olympic_games

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1 计算思维：奥运会比赛数据分析

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```
In [1]: %matplotlib inline
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import matplotlib
        import statsmodels.api as sm

        matplotlib.style.use('fivethirtyeight')
```

```
In [2]: game = pd.read_csv('/Users/chengjun/bigdata/olympic/summer.csv')
        country = pd.read_csv('/Users/chengjun/bigdata/olympic/dictionary.csv')
        # https://www.kaggle.com/the-guardian/olympic-games
```

```
In [3]: import warnings
        warnings.filterwarnings('ignore')

        game['gold']=0
        game['silver']=0
        game['bronze']=0
        game['gold'][game['Medal']=='Gold'] = 1
        game['silver'][game['Medal']=='Silver'] = 1
        game['bronze'][game['Medal']=='Bronze'] = 1
        game['score']=0
        game['score'][game['Medal']=='Gold'] = 4
        game['score'][game['Medal']=='Silver'] = 2
        game['score'][game['Medal']=='Bronze'] = 1
```

```
In [4]: game[:3]
```

```
Out[4]:    Year    City     Sport Discipline             Athlete Country Gender  \
        0  1896  Athens  Aquatics   Swimming       HAJOS, Alfred     HUN    Men
        1  1896  Athens  Aquatics   Swimming    HERSCHMANN, Otto     AUT    Men
        2  1896  Athens  Aquatics   Swimming   DRIVAS, Dimitrios     GRE    Men

                              Event   Medal  gold  silver  bronze  score
        0                100M Freestyle    Gold     1       0       0      4
        1                100M Freestyle  Silver     0       1       0      2
        2  100M Freestyle For Sailors  Bronze     0       0       1      1
```

黑人从游泳项目当中消失了

2 金牌得分的垄断程度

```
In [5]: import powerlaw
        def plotPowerlaw(data,ax,col,xlab):
            fit = powerlaw.Fit(data,xmin=1)
            #fit = powerlaw.Fit(data)
            fit.plot_pdf(color = col, linewidth = 2)
            a,x = (fit.power_law.alpha,fit.power_law.xmin)
            fit.power_law.plot_pdf(color = col, linestyle = 'dotted', ax = ax, \
                                label = r"$\alpha = %d \:\:, x_{min} = %d$" % (a,x))
            ax.set_xlabel(xlab, fontsize = 20)
            ax.set_ylabel('$Probability$', fontsize = 20)
            plt.legend(loc = 0, frameon = False)

        def plotCCDF(data,ax,col,xlab):
            fit = powerlaw.Fit(data,xmin=1)
            #fit = powerlaw.Fit(data)
            fit.plot_ccdf(color = col, linewidth = 2)
            a,x = (fit.power_law.alpha,fit.power_law.xmin)
            fit.power_law.plot_ccdf(color = col, linestyle = 'dotted', ax = ax, \
                                label = r"$\alpha = %d \:\:, x_{min} = %d$" % (a,x))
            ax.set_xlabel(xlab, fontsize = 16)
            ax.set_ylabel('$CCDF$', fontsize = 16)
            plt.legend(loc = 0, frameon = False)
```

```
In [6]: gsb = game.groupby(['Country']).sum()[['gold', 'silver', 'bronze', 'score']]
```

```
In [14]: gsb = gsb.sort_values(['score'], ascending = False)
         gsb[:20]
```

```
Out[14]:          gold  silver  bronze  score
         Country
         USA      2235    1252    1098  12542
         URS       838     627     584   5190
         GBR       546     621     553   3979
         ITA       476     416     404   3140
         FRA       408     491     497   3111
         GER       452     378     475   3039
         HUN       412     316     351   2631
         AUS       312     405     472   2530
         SWE       349     367     328   2458
```

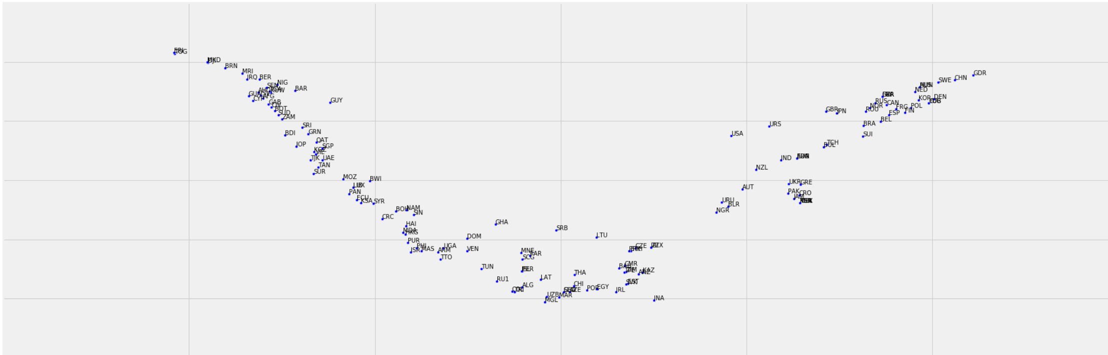
```
GDR        329     271     225   2083
CHN        290     296     221   1973
NED        233     279     339   1829
RUS        239     238     291   1723
JPN        213     272     303   1699
NOR        209     200     145   1381
CAN        155     232     262   1346
ROU        157     195     288   1306
KOR        158     204     167   1207
DEN        150     197     160   1154
FRG        143     167     180   1086
```

In [15]:
```
gsb.index
```

Out[15]:
```
Index([u'USA', u'URS', u'GBR', u'ITA', u'FRA', u'GER', u'HUN', u'AUS', u'SWE',
       u'GDR',
       …
       u'TOG', u'ERI', u'DJI', u'MKD', u'BRN', u'MRI', u'BER', u'NIG', u'BAR',
       u'GUY'],
      dtype='object', name=u'Country', length=147)
```

In [52]:
```
from time import time

from sklearn import manifold
from sklearn.utils import check_random_state

data = gsb
# Perform t-distributed stochastic neighbor embedding.
t0 = time()
# tsne = manifold.TSNE(n_components=2, init='pca', random_state=0, method = 'exact')
# trans_data = tsne.fit_transform(data).T
se = manifold.SpectralEmbedding(n_components=2, n_neighbors=10)
trans_data = se.fit_transform(data).T
t1 = time()
print("t-SNE: %.2g sec" % (t1 - t0))

from matplotlib.ticker import NullFormatter
fig = plt.figure(figsize=(30, 10),facecolor='white')
ax = fig.add_subplot(1, 1, 1)
plt.scatter(trans_data[0], trans_data[1])  # c=colors
for i in range(len(gsb)):
    plt.text(trans_data[0][i], trans_data[1][i], gsb.index[i], fontsize = 10)  # c=colors
#plt.title("t-SNE (%.2g sec)" % (t1 - t0))
ax.xaxis.set_major_formatter(NullFormatter())
ax.yaxis.set_major_formatter(NullFormatter())
plt.show()
```

