# Introduction to Probability

## Lecture 11: Estimators (Part II)

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# Outline

# Estimating Population Size (First Model)

- Suppose we have a sample of a few serial numbers (IDs) of some product
- We assume IDs are running from 1 to an unknown parameter $N$ (so $N = \theta$)
- Each of the IDs is drawn without replacement from the discrete uniform distribution over $\{1, 2, \ldots, N\}$
- This is also known as Tank Estimation Problem or (Discrete) Taxi Problem

$$7, 3, 10, 46, 14$$

**Warning**

- As before, we denote the samples $X_1, X_2, \ldots, X_n$
- Since sampling is without replacement:
  - they are not independent! (but identically distributed)
  - their number must satisfy $n \leq N$

# First Estimator Based on Sample Mean

**Example 1**

Construct an unbiased estimator $T_1$ using the sample mean.

Answer

# Example: Odd Behaviour of $T_1$

- Suppose $n = 5$
- Let the sample be

$$7, 3, 10, 46, 14$$

- The estimator returns:

$$T_1 = 2 \cdot \overline{X}_n - 1 = 2 \cdot \frac{80}{5} - 1 = 31 \quad \text{☹}$$

This estimator will often unnecessarily underestimate the true value $N$.

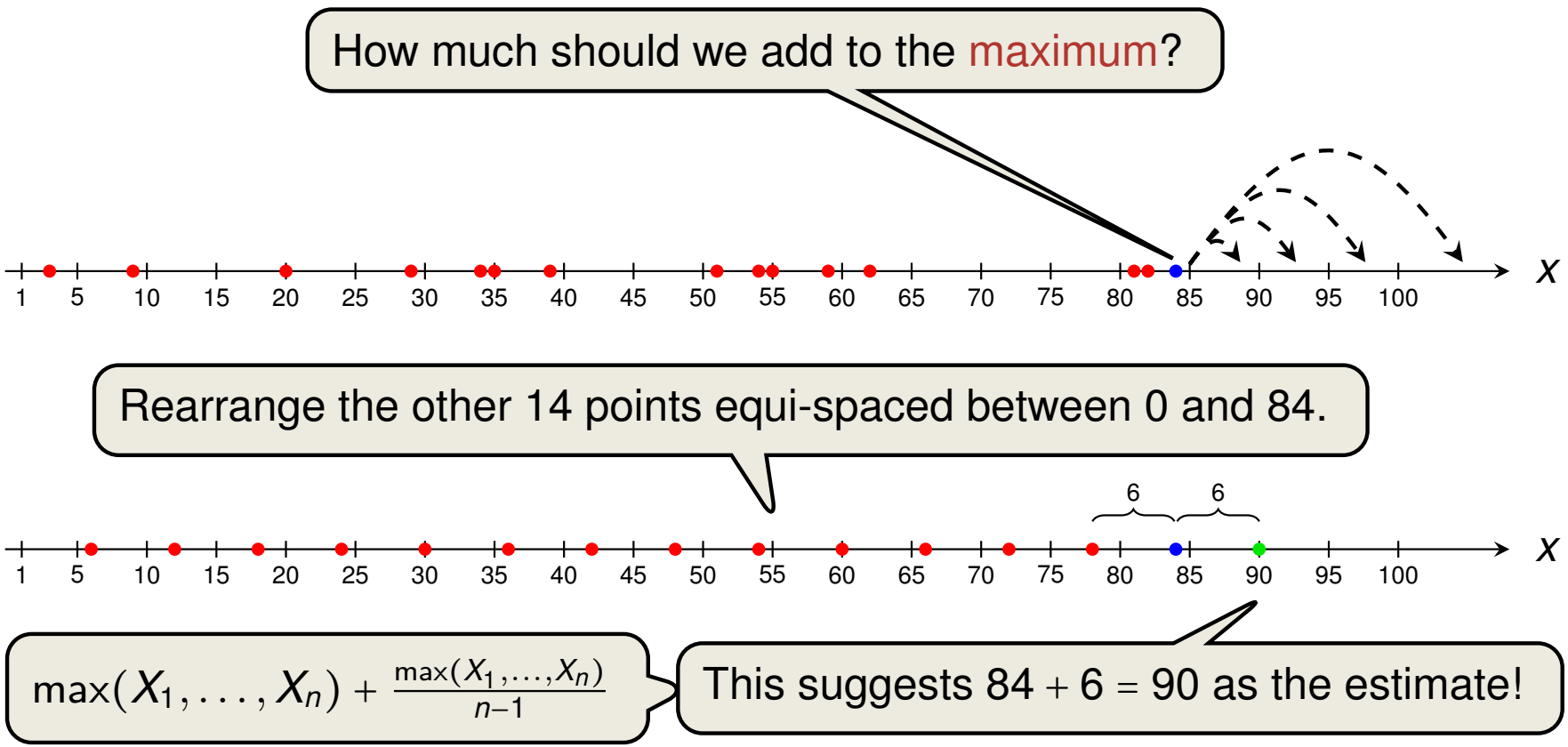
Challenging exercise: Find a lower bound on $\mathbf{P}\left[\, T_1 < \max(X_1, X_2, \ldots, X_n) \,\right]$

