

# Summer School – Neural Networks with Text

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# Introduction Organisation **Data Science Neural Network Basics Tools and Frameworks** Classification with Neural Networks

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Classification with Neural Networks

# What do you expect?



# What are we going to learn?

- Neural Network Basics
- > How to use Neural Network Frameworks and Tools
- > How to use Neural Networks for Text Classification
- > How to use Neural Networks for Text Generation
- > Python ©

# Which Technologies are we going to use?

- > Jupyter Notebook
- > Python
- > Keras

Organisation

**Data Science** 

**Neural Network Basics** 

**Tools and Frameworks** 

Classification with Neural Networks

# **Organisation**

# **Schedule**

Time	Friday, September 28	Saturday, September 20
9:00	Introduction Workshop / NN Basics	Hands on Natural Language Generation
10:30	Coffee Break	
11:00	Tutorial Text Classification	Discussion Natural Language Generation
12:30	Lunch Break	Closing
14:00	Discussion Classification	
14:30	Introduction Natural Language Generation	
15:30	Coffee Break	
16:00	Hands on Natural Language Generation	
17:00	Closing	

Organisation

Data Science

**Neural Network Basics** 

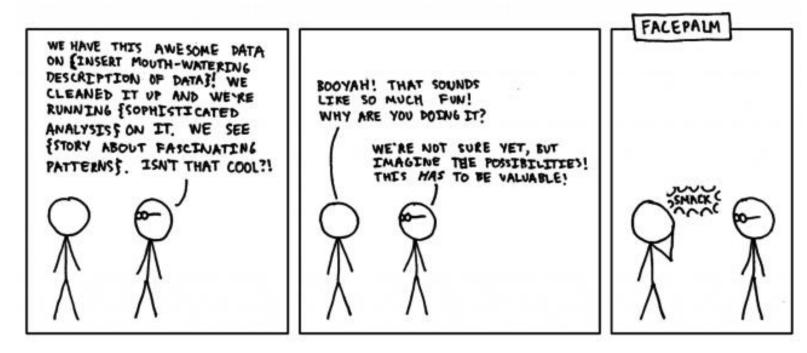
**Tools and Frameworks** 

Classification with Neural Networks

#### **How do Data Scientists work?**

- 1. Define Research Goal
- 2. Retrieve Data
- 3. Prepare Data
- 4. Explore Data
- 5. Model Data
- 6. Present and automate Model

#### 1. Define Research Goal



https://medium.com/the-data-experience/building-a-data-pipeline-from-scratch-32b712cfb1db

#### **Retrieve Data**

## Use open data sites:

- > https://www.gutenberg.org/ (for text)
- https://archive.ics.uci.edu/ml/datasets.html

Use internal data if available

## **Prepare Data**

- Data cleansing (remove false, inconsistent or unnecessary data)
- > Data integration (enrich data with other sources)
- > Data transformation (Transform into suitable format)
- > How to transform text into a model?

# **Explore Data**

- > Understand retrieved data
- > How are variables interacting?
- > Use of descriptive statistics, plotting techniques and simple modeling

#### **Model Data**

> Build a model which suits research goal

- > Machine Learning models
- > Neural Networks
- > Etc.

# **Types of Data**

- > Structured data (e.g. SQL databases)
- > Semi-structured data (e.g. CSV files)
- > Unstructured data (e.g. text files)

- > Machine generated (e.g. server log files)
- Natural Language
- > Audio, video, images
- > Streaming

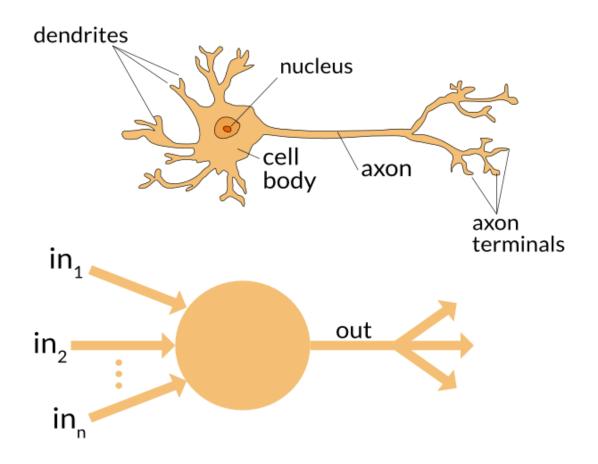
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# **Biological Inspiration**



