation can facilitate the diffusion of productive capabilities.

\textbf{KEYWORDS}\neconomic development; industrial structure; economic complexity; spillovers; high-speed rail

\textbf{INTRODUCTION}\nThe pace and scale of China’s economic expansion has no historical precedent (Etzioni et al., 2012; Felipe et al., 2013; Song et al., 2011; Zhu, 2012). Between 1990 and 2015, China’s overall gross domestic product (GDP) grew by a factor of 30, from less than US$400 billion in 1990 to more than US$10 trillion in 2015, and its GDP per capita (purchasing power parity – PPP) increased by a factor of nearly 10 (from US$1,516 in 1990 to more than US$13,400 in 2015). But what explains China’s remarkable economic success? Here, the literature provides multiple answers, from the advantages of backwardness (Gerschenkron, 1962), to government policies (Amsden, 1992; Evans, 2012; Leftwich, 1995; Lin et al., 2005; Wade, 2004), economic reforms (Lin et al., 2003), financial development (Laubach & Swanson, 2003) and institutional change (Qian, 2001).

What is also evident from the data is that China’s expansion relied on the export of products that were unusually sophisticated for its income level (Hidalgo & Hausmann, 2009; Lin, 2012). Rodrik (2006) estimated the level of sophistication of China’s exports by calculating the average income per capita of countries exporting the same products. He showed that even in 1992, when China’s GDP per capita at PPP and constant prices was US$1,844, its exports were associated with an average level of income of about US$13,500 (China’s GDP per capita in 2015). Rodrik argued that this high level of export sophistication drove China’s great economic expansion, a finding that is supported by the literature on
Multidimensional economic complexity and inclusive green growth

Viktor Stojkoski1,2, Philipp Koch1,3 & César A. Hidalgo1,4,5,6

To achieve inclusive green growth, countries need to consider a multiplicity of economic, social, and environmental factors. These are often captured by metrics of economic complexity derived from the geography of trade, thus missing key information on innovative activities. To bridge this gap, we combine trade data with data on patent applications and research publications to build models that significantly and robustly improve the ability of economic complexity metrics to explain international variations in inclusive green growth. We show that measures of complexity built on trade and patent data combine to explain future economic growth and income inequality and that countries that score high in all three metrics tend to exhibit lower emission intensities. These findings illustrate how the geography of trade, technology, and research combine to explain inclusive green growth.
The policy implications of economic complexity

César A. Hidalgo

1 Introduction

In less than two decades, economic complexity has grown from a handful of papers into an active field of research (Hidalgo, 2013). Today, scholars and practitioners use economic complexity methods to explain variations in diversification patterns (Diamantopoulos et al., 2012; Hidalgo et al., 2009; Jeng, Grimmer, et al., 2011; Yeoh et al., 2010; Yeoh et al., 2011; Yeoh et al., 2011; Yeoh et al., 2011; Yeoh et al., 2011). Economic growth (Chavez et al., 2016; Dejnarattan, 2016; Dejnarattan, 2016; Dejnarattan, 2016) and relatedness (Dejnarattan, 2016) have received much attention. A relatedness (Dejnarattan, 2016) model (Dejnarattan, 2016) of economic growth (Chavez et al., 2016; Dejnarattan, 2016; Dejnarattan, 2016) has been proposed and tested in several countries (Dejnarattan, 2016; Dejnarattan, 2016; Dejnarattan, 2016; Dejnarattan, 2016; Dejnarattan, 2016). Economic complexity is an interdisciplinary framework that explores how economic growth is achieved through the integration of knowledge and relatedness (Dejnarattan, 2016; Dejnarattan, 2016; Dejnarattan, 2016; Dejnarattan, 2016). The goal of this paper is to illustrate the potential of economic complexity to offer an interdisciplinary framework that integrates multiple approaches.

Before diving into the framework, we need to define economic complexity, both as an academic field and as a collection of methods. In brief, economic complexity is the use of network science and machine learning techniques to explain, predict, and advise changes in economic structures. The focus on economic structures is motivated by work showing that these structures explain and predict important macroeconomic outcomes, from economic growth to the intensity of greenhouse gas emissions and income inequality (see a recent review see Hidalgo et al., 2013). This work has helped formalize and explicative insights that have long been present in economic development, from Alexander Hamilton’s Report on Manufactures, a document advocating for the industrial development of the United States (Hamilton, 1791), to recent research on the importance of export structures in economic development (Hausmann et al., 2005; Inho and Winters, 2005; Rodrik, 2006; Saunders and Winters, 2006; Verrecchia and Puzels, 2005).

