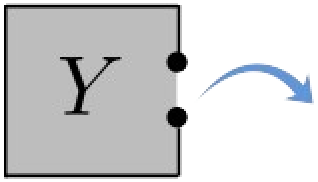
Statistics and Data Science for Engineers
E178 / ME276DS

Statistical inference:
Point estimation

Statistical inference

No inputs



$\{y_i\}_N = \mathcal{D}$.

Inference: Statement based on data.

Assumption: Sampling is iid.

- Y does not change btwn samples
- Samples are independent.

Given $\mathcal{D}$.

Three types of inferences

1) Point estimation : "My best guess for some parameter θ of P_Y is $\hat{\theta}_N$"

2) Confidence intervals : "Parameter θ lies in the interval I with confidence γ"

3) Hypothesis tests :

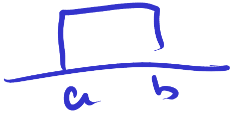
null hypothesis

H_0 : ______

H_1 : ______

" H_0 is rejected in favor of H_1"

" H_0 is not rejected in favor of H_1"



Point estimation

$\mathcal{U}(a,b)$

estimate

Given $\mathcal{D} = \{y_i\}_N \overset{\text{iid}}{\sim} Y$, find a best estimate $\hat{\theta}_N$ of a property or parameter θ

data points.

$E[Y]$

$Var[Y]$

a in $\mathcal{U}(a,b)$

<u>Estimator</u> $\quad \hat{\theta}_N = g_N(y_1, \ldots, y_N)$

$$\{y_i\}_N \xrightarrow{g_N} \hat{\theta}_N \approx \theta$$

Is g_N a good estimator?

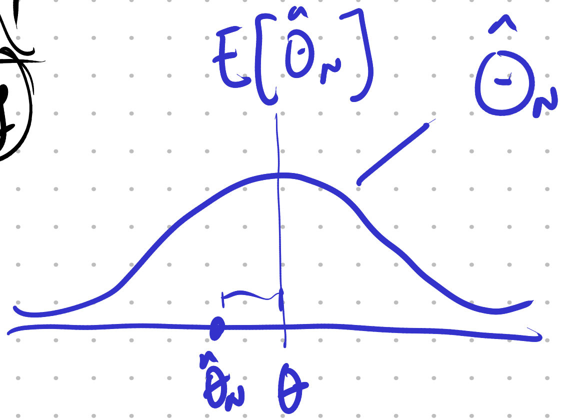
Means that "expect $\hat{\theta}_N \approx \theta$"

Make an assumption about Y

$\{Y_i\}_N \overset{iid}{\sim} Y$

"Estimator"

$$\{Y_i\}_N \xrightarrow{g_N} \hat{\Theta}_N$$



$\hat{\Theta}_N$

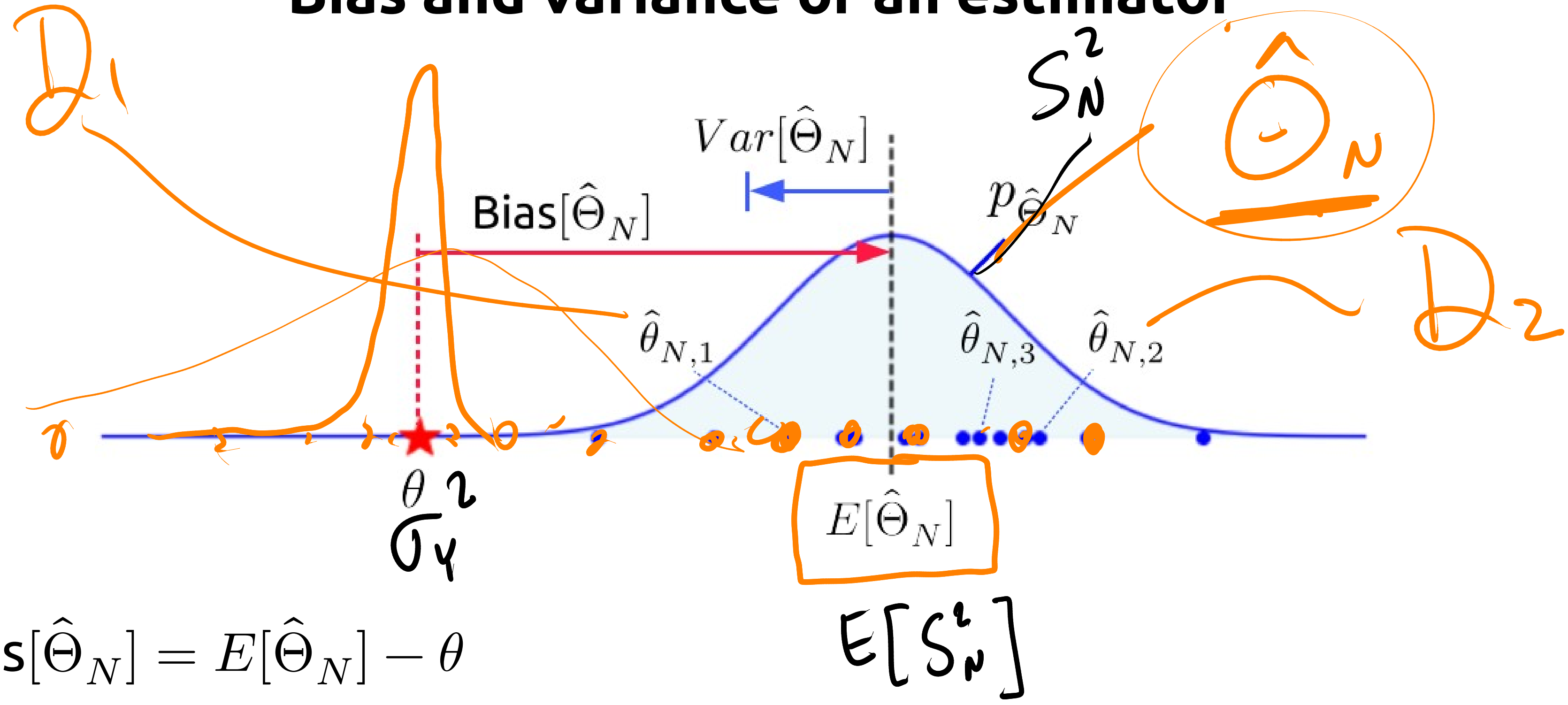
$\{y_1, \ldots, y_{100}\} = D.$

θ ... size of largest apple in the orchard

g_N^1 : $\max(y_1, \ldots, y_{100}) = \hat{\Theta}_N$

g_N^2 : $\max(y_1, \ldots, y_{100}) + 10$ cm.

Bias and variance of an estimator



- $\text{Bias}[\hat{\Theta}_N] = E[\hat{\Theta}_N] - \theta$

- $\text{Var}[\hat{\Theta}_N] = E\left[\left(\hat{\Theta}_N - E[\hat{\Theta}_N]\right)^2\right]$

Estimating the mean

$Y \sim \mu_Y$ $\qquad \mu_Y$

The *sample mean*: $\hat{\mu}_N = g_N(y_1, \ldots, y_N) = \frac{1}{N}\sum_{i=1}^{N} y_i$ $\quad \hat{\theta}_N$

$\bar{Y}_N = g_N(Y_1, \ldots, Y_N) = \frac{1}{N}\sum_{i=1}^{N} Y_i$ $\quad \hat{\Theta}_N$

$$E[\bar{Y}_N] = E\left[\frac{1}{N}\sum_{i=1}^{N} Y_i\right] = \frac{1}{N}\sum E[Y_i]$$

$$= \frac{1}{N}\sum E[Y] = \frac{1}{N} N\, E[Y] = E[Y] = \mu_Y$$

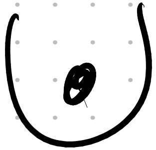
Estimating the mean

Proof

- Bias $[\bar{Y}_N] = 0$
- $Var\,[\bar{Y}_N] = \frac{\sigma_Y^2}{N}$

Prove: $Var[\bar{Y}_N] = Var\left[\frac{1}{N}\sum Y_i\right]$

$= \left(\frac{1}{N}\right)^2 \sum \underbrace{Var[Y_i]}_{=\sigma_Y^2} = \frac{N\sigma_Y^2}{N^2} = \frac{\sigma_Y^2}{N}.$

$N = 1$  $\bar{Y}_N = Y$ $\quad Var[\bar{Y}_N] = \sigma_Y^2$

$N = 10$  $Var[\bar{Y}_N] = \sigma_Y^2 / 10$

Var : σ_Y^2 / N

Std : $\sigma_Y / \sqrt{N}$ ✓

Estimating the variance

σ_Y^2

$\hat{\Theta}_N$

"Unbiased" sample variance:

$\hat{\theta}_N$ ...

$$\hat{\sigma}_N^2 = \frac{1}{N-1}\sum_{i=1}^{N}(y_i - \hat{\mu}_N)^2 \qquad S_N^2 = \frac{1}{N-1}\sum_{i=1}^{N}(Y_i - \bar{Y}_N)^2$$

$$\mathrm{Var}[Y] \approx \frac{1}{N}\sum\left[(y - \hat{\mu}_N)^2\right].$$

Estimating the variance

- Bias $[S_N^2] =$ 0

Proof in the reader.

- $Var[S_N^2] =$ complicated.

Y is Gaussian.

$\Downarrow$

S_N^2 ... χ^2 distribution

Biased sample variance: $$\tilde{S}_N^2 = \frac{1}{N}\sum_{i=1}^{N}(Y_i - \bar{Y}_N)^2$$

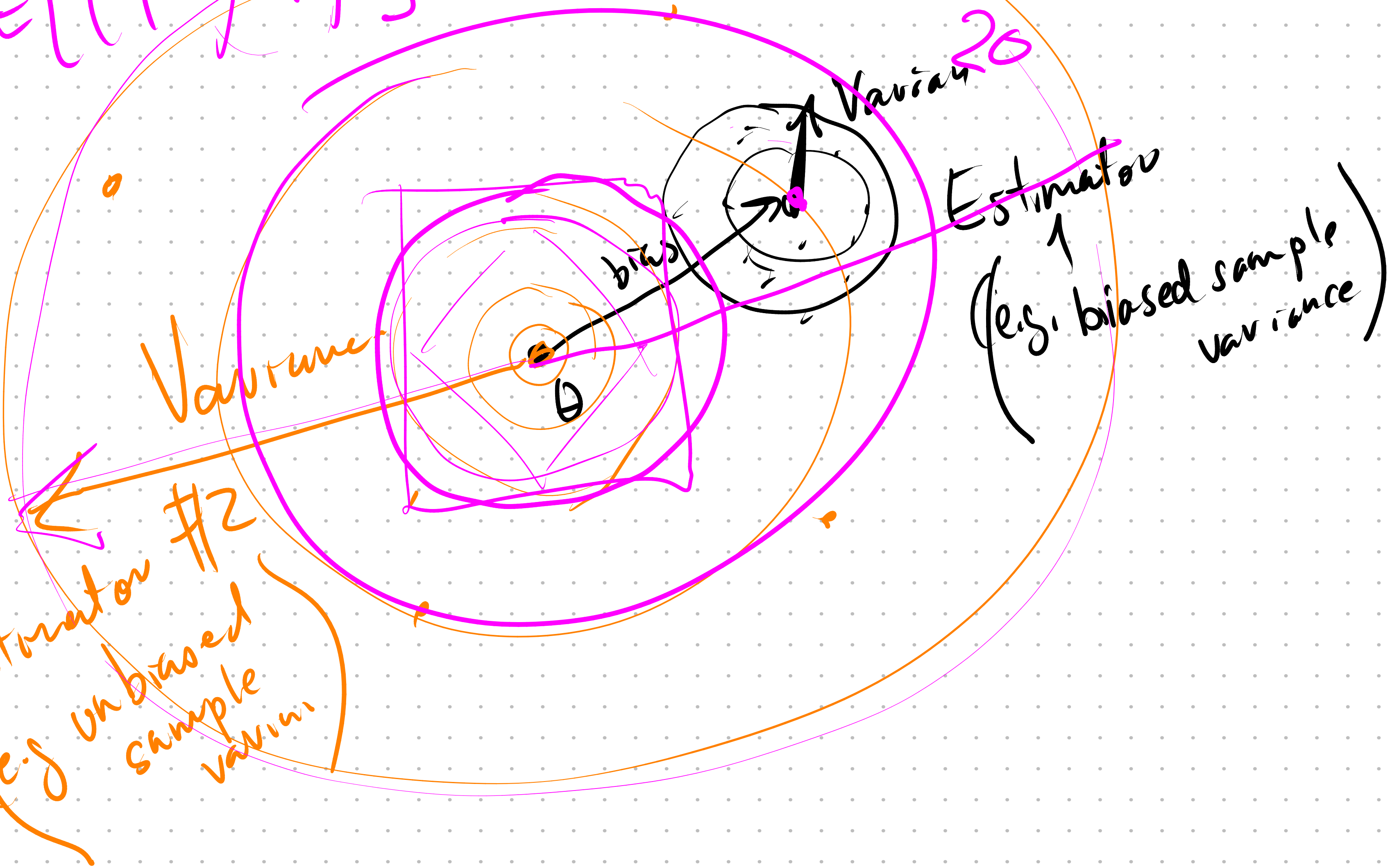
- Bias$[\tilde{S}_N^2] =$ $E[\tilde{S}_N^2] - \sigma_Y^2 = \frac{N-1}{N}\sigma_Y^2 - \sigma_Y^2 = -\frac{1}{N}\sigma_Y^2$

$\tilde{S}_N^2 = \frac{N-1}{N} S_N^2 \longrightarrow E[\tilde{S}_N^2] = \frac{N-1}{N} E[S_N^2] = \frac{N-1}{N} \cdot \sigma_Y^2$

- $Var[\tilde{S}_N^2] =$ Complicated.

smaller than $Var[S_N^2]$.

$$\mathrm{Var} = E\left[(Y-\mu_Y)^2\right].$$

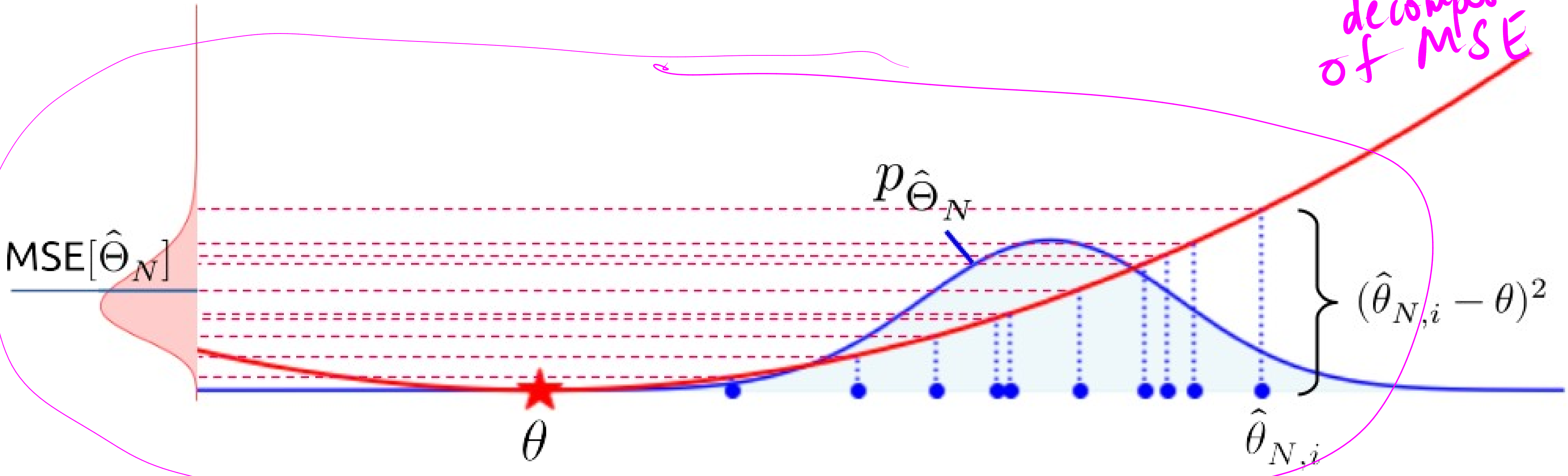


Mean squared error (MSE)

$$\text{MSE}[\hat{\Theta}_N] = E[(\hat{\Theta}_N - \theta)^2]$$

$$= Var[\hat{\Theta}_N] + \left(\text{Bias}[\hat{\Theta}_N]\right)^2$$

prove this Bias/Variance decomposition of MSE



SAMPLE

$\mathsf{MSE}[\bar{Y}_N] = \mathrm{Var}[\bar{Y}_N] + (\mathrm{Bias}[\bar{Y}_N])^2$

$\sigma_Y^2/N + 0 = \sigma_N^2/N.$

$\mathsf{MSE}[S_N^2]$

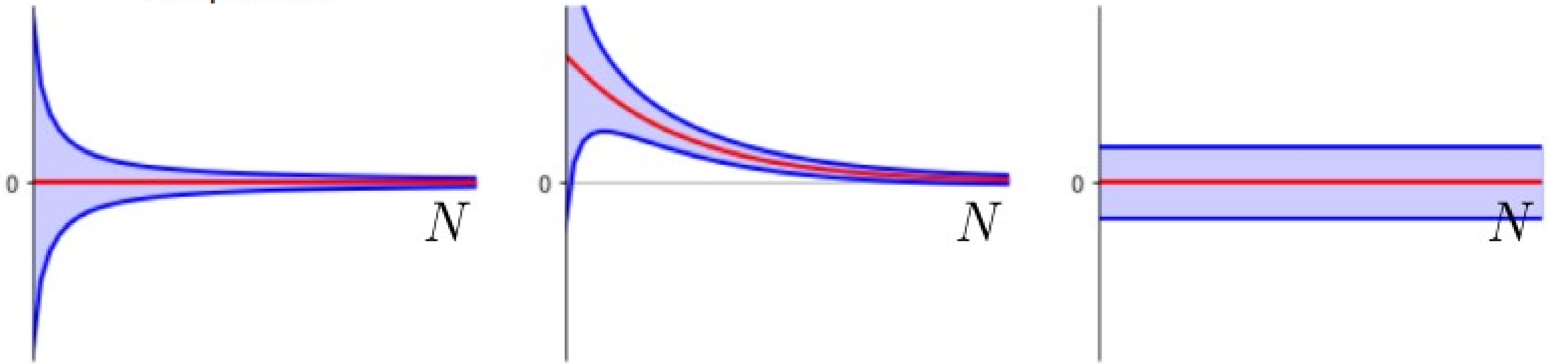
$\mathsf{MSE}[\tilde{S}_N^2]$

Asymptotic properties

- Asymptotic unbiasedness: $\lim\limits_{N\to\infty} \text{Bias}[\hat{\Theta}_N] = 0$

- Consistency: $\lim\limits_{N\to\infty} P\left(|\hat{\Theta}_N - \theta| \geq \epsilon\right) = 0$

Sample mean



Unbiased,
Consistent

Biased ,
Asymptoticall unbiased,
Consistent

Unbiased,
Inconsistent

Maximum Likelihood Estimation (MLE)

$$\hat{\theta}_N = g_N(\mathcal{D})$$ … general point estimation

- MLE:

  1) Pick a parametrization.

  2) Solve: $$\underline{\hat{\theta}}_{\text{MLE}} = \underset{\underline{\theta}}{\text{argmax}}\, \mathcal{L}(\underline{\theta}; \mathcal{D})$$

- Likelihood: $$\mathcal{L}(\underline{\theta}\,; \mathcal{D}) \;=\; \prod_{i=1}^{N} p_Y(y_i; \underline{\theta})$$

Example

- 4 marbles in a bag, all either black or white
- pick 5 times with replacement

Estimate the number of black marbles in the bag.

Log-likelihood

$$
\begin{aligned}
\underline{\hat{\theta}}_{\text{MLE}} &= \underset{\underline{\theta}}{\text{argmax}}\, \mathcal{L}(\underline{\theta}; \mathcal{D}) \\
&= \underset{\underline{\theta}}{\text{argmax}}\; \ln \mathcal{L}(\underline{\theta}; \mathcal{D}) \\
&= \underset{\underline{\theta}}{\text{argmax}}\; \ln \left(\prod_{i=1}^{N} p_Y(y_i; \underline{\theta}) \right) \\
&= \underset{\underline{\theta}}{\text{argmax}}\; \sum_{i=1}^{N} \ln p_Y(y_i; \underline{\theta})
\end{aligned}
$$

Example: Gaussian data

Assume: $Y \sim \mathcal{N}(\mu_Y, \sigma_Y^2) \quad , \quad \underline{\theta} = (\mu_Y, \sigma_Y^2)$

$$
\begin{aligned}
(\hat{\mu}_{\mathsf{MLE}}, \hat{\sigma}^2_{\mathsf{MLE}}) &= \underset{\mu, \sigma^2}{\mathsf{argmax}} \; \sum_{i=1}^{N} \mathsf{ln}\, p_Y(y_i; \mu, \sigma^2) \\
&= \underset{\mu, \sigma^2}{\mathsf{argmax}} \; \sum_{i=1}^{N} \mathsf{ln} \left(\frac{1}{\sqrt{2\pi\sigma^2}} \, \mathsf{exp} \left(-\frac{1}{2} \frac{(y-\mu)^2}{\sigma^2} \right) \right) \\
&= \underset{\mu, \sigma^2}{\mathsf{argmax}} \; \left(-\frac{N}{2} \, \mathsf{ln}(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^{N} (y_i - \mu)^2 \right) \\
&= \underset{\mu, \sigma^2}{\mathsf{argmin}} \; \left(\frac{N}{2} \, \mathsf{ln}(2\pi\sigma^2) + \frac{1}{2\sigma^2} \sum_{i=1}^{N} (y_i - \mu)^2 \right)
\end{aligned}
$$

Example: Gaussian data

$$(\hat{\mu}_{\mathsf{MLE}}, \hat{\sigma}^2_{\mathsf{MLE}}) = \underset{\mu,\sigma^2}{\mathsf{argmin}} \left(\frac{N}{2} \mathsf{ln}(2\pi\sigma^2) + \frac{1}{2\sigma^2} \sum_{i=1}^{N} (y_i - \mu)^2 \right)$$

$$J(\mu, \sigma^2) = \frac{N}{2} \mathsf{ln}(2\pi\sigma^2) + \frac{1}{2\sigma^2} \sum_{i=1}^{N} (y_i - \mu)^2$$

$$\nabla J(\mu, \sigma^2) = \left(\frac{\partial J}{\partial \mu}, \frac{\partial J}{\partial \sigma^2} \right) = 0$$

Example: Gaussian data

$$
\begin{aligned}
\frac{\partial J}{\partial \mu} &= \frac{\partial}{\partial \mu}\left(\frac{1}{2\sigma^2}\sum_{i=1}^{N}(y_i-\mu)^2\right) \\
&= \frac{1}{2\sigma^2}\sum_{i=1}^{N}\frac{\partial}{\partial \mu}(y_i-\mu)^2 \\
&= -\frac{1}{\sigma^2}\sum_{i=1}^{N}(y_i-\mu) \\
&= \frac{N\mu}{\hat{\sigma}^2} - \frac{1}{\sigma^2}\sum_{i=1}^{N} y_i
\end{aligned}
$$

Example: Gaussian data

$$\frac{\partial J}{\partial \sigma^2} = \frac{\partial}{\partial \sigma^2} \left(\frac{N}{2} \ln(2\pi\sigma^2) + \frac{1}{2\sigma^2} \sum_{i=1}^{N} (y_i - \mu)^2 \right)$$

$$= \frac{N}{2\sigma^2} - \frac{1}{2\sigma^4} \sum_{i=1}^{N} (y_i - \mu)^2$$

$$= \frac{1}{2\sigma^2} \left(N - \frac{1}{\sigma^2} \sum_{i=1}^{N} (y_i - \mu)^2 \right)$$

Properties of MLE

- MLE has no finite-sample properties.
  - ➔ not necessarily unbiased
  - ➔ not necessarily minimum MSE.

- MLE has good asymptotic properties.
  - ➔ consistent
  - ➔ usually asymptotically unbiased