In [1]:
```python
from sklearn import datasets
import pandas as pd
iris=datasets.load_iris()
print(iris)
```

```
{'data': array([[5.1, 3.5, 1.4, 0.2],
       [4.9, 3. , 1.4, 0.2],
       [4.7, 3.2, 1.3, 0.2],
       [4.6, 3.1, 1.5, 0.2],
       [5. , 3.6, 1.4, 0.2],
       [5.4, 3.9, 1.7, 0.4],
       [4.6, 3.4, 1.4, 0.3],
       [5. , 3.4, 1.5, 0.2],
       [4.4, 2.9, 1.4, 0.2],
       [4.9, 3.1, 1.5, 0.1],
       [5.4, 3.7, 1.5, 0.2],
       [4.8, 3.4, 1.6, 0.2],
       [4.8, 3. , 1.4, 0.1],
       [4.3, 3. , 1.1, 0.1],
       [5.8, 4. , 1.2, 0.2],
       [5.7, 4.4, 1.5, 0.4],
       [5.4, 3.9, 1.3, 0.4],
       [5.1, 3.5, 1.4, 0.3],
       [5.7, 3.8, 1.7, 0.3],
```

In [2]:
```python
print(type(iris))
```

```
<class 'sklearn.utils.Bunch'>
```

In [3]:
```python
print(iris.keys())
```

```
dict_keys(['data', 'target', 'frame', 'target_names', 'DESCR', 'feature_na
mes', 'filename', 'data_module'])
```

In [4]:
```python
print(type(object))
```

```
<class 'type'>
```

In [5]:
```python
print(type(iris.data))
```

```
<class 'numpy.ndarray'>
```

In [7]:
```python
print(type(iris.target))
```

```
<class 'numpy.ndarray'>
```

In [8]:
```python
print(iris.data.shape)
```

```
(150, 4)
```

In [9]:
```python
print(iris.target_names)
```

```
['setosa' 'versicolor' 'virginica']
```

In [10]:
```
x=iris.data
y=iris.target
print(x)
print(y)
```

```
[[5.1 3.5 1.4 0.2]
 [4.9 3.  1.4 0.2]
 [4.7 3.2 1.3 0.2]
 [4.6 3.1 1.5 0.2]
 [5.  3.6 1.4 0.2]
 [5.4 3.9 1.7 0.4]
 [4.6 3.4 1.4 0.3]
 [5.  3.4 1.5 0.2]
 [4.4 2.9 1.4 0.2]
 [4.9 3.1 1.5 0.1]
 [5.4 3.7 1.5 0.2]
 [4.8 3.4 1.6 0.2]
 [4.8 3.  1.4 0.1]
 [4.3 3.  1.1 0.1]
 [5.8 4.  1.2 0.2]
 [5.7 4.4 1.5 0.4]
 [5.4 3.9 1.3 0.4]
 [5.1 3.5 1.4 0.3]
 [5.7 3.8 1.7 0.3]
```

In [13]:
```
a=pd.DataFrame(x,columns=iris.feature_names)
print(a)
```

```
     sepal length (cm)  sepal width (cm)  petal length (cm)  petal width
(cm)
0                  5.1               3.5                1.4
0.2
1                  4.9               3.0                1.4
0.2
2                  4.7               3.2                1.3
0.2
3                  4.6               3.1                1.5
0.2
4                  5.0               3.6                1.4
0.2
..                 ...               ...                ...
...
145                6.7               3.0                5.2
2.3
146                6.3               2.5                5.0
1.9
147                6.5               3.0                5.2
2.0
148                6.2               3.4                5.4
2.3
149                5.9               3.0                5.1
1.8

[150 rows x 4 columns]
```

In [16]:
```
print(a.head())
```

```
   sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (c
m)
0                5.1               3.5                1.4               0.
2
1                4.9               3.0                1.4               0.
2
2                4.7               3.2                1.3               0.
2
3                4.6               3.1                1.5               0.
2
4                5.0               3.6                1.4               0.
2
```

In [17]:
```
print(a.tail())
```

```
     sepal length (cm)  sepal width (cm)  petal length (cm)  petal width
(cm)
145                6.7               3.0                5.2
2.3
146                6.3               2.5                5.0
1.9
147                6.5               3.0                5.2
2.0
148                6.2               3.4                5.4
2.3
149                5.9               3.0                5.1
1.8
```

