# ICML 2017

THE 34TH INTERNATIONAL CONFERENCE ON MACHINE LEARNING

# WORKSHOP PROGRAM

Thu Aug 10th - Fri Aug 11th

WORKSHOP CHAIRS: ANIMA ANANDKUMAR
FEI SHA

**ICML @ SYDNEY**

INTERNATIONAL CONFERENCE ON MACHINE LEARNING

# ICML 2017 Workshop book

Generated Fri Aug 04, 2017

Workshop organizers make last-minute changes to their schedule. Download this document again to get the lastest changes, or use the ICML mobile application.

## Schedule Highlights

**Aug. 10, 2017**

C4.1, **Lifelong Learning: A Reinforcement Learning Approach** *Chandar, Ravindran, Mankowitz, Mannor, Zahavy*

C4.10, **ICML Workshop on Machine Learning for Autonomous Vehicles 2017** *Li, Urtasun, Gray, Savarese*

C4.11, **Learning to Generate Natural Language** *Miao, Ling, Wen, Cao, Gerz, Blunsom, Dyer*

C4.3, **Workshop on Visualization for Deep Learning** *Jiang, Canny, Chau, Fan, Zhu*

C4.4, **Workshop on Computational Biology** *Pe'er, Leslie, , Azizi, Prabhakaran, Kshirsagar, Carr*

C4.5, **Principled Approaches to Deep Learning** *Pronobis, Gens, Kakade, Domingos*

C4.6, **Video Games and Machine Learning** *Synnaeve, Togelius, Schaul, Vinyals, Usunier*

C4.7, **ML on a budget: IoT, Mobile and other tiny-ML applications** *Varma, Saligrama, Jain*

C4.8, **Workshop on Human Interpretability in Machine Learning (WHI)** *Varshney, Weller, Kim, Malioutov*

C4.9, **Automatic Machine Learning (AutoML 2017)** *Vanschoren, Garnett*

Parkside 1, **Implicit Generative Models** *Ranganath, Goodfellow, Tran, Blei, Lakshminarayanan, Mohamed*

**Aug. 11, 2017**

C4.1, **Time Series Workshop** *Kuznetsov, Liu, Yang, Yu*

C4.10, **Reproducibility in Machine Learning Research** *Ke, Goyal, Lamb, Pineau, Bengio, Bengio*

C4.11, **Interactive Machine Learning and Semantic Information Retrieval** *Glowacka, Buntine, Myllymaki*

C4.3, **Machine Learning in Speech and Language Processing** *Livescu, Sainath, Lu, Ragni*

C4.4, **Private and Secure Machine Learning** *Honkela, Shimizu, Kaski*

C4.5, **Deep Structured Prediction** *Augenstein, Shanmugam, Henelius, Hiranuma, Phillips, Penkov, Weller, Chang, Chechik, Huang, Torres Martins, Meshi, Schwing, Miao*

C4.6, **Picky Learners: Choosing Alternative Ways to Process Data.** *Cortes, Chaudhuri, DeSalvo, Zhang, Zhang*

C4.7, **Reliable Machine Learning in the Wild** *Hadfield-Menell, Steinhardt, Weller, Milli*

C4.8, **Human in the Loop Machine Learning** *Nock, Ong*

C4.9, **Machine Learning for Music Discovery** *Schmidt, Nieto, Gouyon, Lanckriet*

Parkside 1, **Reinforcement Learning Workshop** *Precup*

## Aug. 10, 2017

### Lifelong Learning: A Reinforcement Learning Approach

***Sarath Chandar, Balaraman Ravindran, Daniel J. Mankowitz, Shie Mannor, Tom Zahavy***

**C4.1, Thu Aug 10, 08:30 AM**

One of the most challenging and open problems in Artificial Intelligence (AI) is that of Lifelong Learning:
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“Lifelong Learning is the continued learning of tasks, from one or more domains, over the course of a lifetime, by a lifelong learning system. A lifelong learning system efficiently and effectively (1) retains the knowledge it has learned; (2) selectively transfers knowledge to learn new tasks; and (3) ensures the effective and efficient interaction between (1) and (2).”

Lifelong learning is still in its infancy. Many issues currently exist such as learning general representations, catastrophic forgetting, efficient knowledge retention mechanisms and hierarchical abstractions. Much work has been done in the Reinforcement Learning (RL) community to tackle different elements of lifelong learning. Active research topics include hierarchical abstractions, transfer learning, multi-task learning and curriculum learning. With the emergence of powerful function approximators such as in Deep Learning, we feel that now is a perfect time to provide a forum to discuss ways to move forward and provide a truly general lifelong learning framework, using RL-based algorithms, with more rigour than ever before. This workshop will endeavour to promote interaction between researchers working on the different elements of lifelong learning to try and find a synergy between the various techniques.

**Schedule**

| | |
|---|---|
| 08:30 AM | **Introduction and Overview** |
| 08:40 AM | **Marc G. Bellemare** |
| 09:20 AM | **Poster Spotlights** |
| 10:00 AM | **Poster Session + break** |
| 10:30 AM | **Joelle Pineau** |
| 11:05 AM | **Andrei Rusu** |
| 12:00 PM | **Lunch** |
| 02:00 PM | **Contributed Talks** |
| 03:30 PM | **Doina Precup** |
| 04:10 PM | **Lifelong Learning - Panel Discussion** |

### ICML Workshop on Machine Learning for Autonomous Vehicles 2017

***Li Erran Li, Raquel Urtasun, Andrew Gray, Silvio Savarese***

**C4.10, Thu Aug 10, 08:30 AM**

Although dramatic progress has been made in the field of autonomous driving, there are many major challenges in achieving full-autonomy. For example, how to make perception accurate and robust to accomplish safe autonomous driving? How to reliably track cars, pedestrians, and cyclists? How to learn long term driving strategies (known as driving policies) so that autonomous vehicles can be equipped with adaptive human negotiation skills when merging, overtaking and giving way, etc? How to achieve near-zero fatality?

These complex challenges associated with autonomy in physical world naturally suggest that we take a machine learning approach. Deep learning and computer vision have found many real-world applications such as face tagging. However, perception for autonomous driving has a unique set of requirements such as safety and explainability. Autonomous vehicles need to choose actions, e.g. steering commands which will affect the subsequent inputs (driving scenes) encountered. This setting is well-suited to apply reinforcement learning to determine the best actions to take. Many autonomous driving tasks such as perception and tracking requires large data sets of labeled examples to learn rich and high-performance visual representation. However, the progress is hampered by the sheer expenses of human labelling needed. Naturally we would like to employ unsupervised learning, transfer learning leveraging simulators, and techniques can learn efficiently. The goal of this workshop is to bring together researchers and practitioners from in the field of autonomous driving to address core challenges with machine learning. These challenges include, but are not limited to
accurate and efficient pedestrian detection, pedestrian intent detection, machine learning for object tracking,
unsupervised representation learning for autonomous driving,
deep reinforcement learning for learning driving policies,
cross-modal and simulator to real-world transfer learning,
scene classification, real-time perception and prediction of traffic scenes,
uncertainty propagation in deep neural networks,
efficient inference with deep neural networks

The workshop will include invited speakers, panels, presentations of accepted papers and posters. We invite papers in the form of short, long and position papers to address the core challenges mentioned above. We encourage researchers and practitioners on self-driving cars, transportation systems and ride-sharing platforms to participate. Since this is a topic of broad and current interest, we expect at least 200 participants from leading university researchers, auto-companies and ride-sharing companies.

**Schedule**

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|---|---|
| 08:20 AM | **Opening Remarks** |
| 08:30 AM | **Carl Wellington, Uber ATG** |
| 09:00 AM | **Jose M. Alvarez, TRI** |

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|---|---|
| 09:30 AM | **Learning Affordance for Autonomous Driving (JianXiong Xiao, AutoX)** |
| 10:00 AM | **Coffee** |
| 10:30 AM | **2 x 15 Contributed Talks on Datasets and Occupancy Maps** |
| 11:00 AM | **Beyond Hand Labeling: Simulation and Self-Supervision for Self-Driving Cars (Matt Johnson, University of Michigan)** |
| 11:30 AM | **Visual 3D Scene Understanding and Prediction for ADAS (Manmohan Chandraker, NEC Labs)** |
| 12:00 PM | **Lunch** |
| 02:00 PM | **Deep Reinforcement Learning for Real-World Mobility (Sergey Levine, UC Berkeley)** |
| 02:30 PM | **2 x 15 Contributed Talks on Reinforcement Learning** |
| 03:00 PM | **Coffee and Posters** |
| 03:30 PM | **Min Sun, National Tsing Hua University: Assessing Risk and Adapting Changes on the Road** |
| 04:00 PM | **Amar Shah** |
| 04:30 PM | **3 x 5 min Lightening Talks** |
| 04:45 PM | **Panel Discussion** |
| 05:25 PM | **Closing Remarks** |

Abstracts (8):

Abstract 4: **Learning Affordance for Autonomous Driving (JianXiong Xiao, AutoX) in ICML Workshop on Machine Learning for Autonomous Vehicles 2017**, 09:30 AM

Today, there are two major paradigms for vision-based autonomous driving systems: mediated perception approaches that parse an entire scene to make a driving decision, and behavior reflex approaches that directly map an input image to a driving action by a regressor. In this paper, we propose a third paradigm: a direct perception based approach to estimate the affordance for driving. We propose to map an input image to a small number of key perception indicators that directly relate to the affordance of a road/traffic state for driving. Our representation provides a set of compact yet complete descriptions of the scene to enable a simple controller to drive autonomously. Falling in between the two extremes of mediated perception and behavior reflex, we argue that our direct perception representation provides the right level of abstraction. We evaluate our approach in a virtual racing game as well as real world driving and show that our model can work well to drive a car in a very diverse set of virtual and realistic environments.

Jianxiong Xiao (a.k.a., Professor X) is the Founder and CEO of AutoX Inc., a high-tech startup working on A.I. software solution for self-driving vehicles. AutoX's mission is to democratize autonomy and make autonomous driving universally accessible to everyone. Its innovative camera-first self-driving solution amounts to only a tiny fraction of the cost of traditional LiDar-based approaches. Dr. Xiao has over ten years of research and engineering experience in Computer Vision, Autonomous Driving, and Robotics. In particular, he is a pioneer in the fields of 3D Deep Learning, RGB-D Recognition and Mapping, Big Data, Large-scale Crowdsourcing, and Deep Learning for Robotics. Jianxiong received a BEng. and MPhil. in Computer Science from the Hong Kong University of Science and Technology in 2009. He received his Ph.D. from the Computer Science and Artificial Intelligence Laboratory (CSAIL) at the Massachusetts Institute of Technology (MIT) in 2013. And he was an Assistant Professor at Princeton University and the founding director of the Princeton Computer Vision and Robotics Labs from 2013 to 2016. His work has received the Best Student Paper Award at the European Conference on Computer Vision (ECCV) in 2012 and the Google Research Best Papers Award for 2012, and has appeared in the popular press. He was awarded the Google U.S./Canada Fellowship in Computer Vision in 2012, the MIT CSW Best Research Award in 2011, NSF/Intel VEC Research Award in 2016, and two Google Faculty Awards in 2014 and in 2015 respectively. He co-lead the MIT+Princeton joint team to participate in the Amazon Picking Challenge in 2016, and won the 3rd and 4th place worldwide. More information can be found at: http://www.jianxiongxiao.com.

Abstract 6: **2 x 15 Contributed Talks on Datasets and Occupancy Maps in ICML Workshop on Machine Learning for Autonomous Vehicles 2017**, 10:30 AM

Jonathan Binas, Daniel Neil, Shih-Chii Liu, Tobi Delbruck, DDD17: End-To-End DAVIS Driving Dataset

Ransalu Senanayake and Fabio Ramos, Bayesian Hilbert Maps for Continuous Occupancy Mapping in Dynamic Environments

Abstract 7: **Beyond Hand Labeling: Simulation and Self-Supervision for Self-Driving Cars (Matt Johnson, University of Michigan) in ICML Workshop on Machine Learning for Autonomous Vehicles 2017**, 11:00 AM

Self-driving cars now deliver vast amounts of sensor data from large unstructured environments. In attempting to process and interpret this data there are many unique challenges in bridging the gap between prerecorded data sets and the field. This talk will present recent work addressing the application of deep learning techniques to robotic perception. We focus on solutions to several pervasive problems when attempting to deploy such techniques on fielded robotic systems. The themes of the talk revolve around alternatives to gathering and curating data sets for training. Are there ways of avoiding the labor-intensive human labeling required for supervised learning? These questions give rise to several lines of research based around self-supervision, adversarial learning, and simulation. We will show how these approaches applied to self-driving car problems have great potential to change the way we train, test, and validate machine learning-based

systems.

Bio:
Matthew Johnson-Roberson is Assistant Professor of Engineering in the Department of Naval Architecture & Marine Engineering and the Department of Electrical Engineering and Computer Science at the University of Michigan. He received a PhD from the University of Sydney in 2010. He has held prior postdoctoral appointments with the Centre for Autonomous Systems - CAS at KTH Royal Institute of Technology in Stockholm and the Australian Centre for Field Robotics at the University of Sydney. He is a recipient of the NSF CAREER award (2015). He has worked in robotic perception since the first DARPA grand challenge and his group focuses on enabling robots to better see and understand their environment.

Abstract 8: **Visual 3D Scene Understanding and Prediction for ADAS (Manmohan Chandraker, NEC Labs) in ICML Workshop on Machine Learning for Autonomous Vehicles 2017**, 11:30 AM

Abstract:
Modern advanced driver assistance systems (ADAS) rely on a range of sensors including radar, ultrasound, LIDAR and cameras. Active sensors have found applications in detecting traffic participants (TPs) such as cars or pedestrians and scene elements (SEs) such as roads. However, camera-based systems have the potential to achieve or augment these capabilities at a much lower cost, while allowing new ones such as determination of TP and SE semantics as well as their interactions in complex traffic scenes.

