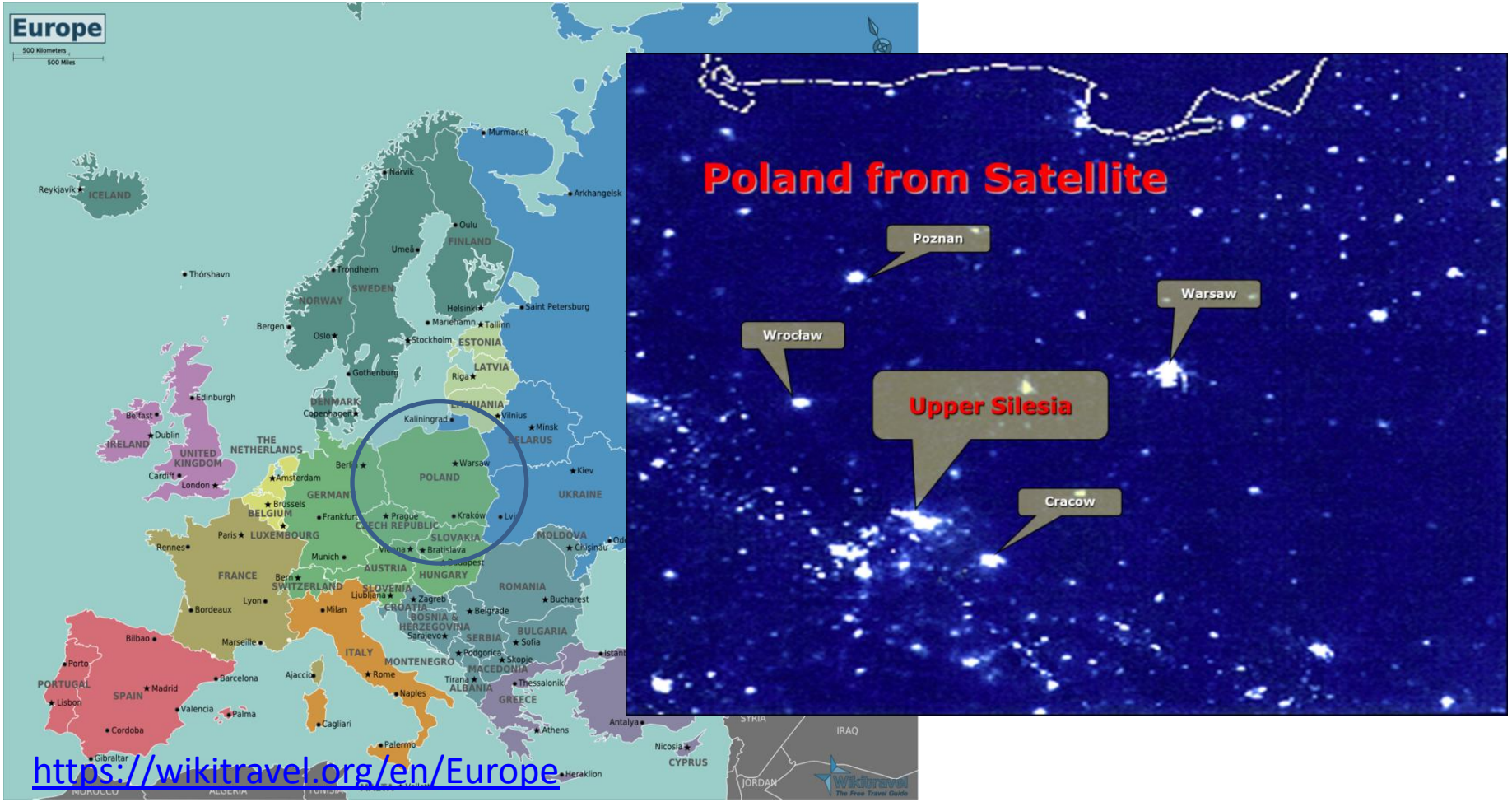
Deep Learning in the Eye Tracking World

Paweł Kasprowski
Silesian University of Technology
Gliwice, Poland

About my home

Silesian University of Technology, Gliwice, Poland...?



https://wikitravel.org/en/Europe

Upper Silesian Industrial Region

14 cities, population about 3 mln

Silesian University of Technology (Politechnika Śląska)

- Rankings among all universities in Poland
  - 2nd place in educating top managers
  - 4th place whose graduates are most desired by employers
  - 6th place among all higher education technology schools in Poland
- **13** Faculties
- More than:
  - **15,000** students
  - **600** PhD students
  - **3,150** employees
  - **150** full-professors

My Faculty

Faculty of Automatic Control, Electronics and Computer Science

(AEI - "vowel faculty")

Majors:
Automatic Control
Electronics and Teleinformatics
Computer Science
Computer Science (English)
Macrofaculty (English)
Bioinformatics

Staff:
40 professors
160 associate professors and lecturers
>2000 students

About me

- Dr hab. inż. Paweł (Paul) Kasprowski (PhD, DSc)
- Associate Professor of SUT
- Vice-Head of Department of Applied Informatics
- University Coordinator of Artificial Intelligence and Data Processing Priority Research Area
- University Coordinator of Informatics Degree Course
- Main research interest:
  - Eye movement analysis
  - Eye movement based biometric identification
  - Eye tracking software and hardware

Tutorial content

- No formulas and math
  - no "gory details" – just the ideas
- Very simple examples
  - just the working code (in Python notebooks)
- Simple datasets to show that it works
- All code available here:
  - https://github.com/kasprowski/etra2021

- *If you don't have any experience with Machine Learning you will be able to start your own experiments with your own data right after the tutorial*

Evironment preparation

- Install Miniconda (https://docs.conda.io/en/latest/miniconda.html)
- Run Anaconda prompt
- Create the environment
  - conda create --name deepeye
- Activate the environment
  - activate deepeye
- Download the code (as a ZIP file or just use git):
  - git clone https://github.com/kasprowski/etra2021
- Install prerequisites:
  - pip install –r requirements.txt

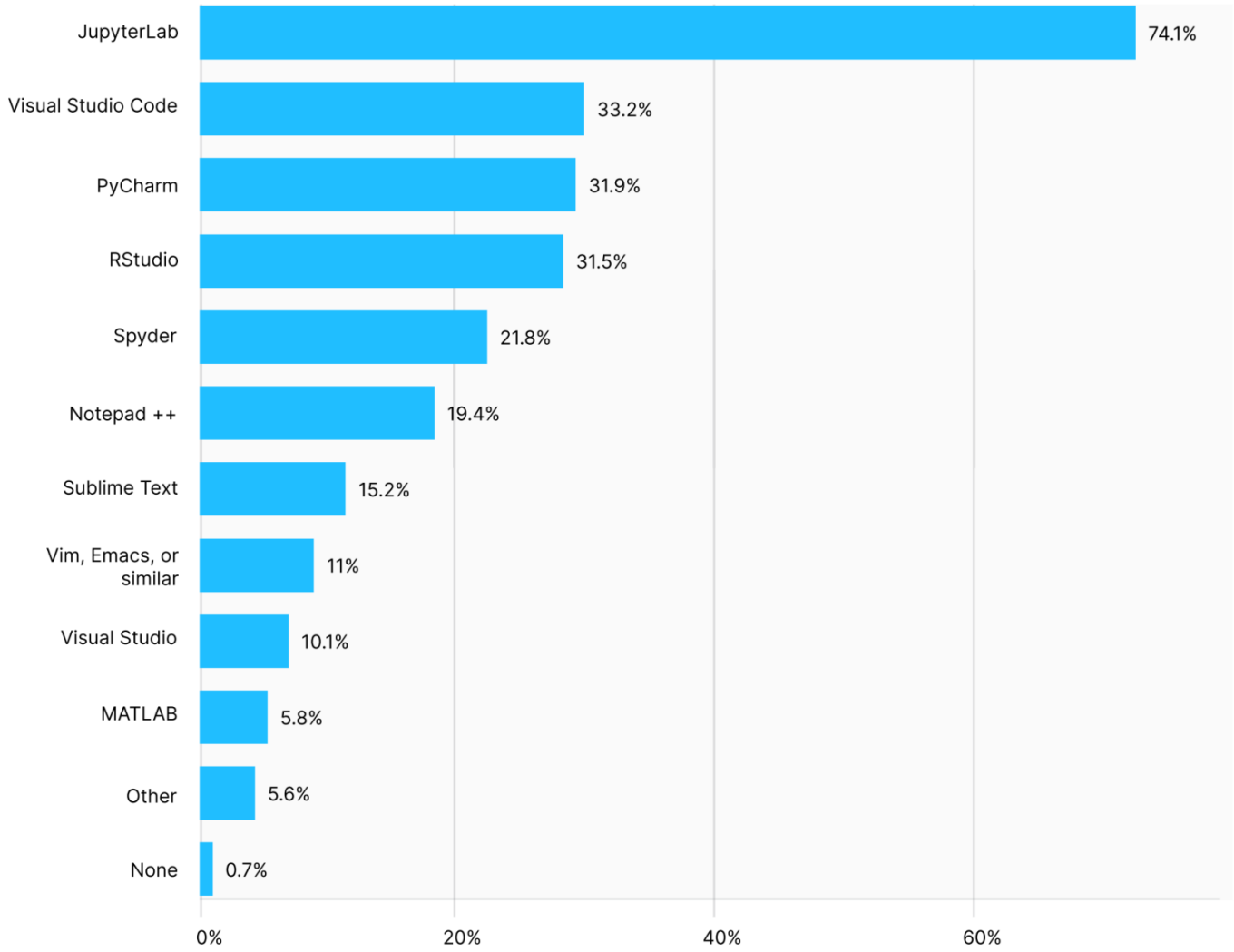
Requirements

- numpy
- pandas
- jupyterlab
- scikit-learn
- tensorflow
- opencv-contrib-python
- matplotlib
- Optional:
  - pygame
  - thorpy

Jupyter Notebook

- Creates files in JSON format that contain "blocks" of code or text (*.ipynb)
- Convenient for scripts
  - REPL (Read-Eval-Print-Loop)
- GUI starts in the web browser
- Uses a kernel that executes code
  - many possible kernels – we will use Python
- The newest version: JupyterLab

Jupyter Lab – the best solution



Working in cloud

- Many possibilities
- The most popular: Google Colab
  - https://colab.research.google.com/
- It is possible to run notebooks loaded directly from GitHub

Code disclaimers

- KISS[1] over DRY[2] principle
  - a lot of code duplications
  - separate examples in separate files/folders
  - hopefully the code is self explanatory
  - not more than 120 lines per file

1) KISS – Keep It Simple Stupid
2) DRY – Don't Repeat Yourself

Tutorial agenda

- Introduction to Machine Learning
  - problems, algorithms, measures, examples
- Neural Networks
  - architectures, implementations, Keras/Tensorflow, examples
- Convolutional Neural Networks
  - idea, advantages, examples
- Recurrent Neural Networks
  - sequences, architectures, examples

Problems to be solved

- Classification
  - assign samples to predefined classes
  - [scan-path -> novice/expert]
- Regression
  - calculate a value for each sample
  - [eye image, glint -> gaze coordinates]
- Conversion
  - convert object into another object
  - [sequence of gazes -> sequence of events]

Task and method

- Task: find a function Y = f(X) where
  - X – **sample** (input)
  - Y – result – class, value (output) – **label**
- Method (learning by example):
  - take some number of samples X with known output Y (**examples**, labeled samples)
  - build the function based on these examples (learning process)
  - use the function to predict the label for unknown samples

Problem of "generality"

- It is relatively easy to create a function that correctly classifies all examples
- But is this function "general" enough?
  - is it able to correctly classify unknown samples?
- The answer is not trivial and that is why we have a lot of different classification methods
- "No free lunch" theorem

Over-fitting

- If the function (model) is optimized for the given data (given examples) it may have poor generality
- This problem is called over-fitting
- Solution is to simplify the model, e.g. stop learning even when it is not perfect for examples

The simplest algorithms

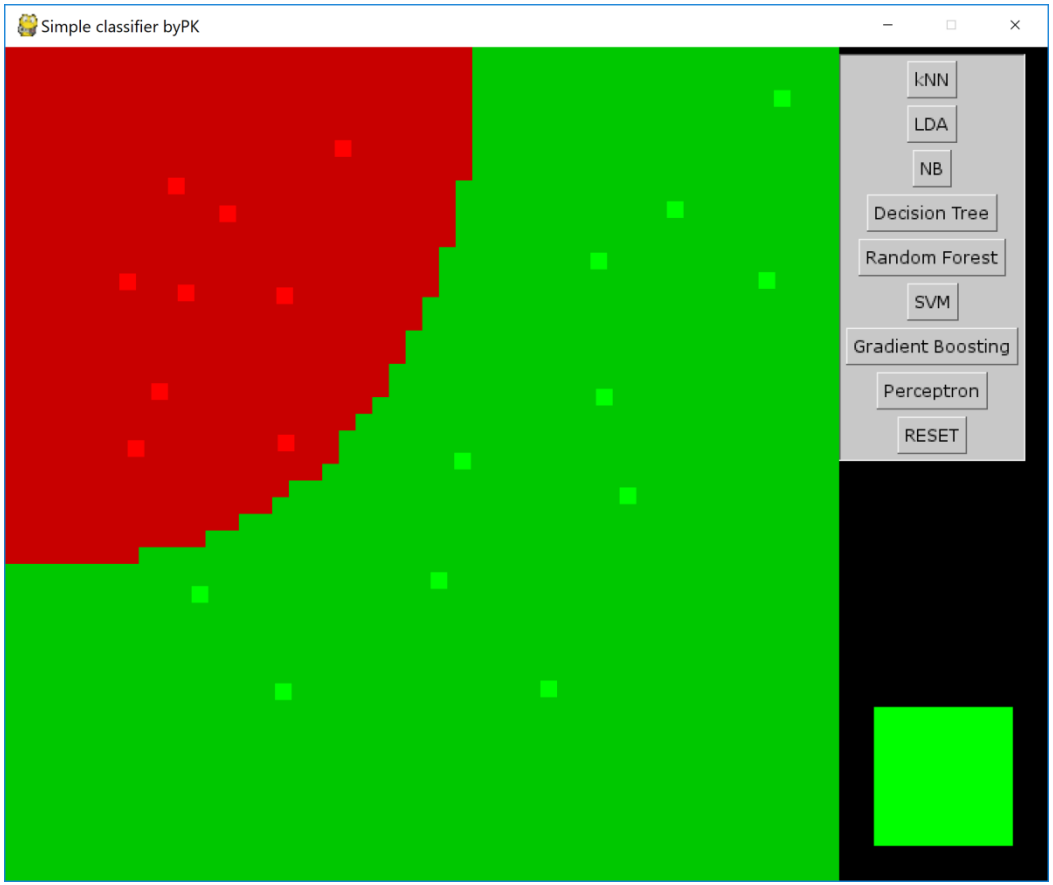
- K-Nearest Neighbors (kNN)
  - a new sample is classified as majority of its K nearest neighboring examples
- Linear Discriminant Analysis (LDA)
  - finds a linear equation separating positive and negative samples
- Naive Bayes
  - the class of a new sample is calculated based on examples using Bayes equation
- Decision Tree
  - the tree is built using examples by seaching for the most discriminative features
  - new samples are going through the tree reaching a leaf with the predicted class

More sophisticated algorithms

- Random Forest
  - a set of randomly generated decision trees voting for the final results
- Support Vector Machines (SVM)
  - recalculates examples into another space where they are easier to separate lineary (kernel trick)
- Neural Networks
  - based on neurons organized into layers

Example

Run: *python classifier*



Hyper parameters

- Classification algorithms have parameters
  - so called hyper parameters
- kNN – the number of neighbors
- Random Forest – the number of trees
- SVM – kernel function, parameters of the function, learning rate etc.
- Good choice of hyper parameters influences the quality of the model!
- Bad news: deep learning methods have A LOT hyper parameters

Evaluating results

- Hyper parameters may be tuned
  - it is important to be able to check if the model is general
- First rule: never check the model using the same data that you used for training (examples)
  - over-fitting!
- The dataset should always be divided into:
  - training set (used to build the model)
  - test set (to check how it works for unknown samples)

Evaluation

- Dividing into training set and test set may be not enough!
  - we optimize the model (by tuning hyper parameters) for the given test set
- The safest way:
  - training set (for learning)
  - validation set (for hyper parameters tuning)
  - test set (for final evaluation)
    - the "holdout" dataset

Cross-validation

- Dynamic division into training and test
  - the same examples are sometimes training and sometimes test samples
- 10-fold cross validation:
  - divide the whole dataset into 10 subsets
  - for each subset
    - train the model using the remaining 9 subsets
    - test the results using the chosen subset
  - average the results
- Folds are randomized but may be stratified
  - the same distribution of classes in each fold

Multinomial classification

- More than two classes
  - E.g. fixations, saccades, smooth-pursuits and glissades
- The model returns a probability for each class
- We choose the class with the highest probability
- Typical output:
  - binary class matrix (one-hot encoding)
    - 1 -> [1,0,0,0,0]
    - 2 -> [0,1,0,0,0]
    - 3 -> [0,0,1,0,0]
    - ...

