

NIPS 2016

Marek & Márius

Stats

5680 registered people, 4500+ in mobile app

Industry + academia

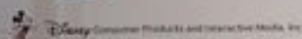
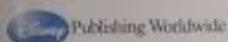
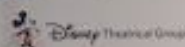
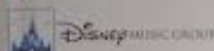
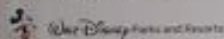
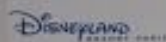
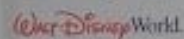
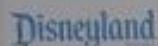
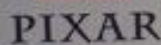
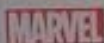
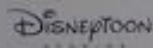
10 tutorials, multiple parallel tracks, 173+198+198 posters, 20 demos, 3 symposia, 28+24 workshops

Majority focused on neural networks, some PGMs



Disney Research

Our Partners:



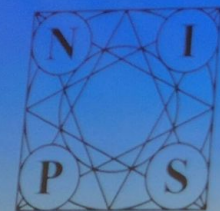
Disney
The Wa
and tec

Nuts and bolts of buildings AI systems

Bias vs variance

Automatization of PhD study

Slides in references



Neural Information
Processing Systems

<http://www.computervisionblog.com/2016/12/nuts-and-bolts-of-building-deep.html>



AI can help save the world
from efficiency savings... ... to radical breakthroughs



89



Dialog-based Language Learning

Jason Weston
Facebook AI Research

Memory Networks, LSTMs with attention etc. in NLP

- Most basic supervised, you are given input + label. Models have chosen to perform well on:
 - QA (AMR tasks, Wikititles, WikiQA)
 - Dialog (Movie Dialog Dataset, ReAct, Ubuntu)
 - Language Modeling, Sentence Completion (CBT)
- But human learning is different, it's unsupervised, noisy

(original) bAbI tasks (Weston et al., 2015)

Many went to the bathroom.
John moved to the bathroom.
Many moved to the kitchen.
Where is Mary? → kitchen.
Where is John? → bathroom.

The supervised learning setting alone is insufficient to capture learning during dialog.

The Dialog-based Supervision Tasks

- We evaluate 10 ways of providing dialog-based supervision



Task 1: Imitating

Tasks 2 to 5: different clues

Task 2: Imitating
Many went to the bathroom.
John moved to the bathroom.
Many moved to the kitchen.
Where is Mary? → kitchen.
Where is John? → bathroom.

Task 3: Imitating
Many went to the bathroom.
John moved to the bathroom.
Many moved to the kitchen.
Where is Mary? → kitchen.
Where is John? → bathroom.

Task 4: Imitating
Many went to the bathroom.
John moved to the bathroom.
Many moved to the kitchen.
Where is Mary? → kitchen.
Where is John? → bathroom.

Task 5: Imitating
Many went to the bathroom.
John moved to the bathroom.
Many moved to the kitchen.
Where is Mary? → kitchen.
Where is John? → bathroom.

Task 6: Forward Prediction

Many went to the bathroom.
John moved to the bathroom.
Many moved to the kitchen.
Where is Mary? → kitchen.
Where is John? → bathroom.

Task 7: Forward Prediction

Many went to the bathroom.
John moved to the bathroom.
Many moved to the kitchen.
Where is Mary? → kitchen.
Where is John? → bathroom.

Task 8: Forward Prediction

Many went to the bathroom.
John moved to the bathroom.
Many moved to the kitchen.
Where is Mary? → kitchen.
Where is John? → bathroom.

Task 9: Forward Prediction

Many went to the bathroom.
John moved to the bathroom.
Many moved to the kitchen.
Where is Mary? → kitchen.
Where is John? → bathroom.

Task 10: Forward Prediction

Many went to the bathroom.
John moved to the bathroom.
Many moved to the kitchen.
Where is Mary? → kitchen.
Where is John? → bathroom.

1) Imitation Learning

• We want to learn a policy that can imitate a human teacher. This is done by observing the teacher's actions and learning from the feedback provided by the teacher.

• The teacher's actions are represented by a sequence of hidden states h_1, h_2, \dots, h_T and actions a_1, a_2, \dots, a_T . The teacher's policy is represented by a function $\pi(a_t | h_t)$.

• The student's policy is represented by a function $\pi(a_t | h_t)$. The student's goal is to learn the teacher's policy by minimizing the loss between the student's actions and the teacher's actions.

