

D7041E “Applied artificial intelligence”

(Please report any found inconsistencies to Evgeny as soon as you find them)

LAB 1: Fundamentals of Machine Learning

1. Introduction

In this lab we will work with data-driven classification problem. The task is to assign an input data one label from a finite set of categories. The challenge here is that there is no model describing each category available in advance. That is we cannot hard-code it in an algorithm, instead we need to learn this model. In this lab you will work with two instance of this problem – the image classification problem and classification of flower types. In particular we will classify hand-written digits from the publicly available dataset MNIST and feature description from IRIS dataset.

For this lab you must submit a report showing the answers to all the questions and screen shots supporting the intermediate steps of the algorithm.

2. Fundamentals of data pre-processing and basic skills in Jupyter

To master basic data pre-processing skills collect your own dataset of images (take at least 5 photos of 5 categories of objects)

Task 1.1 Import your own dataset into Jupyter environment:

1. Make an $(n, x, y, 3)$ array containing all the samples of your dataset. Here n is the number of samples, x and y is the resolution of your photos and 3 is the rgb components.

2. Write a function for plotting a sample PlotSample, which takes the index of a sample as an argument and plots it using the functionality of the **matplotlib** library.
3. Follow the tutorial “Preprocessing for deep learning” (<https://hadrienj.github.io/posts/Preprocessing-for-deep-learning/>), which is also linked from Canvas and perform all the pre-processing steps for your dataset.
 - You need to demonstrate the Jupyter notebook with all the steps.

Task 1.2 Import somebody’s else dataset into Jupyter environment:

1. Two months ago I got an e-mail from my collaborator working with multidigit MNIST dataset (see an example below):



“you asked me to share with you data from my experiments. Here it goes 11 thousand samples. The data are 1024-dimensional embeddings of handwritten digits placed on 9 different positions on a scene. The data is formed as a dictionary within a dictionary. The key to the first dictionary is the number of the position and the key to the second dictionary is the digit itself.” The file with data (“vecs.npy”) is part of the code distribution for Lab1. It took approx. 1 hour for me to be able to load the data as Numpy arrays suitable for input to an AI algorithm. How long time does it take for you?

2. You need to demonstrate a code that automatically forms **two** Numpy arrays for an arbitrary chosen position on the scene – one containing the embeddings and the second one containing the labels in the order presented in the data file.
3. You need to demonstrate a python code for randomly permuting the order of data and the labels.

3. Nearest Neighbour classifier: skills of working with datasets and hyperparameters

The first approach you will test has little to do with learning, however we will use it for mastering the skills of working with datasets as well as a baseline for benchmarking performances of more advanced approaches.

MNIST data set:

One commonly used toy image classification dataset is the MNIST dataset. This dataset consists of 60,000 tiny images that are 28 pixels high and wide. Each image is labeled with one of 10 classes (“0”, “1”, “2”, “3”, “4”, “5”, “6”, “7”, “8”, “9”). These 60,000 images are partitioned into a training set of 50,000 images and a test set of 10,000 images.

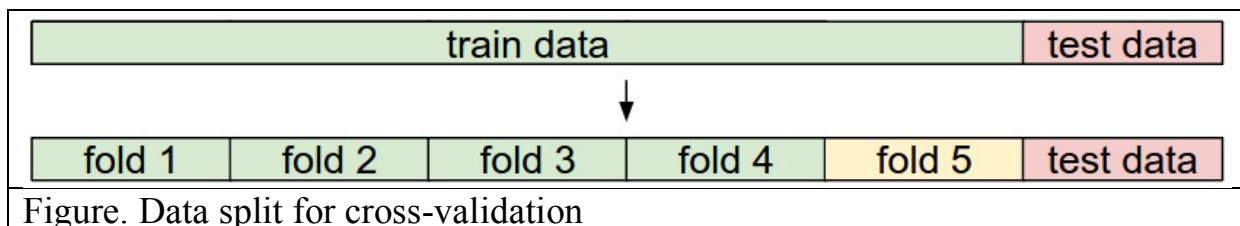
Task 2.1

You are provided with an implementation of a special case of the K-Nearest Neighbors classifier (i.e. 1-NN) using L1 norm. The 1-NN classifier takes a test image, compares it to every single one of the training images, and predicts the label of the closest training image.

1. Run the provided code for 1-NN classifier. What is the accuracy of the method?
2. Modify the code of the NearestNeighbor example so that it uses L2 norm for classification. How the classification accuracy has changed now?
3. The accuracy of the NN classifier that you have observed in the previous two tasks is VERY low. This is due to the bug in the code – find it and fix it. HINT: check the distances computed by Python and those computed by hand for several pairs of images.
4. Extend the code of the NearestNeighbor example with necessary methods, which implement k-NN classifier. That is instead of finding the single closest image in the training set, you will find the top **k** closest images, and have them vote on the label of the test image.

Task 2.2. Hyperparameters, cross-validation

The k-NN classifier requires a setting for k as well as there is an option of choosing one or another distance function (e.g. L1 or L2 norm). These choices are examples of so called **hyperparameters**, which needs to be optimized for best classification accuracy. **In machine learning one should avoid adjusting these parameters based on the test data!** This is rather obvious since in this case your algorithm will be optimized for the particular data set. A typical approach for choosing test parameters is to have yet other data set for validation purposes. In some cases, when the dataset is small, a technique called cross-validation is used. It is illustrated in the figure below.



The training set is split into folds. In the figure above 5 folds are displayed. One fold for example fifth (shown by yellow color) is chosen for validation while other four for training. In cross-validation one iterates the validation fold when choosing the optimal values for hyper parameters. Typical number of folds you can see in practice would be 3-fold, 5-fold or 10-fold cross-validation.

In the very end once the model is trained and the best values of hyperparameters were determined, the model is evaluated a single time on the test data (red).

1. Extend the code of the NearestNeighbor example with necessary methods to find the best value of k using 3-fold cross-validation method. Use L2 norm as the distance function.
2. What is the classification accuracy on the test data for the best value of k ?

3. Support Vector Machines

Support Vector Machines is one of the most widely used algorithms for solving classification problems. The algorithm introduces fundamental AI and data science concepts such as model-based learning, highdimensional spaces, separability in

highdimensional spaces and others. In this part of the lab you will use implementation of SVM from scikit-learn Python library to understand the fundamentals of using SVM.

Task 3.1 Load Iris dataset, split the dataset into the training and the test parts in proportion 80:20. Train SVM with linear, polynomial and RBF kernels for multiclass classification. In this task your solution could be inspired by the following blog: <https://towardsdatascience.com/support-vector-machines-svm-clearly-explained-a-python-tutorial-for-classification-problems-29c539f3ad8>

1. Construct confusion matrices for one-vs-one and one-vs-rest training approaches and each kernel type;
2. Using which kernel the best accuracy and F1 score is achieved?
3. Extract the support vectors for each class in one-vs-rest training case.
4. Plot the decision boundary for features 2 vs. 3 and 3 vs. 4.

Congrats, you have just become familiar with fundamentals of the cutting edge learning techniques for data-driven classification! Well done!