Measures

- Accuracy – the number of correctly classified samples to all samples
  - a problem with unbalanced sets
  - if 90% of test samples is positive the blind classifier achieves 90% accuracy
- Precision – the cost of false positives
  - not belonging to class predicted as belonging
- Recall – the cost of false negatives
  - belonging to class predicted as not belonging
- F1-Score – combination of precision and recall
- Cohen's kappa – compares prediction with random prediction

Measures interpretation

- Example: We have built the model that diagnoses autism based on eye movements
- For every eye movement sample the model returns:
  - ***H*** - if a person is healthy
  - ***S*** - when a person is sick with autism
- We test the model using
  - 18 samples from sick people (***S***)
  - 82 samples from healthy people (***H***)
- We achieve 82% accuracy
  - is it bad or good?
  - it depends: we must examine a confusion matrix

Confusion matrix

Predicted as >> Real class	H	S
H	81	1
S	17	1

P	N
TP	FN
FP	TN

Accuracy 0.82

H:
precision: 0.83
recall: 0.99
F1-score: 0.90

S:
precision: 0.50
recall: 0.06
F1-score: 0.1

Cohen's kappa: 0.07

Measures

Predicted as >> Real class	H	S
H	80	2
S	15	3

P	N
TP	FN
FP	TN

Accuracy 0.83

H:
precision: 0.84
recall: 0.98
F1-score: 0.90

S:
precision: 0.60
recall: 0.17
F1-score: 0.26

Cohen's kappa: 0.20

Measures

Predicted as >> Real class	H	S
H	66	16
S	2	16

P	N
TP	FN
FP	TN

Accuracy 0.82

H:
precision: 0.97
recall: 0.80
F1-score: 0.88

S:
precision: 0.50
recall: 0.89
F1-score: 0.64

Cohen's kappa: 0.53

Measures

Predicted as >> Real class	H	S
H	64	18
S	0	18

P	N
TP	FN
FP	TN

Accuracy 0.82

H:
precision: 1.00
recall: 0.78
F1-score: 0.88

S:
precision: 0.50
recall: 1.00
F1-score: 0.67

Cohen's kappa: 0.56

Example for three classes

Confusion matrix

```
[[24  3  9]
 [ 3 24 24]
 [ 2 15 49]]
```

class	precision	recall	f1-score	support
0	0.83	0.67	0.74	36
1	0.57	0.47	0.52	51
2	0.60	0.74	0.66	66
micro avg	0.63	0.63	0.63	153
macro avg	0.67	0.63	0.64	153
weighted avg	0.64	0.63	0.63	153

Accuracy: 0.63

Summary

- Accuracy is often not enough
  - esp. for unbalanced datasets
- Cohen's kappa is the easiest way to evaluate results
  - but has some drawbacks as well!
- The evaluation depends on the target we want to achieve
  - False Acceptance Rate (FAR=0)
    - no incorrectly classified healthy people
  - False Rejection Rate (FRR=0)
    - no incorrectly classified sick people

Regression

- The model does not search for one of N classes but for a value
  - E.g. gaze coordinates
- Examples:
  - Linear Regression
  - Support Vector Regression
  - Decision Tree Regression
  - Neural Network Regression

Evaluation of regression

- Mean Absolute Error
- Mean Squared Error
  - penalizes predictions differing greatly (outliers)
- Root Mean Squared Error
  - comparable to real values
- Coefficient of Determination (R^2)
  - value 0-1

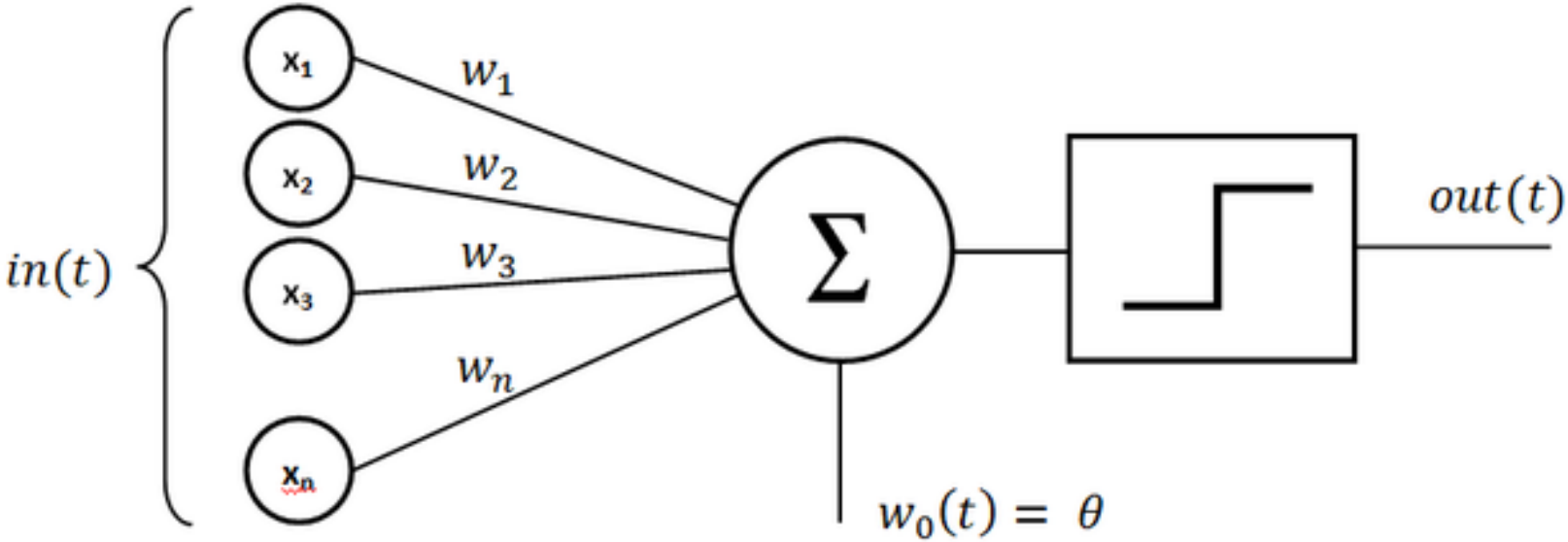
Summary

- There are many different classification algorithms
- There are many ways to tune these algorithms
- There are many measures to estimate the quality of classification/regression
- So what is so special about the deep learning methods?
  - Wait for the following sections!

Neural Networks

Introduction and implementation (Keras)

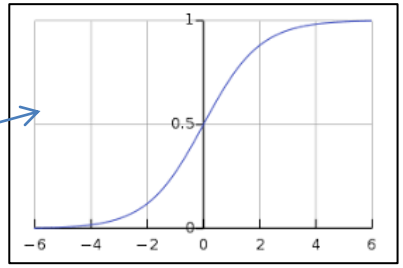
Perceptron (Rosenblatt 1957)

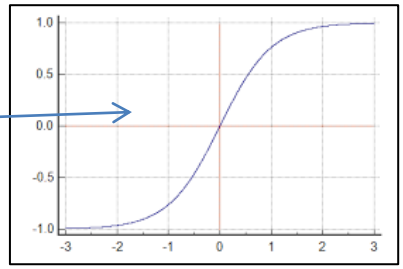


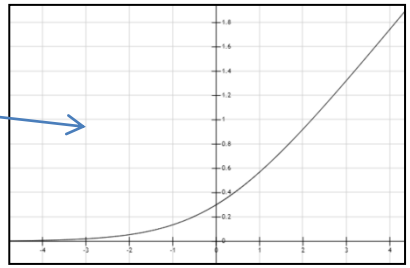
https://pl.wikipedia.org/wiki/Perceptron

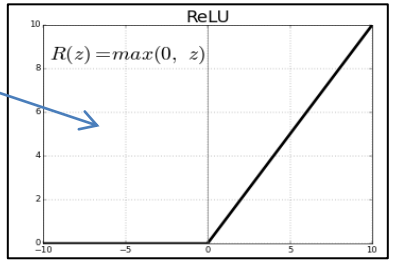
Activation function

- Linear combination of inputs
- Activation functions may be different
  - threshold function
  - sigmoid function
  - tanh function
  - softplus
  - RELU



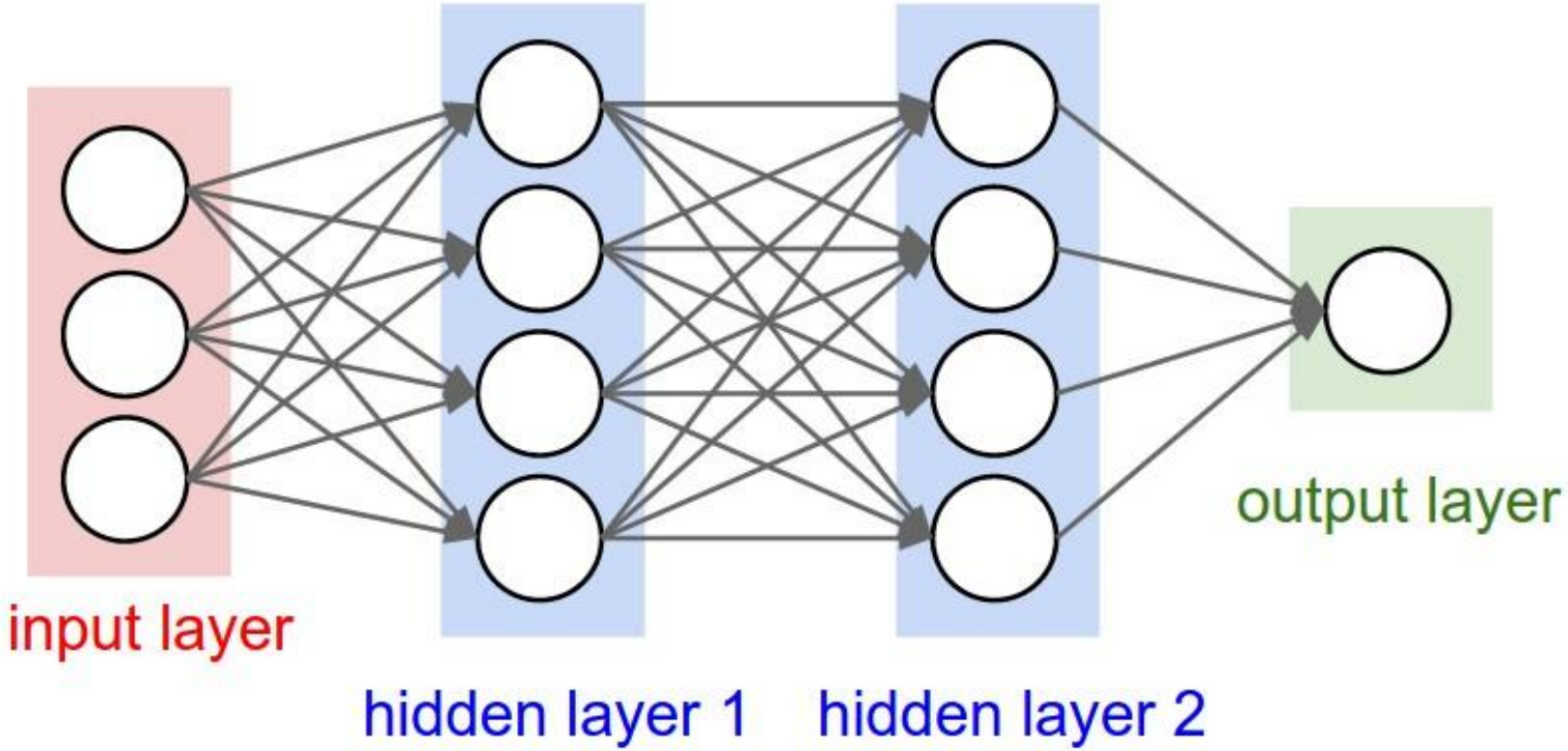






Neural Network

- input layer > hidden layers > output layer



http://cs231n.github.io/convolutional-networks/

Training the network

- Back propagation
  - the state-of-the art method to train the network
  - utilizes the Gradient Descent algorithm
- The algorithm:

  initialize weights

  repeat many times:

    use network to calculate output (Y_{pred}) for some examples (X)

    calculate error (loss) using Y_{pred} and Y (real)

    update weights to minimize loss (using gradients)

Tuning - hyper parameters

- Network structure
  - Number of layers
  - Number of neurons for layer
  - Connections
  - Activation functions for layers
- Loss function
- Optimization algorithm
  - how to change the weights
  - learning rate (how big changes of weights)

Implementations

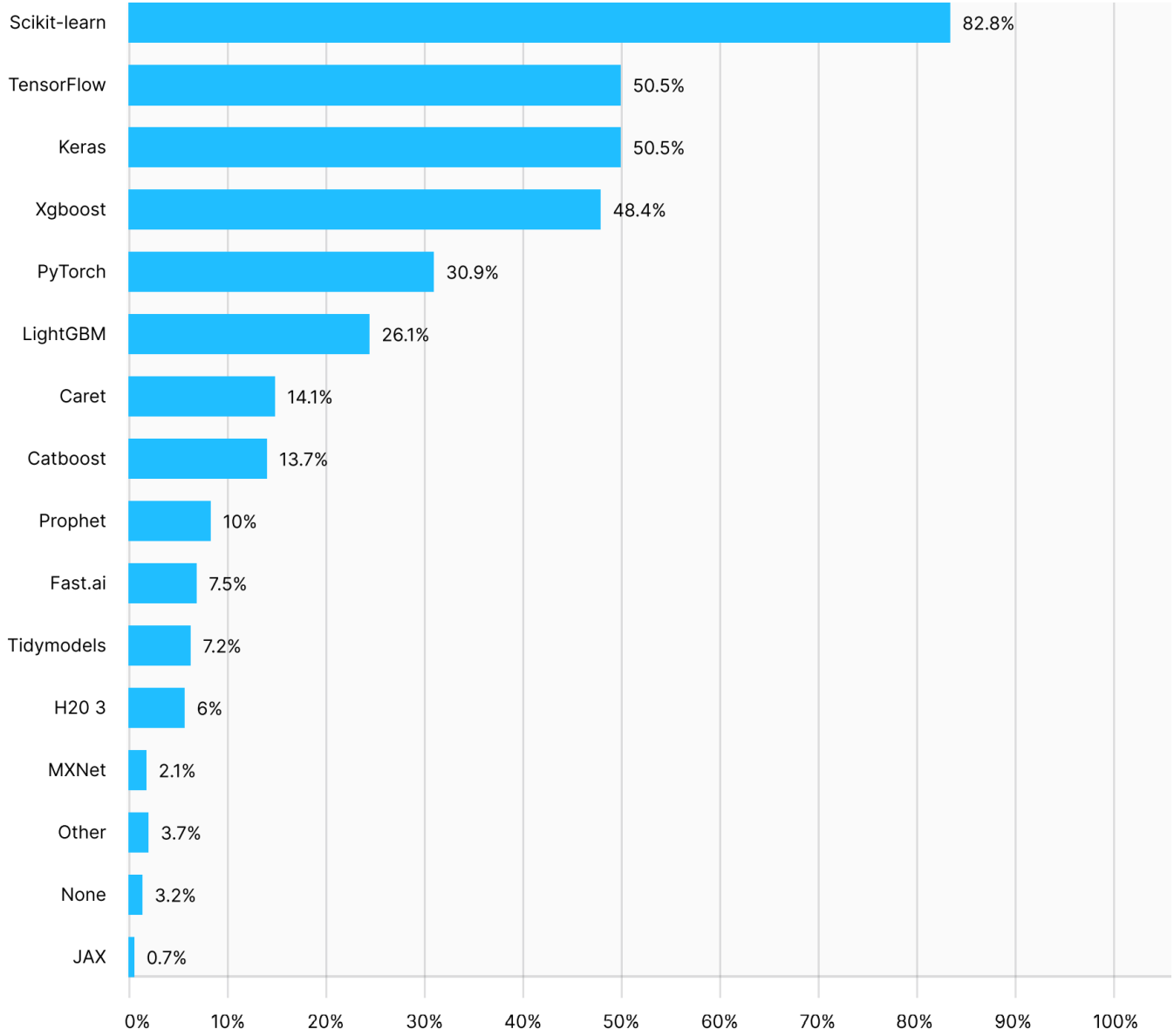
- Many classification libraries like scikit-learn or WEKA implement the neural networks
  - but only the simplest models
- For Deep Learning there are many libraries developed by leading companies:
  - Tensorflow, Google
  - PyTorch, Facebook
  - CNTK, Microsoft
  - …
- We will use the most popular: Keras/Tensorflow

