

HW1

2015 年 10 月 22 日

1 応用統計 HW1

詳細: <http://www.stat.t.u-tokyo.ac.jp/~takemura/ouyoutoukei/>

```
In [4]: #-*- encoding: utf-8 -*-
        '''
        Ouyoutoukei HW1
        '''

        %matplotlib inline
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        from mpl_toolkits.mplot3d import Axes3D
        import statsmodels.api as sm
        np.set_printoptions(precision=3)
        pd.set_option('display.precision', 4)
```

1.1 下準備

データのインポート, 基礎統計量の表示

```
In [5]: # csv をインポート
        df = pd.read_csv( 'odakyu-mansion.csv' )
        # 基礎統計量を表示
        print(df.describe())
```

	time	bus	walk	price	area	bal	kosuu	\
count	185.000	185.000	185.000	185.000	185.000	185.000	185.000	178.000
mean	27.292	2.465	8.470	2929.730	72.682	9.620	89.449	
std	14.076	5.277	5.426	2596.096	27.722	6.479	203.317	
min	3.000	0.000	1.000	630.000	19.120	0.000	1.000	
25%	18.000	0.000	4.000	1490.000	56.850	6.000	21.000	
50%	26.000	0.000	8.000	2180.000	69.020	8.800	35.000	
75%	33.000	0.000	13.000	3580.000	80.990	11.670	73.750	
max	65.000	26.000	19.000	24800.000	230.720	39.670	2080.000	

	floor	tf	year
count	185.000	185.000	185.000
mean	3.681	6.454	80.924
std	2.703	3.420	18.423
min	1.000	2.000	0.000
25%	2.000	4.000	74.000
50%	3.000	5.000	85.000
75%	5.000	8.000	92.000
max	14.000	20.000	99.000

家の向きは東, 西, 南, 北のダミー変数 (0 または 1。南東の場合、南と東の両方に 1) に分解し変換して、

In [6]: # サンプルサイズ

```
data_len = df.shape[0]
```

```
# 家の向きは dummy に
```

```
df['d_N'] = np.zeros(data_len, dtype=float)
```

```
df['d_E'] = np.zeros(data_len, dtype=float)
```

```
df['d_W'] = np.zeros(data_len, dtype=float)
```

```
df['d_S'] = np.zeros(data_len, dtype=float)
```

```
for i, row in df.iterrows():
```

```
    for direction in ["N", "W", "S", "E"]:
```

```
        if direction in str(row.muki):
```

```
            df.loc[i, 'd_{0}'.format(direction)] = 1
```

```
# 先頭 10 件を表示
```

```
print(df.head(10))
```

time	bus	walk	price	area	bal	kosuu	floor	tf	muki	year	d_N	\
0	3	0	6	1680	44.60	3.50	19	4	5	S	68	0
1	3	0	4	2280	48.87	4.05	12	2	4	S	74	0
2	3	0	7	2880	57.00	7.22	26	4	7	S	70	0
3	3	0	2	4340	55.25	7.35	44	3	6	SW	92	0
4	3	0	6	4980	88.02	8.70	30	4	8	SE	74	0
5	3	0	6	9800	121.56	6.71	30	2	3	S	83	0
6	5	0	3	1150	19.12	0.00	35	8	8	NE	70	1
7	5	0	1	3850	52.08	5.67	21	5	9	S	98	0
8	5	0	9	7580	78.60	14.10	68	3	4	W	99	0
9	5	0	6	11870	123.29	14.14	26	2	6	E	98	0

	d_E	d_W	d_S
0	0	0	1
1	0	0	1
2	0	0	1

```

3    0    1    1
4    1    0    1
5    0    0    1
6    1    0    0
7    0    0    1
8    0    1    0
9    1    0    0

```

欠損値は平均値で置き換える。

```
In [7]: df = df.fillna(df.mean())
```

1.2 最小二乗法

被説明変数に与える影響の小さい説明変数を順に取り除いていく。具体的には $p > 0.05$ であるような説明変数を除いていく。

同時に、外れ値の考慮もする。

1.2.1 最小二乗法その1

説明変数 13 個で最小二乗法を実行すると、

```
In [8]: # 定数項も加える
```

```

X = sm.add_constant(df[['time', 'bus', 'walk', 'area',
                        'bal', 'kosuu', 'floor', 'tf', 'd_N', 'd_E', 'd_S', 'd_W', 'year']])