2) Reward-based Learning

• If external rewards are provided, the student can learn to maximize the rewards. This is done by observing the teacher's actions and learning from the feedback provided by the teacher.

• The teacher's actions are represented by a sequence of hidden states h_1, h_2, \dots, h_T and actions a_1, a_2, \dots, a_T . The teacher's policy is represented by a function $\pi(a_t | h_t)$.

• The student's policy is represented by a function $\pi(a_t | h_t)$. The student's goal is to learn the teacher's policy by maximizing the rewards.

3) Forward Prediction

• The student can learn to predict the teacher's actions. This is done by observing the teacher's actions and learning from the feedback provided by the teacher.

• The teacher's actions are represented by a sequence of hidden states h_1, h_2, \dots, h_T and actions a_1, a_2, \dots, a_T . The teacher's policy is represented by a function $\pi(a_t | h_t)$.

• The student's policy is represented by a function $\pi(a_t | h_t)$. The student's goal is to learn the teacher's policy by predicting the teacher's actions.

4) Forward Prediction

• The student can learn to predict the teacher's actions. This is done by observing the teacher's actions and learning from the feedback provided by the teacher.

• The teacher's actions are represented by a sequence of hidden states h_1, h_2, \dots, h_T and actions a_1, a_2, \dots, a_T . The teacher's policy is represented by a function $\pi(a_t | h_t)$.

• The student's policy is represented by a function $\pi(a_t | h_t)$. The student's goal is to learn the teacher's policy by predicting the teacher's actions.

5) Forward Prediction

• The student can learn to predict the teacher's actions. This is done by observing the teacher's actions and learning from the feedback provided by the teacher.

• The teacher's actions are represented by a sequence of hidden states h_1, h_2, \dots, h_T and actions a_1, a_2, \dots, a_T . The teacher's policy is represented by a function $\pi(a_t | h_t)$.

• The student's policy is represented by a function $\pi(a_t | h_t)$. The student's goal is to learn the teacher's policy by predicting the teacher's actions.

6) Forward Prediction

• The student can learn to predict the teacher's actions. This is done by observing the teacher's actions and learning from the feedback provided by the teacher.

• The teacher's actions are represented by a sequence of hidden states h_1, h_2, \dots, h_T and actions a_1, a_2, \dots, a_T . The teacher's policy is represented by a function $\pi(a_t | h_t)$.

• The student's policy is represented by a function $\pi(a_t | h_t)$. The student's goal is to learn the teacher's policy by predicting the teacher's actions.

7) Forward Prediction

• The student can learn to predict the teacher's actions. This is done by observing the teacher's actions and learning from the feedback provided by the teacher.

• The teacher's actions are represented by a sequence of hidden states h_1, h_2, \dots, h_T and actions a_1, a_2, \dots, a_T . The teacher's policy is represented by a function $\pi(a_t | h_t)$.

• The student's policy is represented by a function $\pi(a_t | h_t)$. The student's goal is to learn the teacher's policy by predicting the teacher's actions.

8) Forward Prediction

• The student can learn to predict the teacher's actions. This is done by observing the teacher's actions and learning from the feedback provided by the teacher.

• The teacher's actions are represented by a sequence of hidden states h_1, h_2, \dots, h_T and actions a_1, a_2, \dots, a_T . The teacher's policy is represented by a function $\pi(a_t | h_t)$.

• The student's policy is represented by a function $\pi(a_t | h_t)$. The student's goal is to learn the teacher's policy by predicting the teacher's actions.

9) Forward Prediction

• The student can learn to predict the teacher's actions. This is done by observing the teacher's actions and learning from the feedback provided by the teacher.

• The teacher's actions are represented by a sequence of hidden states h_1, h_2, \dots, h_T and actions a_1, a_2, \dots, a_T . The teacher's policy is represented by a function $\pi(a_t | h_t)$.

• The student's policy is represented by a function $\pi(a_t | h_t)$. The student's goal is to learn the teacher's policy by predicting the teacher's actions.

Related Work

- In the literature, the problem of learning to imitate a human teacher has been studied in a variety of contexts. This includes the problem of learning to imitate a human teacher in a sequence of hidden states and actions.
- The problem of learning to imitate a human teacher in a sequence of hidden states and actions has been studied in a variety of contexts. This includes the problem of learning to imitate a human teacher in a sequence of hidden states and actions.
- The problem of learning to imitate a human teacher in a sequence of hidden states and actions has been studied in a variety of contexts. This includes the problem of learning to imitate a human teacher in a sequence of hidden states and actions.

