Problem 1:

(a) & (b)

for example, we output the second row of the matrix xij:

```
In [1]:
from pyGM import *
import numpy as np
# Load the data points D, and the station locations (lat/lon)
D = np.genfromtxt('data/data.txt',delimiter=None)
loc = np.genfromtxt('data/locations.txt',delimiter=None)
m,n = D. shape # m = 2760 data points, n=30 dimensional # D[i,j] = 1 if
station j observed rainfall on day i
count = np.zeros(30)
for j in range(n):
   for i in range(m):
      if D[i][j] == 1:
          count[j] += 1
x = count/m
count = np.zeros((30, 30, 4))
for i in range(n):
   for j in range(n):
      for k in range(m):
          if D[k][i] == 0 and D[k][j] == 0:
             count[i][j][0] += 1
          if D[k][i] == 1 and D[k][j] == 0:
             count[i][j][1] += 1
          if D[k][i] == 0 and D[k][j] == 1:
             count[i][j][2] += 1
          if D[k][i] == 1 and D[k][j] == 1:
             count[i][j][3] += 1
xij = np.zeros((30, 30, 4))
for i in range(n):
   for j in range(n):
       for k in range(4):
          xij[i][j][k] = count[i][j][k]/m
```

```
In [2]: xij[1]
Out[2]:
array([[ 0.59130435,
                       0.11123188,
                                    0.03514493, 0.26231884],
      [ 0.62644928,
                      0.
                                  0.
                                              0.37355072],
        0.57681159,
                      0.07536232,
                                   0.04963768,
                                                 0.29818841],
                      0.06304348,
        0.51014493,
                                   0.11630435,
                                                 0.31050725],
                                                0.32355072],
        0.55036232,
                      0.05
                                  0.07608696,
        0.5134058 ,
                      0.05507246,
                                   0.11304348,
                                                 0.31847826],
        0.53442029,
                      0.06086957,
                                   0.09202899.
                                                 0.312681161.
                      0.0576087 ,
                                   0.2173913 ,
        0.40905797,
                                                 0.31594203],
        0.30362319,
                      0.04637681,
                                   0.32282609,
                                                 0.32717391],
                      0.05144928,
                                   0.25398551,
        0.37246377,
                                                 0.32210145],
        0.42826087,
                      0.06449275,
                                   0.19818841,
                                                 0.30905797],
        0.44456522,
                      0.04963768,
                                   0.18188406,
                                                 0.32391304],
        0.47246377,
                      0.06195652,
                                   0.15398551,
                                                 0.3115942 ],
        0.32862319,
                      0.04021739,
                                   0.29782609,
                                                 0.33333333],
        0.44021739,
                      0.06050725,
                                   0.18623188,
                                                 0.31304348],
        0.36413043,
                      0.07391304,
                                   0.26231884,
                                                 0.29963768],
                      0.1423913 ,
        0.59202899,
                                   0.03442029,
                                                 0.23115942],
        0.58152174,
                      0.11050725,
                                   0.04492754,
                                                 0.26304348],
        0.59130435,
                      0.1326087 ,
                                   0.03514493,
                                                 0.24094203],
        0.58949275,
                      0.16231884,
                                   0.03695652,
                                                 0.21123188],
                      0.09963768,
                                                 0.27391304],
        0.56268116,
                                   0.06376812,
        0.56956522,
                      0.11992754,
                                   0.05688406,
                                                 0.25362319],
        0.47572464,
                      0.08695652,
                                   0.15072464,
                                                 0.2865942 ],
        0.45108696,
                      0.075
                                  0.17536232,
                                                0.298550721,
                                                 0.24456522],
        0.53985507,
                      0.12898551,
                                   0.0865942 ,
                                   0.04565217,
        0.5807971 ,
                      0.14528986,
                                                 0.22826087],
        0.47898551,
                      0.11123188,
                                   0.14746377,
                                                 0.26231884],
        0.55507246,
                      0.09384058,
                                   0.07137681,
                                                 0.27971014],
        0.51521739,
                      0.09927536,
                                   0.11123188,
                                                 0.27427536],
        0.52246377,
                      0.07934783,
                                   0.10398551,
                                                 0.2942029 ]])
```

(c) First, we calculate the information matrix.

