DDA Lab 3

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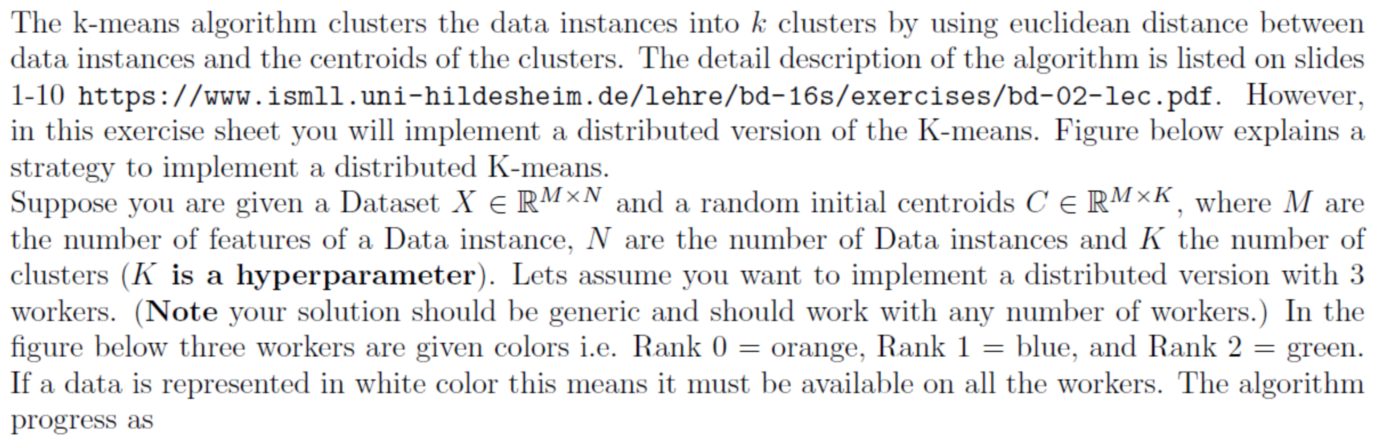
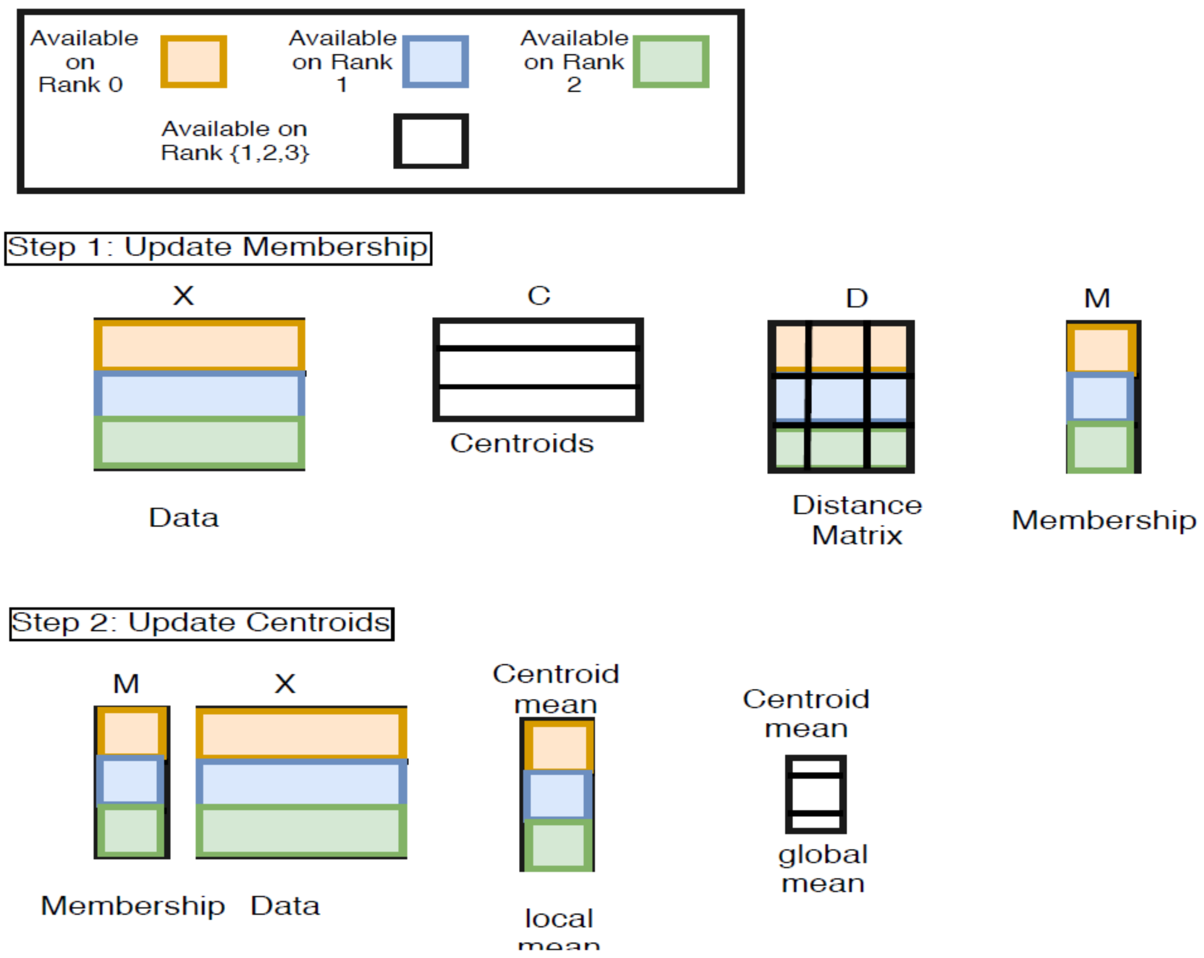
Exercise Sheet 3

