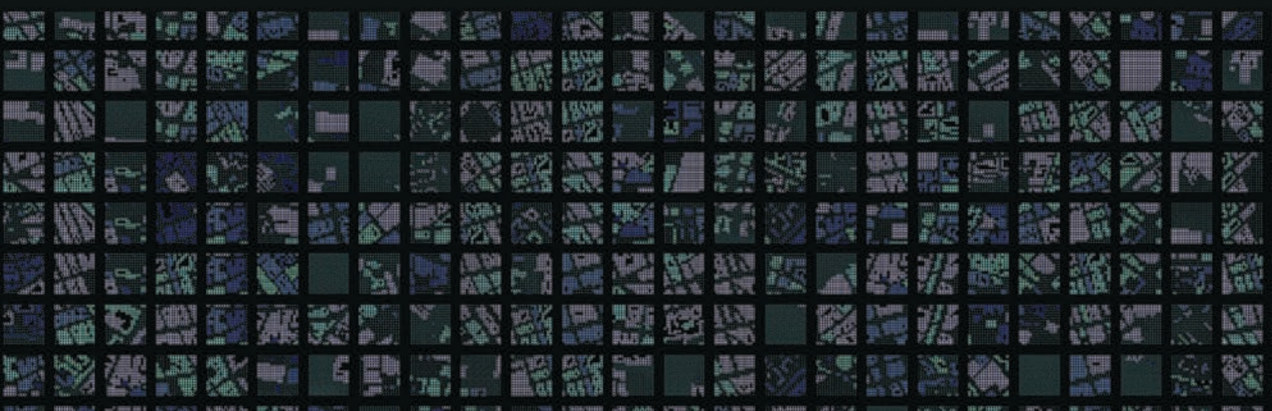
Edited by Silvio Carta

Machine Learning and the City

Applications in Architecture and Urban Design



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For Emma and Oliver
and, in memoriam, Agnese

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Preface

This book stems from the curiosity I have gradually developed over the past 10 years in data science and computational design, and the growing optimism with which I have been approaching this subject.

I grew up studying engineering, modern architecture, and architectural theory, and I've come to appreciate the intersection of functional architecture with the importance of ideas and ideology as driving forces in design. As someone who has always considered the social and human aspect of architecture before the seductive power of the form, and who has learnt to value the importance of the architecture of the 'guts' over the architecture of the 'brain', I approached formal methods in architecture and, later, computational design with scepticism. However, thanks to several influential colleagues I've had the fortune of meeting during my professional life, I learnt to appreciate the beauty of complexity, order, and logic; the elegance of certain mathematical models; and the satisfying feeling of finding elegant solutions to difficult problems. The more I worked in the field of computational design, the more my scepticism faded, leaving room for what I initially mistook for scientific indifference, but which later became enthusiasm and passion for rigorous logic processes (and computers) later on.

My epiphany was probably when I realised that computation can be used for more than just representing design ideas and the simplification of complicated design tasks. I realised that computation can be used to discover new knowledge, uncover hidden aspects of life, and create new things that can improve people's lives. This may seem obvious to readers with a background in mathematics, statistics, and computer science in general, but as architects and designers, our domain knowledge varies between the humanities (history of architecture or philosophy) and engineering (structural design, health and safety, or building performance). It is not uncommon for people to fall into either extreme of this spectrum, often favouring a nondeterministic view of the world.

I discovered that, by having a greater understanding of data and the techniques to manipulate them in my design, my control over the entire process and the outcome improved significantly. Machine learning (ML) methods (and the data wrangling that underpins them) in particular make the entire design process, from conception to execution, more open, transparent, and logically justifiable at any point.

I like to think of ML (and any other computational method in general) as a good colleague. To make the most of them, you must spend some time with them, trying to understand what they are good at and their limitations. You will soon learn when to ask for their help and for what task. Once you know them well enough, you will be able to reasonably guess how they think and operate, and why they come up with a certain solution. Since you understand your colleague's thought process, one can contextualise their choices and recognise when they are useful to your objectives. Simply put, if you understand them well enough, you can rely on them for those parts of your project that are difficult, laborious, or tedious. One can ask them to do the heavy lifting for you, such as handling extremely complex calculations and to suggest how to move forward when the project reaches an impasse. Your colleague can assist by providing intelligence and granular details as needed, they can find correlations between parts of the project that one has not considered, and they can expose new sides of the problem. Finally, they can generate multiple options and scenarios for you to evaluate and test; they can compare these projections based on relevant criteria and assist one in selecting the best design.

If such a colleague sounds a great asset to your design team, it is crucial to remember the importance of getting to know them well, understanding how they work, think, and the rationale behind their suggestions. Otherwise, ML and artificial intelligence (AI) will remain obscure yet fascinating presences around your work.

This book is intended to assist with this task: getting to know your powerful colleague. I honestly hope you will enjoy it as much as I do.

London, June 2021

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This work has taken about two and half years to be completed. During this time, I have contacted and interacted with many interesting colleagues, researchers, and designers who generously offered their time, ideas, and contribution. I am extremely grateful to all contributors who kindly sent me their work and helped shape this ambitious project. As this book includes a large number of contributors, I am sure the reader would understand if I do not mention them all here. I also thank those contributors who took a bit longer than I initially hoped for to get back to me. To those, please accept my apologies for my gentle nudges that, in some extreme cases, have bordered on pestering. I am extremely glad that we eventually succeeded in having all contributions in time and in good order.

I would like to thank those who spent their time in reading drafts of certain parts of this work, providing insightful comments and great suggestions. In particular, I am grateful to Daniel Polani, David Leite Viana, Ian W. Owen, and Constantine Sandis.