Source: https://towardsdatascience.com/the-differences-between-artificial-and-biological-neural-networks-a8b46db828b7

# Perceptron (1)

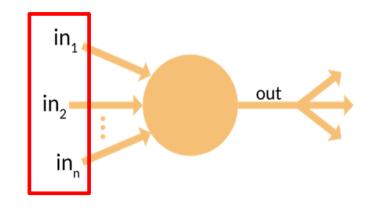
#### Input data:

Numerical values, e.g. blood values of patients:

in1 (Amount of iron) = 1 in2 (Amount of white blood cells) = 5 in3 (Something else) = 0 => Vector: { 1, 5, 0 }

Input data consists of values and its class, e.g.

patient1 =  $\{1, 0, 1\} \rightarrow \text{Klasse 1 (krank)}$ patient2 =  $\{1, 1, 1\} \rightarrow \text{Klasse 0 (nicht krank)}$ 

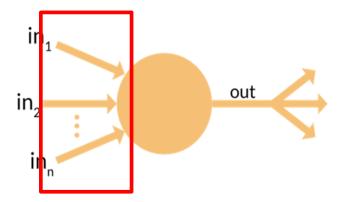


. . .

# Perceptron (2)

## Weights:

- > That is our model
- > Weights will be adjusted during the training in order to calculate the right class for the given training data.



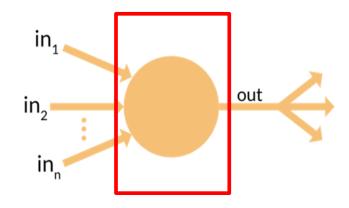
# Perceptron (3)

#### **Prediction:**

The calculation is based on the dot product of the vector of the input data and the vector of the weights

#### **Example:**

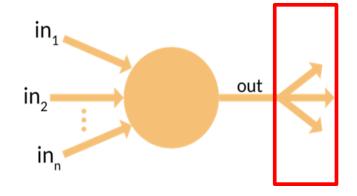
- > Input Data: {2, 3, 2},
- > Weights: {0.5, -0.2, 0.1}
- > Calcuation:
- > 2 \* 0.5 + 3 \* (-0.2) + 2 \* 0.1 = 0.6



# Perceptron (4)

#### **Output:**

- The output is the result of the dot product and an activation function.
- > Determines the class
- > Activation functions can be super simple functions, e.g. thresholds or more complex ones, e.g. Sigmoid



#### **Example:**

- > Result: 0.6,
- > Threshold: 0.5
- > Class → 1

# Perceptron (5)

#### **Training:**

If calculation of prediction outputs a wrong class, then the weights have to be adjusted in order to calcuate the correct class

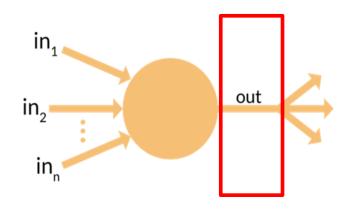
#### **Example:**

> Result: 0.6,

> Threshold: 0.5

> Target class = "0" (Actual class "1")

$$\rightarrow$$
 Error = 0 (Target) - 1 (Result) = -1



# Perceptron (6)

#### **Optimizer:**

- > Our weights have to be adjusted so that the output is less then the treshold (0.5)
- > Optimizer functions can also be simple, e.g. Hebbian learn rule or very complex

#### **Example (Hebbian learn rule):**

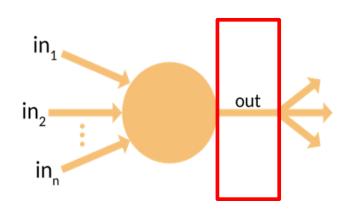
Adjust = Learning rate \* Input value \* Error Adjust1 = 0.02 \* 2 \* (-1) = -0.04

New weight  $1 = Old \ weight + Adjustment$ 0.5 - 0.04 = 0.46

#### Weights:

Weights before: { 0.5, -0.2, 0.1 }

Weights after: { 0.46, -0.26, 0.06 }



#### **Multi Class Problem**

> Previously only two classes: "0" or "1" (Spam, not spam, etc.)