In this talk, we present several technical advances for vision-based ADAS. A common theme is to overcome the challenges posed by lack of large-scale annotations in deep learning frameworks. We introduce approaches to correspondence estimation that are trained on purely synthetic data but adapt well to real data at test-time. We introduce object detectors that are light enough for ADAS, trained with knowledge distillation to retain accuracies of deeper architectures. Our semantic segmentation methods are trained on weak supervision that requires only a tenth of conventional annotation time. We propose methods for 3D reconstruction that use deep supervision to recover fine TP part locations while relying on purely synthetic 3D CAD models. We develop deep learning frameworks for multi-target tracking, as well as occlusion-reasoning in TP localization and SE layout estimation. Finally, we present a framework for TP behavior prediction in complex traffic scenes that accounts for TP-TP and TP-SE interactions. Our approach allows prediction of diverse multimodal outcomes and aims to account for long-term strategic behaviors in complex scenes.

Bio:
Manmohan Chandraker is an assistant professor at the CSE department of the University of California, San Diego and leads the computer vision research effort at NEC Labs America in Cupertino. He received a B.Tech. in Electrical Engineering at the Indian Institute of Technology, Bombay and a PhD in Computer Science at the University of California, San Diego. His personal research interests are 3D scene understanding and reconstruction, with applications to autonomous driving and human-computer interfaces. His works have received the Marr Prize Honorable Mention for Best Paper at ICCV 2007, the 2009 CSE Dissertation Award for Best Thesis at UCSD, a PAMI special issue on best papers of CVPR 2011 and the Best Paper Award at CVPR 2014.

Abstract 10: **Deep Reinforcement Learning for Real-World Mobility (Sergey Levine, UC Berkeley) in ICML Workshop on Machine Learning for Autonomous Vehicles 2017**, 02:00 PM

Abstract:
Deep reinforcement learning algorithms can acquire complex tasks using their own autonomously collected experience. However, applications of deep reinforcement learning to real world tasks have been limited by a number of challenging obstacles: (1) reinforcement learning algorithms tend to require large amounts of experience, often much larger than equivalent supervised learning methods; (2) reinforcement learning often requires risky exploration, which can be extremely dangerous in safety-critical applications such as robotic flight or driving; (3) reinforcement learning methods suffer from problems with stability and convergence. In this talk, I will discuss some of our recent work on making it feasible to use reinforcement learning to train robotic systems that perform well in the real world. Specifically, I will cover methods for transferring skills from simulation to the real world, safe uncertainty-aware exploration methods, and meta-learning algorithms that can dramatically accelerate reinforcement learning.

Bio:
Sergey Levine received a BS and MS in Computer Science from Stanford University in 2009, and a Ph.D. in Computer Science from Stanford University in 2014. He joined the faculty of the Department of Electrical Engineering and Computer Sciences at UC Berkeley in fall 2016. His work focuses on machine learning for decision making and control, with an emphasis on deep learning and reinforcement learning algorithms. Applications of his work include autonomous robots and vehicles, as well as computer vision and graphics. His research includes developing algorithms for end-to-end training of deep neural network policies that combine perception and control, scalable algorithms for inverse reinforcement learning, deep reinforcement learning algorithms, and more.

Abstract 11: **2 x 15 Contributed Talks on Reinforcement Learning in ICML Workshop on Machine Learning for Autonomous Vehicles 2017**, 02:30 PM

David Isele, Akansel Cosgun, To Go or Not to Go: A Case for Q-Learning at Unsignalized Intersections

Tomoki Nishi, Prashant Doshi, Danil Prokhorov, Freeway Merging in Congested Traffic based on Multipolicy Decision Making with Passive Actor Critic

Abstract 13: **Min Sun, National Tsing Hua University: Assessing Risk and Adapting Changes on the Road in ICML Workshop on Machine Learning for Autonomous Vehicles 2017**, 03:30 PM

It is critical for a self-driving car in the wild to assess risk and adapt to changes on the road. In this talk, we will first go over our proposed accident anticipation method which is tested on a large dataset consisting of real-world accident videos. Then, we will present our latest ICCV paper about how to adapt a semantic segmentation model across 4 cities in three continents.

Bio: Min Sun is an assistant professor at National Tsing Hua University in Taiwan. Before that, he was a postdoctoral researcher at Washington University in Seattle and he graduated from the University of Michigan with a Ph.D. degree in EE: System. He also won the best paper award of

3dRR in 2007 and best paper award of CVGIP in 2015 and 2016.

Abstract 15: **3 x 5 min Lightening Talks in ICML Workshop on Machine Learning for Autonomous Vehicles 2017**, 04:30 PM

Kangwook Lee, Hoon Kim, Changho Suh, Crash To Not Crash: Playing Video Games To Predict Vehicle Collisions

Ahmad El Sallab, Mahmoud Saeed, Omar Abdel Tawab, Mohammed Abdou, Meta learning Framework for Automated Driving

Edward Schwalb, Bernhard Bieder, Daniel Wiesenhütter, What Makes It Testable? Conceptual Model for Safety Quantification

## Learning to Generate Natural Language

***Yishu Miao, Wang Ling, Tsung-Hsien Wen, Kris Cao, Daniela Gerz, Phil Blunsom, Chris Dyer***

**C4.11, Thu Aug 10, 08:30 AM**

Research on natural language generation is rapidly growing due to the increasing demand for human-machine communication in natural language. This workshop aims to promote the discussion, exchange, and dissemination of ideas on the topic of text generation, touching several important aspects in this modality: learning schemes and evaluation, model design and structures, advanced decoding strategies, and natural language generation applications. This workshop aims to be a venue for the exchange of ideas regarding data-driven machine learning approaches for text generation, including mainstream tasks such as dialogue generation, instruction generation, and summarization; and for establishing new directions and ideas with potential for impact in the fields of machine learning, deep learning, and NLP.

**Schedule**

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|---|---|
| 08:30 AM | **Invited Talk: Tim Baldwin** |
| 09:15 AM | **Invited Talk: Dani Yogatama** |
| 10:00 AM | **Coffee Break & Poster session 1** |
| 10:30 AM | **Invited Talk: Andre Martins** |
| 11:15 AM | **Spotlight Paper Presentation** |
| 12:00 PM | **Lunch Break & Poster session 2** |
| 02:00 PM | **Invited Talk: Joelle Pineau** |
| 02:45 PM | **Invited Talk: Mark Johnson** |
| 03:30 PM | **Coffee Break & Poster session 3** |
| 04:00 PM | **Invited Talk: Trevor Cohn** |
| 04:45 PM | **Panel Discussion** |

Abstracts (11):

Abstract 1: **Invited Talk: Tim Baldwin in Learning to Generate Natural Language**, 08:30 AM

Invited Talk 1

Abstract 2: **Invited Talk: Dani Yogatama in Learning to Generate Natural Language**, 09:15 AM

Invited Talk 1

Abstract 3: **Coffee Break & Poster session 1 in Learning to Generate Natural Language**, 10:00 AM

Coffee Break & Poster session

Abstract 4: **Invited Talk: Andre Martins in Learning to Generate Natural Language**, 10:30 AM

Invited Talk 3

Abstract 5: **Spotlight Paper Presentation in Learning to Generate Natural Language**, 11:15 AM

Workshop Paper Presentation

Abstract 6: **Lunch Break & Poster session 2 in Learning to Generate Natural Language**, 12:00 PM

Lunch Break & Poster session

Abstract 7: **Invited Talk: Joelle Pineau in Learning to Generate Natural Language**, 02:00 PM

Invited Talk 4

Abstract 8: **Invited Talk: Mark Johnson in Learning to Generate Natural Language**, 02:45 PM

Invited Talk 5

Abstract 9: **Coffee Break & Poster session 3 in Learning to Generate Natural Language**, 03:30 PM

Coffee Break & Poster session 3

Abstract 10: **Invited Talk: Trevor Cohn in Learning to Generate Natural Language**, 04:00 PM

Invited Talk 6

Abstract 11: **Panel Discussion in Learning to Generate Natural Language**, 04:45 PM

Panel Discussion

## Workshop on Visualization for Deep Learning

***Biye Jiang, John Canny, Polo Chau, Xiangmin Fan, Junyan Zhu***

**C4.3, Thu Aug 10, 08:30 AM**

Deep networks have had profound impact across machine learning research and in many application areas. DNNs are complex to design

and train. They are non-linear systems that almost always have many local optima and are often sensitive to training parameter settings and initial state. Systematic optimization of structure and hyperparameters is possible e.g. with Bayesian optimization, but hampered by the expense of training each design on realistic datasets. Exploration is still ongoing for best design principles. We argue that visualization can play an essential role in understanding DNNs and in developing new design principles. With rich tools for visual exploration of networks during training and inference, one should be able to form closer ties between theory and practice: validating expected behaviors, and exposing the unexpected which can lead to new insights. With the rise of generative modeling and reinforcement learning, more interesting directions like understanding and visualization of generative models, visual explanation for driving policy could be explored as well.

As the second edition of this workshop, we are proposing changes based on the lessons we learned last year. We would like to organize a few domain specific tutorials, and panel discussions. We do think machine learning researchers need a lot of tutorials and advice from the visualization/HCI community and vice versa. Many audience in our workshop last year also suggested that more discussion can greatly help us better define such interdisciplinary area.

**Schedule**

| | |
|---|---|
| 08:30 AM | **Opening remark** |
| 08:40 AM | **Becoming friends with every pixel, Phillip Isola (UC Berkeley)** |
| 09:20 AM | **SmoothGrad: removing noise by adding noise Daniel Smilkov, Nikhil Thorat, Been Kim, Fernanda Viegas, Martin M Wattenberg** |
| 09:40 AM | **Towards Visual Explanations for Convolutional Neural Networks via Input Resampling, Benjamin J Lengerich, Sandeep Konam, Eric Xing, Stephanie Rosenthal, Manuela Veloso** |
| 10:00 AM | **Coffee Breaks and Poster session 1** |
| 10:00 AM | **Coffee Breaks and Poster session** |
| 10:30 AM | **Understanding Generative Models in Google Brain Magenta, Cinjon Resnick (Google)** |
| 11:00 AM | **Deep saliency: What is learnt by a deep network about saliency? Sen He, Nicolas Pugeault** |
| 11:15 AM | **Self-supervised attention for Deep Learning explanations, Nathan Hodas, (PNL)** |
| 11:45 AM | **Skip-Frame Embeddings for Feature Adaptation and Visualization, Zain Shah** |
| 12:00 PM | **Lunch Breaks** |
| 02:00 PM | **Quantifying the Interpretability of Deep Visual Representations, Bolei Zhou (MIT)** |
| 02:40 PM | **Visualizing Feature Maps in Deep Neural Networks using DeepResolve - A Genomics Case Study, Ge Liu, David Gifford** |
| 03:00 PM | **Coffee Breaks and Poster session 2** |
| 03:30 PM | **Visual Explanations from Deep Networks, Dhruv Batra (Georgia Tech and Facebook AI Research)** |
| 04:00 PM | **Evolutionary Visual Analysis of Deep Neural Networks, Wen Zhong, Cong Xie, Yuan Zhong, Yang Wang, Wei Xu, Shenghui Cheng, Klaus Mueller** |
| 04:20 PM | **ActiVis: Visual Exploration of Industry-Scale Deep Neural Network Models, Pierre Andrews (Facebook)** |
| 04:50 PM | **Brainstorming on deep learning visualization techniques and tools** |
| 05:30 PM | **Closing remark** |

Abstracts (7):

Abstract 3: **SmoothGrad: removing noise by adding noise Daniel Smilkov, Nikhil Thorat, Been Kim, Fernanda Viegas, Martin M Wattenberg in Workshop on Visualization for Deep Learning**, 09:20 AM

Explaining the output of a deep network remains a challenge. In the case of an image classifier, one type of explanation is to identify pixels that strongly influence the final decision. A starting point for this strategy is the gradient of the class score function with respect to the input image. This gradient can be interpreted as a sensitivity map, and there are several techniques that elaborate on this basic idea. This paper makes two contributions: it introduces SMOOTHGRAD,

a simple method that can help visually sharpen gradient-based sensitivity maps, and it discusses lessons in the visualization of these maps. We publish the code for our experiments and a website with our results.

Abstract 4: **Towards Visual Explanations for Convolutional Neural Networks via Input Resampling, Benjamin J Lengerich, Sandeep Konam, Eric Xing, Stephanie Rosenthal, Manuela Veloso in Workshop on Visualization for Deep Learning**, 09:40 AM

The predictive power of neural networks often costs model interpretability. Several techniques have been developed for explaining model outputs in terms of input features; however, it is difficult to translate such interpretations into actionable insight. Here, we propose a framework to analyze predictions in terms of the model's internal features by inspecting information flow through the network. Given a trained network and a test image, we select neurons by two metrics, both measured over a set of images created by perturbations to the input image: (1) magnitude of the correlation between the neuron activation and the network output and (2) precision of the neuron activation. We show that the former metric selects neurons that exert large influence over the network output while the latter metric selects neurons that activate on generalizable features. By comparing the sets of neurons selected by these two metrics, our framework offers a way to investigate the internal attention mechanisms of convolutional neural networks.

Abstract 8: **Deep saliency: What is learnt by a deep network about saliency? Sen He, Nicolas Pugeault in Workshop on Visualization for Deep Learning**, 11:00 AM

Deep convolutional neural networks have achieved impressive performance on a broad range of problems, beating prior art on established benchmarks, but it often remains unclear what are the representations learnt by those systems and how they achieve such performance. This article examines the specific problem of saliency detection, where benchmarks are currently dominated by CNN-based approaches, and investigates the properties of the learnt representation by visualizing the artificial neurons' receptive fields. We demonstrate that fine tuning a pre-trained network on the saliency detection task lead to a profound transformation of the network's deeper layers. Moreover we argue that this transformation leads to the emergence of receptive fields conceptually similar to the centre-surround filters hypothesized by early research on visual saliency.

Abstract 10: **Skip-Frame Embeddings for Feature Adaptation and Visualization, Zain Shah in Workshop on Visualization for Deep Learning**, 11:45 AM

We present an unsupervised method for visualizing the generalization and adaptation capabilities of pre-trained features on video. Like the skip-grams method for unsupervised learning of word vector representations, we exploit temporal continuity in the target media, namely that neighboring frames are qualitatively similar. By enforcing this continuity in the adapted feature space we can adapt features to a new target task, like house price prediction, without supervision. The domain-specific embeddings can be easily visualized for qualitative introspection and evaluation.