Distributed K-means Clustering



The k-means algorithm clusters the data instances into k clusters by using euclidean distance between data instances and the centroids of the clusters. The detail description of the algorithm is listed on slides 1-10 `https://www.ismll.uni-hildesheim.de/lehre/bd-16s/exercises/bd-02-lec.pdf`. However, in this exercise sheet you will implement a distributed version of the K-means. Figure below explains a strategy to implement a distributed K-means.
Suppose you are given a Dataset $X \in \mathbb{R}^{M\times N}$ and a random initial centroids $C \in \mathbb{R}^{M\times K}$, where M are the number of features of a Data instance, N are the number of Data instances and K the number of clusters (K **is a hyperparameter**). Lets assume you want to implement a distributed version with 3 workers. (**Note** your solution should be generic and should work with any number of workers.) In the figure below three workers are given colors i.e. Rank 0 = orange, Rank 1 = blue, and Rank 2 = green. If a data is represented in white color this means it must be available on all the workers. The algorithm progress as



My system wasn't working with all the categories in the newsgroup data. Below I have used maximum number of categories my system could handle becasue of the memory error.

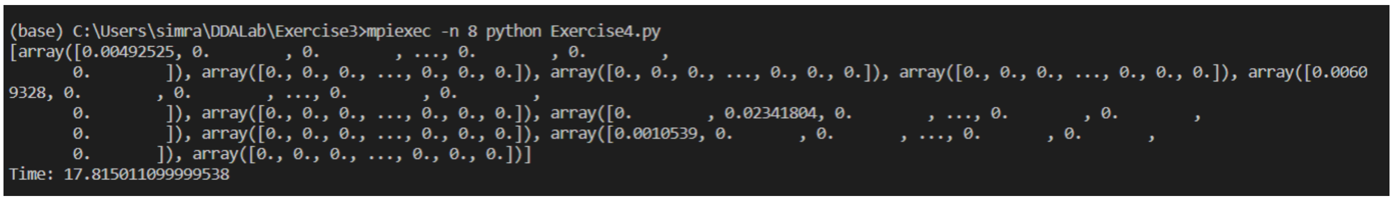
Firstly I have used Sklearn to fetch tfidf vector and used it in the compressed matrix form for distributing among workers. Each worker recieves its chunk along with the randomly initialized centroids and return the local means. After gathering all the local means from each of the worker, the master node calculates the global mean. This process of calculating the global means is continued until the global mean doesnot change anymore and finally the master node returns this global mean.