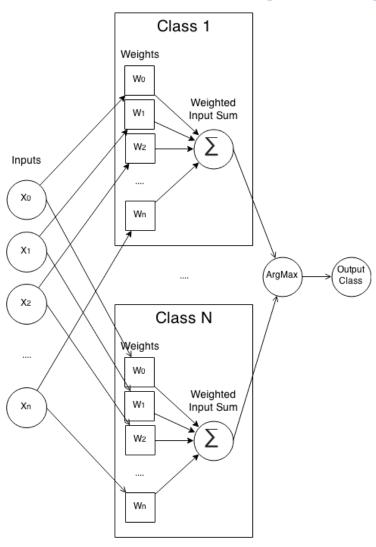
# **Example for Multi Class Problem:**

- > Image Recognition
- > Each picture (dog, cat, mous, etc.) equals to one class

# **Multi Class Classification – Perceptron?**

- > Is it possible to use perceptrons for multiple classes?
- > If not, what could we change to make it work?

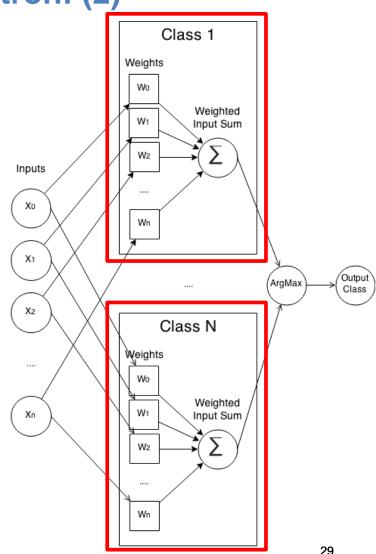
# Multi Class Classification - Perceptron! (1)



Multi Class Classification – Perceptron! (2)

#### **Calculation:**

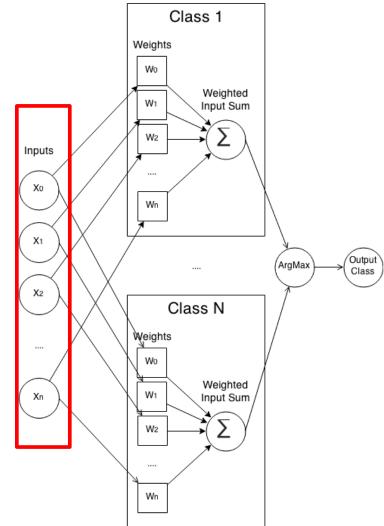
- Each class is one perceptron and will be trained separately
- That is, each class/perceptron has its own set of weights to train
- Calculation remains the same



# Multi Class Classification – Perceptron! (3)

# **Input:**

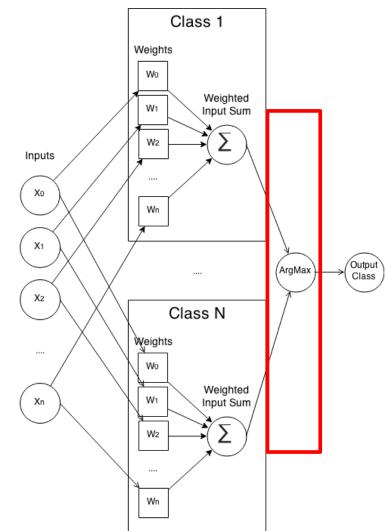
The whole input will be trained with each class weight set



## Multi Class Classification – Perceptron! (4)

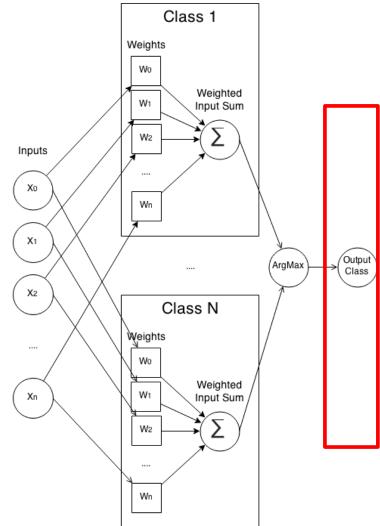
#### **Prediction:**

- > Results of each class weight calculation will be compared
- The class with the highest calculation is the class of prediction (ArgMax Function)



