Deep Learning
in the
Eye Tracking World

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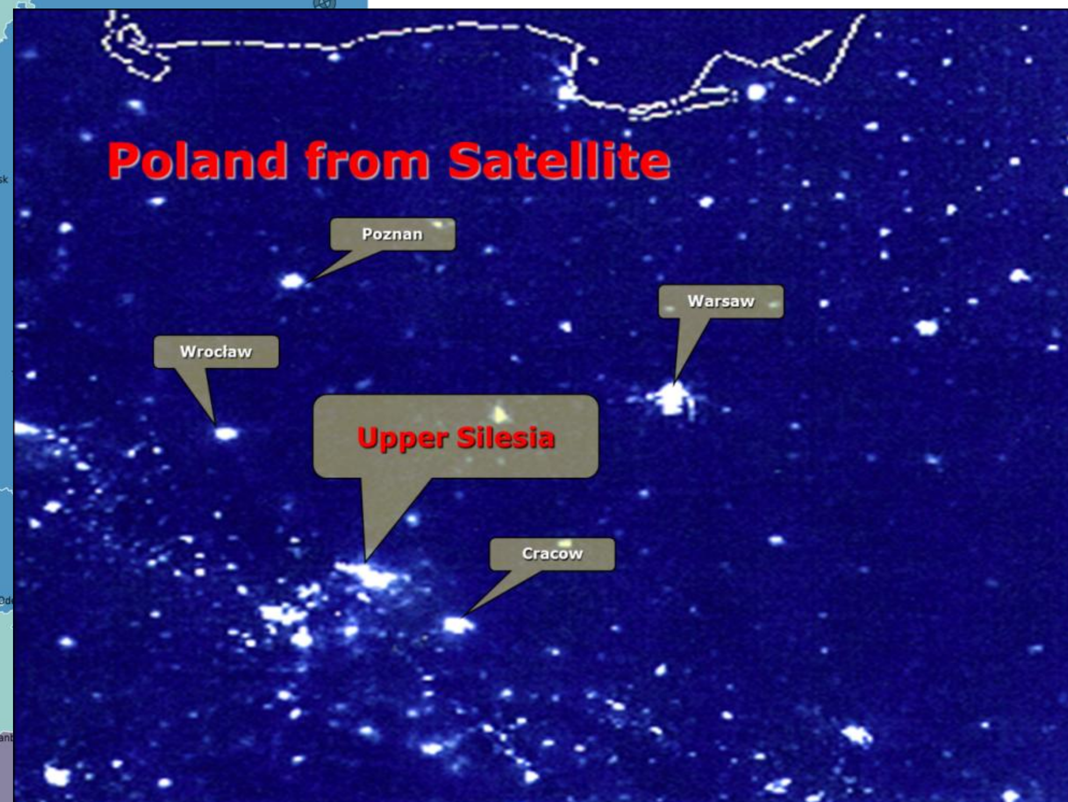
About my home

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



https://wikitravel.org/en/Europe

Upper Silesian Industrial Region

14 cities, population about 3 mln

Politechnika Śląska

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

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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

Tutorial content

- Not so many formulas (only a few)
  - no "gory details" – just the ideas
- Very simple examples (max 100 lines of code)
  - just the working code (in Python/Keras)
- Simple datasets to show that it works (hopefully)

- *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 Python 3.x (64 bit)
  - add to path (installer gives this option)
- Install prerequisites:
  - pip install -r http://www.kasprowski.pl/tutorial/requirements.txt
- Download and unzip the tutorial code from

  http://www.kasprowski.pl/tutorial/code.zip
- or just use git (if you have it installed):

  git clone https://github.com/kasprowski/tutorial2019

Requirements

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

Code disclaimers

- Python is not my native language...
- 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

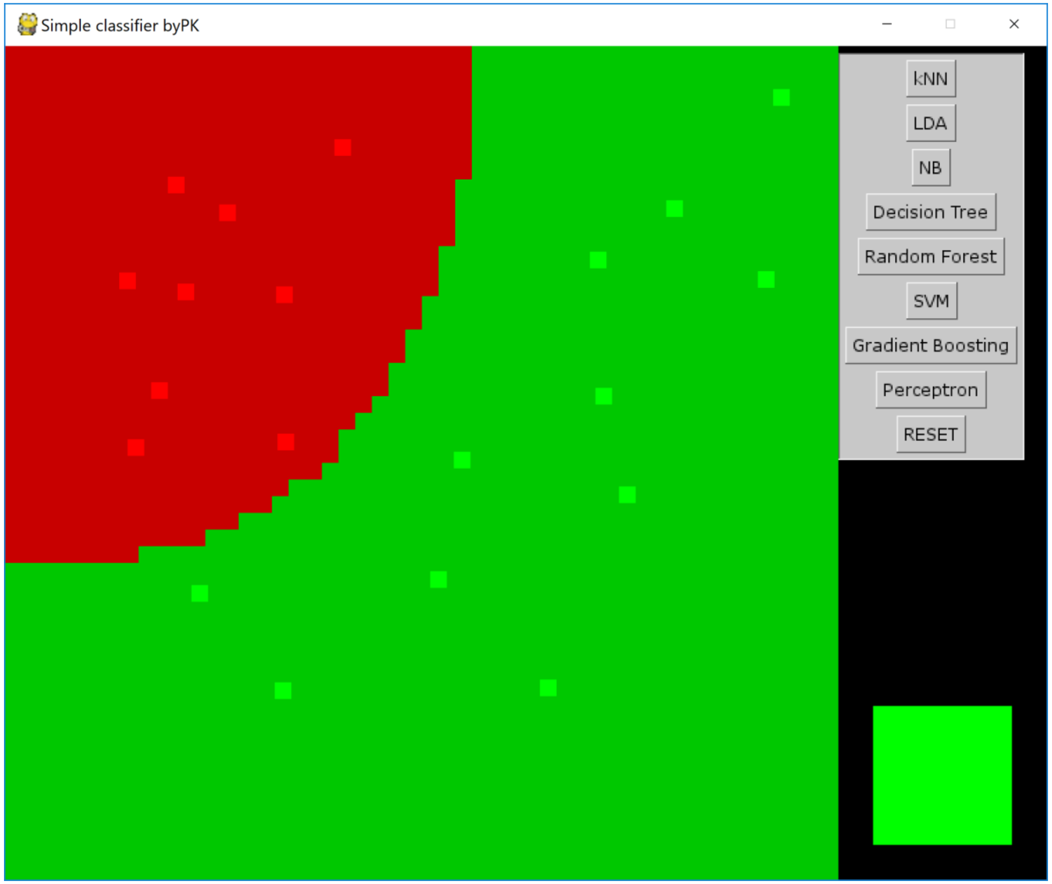
- K-Nearest Neighbors (kNN)
  - a new sample is classified as majority of its K nearest neighboring examples
- Linear Discriminant Analysis (LDA)
  - finds a linear equation separating positive and negative samples
- Naive Bayes
  - the class of a new sample is calculated based on examples using Bayes 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: *classifier/main.py*



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

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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

Example: Linear Regression

- Given a training set of pairs (X,Y) find coefficients of a linear function

$$y = a * x + b$$

- Error function Mean Squared Error

$$E = \frac{1}{n}\sum_{i}^{n}(y_i - \hat{y}_i)^2 = \frac{1}{n}\sum_{i}^{n}(y_i - (ax_i + b))^2$$

- Goal: minimize this function

Linear Regression using Gradient Descent

- Gradient Descent algorithm:

  initialize randomly a and b

  repeat:

  calculate error

  change a and b in such way that error is smaller

  until error is small enough or it is not decreasing

- Question: how to find the direction of change for ***a*** and ***b***?

Gradient Descent

- Gradient dE/da – a function describing how ***E*** changes when ***a*** changes

$$\frac{\delta E}{\delta a} = \frac{-2}{n}\sum_{i}^{n}(\hat{y}_i - y_i)x_i$$

- Gradient dE/db - function describing how ***E*** changes when ***b*** changes

$$\frac{\delta E}{\delta b} = \frac{-2}{n}\sum_{i}^{n}(\hat{y}_i - y_i)$$

Gradient Descent algorithm

- for each step (iteration)
  - calculate error E
  - calculate gradients dE/da and dE/db
  - a = a - learning rate * dE/da
  - b = b - learning rate * dE/db
- Every iteration gives better values of a and b
  - error (**loss**) is smaller
- Learning rate controls how fast the parameters are updated
  - too fast – we may pass the minimum
  - too slow – we may wait forever

Analytical solution

- For linear regression the best parameters may be calculated using equations:

$$a = \frac{\sum_i^N (x_i - \bar{x})(y_i - \bar{y})}{\sum_i^N (x_i - \bar{x})^2}$$

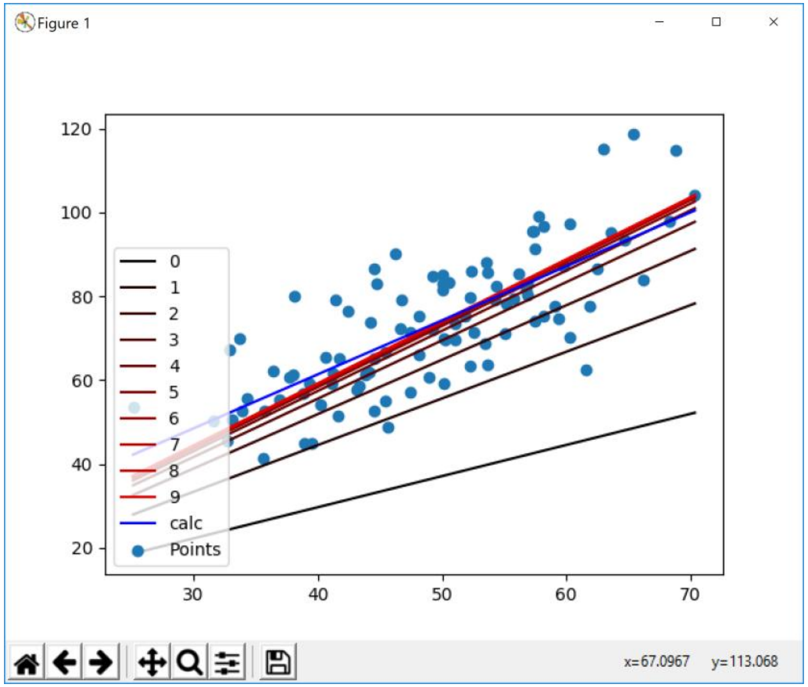
$$b = \bar{y} - a\bar{x}$$

- but the presented example shows how Gradient Descent algorithm works (and we will use this algorithm later!)

Example

Run: *linear/linear_descent.py*

- Simple code calculating linear regression using gradient descent for a set of points



Observations

- If we change initial values of a and b we have different results
  - b is reluctant to change
  - kind of "vanishing gradient" problem
- (1) Change the learning rate for b:
  - nb = b - L*100 * D_b # Update b
- (2) Change the number of iterations
  - epochs = 100 (1000?)
- The results are better!

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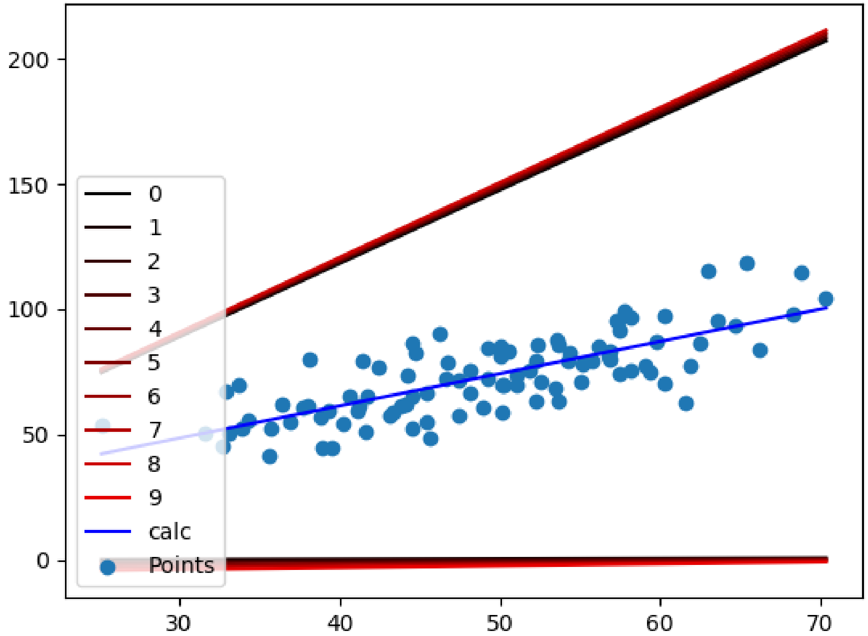
Learning rate

- Change to:
  - L = 0.0004 # The learning rate
- Results jump over the solution
  - too big step!



