# 1. Nested cross-validation exercise

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## Nested cross-validation for k-nearest neighbors

- Use Python 3 to program a nested leave-one-out cross-validation for the k-nearest neighbors (kNN) method so that the number of neighbours k is automatically selected from the set k = [3, 5, 7, 9, 11]. In other words, the base learning algorithm is kNN but the actual learning algorithm, whose prediction performance will be evaluated with nested CV, is kNN with automatic CV-based model selection (see the lectures and the pseudo codes presented on them for more info on this interpretation).
- Compare the C-index produced by nested leave-one-out CV with normal leave-one-out cross-validation with the best value of k.
- As a kNN implementation, use the provided kNN and C-index functions in your exercise.
- Use the CV implementations on the provided subsampled iris data (100 randomly drawn data points from iris) and report the resulting classification accuracy via C-index. Hint: you can use the nested CV example provided on sklearn documentation: https://scikit-learn.org/stable/auto\_examples/model\_selection/plot\_nested\_cross\_validation\_iris.html as a starting point, but do NOT use the ready made CV implementations of sklearn.

As a summary, for completing this exercise implement the following steps:

- 1. Use leave-one-out cross-validation for determining the optimal k-parameter for the data (X.csv, y.csv) from the set k = [3,5,7,9,11]. When you have solved the optimal k-parameter, save the corresponding C-index (call it loo\_c\_index) for this best value of k.
- 2. Similarly, use nested leave-one-out cross-validation (leave-one-out both in outer and inner folds) for determining the C-index (call it nloo\_c\_index) of the kNN + leave-one-out cross-validation based k selection approach.
- 3. Return both this notebook and as a PDF-file made from it in the exercise submit page.

Remember to use the provided C-index and kNN functions in your implementation!

#### Import libraries

```
In [1]: #In this cell import all libraries you need. For example:
    import numpy as np
    import pandas as pd
    import scipy as sp
    import matplotlib.pyplot as plt
    import sklearn
    from sklearn import model_selection
    import time
```

## **Provided functions**

```
In [2]:
         C-index function:
         - INPUTS:
         'y' an array of the true output values
         'yp' an array of predicted output values
         - OUTPUT:
         The c-index value
         def cindex(y, yp):
             n = 0
             h num = 0
             for i in range(0, len(y)):
                 t = y[i]
                 p = yp[i]
                  for j in range(i+1, len(y)):
                      nt = y[j]
                      np = yp[j]
                      if (t != nt):
                          n = n + 1
                          if (p < np \text{ and } t < nt) \text{ or } (p > np \text{ and } t > nt):
                              h num += 1
                          elif (p == np):
                              h_num += 0.5
             try:
                  return h_num/n
             except ZeroDivisionError:
                  return h num/0.5
         .....
         Self-contained k-nearest neighbor
         - INPUTS:
         'X_train' a numpy matrix of the X-features of the train data points
         'y_train' a numpy matrix of the output values of the train data points
         'X_test' a numpy matrix of the X-features of the test data points
         'k' the k-parameter integer value for kNN
         - OUTPUT:
         'y_predictions' a list of the output value predictions
         def knn(X_train, y_train, X_test, k):
             y_train = np.array(y_train, dtype=int)
             y_predictions = []
             for test_ind in range(0, X_test.shape[0]):
                 \#diff = X_{test[test_ind, :].reshape(1, -1) - X_{train}
                 #Modified this, cause of object issues
                 diff = X_test[test_ind].reshape(1, -1) - X_train
                 distances = np.sqrt(np.sum(diff * diff, axis = 1))
                  sort_inds = np.array(np.argsort(distances), dtype=int)
                  counts = np.bincount(y_train[sort_inds[0:k]])
                 y_predictions.append(np.argmax(counts))
             return y_predictions
```