In [19]:
```
print(a.describe())
```

```
       sepal length (cm)  sepal width (cm)  petal length (cm)  \
count         150.000000        150.000000         150.000000
mean            5.843333          3.057333           3.758000
std             0.828066          0.435866           1.765298
min             4.300000          2.000000           1.000000
25%             5.100000          2.800000           1.600000
50%             5.800000          3.000000           4.350000
75%             6.400000          3.300000           5.100000
max             7.900000          4.400000           6.900000

       petal width (cm)
count        150.000000
mean           1.199333
std            0.762238
min            0.100000
25%            0.300000
50%            1.300000
75%            1.800000
max            2.500000
```

In [20]:
```
print(a.min())
```

```
sepal length (cm)    4.3
sepal width (cm)     2.0
petal length (cm)    1.0
petal width (cm)     0.1
dtype: float64
```

In [21]:
```
print(a.max())
```

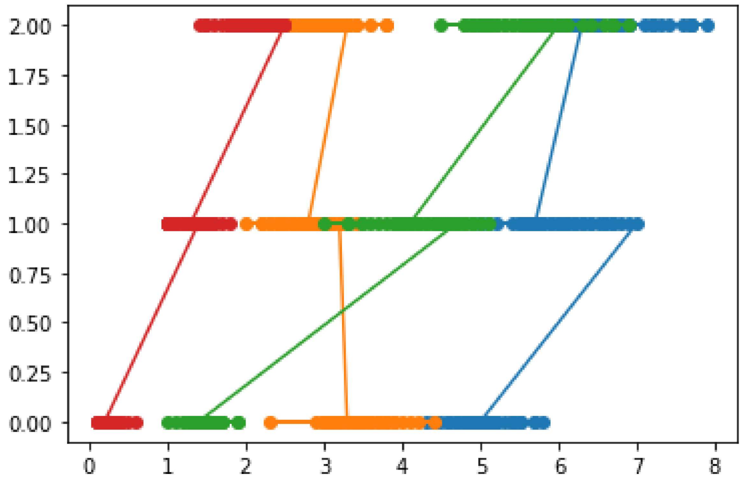
```
sepal length (cm)    7.9
sepal width (cm)     4.4
petal length (cm)    6.9
petal width (cm)     2.5
dtype: float64
```