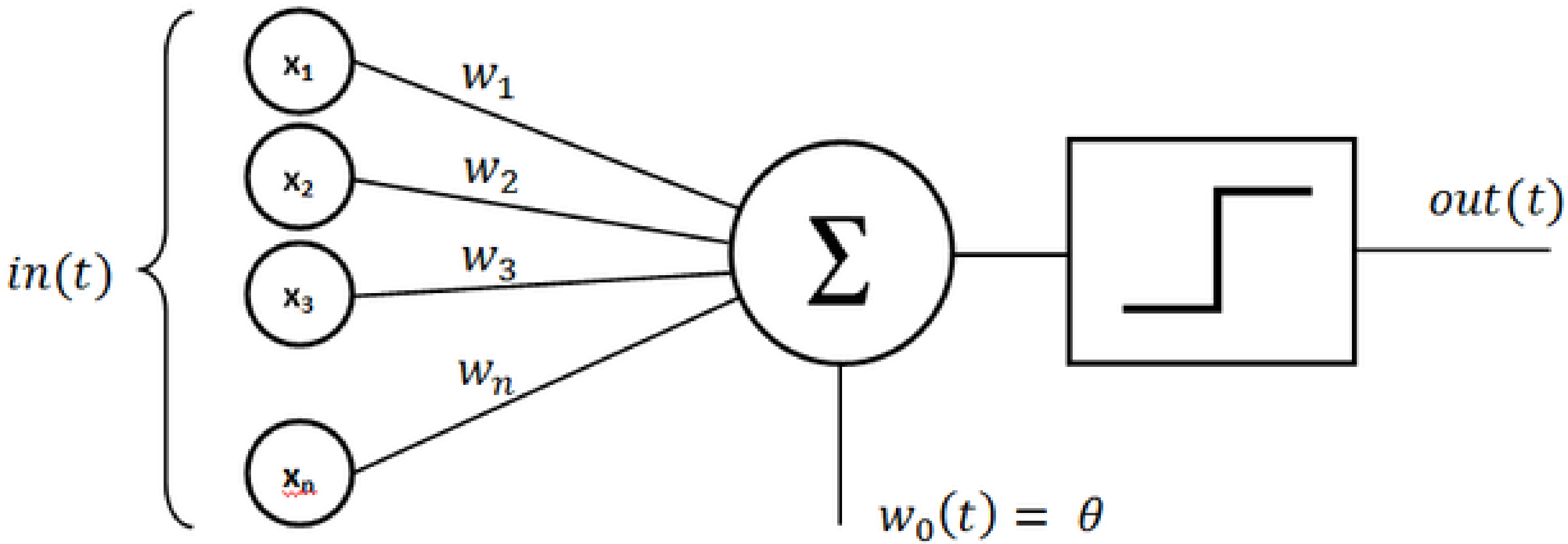
Summary

- 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)

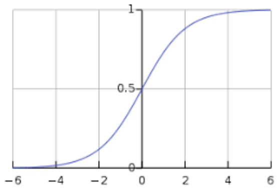
Perceptron (Rosenblatt 1957)

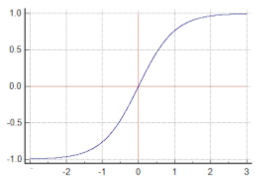


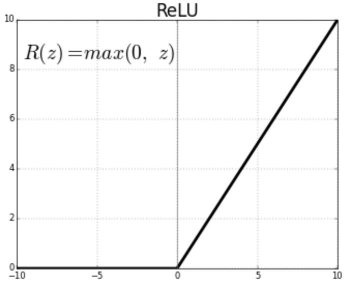
https://pl.wikipedia.org/wiki/Perceptron

The simplest form

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

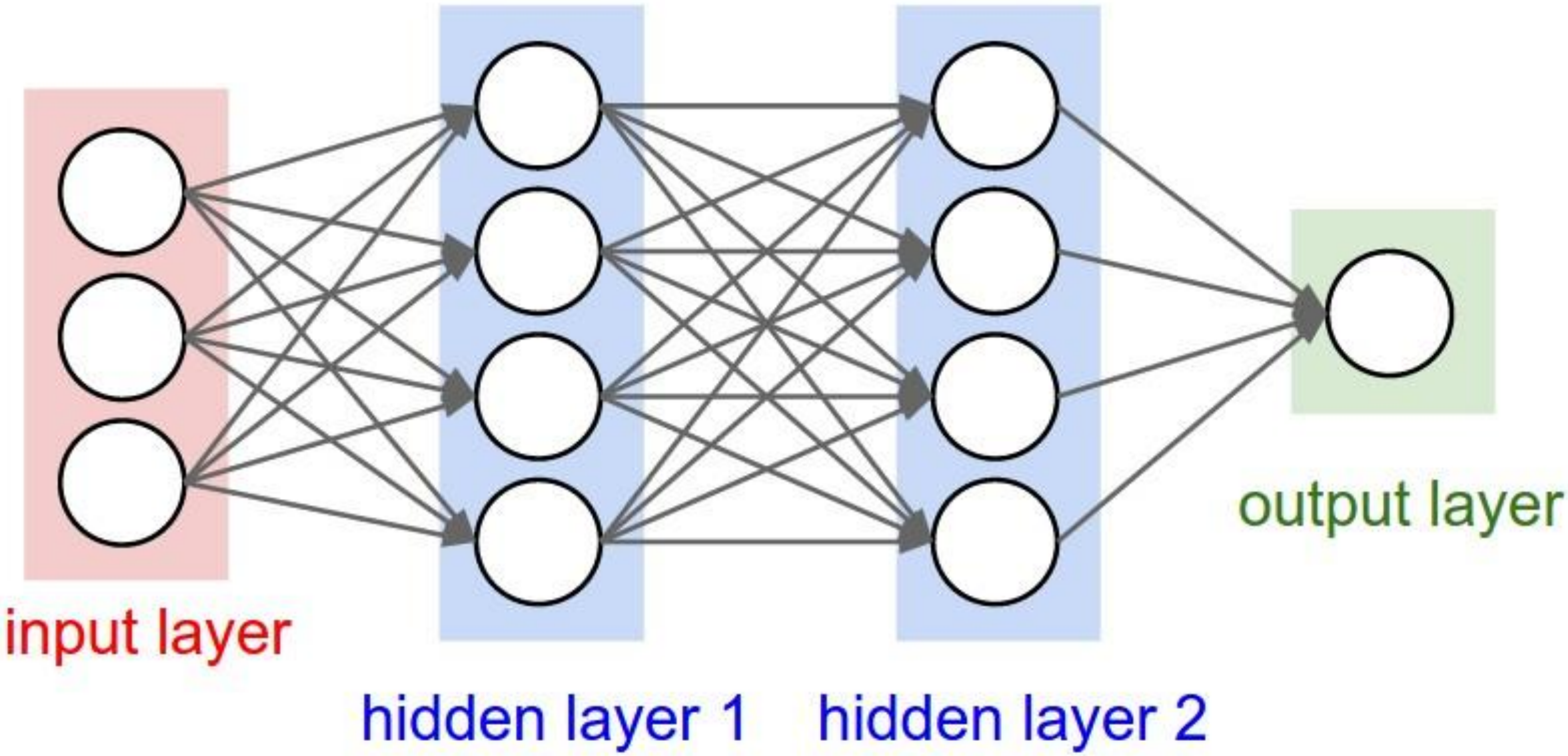






Neural Network

- 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 already mentioned 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

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

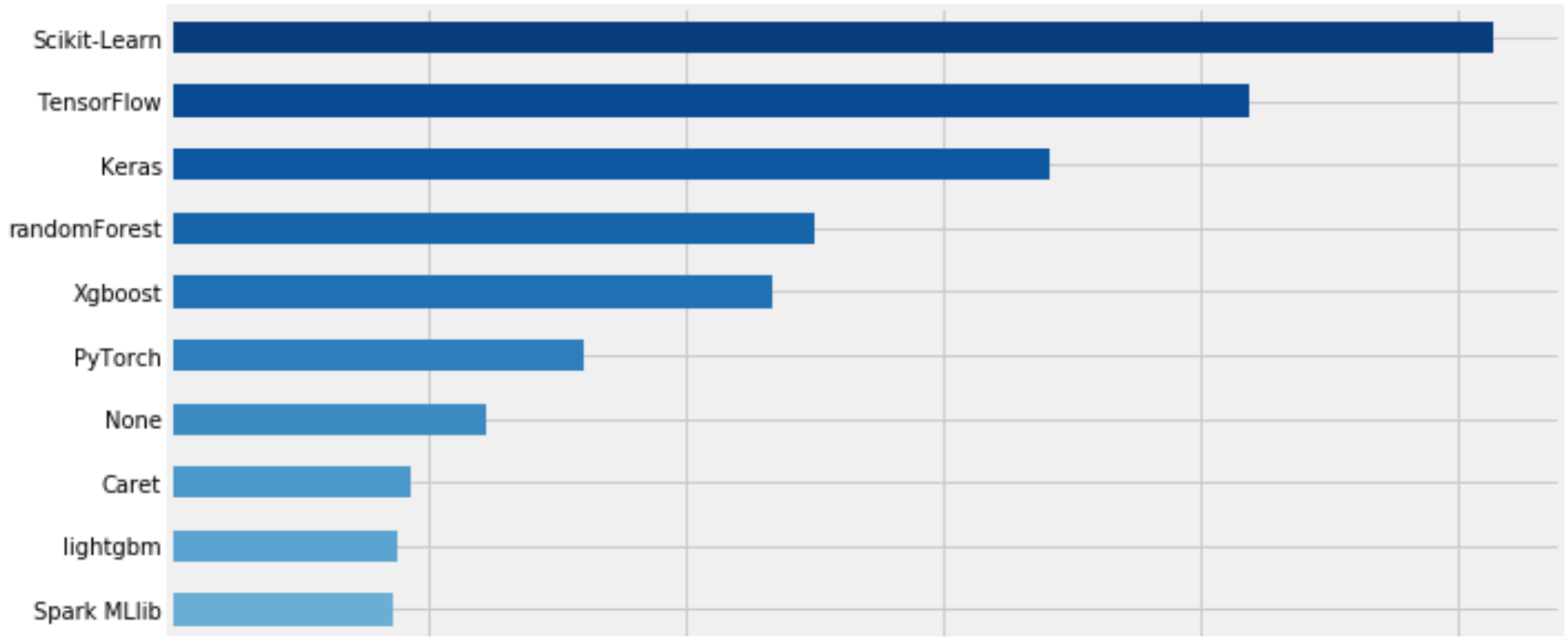
- Many classification libraries like scikit-learn or WEKA implement the neural networks
  – but only the simplest models
- For Deep Learning there are many libraries developed by leading companies:
  – Tensorflow, Google
  – PyTorch, Facebook
  – CNTK, Microsoft
  – ...
- We will use the simplest to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

Keras

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

Kaggle 2018 survey

- What machine learning frameworks have you used in the past 5 years?



https://www.kaggle.com/antgoldbloom/2018-kaggle-survey-eda-platforms-tools-and-more

KDNuggets 2018 poll

- Increase in usage 2017-2018

Table 2: Major Analytics/Data Science/ML Tools with the largest increase in usage

Tool	% change	2018 % share	2017 % share
Keras	108%	22.2%	10.7%
PyTorch	92%	6.4%	3.4%
Amazon Machine Learning	74%	3.3%	1.9%
RapidMiner	65%	52.7%	31.9%
Other free analytics/data mining tools	53%	8.3%	5.4%
DeepLearning4J	39%	3.4%	2.4%
Anaconda	37%	33.4%	24.3%
PyCharm	33%	13.5%	10.1%
Tensorflow	32%	29.9%	22.7%
Excel	24%	39.1%	31.5%
Tableau	21%	26.4%	21.8%

https://www.kdnuggets.com/2018/05/poll-tools-analytics-data-science-machine-learning-results.html

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

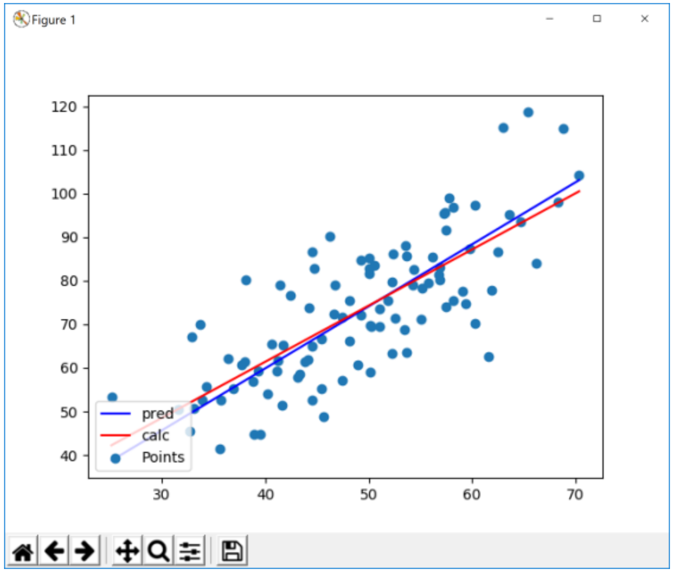
The simplest example

```
# import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
# build model
model = Sequential()
model.add(Dense(1, 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)
```

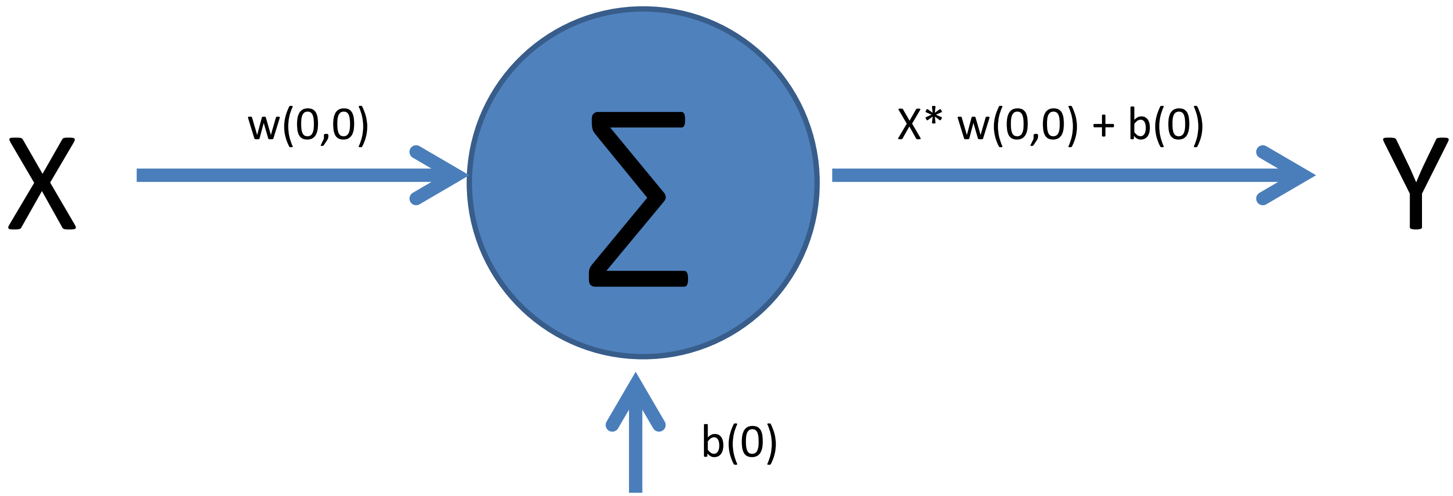
Backprop example

Run: *linear / linear_keras.py*

- Linear regression using back prop
- One input, one output
- Two weights: w_{00} and b_0 (as a and b)



Our VERY simple network...



