

ScalableKMeansPlusPlus

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1 Scalable K-means++

Title: Scalable K-Means Plus Plus

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1.1 Outline of Background

This project is an implementation based on Bahmani, Moseley, Vattani, Kumar and Vassilvitskii's paper *Scalable K Means++* in 2012.

1. **K-means** remains one of the most popular data processing algorithms. This algorithm has been used in many fields such as machine learning, pattern recognition and bioinformatics. However, the original k-means algorithm with random initialization has lots of weakness. For example.
 - A proper initialization is crucial for receiving successful results.
 - For large dataset, it may take long time to achieve convergence.
2. **K-means++** algorithm achieved the goal of finding proper initialization, k-means++ has a deterministic initialization process, however, with downside of its inherent sequential nature, which limits its efficiency ($O(n)$) and applicability to big massive datasets.
3. **k-means||**, aka **Scalable k-means++**, which proposed by this paper, oversamples by sampling each points independently with a larger probability, which is intuitively equivalent to updating the distribution much less frequently, with efficiency ($O(\log n)^*$), which forms **k-means++** in both sequential and parallel settings.

In this project, I'll implement the *Scalable K Means++* algorithm, and compare it to the general *K Means* and *K Means++*.

1.2 Algorithm / Pseudocode

1.2.1 Notations

Let $X = \{x_1, \dots, x_n\}$ be the set of points in d -dimensional Euclidean space, and let k be a positive integer specifying the number of clusters. Let $\|x_i - x_j\|$ denote the Euclidean distance between x_i and x_j . For a point x and a subset $Y \subseteq X$ of points, the distance is defined as $d(x, Y) = \min_{y \in Y} \|x - y\|$. For a subset $Y \subseteq X$ of points, let its centroid be given by

$$\text{centroid}(Y) = \frac{1}{|Y|} \sum_{y \in Y} y$$

Let $C = \{c_1, \dots, c_k\}$ be the set of points and let $Y \subseteq X$. We define the cost of Y with respect to C as

$$\phi_Y(C) = \sum_{y \in Y} d^2(y, C) = \sum_{y \in Y} \min_{i=1, \dots, k} \|y - c_i\|^2$$

1.2.2 k -means++(k) initialization

1. $C \leftarrow$ sample a point uniformly at random from X
2. **while** $|C| < k$ **do**
 - Sample $x \in X$ with probability $\frac{d^2(x, C)}{\phi_X(C)}$
 - $C \leftarrow C \cup \{x\}$
3. **end while**

1.2.3 k -means||(k, l) initialization

1. $C \leftarrow$ sample a point uniformly at random from X
2. $\psi \leftarrow \phi_X(C)$
3. **for** $O(\log \psi)$ times **do**
 - $C' \leftarrow$ sample each point $x \in X$ independently with probability $p_x = \frac{l \cdot d^2(x, C)}{\phi_X(C)}$
 - $C \leftarrow C \cup C'$
4. **end for**
5. For $x \in C$, set w_x to be the number of points in X closer to x than any point in C
6. Recluster the weighted points in C into k clusters

1.3 Draft of unit test

Will verify the code correctness using following tests:

1. Test the Cost function using examples in terms of:
 - non-negative
 - data = c
 - the size of c
2. Test Sampling Probability function using examples in terms of:
 - $0 \leq \text{Pi} \leq 1$
 - sum = 1
3. Test K Means Plus Plus Parallel Probability function using examples in terms of:
 - feasibility
 - labels attributes

1.4 Data simulation

Simulating sample data from three bivariate normal distribution.