Abstract 13: **Visualizing Feature Maps in Deep Neural Networks using DeepResolve - A Genomics Case Study, Ge Liu, David Gifford in Workshop on Visualization for Deep Learning**, 02:40 PM

Although many powerful visualization tools have been developed to interpret neural network decisions in input space, methods to interpret feature map space remain limited. Most existing tools examine a network's response to a specific input sample and thus are locally faithful to that sample. We introduce DeepResolve, a gradient ascent based method that visualizes intermediate layer feature maps in an input independent manner. We examine DeepResolve's capability to 1) discover network linear and non-linear combinatorial logic and summarize overall knowledge of a class, 2) reveal key features for a target class, 3) assess a network's activeness in pattern learning and network's vulnerability in feature space, and 4) analyze multi-task class similarity at high resolution. We demonstrate the value of DeepResolve on synthetic and experimental genomic datasets, and DeepResolve reveals biologically interesting observations from the experimental data.

Abstract 16: **Evolutionary Visual Analysis of Deep Neural Networks, Wen Zhong, Cong Xie, Yuan Zhong, Yang Wang, Wei Xu, Shenghui Cheng, Klaus Mueller in Workshop on Visualization for Deep Learning**, 04:00 PM

Recently, deep learning visualization gained a lot of attentions for understanding deep neural networks. However, there is a missing focus on the visualization of deep model training process. To bridge the gap, in this paper, we firstly define a discriminability metric to evaluate neuron evolution and a density metric to investigate output feature maps. Based on these metrics, a level-ofdetail visual analytics framework is proposed to locally and globally inspect the evolution of deep neural networks. Finally, we demonstrate the effectiveness of our system with two real world case studies.

Abstract 17: **ActiVis: Visual Exploration of Industry-Scale Deep Neural Network Models, Pierre Andrews (Facebook) in Workshop on Visualization for Deep Learning**, 04:20 PM

While deep learning models have achieved state-of-the-art accuracies for many prediction tasks, understanding these models remains a challenge. Despite the recent interest in developing visual tools to help users interpret deep learning models, the complexity and wide variety of models deployed in industry, and the large-scale datasets that they used, pose unique design challenges that are inadequately addressed by existing work. Through participatory design sessions with over 15 researchers and engineers at Facebook, we have developed, deployed, and iteratively improved ActiVis, an interactive visualization system for interpreting large-scale deep learning models and results. By tightly integrating multiple coordinated views, such as a computation graph overview of the model architecture, and a neuron activation view for pattern discovery and comparison, users can explore complex deep neural network models at both the instance- and subset-level. ActiVis has been deployed on Facebook's machine learning platform. We present case studies with Facebook researchers and engineers, and usage scenarios of how ActiVis may work with different models.

## Workshop on Computational Biology

***Dana Pe'er, Christina Leslie, , Elham Azizi, Sandhya Prabhakaran, Meghana Kshirsagar, Ambrose Carr***

**C4.4, Thu Aug 10, 08:30 AM**

The workshop will showcase recent research in the field of Computational Biology. There has been significant development in genomic sequencing techniques as well as imaging technologies that not only generate huge amounts of data but provide unprecedented levels of resolution, that of a single cell and even subcellular resolution. This availability of high dimensional data, at multiple spatial and temporal resolutions and capturing several perspectives of biological phenomena has made machine learning methods increasingly relevant for computational analysis of the data. Conversely, biological data has also exposed unique challenges and problems that call for the development of new machine learning methods. This workshop aims at bringing in researchers working at the intersection of Machine Learning and Biology to present recent advances and open questions in computational biology to the ICML community.

**Schedule**

| | |
|---|---|
| 08:45 AM | **Opening Remarks** |
| 08:50 AM | **Stability and Aggregation of Experimental Results** |
| 09:30 AM | **Spotlight Presentations** |
| 10:00 AM | **Coffee Break** |
| 10:30 AM | **Deep learning approaches to impute, integrate and interpret regulatory genomic data** |
| 11:10 AM | **Uncovering the gene usage of human tissue cells with joint factorized embeddings** |
| 11:30 AM | **Dilated Convolutions for Modeling Long-Distance Genomic Dependencies** |
| 12:00 PM | **Poster Session I** |
| 02:00 PM | **Reasoning from "Messy" Clinical Time Series for Individualizing Care -- Suchi Saria** |
| 02:40 PM | **Ask the doctor – Improving drug sensitivity predictions through active expert knowledge elicitation** |
| 03:00 PM | **Poster Session II** |
| 04:15 PM | **Contrastive Principal Component Analysis** |
| 04:35 PM | **Closing Remarks and Awards** |

Abstracts (1):

Abstract 2: **Stability and Aggregation of Experimental Results in Workshop on Computational Biology**, 08:50 AM

Spearman's correlation measures the association between ranked lists. Given a set of ranked lists, we study two tasks: aggregating the set of ranks into one single ranked list, and computing the agreement of the lists as we traverse it. Applications include the analysis of the stability of feature selection and integration of various sources of information. This is illustrated with two examples respectively: We study the stability of identifying variations in GWAS by considering replication studies. In another study, we aggregate genomic distance, 3D associations, and literature information to findpromising disease associated variations. It turns out that these problems can be tackled by considering a multivariate Spearman's correlation.

## Principled Approaches to Deep Learning

***Andrzej Pronobis, Robert Gens, Sham M. Kakade, Pedro Domingos***

**C4.5, Thu Aug 10, 08:30 AM**

The recent advancements in deep learning have revolutionized the field of machine learning, enabling unparalleled performance and many new real-world applications. Yet, the developments that led to this success have often been driven by empirical studies, and little is known about the theory behind some of the most successful approaches. While theoretically well-founded deep learning architectures had been proposed in the past, they came at a price of increased complexity and reduced tractability. Recently, we have witnessed considerable interest in principled deep learning. This led to a better theoretical understanding of existing architectures as well as development of more mature deep models with solid theoretical foundations. In this workshop, we intend to

review the state of those developments and provide a platform for the exchange of ideas between the theoreticians and the practitioners of the growing deep learning community. Through a series of invited talks by the experts in the field, contributed presentations, and an interactive panel discussion, the workshop will cover recent theoretical developments, provide an overview of promising and mature architectures, highlight their challenges and unique benefits, and present the most exciting recent results.

**Schedule**

| | |
|---|---|
| 08:30 AM | **Welcome and Opening Remarks** |
| 08:45 AM | **Invited Talk 1 - Sanjeev Arora** |
| 09:15 AM | **Contributed Presentation 1** |
| 09:30 AM | **Invited Talk 2 - Surya Ganguli** |
| 10:00 AM | **Coffee Break and Poster Session** |
| 10:45 AM | **Invited Talk 3 - Ruslan Salakhutdinov** |
| 11:15 AM | **Invited Talk 4 - Pedro Domingos** |
| 11:45 AM | **Contributed Presentation 2** |
| 12:00 PM | **Lunch** |
| 01:30 PM | **Invited Talk 5 - Tomaso Poggio** |
| 02:00 PM | **Contributed Presentation 3** |
| 02:15 PM | **Invited Talk 6 - Nathan Srebro** |
| 02:45 PM | **Contributed Presentation 4** |
| 03:00 PM | **Coffee Break 2 and Poster Session** |
| 03:45 PM | **Contributed Presentation 5** |
| 04:00 PM | **Panel Discussion** |
| 05:20 PM | **Closing Remarks and Awards** |

Abstracts (4):

Abstract 2: **Invited Talk 1 - Sanjeev Arora in Principled Approaches to Deep Learning**, 08:45 AM

Do GANs Actually Learn the Distribution? Some Theory and Empirics

The Generative Adversarial Nets or GANs framework (Goodfellow et al'14) for learning distributions differs from older ideas such as autoencoders and deep Boltzmann machines in that it scores the generated distribution using a discriminator net, instead of a perplexity-like calculation. It appears to work well in practice, e.g., the generated images look better than older techniques. But how well do these nets learn the target distribution?

Our paper 1 (ICML'17) shows GAN training may not have good generalization properties; e.g., training may appear successful but the trained distribution may be far from target distribution in standard metrics. We show theoretically that this can happen even though the 2-person game between discriminator and generator is in near-equilibrium, where the generator appears to have "won" (with respect to natural training objectives).

Paper2 (arxiv June 26) empirically tests the whether this lack of generalization occurs in real-life training. The paper introduces a new quantitative test for diversity of a distribution based upon the famous birthday paradox. This test reveals that distributions learnt by some leading GANs techniques have fairly small support (i.e., suffer from mode collapse), which implies that they are far from the target distribution.

Paper 1: "Equilibrium and Generalization in GANs" by Arora, Ge, Liang, Ma, Zhang. (ICML 2017)

Paper 2: "Do GANs actually learn the distribution? An empirical study." by Arora and Zhang (https://arxiv.org/abs/1706.08224)

Abstract 6: **Invited Talk 3 - Ruslan Salakhutdinov in Principled Approaches to Deep Learning**, 10:45 AM

Neural Map: Structured Memory for Deep Reinforcement Learning

A critical component to enabling intelligent reasoning in partially observable environments is memory. Despite this importance, Deep Reinforcement Learning (DRL) agents have so far used relatively simple memory architectures, with the main methods to overcome partial observability being either a temporal convolution over the past k frames or an LSTM layer. In this talk, we will introduce a memory system with an adaptable write operator that is customized to the sorts of 3D environments that DRL agents typically interact with. This architecture, called the Neural Map, uses a spatially structured 2D memory image to learn to store arbitrary information about the environment over long time lags. We demonstrate empirically that the Neural Map surpasses previous DRL memories on a set of challenging 2D and 3D maze environments and show that it is capable of generalizing to environments that were not seen during training.

Joint work with Emilio Parisotto

Abstract 7: **Invited Talk 4 - Pedro Domingos in Principled Approaches to Deep Learning**, 11:15 AM

The Sum-Product Theorem: A Foundation for Learning Tractable Deep Models

Inference in expressive probabilistic models is generally intractable, which makes them difficult to learn and limits their applicability. Sum-product networks are a class of deep models where, surprisingly, inference remains tractable even when an arbitrary number of hidden layers are present. In this talk, I generalize this result to a much broader set of learning problems: all those where inference consists of summing a function over a semiring. This includes satisfiability, constraint satisfaction, optimization, integration, and others. In any semiring, for

summation to be tractable it suffices that the factors of every product have disjoint scopes. This unifies and extends many previous results in the literature. Enforcing this condition at learning time thus ensures that the learned models are tractable. I illustrate the power and generality of this approach by applying it to a new type of structured prediction problem: learning a nonconvex function that can be globally optimized in polynomial time. I show empirically that this greatly outperforms the standard approach of learning without regard to the cost of optimization. (Joint work with Abram Friesen)

Abstract 12: **Invited Talk 6 - Nathan Srebro in Principled Approaches to Deep Learning**, 02:15 PM

Geometry, Optimization and Generalization in Multilayer Networks

What is it that enables learning with multi-layer networks? What causes the network to generalize well despite the model class having extremely high capacity? In this talk I will explore these questions through experimentation, analogy to matrix factorization (including some new results on the energy landscape and implicit regularization in matrix factorization), and study of alternate geometries and optimization approaches.

## Video Games and Machine Learning

***Gabriel Synnaeve, Julian Togelius, Tom Schaul, Oriol Vinyals, Nicolas Usunier***

**C4.6, Thu Aug 10, 08:30 AM**

Good benchmarks are necessary for developing artificial intelligence. Recently, there has been a growing movement for the use of video games as machine learning benchmarks [1,2,3], and also an interest in the applications of machine learning from the video games community. While games have been used for AI research for a long time, only recently have we seen modern machine learning methods applied to video games.

This workshop focuses on complex games which provide interesting and hard challenges for machine learning. Going beyond simple toy problems of the past, and games which can easily be solved with search, we focus on games where learning is likely to be necessary to play well. This includes strategy games such as StarCraft [4,5], open-world games such as MineCraft [6,7,8], first-person shooters such as Doom [9,10], as well as hard and unsolved 2D games such as Ms. Pac-Man and Montezuma's Revenge [11,12,13]. While we see most of the challenges in game-playing, there are also interesting machine learning challenges in modeling and content generation [14]. This workshop aims at bringing together all researchers from ICML who want to use video games as a benchmark. We will have talks by invited speakers from machine learning, from the game AI community, and from the video games industry.

[1] Greg Brockman, Catherine Olsson, Alex Ray, et al. "OpenAI Universe", https://openai.com/blog/universe/ (2016).
[2] Charles Beattie, Joel Z. Leibo, Denis Teplyashin, Tom Ward, Marcus Wainwright, Heinrich Küttler, Andrew Lefrancq, Simon Green, Víctor Valdés, Amir Sadik, Julian Schrittwieser, Keith Anderson, Sarah York, Max Cant, Adam Cain, Adrian Bolton, Stephen Gaffney, Helen King, Demis Hassabis, Shane Legg, Stig Petersen, "DeepMind Lab", arXiv:1612.03801 (2016).
[3] Gabriel Synnaeve, Nantas Nardelli, Alex Auvolat, Soumith Chintala, Timothée Lacroix, Zeming Lin, Florian Richoux, Nicolas Usunier, "TorchCraft: a Library for Machine Learning Research on Real-Time Strategy Games", arXiv:1611.00625 (2016).
[4] Santiago Ontanon, Gabriel Synnaeve, Alberto Uriarte, Florian Richoux, David Churchill, Mike Preuss, "A Survey of Real-Time Strategy Game AI Research and Competition in StarCraft", IEEE Transactions on Computational Intelligence and AI in games 5.4 (2013): 293-311.
[5] StarCraft AI Competition @ AIIDE 2016
[6] Junhyuk Oh, Valliappa Chockalingam, Satinder Singh, and Honglak Lee, "Control of Memory, Active Perception, and Action in Minecraft", ICML (2016).
[7] Chen Tessler, Shahar Givony, Tom Zahavy, Daniel J. Mankowitz, Shie Mannor, "A Deep Hierarchical Approach to Lifelong Learning in Minecraft", arXiv preprint arXiv:1604.07255 (2016).
[8] Matthew Johnson, Katja Hofmann, Tim Hutton, David Bignell, "The Malmo Platform for Artificial Intelligence Experimentation", IJCAI (2016).
[9] Visual Doom AI Competition @ CIG 2016
[10] Volodymyr Mnih, Adrià Puigdomènech Badia, Mehdi Mirza, Alex Graves, Tim Harley, Timothy P. Lillicrap, David Silver, Koray Kavukcuoglu, "Asynchronous Methods for Deep Reinforcement Learning", arXiv preprint arXiv:1602.01783 (2016).
[11] Tejas D. Kulkarni, Karthik R. Narasimhan, Ardavan Saeedi, Joshua B. Tenenbaum, "Hierarchical Deep Reinforcement Learning: Integrating Temporal Abstraction and Intrinsic Motivation", arXiv prepint arXiv:1604.06057 (2016).
[12] Marc G. Bellemare, Sriram Srinivasan, Georg Ostrovski, Tom Schaul, David Saxton, Remi Munos, "Unifying Count-Based Exploration and Intrinsic Motivation", arXiv preprint arXiv:1606.01868 (2016).
[13] Diego Perez-Liebana, Spyridon Samothrakis, Julian Togelius, Tom Schaul, Simon Lucas, "General Video Game AI: Competition, Challenges and Opportunities", AAAI (2016).
[14] Julian Togelius, Georgios N. Yannakakis, Kenneth O. Stanley and Cameron Browne, "Search-based Procedural Content Generation: a Taxonomy and Survey". IEEE TCIAIG (2011).

