

Colin Jh 317564112 Objektiv 4

$$A^T A = I$$

\Leftrightarrow invertible matrix A

$$\|Av\| = \sqrt{\langle Av, Av \rangle} = \sqrt{[Av]^T \cdot Av} = \sqrt{\sqrt{A^T A} \cdot Av} = \sqrt{v^T \cdot \underline{\underline{A}} \cdot v} = \sqrt{v^T \cdot v} = \sqrt{v \cdot v} = \sqrt{v^2} = \|v\|$$

\downarrow \downarrow \downarrow
non zero
non zero
 \Rightarrow non zero

$A^T A = I$
je nach

2. $A = \begin{bmatrix} 1 & 1 & 0 \\ 1 & -1 & 2 \end{bmatrix}, \quad A^T = \begin{bmatrix} 1 & 1 \\ 1 & -1 \\ 0 & 2 \end{bmatrix}$

$$AA^T = \begin{bmatrix} 1 & 1 & 0 \\ 1 & -1 & 2 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & -1 \\ 0 & 2 \end{bmatrix} = \begin{bmatrix} 2 & 0 \\ 0 & 6 \end{bmatrix}$$

$$A^T A = \begin{bmatrix} 1 & 1 \\ 1 & -1 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} 1 & 1 & 0 \\ 1 & -1 & 2 \end{bmatrix} = \begin{bmatrix} 2 & 0 & 2 \\ 0 & 2 & -2 \\ 2 & -2 & 4 \end{bmatrix}$$

AA^T ist stetig \Rightarrow 2.6., $e_1 e_2$ ist lösbar un. abhängig \Rightarrow unf

$-A^T A$ ist stetig \Rightarrow 6,2,0,1

$$\begin{bmatrix} \sqrt{8} & 0 & 0 \\ 0 & \sqrt{2} & 0 \end{bmatrix} \quad \text{Koer} \sum \ell \text{ kann } 7,0$$

durch $\left(\begin{bmatrix} 2 & 0 & 2 \\ 0 & 2 & -2 \\ 2 & -2 & 4 \end{bmatrix} - \begin{bmatrix} 4 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \right)$

$\lambda=0$

$$\begin{bmatrix} 2 & 0 & 2 \\ 0 & 2 & -2 \\ 2 & -2 & 4 \end{bmatrix} \begin{bmatrix} 9 \\ 5 \\ 1 \end{bmatrix} = 0$$

$\lambda=2$

$$\begin{bmatrix} 0 & 0 & 2 \\ 0 & 0 & -2 \\ 2 & -2 & 2 \end{bmatrix} \begin{bmatrix} 9 \\ 5 \\ 1 \end{bmatrix} = 0$$

$\lambda=6$

$$\begin{bmatrix} -4 & 0 & 2 \\ 0 & -4 & -2 \\ 2 & -2 & -2 \end{bmatrix} \begin{bmatrix} 9 \\ 5 \\ 1 \end{bmatrix} = 0$$

$$\begin{cases} a+c=0 \\ b-c=0 \\ 2a-2b+4c=0 \end{cases}$$

$$\begin{cases} 2a=0 \\ -2c=0 \\ 2a-2b+2c=0 \end{cases}$$

$$\begin{cases} -4a+2c=0 \\ -4b-2c=0 \\ 2a-2b-2c=0 \end{cases}$$

$b=a$

$c=2a$

$$\left\{ \begin{array}{l} a = -c \\ b = c \\ c \end{array} \right.$$

$$v_1 = \begin{bmatrix} -1 & 1 & 1 \end{bmatrix}$$

$$v_2 = \begin{bmatrix} 1 & 1 & 0 \end{bmatrix}$$

$$\|v_2\| = 2$$

$$v_3 = \begin{bmatrix} 1 & -1 & 2 \end{bmatrix}$$

$$\|v_3\| = 6$$

$$\|v_1\| = 3$$

\cup f(x) \rightarrow $f^{-1}(x) \rightarrow C_{f^{-1}}$

$$\begin{pmatrix} \frac{\sqrt{6}}{6} & \frac{-\sqrt{2}}{2} & \frac{-\sqrt{2}}{3} \\ \frac{-\sqrt{6}}{6} & \frac{\sqrt{2}}{2} & \frac{\sqrt{2}}{3} \\ \frac{\sqrt{6}}{3} & 0 & \frac{\sqrt{2}}{3} \end{pmatrix}$$