$$\begin{aligned} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} &\sim N_2 \left(\begin{pmatrix} 0 \\ 1 \end{pmatrix}, \begin{pmatrix} 1 & 0.5 \\ 0 & 2 \end{pmatrix} \right) \\ \begin{pmatrix} y_1 \\ y_2 \end{pmatrix} &\sim N_2 \left(\begin{pmatrix} 3 \\ 7 \end{pmatrix}, \begin{pmatrix} 1 & 0.33 \\ 0.33 & 1 \end{pmatrix} \right) \\ \begin{pmatrix} z_1 \\ z_2 \end{pmatrix} &\sim N_2 \left(\begin{pmatrix} -8 \\ 2 \end{pmatrix}, \begin{pmatrix} 2 & 0.66 \\ 0.66 & 2 \end{pmatrix} \right) \end{aligned}$$

```

In [48]: # Prepare
#!/usr/bin/python
from __future__ import division
import os
import sys
import glob
import random
import sklearn
import sklearn.cluster
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib.figure import Figure
from matplotlib.axes import Subplot
%matplotlib inline
plt.style.use('ggplot')

In [49]: # Simulated "Real" Data Set
class SimulatedData:
    def __init__(self, n, data):
        self.data = data
        self.n = n

    def DataSimulation(n):
        mean1 = np.array([0, 1])
        cov1 = np.array([[1, 0.5], [0.5, 2]])

        mean2 = np.array([3, 7])
        cov2 = np.array([[1, 0.33], [0.33, 1]])

        mean3 = np.array([-8, 2])
        cov3 = np.array([[2, 0.66], [0.66, 2]])

        tmp = np.vstack((np.random.multivariate_normal(mean1, cov1, n),
                          np.random.multivariate_normal(mean2, cov2, n),
                          np.random.multivariate_normal(mean3, cov3, n)))
        data = tmp[np.random.choice(range(3*n), size = 3*n, replace=False),]
        return data

    def AsDataFrame(data):
        df = pd.DataFrame(data, columns=["X", "Y"])
        return df

In [50]: data = SimulatedData.DataSimulation(5)
data

Out[50]: array([[ 3.27244498,  6.19079547],
 [ 2.83259403,  5.31488359],
 [-6.29887528,  1.15665735],
 [ 2.26433884,  4.68468001],
 [ 0.28221065,  1.48472561],
 [ 4.05630379,  6.34592495],
 [ 4.16797629,  7.93527882],
 [-10.70344788,  1.63873811],
 [-1.34911855, -2.49537396],

```

```
[ 1.52048191,  1.62214511],
[-9.279794   ,  1.20963785],
[ 1.07200651,  2.15463174],
[-9.58562466,  0.61057195],
[-5.51352065,  3.68254202],
[ 0.84596127,  2.51050088]]])
```