# Multi Class Classification – Perceptron! (5)

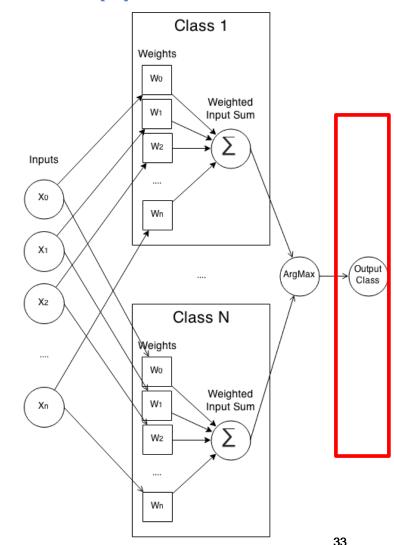
> But how do we train now?



## Multi Class Classification – Perceptron! (6)

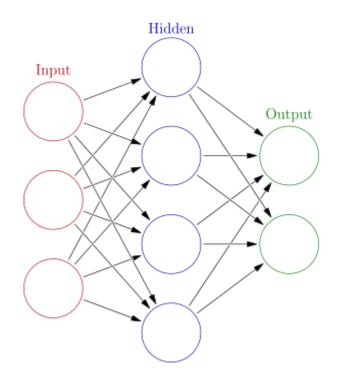
# **Training:**

- If the prediction is wrong, the weights of the predicted class have to be decreased for the particular input
- > Weights of correct (but not predicted) class have to be adjusted upwards

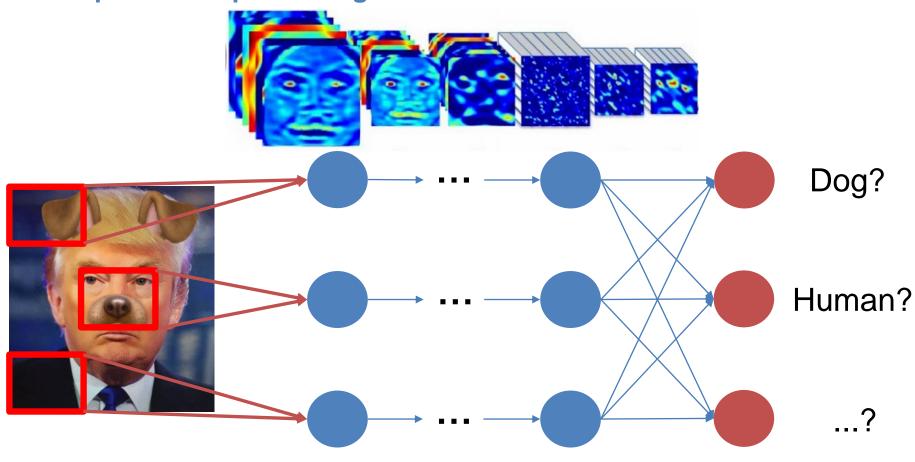


#### **Structure of Multi Layer Perceptrons (aka Neural Networks)**

- Multi Class Perceptrons have one hidden layer where all the calculations is done
- > For more complex problems neural networks with several layers have been developed (and nowadays called "deep")



#### **Example for Deep Learning – Convolutional Neural Network**



Input

Convolution/Pooling Neurons

Fully-connected Neurons 35

# **Summary and terms**

- > Input: Numerical vectors or matrices
- Activation: Can be a threshold or other functions to determine if Neuron fires or not ("0" or "1")
- Learning rate: Determines how fast an algorithm should adjust to new data. A high learning rate adjusts better and faster to new data but also discards learned circumstances
- > Optimizer: Function to optimize model (i.e. weights)
- > **Epochs:** An epoch is a whole iteration of than one iteration of all data to have an optimal model for the given problemall input data. Algorithms need more
- > **Batches:** Sometimes data is too big to put fully into RAM. Then it needs to be processed into slices (aka batches).
- > **Regularization:** Goal is to use as less variables for a model as possible to prevent overfitting, e.g. by dropping out a fixed number of neurons

