Artificial Intelligence!

The Future of Forecasting and S&OP?

Dr. Sven F. Crone
Assistant Professor Lancaster University
Co-Director Research Centre for Marketing & Forecasting
CEO iqast

Q&A via Slido.com #AI-tutorial

sli.do

How to Introduce Slido to Your Audience

At this event, we want to make sure we address your most burning questions. Therefore, we'll be using a simple audience interaction platform called **Slido**.

Slido allows you to submit your questions as well as upvote the questions of other participants. Questions with the highest number of votes will stand a better chance to get answered by speakers.

Throughout the event, you will also be able to express your opinion by voting on live polls.

It's really easy to join.

1. Please take out your smartphones and connect to the WiFi
2. Open the web browser
3. Go to www.slido.com and enter the event code, which is...

www.slido.com → #AI-workshop

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Agenda

AI in Forecasting

- Capabilities of AI
  - The hype
  - How AI can “see”
  - AI Demos
- Using AI in Forecasting
  - AI in Forecasting
  - Case studies
- The Gap
  - Forecasting?
  - State of Forecasting
  - Sizing the Gap

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Deep

Spektrum 1.18 der Wissenschaft

DER SPIEGEL

P.M. MAGAZIN 05

Yps

Deep-Learning

WIRED

Picking up on the most commonly occurring

The New York Times

AI Art at Christie's Sells for $432,500

"Edmond de Belamy, from La Famille de Belamy," by the French art collective Obvious, was sold on Thursday at Christie's New York. Christie's

By Gabe Cohn

FINANCIAL TIMES

myFT

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Artificial intelligence (AI)

October 2018

'Tech tax' necessary to avoid dystopia, says leading economist

Jeffrey Sachs warns AI could lead to wealth being concentrated in the hands of a few thousand people

23 Oct 2018

The five / Five scientific predictions by Professor Stephen Hawking

Facebook an... by today's robb... them up

Toby Walsh

23 Oct 2018

How do we stop... technology falling... hands?

Hannah Fry

INDEPENDENT

NEWS POLITICS VOICES FINAL SAY SPORT CULTURE

ns&i

Premium Bonds

artificial intelligenc...

VOICES

Pepper the AI ro...

She stared at the ceiling, an... It was a perfect politician's...

TECH

How ar... be viola...

AMERICAS

Housto... robot s...

HOME NEW...

Many v... 'trust is...

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The Hype on AI, ML & Deep Learning?

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The Hype on Big Data?

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The Hype on Forecasting?

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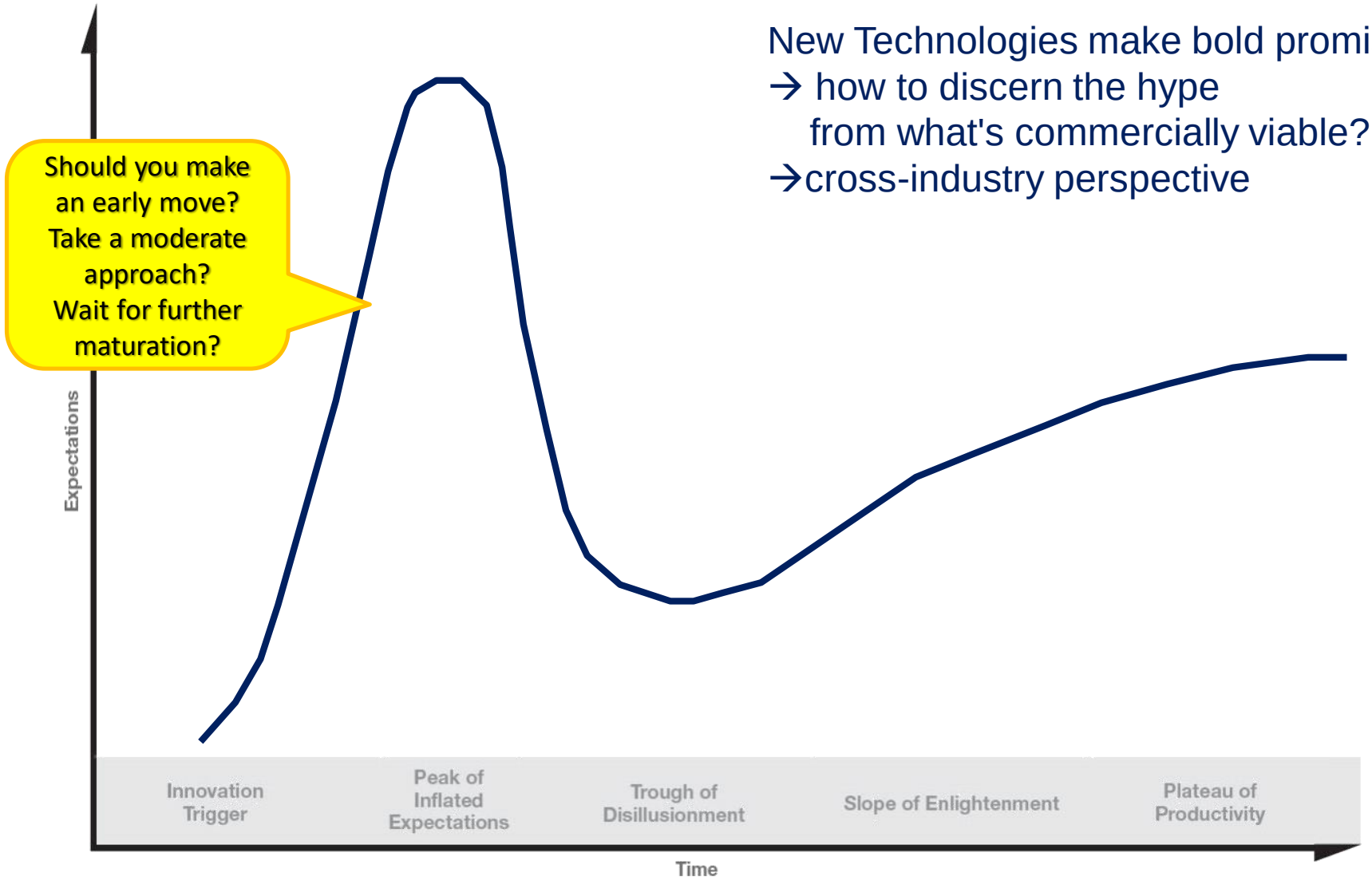
Emerging Technologies Hype Cycle



New Technologies make bold promises
→ how to discern the hype
from what's commercially viable?
→cross-industry perspective

Source: Gartner (July 2017)
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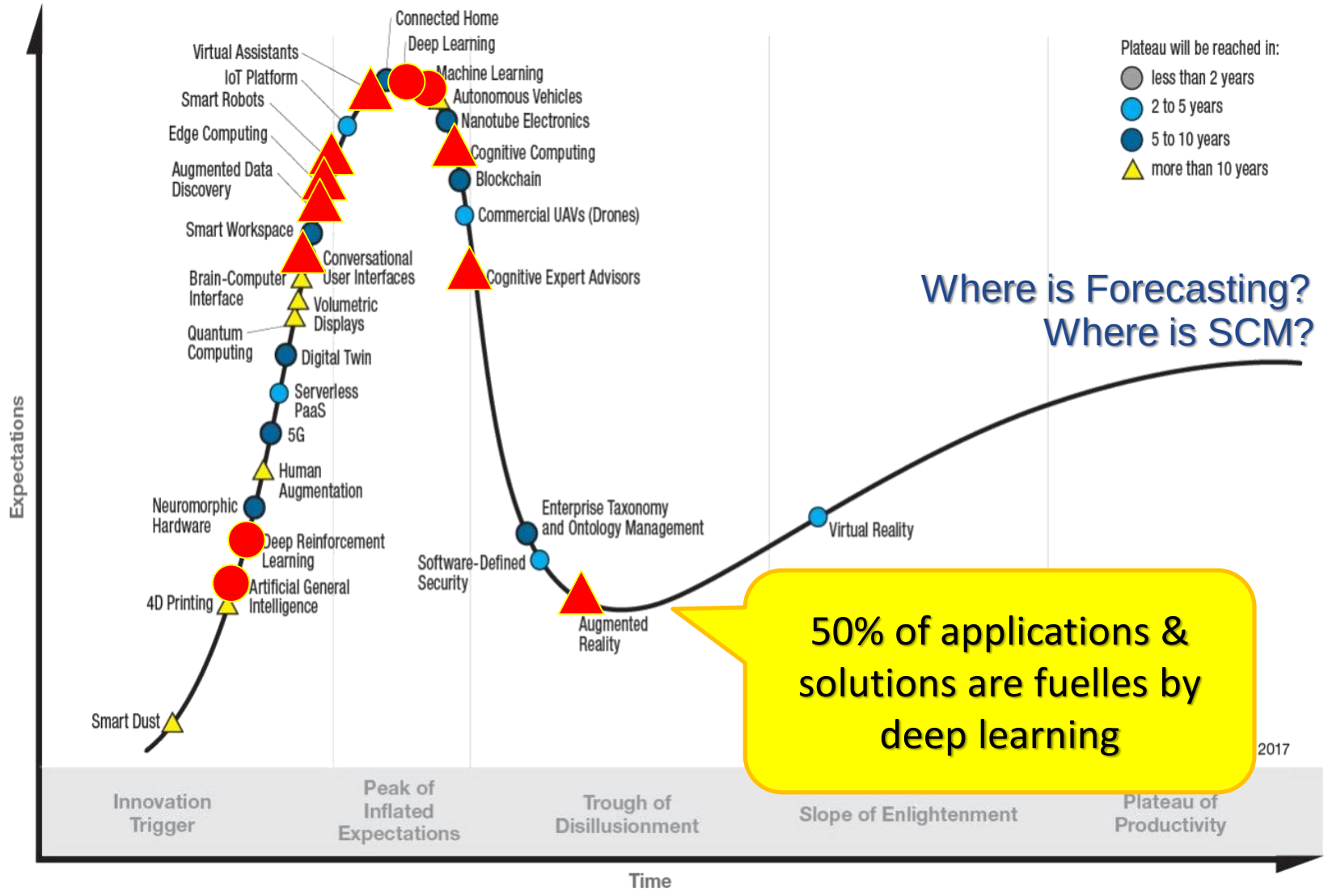
Gartner

Emerging Technologies Hype Cycle



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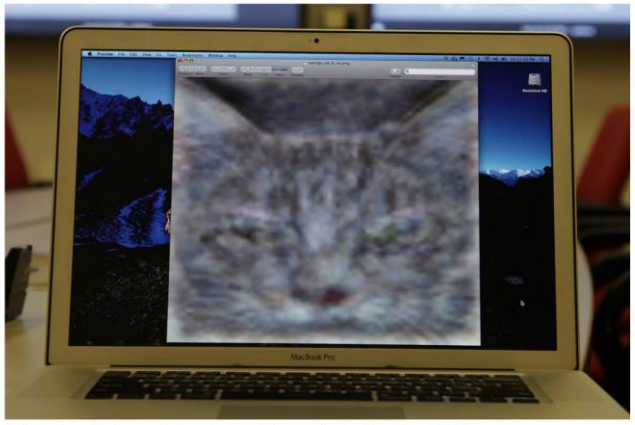
Gartner

The New York Times

How Many Computers to Identify a Cat? 16,000

By JOHN MARKOFF JUNE 25, 2012



An image of a cat that a neural network taught itself to recognize. Jim Wilson/The New York Times

MOUNTAIN VIEW, Calif. — Inside Google's secretive X laboratory, known for inventing self-driving cars and augmented reality gl… small group of researchers be… working several years ago on a sim… human l… a.

