# UNIK4690 Project

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May 20, 2018

## 1 Project description

**The purpose of the software is to recognise text from any surface with uneven lighting. Hence this falls under the "Optical character recognition" (OCR) problem**

As OCRs are still a challenging task even for companiese like Google, ref. reader to Googles OCR translator application on smartphones; "Transalte", drawbacks such as; difficulty finding all the text on the photo becasue of lighting, noise etc., therefore we will have to limit our software significantly.

### 1.1 Initial limitations

- English alphabet + numbers [0-9]
- Homogeneous background
- Computer printed text

### 1.2 Project components

The group have come to the conclusion that the OCR software has 3 main components to it.

1. *Text segmentation*
   - Finding text on an image and returning the text segments
2. *Preprocessing*
   - Do preprocessing on the segmented text; rotation, symbol segmentation, etc.. (preprocessing from its definition, should be done first, however because of simplification we assume we manage to segment out text first.)
3. *Classification*
   - Classification of the symbols

Additionally there is one more very important component for this OCR software to work, ***labled data***. Even though one might not need to code for this part, a good pool of labeled data is needed to be able to classify symbols. More on this later.
(4. *Data classification - Gathering labeled data to train a classification algorithm*)

## 1.3 Component description

This section we will describe our thoughts on how we plan to solve each component, in the form of algorithms, APIs, and datasets. Note that this is our initial thoughts, not necessary the solution we will end up implementing.

As we want to test proof-of-concept while we are coding, we will be making several simplifications. These simplifications will be described further under each component.

### 1.3.1 Text segmentation

**Key fyll ut dette her?**
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### 1.3.2 Preprocessing

**Description**
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### 1.3.3 Classification

**Description**
At this point because of avalible knowledge and the intrest in Convolutional Neural network (CNN), we ended up trying to solve this part both with a CNN, and a Multilayer Peceptron (MLP or Deep neural network (DNN)). Illustration of each of the architectures are avalible, CNN Figure 2, and the MLP network Figure 1.

**Deep Neural Network**
Multilayer peceptron neural networks are relatively straight forward to code, however the challinging part is to decide on good hyperparameters and to not overfit our network.

Reasearch has shown that the choices of parameters can have huge effects on the error rate, even though the researchers might not know why! Emperical testing has showen that some combinations of parameters are better than others. We will also use the same method on sevral of the hyperparameters. More on this below, where a short discription of the hyperparameters follow.

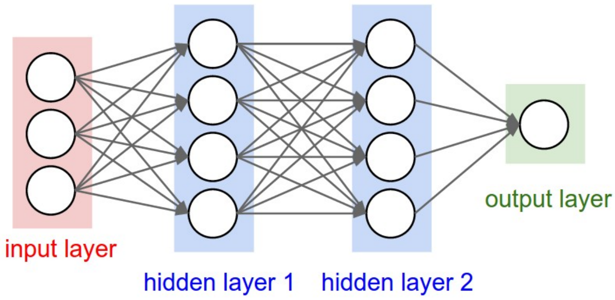


Figure 1: MLP Neural netowrk. Source

**Hyperparameters**

- Number of hidden layers
  - Layers decide how well the software can define the decision borders. Hence increase in layers can have a positive effect, there are aslo cons with the amount of layers. The more layers, the greater the computational power needed to train the system. We will be useing the empirical method to decide how many layers we need
- Number of nodes in each hidden layer
  - Nodes in each hidden layer has the same effect as the number of hidden layers, hence the same applies for this hyperparameter.
- Activation functions
  - The activation function decides which combination of nodes, with their signals, are allowed to propogate through the network. Here we will be using the *rectified linear unit* (RELU) activation function. This is an activation function that allows propogation if the signal is positive, othervise it will forward a zero. The reason for choosing this activation function is because this function handels the *vanishing gradient problem* better than sigmoid and atanh activation functions. More on vanishing gradient problem under "optimization function".
- Loss function
  - The loss function describes how far off the predicted class of the character is from the real class. In our case since we have multiple classes and we are going to use *softmax regression* as the output layer, we also will be using the *cross-entropy loss function.*
- Optimization function

- The backpropogation will train the weights by Gradient Decent Optimization. However as training with several thousand examples, and then optimizing the weights and run the training process, is too costly resource wise, we will have to implement the *mini-batch gradient decent optimizations*. Same principle as gradient decent optimization, but this way we will find the gradient decent for each batch. As long as these batches are randomly choosen, and the sizes are large enough, (we will be using 100 as batch size), these will represent the entire dataset well enough.

- Learning rate
    - Learning rate is a scalar that decides how large the stepts towards the gradient minimum will be, for the weights. Choosing too small of a learningrate we might risk not reaching the bottom of the graph, we also might get stuck in a local minimum. Choosing too large of a learning rate we might risk never settle down on a minimum.

      For the learning rate we will be useing the empirical method too.

- Initialization of the weights and biases
    - Initialization of the weights also seems to be of importance, researchers have found out. This is obvious, as for example setting all the weights to zero, would of course lead to a network with very few active nodes.