Model architecture

- Add a hidden layer

```
model = Sequential()
model.add(Dense(50, input_dim=2))
model.add(Dense(1, activation='sigmoid'))
```

- Add a nonlinear activation

```
model = Sequential()
model.add(Dense(50, input_dim=2, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
```

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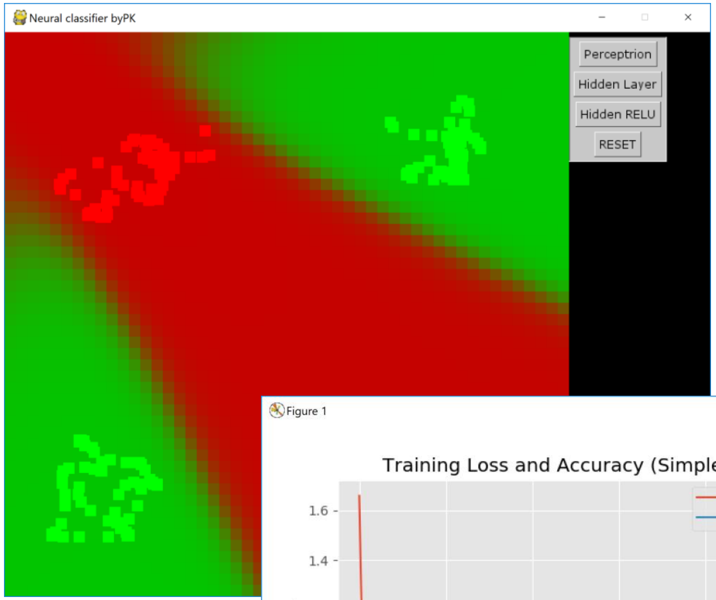
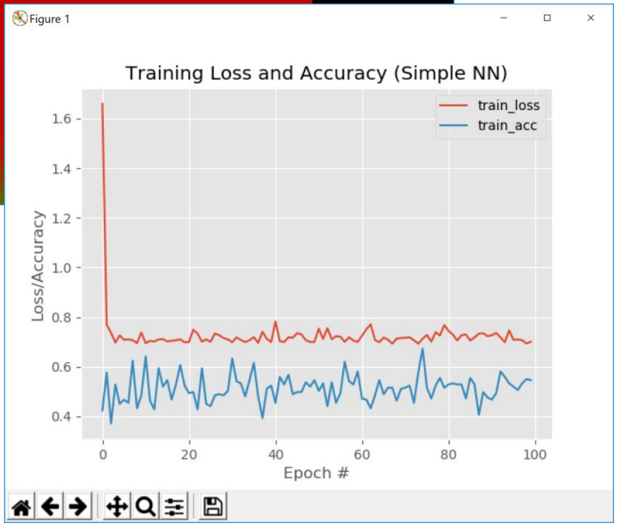
Example

Run: *neural/main.py*

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



- Plot:
  - number of iterations
  - change of loss and accuracy



model.compile parameters

- loss – loss function
  - *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

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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
- Part of EMVIC 2012[1] dataset:
  - 155 samples
  - 3 classes (persons)
  - 16384 attributes (position-vel-acc)
- unbalanced distribution
  - {'a25': 104, 'a41': 39, 'a37': 11}

[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[:,1:]
labels = dataset[:,0]
```

- Preparing – "one hot" encoding

```
lb = LabelBinarizer()
labels = lb.fit_transform(labels)
classesNum= labels.shape[1]
```

The model

Run: *mlp/main.py*

- Simple MLP model:

```
model = Sequential()
model.add(Dense(250, activation='sigmoid'))
model.add(Dense(250, activation='sigmoid'))
model.add(Dense(250, activation='sigmoid'))
model.add(Dense(classesNum, activation='softmax'))
model.compile(loss= 'categorical_crossentropy',
    optimizer="adam", metrics=['accuracy'])
```

Training, testing, reporting

- Training:

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

- Testing:

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

- Reporting (using methods from sklearn):

```
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

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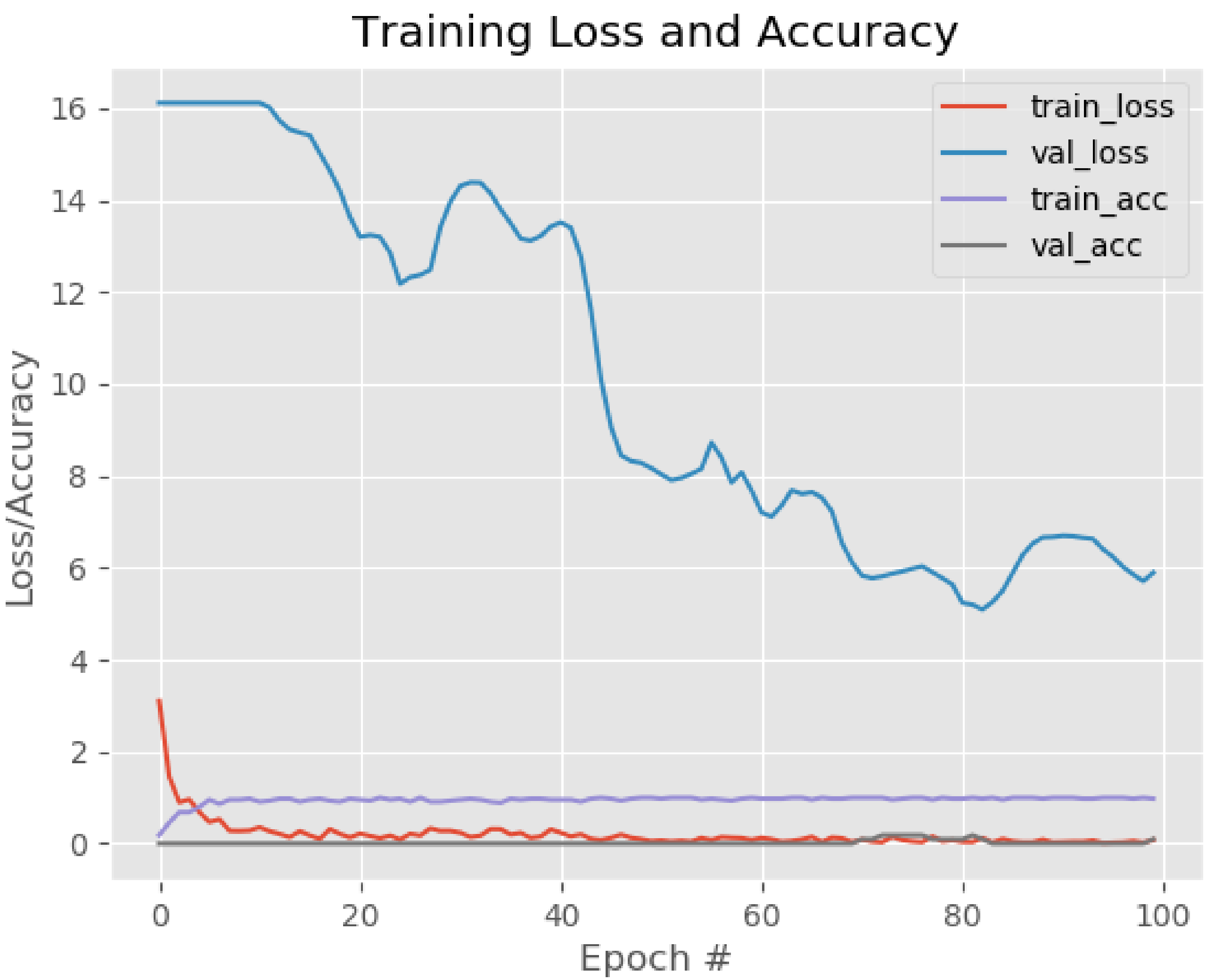
It may be worse...



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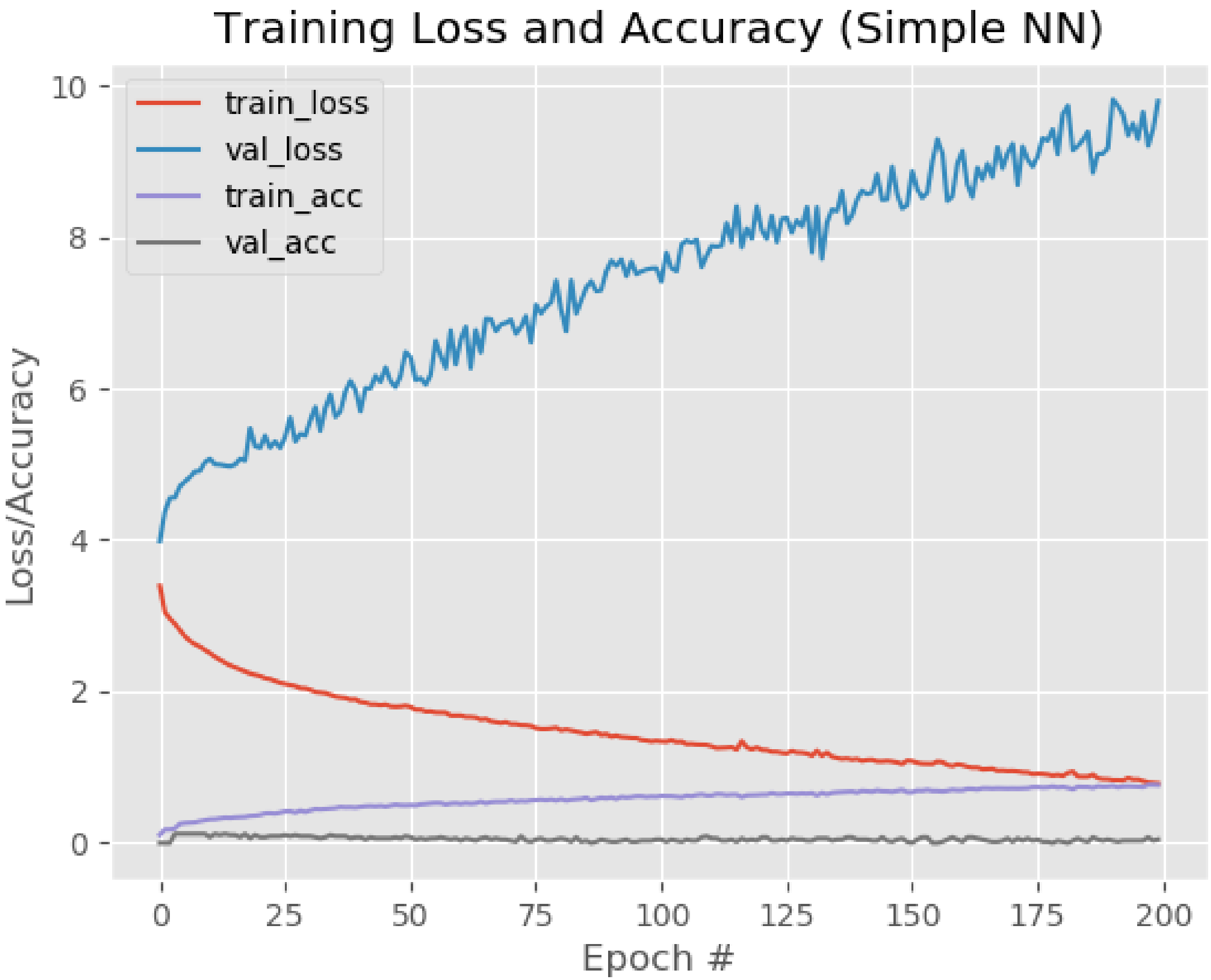
It may be worse...

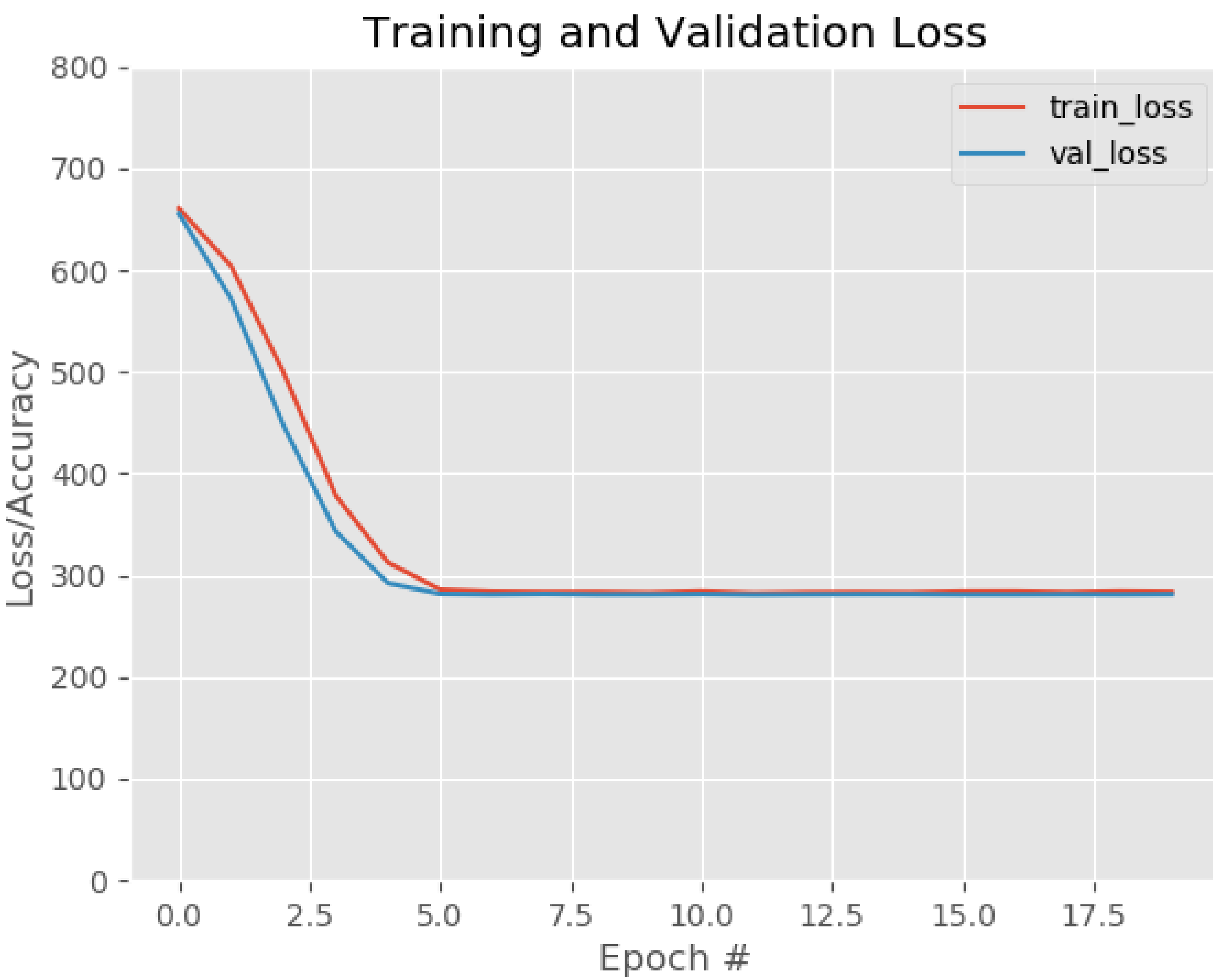
It may be worse...

