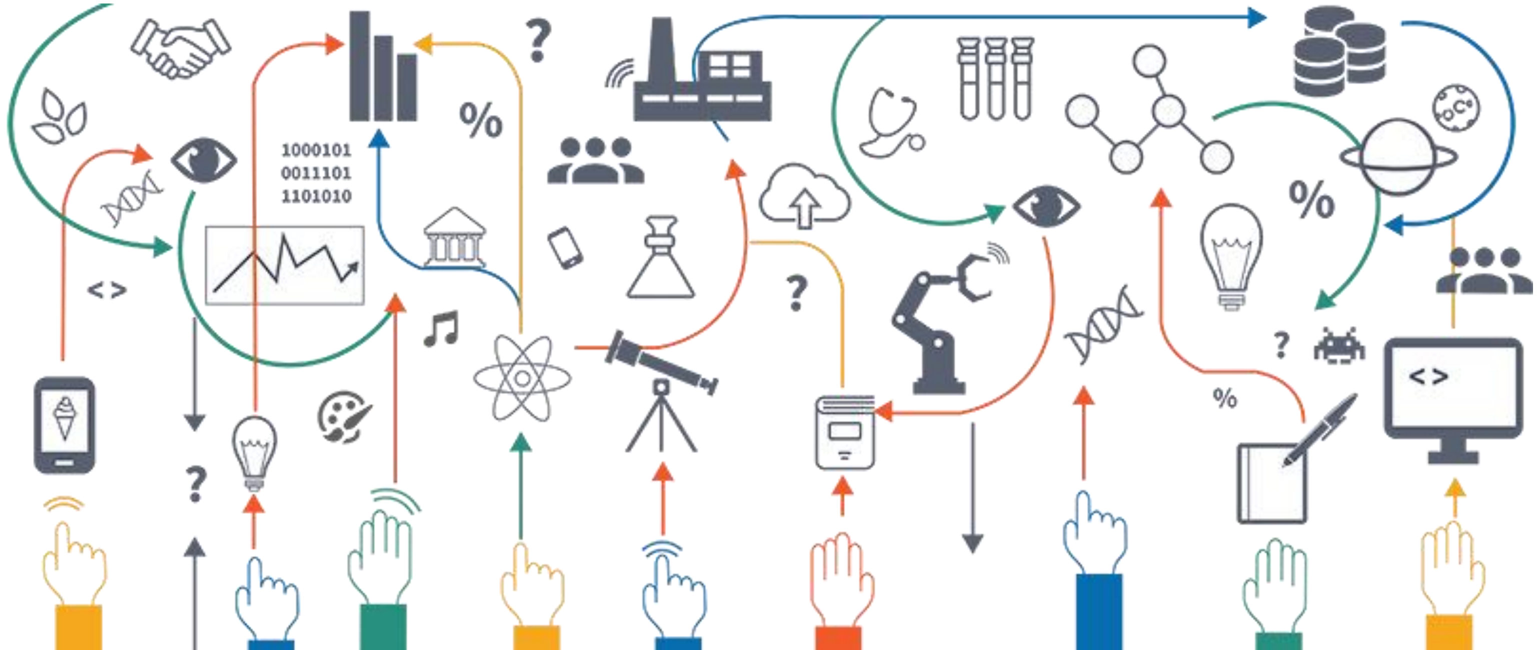
0 – Literature

Mathematics of Data Science

Lecturer: Dominik Dold



University of Vienna, WiSe 2025

Master’s programme in Data Science

Credit: Freepik - Rochak Shukla

1 – Foundations of Probability Theory

1. Prof. Björn Malte Schäfer. Lecture notes on „Computational Statistics and Data Analysis“. https://heibox.uni-heidelberg.de/d/0a433e42dbeb4d2eb6a4/

2. https://blogs.cornell.edu/info2040/2022/11/10/the-monty-hall-problem-using-bayes-theorem/