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The idea for this book originated during some long and fruitful lunch breaks over the past few years with Alessio Malizia who, without probably realising it, nurtured my interest in data science and their human facets.

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Introduction

ML between Routines and Wonder

In recent years, the term machine learning (ML) has been increasingly used in many scientific fields and communication outlets to describe automated processes where computers can make relatively autonomous decisions. On the one hand, there are those who use (and have been using for many years now) ML routinely as part of their job (whether in computer science, finance, physics, astronomy, medical science, statistics etc.). These individuals generally have a solid understanding of both the potentialities and limits of this form of automation. The users of ML chiefly employ it as one of many tools in their skillset to solve the given problems (for example, genome sequencing, predicting market shares etc.). On the other hand, there are people who have a limited understanding of what ML actually is and how it works. For these people, an automation process is where a machine is able to make decisions independently. This often generates wonder as well as concern. ML can be associated with an incredible technological advancement, where tedious, repetitive or very complex human tasks can be assigned to computers that can easily resolve them with a level of speed and efficiency that humans can probably never achieve. When decisions are devolved to programmed automated systems (i.e. computers), it is almost logical to consider the possible implications of such choices. Computers have no responsibility (certainly not in social, ethical or legal terms), no ideological (or political) intent, no regrets and no guilt. From this perspective, it is not difficult to associate deciding machines with dystopian narratives where computers will eventually replace human jobs, making ruthless decisions without considering the social and human context that we normally include in such processes and, in the most pessimistic versions of this narrative, machines replacing humans as they will be deemed somewhat obsolete.

Between these two extreme positions (the daily users of ML and non-experts), lies probably the majority of people who use ML every day without even realising it and who have a general interest in intelligent systems with no real strong opinion about it. One of the underlining arguments of this book is in fact that ML has permeated many of our daily activities and routines already. Some are quite evident (think of the prediction methods used in stock exchanges around the world) and some others are more subtle, running in the background of our lives (for example, the standard predictive text that we have on our phones or the spam filters in our email software).

This book has been designed with this large category in mind, specifically people who would like to know more about ML, to understand the mechanisms by which it works and, hopefully, to take a more proactive approach towards it. The goal is to provide the readers with a robust set of cultural, theoretical and technical coordinates to enable them to be able to understand and contextualise ML approaches, and –in a more active stance—to perhaps start using ML in their work.

Why machine learning?

Artificial intelligence is a large area of research where scientists are trying to design intelligent systems that are able to make decisions independently. In order to decide autonomously, a machine needs to learn and create new links between the data through inference, association, correlation and classification. Computers need to learn from the existing data in order to predict new data and to be able to compute the best solution when more options are available.

Machine learning is the combination of several models and techniques that are based on probability theory, statistics, data science and, on a higher level, applied mathematics. It is these domains that make the computers' decisions possible. Given enough training data, a computer can learn to recognise patterns in the numbers and shapes, as well as in the resulting trends and behaviours. Unlike data mining, where patterns are discovered in the existing data, through machine learning, new information can be both found and predicted.

By having a clearer and deeper understanding of such models and techniques, designers can directly see what determines a choice in an intelligent system. This becomes particularly true in the case of complex systems like cities. The management and control of cities are increasingly characterised by a vast infrastructure of interconnected devices. This requires architects, urban designers and planners to use and design tools that are intelligent in order to handle the growing urban complexity. Machine learning can be increasingly considered the backbone of urban intelligent systems (any system controlled by interconnected machines where a degree of AI is present).

A few initial points

Before going into the details present in this book, it is important to establish a few anchor points that will help to contextualise and understand the role and importance of ML in its multiple applications.

ML is not new. As mentioned several times in this book, the term machine learning was popularised by the computer scientist Arthur Samuel at the end of the 1950s as a way to programme computers to self-learn (in one of the very first applications, this was in order to play checkers). Today ML is widely still associated with computer programming, data science and artificial intelligence (AI). However, it is important to consider that most of the principles underpinning the ML techniques that we use today have their origin in mathematics and statistics. Algorithms like linear regression (one of the simplest ML methods in any textbook) is a direct application of a statistics principle. Put simply, most of the algorithms used in ML are the direct application of statistical methods (Wilmott's Chapter 10 clarifies this point). Samuel may have initiated ML as we know it today, but some of the methods used have a significantly longer history in mathematics and statistics. For example, linear regressions have been in use since the early nineteenth century by either Carl Friedrich Gauss or Adrien-Marie Legendre.

ML is about correlations. As we will see in the chapters that follow, computers are able to learn by finding relationships in the data. At the most basic level, a learning algorithm is a function through which a computer can calculate (and therefore predict) the value of a variable (or multiple variables) based on the given conditions. This is the case of, for example, a linear regression, where the function needs to determine a line that describes how the data points are distributed in a given space. Another basic example is a simple classification problem, where the function that we evaluate is a line (or curve or surface) that is able to separate points (in a two, three or n-dimensional space) more or less accurately in order to determine the groups following certain assigned criteria (more details provided in Chapters 9, 10 and 11). On a more sophisticated level, a ML algorithm is able to infer the rules that underpin the behaviour of a given phenomenon. This applies, for example, to neural networks. A helpful way to consider correlations is to remember the Data-Information-Knowledge-Wisdom (DIKW) pyramid. In this diagram, the learning occurs in the passage from the information (data organised in a meaningful manner) to knowledge (synthesised information that generates new ideas, concepts etc.).