1.5 K-Means || Code

1.5.1 Navïe Version

```
In [51]: class ScalableKMeansPP:
    def __init__(self, data, k, l):
        self.data = data
        self.k = k
        self.l = l

    def KMeansParallel(data, k, l):
        N = data.__len__()
        if k <= 0 or not(isinstance(k,int)) or l <= 0:
            sys.exit()
        # Then we start to Implement the algorithm
        # 1. Sample one point uniformly at random from X
        c = np.array(data[np.random.choice(range(N),1),])
        # 2. To Cost function
        phi = ScalableKMeansPP.CostFunction(c, data)
        # 3. Looping
        for i in range(np.ceil(np.log(phi)).astype(int)):
            cPrime = data[ScalableKMeansPP.SamplingProbability(c,data,l) > np.random.uniform(0,1)]
            c = np.concatenate((c, cPrime))
        # End looping
        # 7. For x in C, set w_x to be the number of pts closest to X
        cMini = [np.argmin(np.sum((c-pts)**2,axis=1)) for pts in data];
        closerPts = [cMini.count(i) for i in range(len(c))]
        weight = closerPts/np.sum(closerPts)
        # 8. Recluster the weighted points in C into k clusters
        allC = data[np.random.choice(range(len(c)),size=1,p=weight),]
        data_final = c
        for i in range(k-1):
            Probability = ScalableKMeansPP.SamplingProbability(allC,data_final,l) * weight
            # choose next centroid
            cPrimeFin = data[np.random.choice(range(len(c)), size=1, p=Probability/np.sum(Probability))]
            allC = np.concatenate((allC,cPrimeFin))
        KMeansPP = sklearn.cluster.KMeans(n_clusters=k, n_init=1, init=allC, max_iter=500, tol=1e-4)
        KMeansPP.fit(data);
        return KMeansPP

    def SamplingProbability(c,data,l):
        cost = ScalableKMeansPP.CostFunction(c,data)
        return np.array([(min(np.sum((c-pts)**2,axis=1))) * 1 / cost for pts in data])

    def CostFunction(c,data):
        return np.sum([min(np.sum((c-pts)**2,axis=1)) for pts in data])
```

```

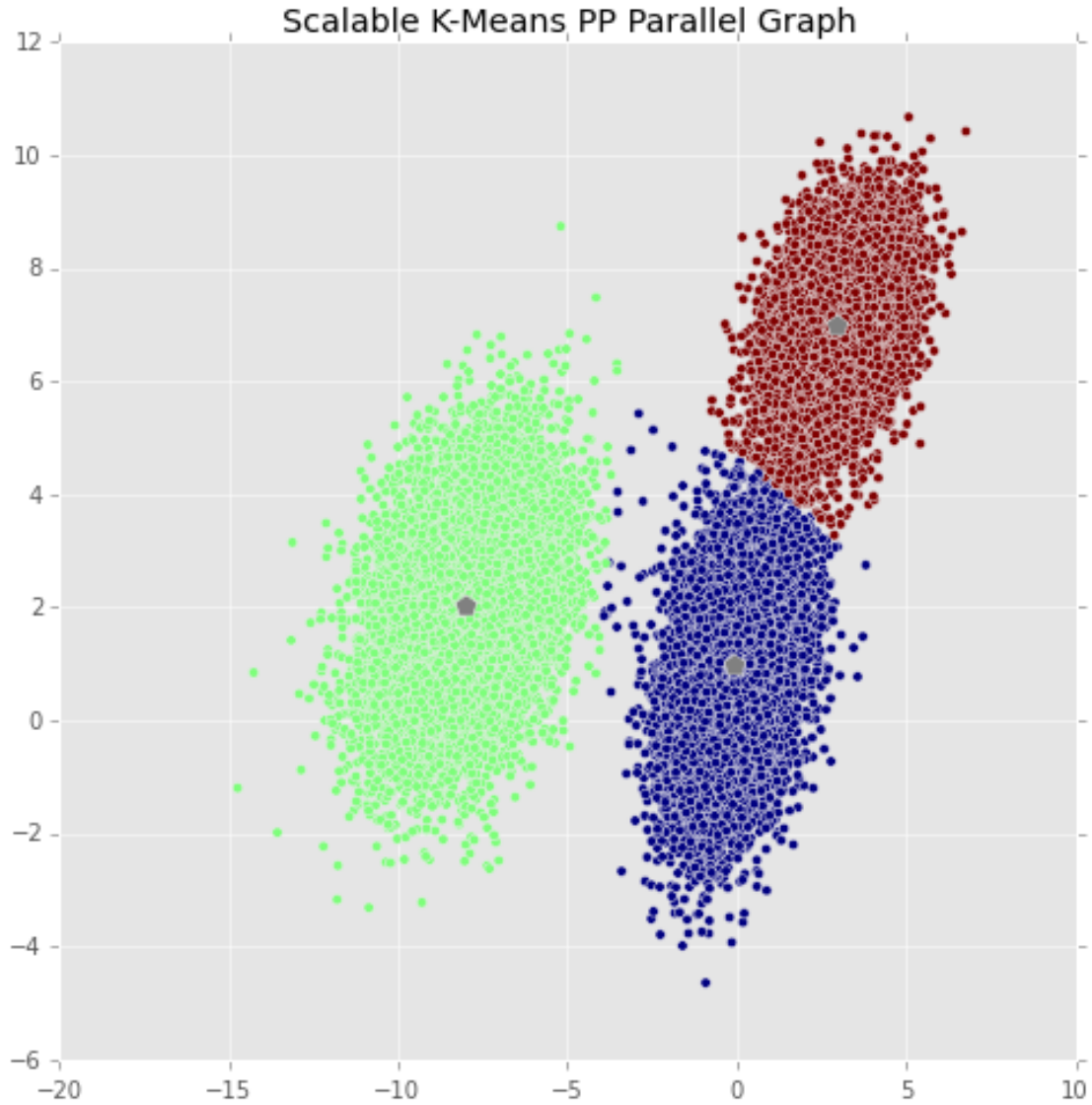
In [52]: data = SimulatedData.DataSimulation(10000)
         ScalableKMeansPP.KMeansParallel(data,3,6)

Out[52]: KMeans(copy_x=True,
               init=array([[ 3.43704,  5.82661],
                           [ 1.19989,  6.19787],
                           [ 2.45681,  6.21065]]),
               max_iter=500, n_clusters=3, n_init=1, n_jobs=1,
               precompute_distances=True, random_state=None, tol=0.0001, verbose=0)

In [69]: k = 3
         start = timeit.default_timer()
         KMeansPP = ScalableKMeansPP.KMeansParallel(data=data, k=k, l=2*k); # paper suggesting using l=
         elapsed = timeit.default_timer() - start
         print(elapsed)
         df = SimulatedData.AsDataFrame(data)
         plt.figure(figsize=(8, 8));
         plt.scatter(df.X,df.Y,c=KMeansPP.labels_);
         plt.scatter(KMeansPP.cluster_centers_[0],KMeansPP.cluster_centers_[1], c='grey', s=100, ma
         plt.title("Scalable K-Means PP Parallel Graph");
         plt.show()

