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In [1]: import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor

plt.rcParams['font.sans-serif'] = ['SimHei', 'Microsoft YaHei', 'DejaVu Sans']
plt.rcParams['axes.unicode_minus'] = False # 用来正常显示负号

# 导入处理图标
df = pd.read_excel('数据1.xlsx', header=0, skiprows=[1, 2])
print(df.head())

height_col = 'height'
weight_col = 'weight'

plt.figure(figsize=(6, 4))
sns.scatterplot(x=height_col, y=weight_col, data=df, color='royalblue')
plt.title('身高与体重关系散点图')
plt.xlabel('身高 (cm)')
plt.ylabel('体重 (kg)')
plt.grid(alpha=0.3)
plt.show()

corr = df[height_col].corr(df[weight_col])
print(f"身高 体重的皮尔逊相关系数", corr)

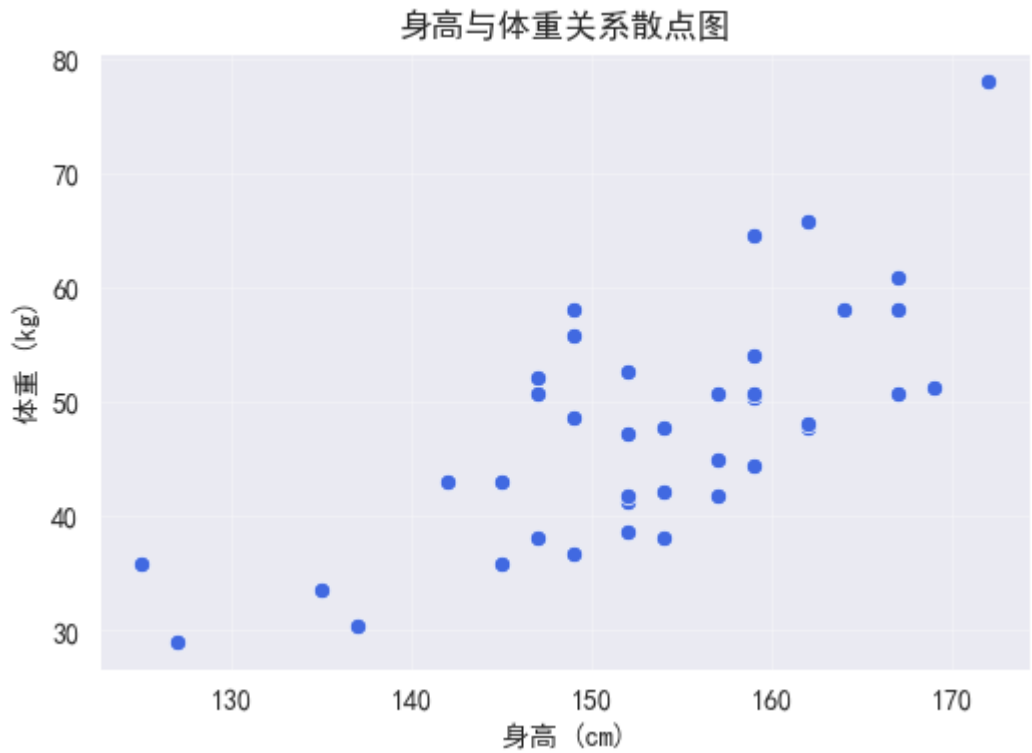
# 回归模型
x = sm.add_constant(df[height_col])
y = df[weight_col]

model = sm.OLS(y, x).fit()
print(model.summary())

plt.figure(figsize=(6, 4))
sns.regplot(x=height_col, y=weight_col, data=df, line_kws={'color': 'red'})
plt.title('身高对体重的线性回归拟合')
plt.xlabel('身高 (cm)')
plt.ylabel('体重 (kg)')
plt.grid(alpha=0.3)
plt.show()

```

	name	age	sex	height	weight
0	KATE	12	女	145	43.1
1	LOUISE	12	女	149	55.8
2	JANE	12	女	135	33.6
3	JACLYN	12	女	162	65.8
4	LILLIE	12	女	127	29.1



身高 体重的皮尔逊相关系数 0.7084378460075293

OLS Regression Results

=====			
Dep. Variable:	weight	R-squared:	0.502
Model:	OLS	Adj. R-squared:	0.489
Method:	Least Squares	F-statistic:	38.29
Date:	Mon, 20 Oct 2025	Prob (F-statistic):	3.15e-07
Time:	20:21:20	Log-Likelihood:	-134.71
No. Observations:	40	AIC:	273.4
Df Residuals:	38	BIC:	276.8
Df Model:	1		
Covariance Type:	nonrobust		
=====			

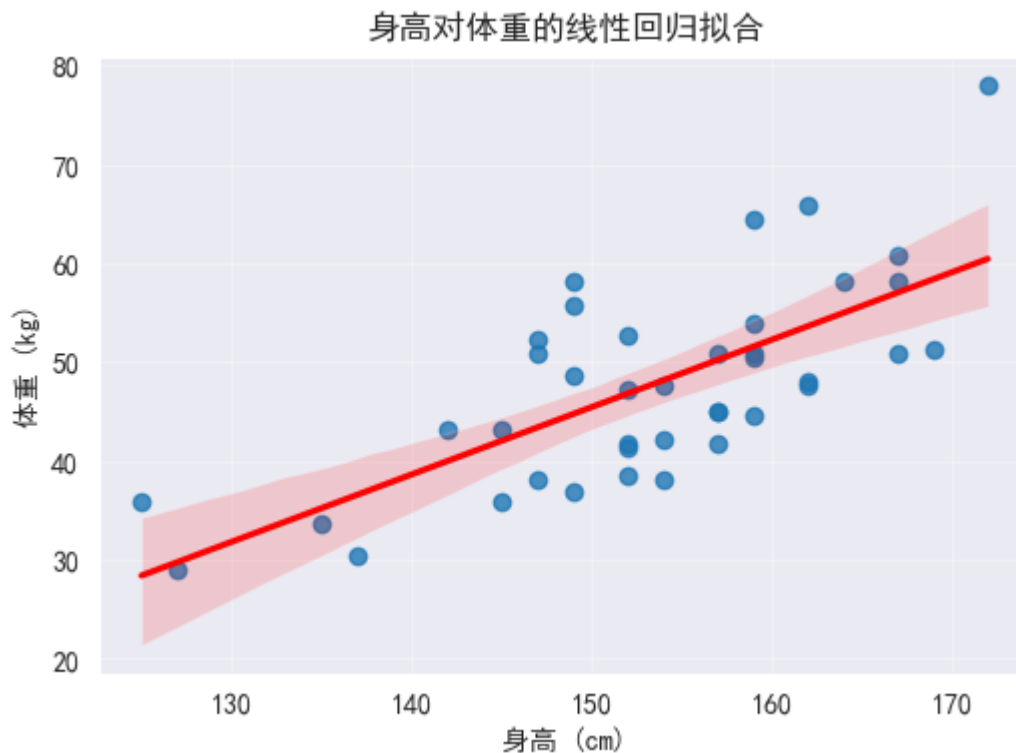
	coef	std err	t	P> t	[0.025	0.975]

const	-56.7486	16.912	-3.355	0.002	-90.986	-22.511
height	0.6813	0.110	6.188	0.000	0.458	0.904
=====						

Omnibus:	3.791	Durbin-Watson:	1.471
Prob(Omnibus):	0.150	Jarque-Bera (JB):	3.564
Skew:	0.697	Prob(JB):	0.168
Kurtosis:	2.555	Cond. No.	2.28e+03
=====			

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 2.28e+03. This might indicate that there are strong multicollinearity or other numerical problems.



回归方程: 体重 = -56.75 + 0.68 * 身高

```
In [2]: df = pd.read_excel('数据2.xlsx', header=0)
print(df.head())
print(df.columns.tolist())
df.columns = df.columns.str.strip()

plt.figure(figsize=(8, 6))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm', fmt=".2f")
plt.title("各变量相关性热力图")
plt.show()

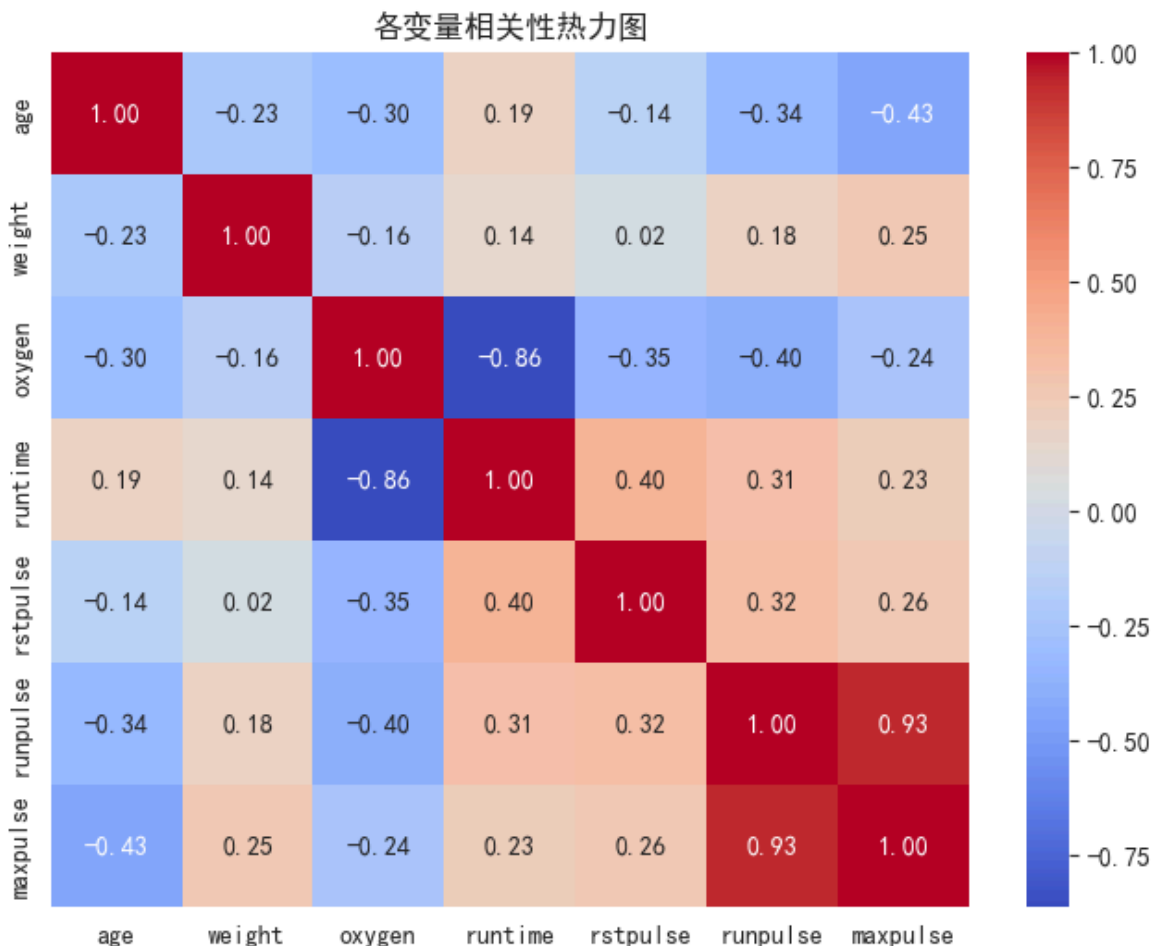
#x = df[['age', 'weight', 'runtime', 'rstpulse', 'runpulse', 'maxpulse']]
#y = df['oxygen']

# 添加常数项
#x = sm.add_constant(x)

import statsmodels.formula.api as smf
formula='oxygen ~ weight + runtime + rstpulse + runpulse + maxpulse'
model = smf.ols(formula, data=df).fit()
print(model.summary2())
```

	age	weight	oxygen	runtime	rstpulse	runpulse	maxpulse
0	44	89.47	44.609	11.37	62	178	182
1	40	75.07	45.313	10.07	62	185	185
2	44	85.84	54.297	8.65	45	156	168
3	42	68.15	59.571	8.17	40	166	172
4	38	89.02	49.874	9.22	55	178	180

['age ', 'weight', 'oxygen', 'runtime', 'rstpulse', 'runpulse', 'maxpulse']



Results: Ordinary least squares

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=====
Model:                OLS                Adj. R-squared:    0.781
Dependent Variable: oxygen                AIC:                150.0062
Date:                 2025-10-20 20:21    BIC:                158.6101
No. Observations:    31                  Log-Likelihood:    -69.003
Df Model:             5                   F-statistic:       22.34
Df Residuals:        25                  Prob (F-statistic): 1.74e-08
R-squared:            0.817               Scale:            6.2280
=====

```

	Coef.	Std.Err.	t	P> t	[0.025	0.975]
Intercept	82.2022	9.1666	8.9675	0.0000	63.3232	101.0813
weight	-0.0501	0.0577	-0.8672	0.3941	-0.1690	0.0689
runtime	-2.9767	0.3762	-7.9122	0.0000	-3.7516	-2.2019
rstpulse	0.0257	0.0617	0.4172	0.6801	-0.1013	0.1527
rulpulse	-0.4016	0.1290	-3.1143	0.0046	-0.6672	-0.1360
maxpulse	0.3874	0.1419	2.7300	0.0114	0.0951	0.6796

```

=====
Omnibus:                1.244                Durbin-Watson:        1.360
Prob(Omnibus):          0.537                Jarque-Bera (JB):     0.569
Skew:                   -0.320                Prob(JB):             0.752
Kurtosis:               3.175                Condition No.:        5340
=====

```

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 5.34e+03. This might indicate that there are strong multicollinearity or other numerical problems.

去除 $p > 0.05$ 的变量

```
In [3]: formula='oxygen ~ runtime - rstpulse + runpulse + maxpulse - weight'
model = smf.ols(formula, data=df).fit()
print(model.summary2())
```

```
Results: Ordinary least squares
=====
Model:                OLS                Adj. R-squared:    0.789
Dependent Variable: oxygen                AIC:              147.1925
Date:                2025-10-20 20:21    BIC:              152.9284
No. Observations:    31                Log-Likelihood:    -69.596
Df Model:            3                 F-statistic:       38.37
Df Residuals:        27                Prob (F-statistic): 7.09e-10
R-squared:           0.810              Scale:           5.9916
-----
                Coef.    Std.Err.    t      P>|t|    [0.025    0.975]
-----
Intercept      80.9008     8.8162    9.1764  0.0000   62.8115   98.9901
runtime       -2.9702     0.3453   -8.6006  0.0000   -3.6788   -2.2616
runpulse      -0.3751     0.1236   -3.0337  0.0053   -0.6288   -0.1214
maxpulse       0.3542     0.1348    2.6270  0.0140    0.0775    0.6309
-----
Omnibus:         0.260              Durbin-Watson:      1.515
Prob(Omnibus):   0.878              Jarque-Bera (JB):    0.293
Skew:           -0.191              Prob(JB):           0.864
Kurtosis:        2.715              Condition No.:      4882
=====
Notes:
[1] Standard Errors assume that the covariance matrix of the
errors is correctly specified.
[2] The condition number is large, 4.88e+03. This might indicate
that there are strong multicollinearity or other numerical
problems.
```

回归模型 = $80.90 - 2.97 * \text{runtime} - 0.38 * \text{runpulse} + 0.35 * \text{maxpulse}$

```
In [4]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from scipy.optimize import curve_fit

df = pd.read_csv('数据3.txt', sep='\\s+', header=0)
print("原始数据: ")
print(df.head())

x = df['x']
y = df['y']

# 负指数增长函数
def neg_exp(x, b0, b1):
    return b0 * (1 - np.exp(-b1 * x))

initial_guess = [1.0, 0.01] # 初始参数猜测
params, cov = curve_fit(neg_exp, x, y, p0=initial_guess)

b0, b1 = params
print(f"\n拟合参数: b0 = {b0:.4f}, b1 = {b1:.4f}")
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y_pred = neg_exp(x, *params)
ss_res = np.sum((y - y_pred)**2)
ss_tot = np.sum((y - np.mean(y))**2)
r2 = 1 - (ss_res / ss_tot)
print(f"模型拟合优度 R² = {r2:.4f}")

plt.figure(figsize=(8,5))
plt.scatter(x, y, label='原始数据', color='royalblue')
plt.plot(x, y_pred, color='red', label=f'拟合曲线: y={b0:.3f}(1-e^(-{b1:.3f}x))')
plt.xlabel("X")
plt.ylabel("Y")
plt.title("负指数增长模型拟合")
plt.legend()
plt.grid(alpha=0.3)
plt.show()

```

原始数据:

	x	y
0	20	0.57
1	30	0.72
2	40	0.81
3	50	0.87
4	60	0.91

拟合参数: $b_0 = 0.9962$, $b_1 = 0.0420$

模型拟合优度 $R^2 = 0.9976$

