Applications and Deep Learning State of the Art

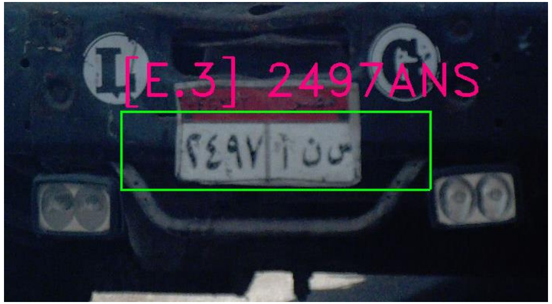
Image Recognition

- Imagenet is the standard benchmark set for image recognition
- Classify 256x256 images into 1000 categories, such as ”person”, ”bike”, ”cheetah”, etc.
- Total 1.2M images
- Many error metrics, including top-5 error: error rate with 5 guesses

Picture from Alex Krizhevsky et al., ”ImageNet Classification with Deep Convolutional Neural Networks”, 2012

Computer Vision: Case Visy Oy

- Computer vision for logistics since 1994
- License plates (LPR), container codes,…
- How to grow in an environment with heavy competition?
  - Be agile
  - Be innovative
  - Be credible
  - Be customer oriented
  - Be technologically state-of-the-art



Kymmenistätuhansista autoista verot maksamatta – poliisin uusi laite käräytti 74 000 autoa

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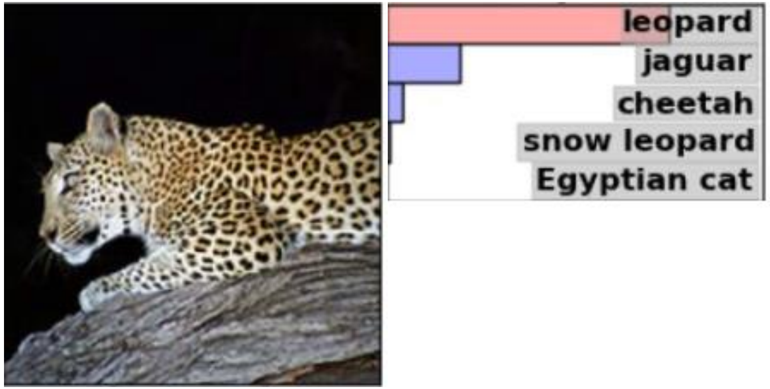
Jussi Sippola HELSINGIN SANOMAT

VESA RANTA

What has changes in 20 years?

- **In 1996:**
  - Small images (*e.g.*, 10x10)
  - Few classes (< 100)
  - Small network (< 4 layers)
  - Small data (< 50K images)

- **In 2016:**
  - Large images (256x256)
  - Many classes (> 1K)
  - Deep net (> 100 kerrosta)
  - Large data (> 1M)



Net Depth Evolution Since 2012

ILSVRC Image Recognition Task:

- 1.2 million images
- 1 000 categories

(Prior to 2012: 25.7 %)

Team	Year	Place	Error (top-5)	Uses external data
SuperVision	2012	1st	16.4%	no
SuperVision	2012	1st	15.3%	Imagenet 22k
Clarifai	2013	1st	11.7%	no
Clarifai	2013	1st	11.2%	Imagenet 22k
MSRA	2014	3rd	7.35%	no
VGG	2014	2nd	7.32%	no
GoogLeNet	2014	1st	6.67%	no

8 layers

16 layers

22 layers

- 2015 winner: MSRA (error 3.57%)
- 2016 winner: Trimps-Soushen (2.99 %)
- 2017 winner: Uni Oxford (2.25 %)

152 layers

152 layers (but many nets)

101 layers (many nets, layers were blocks)

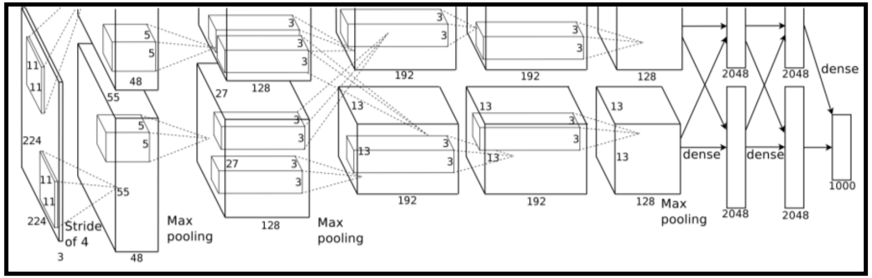
ILSVRC2012

- ILSVRC2012[1] was a game changer
- ConvNets dropped the top-5 error 26.2% → 15.3 %.
- The network is now called *AlexNet* named after the first author (see previous slide).
- Network contains 8 layers (5 convolutional followed by 3 dense); altogether 60M parameters.

[1] Imagenet Large Scale Visual Recognition Challenge

The AlexNet

- The architecture is illustrated in the figure.
- The pipeline is divided to two paths (upper & lower) to fit to 3GB of GPU memory available at the time (running on 2 GPU’s)
- Introduced many tricks for *data augmentation*
- Left-right flip
- Crop subimages (224x224)



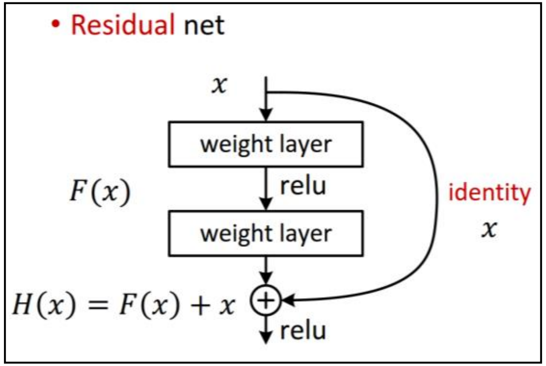
Picture from Alex Krizhevsky et al., ”ImageNet Classification with Deep Convolutional Neural Networks”, 2012

ILSVRC2014

- Since 2012, ConvNets have dominated
- 2014 there were 2 almost equal teams:
  - GoogLeNet Team with 6.66% Top-5 error
  - VGG Team with 7.33% Top-5 error
- In some subchallenges VGG was the winner
- GoogLeNet: 22 layers, only 7M parameters due to fully convolutional structure and clever *inception* architecture
- VGG: 16 layers, 144M parameters

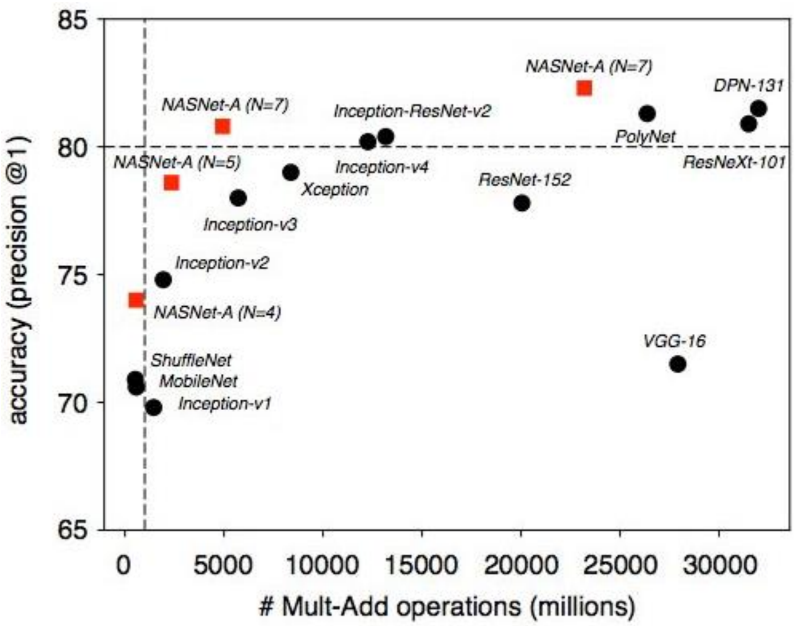
ILSVRC2015

- Winner MSRA (Microsoft Research) with TOP-5 error 3.57 %
- 152 layers! 51M parameters.
- Built from residual blocks (which include the inception trick from previous year)
- Key idea is to add *identity shortcuts*, which make training easier

