

1. Conditional Probability

1.1 Learning Objectives

By the end of this lecture, you will be able to:

- Define and compute conditional probabilities
- Apply the multiplication rule
- Understand how conditioning reduces the sample space
- Use conditional probability in sequential experiments

1.2 Motivating Example

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$$P(\{6\} \mid \text{even}) = \frac{1}{3}$$

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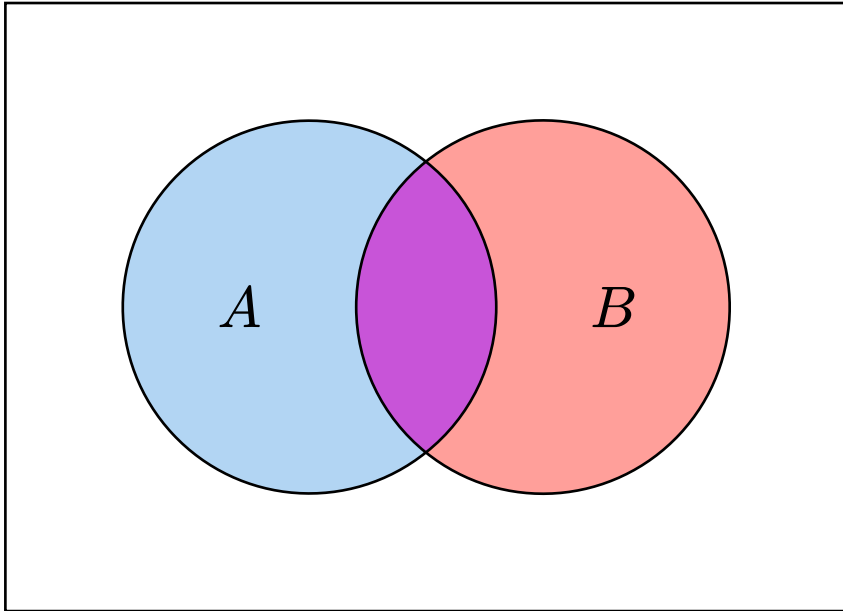
Definition: Conditional Probability

The conditional probability of A given B is:

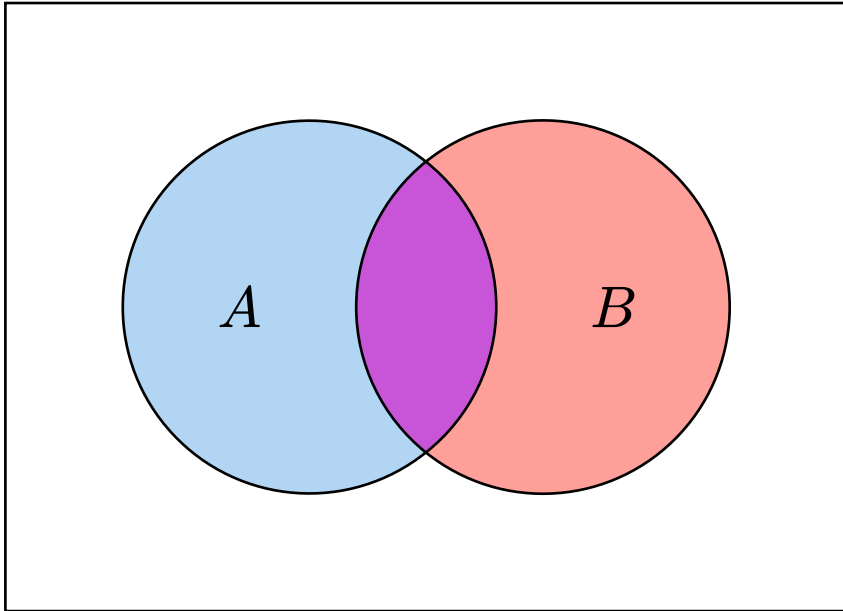
$$P(A \mid B) = \frac{P(A \cap B)}{P(B)}$$

provided $P(B) > 0$.