```

12.001063375006197



1.6 Algorithm Comparison

For algorithm comparison, I will use different sizes of the same sample data to clustering using original k-means, k-means++, k-means||. Test their result and compare the efficiency.

We use “K-Means” and “K-Means++” methods from `sklearn.cluster.KMeans` package.

1.6.1 K-Means

```
In [75]: import timeit
data1 = SimulatedData.DataSimulation(10000)
start = timeit.default_timer()
k = 3
KMeans = sklearn.cluster.KMeans(n_clusters=3, init='random', n_init=10, max_iter=500, tol=0.0001)
KMeans.fit(data1);
```

```

elapsed = timeit.default_timer() - start
print(elapsed)
0.12828452099347487
In [87]: KMeans.fit(data);
df = SimulatedData.AsDataFrame(data)
plt.figure(figsize=(8, 8));
plt.scatter(df.X,df.Y,c=KMeans.labels_);
plt.scatter(KMeans.cluster_centers_[0],KMeans.cluster_centers_[1], c='grey', s=100, marker='x');
plt.title("K-Means");
plt.show()

```



1.6.2 K-Means++

```

In [56]: data1 = SimulatedData.DataSimulation(10000)
start = timeit.default_timer()

```

```

k = 3
KMeansPlusPlus = sklearn.cluster.KMeans(n_clusters=3, init='k-means++', n_init=10, max_iter=500,
KMeansPlusPlus.fit(data1);
elapsed = timeit.default_timer() - start
print(elapsed)

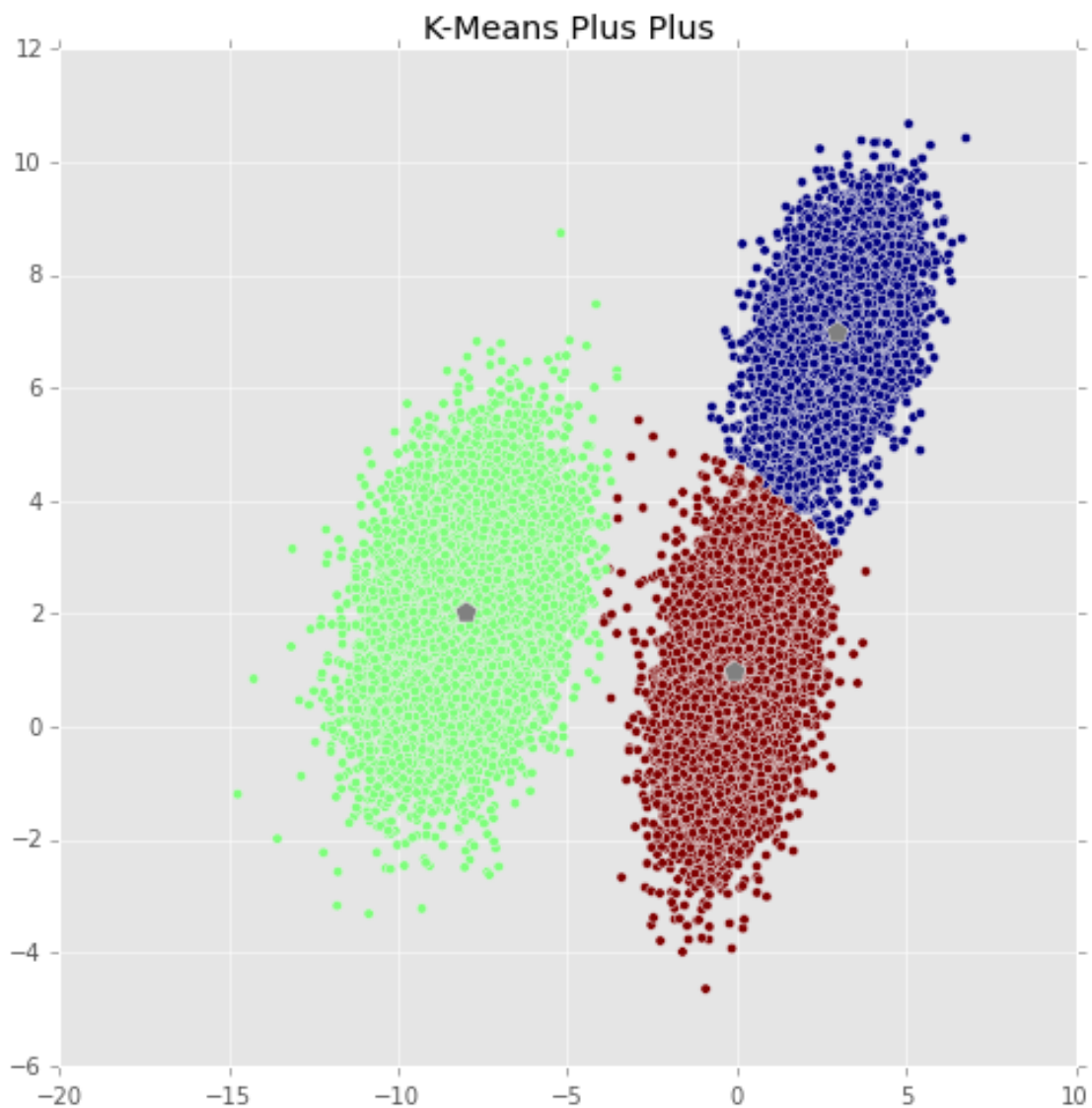
```