But economic complexity is also a peculiar field involving contributions from scholars from a wide range of disciplines. From the
The role of immigrants, emigrants and locals in the historical formation of European knowledge agglomerations

Philipp Koch a,1, Viktor Stojkoski a,1,5 and César A. Hidalgo a,1,5

ABSTRACT

Did migrants make Paris a ‘crèche for the arts’ and Vienna a beacon of classical music? Or was their rise a pure consequence of local activity? We use data on more than 22,000 historical individuals born between the years 1000 and 2000 to estimate the contribution of famous immigrants, emigrants and locals to the knowledge specializations of European regions. We find that the probability that a region develops or keeps specialization in an activity based on the birth of famous physicists, painters, etc. grows with both the presence of immigrants with knowledge about that activity and immigrants with knowledge in related activities. In contrast, we do not find robust evidence that the presence of locals with related knowledge explains entry and exit. We address some endogeneity concerns using fixed-effects models considering any location-specific factors (e.g., the presence of a university attracting scientists).

KEYWORDS

migrant knowledge spillovers; research; economic history; economic complexity

1. INTRODUCTION

Migrants help carry knowledge across space (Cipolla, 1972; Kerr et al., 2017; Li, 2018; Töpfer & Mager, 2013; Williams, 2006), shaping the geography of cultural and economic activities (Cipolla, 1972; Stojkoski et al., 2015; Miguel & Morrison, 2002; Morrison, 2003; Nettke et al., 2018; Putnam & Weil, 1998). But most studies documenting the role of migrants in the diffusion of knowledge use recent data on patents (Barba & Bosch, 2020; Benes et al., 2022; Bozetti et al., 2015; Burgos et al., 2017; Fussell et al., 2012; Hart & Glattfelden, 2011; Miguel & Morrison, 2002; Miguel & Neumark, 2013, 2015; research (Bozetti et al., 2015; Töpfer, 2013) on product exports (Barba & Rapoport, 2010) on art historical spillovers within activities (Bosch, 2012; Bosic et al., 2003; Collins, 1974; Dicarlo et al., 2015; Gaggioli, 2015; Hornung, 2014; M. Moore, 2014; Sozzi, 1953a, 1953b; Walde, 2013, 2012), leaving questions about the role of migrants in the historical formation of knowledge agglomerations relatively unexplored.

To explore the role of migrants in the historical formation of knowledge agglomerations, we use biographical data on more than 22,000 famous individuals—artists, physicists, explorers, philosophers, etc. living in Europe between the years 1000 and 2000. We use these data to investigate how immigrants, emigrants and locals explain the probability that famous individuals specialized in an activity that was not yet present in a region. We study how the knowledge of migrants and local contributors to explain, for example, Paris becoming the birthplace of painters and Vienna of composers.

We can explore these questions by creating measures of knowledge spillovers within and between locations and activities. Consider spillovers across locations within the same activity. The knowledge that migrants carry across borders may impact a location's ability to give birth to famous figures in the activity that the migrants specialize in. That is, immigrant mathematicians may increase the number of places...
Features derived from famous biographies:
- Place of birth/death
- Migration
- Occupation
- Historical importance
- Diversity of occupations
- Average age

Dimensionality reduction techniques:
- Singular value decomposition
- Economic complexity

C

Machine learning (Elastic Net)

D
Country-level GDP per capita estimates

E
Regional GDP per capita estimates

1300

1750

North Am.
(East Co.)
The Growth, Geography, and Implications of Trade in Digital Products

A. Physical trade

B. Digital trade

Change in ECI due to digital trade

Change in trade balance (in USD)

- Digital + physical trade
- Physical trade
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Why people judge humans differently from machines: The role of perceived agency and experience

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Abstract—People are known to judge artificial intelligence using a utilitarian moral philosophy and humans using a more moral philosophy emphasizing perceived intentions. But why do people judge humans and machines differently? Psychology suggests that people may have different moral perception models of humans and machines, and thus, will treat human-like robots more similarly to the way they treat humans. Here we present a randomized experiment where we manipulated people's perception of machine agency (e.g., ability to plan, act and experience, and ability to fail) to explore whether people judge machines that are perceived to be more similar to humans along these two dimensions more similarly to the way they judge humans. We find that people's judgments of machines become more similar to that of humans when they perceive machines as having more agency but not more experience. Our findings indicate that people's use of different moral philosophies to judge humans and machines can be explained by a progression of moral perception models where the perception of agency places a dominant role. These findings add to the body of evidence suggesting that people's judgment of machines becomes more similar to that of humans involving further work on dimensions modulating people's judgment of human and machine actions.

I. INTRODUCTION

Do people judge human and machine actions equally? Recent empirical studies support this is not the case. In fact, several studies have shown that people make strong differences when judging human and machines.