## ML on a budget: IoT, Mobile and other tiny-ML applications

***Manik Varma, Venkatesh Saligrama, Prateek Jain***

**C4.7, Thu Aug 10, 08:30 AM**

We routinely encounter scenarios where at test-time we must predict on a budget. Feature costs in Internet, Healthcare, and Surveillance applications arise due to feature extraction time and feature/sensor acquisition~\cite{trapeznikov:2013b} costs. Data analytics applications in mobile devices are often performed on remote cloud services due to the limited device capabilities, which imposes memory/prediction time costs. Naturally, in these settings, one needs to carefully understand the trade-off between accuracy and prediction cost. Uncertainty in the observations, which is typical in such scenarios, further adds to complexity of the task and requires a careful understanding of both the uncertainty as well as accuracy-cost tradeoffs.

In this workshop, we aim to bring together researchers from various domains to discuss the key aspects of the above mentioned emerging and critical topic. The goal is to provide a platform where ML/statistics/optimization researchers can interact closely with domain

experts who need to deploy ML models in resource-constrained settings (like an IoT device maker), and chart out the foundational problems in the area and key tools that can be used to solve them.

Motivation
==========
Prediction under budget constraints is a critical problem that arise in several settings like medical diagnosis, search engines and surveillance. In these applications, budget constraints arise as a result of limits on computational cost, time, network-throughput and power-consumption. For instance, in search engines CPU cost during prediction-time must be budgeted to enable business models such as online advertising. Additionally, search engines have time constraints at prediction-time as users are known to abandon the service is the response time of the search engine is not within a few tens of milliseconds. In another example, modern passenger screening systems impose constraints on throughput.

An extreme version of these problems appear in the Internet of Things (IoT) setting where one requires prediction on tiny IoT devices which might have at most 2KB of RAM and no floating point computation unit. IoT is considered to be the next multi-billion industry with “smart” devices being designed for production-line, cars, retail stores, and even for toothbrush and spoons. Given that IoT based solutions seem destined to significantly permeate our day-to-day lives, ML based predictions on the device become critical due to several reasons like privacy, battery, latency etc.

Learning under resource constraints departs from the traditional machine learning setting and introduces new exciting challenges. For instance, features are accompanied by costs (e.g. extraction time in search engines or true monetary values in medical diagnosis) and their amortized sum is constrained at test-time. Also, different search strategies in prediction can have widely varying computational costs (e.g., binary search, linear search, dynamic programming). In other settings, a system must maintain a throughput constraint to keep pace with arriving traffic.
In IoT setting, the model itself has to be deployed on a 2-16KB RAM, posing an extremely challenging constraint on the algorithm.

The common aspect of all of these settings is that we must seeks trade-offs between prediction accuracy and prediction cost. Studying this tradeoff is an inherent challenge that needs to be investigated in a principled fashion in order to invent practically relevant machine learning algorithms. This problems lies at the intersection of ML, statistics, stochastic control and information theory. We aim to draw researchers working on foundational, algorithmic and application problems within these areas. We plan on organizing a demo session which would showcase ML algorithms running live on various resource-constrained device, demonstrating their effectiveness on challenging real-world tasks. In addition, we plan to invite Ofer Dekel from Microsoft Research to present a new platform for deploying ML on tiny devices which should provide a easy way to deploy and compare various ML techniques on realistic devices and further spur multiple research directions in this area.

**Schedule**

| | |
|---|---|
| 08:45 AM | **Introduction** |
| 08:50 AM | **Small Deep-Neural-Networks: Their Advantages, and Their Design by Forrest Iandola (DeepScale)** |
| 09:25 AM | **An Adaptive Approximation for Prediction Under a Budget by Venkatesh Saligrama (Boston University)** |
| 10:30 AM | **On-Device Machine Intelligence with Neural Projections by Sujith Ravi (Google)** |
| 11:05 AM | **Core ML: High-performance on-device machine learning by Bill March (Apple)** |
| 11:40 AM | **Building Amazon Alexa’s embedded wake word detector by Shiv Naga Prasad (Amazon)** |
| 12:15 PM | **Lunch Break** |
| 02:00 PM | **The Edge of Machine Learning: Resource-efficient ML in 2 KB RAM for the Internet of Things by Manik Varma (Microsoft)** |
| 02:40 PM | **Spotlight Presentations** |
| 03:00 PM | **Coffee Break** |
| 03:30 PM | **Trading-Off Cost of Deployment Versus Accuracy in Learning Predictive Models by Suchi Saria (JHU)** |
| 04:05 PM | **Resource Efficient Driving Policy by Shaked Sammah (Mobileye)** |
| 04:50 PM | **Small models for Big data---next steps?** |

Abstracts (8):

Abstract 2: **Small Deep-Neural-Networks: Their Advantages, and Their Design by Forrest Iandola (DeepScale) in ML on a budget: IoT, Mobile and other tiny-ML applications**, 08:50 AM

Deep neural networks (DNNs) have led to significant improvements to the accuracy of machine-learning applications. For many problems, such as object classification and object detection, DNNs have led to levels of accuracy that are acceptable for commercial applications. In other words, thanks to DNNs, an ever-growing range of ML-enabled applications are now ready to be put into commercial use. However, the next hurdle is that many DNN-enabled applications can only achieve their highest value when they are deployed on smartphones or other small,

low-wattage, embedded hardware.
When deploying DNNs on embedded hardware, there are a number of reasons why small DNN models (i.e. models with few parameters) are either required or strongly recommended. These reasons include:
- Small models require less bandwidth communication when sending updated models from the cloud to the client (e.g. smartphone or autonomous car)
- Small models train faster
- Small models require fewer memory transfers during inference, and off-chip memory transfers require 100x more power than arithmetic operations
To create DNNs that met the requirements of embedded systems and benefitted from the advantages of small DNNs, we set out in 2015 to identify smaller DNN models that can be deployed on embedded devices. The first result of our efforts was SqueezeNet, a DNN targeted for the object classification problem that achieves the same accuracy as the popular DNN AlexNet but with a 50x reduction in the number of model parameters.
SqueezeNet was created using a few basic techniques including kernel reduction, channel reduction, and delayed pooling. Over the last year, many other researchers have pursued the same goals of small, fast, energy-efficient DNNs for computer-vision problems ranging from object classification to style-transfer. In this talk we review these developments and report our progress in developing a systematic approach to the design of small DNNs.

Abstract 3: **An Adaptive Approximation for Prediction Under a Budget by Venkatesh Saligrama (Boston University) in ML on a budget: IoT, Mobile and other tiny-ML applications**, 09:25 AM

We propose a novel adaptive approximation approach for test-time resource-constrained prediction for classification and sequential-decision making problems. Given an input instance at test-time, a gating function identifies a prediction model or policy for the input among a collection of models or policies. Our objective is to minimize overall average cost without sacrificing accuracy. We present a novel bottom-up method based on adaptively approximating a high-accuracy model in regions where low-cost models are capable of making highly accurate predictions. We pose an empirical loss minimization problem with cost constraints to jointly train gating and prediction models. On a number of benchmark datasets our method outperforms state-of-the-art achieving higher accuracy for the same cost.

Abstract 4: **On-Device Machine Intelligence with Neural Projections by Sujith Ravi (Google) in ML on a budget: IoT, Mobile and other tiny-ML applications**, 10:30 AM

Deep neural networks and other machine learning models have been transformative for building intelligent systems capable of visual recognition, speech and language understanding. While recent advances have led to progress for machine intelligence applications running on the cloud, it is often infeasible to use typical machine learning models on devices like mobile phones or smart watches due to computation and memory constraints — model sizes are huge and cannot fit into the limited memory available on such devices. While these devices could make use of models running on high-performance data centers with CPUs or GPUs, this is not feasible for many applications and scenarios where inference needs to be performed directly “on” device. This requires re-thinking existing machine learning algorithms and coming up with new models that are directly optimized for on-device machine intelligence rather than doing post-hoc model compression.

In this talk, I will introduce a novel “projection-based” machine learning system for training compact neural networks. The approach uses a joint optimization framework to simultaneously train a “full” deep network like feed-forward or recursive neural network and a lightweight “projection” network. Unlike the full deep network, the projection network uses random projection operations that are efficient to compute and operates in bit space yielding a low memory footprint. The system is trained end-to-end using backpropagation. We show that the approach is flexible and easily extensible to other machine learning paradigms, for example, we learn graph-based projection models using label propagation. The trained “projection” models are directly used for inference and achieve significant model size reductions and efficiency on several visual and language tasks while providing competitive performance. We have used the novel networks to power machine intelligence applications on devices such as mobile phones and smart watches, for example a fully on-device Smart Reply model that runs on Android smart watches.

Abstract 5: **Core ML: High-performance on-device machine learning by Bill March (Apple) in ML on a budget: IoT, Mobile and other tiny-ML applications**, 11:05 AM

Considering the limited computing power available on mobile devices, application developers have typically been constrained to either small, simple models or expensive network access to remote servers. This year, Apple introduced Core ML, a new framework for on-device inference.
Core ML combines an open format for encoding a wide-range of models with simple programming interfaces and highly-optimized, on-device evaluation methods. The combination of these factors makes Core ML a powerful tool to bridge the gap between cutting edge ML research and large scale impact on mobile device users.
While on-device inference is typically regarded to be limited by power and computing constraints, we show that optimized methods can achieve excellent performance. We will show this first with a demo of Core ML in action, showing that efficient evaluation of state-of-the-art deep neural networks on a mobile device is possible with an extremely simple programming interface. We then discuss some of the optimizations underlying this performance in detail, including graph optimizations and automatic hardware selection algorithms. We then discuss Core ML’s open-source tools and model format, and highlight several ways in which we hope to work together with the wider machine learning community.

Abstract 6: **Building Amazon Alexa’s embedded wake word detector by Shiv Naga Prasad (Amazon) in ML on a budget: IoT, Mobile and other tiny-ML applications**, 11:40 AM

Alexa is a conversational AI agent that is accessible through several consumer devices such as Echo, Dot, Tap, Echo Show, etc. A key feature is that users can talk to Alexa eyes free and hands free, by invoking a wake up phrase, “Alexa”. Detecting the wake word on the device is one of the grand challenges in far field speech, given the CPU and memory constraints, background noise in household environment, and variation in user’s speech characteristics. We will provide an overview of the technical challenges in this area, and some of the research being conducted at Alexa in efficient ML on edge platforms.

Abstract 8: **The Edge of Machine Learning: Resource-efficient ML in 2 KB RAM for the Internet of Things by Manik Varma (Microsoft) in ML on a budget: IoT, Mobile and other tiny-ML applications**, 02:00 PM

We propose an alternative paradigm for the Internet of Things (IoT) where machine learning algorithms run locally on severely resource-constrained edge and endpoint devices without necessarily needing cloud connectivity. This enables many scenarios beyond the pale of the traditional paradigm including low-latency brain implants, precision agriculture on disconnected farms, privacy-preserving smart spectacles, etc.

Towards this end, we develop novel tree and kNN based algorithm, called Bonsai and ProtoNN, for efficient prediction on IoT devices -- such as those based on the Arduino Uno board having an 8 bit ATmega328P microcontroller operating at 16 MHz with no native floating point support, 2 KB RAM and 32 KB read-only flash memory. Bonsai and ProtoNN maintain prediction accuracy while minimizing model size and prediction costs by: (a) developing novel compressed yet expressive models; (b) sparsely projecting all data into a low-dimensional space in which the models are learnt; and (c) jointly learning all model and projection parameters. Experimental results on multiple benchmark datasets demonstrate that Bonsai and ProtoNN can make predictions in milliseconds even on slow microcontrollers, can fit in KB of memory, have lower battery consumption than all other algorithms while achieving prediction accuracies that can be as much as 30% higher than state-of-the-art methods for resource-efficient machine learning. Bonsai and ProtoNN are also shown to generalize to other resource constrained settings beyond IoT by generating significantly better search results as compared to Bing's L3 ranker when the model size is restricted to 300 bytes.

Abstract 11: **Trading-Off Cost of Deployment Versus Accuracy in Learning Predictive Models by Suchi Saria (JHU) in ML on a budget: IoT, Mobile and other tiny-ML applications**, 03:30 PM

Predictive models are finding an increasing number of applications in many industries. As a result, a practical means for trading-off the cost of deploying a model versus its effectiveness is needed. Our work is motivated by risk prediction problems in healthcare. Cost-structures in domains such as healthcare are quite complex, posing a significant challenge to existing approaches. We propose a novel framework for designing cost-sensitive structured regularizers that is suitable for problems with complex cost dependencies. We draw upon a surprising connection to boolean circuits. In particular, we represent the problem costs as a multi-layer boolean circuit, and then use properties of boolean circuits to define an extended feature vector and a group regularizer that exactly captures the underlying cost structure. The resulting regularizer may then be combined with a fidelity function to perform model prediction, for example. For the challenging real-world application of risk prediction for sepsis in intensive care units, the use of our regularizer leads to models that are in harmony with the underlying cost structure and thus provide an excellent prediction accuracy versus cost tradeoff.

Abstract 12: **Resource Efficient Driving Policy by Shaked Sammah (Mobileye) in ML on a budget: IoT, Mobile and other tiny-ML applications**, 04:05 PM

When attacking the problem of Autonomous Driving, one must take into account strict computational constraints, posed by the desired low cost of sensors and processors, and by the required real-time performance. Specifically, when considering Driving Policy, many of the current state-of-the-art solutions for planning in large state spaces (applied to different problems), are ruled out. We discuss approaches which allow feasible planning, through different representations of the state space, along with the use of both supervised and reinforcement learning algorithms.