0.08849192800698802

```

In [71]: KMeansPlusPlus = sklearn.cluster.KMeans(n_clusters=3, init='random', n_init=10, max_iter=500,
KMeansPlusPlus.fit(data);
df = SimulatedData.AsDataFrame(data)
plt.figure(figsize=(8, 8));
plt.scatter(df.X,df.Y,c=KMeansPlusPlus.labels_);
plt.scatter(KMeansPlusPlus.cluster_centers_[0],KMeansPlusPlus.cluster_centers_[1], c='grey');
plt.title("K-Means Plus Plus");
plt.show()

```



From the result of timeit, we can concluded that K-Means++ is much efficient than the base K-Means. However, it seems that the naive version of Scalable K-Means++ are slower than K-Means++, or even the base K-Means.

The reason would be, the package algorithms using parallel. I will try to optimization my code.

1.7 Optimization Strategies

1. Using alternative method to replace inefficient code in Python
2. Will try on large datasets, if still take too long. Could try to use other languages to write the looping part

1.8 Optimization: Vectorized Version

```
In [79]: class VectorizedScalableKMeansPP(ScalableKMeansPP):
    def __init__(self, data, k, l):
        ScalableKMeansPP.__init__(self, data, k, l)

    def KMeansParallel(data, k, l):
        N = data.__len__()
        # 1. Sample one point uniformly at random from X
        c = data[np.random.choice(range(data.shape[0]),1), :]
        data__ = data[:,np.newaxis,:]
        # 2. To Cost function
        phi = ScalableKMeansPP.CostFunction(c, data)
        # 3. Looping
        for i in range(np.ceil(np.log(phi)).astype(int)):
            d2 = (data__ - c) ** 2
            distance = np.sum(d2, axis=2)
            cMini = np.zeros(distance.shape)
            cMini[range(distance.shape[0]), np.argmin(distance, axis=1)] = 1
            min_dist = distance[cMini == 1]
            phi = np.sum(min_dist)
            for i, cPrime in enumerate(data):
                Probability = 1*min_dist[i]/phi
                u = np.random.uniform(0,1)
                if Probability >= u:
                    c = np.vstack([c, cPrime])
        # End looping
        # 7. For x in C, set w_x to be the number of pts closest to X
        d2 = (data__ - c) ** 2
        distance = np.sum(d2, axis=2)