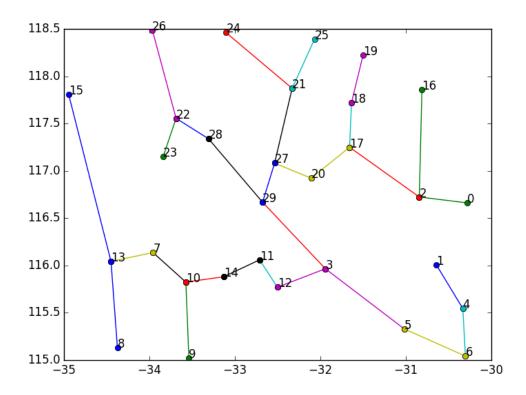
Then, a modified Prim's algorithm will be utilized to find out the maximum spanning tree.

```
In [4]:
\#A = adjacency matrix, u = vertex u, v = vertex v
def weight(A, u, v):
   return A[u][v]
#A = adjacency matrix, u = vertex u
def adjacent(A, u):
   L = []
   for x in range(len(A)):
       if x != u:
          L.insert(0,x)
   return L
\#0 = \max \text{ queue}
def extractMax(Q):
   q = 0[0]
   Q.remove(Q[0])
   return q
#Q = max queue, V = vertex list
def increaseKey(Q, K):
   for i in range(len(Q)):
       for j in range(len(Q)):
          if K[Q[i]] > K[Q[j]]:
             s = Q[i]
             Q[i] = Q[j]
             Q[j] = s
#V = vertex list, A = adjacency list, r = root
def prim(V, A, r):
   u = 0
   v = 0
   # initialize and set each value of the array P (pi) to none
   # pi holds the parent of u, so P(v)=u means u is the parent of v
   P = [None]*len(V)
   # initialize and set each value of the array K (key) to -999999
   K = [-999999]*len(V)
   # initialize the max queue and fill it with all vertices in V
   Q = [0]*len(V)
   for u in range(len(Q)):
      Q[u] = V[u]
   # set the key of the root to 0
   K[r] = 0
   increaseKey(Q, K) # maintain the max queue
```

```
# loop while the max queue is not empty
 while len(Q) > 0:
                          # pop the first vertex off the max queue
      u = extractMax(Q)
      # loop through the vertices adjacent to u
      Adj = adjacent(A, u)
      for v in Adj:
          w = weight(A, u, v) # get the weight of the edge uv
          # proceed if v is in Q and the weight of uv is great than v's key
          if Q.count(v)>0 and w > K[v]:
             # set v's parent to u
             P[v] = u
             # v's key to the weight of uv
             K[v] = w
             increaseKey(Q, K) # maintain the min queue
   return P
V = [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21,
22, 23, 24, 25, 26, 27, 28, 29]
P = prim(V, I, 0)
print(P)
Out [4]:
[None, 4, 0, 29, 6, 3, 5, 10, 13, 10, 14, 12, 3, 7, 11, 13, 2, 2, 17, 18, 17, 27,
28, 22, 21, 21, 22, 20, 29, 27]
```

Last but not least, with the following code we can output the plot of the graph:

```
In [5]:
import matplotlib.pyplot as plt
p,q = loc.shape
fig,ax=plt.subplots(1,1)
for i in range(1,p):
    x = [loc[i][0],loc[P[i]][0]]
    y = [loc[i][1],loc[P[i]][1]]
    plt.plot(x,y,'o-')
for i in range(p):
    plt.text(loc[i][0],loc[i][1],str(i))
plt.show()
```



(d)

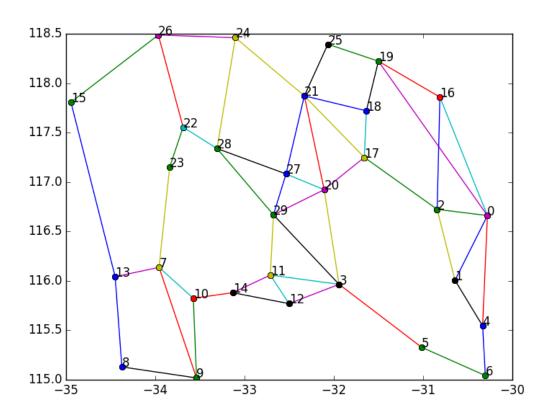
```
In [6]:
ll = I[0][0]
for i in range(1,n):
        I1 = I[i][i] + I[P[i]][i]
        ll += I1
print('log likelihood: {}'.format(ll))

Out [6]:
log likelihood: -11.098614327815277
```

Problem 2:

(a)

The edges are plotted as follows:



(b) & (c)

First, the data will be transferred into pyGM objects.