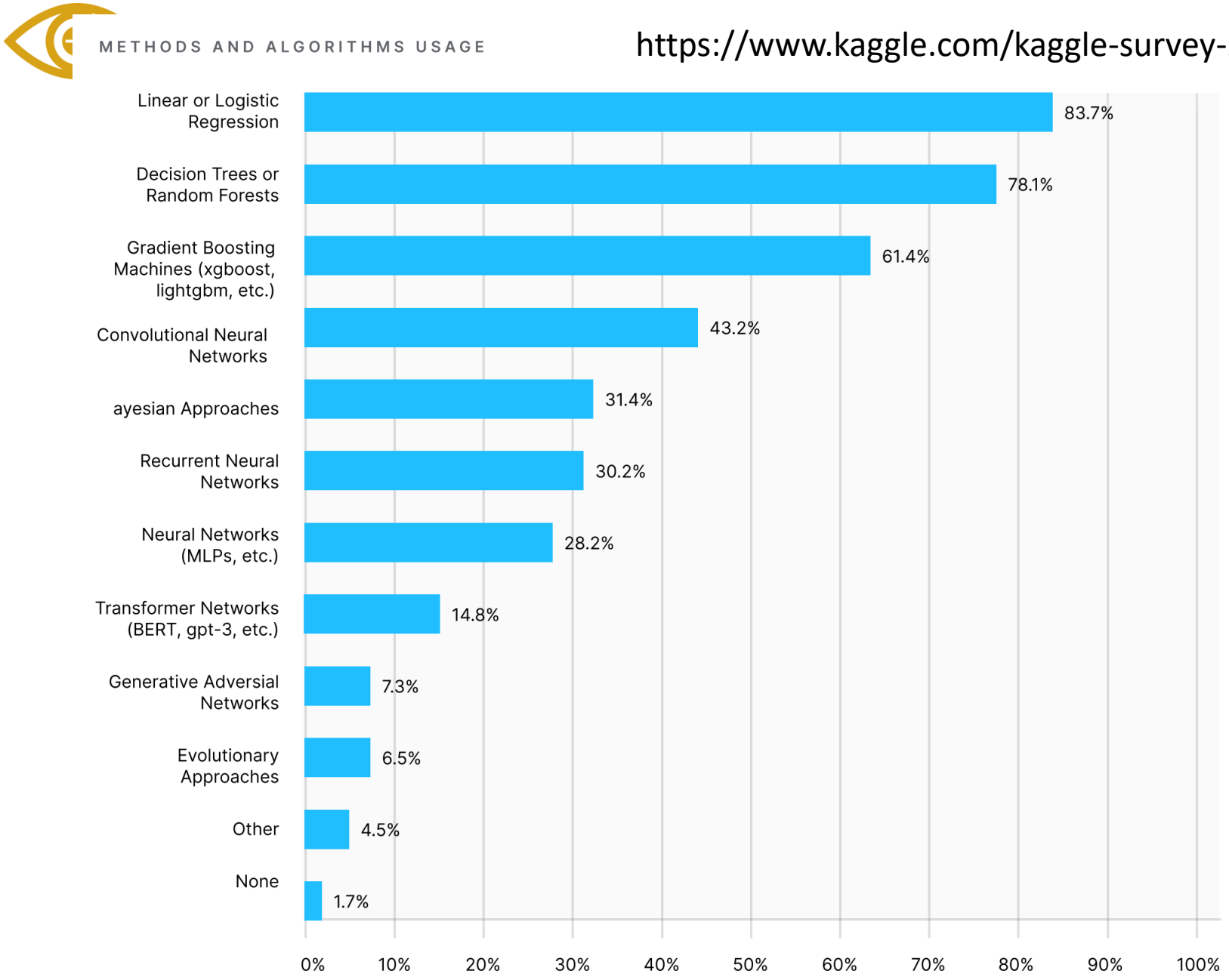
Keras

- General interface to use deep networks
- Works with Tensorflow, Theano, CNTK...
- User-friendly, modular, and extensible
- Created in Google
- Works in Python
- Tensorflow 2 package includes Keras by default
  - that is why we installed Tensorflow and we use Keras

MACHINE LEARNING FRAMEWORK USAGE

https://www.kaggle.com/kaggle-survey-2020




METHODS AND ALGORITHMS USAGE
https://www.kaggle.com/kaggle-survey-2020
Linear or Logistic Regression
83.7%
Decision Trees or Random Forests
78.1%
Gradient Boosting Machines (xgboost, lightgbm, etc.)
61.4%
Convolutional Neural Networks
43.2%
ayesian Approaches
31.4%
Recurrent Neural Networks
30.2%
Neural Networks (MLPs, etc.)
28.2%
Transformer Networks (BERT, gpt-3, etc.)
14.8%
Generative Adversial Networks
7.3%
Evolutionary Approaches
6.5%
Other
4.5%
None
1.7%
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%

Keras basics

- Build the model (network)
  - contains layers with neurons and connections
- Compile the model (model.compile)
  - define loss function and optimizer
- Train the model (model.fit)
  - provide samples with known labels
- Use the model for predictions (model.predict)
  - predict labels of unknown samples

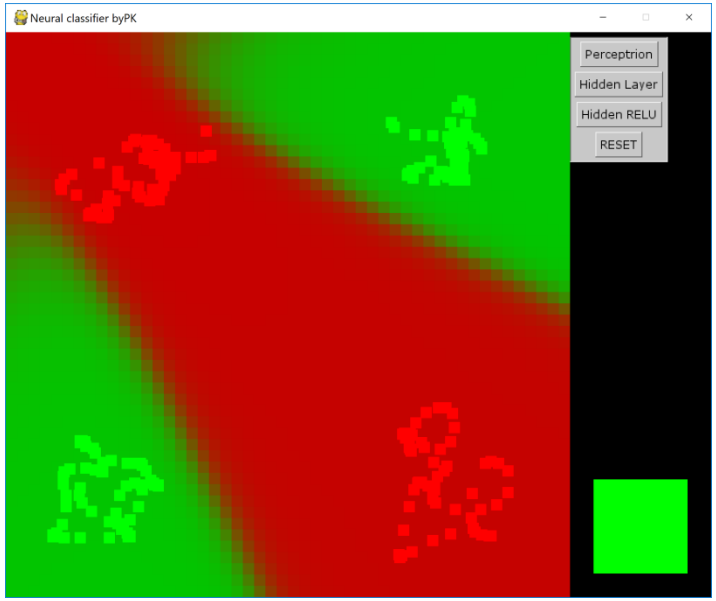
The simplest example

```
# import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
# build model
model = Sequential()
model.add(Dense(10, activation='sigmoid'))
model.add(Dense(10, activation='sigmoid'))
# compile model
model.compile(loss='binary_crossentropy',
    optimizer="adam",metrics=['accuracy'])
# train model
model.fit(samples, labels, epochs=100, batch_size=10)
# use model
predicted = model.predict(sample)
```

Example

Run: *python neural*

- Several architectures
- Works with XOR
- Perceptron network
  - only linear
- RELU – much better



model.compile parameters

- loss – loss function (compares predictions with ground truth)
  - *binary_crossentropy* for 2-class problem
  - *categorical_crossentropy* for many classess (one-hot encoded)
  - *mean_squared_error* for regression
- optimizer – algorithm for back propagation
  - adam
  - SGD
- metrics – metrics to measure after each iteration
  - *accuracy* for classification
  - *mean squared error* for regression

model.fit parameters

- samples – array of samples
- labels – array of labels (one for each sample)
- epochs – number of iterations
- batch_size – number of samples per batch (each back propagation pass)
  - stochastic (1 – backprop after every sample)
  - mini-batch (from 2 to N-1)
  - batch (N – backprop after all samples – one per epoch)
- validation_split – percent of validation samples
- validation_data = (samples, labels)

Input parameters

- samples – a list of samples
  - every sample may be multidimensional (e.g. 3D for images)
- labels – a list of correct labels for each sample
  - a list of values [0,1,4,2,1,4,2...]
  - one-hot encoded:
    - 0 > [1,0,0,0,0]
    - 1 > [0,1,0,0,0]
    - 4 > [0,0,0,0,1]

Real data at last!

- Identification of people based on their eye movements
- A part of EMVIC 2012[1] dataset:
  - 416 samples
  - 8 classes (persons)
  - 8192 attributes (eye positions)
- unbalanced distribution
  - {'a25': 105, 'a37': 63, 'a40': 52, 'a32': 50, 'a41': 39, 'a42': 38, 'a29': 36, 'a28': 33}

[1] Kasprowski, Komogortsev, Karpov: First eye movement verification and identification competition at BTAS 2012,
IEEE Fifth International Conference on Biometrics: Theory, Applications and Systems (BTAS)

Loading and preparing data

- Loading

  dataframe = pandas.read_csv(file)

  dataset = dataframe.values

  samples = dataset[:,4097:]

  labels = dataset[:,0]

- Preparing – "one hot" encoding

  lb = LabelBinarizer()

  labels = lb.fit_transform(labels)

  classesNum= labels.shape[1]

The model

Run: *emvic.ipynb*

- Simple MLP model:

```
model = Sequential()
model.add(Dense(150, activation='sigmoid'))
model.add(Dense(150, activation='sigmoid'))
model.add(Dense(150, activation='sigmoid'))
model.add(Dense(classesNum, activation='softmax'))
model.compile(loss= 'categorical_crossentropy',
    optimizer="adam", metrics=['accuracy'])
```

Training, testing, reporting

- Training with training data:

```
H = model.fit(trainSamples, trainLabels, batch_size=BATCH,
    epochs=EPOCHS)
```

- Testing with test data:

```
mlpResults = model.predict(testSamples)
```

- Reporting (compare prediction results with the ground truth using methods from sklearn package):

```
print(confusion_matrix(testLabels.argmax(axis=1),
    mlpResults.argmax(axis=1)))
print(classification_report(testLabels.argmax(axis=1),
    mlpResults.argmax(axis=1),target_names=lb.classes_))
```

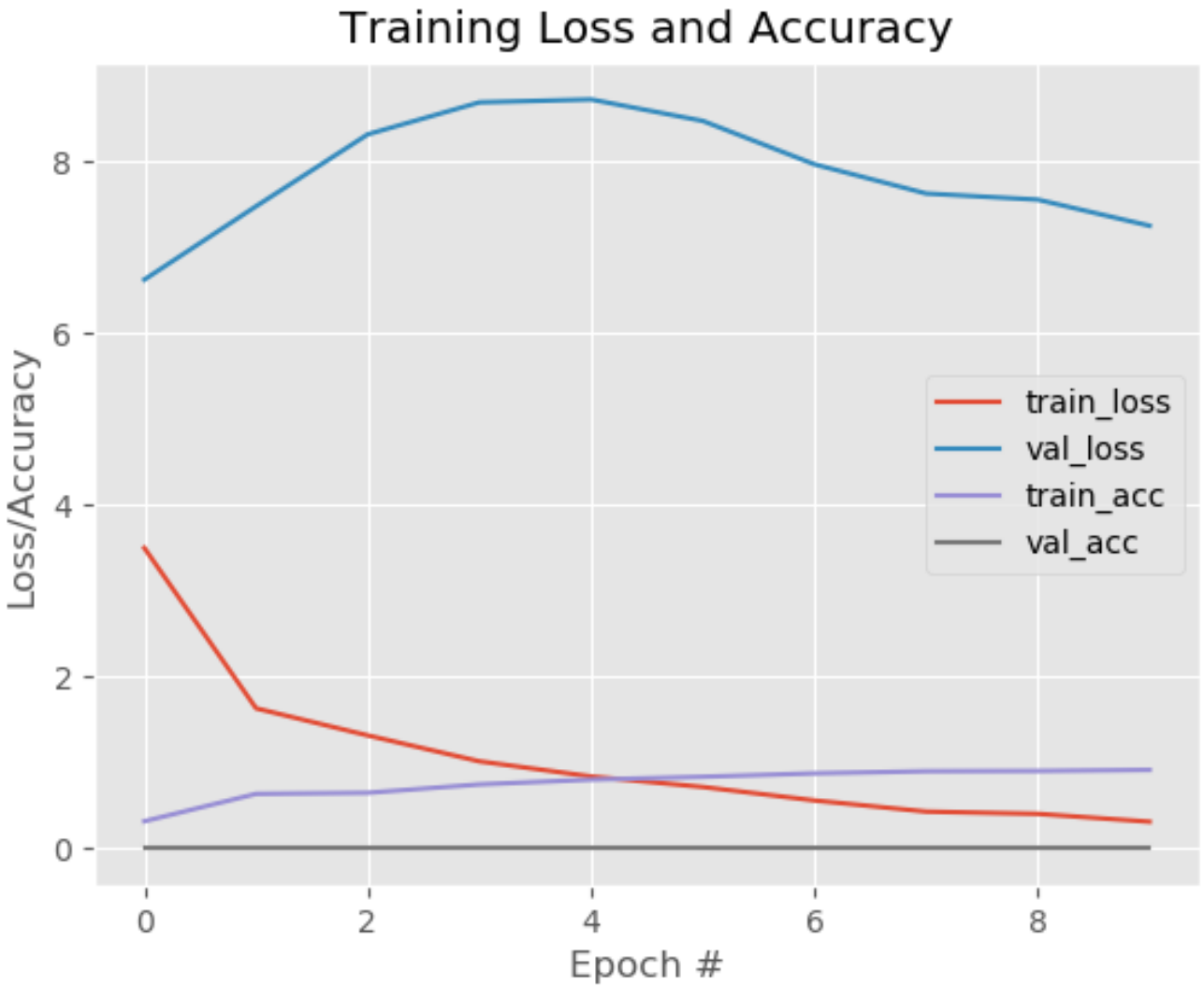
Validation

- Prevents from over-fitting
- Parameters of model.fit
  - validation_split=0.1
  - validation_data=(testSamples,testLabels)
- Division to training and testing
  - (trainSamples, testSamples, trainLabels, testLabels) = train_test_split(samples, labels, test_size=0.25)
- Test only using samples not used for training!

Training results

It may be worse...