Experimental Setting

• We evaluate the performance of different learning methods on a variety of tasks. This includes the problem of learning to imitate a human teacher in a sequence of hidden states and actions.

• The tasks are evaluated on a variety of metrics. This includes the problem of learning to imitate a human teacher in a sequence of hidden states and actions.

• The results are presented in a table. This includes the problem of learning to imitate a human teacher in a sequence of hidden states and actions.

Task Experiments

• We evaluate the performance of different learning methods on a variety of tasks. This includes the problem of learning to imitate a human teacher in a sequence of hidden states and actions.

• The tasks are evaluated on a variety of metrics. This includes the problem of learning to imitate a human teacher in a sequence of hidden states and actions.

• The results are presented in a table. This includes the problem of learning to imitate a human teacher in a sequence of hidden states and actions.

Conclusion

- New framework for learning from dialog feedback.
- Evaluation results.
- Methods: DDPG, Actor-Critic.

Future work

- New general settings: Reward DDA, RL, other types of feedback.
- Improving learning efficiency for more complex tasks.

Forward Prediction: how the hell does it work?

Most interesting result: 10% accuracy without any rewards.

• Task 2: Forward Prediction. The differential between the "right" or "wrong" response from the teacher if you don't "know" what the right answer is.

Conclusion

- New framework for learning from dialog feedback.
- Evaluation results.
- Methods: DDPG, Actor-Critic.

Future work

- New general settings: Reward DDA, RL, other types of feedback.
- Improving learning efficiency for more complex tasks.

TensorFlow w/XLA: TensorFlow, Compiled!

Expressiveness with performance

For release documentation for each Github repository for XLA:
<https://www.tensorflow.org/performance/master/resources/xla-requirements.html>

Jeff Dean
Google Brain team

[@jeff-dean](#)

(presenting work done by the XLA team and Google Brain team)

Highlights

Lots of new ideas & architectures, but few state-of-the-art methods

RL, open platforms - universe.openai.com, project Malmö

GANs

Word2vec-like unsupervised learning of image representation

Video prediction, Image superresolution

TorontoCity dataset

Using Fast Weights to Attend to the Recent Past

<https://arxiv.org/pdf/1610.06258.pdf>

Value Iteration Networks

<https://papers.nips.cc/paper/6046-value-iteration-networks.pdf>

Project Malmo & Universe

<https://www.microsoft.com/en-us/research/project/project-malmo/>

<https://universe.openai.com/>

Learning What and Where to Draw

<https://arxiv.org/pdf/1610.02454v1.pdf>

Weight Normalization: A Simple Reparameterization to Accelerate Training of Deep Neural Networks

<https://arxiv.org/pdf/1602.07868.pdf>

Attend, Infer, Repeat: Fast Scene Understanding with Generative Models

<http://arkitus.com/files/arxiv-attend-infer-repeat.pdf>

R-FCN: Object Detection via Region-based Fully Convolutional Networks

<https://arxiv.org/pdf/1605.06409v2.pdf>

Self Supervised Learning of Visual Representations

<https://arxiv.org/pdf/1603.09246v2.pdf>

Scaling-up: Image Super-resolution and Compression for the masses

<https://arxiv.org/pdf/1609.04802.pdf>

<https://arxiv.org/pdf/1609.05158v2.pdf>



Baidu Research @BaiduResearch · Dec 5

The long lines at #nips2016 speak volumes of the enthusiasm for #AI #machinelearning #deeplearning

↩ 1

🔄 22

❤ 42

⋮



Alex Champandard ♀ @alexjc · Dec 7

Me: **#nips2016** is content-packed, but it's pre-published online and very random.

Petra: Why do people go?

Me: Trying to hire each other! ;-)



4



2



24





Naomi Saphra and 5 others Retweeted



Smerity @Smerity · Dec 8

Celebrating the 20 yr anniversary of LSTM ... being rejected from [#nips1996](#)

(credit for perseverance by Hochreiter & Schmidhuber!)

