Intro to classification - kNN - 2

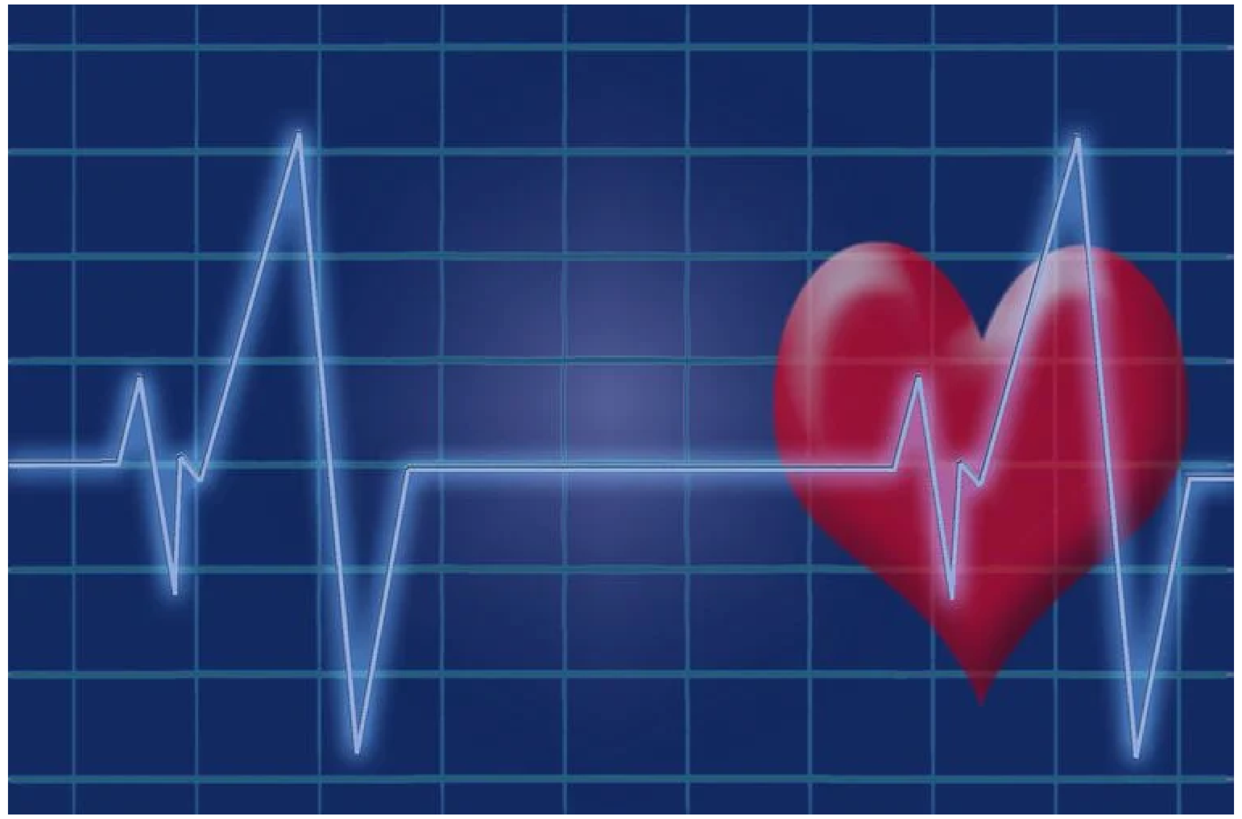
One should look for what is and not what he thinks should be. (Albert Einstein)

Module completion checklist

Objective	Complete
Clean and transform data to run kNN	
Define cross-validation and discuss how to use it	

Stroke Prediction survey: case study

- According to the World Health Organization (WHO), stroke is the 2nd leading cause of death globally
- *Click here* to see a dataset showing the results of a clinical trial of a heart-disease drug survey on a sample of US adults
- Each row in the data provides relevant information about the adult, including whether they had a stroke or not
- We would like to use this data to predict whether a patient is likely to have a stroke based on their demographic information and medical history



