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## Example



- Roll two dice, yielding values  $D_1$  and  $D_2$
- Let  $E$  be event:  $D_1 + D_2 = 4$
- What is  $\Pr(E)$ ?
  - $|\Omega| = 36$ ,  $E = \{(1, 3), (2, 2), (3, 1)\} \rightarrow |E| = 3$
  - $\Pr(E) = 3/36 = 1/12$
  - $\Pr(E) = \frac{|E|}{|\Omega|} = \frac{3}{36} = \frac{1}{12}$
- Let  $F$  be event:  $D_1 = 2$
- $\Pr(E | F)$ ?
  - $F = \{(2, 1), (2, 2), (2, 3), (2, 4), (2, 5), (2, 6)\}$
  - $E \cap F = \{(2, 2)\}$
  - $\Pr(E | F) = 1/6$
  - $\Pr(E | F) = \frac{|E \cap F|}{|F|}$

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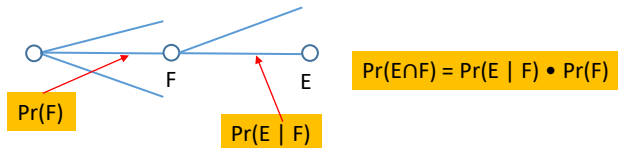
## Chain Rule



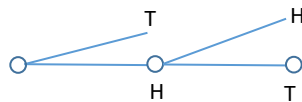
- From  $\Pr(E|F) = \frac{\Pr(E \cap F)}{\Pr(F)} \Rightarrow \Pr(E \cap F) = \Pr(E | F) \cdot \Pr(F)$

### Chain Rule

- Description as a Sequential Tree



- If E and F are independent  $\Rightarrow \Pr(E|F) = \Pr(E)$   $\Pr(E \cap F) = \Pr(E) \cdot \Pr(F)$ 
  - Example: Given the first coin flip is heads, the second coin flip is tails

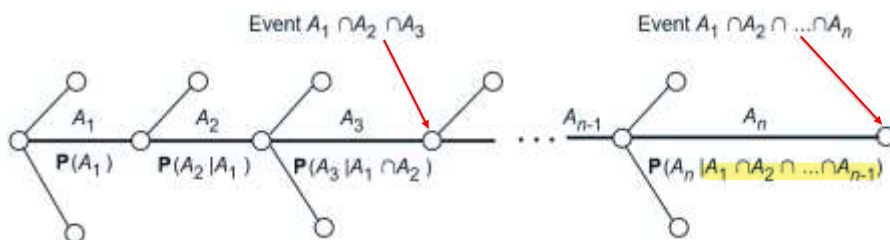


## Multiplication Rule



- Generalized chain rule (Or **Multiplication rule**)

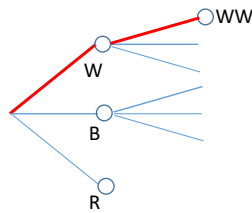
$$\Pr(A_1 \cap A_2 \cap \dots \cap A_n) \\ = \Pr(A_1) \Pr(A_2 | A_1) \Pr(A_3 | A_1 \cap A_2) \dots \Pr(A_n | A_1 \cap A_2 \cap \dots \cap A_{n-1})$$



## Example: Conditional Prob.



- Model a sequence of experiments as a tree
- Example
  - A bag contains 4 blue balls, 3 red balls and 5 white balls
  - Pick two balls from the bag. What is the prob. that picked balls are all white?
  - Pick one ball and w/o replacement pick another ball sequentially. And two ball are all white.



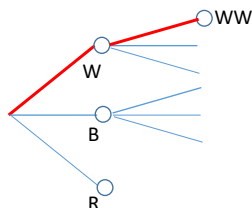
Event W1: First ball is White  
Event W2: Second ball is White

$$\begin{aligned}
 \text{Prob. of red edges} &= \Pr(W1 \cap W2) \\
 &= \Pr(W1) \cdot \Pr(W2 \mid W1) \\
 &= (5/12) \cdot (4/11)
 \end{aligned}$$

## Example: Independent



- Example
  - A bag contains 4 blue balls, 3 red balls and 5 white balls
  - Pick one ball for the first time. Return the ball and pick one ball again. What is the prob. that all two balls are White?