It may be even worse...

It may be even worse...



Sometimes even loss is not decreasing...



So ,this is quite OK

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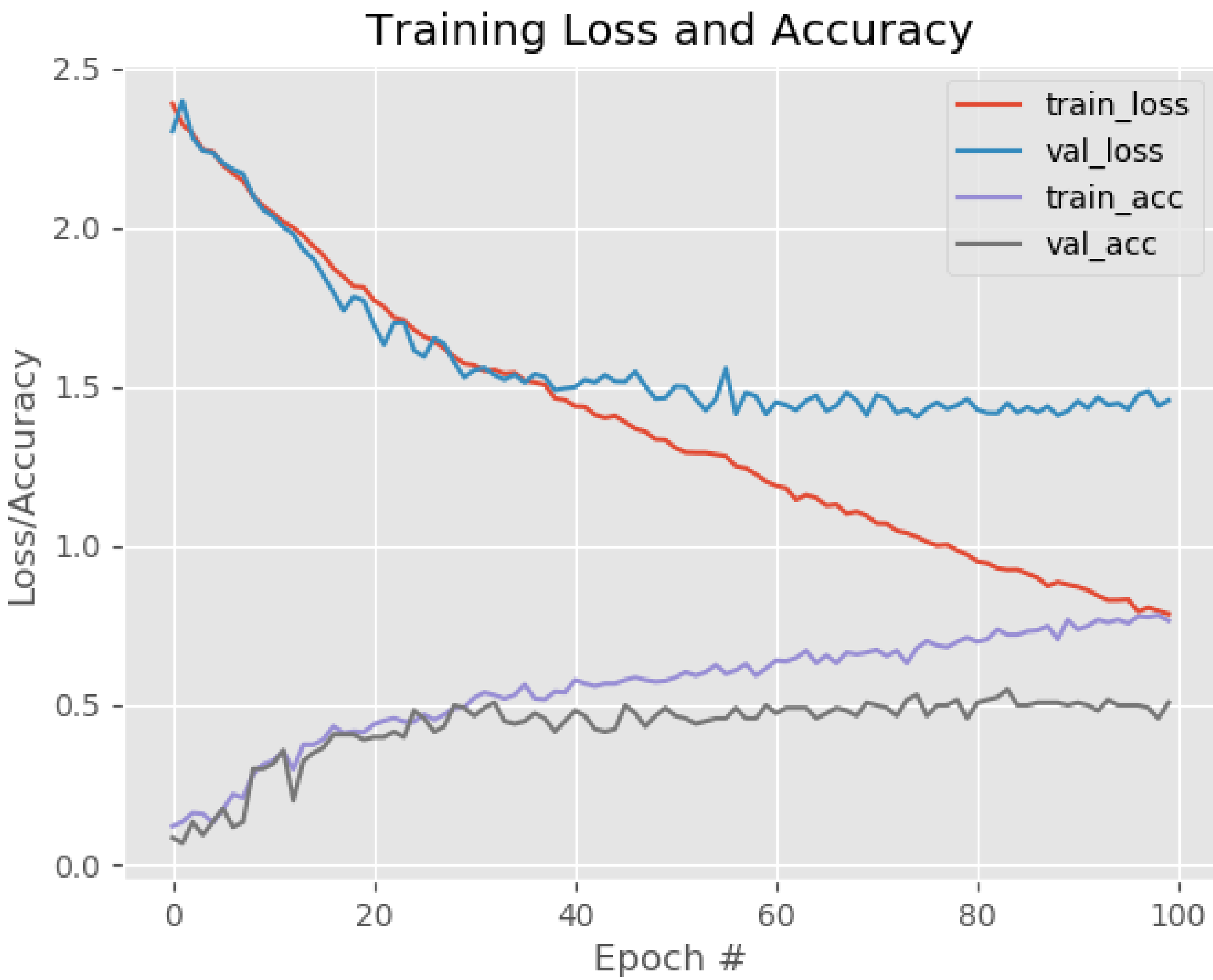
This is worse



pawel@kasprowski.pl

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

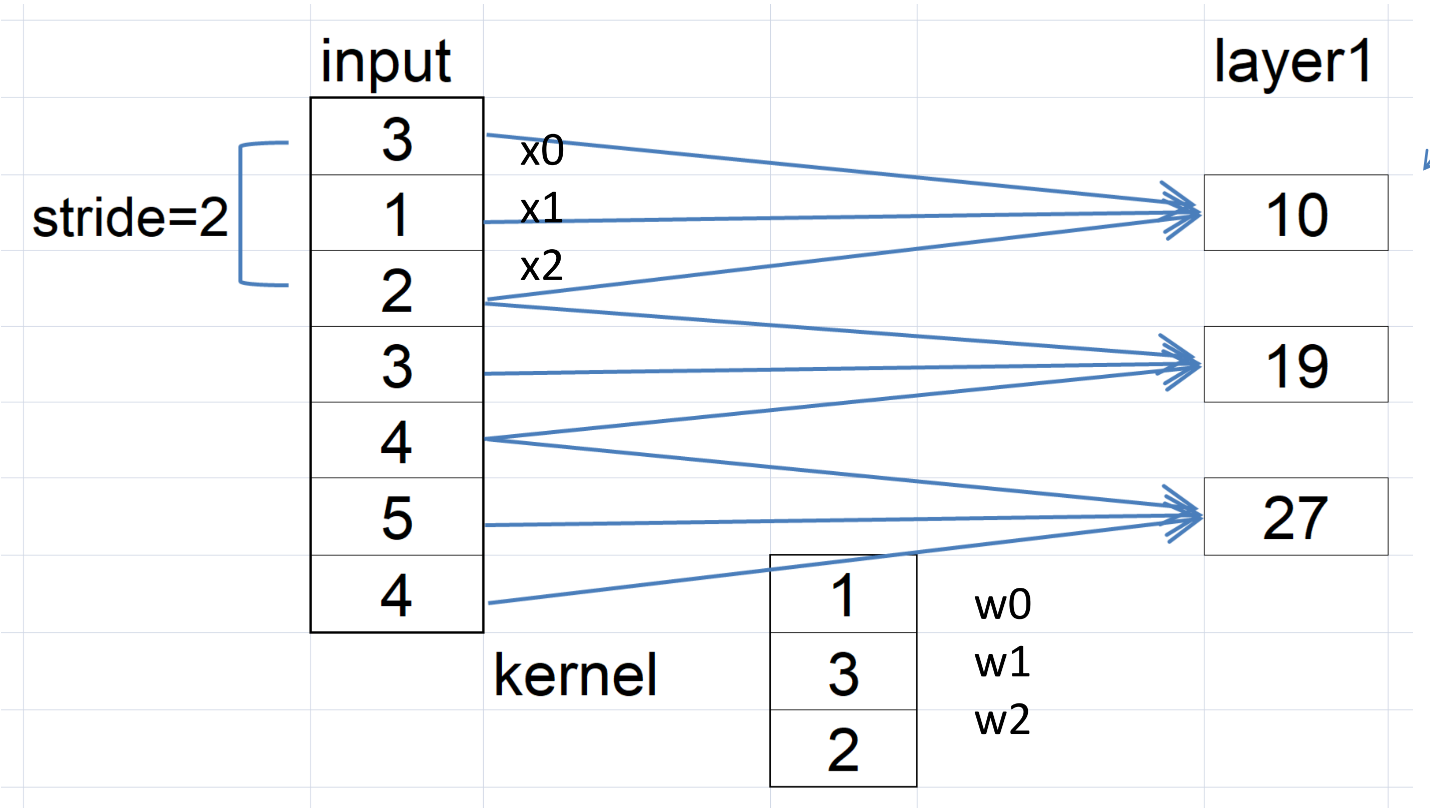
- 1982 – Kunihiko Fukushima, Neocognitron
  - pattern recognition
- 1989 – Yann LeCunn, LeNet-5
- 2010 – ImageNet Competition
  - 1000 classes, over million of images
- 2012 – Alex Krirzevsky, AlexNet
  - 15% error rate for ImageNet (runner-up: 26%)
  - 8 layers
- 2015 – Deep Residual Nets wins ImageNet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

Why now?

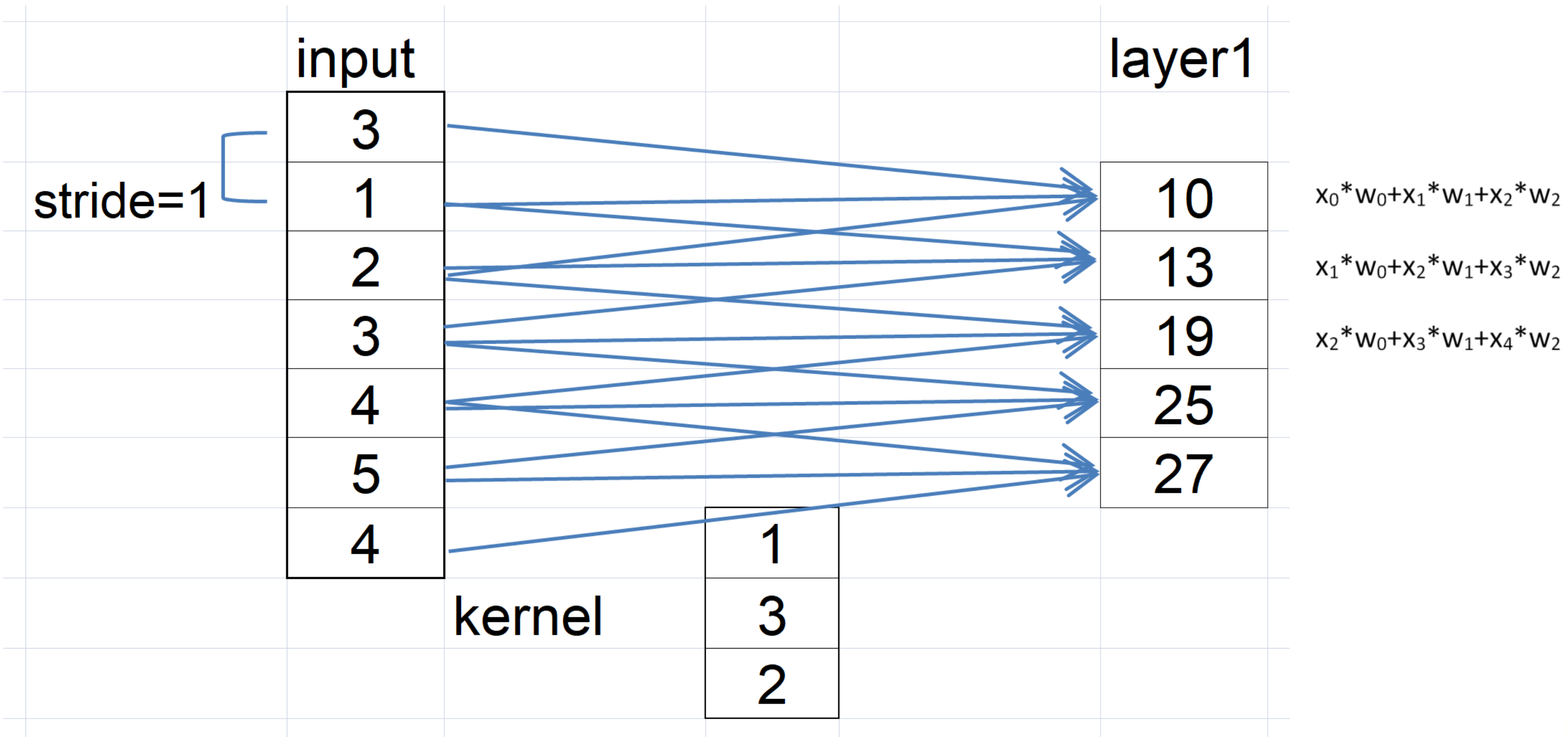
- Neural Network training and predicting involves a lot of calculations
  - Only new computers are capable to calculate it in reasonable time (esp. with CUDA/GPU)
- Neural Network training requires a lot of training data
  - Huge datasets like ImageNet were not available before
  - Everybody may easily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