In [22]:
```
from sklearn import datasets
import pandas as pd
db=datasets.load_diabetes()
print(db)
```

```
{'data': array([[ 0.03807591,  0.05068012,  0.06169621, ..., -0.00259226,
          0.01990842, -0.01764613],
        [-0.00188202, -0.04464164, -0.05147406, ..., -0.03949338,
         -0.06832974, -0.09220405],
        [ 0.08529891,  0.05068012,  0.04445121, ..., -0.00259226,
          0.00286377, -0.02593034],
        ...,
        [ 0.04170844,  0.05068012, -0.01590626, ..., -0.01107952,
         -0.04687948,  0.01549073],
        [-0.04547248, -0.04464164,  0.03906215, ...,  0.02655962,
          0.04452837, -0.02593034],
        [-0.04547248, -0.04464164, -0.0730303 , ..., -0.03949338,
         -0.00421986,  0.00306441]]), 'target': array([151.,  75., 141., 20
6., 135.,  97., 138.,  63., 110., 310., 101.,
         69., 179., 185., 118., 171., 166., 144.,  97., 168.,  68.,  49.,
         68., 245., 184., 202., 137.,  85., 131., 283., 129.,  59., 341.,
         87.,  65., 102., 265., 276., 252.,  90., 100.,  55.,  61.,  92.,
        259.,  53., 190., 142.,  75., 142., 155., 225.,  59., 104., 182.,
        128.,  52.,  37., 170., 170.,  61., 144.,  52., 128.,  71., 163.,
        150.,  97., 160., 178.,  48., 270., 202., 111.,  85.,  42., 170.,
        200., 252., 113., 143.,  51.,  52., 210.,  65., 141.,  55., 134.,
         42., 111.,  98., 164.,  48.,  96.,  90., 162., 150., 279.,  92.,
         83., 128., 102., 302., 198.,  95.,  53., 134., 144., 232.,  81.,
        104.,  59., 246., 297., 258., 229., 275., 281., 179., 200., 200.,
        173., 180.,  84., 121., 161.,  99., 109., 115., 268., 274., 158.,
        107.,  83., 103., 272.,  85., 280., 336., 281., 118., 317., 235.,
         60., 174., 259., 178., 128.,  96., 126., 288.,  88., 292.,  71.,
        197., 186.,  25.,  84.,  96., 195.,  53., 217., 172., 131., 214.,
         59.,  70., 220., 268., 152.,  47.,  74., 295., 101., 151., 127.,
        237., 225.,  81., 151., 107.,  64., 138., 185., 265., 101., 137.,
        143., 141.,  79., 292., 178.,  91., 116.,  86., 122.,  72., 129.,
        142.,  90., 158.,  39., 196., 222., 277.,  99., 196., 202., 155.,
         77., 191.,  70.,  73.,  49.,  65., 263., 248., 296., 214., 185.,
         78.,  93., 252., 150.,  77., 208.,  77., 108., 160.,  53., 220.,
        154., 259.,  90., 246., 124.,  67.,  72., 257., 262., 275., 177.,
         71.,  47., 187., 125.,  78.,  51., 258., 215., 303., 243.,  91.,
        150., 310., 153., 346.,  63.,  89.,  50.,  39., 103., 308., 116.,
        145.,  74.,  45., 115., 264.,  87., 202., 127., 182., 241.,  66.,
         94., 283.,  64., 102., 200., 265.,  94., 230., 181., 156., 233.,
         60., 219.,  80.,  68., 332., 248.,  84., 200.,  55.,  85.,  89.,
         31., 129.,  83., 275.,  65., 198., 236., 253., 124.,  44., 172.,
        114., 142., 109., 180., 144., 163., 147.,  97., 220., 190., 109.,
        191., 122., 230., 242., 248., 249., 192., 131., 237.,  78., 135.,
        244., 199., 270., 164.,  72.,  96., 306.,  91., 214.,  95., 216.,
        263., 178., 113., 200., 139., 139.,  88., 148.,  88., 243.,  71.,
         77., 109., 272.,  60.,  54., 221.,  90., 311., 281., 182., 321.,
         58., 262., 206., 233., 242., 123., 167.,  63., 197.,  71., 168.,
        140., 217., 121., 235., 245.,  40.,  52., 104., 132.,  88.,  69.,
        219.,  72., 201., 110.,  51., 277.,  63., 118.,  69., 273., 258.,
         43., 198., 242., 232., 175.,  93., 168., 275., 293., 281.,  72.,
        140., 189., 181., 209., 136., 261., 113., 131., 174., 257.,  55.,
         84.,  42., 146., 212., 233.,  91., 111., 152., 120.,  67., 310.,
         94., 183.,  66., 173.,  72.,  49.,  64.,  48., 178., 104., 132.,
        220.,  57.]), 'frame': None, 'DESCR': '.. _diabetes_dataset:\n\nDia
betes dataset\n----------------\n\nTen baseline variables, age, sex, body
mass index, average blood\npressure, and six blood serum measurements were
obtained for each of n =\n442 diabetes patients, as well as the response o
f interest, a\nquantitative measure of disease progression one year after
baseline.\n\n**Data Set Characteristics:**\n\n  :Number of Instances: 442
\n\n  :Number of Attributes: First 10 columns are numeric predictive value
s\n\n  :Target: Column 11 is a quantitative measure of disease progression
```

```
one year after baseline\n\n  :Attribute Information:\n      - age     age
in years\n      - sex\n      - bmi      body mass index\n      - bp      av
erage blood pressure\n      - s1      tc, total serum cholesterol\n      -
s2      ldl, low-density lipoproteins\n      - s3      hdl, high-density l
ipoproteins\n      - s4      tch, total cholesterol / HDL\n      - s5
ltg, possibly log of serum triglycerides level\n      - s6      glu, blood
sugar level\n\nNote: Each of these 10 feature variables have been mean cen
tered and scaled by the standard deviation times `n_samples` (i.e. the sum
of squares of each column totals 1).\n\nSource URL:\nhttps://www4.stat.ncs
u.edu/~boos/var.select/diabetes.html\n\nFor more information see:\nBradley
Efron, Trevor Hastie, Iain Johnstone and Robert Tibshirani (2004) "Least A
ngle Regression," Annals of Statistics (with discussion), 407-499.\n(http
s://web.stanford.edu/~hastie/Papers/LARS/LeastAngle_2002.pdf)', 'feature_n
ames': ['age', 'sex', 'bmi', 'bp', 's1', 's2', 's3', 's4', 's5', 's6'], 'd
ata_filename': 'diabetes_data.csv.gz', 'target_filename': 'diabetes_targe
t.csv.gz', 'data_module': 'sklearn.datasets.data'}
```