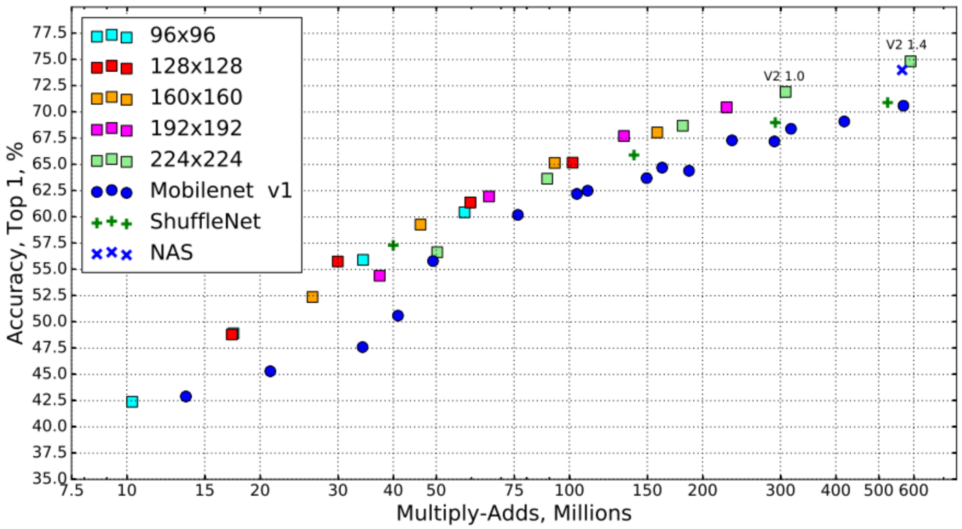


Pictures from MSRA ICCV2015 slides

Some Famous Networks



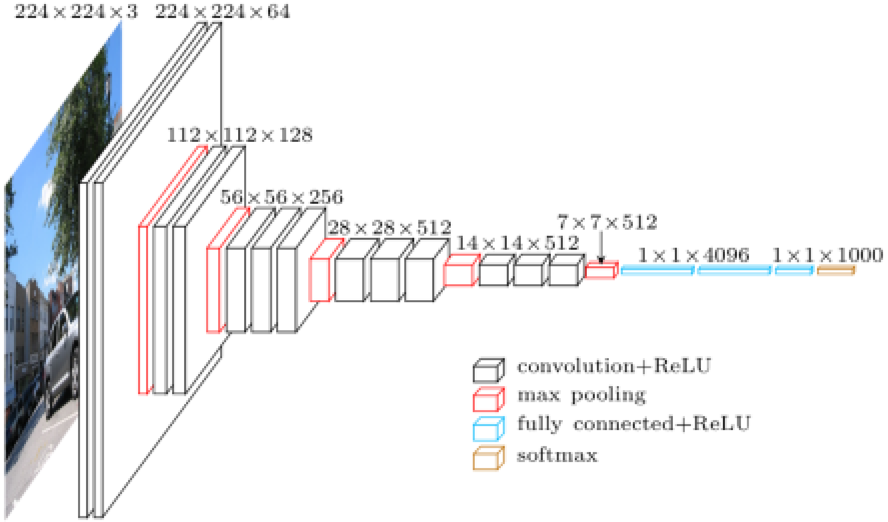
https://research.googleblog.com/2017/11/automl-for-large-scale-image.html



Sandler et al., ” Inverted Residuals and Linear Bottlenecks: Mobile Networks for Classification, Detection and Segmentation,” Jan. 2018. https://arxiv.org/abs/1801.04381

Pretraining

- With small data, people often initialize the net with a *pretrained* network.
- This may be one of the imagenet winners; VGG16, ResNet, …
- See `keras.applications` for some of these.



VGG16 network
source: https://www.cs.toronto.edu/~frossard/post/vgg16/

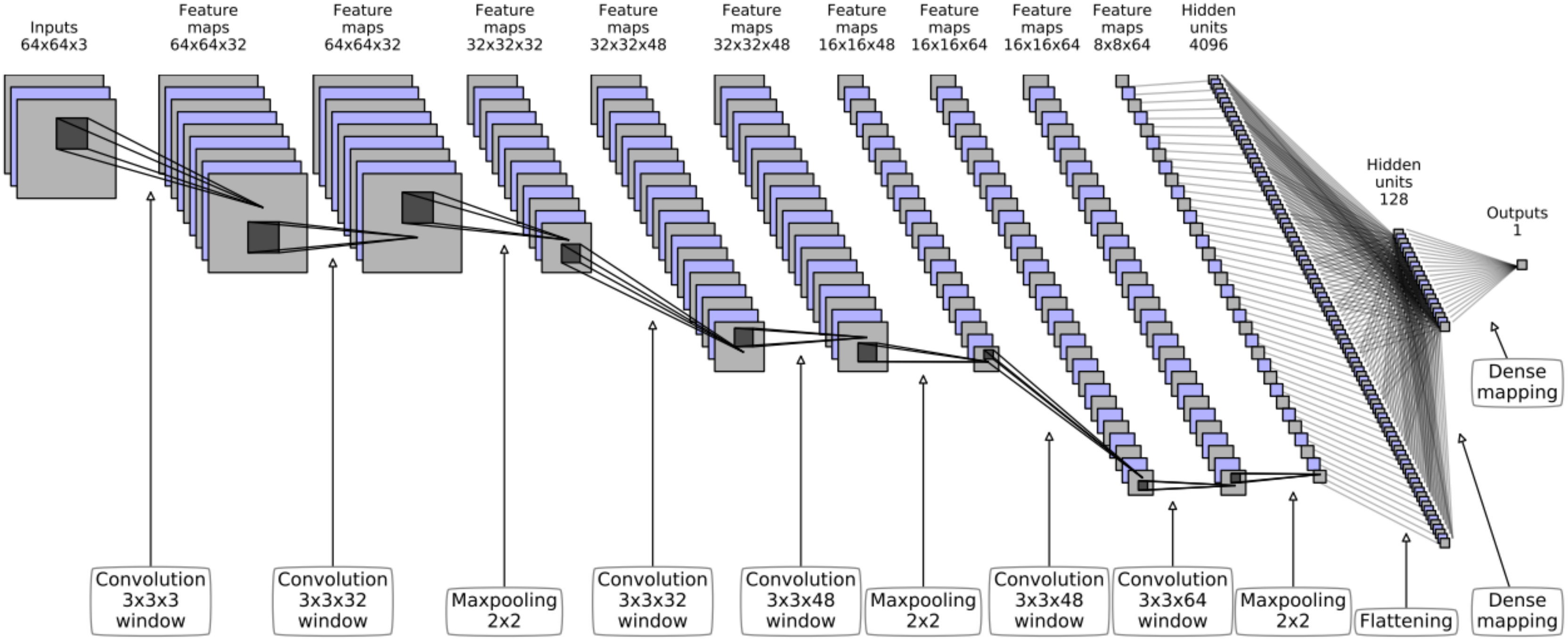
Example: Cats vs. Dogs

- Let’s study the effect of pretraining with classical image recognition task: learn to classify images to **cats** and **dogs.**
- We use the *Oxford Cats and Dogs* dataset.
- Subset of 3687 images of the full dataset (1189 cats; 2498 dogs) for which the ground truth location of the animal’s head is available.

