



# 10th Vienna Deep Learning Meetup

March 23, 2017 @ Automic



Thomas Lidy



Jan Schlüter



Alex Schindler



## 10th Vienna Deep Learning Meetup

### Agenda:

- Welcome
- Automic Introduction (Otto Berkes, CTO CA Technologies)
- Deep Learning for Self-Driving Cars (Oleg Leizerov)
- Hot Topics and Latest News (Tom Lidy, Jan Schlüter)
- Discussion

(end 21:00)



Deep Learning

# **Announcements**

# WE ARE LOOKING FOR



## Experimental Data Scientist

- Social/natural science degree with relevant experience in **applied statistics, economics, business** (marketing is a plus),
- experience with statistical software packages, such as **R** and/or **Python**,
- experience with **data visualisation** techniques (plot.ly and RShiny),
- knowledge about **database marketing**, e.g., **customer and basket segmentation or customer lifetime value**, is a plus,
- **independent** and **well-structured** way of working,
- sound **spoken/written German and English**.

# WE OFFER



Dynamic Environment  
in a Business Transformation Lab

- Digital Marketing with **high-ranked Austrian and international customers**,
- chance to openly develop **new marketing solutions** with **state-of-the-art data science and machine learning tools** (clustering, decision trees, predictive modelling, etc.),
- responsibility in a **dynamic and young team**,
- **adequate salary** with possible mark-up depending on education and previous experience.

“Marketing Consulting & Consumer Intelligence”

# CONTACT US



Point of Origin - Business Transformation Lab  
[www.pointoforigin.at](http://www.pointoforigin.at)

**at Thomas Gradauer**

**tg@pointoforigin.at**





Machine Learning Prague

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# MACHINE LEARNING PRAGUE 2017

**April 21-23, 2017, Prague**

Conference on machine learning in practice

29 9 37 2  
DAYS HOURS MINUTES SECONDS

**Meet the best experts  
on machine learning in  
one place. Speakers  
from Facebook, Google  
and the New York Times.**

**REGISTRATION**

**[www.mlprague.com](http://www.mlprague.com)**

# MACHINE LEARNING PRAGUE 2017

April 21–23, 2017

Conference on machine learning in practice



**Lars  
Backstrom**  
(Facebook)



**Yufeng  
Guo**  
(Google)



**Maria  
Vircikova**  
(Matsuko)



**Chris  
Wiggins**  
(New York  
Times)



**Bradford  
Cross**  
(Prismatic)

10% discount with “vdlmeetup” for our Vienna community!





Deep Learning

# **Latest News**

## **Hot Topics**

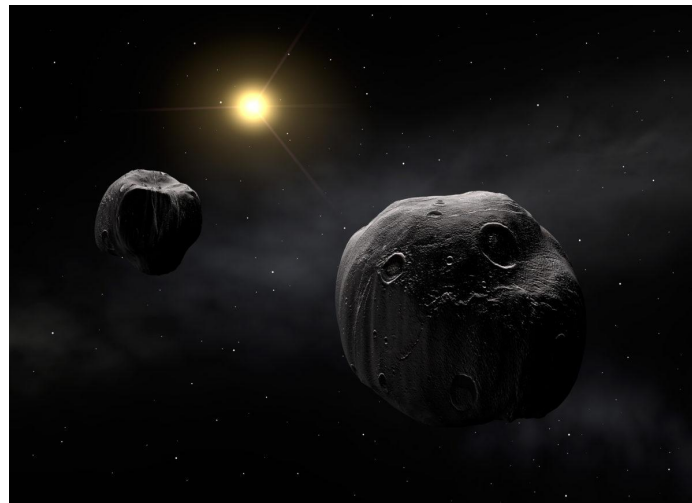
a 5-10 min block at every meetup to briefly present  
“trending topics”

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



# Defending the Planet Against Asteroids with AI

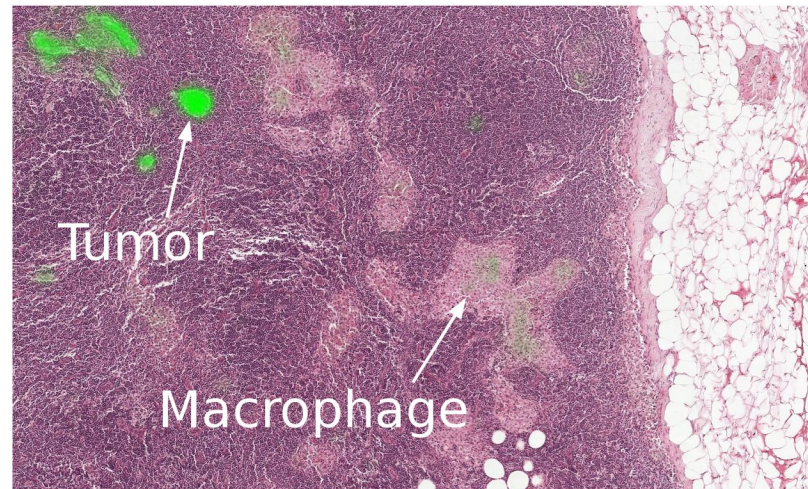
- NASA Lab (FDL) shares how deep learning can help detect, characterize and deflect asteroids
- White House's Asteroid Grand Challenge:
- get researchers to find asteroid threats to human population
- figure out Asteroids shape (from 2D to 3D)
- built an automated meteorite detection system