```

```
# 普通の最小二乗法
```

```

model = sm.OLS(df.price, X)
results = model.fit()

```

```
# 結果を表示
```

```
print(results.summary())
```

OLS Regression Results

```

=====
Dep. Variable:          price    R-squared:                0.805
Model:                  OLS      Adj. R-squared:           0.790
Method:                 Least Squares    F-statistic:        54.26
Date:                  Thu, 22 Oct 2015    Prob (F-statistic):    1.16e-53
Time:                  07:21:42    Log-Likelihood:       -1565.3
No. Observations:      185    AIC:                  3159.
Df Residuals:          171    BIC:                  3204.
Df Model:              13
Covariance Type:       nonrobust

```

```

=====
               coef      std err          t      P>|t|      [95.0% Conf. Int.]
-----

```

const	659.0401	570.899	1.154	0.250	-467.877	1785.957
time	-61.1605	7.044	-8.682	0.000	-75.065	-47.256
bus	-88.3823	21.727	-4.068	0.000	-131.269	-45.495
walk	-55.4500	20.468	-2.709	0.007	-95.852	-15.048
area	70.0731	3.379	20.737	0.000	63.403	76.743
bal	-17.0300	14.871	-1.145	0.254	-46.385	12.325
kosuu	0.0837	0.477	0.176	0.861	-0.858	1.025
floor	-2.9003	43.868	-0.066	0.947	-89.493	83.692
tf	-52.3960	37.057	-1.414	0.159	-125.545	20.753
d_N	-867.1676	653.815	-1.326	0.187	-2157.756	423.420
d_E	-341.6601	225.624	-1.514	0.132	-787.027	103.707
d_S	-684.7974	280.782	-2.439	0.016	-1239.043	-130.552
d_W	-247.0280	232.685	-1.062	0.290	-706.333	212.277
year	9.7516	5.187	1.880	0.062	-0.487	19.990

```
=====
Omnibus:                126.693   Durbin-Watson:                1.586
Prob(Omnibus):           0.000   Jarque-Bera (JB):            2453.138
Skew:                    2.165   Prob(JB):                     0.00
Kurtosis:                20.306   Cond. No.                     1.80e+03
=====
```

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.8e+03. This might indicate that there are strong multicollinearity or other numerical problems.

となる。

p 値を見ると、kosuu, floor がほとんど無関係であるように見える。

kosuu には外れ値が 1 つある (kosuu=2080) ので、それを除いてみる。

1.2.2 最小二乗法その 2

外れ値を除き、

```
In [9]: print(df.loc[161])
        df = df.drop(161)
```

time	57
bus	0
walk	15
price	800
area	57.2
bal	0
kosuu	2080
floor	1
tf	4

```

muki      S
year      67
d_N       0
d_E       0
d_W       0
d_S       1
Name: 161, dtype: object

```

再び最小二乗法を実行すると、

```

In [10]: X = sm.add_constant(df[['time', 'bus', 'walk', 'area', 'bal',
                                   'kosuu', 'floor', 'tf', 'd_N', 'd_E', 'd_S', 'd_W', 'year']])
        model = sm.OLS(df.price, X)
        results = model.fit()
        print(results.summary())

```

OLS Regression Results

```

=====
Dep. Variable:          price    R-squared:                0.805
Model:                  OLS      Adj. R-squared:           0.790
Method:                 Least Squares    F-statistic:        53.92
Date:                   Thu, 22 Oct 2015    Prob (F-statistic):    2.63e-53
Time:                   07:21:42    Log-Likelihood:       -1557.0
No. Observations:       184    AIC:                  3142.
Df Residuals:           170    BIC:                  3187.
Df Model:                13
Covariance Type:        nonrobust

```

```

=====
              coef    std err          t      P>|t|      [95.0% Conf. Int.]
-----
const         648.1009    571.820      1.133    0.259    -480.681    1776.883
time          -61.6799     7.087    -8.703    0.000    -75.670    -47.689
bus           -87.3626    21.797    -4.008    0.000    -130.391    -44.334
walk          -56.4869    20.541    -2.750    0.007    -97.035    -15.939
area           70.1205     3.384    20.720    0.000     63.440     76.801
bal           -16.8531    14.892     -1.132    0.259    -46.250     12.544
kosuu          -0.3897     0.792     -0.492    0.623     -1.954      1.174
floor          -2.9617    43.925     -0.067    0.946    -89.670     83.746
tf            -42.4715    39.401     -1.078    0.283    -120.249     35.306
d_N           -890.6252   655.405     -1.359    0.176   -2184.406     403.156
d_E           -336.1515   226.034     -1.487    0.139    -782.346    110.043
d_S           -688.7604   281.193     -2.449    0.015   -1243.841   -133.680
d_W           -222.7084   235.237     -0.947    0.345    -687.070    241.653
year             9.6658     5.195      1.861    0.065     -0.589     19.920
=====