Network 1: Design and Train from Scratch

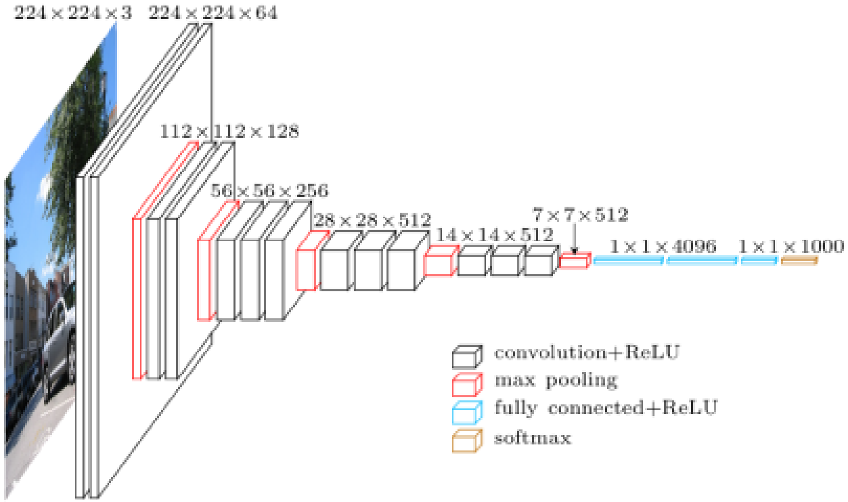
```
# Initialize the model
model = Sequential()

shape = (64, 64, 3)

# Add six convolutional layers. Maxpool after every second convolution.
model.add(Conv2D(filters=32, kernel_size=3, padding="same", activation="relu",
input_shape=shape))
model.add(Conv2D(filters=32, kernel_size=3, padding="same", activation="relu"))
model.add(MaxPooling2D(2, 2)) # Shrink feature maps to 32x32

model.add(Conv2D(filters=48, kernel_size=3, padding="same", activation="relu"))
model.add(Conv2D(filters=48, kernel_size=3, padding="same", activation="relu"))
model.add(MaxPooling2D(2, 2)) # Shrink feature maps to 16x16

model.add(Conv2D(filters=64, kernel_size=3, padding="same", activation="relu"))
model.add(Conv2D(filters=64, kernel_size=3, padding="same", activation="relu"))
model.add(MaxPooling2D(2, 2)) # Shrink feature maps to 8x8

# Vectorize the 8x8x64 representation to 4096x1 vector
model.add(Flatten())

# Add a dense layer with 128 nodes
model.add(Dense(128, activation="relu"))
model.add(Dropout(0.5))

# Finally, the output layer has 1 output with logistic sigmoid nonlinearity
model.add(Dense(1, activation="sigmoid"))
```

Network 1: Design and Train from Scratch



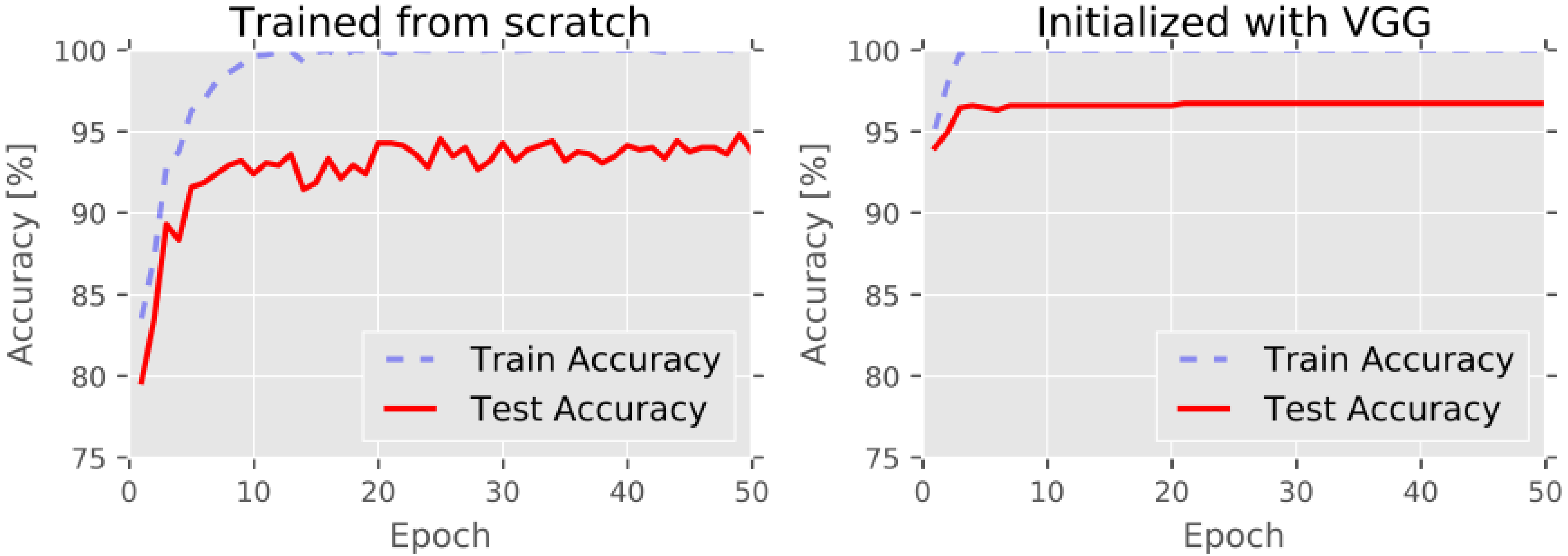
Network 2: Start from a Pretrained Network

```python
# Import the network container and the three types of layers
from keras.applications.vgg16 import VGG16
from keras.models import Model
from keras.layers import Dense

# Initialize the VGG16 network. Omit the dense layers on top.
base_model = VGG16(include_top = False, weights = "imagenet",
input_shape = (64, 64, 3))

# We use the functional API, and grab the VGG16 output here:
w = base_model.output

# Now we can perform operations on w. First flatten it to 4096-dim vector:
w = Flatten()(w)

# Add dense layer:
w = Dense(128, activation = "relu")(w)

# Add output layer:
output = Dense(1, activation = "sigmoid")(w)

# Prepare the full model from input to output:
model = Model(inputs = [base_model.input], outputs = [output])

# Also set the last Conv block (3 layers) as trainable.
# There are four layers above this block, so our indices
# start at -5 (i.e., last minus five):
model.layers[-5].trainable = True
model.layers[-6].trainable = True
model.layers[-7].trainable = True
```



VGG16 network
source: https://www.cs.toronto.edu/~frossard/post/vgg16/

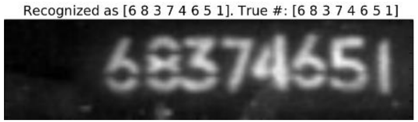
Results

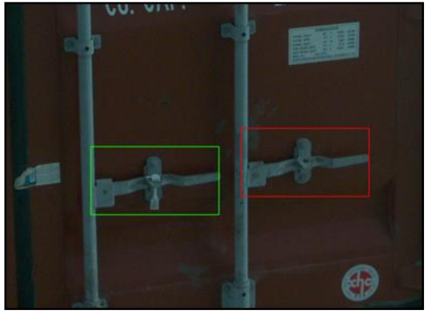


Trained from scratch
Initialized with VGG
Accuracy [%]
Epoch
Train Accuracy
Test Accuracy
100
95
90
85
80
75
0
10
20
30
40
50