- Achieving unbiasedness alone is not a good strategy
- Improvement: find an estimator which always returns a value at least $\max(X_1, X_2, \ldots, X_n)$

# Intuition: Constructing an Estimator based on Maximum Sample

- Suppose $n = 15$
- Our samples are:

$$9, 82, 39, 35, 20, 51, 54, 62, 81, 29, 84, 59, 3, 34, 55$$



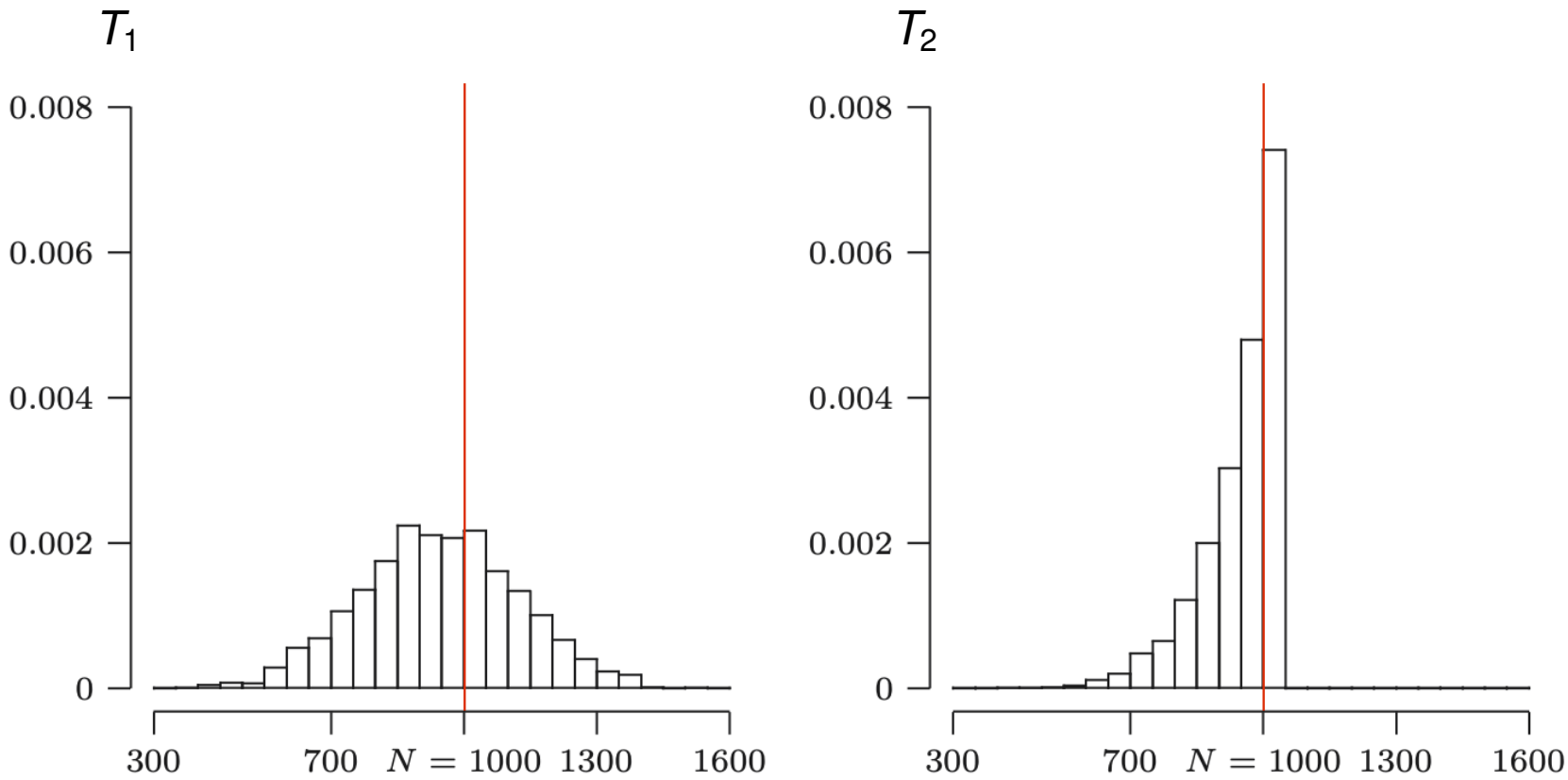
# Deriving the Estimator Based on Maximum Sample

