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about this book

Build a Large Language Model (From Scratch) was written to help you understand and create your own GPT-like large language models (LLMs) from the ground up. It begins by focusing on the fundamentals of working with text data and coding attention mechanisms and then guides you through implementing a complete GPT model from scratch. The book then covers the pretraining mechanism as well as fine-tuning for specific tasks such as text classification and following instructions. By the end of this book, you'll have a deep understanding of how LLMs work and the skills to build your own models. While the models you'll create are smaller in scale compared to the large foundational models, they use the same concepts and serve as powerful educational tools to grasp the core mechanisms and techniques used in building state-of-the-art LLMs.

Who should read this book

Build a Large Language Model (From Scratch) is for machine learning enthusiasts, engineers, researchers, students, and practitioners who want to gain a deep understanding of how LLMs work and learn to build their own models from scratch. Both beginners and experienced developers will be able to use their existing skills and knowledge to grasp the concepts and techniques used in creating LLMs.

What sets this book apart is its comprehensive coverage of the entire process of building LLMs, from working with datasets to implementing the model architecture, pretraining on unlabeled data, and fine-tuning for specific tasks. As of this writing, no

other resource provides such a complete and hands-on approach to building LLMs from the ground up.

To understand the code examples in this book, you should have a solid grasp of Python programming. While some familiarity with machine learning, deep learning, and artificial intelligence can be beneficial, an extensive background in these areas is not required. LLMs are a unique subset of AI, so even if you're relatively new to the field, you'll be able to follow along.

If you have some experience with deep neural networks, you may find certain concepts more familiar, as LLMs are built upon these architectures. However, proficiency in PyTorch is not a prerequisite. Appendix A provides a concise introduction to PyTorch, equipping you with the necessary skills to comprehend the code examples throughout the book.

A high school–level understanding of mathematics, particularly working with vectors and matrices, can be helpful as we explore the inner workings of LLMs. Advanced mathematical knowledge is not necessary to grasp the key concepts and ideas presented in this book.

The most important prerequisite is a strong foundation in Python programming. With this knowledge, you'll be well prepared to explore the fascinating world of LLMs and understand the concepts and code examples presented in this book.

How this book is organized: A roadmap

This book is designed to be read sequentially, as each chapter builds upon the concepts and techniques introduced in the previous ones. The book is divided into seven chapters that cover the essential aspects of LLMs and their implementation.

Chapter 1 provides a high-level introduction to the fundamental concepts behind LLMs. It explores the transformer architecture, which forms the basis for LLMs such as those used on the ChatGPT platform.

Chapter 2 lays out a plan for building an LLM from scratch. It covers the process of preparing text for LLM training, including splitting text into word and subword tokens, using byte pair encoding for advanced tokenization, sampling training examples with a sliding window approach, and converting tokens into vectors that feed into the LLM.

Chapter 3 focuses on the attention mechanisms used in LLMs. It introduces a basic self-attention framework and progresses to an enhanced self-attention mechanism. The chapter also covers the implementation of a causal attention module that enables LLMs to generate one token at a time, masking randomly selected attention weights with dropout to reduce overfitting and stacking multiple causal attention modules into a multihead attention module.

Chapter 4 focuses on coding a GPT-like LLM that can be trained to generate human-like text. It covers techniques such as normalizing layer activations to stabilize neural network training, adding shortcut connections in deep neural networks to train models more effectively, implementing transformer blocks to create GPT models