Università degli
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Summing up

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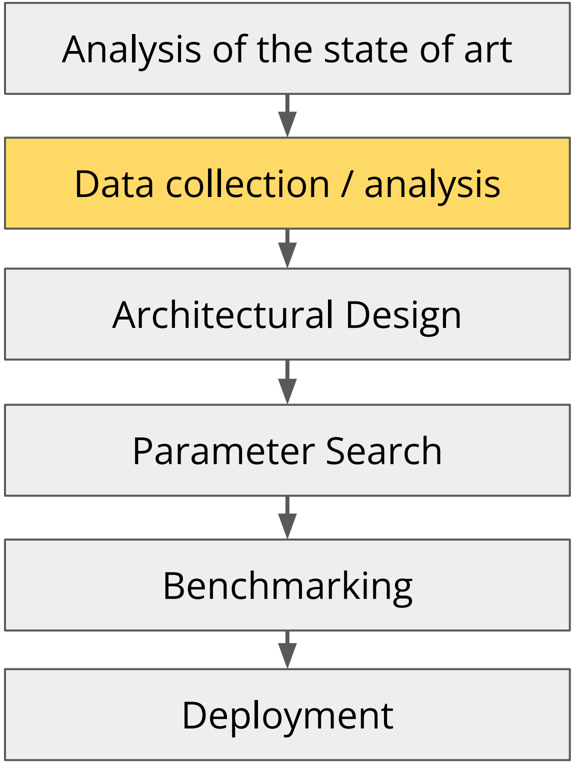
R&D process



Analysis of the state of art

Data collection / analysis

Architectural Design

Parameter Search

Benchmarking

Deployment

pandas

scikit learn

Data preprocessing

Cleaning

Deal with missing data

↓

Encoding

Convert data in a machine-learning suitable format

↓

Normalizing

Normalize the variables

↓

Splitting

Split in train / validation / test

Cleaning

What do we do with missing data?

Three possible strategies:

- discard feature having missing data
- discard samples having missing data
- substitute missing data with plausible content
    - **booleans / categorical**: replace with mode
    - **integers**: replace with median
    - **floats**: interpolate

Encoding of input categorical variables

- Machine learning models can only work with numerical values
- It is necessary to transform the categorical values of the relevant features into numerical ones

One-hot encoding (for input variables)

brand
Fiat
BMW
Lamborghini
Fiat

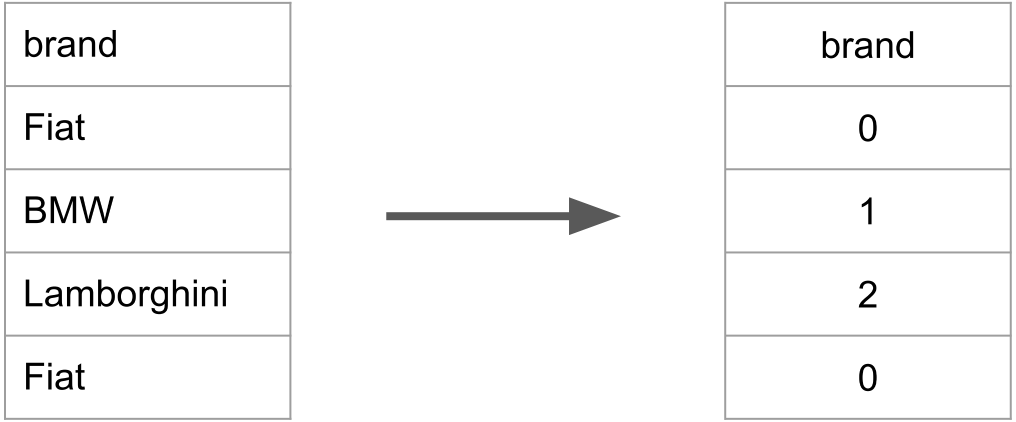
→

brand_fiat	brand_bmw	brand_lambo
1	0	0
0	1	0
0	0	1
1	0	0

Encoding of target categorical variables

- Machine learning models can only work with numerical values
- It is necessary to transform the categorical values of the relevant features into numerical ones

