# Highlights of NIPS 2016

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# Neural Information Processing Systems

- Largest International Conference on Machine Learning.
- Held since 1987 and focuses on AI, ML, Mathematics, Statistics.

Terry's Law on NIPS Participants [1]

[1] Proposed by Terrence Sejnowski, NIPS 2016 Chair

# NIPS 2016: Topics Convered

- 568 Papers (46 oral) accepted among 2400 papers with 6 reviewers per submission.
- Most popular topics were Deep Learning (1 in 4) with application to Computer Vision (1 in 10).

Long-tailed Distribution of Topics [1]

[1] NIPS 2016 Review Process

# NIPS 2016: Impressions

- **Strong industry presence**: Google Deepmind, Facebook AI Research, OpenAI etc
- **Philosophical panel discussions**: Healthy debates on general trends and future of community.
- **Emphasis on Deep Learning**: Studies on applications as well as **theoretical foundations** of Deep Learning.

Tutorial on GANs[1]

Conference Venue[1]

Boston Dynamics[1]

[1] Ian Goodfellow's Tutorial on GAN, Image of Conference Venue, Boston Dynamics Spot Demo

# Generative Adversarial Networks: Overview

$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim p_{\text{data}}(x)} \log D(x) + \mathbb{E}_{x\sim p_x(z)} \log(1-D(G(z)))$$

[1] Goodfellow et al. "Generative adversarial nets" in *NIPS 2016*

# GAN: Tutorials

- Tutorial on GANs by Ian Goodfellow:
  - Applications to generate realistic images.
  - Learn latent manifolds encoding task variability.
  - Theoretical challenges for training models.
- Tutorial on Practical Tips by Soumith Chintala:
  - Tips on data preprocessing, network design and optimizers.

Manifold on MNIST[1]

Tutorial by Chintala[1]

[1] Presentation at DLSS 2015, How to Train Your GAN

# GAN: Applications

## Learning What and Where[1]

- Use text input to generate novel images.
- Architecture for location and content controllable synthesis.

## Information Maximizing GANs[2]

- Unsupervised learning of **disentagled** representations.
- Maximizes mutual information between latent variables and observations.

[1] Reed et al., "Learning what and where to draw" in *NIPS 2016*

[2] Chen et al., "Infogan: Interpretable representation learning by information maximizing generative adversarial nets" in *NIPS 2016*

# Bayesian Deep Learning

- History of Bayesian Neural Networks by Zoubin Gharamani[1]:
  - Derives from Gaussian Process Regression
  - Feature selection possible using Automatic Relevance Determination
  - Current research on variational inference techniques

**Bayesian neural network**

Data: $\mathcal{D} = \{(\mathbf{x}^{(n)}, y^{(n)})\}_{n=1}^{N} = (X, \mathbf{y})$

Parameters $\boldsymbol{\theta}$ are weights of neural net

| | |
|---|---|
| prior | $p(\boldsymbol{\theta}\|\boldsymbol{\alpha})$ |
| posterior | $p(\boldsymbol{\theta}\|\boldsymbol{\alpha}, \mathcal{D}) \propto p(\mathbf{y}\|X, \boldsymbol{\theta})p(\boldsymbol{\theta}\|\boldsymbol{\alpha})$ |
| prediction | $p(y'\|\mathcal{D}, \mathbf{x}', \boldsymbol{\alpha}) = \int p(y'\|\mathbf{x}', \boldsymbol{\theta})p(\boldsymbol{\theta}\|\mathcal{D}, \boldsymbol{\alpha})\, d\boldsymbol{\theta}$ |

[1] Keynote Talk by Zoubin Gharamani

# Deep Learning and Graphical Models

## Combined training of Graphical Models and Deep Neural Networks using Variational Inference[1]

**Modeling idea:** graphical models on latent variables, neural network models for observations

**Inference:** recognition networks output conjugate potentials, then apply fast graphical model inference

**Application:** learn syllable representation of behavior from video

[1] Johnson et al., "Composing graphical models with neural networks for structured representations and fast inference" in *NIPS 2016*

# Dropout as a Bayesian Approximation

Dropout is equivalent to variational inference in Deep GPs with specific kernel function

[1] Gal et al., "A theoretically grounded application of dropout in recurrent neural networks" in *NIPS 2016*

# Value Iteration Networks

# Recurrent Neural Networks: Overview

# RNN: Symposia

# RNN: Applications

# Learning to learn: Meta-learning

# One-shot Learning

# Neural Turing Machines: Overview

# NTM: Applications

# General AI: Unsupervised Learning

# Boston Robotics Demo

# Efficient seeding for K-Means

# RocketAI: The AI Bubble

# Sightseeing in Barcelona

# Thank you!

Questions or Comments?