LIVESCIENCE

How Computers Can Teach Themselves to Recognize Cats

By Tanya Lewis, Staff Writer | May 28, 2015 07:03am ET

MORE

Credit: Michelangelus | Shutterstock.com

In June 2012, a network of 16,000 computers trained itself to recognize a cat by looking at 10 million images from YouTube videos. Today, the technique is used in everything from Google image searches to Facebook's newsfeed algorithms.

The feline recognition feat was accomplished using "deep … an approach to machine learning that works by exposing a

h

WIRED

Picking up on the most commonly oc… images featured on YouTube, the sys… achieved 81.7 percent accuracy in de… human faces, 76.7 percent accuracy … identifying human body parts and 74… accuracy when identifying cats.

REVIEW

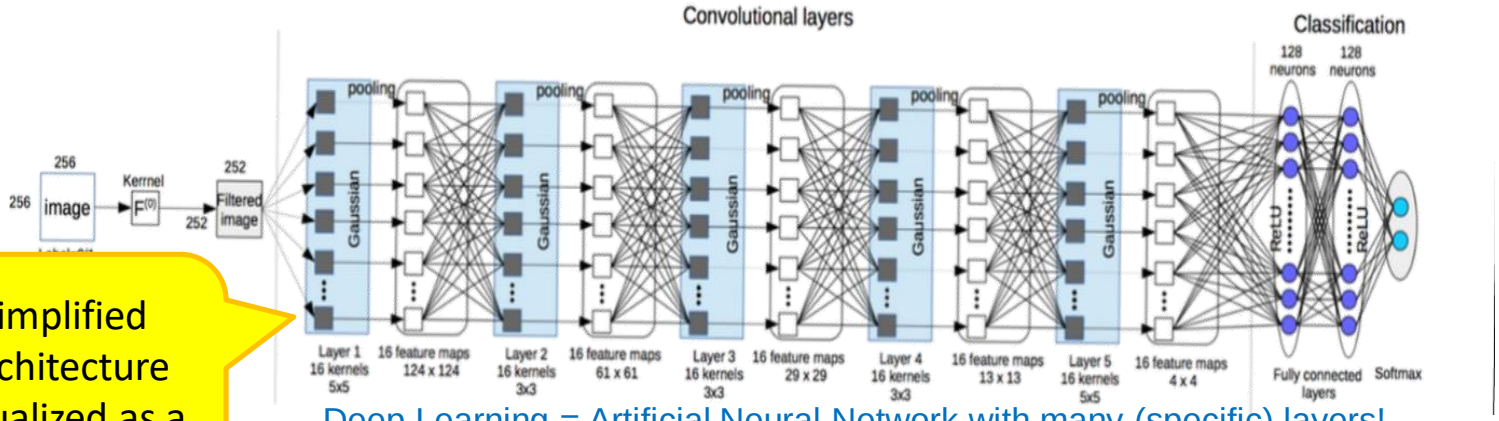
doi:10.1038/nature14539

Deep learning

Yann LeCun[1,2], Yoshua Bengio[3] & Geoffrey Hinton[4,5]

Deep learning allows compu… …iple processing layers to learn representations of data with multiple levels o… …improved the state-of-the-art in speech rec-ognition, visual object r… …s such as drug discovery and genomics. Deep learning discovers intri… …gation algorithm to indicate how a machine should change its inte… …ion in each layer from the representation in the previous layer. D… …s in processing images, video, speech and audio, whereas recur… …and speech.

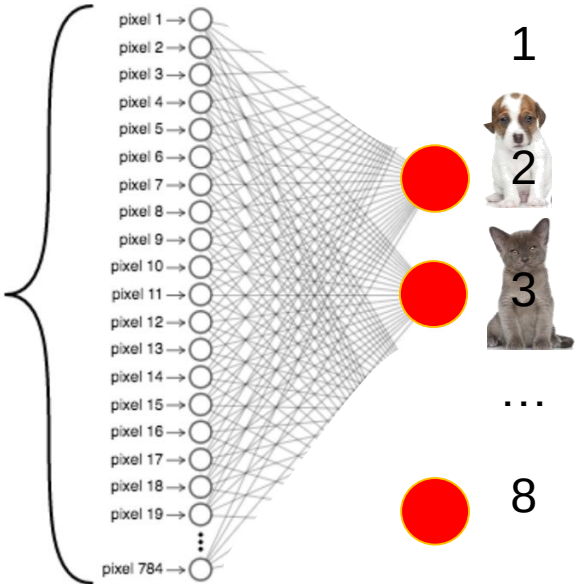
How does a Neural Network „see“?



simplified Architecture visualized as a directed graph

Deep Learning = Artificial Neural Network with many (specific) layers!

28 x 28
= 784 pixels



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The New York Times

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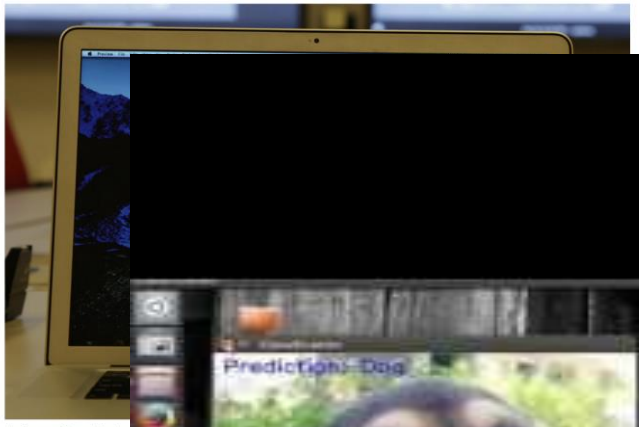

An image of a cat that a

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LIVESCIENCE

How Computers Can Teach Themselves to Recognize Cats

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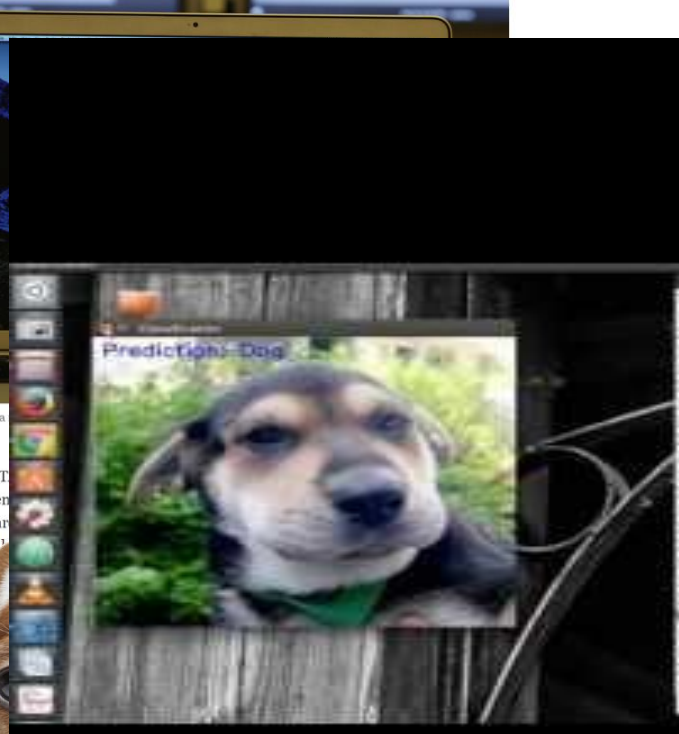
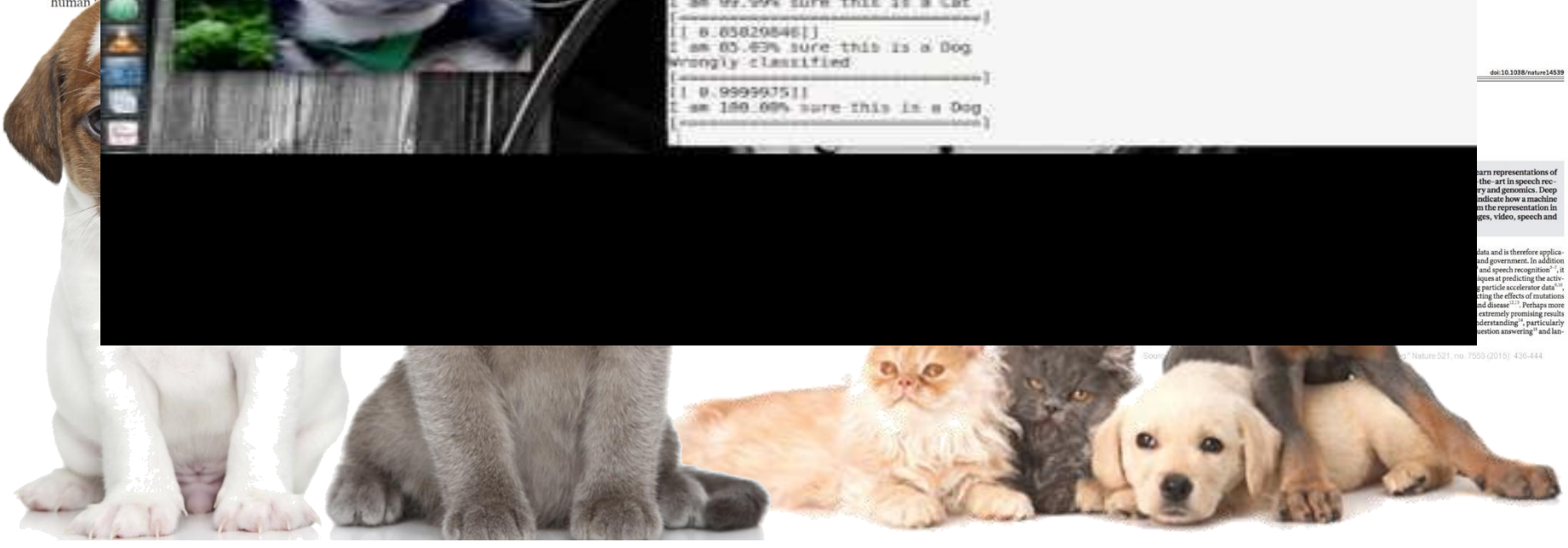
doi:10.1038/nature14539

earn representations of
the-art in speech rec-
ry and genomics. Deep
ndicate how a machine
m the representation in
ages, video, speech and

data and is therefore applica-
and government. In addition
and speech recognition[5–7], it
iques at predicting the activ-
particle accelerator data[8–10],
cting the effects of mutations
nd disease[11,12]. Perhaps more
extremely promising results
derstanding[13], particularly
estion answering[14] and lan-