Example 2

Construct an unbiased estimator $T_2$ using $\max(X_1, \ldots, X_n)$

Answer

# Empirical Analysis of the two Estimators




Source: Modern Introduction to Statistics

Figure: Histogram of 2000 values for $T_1$ and $T_2$, when $N = 1000$ and $n = 10$.

Can we find a quantity that captures the superiority of $T_2$ over $T_1$?

# Outline

# Mean Squared Error

**Mean Squared Error Definition**

Let $T$ be an estimator for a parameter $\theta$. The mean squared error of $T$ is

$$\mathbf{MSE}[\,T\,] = \mathbf{E}\left[\,(T-\theta)^2\,\right].$$

- According to this, estimator $T_1$ better than $T_2$ if $\mathbf{MSE}[\,T_1\,] < \mathbf{MSE}[\,T_2\,]$.

**Bias-Variance Decomposition**

The mean squared error can be decomposed into:

$$\mathbf{MSE}[\,T\,] = \underbrace{(\mathbf{E}[\,T\,]-\theta)^2}_{=\text{Bias}^2} + \underbrace{\mathbf{V}[\,T\,]}_{=\text{Variance}}$$

- If $T_1$ and $T_2$ are both unbiased, $T_1$ is better than $T_2$ iff $\mathbf{V}[\,T_1\,] < \mathbf{V}[\,T_2\,]$.