```
t-SNE: 0.014 sec
```



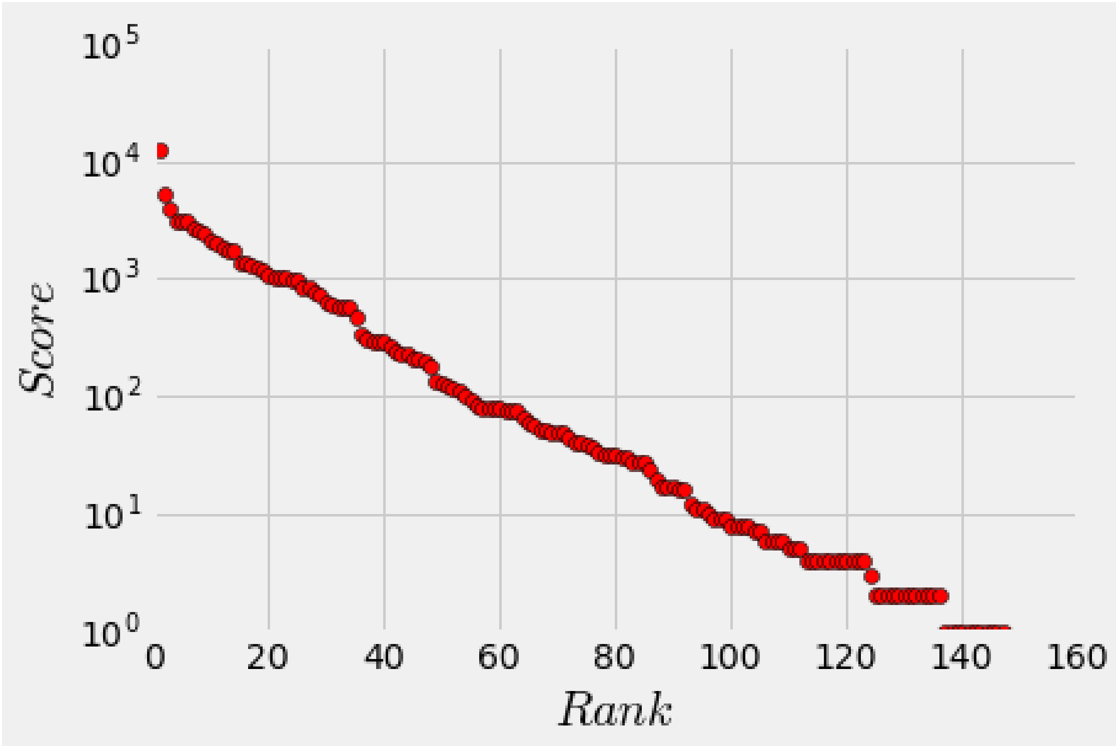
```
In [17]: gsb['rank']=range(1, len(gsb)+1)
```

```
In [27]: gsb[:5]
```

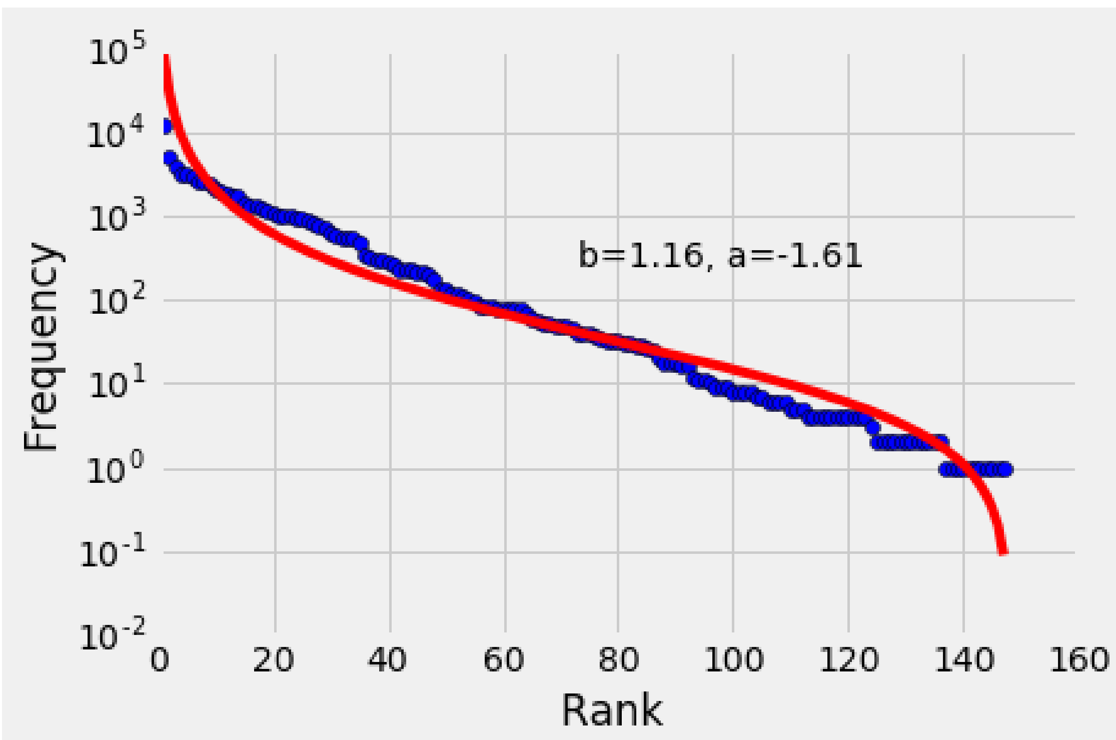
```
Out[27]:
```

Country	gold	silver	bronze	score	rank
USA	2235	1252	1098	12542	1
URS	838	627	584	5190	2
GBR	546	621	553	3979	3
ITA	476	416	404	3140	4
FRA	408	491	497	3111	5

```
In [31]: plt.plot(gsb['rank'], gsb.score, 'ro')
         #plt.xscale('log');
         plt.yscale('log')
         plt.xlabel(r'$Rank$', fontsize = 20)
         plt.ylabel(r'$Score$', fontsize = 20)
         plt.show()
```

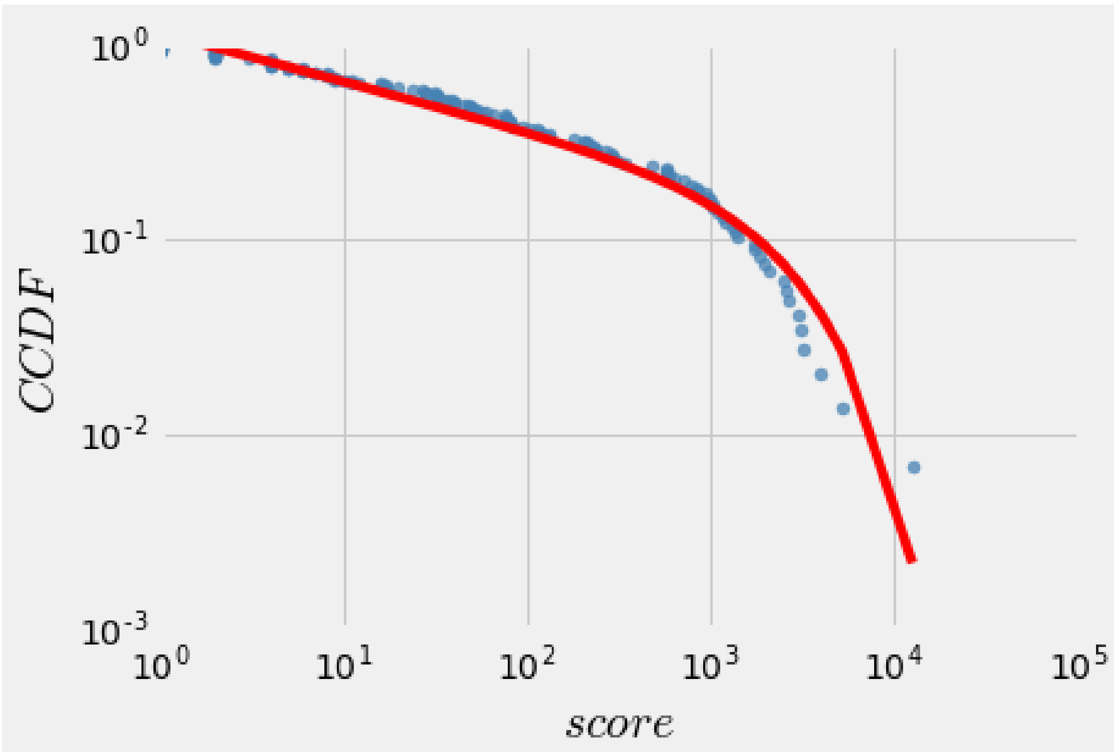