Labeling (for estimated variables)



brand
Fiat
BMW
Lamborghini
Fiat

brand
0
1
2
0

Normalizing

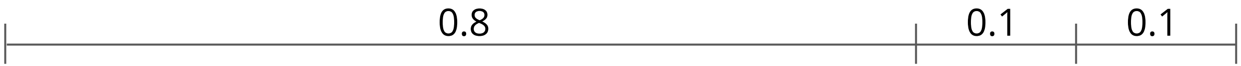
- The range of the variables affect their importance
- We need to normalize them so that each variable resides in the same range
    - **min - max normalization**
        - if the variable under analysis has a specific range, it’s possible to use this normalization
        - `from sklearn.preprocessing import MinMaxScaler`
    - **standardization**
        - if the range is unknown a priori
        - sets the mean to 0 and the variance to 1
        - `sklearn.preprocessing import StandardScaler`

Splitting

It is possible to split in train, validation and test with the following code:

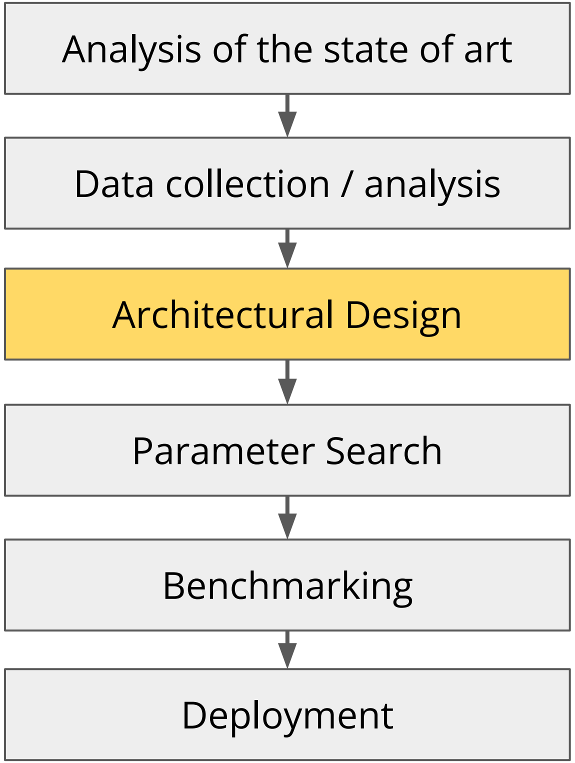
```
# define percentage of splitting
train_perc = 0.8
val_perc = 0.1
# test_perc will be: 1 - train_perc - val_perc

# split train validation and test
train = df.sample(frac = train_perc, random_state=1)
test = df.drop(train.index).sample(frac = val_perc/(1-train_perc), random_state=1)
val = df.drop(train.index).drop(test.index)
```



$$(1 - 0.8)x = 0.1 \qquad x = \frac{0.1}{1-0.8}$$

R&D process



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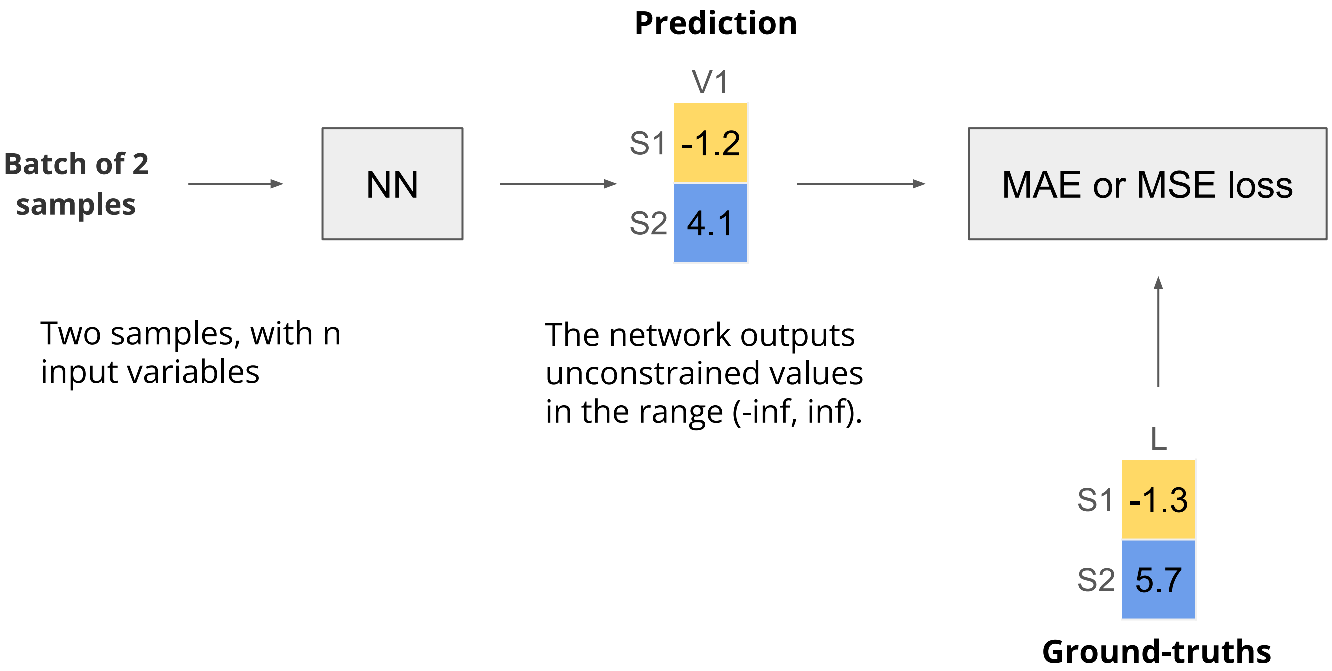
PyTorch