Dataset

- In order to implement what you learn in this course, we will be using the `healthcare-dataset-stroke-data` dataset
- We will be working with columns from the dataset such as:

- `stroke`
- `gender`
- `age`
- `hypertension`
- `heart_disease`
- `ever_married`

- We will be using different columns of the dataset to predict `stroke` as the target variable

Loading packages

Let’s load the packages we will be using:

```
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from pathlib import Path

# We will introduce it when we use it
import pickle
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import scale,StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn import metrics
```

Directory settings

- In order to maximize the efficiency of your workflow, you should encode your directory structure into `variables`
- We will use the `pathlib` library
- Let the `main_dir` be the variable corresponding to your `course` folder
- Let `data_dir` be the variable corresponding to your `data` folder

```
# Set 'main_dir' to location of the project folder
home_dir = Path(".").resolve()
main_dir = home_dir.parent.parent
print(main_dir)
```

```
data_dir = str(main_dir) + "/data"
print(data_dir)
```

Load data into Python

- Let's load the entire dataset
- We are now going to use the function `read_csv` to read in our `healthcare-dataset-stroke-data.csv` dataset

```
df = pd.read_csv(str(data_dir)+"/"+ 'healthcare-dataset-stroke-data.csv')
print(df.head())
```

```
      id  gender   age  ...   bmi   smoking_status stroke
0   9046    Male  67.0  ...  36.6  formerly smoked      1
1  51676  Female  61.0  ...   NaN     never smoked      1
2  31112    Male  80.0  ...  32.5     never smoked      1
3  60182  Female  49.0  ...  34.4           smokes      1
4   1665  Female  79.0  ...  24.0     never smoked      1

[5 rows x 12 columns]
```

Subset data

- Remove any columns from the dataframe that are not numeric or categorical as we will not be using them in our models

```
df = df[['age', 'avg_glucose_level', 'heart_disease', 'ever_married', 'hypertension',
'Residence_type', 'gender', 'smoking_status', 'work_type', 'stroke', 'id']]
print(df.head())
```

```
    age  avg_glucose_level  heart_disease  ...      work_type  stroke     id
0  67.0             228.69              1  ...        Private       1   9046
1  61.0             202.21              0  ...  Self-employed       1  51676
2  80.0             105.92              1  ...        Private       1  31112
3  49.0             171.23              0  ...        Private       1  60182
4  79.0             174.12              0  ...  Self-employed       1   1665

[5 rows x 11 columns]
```

Convert target to binary

- Let's check if the target is binary, and convert it to binary if it is not already

```
# Target not binary - calculate the mean and assign the above mean to 1 and below to 0
threshold = np.mean(df['stroke'])
df['stroke'] = np.where(df['stroke'] > threshold, 1,0)
```

```
# Target is binary
print(df['stroke'])
```

