

PART 1 - Data Preprocessing.

workflow

Data Preprocessing

- import data
- clean data - * important step IRL.
- split into train & test sets.

Modelling

- Build Model
- Train Model
- Make Predictions.

Evaluation

- calculate performance matrix
- Make verdict.

Train-Test split.

usually 80/20 percent

↓
Training

→ Used trained model on test set that has known results to compare with models result.

Feature-Scaling

Remember (always applied to columns & ^{never on} not rows)

① Normalization
$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

Most values b/w $[0, 1]$

where x is the value of column

x_{\min} is lowest & x_{\max} is highest

② Standardization
$$x' = \frac{x - \mu}{\sigma}$$
 where μ is mean/average

Most values except $[+3, -3]$ extremes or outliers.

σ is std. deviation

- with unscaled features, the lower valued/unit column become irrelevant & make small difference to large scale values.

Practical.

↪ allows to import a library or function or any module.

(1) import libraries

- (1) numpy - works with arrays for inputs.
- (2) matplotlib - for charts/graph/visualizations.
- (3) pandas - import dataset / create matrix of features & dependent variable vector.

◦ Libraries - ensemble of module containing ^{functions} ~~modules~~ & classes.

- import numpy as np
we can call with np ^{now} ~~now~~.
- import matplotlib.pyplot as plt.
↪ interested in this module.
- import pandas as pd.

(2) Import dataset

- (1) dataset = Pd.read_csv(filename.extension).
- create a dataframe with all values in data set.

(2) create 2 new entities

(1) matrix of features & (2) dependent variable vector

* features - the column with which we are going to predict
(independent variables) dependent variable.

* dependent variables - last column, that need to be predicted of dataset

full form - index location

feature of pandas, allows us to take index of columns/rows we want to extract.

* `x = dataset.iloc[:, :-1].values`

↓
Takes all rows (in python it means a range, without

LB or UB means all).

Here `[:, :-1]`

↓
Row
all

↓
column
(all except last).

so,

* `y = dataset.iloc[:, -1]`

③ Handling Missing Values.

Method I: Just delete the row of missing value.

- works good for large datasets, with low % of missing data.

Method II: Replace missing value by average of all data in column.

* Scikitlearn - has lot of tools & preprocessing tools for this task.

* we use a module called impute in scikitlearn & a class import the SimpleImputer from it.

`imputer = SimpleImputer(missing_values=np.nan,`

`strategy = mean)`

↓
value to replace
↑
to be replaced with

- Now, this object class has functions that will be used to find missing values & then impute it.

• `imputer.fit(x[:, 1:3])`

↑
expects all the column with numeric

• `imputer.transform(x[:, 1:3])`

↑
value
↑
of x
← returns new updated matrix of features

So to change original as it ~~go~~ have feature matrix

- $X[:, 1:3] = \text{imputer.transform}(X[:, 1:3])$

④ Encoding Categorical Data.

* It will be difficult to co-relate / compute these features with categorical string data, Thus we need to turn these categories to numbers.

Idea

Method I: Encode France to 0

Spain to 1

Germany to 2

- However model may interpret as order / numeric order & interpret as the order matters.

Better To-Do: ~~Turn~~ Turn to one hot encoding i.e.

turn the category into total columns with total no. of distinct category.

So for France Spain & Germany we get

for France 1 0 0

Spain 0 1 0

Germany 0 0 1

① Encode Independent Variable

- For this we use 2 classes

① ColumnTransformer class from composed module of skit

② OneHotEncoder class from preprocess module of skit
what kind of transformation
 on which indexes

① $ct = \text{ColumnTransformer}(\text{transformers}, \text{remainder})$
to specify we are doing
 encoding transformation class name
 to encode to ↓
 columns that won't
 be applied for
 transformations.

* $\text{transformers} = [(\text{'encoder'}, \text{'OneHotEncoder'})],$
 $[0]] \rightarrow \text{indexes to transform/encode}$

codename to say we wanna
keep columns as it is &
won't apply transformation.

Remainders z: 'passthrough'

↑
If we don't apply the remaining columns
won't be added.

• with this class, we can fit and transform at once
with function

~~data~~ $x = \text{Ct.fit_transform}(x)$

↑
Machine learning use ~~np~~ numpy array so we
need to convert it to np array

We call $x = \text{np.array}(\text{Ct.fit_transform}(x))$

② Encode Dependent Variable.