```

Omnibus:	125.689	Durbin-Watson:	1.592
Prob(Omnibus):	0.000	Jarque-Bera (JB):	2436.830
Skew:	2.153	Prob(JB):	0.00
Kurtosis:	20.301	Cond. No.	1.37e+03

=====

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
 [2] The condition number is large, 1.37e+03. This might indicate that there are strong multicollinearity or other numerical problems.

やはり kosuu, floor の p 値が大きいのので、説明変数から除くと、

1.2.3 最小二乗法その 3

```
In [11]: X = sm.add_constant(df[['time', 'bus', 'walk', 'area',
                                'bal', 'tf', 'd_N', 'd_E', 'd_S', 'd_W', 'year']])
        model = sm.OLS(df.price, X)
        results = model.fit()
        print(results.summary())
```

OLS Regression Results

=====

Dep. Variable:	price	R-squared:	0.805
Model:	OLS	Adj. R-squared:	0.792
Method:	Least Squares	F-statistic:	64.35
Date:	Thu, 22 Oct 2015	Prob (F-statistic):	4.59e-55
Time:	07:21:42	Log-Likelihood:	-1557.1
No. Observations:	184	AIC:	3138.
Df Residuals:	172	BIC:	3177.
Df Model:	11		
Covariance Type:	nonrobust		

=====

	coef	std err	t	P> t	[95.0% Conf. Int.]
const	647.4256	568.107	1.140	0.256	-473.933 1768.784
time	-61.7145	7.051	-8.753	0.000	-75.631 -47.797
bus	-88.0394	21.589	-4.078	0.000	-130.653 -45.426
walk	-55.9212	20.403	-2.741	0.007	-96.194 -15.649
area	70.0917	3.349	20.932	0.000	63.482 76.701
bal	-16.5189	14.746	-1.120	0.264	-45.626 12.588
tf	-52.1050	27.938	-1.865	0.064	-107.251 3.041
d_N	-869.5508	649.087	-1.340	0.182	-2150.753 411.652
d_E	-336.5608	222.059	-1.516	0.131	-774.872 101.751
d_S	-682.6687	278.482	-2.451	0.015	-1232.352 -132.985
d_W	-238.6622	231.247	-1.032	0.303	-695.109 217.784

year	9.8681	5.142	1.919	0.057	-0.281	20.018
------	--------	-------	-------	-------	--------	--------

```
=====
```

Omnibus:	125.761	Durbin-Watson:	1.586
Prob(Omnibus):	0.000	Jarque-Bera (JB):	2414.208
Skew:	2.159	Prob(JB):	0.00
Kurtosis:	20.212	Cond. No.	924.

```
=====
```

Warnings:

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

となる。さらに、bal と南向き以外の方角のダミー変数を説明変数から除く。

1.2.4 最小二乗法その4

```
In [12]: X = sm.add_constant(df[['time', 'bus', 'walk', 'area', 'tf', 'year', 'd_S']])
        model = sm.OLS(df.price, X)
        results = model.fit()
        print(results.summary())
```

OLS Regression Results

```
=====
```

Dep. Variable:	price	R-squared:	0.799
Model:	OLS	Adj. R-squared:	0.791
Method:	Least Squares	F-statistic:	99.83
Date:	Thu, 22 Oct 2015	Prob (F-statistic):	6.87e-58
Time:	07:21:42	Log-Likelihood:	-1559.8
No. Observations:	184	AIC:	3136.
Df Residuals:	176	BIC:	3161.
Df Model:	7		
Covariance Type:	nonrobust		

```
=====
```

	coef	std err	t	P> t	[95.0% Conf. Int.]
const	351.2443	548.343	0.641	0.523	-730.929 1433.418
time	-63.7175	7.012	-9.087	0.000	-77.556 -49.879
bus	-84.9009	21.357	-3.975	0.000	-127.050 -42.752
walk	-54.6035	20.293	-2.691	0.008	-94.653 -14.554
area	69.5406	3.241	21.459	0.000	63.145 75.936
tf	-58.8849	27.183	-2.166	0.032	-112.531 -5.239
year	8.3053	5.081	1.634	0.104	-1.723 18.334
d_S	-433.0197	250.589	-1.728	0.086	-927.566 61.527

```
=====
```