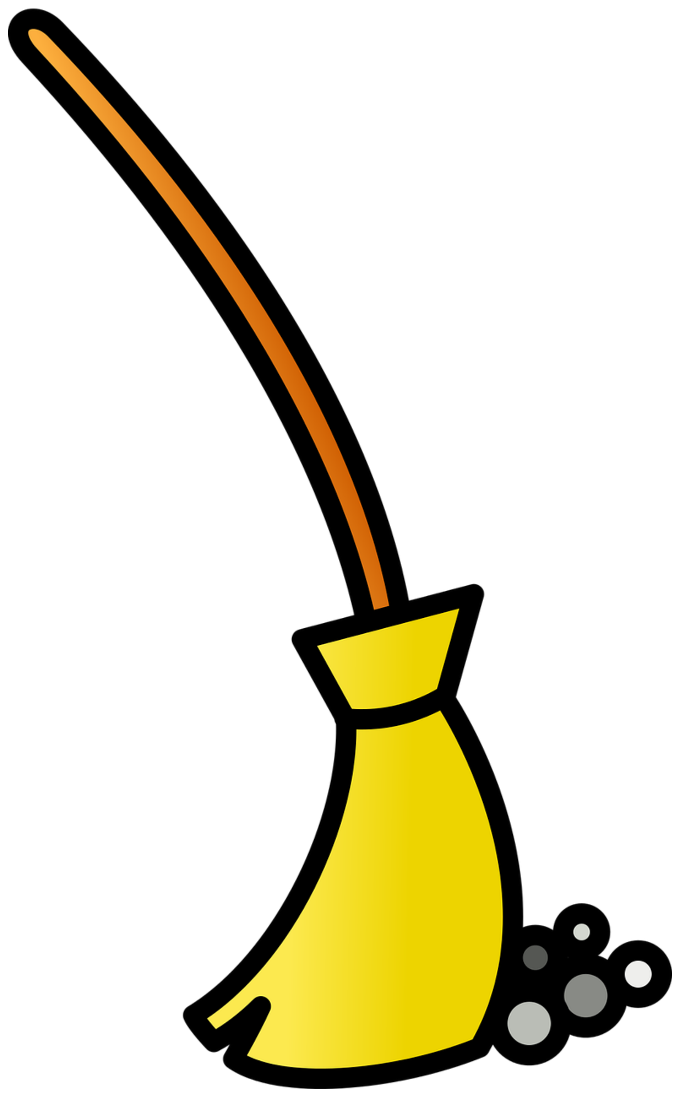
```
0       1
1       1
2       1
3       1
4       1
       ..
5105    0
5106    0
5107    0
5108    0
5109    0
Name: stroke, Length: 5110, dtype: int64
```

ID variables

- We will not use certain columns such as ID variables or variables with more than 50% NAs
  - **`id`**
- We want to see if the independent variables would predict `stroke` well

Data cleaning steps for kNN

- There are a few steps to remember to take before jumping into splitting the data and training the model
- Let's look at what it means to scale our predictors, and why it's necessary with kNN
- We will also talk through why we need to make sure the target variable is labeled



i. Make sure the target is labeled
ii. Check for NAs (null values)
iii. Encode categorical data into numerical
iv. Split into train and test
v. Scale the predictors

The data at first glance

- Look at the first 3 rows and the data types

```
# The first 3 rows.
print(df.head(3))
```

```
    age  avg_glucose_level  heart_disease  ...
work_type  stroke      id
0  67.0             228.69              1  ...
Private       1   9046
1  61.0             202.21              0  ...   Self-
employed       1  51676
2  80.0             105.92              1  ...
Private       1  31112

[3 rows x 11 columns]
```

```
# The data types.
print(df.dtypes)
```

```
age                  float64
avg_glucose_level    float64
heart_disease          int64
ever_married          object
hypertension           int64
Residence_type        object
gender                object
smoking_status        object
work_type             object
stroke                 int64
id                     int64
dtype: object
```

- Frequency table of the target variable

```
print(df['stroke'].value_counts())
```

```
0    4861
1     249
Name: stroke, dtype: int64
```

Data prep: check for NAs

- We now check for NAs and there are multiple methods to deal with them

```
 # Check for NAs.
print(df.isnull().sum())
```

```
age                          0
avg_glucose_level            0
heart_disease                0
ever_married                 0
hypertension                 0
Residence_type               0
gender                       0
smoking_status            1544
work_type                    0
stroke                       0
id                           0
dtype: int64
```

Data prep: check for NAs

- If we do have NA, we could replace them with a mean or 0

```
percent_missing = df.isnull().sum() * 100 / len(df)
print(percent_missing)
```

```
age                   0.000000
avg_glucose_level     0.000000
heart_disease         0.000000
ever_married          0.000000
hypertension          0.000000
Residence_type        0.000000
gender                0.000000
smoking_status       30.215264
work_type             0.000000
stroke                0.000000
id                    0.000000
dtype: float64
```

Data prep: check for NAs

```
# Delete columns containing either 50% or more than 50% NaN Values
perc = 50.0
min_count =  int(((100-perc)/100)*df.shape[0] + 1)
df = df.dropna(axis=1,
               thresh=min_count)
print(df.shape)
```

```
(5110, 11)
```

```
# Function to impute NA in both numeric and categorical columns
def fillna(df):
    # Fill numeric columns with mean value
    df = df.fillna(df.mean())
    # Fill categorical columns with mode value
    df = df.fillna(df.mode().iloc[0])
    return df

df = fillna(df)
```

```
/opt/conda/envs/sdaia-python-classification/bin/python:3: FutureWarning: Dropping of
nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a
future version this will raise TypeError.  Select only valid columns before calling the
reduction.
```