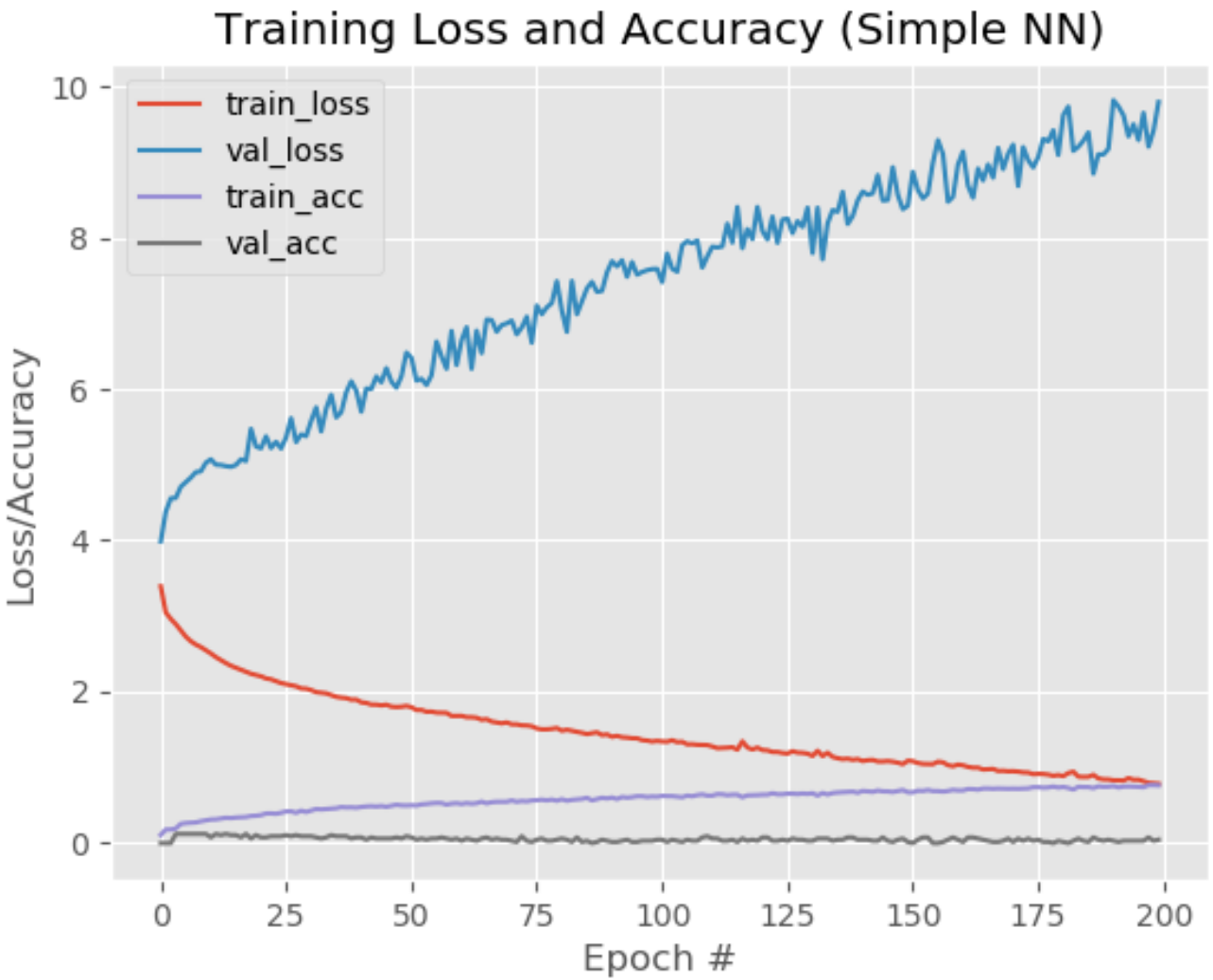
It may be worse...



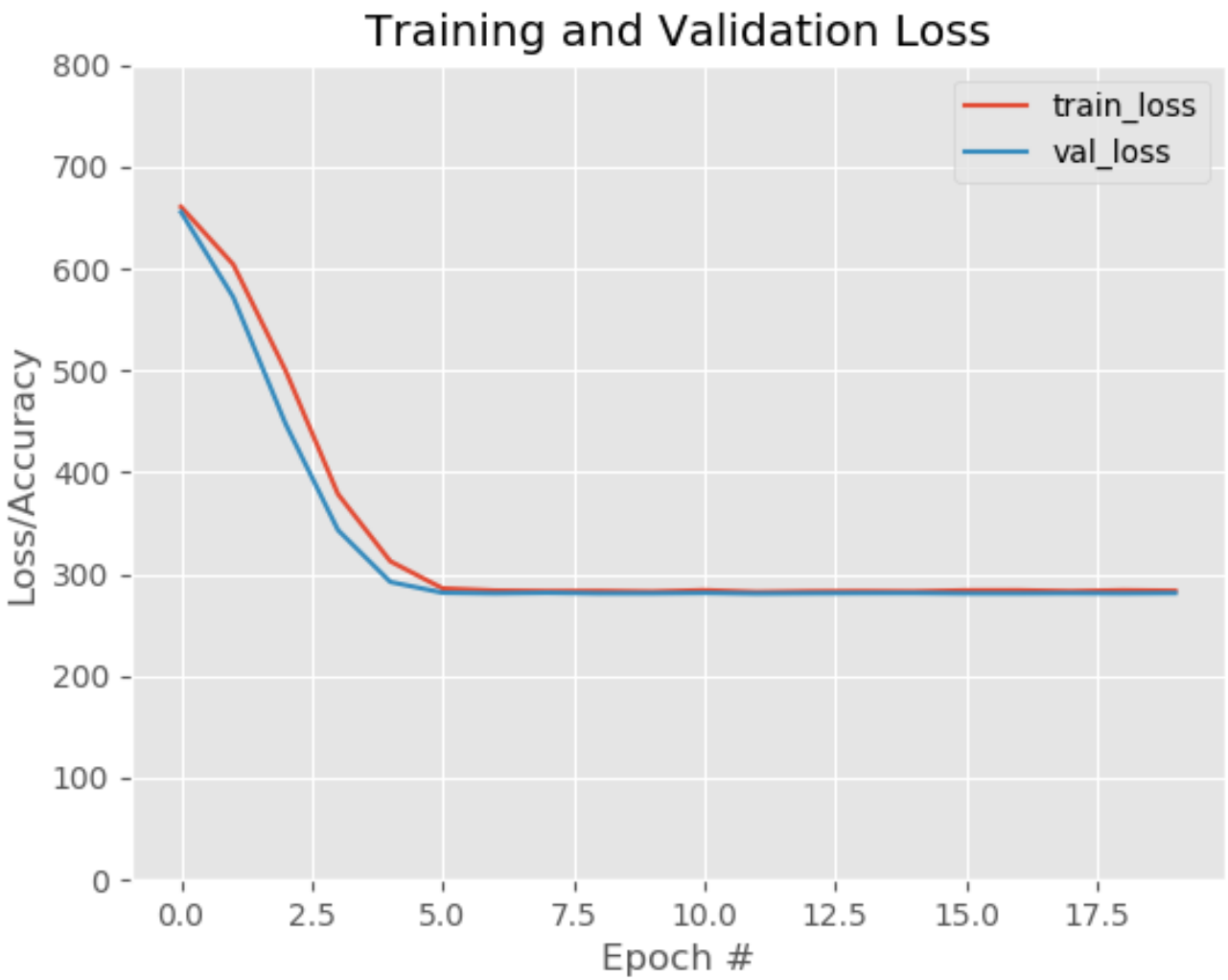
It may be worse...

It may be even worse...

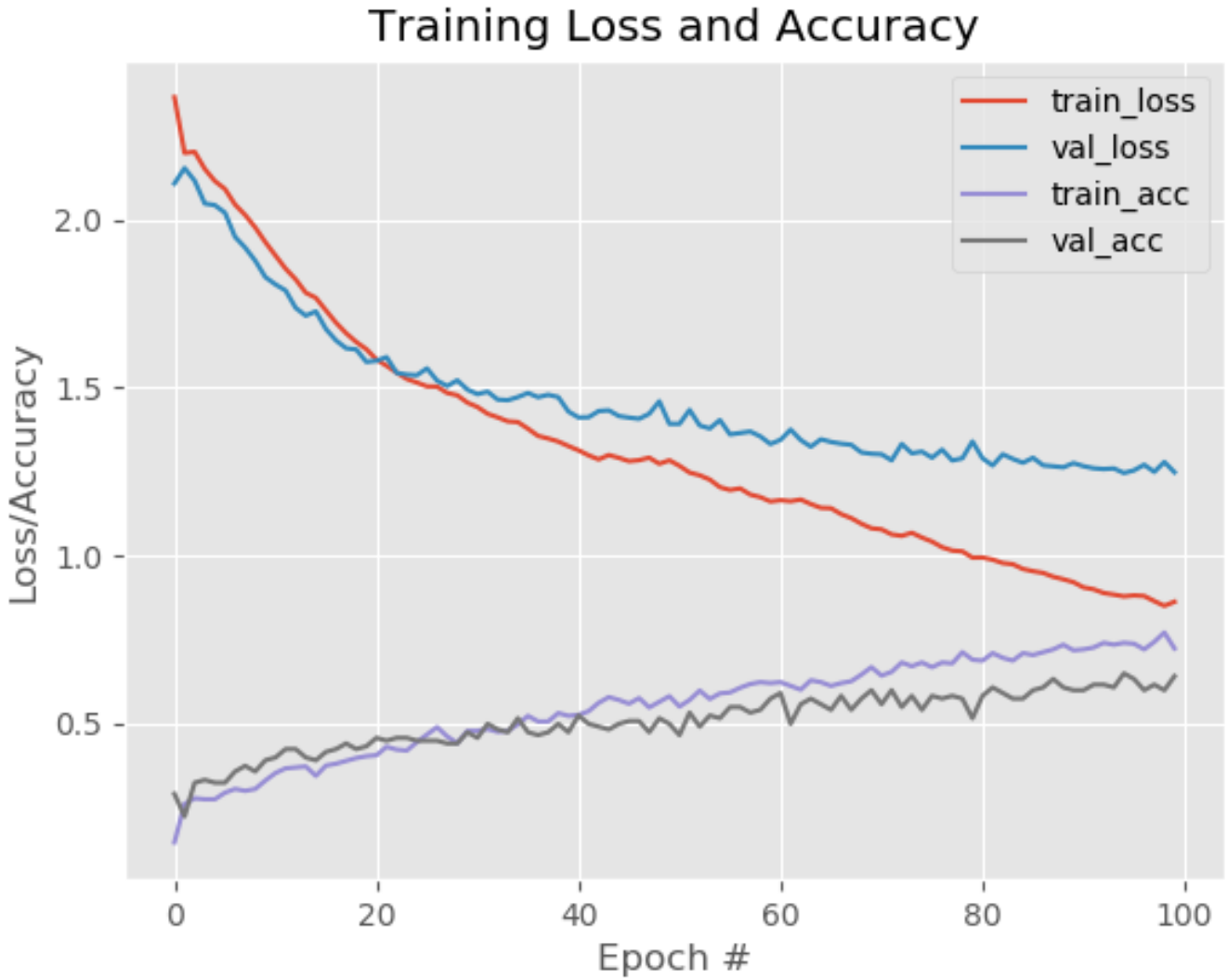
It may be even worse...



Sometimes even loss is not decreasing...



So ,this is quite OK



This is worse

Possible additions (sklearn)

- Choose 100 best attributes

  newSamples = SelectKBest(k=100).fit_transform(samples, labels)

- Add weights to classes

  class_weights = class_weight.compute_class_weight(
  'balanced',np.unique(labels),labels)

  d_class_weights = dict(enumerate(class_weights))

- Normalize the dataset

  normalize(samples)

Comparison with Decision Tree

- Code for Decision Tree:

```
from sklearn.tree import DecisionTreeClassifier
treemodel = DecisionTreeClassifier()
treemodel.fit(trainSamples, trainLabels)
treeResults = treemodel.predict(testSamples)
```

- Results:
  - Comparable...

Problems with neural networks

- Configuration is complicated (many hyper parameters)
  - layers, number of neurons
  - activation functions
  - optimizers
- Training is challenging
  - A lot of computations – a lot of weights
  - A lot of examples needed
- Training of many layers may fail
  - Vanishing gradient problem
  - Exploding gradient problem

Question for today

- So why Deep Learning has become so popular?
- Next part is about it!

Convolutional Neural Networks

Going really deep...

Curse of dimensionality

- If the number of features is too big we have the 'curse of dimensionality' problem
  - number of possible 'states' is too big to find any similarities in data
- Typical dataset:
  - A lot of irrelevevant features
  - Correlations between features
- For example:
  - Images and pixel values as features
  - 10000 features for 100x100 images!

Feature extraction

- All previously mentioned algrorithms treat input as a set of independent features
  - preferably not correlated
- So the first and most important part of classification is **feature extraction** from real data
- For instance in image classification it could be [1]:
  - **Color** - Color Channel Statistics (Mean, Standard Deviation) and Color Histogram
  - **Shape** - Hu Moments, Zernike Moments
  - **Texture** - Haralick Texture, Local Binary Patterns (LBP)
  - **Others** - Histogram of Oriented Gradients (HOG), Threshold Adjancency Statistics (TAS)

[1] https://gogul09.github.io/software/image-classification-python

Convolutional Neural Networks

- Network that is not "dense"
  - neuron from layer N+1 is not connected to every neuron in layer N
- It preserves "local connectivity"
  - Features (pixels) close to each other are processed together
- Such a network is in fact doing automatic feature extraction in input layers
- Two key properties:
  - not all neurons are connected
  - there are common weights for many connections

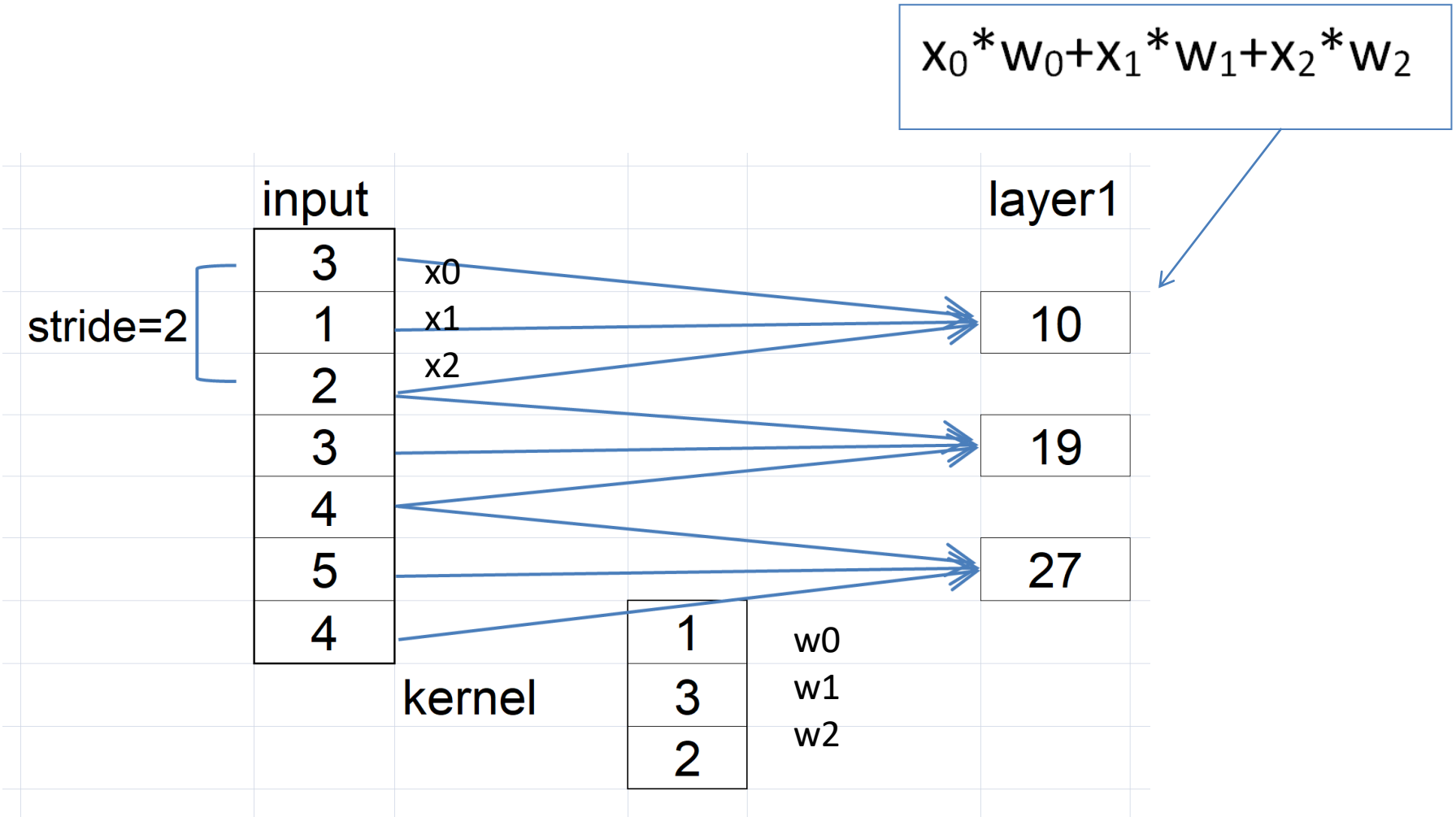
Brief history

- 1982 – Kunihiko Fukushima, Neocognitron
  - pattern recognition
- 1989 – Yann LeCunn, LeNet-5
- 2010 – ImageNet Competition
  - 1000 classes, over million of images
- 2012 – Alex Krirzevsky, AlexNet
  - 15% error rate for ImageNet (runner-up: 26%)
  - 8 layers
- 2015 – Deep Residual Nets wins ImageNet
  - over 100 layers!