# AI to Diagnose Breast Cancer

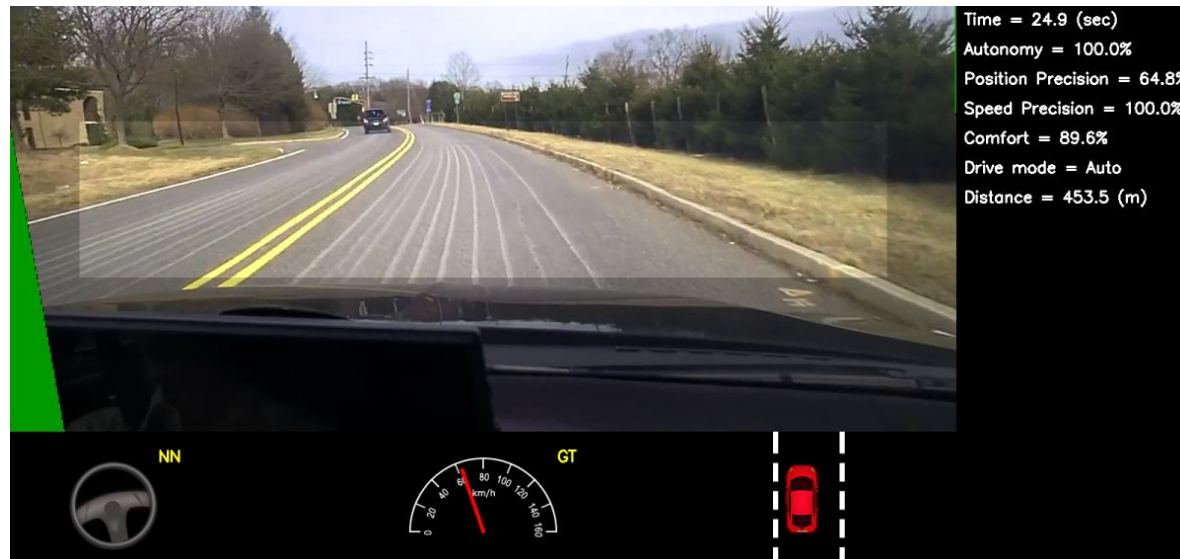
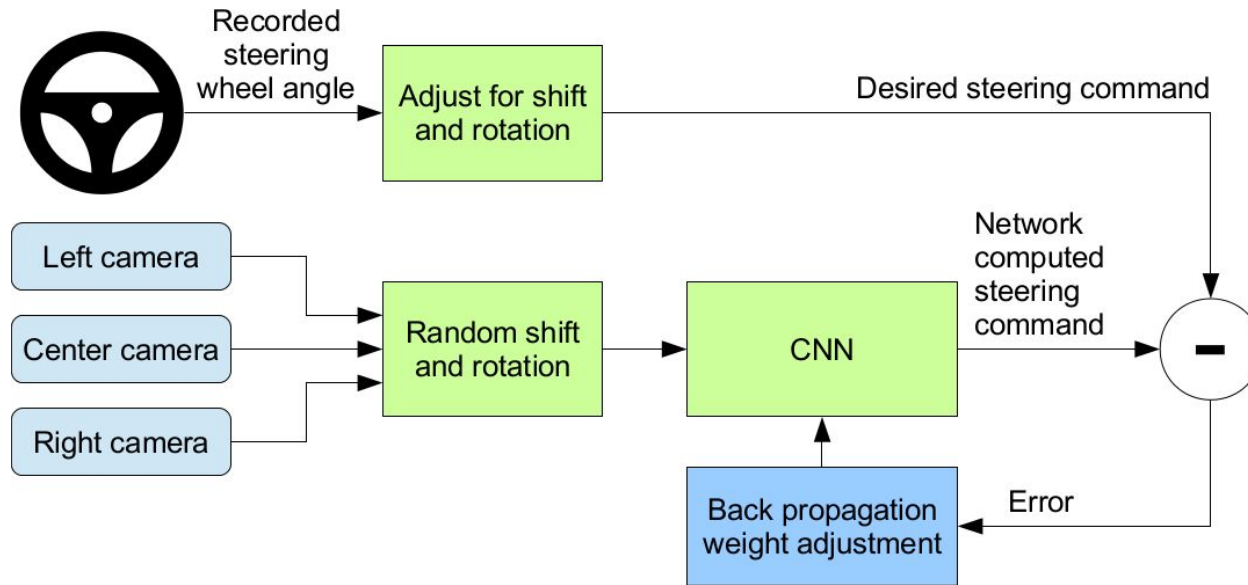
- Google researchers developed a deep learning framework that automatically identifies tumors
- localization of breast cancer that has spread to lymph nodes
- using TensorFlow
- AI model matched or exceeded the performance of a pathologist
- keep human in the loop: AI will flag things a human will miss. But it sometimes will falsely identify something as cancer, whereas a human pathologist is better at coming to a final decision