Source: "" Nature 521, no. 7553 (2015): 436-444



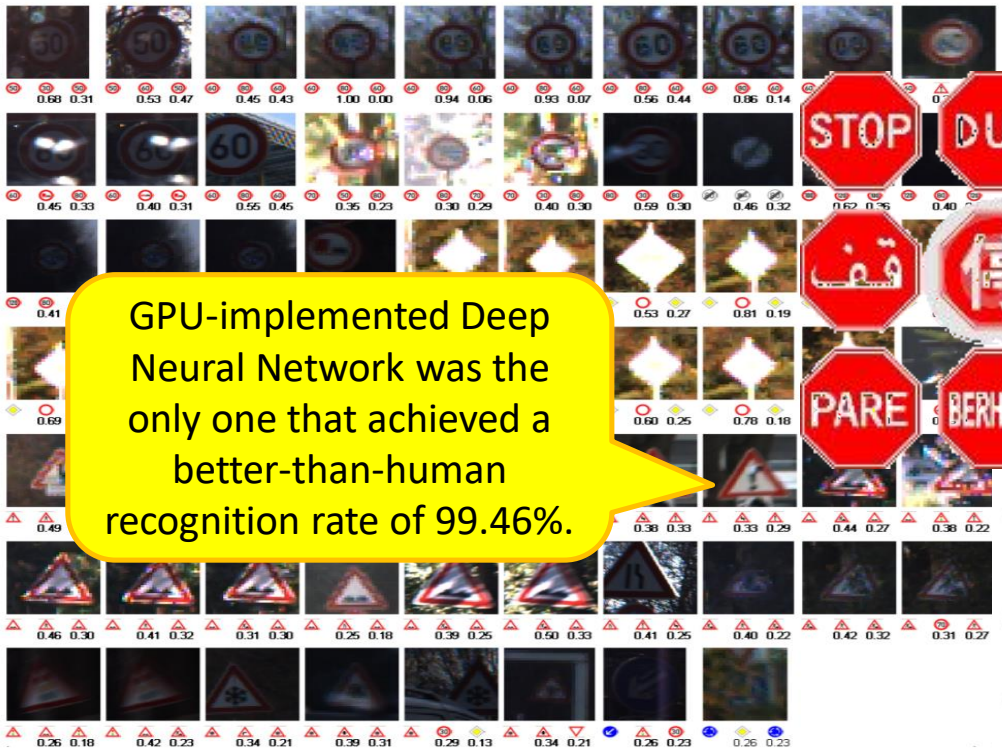


SUPERHUMAN VISUAL PATTERN RECOGNITION

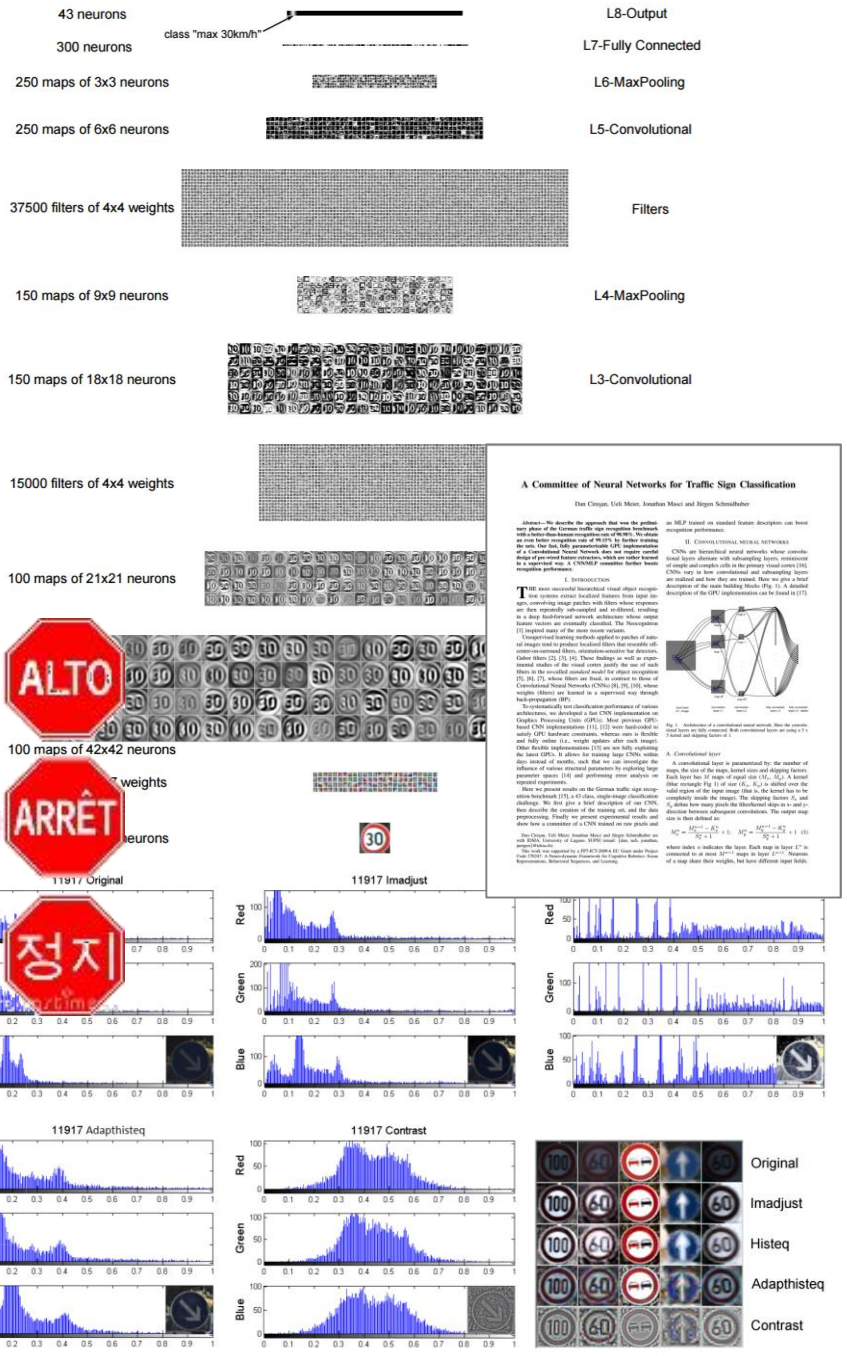
JÜRGEN SCHMIDHUBER 2013

2011: First Superhuman Visual Pattern Recognition

IJCNN 2011 competition in Silicon Valley:
twice better than humans
three times better than the closest artificial competitor
six times better than the best non-neural method



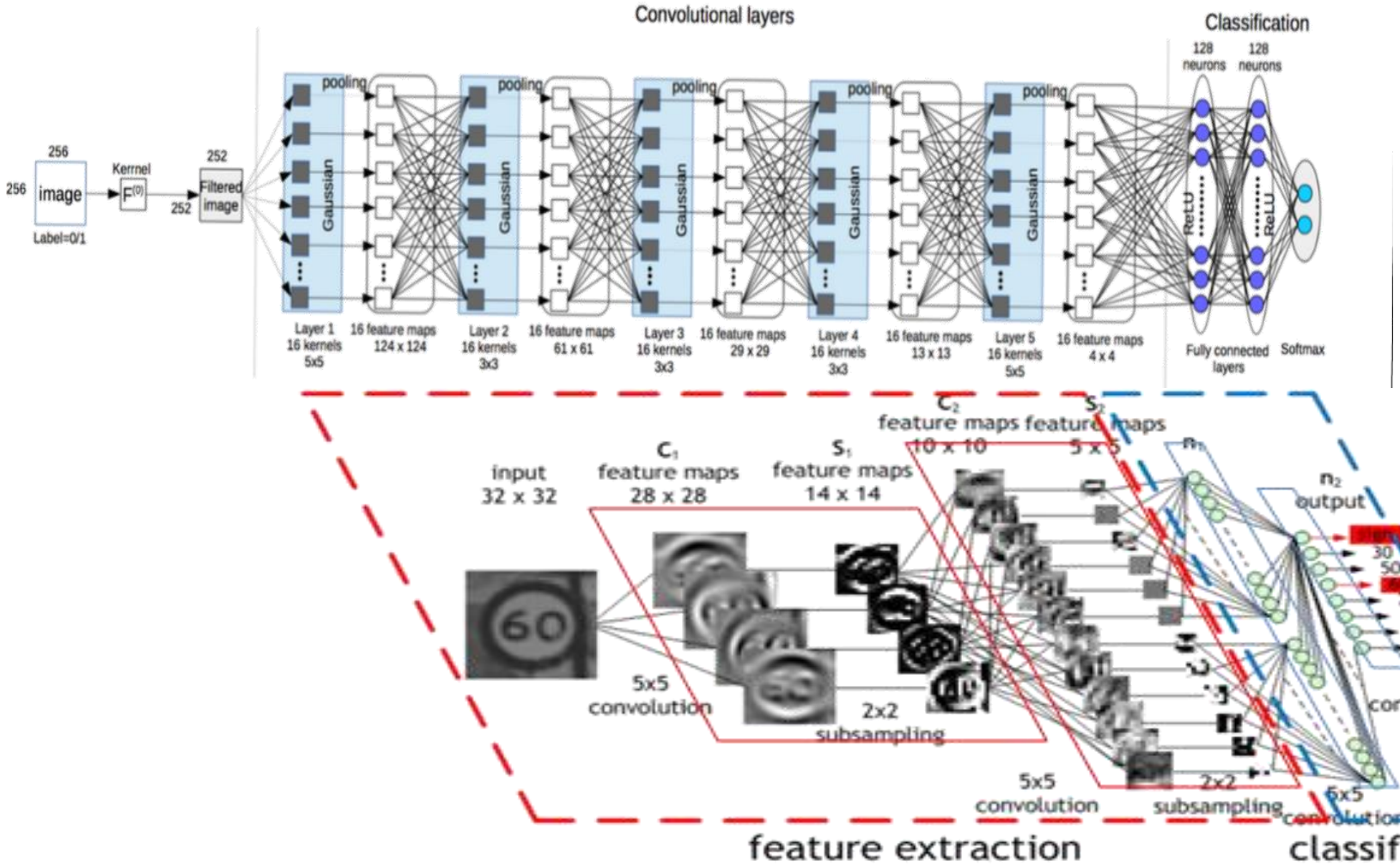
GPU-implemented Deep Neural Network was the only one that achieved a better-than-human recognition rate of 99.46%.



A Committee of Neural Networks for Traffic Sign Classification

Figure 5: The 68 errors of the MCDNN, with correct label (left) and first (middle) and second best (right) predictions. Best seen in color.

How does a ANN „see“?



Why not before? Needed to overcomevanishing gradient problem
→ parameterisation (Optimisation!) like before with backprop!