CNN - 1D example

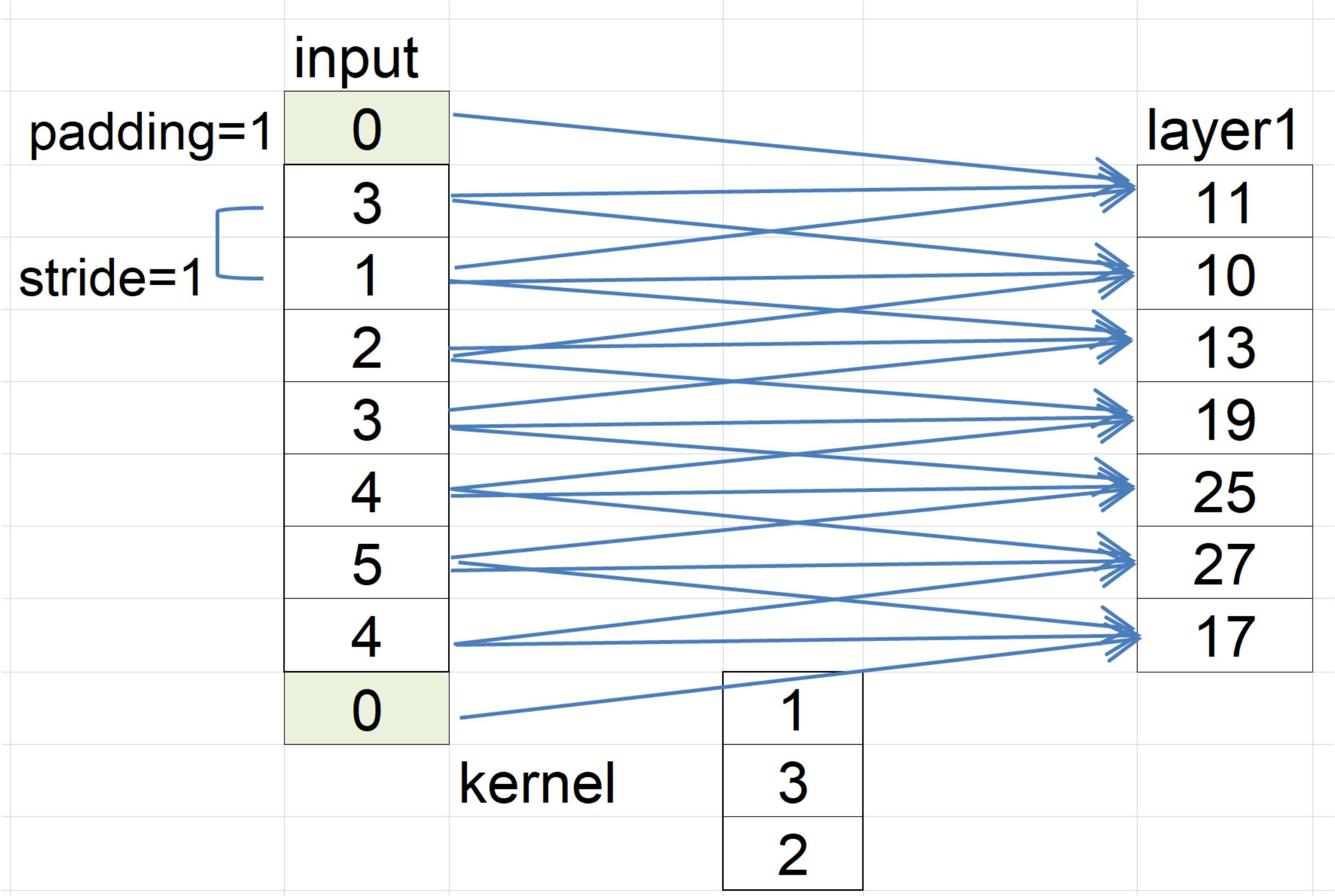
$x_0 * w_0 + x_1 * w_1 + x_2 * w_2$



CNN - stride=1

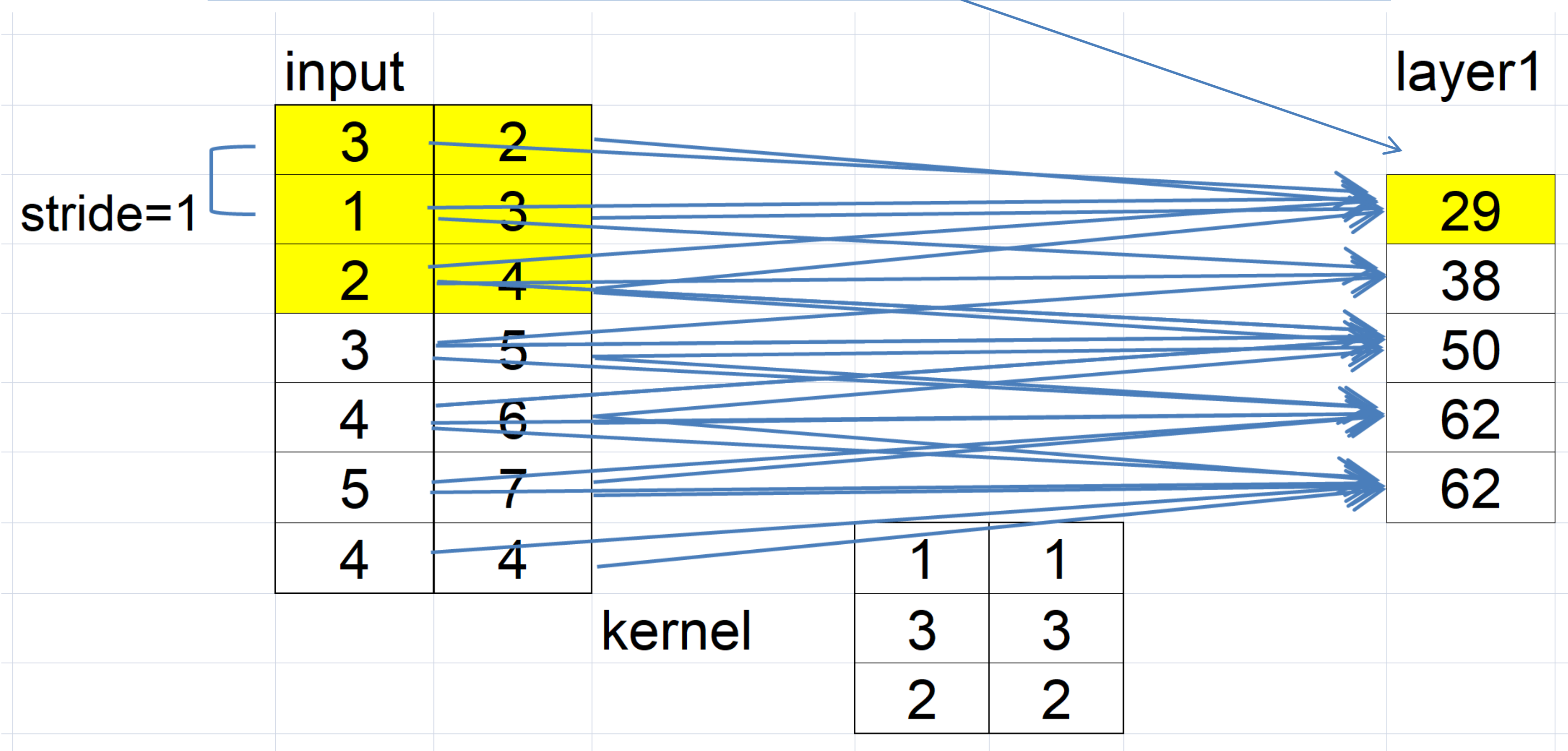

input
layer1
stride=1
3
1
2
3
4
5
4
10
13
19
25
27
kernel
1
3
2
x0*w0+x1*w1+x2*w2
x1*w0+x2*w1+x3*w2
x2*w0+x3*w1+x4*w2

CNN - stride=1, padding=1



CNN - 2D

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



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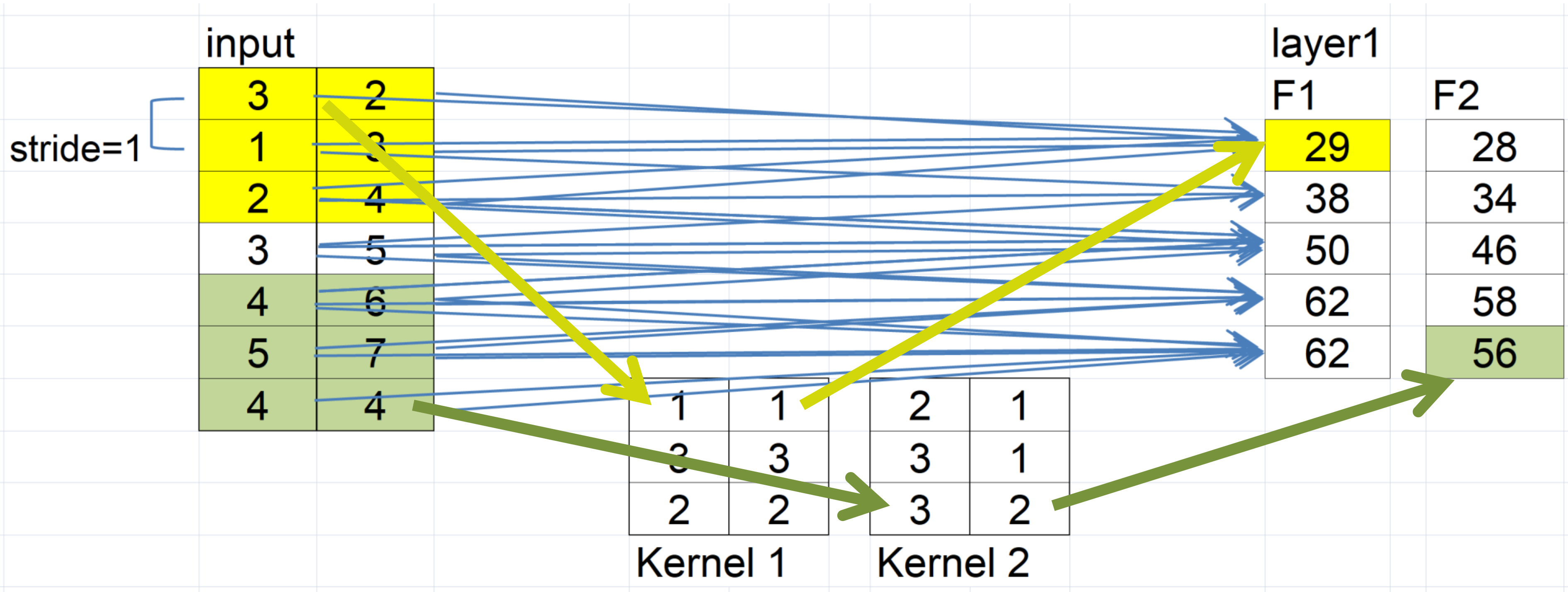
CNN – 2D, many filters



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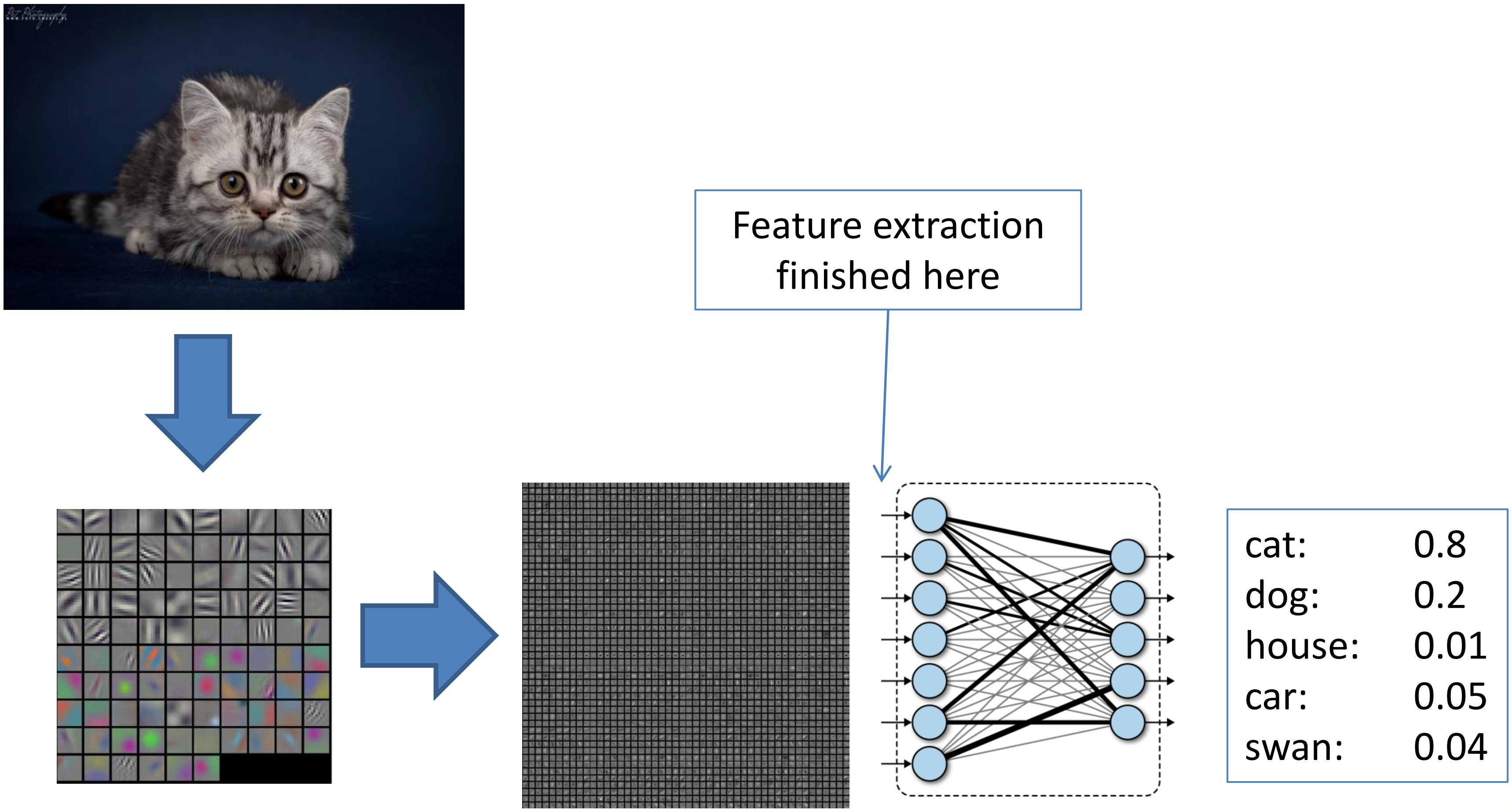
Convolutional Layer

- 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



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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

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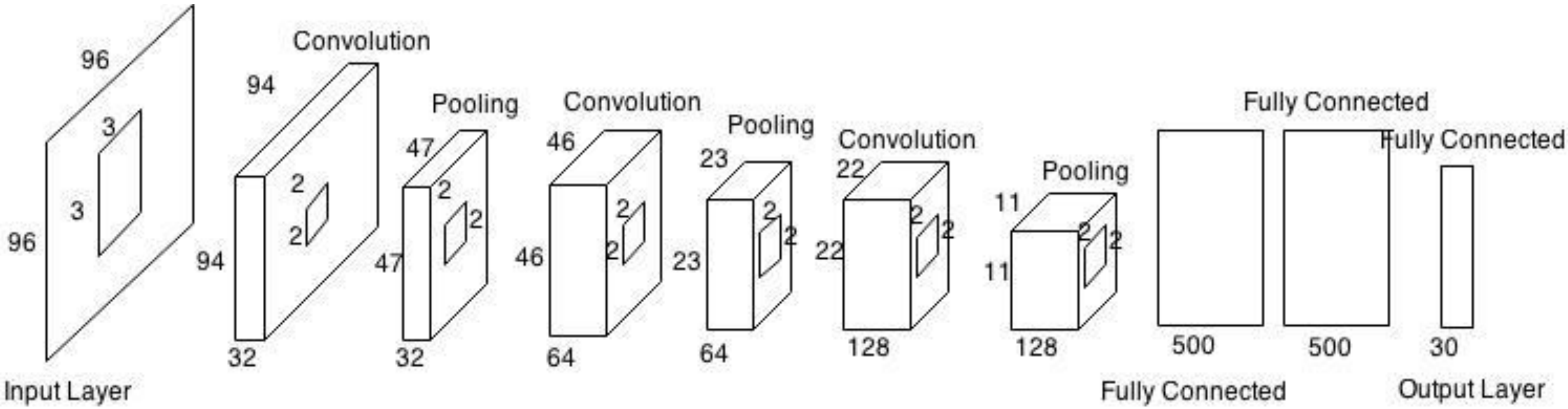
Cascade of layers