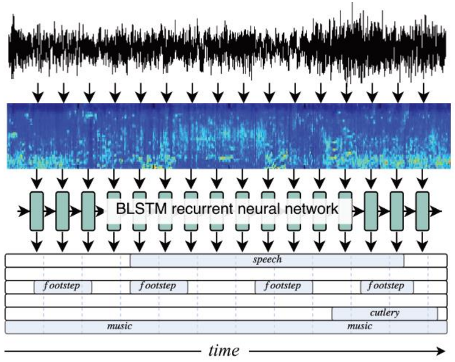
Research at TUT

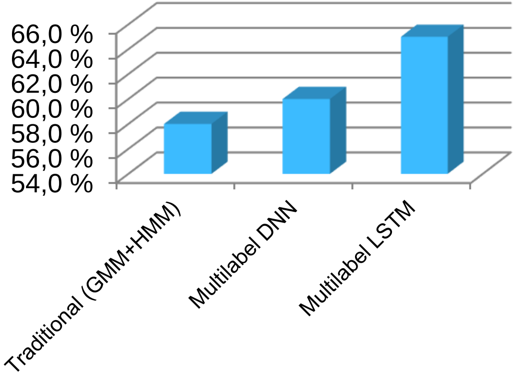
Images



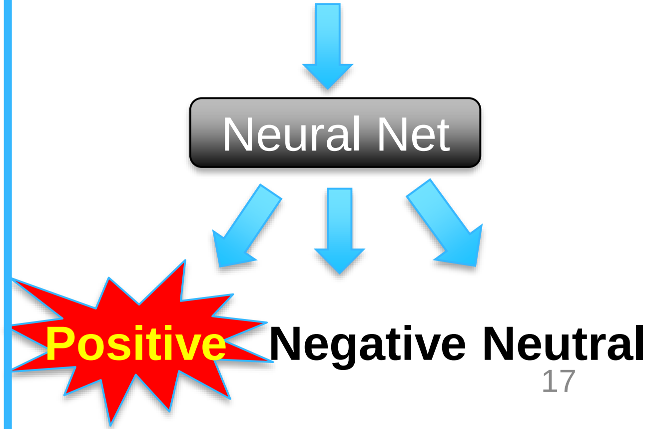


Sound



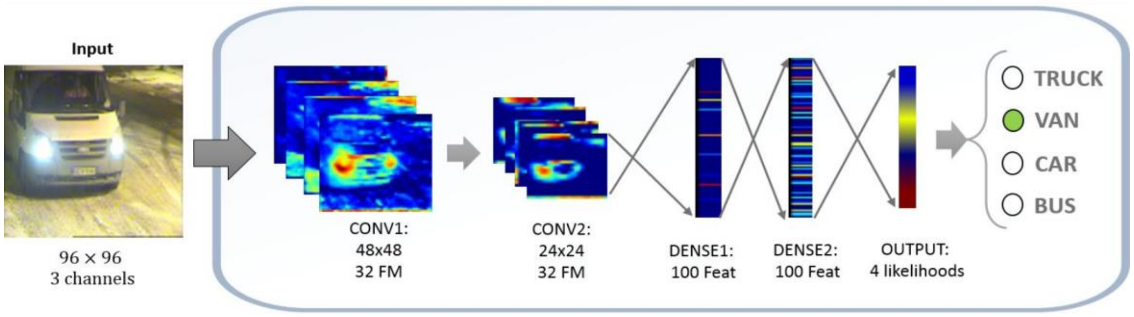


Text



Example case

- TUT has studied shallow convolutional architectures for fast/real time detection tasks
- For example, Automatic Car Type Detection from Picture: **Van, Bus, Truck** or **Normal Vehicle**
- The network recognizes the car type (4 classes) with 98% accuracy (13 000 images).



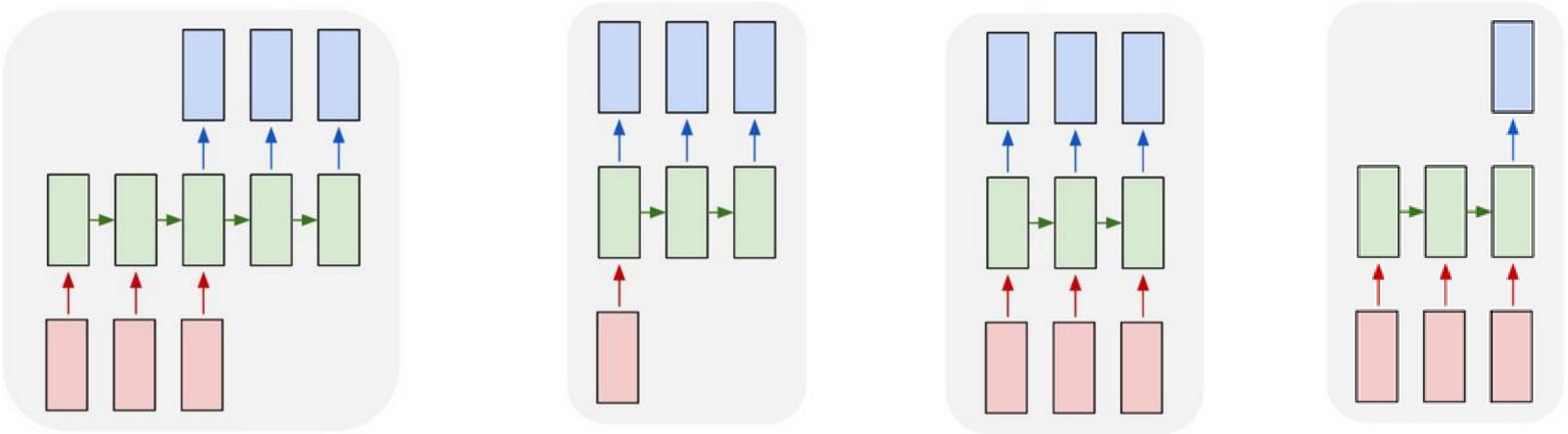
Components of the Network

```
% Pass image through 2 conv layers:

for layerIdx = 1 : 2

    blob = convolve(blob, layers{layerIdx});
    blob = maxpool(blob, 2);
    blob = relu(blob);

end

% Pass image through 2 dense layers:

for layerIdx = 3 : 4

    blob = layers{layerIdx} * blob;
    blob = relu(blob);

end

% Pass image through the output layer:

blob = layers{end} * blob;
prediction = softmax(blob);
```

- **Convolution**: 5x5 window
- **Maxpooling**: 2x2 downsampling with the maximum
- **Relu**: max(x, 0)
- **Matrix multiplication**
- **Softmax**: $[\sigma(\mathbf{x})]_k = \frac{\exp(x_k)}{\sum \exp(x_k)}$