Omnibus:	134.268	Durbin-Watson:	1.605
Prob(Omnibus):	0.000	Jarque-Bera (JB):	2841.632
Skew:	2.343	Prob(JB):	0.00

Kurtosis: 21.673 Cond. No. 730.
=====

Warnings:

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

p 値が大きい南向きのダミー変数 d_E、築年数 year も説明変数から除く。

1.2.5 最小二乗法その 5

```
In [13]: X = sm.add_constant(df[['time', 'bus', 'walk', 'area', 'tf']])
        model = sm.OLS(df.price, X)
        results = model.fit()
        print(results.summary())
```

OLS Regression Results

```
=====
Dep. Variable:          price    R-squared:          0.791
Model:                  OLS      Adj. R-squared:      0.785
Method:                 Least Squares    F-statistic:      135.0
Date:                   Thu, 22 Oct 2015    Prob (F-statistic):  1.25e-58
Time:                   07:21:42    Log-Likelihood:      -1563.2
No. Observations:       184    AIC:                  3138.
Df Residuals:           178    BIC:                  3158.
Df Model:                5
Covariance Type:        nonrobust
=====
```

	coef	std err	t	P> t	[95.0% Conf. Int.]
const	659.1196	411.570	1.601	0.111	-153.066 1471.305
time	-63.7977	6.742	-9.463	0.000	-77.102 -50.494
bus	-92.8873	21.396	-4.341	0.000	-135.109 -50.666
walk	-58.2817	20.499	-2.843	0.005	-98.734 -17.829
area	69.1817	3.222	21.470	0.000	62.823 75.541
tf	-46.2762	26.810	-1.726	0.086	-99.183 6.631

```
=====
Omnibus:                131.166    Durbin-Watson:          1.607
Prob(Omnibus):           0.000    Jarque-Bera (JB):        2595.213
Skew:                    2.288    Prob(JB):                 0.00
Kurtosis:                20.820    Cond. No.                 383.
=====
```

Warnings:

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

p 値が大きい tf を取り除く

1.2.6 最小二乗法その6

```
In [14]: X = sm.add_constant(df[['time', 'bus', 'walk', 'area']])
        model = sm.OLS(df.price, X)
        results = model.fit()
        print(results.summary())
```

OLS Regression Results

```
=====
Dep. Variable:          price    R-squared:                0.788
Model:                  OLS      Adj. R-squared:            0.783
Method:                 Least Squares    F-statistic:        166.1
Date:                  Thu, 22 Oct 2015    Prob (F-statistic):    3.96e-59
Time:                  07:21:42    Log-Likelihood:       -1564.7
No. Observations:      184    AIC:                    3139.
Df Residuals:          179    BIC:                    3155.
Df Model:               4
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[95.0% Conf. Int.]	
const	326.0739	365.543	0.892	0.374	-395.254	1047.401
time	-64.2877	6.773	-9.492	0.000	-77.653	-50.923
bus	-95.0077	21.478	-4.423	0.000	-137.391	-52.625
walk	-52.6312	20.348	-2.587	0.010	-92.783	-12.479
area	69.2456	3.240	21.373	0.000	62.852	75.639