U \rightarrow $C_f \rightarrow C_{f^{-1}}$

$$v_1 = \frac{1}{\sqrt{6}} \cdot A \cdot v_1 = \frac{1}{\sqrt{6}} \begin{bmatrix} 1 & 1 & 0 \\ 1 & -1 & 2 \end{bmatrix} \begin{bmatrix} \frac{\sqrt{6}}{6} \\ \frac{-\sqrt{6}}{6} \\ \frac{\sqrt{6}}{3} \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$v_2 = \frac{1}{\sqrt{2}} \cdot A \cdot v_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 & 0 \\ 1 & -1 & 2 \end{bmatrix} \begin{bmatrix} \frac{\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2} \\ 0 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$A = \cup \sum v^T = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} \frac{\sqrt{6}}{6} & 0 & 0 \\ 0 & \frac{\sqrt{2}}{2} & 0 \end{bmatrix} \begin{pmatrix} \frac{\sqrt{6}}{6} & \frac{-\sqrt{2}}{2} & \frac{-\sqrt{2}}{3} \\ \frac{-\sqrt{6}}{6} & \frac{\sqrt{2}}{2} & \frac{\sqrt{2}}{3} \\ \frac{\sqrt{6}}{3} & 0 & \frac{\sqrt{2}}{3} \end{pmatrix}$$

Graph

3.

• C₂ f(x) = 0.087 x^2 C₁ leq B, S, leq k ln N

$$\textcircled{8} \quad z_0 = \sum_{i=1}^n c_i e_i$$

$$\delta_{12} = \frac{C_0^{12,50}}{|(C_0^{12,50})|}$$

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$$b_{12,1} = \frac{c_0 b_{12}}{\|c_0 b_{12}\|} = \frac{c_0 \cdot \frac{c_0^{12, b_0}}{\|c_0^{12, b_0}\|}}{\|c_0 \cdot \frac{c_0^{12, b_0}}{\|c_0^{12, b_0}\|}\|} = \frac{c_0^{12+1} \cdot b_0 \cdot \frac{1}{\cancel{\|c_0^{12, b_0}\|}}}{\cancel{\|c_0^{12+1} \cdot b_0\|} \cdot \frac{1}{\cancel{\|c_0^{12, b_0}\|}}} \cdot \frac{c_0^{12+1} \cdot b_0}{\|c_0^{12+1} \cdot b_0\|} \quad \text{Def 3}$$

and we can see that $\lambda_i v_i = \lambda_i v_i$

$$C_0^{1d} \cdot v_i = \lambda$$

$$b_k = \frac{c_0^k \cdot b_0}{\|c_0^k \cdot b_0\|} = \frac{(VD^k V^{-1})^k \cdot b_0}{\|(VD^k V^{-1})^k \cdot b_0\|} = \frac{VD^k \sum_{i \in e_i}}{\|VD^k \sum_{i \in e_i}\|} = \frac{V \sum_{i \in e_i} D^k \cdot c_i}{\|VD^k \sum_{i \in e_i}\|} =$$

only one vector

$$\sum_{j \neq i} D_{i,j} = 0 \Rightarrow D_{i,i} = 0, \quad D_{i,i}^{\frac{1}{2}} = (D_{i,i})^k = \lambda_i^{\frac{1}{k}} \cdot e_i \quad \text{per} \quad \text{if} \quad \lambda_i > 0 \quad \text{then} \quad \text{if} \quad \lambda_i < 0$$

$$\frac{v \sum \lambda_i^k c_i e_i}{\|v \sum \lambda_i^k c_i e_i\|} = \frac{c_i \lambda_i^k}{\|c_i \lambda_i^k\|} \cdot \frac{v \cdot \sum (\frac{\lambda_i}{\lambda_i})^k \frac{c_i}{c_i} e_i}{\|v \sum (\frac{\lambda_i}{\lambda_i})^k \frac{c_i}{c_i} e_i\|}$$

$\lambda_1 > \lambda_2 > \dots$ כ' λ_n ני' גל $\frac{\lambda_i}{\lambda} \rightarrow$ ס. ק. \Rightarrow ל' נ. ו. ו. (ב)

infidels called pop

$$\frac{c_i \lambda_i^k}{\|c_i \lambda_i^k\|^k} \frac{v \cdot e_i}{\|v \vee e_i\|} = \frac{c_i^k}{c_i^k} \cdot \frac{\lambda_i^k}{\|\lambda_i^k\|^k} \cdot \frac{v_i}{\|v_i\|}$$

$\lambda_i^k > 0$
 $c_i > 0$

else

$-v_i$

$$f(\sigma) = U \cdot \text{diag}(\sigma) \cdot U^T \cdot X$$

U ~ n \times n \quad j \in \{1, \dots, n\} \\
 x \in \mathbb{R}^n

f(\sigma)

ההכרזה מושגית על ידי $U^T V$. מושגיה של V הן $V \cdot \text{diag}(\sigma) \cdot U^T$ ו- U .

$$[x]_v = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} : v \text{ の } n \times 1 \text{ の } (1 \times n) \text{ の } v^T x$$

$$x = \sum_{i=1}^n q_i \cdot \cos_i$$

• U nraasf Go, morjul woof na o; , jie gocn fin U l preule s ob,
• U n gocna u: R o' n o o; L e mouui

more difficult to find and more costly.

$$f(\sigma) = U \cdot \text{diag}(\sigma) \cdot U^T \cdot x = U \cdot \text{diag}(\sigma) \cdot U^T \cdot \sum_{i=1}^n k_i u_i \alpha_i =$$

$$\sum_{i=1}^n u \cdot \text{diag}(o) \cdot \underbrace{U^\dagger}_{\text{blue}} \cdot u_i \cdot o_i$$

$$\sum_{i=1}^n \cup \text{diag}(\alpha) \ e_i \cdot \underline{\alpha_i} =$$

$$\sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j \cdot u_j =$$

$$\left[\sum_{i=1}^n (\alpha_i \cdot u_i \cdot \sigma_i) \right]$$

תנו α ו- C יקיים כך ש-

$$[\Sigma_{\sigma} f]_j = \text{sum over } \sigma$$

$$\frac{\partial f_i(\sigma)}{\partial \sigma_j} = \left(\sum_{i=1}^n (\alpha_i \cdot u_i^i \cdot \sigma_i) \right) = \underbrace{\sum_{\substack{i=1 \\ i \neq j}}^n \alpha_i \cdot u_i^i \cdot \sigma_i + \alpha_j \cdot u_j^i \cdot (\sigma_j - \sum_{i=1}^n \alpha_i \cdot u_i^i \cdot \sigma_i)}$$

$$\frac{\alpha_i \cdot u_i^i}{\sum \alpha_i \cdot u_i^i} = \underline{\underline{\alpha_j \cdot u_j^i}}$$

(*) $[\Sigma_{\sigma} f]_j = \alpha_j \cdot u_j^i$

נוכיח כי α_i הוא אחד מ- n האיברים

$$U^T x = \alpha$$

$$U^T = U^T \quad \text{יקי}$$

$$\alpha_j = \sum_{k=1}^n u_j^k \cdot x_k \quad \text{פ.}$$

(*) $[\Sigma_{\sigma} f]_j = u_j^i \cdot \sum_{k=1}^n u_j^k \cdot x_k =$

$$\sum_{k=1}^n u_j^k \cdot x_k \cdot u_j^i =$$

$$\underline{\underline{\langle u_j, x \rangle \cdot u_j^i}}$$

$$\mathcal{T}_\sigma: \mathbb{R}^d \rightarrow \mathbb{R}^d$$

$$g(\sigma) = f(\sigma) - y$$

$$\mathcal{L}(\sigma) = \frac{1}{2} \| \sigma \|^2$$

? no)

$$\mathcal{T}_\sigma(g) = \mathcal{T}_\sigma(f) - f$$

so $\mathcal{T}_\sigma(g) = \mathcal{T}_\sigma(f) - \mathcal{L}(\sigma)$

$$\mathcal{T}_\sigma(l) := (\mathcal{T}_\sigma(l))_i = \frac{\partial \mathcal{L}}{\partial \sigma_i} = \frac{\frac{1}{2} \sum_{j=1}^n \sigma_j^2 + (\sigma_i + h)^2 - \sum \sigma_j^2}{\partial \sigma_i} =$$

$$\frac{\frac{1}{2}(\sigma_i^2 + 2\sigma_i h + h^2 - \sum \sigma_j^2)}{\partial \sigma_i} = \frac{1}{2} \cdot 2\sigma_i + h = \underline{\underline{\sigma_i}}$$

$$h(\sigma) = \log g(\sigma)$$

implies $\mathcal{T}_\sigma(h)$

$$\nabla h(\sigma) = \mathcal{T}_\sigma(h) = \mathcal{T}_\sigma(\log g) =$$

- gradient $\mathcal{T}_\sigma(h)$

$$\mathcal{T}_{g(\sigma)}(l) \cdot \mathcal{T}_\sigma(g) =$$

$$(f(\sigma) - y)^T \mathcal{T}_\sigma(f)$$

C.

normalization

softmax

$$\frac{e^{x_i}}{\sum e^{x_i}} = \frac{e^{x_i} \cdot e^{x_i}}{\sum e^{x_i}} = \frac{e^{x_i}}{\sum e^{x_i}} \cdot \frac{e^{x_i}}{\sum e^{x_i}} = -\underbrace{(scx)_i}_{-\sum e^{x_i}} \cdot \underbrace{(scx)_i}_{\sum e^{x_i}}$$

$$\frac{e^{x_i} \cdot \sum e^{x_i} - e^{x_i} \cdot e^{x_i}}{(\sum e^{x_i})^2} = \frac{e^{x_i} \cdot \sum e^{x_i} - (\sum e^{x_i})^2}{(\sum e^{x_i})^2} = \frac{(\sum e^{x_i})^2 - (\sum e^{x_i})^2}{(\sum e^{x_i})^2} = \underbrace{(scx)_i}_{\sum e^{x_i}} - \underbrace{(scx)_i}_{\sum e^{x_i}}$$

7.

$$f(x,y) = x^2 + xy - y^5$$

$$\nabla f(x,y) = \begin{bmatrix} 2x^2 + y \\ x - 5y^4 \end{bmatrix}$$

$$H f(x,y) = \begin{bmatrix} 6x & -5 \\ -5 & -20y^3 \end{bmatrix}$$

8.

$$P(|\bar{x} - E\bar{x}| \geq \epsilon) \leq \frac{\text{Var}(\bar{x})}{\epsilon^2}$$

אלאג רעט סט'

ההוכחה מושגת באמצעות הוכחה של קיומו של גבול עבור $\lim_{n \rightarrow \infty} \text{Var}(\bar{x}_n)$.

$$P(|\bar{x}_n - \theta| \geq \epsilon) \leq \frac{\text{Var}(\bar{x}_n)}{\epsilon^2} = \frac{\frac{\sigma^2}{n}}{\epsilon^2} = \frac{\sigma^2}{n\epsilon^2}$$

אלאג גבול

$$\lim_{n \rightarrow \infty} \frac{\sigma^2}{n\epsilon^2} = 0$$

∴

ההוכחה מושגת באמצעות הוכחה של קיומו של גבול עבור $\lim_{n \rightarrow \infty} P(|\bar{x}_n - \theta| \geq \epsilon)$.

a.

לעומת פונקציית האנרגיה חישובית נקבל:

$$L(\mu, \sigma^2, x_1, \dots, x_n) = (2\pi\sigma^2)^{\frac{n}{2}} e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2}$$

השאלה מתחילה בפונקציית האנרגיה חישובית ופונקציית האנרגיה חישובית.

$$L(\mu, \Sigma, x_1, \dots, x_n) = \prod_{i=1}^n f(x_i; \mu, \Sigma) = \prod_{i=1}^n (2\pi\sigma^2)^{\frac{n}{2}} e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2} \cdot$$

$$\cdot \frac{-\frac{1}{2}}{(2\pi\sigma^2)^{\frac{n}{2}}}$$

$$f(x_i) = \frac{1}{\sqrt{(2\pi\sigma^2)^n}} \cdot e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2}$$

השאלה מתחילה בפונקציית האנרגיה חישובית.

$$L(\mu, \Sigma, x_1, \dots, x_n) = P(x_1, x_2, \dots, x_n | \mu, \Sigma) =$$

$$\prod_{i=1}^n f(x_i; \mu, \Sigma) = \prod_{i=1}^n \frac{1}{\sqrt{(2\pi\sigma^2)^n}} \cdot e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2}$$

השאלה מתחילה בפונקציית האנרגיה חישובית.

$$\prod_{i=1}^n \frac{1}{\sqrt{(2\pi\sigma^2)^n}} \cdot e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2}$$

Plot

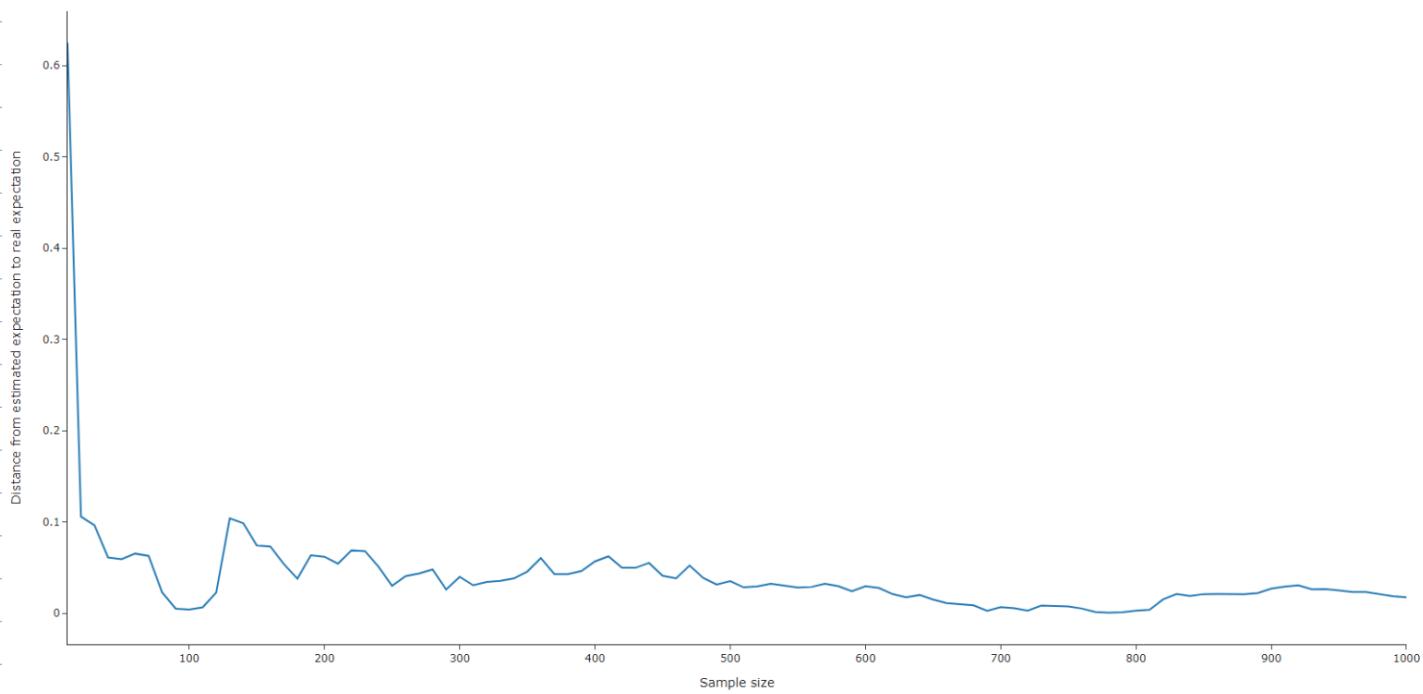
Univariate Gaussian

1.

(9.97639160436368, 1.0070307407539743)

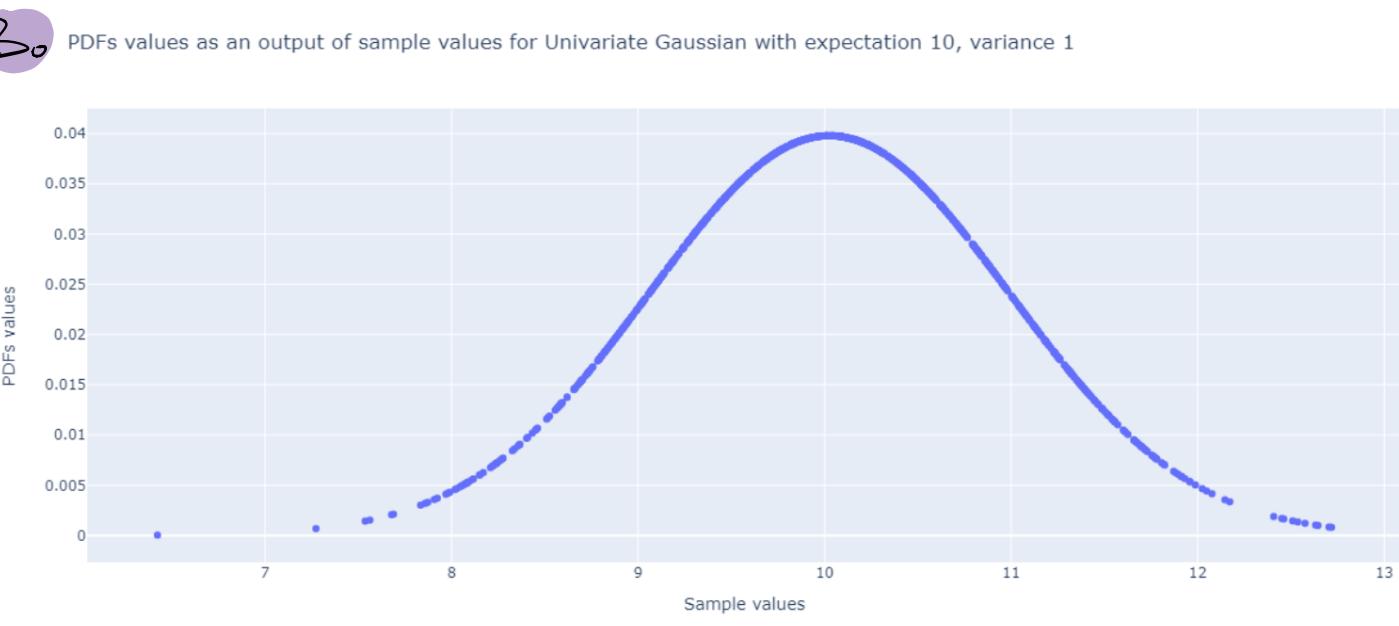
2.

Distance from estimated expectation to real expectation as an output of sample size for Univariate Gaussian with expectation 10, variance 1



3.

PDFs values as an output of sample values for Univariate Gaussian with expectation 10, variance 1



Multivariate Gaussian

4.

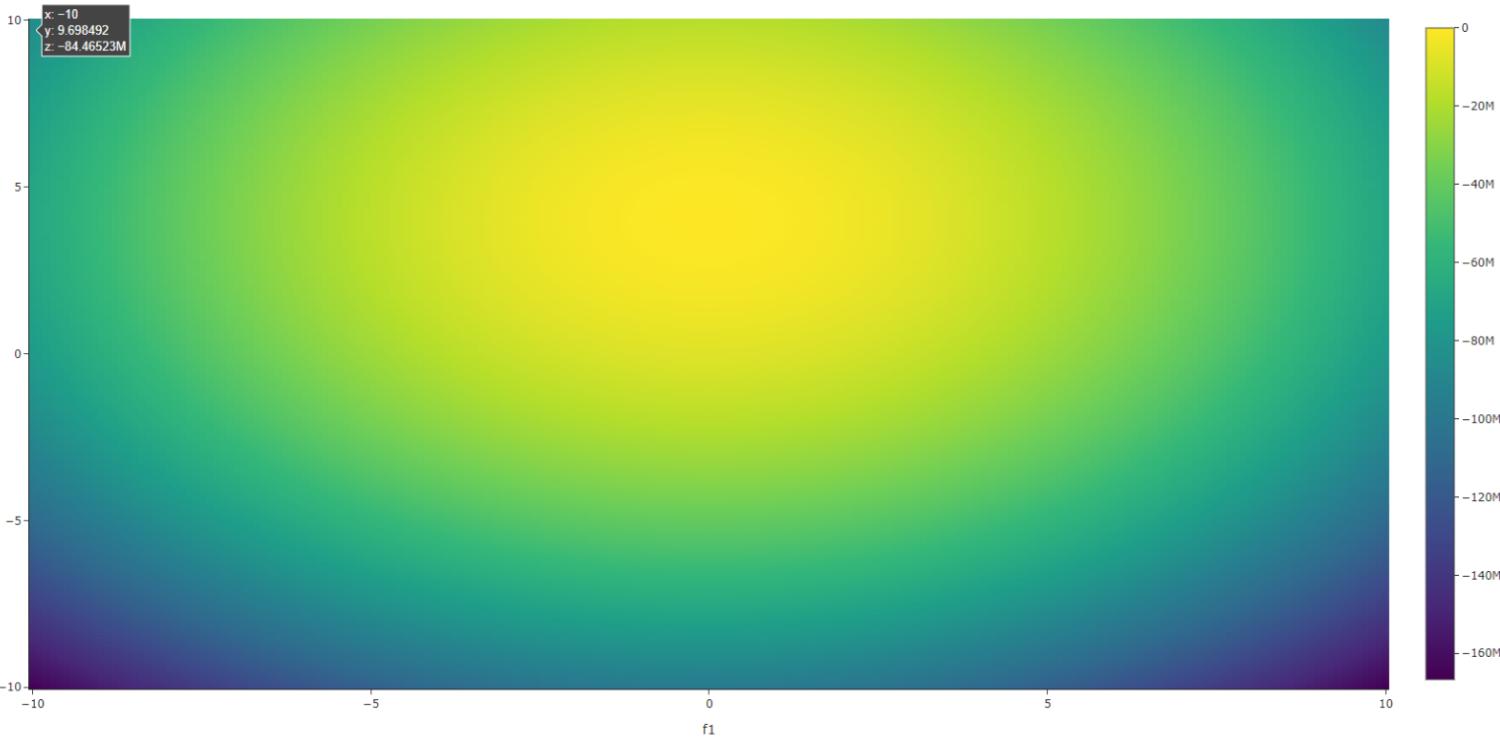
μ :

```
[-0.03938902  0.11141852  3.98902775 -0.05205757]
[[ 0.97179968  0.22416488  0.01212463  0.51000642]
 [ 0.22416488  1.94581196 -0.12206255  0.019183 ]
 [ 0.01212463 -0.12206255  1.01683408 -0.0105179 ]
 [ 0.51000642  0.019183   -0.0105179   1.00318671]]
```

Σ :

5.

Log likelihood As Function of $[f_1, 0, f_3, 0]$ expectation values



6.

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maximum log-likelihood achieved for f1 -0.050, f3 3.970
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