Garbage In, Garbage Out. As new knowledge (learning) happens as the consequence of algorithms finding correlations in the data, it is important to stress the relevance of the initial data used in the learning process. The idea that the input data play a key role in the type of output that is obtained has been highlighted since the time of Charles Babbage: "[…] *if you put into the machine wrong figures, will the right answers come out?*" (Babbage 1864, p. 67). This idea will help when considering questions about algorithmic bias and unfairness, specifically in cases where the inputted data is not scrutinised and the bias is generally attributed to the way in which the algorithm has been designed. Another important facet of this question is the fact that humans need to prepare the input data in such a way that a computer can process them. As we will see in the following chapters, this puts significant stress on programmers (in a general sense, whoever uses a ML method) where the real phenomenon as perceived by humans need to be represented by data and their attributes (i.e. measurable properties) that are machine-readable.

Description and prediction. The data used in ML can be thought of as an abstraction of a given real phenomenon. The first challenge is to find the correct way to represent a phenomenon (for example, through a set of attributes and properties that will result useful in the subsequent stages of the learning process). We call this the analytical phase, where reality is represented by a number of selected elements. The second challenge is to be able to describe the phenomenon through a model, specifically a representation of the reality that is adequate for the expected results. This is usually called modelling. Once the reality is represented through an artificial system (the model), new data is inputted and the algorithm will process the new information. The outcome of this computation is a prediction of how reality will be with the new data. In short, the algorithm learns from a real scenario to predict a new one if and when certain conditions vary. In most cases, prediction is the main reason why ML methods are developed and applied. Accuracy in prediction is one of the measures used to evaluate how efficient algorithms and models are. The final step in this process is the prescription of how parameters should be changed in order to obtain the desired result.

Prediction Vs Generation. Machine learning approaches can be characterised and classified in many ways depending on their architecture, the data structure that they use, the algorithms that underpin them, the methods they use to classify and discriminate data etc. Some of the basic categorisations of the most common methods are presented in this book (Chapters 10 to 12). However, we would like to point out the important distinctions between the methods covered in this book. As mentioned, one of the key principles underpinning the learning of machines is the ability of an algorithm to divide data into groups (classes, categories, clusters etc.). In very simple terms, these algorithms establish a line (or curve or surface) among the points of a dataset, generating different groups. This line is called the decision boundary. In other words, these are discriminative models, where machines learn how to separate new data based on the experience (training) of a given initial dataset. As an alternative to discriminative models, there are generative models, where –oversimplifying– algorithms learn how the data are generated in probability terms. Because of that, generative models are able to create new data based on the joint probability distribution of the dataset (or, more precisely, new configurations of the data). Among the many examples contained in this book, one of the most promising techniques is perhaps Generative Adversarial Networks (GANs). The progress made by many researchers (Goodfellow et al. 2014, Karras et al. 2017 among others) in developing this architecture and related methods is particularly promising for architecture and design. Prediction techniques are very useful for designers to use as they can help them analyse and understand how cities (or architecture in general) perform and how they can be improved. However, generative models can also be used as part of the creative design process, alongside many other traditional skills and tools.

Not all training is learning. The fact that an algorithm can apply probabilistic methods to predict the distribution of a certain dataset does not necessarily imply that the outcome will be knowledge or even useful in any way. One of the classic examples is the case of overfitting. In over-simplified terms, this happens when the accuracy with which we look at an initial dataset (used for training) is too high and the algorithm is "too precise" when classifying the training set. It "too well". When the same model is then applied to a new dataset (representing a new case, a new possible scenario etc.), the algorithm is not able to predict the distribution of the new data. The same applies when the generalisation applied to the initial dataset is too high, as the model does not have enough information to be able to compute a satisfactory prediction using the new data. This is called underfitting. A working ML model should be able to predict a new data distribution by considering a sufficient level of generalisation, despite the existence of incomplete data in the training set (that is usually significantly smaller than the new dataset) and the noise that comes with it. In other words, a good model should have a good "fit". This is a measure that indicates how efficiently the model is able to approximate a target function (i.e. the method needed to solve the initial problem given). Adding an extra level of sophistication, in the case of neural networks the model needs to predict how the data pass through the different layers and which neuron (node in the network) is connected to the others. In the case of neural networks (NN), in addition to the training data and the target function, the model needs to also consider the precision of the outcome (prediction). This level of accuracy is computed through a metric called the loss function. The more the loss function is minimised, the better the predictions (the model makes fewer errors in the prediction) and the fitter the model. The loss function is usually represented by a curve that, in a good model, tends to flatten. This means that the model achieved good prediction results and is learning correctly. There are many variables that determine the success of the model. One of them is the learning rate at which the model makes predictions, which is the speed at which the model learns). If the learning rate is too high, then the model has not had enough time to learn. If it is too low, then the model will take a long time to compute useful results.

Accountability and responsibility. Once the ML model works in a satisfactory way, it predicts new knowledge that can be helpful to researchers and designers, enabling them to better understand existing phenomena as well as to imagine new scenarios. These predictions are as good as the data that has been inputted into the model and the design of the architecture of the model as a whole. A helpful analogy is to think of a ML model as a car. This can be more or less powerful, spacious and fast but this does not relate to the start and the end of the journey that people make with it. As cars have no bearing on how and why people use them, so do ML models and algorithms have no accountability as to what predictions are made as the output. This responsibility is with the people who design them, use them and with those who have generated, selected and prepared the data used. There are a growing number of studies that have sought to help designers and researchers understand the importance of the ethical use of data. We have included some of this key work in the last section of this book to provide you with a solid starting point for your own work.

ML and the City

Cities are probably the most complex and sophisticated manifestations of collective human life. They are the place where a plethora of social and cultural values, needs, ambitions, and a certain degree of freedom converge. Each city can be defined by its own organisational structure and degree of indeterminacy where tensions emerge and balances are struck between the human intention of providing and following rules and the natural human tendency towards flexibility, interpretation and individual expression. One of the main reasons behind the inherited complexity of cities is the diversity that people bring with them when cohabiting a territory. It is exactly this richness that makes cities attractive to an increasing number of people.