        cMini = np.zeros(distance.shape)
        cMini[range(distance.shape[0]), np.argmin(distance, axis=1)] = 1
        weight = np.array([np.count_nonzero(cMini[:, i]) for i in range(c.shape[0])]).reshape(-1)
        # 8. Recluster the weighted points in C into k clusters
        allC = c[np.random.choice(range(c.shape[0]),1), :]
        data_final = c
        index = np.where(data_final==allC)[0]
        data_final = np.delete(data_final,index[0],axis=0)
        weight = np.delete(weight,index[0])
        for i in range(k-1):
            Probability = ScalableKMeansPP.SamplingProbability(allC,data_final,1) * weight
            # choose next centroid
            c = data_final[np.random.choice(range(data_final.shape[0]),size=1, p=Probability/np
```

```

        index = np.where(data_final==c)[0]
        allC = np.vstack([allC, c])
        #Remove the selected center and its corresponding weight
        data_final = np.delete(data_final,index[0],axis=0)
        weight = np.delete(weight,index[0])
        vKMeansPP = sklearn.cluster.KMeans(n_clusters=k, n_init=1, init=allC, max_iter=500, tol=1e-4)
        vKMeansPP.fit(data)
        return vKMeansPP

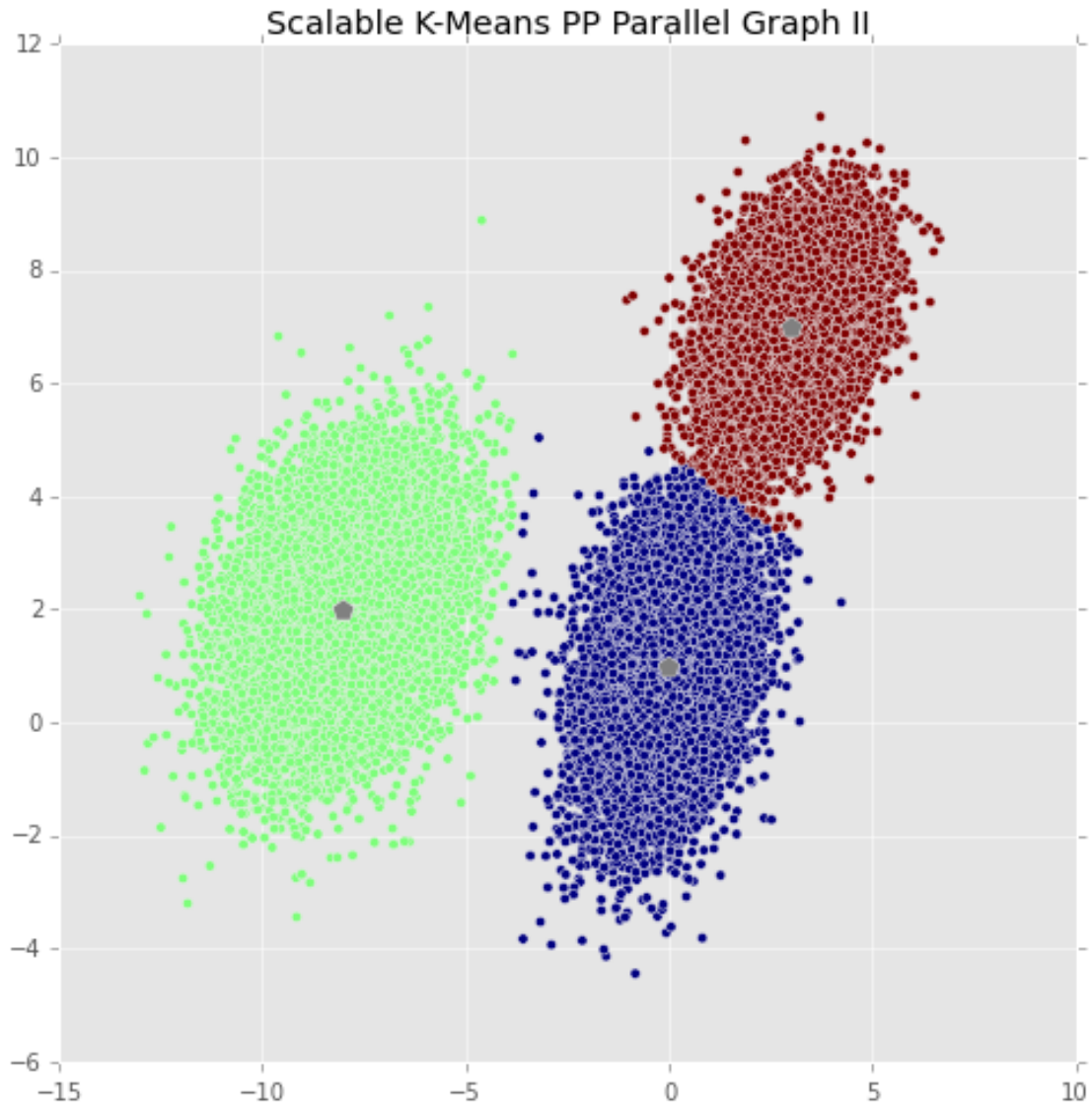
In [80]: data = SimulatedData.DataSimulation(10000)
        VectorizedScalableKMeansPP.KMeansParallel(data,3,6)

Out[80]: KMeans(copy_x=True,
               init=array([[ -2.33086,  0.71013],
                           [ 3.51431,  7.72725],
                           [-8.37233,  3.60263]]),
               max_iter=500, n_clusters=3, n_init=1, n_jobs=1,
               precompute_distances=True, random_state=None, tol=0.0001, verbose=0)

In [85]: start = timeit.default_timer()
        KMeansPP2 = VectorizedScalableKMeansPP.KMeansParallel(data=data, k=k, l=2*k);
        elapsed = timeit.default_timer() - start
        print(elapsed)
        df = SimulatedData.AsDataFrame(data)
        plt.figure(figsize=(8, 8));
        plt.scatter(df.X,df.Y,c=KMeansPP2.labels_);
        plt.scatter(KMeansPP2.cluster_centers_[0],KMeansPP2.cluster_centers_[1], c='grey', s=100, marker='x');
        plt.title("Scalable K-Means PP Parallel Graph II");
        plt.show()

1.8935244909953326