In [23]:
```python
import matplotlib.pyplot
import matplotlib.pyplot as plt
plt.plot(x,y,marker='o')
plt.show()
```



In [24]:
```python
print(type(db))
```

```
<class 'sklearn.utils.Bunch'>
```

In [25]:
```python
print(db.keys())
```

```
dict_keys(['data', 'target', 'frame', 'DESCR', 'feature_names', 'data_file
name', 'target_filename', 'data_module'])
```

In [26]:
```
x=db.data
y=db.target
print(x)
print(y)
```

```
[[ 0.03807591  0.05068012  0.06169621 ... -0.00259226  0.01990842
  -0.01764613]
 [-0.00188202 -0.04464164 -0.05147406 ... -0.03949338 -0.06832974
  -0.09220405]
 [ 0.08529891  0.05068012  0.04445121 ... -0.00259226  0.00286377
  -0.02593034]
 ...
 [ 0.04170844  0.05068012 -0.01590626 ... -0.01107952 -0.04687948
   0.01549073]
 [-0.04547248 -0.04464164  0.03906215 ...  0.02655962  0.04452837
  -0.02593034]
 [-0.04547248 -0.04464164 -0.0730303  ... -0.03949338 -0.00421986
   0.00306441]]
[151.  75. 141. 206. 135.  97. 138.  63. 110. 310. 101.  69. 179. 185.
 118. 171. 166. 144.  97. 168.  68.  49.  68. 245. 184. 202. 137.  85.
 131. 283. 129.  59. 341.  87.  65. 102. 265. 276. 252.  90. 100.  55.
  61.  92. 259.  53. 190. 142.  75. 142. 155. 225.  59. 104. 182. 128.
  52.  37. 170. 170.  61. 144.  52. 128.  71. 163. 150.  97. 160. 178.
  48. 270. 202. 111.  85.  42. 170. 200. 252. 113. 143.  51.  52. 210.
  65. 141.  55. 134.  42. 111.  98. 164.  48.  96.  90. 162. 150. 279.
  92.  83. 128. 102. 302. 198.  95.  53. 134. 144. 232.  81. 104.  59.
 246. 297. 258. 229. 275. 281. 179. 200. 200. 173. 180.  84. 121. 161.
  99. 109. 115. 268. 274. 158. 107.  83. 103. 272.  85. 280. 336. 281.
 118. 317. 235.  60. 174. 259. 178. 128.  96. 126. 288.  88. 292.  71.
 197. 186.  25.  84.  96. 195.  53. 217. 172. 131. 214.  59.  70. 220.
 268. 152.  47.  74. 295. 101. 151. 127. 237. 225.  81. 151. 107.  64.
 138. 185. 265. 101. 137. 143. 141.  79. 292. 178.  91. 116.  86. 122.
  72. 129. 142.  90. 158.  39. 196. 222. 277.  99. 196. 202. 155.  77.
 191.  70.  73.  49.  65. 263. 248. 296. 214. 185.  78.  93. 252. 150.
  77. 208.  77. 108. 160.  53. 220. 154. 259.  90. 246. 124.  67.  72.
 257. 262. 275. 177.  71.  47. 187. 125.  78.  51. 258. 215. 303. 243.
  91. 150. 310. 153. 346.  63.  89.  50.  39. 103. 308. 116. 145.  74.
  45. 115. 264.  87. 202. 127. 182. 241.  66.  94. 283.  64. 102. 200.
 265.  94. 230. 181. 156. 233.  60. 219.  80.  68. 332. 248.  84. 200.
  55.  85.  89.  31. 129.  83. 275.  65. 198. 236. 253. 124.  44. 172.
 114. 142. 109. 180. 144. 163. 147.  97. 220. 190. 109. 191. 122. 230.
 242. 248. 249. 192. 131. 237.  78. 135. 244. 199. 270. 164.  72.  96.
 306.  91. 214.  95. 216. 263. 178. 113. 200. 139. 139.  88. 148.  88.
 243.  71.  77. 109. 272.  60.  54. 221.  90. 311. 281. 182. 321.  58.
 262. 206. 233. 242. 123. 167.  63. 197.  71. 168. 140. 217. 121. 235.
 245.  40.  52. 104. 132.  88.  69. 219.  72. 201. 110.  51. 277.  63.
 118.  69. 273. 258.  43. 198. 242. 232. 175.  93. 168. 275. 293. 281.
  72. 140. 189. 181. 209. 136. 261. 113. 131. 174. 257.  55.  84.  42.
 146. 212. 233.  91. 111. 152. 120.  67. 310.  94. 183.  66. 173.  72.
  49.  64.  48. 178. 104. 132. 220.  57.]
```

