

# NMST 434,

## Exercise session VII : M –estimators II

April 8, 2019

### Example: M-estimators of location for univariate distributions

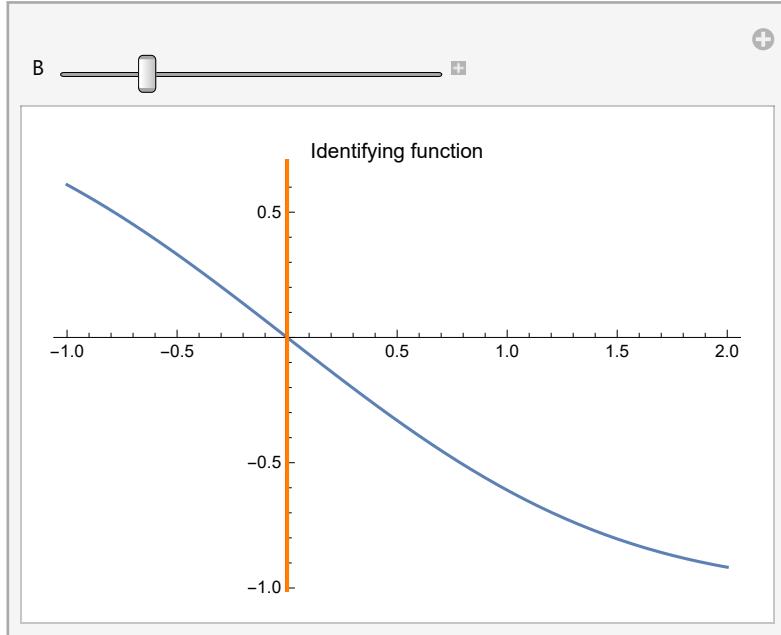
*Truedist* is the true distribution from the location family whose parameter we estimate  
*Mdist* is the distribution whose maximum likelihood estimating equations we use for the construction of M estimators. In this case, function  $\psi_0$  is taken to be  $-\partial \log [f[x; \mu]] / \partial \mu$ .  
 alternatively, function  $\psi_0$  can be specified directly as in the case of the Huber loss function or the Tukey biweight function.  
 In the special case *Mdist*=*Truedist* we get the usual maximum likelihood estimators as the M-estimators, and the asymptotic variance in the final computation is, in fact, the Rao-Cramér bound.

```
Clear["Global`*"]
$Assumptions = Element[\mu, Reals] && b > 0;
(*Mdist=NormalDistribution[];*)
Mdist = StudentTDistribution[1];
Truedist = NormalDistribution[];
(*Truedist=LogisticDistribution[];*)
(*Truedist=ExponentialDistribution[1];*)
(*Truedist=StudentTDistribution[6];*)
f[x_] = PDF[Mdist, x];
\psi0[t_] = - D[f[t], t] / f[t]
(*b=1;*)
\psi0[t_] = Min[b, Max[t, -b]]; (* !!! For non-differentiable functions \psi0,
the asymptotic variance matrices may be incorrect - formally,
one would have to use Theorem 10 !!! *)
(*\psi0[t_]=t\left(1-\frac{t^2}{b^2}\right)^2 Boole[Abs[t]\leq b];*)
(*Plot[\psi0[t],{t,-3b/2,3b/2},PlotLabel\rightarrow "Function \psi"]*)
\psi[x_] = \psi0[x - \mu];
\Gamma = Integrate[(D[\psi[x], {\mu}] /. \mu \rightarrow 0) PDF[Truedist, x], {x, -\infty, \infty}]
\Sigma = Integrate[(\psi[x]^2 /. \mu \rightarrow 0) PDF[Truedist, x], {x, -\infty, \infty}]
Var1 = \Sigma / (\Gamma^2)
-Erf[\frac{b}{\sqrt{2}}]
e^{-\frac{b^2}{2}} \left( -b \sqrt{\frac{2}{\pi}} + e^{\frac{b^2}{2}} \operatorname{Erf}\left[\frac{b}{\sqrt{2}}\right] + b^2 e^{\frac{b^2}{2}} \operatorname{Erfc}\left[\frac{b}{\sqrt{2}}\right] \right)
e^{-\frac{b^2}{2}} \left( -b \sqrt{\frac{2}{\pi}} + e^{\frac{b^2}{2}} \operatorname{Erf}\left[\frac{b}{\sqrt{2}}\right] + b^2 e^{\frac{b^2}{2}} \operatorname{Erfc}\left[\frac{b}{\sqrt{2}}\right] \right)
\operatorname{Erf}\left[\frac{b}{\sqrt{2}}\right]^2
```

For simple distributions (normal or exponential) we plot the mean, median, and the estimating function of the M-estimator (as a function of the tuning parameter b). The root of the estimating

function is the M-estimate.

```
OF = Integrate[(ψ[x]) PDF[Truedist, x], {x, -∞, ∞}];
Manipulate[Plot[OF /. b → B, {μ, -1, 2},
  PlotLabel → "Identifying function", Epilog → {Directive[Red, Thick],
    Line[{{Mean[Truedist], -5}, {Mean[Truedist], 5}}], Directive[Orange, Thick],
    Line[{{Median[Truedist], -5}, {Median[Truedist], 5}}]}, {{B, 1}, 0, 5}],
  Mean[Truedist],
  Median[Truedist]]
```



0

0

Computation of the asymptotic variance of Huber's M-estimator of location using Theorem 10, see Example 40.

```
Var2 =
  Integrate[x^2 PDF[Truedist, x], {x, -b, b}] + b^2 (1 - CDF[Truedist, b] + CDF[Truedist, -b])
  (CDF[Truedist, b] - CDF[Truedist, -b])^2
% //
N

$$\frac{-b e^{-\frac{b^2}{2}} \sqrt{\frac{2}{\pi}} + \text{Erf}\left[\frac{b}{\sqrt{2}}\right] + b^2 \left(1 - \frac{1}{2} \text{Erfc}\left[-\frac{b}{\sqrt{2}}\right] + \frac{1}{2} \text{Erfc}\left[\frac{b}{\sqrt{2}}\right]\right)}{\left(\frac{1}{2} \text{Erfc}\left[-\frac{b}{\sqrt{2}}\right] - \frac{1}{2} \text{Erfc}\left[\frac{b}{\sqrt{2}}\right]\right)^2}$$

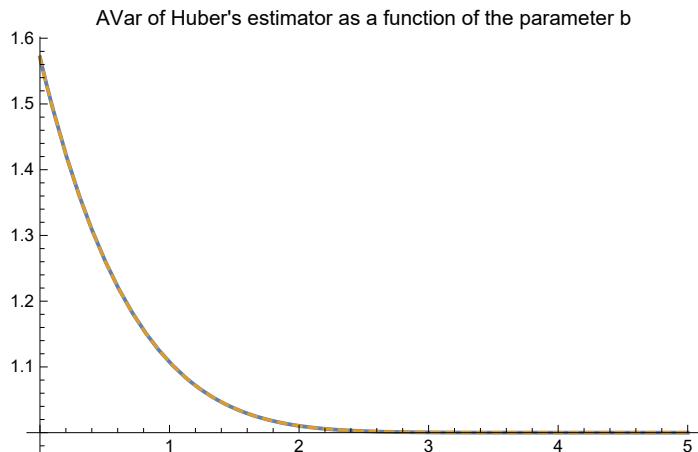

$$\left(-0.797885 \times 2.71828^{-0.5 b^2} b + \text{Erf}[0.707107 b] + b^2 (1 - 0.5 \text{Erfc}[-0.707107 b] + 0.5 \text{Erfc}[0.707107 b])\right) /$$


$$(0.5 \text{Erfc}[-0.707107 b] - 0.5 \text{Erfc}[0.707107 b])^2$$

```

Comparison of the asymptotic variances for Huber's estimator computed using Theorems 9 and 10. Neither variance expression is true if the distribution is not symmetric, i.e. when  $\mu$  is misspecified.

```
Plot[{Var1, Var2}, {b, 0, 5}, PlotRange -> All, PlotStyle -> {{Thick}, Dashed},
PlotLabel -> "AVar of Huber's estimator as a function of the parameter b"]
```

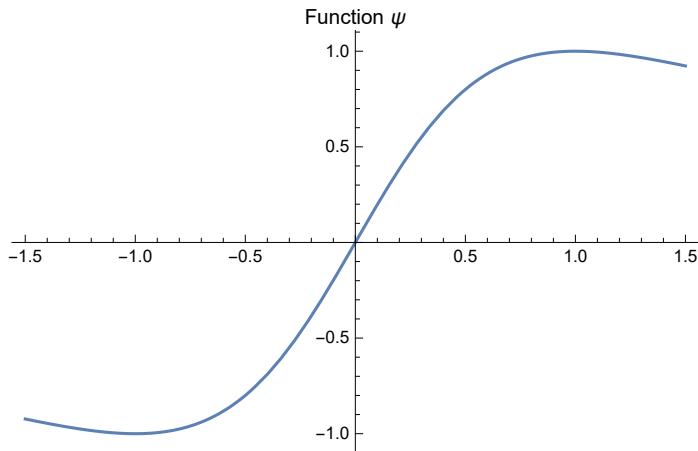


## Example: M-estimation of location and scale for univariate distributions

*Truedist* is the true distribution from the location-scale family whose parameters we estimate  
*Mdist* is the distribution whose maximum likelihood estimating equations we use for the construction of M estimators. In this case, function  $\psi_0$  is taken to be  $-\partial \log [f[x; \mu, \sigma]]/\partial \mu$ .  
alternatively, function  $\psi_0$  can be specified directly as in the case of the Huber loss function or the Tukey biweight function.

In the special case *Mdist*=*Truedist* we get the usual maximum likelihood estimators as the M-estimators, and the asymptotic variance in the final computation is, in fact, the Rao-Cramér bound.

```
Clear["Global`*"]
$Assumptions = Element[\mu, Reals] && \sigma > 0;
(*Mdist=NormalDistribution[];*)
Mdist = StudentTDistribution[1];
Truedist = NormalDistribution[]; (*LogisticDistribution[];*)
(*Truedist=StudentTDistribution[6];*)
f[x_] = PDF[Mdist, x];
\psi0[t_] = - \frac{D[f[t], t]}{f[t]};
b = 1;
(*\psi0[t_]=Min[b,Max[t,-b]];(* !!! For non-differentiable functions \psi0,
the asymptotic variance matrices may be incorrect - formally,
one would have to use Theorem 10 !!! *) *)
(*\psi0[t_]=t\left(1-\frac{t^2}{b^2}\right)^2 Boole[Abs[t]\leq b];*)
Plot[\psi0[t], {t, -3 b / 2, 3 b / 2}, PlotLabel -> "Function \psi"]
\kappa = Integrate[\psi0[x] x PDF[Truedist, x], {x, -\infty, \infty}];
(* standardization constant that ensures correct identification of parameter \sigma *)
N[\kappa]
\psi[x_] = {\psi0[\frac{x-\mu}{\sigma}], \psi0[\frac{x-\mu}{\sigma}] \frac{x-\mu}{\sigma} - \kappa};
D[\psi[x], {{\mu, \sigma}}]
Outer[Times, \psi[x], \psi[x]]
```



0.688641

$$\begin{aligned}
 & \left\{ \left\{ \frac{4(x-\mu)^2}{\left(1 + \frac{(x-\mu)^2}{\sigma^2}\right)^2 \sigma^3} - \frac{2}{\left(1 + \frac{(x-\mu)^2}{\sigma^2}\right) \sigma}, \frac{4(x-\mu)^3}{\left(1 + \frac{(x-\mu)^2}{\sigma^2}\right)^2 \sigma^4} - \frac{2(x-\mu)}{\left(1 + \frac{(x-\mu)^2}{\sigma^2}\right) \sigma^2} \right\}, \right. \\
 & \left\{ \frac{4(x-\mu)^3}{\left(1 + \frac{(x-\mu)^2}{\sigma^2}\right)^2 \sigma^4} - \frac{4(x-\mu)}{\left(1 + \frac{(x-\mu)^2}{\sigma^2}\right) \sigma^2}, \frac{4(x-\mu)^4}{\left(1 + \frac{(x-\mu)^2}{\sigma^2}\right)^2 \sigma^5} - \frac{4(x-\mu)^2}{\left(1 + \frac{(x-\mu)^2}{\sigma^2}\right) \sigma^3} \right\} \} \\
 & \left\{ \left\{ \frac{4(x-\mu)^2}{\left(1 + \frac{(x-\mu)^2}{\sigma^2}\right)^2 \sigma^2}, \frac{2(x-\mu) \left( -2 + \frac{2(x-\mu)^2}{\left(1 + \frac{(x-\mu)^2}{\sigma^2}\right) \sigma^2} + \sqrt{2 \in \pi} \operatorname{Erfc} \left[ \frac{1}{\sqrt{2}} \right] \right)}{\left(1 + \frac{(x-\mu)^2}{\sigma^2}\right) \sigma} \right\}, \right. \\
 & \left. \left\{ \frac{2(x-\mu) \left( -2 + \frac{2(x-\mu)^2}{\left(1 + \frac{(x-\mu)^2}{\sigma^2}\right) \sigma^2} + \sqrt{2 \in \pi} \operatorname{Erfc} \left[ \frac{1}{\sqrt{2}} \right] \right)}{\left(1 + \frac{(x-\mu)^2}{\sigma^2}\right) \sigma}, \right. \right. \\
 & \left. \left. \left\{ -2 + \frac{2(x-\mu)^2}{\left(1 + \frac{(x-\mu)^2}{\sigma^2}\right) \sigma^2} + \sqrt{2 \in \pi} \operatorname{Erfc} \left[ \frac{1}{\sqrt{2}} \right] \right\}^2 \right\} \right\}
 \end{aligned}$$

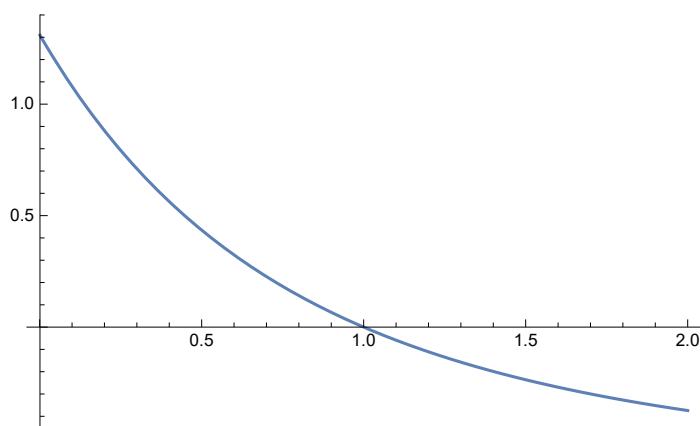
Check that the estimator of scale is (Fisher) consistent, i.e. that it identifies  $\sigma$

```

 $\epsilon = 1/1000;$ 
 $\text{Integrate}\left[\left(\psi\theta\left[\frac{x-\mu}{\sigma}\right]\frac{x-\mu}{\sigma} - \kappa/. \mu \rightarrow 0 // \text{Simplify}\right) \text{PDF}[\text{Truedist}, x], \{x, -\infty, \infty\}\right]$ 
 $\text{Plot}[\%, \{\sigma, \epsilon, \text{Max}[b, 2]\}]$ 
 $\text{FindRoot}[\%, \{\sigma, \epsilon, 2\}]$ 

$$\sqrt{2 e \pi} \text{Erfc}\left[\frac{1}{\sqrt{2}}\right] - e^{\frac{\sigma^2}{2}} \sqrt{2 \pi} \sigma \text{Erfc}\left[\frac{\sigma}{\sqrt{2}}\right]$$


```



$\{\sigma \rightarrow 1.\}$

Matrices  $\Gamma$  and  $\Sigma$  for the computation of influence functions and asymptotic variances

```

 $\Gamma = \text{Integrate}\left[\left(D[\psi[x], \{\{\mu, \sigma\}\}]\right) /. \{\mu \rightarrow 0, \sigma \rightarrow 1\}\right] \text{PDF}[\text{Truedist}, x], \{x, -\infty, \infty\}$ 
 $\Sigma = \text{Integrate}\left[\left(\text{Outer}[\text{Times}, \psi[x], \psi[x]]\right) /. \{\mu \rightarrow 0, \sigma \rightarrow 1\}\right] \text{PDF}[\text{Truedist}, x], \{x, -\infty, \infty\}$ 

$$\left\{\left\{-2 + \sqrt{2 e \pi} \text{Erfc}\left[\frac{1}{\sqrt{2}}\right], 0\right\}, \left\{0, 2 - 2 \sqrt{2 e \pi} \text{Erfc}\left[\frac{1}{\sqrt{2}}\right]\right\}\right\}$$


$$\left\{\left\{-2 + 2 \sqrt{2 e \pi} \text{Erfc}\left[\frac{1}{\sqrt{2}}\right], 0\right\}, \left\{0, 2 - 2 e \pi \text{Erfc}\left[\frac{1}{\sqrt{2}}\right]^2\right\}\right\}$$

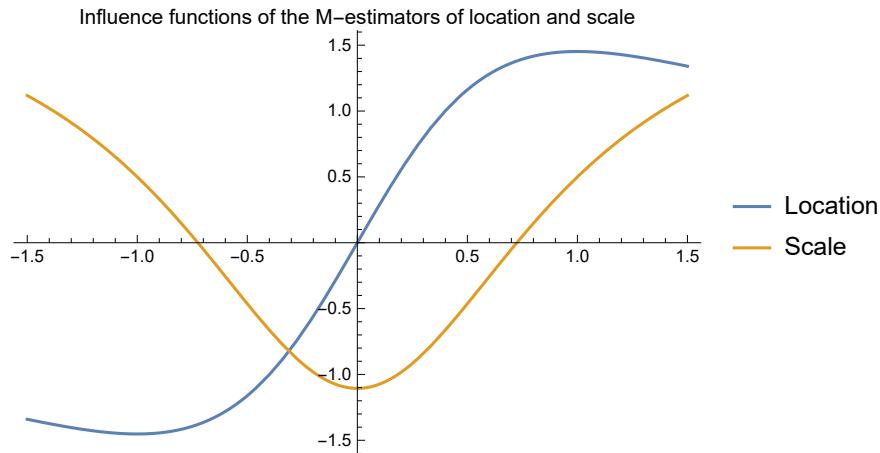

```

Influence functions of the M-estimators of location and scale

```

Plot[Evaluate[-Inverse[Γ].ψ[x] /. {μ → 0, σ → 1} // Simplify], {x, -3 b/2, 3 b/2},
PlotLabel → "Influence functions of the M-estimators of location and scale",
PlotLegends → {"Location", "Scale"}]
Limit[ψ[t], t → ∞]

```



$$\left\{ 0, \sqrt{2 e \pi} \operatorname{Erfc}\left[\frac{1}{\sqrt{2}}\right] \right\}$$

Asymptotic variance matrix of the M-estimators of location and scale

```

Inverse[Γ].Σ.Inverse[Γ] /. {μ → 0, σ → 1} // Simplify // MatrixForm
% // N // MatrixForm

```

$$\begin{pmatrix} \frac{2 \left(-1+\sqrt{2 e \pi} \operatorname{Erfc}\left[\frac{1}{\sqrt{2}}\right]\right)^3}{\left(2-3 \sqrt{2 e \pi} \operatorname{Erfc}\left[\frac{1}{\sqrt{2}}\right]+2 e \pi \operatorname{Erfc}\left[\frac{1}{\sqrt{2}}\right]^2\right)^2} & 0 \\ 0 & \frac{\left(-2+\sqrt{2 e \pi} \operatorname{Erfc}\left[\frac{1}{\sqrt{2}}\right]\right)^2 \left(2-2 e \pi \operatorname{Erfc}\left[\frac{1}{\sqrt{2}}\right]^2\right)}{\left(4-6 \sqrt{2 e \pi} \operatorname{Erfc}\left[\frac{1}{\sqrt{2}}\right]+4 e \pi \operatorname{Erfc}\left[\frac{1}{\sqrt{2}}\right]^2\right)^2} \end{pmatrix}$$

$$\begin{pmatrix} 1.31312 & 0. \\ 0. & 0.722933 \end{pmatrix}$$

Fisher information matrix of the true distribution, to compare with the asymptotic variance of the M-estimators above

$$U = -\frac{D\left[\frac{1}{\sigma} \operatorname{PDF}[\text{Truedist}, \frac{t-\mu}{\sigma}], \{\{\mu, \sigma\}\}\right]}{\frac{1}{\sigma} \operatorname{PDF}[\text{Truedist}, \frac{t-\mu}{\sigma}]};$$

```

FIM = Integrate[Outer[Times, U, U] PDF[Truedist, t] /. {μ → 0, σ → 1}, {t, -∞, ∞}];
Inverse[FIM] // MatrixForm
% // N // MatrixForm

```

$$\begin{pmatrix} 1 & 0 \\ 0 & \frac{1}{2} \end{pmatrix}$$

$$\begin{pmatrix} 1. & 0. \\ 0. & 0.5 \end{pmatrix}$$

Derivative of  $\log(\det(\Sigma))$  is  $(\Sigma^{-1})^T$

```

d = 5; (* dimension *)
A = D[Log[Det[Table[xi,j, {i, 1, d}, {j, 1, d}]]], {Table[xi,j, {i, 1, d}, {j, 1, d}]}];
Short[A]
B = Transpose[Inverse[Table[xi,j, {i, 1, d}, {j, 1, d}]]];
Cond = Flatten[Table[xi,j → RandomReal[], {i, 1, d}, {j, 1, d}]]
(* Evaluate the matrices randomly *)
(A /. Cond)
(B /. Cond)

{ { <<1>> / ( ( <<35>> + x1,2 x2,3 x3,4 x4,5) x5,1 - ( <<1>> ) x5,2 + <<1>> -
    ( <<35>> + <<1>> ) <<1>> + ( <<35>> + x1,1 x2,2 x3,3 x4,4) x5,5 ), <<1>>, <<1>>, <<1>>,
    ( <<1>> ) x5,1 - ( <<1>> ) x5 <<1>> <<1>> + <<1>> - ( <<1>> ) x5,4 } , <<3>>, { <<1>>, <<4>> } }
<<6>> + ( <<35>> + <<1>> ) x <<1>>
} , <<3>>, { <<1>>, <<4>> } }

{x1,1 → 0.366887, x1,2 → 0.494812, x1,3 → 0.240495, x1,4 → 0.776986, x1,5 → 0.41083,
x2,1 → 0.700019, x2,2 → 0.174995, x2,3 → 0.000197526, x2,4 → 0.212031, x2,5 → 0.819566,
x3,1 → 0.793623, x3,2 → 0.224809, x3,3 → 0.225649, x3,4 → 0.504024, x3,5 → 0.774389,
x4,1 → 0.210544, x4,2 → 0.214303, x4,3 → 0.40724, x4,4 → 0.397694, x4,5 → 0.77483,
x5,1 → 0.0818745, x5,2 → 0.675729, x5,3 → 0.329053, x5,4 → 0.898553, x5,5 → 0.669066}

{ {12.5267, 38.8483, 24.2904, -31.0934, -10.9561},
  {5.2204, 19.1313, 8.73438, -15.6144, -3.28618},
  {-9.57831, -37.0004, -20.7786, 30.1337, 8.29059},
  {5.15826, 18.0134, 13.7601, -15.9884, -4.11902},
  {-8.97409, -25.3249, -17.5, 21.8576, 7.42188} }

{ {12.5267, 38.8483, 24.2904, -31.0934, -10.9561},
  {5.2204, 19.1313, 8.73438, -15.6144, -3.28618},
  {-9.57831, -37.0004, -20.7786, 30.1337, 8.29059},
  {5.15826, 18.0134, 13.7601, -15.9884, -4.11902},
  {-8.97409, -25.3249, -17.5, 21.8576, 7.42188} }

```

## Example: Multivariate M-estimation of location and scatter

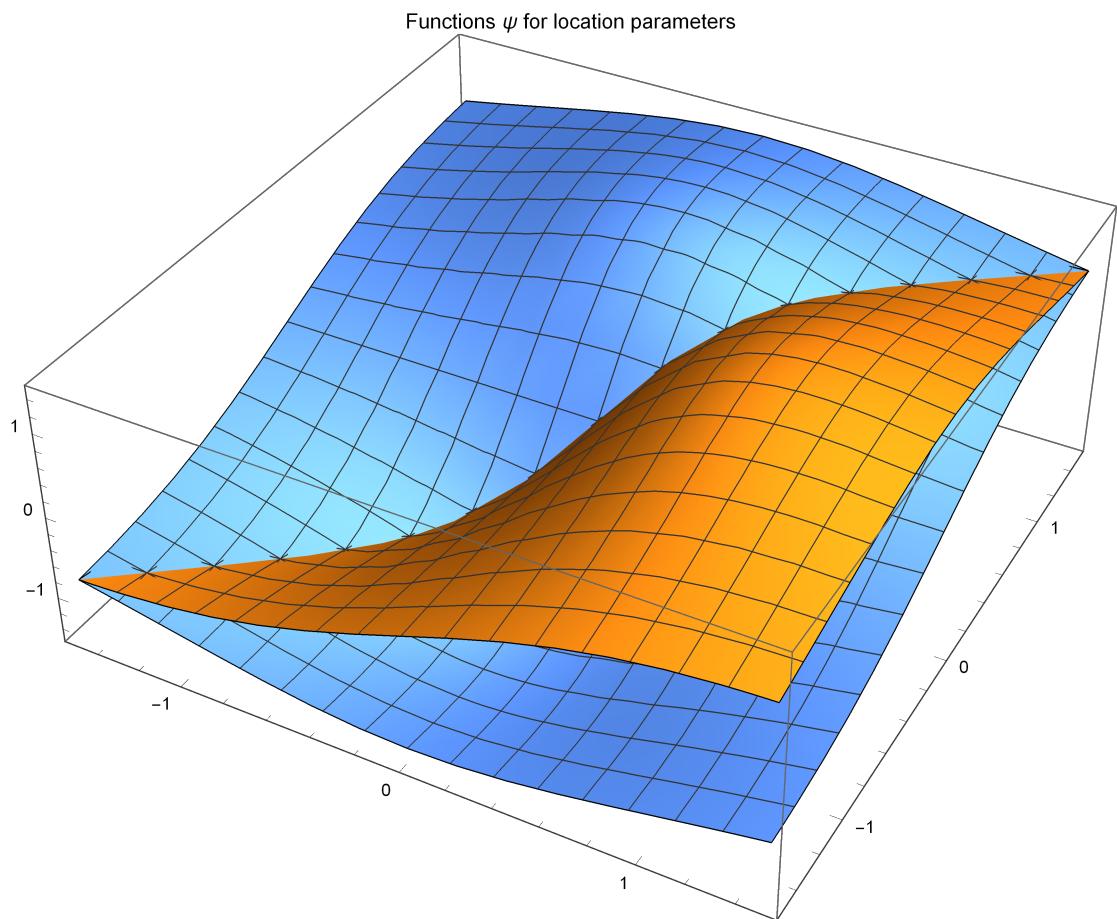
```

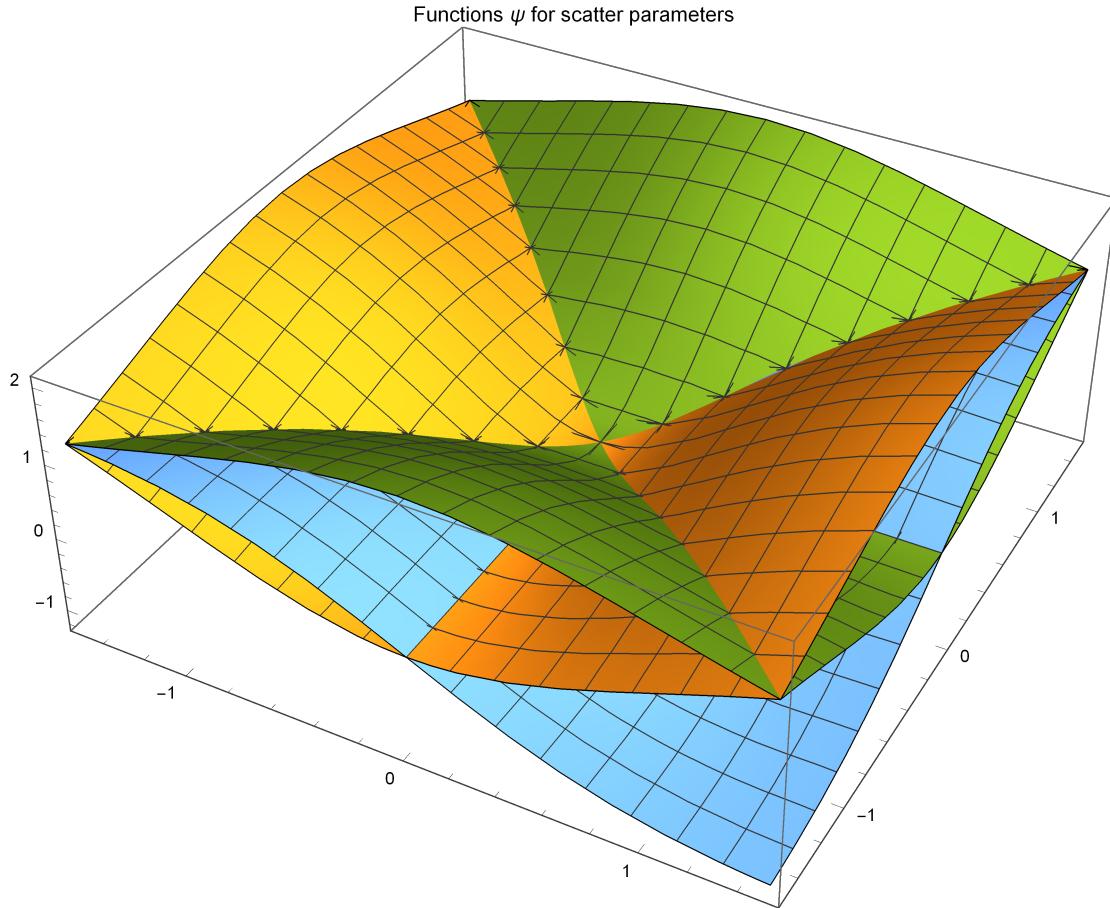
Clear["Global`*"];
$Assumptions = μ1 ∈ Reals && μ2 ∈ Reals && σ1 > 0 && σ2 > 0 && -1 < ρ < 1;
μ = {μ1, μ2};
Σ = {{σ1^2, ρ σ1 σ2}, {ρ σ1 σ2, σ2^2}};
θ = {μ1, μ2, σ1, ρ, σ2};
Truedist = MultinormalDistribution[DiagonalMatrix[{1, 1}]];
b = 1;
(*ψ0[t_]:=Min[b,Max[t,-b]]/t;(* !!! For non-differentiable functions ψ0,
the asymptotic variance matrices may be incorrect - formally,
one would have to use Theorem 10 !!! *) *)
(*ψ0[t_]:=1;*)
ψ0[t_] = 
$$\frac{(2+1)}{t^2+1};$$

(* Corresponds to t-distribution with 1 degree of freedom - Cauchy distribution *)
(*ψ0[t_]:=t\left(1-\frac{t^2}{b^2}\right)^2 \text{Boole}[Abs[t]\leq b]/t;*)

Plot3D[Evaluate[
ψ0[ $\sqrt{((x1, x2) - \{0, 0\}) . \text{Inverse}[\text{DiagonalMatrix}[\{1, 1\}]] . ((x1, x2) - \{0, 0\})}]$ 
{x1, x2}], {x1, -3b/2, 3b/2}, {x2, -3b/2, 3b/2}, PlotRange → All,
PlotLabel → "Functions ψ for location parameters", ImageSize → Large]
Plot3D[Evaluate[
ψ0[ $\sqrt{((x1, x2) - \{0, 0\}) . \text{Inverse}[\text{DiagonalMatrix}[\{1, 1\}]] . ((x1, x2) - \{0, 0\})}]$ 
{x1^2, x1 x2, x2^2}], {x1, -3b/2, 3b/2}, {x2, -3b/2, 3b/2}, PlotRange → All,
PlotLabel → "Functions ψ for scatter parameters", ImageSize → Large]
κ = NIntegrate[
ψ0[ $\sqrt{((x1, x2) - \{0, 0\}) . \text{Inverse}[\text{DiagonalMatrix}[\{1, 1\}]] . ((x1, x2) - \{0, 0\})}]$ 
x1^2 PDF[Truedist, {x1, x2}], {x1, -∞, ∞}, {x2, -∞, ∞}]
ψ[x1_, x2_] = Delete[Join[ψ0[ $\sqrt{((x1, x2) - \mu) . \text{Inverse}[\Sigma] . ((x1, x2) - \mu)}]$ ] ((x1, x2) - μ),
Flatten[ $\frac{\psi0[\sqrt{((x1, x2) - \mu) . \text{Inverse}[\Sigma] . ((x1, x2) - \mu)}]}{\kappa}$ ]
Outer[Times, {x1, x2} - μ, {x1, x2} - μ] - Σ], 5];

```





0.807817

Check that we correctly identified all the parameters. Integrals should be all zero at the true value of the parameters.

(addition and subtraction of 1 only to avoid warnings “Integral may be zero”)

```
NIntegrate[
  (1 + (\psi[x1, x2] /. {μ1 → 0, μ2 → 0, σ1 → 1, σ2 → 1, ρ → 0})) PDF[Truedist, {x1, x2}],
  {x1, -∞, ∞}, {x2, -∞, ∞}, AccuracyGoal → 10, WorkingPrecision → 10] - 1
{ -7.1348 × 10-6, -7.1348 × 10-6, -8.0673 × 10-6, -0.0000350292, -8.0673 × 10-6}
```

If the integrals in  $\Gamma$  and  $V$  can be computed exactly (only for the estimating equations from the multivariate normal distribution)

```
Γ =
Integrate[(D[\psi[x1, x2], {{μ1, μ2, σ1, σ2}}] /. {μ1 → 0, μ2 → 0, σ1 → 1, σ2 → 1, ρ → 0}),
PDF[Truedist, {x1, x2}], {x1, -∞, ∞}, {x2, -∞, ∞}]
V = Integrate[(Outer[Times, ψ[x1, x2], ψ[x1, x2]] /. {μ1 → 0, μ2 → 0, σ1 → 1,
σ2 → 1, ρ → 0}) PDF[Truedist, {x1, x2}], {x1, -∞, ∞}, {x2, -∞, ∞}]
```

Numerical computation of matrices  $\Gamma$  and  $V$

```

 $\Gamma = \text{NIntegrate}[(1 + D[\psi[x_1, x_2], \{\{\mu_1, \mu_2, \sigma_1, \rho, \sigma_2\}\}] /. \{\mu_1 \rightarrow 0, \mu_2 \rightarrow 0, \sigma_1 \rightarrow 1, \sigma_2 \rightarrow 1, \rho \rightarrow 0\}) PDF[\text{Truedist}, \{x_1, x_2\}], \{x_1, -\infty, \infty\}, \{x_2, -\infty, \infty\}, \text{AccuracyGoal} \rightarrow 10, \text{WorkingPrecision} \rightarrow 10] - 1$ 
 $V = \text{NIntegrate}[(1 + \text{Outer}[\text{Times}, \psi[x_1, x_2], \psi[x_1, x_2]]) /. \{\mu_1 \rightarrow 0, \mu_2 \rightarrow 0, \sigma_1 \rightarrow 1, \sigma_2 \rightarrow 1, \rho \rightarrow 0\}) PDF[\text{Truedist}, \{x_1, x_2\}], \{x_1, -\infty, \infty\}, \{x_2, -\infty, \infty\}, \text{AccuracyGoal} \rightarrow 10] - 1$ 
 $\left\{ \begin{array}{l} \{-0.8078349055, 0.000051534, -0.0000200891, 0.000201665, 0.000201665\}, \\ \{0.000051534, -0.8078349055, 0.000201665, 0.000201665, -0.0000200891\}, \\ \{1.813 \times 10^{-6}, 0.000086699, -1.03528420564, -6.8513 \times 10^{-6}, 0.321575302\}, \\ \{-0.0000118492, -0.0000118492, -6.8513 \times 10^{-6}, -0.6783948821, -6.8513 \times 10^{-6}\}, \\ \{0.000086699, 1.813 \times 10^{-6}, 0.321575302, -6.8513 \times 10^{-6}, -1.03528420564\} \end{array} \right\}$ 
 $\left\{ \begin{array}{l} \{0.864823, 1.65399 \times 10^{-8}, -5.9907 \times 10^{-10}, 8.71367 \times 10^{-9}, 1.27134 \times 10^{-8}\}, \\ \{1.65399 \times 10^{-8}, 0.864823, 1.27134 \times 10^{-8}, 8.71367 \times 10^{-9}, -5.99071 \times 10^{-10}\}, \\ \{-5.9907 \times 10^{-10}, 1.27134 \times 10^{-8}, 0.791338, 1.71269 \times 10^{-8}, -0.402887\}, \\ \{8.71367 \times 10^{-9}, 8.71367 \times 10^{-9}, 1.71269 \times 10^{-8}, 0.597113, 1.71269 \times 10^{-8}\}, \\ \{1.27134 \times 10^{-8}, -5.99071 \times 10^{-10}, -0.402887, 1.71269 \times 10^{-8}, 0.791338\} \end{array} \right\}$ 

```

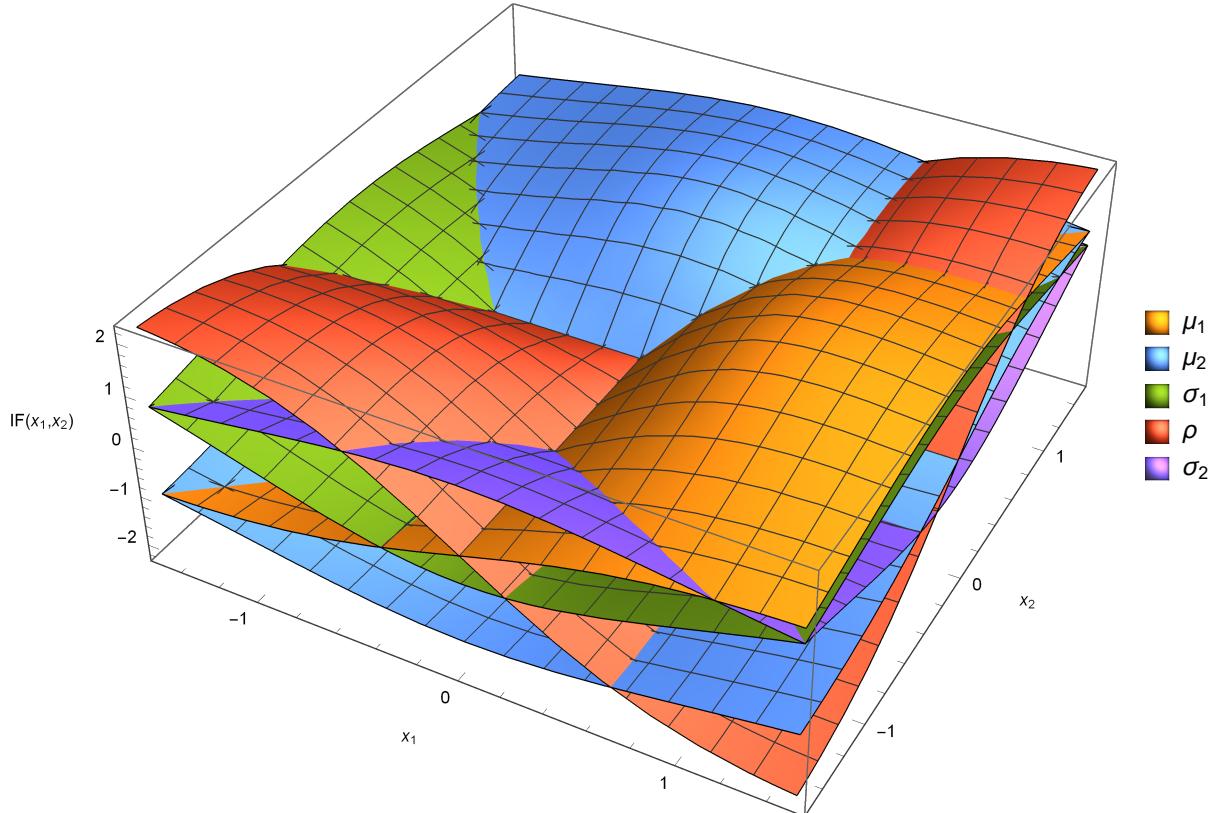
Influence function of the M-estimators of location and scatter

```

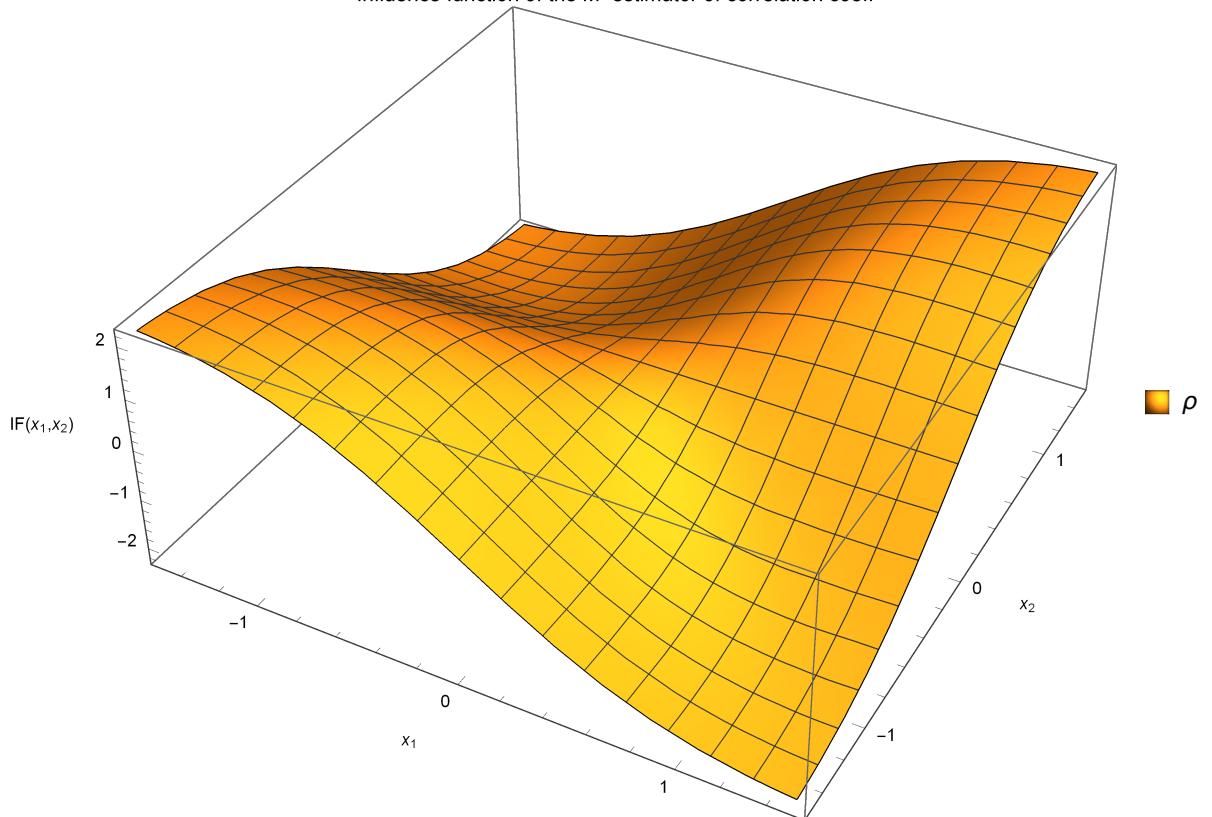
IF =
Evaluate[-Inverse[\Gamma].\psi[x_1, x_2] /. \{\mu_1 \rightarrow 0, \mu_2 \rightarrow 0, \sigma_1 \rightarrow 1, \sigma_2 \rightarrow 1, \rho \rightarrow 0\} // Simplify];
Plot3D[IF, \{x_1, -3 b/2, 3 b/2\}, \{x_2, -3 b/2, 3 b/2\},
PlotLabel \rightarrow "Influence functions of bivariate M-estimators of location and scatter",
PlotLegends \rightarrow \{"\mu_1", "\mu_2", "\sigma_1", "\rho", "\sigma_2"\},
AxesLabel \rightarrow \{"x_1", "x_2", "IF(x_1,x_2)"\}, ImageSize \rightarrow Large, PlotRange \rightarrow All]
Plot3D[IF[[4]], \{x_1, -3 b/2, 3 b/2\}, \{x_2, -3 b/2, 3 b/2\},
PlotLabel \rightarrow "Influence function of the M-estimator of correlation coef.",
PlotLegends \rightarrow \{"\rho"\}, AxesLabel \rightarrow \{"x_1", "x_2", "IF(x_1,x_2)"\},
ImageSize \rightarrow Large, PlotRange \rightarrow All]

```

Influence functions of bivariate M-estimators of location and scatter



Influence function of the M-estimator of correlation coef.



Asymptotic variance matrix of the M-estimator of location and scatter

```

Chop[Inverse[\[Gamma]].V.Inverse[\[Gamma]], 10-10] // MatrixForm
\left( \begin{array}{ccccc} 1.3252 & 0.000169101 & 0.0000569996 & 0.000717912 & 0.000451613 \\ 0.000169101 & 1.3252 & 0.000451613 & 0.000717912 & 0.0000569996 \\ 0.0000484434 & 0.000199507 & 0.705628 & -0.0000200074 & 0.0569682 \\ -0.0000421696 & -0.0000421696 & -0.000020135 & 1.29745 & -0.000020135 \\ 0.000199507 & 0.0000484434 & 0.0569682 & -0.0000200074 & 0.705628 \end{array} \right)

```

Inverse Fisher information matrix for multivariate normal distribution

```

U = - (D[PDF[MultinormalDistribution[{\mu1, \mu2}, \[Sigma]], {x1, x2}], {\[Theta]}) /
    PDF[MultinormalDistribution[{\mu1, \mu2}, \[Sigma]], {x1, x2}]) // Simplify;
FIM = Integrate[(Outer[Times, U, U] PDF[MultinormalDistribution[
    DiagonalMatrix[{1, 1}]], {x1, x2}]) /. 
  {\mu1 \[Rule] 0, \mu2 \[Rule] 0, \sigma1 \[Rule] 1, \sigma2 \[Rule] 1, \rho \[Rule] 0}, {x1, -\[Infinity], \[Infinity]}, {x2, -\[Infinity], \[Infinity]}];
Inverse[FIM] // MatrixForm
\left( \begin{array}{ccccc} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{2} & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{2} \end{array} \right)

```