PyTorch Lightning

Regression setup

- network predicts directly the values of the continuous variable
- loss and performance score are: MAE or MSE



Prediction

	V1
S1	-1.2
S2	4.1

Batch of 2 samples

NN

MAE or MSE loss

Two samples, with n input variables

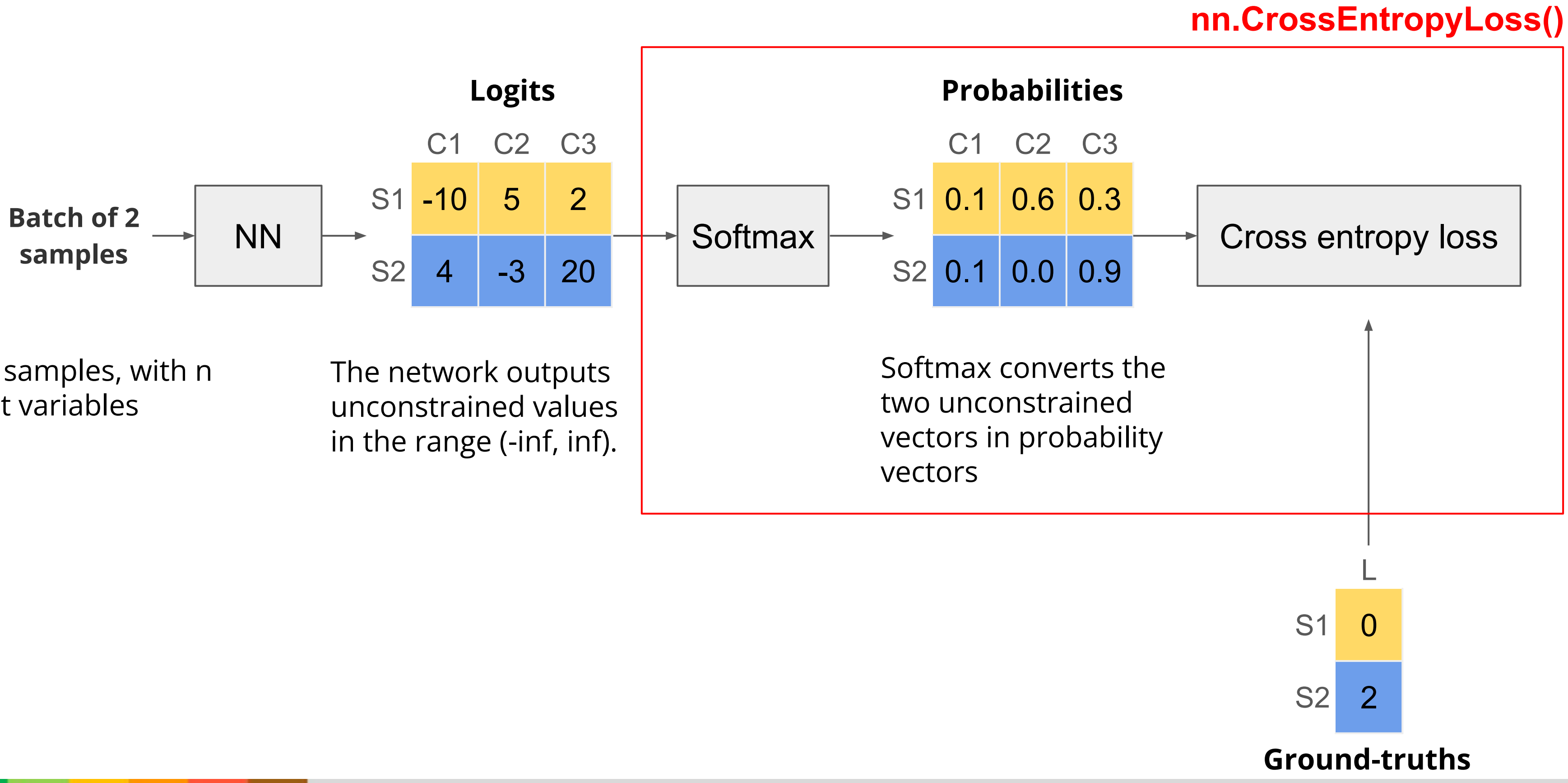
The network outputs unconstrained values in the range (-inf, inf).