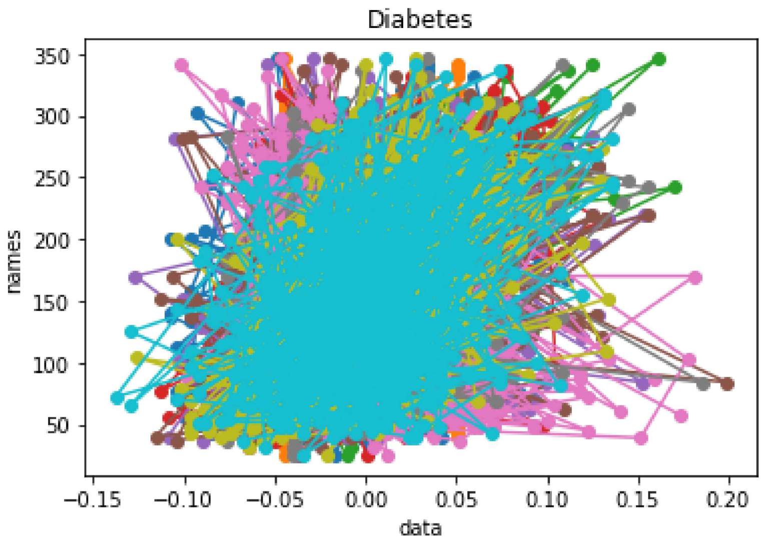
In [28]:
```
b=pd.DataFrame(x,columns=db.feature_names)
print(b)
```

```
          age       sex       bmi        bp        s1        s2        s3  \
0    0.038076  0.050680  0.061696  0.021872 -0.044223 -0.034821 -0.043401
1   -0.001882 -0.044642 -0.051474 -0.026328 -0.008449 -0.019163  0.074412
2    0.085299  0.050680  0.044451 -0.005671 -0.045599 -0.034194 -0.032356
3   -0.089063 -0.044642 -0.011595 -0.036656  0.012191  0.024991 -0.036038
4    0.005383 -0.044642 -0.036385  0.021872  0.003935  0.015596  0.008142
..        ...       ...       ...       ...       ...       ...       ...
437  0.041708  0.050680  0.019662  0.059744 -0.005697 -0.002566 -0.028674
438 -0.005515  0.050680 -0.015906 -0.067642  0.049341  0.079165 -0.028674
439  0.041708  0.050680 -0.015906  0.017282 -0.037344 -0.013840 -0.024993
440 -0.045472 -0.044642  0.039062  0.001215  0.016318  0.015283 -0.028674
441 -0.045472 -0.044642 -0.073030 -0.081414  0.083740  0.027809  0.173816

           s4        s5        s6
0   -0.002592  0.019908 -0.017646
1   -0.039493 -0.068330 -0.092204
2   -0.002592  0.002864 -0.025930
3    0.034309  0.022692 -0.009362
4   -0.002592 -0.031991 -0.046641
..        ...       ...       ...
437 -0.002592  0.031193  0.007207
438  0.034309 -0.018118  0.044485
439 -0.011080 -0.046879  0.015491
440  0.026560  0.044528 -0.025930
441 -0.039493 -0.004220  0.003064

[442 rows x 10 columns]
```

In [30]:
```
import matplotlib.pyplot
import matplotlib.pyplot as plt
plt.plot(x,y,marker='o')
plt.xlabel('data')
plt.ylabel('names')
plt.title('Diabetes')
plt.show()
```



In [ ]: