Assignment 2: Classification benchmarks with Logistic Regression and Neural Networks

Cultural Data Science, 2023

Author: Aleksander Moeslund Wael Student no. 202005192

Assignment notes (Ross)

For this assignment, we'll be writing scripts which classify the Cifar10 dataset.

You should write code which does the following:

- 1. Load the Cifar10 dataset
- 2. Preprocess the data (e.g. greyscale, reshape)
- 3. Train a classifier on the data
- 4. Save a classification report

You should write one script which does this for a logistic regression classifier and one which does it for a neural network classifier. In both cases, you should use the machine learning tools available via scikit-learn.

Introduction

This repository contains scripts for performing image classification on the Cifar10 dataset using logistic regression and a neural network classifier.

Data

The Cifar10 dataset consists of 60K 32x32 colour images in 10 classes, with 6K images per class.

Models

The src folder contains two Python scripts, lr_classifier.py and nn_classifier.py, which provide the pipelines for importing, preprocessing and performing a classification task on the data.

The lr_classifier.py script uses multinomial logistic regression to classify the images, whereas the nn_classifier.py script uses a multi-layer Perceptron classifier, both models implemented with scikit-learn for Python.

Pipeline

The Python scripts are structured as follows:

- 1. Import data
- 2. Preprocess data

- 3. Load the model
- 4. Fit the model to the training data
- 5. Predict test data
- 6. Print and save a classification report to out folder

How to run

NOTE: Depending on your OS, run either <u>WIN_*</u> (on Windows) or <u>MACL_*</u> (on MacOS or Linux).

1. Clone repository to desired directory

```
git clone https://github.com/alekswael/assignment2-image-classification-
cd assignment2-image-classification
```

2. Run setup script

The setup script does the following:

- 1. Creates a virtual environment for the project
- 2. Activates the virtual environment
- 3. Installs the correct versions of the packages required
- 4. Deactivates the virtual environment

```
bash WIN_setup.sh
```

3. Run pipeline

Run script in a bash terminal.

The script does the following:

- 1. Activates the virtual environment
- 2. Runs either lr_classifier.py or nn_classifier.py located in the src folder
- 3. Deactivates the virtual environment

```
bash WIN_run_lr_classifier.sh
bash WIN_run_nn_classifier.sh
```

Note on model tweaks

Some model parameters can be set through the argparse module. However, this requires running the Python script seperately OR altering the run*.sh file to include the arguments. The Python scripts are located in the src folder. Make sure to activate the environment before running the Python script.

```
nn_classifier.py [-h] [-hls HIDDEN_LAYER_SIZES] [-i MAX_ITER] [-l LEARNING_RATE]
[-s EARLY_STOPPING]
options:
                      show this help message and exit
  -h, --help
  -hls HIDDEN_LAYER_SIZES, --hidden_layer_sizes HIDDEN_LAYER_SIZES
                        The ith element represents the number of neurons in the
ith hidden layer. If a single layer, DO NOT put a comma. Specify values WITHOUT
SPACES. (default: 64,10)
  -i MAX_ITER, --max_iter MAX_ITER
                       Maximum number of iterations. (default: 70)
  -1 LEARNING_RATE, --learning_rate LEARNING_RATE
                        Learning rate schedule for weight updates (default:
adaptive)
  -s EARLY_STOPPING, --early_stopping EARLY_STOPPING
                        Whether to use early stopping to terminate training when
validation score is not improving. (default: True)
```

Repository structure

This repository has the following structure:

```
MACL_run_lr_classifier.sh
MACL_setup.sh
README.md
requirements.txt
WIN_run_lr_classifier.sh
WIN_run_nn_classifier.sh
WIN_setup.sh
—out
—src
```

```
lr_classifier.py
nn_classifier.py
```

Remarks on findings

When comparing the classification reports, it seems the NN-classifier performs a bit better at 38% acc compared to the LR-classifier at 30% acc, although both performances are somewhat underwhelming compared to chance level (10% acc).

R-classifier			C1		
	precision	recall	f1-score	support	
airplane	0.34	0.38	0.36	1000	
automobile	0.36	0.38	0.37	1000	
bird	0.25	0.20	0.22	1000	
cat	0.21	0.15	0.18	1000	
deer	0.24	0.20	0.22	1000	
dog	0.29	0.29	0.29	1000	
frog	0.27	0.30	0.29	1000	
horse	0.29	0.30	0.30	1000	
ship	0.35	0.40	0.37	1000	
truck	0.39	0.45	0.41	1000	
accuracy			0.31	10000	
macro avg	0.30	0.31	0.30	10000	
veighted avg	0.30	0.31	0.30	10000	

NN-classifier				
	precision	recall	f1-score	support
airplane	0.42	0.33	0.37	1000
automobile	0.43	0.47	0.45	1000
bird	0.28	0.40	0.33	1000
cat	0.27	0.16	0.20	1000
deer	0.32	0.20	0.25	1000
dog	0.37	0.34	0.35	1000
frog	0.31	0.53	0.39	1000
horse	0.45	0.35	0.40	1000
ship	0.47	0.48	0.47	1000
truck	0.44	0.46	0.45	1000
accuracy			0.37	10000
macro avg	0.38	0.37	0.37	10000
weighted avg	0.38	0.37	0.37	10000