### Your implementation here

```
In [3]: # In this cell implement the required tasks with comments on the code.
#Reading the csv-files into pandas dataframes
X_path = 'X.csv'
y_path = 'y.csv'
X = pd.read_csv(X_path).to_numpy()
y = pd.read_csv(y_path).to_numpy(dtype=int)
```

```
In [4]:
         #loo-cv
         1111111
         Get indices for leave one out -cross validation
         - INPUTS:
         'X' the feature matrix
         'y' the labels
         'n' number of loo iterations
         - OUTPUT:
         'train_indices' an array of indices for the train-data
         'test indices' an array of indices for the test-data
         def loo_split(X):
             X_{indices} = np.arange(0, len(X))
             test_indices = []
             train_indices = []
             for i in range(0, len(X)):
                 test_indices.append(i)
                 train_indices.append(X_indices[np.arange(len(X))!=i])
             return(train_indices, test_indices)
In [5]:
         #The set of possible k-values to be tested
         k = [3,5,7,9,11]
In [6]:
         #leave-one-out cross-validation with own loo_split
         def get_best_k_orig(X, y, k, loosplit):
             t0 = time.time()
             loo_c_index = 0
             best k = 0
             for i in k:
                 yp = []
                 for j in range(0, len(X)):
                     X_train = X[loosplit[0][j]]
                     X_test = X[loosplit[1][j]].reshape(1, 4)
                     y_train = y[loosplit[0][j]].flatten()
                     y_test = y[loosplit[1][j]].flatten()
                     yp.append(knn(X_train, y_train, X_test, i))
                     #print(model)
                 c_{index} = cindex(y, yp)
                 if c_index >= loo_c_index:
                     loo_c_index = c_index
                     best_k = i
                 #print('For k:' + str(i) + ' C-index is ' +str(c_index))
             #print('Best C-index is ' + str(loo_c_index) + ' where k is ' + str(be
             t1 = time.time()
             time_total = t1-t0
             return(best_k, loo_c_index, time_total)
         loosplit = loo_split(X)
         get_best_k_orig(X, y, k, loosplit)
```

```
In [7]:
         #leave-one-out cross-validation with sklearn loo implementation
         def get_best_k(X, y, k, model):
             t0 = time.time()
             loo_c_index = 0
             best_k = 0
             for i in k:
                 yp = []
                 for train_i, test_i in model.split(X):
                     X_train, X_test = X[train_i], X[test_i]
                     y_train, y_test = y[train_i].reshape(-1), y[test_i].reshape(-1
                     yp.append(knn(X_train, y_train, X_test, i))
                     #print(model)
                 c_{index} = cindex(y, yp)
                 if c_index >= loo_c_index:
                     loo_c_index = c_index
                     best_k = i
                 #print('For k:' + str(i) + ' C-index is ' +str(c_index))
             #print('Best C-index is ' + str(loo_c_index) + ' where k is ' + str(be
             t1 = time.time()
             time_total = t1-t0
             return(best_k, loo_c_index, time_total)
         loo = sklearn.model_selection.LeaveOneOut()
         get_best_k(X, y, k, loo)
```

Out[7]: (7, 0.9742804654011022, 0.06511998176574707)

```
In [8]:
        #nested leave-one-out cross-validation using the sklearn loo-cv -objects
         nloo_c_index_l = []
         best k = 0
         time_0 = time.time()
         for i in k:
             inner_cv = sklearn.model_selection.LeaveOneOut()
             outer_cv = sklearn.model_selection.LeaveOneOut()
             yp = []
             #outer loop train-test sets
             for train_i, test_i in outer_cv.split(X):
                 X_train, X_test = X[train_i], X[test_i]
                 y_train, y_test = y[train_i].reshape(-1), y[test_i].reshape(-1)
                 #inner loop
                 best_ik, nloo_c_index, inner_time = get_best_k(X_train, y_train, k
                 nloo_c_index_l.append(nloo_c_index)
                 yp.append(knn(X_train, y_train, X_test, i))
                 #print(model)
             #print('For k:' + str(i) + ' C-index is ' +str(c_index))
         time 1 = time.time()
         time_total = time_1-time_0
         print('C-index average is ' + str(np.mean(nloo_c_index_l)))
         print('This took ' + str(time_total) + ' seconds.')
```

C-index average is 0.9745928694670772 This took 15.181504964828491 seconds.

```
In [9]:
        #With own loo-implementation
         nloo_c_index_l = []
         best k = 0
         time_0 = time.time()
         for i in k:
             outer_cv_split = loo_split(X)
             yp = []
             #outer loop train-test sets
             for train_i, test_i in outer_cv.split(X):
                 X_train, X_test = X[train_i], X[test_i]
                 y_train, y_test = y[train_i].reshape(-1), y[test_i].reshape(-1)
                 #inner loop
                 inner_cv_split = loo_split(X_train)
                 best_ik, nloo_c_index, inner_time = get_best_k_orig(X_train, y_tra)
                 nloo_c_index_l.append(nloo_c_index)
                 yp.append(knn(X_train, y_train, X_test, i))
                 #print(model)
             #print('For k:' + str(i) + ' C-index is ' +str(c_index))
         time 1 = time.time()
         time_total = time_1-time_0
         print('C-index average is ' + str(np.mean(nloo_c_index_l)))
         print('This took ' + str(time_total) + ' seconds.')
```

C-index average is 0.9745928694670772 This took 12.41414999961853 seconds.

The c-index produced by the nested leave-one-out cross-validation is a little bit better than the c-index we got from only one round of cross-validation. The time it took for the notebook to process the nested leave-one-out -implementation was way longer, even for a dataset this small. It is not most likely a good choice for datasets any larger.