Consider the recent experiments from Malle et al. (2015) asking people to judge a trolley problem [10, 15]. In a trolley problem, people can pull a lever to divert an out-of-control trolley sacrificing a few people to save many. Malle et al. (2015) found that people expected robots to pull the lever and act utilitarian (sacrifice one person to save four) compared to humans (which were not judged as severely for not pulling the lever) [12]. This idea was expanded by [14], Using a set of over 80 randomized experiments comparing people's reactions to the actions of humans and machines, the authors concluded that people judge humans and machines using different moral philosophies: a consequentialist philosophy (focused on outcomes) for machines and a more moral philosophy focused more on intention when it comes to humans. Why do people differ in moral philosophies to judge humans and machines? Psychology suggests that people may perceive the minds of machines and humans differently [8, 11], and therefore, may treat more human-like robots more similarly to the way they treat humans [9]. This idea is related to various experiments where robots were endowed with human-like characteristics [19, 27, 28, 22, 28, 29, 25], For instance, Power and Petre (2006) used a robot with tunable chin length and tone of voice to explore the connection between the robot's appearance and its perceived personality [24]. Weyns et al. (2014) compared anthropomorphized and non-anthropomorphized self-driving cars to show that people treat the anthropomorphized self-driving cars more [27]. Malle et al. (2014) explored the impact of a robot's appearance in people's judgment of moral actions (trolley problem), finding that people judge more human-like robots more similarly to the way they judge humans [22]. Yet, these experiments did not provide an explicit quantitative moral perception model explaining people's judgment of more and less human-like machines.

Here we explore how perceived agency and experience, two key dimensions of moral perception [11], affect people's judgments of machines. Agency is related to an agent's ability to plan (e.g., to create a strategy for action that considers potential consequences) and to act (e.g., the capacity to affect or control the immediate environment). Thus, agency is related to moral responsibility for performed actions (higher agency, higher expected responsibility) [17]. Experience, in the context of this paper, is used to describe the ability to feel (e.g., the ability to experience sensations such as pain, sadness, guilt, or anger). It is, thus, related to the concept of moral status (not to be confused with the idea of expertise) and to the right of an agent to be treated with dignity. These two dimensions represent a basic mind perception model that has been used previously to explain the cognition and behavior of alters using representations of their perceived mental abilities [3, 6, 7, 39, 11]. Usually, mind perception models involve low dimensional representations of an alter's characteristics, such as the warmth and competence model used to explain stereotypes [3]. That model, for instance, says that people tend to protect those high in warmth and low in competence (e.g., babies) but fear those high in competence and low in warmth (e.g., killer robots).
11. Create a Constituent Assembly to pass to the Sixth Republic

14. Increase number of doctors in rural underserved areas
The Infinite Alphabet
and the laws of knowledge

(signed January 2023, due Dec 2024)
What makes the study of knowledge difficult is the fact that it is non-interchangeable, or non-fungible (e.g. you cannot replace a pianist with a surgeon).

Non-fungibility limits factor mobility among sectors, and the use of aggregation in its analysis.
The Infinite Alphabet

Book Structure:

The book is organized around three parts focused on three principles (laws) governing:

1. The growth (& decay) of knowledge (time).
2. The diffusion of knowledge (space).
3. The valuation of knowledge (value).
The Infinite Alphabet

Part I

During the twentieth century the study of knowledge focused on learning curves which explore the accumulation of knowledge in a narrow domain.

Leon Thurstone’s 1919 PhD Thesis on individual learning curves

Theodore Wright’s 1935 article on the cost of manufacturing airframes

Rapping 1965 Liberty Ships study

Learning curve of cost as a function of volume
The Infinite Alphabet

Part I

With the introduction of Moore’s law in 1965, the study of knowledge moved from learning to experience curves, the latter describing the growth of knowledge at the industry scale. Later, this provided room for the creation of theories of disruptive innovation.
The Infinite Alphabet

Part I

More recently we started making progress on the understanding of forgetting, describing the decay of knowledge.
Late in the 20th century people began studying the spatial diffusion of knowledge, using mostly patent citations. But again, the focus remained on narrow domains (where non-fungibility plays a limited role).
In the 21st century the use of big data and network science tools helped us map patterns of relatedness, and study the intricate and non-trivial networks of intersector factor mobility. This was finally a way to incorporate non-fungibility into the literature.
This led to the development of economic complexity metrics, which can take non-fungibility into account by using matrix factorization techniques to measure the value of geographic concentrations of knowledge. These metrics explain future economic growth, inequality, and emissions, among other things.
The Infinite Alphabet

Understanding the laws of knowledge is important because the world is no stranger to multiple failed attempts to engineer cities of knowledge. Attempts that blatantly ignore these principles.
The book is written by matching biographical stories on the scientists, inventors, and entrepreneurs illustrating key parts of these principles, with the academic literature that validates each of these principles.