Recurrent Networks

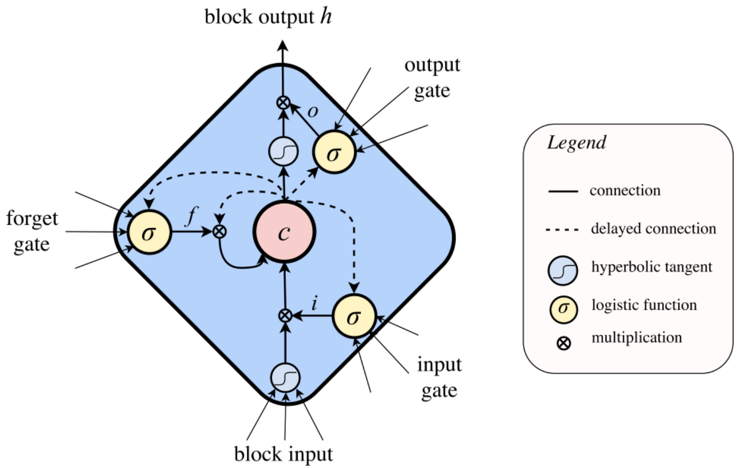
- Recurrent networks process sequences of arbitrary length; *e.g.*,
  - Sequence → sequence
  - Image → sequence
  - Sequence → class ID



Picture from http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Recurrent Networks

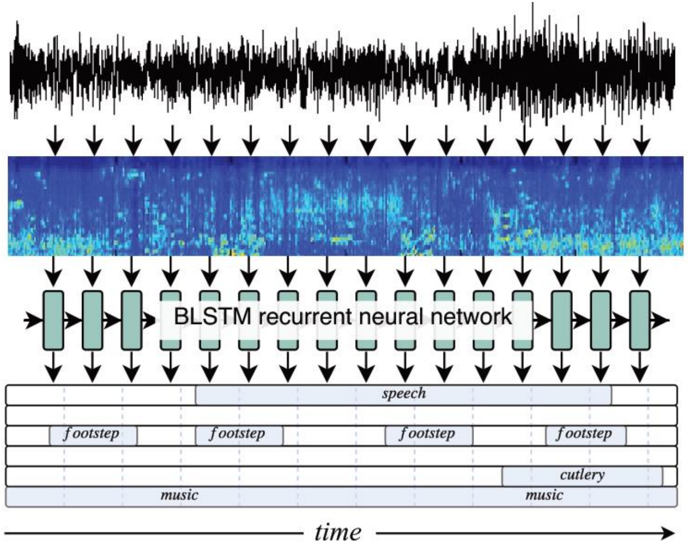
- Recurrent net consist of special nodes that remember past states.
- Each node receives 2 inputs: the data and the previous state.
- Keras implements *SimpleRNN, LSTM* and *GRU* layers.
- Most popular recurrent node type is *Long Short Term Memory* (LSTM) node.
- LSTM includes also *gates*, which can turn on/off the history and a few additional inputs.



Picture from G. Parascandolo M.Sc. Thesis, 2015.
http://urn.fi/URN:NBN:fi:tty-201511241773

Recurrent Networks

- An example of use is from our recent paper.
- We detect acoustic events within 61 categories.
- LSTM is particularly effective because it remembers the past events (or the context).
- In this case we used a *bidirectional* LSTM, which remembers also the future.
- BLSTM gives slight improvement over LSTM.



Picture from Parascandolo et al., ICASSP 2016

LSTM in Keras

- LSTM layers can be added to the model like any other layer type.
- This is an example for natural language modeling: *Can the network predict next symbol from the previous ones?*
- Accuracy is greatly improved from N-Gram etc.

```
model = Sequential()

model.add(LSTM(512, return_sequences=True,
               input_shape=(maxlen, len(symbols))))
model.add(Dropout(0.2))

model.add(LSTM(512, return_sequences=False))
model.add(Dropout(0.2))

model.add(Dense(len(symbols)))
model.add(Activation('softmax'))

model.compile(loss='categorical_crossentropy', optimizer='rmsprop')
```

Text Modeling

- The input to LSTM should be a sequence of vectors.
- For text modeling, we represent the symbols as binary vectors.

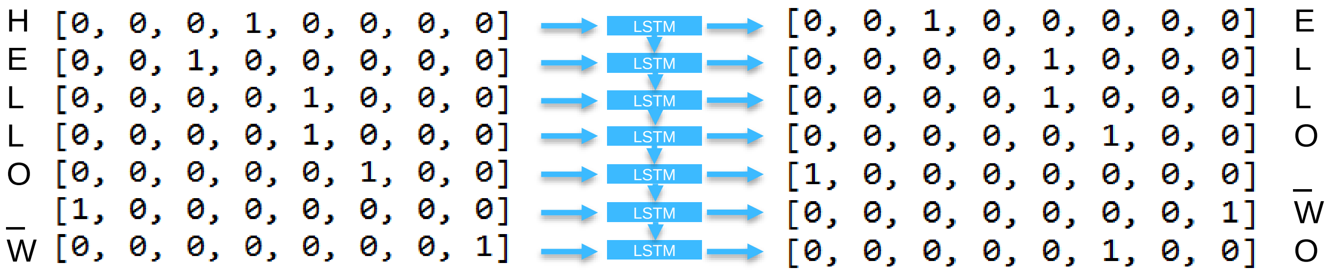
```python
from sklearn import preprocessing

lb = preprocessing.LabelBinarizer()
symbol_list = list("hello world")
lb.fit(symbol_list)
binary_table = lb.transform(symbol_list)
```

```
           _  d  e  h  l  o  r  w
array([[0, 0, 0, 1, 0, 0, 0, 0],
       [0, 0, 1, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 1, 0, 0, 0],
       [0, 0, 0, 0, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 0, 0],
       [1, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 1],
       [0, 0, 0, 0, 0, 1, 0, 0],
       [0, 0, 0, 0, 0, 0, 1, 0],
       [0, 0, 0, 0, 1, 0, 0, 0],
       [0, 1, 0, 0, 0, 0, 0, 0]])
```

Time

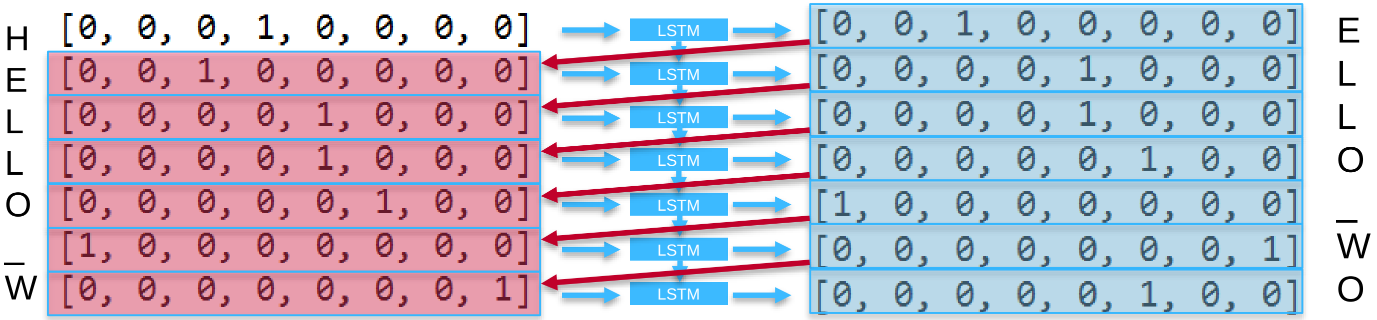
Text Modeling

- The prediction target for the LSTM net is simply the input delayed by one step.
- For example: we have shown the net these symbols: [’h’, ’e’, ’l’, ’l’, ’o’, ’_’, ’w’]
- Then the network should predict ’o’.