      We will be using the initialization of zeros for the biases, not any apperant reason. Based on our reasearch, it seems people have gotten decent results when using this initialization. For the weights we will be using a gaussian distribution, mean=0, standard diviation=1. Again this is aslo something that we have read should be a good initialization for the weights, no other reason.

- Number of epochs
    - Number of epochs are only relevant when we have a small number of dataset. When we have a small dataset we might want to run the software on the same dataset several times. This might result in overfitting the software to the dataset, therefore it is really important to be carfull of the number of epochs, in cases with small datasets.

### Convolutional Neural Network

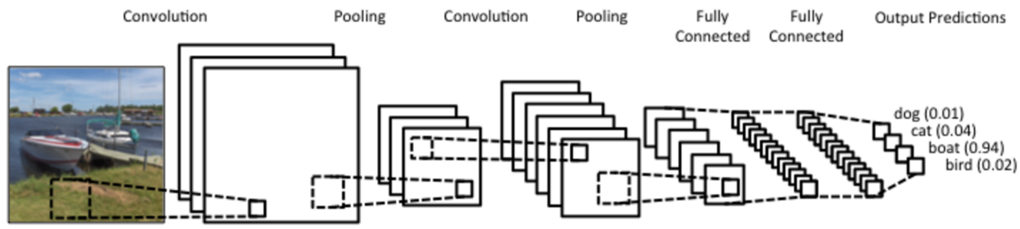


Figure 2: MLP Neural netowrk. Source

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**Limitation - proof of concept**

**Description**
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### 1.3.4 Labled Data

**Description**
Labled data is needed because our classifiers need to be trained to understand the difference between the charecters. This is usually done by training a classifier with a set of training data, labels are needed in our case, since it is a supervised machine learning algorithm we want to use. As the training data is used to train the software, we will need data to test our software as well, hence the need for test data. The test data is used to get a measure of what the error rate of our software is, based on the results we can then tune the hyperparameters to get a better/smaller error rate. Lastly we will need validation data. This is an independent dataset that the software is not familiar with. The accuracy of the software on the validation set will then be a measure of how good the software can classify the characters.

**Limitation - proof of concept**
As we have limited us to the English alphabet and numbers ranging from [0-9], we will need labeled data for each of these 36 characters; training, test and validation sets. As the concept of classifying only numbers vs all 36 charecters does not differ that much, we will first see if we can solve the OCR problem with just numbers. Therfore we only need a dataset containing numbers at first. Thereafter we will search for a dataset containing all the characters we need.

**Dataset**

**MNIST**
This is a dataset containing handwritten numbers [0-9]. It has a training set of 60.000 examples and a test set of 10.000 examples. (ref. reader to http://yann.lecun.com/exdb/mnist/).

## Report

**Week 1** 19.04.18

- Feedback on project proposal
- Overview of project
  - simplification
  - binary image → numbers → straight text → Classify
- init; github - atom
- first test of charcter Segmentation

- Charcter Segmentation - Projection Histograms - OpenCV
  - By projection the histogram of the binary image on the Y-axis, we can find where the sentences/lines of text appears. Following, a projection histogram on the X-axis can discover where the charecters appear.

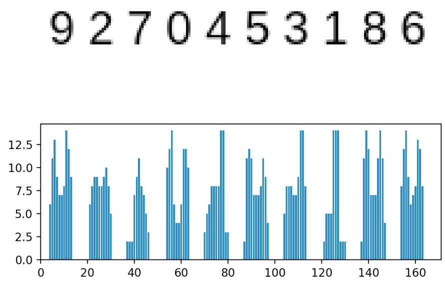
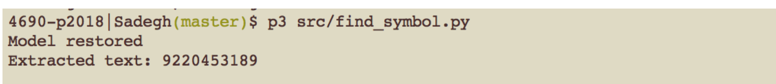



Figure 3: [0-9] segmented with projection histogram

- Classification - Perceptron neural network - TensorFlow
  - MNIST dataset - Datasett consisting of several thousand handwritten labeled numbers
    - Numbers ranging from [0-9]
    - Images are 28x28pixels
  - Hyperparameter tuneing
    - Activation function
    - Number of hidden layers
    - Nodes in hidden layers
    - Cost function
    - Optimization function
    - Learning rate
  - Theoretic accuracy of the network with 2 hidden layers  98%
    - Measured accuracy  97%



```
4690-p2018|Sadegh(master)$ p3 src/find_symbol.py
Model restored
Extracted text: 9220453189
```

Figure 4: First output with classification. input see Figure 3

**Week 3** 03.05.18

- Rotation of text
  - Hough transform
  - *cv2.minAreaRect()*
- How to distinguish between upside-down, and verticle vs horisontal text segments
  - Classifiy in all 4 rotations, and choose the classification with highest avrage confidence
- Classification - Perceptron neural network - Error
  - Error rate too high, test-set accuracy 97%, validation set accuracy < 50%
  - CNN - TensorFlow Estimator API
    - Challenging documantation; load/save models
  - Dataset - FNIST - Group contribution
    - Dataset including several fonts
    - English alphabet, and numbers [0-9]

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