<https://news.developer.nvidia.com/google-uses-ai-to-diagnose-breast-cancer/>

<http://money.cnn.com/2017/03/03/technology/google-breast-cancer-ai/>

# End to End Learning for Self-Driving Cars





# Deep Voice: Real-time Neural Text-to-Speech

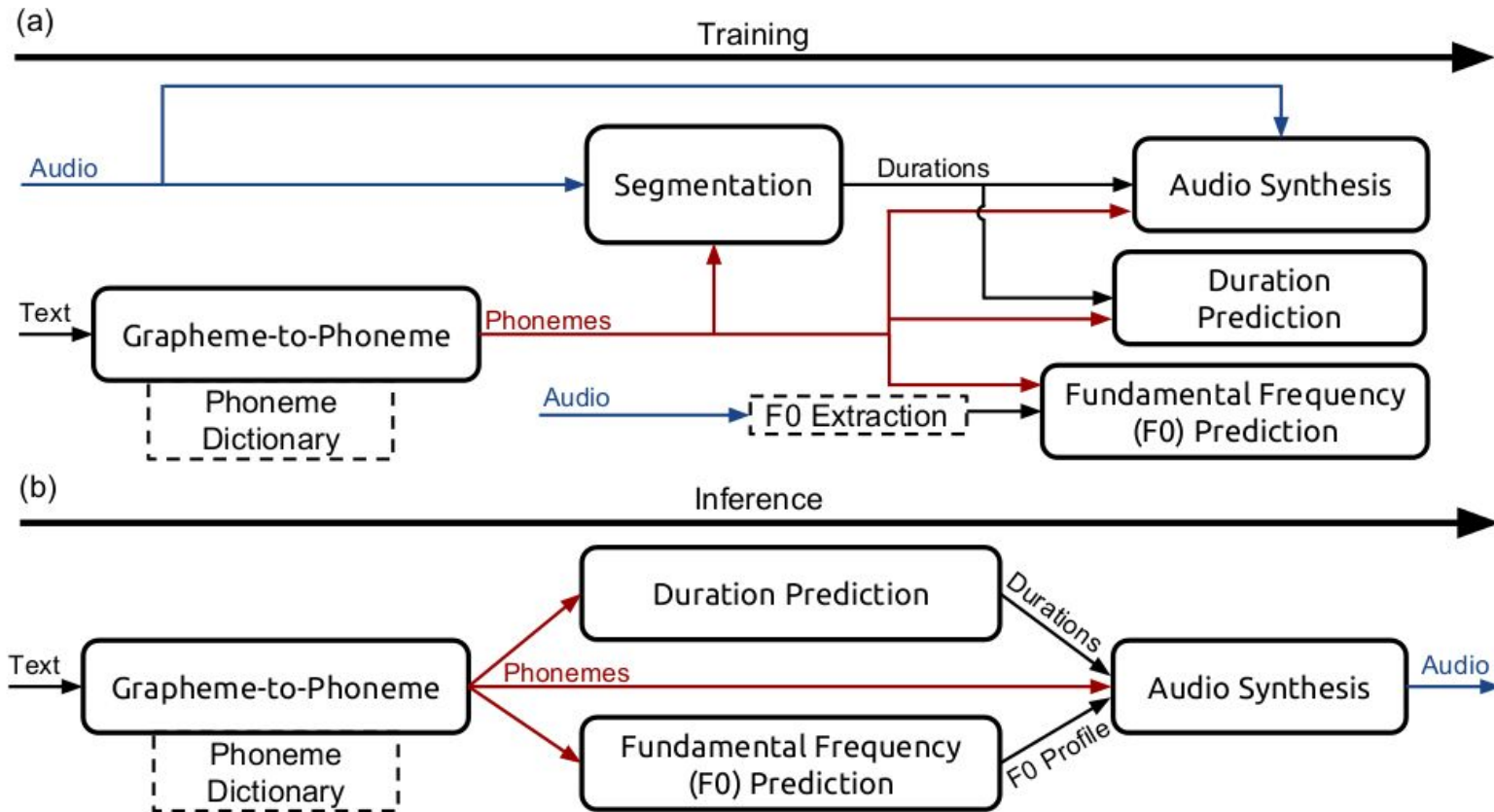
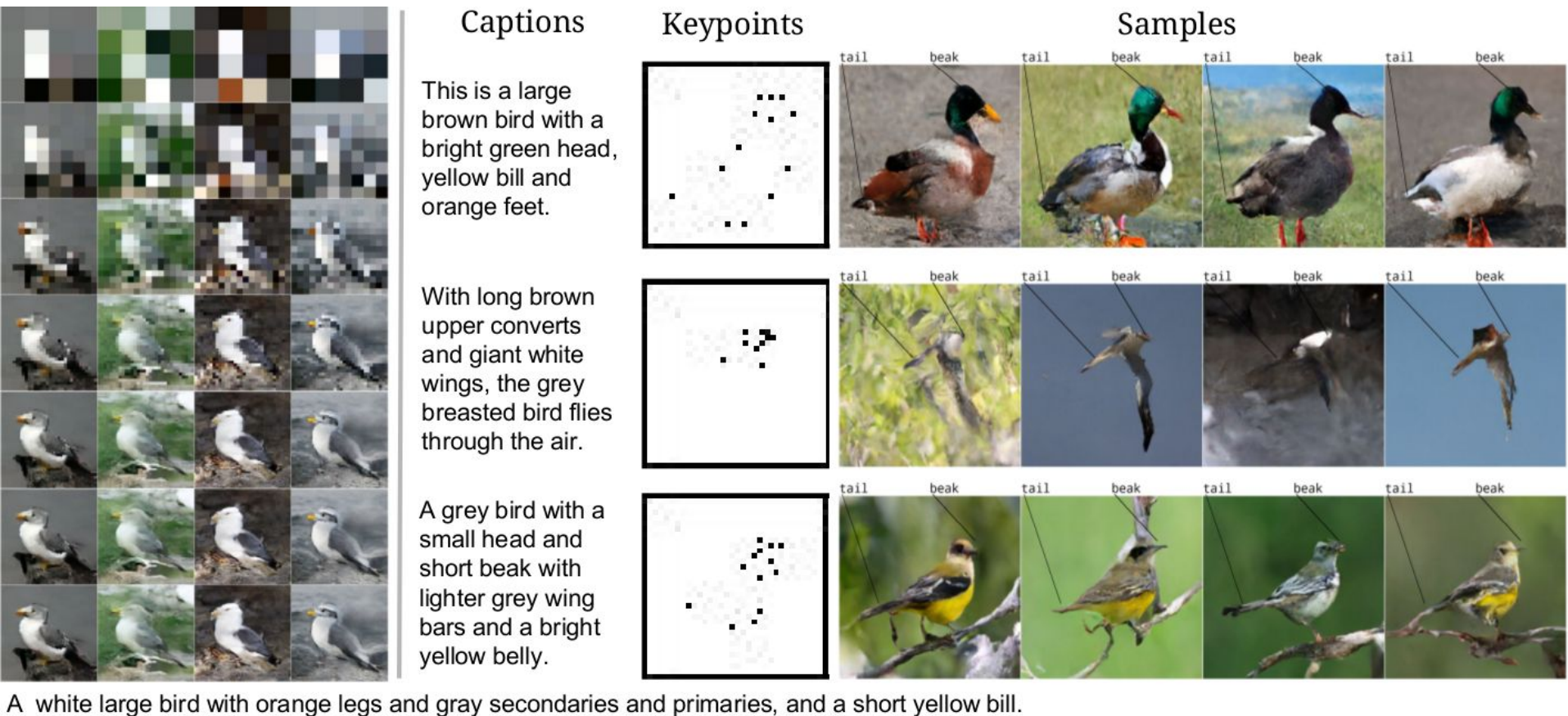


Figure 1. System diagram depicting (a) training procedure and (b) inference procedure, with inputs on the left and outputs on the right. In our system, the duration prediction model and the F0 prediction model are performed by a single neural network trained with a joint loss. The grapheme-to-phoneme model is used as a fallback for words that are not present in a phoneme dictionary, such as CMUDict. Dotted lines denote non-learned components.



# Parallel Multiscale Autoregressive Density Estimation



*Figure 4.* Text-to-image bird synthesis. The leftmost column shows the entire sampling process starting by generating  $4 \times 4$  images, followed by six upscaling steps, to produce a  $256 \times 256$  image. The right column shows the final sampled images for several other queries. For each query the associated part keypoints and caption are shown to the left of the samples.