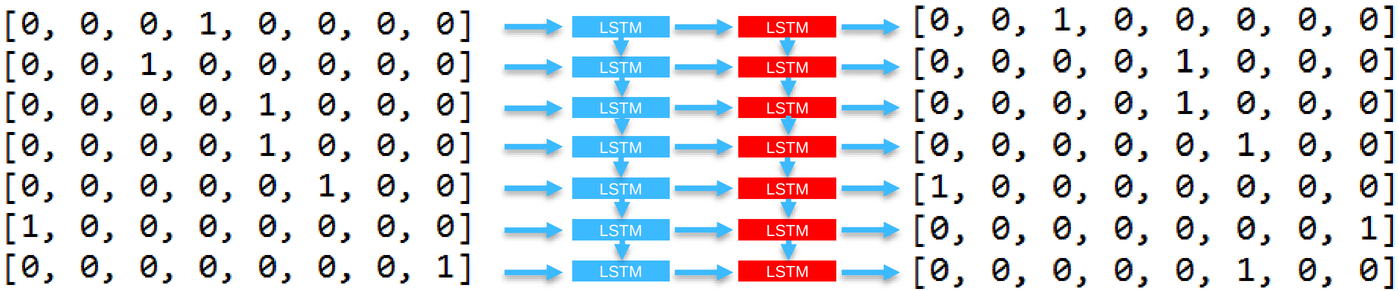
Text Modeling

- Trained LSTM can be used as a text generator.
- Show the first character, and set the predicted symbol as the next input.
- Randomize among the top scoring symbols to avoid static loops.



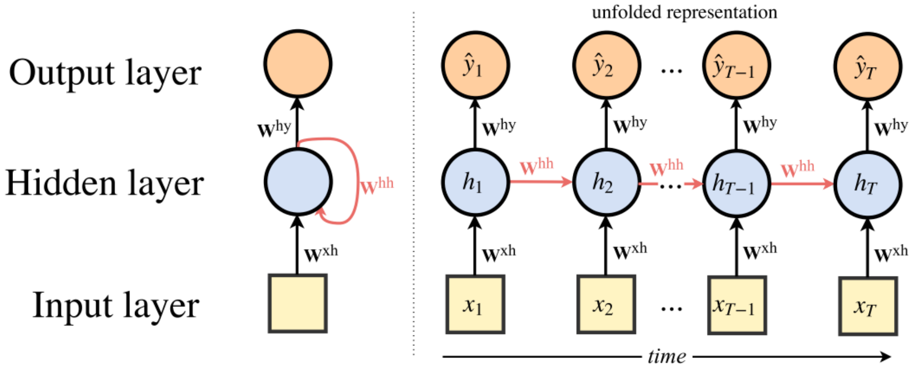
Many LSTM Layers

- A straightforward extension of LSTM is to use it in multiple layers (typically less than 5).
- Below is an example of two layered LSTM.
- Note: Each blue block is exactly the same with, *e.g.*, 512 LSTM nodes. So is each red block.



LSTM Training

- LSTM net can be viewed as a very deep non-recurrent network.
- The LSTM net can be *unfolded* in time over a sequence of time steps.
- After unfolding, the normal gradient based learning rules apply.



Picture from G. Parascandolo M.Sc. Thesis, 2015.
http://urn.fi/URN:NBN:fi:tty-201511241773

Text Modeling Experiment

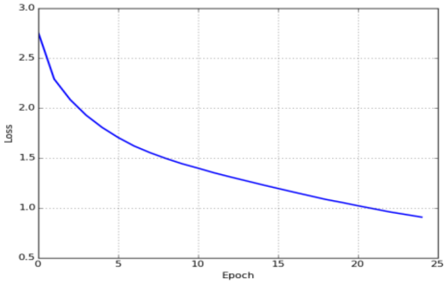
- Keras includes an example script: https://github.com/fchollet/keras/blob/master/examples/lstm_text_generation.py
- Train a 2-layer LSTM (512 nodes each) by showing Nietzche texts.
- A sequence of 600901 characters consisting of 59 symbols (uppercase, lowercase, special characters).

```
SUPPOSING that Truth is a woman--what then? Is there not ground
for suspecting that all philosophers, in so far as they have been
dogmatists, have failed to understand women--that the terrible
seriousness and clumsy importunity with which they have usually paid
their addresses to Truth, have been unskilled and unseemly methods for
winning a woman? Certainly she has never allowed herself to be won
```

Sample of training data

Text Modeling Experiment

- The training runs for a few hours on a Nvidia high end GPU (Tesla K40m).
- At start, the net knows only a few words, but picks up the vocabulary rather soon.




```
it is the sere the the the the and
the the and of the hos an the the
and and the the the the the the an
the the the the and the the ant an
the and on the the the he the the
he hor an the the hore the the the
he the he ans ante an the anle the
and and of the the hor and the the
the the he the the the the the the
the he the the the and the the the
the the the and of an the the he
the the the the the the the he
```

Epoch 1

```
artists if they happored and for
the concerced and man actored of
shere all their accorition of the
world the belirition and in the all
of the prose qoominity and in no
berigation of the exprores in a
dondicted and for
the forter prosoment that a
condicted and of the menters of the
soul of the dost and the for the
```

Epoch 3

```
manifold was not the little have a
strong and contrary, his can be
true to be a great need in the will
to prove and consequence
in short, something hably on the
development of the intellectual and
truth, and consequently, a little
truth and possible all the higher
things than the mastering sense of
the
servant of the enjigh of the sense
of the serve (and who has the goal
it of this fantasic and the di
```

Epoch 25

Text Modeling Experiment

- Let’s do the same thing for Finnish text: All discussions from Suomi24 forum are released for public.
- The message is nonsense, but syntax close to correct: A foreigner can not tell the difference.

```
kusta siin koista siin kuusta siin
kuiken kaisin kuukan kuinan koikan
ja kainan kuiten kain tuinen kuinan
kuisen siin kuinin siin kutta sitä
koista siin taikaa tuiten sain
koina siin kaikan kuitan eli siin
tiinen suin tuiten siin siitä
kuikaa siitä kuin tuin kankaa kuin
vaitan kuinan tuinen kiinin kaitaa
kaikaan kuinen kuka siinen kun
kuina kutta ja taisin kain
kaikaisin koin kaikon kainan kuina
```

Epoch 1

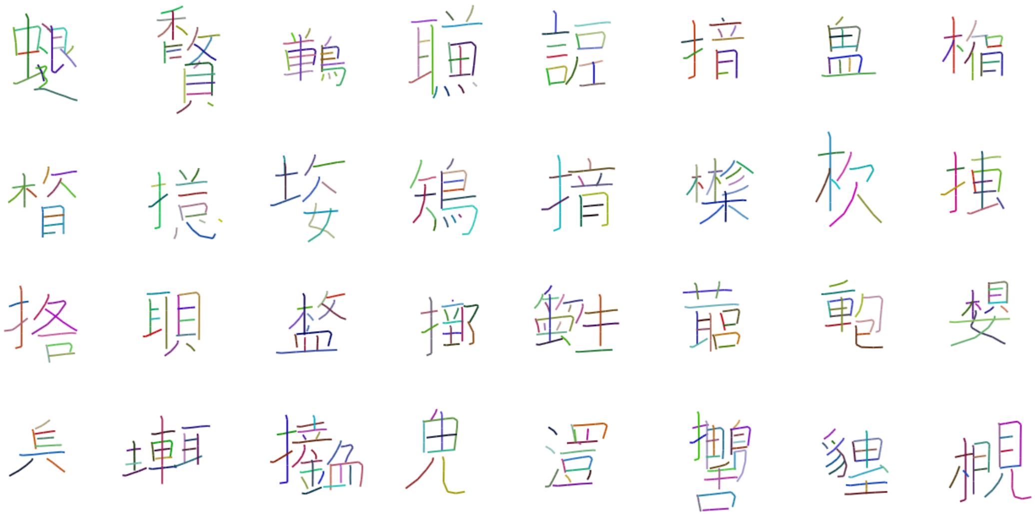
```
niin se vaikka en ole ole kokemista
koko on talletuksen jos on
tarvitalle vaan muutansa tulee
voimattaa koko paljon ja henkin
alkoita ja kanvattaa ovat joskaan
hänen taivalliset kokotalle
toiminetto en ole maanaan.

suukaan tule vielä koitaan saa
varhan haluaa elämään se jotain
toisesta olen työnyt tulee en ole
vaikka sanon tapahtamisen raukan
```