```
=====
Omnibus:                 133.686    Durbin-Watson:           1.557
Prob(Omnibus):           0.000    Jarque-Bera (JB):        2729.285
Skew:                    2.342    Prob(JB):                 0.00
Kurtosis:                21.277    Cond. No.                 338.
=====
```

Warnings:

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

修正済み $R^2 = 0.783$, F 統計量の p 値 $3.96e-59$ を見ると、「新宿駅からの乗車時間」, 「バスの乗車時間」, 「徒歩時間」, 「部屋の広さ」の4つで十分に住宅価格を説明できていると考えられる。

最小二乗法 1~6 と比較しても、AIC・BIC は殆ど変わらないか、改善している。

あとは残差を検討して、誤差項に関する諸仮定が満たされているかをチェックする。

1.3 残差の分析

残差に関する仮定は:

- 誤差項の平均が 0

- 誤差項の分散が一定
- 誤差項は互いに独立
- 誤差項は（少なくとも近似的には）正規分布に従う
- 誤差項と各説明変数の相関係数は 0

であった。

全ての項目を厳密にチェックする方法を知らないので、出来る項目だけを確認します。

1.3.1 まずは、横軸に予測値（価格）を、縦軸に残差をとって点をプロットする。

In [15]: # 回帰に使った変数だけを抜き出す

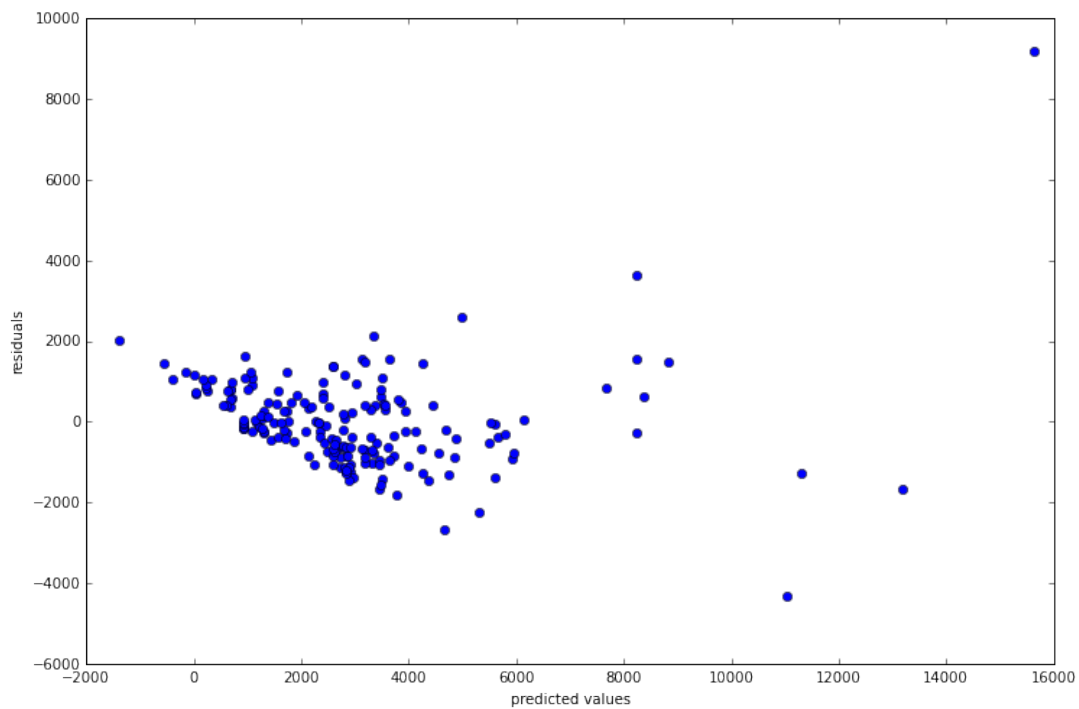
```
new_df = df.loc[:, ['price', 'time', 'bus', 'walk', 'area']]
# 説明変数行列
exp_matrix = new_df.loc[:, ['time', 'bus', 'walk', 'area']]
# 回帰係数ベクトル
coefs = results.params
# 理論価格ベクトル
predicted = exp_matrix.dot(coefs[1:]) + coefs[0]
# 残差ベクトル
residuals = new_df.price - predicted
```

残差を *plot*

```
fig, ax = plt.subplots(figsize=(12, 8))
plt.plot(predicted, residuals, 'o', color='b', linewidth=1, label="residuals distribution")
plt.xlabel("predicted values")
plt.ylabel("residuals")
plt.show()
```

残差平均

```
print("residuals mean:", residuals.mean())
```



residuals mean: -4.152041029832933e-12

平均はほぼ 0 であり、グラフでも 0 付近に点が集中していることがわかる: 仮定 1 は満たす
 しかしながら、右側にいくつか外れ値が見える。右上の 1 点を除いて、再度回帰分析を行う。

1.3.2 最小二乗法その 7

```
In [16]: print(new_df.loc[12] )
          new_df = new_df.drop(12)
```

```
X = sm.add_constant(new_df[['time', 'bus', 'walk', 'area']])
model = sm.OLS(new_df.price, X)
results = model.fit()
print(results.summary())
```

```
price    24800.00
time         4.00
bus         0.00
walk        8.00
area       230.72
Name: 12, dtype: float64
```

OLS Regression Results

