# Deep Learning Meetup

May 17, 2017 @ Casinos Austria



Thomas Lidy



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**Alex Schindler** 



#### Agenda:

- Welcome
- Introduction by Casinos Austria (Isabell Brandenberger)
- Announcements 1: Jobs
- A Comparison of Deep Learning Frameworks for Distributed Training (Peter Ruch)
- Announcements 2: Event
- An Introduction to Bidirectional LSTM-HMM for Sound Event Detection (Ana Jalali)
- Hot Topics and Latest News (Tom Lidy, Jan Schlüter)
- Discussion



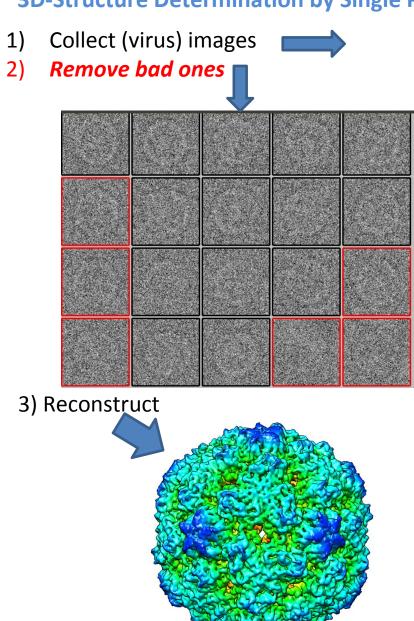
#### **Announcements 1:**

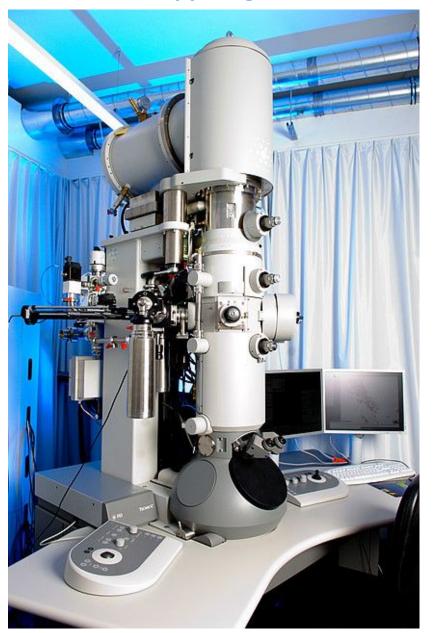
**Jobs & Projects** 



#### **Project at Med Uni Wien:**

#### **3D-Structure Determination by Single Particle Electron Microscopy Image Reconstruction**





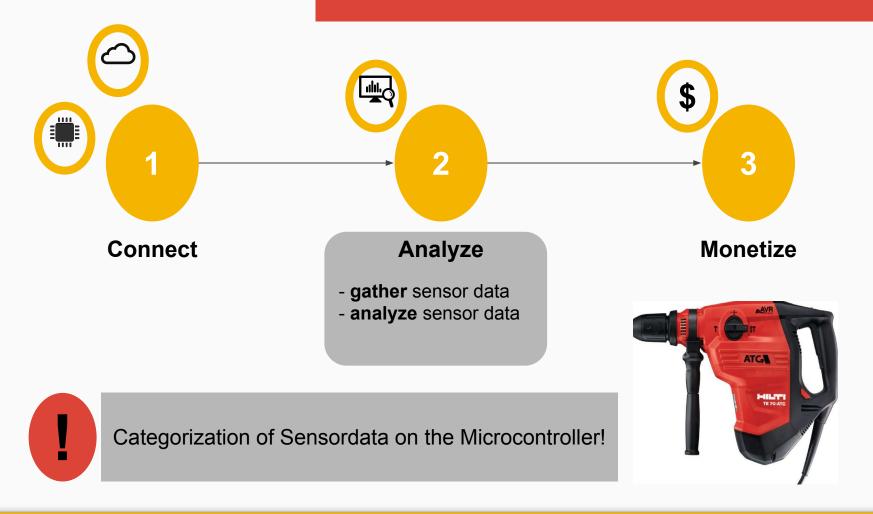
#### So far only one paper with a difficult-to-install software

- has to be trained for each molecular assembly
- + however many viruses are spherical allowing for a more general approach
- + needs only to learn to distinguish "bad ones" and "good ones"
  - DeepPicker: a Deep Learning Approach for Fully Automated Particle Picking in Cryo-EM
  - Feng Wang, Huichao Gong, Gaochao liu, Meijing Li, Chuangye Yan, Tian Xia, Xueming Li, Jianyang Zeng (Submitted on 6 May 2016)
  - Particle picking is a time-consuming step in single-particle analysis and often requires significant interventions from users, which has become a bottleneck for future automated electron cryo-microscopy (cryo-EM). Here we report a deep learning framework, called DeepPicker, to address this problem and fill the current gaps toward a fully automated cryo-EM pipeline. DeepPicker employs a novel cross-molecule training strategy to capture common features of particles from previously-analyzed micrographs, and thus does not require any human intervention during particle picking. Tests on the recently-published cryo-EM data of three complexes have demonstrated that our deep learning based scheme can successfully accomplish the human-level particle picking process and identify a sufficient number of particles that are comparable to those manually by human experts. These results indicate that DeepPicker can provide a practically useful tool to significantly reduce the time and manual effort spent in single-particle analysis and thus greatly facilitate high-resolution cryo-EM structure determination.
  - arXiv:1605.01838 [q-bio.QM] or arXiv:1605.01838v1 [q-bio.QM]
  - Contact: Dieter Blaas dieter.blaas@meduniwien.ac.at