# Introduction Organisation **Data Science Neural Network Basics Tools and Frameworks** Classification with Neural Networks

### **Tools and Frameworks**

### **Prerequisites**

- > Git (https://git-scm.com/downloads)
- > Sourcecode (https://github.com/spinfo/LSS\_DLwithText)
- > Anaconda (https://www.anaconda.com/download/)
- > Keras (

# How do I get started with DL?

...pretty good question

### How do I get started with DL?

# ...pretty good question

























### Best way to learn?

... **DIY!** 







## Why Keras?

> Quickly train and test model

### From Standard layer:

- > Wraps multiple frameworks
- Simplified interface to Theano, CNTK or TensorFlow
- TensorFlow is default API

> Write and debug custom models and layers:





# **Pipeline**

- 1. Define Network
- 2. Compile it
- 3. Fit it
- 4. Evaluate it
- 5. Make Predictions



### **Define Network**

- > Create an instance of the sequential class
- > Define sequence of layers
- > Add new lines (each line is a new layer)
- > First Layer: number of inputs (can differ depending to the network type)

```
model = Sequential()
model.add(Dense(32, activation='relu', input_shape=(784,)))
model.add(Dense(10, activation='softmax'))
model.summary()
```



## **Compile it**

- Transforms a simple sequence of layers into a highly efficient series of matrix transforms
- Intended to be executed on the GPU (depending on the configuration set)
- Optimization: Train the network
- Loss Function: Evaluate the network



#### Fit Network

- > Adapting the weights of the training data set
- > Input X → Matrix of input patterns
- > Output Y → Array of matching output patterns

```
1 X = count_vectorizer.fit_transform(traindf['text'])

1 label_map = {'HillaryClinton':1, 'realDonaldTrump':-1}
2 Y = list(traindf['handle'].apply(lambda x: label_map[x]))

1 print(X.shape)
2 print(len(Y))

(5600, 49)
5600

1 model.fit(X, Y, batch_size=32, epochs=10)
```



### **Evaluate Network and use it to make predictions**

- > How good does model work? Evaluate it!
  - > Input X → Matrix of input patterns (test data)
  - > Output Y -> Array of matching output patterns (test data)
- > Try out trained model with completely new data
- > What will it predict?

```
: model.evaluate(
    data,
    labels,
    batch_size=32,
    verbose=1,
    sample_weight=None)

32/1000 [......] - ETA: 0s
: [0.69383435416221617, 0.539000000000000]
: model.predict(
    data,
    batch_size=32,
    verbose=1)

32/1000 [......] - ETA: 0s
```

Introduction

Organisation

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Classification with Neural Networks

### How to transform a text into a model?

- Neural Networks need numerical vectors to compute output
- Transformation from text to model is done via word embeddings
- There are plenty algorithms for generating word embeddings

## Word embedding

## Simplest word embedding is **Bag of Words**:

- > Input: "My dog has a dog name", "My dog is cute"
- > Bag of Words:

```
Sent1: { "My" : 1, "dog" : 2, "has" : 1, "a" : 1, "name" : 1, "is" : 0, "cute" : 0 }

Sent2: { "My" : 1, "dog" : 1, "has" : 0, "a" : 0, "name" : 0, "is" : 1, "cute" : 1 }

→

Sent1: { 1, 2, 1, 1, 1, 0, 0 }

Sent1: { 1, 1, 0, 0, 0, 1, 0 }
```

## Word embedding

### **Bag of Words**:

- > Features: Words
- Values in Vector: Total Word Count in document
- (other features (lemma, ngrams,..) and values (weigthed,...) are possible)

Feature Vector serves as Input Vector for Neural Network

### And the labels?

- each output node of the Neural Network represents a label
- > the higher the output value, the more probable the label is

# Let's get our hands dirty!