- We are now ready to convert our data to numerical values

Data prep: ready for kNN

- The next step of our data cleanup is to ensure the target variable is binary and has a label
- Let's look at the `dtype` of `stroke`

```
print(df['stroke'].dtypes)
```

```
int64
```

- We want to convert this to `bool` so that is a binary class

```
# Identify the the two unique classes
unique_values = sorted(df['stroke'].unique())
df['stroke'] = np.where(df['stroke'] == unique_values[0], False,True)
```

```
# Split the data into X and y
columns_to_drop_from_X = ['stroke'] + ['id']
X = df.drop(columns_to_drop_from_X, axis = 1)
y = np.array(df['stroke'])
```

Data prep: numeric variables

- In `kNN`, we use **numeric data** as predictors
- In some cases, we can **convert categorical data to integer values**

```
print(X.dtypes)
```

```
age                  float64
avg_glucose_level    float64
heart_disease          int64
ever_married          object
hypertension           int64
Residence_type        object
gender                object
smoking_status        object
work_type             object
dtype: object
```

```
X = pd.get_dummies(X, columns = ['heart_disease',
'ever_married', 'hypertension', 'Residence_type',
'gender', 'smoking_status', 'work_type'],
dtype=float, drop_first=True)
print(X.dtypes)
```

```
age                              float64
avg_glucose_level                float64
heart_disease_1                  float64
ever_married_Yes                 float64
hypertension_1                   float64
Residence_type_Urban             float64
gender_Male                      float64
gender_Other                     float64
smoking_status_never smoked      float64
smoking_status_smokes            float64
work_type_Never_worked           float64
work_type_Private                float64
work_type_Self-employed          float64
work_type_children               float64
dtype: object
```

Module completion checklist

Objective	Complete
Clean and transform data to run kNN	✔
Define cross-validation and discuss how to use it	

Introducing cross-validation

- Before applying any machine learning algorithms on the data, we usually need to split the data into a **train set** and a **test set**
- But now, we are doing this **multiple times**
- We have a new **test set** for each fold `n`
- The rest of the data is the **train set**

Why do we use cross-validation?

- Cross-validation is helpful in multiple ways:
  - It tunes our model better by running it multiple times on our data (instead of just once on the train set and once on the test set)
  - You get assurance that your model has most of the patterns from the data correct and it's not picking up too much on the noise
  - It finds optimal parameters for your model because it runs multiple times

Cross-validation: train and test

Train

- This is the data that you train your model on
- Use a larger portion of the data to train so that the model gets a large enough sample of the population
- Usually about **70%** of your dataset
- **When there is not a large population to begin with, cross-validation techniques can be implemented**