LCF

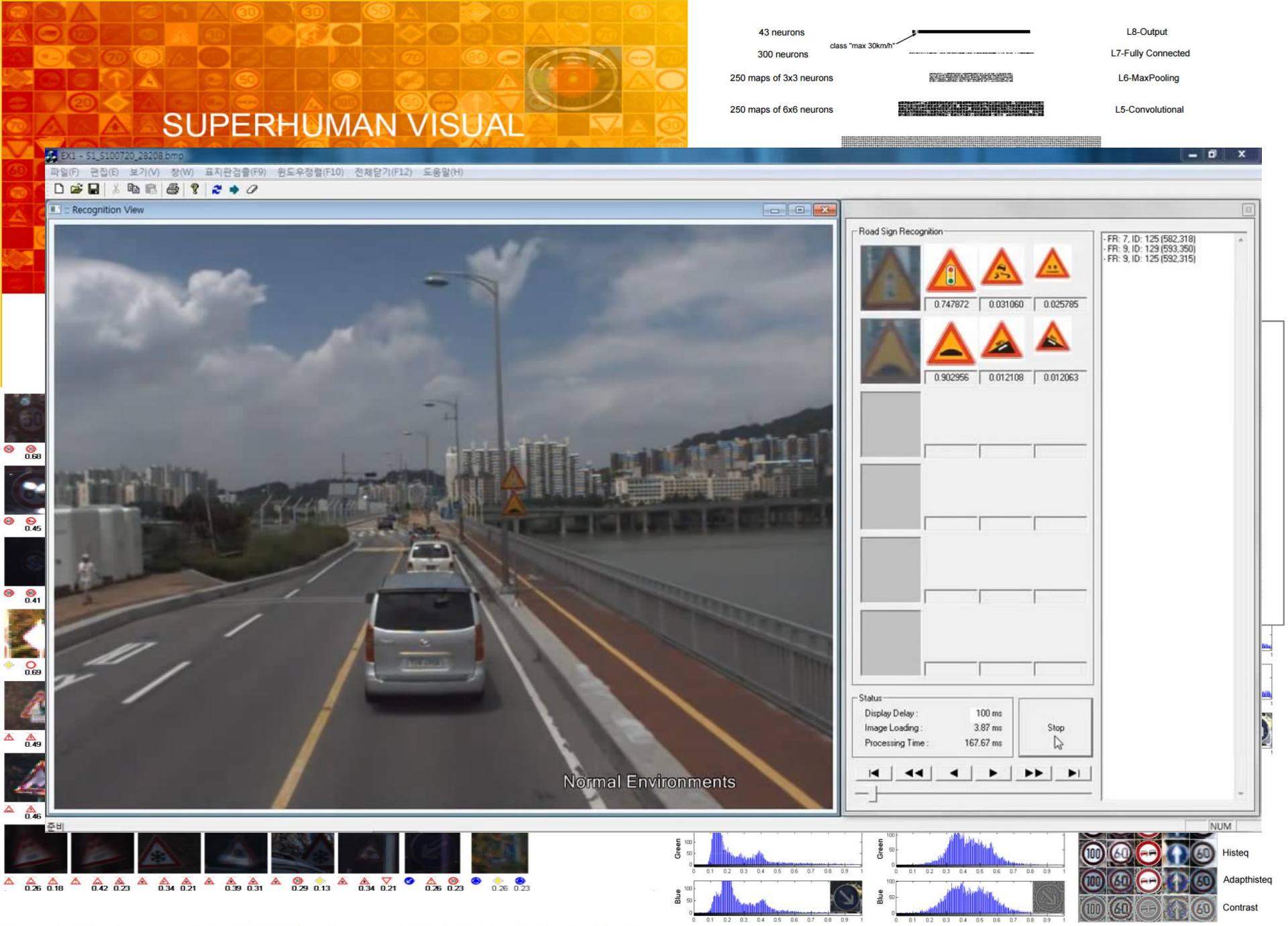
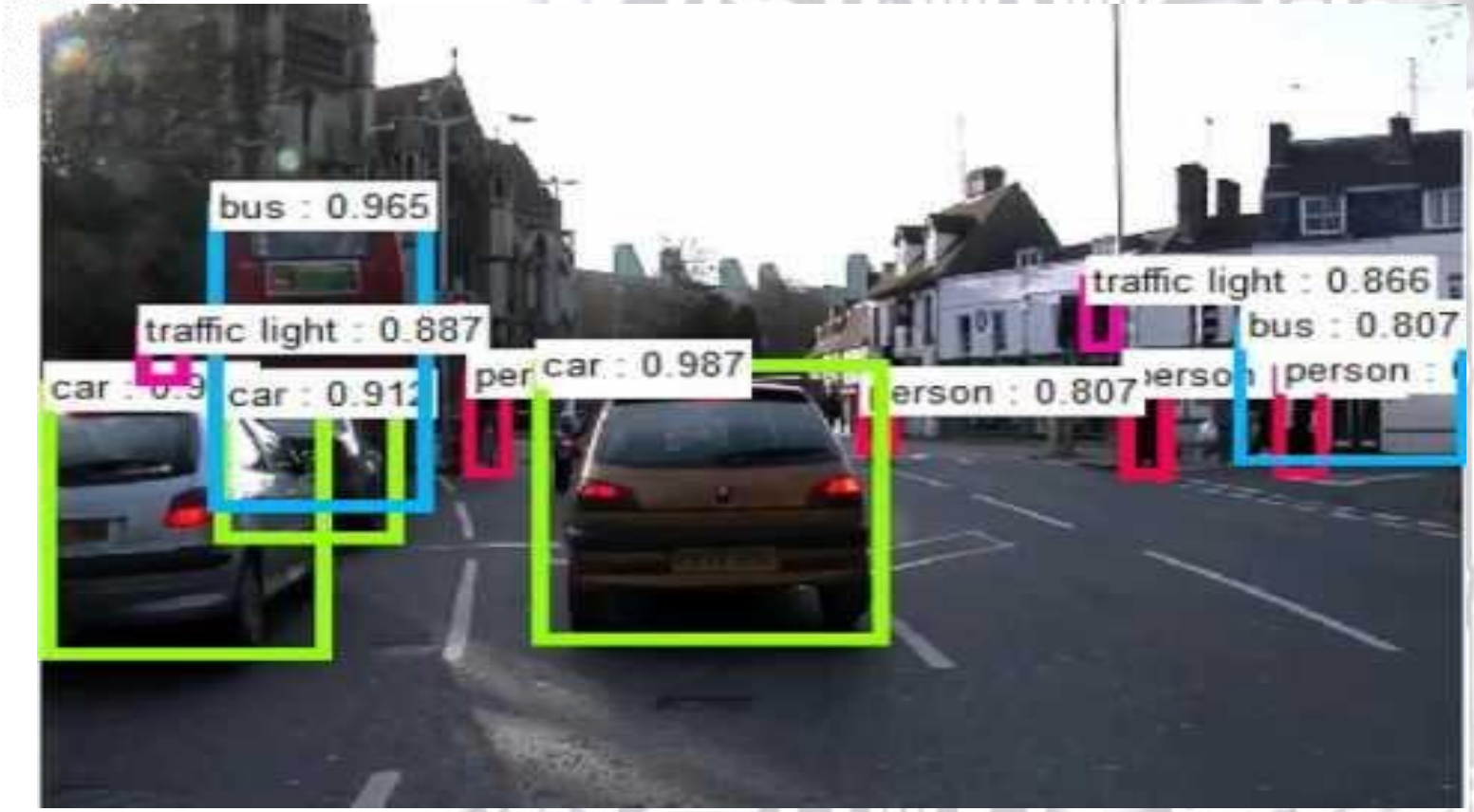


Figure 5: The 68 errors of the MCDNN, with correct label (left) and first (middle) and second best (right) predictions. Best seen in color.

AI & Deep Learning in Autonomous cars, Speech Recognition, Image recognition …



https://www.youtube.com/watch?v=DeCFxPQlOVk

Narrow AI

PERFORMS TASKS THAT NORMALLY REQUIRE HUMAN INTELLIGENCE, BUT CAN ONLY PERFORM TASKS IN A VERY SPECIFIC AND NARROWLY DEFINED DOMAIN.

General AI

"HUMAN-LEVEL AI".
HAS A *GENERAL PROBLEM SOLVING ABILITY* THAT ENABLES IT TO LEARN NEW TASKS ACROSS SEVERAL DOMAINS.

… Superintelligent AI

Unsupervised Deep Learning in Games

- → in 43 out of 49 cases DeepMind outperformed programs designed to play that particular game
- → in ¾ it defeated professional human players.
- → *Super-human* performance ?!

https://www.youtube.com/watch?v=V1eYniJ0Rnk

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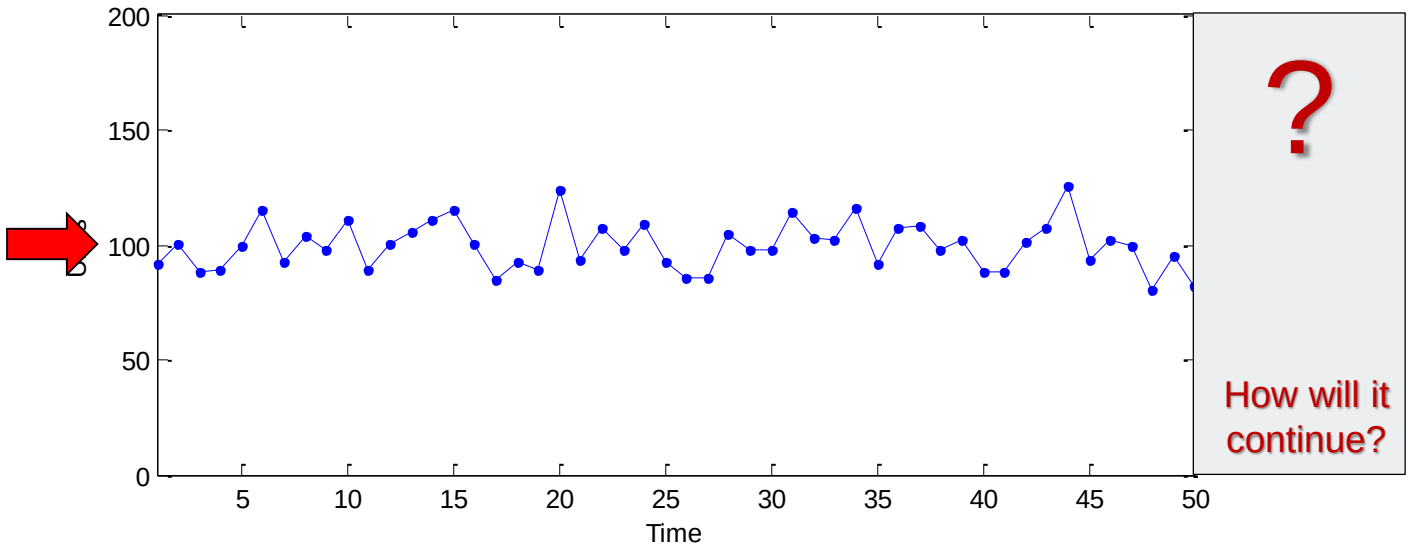
LCF

What is Forecasting?

This is a time series …

(a collection of observations made sequentially in time)

Jan 2016	91.36
Feb 2016	100.77
Mar 2016	87.85
Apr 2016	88.86
May 2016	99.93
Jun 2016	115.32
July 2016	92.30
Aug 2016	103.71
Sep 2016	97.74
Oct 2016	111.17
...	...
Dec 2016	89.26



… how will it continue?