```
=====
Dep. Variable:          price    R-squared:                0.790
Model:                  OLS      Adj. R-squared:            0.786
Method:                 Least Squares    F-statistic:        167.7
```

```

Date:                Thu, 22 Oct 2015    Prob (F-statistic):        3.01e-59
Time:                07:21:42    Log-Likelihood:            -1510.6
No. Observations:    183    AIC:                3031.
Df Residuals:        178    BIC:                3047.
Df Model:            4
Covariance Type:      nonrobust

```

```

=====
              coef      std err          t      P>|t|      [95.0% Conf. Int.]
-----
const      1050.7368    292.682      3.590      0.000      473.164  1628.309
time       -59.3635      5.298     -11.205      0.000     -69.819  -48.908
bus        -94.7889     16.739      -5.663      0.000    -127.822  -61.756
walk       -54.4831     15.859      -3.435      0.001     -85.779  -23.187
area        56.8131      2.775     20.474      0.000      51.337   62.289
=====

Omnibus:                 30.767    Durbin-Watson:                1.428
Prob(Omnibus):            0.000    Jarque-Bera (JB):           70.111
Skew:                     0.741    Prob(JB):                   5.97e-16
Kurtosis:                 5.645    Cond. No.                    340.
=====

```

Warnings:

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

In [17]: # 説明変数行列

```
exp_matrix = new_df.loc[:, ['time', 'bus', 'walk', 'area']]
```

```
# 回帰係数ベクトル
```

```
coefs = results.params
```

```
# 理論価格ベクトル
```

```
predicted = exp_matrix.dot(coefs[1:]) + coefs[0]
```

```
# 残差ベクトル
```

```
residuals = new_df.price - predicted
```

```
# 残差を plot
```

```
fig, ax = plt.subplots(figsize=(12, 8))
```

```
plt.plot(predicted, residuals, 'o', color='b', linewidth=1, label="residuals distribution")
```

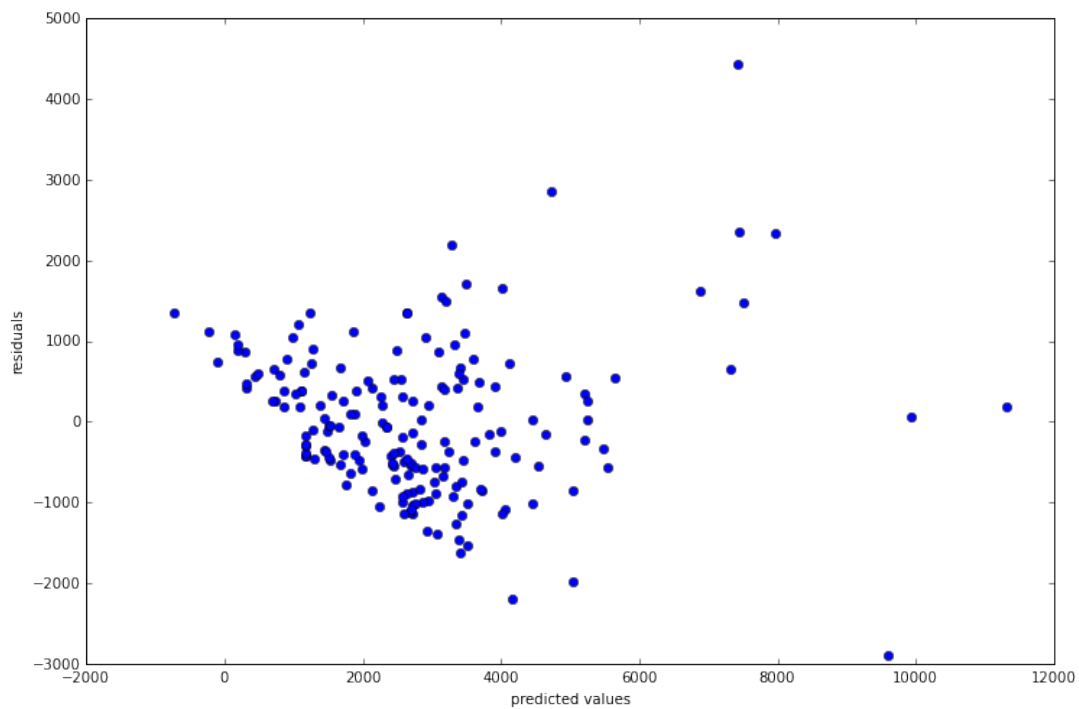
```
plt.xlabel("predicted values")
```