1.4 Visualizing Conditional Probability

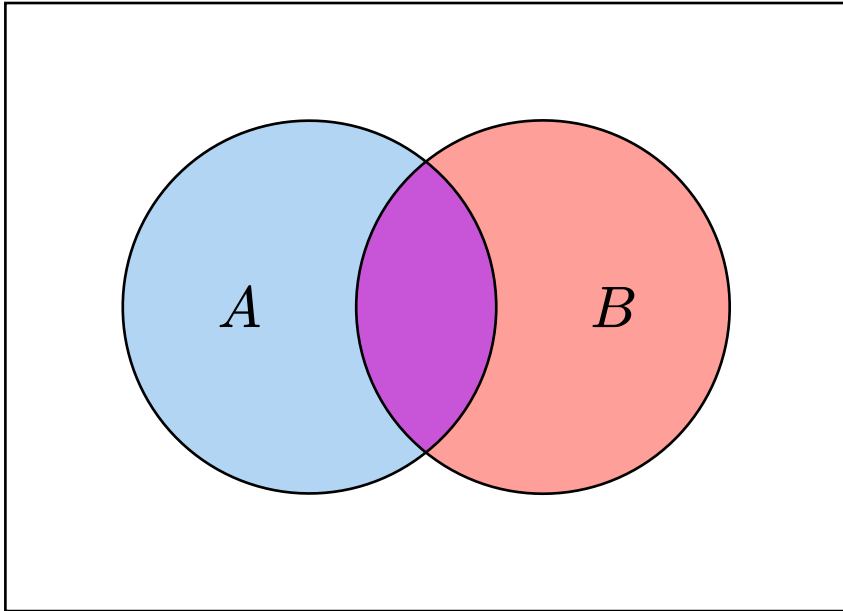


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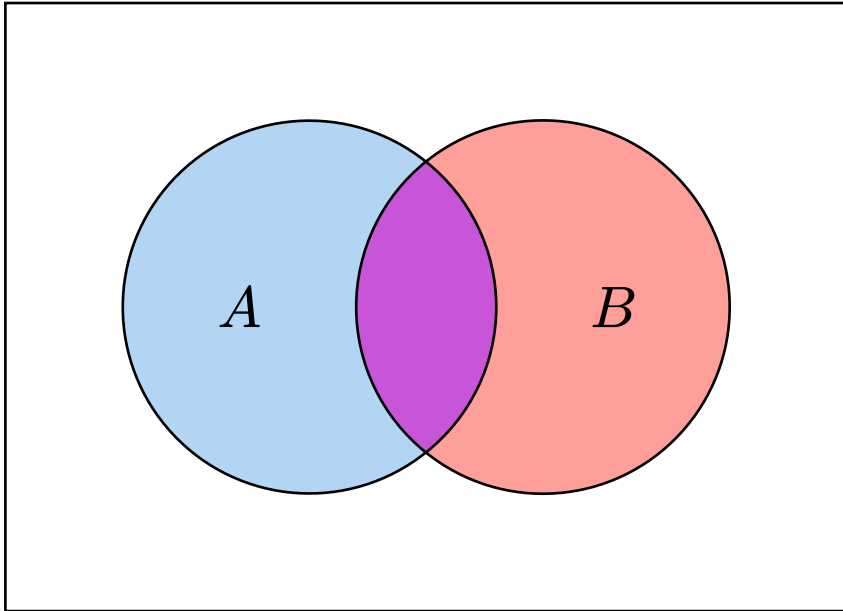
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Note: We only look at lines where B occurred, then ask: among those, what fraction also has A ?

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Line	X	S	$X = 1$ and $S = 6$	$X = 1 \mid S = 6$
1	3	8	No	NA
2	1	6	Yes	Yes
3	2	7	No	NA
4	5	6	No	No
5	1	4	No	NA
6	4	6	No	No

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6	4	6	No	No

- $P(X = 1 \text{ and } S = 6) = \frac{1}{36}$ (1 Yes out of 6 lines total)
- $P(X = 1 \mid S = 6) = \frac{1}{3}$ (1 Yes out of 3 non-NA lines)

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There are 13 hearts, and exactly 1 is an Ace.

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Rearranging the definition:

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Note: Very useful for sequential experiments!

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$$\begin{aligned}P(A_1 \cap A_2) &= P(A_1) \cdot P(A_2 \mid A_1) \\&= \frac{4}{52} \cdot \frac{3}{51} \\&= \frac{12}{2652} = \frac{1}{221}\end{aligned}$$

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After drawing an Ace, only 3 Aces remain among 51 cards.

2. Tree-Based Modeling

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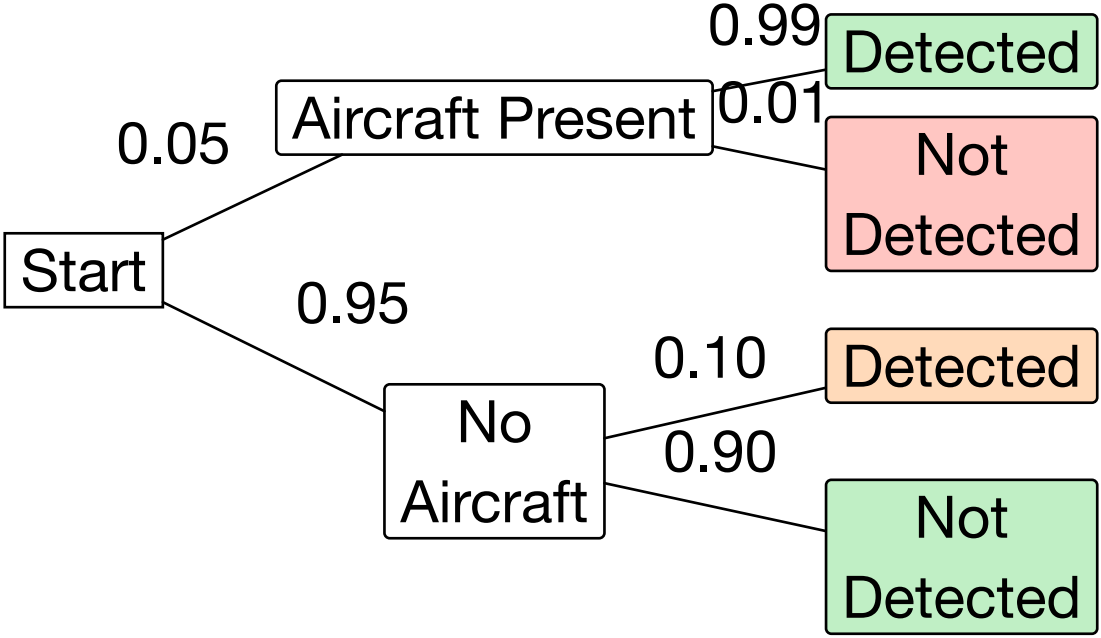
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Questions:

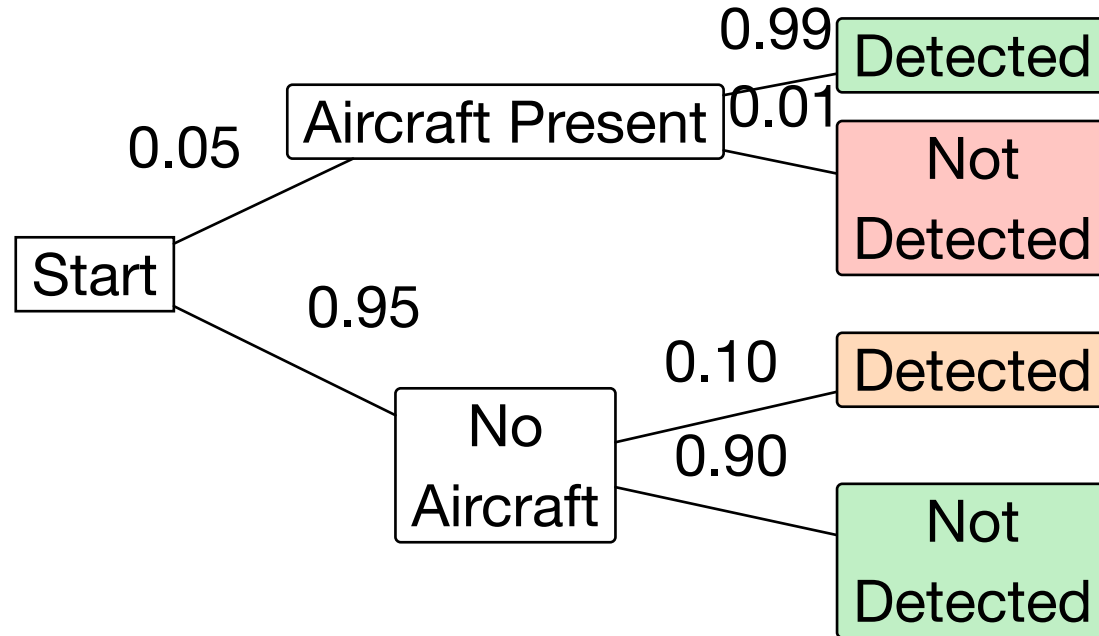
1. What is the probability of a **false alarm**?
2. What is the probability of **missed detection**?

Bertsekas and Tsitsiklis

2.2 Visualizing with a Tree Diagram

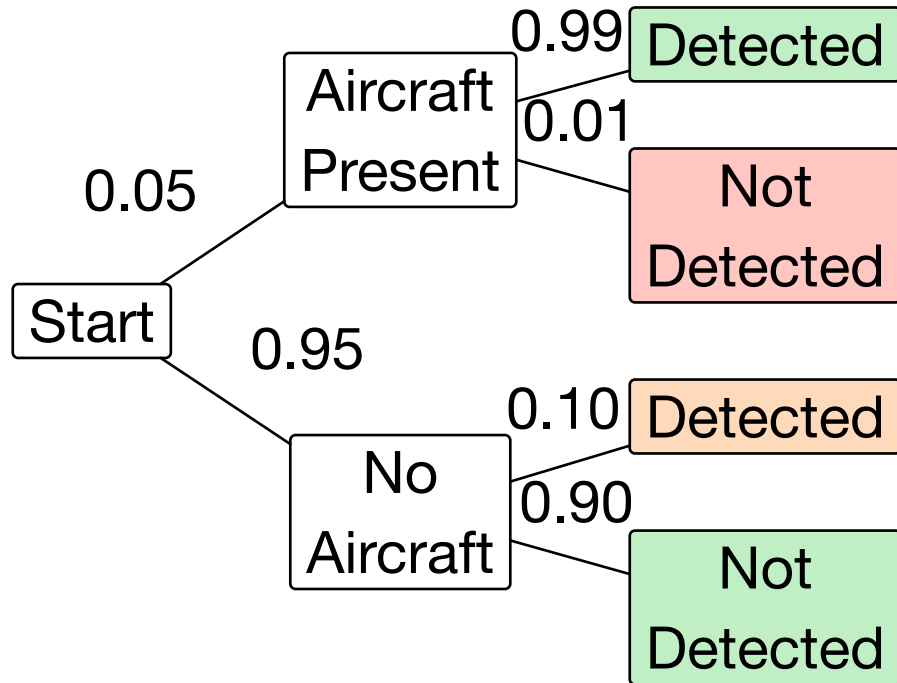


2.2 Visualizing with a Tree Diagram



Each **path** from start to end represents a possible outcome.

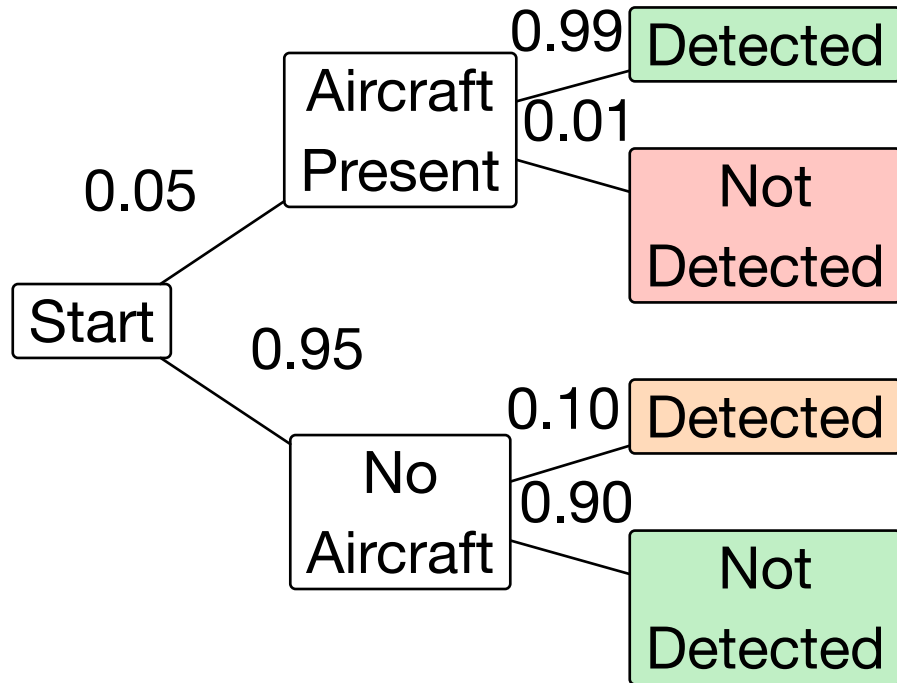
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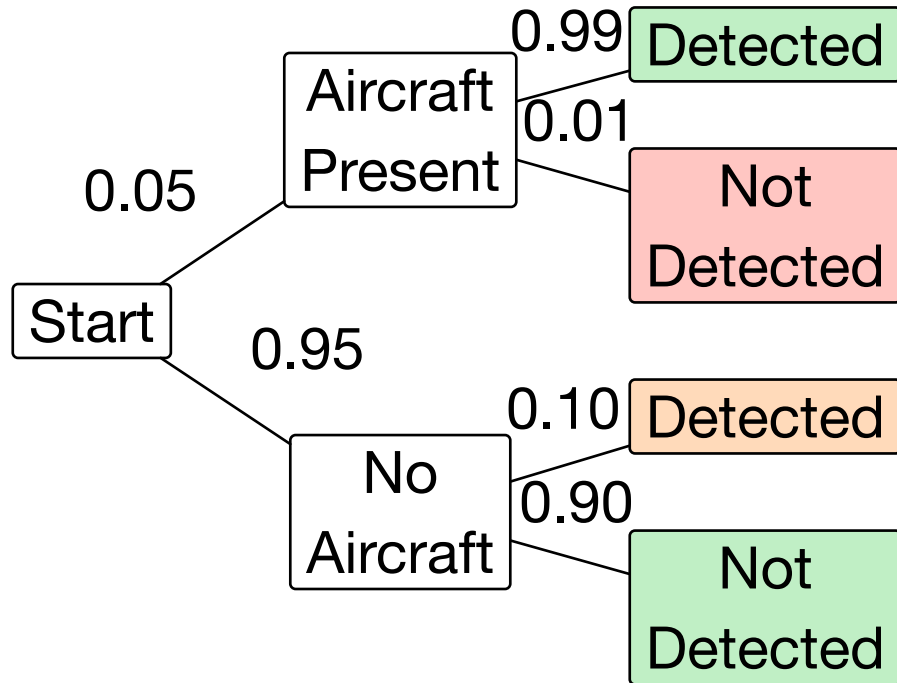
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Also consider the complements:

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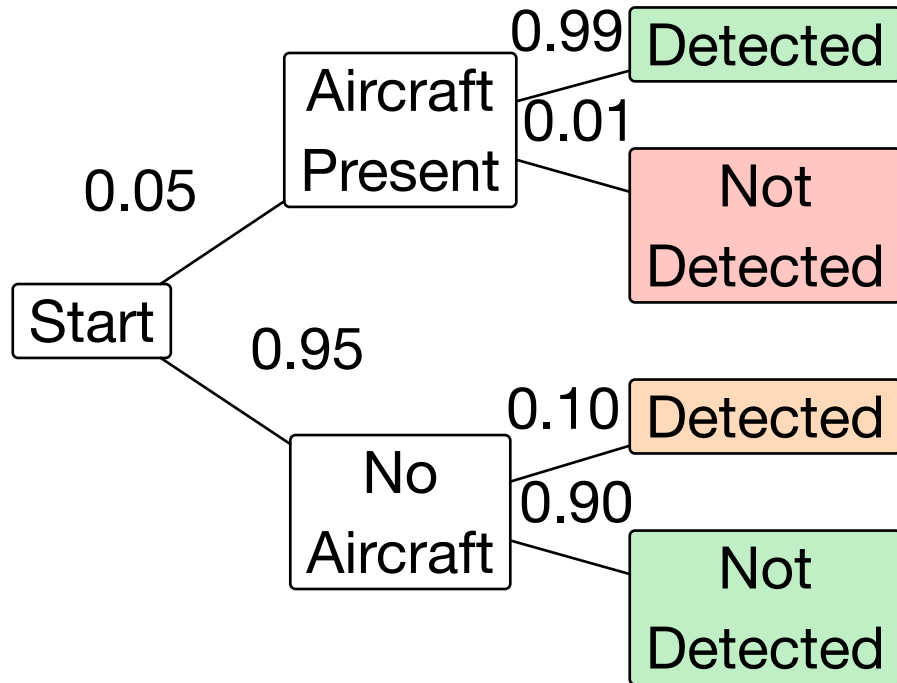
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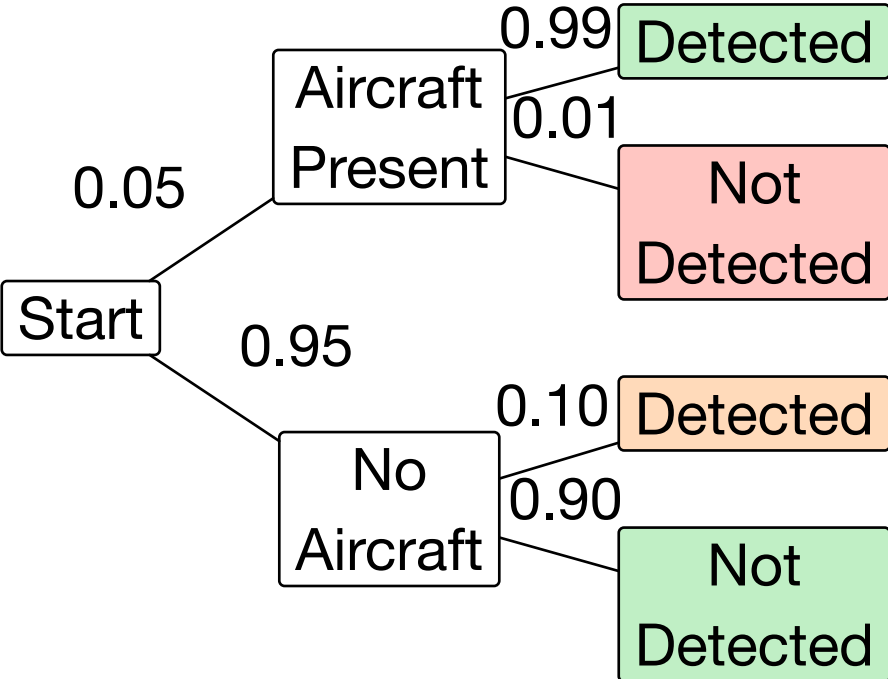
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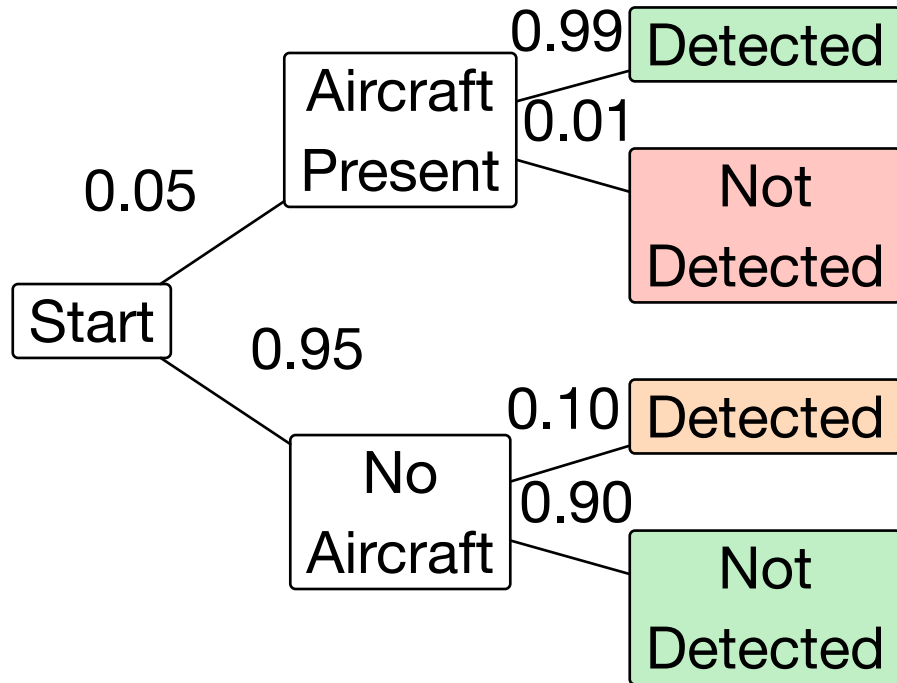
Missed detection: $A \cap B^c$