”Estimation how the sequence of observations observed in the past will continue into the future”

[Makridakis, Wheelwright, Hyndman, 1998]

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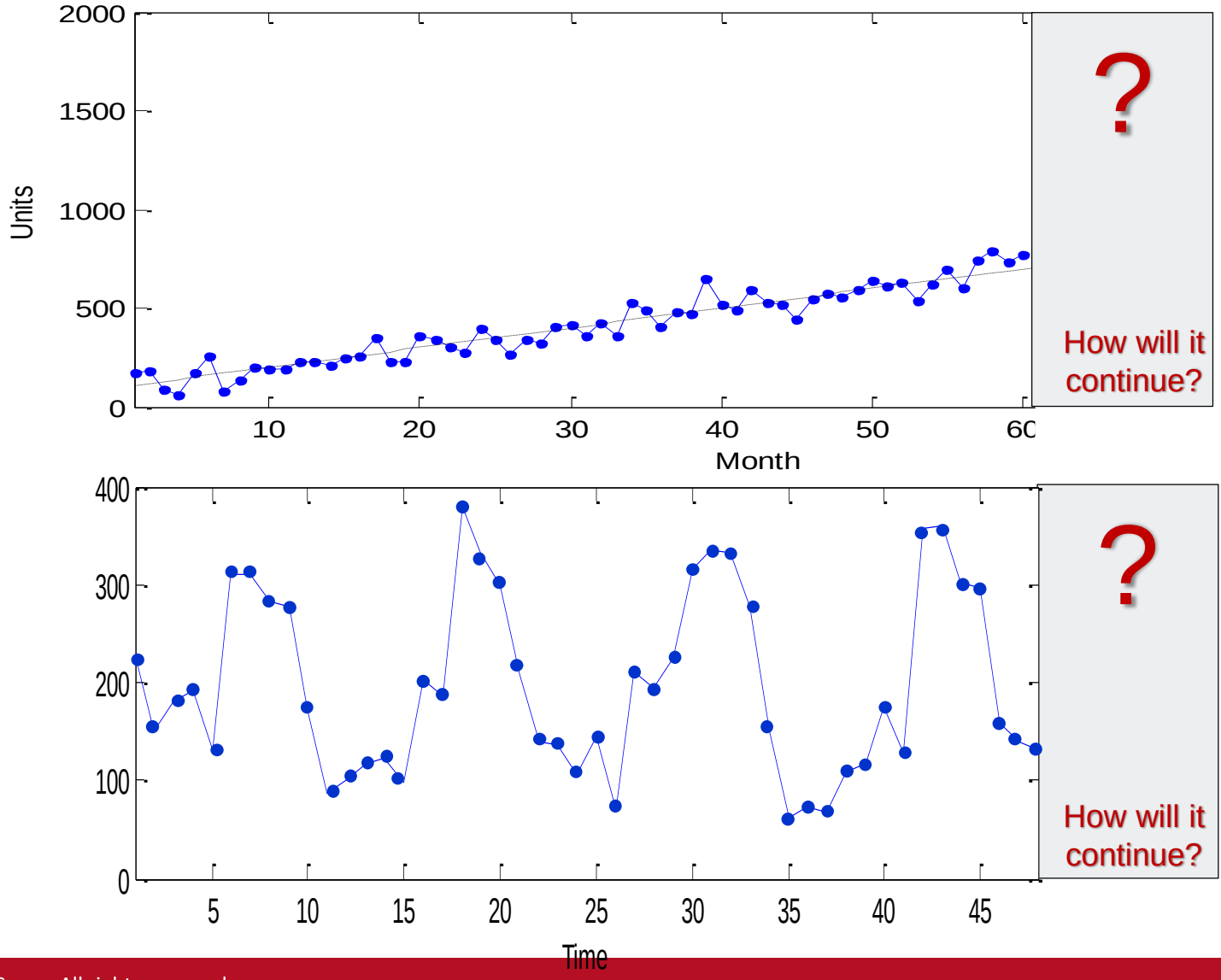
What is Forecasting?



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Why Forecast with AI?

Oh, pls repeat
for 40000 items
every day
in 1000 locations
…

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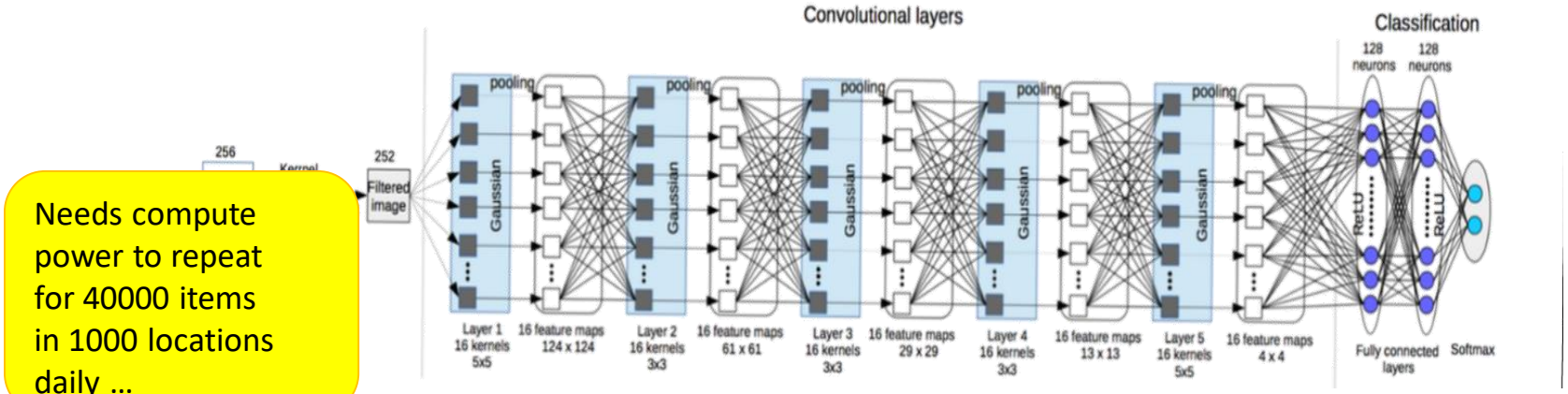
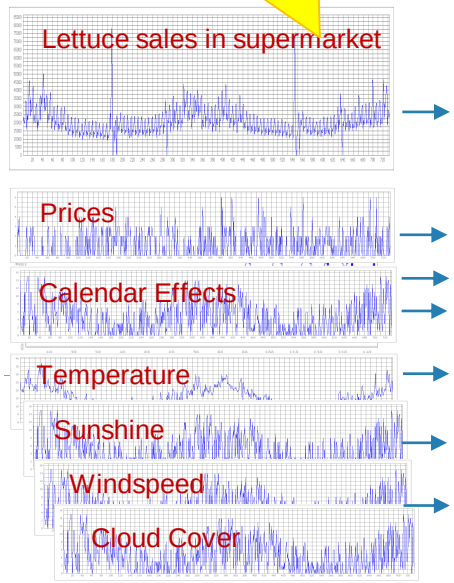
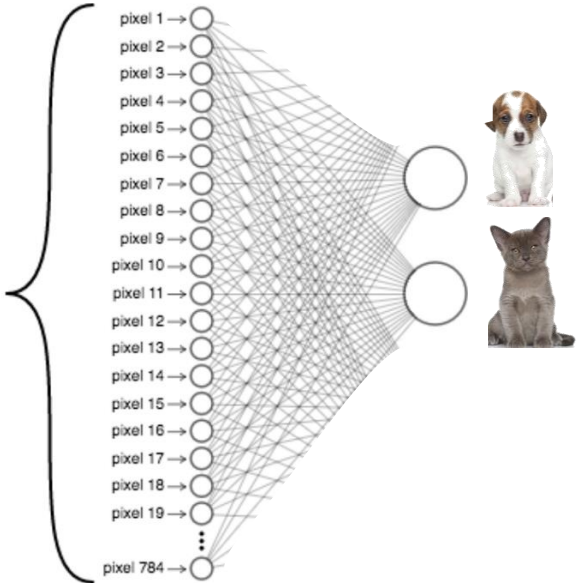
How does a Neural Network „see“?



Needs compute power to repeat for 40000 items in 1000 locations daily …





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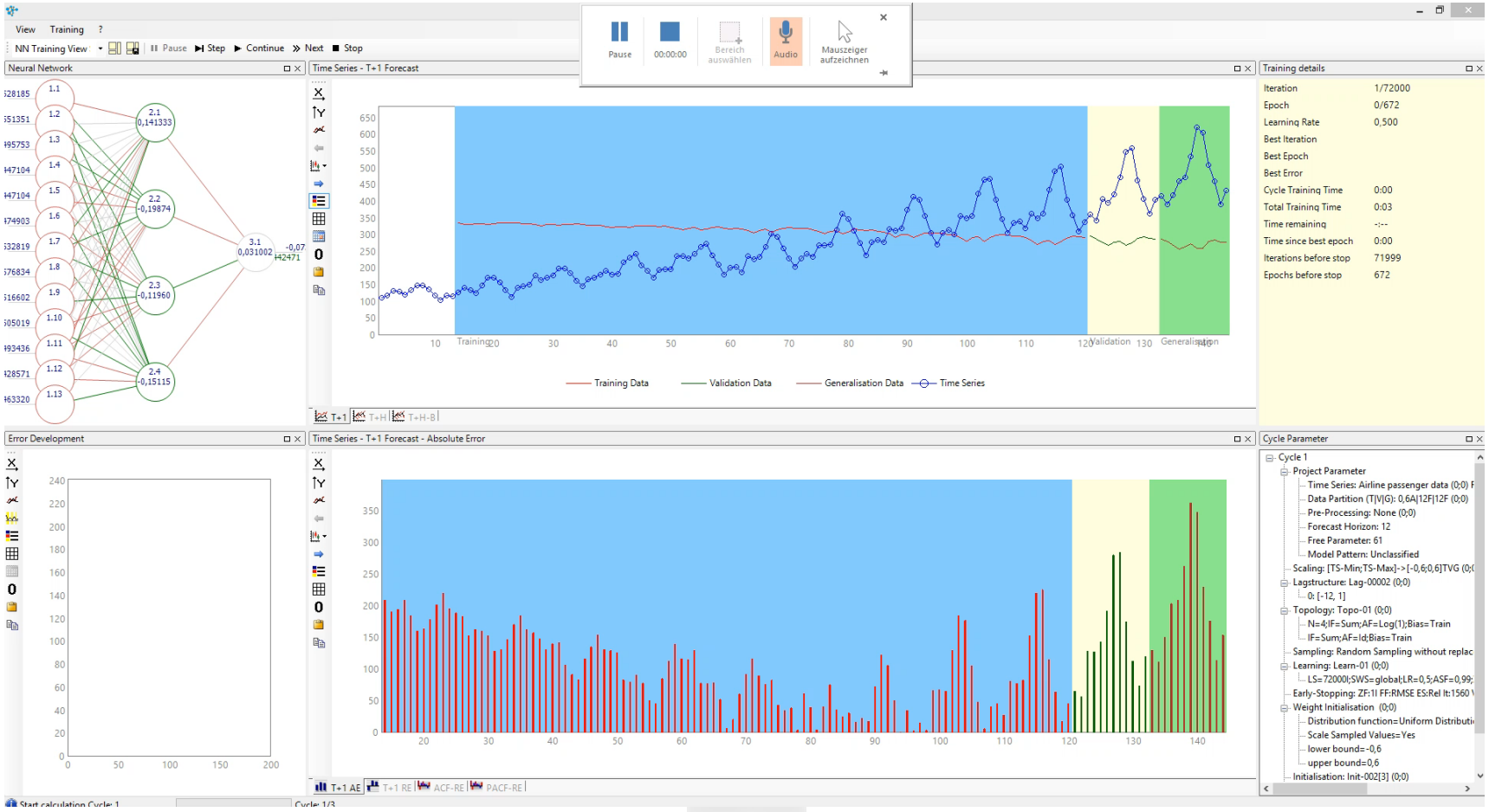
Neural Network Demo



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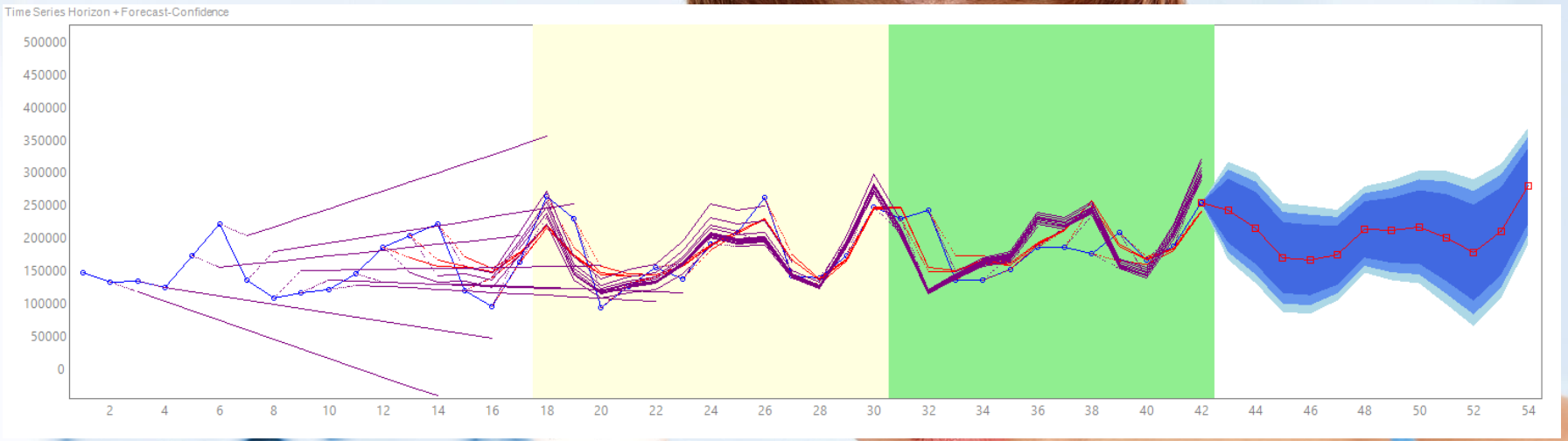
FMCG Forecasting for manufacturing @ BDF Beiersdorf



Median sMAPE	Test
Seasonal Linear Regression (35B)	18.20
SLR + Judgment	18.02
MLP AR, SinCos + Selection	9.00
Improvement	-9.02
Improvement in %	-49.83%

NNET achieves super-human forecast accuracy

sMAPE test	SAP error	iqast error	Δ error	Δ error %	# items
Canada	40,7	33,8	-6,9	-16,9%	47
Germany	55,4	51,7	-3,7	-6.8%	155
France	43,7	42,6	-1,2	-2.7%	262
Greece				-3.3%	196
Italy				-6.5%	175
Netherlar				-5.1%	154
Poland				14.7%	78
South Africa	37,3	35,9	4	-3.7%	36
Average				-7.5%	

NNET achieves super-human selection accuracy

iqast SAP APO

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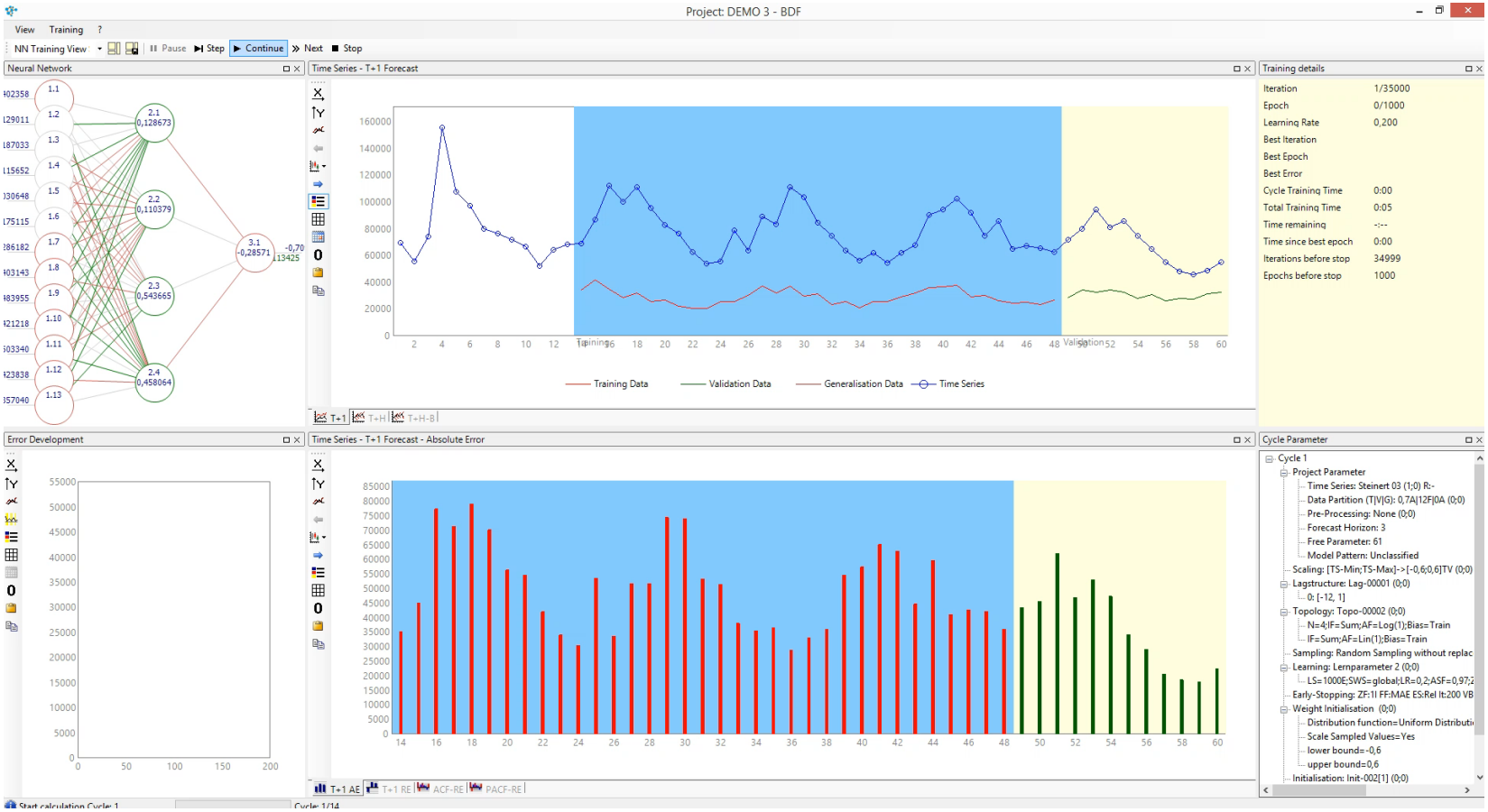
Neural Network Demo



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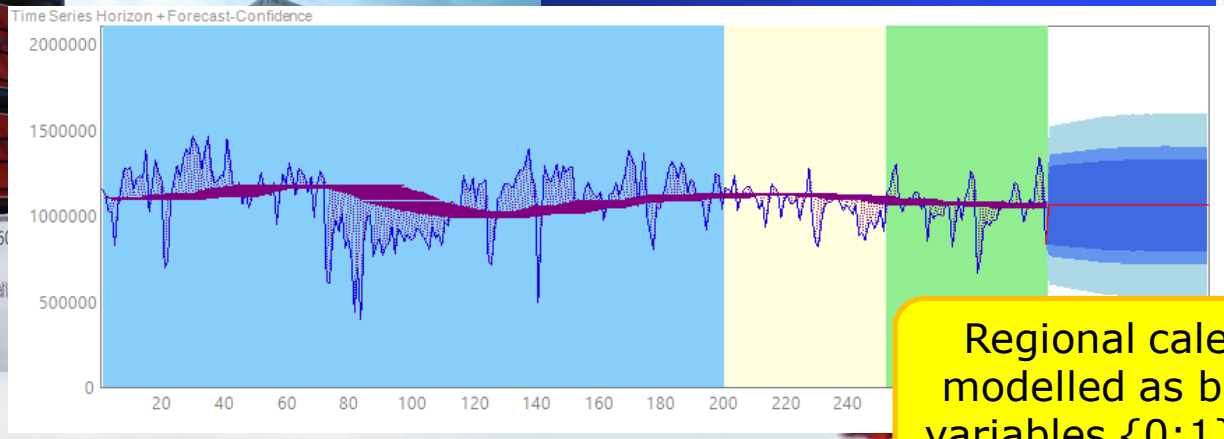
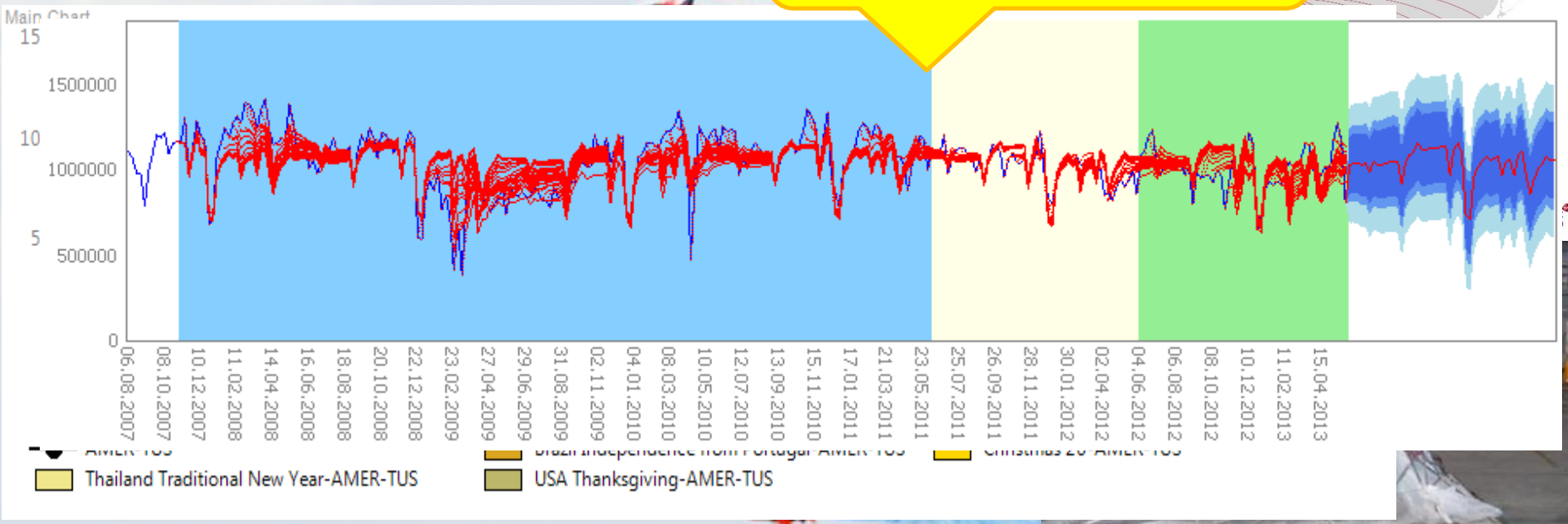
Container forecasts @

virgin atlantic cargo



Regional calendar events modelled as binary dummy variables {0;1} in occurence



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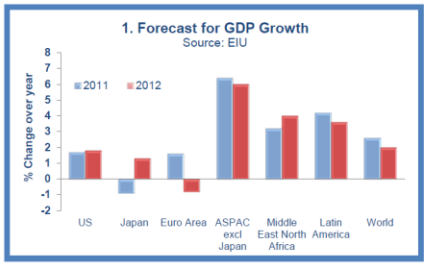
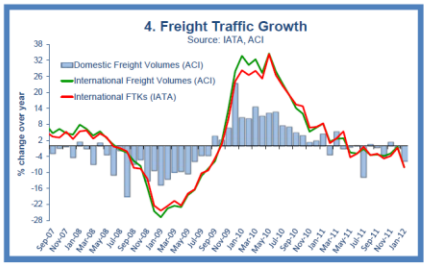
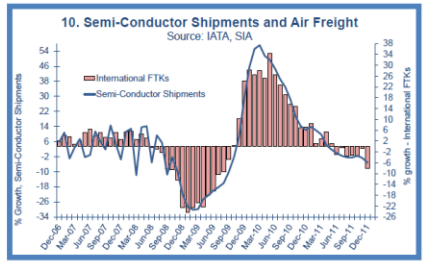
Container forecasts @ virgin atlantic cargo

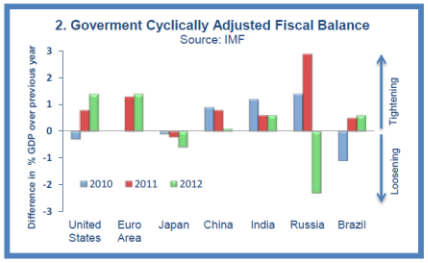
Expand Models with more variables?

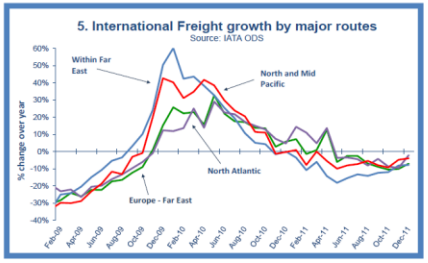
- Internal factors, eg. Capacity (different hullspace)
- External factors, eg. GDP growth, industry leading indicators, Global PMI, OECD Confidence index etc.

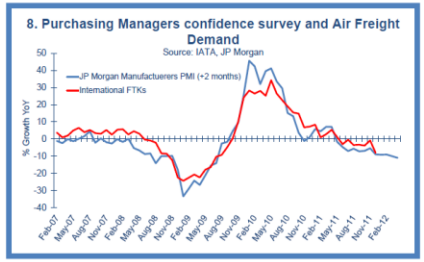


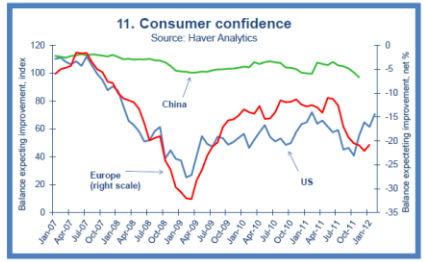


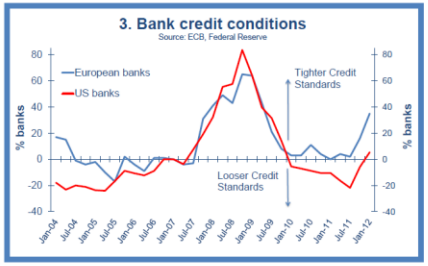


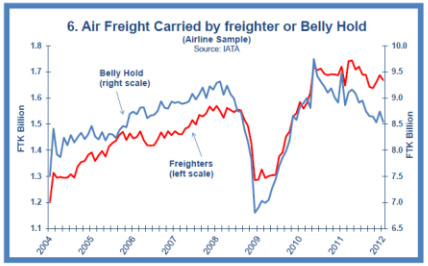


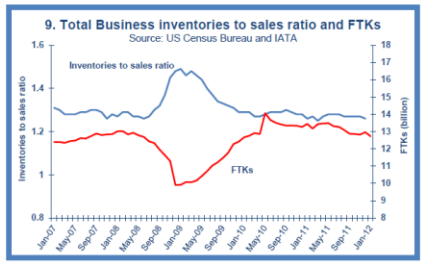


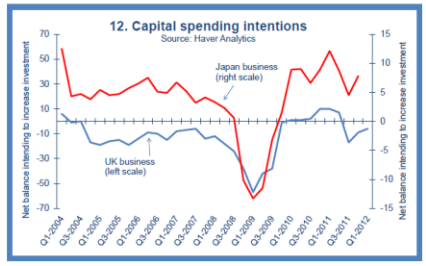












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Beer Forecasting for manufacturing @ AB InBev

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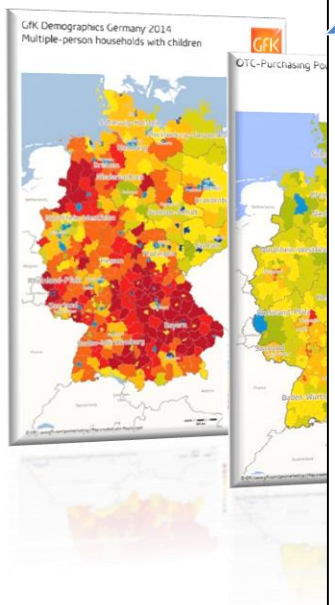
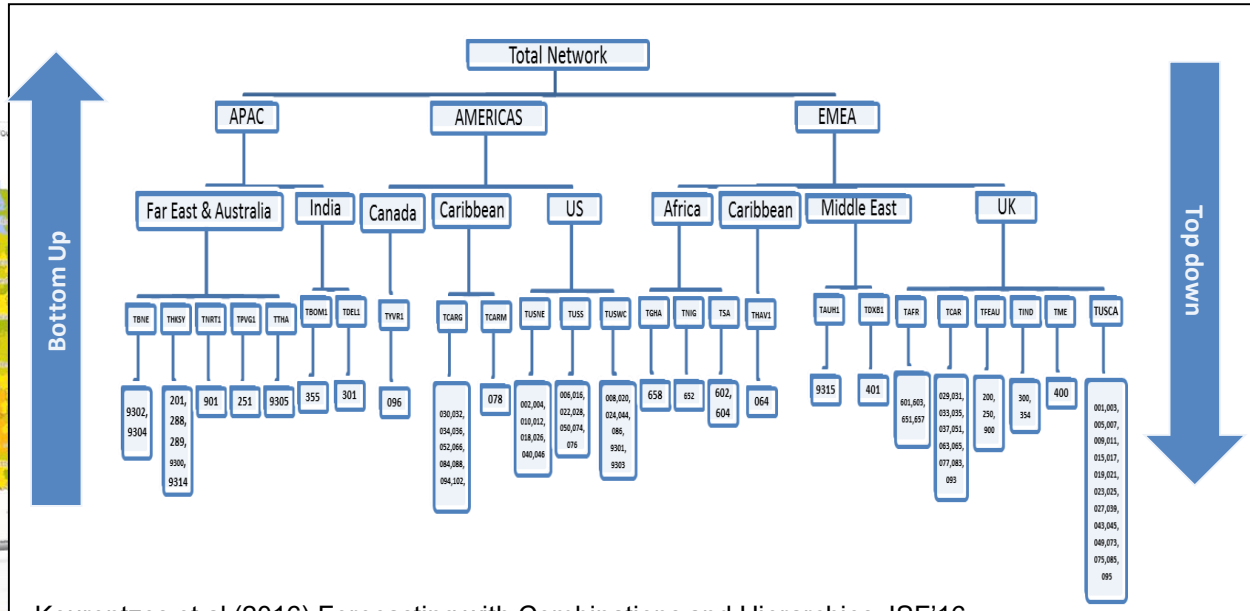
Beer Forecasting for manufacturing @ ABInBev

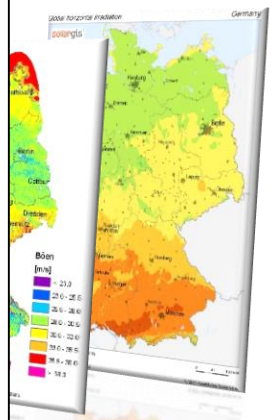
Drivers for Consumer Demand?

- Weather **+5 - 8%**
- Price & Price promotions **+10 - 700%**
- Marketing **+2 - 3%**
- Politics & regulation **-0 - 100%**
- Changes in Retail strtures
- Manufacturer consolidation
- Regional Preferences
- etc.

→
- **only few are regional**
- **these have lesser impact!**







Kourentzes et al (2016) Forecasting with Combinations and Hierarchies, ISF'16
Hyndman et al. (2011) Optimal combination forecasts for hierarchical time series
(→ R-package hts, MAPA etc.)

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Beer Forecasting for manufacturing @ ABInBev

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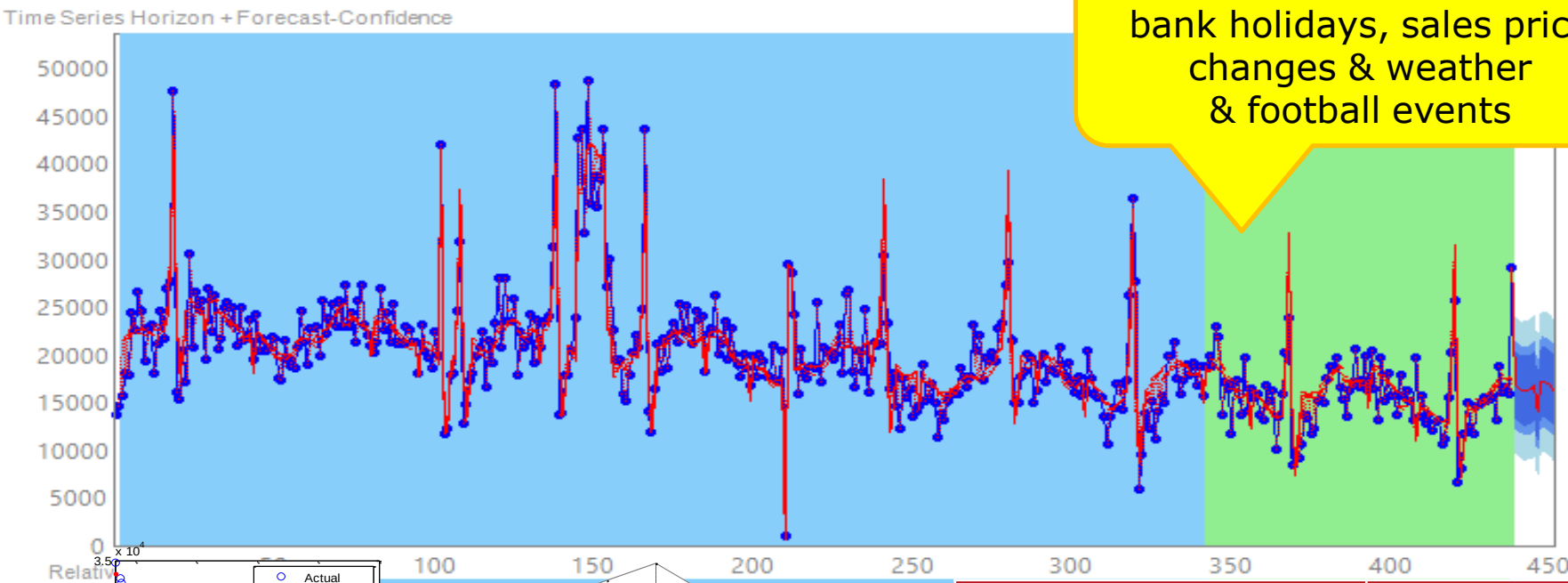
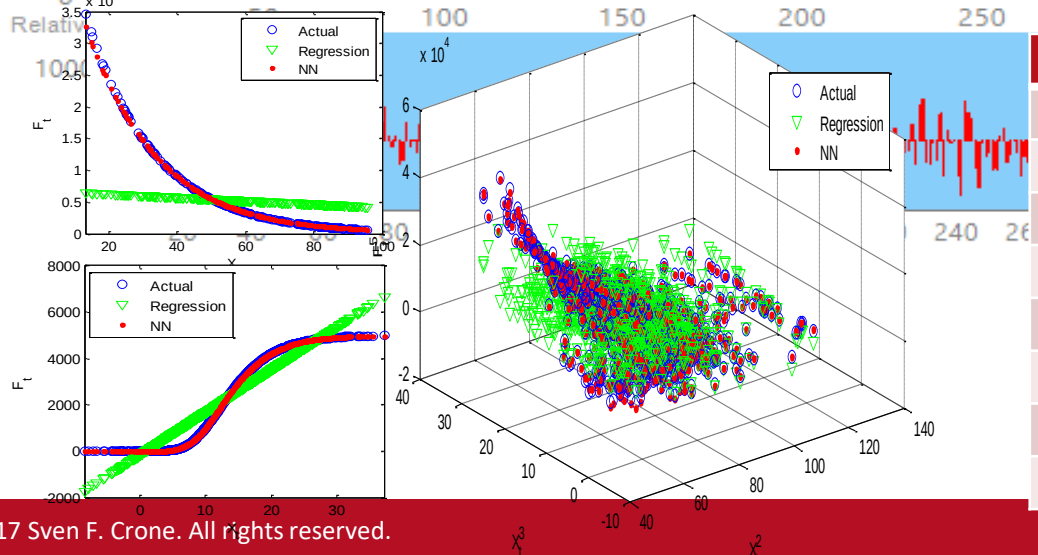
Beer Forecasting for manufacturing @ AB InBev

Forecast from MLP including bank holidays, sales price changes & weather & football events





Forecast Algorithm	Test sMAPE Error
Naive Level	23.91%
Naive Season	21.84%
Single Exponential Smoo	
Seasonal ARIMA	
Additive Exponential Sm	
Dynamic Regression	13.37%
Neural Networks	13.01%
Human Expert Demand Planner	14.42%

achieves „super-human“ forecast accuracy

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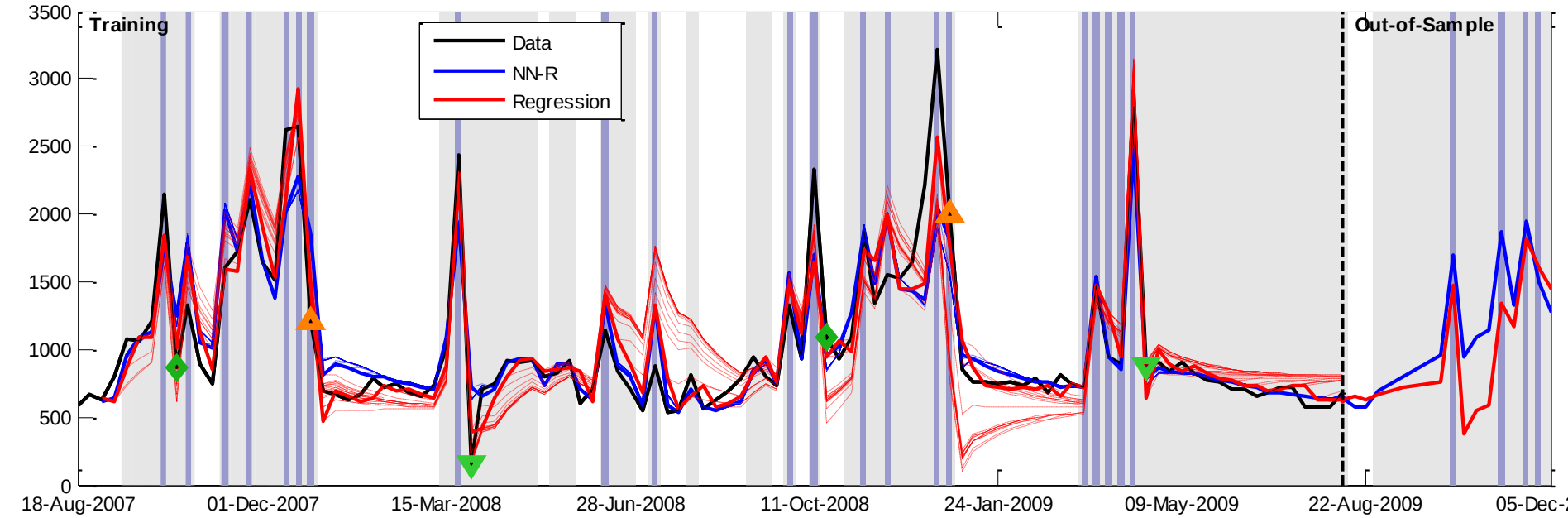
Neural Nets in Retail & Promos

Fit appropriate forecasting models to:

- **Predict future value**
- **Understand effect (elasticity) of each exogenous factor → affect forecasts**

Time Series: 5 | Product: 1080215 (Trend: 0, Season13: 0, Season52: 1)

f(X) = +125.37*Constant +0.71*Lag1 +0.07*Lag2 +610.76*Adcode: 401 +617.24*Discount -1569.46*Xmas -696.48*Xmas+1 +1209.29*Xmas-2 -1581.59*Easter-1 -894.91*Labour



CIF 2016

International Time Series Forecasting Competition

Computational Intelligence in Forecasting

#	Method		SMAPE	SD #
1	LSTM-Deseasonalized	Microsoft	0.105 +- 0.107	1
2	LSTMs and ETS	Microsoft	0.108 +- 0.116	2
3	*ETS		0.119 +- 0.142	9
4	MLP	iqast	0.121 +- 0.135	7
5	REST		0.124 +- 0.133	6
6	*FRBE		0.129 +- 0.162	13
7	HEM		0.130 +- 0.147	11
8	*Avg		0.131 +- 0.133	5
9	*BaggedETS		0.131 +- 0.176	17
10	LSTM	Microsoft	0.133 +- 0.155	12
11	Fuzzy c-regression		0.137 +- 0.127	4
12	PB-GRNN		0.145 +- 0.166	14
13	PB-RF		0.145 +- 0.166	15
14	*ARIMA		0.146 +- 0.218	21
15	*RW		0.146 +- 0.137	8
16	*Theta		0.148 +- 0.122	3
17	PB-MLP		0.149 +- 0.172	16
18	TSFIS		0.151 +- 0.147	10
19	*Boot.EXPOS		0.153 +- 0.206	20
20	MTSFA		0.165 +- 0.180	18
21	FCDNN		0.166 +- 0.194	19
22	MSAKAF		0.204 +- 0.225	22
23	HFM		0.224 +- 0.251	23
24	CORN		0.288 +- 0.263	24

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IRAFM

CIF 2016
CERTIFICATE OF ACHIEVEMENT

awarded to

SLAWEK SMYL
(Microsoft, USA)

for the victory in

THE INTERNATIONAL TIME SERIES COMPETITION
COMPUTATIONAL INTELLIGENCE IN FORECASTING

with his method

LSTM NEURAL NETWORK APPLIED TO DESEASONALIZED DATA

Martin Štěpnička
IRAFM, University of Ostrava
CIF Organising Committee

Michal Burda
IRAFM, University of Ostrava
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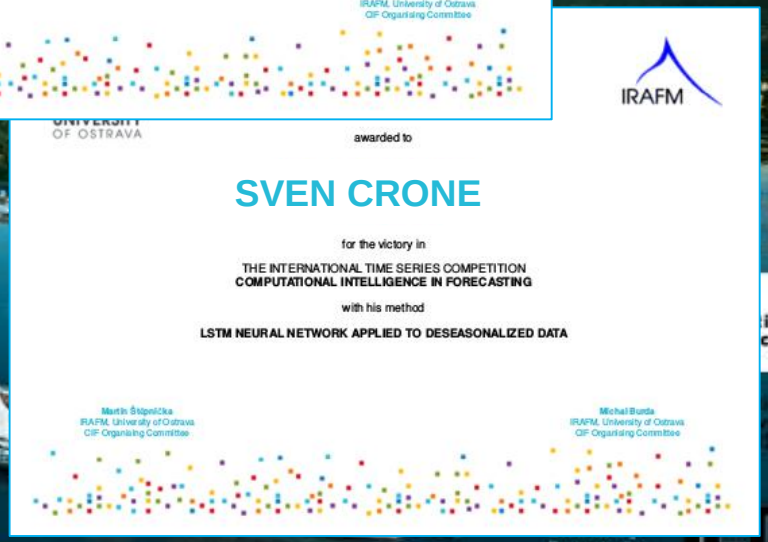

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CIF Organising Committee

IEEE WCCI 2016
Vancouver Canada

iqast Intelligent Forecasting for SAP APO DP

pioneers in forecasting with artificial intelligence

New AI forecasting engine for SAP APO DP

- intelligent model selection
- intelligent forecast algorithms
- intelligent safety stocks

AB InBev SANOFI Beiersdorf Bayer Business Services Johnson & Johnson janssen Hapag-Lloyd

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How to get started?

NDA → Demo on your data (probono) → POC on 2-3data subsets → Project / Pilot study with contract → RFI for software

1-2 man days
skype call results

need historical sales
explanatory variables
(price, promo, …)

5 man-days analysis
Kick-off on site
Final results on site
<€10k

10-20 man-days analysis
scalability to other countries
product categories

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Take aways

- AI is hyped, but here to stay
- AI (aka Deep Learning Neural Networks) is a driver for Digitalisation and Industry 4.0
- Forecast accuracy is a core obstacle in SCM
- AI is largely ignored in Forecasting for SCM
- Innovators are leading the way
  - High opportunities from low-cost pilot studies
  - Try new algorithms!
    - Neural Networks
    - Support Vector Regression
    - Decision Trees
    - K-Nearest Neighbours
    - …

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