```
In [30]: from flownetwork import flownetwork as fn

         fn.DGBDPlot(gsb.score)
```



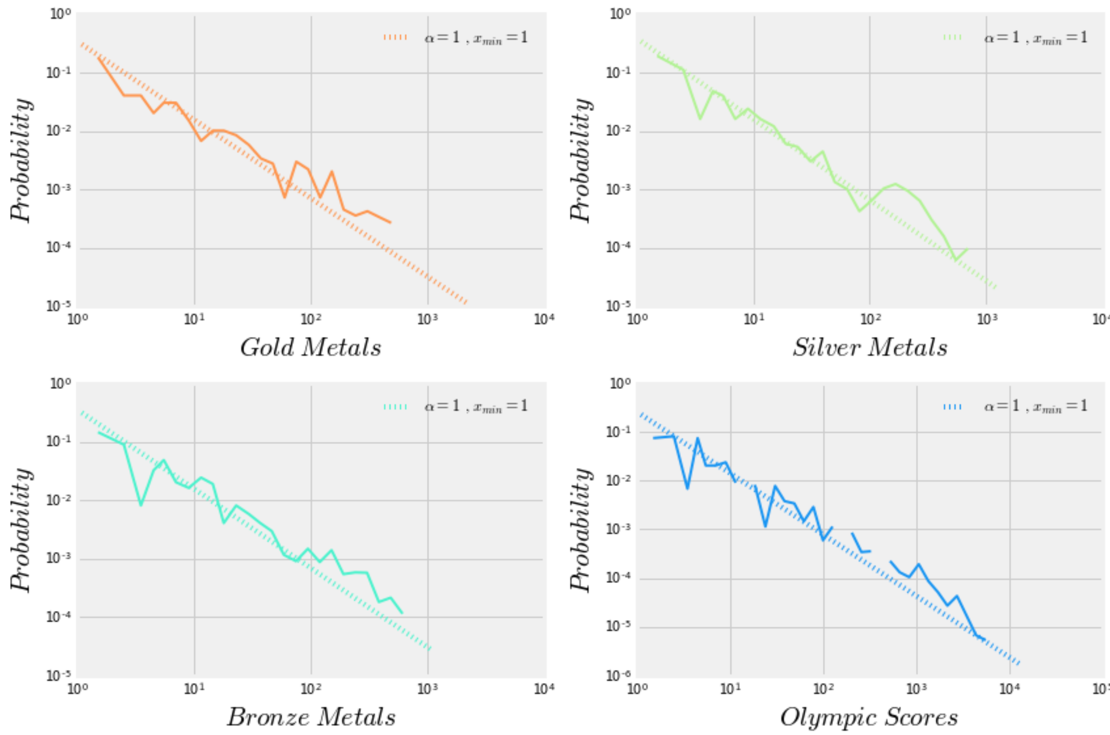
```
In [36]: fn.powerLawExponentialCutOffPlot(gsb.score, '$score$', '$CCDF$')
```

```
Out[36]: [0.13616703455127721,
          -0.25190827875999861,
          -0.00031073938596815‌13,
          0.9626301352057971]
```

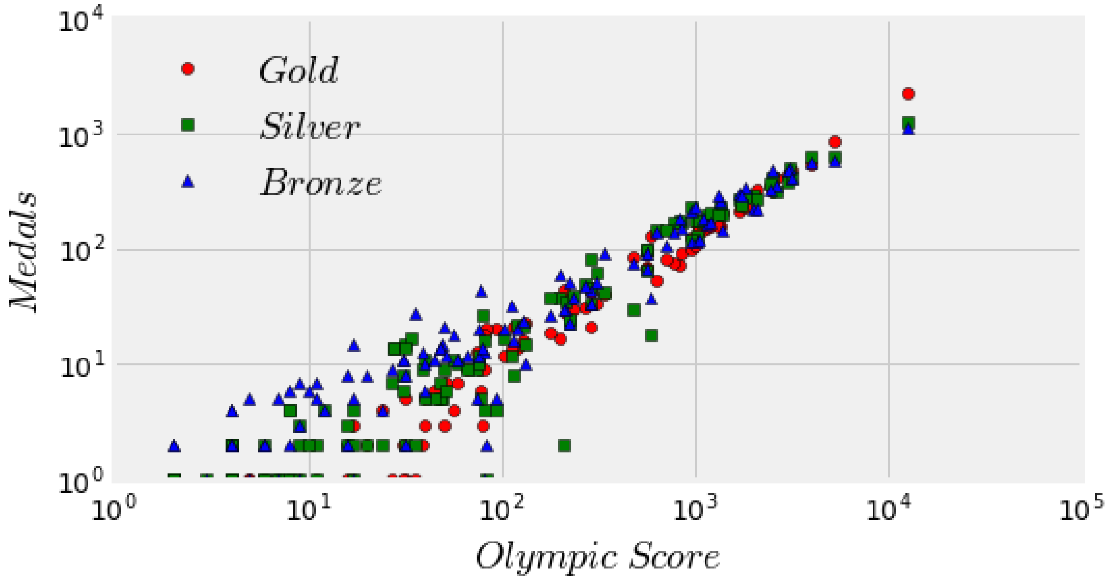



```
In [211]: import matplotlib.cm as cm
          cmap = cm.get_cmap('rainbow_r',6)

          fig = plt.figure(figsize=(12, 8),facecolor='white')
          ax = fig.add_subplot(2, 2, 1)
          plotPowerlaw(gsb.gold, ax,cmap(1), '$Gold\;Metals$')
          #plotCCDF(gsb.score, ax,cmap(4), '$Gold\;Metals$')
          ax = fig.add_subplot(2, 2, 2)
          plotPowerlaw(gsb.silver, ax,cmap(2), '$Silver\;Metals$')

          ax = fig.add_subplot(2, 2, 3)
          plotPowerlaw(gsb.bronze, ax,cmap(3), '$Bronze\;Metals$')

          ax = fig.add_subplot(2, 2, 4)
          plotPowerlaw(gsb.score, ax,cmap(4), '$Olympic\;Scores$')

          plt.tight_layout()
```

```
Values less than or equal to 0 in data. Throwing out 0 or negative values
Values less than or equal to 0 in data. Throwing out 0 or negative values
Values less than or equal to 0 in data. Throwing out 0 or negative values
```

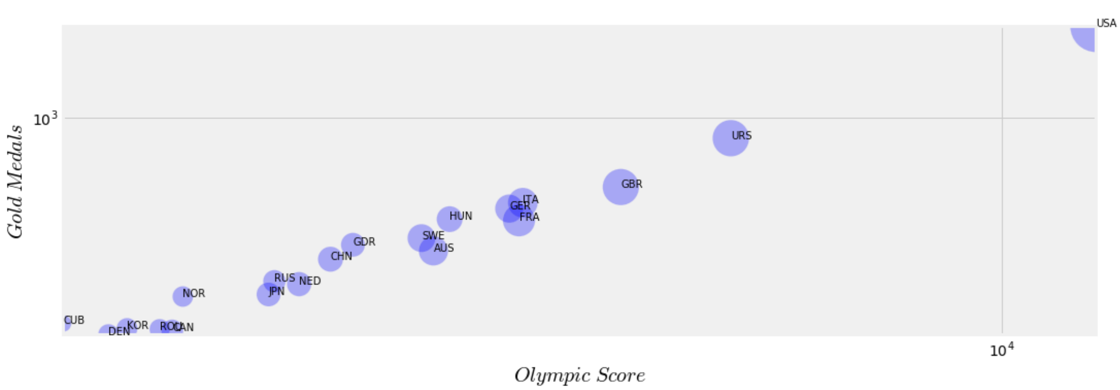


In [14]:
```
fig = plt.figure(figsize=(8, 4),facecolor='white')