#### What do we do?

#### NEED people with ML Background!





#### **Data Scientist**



Automic is market leader in Business Automation. To take our products to the next level, we're evolving them towards intelligent automation – achieve more with less effort. Your tasks as a data scientist at Automic will include

- o Data Cleansing
- o Exploratory Data Analysis
- o Present and communicate results
- o Help teams in productizing findings
- o Define data processing and analysis pipeline

More information:

http://www.karriere.at/jobs/4774436

#### **Announcements 2:**

**Event** 





http://mostly.ai/summit



### **Latest News Hot Topics**

a 5-10 min block at every meetup to briefly present "trending topics"

Send us contributions (tom.lidy@gmail.com) or come with slides to do a 5-10 min block yourself!



#### **Tacotron**

 Yet another text-to-speech system: compared to Deep Voice (last meetup), this is trained end-to-end

 Only text input, infers pronunciation, disambiguation, prosody on its own

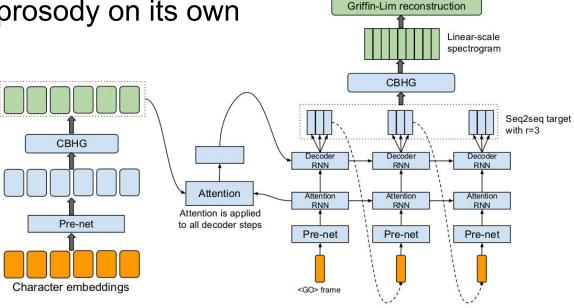
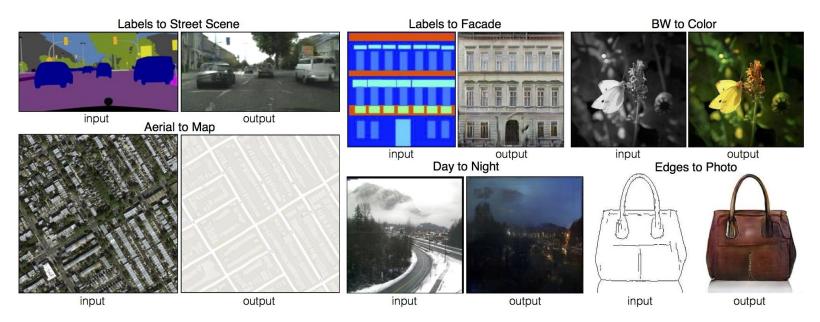


Figure 1: Model architecture. The model takes characters as input and outputs the corresponding raw spectrogram, which is then fed to the Griffin-Lim reconstruction algorithm to synthesize speech.



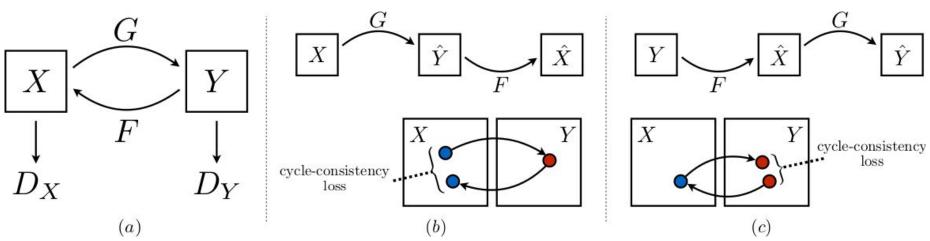
 Based on pix2pix: Fully-convolutional architecture to transform an image into another



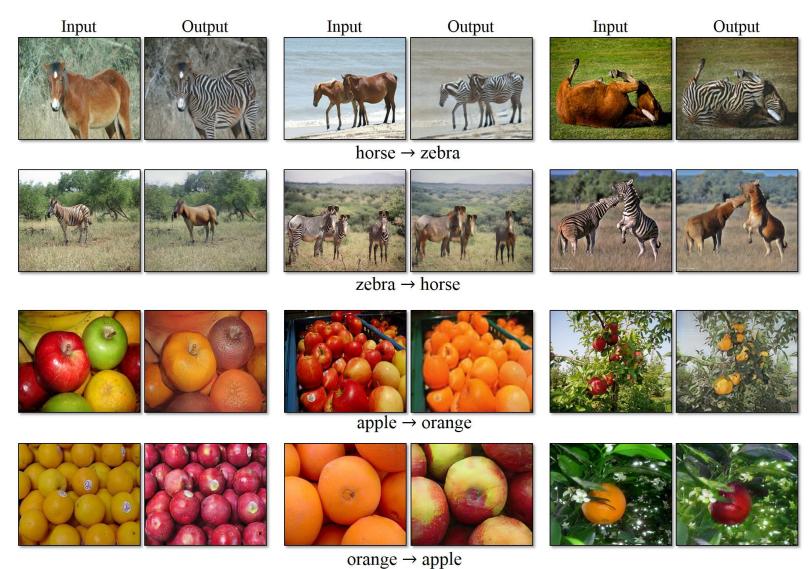
Interactive demo: <a href="https://affinelayer.com/pixsrv/">https://affinelayer.com/pixsrv/</a>