• we use LabelEncoder class from preprocessing from scikit

$\text{lbl} = \text{LabelEncoder}()$

↑
only one column with text
value, so its obvious what
needs to be performed

$y = \text{lbl.fit_transform}(y)$

↑
doesn't need to be numpy array since
its single dependent var. array.

⑤ Splitting Dataset into Train & Test set.

* We apply feature scaling after splitting data.

↓
because we only use train set for ML model while test set
represents real world data. & shouldn't be altered.
~~It just needs to be fed to model & get op.~~

- Also when applying feature scaling we use mean & standard deviation that might leak some info to train set which isn't supposed to happen. The ML model will get into on test set & may fit itself for it.

- We scale test later after splitting & scaling train set.
For this will use sklearn module that has.
model = Selection class with train-test-split fn.

- We split into 4. 2 feature matrices & 2 depend variables.

$x_{\text{train}}, x_{\text{test}}, y_{\text{train}}, y_{\text{test}} = \text{train_test_split}(x, y$
 ~ 2 more args ~ $\text{train_size} = 0.8$, $\text{test_size} = 0.2$, $\text{random_state} = 1$)

Annotations:
 - x_{train} expects first feature mat
 - y_{train} expects dep. var
 - $\text{random_state} = 1$ int type seed for random value.

⑥ Feature Scaling (not necessary for all models), works well all the time

2 techniques ① Standardization (with mean(μ) & deviation(σ)).
 $\rightarrow (+3, -3)$

② Normalization: (with x_{min} & x_{max}).
 $\rightarrow (0, 1)$

works/recommended if we have normal distribution among most of our features.
 (recommended for specific situations).

• For this step, we use same scikit module.
 from sklearn.preprocessing import StandardScaler
 \uparrow
 class.

SC = StandardScaler() ← automatically applies standardisation.

• Dummy variables → variable columns after encoding categorical data.

- We don't need to apply standardisation to dummy variables since they are already b/w $(-3, 3)$ or $(0, 1)$.

① First we fit our scaler on training sets.

so $x_train[:, 3:] = sc.fit_transform(x_train[:, 3:])$
↑
everything after 2 with 3rd column

② Next we fit x-test.

- we only apply transform method here since this data is like new data received IRL by model.

- The features of test set need to be scaled by the same scaler used on training set.

- we don't calculate a new fit. we got that from fit-transform earlier
 $x_test[:, 3:] = sc.transform(x_test[:, 3:])$

SUMMARY:

① All Libraries for Preprocessing

- import pandas as pd [General]
- " numpy as np
- from sklearn.impute import SimpleImputer (for Missing Values)
- " sklearn.compose ColumnTransformer (for encoding categorical data)
- " sklearn.preprocessing OneHotEncoder (for encoding label/dependent data)
- " " " LabelEncoder (for splitting feature)
- " sklearn.model_selection train_test_split (for splitting feature)
- " sklearn.preprocessing StandardScaler (for Scaling)

② To import dataset (and assign dep. & indep. variable)

```
dataset = pd.read_csv('./loadfilename')
```

```
X = dataset.iloc[:, :-1].values
```

```
y = " "[:, 1].values
```

③ Handle Missing data

```
imp = SimpleImputer(missing_values = np.nan, strategy = 'mean')
```

```
imp.fit(X[:, 1:3])
```

```
X[:, 1:3] = imp.transform(X[:, 1:3])
```

→ first fit to compute then transform to replace

④ Encoding Categorical Data

① Indep. variable

```
colTr = ColumnTransformer(transformers = [('encoding', OneHotEncoder(), [0])], remainder = 'passthrough')
```

```
X = np.array(colTr.fit_transform(X))
```

② Dep. variable

```
lbEnc = LabelEncoder()
```

```
y = lbEnc.fit_transform(y)
```

⑤ Split Data

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2,  
                                                    random_state = 0)
```

⑥ Scaling (only when necessary)

```
sclr = StandardScaler()
```

```
X_train[:, 3:] = sclr.fit_transform(X_train[:, 3:])
```

```
y_train[:, 3:] = sclr.transform(X_test[:, 3:])
```