plt.plot(gsb['score'], gsb['gold'], 'ro', label = '$Gold$')
plt.plot(gsb['score'], gsb['silver'], 'gs', label = '$Silver$')
plt.plot(gsb['score'], gsb['bronze'], 'b^', label = '$Bronze$')
plt.xscale('log'); plt.yscale('log')
plt.xlabel(r'$Olympic\;Score$', fontsize = 20)
plt.ylabel(r'$Medals$', fontsize = 20)
plt.legend(loc = 2, numpoints = 1, fontsize = 20, frameon = False)
plt.show()
```



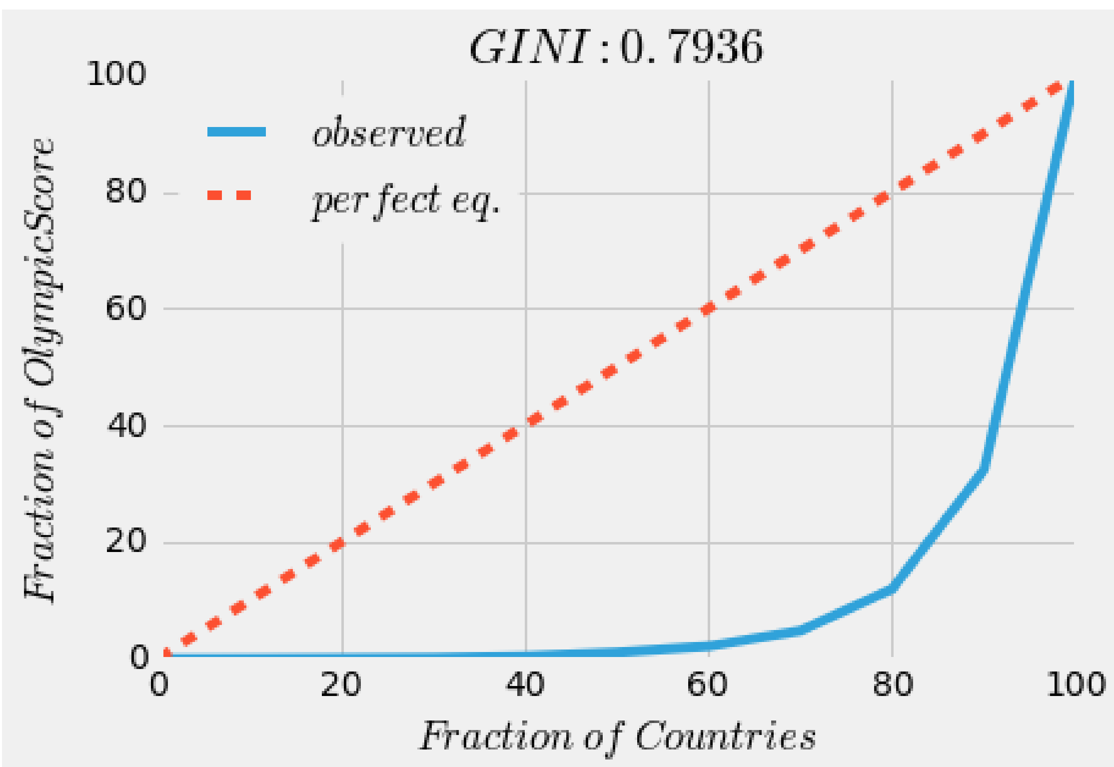

```
In [17]: gsb20 = gsb.sort_values('gold', ascending = False)[:20]
```

```
In [18]: fig = plt.figure(figsize=(16, 5),facecolor='white')
         plt.scatter(gsb20['score'], gsb20['gold'], s = gsb20['silver']*2, alpha = 0.3)

         for k, i in enumerate(gsb20.index):
             plt.text(gsb20['score'][k], gsb20['gold'][k], i, fontsize = 10)
         plt.xscale('log'); plt.yscale('log')
         plt.xlim((0, np.max(gsb20.score)))
         plt.ylim((0, np.max(gsb20.gold)))

         plt.ylabel(r'$Gold\;Medals$', fontsize = 20)
         plt.xlabel(r'$Olympic\;Score$', fontsize = 20)

         plt.show()
```



```
In [20]: def gini_coefficient(v):
             bins = np.linspace(0., 100., 11)
             total = float(np.sum(v))
             yvals = []
             for b in bins:
                 bin_vals = v[v <= np.percentile(v, b)]
                 bin_fraction = (np.sum(bin_vals) / total) * 100.0
                 yvals.append(bin_fraction)
             # perfect equality area
             pe_area = np.trapz(bins, x=bins)
             # lorenz area
             lorenz_area = np.trapz(yvals, x=bins)
             gini_val = (pe_area - lorenz_area) / float(pe_area)
             return bins, yvals, gini_val
```

```
In [23]: score_all = game.groupby(['Country']).sum()['score']
         bins, result, gini_val = gini_coefficient(score_all)

         plt.plot(bins, result, label="$observed$")
         plt.plot(bins, bins, '--', label="$perfect\; eq.$")
         plt.xlabel("$Fraction\; of\; Countries$")
         plt.ylabel("$Fraction\; of \;Olympic Score$")
         plt.title("$GINI: %.4f$" %(gini_val))
         plt.legend(loc=0)
         plt.show()
```




```
In [11]: game['award']=1
```

```
In [12]: country[:3]
```

```
Out[12]:        Country Code  Population  GDP per Capita
         0  Afghanistan  AFG  32526562.0      594.323081
         1      Albania  ALB   2889167.0     3945.217582
         2      Algeria  ALG  39666519.0     4206.031232
```

```
In [22]: disciplines = game.Discipline.unique()
```

```
In [43]: gg = game.groupby(['Discipline', 'Country']).sum()
```

```
In [123]: ggds = gg['score']['Swimming']
          ggds_max = ggds.sort_values(ascending = False).iloc[0]
          gg_sum = np.sum(ggds)
          gg_max  = ggds.sort_values(ascending = False)
          gg_max_value, gg_max_index = gg_max.iloc[0], gg_max.index[0]
          gg_max_ratio = np.float(gg_max_value)/gg_sum
          print gg_max_value, gg_max_ratio, gg_max_index
```

```
2627 0.423231835025 USA
```

```
In [44]: np.array(gg['award']['Croquet'])
```

```
Out[44]: array([8])
```

```
In [45]: gini_coefficient(np.array(gg['award']['Cricket']))[2]
```

```
Out[45]: -0.8000000000000004
```

```
In [128]: for i in disciplines:
              if len(gg['award'][i]) > 10:
                  print i, gini_coefficient(gg['award'][i])[2]
```

```
Swimming 0.750646879756
Athletics 0.744624690679
Cycling Road 0.492698412698
Cycling Track 0.621390374332
Fencing 0.689336639802
Artistic G. 0.539752734189
Shooting 0.661304347826
Tennis 0.588851351351
Weightlifting 0.530118443316
Wrestling Gre-R 0.542987249545
Water polo 0.415909090909
Archery 0.593920972644
Jumping 0.411009174312
Football 0.323513694055
Rowing 0.619422572178
Sailing 0.632371505861
Diving 0.619897959184
Boxing 0.587695749441
Wrestling Free. 0.600846023689
Hockey 0.498734177215
Dressage 0.417602996255
Eventing 0.47250755287
Modern Pentath. 0.53275862069
```

```
Basketball 0.49476284585
Canoe / Kayak F 0.528179824561
Handball 0.307913669065
Judo 0.573319755601
Volleyball 0.364346895075
Canoe / Kayak S 0.368888888889
Rhythmic G. 0.483870967742
Table Tennis 0.623611111111
Mountain Bike 0.236666666667
Taekwondo 0.366964285714
Triathlon 0.2
Canoe Sprint 0.393939393939
Gymnastics Artistic 0.456060606061
Wrestling Freestyle 0.26338028169
```

```
In [48]: for i in disciplines:
             if len(gg['score'][i]) > 10:
                 print i, gini_coefficient(gg['score'][i])[2]
```

```
Swimming 0.779764781698
Athletics 0.758814536046
Cycling Road 0.548517520216
Cycling Track 0.663709215799
Fencing 0.729624770401
Artistic G. 0.582544085595
Shooting 0.69337797619
Tennis 0.661027190332
Weightlifting 0.591250903832
Wrestling Gre-R 0.602675059009
Water polo 0.506969990319
Archery 0.675243902439
Jumping 0.464
Football 0.412260097393
Rowing 0.656681657565
Sailing 0.684247331616
Diving 0.666118421053
Boxing 0.648324324324
Wrestling Free. 0.668672046955
Hockey 0.552040512362
Dressage 0.51077170418
Eventing 0.516174582798
Modern Pentath. 0.582019704433
Basketball 0.628854254423
Canoe / Kayak F 0.557377819549
Handball 0.439381898455
Judo 0.632790224033
Volleyball 0.510224667584
Canoe / Kayak S 0.497619047619
Rhythmic G. 0.575115207373
Table Tennis 0.725609756098
Mountain Bike 0.39
Taekwondo 0.499166666667
Triathlon 0.364285714286
Canoe Sprint 0.448701298701
Gymnastics Artistic 0.538311688312
```

```
Wrestling Freestyle 0.474647887324
```

3 金牌得分与人口和GDP的关系

```
In [54]: score_all['AFG']
```

```
Out[54]: 2
```

```
In [60]: len(score_all.index)
```

```
Out[60]: 147
```

```
In [24]: len(country)
```

```
Out[24]: 201
```

```
In [25]: medal_score = []
         for i in country.Code:
             if i in score_all.index:
                 medal_score.append(score_all[i])
             else:
                 medal_score.append(0)
```

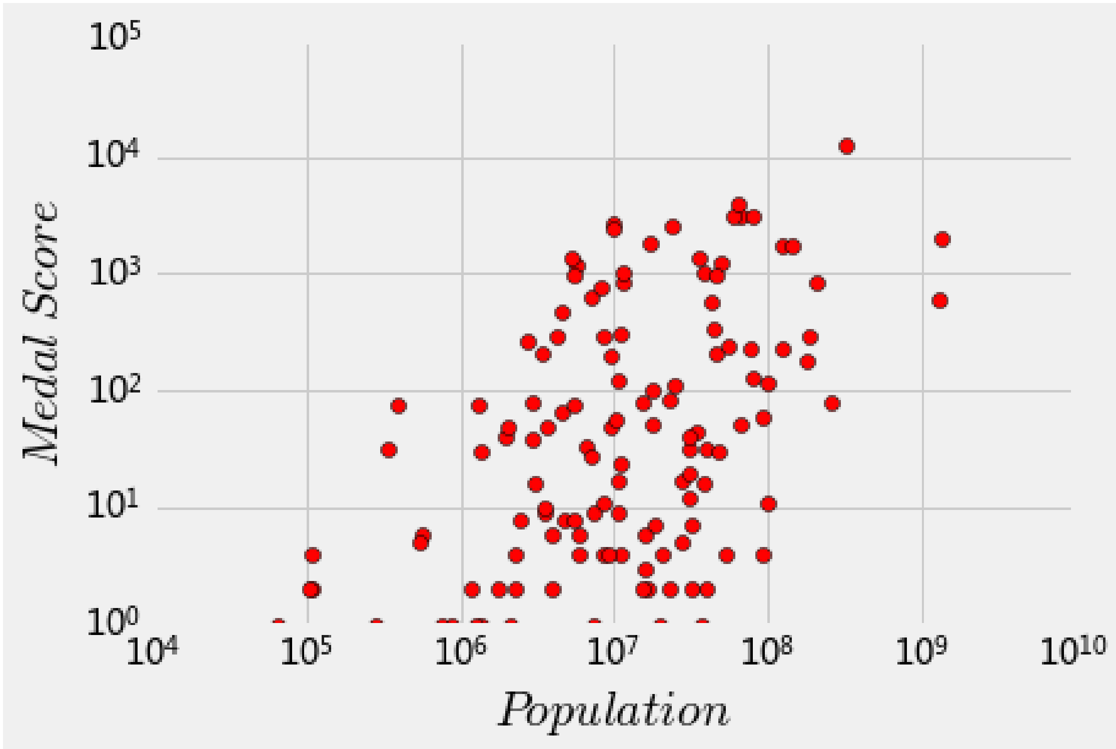
```
In [26]: country['medal_score'] = medal_score
```

```
In [27]: country[:3]
```

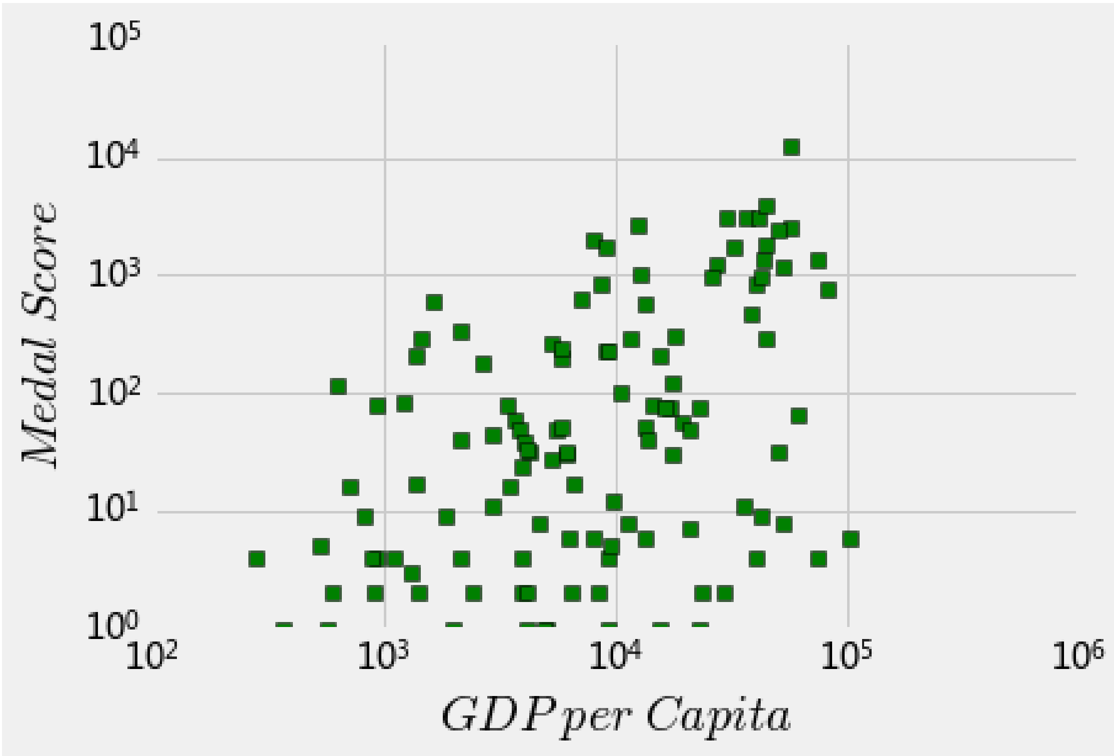
Out[27]:

	Country	Code	Population	GDP per Capita	medal_score
0	Afghanistan	AFG	32526562.0	594.323081	2
1	Albania	ALB	2889167.0	3945.217582	0
2	Algeria	ALG	39666519.0	4206.031232	32

```
In [70]: matplotlib.style.use('fivethirtyeight')

         plt.plot(country['Population'], country['medal_score'], 'ro')
         plt.xscale('log'); plt.yscale('log')
         plt.xlabel(r'$Population$', fontsize = 20)
         plt.ylabel(r'$Medal\; Score$', fontsize = 20)
         plt.show()
```



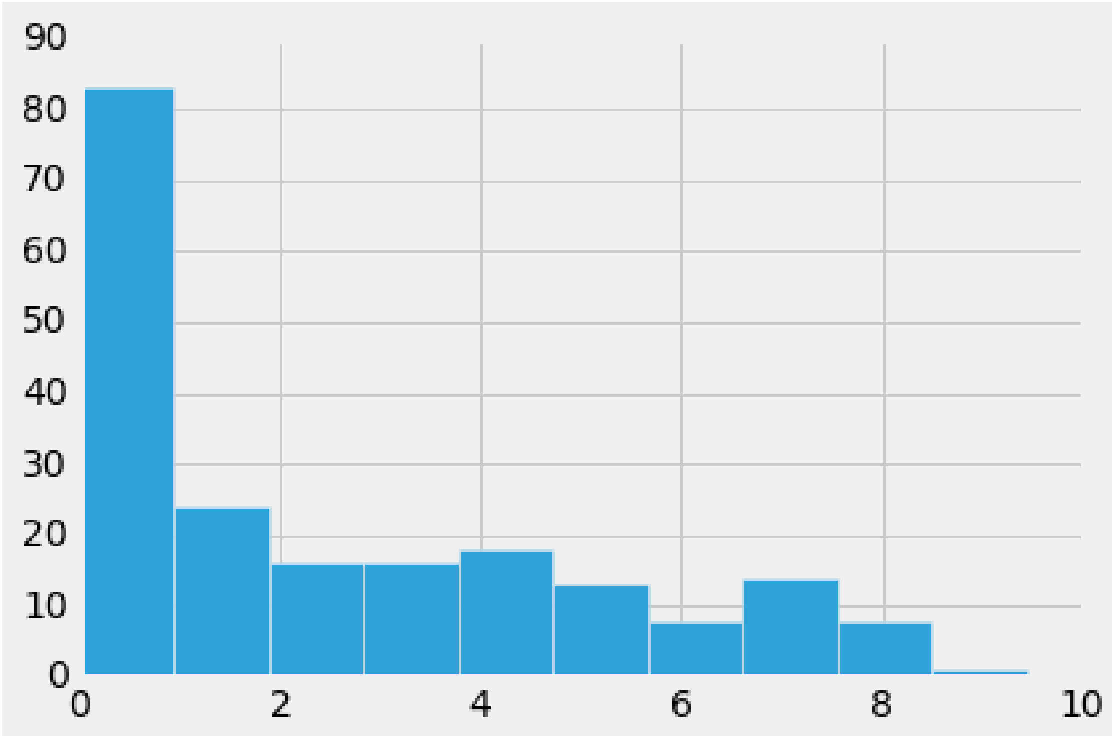