The study of urban complexity and the mechanisms that underpin cities is nothing new. Scientific approaches to urban contexts can be traced back to various disciplines from the history of architecture to social studies, and from planning to geography. This latter has probably made the biggest contribution to the development of urban studies with "*quantitative geography and urban modelling, digital mapping and geographic information systems, and in urban cybernetics theory and practice*" as explained by Kitchin (2016, p. 4). In the field of architecture and urban studies, the seminal work of Lionel March (geometry and the spatial organisation of the built environment), George Stiny and James Gips (shape grammar), Bill Hillier and Julienne Hanson (space syntax) and Michael Batty (urban modelling) carried out in the 1970s and 1980s, and, to a lesser extent, Christopher Alexander (1964's on the synthesis of form) comes to mind. Their work paved the way for many of todays' computational and mathematical approaches to architecture including formal methods in architecture (see Leite Viana, Morais and Vieira Vaz 2018), urban informatics (Foth 2008), city information modelling (see Stojanovski 2018), the mathematics of spatial configurations (see Ostwald 2011, Ostwald and Williams 2015, Ostwald and Dawes 2018), sense-able cities (see Ratti 2010), and the connected city (Neal 2012) to name but a few.

These approaches and theories can be considered further developments that go in a sort of linear direction, naturally branching off from the main directions suggested in the 1970s and 1980s. This book suggests that there has been a major breakthrough in this development that has the potential to yield radical changes in the way that we understand and design cities and their complexities. We argue that the introduction of data science, ML approaches and, generalising, AI to urban studies and design can have a significant impact on cities in the coming years. It is true that urban complexities cannot be entirely reduced to data, a process often called datafication (see Cukier and Mayer-Schoenberger 2014). It is more generally known as dataism (see Harari 2016) by journalists and cultural commentators. However, it is also true that many aspects of our lives, certainly those pertaining to urban life, can be sampled, modelled and predicted through the data that represents them. This is a long-established practice in statistics, physics, mathematics, astronomy, engineering and related fields. Within the context of this book, we consider data science and ML to be a plane intersecting all these fields, at least in disciplinary terms.

By looking at the city through the lens of the data that represent its complexity and richness, researchers and designers are in an advantaged position to filter the noise that usually characterises urban questions (anything from subjective perspectives to ideological or political views etc) in order to be able to focus on the essential aspects of an observed phenomenon. We can look at this through the analogy of a tree. The ability to generate models based on abstraction (data) allows the viewer to look past the leaves, flowers and birds resting on the tree (symbolising all the beautiful and interesting aspects of cities) to focus solely on the branches and their structure.

The most important aspect of the application of ML and AI to cities is the fact that filtering through the leaves, the focus on the branches and the abstraction of the essential elements of each phenomenon is done through and by computers. The algorithms that we have designed allow for a certain degree of autonomy when making decisions and drawing conclusions which eventually need to be evaluated. Their meaning needs to be assigned to them by humans. As we can extensively see in this book, computers and the logic by which they operate enhance the work of researchers and designers by offering new and powerful ways of observing cities inclusive of their complexities and indeterminacies. Designers are now offered a new skillset with which they can find correlations (and sometime causations) that were not visible before. They can predict how a scenario may work in the future under certain given conditions, and they can simulate, forecast and anticipate how cities will react to certain changes. In short, we can now scientifically and quantitatively see what we so far have only predicted and imagined using our intuition and qualitative interpretation of cities and urban questions.

Aims of this book

The resources available to designers and researchers who want to learn more about ML with the aim of integrating it into their work can be categorised into two groups. On the one hand, textbooks and technical literature offer information about the statistical and mathematical principles and techniques underpinning the use of ML for general purposes. They may be more oriented to computer science students and thus contain statistical models and relative functions. Alternatively, they may be intended for the general public including people interested in applied mathematics and statistics. The first group addresses the general audience of people interested in mathematics, statistics and computer programming, and it does not generally refer to design, architecture or urban questions. Designers who are interested in ML may find it challenging to appreciate the depth of such specialised resources without a background and/or previous training in data or computer science. On the other hand, there are publications within the field of the built environment, specifically architecture and urban design, where the emphasis is on projects, design tools and the final results. Within these categories, designers may also find relevant resources from city-related subjects including urban geography, urban sociology and urban studies. Most of these have extensively covered the impact of automation and new digital technologies for use in city. Designers accessing resources of this second group will most likely find it interesting and stimulating yet lacking the necessary information to move beyond a general understanding of the subject.

In short, technical publications on ML may be inaccessible without previous training on the subject. Analytical work on the impact of AI and ML on the city does not usually contain clear guidance on how to start working with ML methods.

This book has been designed to support designers and researchers in their access to ML and to provide them with clear references to further their studies and practice in this field.

We hope that, with this book, readers will be able to: i) understand the ideas and techniques underpinning ML, ii) to start using some ML techniques and to be able to read the existing projects at a deeper level (for example, understating the statistical model used and the logic behind a certain application), iii) to have a solid framework of references to further their studies, allowing them to discuss and analyse ML-related topics in other fields (architectural criticism, design history, social and urban studies) with a greater understanding of the subject and finally, iv) to have a greater appreciation of the impact of ML and AI to the contemporary city. This last point is twofold. Firstly, there is the technological perspective whereby this book aims to help readers understand how new technologies underpin smart cities and how informational systems work. Secondly, this work addresses the social dimension of ML. This is where readers will be able to further their understanding of the mechanisms through which ML works. Readers will be able to see how the programmers and designers involved in the process make decisions and assumptions, and how these have an impact on the ways in which the technology works and therefore how people live their lives within the urban context.