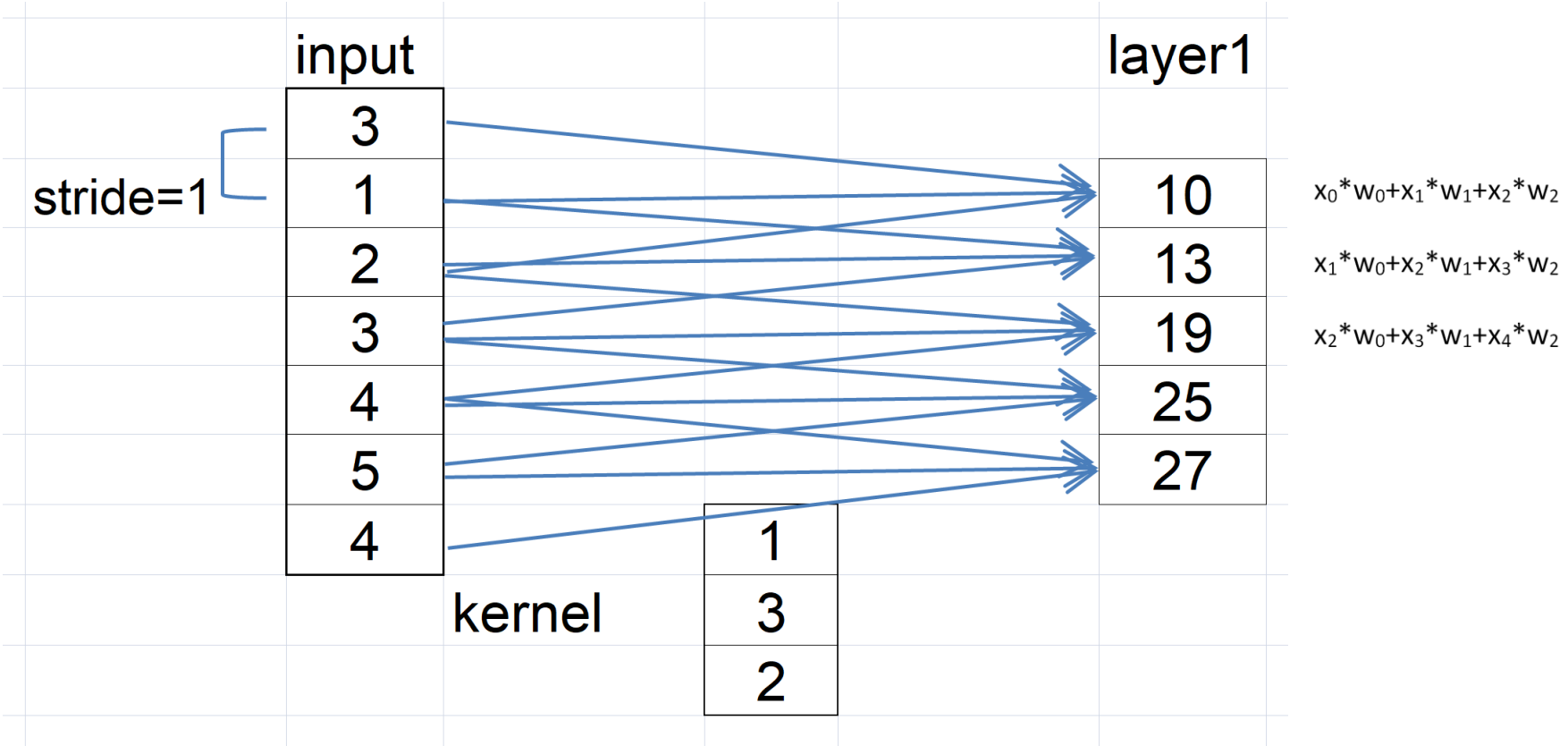
Why now?

- Neural Network training and predicting involves a lot of calculations
  - Only new computers are capable to calculate it in reasonable time (esp. with CUDA/GPU)
- Neural Network training requires a lot of training data
  - Huge datasets like ImageNet were not available before
  - Everybody may easily create their own dataset using internet resources
- Some advancement in algorithms

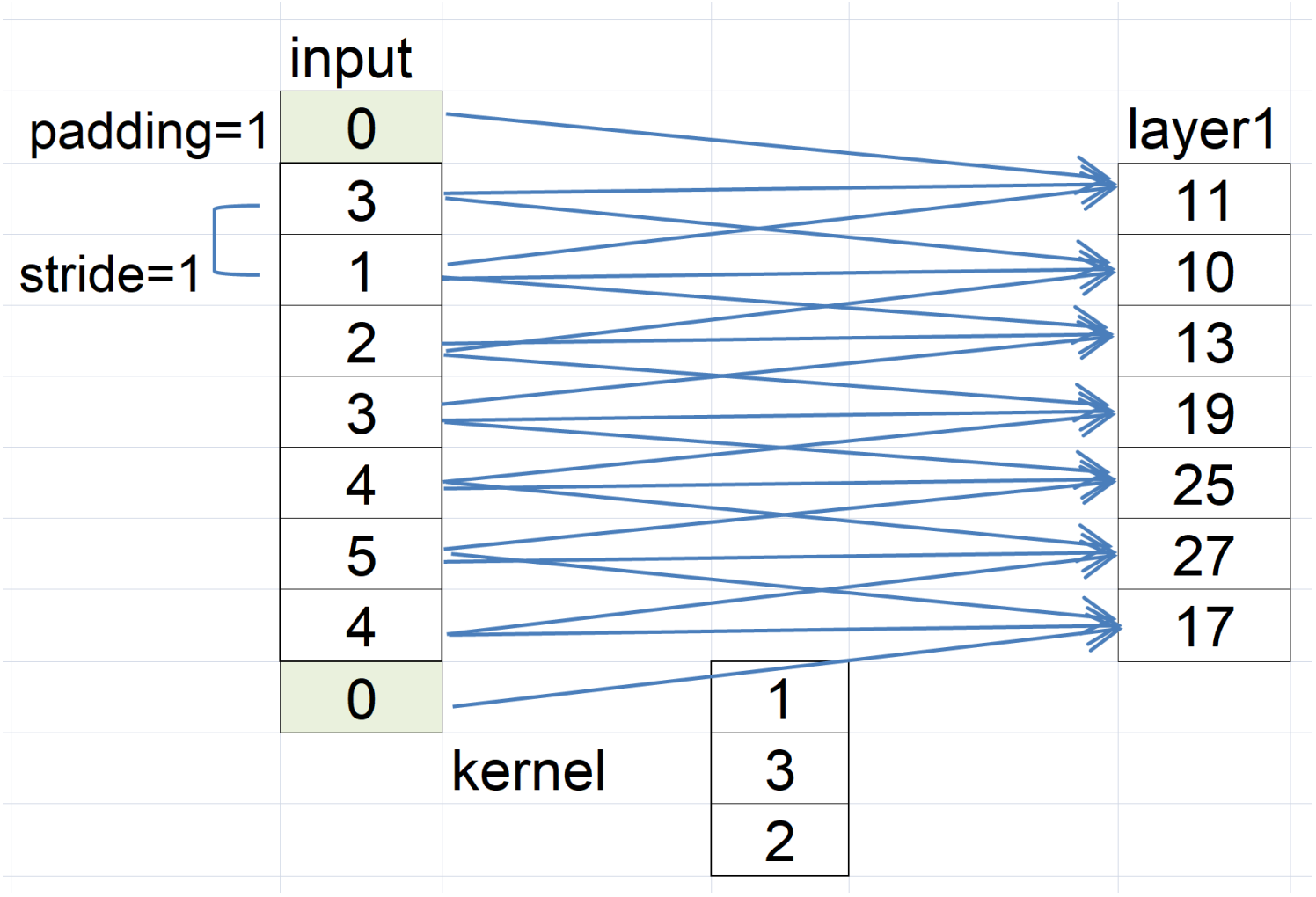
CNN - 1D example



CNN - stride=1


input
layer1
stride=1
3
1
2
3
4
5
4
10
13
19
25
27
kernel
1
3
2
$x_0*w_0+x_1*w_1+x_2*w_2$
$x_1*w_0+x_2*w_1+x_3*w_2$
$x_2*w_0+x_3*w_1+x_4*w_2$

CNN - stride=1, padding=1



CNN - 2D

$$x_{00}*w_{00}+x_{01}*w_{01}+x_{02}*w_{02}+x_{10}*w_{10}+x_{11}*w_{11}+x_{12}*w_{12}$$

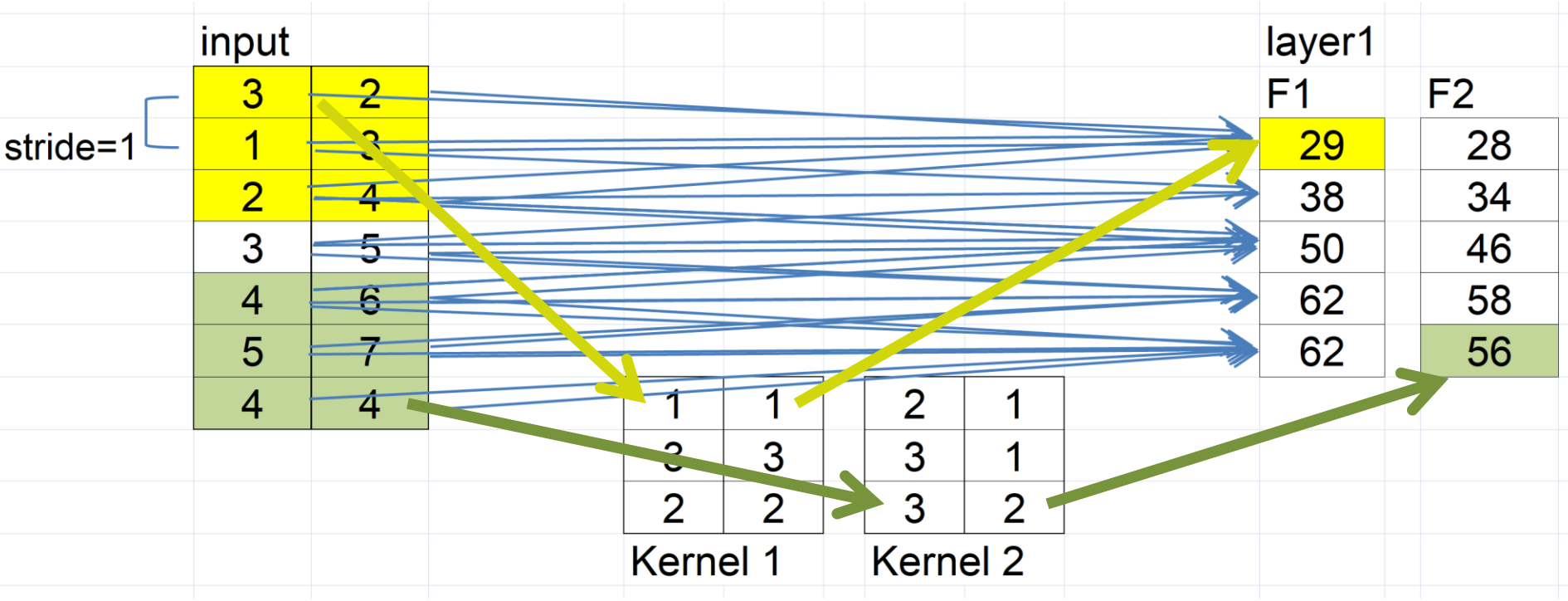
stride=1

input		layer1
3	2	29
1	3	38
2	4	50
3	5	62
4	6	62
5	7	
4	4	

kernel

1	1
3	3
2	2

CNN – 2D, many filters



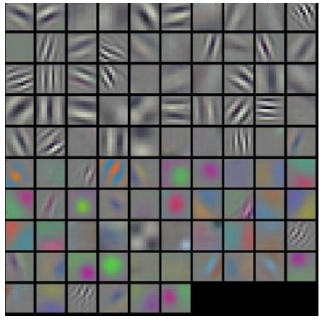
Convolutional Layer

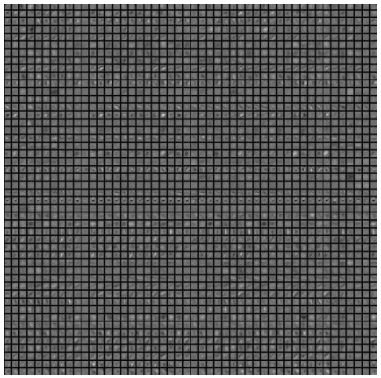
- Parameters:
  - filters – how many kernels
  - kernel size – 1D or 2D
  - stride – step for applying the kernel
  - padding – add borders with zeroes
    - VALID – no padding
    - SAME – padding to preserve size (if STRIDE=1)
- Keras:
  - Conv2D(filters=64, kernel_size=(3,3), padding=SAME, input_shape=(32,32))

Advantages of CNN

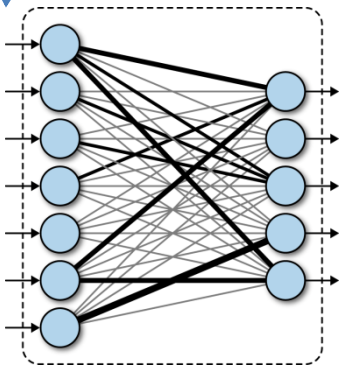
- Takes into account spatial/temporal relationships between features
- May find patterns in data
- Builds own filters that extract useful information
- The output from convolutional layer is a set of filters representing various properties of the image
  - i.e. features! – which are automatically created

Example of CNN





Feature extraction finished here



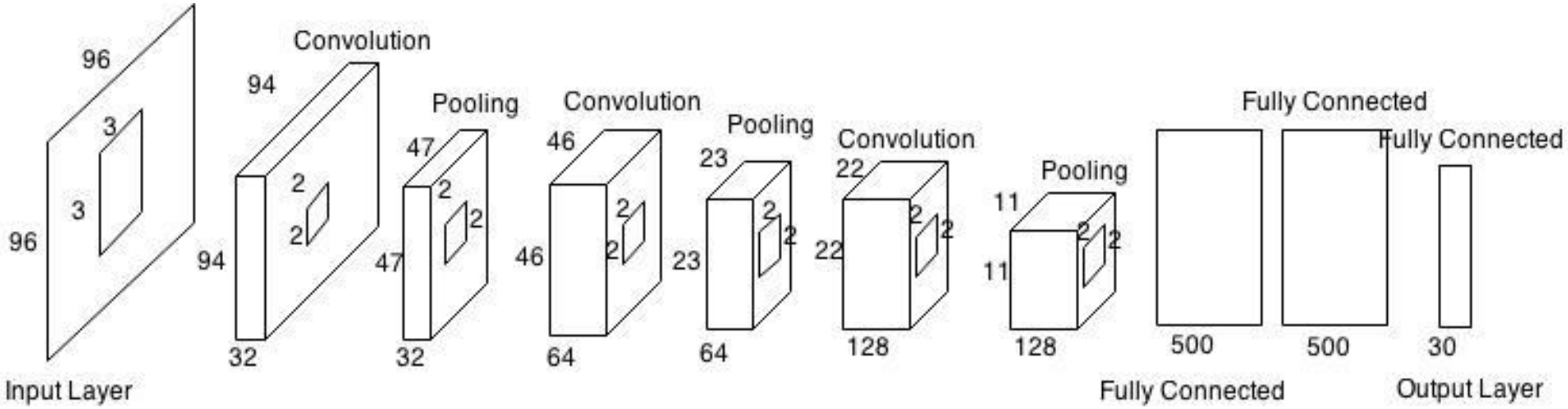
cat:	0.8
dog:	0.2
house:	0.01
car:	0.05
swan:	0.04