[#nips2016](#)



2



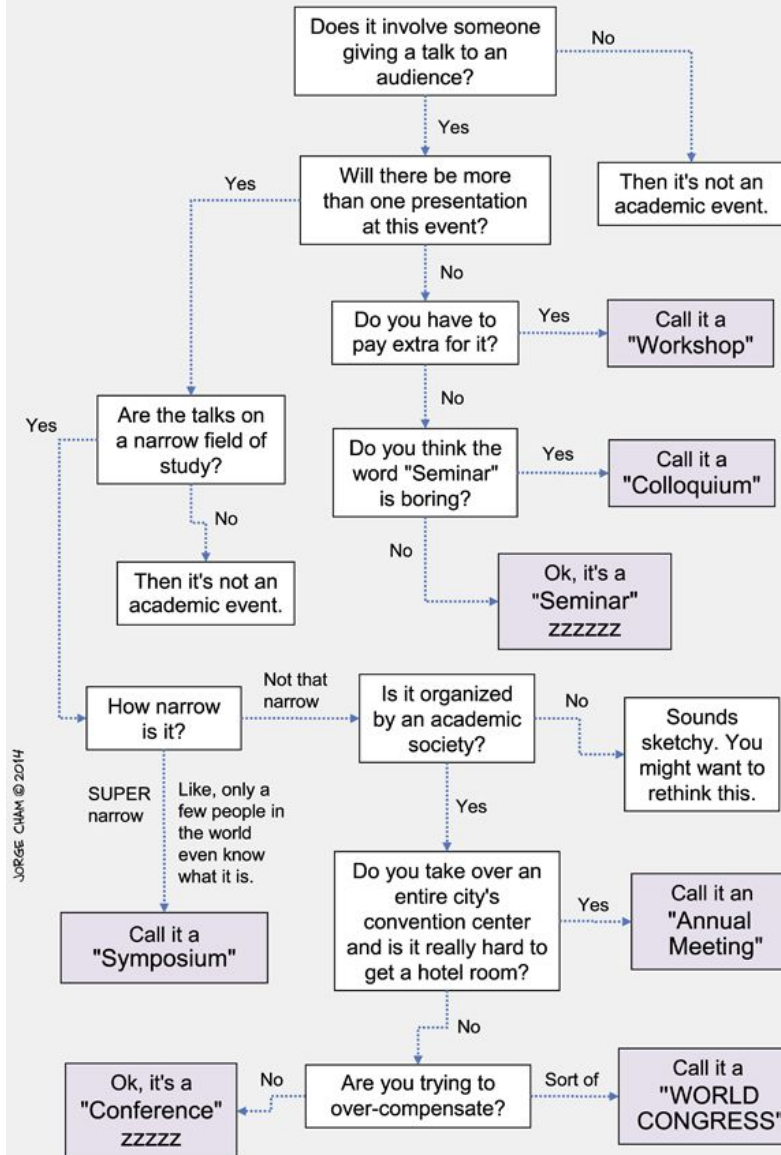
108



223



What to call your Academic Event:



JORGE CHAN © 2014

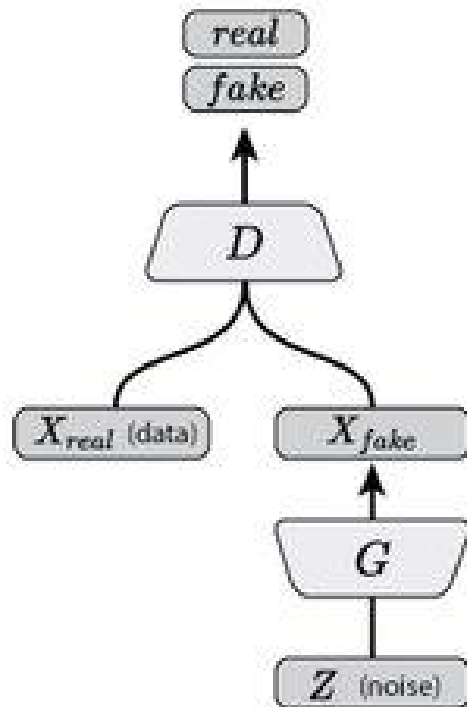
Other quick takeaways

- Andrew Ng:
 - Almost all of the value is created by Supervised Learning.
 - For some products at Baidu, the main purpose is to acquire data from users, not revenue.
 - Current machine learning techniques work best when training data and real data come from the same distribution. Real systems rarely exhibit this.
 - If you design a ML system for the real world, comparing against human baseline needs to be the norm
- Want to win Kaggle competitions?
 - XGBoost for tabular data
 - CNNs for images
 - RNNs for time series predictions
- Nando
 - “If your job is to come up with algos that learn sigmoid based networks, you are out of job. Not so much for ReLus”
- RNN Panel
 - “You know, my wife is a local minimum, but you can live with a local minimum -- you have finite time”.
 - “I do not think there is a disagreement, I see it as a difference in tactis.”
- GANs
 - “The best idea in ML in the past 20 years” -- LeCun
 - Simple to put together, extra finicky to train