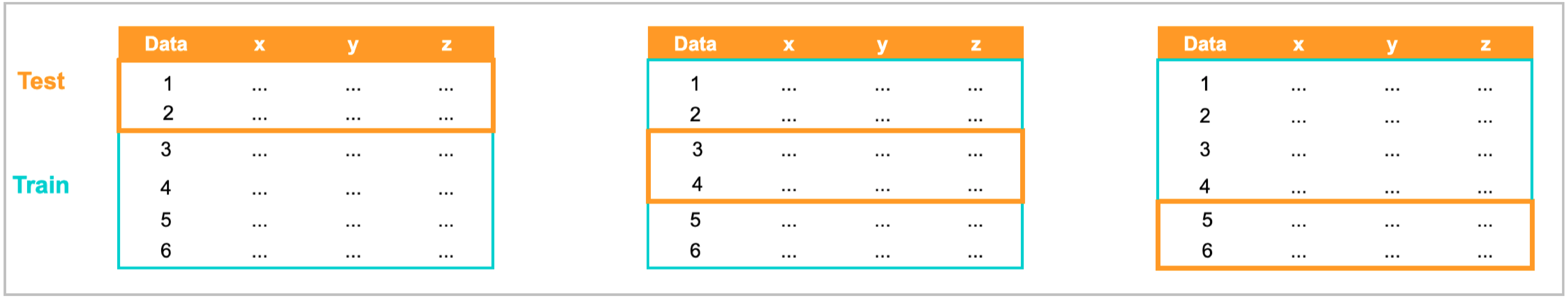
Test

- This is the data that you test your model on
- Use a smaller portion to test your trained model on
- Usually about **30%** of your dataset
- **When cross-validation is implemented, small test sets will be held out multiple times**

Cross-validation: n-fold

Here is how cross-validation works:

1. Split the dataset into several subsets ("n" number of subsets) of equal size
2. **Use each subset as the test dataset** and **use the rest of the data as the training dataset**
3. Repeat the process for every subset you create



Train and test: small scale before n-fold

- Before we actually use n-fold cross-validation:
  - We split our data into a train and test set
  - We run kNN initially on the training data

```
# Set the seed.
np.random.seed(1)

# Split into train and test.
X_train, X_test, y_train, y_test = train_test_split(X,
                                                    y,
                                                    test_size = 0.3)
```

- Success! Now let's scale our predictors

Data prep: scaling variables

- Once the data is converted to `numeric` (if necessary), we **scale** the dataset to make sure that we can properly calculate the relationship between variables
- There are a few methods to scale data and we will use the `scale` function from `sklearn.preprocessing`
- A few things to remember about `scale`:
  - It is a generic function whose default method **centers** and/or scales the columns of a numeric matrix
  - It will convert your dataset to have a `mean` of `0` and a `standard deviation` of `1`

sklearn.preprocessing.scale

`sklearn.preprocessing.scale` (*X, axis=0, with_mean=True, with_std=True, copy=True*) [source]

Standardize a dataset along any axis

Center to the mean and component wise scale to unit variance.

Read more in the User Guide.

Parameters: **X** : *{array-like, sparse matrix}*

The data to center and scale.

axis : *int (0 by default)*

axis used to compute the means and standard deviations along. If 0, independently standardize each feature, otherwise (if 1) standardize each sample.

with_mean : *boolean, True by default*

If True, center the data before scaling.

with_std : *boolean, True by default*

If True, scale the data to unit variance (or equivalently, unit standard deviation).

copy : *boolean, optional, default True*

set to False to perform inplace row normalization and avoid a copy (if the input is already a numpy array or a scipy.sparse CSC matrix and if axis is 1).

Data prep: scaling variables

- We scale only our predictors
- We scale our X and y predictors separately

```
# Scale X.
X_train = scale(X_train)
X_test = scale(X_test)
```

```
print(X_train[0:2])
```

```
[[ 0.60884288  0.63825752 -0.23816135  0.71900176 -0.33037446  0.99414629
   1.17402064  0.          0.69941096 -0.42534432 -0.06910341  0.86404979
  -0.43810503 -0.3922639 ]
 [-1.88698872 -0.38666334 -0.23816135 -1.39081718 -0.33037446 -1.00588818
  -0.85177378  0.          0.69941096 -0.42534432 -0.06910341 -1.15734072
  -0.43810503  2.54930418]]
```

```
print(X_test[0:2])
```

```
[[-0.04508466  0.12994683 -0.24077171  0.73532545 -0.32444284 -1.04061541
  -0.81405762 -0.02554881 -1.43949446 -0.43189409 -0.0572036  -1.1562397
  -0.43401854 -0.39840954]
 [ 1.52709552 -0.64601991 -0.24077171  0.73532545 -0.32444284  0.96096982
  -0.81405762 -0.02554881 -1.43949446 -0.43189409 -0.0572036   0.86487257
  -0.43401854 -0.39840954]]
```

Knowledge check

Module completion checklist

Objective	Complete
Clean and transform data to run kNN	✔
Define cross-validation and discuss how to use it	✔

Congratulations on completing this module!

You are now ready to try Tasks 1-8 in the Exercise for this topic