CNN Layers in Keras

- Conv2D(filters=16, kernel_size=(3, 3), padding="same",input_shape=(120,120))
  - classic layer
- MaxPooling2D(pool_size=(2, 2))
  - calculate max for given area
  - reduces size
- Dropout(rate=0.25)
  - randomly set rate percent of weights to zero
  - helps to prevent overfitting
- BatchNormalization(axes=-1)
  - normalizes output from the layer

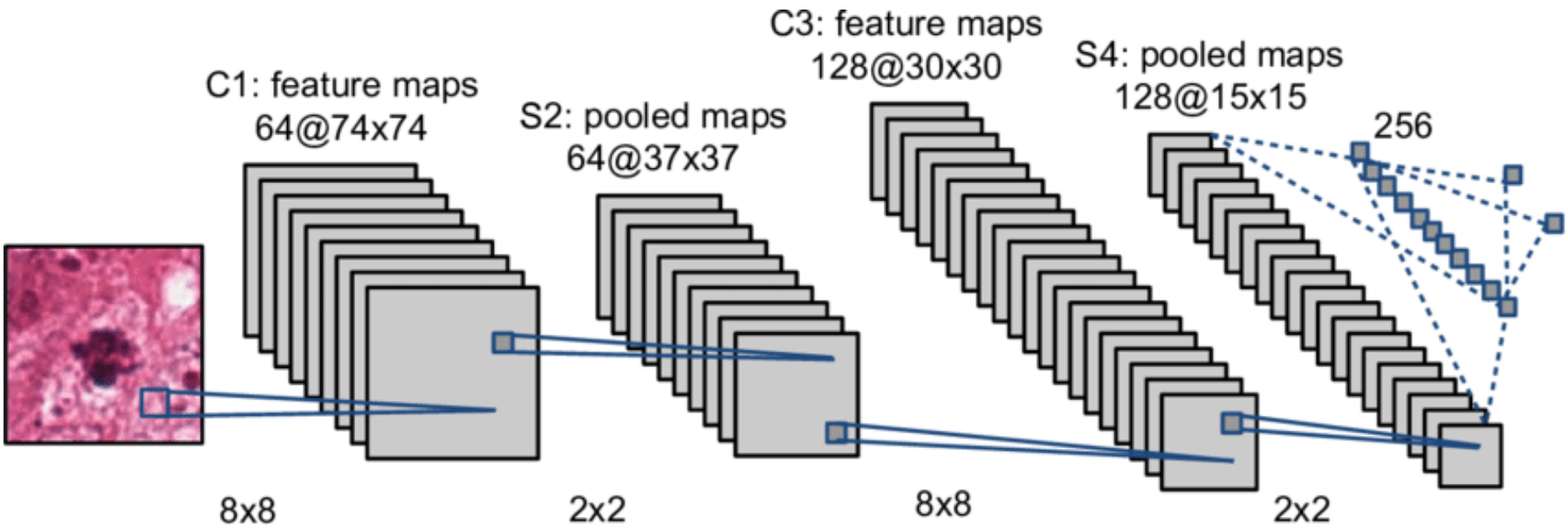
Cascade of layers

- Conv2D>MaxPooling>Conv2D>MaxPooling>Dropout
- Example:



https://www.hackerearth.com/practice/notes/

Another example



https://www.researchgate.net/publication/266734716

Artificial example

- Classification of artificial images
  - black images with white dashes
- Three algorithms:
  - Decision Tree
  - Classic Neural Networks (flat - MLP)
  - Convolutional Neural Network (CNN)
- 200 generated images for each class

Run: *stripes.ipynb*

Flat models

- Each pixel is treated as a separate feature
  - 10.000 features for 100x100 images
- Two applications:
  - Classic Decision Tree algorithm

```
model = sklearn.tree.DecisionTreeClassifier()
```

  - MLP network

```
model = Sequential()
model.add(Flatten())
model.add(Dense(50, activation='sigmoid'))
model.add(Dense(classes_number, activation='softmax'))
```

Standard CNN Model

- Two parts:
  - Convolutional
    - extracting different image features using filters
  - Dense
    - classic neural network with all layers connected
- Convolutional part:
  - Conv2D > MaxPooling2D > Conv2D > MaxPooling2D > Dropout
- Dense part
  - Flatten > Dense > Dense

CNN architecture

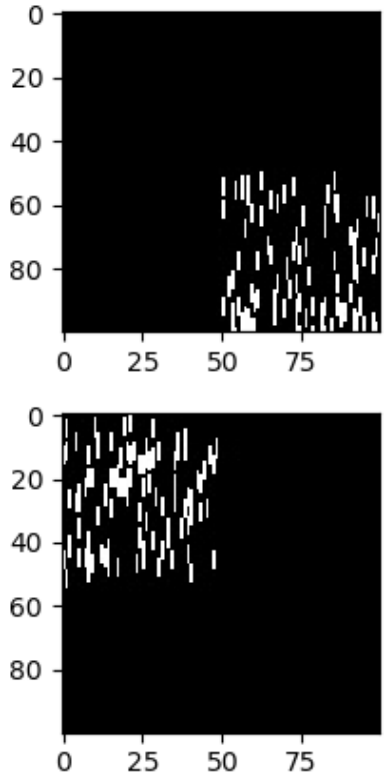
- Convolutional part

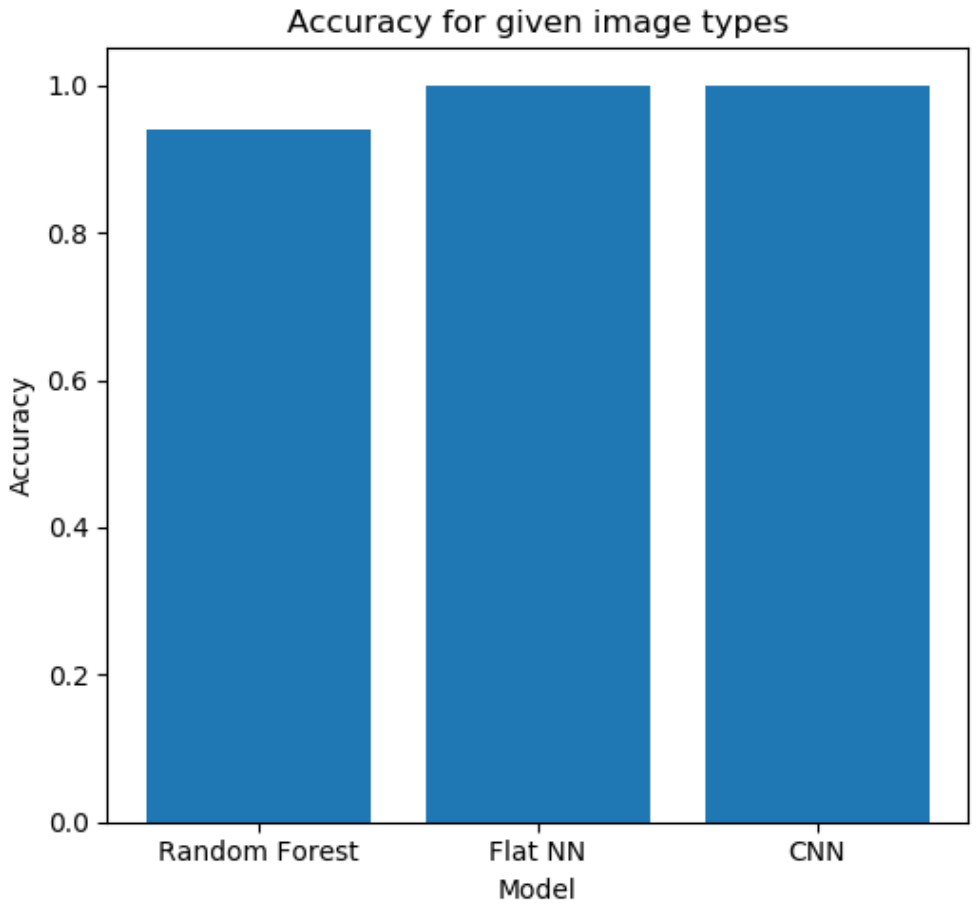
```
model = Sequential()
model.add(Conv2D(16, (3, 3), padding="same", input_shape=inputShape))
model.add(Activation("relu"))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(32, (3, 3), padding="same"))
model.add(Activation("relu"))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
```

- Dense part

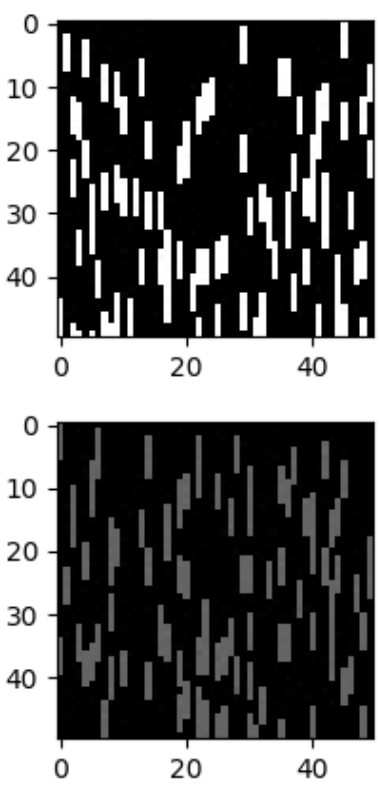
```
model.add(Flatten())
model.add(Dense(512))
model.add(Activation("sigmoid"))
model.add(Dense(512))
model.add(Activation("sigmoid"))
```