	L
S1	-1.3
S2	5.7

Ground-truths

Pipeline for classification in Pytorch

In Pytorch, nn.CrossEntropyLoss combines softmax and cross entropy loss



Logits

	C1	C2	C3
S1	-10	5	2
S2	4	-3	20

Probabilities

	C1	C2	C3
S1	0.1	0.6	0.3
S2	0.1	0.0	0.9

Ground-truths

	L
S1	0
S2	2

Two samples, with n input variables

The network outputs unconstrained values in the range (-inf, inf).

Softmax converts the two unconstrained vectors in probability vectors

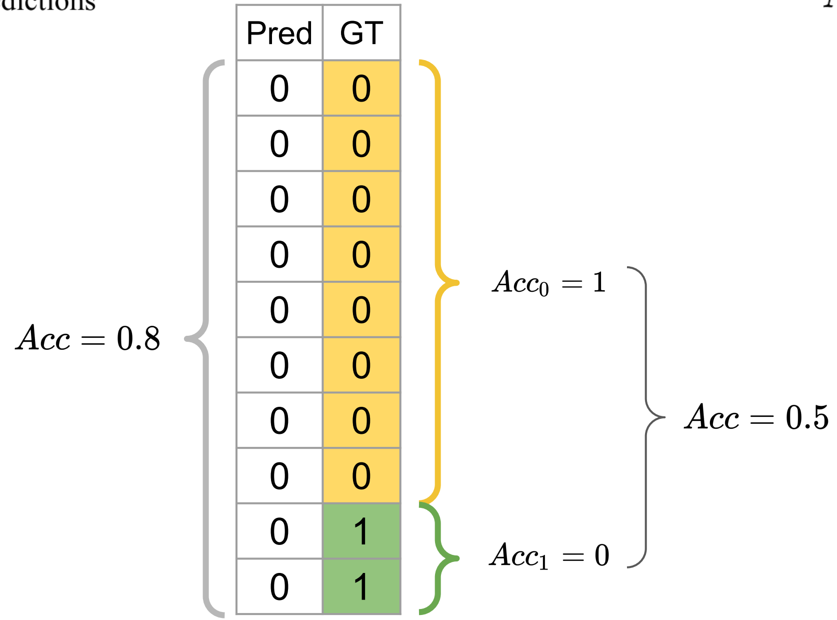
Accuracy

Micro

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

Macro

$$\text{Accuracy} = \frac{1}{N}\sum_{c=1}^{N}\frac{\text{\# correct preds for class c}}{\text{\# samples of class c}}$$



Pred	GT
0	0
0	0
0	0
0	0
0	0
0	0
0	0
0	0
0	1
0	1

$Acc = 0.8$

$Acc_0 = 1$

$Acc_1 = 0$

$Acc = 0.5$

Torchmetrics

```
import torchmetrics

# define input and ground truth
inp = torch.tensor([0,0,0,0,0,0,0,0,0,0])
gt  = torch.tensor([0,0,0,0,0,0,0,0,1,1])
```

```
# define metric objects
acc_micro = torchmetrics.Accuracy(task = 'multiclass', num_classes = 2, average = 'micro')
acc_macro = torchmetrics.Accuracy(task = 'multiclass', num_classes = 2, average = 'macro')
```

Initialization

```
# update metrics
acc_micro.update(inp, gt)
acc_macro.update(inp, gt)

# you can update the metrics with more batches ..
```

Update of the metric.
One update for each batch.

```
# at the end, compute the final score
micro = acc_micro.compute()
macro = acc_macro.compute()
```