3. Andrew Rothman, „Statistical Learning Theory Part 1: Hoeffding‘s Inequality Derivation & Simulation“. https://anr248.medium.com/statistical-learning-theory-hoeffdings-inequality-derivation-simulation-e3a97100d147

2 – Analysing High-Dimensional Data

1. Topics in Mathematics of Data Science. (A. S. Bandeira, A. Singer, T. Strohmer).
   https://people.math.ethz.ch/~abandeira//BandeiraSingerStrohmer-MDS-draft.pdf

2. Prof. Nick Harvey. Lecture notes „CPSC 536N: Randomized Algorithms".
   https://www.cs.ubc.ca/~nickhar/W12/Lecture6Notes.pdf (University of British Columbia)

3. Ulrike von Luxburg. "A Tutorial on Spectral Clustering".
   https://people.csail.mit.edu/dsontag/courses/ml14/notes/Luxburg07_tutorial_spectral_clustering.pdf (Max Planck Institute for Biological Cybernetics)

3 – Learning from Structured Data

1. Topics in Mathematics of Data Science. (A. S. Bandeira, A. Singer, T. Strohmer). https://people.math.ethz.ch/~abandeira//BandeiraSingerStrohmer-MDS-draft.pdf

2. Yehuda Koren, Robert Bell, Chris Volinksy. *Matrix Factorization Techniques for Recommender Systems. IEEE Computer, Vol. 42, Issue 8. DOI: https://doi.org/10.1109/MC.2009.263*

3. Blog post by Simon Funk. https://sifter.org/~simon/journal/20061211.html

4. Daniel D. Lee & H. Sebastian Seung. *Algorithms for Non-negative Matrix Factorization.* NeurIPS 2000. https://papers.nips.cc/paper/1861-algorithms-for-non-negative-matrix-factorization

5. B. Perozzi, R. Al-Rfou, S. Skiena. *DeepWalk: Online Learning of Social Representations*. DOI: https://doi.org/10.48550/arXiv.1403.6652

6. Omer Levy, Yoav Goldberg. *Neural World Embedding as Implicit Matrix Factorization*. NeurIPS 2014. https://papers.nips.cc/paper_files/paper/2014/hash/b78666971ceae55a8e87efb7cbfd9ad4-Abstract.html

7. J. Qiu et al. *Network Embedding as Matrix Factorization: Unifying DeepWalk, LINE, PTE, and node2vec.* DOI: https://doi.org/10.48550/arXiv.1710.02971

8. Daniel Ruffinelli, Samuel Broscheit, Rainer Gemulla. *You CAN Teach an Old Dog New Tricks! On Training Knowledge Graph Embeddings.* ICLR 2020. http://www.openreview.net/pdf?id=BkxSmlBFvr

9. Keyulu Xu, Weihua Hu, Jure Leskovec, Stefanie Jegelka. How Powerful are Graph Neural Networks? ICLR 2019. DOI: https://doi.org/10.48550/arXiv.1810.00826

10. Pan Li & Jure Leskovec. *Graph Neural Networks – Foundations, Frontiers, and Applications (Chapter 5). https://graph-neural-networks.github.io/static/file/chapter5.pdf*

4 – Function Approximation and Supervised Learning

1. Prof. Philipp Petersen. Lecture notes on „Mathematics of Machine Learning“, Vienna 2025.
2. Philipp Petersen & Jakob Zech. *Mathematical theory of deep learning.* https://doi.org/10.48550/arXiv.2407.18384
3. Prof. Chinmay Hegde. Lecture notes on "Foundations of Deep Learning", NYU 2022. https://chinmayhegde.github.io/fodl/
4. https://nonagon.org/ExLibris/bernstein-proves-weierstrass
5. Anton R. Schep. *Weierstrass' proof of the Weierstrass approximation theorem*. https://people.math.sc.edu/schep/weierstrass.pdf
6. Steven Buchanan. *A cute proof of Weierstrass approximation*. https://stevenbuchanan.net/posts/weierstrass-approximation/