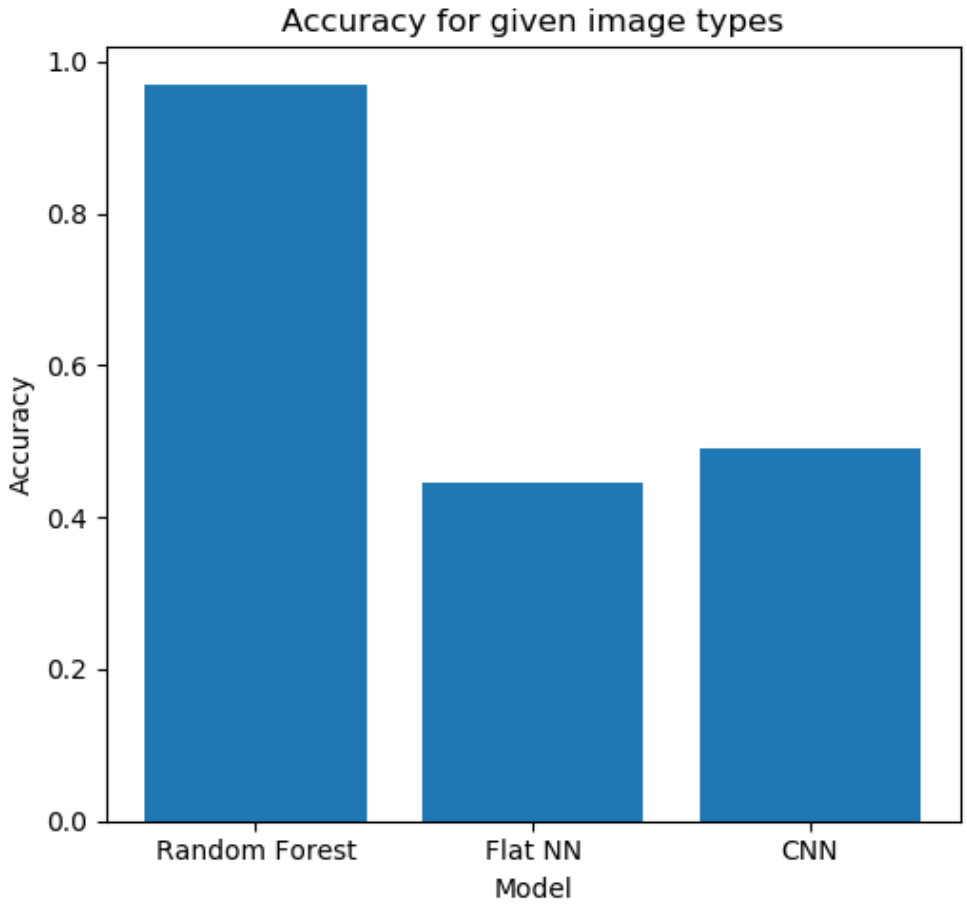
Different areas



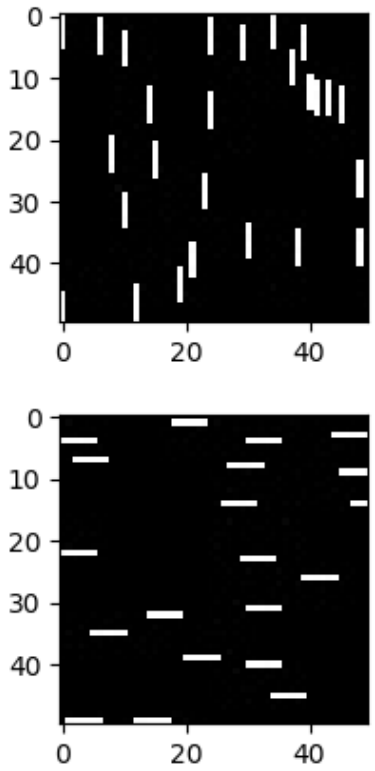


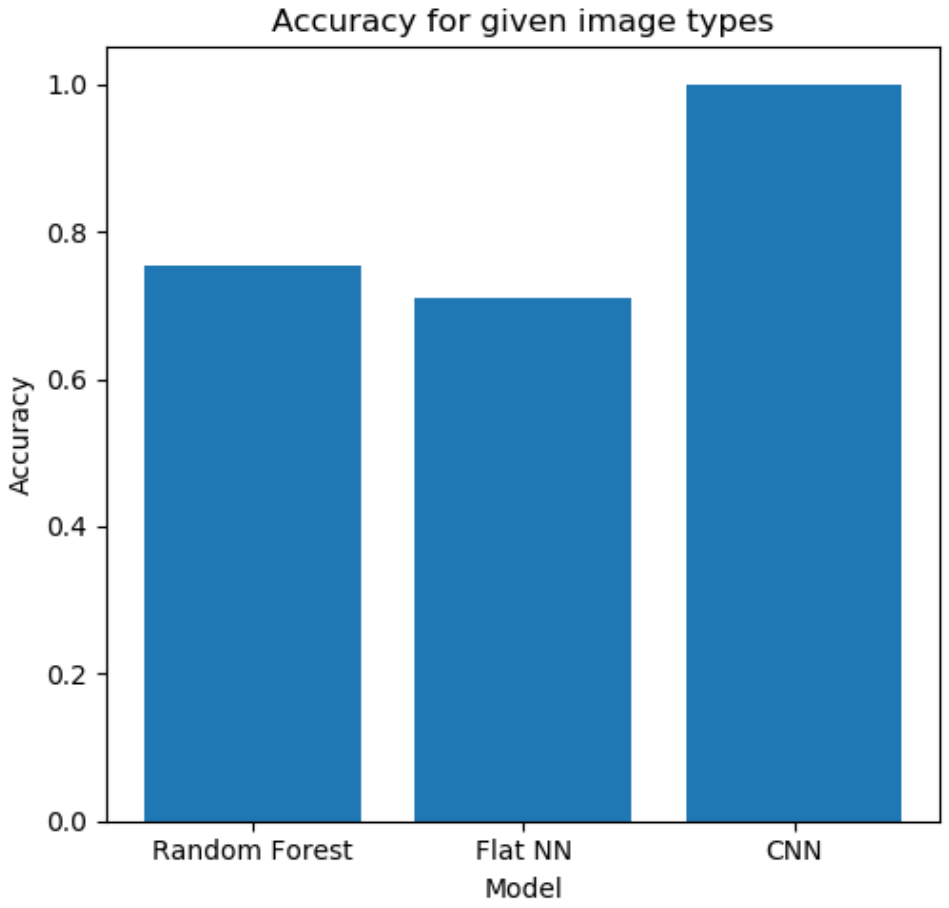
Different intensities/colors





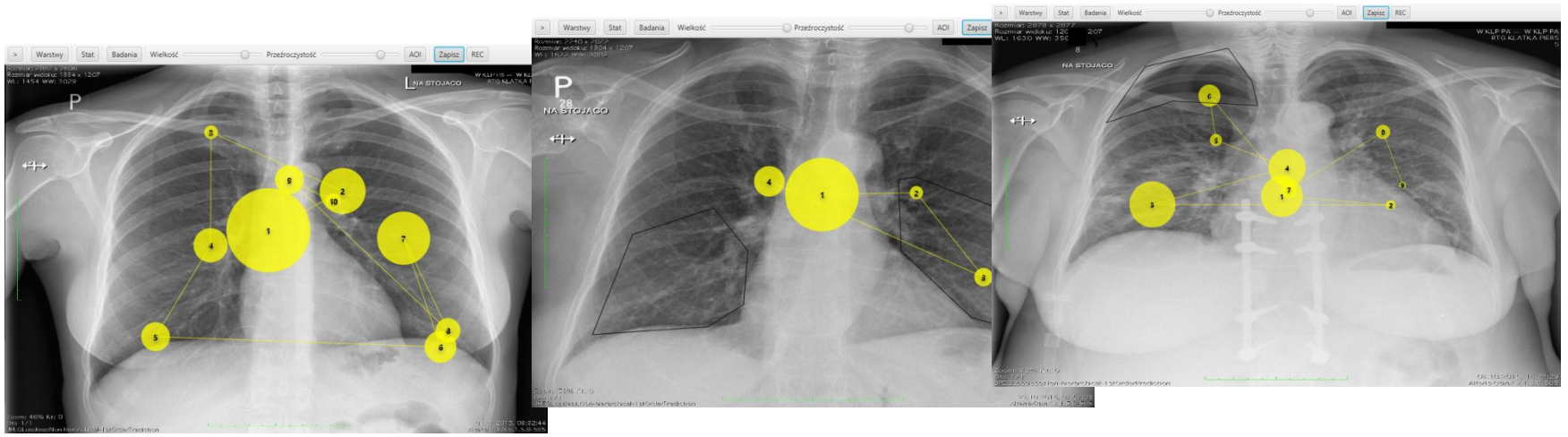
Different direction of dashes





Example for eye tracking

- Specialists, residents and laymen observed the same set of chest radiographs
- Eye movement of a person were registered during each session
- Task: distinguish type of the observer (specialist vs resident vs layman)



Input data [1]

- Text files in tabular format

```
timstamp,smoothx,smoothy,rawx,rawy,fixation
610288046, 913.17, 515.64, 823.76, 475.20, 1
610288063, 913.31, 516.22, 855.16, 492.03, 1
610288079, 913.65, 517.81, 862.49, 508.85, 1
610288096, 913.48, 517.75, 852.26, 477.54, 1
...
```

- 611 samples
- From 200 to 660 readings (rows) per sample

[1] Kasprowski, Harezlak, Kasprowska: Development of diagnostic performance & visual processing in different types of radiological expertise. ETRA 2018

Tree

Run: *radio_tree.ipynb*

- Takes all values (without the timestamp!)
- Pads samples to 700 (filling with zeroes)
- Result:
  - Accuracy approx. 40%
  - Cohen's Kappa approx. 0.07

Conversion to images

- Plot all points from a file on image
- Use GaussianBlur
- Result: a saliency map

CNN Model

- #Convolutional Layer 0
  - model.add(Conv2D(16, (3, 3), padding="same",input_shape=inputShape))
  - model.add(Activation("relu"))
  - model.add(MaxPooling2D(pool_size=(2, 2)))
- #Convolutional Layer 1
  - model.add(Conv2D(32, (3, 3), padding="same",input_shape=inputShape))
  - model.add(Activation("relu"))
  - model.add(MaxPooling2D(pool_size=(2, 2)))
- #Convolutional Layer 2
  - model.add(Conv2D(64, (3, 3), padding="same",input_shape=inputShape))
  - model.add(Activation("relu"))
  - model.add(MaxPooling2D(pool_size=(2, 2)))
  - model.add(Dropout(0.25))
- #Dense Layer
  - model.add(Flatten())
  - model.add(Dense(512))
  - model.add(Activation("sigmoid"))
  - model.add(Dense(256))
  - model.add(Activation("sigmoid"))
- #Final classifier
  - model.add(Dense(numClasses))
  - model.add(Activation("softmax"))

CNN

Run: *radio_cnn.ipynb*

- CNN network using images
  - Accuracy approx. 70%
  - Cohen's Kappa approx. 0.5

Callbacks

- It is possible to add a callback to the fit() function
  - executed for every epoch
- Examples:
  - History – remembers metrics for every step
  - ModelCheckpoint – saves model after step
  - EarlyStopping – stops training when no progress
  - RemoteMonitor – sends results in POST requests
  - LambdaCallback – call to your own function

ModelCheckpoint callback

- The callback that saves the models to files:

```
checkpt = ModelCheckpoint (
    filepath='model.{epoch:02d}-{val_loss:.2f}.h5',
    save_best_only=True)
```

- Using the callback:

```
model.fit(..., callbacks = [checkpt],...)
```

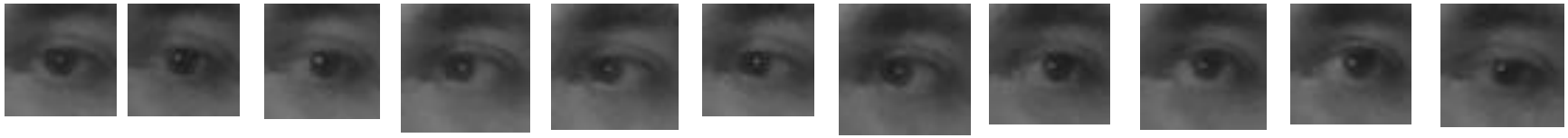
EarlyStopping callback

- The callback that stops training when for 3 consecutive epochs the val_loss doesn't decrease

```
chkpt = EarlyStopping(monitor='val_loss', patience=3)
```

Regression example

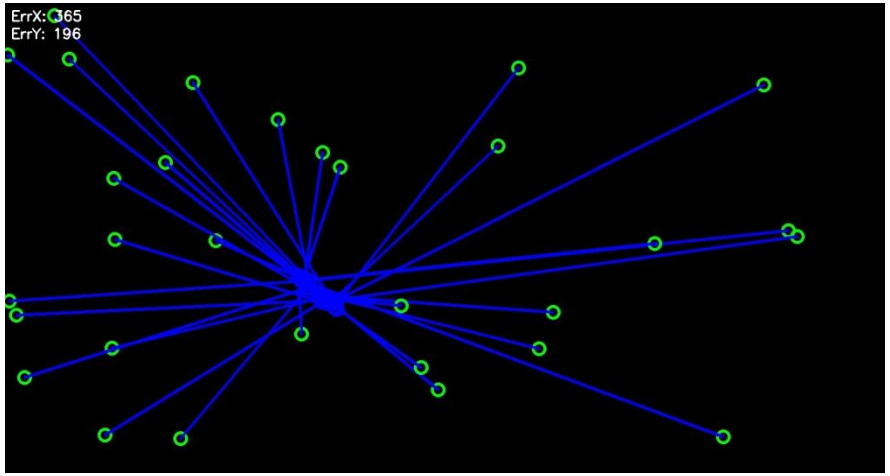
- Input: low resolution eye images
- Output: gaze location (x,y)

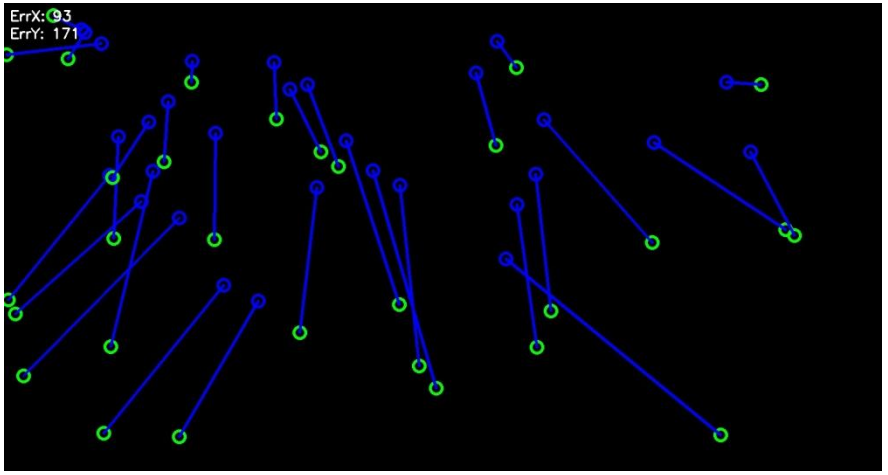


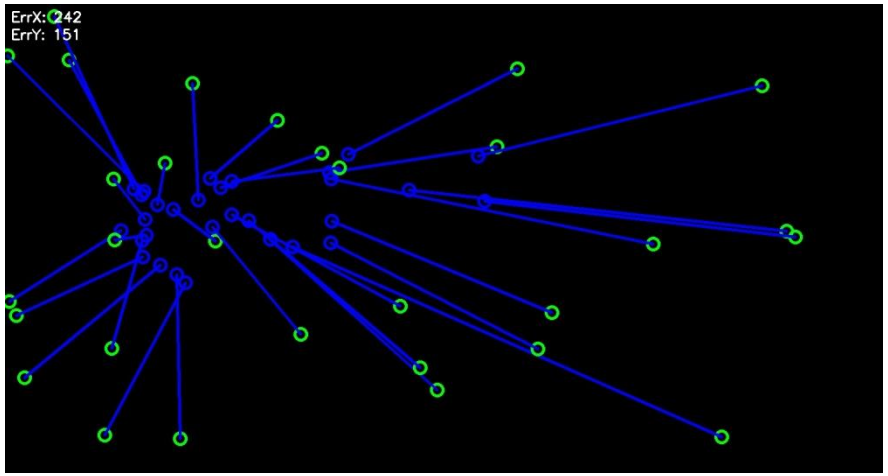
- Solution:
  - CNN model returning two values: (x,y) gaze coordinates

Run: *eye_to_gaze.ipynb*

Training the model







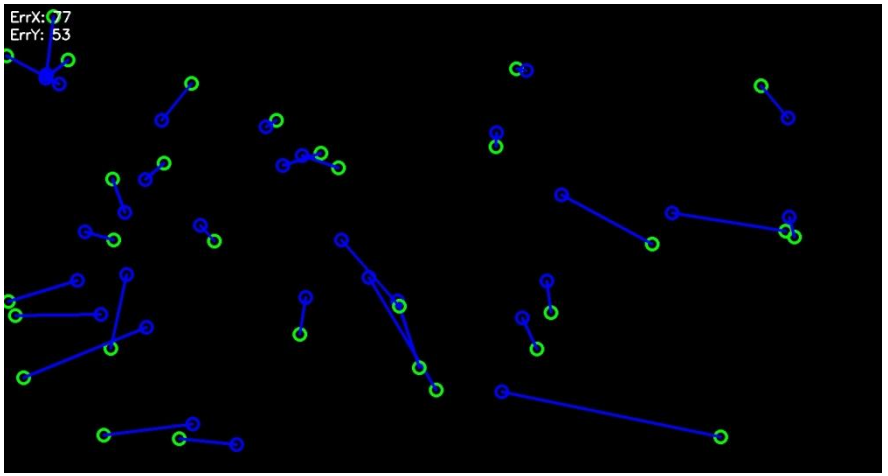
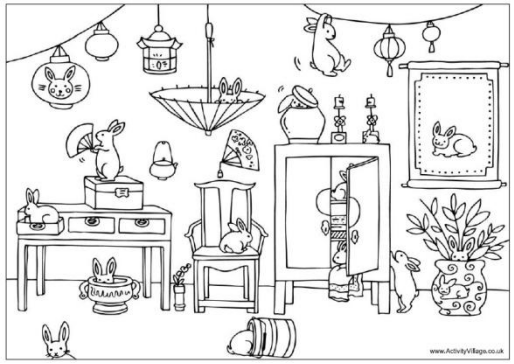


Image prediction example [1]

- Four images, 18 observations of each image
- Task: predict image observed from eye movements

Na kolejnym obrazku policz ile widzisz króliczków.
Zapamiętaj ten wynik, bo będzie potrzebny!
Na koniec zostaniesz zapytany o ich liczbę.



[1] Kasprowski, Harezlak: Gaze Self-Similarity Plot-A New Visualization Technique. *Journal of Eye Movement Research*. 2017

Using Conv1D

- Ready-to-use Keras layer
  - gets 2D samples instead of 3D images
- Our samples:
  - chunks od 100 recordings, two values (X, Y) for each
- Our labels:
  - one-hot encoded four images: bus, cat, txt, rab
- Our model:
  - stack of Conv1D layers

Example code

Run: *paths.ipynb*

- Code using DecisionTree (with flattened samples):
  - Accuracy: 0.41, Kappa: 0.10
- CNN code:
  - almost perfect after 10 iterations!
- Note aside:
  - the experiment is not quite fair: sequences from the same file may be used in training and test set!
- But: It shows that when the same pattern repeats in data (even in different locations) CNN deals with it perfectly (and DecisionTrees does not...)

Summary

- CNNs are really powerful but it is sometimes difficult to build your own architecture that works
- So, using a ready and working architecture may be useful
- There are ready to use networks implemented in Keras
- These networks are also pretrained!

Ready to use pretrained models

- Xception
- VGG16
- VGG19
- ResNet, ResNetV2, ResNeXt
- InceptionV3
- InceptionResNetV2
- MobileNet
- MobileNetV2
- DenseNet
- NASNet

Usage of pretrained networks

- Loading is simple:
  - model = ResNet50(weights='imagenet')
- The weights may be updated for our problem
  - typically we need to update only a few top layers (trainable=False for all other)
    - for CNNs it is commonly only the "flat" part of the network
- Most architectures are quite deep
- Most are optimized to categorize images

Using a pretrained model

Run: *test_eye_model.ipynb*

- The script
  - loads and prepares eye images
  - loads the pretrained model "model_XXX.h5"
  - uses the model to find gaze coordinates (X,Y)
- The model was trained using more images and gives better results!

Sequence

- What if my samples come in a sequence and the result (label) should depend not only on the corresponding sample but on the samples previous in the sequence?
- The answer is:

  Recurrent Neural Network (RNN)

Recurrent Neural Networks

The network that remembers...

Problem statement

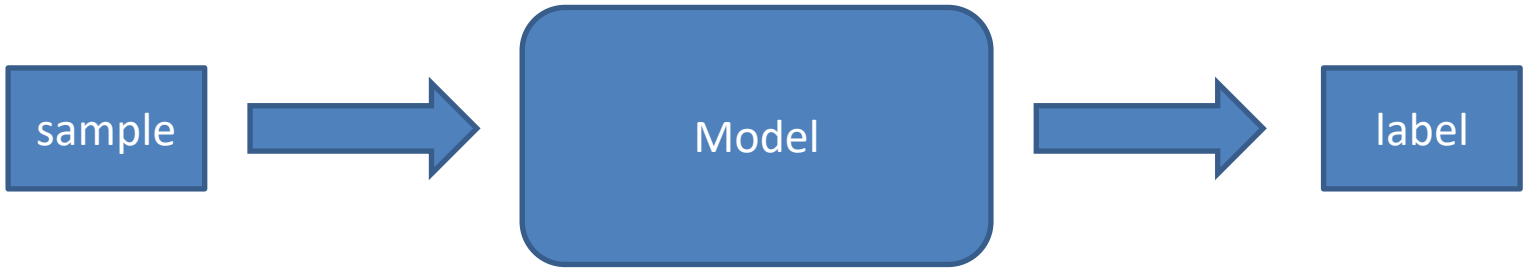
- Till now we created models (functions) that map (convert) a sample to a label
  - sample -> label
- Set of samples was converted to a set of labels
  - each sample was treated independently and the model produced one label for each sample
- There are applications were there is a sequence of samples which should be converted to a sequence of labels
  - label value depends not only on one sample but also on previous samples (and previous labels!)