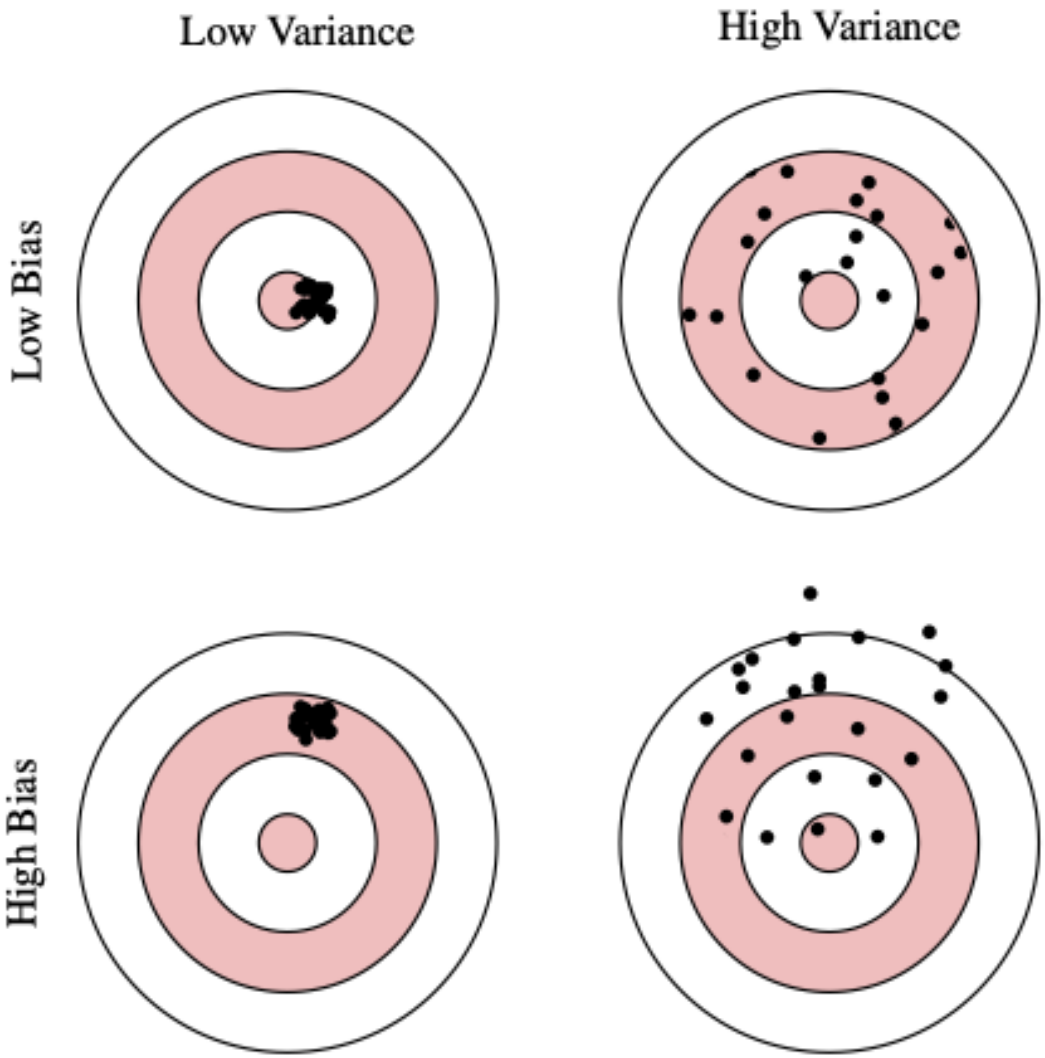
# Bias-Variance Decomposition: Derivation

Example 3

We need to prove: $\mathbf{MSE}[T] = (\mathbf{E}[T] - \theta)^2 + \mathbf{V}[T]$.

Answer

# Bias-Variance Decomposition: Illustration




Source: Edwin Leuven (Point Estimation)

## Example 4

It holds that $\textbf{MSE}[\ T_1\ ] = \Theta\left(\frac{N^2}{n}\right)$, where $T_1 = 2 \cdot \overline{X}_n - 1$.

Answer

# Analysis of the MSE for $T_2$ (non-examinable)

Example 5

It holds that $\mathbf{MSE}[\,T_2\,] = \Theta\left(\frac{N^2}{n^2}\right)$, where $T_2 = \frac{n+1}{n} \cdot \max(X_1, \ldots, X_n) - 1$.