## Workshop on Human Interpretability in Machine Learning (WHI)

***Kush Varshney, Adrian Weller, Been Kim, Dmitry Malioutov***

**C4.8, Thu Aug 10, 08:30 AM**

This workshop will bring together researchers who study the interpretability of predictive models, develop interpretable machine learning algorithms, and develop methodology to interpret black-box machine learning models (e.g., post-hoc interpretations). This is a very exciting time to study interpretable machine learning, as the advances in large-scale optimization and Bayesian inference that have enabled the rise of black-box machine learning are now also starting to be exploited to develop principled approaches to large-scale interpretable machine learning. Participants in the workshop will exchange ideas on these and allied topics, including:

- Quantifying and axiomatizing interpretability
- Psychology of human concept learning
- Rule learning,Symbolic regression and case-based reasoning
- Generalized additive models, sparsity and interpretability
- Visual analytics
- Interpretable unsupervised models (clustering, topic models, e.t.c)
- Interpretation of black-box models (including deep neural networks)
- Causality of predictive models
- Verifying, diagnosing and debugging machine learning systems
- Interpretability in reinforcement learning.

Doctors, judges, business executives, and many other people are faced with making critical decisions that can have profound consequences. For example, doctors decide which treatment to administer to patients, judges decide on prison sentences for convicts, and business executives decide to enter new markets and acquire other companies. Such decisions are increasingly being supported by predictive models learned by algorithms from historical data.

The latest trend in machine learning is to use highly nonlinear complex systems such as deep neural networks, kernel methods, and large ensembles of diverse classifiers. While such approaches often produce impressive, state-of-the art prediction accuracies, their black-box nature offers little comfort to decision makers. Therefore, in order for predictions to be adopted, trusted, and safely used by decision makers in mission-critical applications, it is imperative to develop machine learning methods that produce interpretable models with excellent predictive accuracy. It is in this way that machine learning methods can have impact on consequential real-world applications.

**Schedule**

| | | |
|---|---|---|
| 08:30 AM | **A. Dhurandhar, V. Iyengar, R. Luss, and K. Shanmugam, "A Formal Framework to Characterize Interpretability of Procedures"** | *Shanmugam* |

| | | |
|---|---|---|
| 08:45 AM | **A. Henelius, K. Puolamäki, and A. Ukkonen, "Interpreting Classifiers through Attribute Interactions in Datasets"** | *Henelius* |
| 09:00 AM | **S. Lundberg and S.-I. Lee, "Consistent Feature Attribution for Tree Ensembles"** | *Hiranuma* |
| 09:15 AM | **Invited Talk: D. Sontag** | |
| 10:30 AM | **S. Penkov and S. Ramamoorthy, "Program Induction to Interpret Transition Systems"** | *Penkov* |
| 10:45 AM | **R. L. Phillips, K. H. Chang, and S. Friedler, "Interpretable Active Learning"** | *Phillips* |
| 11:00 AM | **C. Rosenbaum, T. Gao, and T. Klinger, "e-QRAQ: A Multi-turn Reasoning Dataset and Simulator with Explanations"** | |
| 11:15 AM | **Invited Talk: T. Jebara** | |
| 02:00 PM | **W. Tansey, J. Thomason, and J. G. Scott, "Interpretable Low-Dimensional Regression via Data-Adaptive Smoothing"** | |
| 02:15 PM | **Invited Talk: P. W. Koh** | |
| 03:30 PM | **I. Valera, M. F. Pradier, and Z. Ghahramani, "General Latent Feature Modeling for Data Exploration Tasks"** | |
| 03:45 PM | **A. Weller, "Challenges for Transparency"** | *Weller* |
| 04:00 PM | **ICML WHI 2017 Awards Ceremony** | |
| 04:05 PM | **Panel Discussion: Human Interpretability in Machine Learning** | |

Abstracts (7):

Abstract 1: **A. Dhurandhar, V. Iyengar, R. Luss, and K. Shanmugam, "A Formal Framework to Characterize Interpretability of Procedures" in Workshop on Human Interpretability in Machine Learning (WHI)**, *Shanmugam* 08:30 AM

We provide a novel notion of what it means to be interpretable, looking past the usual association with human understanding. Our key insight is that interpretability is not an absolute concept and so we define it relative to a target model, which may or may not be a human. We define a framework that allows for comparing interpretable procedures by linking it to important practical aspects such as accuracy and robustness. We characterize many of the current state-of-the-art interpretable methods in our framework portraying its general applicability.

Abstract 2: **A. Henelius, K. Puolamäki, and A. Ukkonen, "Interpreting Classifiers through Attribute Interactions in Datasets" in Workshop on Human Interpretability in Machine Learning (WHI)**, *Henelius* 08:45 AM

In this work we present the novel ASTRID method for investigating which attribute interactions classifiers exploit when making predictions. Attribute interactions in classification tasks mean that two or more attributes together provide stronger evidence for a particular class label. Knowledge of such interactions makes models more interpretable by revealing associations between attributes. This has applications, e.g., in pharmacovigilance to identify interactions between drugs or in bioinformatics to investigate associations between single nucleotide polymorphisms. We also show how the found attribute partitioning is related to a factorisation of the data generating distribution and empirically demonstrate the utility of the proposed method.

Abstract 3: **S. Lundberg and S.-I. Lee, "Consistent Feature Attribution for Tree Ensembles" in Workshop on Human Interpretability in Machine Learning (WHI)**, *Hiranuma* 09:00 AM

It is critical in many applications to understand what features are important for a model, and why individual predictions were made. For tree ensemble methods these questions are usually answered by attributing importance values to input features, either globally or for a single prediction. Here we show that current feature attribution methods are inconsistent, which means changing the model to rely more on a given feature can actually decrease the importance assigned to that feature. To address this problem we develop fast exact solutions for SHAP (SHapley Additive exPlanation) values, which were recently shown to be the unique additive feature attribution method based on conditional expectations that is both consistent and locally accurate. We integrate these improvements into the latest version of XGBoost, demonstrate the inconsistencies of current methods, and show how using SHAP values results in significantly improved supervised clustering performance. Feature importance values are a key part of understanding widely used models such as gradient boosting trees and random forests. We believe our work improves on the state-of-the-art in important ways, and may impact any current user of tree ensemble methods.

Abstract 5: **S. Penkov and S. Ramamoorthy, "Program Induction to Interpret Transition Systems" in Workshop on Human Interpretability in Machine Learning (WHI)**, *Penkov* 10:30 AM

Explaining and reasoning about processes which underlie observed black-box phenomena enables the discovery of causal mechanisms, derivation of suitable abstract representations and the formulation of more robust predictions. We propose to learn high level functional programs in order to represent abstract models which capture the invariant structure in the observed data. We introduce the $\pi$-machine (program-induction machine) -- an architecture able to induce interpretable LISP-like programs from observed data traces. We propose an optimisation procedure for program learning based on backpropagation, gradient descent and A* search. We apply the proposed method to two problems: system identification of dynamical systems and explaining the behaviour of a DQN agent. Our results show

that the π-machine can efficiently induce interpretable programs from individual data traces.

Abstract 6: **R. L. Phillips, K. H. Chang, and S. Friedler, "Interpretable Active Learning" in Workshop on Human Interpretability in Machine Learning (WHI)**, *Phillips* 10:45 AM

Active learning has long been a topic of study in machine learning. However, as increasingly complex and opaque models have become standard practice, the process of active learning, too, has become more opaque. There has been little investigation into interpreting what specific trends and patterns an active learning strategy may be exploring. This work expands on the Local Interpretable Model-agnostic Explanations framework (LIME) to provide explanations for active learning recommendations. We demonstrate how LIME can be used to generate locally faithful explanations for an active learning strategy, and how these explanations can be used to understand how different models and datasets explore a problem space over time. In order to quantify the per-subgroup differences in how an active learning strategy queries spatial regions, we introduce a notion of uncertainty bias (based on disparate impact) to measure the discrepancy in the confidence for a model's predictions between one subgroup and another. Using the uncertainty bias measure, we show that our query explanations accurately reflect the subgroup focus of the active learning queries, allowing for an interpretable explanation of what is being learned as points with similar sources of uncertainty have their uncertainty bias resolved. We demonstrate that this technique can be applied to track uncertainty bias over user-defined clusters or automatically generated clusters based on the source of uncertainty.

Abstract 11: **I. Valera, M. F. Pradier, and Z. Ghahramani, "General Latent Feature Modeling for Data Exploration Tasks" in Workshop on Human Interpretability in Machine Learning (WHI)**, 03:30 PM

This paper introduces a general Bayesian non- parametric latent feature model suitable to per- form automatic exploratory analysis of heterogeneous datasets, where the attributes describing each object can be either discrete, continuous or mixed variables. The proposed model presents several important properties. First, it accounts for heterogeneous data while can be inferred in linear time with respect to the number of objects and attributes. Second, its Bayesian nonparametric nature allows us to automatically infer the model complexity from the data, i.e., the number of features necessary to capture the latent structure in the data. Third, the latent features in the model are binary-valued variables, easing the interpretability of the obtained latent features in data exploration tasks.

Abstract 13: **ICML WHI 2017 Awards Ceremony in Workshop on Human Interpretability in Machine Learning (WHI)**, 04:00 PM

Join us in recognizing the best papers of the workshop.

## Automatic Machine Learning (AutoML 2017)

***Joaquin Vanschoren, Roman Garnett***

**C4.9, Thu Aug 10, 08:30 AM**

Machine learning has achieved considerable successes in recent years and an ever-growing number of disciplines rely on it. However, this success crucially relies on human machine learning experts, who select appropriate features, workflows, machine learning paradigms, algorithms, and their hyperparameters. As the complexity of these tasks is often beyond non-experts, the rapid growth of machine learning applications has created a demand for off-the-shelf machine learning methods that can be used easily and without expert knowledge. We call the resulting research area that targets progressive automation of machine learning AutoML.

**Schedule**

| | |
|---|---|
| 08:30 AM | **Welcome** |
| 08:40 AM | **Generalizing from Few Examples with Meta-Learning, Hugo Larochelle (Google)** |
| 09:20 AM | **Thompson Sampling for Asynchronous Parallel Bayesian Optimisation. Kirthevasan Kandasamy.** |
| 09:40 AM | **Neural Block Sampling. Tongzhou Wang, Yi Wu, Dave Moore and Stuart Russell.** |
| 10:30 AM | **Rob DeLine (Microsoft)** |
| 11:10 AM | **Spotlight session 1** |
| 11:30 AM | **Poster session 1** |
| 12:00 PM | **Lunch** |
| 02:00 PM | **Himabindu Lakkaraju (Stanford)** |
| 02:40 PM | **YellowFin and the Art of Momentum Tuning. Jian Zhang, Ioannis Mitliagkas and Christopher Re.** |
| 03:00 PM | **Coffee** |
| 03:30 PM | **Spotlight session 2** |
| 03:50 PM | **Poster session 2** |
| 04:30 PM | **The future of AutoML** |

Abstracts (4):

Abstract 2: **Generalizing from Few Examples with Meta-Learning, Hugo Larochelle (Google) in Automatic Machine Learning (AutoML 2017)**, 08:40 AM

A lot of the recent progress on many AI tasks was enable in part by the availability of large quantities of labeled data. Yet, humans are able to learn concepts from as little as a handful of examples. Meta-learning is a very promising framework for addressing the problem of generalizing from small amounts of data, known as few-shot learning. In meta-learning, our model is itself a learning algorithm: it takes as input a training set and outputs a classifier. For few-shot learning, it is (meta-)trained directly to produce classifiers with good generalization performance for problems with very little labeled data. In this talk, I'll

review recent research that has made exciting progress on this topic.

Abstract 3: **Thompson Sampling for Asynchronous Parallel Bayesian Optimisation. Kirthevasan Kandasamy. in Automatic Machine Learning (AutoML 2017)**, 09:20 AM

We design and analyse variations of Thompson sampling (TS) for Bayesian optimisation (BO) in settings where function evaluations are expensive, but can be performed in parallel. Our theoretical analysis shows that a direct application of the sequential Thompson sampling algorithm in either synchronous or asynchronous parallel settings yields a surprisingly powerful result: making $n$ evaluations distributed among $M$ workers is essentially equivalent to performing $n$ evaluations in sequence. Further, by modeling the time taken to complete a function evaluation, we show that, under a time constraint, asynchronously parallel TS achieves asymptotically lower regret than both the synchronous and sequential versions. These results are complemented by an experimental analysis, showing that synchronous TS outperforms a suite of existing parallel BO algorithms in simulations and in a hyper-parameter tuning application. In addition, the proposed procedure is conceptually and computationally much simpler than existing work for parallel BO.

Abstract 4: **Neural Block Sampling. Tongzhou Wang, Yi Wu, Dave Moore and Stuart Russell. in Automatic Machine Learning (AutoML 2017)**, 09:40 AM

Efficient Monte Carlo inference often requires manual construction of model-specific proposals. We propose an approach to automated proposal construction by training neural networks to provide fast approximations to block Gibbs conditionals. The learned proposals generalize to occurrences of common structural motifs both within a given model and across models, allowing for the construction of a library of learned inference primitives that can accelerate inference on unseen models with no model-specific training required.

Abstract 10: **YellowFin and the Art of Momentum Tuning. Jian Zhang, Ioannis Mitliagkas and Christopher Re. in Automatic Machine Learning (AutoML 2017)**, 02:40 PM

Hyperparameter tuning is one of the big costs of deep learning. State-of-the-art optimizers, such as Adagrad, RMSProp and Adam, make things easier by adaptively tuning an individual learning rate for each variable. This level of fine adaptation is understood to yield a more powerful method. However, our experiments suggest that simple momentum SGD is typically just as good or better. Motivated by these results, we revisit momentum SGD and analyze its robustness in learning rate misspecification and objective curvature variation. Based on these insights, we design YellowFin, an automatic tuner for a single momentum and a single learning rate in SGD. We empirically show YellowFin converges in fewer iterations than Adam on large ResNet and LSTM models, a speedup of up to 2.8x. We also describe closed-loop YellowFin, an extension that uses a novel momentum-sensing component along with a negative-feedback loop mechanism to compensate for the dynamics of certain settings, like asynchronous parallelization. We show that closed-loop YellowFin is up to 2.7x faster than Adam under

## Implicit Generative Models

***Rajesh Ranganath, Ian Goodfellow, Dustin Tran, David Blei, Balaji Lakshminarayanan, Shakir Mohamed***

**Parkside 1, Thu Aug 10, 08:30 AM**

Probabilistic models are a central implement in machine learning practice. They form the basis for models that generate realistic data, uncover hidden structure, and make predictions. Traditionally, probabilistic models in machine learning have focused on prescribed models. Prescribed models specify a joint density over observed and hidden variables that can be easily evaluated. The requirement of a tractable density simplifies their learning but limits their flexibility --- several real world phenomena are better described by simulators that do not admit a tractable density. Probabilistic models defined only via the simulations they produce are called implicit models.