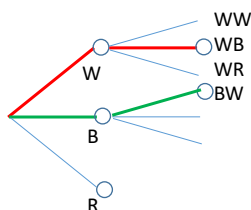
Event W1: First ball is White  
Event W2: Second ball is White

$$\begin{aligned}
 \text{Prob. of red edges} &= \Pr(W1 \cap W2) \\
 &= \Pr(W1) \cdot \Pr(W2) \\
 &= (5/12) \cdot (5/12)
 \end{aligned}$$

## Example: Multiple Paths



- Model a sequence of experiments as a tree
- Example
  - A bag contains 4 blue balls, 3 red balls and 5 white balls
  - Pick two balls from the bag. What is the prob. that 1 ball is white and 1 ball is blue?
  - Pick one ball and w/o replacement pick another ball sequentially. What is the probability to the first pick is white ball and the second is blue ball?



Event W1: First ball is White  
Event B2: Second ball is Blue

$$\begin{aligned}
 \text{Prob. of red edges} &= \Pr(W1 \cap B2) \\
 &= \Pr(W1) \cdot \Pr(B2 | W1) \\
 &= (5/12) \cdot (4/11) \\
 \text{Prob. of green edges} &= (4/12) \cdot (5/11)
 \end{aligned}$$

→ What is the prob. that the first ball is White and the second is Blue?

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## Polynomial Identities: Revisit



- Let  $F(x) \neq G(x)$
- Randomized algorithm: Perform  $k$  trials and decide  $F(x)=G(x)$  if all trials claim  $F(x)=G(x)$
- With replacement
  - Select  $r_i$  uniformly at random repeatedly from  $R = \{1, 2, \dots, 100d\}$
  - Return  $r_i$  to  $R$  after the trial
  - Let  $F_i$  be an event that  $i$ -th trial fails →  $F(r_i) = G(r_i)$
  - $\Pr(F_1) = \Pr(F_2) = \dots = \Pr(F_k) \leq 1/100$
  - $\Pr(\text{Randomized algorithm fails}) = \Pr(F_1 \cap F_2 \cap \dots \cap F_k) \leq \left(\frac{1}{100}\right)^k$

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## Polynomial Identities: Revisit



- Without replacement

- Discard  $r_i$  after the  $i$ -th trial
- After the  $i$ -th trial, there are  $100d-i$  elements in  $\mathbf{R}$  and at most  $d-i$  roots in  $\mathbf{R}$ 
  - $\rightarrow \Pr(F_i \mid F_1 \cap F_2 \cap \dots \cap F_{i-1}) \leq \frac{d-(i-1)}{100d-(i-1)}$
- $\Pr(\text{Randomized algorithm fails})$ 
  - $= \Pr(F_1 \cap F_2 \cap \dots \cap F_k)$
  - $= \Pr(F_1) \Pr(F_2 \mid F_1) \Pr(F_3 \mid F_1 \cap F_2) \dots \Pr(F_k \mid F_1 \cap F_2 \cap \dots \cap F_{k-1})$
  - $\leq \prod_{i=1}^k \frac{d-(i-1)}{100d-(i-1)} < \left(\frac{1}{100}\right)^k$

Only **SLIGHTLY** better than with replacement algorithm

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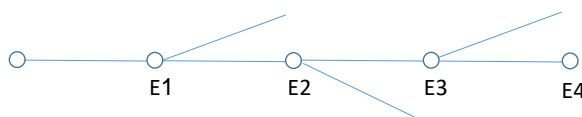
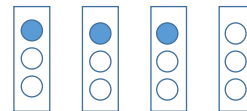
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## Example: Project Team



- With 12 students and make four project teams each of which consists of three randomly selected students
- Family name distribution: 4 Kim's (Let AKim, BKim, CKim, DKim) and 8 other surnames
- Probability that each team has exactly one Kim
- Solution
  - E1: AKim is in any one team
  - E2: AKim and BKim in different teams
  - E3: AKim, BKim and CKim in different teams
  - E4: AKim, Bkim, Ckim, and DKim in different teams
  - $\Pr(E4 \mid E1 \cap E2 \cap E3) = 3/9$



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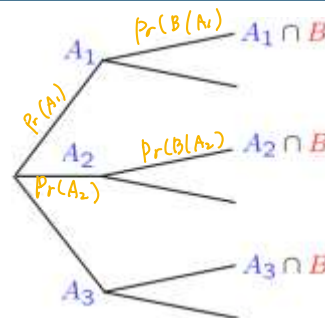
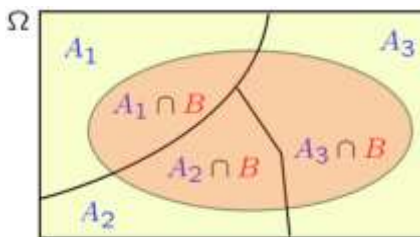
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## Total Probability Theorem