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



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

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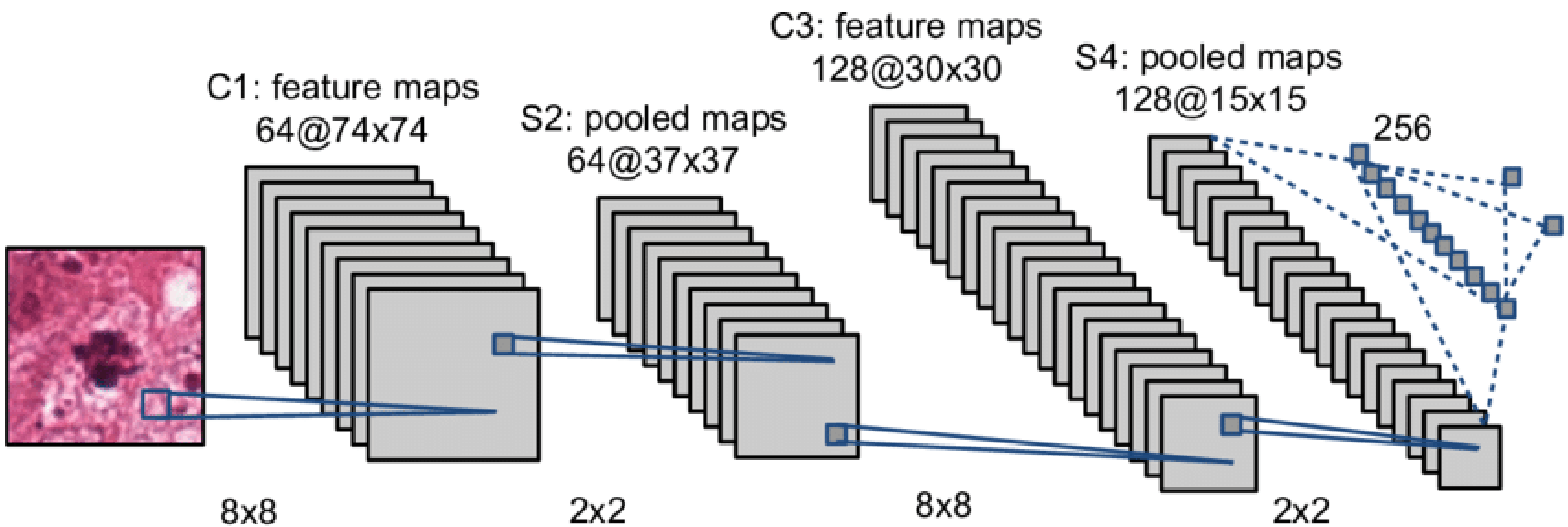
Another example



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: *cnn1/images_test.py*

Run: *cnn1/images_test_4classes.py*

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

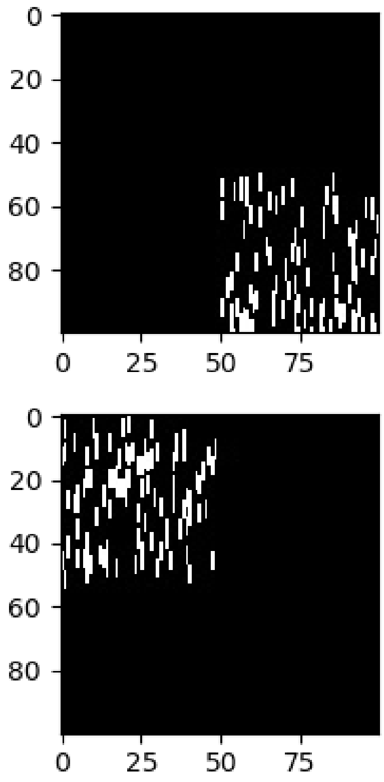
- Convolutional part

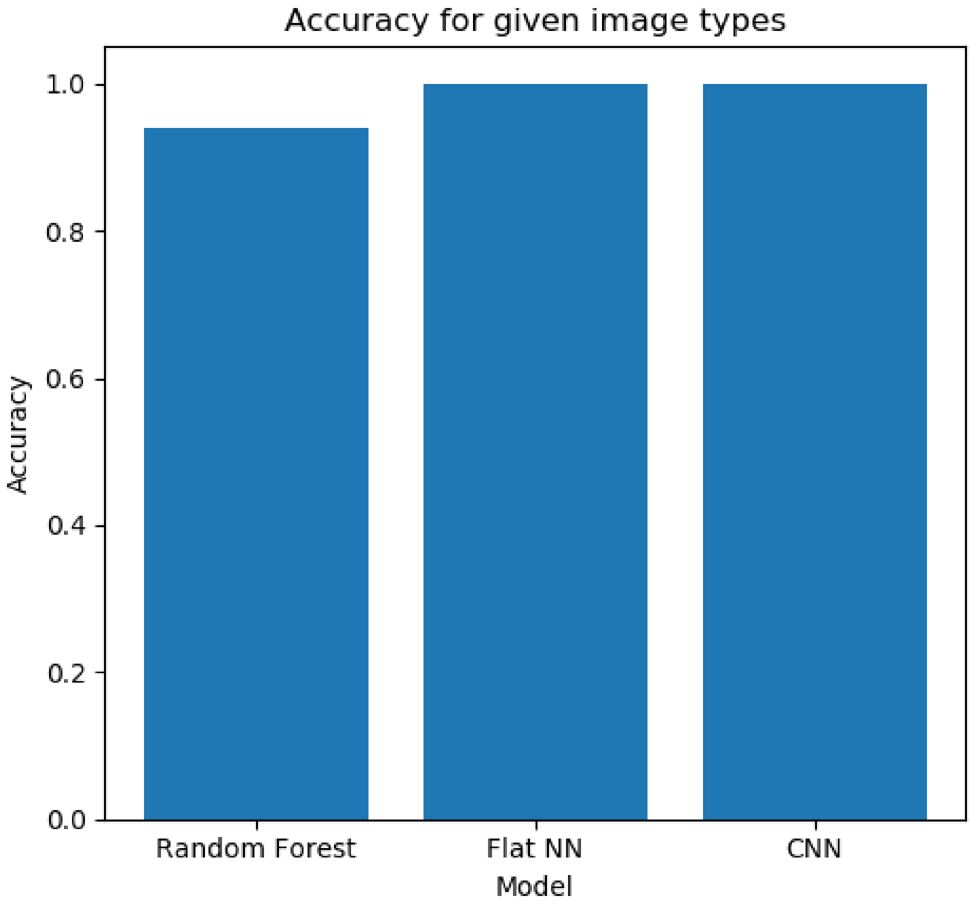
```
model = Sequential()
model.add(Conv2D(16, (3, 3), padding="same", input_shape=inputShape))
model.add(Activation("relu"))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(32, (3, 3), padding="same"))
model.add(Activation("relu"))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))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

- Dense part

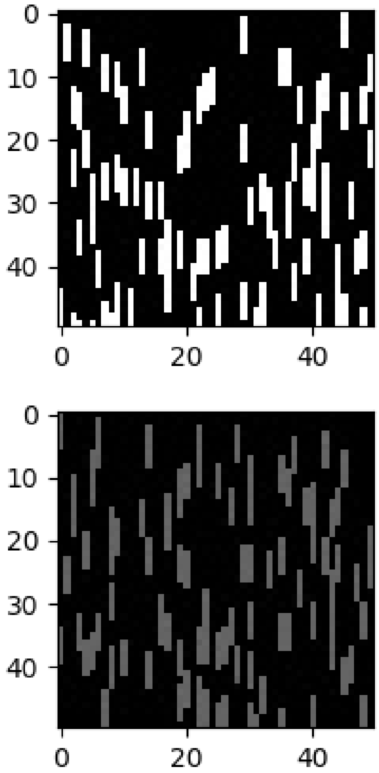
```
model.add(Flatten())
model.add(Dense(512))
model.add(Activation("sigmoid"))
model.add(Dense(512))
model.add(Activation("sigmoid"))
```

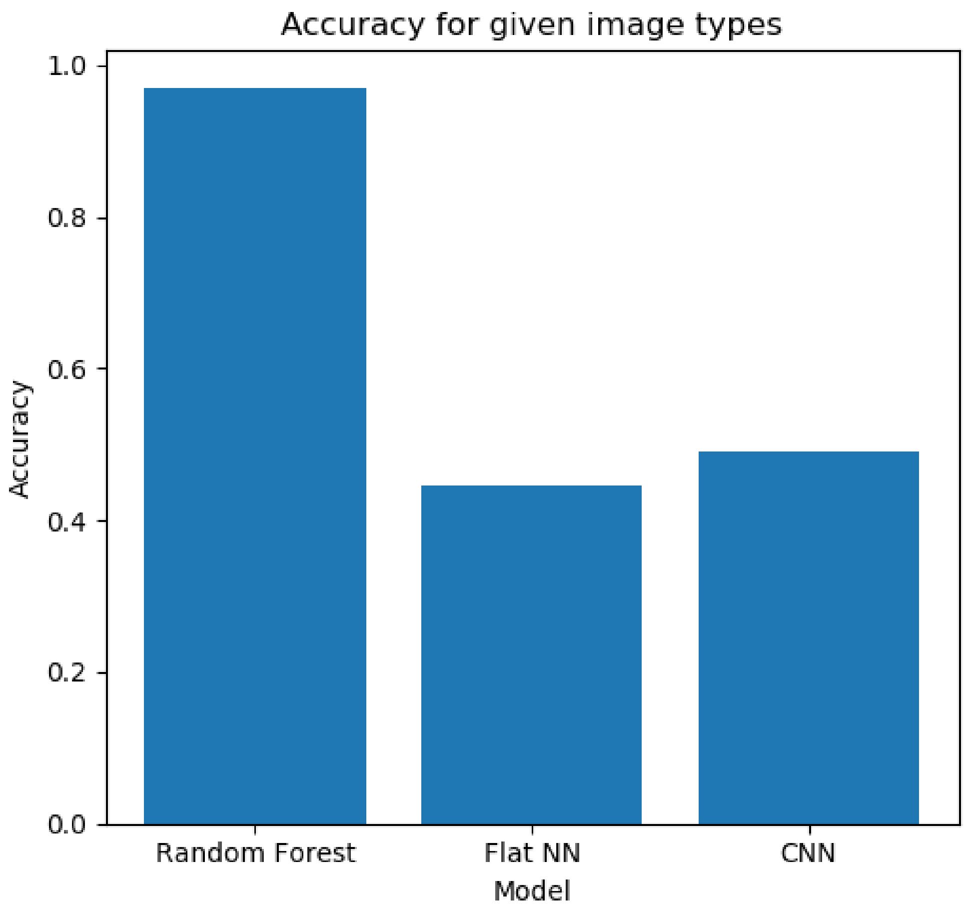
Different areas



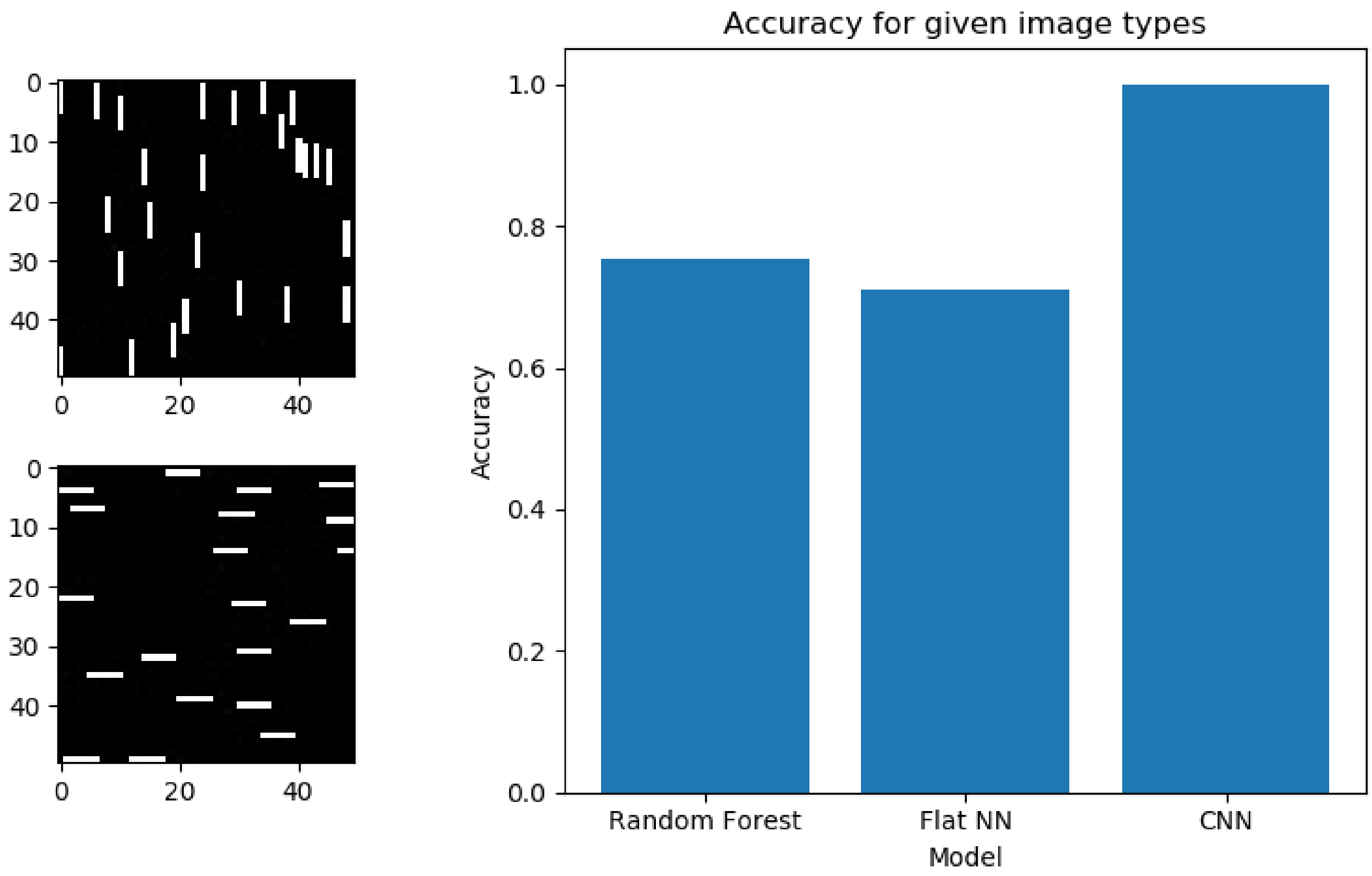


Different intensities/colors

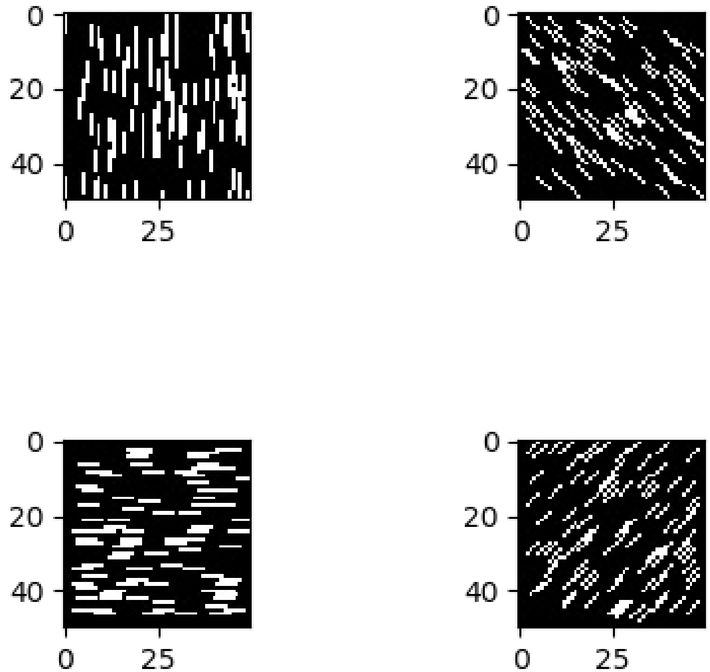


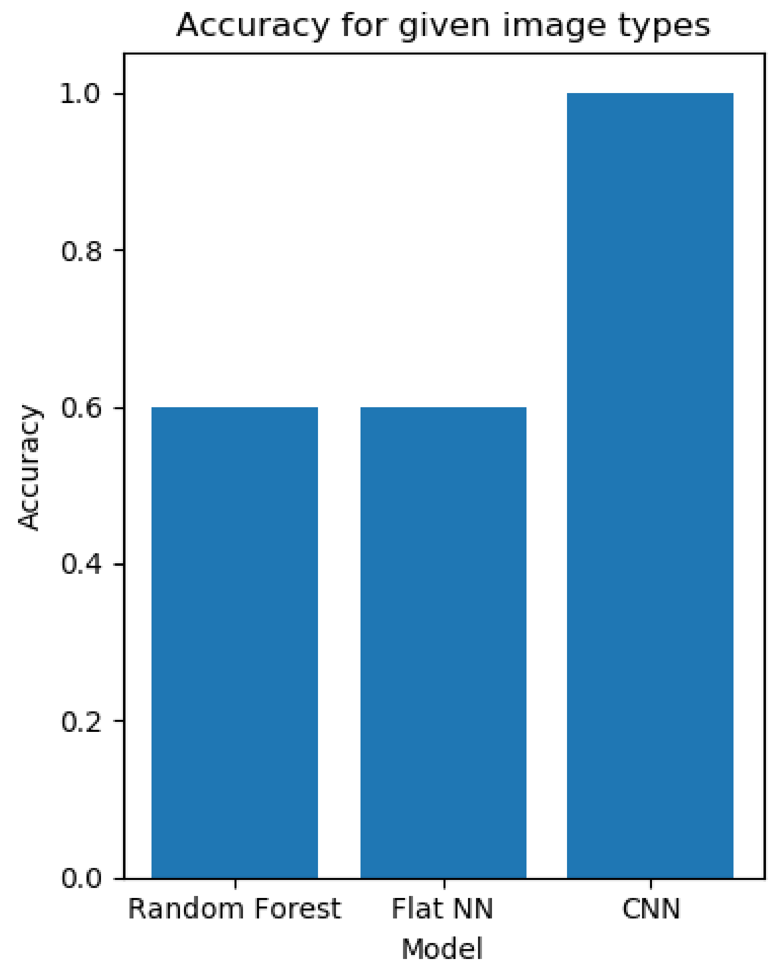


Different direction of dashes



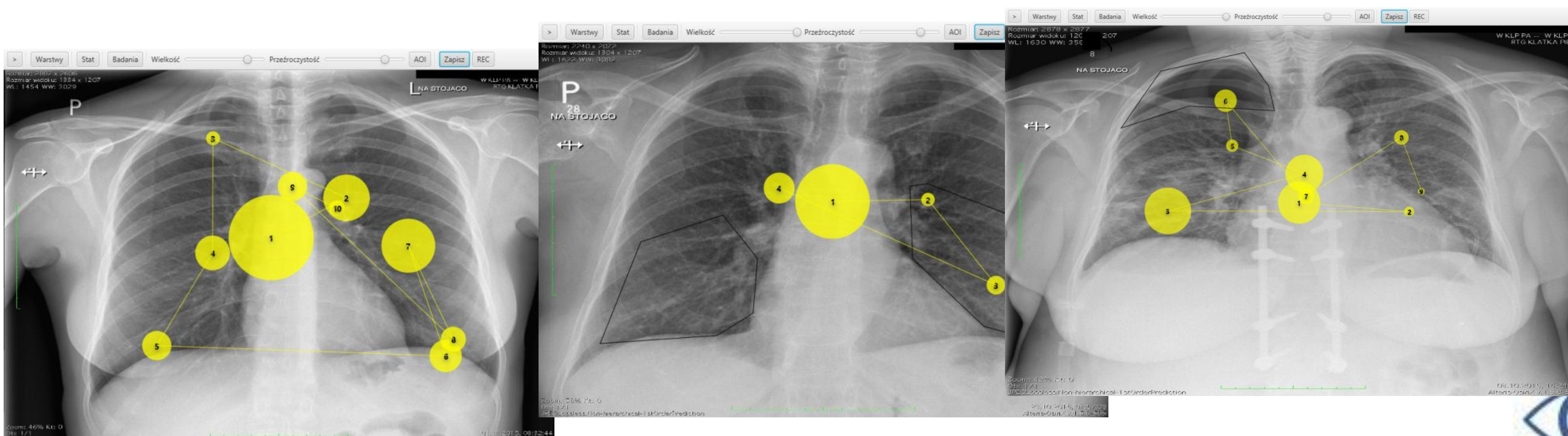
Four different directions





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)



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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/classify_tree.py*

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

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Conversion to images

Run: *radio/prepare_img.py*

- 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/classify_cnn.py*

- 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)
```