(a)

```
In [7]:
import numpy as np
import matplotlib.pyplot as plt
loc = np.genfromtxt('data/locations.txt',delimiter=None)
E = np.genfromtxt('data/edges.txt', delimiter=None)
X = [Var(i,2) \text{ for } i \text{ in } range(30)]
P = [Factor(X[i], 0.0) \text{ for } i \text{ in } range(n)]
for i in range(n):
 P[i][0] = 1-x[i]
 P[i][1] = x[i]
W = [[0] * n for i in range(n)]
for i in range(n):
 W[i][i] = x[i]
 for j in range(i+1, n):
   W[i][j] = Factor([X[i], X[j]], 0.0)
   W[i][j][0,0] = xij[i][j][0]
   W[i][j][1,0] = xij[i][j][1]
   W[i][j][0,1] = xij[i][j][2]
   W[i][j][1,1] = xij[i][j][3]
   W[j][i] = W[i][j]
```

The empirical marginal probabilities are already included in xij, which is calculated in problem1 part b. The marginal probability of edge (i, j) can be found in xij[i][j].

The IPF process is operate with the following code.

```
In [8]:
factors = [Factor([X[int(e[0])], X[int(e[1])]], 1.0)] for e in E]
pri = [1.0 \text{ for } Xi \text{ in } X]
for i in range(15):
   11 = 0
   for j, e in enumerate(E):
       model_ve = GraphModel(factors)
       k,l = int(e[0]), int(e[1])
       pri[k], pri[l] = 2.0, 2.0
       order = eliminationOrder(model ve, orderMethod = 'minfill', priority =
pri)[0]
       sumElim = lambda F,Xlist: F.sum(Xlist) # helper function for eliminate
       model ve.eliminate(order[:-2], sumElim) # eliminate all but last two
       p = model ve.joint()
       p /= p.sum()
       factors[j] *= W[k][l]/p # update the factors
       pri[k], pri[l] = 1.0, 1.0
   # calculating the Z value
   model ve = GraphModel(factors)
   order = eliminationOrder(model ve, orderMethod = 'minfill', priority = pri)[0]
   sumElim = lambda F,Xlist: F.sum(Xlist) # helper function for eliminate
   model ve.eliminate(order, sumElim) # eliminate all variables to get Z
   Z = model ve.joint()
   # calculating the log likelihood
   for k in range(m):
       for j,e in enumerate(E):
          u, v = int(e[0]), int(e[1])
          a, b = int(D[k][u]), int(D[k][v])
          ll += log(factors[j][a,b])
   ll /= m
   ll -= log(Z.table)
   print('step: {} log likelihood: {} logZ: {}'.format(i+1, ll, log(Z.table)))
Out [8]:
step: 1 log likelihood: -10.527552408560377 logZ: 20.79441541679836
step: 2 log likelihood: -9.766228337941332 logZ: 20.79441541679836
step: 3 log likelihood: -9.709305478153006 logZ: 20.79441541679836
step: 4 log likelihood: -9.695579756168586 logZ: 20.79441541679836
step: 5 log likelihood: -9.692246358683846 logZ: 20.79441541679836
step: 6 log likelihood: -9.691553503619216 logZ: 20.79441541679836
step: 7 log likelihood: -9.691414842252 logZ: 20.794415416798362
step: 8 log likelihood: -9.691386009889872 logZ: 20.794415416798362
step: 9 log likelihood: -9.69137972473651 logZ: 20.794415416798362
step: 10 log likelihood: -9.691378298007859 logZ: 20.794415416798362
step: 11 log likelihood: -9.691377938590907 logZ: 20.794415416798362
step: 12 log likelihood: -9.691377836134777 logZ: 20.794415416798362
step: 13 log likelihood: -9.691377806937822 logZ: 20.794415416798362
step: 14 log likelihood: -9.691377799601709 logZ: 20.794415416798362
step: 15 log likelihood: -9.691377798040286 logZ: 20.794415416798362
```