Machine Learning in VLSI Computer-Aided Design
To Shaza, Adam, Ella, and Lily

Abe

To Peggy, Will, and Tom

Duane

To Karen and Thomas

Xin

Tell me and I forget.
Teach me and I remember.
Involve me and I learn.

Ben Franklin
As an active branch of applied computer science, the field of VLSI computer-aided
design (VLSI CAD) has always been at the technological forefront in incorporating
cutting-edge algorithms in the software tools and methodologies that electronics
engineers have used to weave the digital fabric of our world.

This book amply demonstrates that in line with its historical track record, VLSI
CAD has also been at the leading edge in making good use of machine-learning
technologies to further automate the design, verification, and implementation of the
most advanced chips.

Machine learning and VLSI CAD have in common several main characteristics
that may have greatly facilitated their interlock. The first is that they are both
consumers of Big Data. In fact, Moore’s law has essentially guaranteed that chip
data grow exponentially big to the point that having tens of billions of transistors in
a chip is now so common and almost taken for granted. The second characteristic
that they have in common is a structured approach for controlling complexity. In
machine learning, this approach is most apparent in the use of layered networks
as inference and generalization engines. In VLSI CAD, complexity is controlled
through a well-defined abstraction hierarchy, going from the transistor and its
technology as raw data to the chip architecture as a model of processing and
computation. The third common characteristic of the two fields is their focus on
computational efficiency, be it to shorten turn-around time in chip design, as is the
case in VLSI CAD, or to promptly detect patterns in time series as is the case
in mission-critical cloud analytics. The fourth common characteristic is a focus
on automated optimization and synthesis that VLSI CAD has spearheaded, and
synthesis is now becoming an important trend for the design of neural networks
in machine learning as well.

It is therefore almost natural to think of VLSI CAD engineers as the original
data scientists who have been instrumental not only in dealing with big data in the
context of chip design but also in enabling the very chips that have ushered the Big
Data era and made it a social and business reality.

The various chapters of this timely and comprehensive book should give the
reader a thorough understanding of the degree to which machine learning methods
have percolated into the various layers of the chip design hierarchy. From lithogra-
phy and physical design to logic and system design, and from circuit performance
estimation to manufacturing yield prediction, VLSI CAD researchers have already
brought state-of-the-art algorithms from supervised, unsupervised, and statistical
learning to bear on pressing CAD problems such as hotspot detection, design-space
exploration, efficient test generation, and post-silicon measurement minimization.

Machine learning in VLSI CAD is expected to play an increasingly important
role not only in improving the quality of the models used in individual CAD tools
but also in enhancing the quality of chip designs that result from the execution of
entire CAD flows and methodologies.

As the semiconductor industry embraces the rising swell of cognitive systems
and edge intelligence, this book could serve as a harbinger and an example of the
osmosis that will exist between our cognitive structures and methods, on the one
hand, and the hardware architectures and technologies that will support them, on
the other.

The value proposition of automation is that it compresses schedules, reduces
costs, and eliminates human errors. In the case of VLSI CAD, the automation has
achieved not only these objectives but also the infinitely more important outcome
of a seamless implementation of a positive feedback loop whereby computers are
used to design more powerful computers. This positive feedback loop is the invisible
hand of Moore’s law.

As we transition from the computing era to the cognitive one, it behooves us
to remember the success story of VLSI CAD and to earnestly seek the help of the
invisible hand so that our future cognitive systems are used to design more powerful
cognitive systems. This book is very much aligned with this ongoing transition from
computing to cognition, and it is with deep pleasure that I recommend it to all those
who are actively engaged in this exciting transformation.

IBM T. J. Watson Research Center
Yorktown Heights, NY, USA
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Dr. Ruchir Puri
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