```



1.9 Efficiency Comparson: Profiling

```
In [ ]: ! pip install --pre line-profiler &> /dev/null
! pip install psutil &> /dev/null
! pip install memory_profiler &> /dev/null
```

```
In [18]: %load_ext line_profiler
```

```
In [ ]: %lprun -f ScalableKMeansPP.KMeansParallel ScalableKMeansPP.KMeansParallel(data = data, k=3, l =
```

```
In [ ]: Timer unit: 1e-06 s
```

```
Total time: 13.3943 s
File: <ipython-input-125-d01bb3e3c9ef>
Function: KMeansParallel at line 7
```

Line #	Hits	Time	Per Hit	% Time	Line Contents
=====					
7					def KMeansParallel(data, k, l):
8	1	4	4.0	0.0	N = data.__len__()
9	1	2	2.0	0.0	if k <= 0 or not(isinstance(k,int)) or
10					sys.exit()
11					# Then we start to Implement the algor
12					# 1. Sample one point uniformly at ran
13	1	3501	3501.0	0.0	c = np.array(data[np.random.choice(range
14					# 2. To Cost function
15	1	270143	270143.0	2.0	phi = ScalableKMeansPP.CostFunction(c,
16					# 3. Looping
17	16	56	3.5	0.0	for i in range(np.ceil(np.log(phi)).as
18	15	12559007	837267.1	93.8	cPrime = data[ScalableKMeansPP.Samp
19	15	127	8.5	0.0	c = np.concatenate((c, cPrime))
20					# End looping
21					# 7. For x in C, set w_x to be the num
22	1	369043	369043.0	2.8	cMini = [np.argmin(np.sum((c-pts)**2,a
23	1	174695	174695.0	1.3	closerPts = [cMini.count(i) for i in r
24	1	114	114.0	0.0	weight = closerPts/np.sum(closerPts)
25					# 8. Recluster the weighted points in
26	1	112	112.0	0.0	allC = data[np.random.choice(range(len
27	1	1	1.0	0.0	data_final = c
28	3	5	1.7	0.0	for i in range(k-1):
29	2	3734	1867.0	0.0	Probability = ScalableKMeansPP.Samp
30					# choose next centroid
31	2	278	139.0	0.0	cPrimeFin = data[np.random.choice(
32	2	13	6.5	0.0	allC = np.concatenate((allC,cPrime)
33	1	23	23.0	0.0	KMeansPP = sklearn.cluster.KMeans(n_cl
34	1	13424	13424.0	0.1	KMeansPP.fit(data);
35	1	2	2.0	0.0	return KMeansPP