```
plt.ylabel("residuals")
```

```
plt.show()
```

```
# 残差平均
```

```
print("residuals mean:", residuals.mean())
```



residuals mean: 1.6127378728159302e-12

最小二乗法 6 の結果に比べ、ばらつきが均等になった。

1.3.3 次に、縦軸に残差、横軸に各説明変数の観測値をとって、残差のばらつきを見る。

In [18]: # 残差を *plot*

```
fig = plt.figure(figsize=(18, 10))
ax1 = plt.subplot(2, 2, 1)
plt.plot(exp_matrix['time'], residuals, 'o', color='b', linewidth=1, label="residuals - tim")
plt.xlabel("time")
plt.ylabel("residuals")
plt.legend()

ax2 = plt.subplot(2, 2, 2, sharey=ax1)
plt.plot(exp_matrix['bus'], residuals, 'o', color='b', linewidth=1, label="residuals - bus")
plt.xlabel("bus")
plt.ylabel("residuals")
plt.legend()

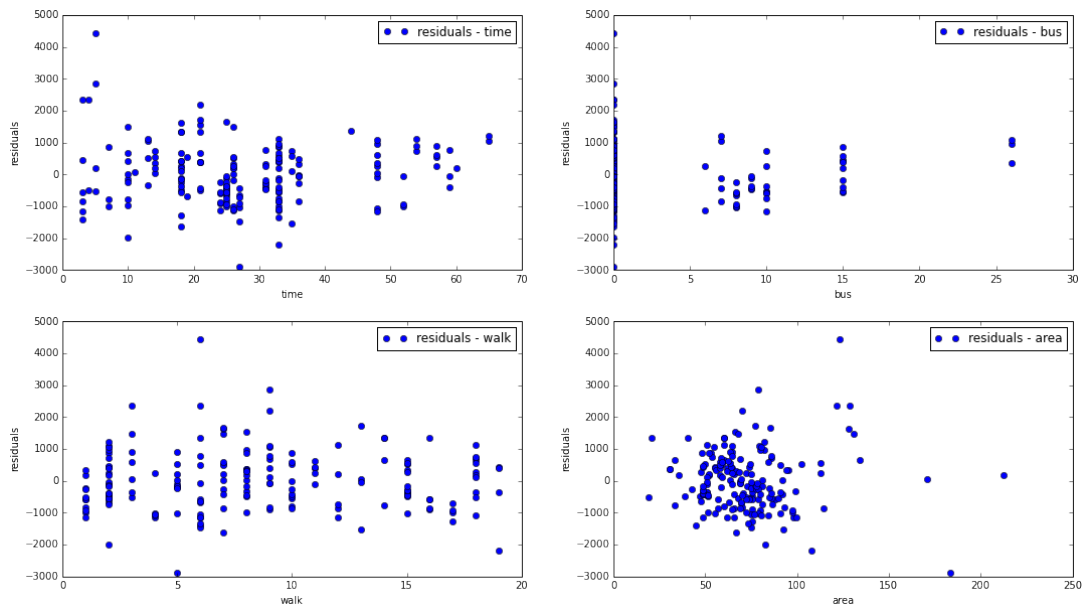
ax3 = plt.subplot(2, 2, 3, sharey=ax1)
plt.plot(exp_matrix['walk'], residuals, 'o', color='b', linewidth=1, label="residuals - wal")
plt.xlabel("walk")
plt.ylabel("residuals")
plt.legend()
```

```

ax4 = plt.subplot(2, 2, 4, sharey=ax1)
plt.plot(exp_matrix['area'], residuals, 'o', color='b', linewidth=1, label="residuals - area")
plt.xlabel("area")
plt.ylabel("residuals")
plt.legend()

plt.show()

```



どの説明変数と残差の間にも特徴的な相関関係は見られない: 仮定 5 は満たす。

area 変数だけ残差のばらつき方が異なるので、何らかの対策をとったほうが良い可能性がある (すみません、わかりません)。

1.4 まとめ

当てはまりの良い回帰モデルを作ることが出来たが、残差の性質、特に等分散性の仮定を置いて良いのかについては問題が残った。等分散性の仮定に問題がある場合は、重みを付けて最小二乗法を使う必要があるので、慎重に考える必要がある。

In []: