**Course: Practical Machine Learning**

Goal: Be able to design own problem that can be solved with machine learning and apply most advanced machine learning techniques to get final solution.

Prerequisites: Knowledge of Python, math (or have taken the previous course on Practical Data Science), simple linear algebra.

**Week 1: Machine learning intro**

* Goals, methods, structure of Machine Learning.
* Technologies and characteristics of Machine Learning algorithms.
* Supervised, unsupervised machine learning and reinforcement.
* Examples of Machine Learning Projects.
* Linear regression.
* Single variable and multivariable regression.
* Multivariate regression.
* Cost function.
* Optimization.
* Gradient Descent.
* Normal equation.
* Feature engineering.
* Overfitting and how to detect it.
* Ways to prevent overfitting.
* Early stopping.
* Dropout.
* Various forms of regularization.
* Train/cross-validation/test splitting.
* Bias-variance tradeoff and learning curves.

Goal: get an idea what Machine Learning can do for you, start to think about final projects, understand linear regression, overfitting and the ways to prevent it.

**Week 2: Classification**

* Logistic Regression (decision boundary,cost function, optimization with gradient descent).
* Multivariate classification.
* Skewed output and ways to deal with it (ROC curves, precision and recall).
* Support Vector Machines.
* SVM with linear and non-linear kernels.
* Decision Trees (structure, how to train)
* Overfitting (degenerate split and gain ratio).
* Multi-class classification and continuous regression with decision trees.
* Ensemble learning.
* Random forest.
* How to optimize random forest.
* Boosting.

Goal: Understand different classification models and when each of them should be applied. Topic of the capstone project should be defined.

**Week 3: Unsupervised learning**

* Methods to find patterns in data.
* Clustering techniques.
* K-means clustering (how does it work and how to choose optimal number of cluster).
* Principal Component Analysis.
* Correlation matrix.
* Singular value decomposition.
* How to choose the number of principal components.
* Machine Learning Pipeline.
* Approaches to design machine learning systems.
* Error analysis.
* How much data do you need. Techniques to augment data.

Goal: Be able to design own machine learning project, know what type of techniques should be applied, how to improve the performance of machine learning algorithms, and where to search help.

**Week 4: Deep Learning**

* Deep learning.
* Neural Networks.
* Neuron.
* Forward propagation in Neural Networks.
* Calculations of gradients (by finite differences, by backpropagation).
* Random Initialization.
* Convolutional Neural Networks.
* Convolutional Layer.
* Stride and Padding.
* Layers in CNNs (Rectified Linear Unit layer, Pooling layer, Dropout layer, Network in Network layer, Fully Connected layer)
* Transfer learning.
* Examples of CNNs (winners of ImageNet competition)
* Recurrent Neural Networks (structure, unrolling)
* Training RNNs.
* How to deal with Vanishing and Exploding Gradients.

Goal: Understand Deep Learning concepts and various types of Deep Learning techniques. Be able to apply Neural Networks for image classification.