- Consider events,  $A_1, A_2, \dots, A_n$  *Partition*
  - Mutually disjoint: For any,  $1 \leq j \neq k \leq n$ ,  $A_j \cap A_k = \emptyset$
  - Exhaustive:  $A_1 \cup A_2 \cup \dots \cup A_n = \Omega$  *모음이*
- $$\Pr(B) = \Pr(B \cap A_1) + \Pr(B \cap A_2) + \dots + \Pr(B \cap A_n)$$

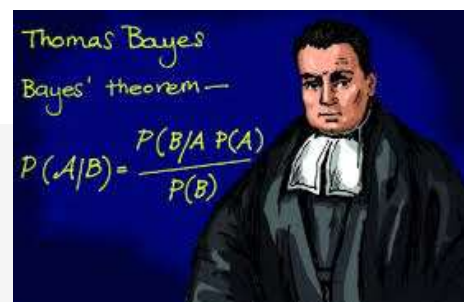
$$= \Pr(B|A_1) \cdot \Pr(A_1) + \Pr(B|A_2) \cdot \Pr(A_2) + \dots + \Pr(B|A_n) \cdot \Pr(A_n)$$

$$\begin{aligned} B &= B \cap \Omega \\ &= B \cap (A_1 \cup A_2 \cup \dots \cup A_n) \\ &= (B \cap A_1) \cup (B \cap A_2) \cup \dots \cup (B \cap A_n) \\ &= \Pr(B \cap A_1) + \dots + \Pr(B \cap A_n) \end{aligned}$$



## Bayes' Theorem (Law/Rule)

- Rev. Thomas Bayes (1702-1761) was a British minister



BABY JUNIORS KIDS MENS MATERNI

## Bayes' Theorem



### Theorem 1.6: Law of Total Probability

- $E = (E \cap F) \cup (E \cap \bar{F})$  Note  $(E \cap F) \cap (E \cap \bar{F}) = \emptyset$

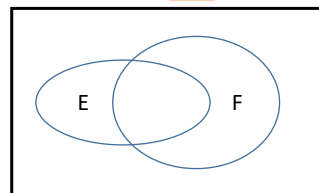
- $\Pr(E) = \Pr(E \cap F) + \Pr(E \cap \bar{F})$   
 $= \Pr(E | F) \Pr(F) + \Pr(E | \bar{F}) \Pr(\bar{F})$

- $\Pr(F | E) = \frac{\Pr(E \cap F)}{\Pr(E)} = \frac{\Pr(E | F) \Pr(F)}{\Pr(E)}$   
 $= \frac{\Pr(E | F) \Pr(F)}{\Pr(E | F) \Pr(F) + \Pr(E | \bar{F}) \Pr(\bar{F})}$

- More generally,

- Let  $F_1, F_2, \dots, F_n$  be mutually exclusive and exhaustive events
- Given  $E$  observed, want to determine which of  $F_j$  also occurred

$$\Pr(F_j | E) = \frac{\Pr(E | F_j) \Pr(F_j)}{\sum_{i=1}^n \Pr(E | F_i) \Pr(F_i)}$$



$$\Omega = F \cup \bar{F}$$

## Spam Email



- Frequently used words and phrases in spam email

- "Dear Friend", "Prize", "Make Money Fast(MMF)", "Hot", "Million", ...

- 60% of all emails are spam →  $\Pr(F) = 0.6$   
 $\Pr(\bar{F}) = 0.4$

- 50% of spams have MMF →  $\Pr(E | F) = 0.5$
- 10% of non-spams have MMF →  $\Pr(E | \bar{F}) = 0.1$

- An email has MMF. What is the probability that the email is spam?

- $E$ : Email has MMF
- $F$ : Email is spam



$$\Pr(F | E) = \frac{\Pr(E | F) \Pr(F)}{\Pr(E | F) \Pr(F) + \Pr(E | \bar{F}) \Pr(\bar{F})}$$

Learn: Naïve Bayesian Filtering (NBF)

## Another Example



### • Three coins

- Two of them are un-biased and one is biased such that  $\Pr(\text{Heads}) = 2/3$
- Flip three coins in a random order and found that first and second coins are heads and third is tails
- Compute the probability that the first coin is the biased coin

### • Solution

- Observed event: (H,H,T)
- F1: First coin is biased, (similarly F2, F3)
- $\Pr(F1 \mid (H, H, T)) = ?$

#### Important:

- Sample space
- How to partition the sample space?
- Define events with proper symbols

## YAE: Mamma Mia

### • Child is born with (A, a) gene pair

(Event (A,a))