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Use the multiplication rule:

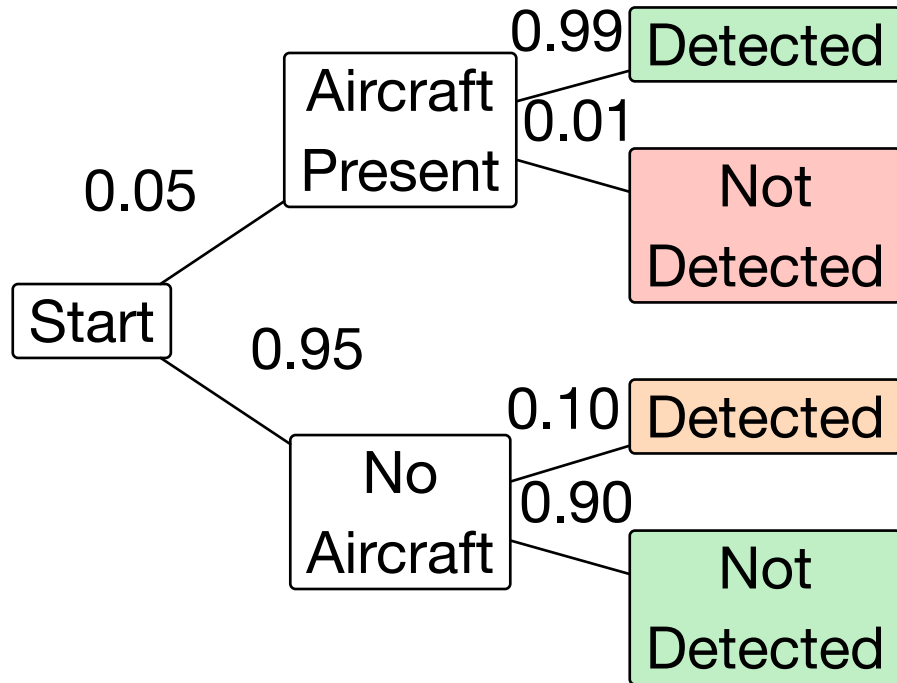
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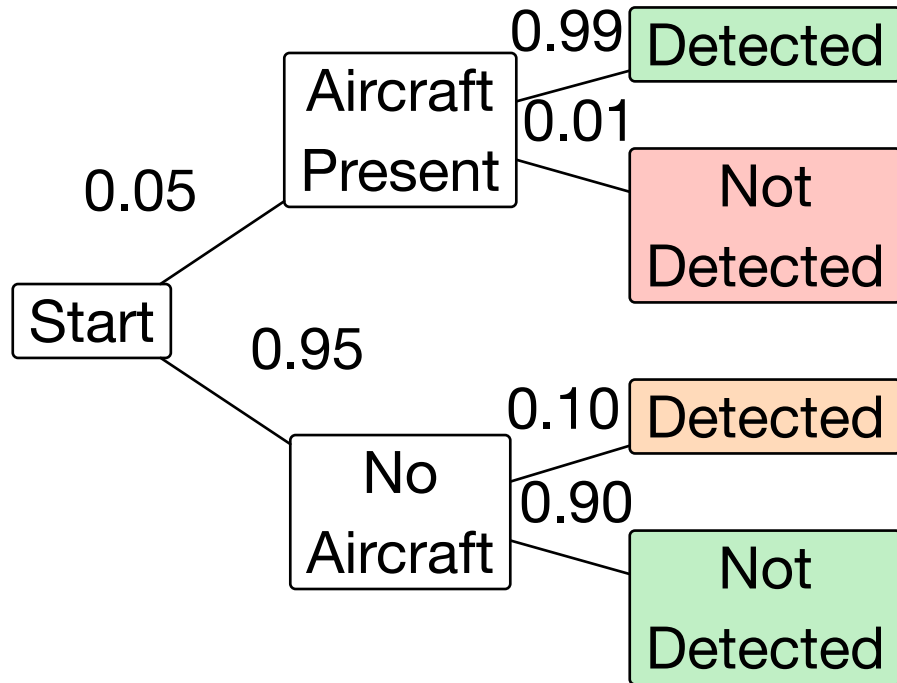
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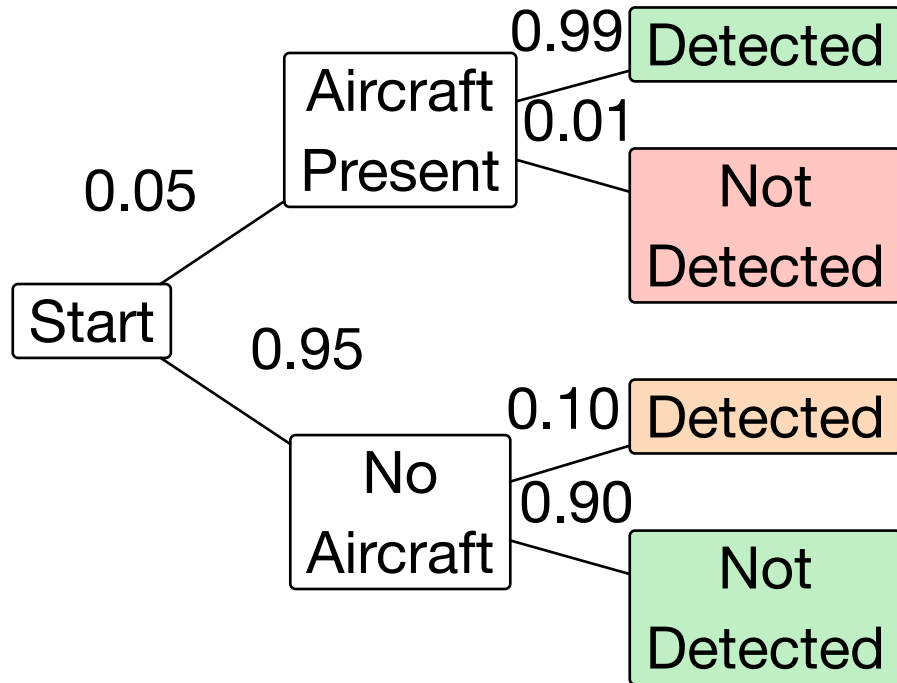