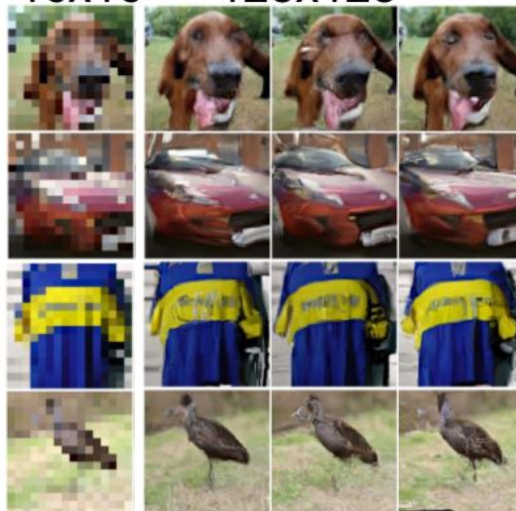


# Parallel Multiscale Autoregressive Density Estimation

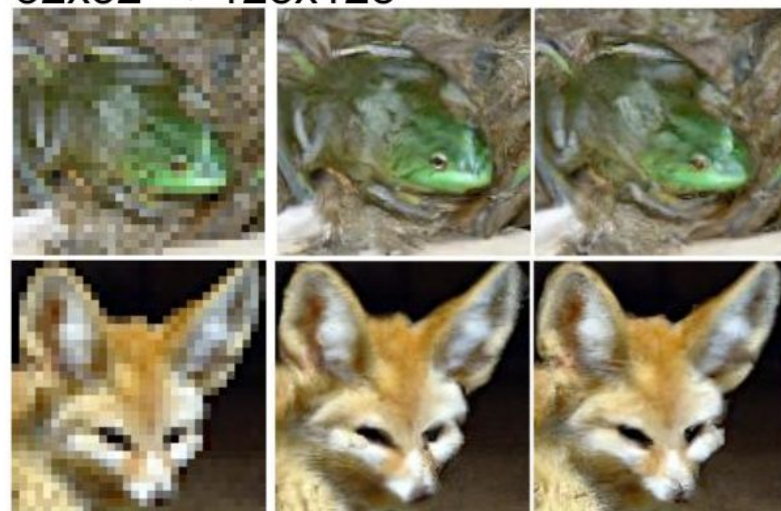
8x8  $\rightarrow$  128x128



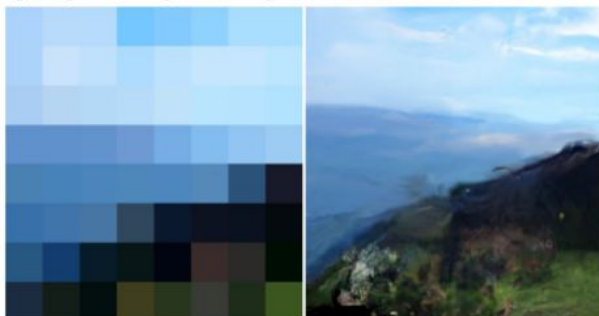
16x16  $\rightarrow$  128x128



32x32  $\rightarrow$  128x128



8x8  $\rightarrow$  512x512



16x16  $\rightarrow$  512x512



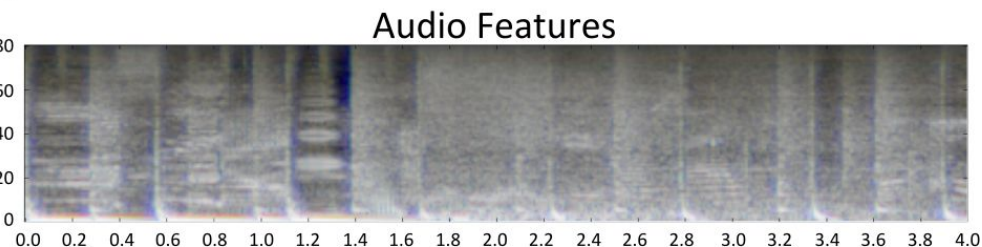
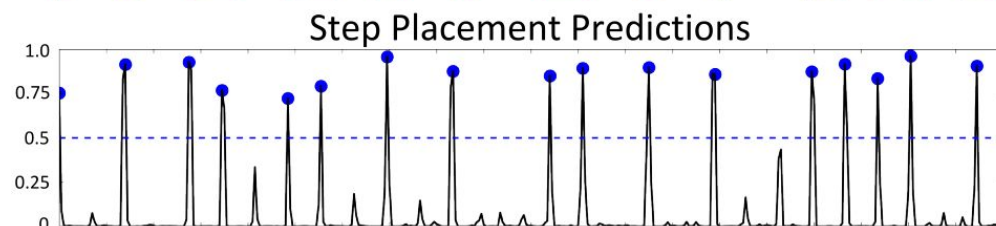
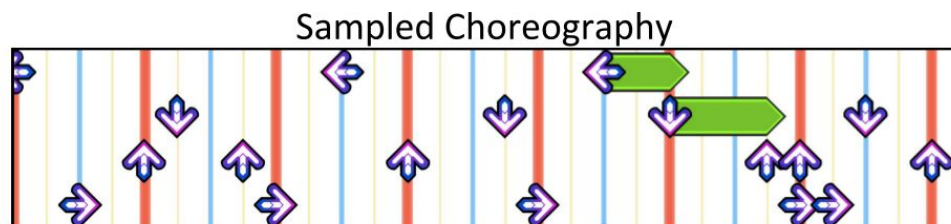
32x32  $\rightarrow$  512x512



