

527_project, M,P estimator

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Contents

Why M and P estimators?	1
Definition	1
Estimation Procedure	1
P-estimator	2
Definition	2
Key Characteristics	2
Analysis the Dataset	2

Why M and P estimators?

M-estimator: Reduces the influence of large residuals by using robust loss functions, ensures that a few extreme outliers do not affect the model fit. P-estimator:

Designed to be even more robust than M-estimators, especially for datasets with a high proportion of outliers. Using robust statistical principles to minimize the effect of large residuals # M-estimator

Definition

An **M-estimator** minimizes a general loss function ρ instead of the sum of squared residuals used in ordinary least squares (OLS). It is defined as:

$$\hat{\beta} = \arg \min_{\beta} \sum_{i=1}^n \rho(y_i - X_i \beta)$$

where: - $\rho(x)$ is a robust loss function (e.g., Huber loss, Tukey's biweight). - y_i is the response variable, X_i is the predictor variable(s), and β represents the model parameters.

Estimation Procedure

The solution is typically found by solving the following first-order condition:

$$\sum_{i=1}^n \psi(y_i - X_i \hat{\beta}) X_i = 0$$

where: - $\psi(x) = \frac{\partial \rho(x)}{\partial x}$ is the influence function that limits the impact of large residuals.

Common Loss Functions

1. Huber Loss:

$$\rho(x) = \begin{cases} \frac{1}{2}x^2, & \text{if } |x| \leq c \\ c|x| - \frac{1}{2}c^2, & \text{if } |x| > c \end{cases}$$

2. Tukey's Biweight:

$$\rho(x) = \begin{cases} c^2 \left(1 - \left(1 - \frac{x^2}{c^2} \right)^3 \right), & \text{if } |x| \leq c \\ c^2, & \text{if } |x| > c \end{cases}$$

P-estimator

Definition

A **P-estimator** is designed to provide even higher robustness than M-estimators. It minimizes a robust scale estimate of residuals while controlling for outlier contamination. It is often used in combination with S-estimators to achieve a balance between robustness and efficiency.

The P-estimator solves:

$$\hat{\beta} = \arg \min_{\beta} \frac{1}{n} \sum_{i=1}^n w_i \cdot \rho(y_i - X_i \beta)$$

where: - w_i are robustness weights that adaptively reduce the impact of outliers.

Key Characteristics

1. P-estimators can handle a higher proportion of outliers than M-estimators.
2. They are less efficient in clean datasets but more robust in contaminated ones.

Analysis the Dataset

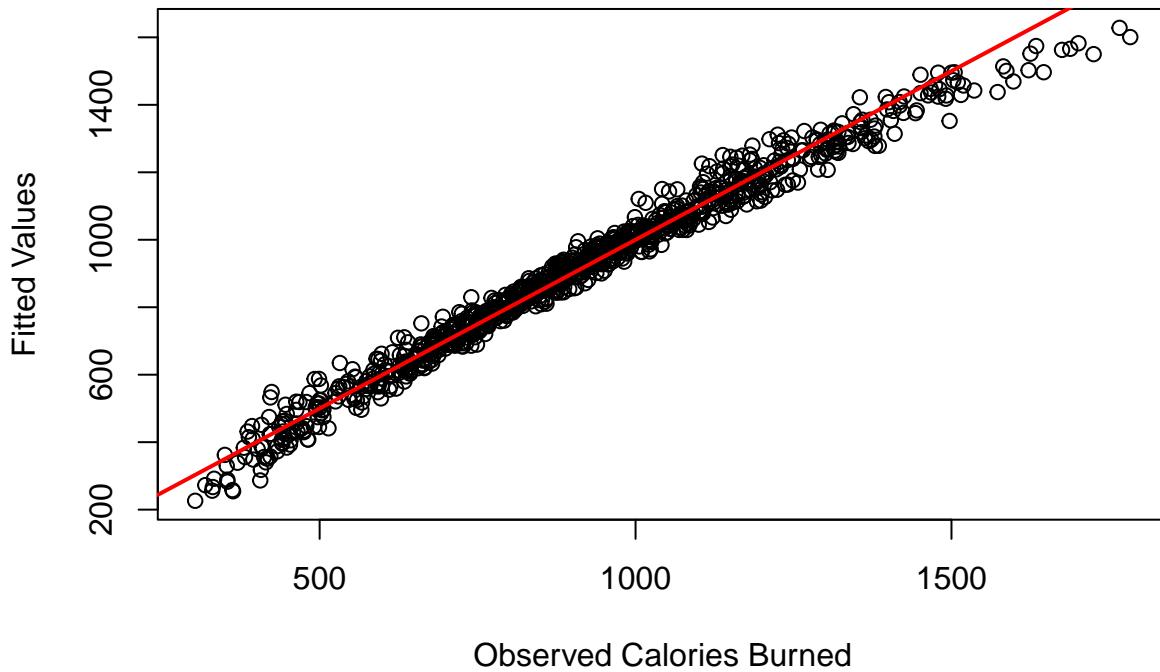
```
## 
## Call: rlm(formula = Calories_Burned ~ ., data = gym_data, method = "M")
## Residuals:
##      Min       1Q   Median       3Q      Max 
## -124.758  -23.392   -1.135  22.859  182.247 
## 
## Coefficients:
##                               Value Std. Error t value
## (Intercept)             -966.7005   80.7598 -11.9701
## Age                   -3.3626    0.0970 -34.6612
## GenderMale              82.2678    4.2344  19.4284
## Weight..kg.            -0.8572    0.4720 -1.8162
## Height..m.              89.4294   43.4451   2.0584
## Max_BPM                 0.0897    0.1023   0.8770
## Avg_BPM                  6.1062    0.0820  74.4962
## Resting_BPM               0.3039    0.1607   1.8912
## Session_Duration..hours. 710.8228    5.4578 130.2402
## Workout_TypeHIIT          -1.9409    3.3707 -0.5758
## Workout_TypeStrength      -2.3849    3.2459 -0.7347
## Workout_TypeYoga           -5.1514    3.3083 -1.5571
```

```

## Fat_Percentage           -0.2618   0.3106  -0.8428
## Water_Intake..liters.    -1.9311   3.0008  -0.6435
## Workout_Frequency..days.week. 0.6175   2.3565   0.2621
## Experience_Level         0.0661   3.6790   0.0180
## BMI                      2.9298   1.4362   2.0400
##
## Residual standard error: 34.39 on 956 degrees of freedom

```

M-estimator Regression



```

## [1] 1543.91
##
## Call:
## lmrob(formula = Calories_Burned ~ ., data = gym_data, method = "S")
## \--> method = "S"
## Residuals:
##      Min       1Q     Median       3Q      Max 
## -126.632  -18.857   3.301   27.238  197.239 
## 
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)    
## (Intercept)             -870.91957  121.42784 -7.172  1.48e-12 ***
## Age                     -3.08847   0.13849 -22.302 < 2e-16 ***
## GenderMale              81.53791   6.41026 12.720 < 2e-16 ***
## Weight..kg.             -0.37247   0.70096 -0.531   0.595  
## Height..m.              46.29317  64.70402  0.715   0.474  
## Max_BPM                 0.03907   0.15657  0.250   0.803  
## Avg_BPM                 5.85889   0.13075 44.809 < 2e-16 ***
## Resting_BPM              0.39064   0.24507  1.594   0.111  
## Session_Duration..hours. 705.66285  8.66079 81.478 < 2e-16 ***
## Workout_TypeHIIT        -1.13985   5.13523 -0.222   0.824  
## Workout_TypeStrength     0.81928   4.95517  0.165   0.869  

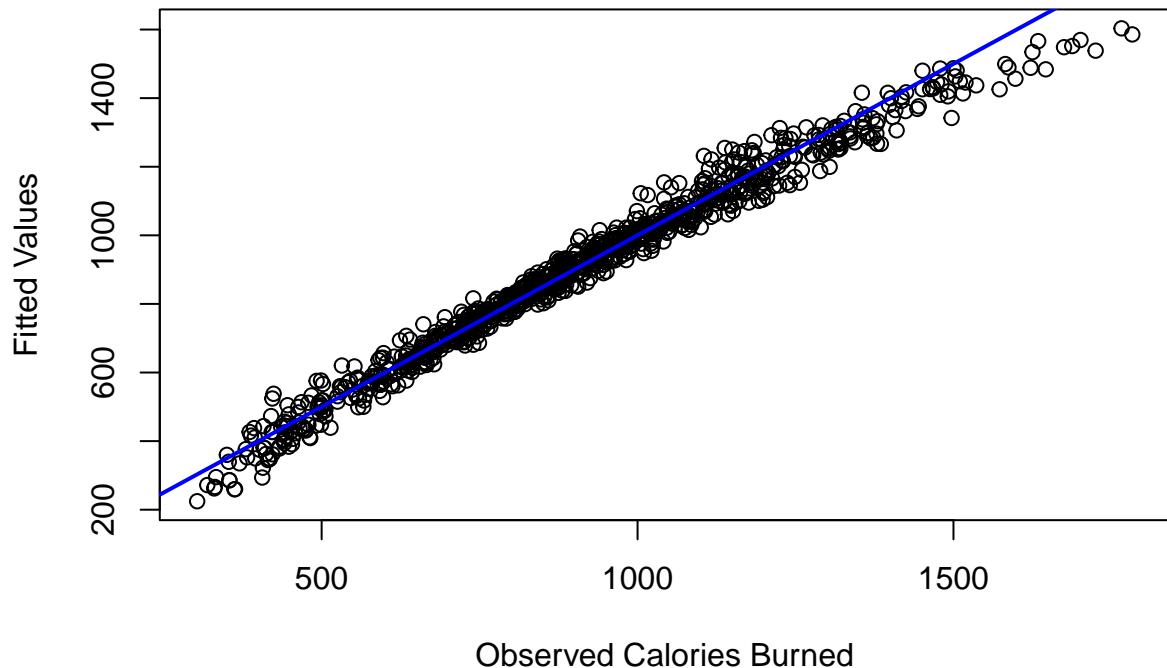
```

```

## Workout_TypeYoga           -1.14183   5.17927  -0.220   0.826
## Fat_Percentage            -0.13587   0.47654  -0.285   0.776
## Water_Intake..liters.     -5.32298   4.40471  -1.208   0.227
## Workout_Frequency..days.week. -1.50224   3.60250  -0.417   0.677
## Experience_Level           6.09505   5.41836   1.125   0.261
## BMI                         1.86139   2.13657   0.871   0.384
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Robust residual standard error: 34.2
## Multiple R-squared:  0.9927, Adjusted R-squared:  0.9926
##
## Robustness weights:
## 157 observations c(4,7,16,24,35,45,51,67,70,78,82,90,91,100,104,106,107,108,116,119,125,130,137,140
## are outliers with |weight| = 0 (< 0.0001);
## 30 weights are ~= 1. The remaining 786 ones are summarized as
##   Min.    1st Qu.   Median    Mean    3rd Qu.    Max.
## 0.0003622 0.4516000 0.7626000 0.6658000 0.9356000 0.9989000
## Algorithmic parameters:
##      tuning.chi          bb      tuning.psi      refine.tol
##      1.548e+00        5.000e-01      4.685e+00      1.000e-07
##      rel.tol          scale.tol      solve.tol      zero.tol
##      1.000e-07        1.000e-10      1.000e-07      1.000e-10
##      eps.outlier      eps.x warn.limit.reject warn.limit.meanrw
##      1.028e-04        3.620e-10      5.000e-01      5.000e-01
##      nResample       max.it      best.r.s      k.fast.s      k.max
##      500              50             2             1            200
##      maxit.scale     trace.lev      mts      compute.rd fast.s.large.n
##      200              0             1000            0            2000
##      psi              subsampling      cov
##      "bisquare"      "nonsingular" ".vcov.w"
## compute.outlier.stats
##      "S"
## seed : int(0)

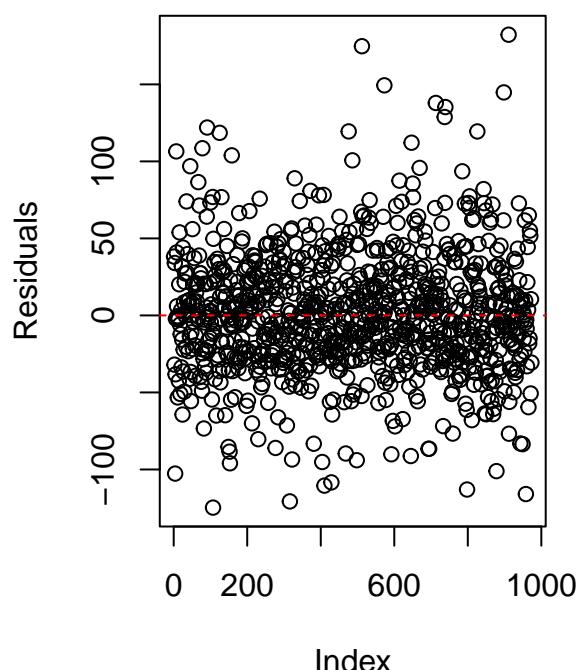
```

P-estimator Regression

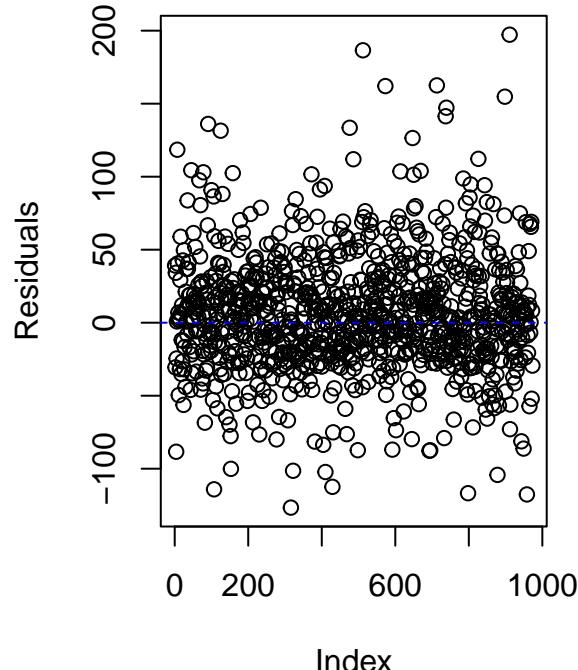


```
## [1] 1643.805  
## M-estimator Residual Standard Error: 39.29262  
## P-estimator Residual Standard Error: 40.54387
```

Residuals of M-estimator



Residuals of P-estimator



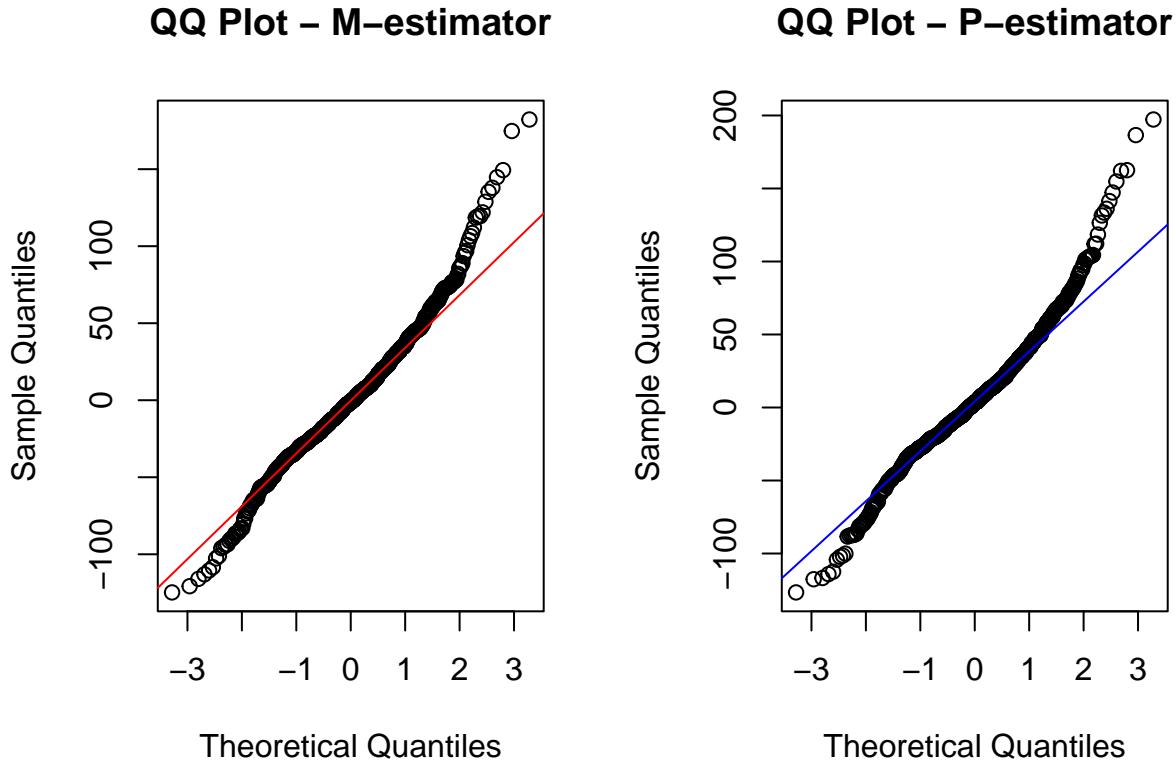
```
##      AIC      BIC
```

```

## 9939.092 10022.058
##      AIC      BIC
## 10000.09 10083.06

```

Both AIC and BIC suggest that M model is better.



```

##
## Shapiro-Wilk normality test
##
## data: residuals_m
## W = 0.9798, p-value = 2.282e-10
##
## Shapiro-Wilk normality test
##
## data: residuals_p
## W = 0.97283, p-value = 1.626e-12

```

The result show the residuals of both M and P estimators are normally distributed.