Conventional NN

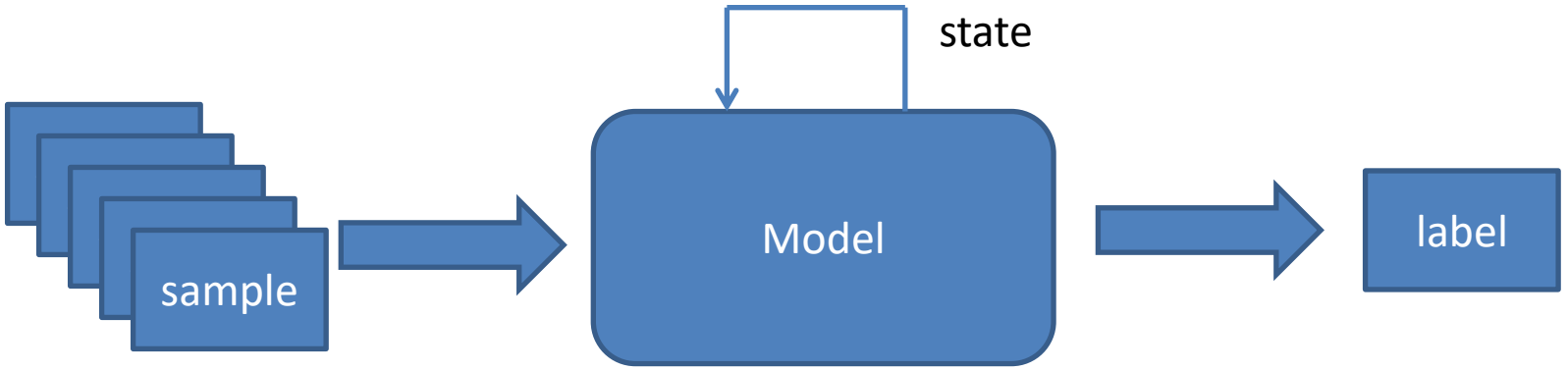
- Conventional NN
  - sample -> MODEL -> label
- Recurrent NN
  - sequence of samples -> MODEL -> label (or sequence of labels)
- MODEL has state (memory)!
  - current output depends on previous samples and outputs
- Instead of $Y_t = f(X_t)$, now we have:
  - $Y_t = f(X_t, X_{t-1}, X_{t-2}, ..., Y_{t-1}, Y_{t-2}, ...)$

Recurrent NN

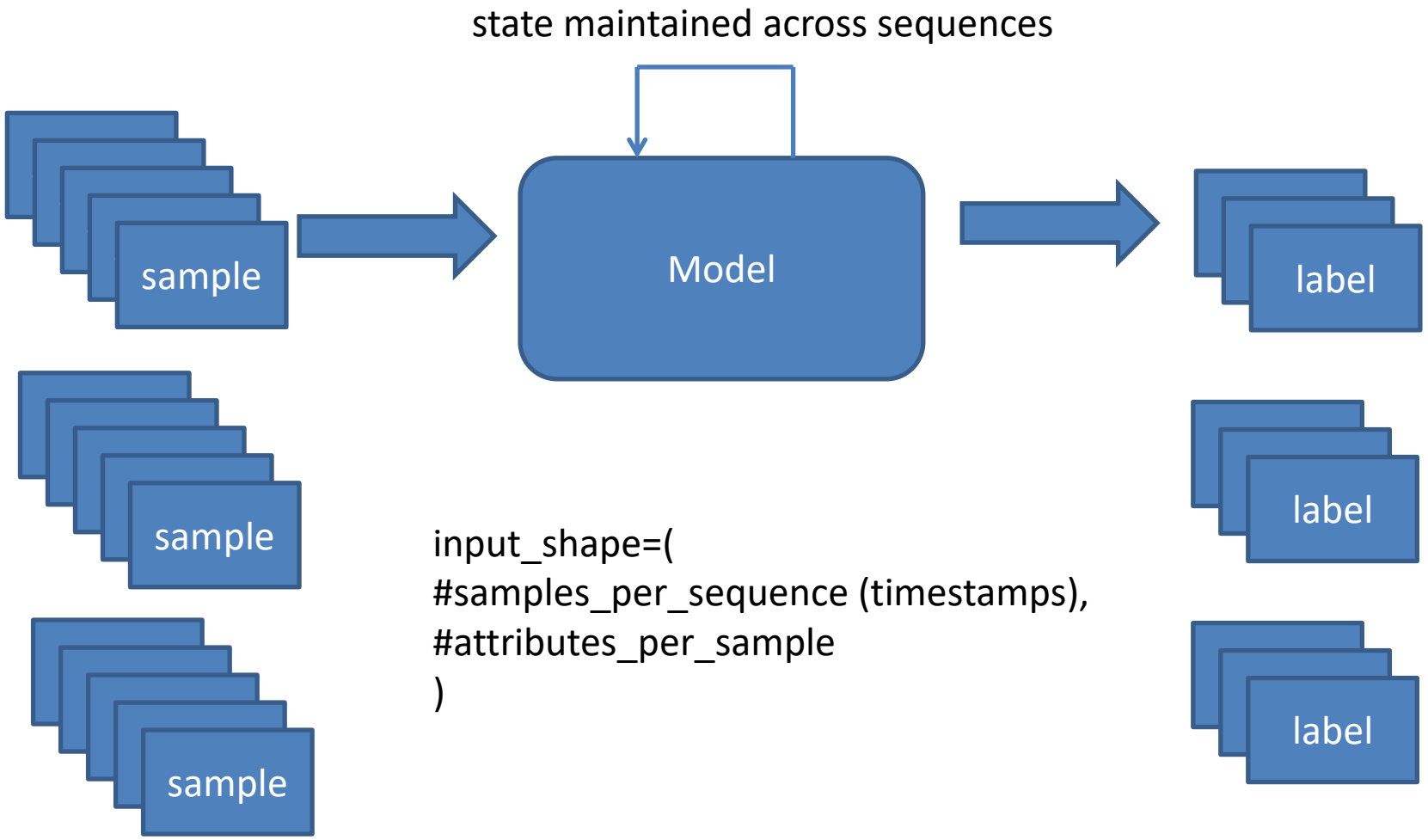
- Classic NN



- Recurrent NN



Full RNN


state maintained across sequences
sample
sample
sample
Model
label
label
label
input_shape=(
#samples_per_sequence (timestamps),
#attributes_per_sample
)

Applications

- Image -> text description
  - seq_in=1, seq_out=10
- English sentence (words) -> Polish sentence
  - seq_in=20, seq_out=20
- Text (sequence of words) -> next word
  - seq_in=10, seq_out=1

RNN layers in Keras

- Layers with memory!
- RNN
- SimpleRNN
- GRU (Gated Recurrent Unit)
  - additional gate
- LSTM (Long Short-Term Memory Layer)
  - even more gates (input, output, forget)
- ConvLSTM2D

LSTM layer main parameters

- units – number of units (output size)
- input_shape=(timestamps, attributes)
  - timestamps = the number of samples in sequence
  - attribute = the number of attributes per sample
- return_sequences
  - False – return only the last state Y_t
  - True – return all states $Y_1 ... Y_t$ - output becomes a matrix of size: (units,timestamps)
- stateful
  - False – reset state after each batch
  - True – maintain state until model.reset_states() called

Sequence to value

digits2numbers.ipynb After 1000 iterations:error <1

- Sequence of digits to number
- Input: sequence of digits [1,3,4] <- shape (B,3,1)
- Output: one value: 134 < shape (B,1)
- Model:

```
model = Sequential()
model.add(LSTM(128,input_shape=(3,1)))
model.add(Dense(1))
model.compile(loss='mean_absolute_error',
    optimizer="adam",metrics=['mae'])
```

Value to sequence

numbers2digits.ipynb

- Number to sequence of digits
- Input: one value: 134 < shape (B,1)
- Output: sequence of digits [1,3,4] <- shape (B,3,1)
- Problem: output from the network is float
  - Every digit must be encoded to one-hot
  - 10 digits [0123456789]
  - label: [1,3,4] is converted to:
  - [[0100000000],[0001000000],[0000100000]]
- Every label has shape: (3,10)

Value to sequence

- Input: one value
- Output: matrix (3,10)
- Model

After 2000 iterations:
almost 80% correct digits,
almost 40% correct numbers

```
model = Sequential()
model.add(Dense(16, input_dim=1) )
model.add(RepeatVector(3)) #sequence length
model.add(LSTM(128, return_sequences=True))
model.add(LSTM(128, return_sequences=True))
model.add(LSTM(128, return_sequences=True))
model.add(Dense(10,activation='softmax'))
```

More interesting examples

numbers2words.ipynb

- Translates a number into text description (in Polish)
- Model:

```
model = Sequential()
model.add(Dense(16, input_dim=1) )
model.add(RepeatVector(OUTPUT_SEQUENCE_LEN))
model.add(LSTM(128, return_sequences=True))
model.add(LSTM(128, return_sequences=True))
model.add(Dense(33,activation='softmax'))
```

(33 – the number of possible characters)

Data preparation

- Samples: just values (120)
- Labels: sequences of letters ('sto dwadzieścia')
- Max length of the sequence: 30 letters
  - output: (sequence_length, one_hot) => (30,33)
- Results:
  - translates number to word description
  - after 10000 iterations – quite good

Words to number

words2numbers.ipynb

- translates word description into the number

- Model

```
model = Sequential()
model.add(LSTM(128,input_shape=(None,1),
                                    return_sequences=True))
model.add(LSTM(128))
model.add(Dense(1))
```

Analysis

- Preparation
  - Input as text 'sto dwadzieścia'
  - Encode to a list of numbers: [23,20,11,3,7,...]
  - Add a dimension: [[23],[20],[11],[3],[7],...]
  - Add trailing zeroes to have every sequence of the same length (30)
- Feed LSTM with batches of 50 texts
- After 2000 epochs the mean error is lower than 3

RNN for eye movement data

- Example: Creating artificial scanpaths
- Input data [1]:
  - 57 genuine scanpaths recorded during image observation

[1] Skurowski, Kasprowski: Evaluation of Saliency Maps in a Hard Case – Images of Camouflaged Animals Best Paper of 2018 IEEE International Conference on Image Processing, Applications and Systems (IPAS)

Preprocessing

- The model tries to predict gaze coordinates (x,y) based on previous 20 gaze coordinates
- Each scanpath preprocessed to form:
  - sequences – 20 subsequent recordings (x,y)
  - labels – single recording directly after the 20
- 57 scanpaths -> 5757 sequences of length 20 each
- RNN architecture:

```
model = Sequential()
model.add(LSTM(128,input_shape=(20,2)
                                    ,return_sequences=True))
model.add(LSTM(128))
model.add(Dense(64))
model.add(Dense(2))
```

Training

Run: *animals.ipynb*

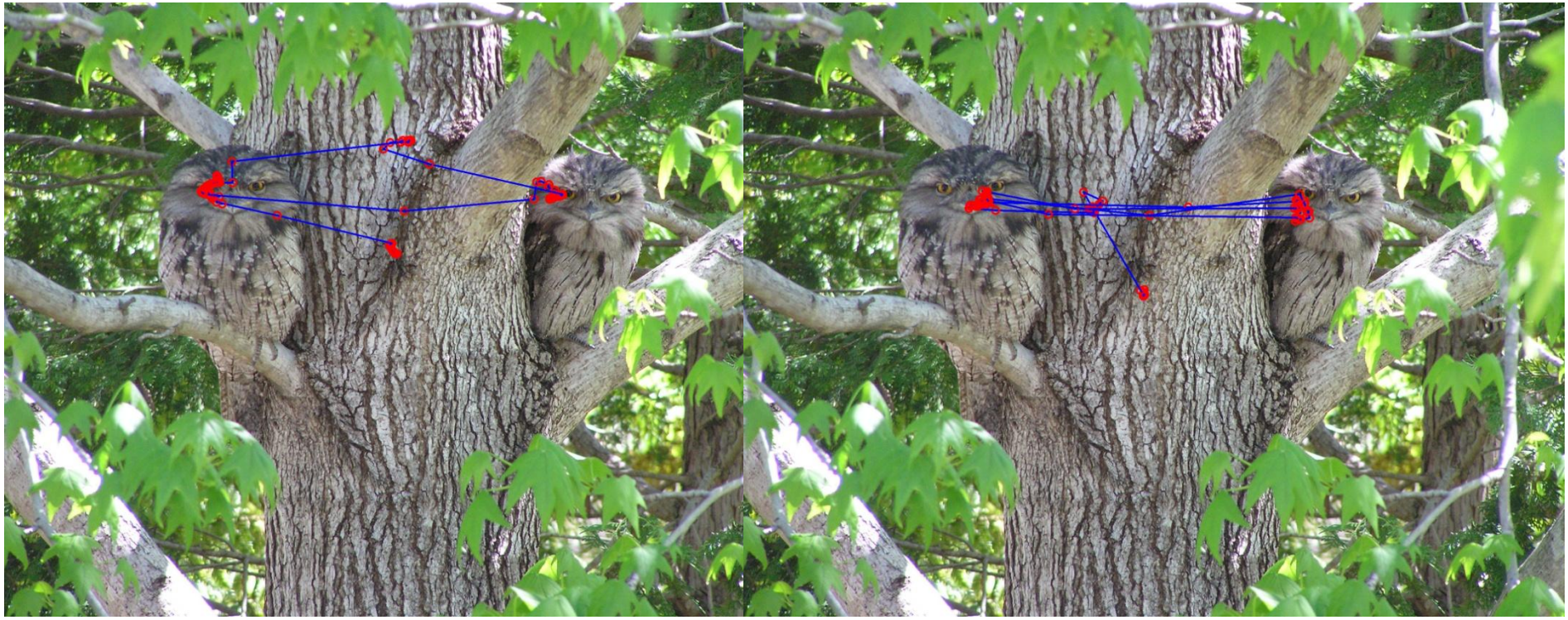
- Loss function: mean absolute error
  - model.compile(loss="mean_absolute_error", optimizer="adam", metrics=["mae"])
- Fitting in subsequent runs (loop)
- After each iteration the image with all predicted gazes is saved in /animals_img folder:
  - animal-11_eNN.jpg
  - where NN is the epoch number
- The final model is saved:
  - model.save(*"model_rnn.h5")*

Using the model

Run: *test_animals.py*

- Loads the model:
  - model = load_model(*"model_rnn.h5")*
- Uses the model to create artificial scanpaths
  - predictions = model.predict(sampleSequence)
- Creates images with scanpaths in /scanpaths folder
  - save_scanpath(sequence, name)

Real vs. generated



It is not possible to tell the difference!

Summary

- Recurrent Neural Networks
  - remember previous state
  - input is present and past (also previous decisions)
- The most popular implementation:
  - Long Short-Term Memory Units (LSTM)
- RNNs proved to be extremaly good at translating and even producing texts
- RNN works much better when the number of possible inputs and outputs is limited
  - there are better methods for time series prediction (for now!)

Conclusion

What you should remember...

Quick recap

- Classification
  - many algorithms and measures, the interpretation of results may be tricky
- Neural Networks
  - easy implementation in Keras, training requires a lot of data
- Convolutional Neural Networks
  - automatically building conv filters using examples, powerful for image classification
- Recurrent Neural Networks
  - ideal for sequences, have memory (state), powerful for text analysis

Final remarks

- It is relatively easy to implement deep learning for your own experiment
  - There are simple plug-in libraries
- The main problems:
  - we need a lot of **labeled** data to train the network
    - it is important to check the quality of data!
  - architecture of the network is very important
    - it is easy to do a mistake with parameters
- The field is very dynamic – new algorithms are created constantly (GANs, hypernetworks, transformers,...)
- Unfortunately frequently we know only that it works but we don't know what is going on inside...

THANK YOU FOR YOUR ATTENTION