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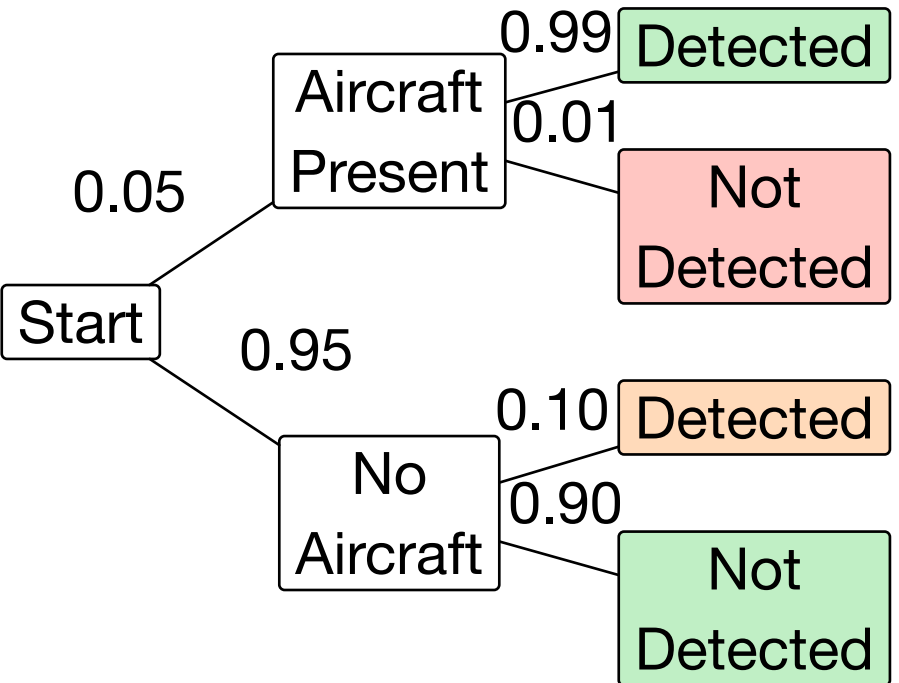


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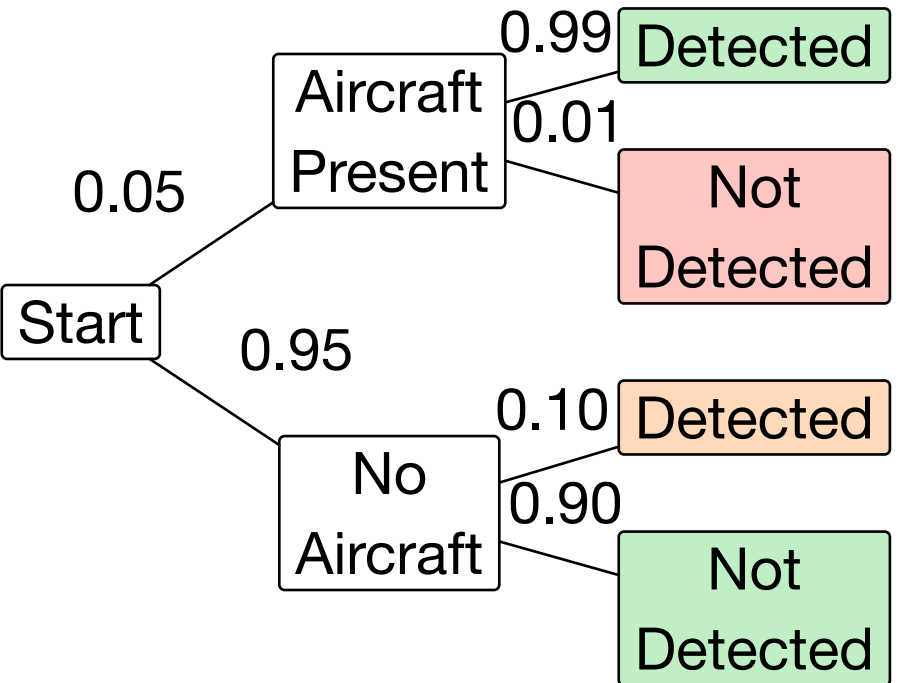
About **9.5% chance** of a false alarm.