- Mother has (A, A) gene pair
- Two possible fathers:
  - Adam: (a,a), Bob: (A,a)
- Mother's belief:  $\Pr(\text{Adam}) = p$ ,  $\Pr(\text{Bob}) = (1-p)$
- What is probability that the father is Adam?
- $\Pr(\text{Adam} \mid (A,a)) = ?$

$$\Pr((A,a) \mid \text{Adam}) = 1$$

$$\Pr((A,a) \mid \text{Bob}) = \frac{1}{2}$$





# Probability Inference

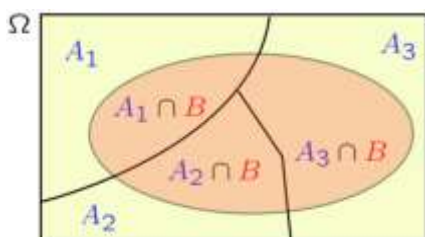


## • Bayes' Theorem

$$\text{Posterior} \quad \text{Likelihood} \quad \text{Prior}$$

$$\Pr(F | E) = \frac{\Pr(E | F)\Pr(F)}{\Pr(E)}$$

## • Probability changes after evidences (E) are observed



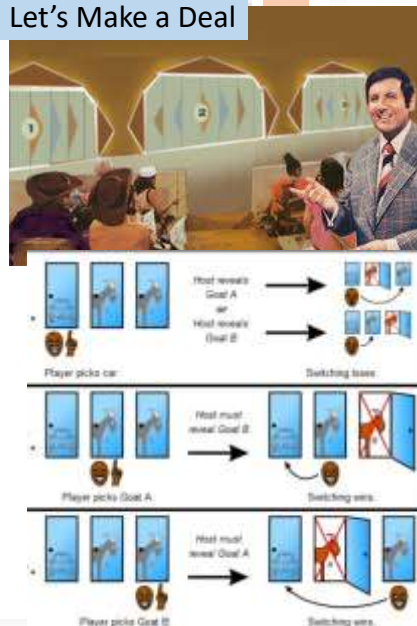
**Inference:** There are multiple “causes” (A1, A2, ...) that may result in an “effect” (B). Given an effect, what is the prob. that a certain cause trigger the effect?

# Monty Hall Problem



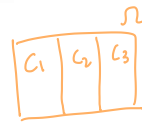
Suppose you're on a game show, and you're given the choice of three doors: Behind one door is a car; behind the others, goats. You pick a door, say No. 1, and the host, who knows what's behind the doors, opens another door, say No. 3, which has a goat. He then says to you, "Do you want to change your choice?" Is it to your advantage to switch your choice?

## Let's Make a Deal



Marilyn Savant  
vs  
Erdős

## Monty Hall Problem



- Without loss of generality, assume the player picks door 1
- Define events
  - $C_1$ : Car is behind door 1 ( Similarly  $C_2, C_3$ )  $\rightarrow \Pr(C_1) = 1/3$
  - $X_1$ : Player pick door 1
  - $H_3$ : Host open door 3
  - $\Pr(H_3 \mid \underbrace{C_1 \cap X_1}_{\substack{\text{2 choices} \\ \text{(door 2, 3)}}}) = \frac{1}{2}, \Pr(H_3 \mid \underbrace{C_2 \cap X_1}_{\substack{\text{1 choice} \\ \text{(door 3)}}}) = 1, \Pr(H_3 \mid \underbrace{C_3 \cap X_1}_{\substack{\text{1 choice} \\ \text{(door 2)}}}) = 0$
- Probability of win after switching =  $\Pr(C_2 \mid H_3 \cap X_1)$ 
  - $\rightarrow$  Show that it is  $2/3$

Refer to Wikipedia

## Random Bit Generator



- A random number bit generator produces a series of random bits, with probability  $p$  of producing a 1
  - Each bit generated is an independent trial
  - $E$ : First  $n$  bits are all 1's, followed by a single 0
- $\Pr(E)$ ?
  - $\Pr(\text{first } n \text{ 1's}) = \Pr(1^{\text{st}} \text{ bit} = 1) \cdot \Pr(2^{\text{nd}} \text{ bit} = 1) \cdots \Pr(n\text{-th bit} = 1)$   
 $= p^n$
  - $\Pr(E) = \Pr(\text{first } n \text{ 1's}) \cdot \Pr(n+1^{\text{st}} \text{ bit} = 0)$   
 $= p^n(1-p)$
- Let  $F$ :  $k$  out of  $n$  random bits are 1
  - $\Pr(\text{First } k \text{ bits are 1, then } n-k \text{ 0's}) = p^k(1-p)^{n-k}$
  - $\Pr(k \text{ out of } n \text{ random bits are 1}) = \binom{n}{k} p^k(1-p)^{n-k}$