More generally, Machine Learning and the City Reader aims to first provide a clear timeline of the development of machine learning techniques and its relationship with AI, robotics and computing in general (Sections 1, 2 and 5). Secondly, this book tries to demystify some of the common ideas that ML and AI are obscure black-box technologies where one inputs data into a computer to gain new knowledge as an output without any degree of control (Sections 3 and 4). By doing this and providing a clear explanation of how ML works when it is applied to an urban scale, this book aims to increase the number of designers and researchers willing to engage with ML and AI in their work.

Structure of the book

This book is organised into 5 sections covering the origins of machine learning, the description of how a machine can think and learn, some of the technical aspects that underpin ML, its application in a city and, finally, the human dimension of ML and its consequences for urban design and the city. Each section couples theoretical and technical contributions written by key scholars in their field with concrete examples and projects by designers who employ ML methods as part of their working routines. The aim for each section is to provide authoritative references with a direct link to their application in the urban context and design in general. This enables any readers to be able to understand the use of ML approaches and their possible results in design using spatial and societal terms.

The first section "**Increasing urban complexity**" suggests a possible starting point for the use of ML and computational methods in general in the city. As the level of complexity of urban questions (from infrastructures to people's cultural diversity) increases and computer-operated technologies become increasingly more pervasive, designers and thinkers have had to integrate new methods into their work in order to be able to better understand the growing complexity. This section describes the gradual increase in complexity through the work of **Sean Hanna** (Bartlett School of Architecture, UCL) where he describes the intelligibility of cities and their urban complexity through patterns and scales. In Chapter 2, **Cassey Lee (**Institute of Southeast Asian Studies -ISEAS, Singapore) explains how these patterns emerge in complex systems and how this emergence links to the notion of universal computation. One of the most common representations of urban patterns (and patterns in complex systems in general) are fractals. In Chapter 3, **Pierre Frankhauser** (University of Franche-Comté) and **Denise Pumain** (University Paris Pantheon-Sorbonne) provide insight int fractals (as an automated way for urban structures to grow) and their development and relevance in spatial practices: "*The irregular and fragmented forms of relief or, urban patterns, the ramifications of hydrographic or transport systems, the hierarchized structures of the world's territories and city systems all have properties, and fractal analysis could propose new interpretations"* (Chapter 3). Two projects are associated with this section. In Project 1, **Ljubomir Jankovic** (University of Hertfordshire) provides an example of the computational methods applied to emergence and urban analysis, while **Nahid Mohajeri** (UCL) and **Agust Gudmundsson** (Royal Holloway University of London) illustrate a method used to analyse the evolution and complexity of urban street networks. The first section lays the important foundation for the syllogistic idea behind this book. The degree of complexity of cities today is increasing exponentially. If everything in nature (and therefore in cities) is computable (Wolfram 2002) and computation is cognition (Scheultz 2002), we can only understand the city today in its complexity through computation.

The second section "**Machines that think**" introduces the key concepts in Artificial Intelligence and Machine Learning. The starting point is **John McCarthy**'s text 'Artificial Intelligence, Logic and Formalizing Common Sense' (Chapter 4) where the initial distinctions are drawn between human and machine behaviours. Originally written in 1989, this chapter explains the importance of the relations between artificial intelligence (AI), mathematical logic and the formalisation of common-sense knowledge and reasoning. It also approaches the other problems of concern regarding both AI and philosophy, as well as formalised languages. Following on from this, 'Defining Artificial Intelligence' by **David B. Fogel** (Chapter 5) considers AI to be a field of scientific research and human progress. This chapter offers key descriptions and explanations of the methods that allow machines to "*improve themselves by learning from experience and to explain the fundamental theoretical and practical considerations of applying them to problems of machine learning*" (Chapter 5).

Next, **Shelly Fan** describes the passage from the initial enthusiasm for AI during the 1950s and 1960s to the ebbs and flows that have characterised the history of AI from the 1970s to date, including the AI winter (1970s), the 5th generation computer systems (1980s) and the Good Old-Fashioned Artificial Intelligence (1990s) through to the strong reliance on ML techniques in AI systems in the last 2 decades. Thanks to machine learning, AI systems have become increasingly more reliable and precise in their categorisation, clustering, decision-making and predictions. In her text *AI: from copy of human brain to independent learner* (Chapter 6), Fan elaborates on this crucial passage by explaining how AI has moved away from being designed as a copy of the human brain to gradually becoming a system programmed to learn independently. **Keith D. Foote**, in Chapter 7, describes the history of the use of ML in computing and its progress towards becoming AI. In his *The History of Machine Learning and Its Convergent Trajectory towards AI*, Foote describes and comments on several key definitions and moments in the history of ML ranging from what an algorithm is and the Hebb's Rule to the rise of the computer vision and advancements in Natural Language Processing (NLP). To conclude this part dedicated to the history and development of ML and AI, **Iyad Rahwan** (Massachusetts Institute of Technology, Cambridge, MA, USA and Max Planck Institute for Human Development, Berlin, Germany), **Manuel Cebrian** (MIT), Nick Obradovich (MIT), **Josh Bongard** (University of Vermont, Burlington, VT, USA), **Jean-François Bonnefon** (Toulouse School of Economics (TSM-R), CNRS, Université Toulouse Capitole, Toulouse, France), **Cynthia Breazeal** (MIT), **Jacob W. Crandall** (Brigham Young University, Provo, UT, USA), **Nicholas A. Christakis** (Yale University, New Haven, CT, USA), **Iain D. Couzin** (Max Planck Institute and University of Konstanz, Germany), **Matthew O. Jackson** (Stanford University, Stanford, CA, USA; Canadian Institute for Advanced Research, Toronto, Ontario, Canada and The Sante Fe Institute, Santa Fe, NM, USA), **Nicholas R. Jennings** (Imperial College London, London, UK), **Ece Kamar** (Microsoft Research, Redmond, WA, USA), **Isabel M. Kloumann** (Facebook AI, Facebook Inc, New York, NY, USA), **Hugo Larochelle** (Google Brain, Montreal, Québec, Canada), **David Lazer** (Northeastern University, Boston, MA, USA and Institute for Quantitative Social Science, Harvard University, Cambridge, MA, USA), **Richard McElreath** (Max Planck Institute, Leipzig, Germany and University of California, CA, USA), **Alan Mislove** (Northeastern University, Boston, MA, USA), **David C. Parkes**

