**Recent Trends in Machine Learning**

**Semester: January**

**Credits: 3**

**Objective:** The course builds on the content of Machine Learning, providing students with a deeper understanding of machine learning techniques and a wider variety of extant learning models. Students will be prepared to develop advanced machine learning applications and perform research at a state-of-the-art level.

**Learning Outcomes**: Students, on successful completion of the course, will be able to

1. Design, train, test, and deploy modern convolutional neural networks (CNNs).
2. Utilize the principles of adversarial learning to increase the robustness of a machine learning model.
3. Design, train, test, and deploy generative adversarial networks (GANs).
4. Utilize recurrent neural networks (RNNs) to model and predict time series.
5. Utilize deep neural networks to solve difficult tabula rasa reinforcement learning problems.
6. Apply state-of-the-art machine learning methods to solve problems in speech processing, speech synthesis, natural language understanding, natural language synthesis, computer vision, and intelligent agent design.

**Prerequisites:** None

**Course Outline**:

1. Overview of modern machine learning methods
2. Convolutional neural networks
   1. Fundamentals
   2. Inception modules
   3. Residual layers
   4. Squeeze and excitation
   5. Detection models
   6. Semantic segmentation models
   7. Instance-aware segmentation models
3. Transfer learning
   1. Inductive transfer learning
   2. Transductive transfer learning
   3. Unsupervised transfer learning
4. Automatic learning
   1. Automated feature engineering
   2. Automated model selection
   3. Automated optimization algorithm selection
5. Deep unsupervised learning
   1. Generative adversarial networks (GANs)
   2. Cycle GANs
   3. Wasserstein GANs
   4. Variational autoencoders
6. Practical techniques for deep learning models
   1. Weight initialization
   2. Dropout
   3. Adam optimization
   4. Batch normalization
7. Time series processing
   1. Hidden Markov models (HMMs)
   2. Recurrent neural networks (RNNs) and backpropagation through time
   3. Word embedding for natural language processing
   4. Long short term memory (LSTM) units
   5. Gated recurrent units (GRUs)
   6. Attention mechanisms for RNNs
8. Deep Reinforcement learning
   1. Policy gradients
   2. Actor/critic methods
   3. Imitation learning
   4. Exploration/exploitation
   5. Meta learning
   6. Monte Carlo methods
9. Applications
   1. Speech recognition
   2. Speech synthesis
   3. Conversational agents
   4. Recommendation systems
   5. Anomaly detection
   6. Computer vision systems

**Laboratory Session(s):**

1. Preparing the environment for machine learning tools
2. CNNs and residual layers
3. Generative adversarial networks (GANs)
4. Deep learning techniques
5. Introductory time series processing
6. Time series processing with LSTMs and GRUs
7. Deep reinforcement learning
8. Deep speech recognition
9. Recommendation systems
10. Anomaly detection
11. Computer vision

**Learning Resources:**

**Textbooks**: No designated textbook. Emphasis is on recent papers in major machine learning conferences. Class notes and handouts will be provided.

**Reference Books**:

Goodfellow, I., Bengio, Y., and Courville, A. (2016), *Deep Learning*, MIT Press.

Sutton, R.S. and Barto, A.G. (2018), *Reinforcement Learning: An Introduction*, 2nd edition, MIT Press.

**Journals and Magazines**:

*IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI).* IEEE

*Journal of Machine Learning Research (JMLR)*. Microtome

**Others**:

Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR). IEEE

Proceedings of the *Advances in Neural Information Processing Systems (NeurIPS)* conference. Neural Information Systems Foundation, Inc.

Proceedings of the *International Conference on Machine Learning (ICML)*. International Machine Learning Society.

Lecture notes: posted online.

**Teaching and Learning Methods**:

1. **Use of online resources outside of class:** Students will be periodically assigned online video lectures prior to the face-to-face lecture.
2. **Lectures**
3. **In-class tutorials**: Tutorials on important data analysis and modeling tools will be given in class periodically.
4. **Laboratory sessions**: Students will be required to perform a series of exercises in data analysis and submit a lab report.
5. **Homework**: Several homework exercises requiring students to apply the knowledge acquired from lecture and discussion will be assigned and graded.
6. **Project**: Students will propose and execute a plan for a significant machine learning project in groups of 1-3.

**Time Distribution and Study Load**:

* In-class lecture/discussion: 30 hours.
* Laboratory sessions: 45 hours.
* Self study: 45 hours.
* Homework: 30 hours.
* Project work: 30 hours.

**Evaluation Components**

1. Term project (20%)
2. Midterm examination (20%)
3. Final examination (20%)
4. Homework (20%)
5. Lab reports (20%)

A grade of “A” indicates excellent and insightful understanding of the key concepts and ability to implement sophisticated systems; “B” indicates a good understanding of the key concepts and ability to implement basic techniques; “C” indicates barely acceptable understanding and implementation ability; and “D” indicates poor understanding and implementation ability.