Vanilla GAN

Vanilla GAN

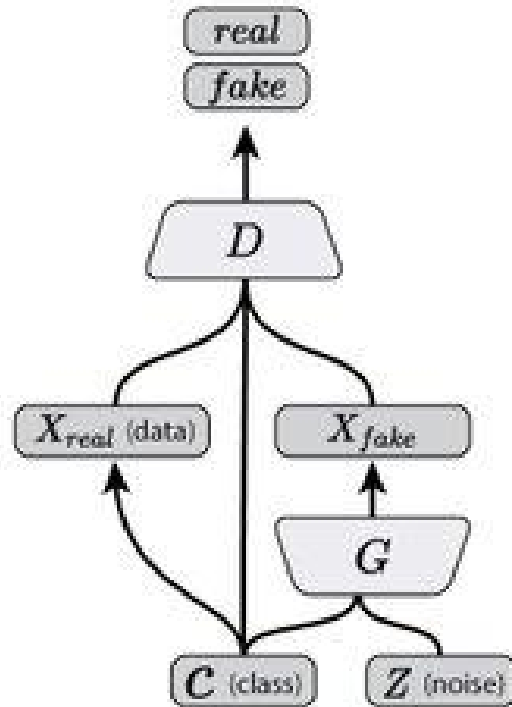
(Goodfellow, et al., 2014)



Discriminator Looks at Latent Variables

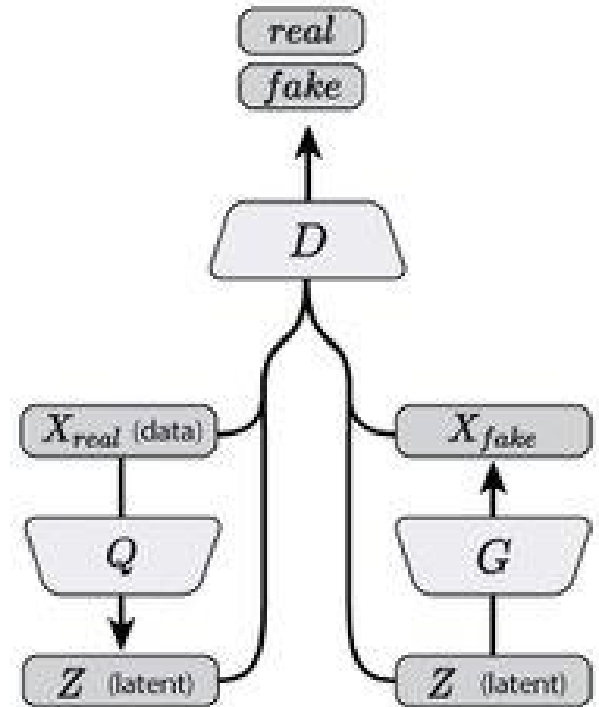
Conditional GAN

(Mirza & Osindero, 2014)



Bidirectional GAN

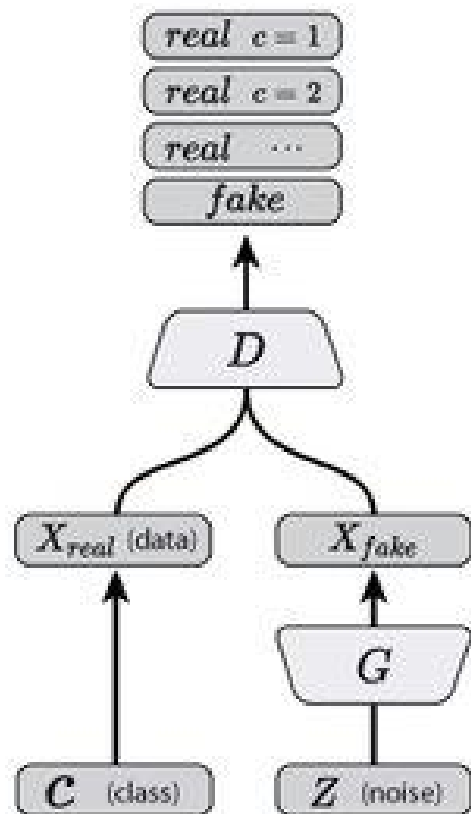
(Donahue, et al., 2016; Dumoulin, et al., 2016)