Figure 7. Upscaling low-resolution images to  $128 \times 128$  and  $512 \times 512$ . In each group of images, the left column is made of real images, and the right columns of samples from the model.

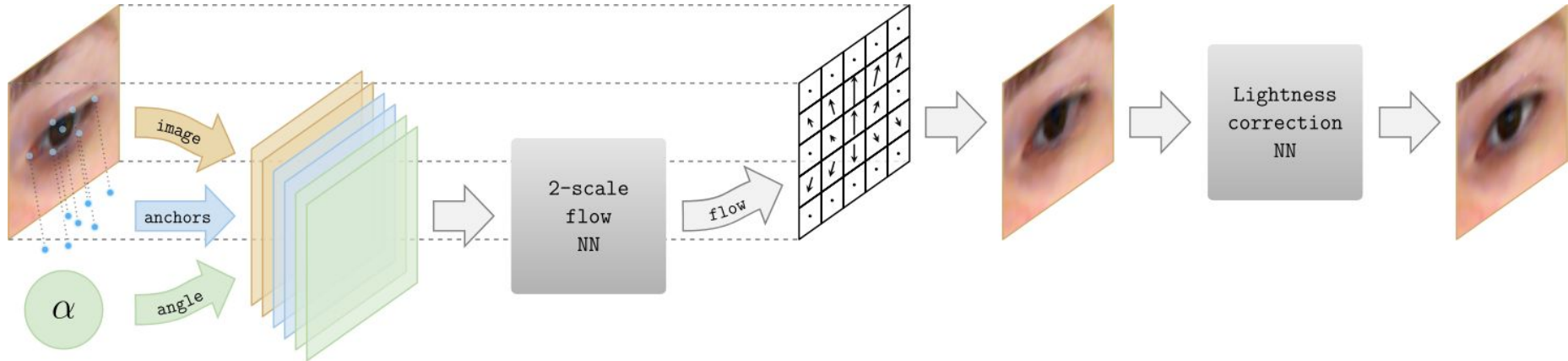


# Dance Dance Convolution





# DeepWarp: Photorealistic Image Resynthesis for Gaze Manipulation

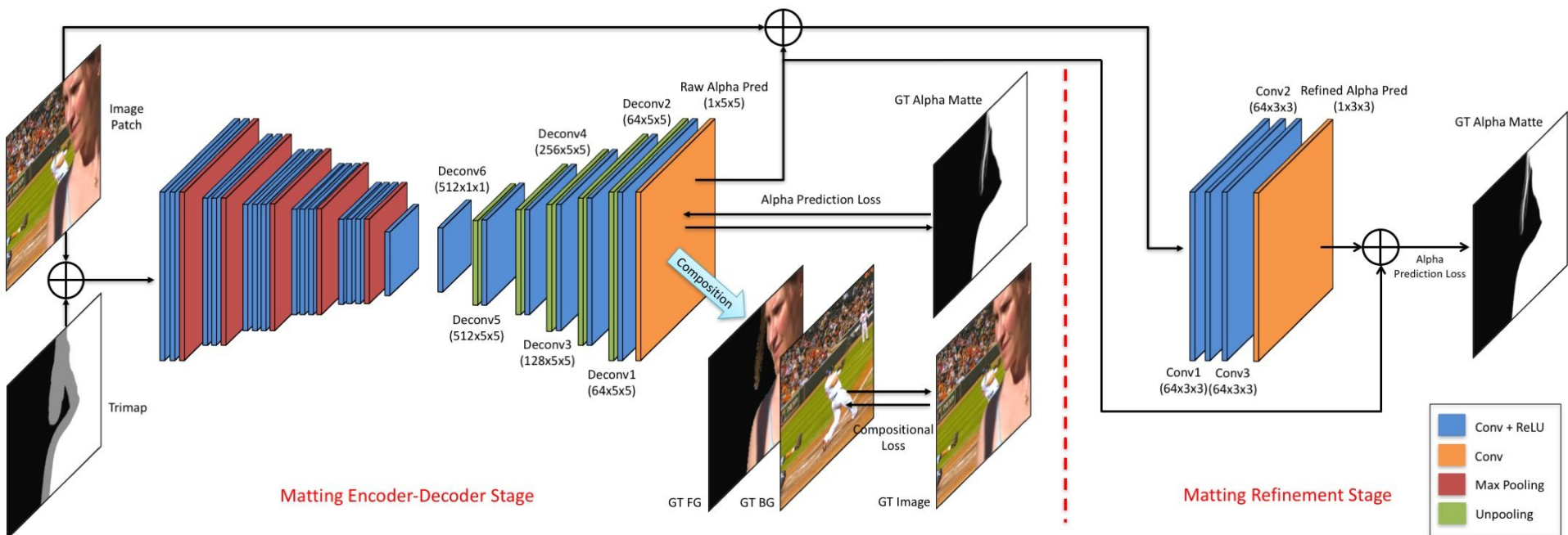
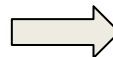