```
In [72]: plt.plot(country['GDP per Capita'], country['medal_score'], 'gs')
         plt.xscale('log'); plt.yscale('log')
         plt.xlabel(r'$GDP \;per\; Capita$', fontsize = 20)
         plt.ylabel(r'$Medal\; Score$', fontsize = 20)
         plt.show()
```




```
In [29]: import statsmodels.formula.api as smf


         data = pd.DataFrame({'y':country['medal_score'], \
                             'xg':country['GDP per Capita'],\
                             'xp': country['Population']
                             })

         data['y_log'] = np.log(data.y + 1)
         data['xg_log'] = np.log(data.xg)
         data['xp_log'] = np.log(data.xp)

         lm = smf.ols(formula='y ~ xg + xp', data=data).fit()
         constant, beta1, beta2 = lm.params
         r2=lm.rsquared
         print constant, beta1, beta2, r2
```

```
-98.151090209 0.0269927515178 2.06731854693e-06 0.237309791323
```

```
In [35]: plt.hist(data.y_log)
         plt.show()
```




```
In [38]: data.describe()

Out[38]:                  xg            xp             y       y_log      xg_log  \
         count     176.000000  1.960000e+02    201.000000  201.000000  176.000000
         mean    12882.556131  3.722825e+07    298.621891    2.448240    8.564584
         std     17747.141203  1.399655e+08   1075.062857    2.607275    1.443510
         min       277.068309  1.022200e+04      0.000000    0.000000    5.624264
         25%      1781.096847  1.638278e+06      0.000000    0.000000    7.484306
         50%      5233.583395  7.450124e+06      4.000000    1.609438    8.562851
         75%     15494.683646  2.557454e+07     76.000000    4.343805    9.648250
         max    101449.968168  1.371220e+09  12542.000000    9.436918   11.527321

                    xp_log
         count  196.000000
         mean    15.496793
         std      2.261906
         min      9.232298
         25%     14.304578
         50%     15.823553
         75%     17.056713
         max     21.038967

In [56]: lm2 = smf.ols(formula='y_log ~ xg_log + xp_log + xg_log * xp_log',\
                       data=data).fit()
         lm2.summary()

Out[56]: <class 'statsmodels.iolib.summary.Summary'>
         """
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  y_log   R-squared:                       0.631
Model:                            OLS   Adj. R-squared:                  0.624
Method:                 Least Squares   F-statistic:                     97.99
Date:                Wed, 17 May 2017   Prob (F-statistic):           5.02e-37
Time:                        22:03:30   Log-Likelihood:                -332.80
No. Observations:                 176   AIC:                             673.6
Df Residuals:                     172   BIC:                             686.3
Df Model:                           3
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [95.0% Conf. Int.]
---------------------------------------------------------------------------------
Intercept         2.0040      7.773      0.258      0.797       -13.338    17.346
xg_log           -1.2513      0.873     -1.434      0.153        -2.974     0.471
xp_log           -0.5376      0.479     -1.122      0.263        -1.483     0.408
xg_log:xp_log     0.1473      0.054      2.729      0.007         0.041     0.254
==============================================================================
Omnibus:                        0.682   Durbin-Watson:                   2.028
Prob(Omnibus):                  0.711   Jarque-Bera (JB):                0.801
Skew:                          -0.081   Prob(JB):                        0.670
Kurtosis:                       2.712   Cond. No.                     8.86e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 8.86e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

In [59]:
```
lm = smf.ols(formula='y_log ~ xg_log + xp_log', data=data).fit()
constant, beta1, beta2 = lm.params
r2=lm.rsquared
print constant, beta1, beta2, r2
```

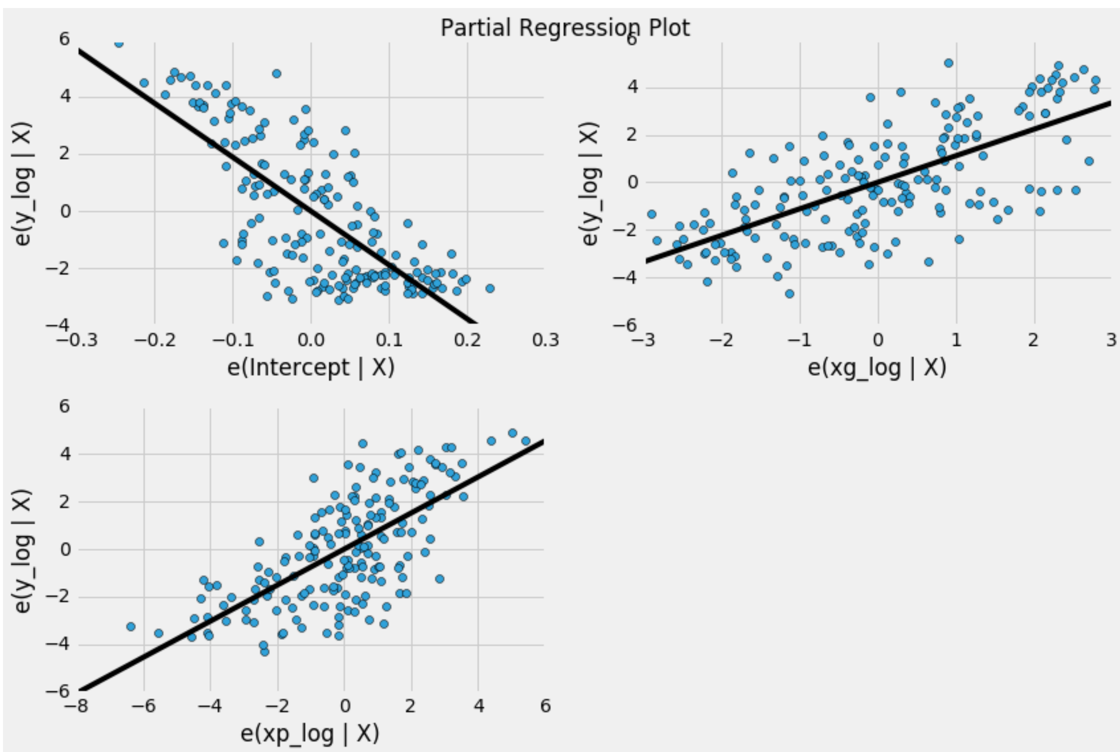
```
-18.9124276636 1.11805464157 0.759578169765 0.61488776675
```