(Harvard University, Cambridge, MA, USA), **Alex 'Sandy' Pentland** (Massachusetts Institute of Technology, Cambridge, MA, USA), **Margaret E. Roberts** (University of California, San Diego, San Diego, CA, USA), **Azim Shariff** (University of British Columbia, Vancouver, British Columbia, Canada), **Joshua B. Tenenbaum** (Massachusetts Institute of Technology, Cambridge, MA, USA), and **Michael Wellman** (University of Michigan, Ann Arbor, MI, USA) in Chapter 8, *Future development of ML – Machine Behaviour* provide a series of key points to understand the significant impact that ML has on intelligent systems and the Internet of Things (IoT). In this chapter, Rahwan and colleagues focus on the importance of understanding the behaviour of artificial intelligence systems in order for humans to be able to control their actions and behaviour, while "*reap*[ing] *their benefits and minimiz*[ing] *their harms*" (Chapter 8).

Section 2 includes 7 projects that introduce how ML and artificial intelligent systems can be applied in architecture and urban contexts. These include the works of Plan Generation from a Program Graph (Project 3) by **Ao Li**, **Runjia Tian**, **Xiaoshi Wang** and **Yueheng Lu** (Harvard GSD), Genetic Algorithms and Care Homes (Project 4) by **Silvio Carta, Tommaso Turchi**, **Stephanie St. Loe** (University of Hertfordshire) and **Joel Simon**, (Project 5) **Roberto Bottazzi** and **Tasos Varoudis** (Bartlett School of Architecture, UCL)' N2P2 - Neural Networks and Public Places, **Matias del Campo** and **Sandra Manninger** (SPAN)'s Project 6 on Urban Fictions: Lines, Surfaces and Quasi-Intelligent Machines and **Stanislas Chaillou** (Spacemaker AI)'s Latent Typologies. Architecture in Latent Space (Project 7), Enabling Alternative Architectures (Project 8) by **Nate Peters** (Harvard Graduate School of Design) and finally, Distant Readings of Architecture: A Machine View of the City (Project 9) by **Andrew Witt** (Certain Measures) are also included.

The third section "**How machines learn**" is dedicated to the description of the ways in which ML works from the computational, probabilistic, statistic and mathematical viewpoints. In Chapter 9, *What Is Machine Learning?*, **Jason Bell** introduces the key concepts of ML and basic examples of their application. In Chapter 10 *Mathematics for ML*, **Paul Wilmott** explains the key mathematical concepts including Principal Components Analysis (PCA), Maximum Likelihood Estimation (MLE), confusion matrix, cost functions, gradient descent, training, testing, validation and other fundamental notions that are recurrent in ML. In Chapter 11 *Machine Learning for Urban Computing* **Bilgeçağ Aydoğdu and Albert Ali Salah** (Utrecht University) explain how the methods introduced by Wilmott are applied in general terms, and to the city in particular. This chapter provides a second list of the key concepts in ML, including classification, artificial neural networks (ANNs), pattern discovery and clustering, and Bayesian approaches. In his *Autonomous Artificial Intelligent Agents* writing (Chapter 12), **Iaroslav Omelianenko** (NewGround) introduces the idea of Autonomous Artificial Intelligent Agents and how genetic algorithms can be designed and deployed in urban simulations. This section features four projects that illustrate how some of the techniques described can be applied in real design projects. **Sherif Tarabishy, Stamatios Psarras, Marcin Kosicki** and **Martha Tsigkari** (Foster and Partners) (Project 10) present the recent methods for Machine learning for spatial and visual connectivity. **Zhoutong Wang, Qianhui Liang, Fabio Duarte, Fan Zhang, Louis Charron, Lenna Johnsen, Bill Cai** and **Carlo Ratti** (MIT Senseable City Lab) describe their recent project: *Navigating indoor spaces using machine learning: train stations in Paris* (Project 11) This is where they used Deep Convolutional Neural Networks

(DCNN) using photographic images as the input. Project 12 describes the work of **Rolando Armas** (Shinshu University), **Hernán Aguirre** (Shinshu University)**, Fabio Daolio** (University of Stirling) and **Kiyoshi Tanaka** (Shinshu University): Evolutionary design optimization of traffic signals applied to Quito city, where evolutionary computation and machine learning methods are applied to analyse transportation systems. Finally, this section includes **Patrik Schumacher**'s (Zaha Hadid Architects) *Constructing Agency: Self-directed Robotic Environments* (Project 13), where architectural and human agents are modelled using a Unity game engine to design the "*densification and transformation of a North London urban district into a creative industry hub via four incubator projects elaborated by four design teams working in parallel and with mutual awareness*" (Project 13).

