Different Approaches to Probability Theory Data Science and A.I. Lecture Series

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 - Axiomatic probability

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where:

- m: Number of times event A occurs.
- $\bullet~n$: Total number of trials under identical conditions.

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• Example: Probability that an employee's salary is less than Rs. 150.

Salary Range (Rs.)	Number of Employees
Below 100	20
100-150	40
150-200	50
200 and above	15

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- Employees with salary < 150: 20 + 40 = 60

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- Total employees: 20 + 40 + 50 + 15 = 125
- Employees with salary < 150: 20 + 40 = 60
- Probability:

$$P(\text{Salary} < 150) = \frac{60}{125} = 0.48$$

• Toss a coin 200 times and record the number of heads.

Number of Tosses (n)	Number of Heads (m)	Proportion m/n
1	1	1.0
2	2	1.0
3	2	0.67
4	3	0.75
10	6	0.6
50	29	0.58
200	105	0.525

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$$\lim_{n\to\infty}\frac{m}{n}=0.5$$

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• Probability of getting heads is $\frac{1}{2}$.

• Experimental conditions may change over time.

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- Experimental conditions may change over time.
- $\lim_{n\to\infty} \frac{m}{n}$ may not converge to a unique value.

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