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Sommario/riassunto	This book presents recent advances towards the goal of enabling efficient implementation of machine learning models on resource- constrained systems, covering different application domains. The focus is on presenting interesting and new use cases of applying machine learning to innovative application domains, exploring the efficient hardware design of efficient machine learning accelerators, memory optimization techniques, illustrating model compression and neural architecture search techniques for energy-efficient and fast execution on resource-constrained hardware platforms, and understanding hardware-software codesign techniques for achieving even greater energy, reliability, and performance benefits. Discusses efficient implementation of machine learning in embedded, CPS, IoT, and edge computing; Offers comprehensive coverage of hardware design, software design, and hardware/software co-design and co- optimization; Describes real applications to demonstrate how embedded, CPS, IoT, and edge applications benefit from machine learning.