Epoch 4

```
mitään toisten on kokemusta kuin tehdä
sinun vielä kerran vaihtaa kun olen
kokeillut maan kanssa. ja sitten tulisi
halua kaikki kaupat talletukset

- paras grafiikka peleissä ja ulkoasussa

ensimmäinen bonus: 10 ilmaiskierrosta
peliin liikkun kunnoin tuomittaa kun ei
ole valita yksi alla on
kerrottu sitä miten saattaa minun kanssa.
samoin suustaa kokonaan ja painan si
```

Epoch 44

Fake Chinese Characters

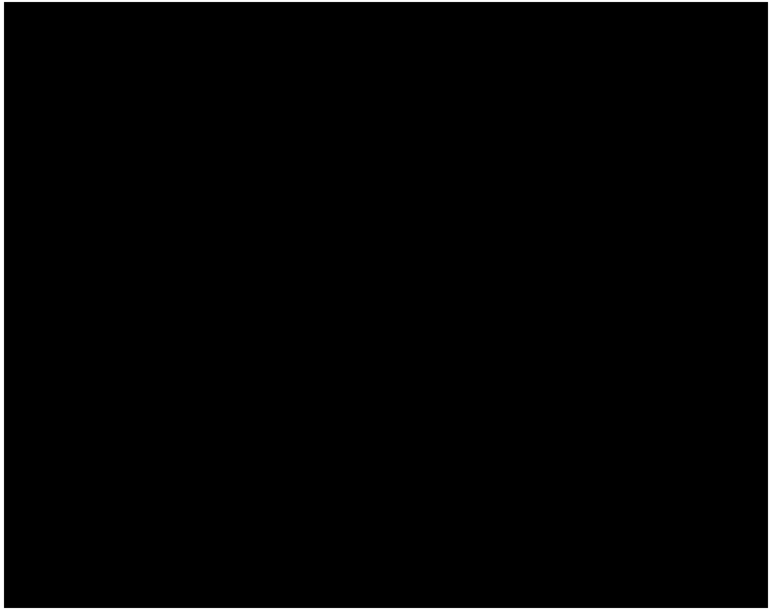


http://tinyurl.com/no36azh

EXAMPLES

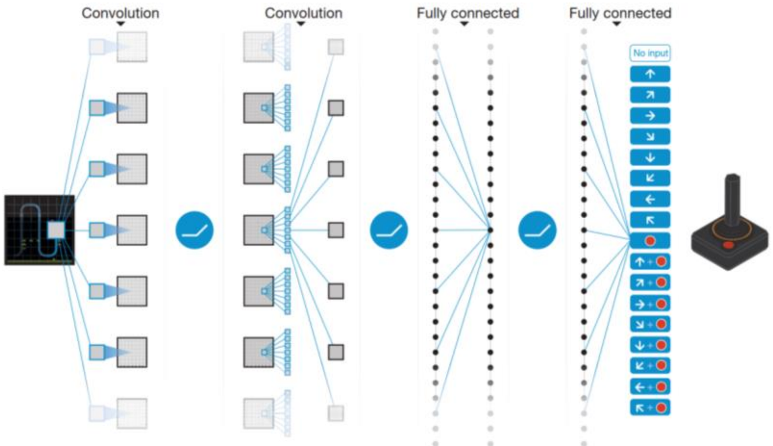
Age / Gender / Expression Recognition

- TUT age estimation demo is an example of modern computer vision
- System estimates the age in real time
- Trained using a 500 K image database
- Average error ±3 years

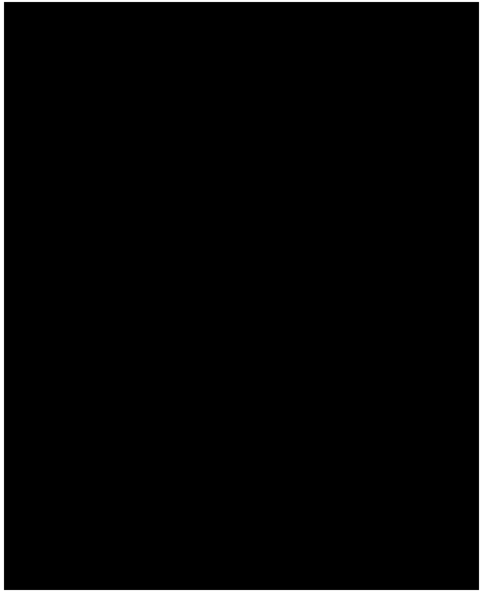


Deep Net Learns to Play

- Mnih *et al.* (Google Deepmind, 2015) trained a network to play computer games



- Better than human in many classic 1980’s games: *Pinball, Pong, Space Invaders.*



Computer and Logical Reasoning

- Logical reasoning is considered as a humans-only skill
- In this example, the computer was shown 1,000 question and answers
- In all 10 categories, the computer answers with > 95 % accuracy (except Task 7: 85 %)

Task 1: Single Supporting Fact
Mary went to the bathroom.
John moved to the hallway.
Mary travelled to the office.
Where is Mary? A:office

Task 3: Three Supporting Facts
John picked up the apple.
John went to the office.
John went to the kitchen.
John dropped the apple.
Where was the apple before the kitchen? A:office

Task 5: Three Argument Relations
Mary gave the cake to Fred.
Fred gave the cake to Bill.
Jeff was given the milk by Bill.
Who gave the cake to Fred? A: Mary
Who did Fred give the cake to? A: Bill

Task 7: Counting
Daniel picked up the football.
Daniel dropped the football.
Daniel got the milk.
Daniel took the apple.
How many objects is Daniel holding? A: two

Task 9: Simple Negation
Sandra travelled to the office.
Fred is no longer in the office.
Is Fred in the office? A:no
Is Sandra in the office? A:yes

Weston et al., ”Towards AI-complete question answering”, ICLR2016.

From Image to Text

"man in black shirt is playing guitar."