Arguably starting with generative adversarial networks, research on implicit models in machine learning has exploded in recent years. This workshop's aim is to foster a discussion around the recent developments and future directions of implicit models.

Implicit models have many applications. They are used in ecology where models simulate animal populations over time; they are used in phylogeny, where simulations produce hypothetical ancestry trees; they are used in physics to generate particle simulations for high energy processes. Recently, implicit models have been used to improve the state-of-the-art in image and content generation. Part of the workshop's focus is to discuss the commonalities among applications of implicit models.

Of particular interest at this workshop is to unite fields that work on implicit models. For example:

+ Generative adversarial networks (a NIPS 2016 workshop) are implicit models with an adversarial training scheme.

+ Recent advances in variational inference (a NIPS 2015 and 2016 workshop) have leveraged implicit models for more accurate approximations.

+ Approximate Bayesian computation (a NIPS 2015 workshop) focuses on posterior inference for models with implicit likelihoods.

+ Learning implicit models is deeply connected to two sample testing and density ratio estimation.

We hope to bring together these different views on implicit models, identifying their core challenges and combining their innovations.

We invite submission of 4 page papers for posters, contributed talks, and travel awards. Topics of interests are: implicit models, approximate Bayesian computation, generative adversarial networks, learning and inference for implicit models, implicit variational approximations, evaluation of implicit models and two sample testing. We encourage both theoretical and applied submissions.

**Schedule**

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|---|---|
| 08:30 AM | **Introduction** |

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|---|---|
| 08:40 AM | **Kerrie Mengerson: Probabilistic Modelling in the Real World** |
| 09:10 AM | **Yingzhen Li: Approximate Inference with Amortised MCMC** |
| 09:20 AM | **Zenna Tavares: Adversarial Inversion for Amortized Inference** |
| 09:30 AM | **Spotlight Session 1** |
| 10:30 AM | **Stefano Ermon: Generative Adversarial Imitation Learning** |
| 11:00 AM | **Jun-Yan Zhu: Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks** |
| 11:10 AM | **Spotlight session 2** |
| 12:30 PM | **Lunch** |
| 02:00 PM | **Qiang Liu: Wild Variational Inference with Expressive Variational Families** |
| 02:30 PM | **Sanjeev Arora: Do GANs actually learn the distribution? Some theory and experiments.** |
| 03:00 PM | **Break** |
| 03:30 PM | **Dougal Sutherland: Evaluating and Training Implicit Generative Models with Two-Sample Tests** |
| 04:00 PM | **Lars Mescheder: The Numerics of GANs** |
| 04:10 PM | **Eric Nalisnick: The Amortised bootstrap** |
| 04:20 PM | **Philemon Brakel: Maximizing Independence with GANs for Non-linear ICA** |
| 04:30 PM | **Panel** |

## Aug. 11, 2017

### Time Series Workshop

***Vitaly Kuznetsov, Yan Liu, Scott Yang, Rose Yu***

**C4.1, Fri Aug 11, 08:30 AM**

Time series data is ubiquitous. In domains as diverse as finance, entertainment, transportation and health-care, we observe a fundamental shift away from parsimonious, infrequent measurement to nearly continuous monitoring and recording. Rapid advances in diverse sensing technologies, ranging from remote sensors to wearables and social sensing, are generating a rapid growth in the size and complexity of time series archives. Thus, although time series analysis has been studied extensively, its importance only continues to grow. Furthermore, modern time series data pose significant challenges to existing techniques both in terms of the structure (e.g., irregular sampling in hospital records and spatiotemporal structure in climate data) and size. These challenges are compounded by the fact that standard i.i.d. assumptions used in other areas of machine learning are not appropriate for time series and new theory, models and algorithms are needed to process and analyse this data.

The goal of this workshop is to bring together theoretical and applied researchers interested in the analysis of time series and development of new algorithms to process sequential data. This includes algorithms for time series prediction, classification, clustering, anomaly and change point detection, correlation discovery, dimensionality reduction as well as a general theory for learning and comparing stochastic processes. We invite researchers from the related areas of batch and online learning, reinforcement learning, data analysis and statistics, econometrics, and many others to contribute to this workshop.

Our workshop will build on the success of past two time series workshops that were held at NIPS and KDD (also co-organized by the proposers). The workshop will attract a broader audience from ICML community. In particular, when we have the KDD workshop on time series in 2015 held in Sydney, it attracts many local researchers in Australia who work on time series research or related applications. We expect the proposed workshop will be a hit given its large interest in the ICML community as well as the local interest in Sydney.

**Schedule**

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|---|---|
| 09:20 AM | **Opening remarks: Vitaly Kuznetsov** |
| 09:50 AM | **Suchi Saria** |
| 10:35 AM | **Morning Coffee Break** |
| 11:00 AM | **Poster Session** |
| 12:00 PM | **Lunch Break** |
| 02:00 PM | **Structured Black Box Variational Inference for Latent Time Series Models** |
| 02:25 PM | **Rob Hyndman** |
| 03:15 PM | **Afternoon Coffee Break** |
| 03:45 PM | **Online Variational Bayesian Inference: Algorithms for Sparse Gaussian Processes and Theoretical Bounds** |
| 04:15 PM | **Vijay M. Janakiraman** |
| 05:00 PM | **Closing Remarks** |

### Reproducibility in Machine Learning Research

***Nan Ke, Anirudh Goyal, Alex Lamb, Joelle Pineau, Samy Bengio, Yoshua Bengio***

**C4.10, Fri Aug 11, 08:30 AM**

This workshop focuses on issues of reproducibility and replication of results in the Machine Learning community. Papers from the Machine Learning community are supposed to be a valuable asset. They can help to inform and inspire future research. They can be a useful educational tool for students. They can give guidance to applied researchers in industry. Perhaps most importantly, they can help us to answer the most fundamental questions about our existence - what does it mean to learn and what does it mean to be human? Reproducibility, while not always possible in science (consider the study of a transient astrological phenomenon like a passing comet), is a powerful criteria for improving the quality of research. A result which is reproducible is more likely to be robust and meaningful and rules out many types of experimenter error (either fraud or accidental).

There are many interesting open questions about how reproducibility issues intersect with the Machine Learning community:

* How can we tell if papers in the Machine Learning community are reproducible even in theory? If a paper is about recommending news sites before a particular election, and the results come from running the system online in production - it will be impossible to reproduce the published results because the state of the world is irreversibly changed from when the experiment was ran.
* What does it mean for a paper to be reproducible in theory but not in practice? For example, if a paper requires tens of thousands of GPUs to reproduce or a large closed-off dataset, then it can only be reproduced in reality by a few large labs.
* For papers which are reproducible both in theory and in practice - how can we ensure that papers published in ICML would actually be able to replicate if such an experiment were attempted?
* What does it mean for a paper to have successful or unsuccessful replications?
* Of the papers with attempted replications completed, how many have been published?
* What can be done to ensure that as many papers which are reproducible in theory fall into the last category?
* On the reproducibility issue, what can the Machine Learning community

learn from other fields?

Our aim in the following workshop is to raise the profile of these questions in the community and to search for their answers. In doing so we aim for papers focusing on the following topics:
* Analysis of the current state of reproducibility in machine learning venues
* Tools to help increase reproducibility
* Evidence that reproducibility is important for science
* Connections between the reproducibility situation in Machine Learning and other fields
* Replications, both failed and successful, of influential papers in the Machine Learning literature.

## Interactive Machine Learning and Semantic Information Retrieval

***Dorota Glowacka, Wray Buntine, Petri Myllymaki***

**C4.11, Fri Aug 11, 08:30 AM**

Retrieval techniques operating on text or semantic annotations have become the industry standard for retrieval from large document collections. However, traditional information retrieval techniques operate on the assumption that the user issues a single query and the system responds with a ranked list of documents. In recent years we have witnessed a substantial growth in text data coming from various online resources, such as online newspapers, blogs, specialised document collections (e.g. arXiv). Traditional information retrieval approaches often fail to provide users with adequate support when browsing such online resources, hence in recent years there has been a growing interest in developing new algorithms and design methods that can support interactive information retrieval. The aim of this workshop is to explore new methods and related system design for interactive data analytics and management in various domains, including specialised text collections (e.g. legal, medical, scientific) as well as for various tasks, such as semantic information retrieval, conceptual organization and clustering of data collections for sense making, semantic expert profiling, and document recommender systems.
Of interest, also, is probabilistic and machine learning formulations of the interactive information retrieval task above and beyond the simple "stochastic language models" framework developed in the information retrieval community.
The primary audience of the workshop are researchers and practitioners in the area of interactive and personalised system design as well as interactive machine learning both from academia and industry.

**Schedule**

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|---|---|
| 09:00 AM | **Welcome** |
| 09:15 AM | **Using Web Text Based Analytics to Gather Customer Insights** |
| 09:35 AM | **Intent Driven Dynamic Product Ranking System for Fashion E-commerce** |
| 10:00 AM | **Coffee Break** |
| 10:30 AM | **Towards End-to-End Reinforcement Learning of Dialogue Agents for Information Access** |
| 11:30 AM | **Learning to Select Relevant and Diverse Subsets** |
| 12:00 PM | **Lunch Break** |
| 02:00 PM | **Focused Reading: Reinforcement Learning for What Documents to Read** |
| 02:20 PM | **CCA: Attention Based Cross Modal Retrieval on Webpages** |
| 02:40 PM | **User Study for Measuring Linguistic Complexity and its Reduction by Technology on a Patent Website** |
| 03:00 PM | **Poster Session** |

## Machine Learning in Speech and Language Processing

***Karen Livescu, Tara Sainath, lianglu Lu, Anton Ragni***

**C4.3, Fri Aug 11, 08:30 AM**

This workshop continues a tradition of MLSLP workshops held as satellites of ICML, ACL, and Interspeech conferences. While research in speech and language processing has always involved machine learning (ML), current research is benefiting from even closer interaction between these fields. Speech and language processing is continually mining new ideas from ML and ML, in turn, is devoting more interest to speech and language applications. This workshop is a venue for locating and incubating the next waves of research directions for interaction and collaboration. The workshop will (1) discuss emerging research ideas with potential for impact in speech/language and (2) bring together relevant researchers from ML and speech/language who may not regularly interact at conferences. Example topics include new directions for deep learning in speech/language, reinforcement learning, unsupervised/semi-supervised learning, domain adaptation/transfer learning, and topics at the boundary of speech, text, and other modalities.

**Schedule**

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|---|---|
| 09:15 AM | **Andrew McCallum** |
| 10:00 AM | **Joelle Pineau: Neural Models for Interactive Dialogue Systems** |
| 10:45 AM | **Break** |
| 11:00 AM | **Jason Weston: (Towards) Learning from Conversing** |
| 11:45 AM | **Tasha Nagamine** |

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|---|---|
| 12:30 PM | **Lunch Break** |
| 02:00 PM | **Poster Session** |

Abstracts (2):

Abstract 2: **Joelle Pineau: Neural Models for Interactive Dialogue Systems in Machine Learning in Speech and Language Processing**, 10:00 AM

Reinforcement learning provides a rich framework to cast the problem of learning a dialogue strategy for conversational AI agents. In this talk I will present recent results on building dialogue systems from large corpuses using neural architectures. I will highlight several challenges related to data acquisition, algorithmic development, performance evaluation, and user studies.

Abstract 4: **Jason Weston: (Towards) Learning from Conversing in Machine Learning in Speech and Language Processing**, 11:00 AM

An (end-to-end) dialogue agent might be far from knowing and understanding
everything, but _if_ it can learn _while_ it is conversing with humans, maybe
it can move towards that goal?

We look at some key ingredients we will need:
(i) ability to learn from textual feedback, i.e. the things said to it,
(ii) ability to ask (useful) questions and learn from the replies,
(iii) bootstrapping the model so that it doesn't take 6 months - 2 years to say
something (like a human baby),
(iv) making this a elegant unified system, and not a bunch of hacks.

This talk describes joint work with Jiwei Li, Alexander H. Miller, Sumit Chopra
and Marc'Aurelio Ranzato.

## Private and Secure Machine Learning

***Antti Honkela, Kana Shimizu, Samuel Kaski***

**C4.4, Fri Aug 11, 08:30 AM**

There are two complementary approaches to private and secure machine learning: differential privacy can guarantee privacy of the subjects of the training data with respect to the output of a differentially private learning algorithm, while cryptographic approaches can guarantee secure operation of the learning process in a potentially distributed environment. The aim of this workshop is to bring together researchers interested in private and secure machine learning, to stimulate interactions to advance either perspective or to combine them.

**Schedule**

| | |
|---|---|
| 08:30 AM | **Opening** |
| 08:35 AM | **Deep Learning with Differential Privacy: Two Approaches** |
| 09:20 AM | **Priv'IT: Private and Sample Efficient Identity Testing** |
| 09:40 AM | **Differentially Private Learning of Undirected Graphical Models using CGMs** |
| 10:00 AM | **Coffee break & Posters 1** |
| 10:30 AM | **Differentially Private Submodular Maximization: Data Summarization in Disguise** |
| 10:50 AM | **The Hybrid Model for Privacy and its Benefits** |
| 11:10 AM | **Posters 2** |
| 12:00 PM | **Lunch** |
| 02:00 PM | **Privacy-preserving machine learning and data mining using the Sharemind platform** |
| 02:45 PM | **Privacy-preserving entity resolution and logistic regression on encrypted data** |
| 03:05 PM | **Coffee break & Posters 3** |
| 03:30 PM | **Detecting Causative Attacks using Data Provenance** |
| 03:50 PM | **Panel discussion** |

Abstracts (9):

Abstract 1: **Opening in Private and Secure Machine Learning**, 08:30 AM

Introductory comments from organizers

Abstract 2: **Deep Learning with Differential Privacy: Two Approaches in Private and Secure Machine Learning**, 08:35 AM

We discuss two recently proposed approaches towards offering differential privacy for training data. The first approach modifies the SGD procedure so that the updates to the model's weights are provably differentially private. The second approach, called Private Aggregation of Teacher Ensembles (PATE) is particularly suitable for training classifiers. PATE combines, in a black-box fashion, multiple models trained with disjoint datasets and aggregates their results---enforcing differential privacy---to train a "student" model who is never directly exposed to sensitive data.