The fourth section "**Application to the city**" describes how ML can be applied to urban projects in both analytical and design approaches. In Chapter 13, **Martin Dodge** (University of Manchester) and **Rob Kitchin** (National University of Ireland) introduce the notions of code/space and the transduction of space. These are two key concepts elaborated on within human and urban geography that are of relevance when seeking to understand how cities can be analysed in their growing complexity. Partially based on the idea of the transduction of space (Mackenzie 2002), code/space revolves around the analysis of the mutual relationships between software (code) and space (both physical and digital). This notion is considered to be key when it comes to understanding how new models of space and cities can be generated through computing and, more specifically, ML. **Mark Graham** (Oxford Internet Institute), **Matthew Zook** and **Andrew Boulton** (University of Kentucky) continue in Chapter 14 to explain the importance of the virtual aspects of urban spaces. Through an analysis of digital augmentations, they explore the ways in which our everyday lived geographies are changing. In Chapter 15, **Marcus Foth, Fahame Emamjome**, **Peta Mitchell** and **Markus Rittenbruch** (Queensland University of Technology) discuss the importance of urban analytics in: *Spatial Data in Urban Informatics: Contentions of the Software-Sorted City*. They generalise the idea of urban informatics, where intelligent systems, powered by IoT, ML and AI can provide new ways of designing, monitoring and living in the city. The chapters that follow in this section introduce the concrete applications of the approaches and methods explained so far. **Vahid Moosavi** (ETH) in Chapter 16 provides a clear example of how deep learning can be applied at the city level. **Snoweria Zhang** and **Luc Wilson** (KPF Urban Interface) (Chapter 17) present some recent computational approaches developed for large-scale urban projects in Computational Urban Design: Methods and Case Studies. **Diana Alvarez Marin** (ETH) presents her work *Indexical Cities*. Personal city models with data as the infrastructure (Chapter 18), shows how she investigated the methods used to infer the intrinsic characteristics of cities. In Chapter 19, *Machine Learning, Artificial Intelligence, and Urban Assemblages*, **Serjoscha Düring** (Austrian Institute of Technology AIT), **Reinhard Koenig** (*Austrian Institute of Technology AIT, Austria and Bauhaus-University Weimar, Germany*), **Nariddh Khean, Diellza Elshani, Theodoros Galanos, Angelos Chronis** (Austrian Institute of Technology AIT) discuss the importance of computation in data-driven projects and analytics. In particular, they present their recent work on "*generative methods for urban spatial configurations that integrate a number of different simulation engines, along with InFraRed, into one framework* [to] *quickly explore thousands of urban design alternatives by generating a diverse and informative design and performance dataset*"

(Chapter 19). Finally, in Chapter 20 *Machine Learning and Design Fiction* **Franziska Pilling, Haider Ali Akmal, Joseph Lindley** and **Paul Coulton** (Lancaster University) explain how AI and ML methods are used to "explore transparency around human-AI cohabitation in an urban environment" as a part of Lancaster City Council's AI for Lancaster programme. Section III includes ten projects that, taken as a sample, represent the current state-of-the-art regarding the application of ML methods to the city. Project 14 (*A Tale of Many Cities: Universal Patterns in Human Urban Mobility*) by **Anastasios Noulas** (University of Cambridge), **Salvatore Scellato** (University of Cambridge), **Renaud Lambiotte** (Université Catholique de Louvain), **Massimiliano Pontil** (UCL) and **Cecilia Mascolo** (University of Cambridge), and Project 15 by **Gwo-Jiun Horng** (Southern Taiwan University of Science and Technology) (Using Cellular Automata for Parking Recommendations in Smart Environments) illustrate how these techniques are used to address practical urban problems like urban mobility and circulation. A number of projects showcase how neural networks are employed to analyse urban conditions, to generate new urban forms and to transform existing topologies. These include **Sean Wallish**'s (University of British Columbia) *Gan Hadid* (Project 16), **Elizabeth Christoforetti** and **Romy El Sayah**'s (GSD Harvard) *Collective Design for Collective Living* (Project 17), **Erik Swahn**'s (KTH School of Architecture in Stockholm) *Architectural Machine Translation* (Project 18), **Jose Luis García del Castillo y López**'s (Harvard GSD) Project 20: *Style transfer/Boston landscape*, **Benjamin Ennemoser**'s (University of Texas A&M, USA)'s *ML-City* (Project 21), and Project 22 *GAN-Loci* by **Kyle Steinfeld** (UC Berkeley). In Project 19 **Hui Wang** (School of Architecture, Tsinghua University), **Elisabete A Silva** (Department of Land Economy, University of Cambridge) and **Lun Liu** (School of Government, Peking University) demonstrate their method that was used to evaluate large-scale areas and urban street views using deep learning-based models. Finally, **Iacopo Testi** (Rhea Group and Urban AI) presents his project *Urban Forestry Science* (Project 23), where he developed a method based on convolutional neural networks (CNN) to analyse urban forestry in Madrid, Spain.

While the use of ML in intelligent systems may suggest new and promising urban futures, it also includes some inevitable degree of uncontrolled effects for both people and the built environment that they live in. The fifth section **ML and Humans** offers a discussion about some of the less direct aspects that are inherited with any algorithmic approach that require a certain level of awareness and control, specifically when focusing on the human-machine relationship. This discussion starts with the seminal work that Danah Boyd and Kate Crawford carried out asking critical questions about the use of data (see, for example, Boyd and Kate Crawford 2012). Building on their work, in Chapter 21 *Ten Simple Rules for Responsible Big Data Research*, **Matthew Zook** (University of Kentucky), **Solon Barocas** (Microsoft Research), **Danah Boyd** (Microsoft Research), **Kate Crawford** (Microsoft Research), **Emily Keller** (Data & Society, New York), **Seeta Peña Gangadharan** (London School of Economics), **Alyssa Goodman** (Harvard University), **Rachelle Hollander** (National Academy of Engineering, Washington), **Barbara A. Koenig** (University of California-San Francisco), **Jacob Metcalf** (Ethical Resolve, Santa Cruz), **Arvind Narayanan** (Princeton University), **Alondra Nelson** (Columbia University) **and Frank Pasquale** (University of Maryland) provide a set of recommendations that can be helpful to any researcher and designer working with data and people. In Chapter 22 *A Unified*