The **proposed system** takes an input eye region, feature points (anchors) as well as a correction angle and sends them to the multi-scale neural network predicting a flow field. The flow field is then applied to the input image to produce an image of a redirected eye. Finally, the output is enhanced by processing with the lightness correction neural network.





# Deep Image Matting





# Colorization as a Proxy Task for Visual Understanding

Learning a representation via  $(x, y)$  pairs

## Classification

$$\left( \text{flamingo image}, \text{"flamingo"} \right), \left( \text{hay image}, \text{"hay"} \right), \dots$$

## Self-supervision

Ex. 1: **Inpainting** (remove patch and then predict it)

$$\left( \text{flamingo image with patch removed}, \text{flamingo patch} \right), \left( \text{hay image with patch removed}, \text{hay patch} \right), \dots$$

Ex. 2: **Context** (given two patches, predict their spatial relation)

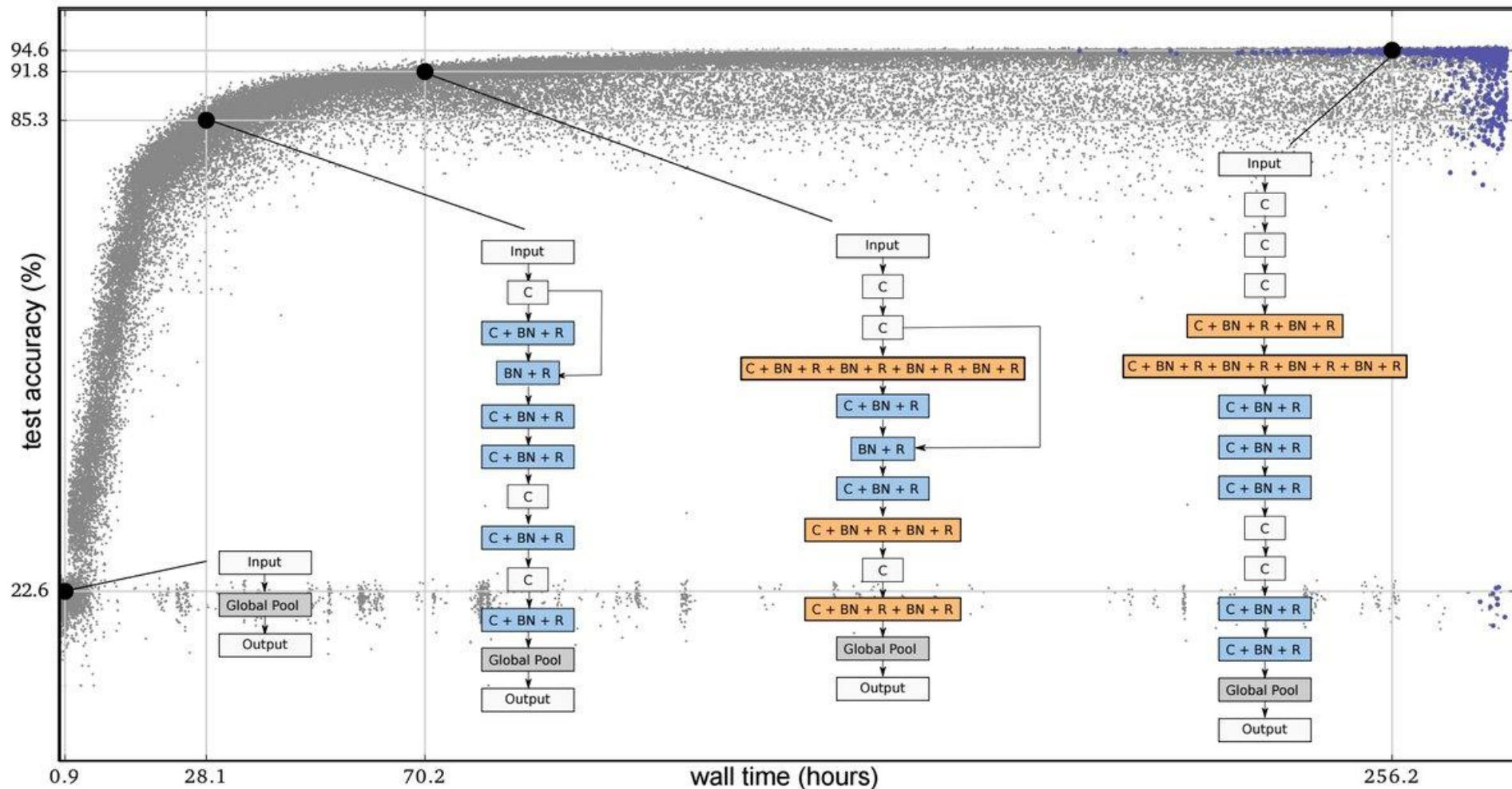
$$\left( \left\{ \text{flamingo patch 1}, \text{flamingo patch 2} \right\}, \text{"south east"} \right), \left( \left\{ \text{hay patch 1}, \text{hay patch 2} \right\}, \text{"west"} \right), \dots$$