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Similarly:

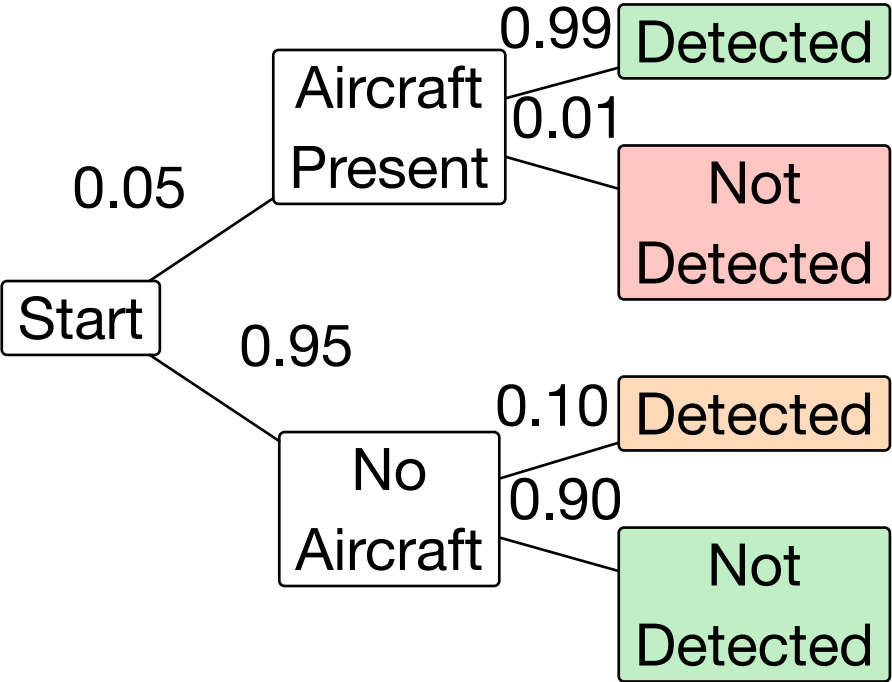
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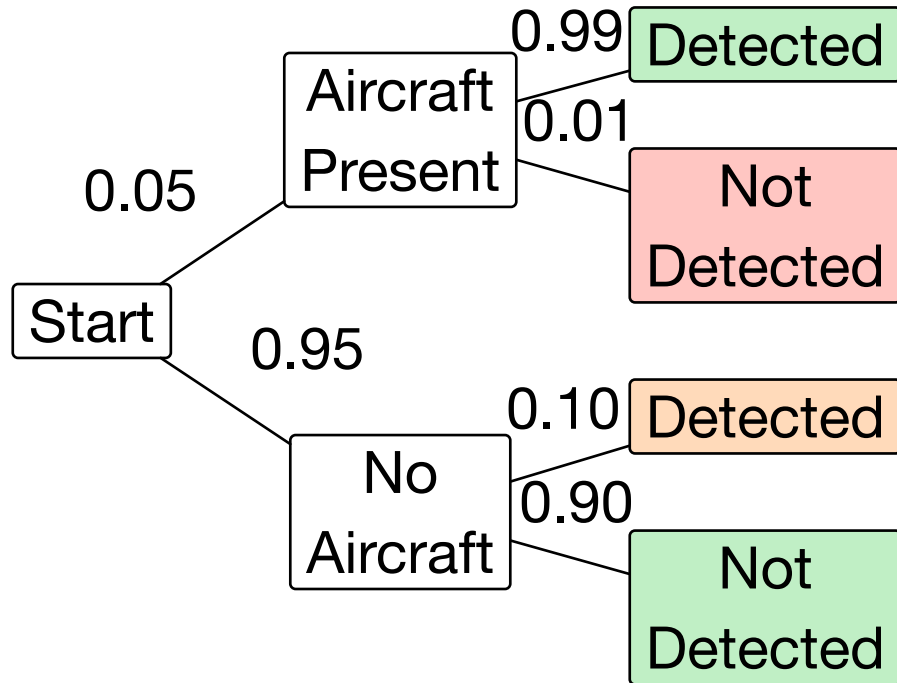
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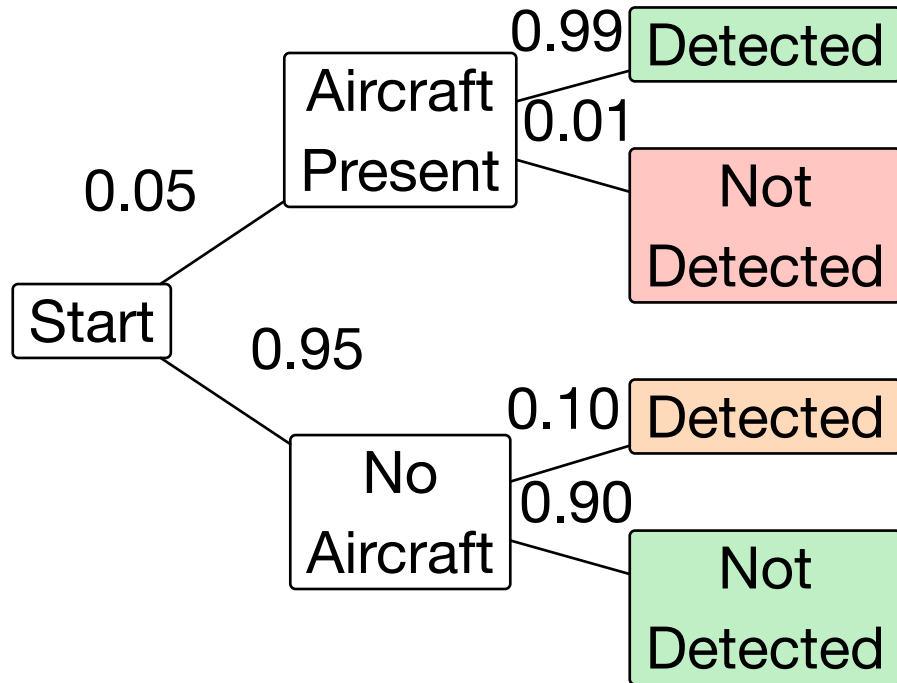
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Only **0.05% chance** of missing a present aircraft.