Abstract 3: **Priv'IT: Private and Sample Efficient Identity Testing in Private and Secure Machine Learning**, 09:20 AM

We develop differentially private hypothesis testing methods for the small sample regime. Given a sample D from a categorical distribution p over some domain Sigma, an explicitly described distribution q over Sigma,

some privacy parameter epsilon, accuracy parameter alpha, and requirements beta_I and beta_II for the type I and type II errors of our test, the goal is to distinguish between p=q and dtv(p,q) >= alpha.
We provide theoretical bounds for the sample size |D| so that our method both satisfies (epsilon,0)-differential privacy, and guarantees beta_I and beta_II type I and type II errors. We show that differential privacy may come for free in some regimes of parameters, and we always beat the sample complexity resulting from running the chi^2-test with noisy counts, or standard approaches such as repetition for endowing non-private chi^2-style statistics with differential privacy guarantees. We experimentally compare the sample complexity of our method to that of recently proposed methods for private hypothesis testing.

Abstract 4: **Differentially Private Learning of Undirected Graphical Models using CGMs in Private and Secure Machine Learning**, 09:40 AM

We investigate the problem of learning discrete, undirected graphical models in a differentially private way. Approaches to this problem range from privileged algorithms that conduct learning completely behind the privacy barrier to schemes that release private summary statistics paired with algorithms to learn parameters from those statistics. We show that the approach of releasing noisy sufficient statistics using the Laplace mechanism achieves a good trade-off between privacy, utility, and practicality. A naive learning algorithm that uses the noisy sufficient statistics ``as is'' outperforms general-purpose differentially private learning algorithms. However, it ignores knowledge about the data generating process, is on uncertain theoretical foundations, and exhibits certain pathologies. We develop a more principled approach that applies the formalism of collective graphical models to perform inference over the true sufficient statistics within an expectation-maximization framework. We show that this learns better models than competing approaches on both synthetic data and on real human mobility data used as a case study.

Abstract 6: **Differentially Private Submodular Maximization: Data Summarization in Disguise in Private and Secure Machine Learning**, 10:30 AM

How can we extract representative features from a dataset containing sensitive personal information, while providing individual-level privacy guarantees? Many data summarization applications are captured by the general framework of submodular maximization. As a consequence, a wide range of efficient approximation algorithms for submodular maximization have been developed. However, when such applications involve sensitive data about individuals, their privacy concerns are not automatically addressed by these algorithms.
To remedy this problem, we propose a general and systematic study of differentially private submodular maximization. We present privacy-preserving algorithms for both monotone and non-monotone submodular maximization under cardinality, matroid, and p-extendible system constraints, with guarantees that are competitive with optimal solutions. Along the way, we analyze a new algorithm for non-monotone submodular maximization under a cardinality constraint, which is the first (even non-privately) to achieve a constant approximation ratio with a linear number of function evaluations. We additionally provide two concrete experiments to validate the efficacy of these algorithms. In the first experiment, we privately solve the facility location problem using a dataset of Uber pickup locations in Manhattan. In the second experiment, we perform private submodular maximization of a mutual information measure to select features relevant to classifying patients by diabetes status.

Abstract 7: **The Hybrid Model for Privacy and its Benefits in Private and Secure Machine Learning**, 10:50 AM

Differential privacy has been recognized as the most suitable statistical data privacy definition in the academic community [1] and has spurred a decade-long effort to develop algorithms that satisfy the definition. Although by now, broadly speaking, differentially private algorithms are known for most machine learning primitives [2] including deep learning [3], they have seen limited adoption in practice. In particular, the two known large-scale commercial deployments of differential privacy (Google's RAPPOR [4] and Apple's learning system [5]) both operate in the so-called "local" model, where the data privatization occurs before it reaches the data collector. In contrast, most of the academic work has focused on developing algorithms for the "central" or "trusted data curator" models, in which all user data is collected by the curator before privatization techniques are applied [2].

In this talk, I will compare and contrast the "local" and the "central" models from the perspectives of privacy guarantees they provide for the users and the utility of the data for the data collector. I will then discuss implications these competing considerations may have for adoption of one model over the other by companies, depending on the size of the company's user base [6].

I will then describe a hybrid model of differential privacy proposed by [7], that considers a combination of regular and opt-in users who desire the differential privacy guarantees of the local privacy model and the central model, respectively. Using the task of privately computing the head of a search log, I will demonstrate that within this model, it is possible to design a new type of blended algorithm, that provides significant improvements in the utility of obtained data. I will present both the new algorithm and experimental results of its performance (attaining NDCG values exceeding 95% for reasonable privacy parameter values) on two large search click data sets.

I will conclude by arguing that since many companies already rely on a group of beta testers with whom they have higher levels of mutual trust, the hybrid model is appropriate for many real-world scenarios. Combined with the findings of the significant improvements in utility that operating in this model may bring even when the percentage of users opting-in to the "central" privacy model is low [7], I will build a case for further algorithmic and ML research in the hybrid model. It can be a step to a viable approach for achieving broader practical adoption of differential privacy and a lens for putting the collaboration of differential privacy researchers with researchers from the secure distributed learning communities on a formal footing.

Abstract 10: **Privacy-preserving machine learning and data mining using the Sharemind platform in Private and Secure Machine Learning**, 02:00 PM

We have built the Sharemind platform for privacy-preserving computations, based on additively sharing the secrets among three parties and a large, passively secure protocol set built on top of this representation of private data. Using this protocol set, we have built various privacy-preserving numerical, statistical, anomaly detection, and combinatorial applications and prototypes on top of Sharemind, some of them for use-cases with a large number of inputs and correspondingly large computation size.

In this talk, I explain the basics of Sharemind and the construction of applications which may be of interest to the ML community. This covers the linear regression and principal component analysis, genetic algorithms, frequent itemset mining. I also explain how differentially private computations have been done on top of Sharemind: we implemented the sample-and-aggregate mechanism by Nissim et al. and Smith, as well as a technique to keep track of personalized differential privacy budgets by Ebadi et al. There are important differences between normal and privacy-preserving applications, when it comes to the relative efficiency of certain algorithmic steps. These have affected the construction of the applications that I'm going to talk about.

Abstract 11: **Privacy-preserving entity resolution and logistic regression on encrypted data in Private and Secure Machine Learning**, 02:45 PM

We consider a scenario of two data providers, A and B, each of whom manage a dataset of private information consisting of two different feature sets related to common customers/entities. They jointly aim to learn a linear model using stochastic gradient algorithms like SGD/SAG. The setting is federated learning, where data is kept locally and a shared model is learned on top of local computation. Notice that, in contrast with the large majority of work on distributed learning, in our scenario data is split vertically, i.e. by features. We also assume that only A knows the target variable. We propose a secure system solving the problem in two phases: privacy-preserving entity resolution and logistic regression over encrypted data. With the aid of a coordinator, C, we design a three-party protocol that is secure under the honest-but-curious adversary model. Our system allows A and B to learn a classifier collaboratively, without either exposing their data in the clear or even sharing which entities they have in common.

Privacy-preserving entity resolution. When the dataset is vertically partitioned across multiple organisations the problem arises of how to identify the corresponding entities, namely entity resolution. Entity resolution is usually done on identifying features such as name, address, etc. We perform privacy-preserving entity resolution using anonymous linkage codes, which map entity information onto a code from which it is impossible to reconstruct any entity data. We use the cryptographic longterm key (CLK) anonymous linkage code, which provides both privacy and error tolerance. The CLKs are used in a comparison function which estimates the likelihood that two entities match. Parties A and B create CLKs for each entry in their datasets and sent them to C, which performs the entity resolution. The protocol results in two permutations, one for each data provider, and a mask. The permutations describe how A and B should rearrange their dataset so as to be consistent with each other and the mask. The mask specifies whether a row corresponds to a record available in both datasets, thus a record which will be used for learning; it also implicitly excludes records that are not matched accross A and B. The mask itself is only sent to data providers in encrypted form to prevent revealing the common entities. For simplicity, we omit mention of the permutations and mask in what follows.

Logistic regression on encrypted data Learning is performed on data encrypted with the Paillier partially homomorphic encryption scheme, an asymmetric scheme which permits both adding encrypted values and scaling encrypted values by unencrypted ones. These properties allow us to implement most of the linear algebra necessary for gradient descent optimization on encrypted data. Only C possesses the private key. We approximate the logistic loss and its gradient via Taylor expansion around 0 which results in polynomials that A and B can evaluate collaboratively and securely by only transmitting intermediate values that are encrypted with the Paillier scheme. Experimental results have shown that wecan match the accuracy of exact logistic loss using a merely second-order Taylor approximation to the loss (hence linear approximation to the gradient) at the price of rescaling features into the interval [–1, 1] and of applying L1 /L2 regularization. Party C orchestrates the optimization algorithm, taking care of the stochastic learning parameters (regularization, learning rate, momentum, etc.), triggering gradient computations by A and B, and using the logistic loss on hold-out data to determine when to stop training so as to avoid overfitting. We have proven the practicality of our system in commercial deployments. Our system is capable of scaling to millions of records with hundreds of features.

Abstract 13: **Detecting Causative Attacks using Data Provenance in Private and Secure Machine Learning**, 03:30 PM

The reliance of machine learning methods on quality training data presents a security vulnerability in which adversaries may inject poisonous samples into the training dataset to manipulate the learned classifier. A highly-publicized example of this is the recent attack on Microsoft’s AI chat bot, Tay, which learned offensive and racist language from Twitter users. Defending against these types of attacks, called causative attacks, is particularly challenging in online learning and other environments where the model must be periodically retrained to account for dataset shifts.

One countermeasure, called Reject on Negative Impact (RONI) (Nelson et al., 2009), detects whether a given sample is poisoned by comparing the performance of the classifier on a trusted test set before and after the sample is added to a trusted training set. Compared to clustering-based methods, RONI is likely to perform better on heterogeneous datasets. However, this method requires that the classifier be re-trained for each sample, which may be infeasible in big-data settings. Moreover, it relies strongly on the coverage of the test set. Finally, it requires that some of the collected data is trusted.

In this talk, we demonstrate how data provenance can be used to aid in the detection of poisoned data. By utilizing a provenance framework, cryptographically protected meta-data describing the origin and history of each data point can be collected. This may include information about the device from which the data was gathered, its firmware version, user id, and timestamp among others. Our method uses this provenance meta-data to segment the untrusted data into groups where the probability of poisoning is highly correlated across samples in each group. The data points in each group are then evaluated together by comparing the performance of the classifier trained with and without that group. Since groups of data points are evaluated together, this method reduces the number of times the classifier must be trained and amplifies the effect of the evaluated data points on the classifier, thereby improving accuracy.

Additionally, we present a methodology to address cases where the entire dataset is untrusted. Using provenance meta-data, the dataset is first segmented into groups that are evaluated together. It is then split into a training and a test set, and, for each group, classifiers are trained with and without the group. The performance of each classifier is then evaluated on a test set with data points from the group removed, preventing poisoned data in the test set from manipulating the evaluation of its own group. We present a detailed analysis of new attacks that arise when trusted data are unavailable and provide defense mechanisms to

prevent them. Lastly, we show the results of simulations that evaluated the ability of our methods to detect poisoning attacks on logistic regression classifiers.

### Deep Structured Prediction

***Isabelle Augenstein, Kai-Wei Chang, Gal Chechik, Bert Huang, Andre Filipe Torres Martins, Ofer Meshi, Alex Schwing, Yishu Miao***

**C4.5, Fri Aug 11, 08:30 AM**

In recent years, deep learning has revolutionized machine learning. Most successful applications of deep learning involve predicting single variables (e.g., univariate regression or multi-class classification). However, many real problems involve highly dependent, structured variables. In such scenarios, it is desired or even necessary to model correlations and dependencies between the multiple input and output variables. Such problems arise in a wide range of domains, from natural language processing, computer vision, computational biology and others.

Some approaches to these problems directly use deep learning concepts, such as those that generate sequences using recurrent neural networks or that output image segmentations through convolutions. Others adapt the concepts from structured output learning. These structured output prediction problems were traditionally handled using linear models and hand-crafted features, with a structured optimization such as inference. It has recently been proposed to combine the representational power of deep neural networks with modeling variable dependence in a structured prediction framework. There are numerous interesting research questions related to modeling and optimization that arise in this problem space.

This workshop will bring together experts in machine learning and application domains whose research focuses on combining deep learning and structured models. Specifically, we aim to provide an overview of existing approaches from various domains to distill from their success principles that can be more generally applicable. We will also discuss the main challenges that arise in this setting and outline potential directions for future progress. The target audience consists of researchers and practitioners in machine learning and application areas.

### Picky Learners: Choosing Alternative Ways to Process Data.

***Corinna Cortes, Kamalika Chaudhuri, Giulia DeSalvo, Ningshan Zhang, Chicheng Zhang***

**C4.6, Fri Aug 11, 08:30 AM**

Picky Learners consists of a broad range of learning scenarios where the learner does not simply process every data point blindly, but instead can choose to incorporate them in alternative ways. Despite the growing costs of processing and labelling vast amounts of data, only isolated efforts have tackled this problem primarily in the areas of active learning, learning with rejection and on-line learning with feedback graphs.

In active learning, the learner can choose whether or not to query for a label of each data point, thereby paying different costs for each data point. A key advantage in this setting is that the number of examples queried to learn a concept may be much smaller than the number of examples needed in standard supervised learning. More recently, some have used variations of confidence-based models to determine which labels to query. Confidence-based models lie under the more general framework of learning with rejection, which is a key learning scenario where the algorithm can abstain from making a prediction, at the price of incurring a fixed cost. In this scenario, our picky learners can thus choose to abstain from providing a label. In the on-line setting, one can cast learning with rejection under the more general topic of on-line learning with feedback graphs, a setting that interpolates between bandit and full expert scenario in that the player observes a variety of different expert losses after choosing an action. On-line learning with feedback graphs can then in turn be connected back to active learning where depending on the feedback graph only certain labels are requested.