Discriminator Predicts Latent Variables

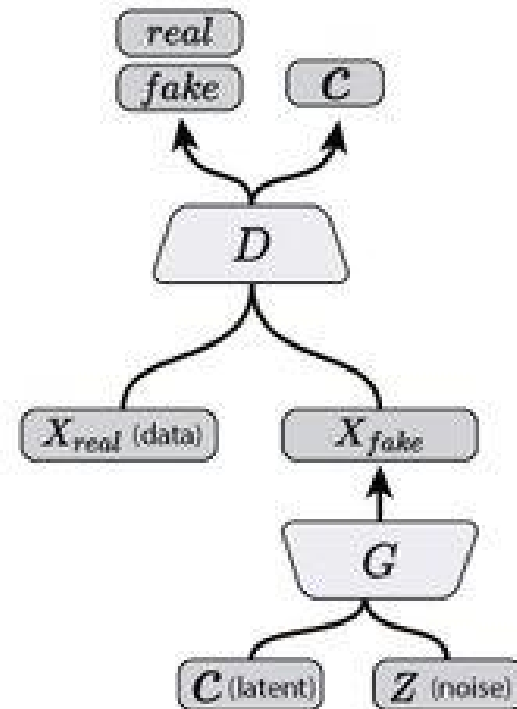
Semi-Supervised GAN

(Odena, 2016; Salimans, et al., 2016)



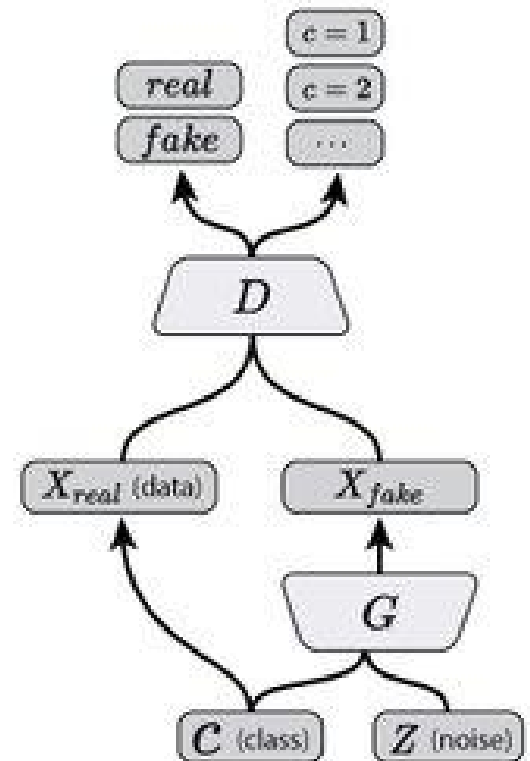
InfoGAN

(Chen, et al., 2016)



Auxiliary Classifier GAN

(Odena, et al., 2016)



Was it worth it?