Ex. 3: **Colorization** (predict color given intensity)

$$\left( \text{grayscale flamingo}, \text{color flamingo} \right), \left( \text{grayscale hay}, \text{color hay} \right), \dots$$



# Large-Scale Evolution of Image Classifiers





# Large-Scale Evolution of Image Classifiers

STUDY	PARAMS.	C10+	C100+	REACHABLE?
MAXOUT (GOODFELLOW ET AL., 2013)	–	90.7%	61.4%	NO
NETWORK IN NETWORK (LIN ET AL., 2013)	–	91.2%	–	NO
ALL-CNN (SPRINGENBERG ET AL., 2014)	1.3 M	92.8%	66.3%	YES
DEEPLY SUPERVISED (LEE ET AL., 2015)	–	92.0%	65.4%	NO
HIGHWAY (SRIVASTAVA ET AL., 2015)	2.3 M	92.3%	67.6%	NO
RESNET (HE ET AL., 2016)	1.7 M	93.4%	72.8% <sup>†</sup>	YES
EVOLUTION (OURS)	5.4 M	94.6%		N/A
	40.4 M		76.3%	
WIDE RESNET 28-10 (ZAGORUYKO & KOMODAKIS, 2016)	36.5 M	96.0%	80.0%	YES
WIDE RESNET 40-10+D/O (ZAGORUYKO & KOMODAKIS, 2016)	50.7 M	96.2%	81.7%	NO
DENSENET (HUANG ET AL., 2016A)	25.6 M	96.7%	82.8%	NO



Alex J. Champandard

@alexjc

Folgen



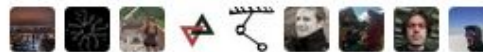
17/ With enough compute to raise planet temperature by 0.1°C, they failed to show interesting results or address useful research problems.

RETWEETS

7

GEFÄLLT

39



11:45 - 6. März 2017

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<https://arxiv.org/abs/1703.01041>



## More

- Embedding Watermarks into Deep Neural Networks  
<http://arxiv.org/abs/1701.04082>
- WebCaricature: a benchmark for caricature face recognition  
<http://arxiv.org/abs/1703.03230>
- Using Deep Learning and Google Street View to Estimate the Demographic Makeup of the US  
<http://arxiv.org/abs/1702.06683>
- Skip Connections as Effective Symmetry-Breaking  
<http://arxiv.org/abs/1701.09175>
- Batch Renormalization: Towards Reducing Minibatch Dependence in Batch-Normalized Models  
<https://arxiv.org/abs/1702.03275>



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## More

- Google Cloud acquired Kaggle:  
<https://techcrunch.com/2017/03/07/google-is-acquiring-data-science-community-kaggle/>
- Keras 2.0 released (with many API changes!):  
<https://blog.keras.io/introducing-keras-2.html>





# Deep Learning Tips and Tricks for the practitioner

- Shuffle the data
- Use dropout
- Use Max pooling
- Instead of Sigmoid or TanH use ReLU or better PReLU
- Use ReLU or PreLU's gates not before max pooling
- Use Batch Normalization
- Expand your dataset: collect more data or use data augmentation
- If you can't and you use the smaller models: try ensembles
- use 1x1 CNN's layer where appropriate
- .....

<https://nmarkou.blogspot.co.at/2017/02/the-black-magic-of-deep-learning-tips.html>



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**Thank you for coming!**

**Next**  
**Deep Learning Meetup:**

**17 May 2017 @ Casinos Austria Hub (tbc)**



Thomas Lidy



Jan Schlüter



Alex Schindler