In [60]:
```
lm.summary()
```

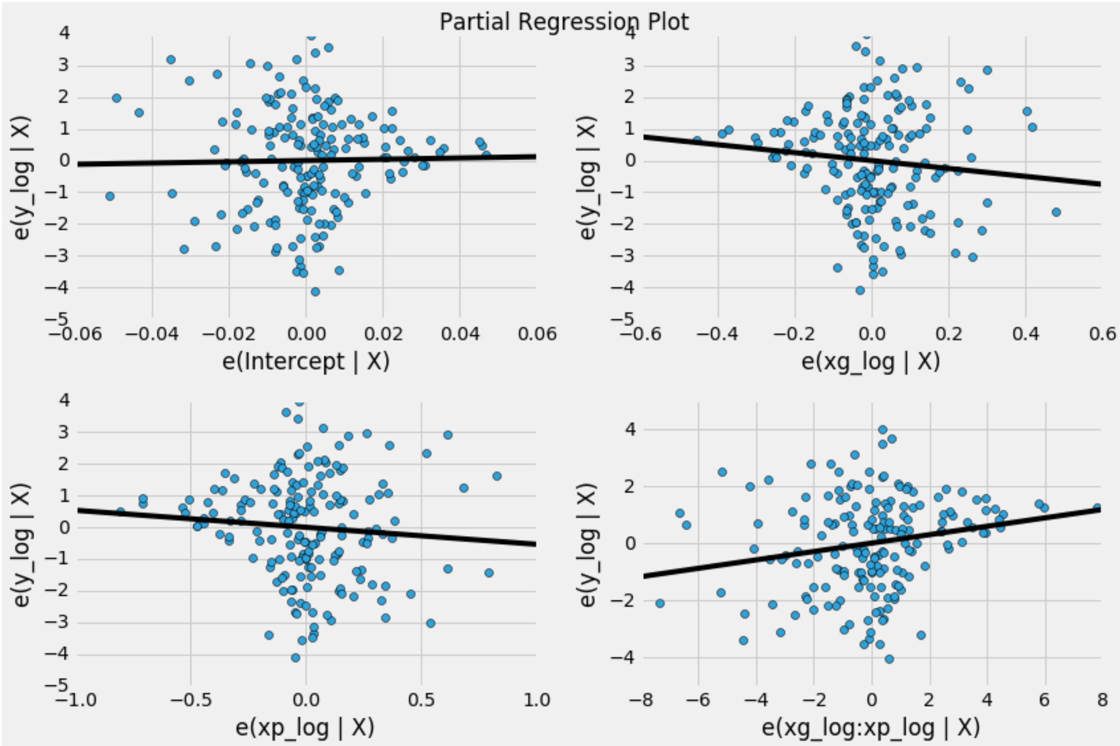
Out[60]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  y_log   R-squared:                       0.615
Model:                            OLS   Adj. R-squared:                  0.610
Method:                 Least Squares   F-statistic:                     138.1
Date:                Wed, 17 May 2017   Prob (F-statistic):           1.42e-36
Time:                        22:03:52   Log-Likelihood:                -336.53
No. Observations:                 176   AIC:                             679.1
Df Residuals:                     173   BIC:                             688.6
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [95.0% Conf. Int.]
```

```
==============================================================================
Intercept    -18.9124      1.311    -14.428      0.000     -21.500   -16.325
xg_log         1.1181      0.087     12.779      0.000       0.945     1.291
xp_log         0.7596      0.061     12.432      0.000       0.639     0.880
==============================================================================
Omnibus:                        3.667   Durbin-Watson:                   2.008
Prob(Omnibus):                  0.160   Jarque-Bera (JB):                3.019
Skew:                          -0.212   Prob(JB):                        0.221
Kurtosis:                       2.519   Cond. No.                         190.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
"""
```

In [61]:
```
fig = plt.figure(figsize=(12,8))
fig = sm.graphics.plot_partregress_grid(lm, fig = fig)
plt.show()
```



In [57]:
```
fig = plt.figure(figsize=(12,8))
fig = sm.graphics.plot_partregress_grid(lm2, fig = fig)
plt.show()
```



4 垄断程度随时间变化

In [74]:
```
game[:3]
```

Out[74]:
```
   Year    City     Sport Discipline              Athlete Country Gender  \
0  1896  Athens  Aquatics   Swimming        HAJOS, Alfred     HUN    Men
1  1896  Athens  Aquatics   Swimming    HERSCHMANN, Otto     AUT    Men
2  1896  Athens  Aquatics   Swimming  DRIVAS, Dimitrios     GRE    Men

                        Event   Medal  award  score
0              100M Freestyle    Gold      1      4
1              100M Freestyle  Silver      1      2
2  100M Freestyle For Sailors  Bronze      1      1
```

In [77]:
```
years = game.Year.unique()
years
```

Out[77]:
```
array([1896, 1900, 1904, 1908, 1912, 1920, 1924, 1928, 1932, 1936, 1948,
       1952, 1956, 1960, 1964, 1968, 1972, 1976, 1980, 1984, 1988, 1992,
       1996, 2000, 2004, 2008, 2012])
```

In [78]:
```
ggy = game.groupby(['Year', 'Country']).sum()['score']
```

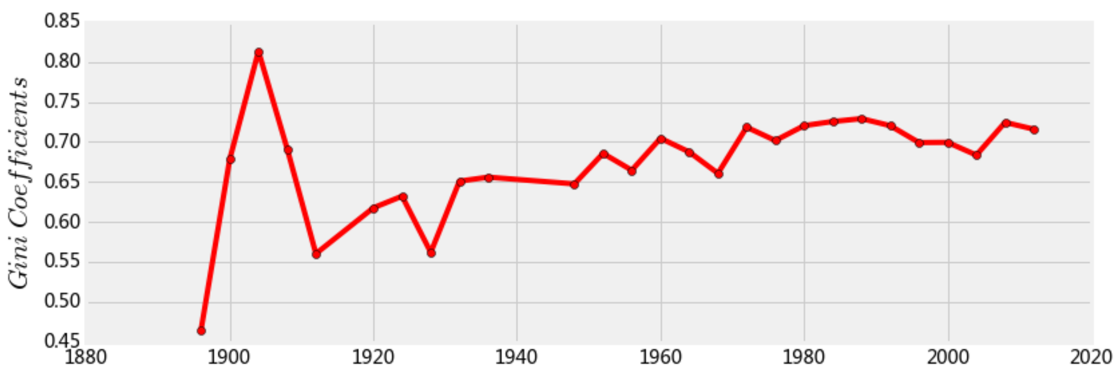
In [81]:
```
ggy[1896]
```

Out[81]:
```
Country
AUS      8
```

```
AUT     12
DEN     11
FRA     30
GBR     16
GER    116
GRE    102
HUN     13
SUI      8
USA     60
ZZX     14
Name: score, dtype: int64
```

In [83]:
```python
gini = [gini_coefficient(ggy[i])[2] for i in years]
```

In [87]:
```python
fig = plt.figure(figsize=(12, 4),facecolor='white')

plt.plot(years, gini, 'r-o')
plt.ylabel(r'$Gini\; Coefficients$', fontsize = 20)
plt.show()
```



In [88]:
```python
gini
```

Out[88]:
```
[0.46512820512820519,
 0.67843295638126011,
 0.81324392288348701,
 0.69133234274393263,
 0.56039272030651333,
 0.61761978361669245,
 0.63218225419664265,
 0.56204156479217604,
 0.65095890410958912,
 0.65595353339787021,
 0.6475418410041841,
 0.68561808561808557,
 0.66457225712904788,
 0.70452995616171454,
 0.68741976893453138,
 0.66071876305892185,
 0.71833821376281115,
```

```
         0.70165508109897379,
         0.7202979515828678,
         0.72544326241134749,
         0.72905575791538246,
         0.72022900763358777,
         0.69916550764951313,
         0.699421965317919,
         0.68351672060409929,
         0.72438455008488967,
         0.71583296114336759]
```

```
In [89]: years
```

```
Out[89]: array([1896, 1900, 1904, 1908, 1912, 1920, 1924, 1928, 1932, 1936, 1948,
               1952, 1956, 1960, 1964, 1968, 1972, 1976, 1980, 1984, 1988, 1992,
               1996, 2000, 2004, 2008, 2012])
```

5 单项垄断者

```
In [91]: game[:3]
```

```
Out[91]:    Year    City     Sport Discipline            Athlete Country Gender  \
         0  1896  Athens  Aquatics   Swimming       HAJOS, Alfred     HUN    Men
         1  1896  Athens  Aquatics   Swimming    HERSCHMANN, Otto     AUT    Men
         2  1896  Athens  Aquatics   Swimming  DRIVAS, Dimitrios     GRE    Men