In [ ]:

```
# importing Libraries
import numpy as np
np.random.seed(0)
import pandas as pd
import random
from sklearn.datasets import fetch_20newsgroups
from sklearn.feature_extraction.text import TfidfVectorizer
from mpi4py import MPI

# Setting MPI
comm = MPI.COMM_WORLD
rank = comm.Get_rank()
size = comm.Get_size()

# Initializing centroids and data chunks to None
centroids = None
data_chunks = None
K = 3             # number of centroids

def K_means_local(data, classes):      # function calculates local means for workers
    local_centroids = []
    for k in range(classes.shape[0]):
        c = 0
        summ = 0
        for i, instance in enumerate(data):    # for each data point the membership array g
            if i == k:                             # for that instance
                c += 1
                summ += instance                  # summing over all the instances for the
        local_centroids.append(summ/c)
    return local_centroids

startTime = MPI.Wtime()
if rank == 0:
    categories = ['alt.atheism','talk.religion.misc', 'comp.graphics', 'sci.space','misc.fo
    newsgroups = fetch_20newsgroups(subset = 'train', categories = categories)
    vectorizer = TfidfVectorizer()
    vectors = vectorizer.fit_transform(newsgroups.data)
    M, N = vectors.shape
    step = M//size

    centroids = np.random.uniform(0, 1, size = (K, N))  # centroids initialized using unifo

    data_chunks = []                  # splitting data for distribution among workers
    for i in range(size - 1):
        data_chunks.append(vectors[i*step:(i+1)*step, :])
    data_chunks.append(vectors[(size - 1)*step:, : ])

centroid = comm.bcast(centroids, root = 0)     # broadcasting centroids among all workers
worker_chunk = comm.scatter(data_chunks, root = 0)    # scattering data among all workers
M_chunk, N_chunk = worker_chunk.shape
K_chunk = centroid.shape[0]

changeInCentroid = True
while changeInCentroid:        # this condition checks if old global mean and new global mea
    Distance_matrix = np.zeros((M_chunk, K_chunk))
    for i, ele in enumerate(worker_chunk.toarray()):
        for j, center in enumerate(centroid):
            Distance_matrix[i, j] = np.linalg.norm(ele - center)    # calculating distance
    membership = np.argmin(Distance_matrix, axis=1).reshape(-1, 1)   # Assigning the class
                                                                           # distance to th
    local_means = K_means_local(worker_chunk.toarray(), membership)

    LocalMeans = comm.gather(local_means, root = 0)

    global_mean = []    # global means are calculated by gathering local means from all wor
    if rank == 0:
        for k in range(K):
            local_sum = 0
            for means in LocalMeans:
                local_sum += means[k]
            global_mean.append(local_sum/K)

        total_clusters = 0   # condition checks if elements of old global means are same as
        for i in range(K):
            if all(item in centroid[i] for item in global_mean[i]):
                total_clusters += 1

        if total_clusters == K:       # if same then exit the while loop
            changeInCentroid = False

    else:
        global_mean = None

    centroid = global_mean           # swapping old global mean with the new global mean
    centroid = comm.bcast(centroid)     # new means are broadcasted among workers
    changeInCentroid = comm.bcast(changeInCentroid)

if rank == 0:
    print(global_mean)
    print('Time:', MPI.Wtime()-startTime)
```

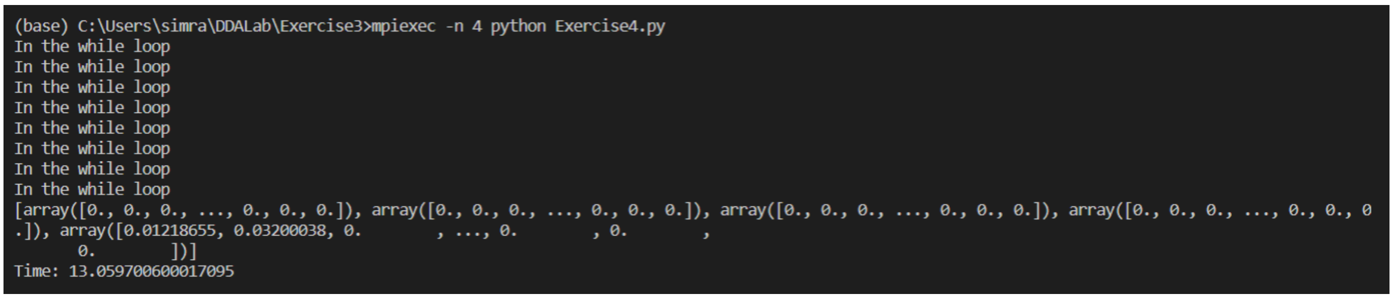
The snippet below is an example where clustering is performed for 10 centroids using 8 processors.

The returned global means are also sparse vectors.



```
(base) C:\Users\simra\DDALab\Exercise3>mpiexec -n 8 python Exercise4.py
[array([0.00492525, 0.        , 0.        , ..., 0.        , 0.        ,
       0.        ]), array([0., 0., 0., ..., 0., 0., 0.]), array([0., 0., 0., ..., 0., 0., 0.]), array([0., 0., 0., ..., 0., 0., 0.]), array([0.0060
9328, 0.        , 0.        , ..., 0.        , 0.        ,
       0.        ]), array([0., 0., 0., ..., 0., 0., 0.]), array([0.        , 0.02341804, 0.        , ..., 0.        , 0.        ,
       0.        ]), array([0., 0., 0., ..., 0., 0., 0.]), array([0.0010539, 0.       , 0.       , ..., 0.       , 0.       ,
       0.       ]), array([0., 0., 0., ..., 0., 0., 0.])]
Time: 17.815011099999538
```

The snippet below shows for a particular number of clusters and using 4 processors, the global means are changed for the following number of times i.e., for as many times we enter the while loop.



```
(base) C:\Users\simra\DDALab\Exercise3>mpiexec -n 4 python Exercise4.py
In the while loop
In the while loop
In the while loop
In the while loop
In the while loop
In the while loop
In the while loop
In the while loop
[array([0., 0., 0., ..., 0., 0., 0.]), array([0., 0., 0., ..., 0., 0., 0.]), array([0., 0., 0., ..., 0., 0., 0.]), array([0., 0., 0., ..., 0., 0., 0
.]), array([0.01218655, 0.03200038, 0.        , ..., 0.        , 0.        ,
       0.        ])]
Time: 13.059700600017095
```

Plotting the table for the processing time taken by different workers for different number of clusters.

In [28]:

```
import pandas as pd
worker_cluster = {'P:1':[20.51608830000623, 22.366360500018345, 25.205691699986346, 28.9186
                'P:2': [13.031800500000827, 14.967241600010311, 17.419258799985982, 20.1647
                'P:4': [11.452122200018493, 12.73154280000017, 14.40143420000095, 18.062123
                'P:6': [10.815635600010864, 12.329959599999711, 14.318328599998495, 16.3183
                'P:8': [10.891213700000662, 13.07798780000303, 13.748115299997153, 17.81501
    }

time = pd.DataFrame.from_dict(worker_cluster, orient = 'index')
time.columns = ['K:3', 'K:5', 'K:7', 'K:10']
time2 = time.style.set_properties(**{
    'background-color': 'grey',
    'font-size': '20pt',
})
time2
```

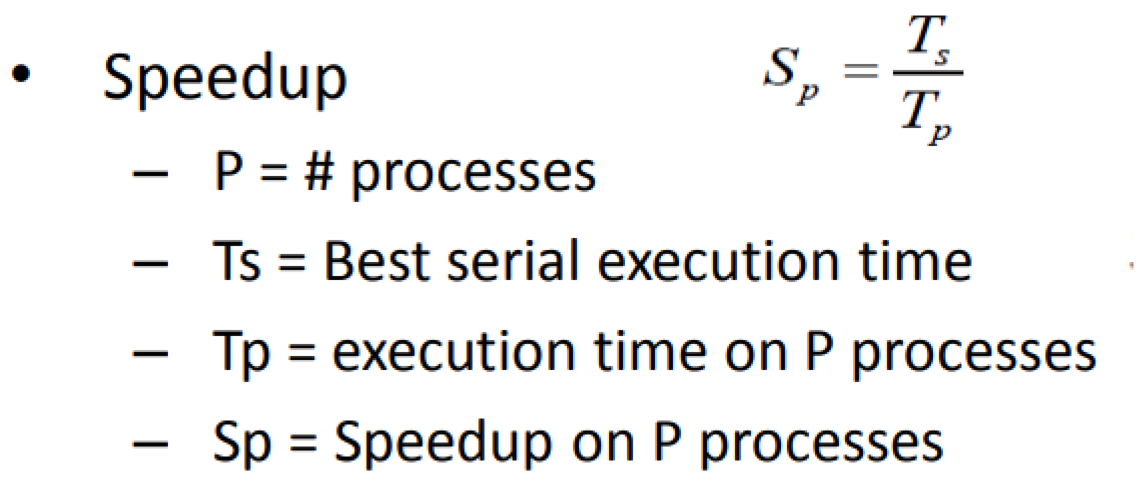
Out[28]:

	K:3	K:5	K:7	
P:1	20.516088	22.366361	25.205692	28.9186
P:2	13.031801	14.967242	17.419259	20.1647
P:4	11.452122	12.731543	14.401434	18.0621
P:6	10.815636	12.329960	14.318329	16.3183
P:8	10.891214	13.077988	13.748115	17.8150

As the number of processors is increased, the processing time decreases with the exceptions in the end as more and more processors are introduced the communication among them is to

be maintained which is added as an overhaed cost resulting in the increased processing time for the more number of processors. Also, as we increase the number of clusters among which the data is divided the processing time is increased as the distance matrix calculation is increased when using more clusters.

Speed Up



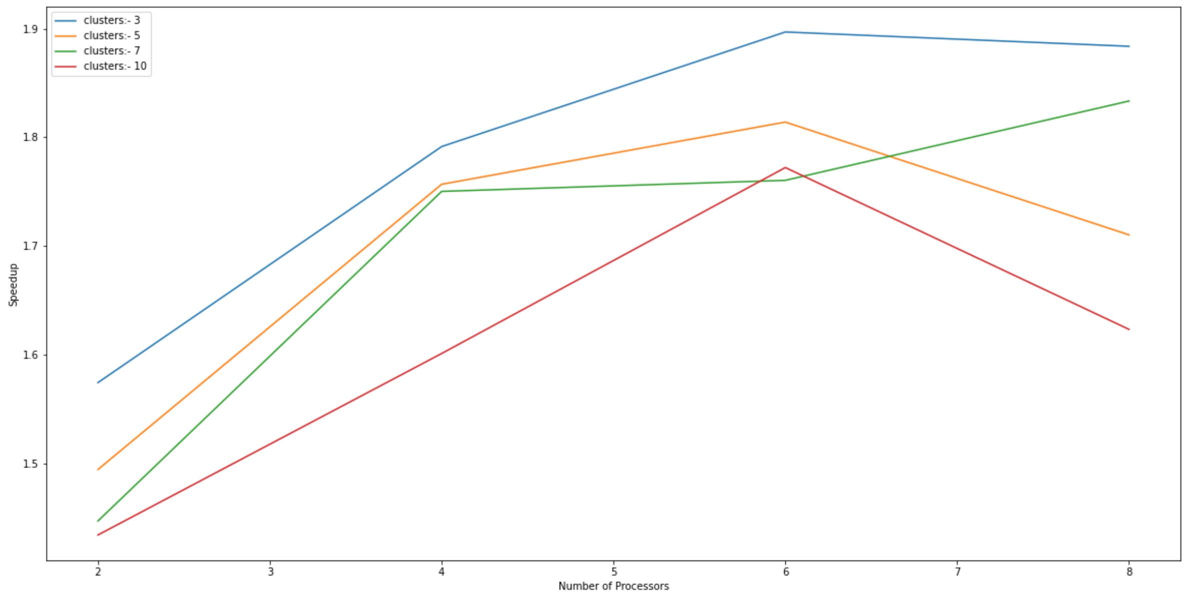
- Speedup $S_p = \frac{T_s}{T_p}$
  - P = # processes
  - Ts = Best serial execution time
  - Tp = execution time on P processes
  - Sp = Speedup on P processes

In [29]:

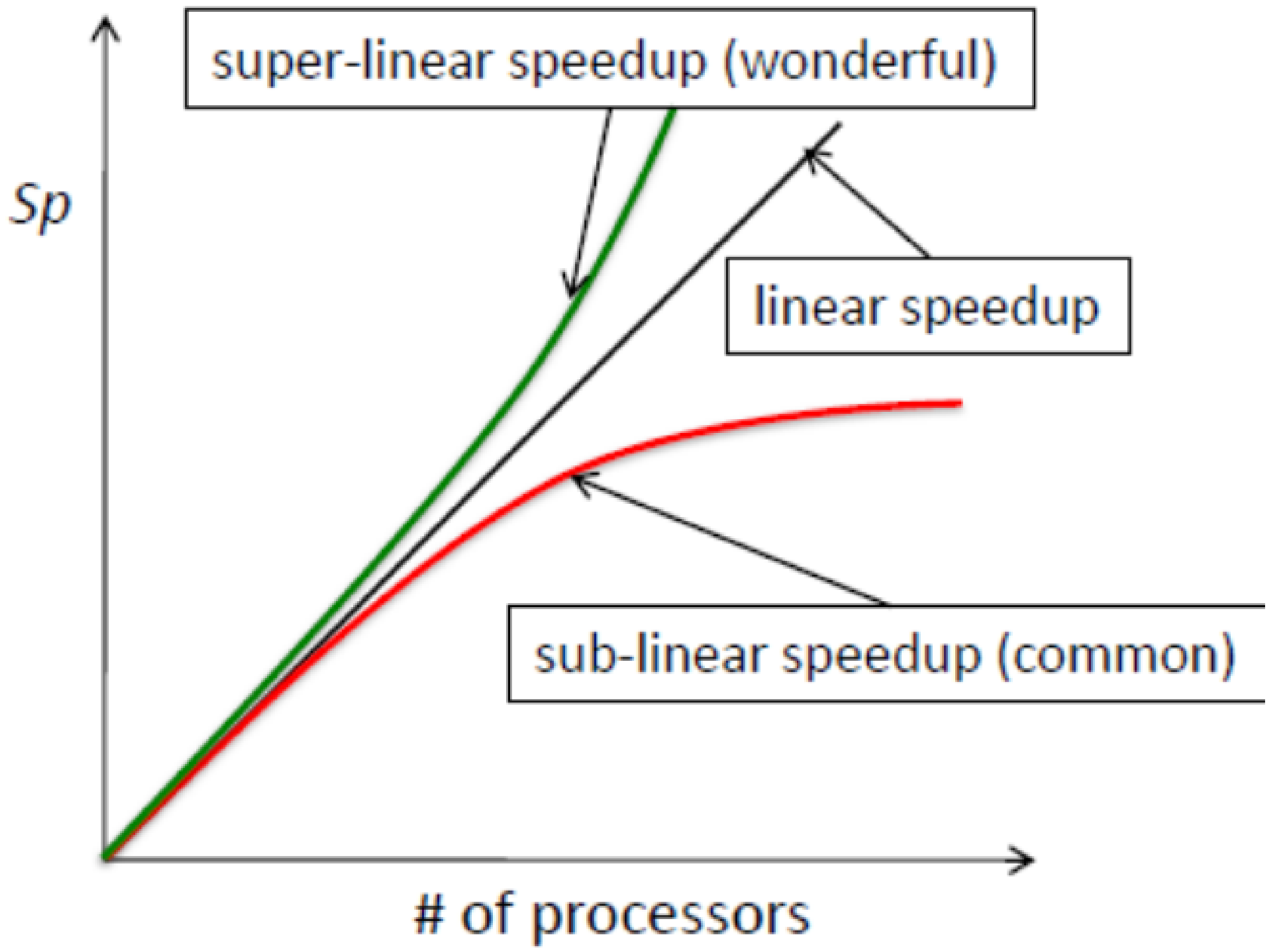
```
def speedup(p1, pp):
    return p1/pp
```

In [35]:

```
import matplotlib.pyplot as plt
fig = plt.figure(figsize = (20, 10))
for j,k in enumerate([3, 5, 7, 10]):
    cluster = []
    for i in range(5):
        cluster.append(time.iloc[i, j])
    speed_clus = [speedup(cluster[0], cluster[j]) for j in range(1,5)]
    plt.plot([2,4,6,8], speed_clus, label = f'clusters:- {k}')
plt.legend()
plt.xlabel('Number of Processors')
plt.ylabel('Speedup')
plt.show()
```



Comparing our plot to the graph below, when using 3, 5 and 10 clusters we get sub-linear speedup but when using 10 clusters we get super-linear speedup which is good. Since speedup is given by the division of time taken by sequential execution to the time taken by parallel execution and larger the speedup implies that the time taken by parallel execution is very less as compared to the sequential execution and vice-versa.


super-linear speedup (wonderful)
Sp
linear speedup
sub-linear speedup (common)
# of processors

```
In [ ]:
```