Combined model

- Problem
  - We have both images and descriptions as a set of features
- Possible solutions
  - Classify independently images and feature sets, use voting to choose a final label

  or

  - Build a network that combines two types of inputs

Example

Run: *radio/combined_model.py*

- Loads images and a CSV file with 14 attributes
  - samplesIMG
  - samplesCSV
- Builds two networks
  - CNN for images - *cnnmodel*
  - MLP for attributes - *flatmodel*
- Concatenates both networks

Concatenation

- Build the model using cnnmodel and flatmodel

```
combined = concatenate([cnnmodel.output, flatmodel.output])
combined = Dense(16, activation="sigmoid")(combined)
combined = Dense(numClasses, activation="sigmoid")(combined)
model = Model(inputs=[cnnmodel.input, flatmodel.input],
    outputs=combined)
model.compile(loss=loss, optimizer="adam",metrics=['accuracy'])
```

- Fit using both sets

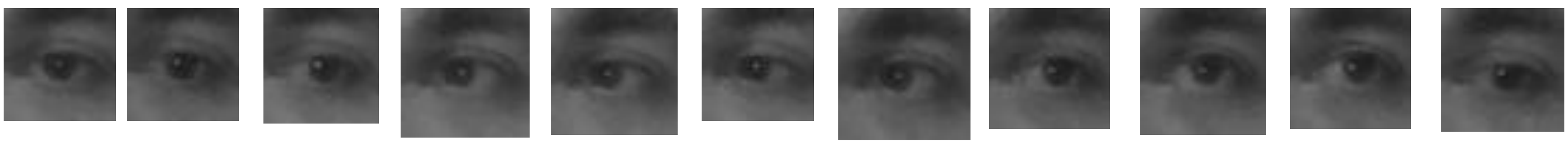
```
model.fit([samplesIMG,samplesCSV], labels, batch_size=BATCH,
    epochs=EPOCHS,validation_split=0.25)
```

- Predict using both sets

```
results = model.predict([samplesIMG,samplesCSV])
```

Regression example

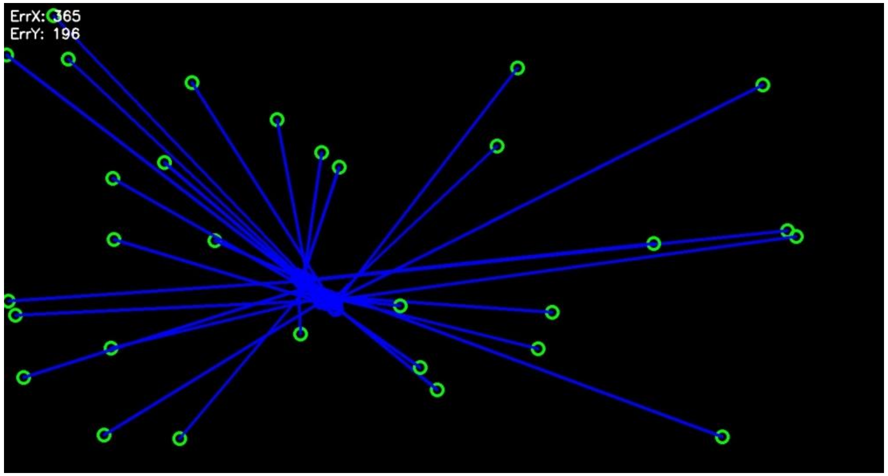
- Input: low resolution eye images
- Output: gaze location (x,y)

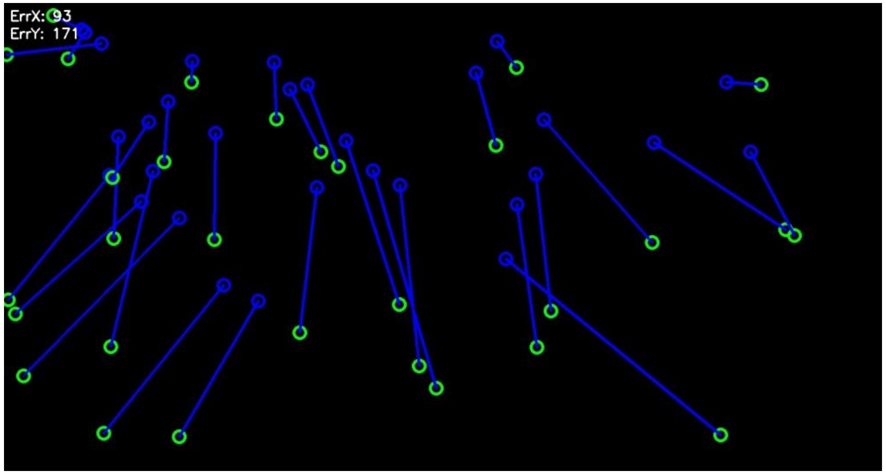


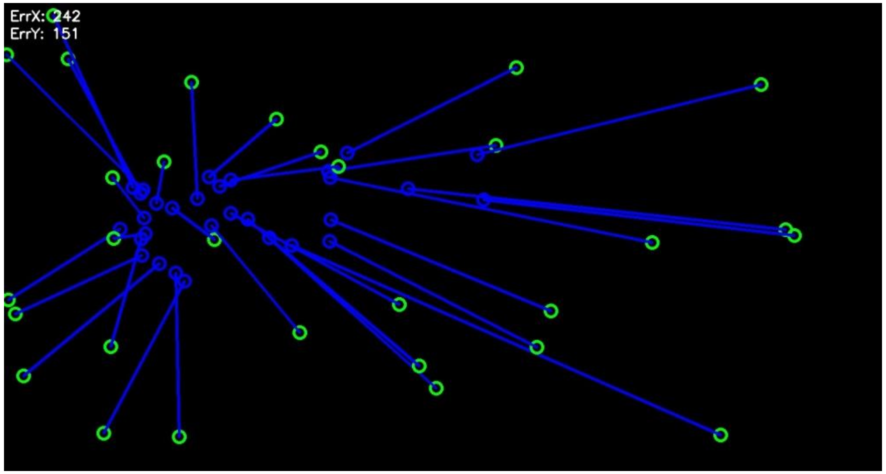
- Solution:
  - CNN model returning two values: (x,y) gaze coordinates

Run: *eyes/eye_to_gaze.py*

Training the model







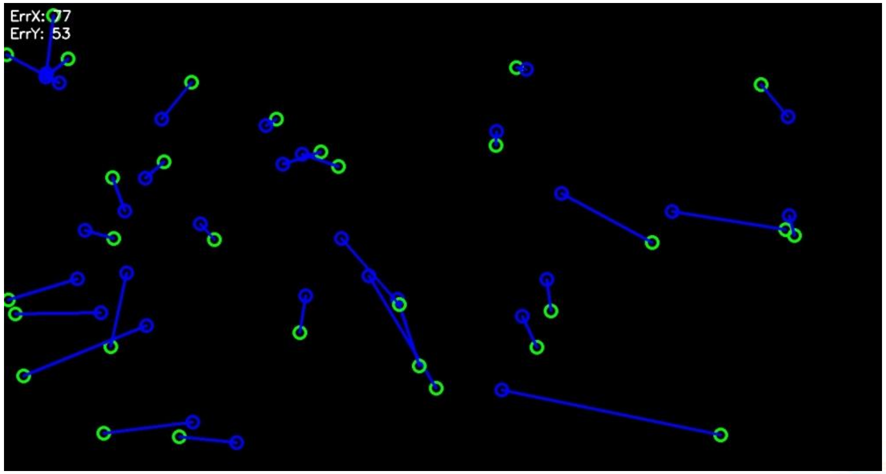
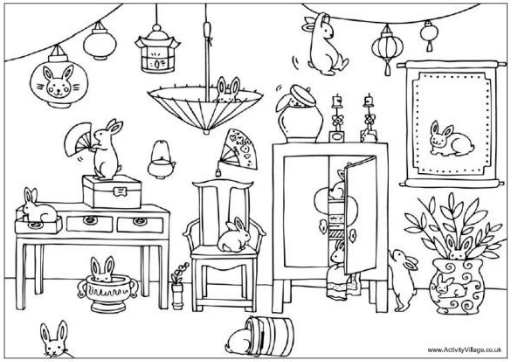