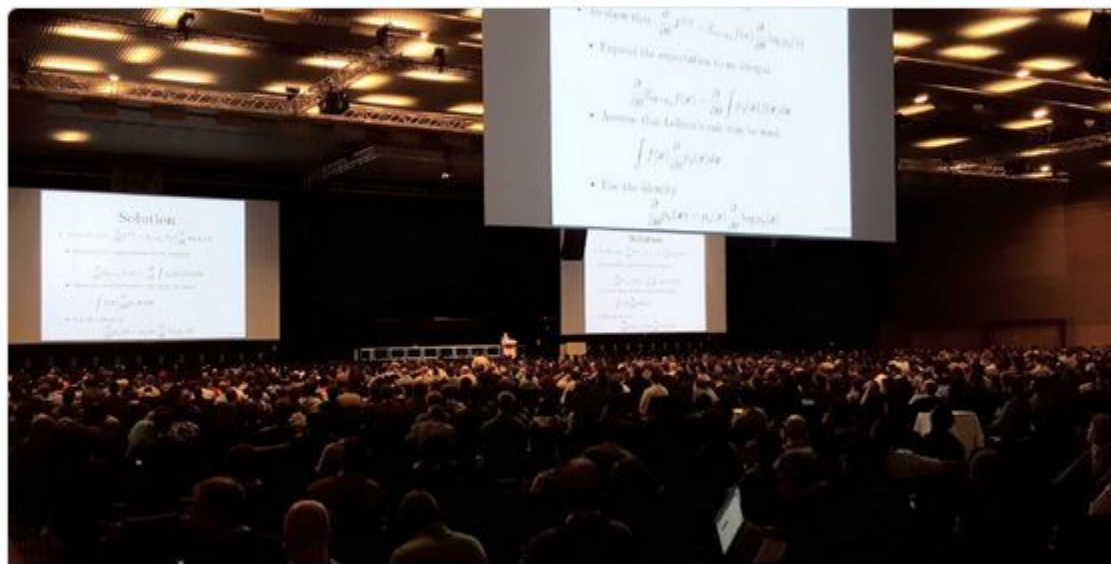


Alex Champandard ♀
@alexjc



Following

These 50 Lessons are particularly useful & well written! But you could have learned >90% without going to [#NIPS2016](#).



50...

11...

blog.ought.com

Was it worth it?



Alex Champandard ♀ @alexjc · 3h

The field of [#ML](#), thanks to arXiv / reddit / Twitter, is more accessible than ever for anyone regardless of their location or resources.

↩ 2 ↻ 1 ❤ 5 ...



Alex Champandard ♀ @alexjc · 3h

If you're considering NIPS next year, ask yourself if you'd like to meet the authors of papers you read in-depth. If not, just go to arXiv!

↩ 1 ↻ ❤ 3 ...



Alex Champandard ♀ @alexjc · 3h

Even beginner tutorials are better online, whether MOOC or otherwise. Sessions at NIPS were good but live talks can't match well-prepared!

↩ 1 ↻ 1 ❤ 3 ...



Andrej Karpathy @karpathy · Dec 3

We're going to NIPS to talk about ICLR papers



6



41



264



Example of stuff that is already (quite) old: Weight Norm

<https://arxiv.org/pdf/1602.07868.pdf>

References

- NIPS Review Process:
<http://www.tml.cs.uni-tuebingen.de/team/luxburg/misc/nips2016/index.php>
- Towards biologically plausible Deep Learning -Yoshua Bengio:
<http://www.iro.umontreal.ca/~bengioy/talks/Brains+Bits-NIPS2016Workshop.pptx.pdf>
 - Video from a similar talk:
https://archive.org/details/Redwood_Center_2016_09_27_Yoshua_Bengio
- Magenta Demo
 - <https://magenta.tensorflow.org/2016/12/16/nips-demo/>
- Andrew Ng Tutorial Slides
 - [https://www.dropbox.com/s/dyjdq1prjbs8pmc/NIPS2016%20-%20Pages%202-6%20\(1\).pdf?dl=0](https://www.dropbox.com/s/dyjdq1prjbs8pmc/NIPS2016%20-%20Pages%202-6%20(1).pdf?dl=0)
- A list of code for work presented at NIPS
 - https://www.reddit.com/r/MachineLearning/comments/5hwqeb/project_all_code_implementations_for_nips_2016/
 -

Other NIPS reviews/writeups

- <http://www.slideshare.net/SebastianRuder/nips-2016-highlights-sebastian-ruder>
- <http://inverseprobability.com/2016/12/13/nips-highlights.html>
- <https://beamandrew.github.io/deeplearning/2016/12/12/nips-2016.html>
- <https://www.linkedin.com/pulse/nips-2016-towards-end-dynamic-dialogue-system-vishal-bhalla>
- <https://medium.com/@libfun/nips-2016-experience-and-highlights-104e19e4ac95#.ngf9jdu3e>
- <https://www.linkedin.com/pulse/some-general-take-aways-from-nips2016-igor-carron>
- <http://www.inference.vc/my-summary-of-adversarial-training-nips-workshop/>
- <https://tryolabs.com/blog/2016/12/06/major-advancements-deep-learning-2016/>
- <http://apeiroto.pe/ml/nips-2016.html>
- <http://www.machinedlearnings.com/2016/12/nips-2016-reflections.html>
- <http://blog.aylien.com/highlights-nips-2016/>
-