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This is exactly the multiplication rule, visualized!

3. Problem-Solving Strategies

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Equivalent simpler event: $R = 3$ and $B = 1$

Check both directions:

- If $R = 3, B = 1$, then $R + B = 4$ and $B > 0$ ✓
- If $R + B = 4, B > 0$, then $R = 3, B = 1$ ✓

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Note: Like programming: creative process, not formula-based

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3.4 Chain Rule (Extended Multiplication)

For multiple events:

$$P(A_1 \cap A_2 \cap A_3) = P(A_1) \cdot P(A_2 \mid A_1) \cdot P(A_3 \mid A_1 \cap A_2)$$

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In general:

$$P\left(\bigcap_{i=1}^n A_i\right) = P(A_1) \cdot P(A_2 \mid A_1) \cdot P(A_3 \mid A_1 A_2) \cdot \dots \cdot P(A_n \mid A_1 \dots A_{n-1})$$

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This “chains” conditional probabilities together.

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$$\begin{aligned}P(H_1 \cap H_2 \cap H_3) &= P(H_1) \cdot P(H_2 \mid H_1) \cdot P(H_3 \mid H_1 H_2) \\&= \frac{13}{52} \cdot \frac{12}{51} \cdot \frac{11}{50} \\&= \frac{1716}{132600} \approx 0.0129\end{aligned}$$

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3. **Additivity:** If A_1, A_2 disjoint:

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\checkmark

So all our probability rules apply to conditional probabilities too!

3.7 Common Mistakes with Conditional Probability

Two hugely common errors:

1. $P(A | B) \neq P(B | A)$ (confusion of the inverse)
2. $P(A \text{ and } B) \neq P(A | B)$ (confusing joint and conditional)

3.8 Mistake 1: Confusion of the Inverse

$P(A \mid B) \neq P(B \mid A)$ in general!

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Example:

- $P(\text{has fever} | \text{has flu}) \approx 0.9$ (most flu patients have fever)
- $P(\text{has flu} | \text{has fever}) \approx 0.1$ (most fevers aren't from flu)

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These condition on **different events**, so they're completely different probabilities.

3.9 Mistake 2: Joint vs. Conditional

$P(A \text{ and } B) \neq P(A | B)$ in general!

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- $P(X = 1 \text{ and } S = 6) = \frac{1}{36}$
 - Fraction of **all** rolls where both happen

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Note: Use the notebook view: joint probability counts all lines, conditional counts only non-NA lines

3.10 Connecting to Code

Python:

```
1 import random
2
3 def
  simulate_conditional_prob(n_trials=100000
4     count_first_ace = 0
5     count_both_aces = 0
6
7     for _ in range(n_trials):
8         deck = list(range(52)) # 0-3
          are Aces
9         random.shuffle(deck)
10
11         if deck[0] < 4: # First card is
          an Ace
12             count_first_ace += 1
13             if deck[1] < 4: # Second
          card is also an Ace
```

 Python

```
14         count_both_aces += 1
15
16         # P(second ace | first ace) = rate
          among trials where first is ace
17         conditional_prob = count_both_aces /
          count_first_ace
18         return conditional_prob
19
20 print(f"P(2nd Ace | 1st Ace) simulated:
          {simulate_conditional_prob():.4f}")
21 print(f"P(2nd Ace | 1st Ace)
          theoretical: {3/51:.4f}")
```

3.10 Connecting to Code

R:

```
1 simulate_conditional_prob <-  
function(n_trials = 100000) {  
2   count_first_ace <- 0  
3   count_both_aces <- 0  
4  
5   for (i in 1:n_trials) {  
6     deck <- sample(1:52) # 1-4 are Aces  
7  
8     if (deck[1] <= 4) { # First card is  
       an Ace  
9       count_first_ace <- count_first_ace  
        + 1  
10      if (deck[2] <= 4) { # Second card  
        is also an Ace  
11        count_both_aces <-  
         count_both_aces + 1  
12      }  
    }  
  }  
}
```



```
13   }  
14 }  
15  
16 # P(second ace | first ace) = rate  
   among trials where first is ace  
17 conditional_prob <- count_both_aces /  
   count_first_ace  
18 return(conditional_prob)  
19 }  
20  
21 cat("P(2nd Ace | 1st Ace) simulated:",  
   simulate_conditional_prob(), "\n")  
22 cat("P(2nd Ace | 1st Ace) theoretical:",  
   3/51, "\n")
```

3.11 Summary

Concept	Formula
Conditional Probability	$P(A B) = \frac{P(A \cap B)}{P(B)}$
Multiplication Rule	$P(A \cap B) = P(A) \cdot P(B A)$
Chain Rule	$P(A_1 \cap \dots \cap A_n) = \prod P(A_i A_1 \dots A_{i-1})$

3.13 Recap

Today we covered:

- Conditional probability: probability given new information
- Multiplication rule: $P(A \cap B) = P(A) \cdot P(B | A)$
- Chain rule extends to multiple events
- $P(A | B) \neq P(B | A)$ - order matters!
- Next: Bayes' rule and total probability