In [82]: %lprun -f VectorizedScalableKMeansPP.KMeansParallel VectorizedScalableKMeansPP.KMeansParallel(

In []: Timer unit: 1e-06 s

Total time: 3.66441 s
File: <ipython-input-114-00df5cba66a8>
Function: KMeansParallel at line 5

Line #	Hits	Time	Per Hit	% Time	Line Contents
=====					
5					def KMeansParallel(data, k, l):
6	1	7	7.0	0.0	N = data.__len__()
7					# 1. Sample one point uniformly at ran
8	1	3579	3579.0	0.1	c = data[np.random.choice(range(data.s
9	1	4	4.0	0.0	data2 = data[:,np.newaxis,:]
10					# 2. To Cost function
11	1	264291	264291.0	7.2	phi = ScalableKMeansPP.CostFunction(c,
12					# 3. Looping
13	16	49	3.1	0.0	for i in range(np.ceil(np.log(phi)).as
14	15	505753	33716.9	13.8	d2 = (data2 - c) ** 2
15	15	254088	16939.2	6.9	distance = np.sum(d2, axis=2)
16	15	36050	2403.3	1.0	cMini = np.zeros(distance.shape)

17	15	86425	5761.7	2.4
18	15	33310	2220.7	0.9
19	15	796	53.1	0.0
20	450015	577435	1.3	15.8
21	450000	646465	1.4	17.6
22	450000	597961	1.3	16.3
23	450000	508532	1.1	13.9
24	75	2341	31.2	0.1
25				
26				
27	1	67089	67089.0	1.8
28	1	32498	32498.0	0.9
29	1	5074	5074.0	0.1
30	1	6751	6751.0	0.2
31	1	15825	15825.0	0.4
32				
33	1	87	87.0	0.0
34	1	2	2.0	0.0
35	1	16	16.0	0.0
36	1	48	48.0	0.0
37	1	32	32.0	0.0
38	3	4	1.3	0.0
39	2	2686	1343.0	0.1
40				
41	2	140	70.0	0.0
42	2	17	8.5	0.0
43	2	43	21.5	0.0
44				
45	2	62	31.0	0.0
46	2	55	27.5	0.0
47	1	20	20.0	0.0
48	1	16874	16874.0	0.5
49	1	3	3.0	0.0

```

cMini[range(distance.shape[0]), np
min_dist = distance[cMini == 1]
phi = np.sum(min_dist)
for i, cPrime in enumerate(data):
    Probability = l*min_dist[i]/ph
    u = np.random.uniform(0,1)
    if Probability >= u:
        c = np.vstack([c, cPrime])
# End looping
# 7. For x in C, set w_x to be the num
d2 = (data2 - c) ** 2
distance = np.sum(d2, axis=2)
cMini = np.zeros(distance.shape)
cMini[range(distance.shape[0]), np.argin
weight = np.array([np.count_nonzero(cM
# 8. Recluster the weighted points in c
allC = c[np.random.choice(range(c.shape
data_final = c
index = np.where(data_final==allC)[0]
data_final = np.delete(data_final, index
weight = np.delete(weight, index[0])
for i in range(k-1):
    Probability = ScalableKMeansPP.Samp
    # choose next centroid
    c = data_final[np.random.choice(range
    index = np.where(data_final==c)[0]
    allC = np.vstack([allC, c])
    #Remove the selected center and it
    data_final = np.delete(data_final, i
    weight = np.delete(weight, index[0])
vKMeansPP = sklearn.cluster.KMeans(n_c
vKMeansPP.fit(data)
return vKMeansPP

```

By profiling, it is clear that **Vectored KMeansParallel** function is significantly faster than the naive **KMeansParallel** function. (move than three times faster) The total time was improved from 13.4s to 3.66s.