In short, our picky learners can choose to query for the label (active learning), choose to abstain on the label (learning with rejection) or choose to receive different expert losses (on-line learning with feedback graphs). All of three of these fields attempt in different ways to reduce the cost of processing the data by allowing for picky learners, but the connections between these topics has not been fully explored in terms of both theory and practice. The goal of this workshop is then to bring together researchers and practitioners in these three areas in order to bridge the gap between active learning, learning with rejection, and on-line learning with feedback graphs. We expect that the fruitful collaborations started in this workshop will result in novel research that will help develop each field.

**Schedule**

| | |
|---|---|
| 09:00 AM | **Opening Remarks** |
| 09:05 AM | **Nina Balcan** |
| 09:45 AM | **Why adaptively collected data have negative bias and how to correct for it.** |
| 10:05 AM | **Morning Break** |
| 10:30 AM | **Panel discussion** |
| 11:05 AM | **Active Learning in Expert Systems Experiments on StackExchange Data.** |
| 11:25 AM | **Brief Study of In-Domain Transfer and Learning from Fewer Samples using A Few Simple Priors** |
| 11:45 AM | **Active Multi-Label Learning with Varying Queries** |
| 12:05 PM | **Lunch break** |
| 02:00 PM | **Alekh Agarwal** |
| 02:40 PM | **Data Driven Feature Learning** |
| 03:00 PM | **Afternoon Break** |
| 03:30 PM | **Michal Valko** |
| 04:10 PM | **Active Learning from Peers** |
| 04:30 PM | **Claudio Gentile** |

05:10 PM **Liran Szlak**

Abstracts (5):

Abstract 6: **Active Learning in Expert Systems Experiments on StackExchange Data. in Picky Learners: Choosing Alternative Ways to Process Data.**, 11:05 AM

We study adaptive matching in expert systems. Expert systems consist of a set of servers or experts of varying expertise, to which clients or tasks of varying types arrive. The task type is apriori unknown, and the task must be matched to the appropriate expert. We consider in particular the setting of Q&A platforms, focussing on real data from the StackExchange platform. We provide algorithms for efficient routing of questions to suitable responders, and validate our algorithms on StackExchange data.

Abstract 7: **Brief Study of In-Domain Transfer and Learning from Fewer Samples using A Few Simple Priors in Picky Learners: Choosing Alternative Ways to Process Data.**, 11:25 AM

Domain knowledge can often be encoded in the structure of a network, such as convolutional lay- ers for vision, which has been shown to increase generalization and decrease sample complexity, or the number of samples required for success- ful learning. In this study, we ask whether sam- ple complexity can be reduced for systems where the structure of the domain is unknown before- hand, and the structure and parameters must both be learned from the data. We show that sample complexity reduction through learning structure is possible for at least two simple cases. In study- ing these cases, we also gain insight into how this might be done for more complex domains.

Abstract 8: **Active Multi-Label Learning with Varying Queries in Picky Learners: Choosing Alternative Ways to Process Data.**, 11:45 AM

We introduce the problem of active multi-label learning where the queries are restricted to come from randomly varying subsets. This setting cap- tures crowd sourcing scenarios where there are multiple experts with different types of expertise, and not all experts are available at all times. We generalize the framework of adaptive submodular- ity and prove the first near optimal approximation bound for a greedy policy for this setting. We instantiate this framework for multi-label learning and evaluate it in multiple benchmark domains with promising results.

Abstract 11: **Data Driven Feature Learning in Picky Learners: Choosing Alternative Ways to Process Data.**, 02:40 PM

We present a regression-based feature learning algorithm that generates new features from a set of available features (raw data points). Be- ing data-driven, it requires no domain knowl- edge and is hence generic. Such a representa- tion is learnt by mining pairwise feature associ- ations, identifying the linear or non-linear rela- tionship between each pair, applying regression and selecting those relationships that are stable. Our experimental evaluation on 20 datasets taken from UC Irvine and Gene Expression, across dif- ferent domains, provides evidence that the fea- tures learnt through our model can improve the overall prediction accuracy, substantially, over the original feature space across 8 different clas- sifiers without any domain knowledge.

Abstract 14: **Active Learning from Peers in Picky Learners: Choosing Alternative Ways to Process Data.**, 04:10 PM

This paper addresses the challenge of learn- ing from peers in an online multitask setting. Instead of always requesting a label from a human oracle, the proposed method first de- termines if the learner for each task can ac- quire that label with sufficient confidence from its peers either as a task-similarity weighted sum, or from the single most similar task. If so, it saves the oracle query for later use in more difficult cases, and if not it queries the human oracle. Experiments over three multitask learning benchmark datasets show clearly superior performance over baselines such as assuming task independence, learning only from the oracle and not learning from peer tasks.

## Reliable Machine Learning in the Wild

***Dylan Hadfield-Menell, Jacob Steinhardt, Adrian Weller, Smitha Milli***

**C4.7, Fri Aug 11, 08:30 AM**

When can we trust that a system that has performed well in the past will continue to do so in the future? Designing systems that are reliable in the wild is essential for high stakes applications such as self-driving cars and automated surgical assistants. This workshop aims to bring together researchers in diverse areas such as reinforcement learning, human-robot interaction, game theory, cognitive science, and security to further the field of reliability in machine learning. We will focus on three aspects — robustness (to adversaries, distributional shift, model misspecification, corrupted data); awareness (of when a change has occurred, when the model might be miscalibrated, etc.);and adaptation (to new situations or objectives). We aim to consider each of these in the context of the complex human factors that impact the successful application or meaningful monitoring of any artificial intelligence technology. Together, these will aid us in designing and deploying reliable machine learning systems.

## Human in the Loop Machine Learning

***Richard Nock, Cheng Soon Ong***

**C4.8, Fri Aug 11, 08:30 AM**

For details see:
http://machlearn.gitlab.io/hitl2017/

As machine learning systems become more ubiquitous in everybody's day-to-day life or work, society and industry is in an intermediate state between fully manual and fully automatic systems. The gradient undoubtedly points towards full automation, but moving forward in this direction is going to face increasing challenges due to the fact that current machine learning research tends to focus on end to end systems, which puts aside the fact that for practical applications there are still gaps or caveats in the automation. Parts of these come from the presence of (or the necessity to have) the Human in the Loop.

There are two main locations for the Human in the automated system: (i) upstream, in which case the focus is mainly in the inputs of the algorithm. This can be essential for personalised assistants, that describe environments where the machine learning method is tightly embedded

into the system. Such environments pose additional challenges related to privacy at large; (ii) downstream: other domains have machine learning approaches analyse parts of the data, and human experts use the results and intuition to make decisions.

The Human dependences between these two locations is also neither straightforward nor acyclic — some applications tend to have feedback effects on data as actions or interventions are undertaken based on machine learning predictions. Furthermore there are often very few rounds of decision making in practice, but each round may affect the statement of the problems related to the Human presence, as witnessed for example by eventual privacy leakages.

This workshop aims to bring together people who are working on systems where machine learning is only part of the solution. Participants will exchange ideas and experiences on human in the loop machine learning.

Topics of interest include:
- System architectures that allow for human decision making
- User interfaces for interacting with machine learning systems
- Validation of human in the loop software systems
- Viewpoints from traditional fields such as reinforcement learning and Bayesian optimisation
- Challenges related to the human presence in the loop (privacy, bias, fairness, etc.)
- Case studies of deployed machine learning

## Machine Learning for Music Discovery

***Erik Schmidt, Oriol Nieto, Fabien Gouyon, Gert Lanckriet***

**C4.9, Fri Aug 11, 08:30 AM**

The ever-increasing size and accessibility of vast music libraries has created a demand more than ever for machine learning systems that are capable of understanding and organizing this complex data. While this topic has received relatively little attention within the machine learning community, it has been an area of intense focus within the community of Music Information Retrieval (MIR), where significant progress has been made, but these problems remain far from solved.

Furthermore, the recommender systems community has made great progress in terms of collaborative feedback recommenders, but these approaches suffer strongly from the cold-start problem. As such, recommendation techniques often fall back on content-based machine learning systems, but defining musical similarity is extremely challenging as myriad features all play some role (e.g., cultural, emotional, timbral, rhythmic).

We seek to use this workshop to bring together a group of world-class experts to discuss these challenges and share them with the greater machine learning community. In addition to making progress on these challenges, we hope to engage the machine learning community with our nebulous problem space, and connect them with the many available datasets the MIR community has to offer (e.g., AcousticBrainz, Million Song Dataset), which offer near commercial scale to the academic research community.

**Schedule**

| | |
|---|---|
| 08:30 AM | **Welcome Remarks** |
| 08:40 AM | **Matrix Co-Factorisation and Applications to Music Analysis** |
| 09:20 AM | **Learning a Large-Scale Vocal Similarity Embedding** |
| 10:30 AM | **Aligned Hierarchies - A Multi-Scale Structure-Based Representation for Music** |
| 11:10 AM | **Mining Creation Methods from Music Data for Automated Content Generation** |
| 02:00 PM | **NSynth: Unsupervised Understanding of Musical Notes** |
| 02:40 PM | **Multi-Level and Multi-Scale Feature Aggregation Using Sample-level Deep Convolutional Neural Networks for Music Classification** |
| 03:30 PM | **Music Highlight Extraction via Convolutional Recurrent Attention Networks** |
| 03:50 PM | **Kapre: On-GPU Audio Preprocessing Layers for a Quick Implementation of Deep Neural Network Models with Keras** |
| 04:10 PM | **Ephemeral Context to Support Robust and Diverse Recommendations** |
| 04:30 PM | **Closing Remarks** |

## Reinforcement Learning Workshop

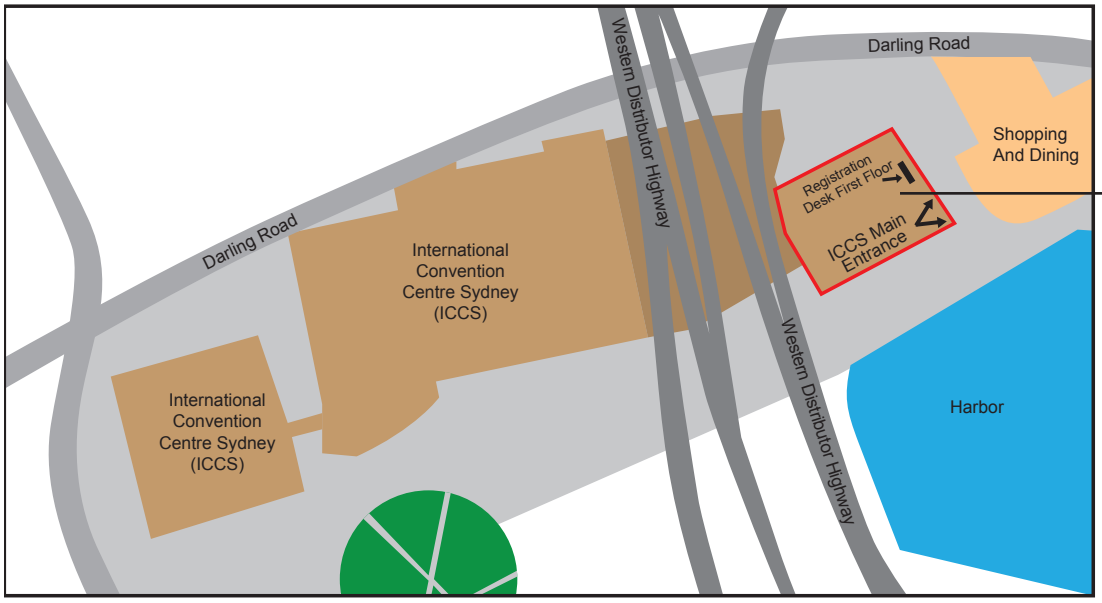
***Doina Precup***

**Parkside 1, Fri Aug 11, 08:30 AM**

The workshop will contain presentations of late-breaking reinforcement learning results in all areas of the field, including deep reinforcement learning, exploration, transfer learning and using auxiliary tasks, theoretical result etc, as well as applications of reinforcement learning to various domains. A panel discussion on the most interesting and challenging current research directions will conclude the workshop.

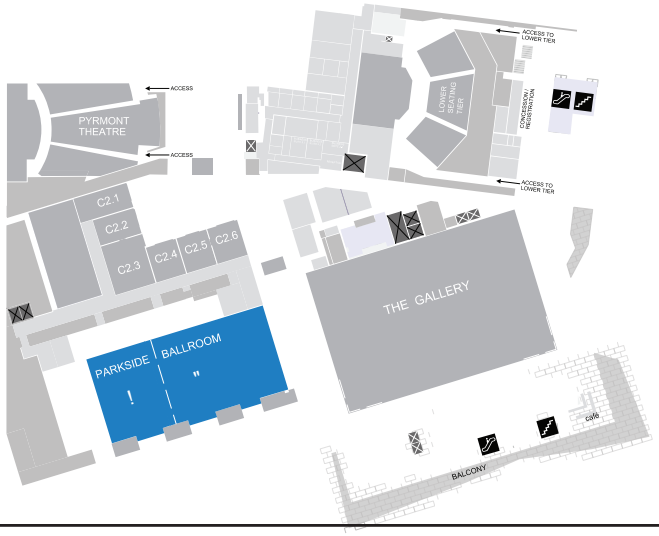
# CONFERENCE MAPS

CONVENTION CENTRE

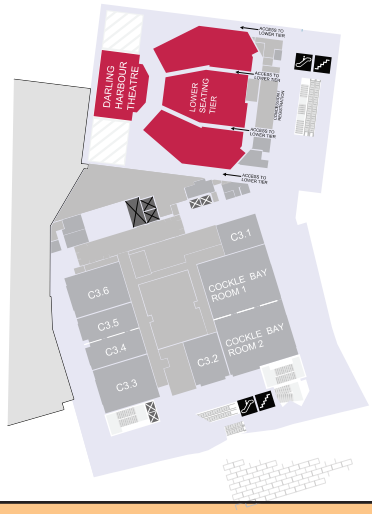



All Events Will Take Place In The Main Building Here

## Floor 2 - Parkside Ballrooms Only




## Floor 3 - Darling Harbour Theater




## Floor 4 - Most Events


## Floor 4 - Workshops