Please do the following:

1. Choose a paper from the paper list below.
2. Send the following information to nakajima@tu-berlin.de **(by 12.6.2019)**.
   - Full name
   - Affiliation (University, Department, master/bachelor)
   - Matr. No.
   - Email address
   - The paper title of your choice

   I'll assign an adviser to each student and let you know her/his email address **(by 17.6.2019)**.
3. Contact your adviser for a meeting.
4. Prepare slides for your talk (ca 15-20min) in the block-seminar **on 13.7.2020.**
5. Attend the block-seminar, give your talk, discuss on other's talks!

Below is the list of papers:

1 Data Structure/Indexing

- M. Datar, N. Immorlica, P. Indyk, V.S. Mirrokn, "Locality-sensitive hashing scheme based on p-stable distributions," In SCG, pages 253–262, 2004.
- Prateek Jain, Sudheendra Vijayanarasimhan, Kristen Grauman, "Hashing Hyperplane Queries to Near Points with Applications to Large-Scale Active Learning," 2010.
- P. Li, M. Mitzenmacher, A. Shrivastava, "Coding for Random Projections," 2014
- *M. Drosou, E. Pitoura, " Diverse set selection over dynamic data. IEEE Transactions on Knowledge and Data Engineering," 26(5):1102–1116, 2014.

2 Distributed/Federated Learning

- S. Augenstein et al., "Generative Models for Effective ML on private, Decentralized Datasets, " ICLR 2020.
- L. Hasenclever et al., "Distributed Bayesian Learning with Stochastic Natural-gradient Expectation Propagation and the Posterior Server, " JMLR, vol.18, pages 1–37, 2017.

3 Deep Learning

- *G. E. Hinton et al., "Dropout: a simple way to prevent neural networks from overfitting," JMLR, vol.15, 2014.
- G. Montufar et al., "On the Number of Linear Regions of Deep Neural Networks," NIPS 2014.
- *K. He et al, "Deep Residual Learning for Image Recognition," CVPR 2015.
- *S. Ioffe et al, "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift," ICML 2015.
- S. Santurkar,et al., "How Does Batch Normalization Help Optimization?" arXiv:1805.11604, 2018.
- H. He, B. Xin, D. Wipf, "From Bayesian Sparsity to Gated Recurrent Nets," NIPS 2017.
- T. Burda et al., "Impotance Weghted Autoencoders," ICLR 2016.
- *T. N. Kipf et al., "Semi-supervised Classification with Graph Convolutional Netorks," ICLR 2017.

4 Domain Adaptation/Translation

- Kang et al., "Contrastive Adaptation Network for Unsupervised Domain Adaptation," CVPR 2019.
- *Zhu et al., "Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks," ICCV 2017.
- A. D. Bull, "Spatially-adaptive Sensing in Nonparametric Regression," The Annals of Statistics, vol.41, 2013.

5 Generative Models

- *D. P. Kingma, M. Welling, "Auto Encoding Variational Bayes," 2014
- A. Alemi et al., "Fixing a Broken ELBO," ICML 2018.
- J. Behrmann et al., "Invertible Residual Networks," arXiv:1811.00995.
- P. Wirnsberger et al., "Targeted Free Energy Estimation via Learned Mappings," arXiv:2002.04913.
- G. Alain, Y. Bengio, "What Regularized Auto-encoders Learn from the Data Generating Distribution," Journal of Machine Learning Reserach, 15, 3743-3773, 2014.
- *Laurent Dinh, David Krueger, Yoshua Bengio, "NICE: Non-linear Independent Components Estimation," ICLR workshop 2015, arXiv:1410.8516 [cs.LG]
- Nowozin et al, "f-GAN: Training Generative Neural Samplers using Variational Divergence Minimization," NIPS 2016

6 Adversarial Attack/Defense

- S.-M. Moosavi-Dezfooli et al., "Robustness via Curvature Regularizatio, and vice versa," CVPR 2018.
- A. Fawzi et al., "Empirical study of the topology and geometry of deep networks," CVPR 2018.
- J. H. Jacobsen et al., "Excessive Invariance Causes Adversarial Volnerability " ICLR 2019.
- A. Madry, A. Makelov, L. Schmidt, D. Tsipras, and A. Vladu, "Towards deep learning models resistant to adversarial attacks," arXiv preprint arXiv:1706.06083, 2017.
- P. Samangouei, M. Kabkab, and R. Chellappa, "Defense-gan: Protecting classifiers against adversarial attacks using generative models," in International Conference on Learning Representations, vol. 9, 2018.
- Athalye, N. Carlini, and D. Wagner, "Obfuscated gradients give a false sense of security: Circumventing defenses to adversarial examples," arXiv preprint arXiv:1802.00420, 2018.

7 Anomaly Detection, Uncertainty Estimation

- D. Hendrycks et al., "Deep Anomaly Detection with Outlier Exposure," ICLR 2018.
- Y. Gal, Z. Ghahramani, "Dropout as a Bayesian Approximation: Representing Model Uncertainty in Deep Learning," ICML2016.

8 Scalable Bayesian Learning

- *R. Ranganath et al., "Black box Variational Inference," AISTATS 2014.
- Masegosa et al., "Probabilistic models with deep neural networks," arXiv:1908.03442, 2019.
- Regli et al, "Alpha-Beta Divergence For Variational Inference," arXiv:1805.01045, 2018.
- *Diederik P. Kingma, Tim Salimans, Max Welling, "Variational Dropout and the Local Reparameterization Trick," NIPS2015.
- T. D. Kim and S. Choi, "Scalable Variational Bayesian Matrix Factorization with Side Information," AISTATS 2016.

9 Monte Carlo (Stochastic) Gradient Estimators

- S. Mohamed et al., "Monte Carlo Gradient Estimation in Machine Learning," arXiv:1906.10652.
- G. Roeder et al., "Sticking the Landing: Simple, Lower-Variance Gradient Estimators for Variational Inference," NIPS 2017.
- S.Nowozin, "Debiasing Evidence Approximations: On Importance-weighted Autoencoders and Jackknife Variational Inferencee," ICLR 2018.
- Y. Luo et al., "SUMO: Unbiased Estimation of Log Marginal Probability for Latent Variable models," ICLR 2020.

10 Kernel Approximation

- Si, Hsieh, Dhillon , "Memory Efficient Kernel Approximation," Journal of Machine Learning Research, vol.18, pp.1-32, 2017.
- Rahimi and Recht, "Weighted Sum of Random Kitchen Sinks."