Image prediction example [1]

- 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: *images/images_cnn.py*

- 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: *eyes/test_model.py*

- 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

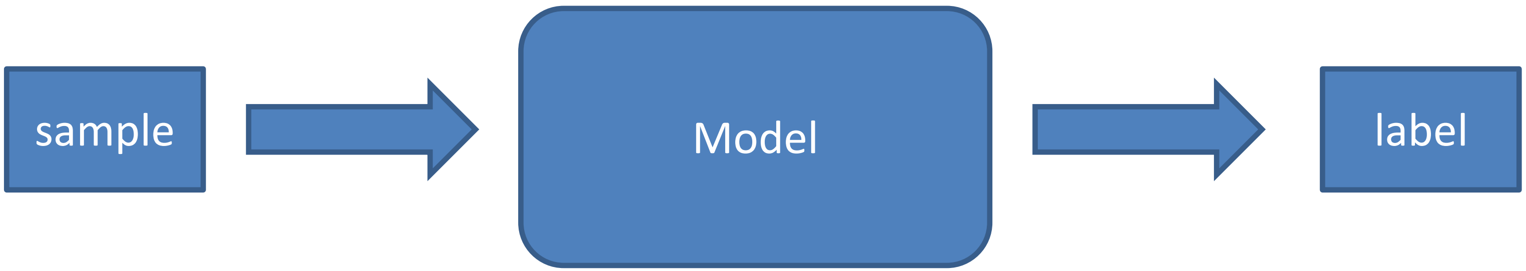
- Till now we created models (functions) that map (convert) a sample to a label
  - sample -> label
- Set of samples was converted to a set of labels
  - each sample was treated independently and the model produced one label for each sample
- There are applications were there is a sequence of samples 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

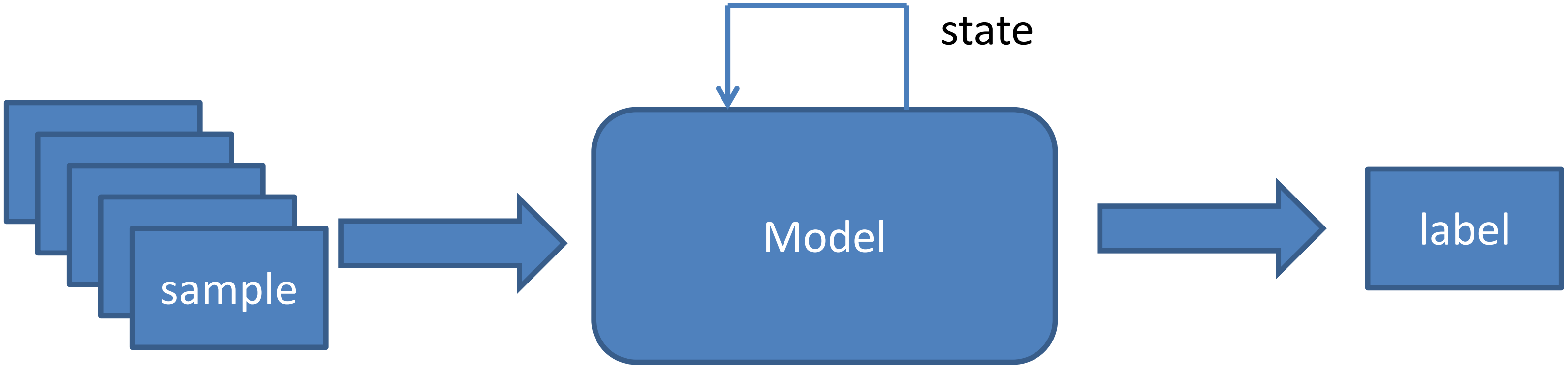
- Conventional NN
  - sample -> MODEL -> label
- Recurrent NN
  - sequence of samples -> MODEL -> label (or sequence of labels)
- MODEL has state (memory)!
  - current output depends on previous samples and outputs
- Instead of $Y_t = f(X_t)$, now we have:
  - $Y_t = f(X_t, X_{t-1}, X_{t-2}, \ldots,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

Recurrent NN

- Classic NN

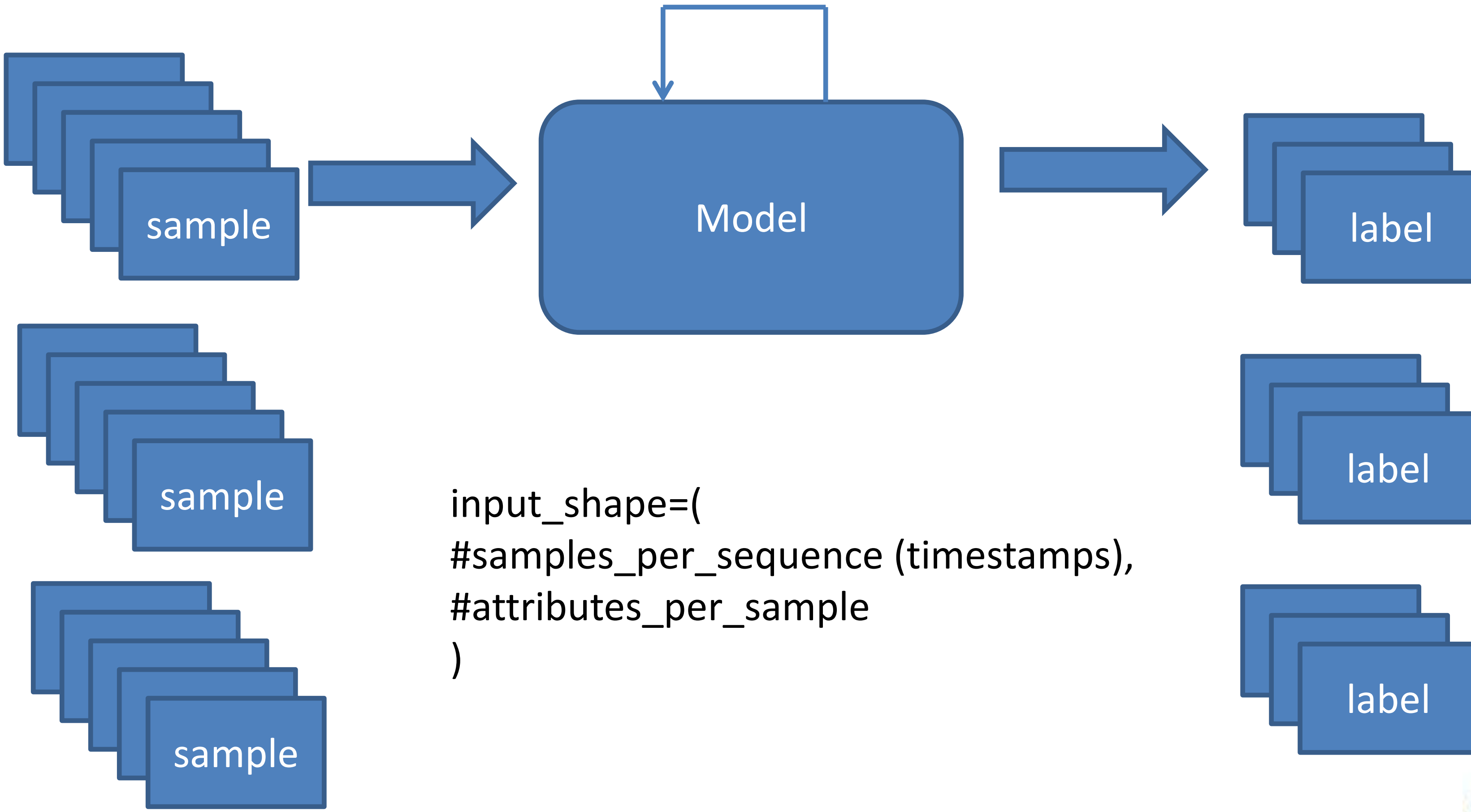


- Recurrent NN



Full RNN

state maintained across sequences



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 $Y_1 \ldots Y_t$ - output becomes a matrix of size: (units,timestamps)
- stateful
  - False – reset state after each batch
  - True – maintain state until model.reset_states() called

Example

- Network learning roman->arabic numbers translation
- Input: roman number
- Output: arabic number
- Examples:
  - *IN: MDCCXXXI, OUT: 1731*
  - *IN: DCXLIX, OUT: 649*
  - etc.

Run: *rnn/roman_rnn.py*

Code analysis

- Input and output
  - INPUT_TS = 14 chars from romans='MDCLXVI '
  - OUTPUT_TS = 4 chars from digits='0123456789 '
- One-hot encoding
  - 'M' becomes (F, F, F, F, F, F, T, F) – 1 of 8 possible characters
- Model
  - model = Sequential()
  - model.add(LSTM(128, input_shape=(INPUT_TS, len(romans))))
  - model.add(RepeatVector(OUTPUT_TS))
  - model.add(LSTM(128, return_sequences=True))
  - model.add(Dense(len(digits), activation='softmax'))
- Prediction
  - preds = model.predict_classes(roman_sequence, verbose=0)

Results

- 750 examples for training
- 250 (different than training!) examples for testing
- After 200 iterations – 95% of correct translations!
  - The network does not know any rules of translation – just learns from examples...

Analysis of the network's structure

- input: 'MXVII   ' encoded to (14,8)
  - 14 samples in a sequence
  - every sample one of 8 possibilities ('MDCLXVI<space>')
- LSTM(128, input_shape=(14, 8))
  - output: (128)
- RepeatVector(4) [output sequence will have length=4]
  - output: (4,128)
- LSTM(128, return_sequences=True)
  - output (4,128) – because sequences is True
- Dense(11, activation='softmax')
  - output (4, 11) – 4 chars each one from 11 possibilities ('0123456789<space>')

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/animal_rnn.py*

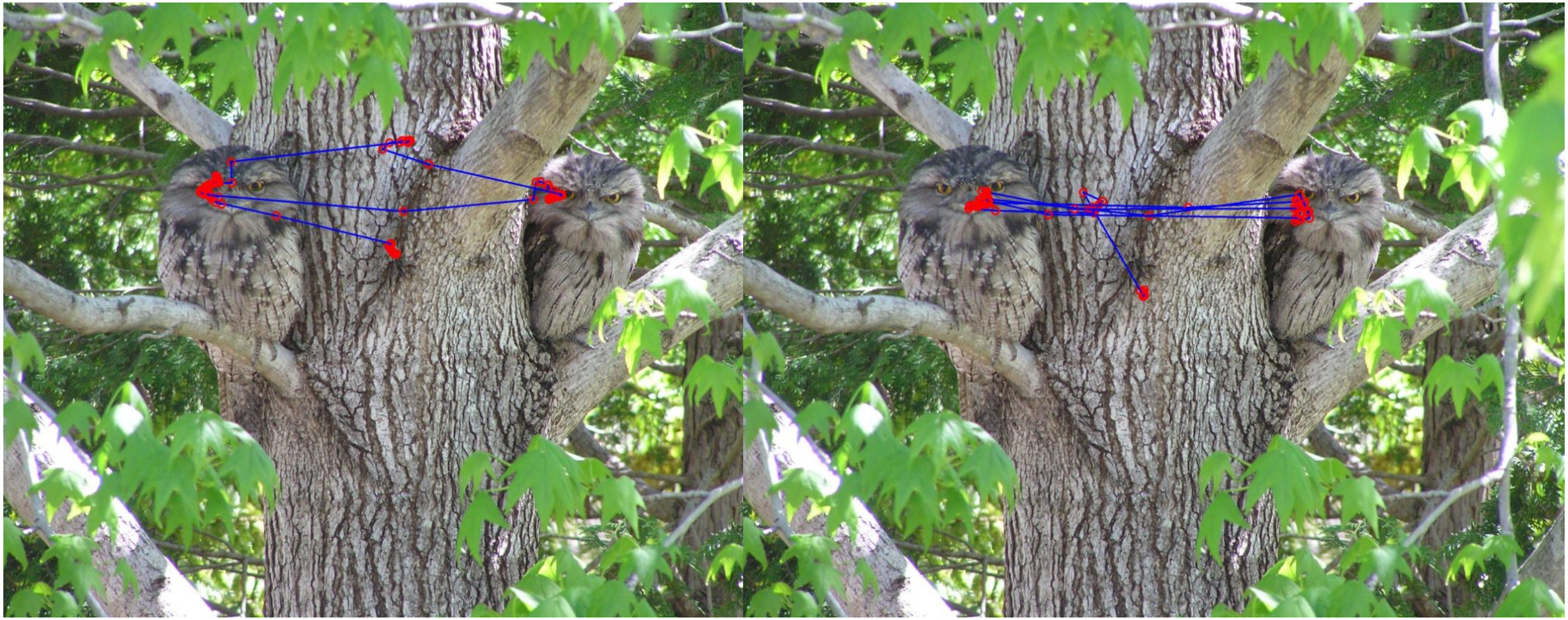
- Loss function: mean absolute error
  - model.compile(loss="mean_absolute_error", optimizer="adam", metrics=["mae"])
- Fitting in subsequent runs (loop)
- After each iteration the image with all predicted gazes is saved in /img folder:
  - animal-11_eNN.jpg
  - where NN is the epoch number
- The final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

Using the model

Run: *animals/test_model.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
- Two main problems:
  - we need a lot of data to train the network
  - architecture of the network is very important
- The field is very dynamic – new algorithms are created constantly
- Unfortunately frequently we know only that it works but we don't know what happens inside...

THANK YOU FOR YOUR ATTENTION