University	Stanford	Vrije Universiteit	Berkeley	Oxford
Bachelor Title	Computer Science	Computer Science	Computer Science	Computer Science
University Type	University	University	University	University
Prerequisites	- Computer Science principles and skills - Probability Theory - Multivariable Calculus - Linear Algebra	- Linear Algebra - Calculus - Probability - Programming Experience	- Multivariable calculus - Linear algebra - Discrete mathematics and probability theory	- Continuous Mathematics - Linear Algebra - Probability - Design and Analysis of Algorithms
Topics extent (Beyond what TUD ML course offers)	- Neural Networks - Deep Learning - Self-Supervised learning - Reinforcement Learning - Decision Trees - Model-based RL - Learning Theory	- Neural Networks - Deep Learning - Tree models, Decision trees - Models for sequential data - Recommender Systems - Reinforcement learning - Deep q-learning	- Neural Networks - Decision Trees - Learning Theory - CNN - Decision Trees	- Neural Networks - CNN - Recurrent neural networks and LSTMs - Reinforcement learning
Assessment	- 40% Assignments (Theory + Programming) - 40% Final Project (In groups) - 20% Midterm	- 50% Written Exam - 50% practical assignment (made in groups of 5)	- 40% homework - 20% midterm - 20% final exam - 20% project	- Final Exam - Weekly Practicals (Theory + programming with Lua)
Teaching Material	- (Pre)recorded lectures on Mondays - 1 Lab session on Wednesdays - 1 Homework friday (on campus) - Optional weekly discussion sections led by TAs (interactive/small groups) - Lecture notes	- Deep learning book (https://www.deeplearningbook.org/) - Slides (twice aweek) - Optional homework - Pre-recorded videos of the slides	- 3 hours of lectures - 1 hour of discussion - Textbooks - An introduction to statistical analysis with applications in R - The elements of statistical learning: Data Mining	- (pre)recorded lectures - Textbooks: - C. M. Bishop. Pattern Recognition and Machine Learning. Springer 2006. - Kevin P. Murphy. Machine Learning: A Probabilistic Perspective. MIT Press 2012. - Ian Goodfellow, Yoshua Bengio and Aaron Courville. Deep Learning. MIT Press 2016.
Observed Instructional Designs	**(Teacher-centered/Dirct instruction) Lecture-based:** Weekly lectures introduce the main material	**(Teacher-centered/Dirct instruction) Lecture-based:** Weekly lectures introduce the main material	**(Teacher-centered/Dirct instruction) Lecture-based:** Weekly lectures introduce the main material	**(Teacher-centered/Dirct instruction) Lecture-based:** Weekly lectures introduce the main material
	Project-based/Problem-based/Cooperative-Learning/Field-work: Project is 40% of the final grade	**Case-based/Inquiry-based:** Weekly homework	**Project-based/Problem-based/Cooperative-Learning/Field-Work:** Project is 20% of the final grade	**Case-based/Inquiry-based:** Weekly assignements
	Case-based/Inquiry-based: Weekly assignements		**Directed Discussion:** 1 hour a week of discussions	**Flipped Instruction**: The learning material is intentionally pre-recorded and dives deeper during the lectures
	Scaffolding (Student-based): Lab sessions where TA's provide help if needed			
	Directed Discussion: Discussions in small groups led by TAs			
	Flipped Instruction: The learning material is intentionally pre-recorded and dives deeper during the lectures			

University	University of virginia	Massachusetts Institute of Technology	Technical University of Delft
Bachelor Title	Computer Science	Computer Science and Engineering	Computer Science and Engineering
University Type	University	Institute of Technology	Technical University
Prerequisites	- Calculus and Linear Algebra - Probability and Statistics - Proficiency in Python	- Introduction to Algorithms - Linear algebra - Multivariate Calculus	- OOP - ADS - Calculus - Linear Algebra - Probability Theory and Statistics
Topics extent (Beyond what TUD ML course offers)	- Neural networks - deep learning - CNNs and RNNs	- Neural networks - CNNs - State machines and MDP's	
Assessment	- 72% four Homeworks - 25% Project - 3% Class participation	- 5% Excersises - 20% Homework - 5% lab attendence - 20% lab checkoffs - 20% quizzes - 30% final	- 100% Final exam - 0% labs

Teaching Material	- Slides
	- Understanding Machine Learning: From Theory to Algorithms (https://www.cs.huji.ac.il/w~shais/UnderstandingMachineLearning/understanding-machine-learning-theory-algorithms.pdf)
		- 2 lectures a week
		- Monday small lecture and working through homework
		- Wednesday quiz followed by lab assignments with a student partner
			- 2 weekly lectures
			- 1 TA labs (4 hours)
			- prtools python library
			- Weekly exercises
			- Books
			    - Goodfellow, Bengio, Courville (2016). Deep Learning
			    - Bishop (2006). Pattern Recognition and Machine Learning
			    - lecture notes by Andrew Ng (course CS229, Standford University)

Observed Instructional Designs	**(Teacher-centered/Dirct instruction) Lecture-based:** Weekly lectures introduce the main material	**(Teacher-centered/Dirct instruction) Lecture-based:** Weekly lectures introduce the main material	**(Teacher-centered/Dirct instruction) Lecture-based:** Weekly lectures introduce the main material
	Case-based/Inquiry-based: Weekly Homework	**Case-based/Inquiry-based:** Weekly Homework	**Case-based/Inquiry-based:** Weekly Labs/exercises
	Interactive Lecture: Class participation nature of the lectures	**Scaffolding (Student-based):** Lab sessions where TA's provide help if needed	**Scaffolding (Student-based):** Lab sessions where TA's provide help if needed
	Project-based/Problem-based/Cooperative-Learning/Fieldwork: Project is 25% of the final grade	**Prior Knowledge Assessment**: Through the use of weekly quizzes	
		Modelled Teaching: Monday sessions go through the homework	
		Peer Assissted Learning: Lab assignment done with a partner	