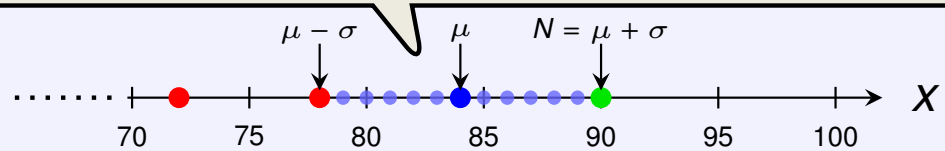
Answer

- $T_2$ is unbiased $\Rightarrow$ need $\mathbf{V}[\,T_2\,]$ which reduces to $\mathbf{V}[\,\max(X_1, \ldots, X_n)\,]$
- One can prove:

For details see Dekking et al.

$$\mathbf{V}[\,\max(X_1, \ldots, X_n)\,] = \cdots = \frac{n(N+1)(N-n)}{(n+2)(n+1)^2} = \Theta\left(\frac{N^2}{n^2}\right)$$

Equi-spaced (idealised) configuration suggests a standard deviation of $\sigma \approx \frac{N}{n}$




Maximum could have equally likely taken any value between 79 and 90

- $\mathbf{MSE}[\,T_2\,]$ is much lower than $\mathbf{MSE}[\,T_1\,] = \Theta\left(\frac{N^2}{n}\right)$, i.e., $\frac{\mathbf{MSE}[\,T_1\,]}{\mathbf{MSE}[\,T_2\,]} = \frac{n+2}{3}$
- $\Rightarrow$ confirms simulations suggesting that $T_2$ is better than $T_1$!
- can be shown $T_2$ is the best unbiased estimator, i.e., it minimises MSE.

# Outline

# A New Estimation Problem

**Previous Model**

- Population/ID space $S = \{1, 2, \ldots, N\}$
- We take uniform samples from $S$ without replacement
- **Goal:** Find estimator for $N$

Similar idea applies to situations where elements are not labelled before we see them first time (Mark & Recapture Method)

**New Model**

- Population/ID space of size $|S| = N$
- We take uniform samples from $S$ with replacement
- **Goal:** Find estimator for $N$

- Suppose $n = 6$, $N = 11$, $S = \{3, 4, 7, 8, 10, 15.83356, 20, 21, 56, 81, 10000\}$
- Let the sample be