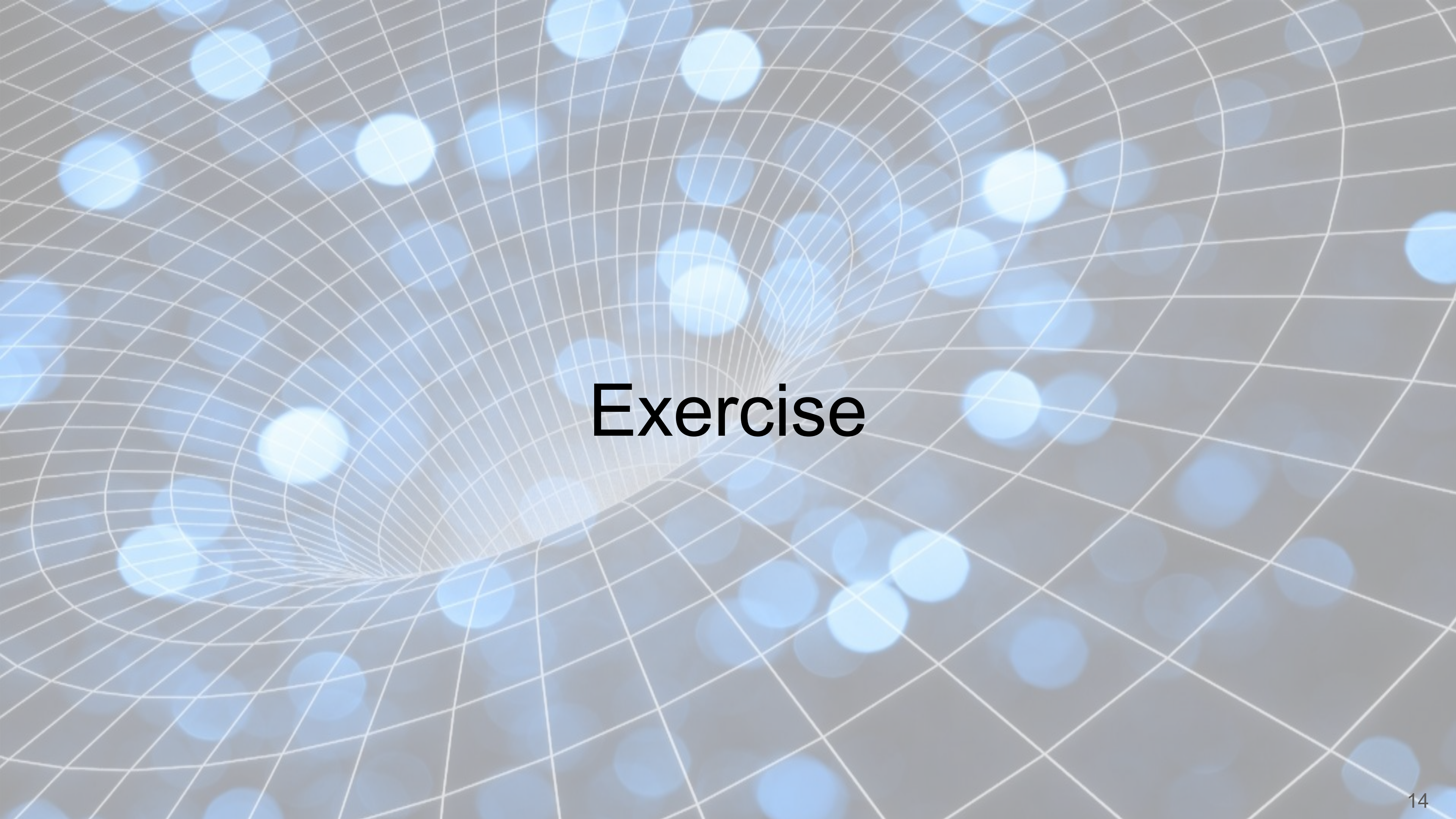
Final computation of the metric

```
# print
print(f'Micro accuracy is {micro:0.2f} while macro accuracy is {macro:0.2f}')
```

```
# reset the metric object (optional)
acc_micro.reset()
acc_macro.reset()
```

Reset of the metric

It will print: “Micro accuracy is 0.80 while macro accuracy is 0.50”



Exercise

Exercise 1 - Data analysis + neural prediction

- Given the dataset “traffic_violations” with target variable “is_arrested”:

1. explore the data
2. decide which variables should be dropped (e.g. 'country_name', 'stop_date', 'stop_time')
3. clean data
4. encode data
5. normalize data
6. split data in train, validation and test using the code in slide 8
7. set up the training of a neural network
8. train the system
9. test the performance in terms of micro and macro accuracy
10. compute also the confusion matrix