Framework of Five Principles for AI in Society, **Luciano Floridi** (University of Oxford) and **Josh Cowls** (Alan Turing Institute) provide a set of ethical principles used for the adoption of AI (and ML) that all designers and researchers should consider in their work. If the conscious use of data is the key to improving the quality of our projects, it is equally important to be aware of the consequences of potential digital inequalities. **Matthew T. McCarthy** (University of Wisconsin-Milwaukee) explores the notion of algorithmic divide in Chapter 23 by highlighting possible "*complications relating to identity, social sorting, use, agency, and global development that are inextricably related to the issues above and to the study of big data*" (Chapter 23). Having set out some of the useful principles that we should all consider when working with data and people, we introduce some of the key concepts and strategies that may help to move the discussion around data and ML forward. The last part of this section is dedicated to the future of ML and, by extension, the future of the urban environment based on it. **Julian Bleecker** (Near Future Laboratory) in Chapter 24 discusses his idea of Design Fiction as a way to generate future scenarios in design, science, fact and fiction. Bleeker's work on Design Fiction is increasingly used by designers as a successful strategy to explore the possible consequences (both in a positive and negative light) of technology for people. Bleecker's work explains how design fiction can be used to influence the general public's understanding or expectations about new technology, thus providing this technique with an active design role. We then introduce an extreme position where the development of intelligent systems and AI may reach a point in the future when the current balance of human-machine is completely altered. In Chapter 25 *Superintelligence and Singularity*, **Ray Kurzweil** (Google) discusses this perspective, introducing a future where we will witness a "*merger of our biological thinking and existence with our technology, resulting in a world that is still human but that transcends our biological roots*" (Chapter 25). Finally, in Chapter 26, **Vincent J. Del Casino Jr** (San José State University), **Lily House-Peters** (California State University), **Jeremy W. Crampton** (University of Kentucky) and **Hannes Gerhardt** (University of West Georgia) examine one of the physical embodiments of AI: robots and their relationship with people (both designers and users), in a reflection on new social geographies. Although not specifically covered in this book, robots offer an interesting point of connection between human and machines, where ML and AI may have a closer encounter with humans. The last section includes 5 projects that embody some of the principles set out in the chapters. Project 24 *Experiments in Synthetic Data* by **Forensic Architecture** illustrates how ML can be used in open source investigations to deal with incomplete or challenging datasets. In Project 25 *Emotional AI in Cities: Cross Cultural Lessons from UK and Japan on Designing for An Ethical Life*, **The Emotional AI Lab –Vian Bakir** (Bangor University, UK), **Nader Ghotbi** (Ritsumeikan Asia Pacific University, Japan), **Tung Manh Ho** (Ritsumeikan Asia Pacific University, Japan), **Alexander Laffer** (Bangor University, **Peter Mantello** (Ritsumeikan Asia Pacific University, Japan), **Andrew McStay**, (Bangor University, UK), **Diana Miranda** (University of Stirling), **Hiroshi Miyashita** (Chuo University, Japan), **Lena Podoletz** (University of Edinburgh, UK), **Hiromi Tanaka** (Meiji University, Japan), **Lachlan Urquhart** (University of Edinburgh, UK)**–** showcase their approach to emotional AI where they "*explore how we may best live with technologies that pertain to sense, profile, learn and interact with people's feelings, emotions and moods*" (Project 25). In Project 26 *Decoding Urban Inequality* **Kadeem Khan** (Facebook) explains how ML methods can be used to serve noble purposes like providing useful insights on spatial inequality in cities like Nairobi, Kenya.

The last 2 projects show how design fiction can be used to examine possible scenarios. In Project 27, **Maria Luce Lupetti** (TU Delft) presents her work on *Amsterdam 2040*. This is a fictional future scenario that illustrates design fiction methods in action. **Jason Shun Wong** (Project 28) also presents his work *Committee of Infrastructure* where there is a fictional Los Angeles city council meeting where people need to address "*issue of agency, representation, and intention within the domain of machine learning and artificial intelligence* (AI)" (Project 28).

What is next?

This book collects some of the key texts and projects that represent the current use of computational methods in architecture and urban design with a specific focus on ML. This is underpinned by a growing level of interest in the application of not only computer science and digital technologies but data science as well. It is, in fact, becoming increasingly apparent that in order to use these new technologies and methods, designers and researchers need to become familiar with some of the fundamentals of the scientific approaches to data. In the 1990s and 2000s architects concentrated on the discovery and testing of new technologies (new 3D modelling and parametric software and CAD/CAM technologies for example) and their potentiality for architecture and cities. It was the time of form-finding and the first establishment of parametric architecture. In the 2010s, it became clear to designers that more of an understanding of the nature of data is needed. A number of architects and designers are increasingly characterised by a hybrid profile where the spatial practice of architecture is combined with data science and a deeper understanding of how the data should be used, analysed and read. Computational design is a growing discipline and this is evident in the number of new academic and training courses that include computation in their curriculum around the world, in the number of large and small architectural practices that have a computational branch (this extends to the AEC industry at large), and in the interest of individuals that want to include computational methods in their skillset. Fast-forward to 10 - 20 years from now, it is not difficult to imagine that data science and computational methods may be part of architectural training and the expertise of designers (Carta 2020). We hope that this book, with its insightful contributions from world-leading researchers and designers, will help all those who want to increase their understanding and knowledge of ML and AI and start using some of the techniques in their own work.

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