$$10, 81, 20, 3, 81, 10000$$

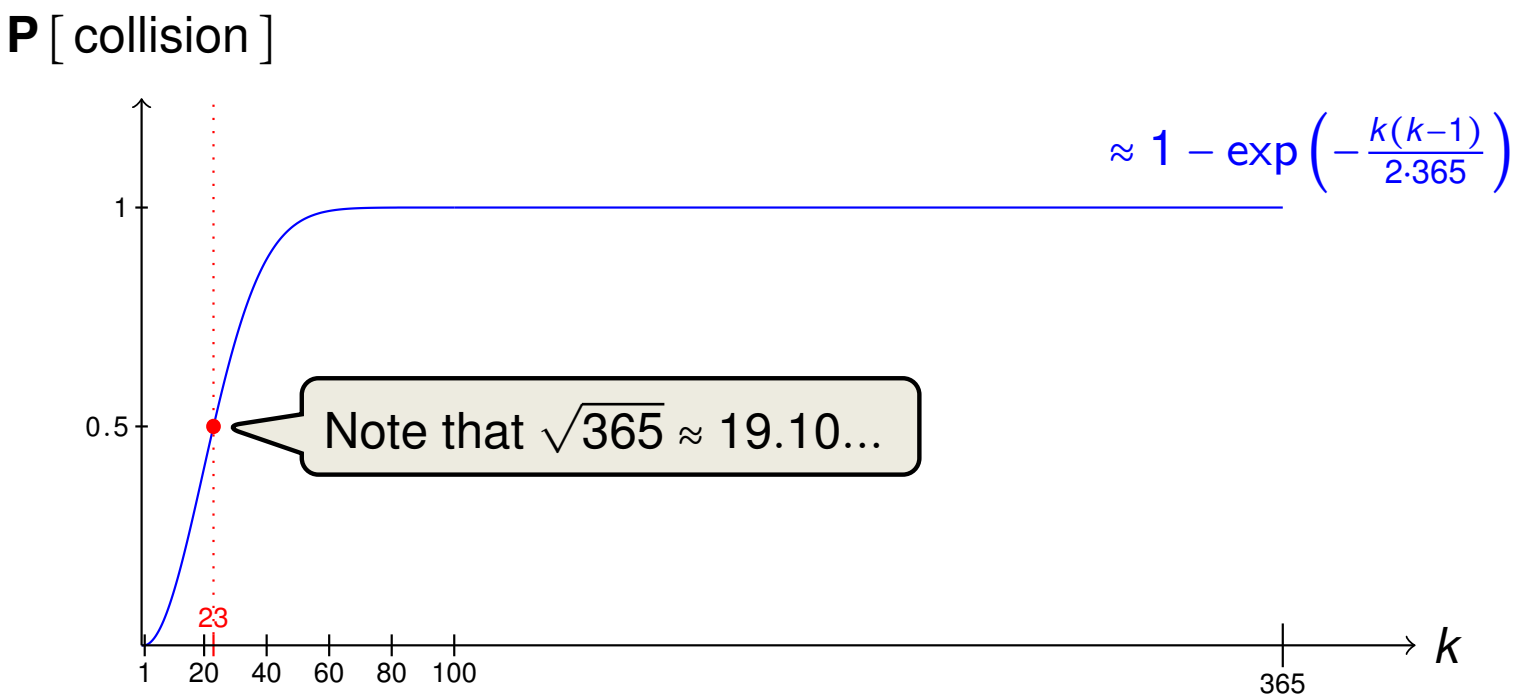
Let us call this a **collision**

As we do not know $S$, our only clue are elements that **were sampled twice.**

# Birthday Problem

**Birthday Problem:** Given a set of $k$ people

- What is the probability of having two with the same birthday (i.e., having at least one collision)?
- What is the expected number of people one needs to ask until the first collision occurs?



# Estimation via Collision: The Algorithm

Recall: As we do not know $S$, our only information are **collisions**.

FIND-FIRST-COLLISION($S$)

1: $C = \varnothing$
2: **For** $i = 1, 2, \ldots$
3: Take next i.i.d. sample $X_i$ from $S$
4: **If** $X_i \notin C$ **then** $C \leftarrow C \cup \{X_i\}$
5: **else return** $T(i)$
6: **End For**

$T(i)$ will be the value of the estimator if algo returns after $i$ rounds. (We want $T$ unbiased)

- Running Time: The expected time until the algorithm stops is:
  = the expected number of samples until a collision...

Same as the birthday problem, but now with $|S| = N$ days... ☺

Expected Running Time (Knuth, Ramanujan)

$$\sqrt{\frac{\pi N}{2}} - \frac{1}{3} + O\left(\frac{1}{\sqrt{N}}\right).$$

**Exercise:** Prove a bound of $\leq 2 \cdot \sqrt{N}$

# Estimation via Collision: Getting the Estimator Unbiased

**Example 6**

One can define $T(i)$, $i \in \mathbb{N}$, such that $\mathbf{E}[\,T\,] = |S|$ for any finite, non-empty set $S$.

Answer

# Extra Slide on the Collision Algorithm (non-examinable)

+ The algorithm runs in (expected) sublinear time $O(\sqrt{N})$, where $N := |S|$
– The algorithm does not take a pre-specified and fixed number of samples

What can we do with a fixed number of samples $n$?

- We cannot find an unbiased estimator that works for any $N$ (similar to Lecture 10, Slide 22)
- Could use hypothesis testing: For a fixed sample $(x_1, x_2, \ldots, x_n)$ with $c$ collisions, what is the probability to have $c$ collisions under hypothesis that $N \geq x$ (or $N = x$) for some value $x$?
- Bayesian Approach: Assume unknown parameter $N$ comes from a (known) probability distribution (called prior distribution). For a fixed sample $(x_1, x_2, \ldots, x_n)$, update the probability distribution (called posterior distribution)

$$N \sim \text{Exp}(1/1000) \xrightarrow{X_1 = x_1, \ldots, X_n = x_n} N \sim \left(\text{Exp}(1/1000) \,\middle|\, X_1 = x_1, \ldots, X_n = x_n\right)$$