Fullstack-ai

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Preface

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1 Introduction

This book is a collection of notes, tutorials, and examples employed for the Fullstack AI course at the Autonoma de Occidente University in Cali, Colombia. The course has been designed to provide a comprehensive introduction to the development process of AI systems, focusing on the practical aspects. The course was created to be accessible to students with a wide range of backgrounds, including students without prior AI experience.

The course was created and developed by Dr. Henry Ruiz, who currently works as a research scientist at Texas A&M AgriLife Research. The course is based on the author's experience in developing AI systems for a wide range of applications, including agriculture, healthcare, and finance.

2 Curriculum

1. **Setting up end-to-end AI projects**: Just like any software solution, ML systems require a well-structured methodology to ensure high success rates. The challenge often lies not in the ML algorithms themselves, but in integrating these algorithms with the rest of the software and hardware components of the system to solve real-world problems. It's noted that 60 out of 96 failures are due to non-ML components, and 60% of models never reach production. This section discuss some of the challenges encountered in AI system development and provides a guide for building AI systems. This guide includes defining the problem, gathering data, evaluating different ML methodologies, and integrating the model into an AI system.

2. **Defining the stack technology**: The number of available tools to work with ML seems endless, and selecting the appropiate tools depends on the kind of problem, type of solution, deployment model, capacity building, team experience, cost, hardware and software infrastructure, etc. This section will discuss different tools used in production to develop and implement ML systems and how they can be integrated.

3. **Data Management**: Data is the most important asset in AI systems. The quality of the data will determine the quality of the model. This section will discuss the best practices for managing data in AI systems, including data collection, data cleaning, data storage, and data processing. It will also discuss how to select the appropiate data management tools for data storage, data processing, and data visualization.

4. **Machine Learning Teams**: Machine Learning talents are expensive and scarce, and machine Learning teams have diverse roles. Managing and leading ML and Data Science teams require unique skills. Here we will learn more about these roles' importance and impact within the organization.

5. **Training debuging and desin patterns for ML solutions**: This section will discuss the best practices for training ML models, including data preprocessing, model selection, model training, and model evaluation. It will also discuss how to debug ML models and how to use design patterns to build scalable and maintainable ML systems.In engineering disciplines, design patterns capture best practices and solutions to commonly occurring problems. They codify the knowledge and experience of experts into advice that all practitioners can follow.

6. **Testing and Deployment**: A machine learning model can only begin to add value to an organization when that model's insights routinely become available to the users for

which it was built. The process of taking a trained ML model and making its predictions available to users or other systems is known as deployment. Let's learn together about troubleshooting and deploying ML models in production and how we can ship ML models to production using different deployments strategies and scenarios.

7. **ML operation: DevOps -> MLOps -> LLMOps -> FMOps:** The development of ML systems is a complex process that requires the collaboration of different teams, including data scientists, software engineers, and operations teams. This section will discuss the challenges of integrating ML models into production systems and the best practices for managing ML models in production.MLOps is a methodology for ML engineering that unifies ML system development (the ML element) with ML system operations (the Ops element). It advocates formalizing and (when beneficial) automating critical steps of ML system construction. This course will discuss how MLOps maximize the capacities and resources of ML teams by providing a set of standardized processes and technology capabilities for building, deploying, and operationalizing ML systems rapidly and reliably

3 Summary

In summary, this book has no content whatsoever.