                               Event   Medal  award  score
         0              100M Freestyle    Gold      1      4
         1              100M Freestyle  Silver      1      2
         2  100M Freestyle For Sailors  Bronze      1      1
```

```
In [131]: gg = game.groupby(['Discipline', 'Country']).sum()
          for i in disciplines:
              ggds = gg['score'][i]
              ggds_max = ggds.sort_values(ascending = False).iloc[0]
              gg_sum = np.sum(ggds)
              gg_max  = ggds.sort_values(ascending = False)
              gg_max_value, gg_max_index = gg_max.iloc[0], gg_max.index[0]
              gg_max_ratio = np.float(gg_max_value)/gg_sum
              if gg_max_ratio >= .5:
                  print i, gg_max_ratio, gg_max_index
```

```
Basque Pelota 0.666666666667 ESP
Cricket 0.666666666667 GBR
Croquet 1.0 FRA
Golf 0.914634146341 USA
Lacrosse 0.64367816092 CAN
Roque 1.0 USA
Jeu de Paume 0.571428571429 USA
Rackets 1.0 GBR
Water Motorspor 0.8 GBR
Vaulting 0.694444444444 BEL
Ice Hockey 0.516129032258 CAN
Table Tennis 0.655487804878 CHN
```

```
Softball 0.5 USA
Synchronized Swimming 0.571428571429 RUS
Gymnastics Rhythmic 0.612244897959 RUS
```

```
In [134]: gg = game[game['Year'] > 1990].groupby(['Discipline', 'Country']).sum()
          disciplines_1990 = game[game['Year'] > 1990]['Discipline'].unique()
          for i in disciplines_1990:
              ggds = gg['score'][i]
              ggds_max = ggds.sort_values(ascending = False).iloc[0]
              gg_sum = np.sum(ggds)
              gg_max  = ggds.sort_values(ascending = False)
              gg_max_value, gg_max_index = gg_max.iloc[0], gg_max.index[0]
              gg_max_ratio = np.float(gg_max_value)/gg_sum
              if gg_max_ratio >= .5:
                  print i, gg_max_ratio, gg_max_index
```

```
Diving 0.533163265306 CHN
Basketball 0.501492537313 USA
Dressage 0.515306122449 GER
Table Tennis 0.685314685315 CHN
Softball 0.5 USA
Synchronized Swimming 0.571428571429 RUS
Gymnastics Rhythmic 0.612244897959 RUS
```

```
In [154]: game_dat = game[game['Year'] < 1990][game['Year'] < 1970]
          gg = game_dat.groupby(['Discipline', 'Country']).sum()
          disciplines_1990 = game_dat['Discipline'].unique()
          for i in disciplines_1990:
              ggds = gg['score'][i]
              ggds_max = ggds.sort_values(ascending = False).iloc[0]
              gg_sum = np.sum(ggds)
              gg_max  = ggds.sort_values(ascending = False)
              gg_max_value, gg_max_index = gg_max.iloc[0], gg_max.index[0]
              gg_max_ratio = np.float(gg_max_value)/gg_sum
              if gg_max_ratio >= .5:
                  print i, gg_max_ratio, gg_max_index
```

```
Basque Pelota 0.666666666667 ESP
Cricket 0.666666666667 GBR
Croquet 1.0 FRA
Golf 0.914634146341 USA
Diving 0.671052631579 USA
Lacrosse 0.64367816092 CAN
Roque 1.0 USA
Jeu de Paume 0.571428571429 USA
Rackets 1.0 GBR
Water Motorspor 0.8 GBR
Vaulting 0.694444444444 BEL
Ice Hockey 0.516129032258 CAN
Basketball 0.587275693312 USA
Handball 0.590604026846 GER
Volleyball 0.5 URS

/Users/chengjun/anaconda/lib/python2.7/site-packages/ipykernel/__main__.py:1: UserWarning: Boolean Seri
  if __name__ == '__main__':
```

```
In [151]: game_dat = game[game['Year'] < 1970][game['Year'] > 1950]
          gg = game_dat.groupby(['Discipline', 'Country']).sum()
          disciplines_1990 = game_dat['Discipline'].unique()
          for i in disciplines_1990:
              ggds = gg['score'][i]
              ggds_max = ggds.sort_values(ascending = False).iloc[0]
              gg_sum = np.sum(ggds)
              gg_max  = ggds.sort_values(ascending = False)
              gg_max_value, gg_max_index = gg_max.iloc[0], gg_max.index[0]
              gg_max_ratio = np.float(gg_max_value)/gg_sum
              if gg_max_ratio >= .5:
                  print i, gg_max_ratio, gg_max_index
```

```
Diving 0.657142857143 USA
Swimming 0.5 USA
Basketball 0.574074074074 USA
Volleyball 0.5 URS

/Users/chengjun/anaconda/lib/python2.7/site-packages/ipykernel/__main__.py:1: UserWarning: Boolean Seri
  if __name__ == '__main__':
```

```
In [155]: game_dat = game[game['Year'] < 1950][game['Year'] > 1930]
          gg = game_dat.groupby(['Discipline', 'Country']).sum()
          disciplines_1990 = game_dat['Discipline'].unique()
          for i in disciplines_1990:
              ggds = gg['score'][i]
              ggds_max = ggds.sort_values(ascending = False).iloc[0]
              gg_sum = np.sum(ggds)
              gg_max  = ggds.sort_values(ascending = False)
              gg_max_value, gg_max_index = gg_max.iloc[0], gg_max.index[0]
              gg_max_ratio = np.float(gg_max_value)/gg_sum
              if gg_max_ratio >= .5:
                  print i, gg_max_ratio, gg_max_index
```

```
Diving 0.952380952381 USA
Water polo 0.512315270936 HUN
Hockey 0.613496932515 IND
Modern Pentath. 0.52380952381 SWE
Basketball 0.618784530387 USA
Handball 0.590604026846 GER
Polo 0.571428571429 ARG

/Users/chengjun/anaconda/lib/python2.7/site-packages/ipykernel/__main__.py:1: UserWarning: Boolean Seri
  if __name__ == '__main__':
```

```
In [153]: game_dat = game[game['Year'] < 1930][game['Year'] > 1910]
          gg = game_dat.groupby(['Discipline', 'Country']).sum()
          disciplines_1990 = game_dat['Discipline'].unique()
          for i in disciplines_1990:
              ggds = gg['score'][i]
              ggds_max = ggds.sort_values(ascending = False).iloc[0]
              gg_sum = np.sum(ggds)
              gg_max  = ggds.sort_values(ascending = False)
              gg_max_value, gg_max_index = gg_max.iloc[0], gg_max.index[0]
              gg_max_ratio = np.float(gg_max_value)/gg_sum
              if gg_max_ratio >= .5:
                  print i, gg_max_ratio, gg_max_index
```

```
Diving 0.555555555556 USA
Dressage 0.521739130435 SWE
Modern Pentath. 0.964285714286 SWE
Sailing 0.5168 NOR
Archery 0.655172413793 BEL
Vaulting 0.694444444444 BEL
Ice Hockey 0.516129032258 CAN
Rugby 0.615384615385 USA
```

```
/Users/chengjun/anaconda/lib/python2.7/site-packages/ipykernel/__main__.py:1: UserWarning: Boolean Seri
  if __name__ == '__main__':
```

In [42]:
```python
from echarts import Echart, Legend, Bar, Axis
from IPython.display import HTML

chart = Echart('GDP', 'This is a fake chart')
chart.use(Bar('China', [2, 3, 4, 5]))
chart.use(Legend(['GDP']))
chart.use(Axis('category', 'bottom', data=['Nov', 'Dec', 'Jan', 'Feb']))
```

Out[42]: <echarts.Echart at 0x1123cd050>

In [63]:
```python
chart.plot()
```

https://data-journalism.github.io/olympic/index.html

In [40]:
```python
from IPython.display import display_html, HTML
HTML('<iframe src=https://data-journalism.github.io/olympic/index.html width=1000 height=1500>
```

Out[40]: <IPython.core.display.HTML object>

In [ ]: