Computer Science

CSC380: Principles of Data Science

Statistics 3

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1

1

Review: Maximum Likelihood Estimation

Suppose $x_i \sim p(x;\theta)$, the **joint probability** over N i.i.d $x_1,...,x_N$

$$p(x_1,\dots,x_N;\theta) = \prod_{i=1}^N p(x_i;\theta)$$

Maximum Likelihood Estimator (MLE) as the name suggests, maximizes the likelihood function.

$$\hat{\theta}^{\text{MLE}} = \arg\max_{\theta} \mathcal{L}_N(\theta) = \prod_{i=1}^N p(x_i;\theta)$$

Log Likelihood Maximum

$$\hat{\theta}^{\text{MLE}} = \arg\max_{\theta} \ \log \mathcal{L}_N(\theta) = \sum_{i=1}^N \log p(x_i;\theta)$$

Finding the MLE:
1. closed-form
2. iterative methods

2

Maximum Likelihood Estimator Properties

1) The MLE is a **consistent** estimator:

$$\lim_{n\to\infty} \hat{\theta}_n^{\mathrm{MLE}} \xrightarrow{P} \theta_*$$

Roughly, converges to the true value.

2) The MLE is **efficient**: roughly, has the lowest mean squared error among all consistent estimators.

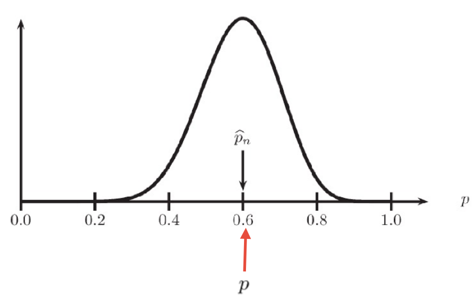
$$\mathrm{MSE}(\hat{\theta}_n) = \mathbf{E}[(\hat{\theta}_n - \theta)^2]$$

3) The MLE is **Normal**: roughly, the estimator (which is a <u>random variable</u>) approaches a Normal distribution.

3

Maximum Likelihood Estimator Properties

3) The MLE is **Normal**: roughly, the estimator (which is a <u>random variable</u>) approaches a Normal distribution.



- We pick k different samples (each sample has N i.i.d observations)
- We pose a model with unknown parameter
- Get MLE estimation for the parameter (a total of k estimators)
- The distribution of k estimators is roughly normal distribution
  - Expectation
  - Variance

Q: for sample mean, what's E[X] and Var[X]?

4

Sample Mean: Expectation and Variance

Review: Bernoulli Expectation and Variance

$$X = \begin{cases} 1 & \text{with probability } p \\ 0 & \text{with probability } 1-p \end{cases}$$

Tosing a biased coin

Warning: The meaning here of \`p' is π in previous slides.

$$E[X] = p \cdot 1 + (1-p) \cdot 0 = p$$
$$E[X^2] = p \cdot 1^2 + (1-p) \cdot 0^2 = p$$
$$Var[X] = E[X^2] - (E[X])^2 = p - p^2$$

Standard Dev: $\sigma = \sqrt{Var[X]} = \sqrt{p - p^2}$

Sanity Check: Example $p = 1/2$ (fair coin)

The mean is $1/2$.

$$Var[X] = 0.5 - 0.25 = \frac{1}{4} \quad \sigma = \sqrt{\frac{1}{4}} = \frac{1}{2}$$

Intuitively The avg distance from 0.5 to either 0 or 1 is 0.5

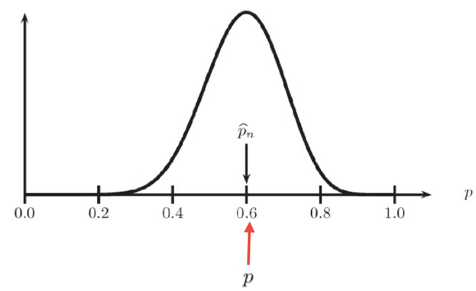
Expectation of the Sample Mean

7

Recall: An estimator $\hat{\theta}$ is a RV (Random Variable).

Example Let $X_1, \ldots, X_N \overset{\text{iid}}{\sim} \text{Bernoulli}(p)$ and estimate $\hat{p}$ be the *sample mean*,

$$\hat{p} = \frac{1}{N} \sum_i X_i$$



Question What is the expected value of $\hat{p}$?

Notation: $X \coloneqq (X_1, \ldots, X_N)$

$$\mathbf{E}[\hat{p}(X)] = \mathbf{E}\left[\frac{1}{N}\sum_i X_i\right] \overset{(a)}{=} \frac{1}{N}\sum_i \mathbf{E}\left[X_i\right] \overset{(b)}{=} \frac{1}{N} N p = p$$

(a) Linearity of Expectation Operator

(b) Mean of Bernoulli RV = p

Conclusion *On average* $\hat{p} = p$ *(it is unbiased)*

7

Variance of the Sample Mean

8

Example Let $X_1, \ldots, X_N \overset{\text{iid}}{\sim} \text{Bernoulli}(p)$ and estimate $\hat{p}$ be the *sample mean.* Calculate the variance of $\hat{p}$:

quiz candidate

$$\mathbf{Var}(\hat{p}) = \mathbf{Var}\left(\frac{1}{N}\sum_i X_i\right) \overset{(a)}{=} \frac{1}{N^2}\mathbf{Var}\left(\sum_i X_i\right) \overset{(b)}{=} \frac{1}{N^2}\sum_i \mathbf{Var}\left(X_i\right)$$

$$\overset{(c)}{=} \frac{1}{N^2}\sum_i p(1-p) = \frac{1}{N}p(1-p) = \frac{1}{N}\mathbf{Var}(X)$$

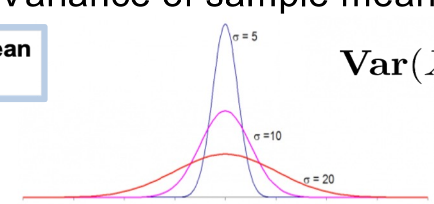
(a) $\mathbf{Var}(cX) = c^2\mathbf{Var}(X)$

(b) Independent RVs

(c) Var(X) = p(1-p) for Bernoulli

In General Variance of sample mean $\bar{X}$ for RV with variance σ^2;

STDEV of sample mean decreases as $1/\sqrt{N}$



$$\mathbf{Var}(\bar{X}) = \frac{\sigma^2}{N}$$

Decreases linearly with number of samples N

8

All Facts about Sample Mean

Experiment Flip a coin 100 times and observe 73 heads, 27 tails

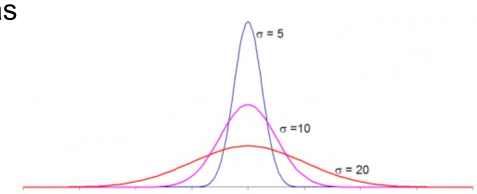
- We don't know the coin bias. By intuition, we guess coin bias is sample mean 0.73.
- We are told that maximum likelihood estimation is a method that can estimate the parameter of an assumed probability distribution.
- So we pose a model of bernoulli, and calculate the estimator that can maximum the log likelihood function.
- We find the maximum likelihood estimator is sample mean = our intuition!

9

All Facts about Sample Mean

Experiment Flip a coin 100 times and observe 73 heads, 27 tails

- If we repeatedly flip a coin 100 times (N=100), say 1000 trails (1000 samples). We will get 1000 sample means. So sample mean is also a RV. It has a distribution.
- Pile 1000 sample means up, we get a distribution (roughly normal). The mean of the distribution (expectation) = true coin bias.
- If we flip a coin 10,000 times (N=10,000), repeat for 1000 trails (1000 samples). The variance of the distribution is very small. We can trust the sample mean more when estimating true coin bias



10

11

Sample Variance: Expectation

11

12

Unbiasedness of the Sample Variance?

Recall: Sample mean is an unbiased estimator for the true mean.
How about the sample variance?

Ex. Let $X_1, \ldots, X_N$ be drawn (iid) from any distribution with $\mathbf{Var}(X) = \sigma^2$ and,

$$\hat{\sigma}^2 = \frac{1}{N}\sum_i (X_i - \hat{\mu})^2$$

Source of bias: plug-in mean estimate

Then the sample variance is a **biased estimator**.

$$\mathbf{E}[\hat{\sigma}^2] = \frac{1}{N}\sum_i \mathbf{E}\left[(X_i - \hat{\mu})^2\right] = \text{boring algebra} = \frac{N-1}{N}\sigma^2$$

tends to underestimate

Q: is this estimator consistent or not? Consistent!

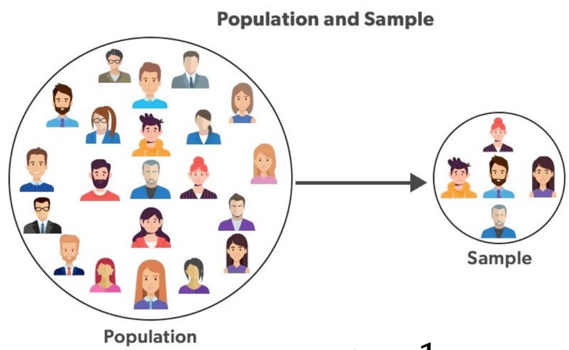
Correcting bias yields unbiased variance estimator:

$$\hat{\sigma}^2_{\text{unbiased}} = \frac{N}{N-1}\hat{\sigma}^2 = \frac{1}{N-1}\sum_i (X_i - \hat{\mu})^2 \qquad E\left[\hat{\sigma}^2_{unbiased}\right] = \sigma^2$$

12

Sample Variance estimator vs MLE estimator

13



$\widehat{\mu}, \widehat{\sigma}$

Pose a Gaussian model with unknown parameters: μ, σ

$$\widehat{\sigma}^2 = \frac{1}{n}\sum_i (x_i - \widehat{\mu})^2$$ MLE: Biased

$$\widehat{\mu} = \frac{1}{n}\sum_i x_i$$

$$\widehat{\sigma}^2_{unbiased} = \frac{1}{n-1}\sum_i (x_i - \widehat{\mu})^2$$ Unbiased

For parameter mean: sample mean --- unbiased, consistent, efficient.

For parameter variance: biased or unbiased?

13

Numpy Background

14

- Often, you have a matrix of data: e.g., movie review score

User \ Movie	Inception	Jurassic park	Batman
A	5	2	3
B	1	4	2
C	4	3	3
D	1	2	3

Numpy arrays can be 2d

```
A = np.array([[1,2,3],[4,5,6]])
A[0,1]
⇒ 2
mean(A,0)
⇒ array([2.5, 3.5, 4.5])
mean(A,1)
⇒ array([2., 5.])
```

means $\begin{pmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{pmatrix}$

access A[0,1] means 1st row, 2nd column

computes average for each column

computes average for each row

var(A,0), var(A,1) works the same way!

14

More on Unbiased Estimator

15

Task: Compare the **MSE** (mean squared error) of the two variance estimators for N=5.

$\mathrm{MSE}(\hat{\theta}_n) = \mathbf{E}[(\hat{\theta}_n - \theta)^2]$

```
import numpy as np
import numpy.random as ra
X = ra.randn(10_000,5)   # 10k by 5 matrix of 𝒩(0,1) => 10k random trials

np.mean((var(X,1,ddof=0) - 1)**2)
⟹ 0.36310526687176103
```

ddof=0 uses 1/N

$$\hat{\sigma}^2 = \frac{1}{n}\sum_i (x_i - \hat{\mu})^2$$

```
np.mean((var(X,1,ddof=1) - 1)**2)
⟹ 0.5071783438808787
```

ddof=1 uses 1/(N-1)

$$\hat{\sigma}^2_{unbiased} = \frac{1}{n-1}\sum_i (x_i - \hat{\mu})^2$$

biased version is more accurate! (but recall that it will underestimate)

There is a trade off between bias and variance!!

15

Bias-Variance Tradeoff

16

Is an unbiased estimator "better" than a biased one? It depends…

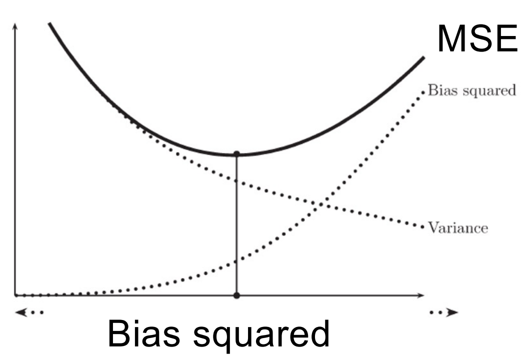
Evaluate the quality of estimate $\hat{\theta}$ using **mean squared error**,

$$\mathrm{MSE}(\hat{\theta}) = \mathbf{E}\left[(\hat{\theta} - \theta)^2\right] = \mathrm{bias}^2(\hat{\theta}) + \mathbf{Var}(\hat{\theta})$$

- MSE for unbiased estimators is just,

$$\mathrm{MSE}(\hat{\theta}) = \mathbf{Var}(\hat{\theta})$$

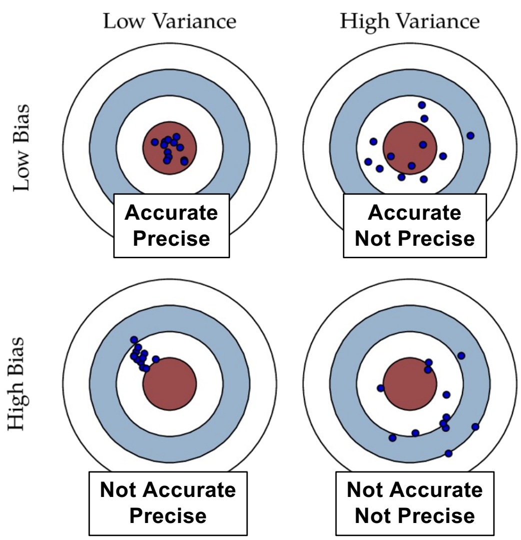
- Bias-variance is fundamental tradeoff in statistical estimation
- MSE increases as **square** of bias
- Biased estimator can be more accurate than an unbiased one.



16

Bias-Variance Tradeoff

Suppose an archer takes multiple shots at a target…



$$\text{MSE}(\hat{\theta}) = \text{bias}^2(\hat{\theta}) + \textbf{Var}(\hat{\theta})$$

- Bias: distance from the center of target
- Variance: distance from the center of mutiple shots

MSE: MLE < Sample variance

- higher bias and lower var can be more efficient than lower bias and higher var.

Bias-Variance Decomposition

quiz candidate

$$\begin{aligned}
\text{MSE}(\hat{\theta}) &= \mathbf{E}\left[(\hat{\theta}(X) - \theta)^2\right] \\
&= \mathbf{E}\left[\left(\hat{\theta} - \mathbf{E}[\hat{\theta}] + \mathbf{E}[\hat{\theta}] - \theta\right)^2\right] \\
&= \mathbf{E}[(\hat{\theta} - \mathbf{E}[\hat{\theta}])^2] + 2(\mathbf{E}[\hat{\theta}] - \theta)\mathbf{E}[\hat{\theta} - \mathbf{E}[\hat{\theta}]] + \mathbf{E}\left[\left(\mathbf{E}[\hat{\theta}] - \theta\right)^2\right] \\
&= \left(\mathbf{E}[\hat{\theta}] - \theta\right)^2 + \mathbf{E}[(\hat{\theta} - \mathbf{E}[\hat{\theta}])^2] \\
&= \text{bias}^2(\hat{\theta}) + \text{Var}(\hat{\theta})
\end{aligned}$$

Intuition Check

Compare the results of two coin flip experiments…

Experiment 1 Flip 100 times and observe 73 heads, 27 tails

Experiment 2 Flip 1,000 times and observe 730 heads, 270 tails

Question The MLE estimate of coin bias for both experiments is equivalent $\hat{\theta} = 0.73$. Which should we trust more? Why?

Answer: biases are the same (MLE use sample mean and therefore unbiased). Variance is smaller for experiment 2 (larger N). The estimator in Experiment 2 has smaller MSE.