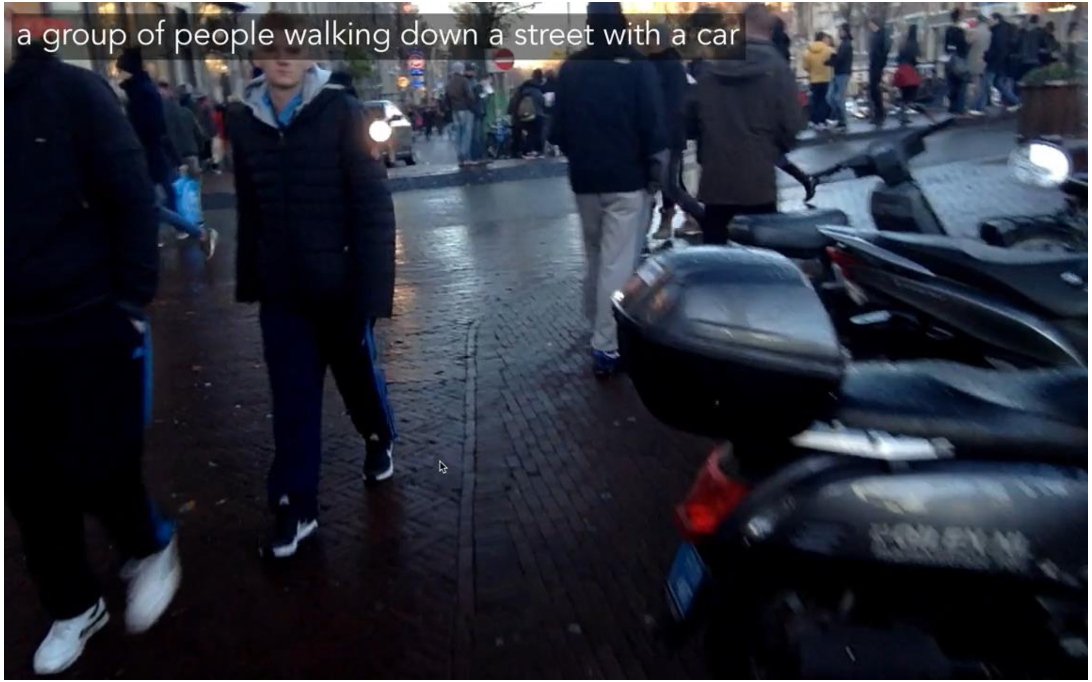
"construction worker in orange safety vest is working on road."

"two young girls are playing with lego toy."

"boy is doing backflip on wakeboard."

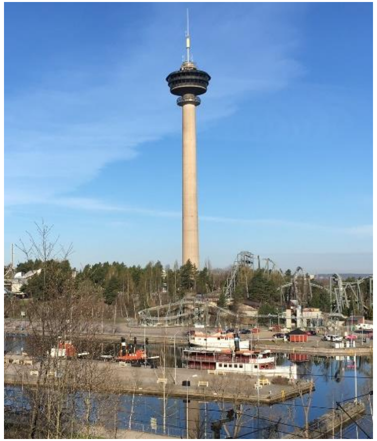
Karpathy *et al.*, "Deep Visual-semantic Alignments for Generating Image Descriptions," CVPR 2015, June 2015.

From Video to Text



https://www.youtube.com/watch?v=8BFzu9m52sc

Artistic Style Transfer



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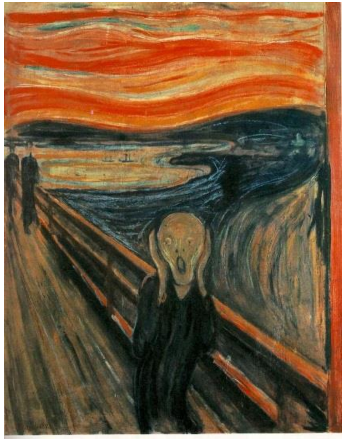

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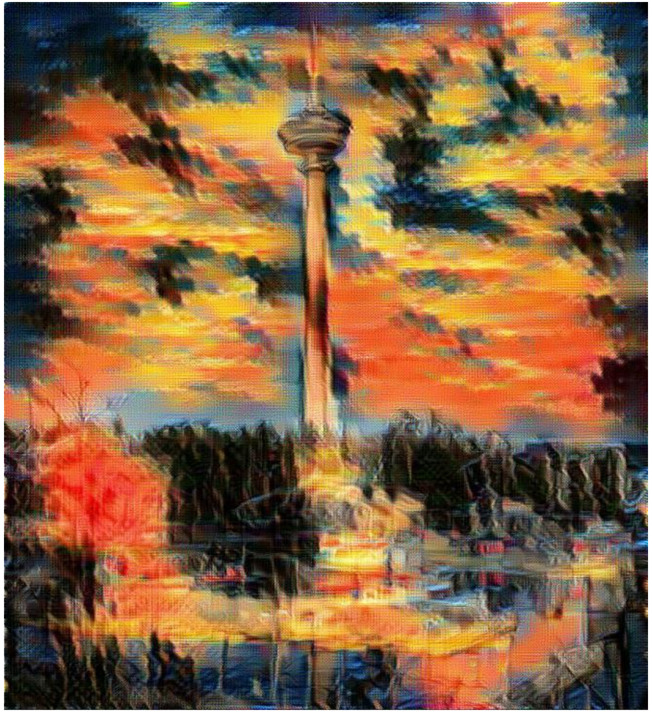
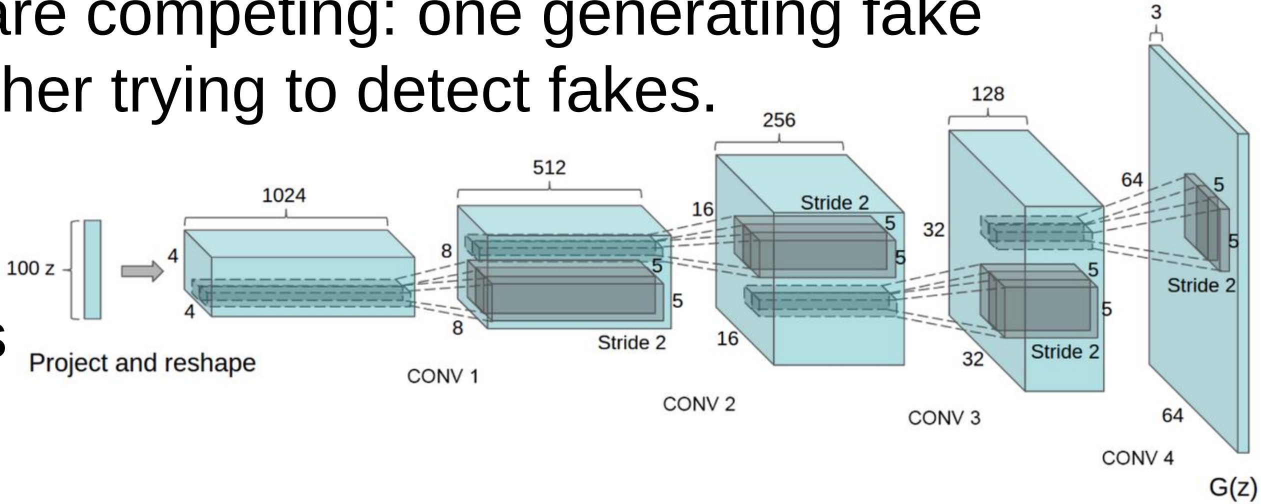


Check out Prisma App

Generative Adversarial Networks

- Recent work on generative adversarial networks (GAN's) has produced impressive results on generating synthetic images.
- Two networks are competing: one generating fake samples, the other trying to detect fakes.
- Generator transforms random vectors to images.



GAN for Faces

- State of the art generates extremely realistic face images.
- Still, each is far from any of the training samples.
- Karras *et al.*, ” A Style-Based Generator Architecture for Generative Adversarial Networks”, ICLR2019. https://vimeo.com/306599518

To Conclude...

- During the last ten years, the landscape of artificial intelligence has reached a new level of maturity:
  - **Infrastructure** has been built to allow low cost access to high-performance computing.
  - **Publicity** of the results has become a standard model in dissemination of the research results.
  - **Resources** have increased: Companies are extremely active in AI research, and aggressively headhunting for the best talents in the field.
  - **Methods** have been improved and computers are increasingly able to solve human-like tasks.