- pix2pix requires matching input-output pairs
- CycleGAN works with collections without 1:1 mapping
- Trains two transformators and two discriminators:
  - transformator has to convince discriminator of other domain that its modified real image is also real
  - performing both transformations should result in the original image ("cycle consistency")







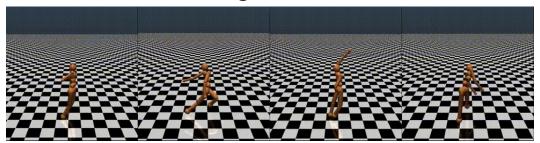






#### **Evolution vs. Reinforcement Learning**

- Task: Learn a policy mapping states to actions maximizing a reward. Policy can be a neural network.
- Reinforcement learning: Policy maps to a probability distribution over actions, updated via backpropagation of reward to all preceding (state, action) pairs. Actions need to be chosen stochastically, otherwise the agent will always do the same and not learn.
- OpenAl paper: Random noise on parameters of policy neural network works almost as well (evolutionary algorithm), but can be parallelized much better, and is thus faster than RL when using lots of machines.





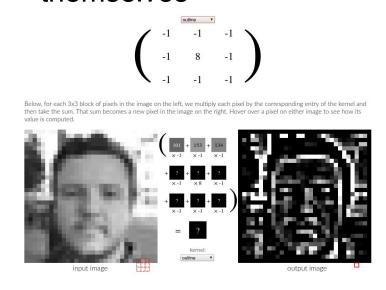


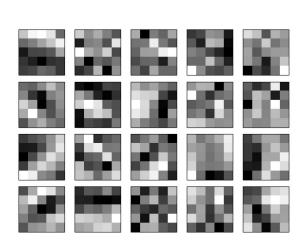
- Caffe is a C++ Deep Learning framework
- Nvidia + Facebook teamed up to Caffe 2 on top of Caffee
- Python and C++ APIs ("work interchangeably")
- accelerated with the latest NVIDIA Pascal GPUs
- uses NVIDIA Deep Learning libraries cuDNN, cuBLAS and NCCL for high-performance
- scales across multiple GPUs within a single node
- advances over Caffe 1:
  - large-scale distributed training
  - mobile deployment (cur. Android)
  - flexibility for future directions such as reduced precision, quantized computation, ...



#### **Understand CNN / Image Kernels**

- CNN filter kernels work essentially like image filter kernels in Photoshop, etc.
- Mini-Tutorial to understand image processing kernels: <a href="http://setosa.io/ev/image-kernels">http://setosa.io/ev/image-kernels</a>
- CNNs use the same principle but <u>learn</u> the kernels by themselves











#### **Deep Learning Tutorial**

"Deep Learning in 7 lines of code"

• using Tflearn - Tensorflow - Python - iPython notebook https://chatbotslife.com/deep-learning-in-7-lines-of-code-7879a8ef8cfb?imm\_mid=0f126

2

```
# Build neural network

net = tflearn.input_data(shape=[None, 5])

net = tflearn.fully_connected(net, 32)

net = tflearn.fully_connected(net, 32)

net = tflearn.fully_connected(net, 2, activation='softmax')

net = tflearn.regression(net)

# Define model and setup tensorboard

model = tflearn.DNN(net, tensorboard_dir='tflearn_logs')

# Start training (apply gradient descent algorithm)

model.fit(train_x, train_y, n_epoch=500, batch_size=16, show_metric=True)

sample code from tflearn ANN hosted with ◆ by GltHub

view raw
```

based on "How Neural Networks Work" Mini-tutorial <a href="https://chatbotslife.com/how-neural-networks-work-ff4c7ad371f7">https://chatbotslife.com/how-neural-networks-work-ff4c7ad371f7</a>

and "Tensorflow demystified"

https://chatbotslife.com/tensorflow-demystified-80987184faf7



#### **NVIDIA** Deep Learning Institute (DLI)



- hands-on training for developers, data scientists, and researchers
- self-paced online labs and instructor-led workshops
- "free or low-cost"
- use open-source frameworks, e.g. Caffe, Theano, and Torch
- Tasks:
  - Signal Processing
  - Image Classification
  - Object Detection
  - Image Segmentation (also Medical, Genomics...)
  - Time Series Data with RNNs



#### Thank you for coming!

## Next Deep Learning Meetup:

20 June 2017 @ Fachhochschule Technikum

#### AI Summit Vienna:

4 Sep 2017 @ WU Wien Learning Center



Thomas Lidy



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