



Pro Deep Learning with TensorFlow

A Mathematical Approach to Advanced Artificial Intelligence in Python

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Motivation:- Paper for my internship this summer implementing state of the art deep learning algorithms.
- Gain the skills to do DL research in Berkeley.

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Technical Reviewer: Mandeep Sureshwar. Author of Mastering ML with Python in 6 Steps. BS in Physics, Math, CS and MS in "Project management."

Introduction

- Deep Learning: Modeling the world in terms of a hierarchy of concepts.

↳ Just like the human brain, it allows us to model complex concepts that go unnoticed in traditional modeling techniques. Leverages huge amounts of unstructured data.

↳ Understanding the scientific and mathematical principles behind DL lets us maximize the "black box" power.

- Why TensorFlow?

↳ Flexibility for research purposes and ease of use.

↳ "Capability of loading models with ease in a live production environment using its serving capabilities."

- Goals of this book:

- 1) Learn DL from scratch and deploy meaningful DL solutions.
- 2) Using TensorFlow and optimizing different DL architectures.
- 3) Use demonstrated prototypes to build new DL applications.

- Resources Provided:

↳ Example code is provided in Python notebooks and scripts

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- Linear Algebra, Probability, Calculus, Optimization, ML Formulation

Chapter 2: Introduction to Deep-Learning Concepts and TensorFlow

- Evolution of deep learning over the years
- building blocks of neural networks and methods of learning
 - ↳ Perceptron-learning rule, backpropagation methods.
- TensorFlow coding paradigm

Chapter 3: Convolutional Neural Networks

- CNN's for image processing
- Object recognition and detection, object classification, localization, segmentation.
- Convolution in detail. Backpropagation through convolutional and pooling layers.
- Equivariance and Translation Invariance.

Chapter 4: Natural Language Processing Using Recurrent Neural Networks

- Vector space models for text processing
- Word-to-vector embedding models (continuous bag of words, skip-gram)
- RNN, LSTM, bidirectional RNN, GRU

- Language modeling. Using networks in real-world problems.
- Backpropagation for RNNs and LSTMs. Vanishing gradient problem.

Chapter 5: Unsupervised Learning with Restricted Boltzmann Machines and Auto-encoders

- Bayesian Inference and Markov Chain Monte Carlo (MCMC) methods. E.g. Metropolis Algorithm and Gibbs sampling.
 - ↳ RBM training process requires understanding sampling.
 - ↳ Contrastive divergence
- Use of RBMs for collaborative filtering in recommender systems and in unsupervised pre-training of Deep Belief Networks (DBN).
- Types of autoencoders: Sparsely encoded, denoising encoders, etc.
- Internal features from auto-encoders used for dimensionality reduction as well as supervised learning.
- Data preprocessing: PCA and ZCA.

Chapter 6: Advanced Neural Networks

- Fully convolutional NN's, R-CNN, Fast R-CNN, Faster, U-Net, etc.
 - ↳ Semantic segmentation, object detection, localization
- Image segmentation methods.
- Generative Adversarial Network (GAN)
 - ↳ Image generation, inpainting, abstract reasoning, semantic segmentation, video generation, inter-domain style transfer, text-to-image generation, etc.

Key Learnings from this Book:

- Understand full-stack deep learning using TensorFlow and gain a solid mathematical foundation for DL.
- Deploy complex deep-learning solutions in production w/ TF.
- Carry out research on deep learning and perform experiments w/ TF.

Chapter 1: Mathematical Foundations

Layers of artificial "neurons" stacked on top of each other to identify complex features from input data and solve complex real-world problems.

Deep Learning

→ Used for both supervised and unsupervised machine-learning tasks.

→ Applications in areas like computer vision, video analytics, pattern recognition, anomaly detection, text processing, sentiment analysis, recommender systems, and more.

→ Widespread use in robotics, self-driving car mechanisms, and AI systems in general.

Mathematical



Machine Learning



Deep Learning

→ Selecting the right algorithm for a ML problem.

→ Tuning ML/DL models better and understand reasons for unexpected performance.

35% 25% 15%
→ Linear Algebra, Prob. and Stat., Calculus,
Optimization and Formulation of ML algorithms.
25%.

Linear Algebra

Mathematics that deals with vectors and their transformation to another vector space. Since ML and DL deals with multi-dimensional data, lin. alg. plays a crucial role in almost every ML and DL algorithm.

- Vector: Refer to [Notability/Learning/LinearAlgebra/MatrixBuildingBlocks](#)
- Scalar: "
- Matrix: "
- Tensor: "