## Search, Hashing and Bitcoin



- A fundamental operation in data analysis is to **find (search)** an object in a big dataset
- Many search algorithms
  - BST (Binary Search Tree)
  - Hashing
  - Usually, hashing is the simplest, yet the most efficient algorithm
    - Complexity =  $O(1)$
- A hash function maps a large number to a smaller number, deterministically
  - One-way function
  - Given an input it is easy to compute its output, but the reverse is difficult
- Bitcoin
  - POW(Proof Of Work)
  - Given an output, find inputs that are close enough
  - SHA256 (256 bit Secure Hashing Algorithm)

$$h(x) = y$$

difficult

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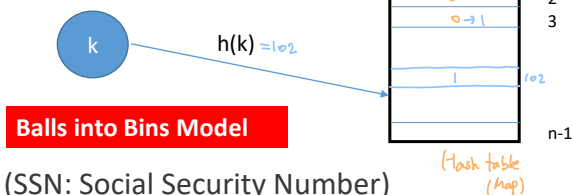
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## Hash Table



- Key, Hash function, and Hash table

$k$        $h(k)$



- Example: 주민번호 (SSN: Social Security Number)

- Each person has a unique **key** of 13 digits
  - Key space ( $K$ ) =  $10^{13}$
- There are  $< 10^8$  unique keys



- Hash function  $h: K \rightarrow (0, 1, \dots, n-1)$

- Simple uniform hash function: Each key is equally likely to hash to any of  $n$  slots (buckets)

- Collision

- Two different keys are mapped to the same slot

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## Hash Table



- m keys are hashed into a hash table of n slots

- Each key hashing is an independent trial
- E: At least one key hashed to the first slot
- $\Pr(E)$ ? ↪  $\bar{E}$  : No key hashed to the slot

Hint: Think out independent events.  
Then AND (intersection) of them.

- Solution

- $F_i$ : Key  $i$  not hashed to the first slot ( $1 \leq i \leq m$ )
- $\Pr(F_i) = 1 - 1/n = (n-1)/n$ , for all  $0 \leq i \leq m$  →  $\frac{n-1}{n} = 1 - (\frac{1}{n})$
- $\Pr(\text{no keys hashed to the first slot}) = \Pr(F_1 \cap F_2 \cap \dots \cap F_m)$
- $\Pr(E) = 1 - \Pr(F_1 \cap F_2 \cap \dots \cap F_m)$  |||

$$\Pr(\bar{E}) \equiv \underbrace{F_1 \cap F_2 \cap F_3 \cap \dots \cap F_m}_{\text{independent}}$$

$$= \Pr(F_1) \cdot \Pr(F_2) \cdot \dots \cdot \Pr(F_m)$$

$$\Pr(E) = 1 - \Pr(\bar{E}) = 1 - \left(\frac{n-1}{n}\right)^m$$

- Like the *birthday problem*

- Among m friends, at least one friend has the same birthday as you ( $n = 365$ )

## Hash Table



- m keys are hashed into a hash table of n slots
- E: At least one of slots (1 to k) has keys hashed to it

- Solution

- $E_i$ : At least one key hashed into the i-th slot

$$\begin{aligned} \Pr(E) &= \Pr(E_1 \cup E_2 \cup \dots \cup E_k) \\ &= 1 - \Pr(\overline{E_1 \cup E_2 \cup \dots \cup E_k}) \\ &= 1 - \Pr(\overline{E_1} \cap \overline{E_2} \cap \dots \cap \overline{E_k}) \end{aligned}$$

**$E_i$  &  $E_j$  independent ?**

$$= 1 - \left(\frac{n-k}{n}\right)^m$$

## Odds

ex) 7:1 vs SSQ

7:1 wins the game.

- **Odds** of an event (H) is defined as

$$\frac{\Pr(H)}{\Pr(\bar{H})} = \frac{\Pr(H)}{1 - \Pr(H)}$$

SSQ wins the game

- Odds of H given evidence E ← result of the first game. (total 7 games)

$$\frac{\Pr(H | E)}{\Pr(\bar{H} | E)} = \frac{\Pr(H) \Pr(E | H) / \Pr(E)}{\Pr(\bar{H}) \Pr(E | \bar{H}) / \Pr(E)}$$

Bayes's theory

$$= \frac{\Pr(H) \Pr(E | H)}{\Pr(\bar{H}) \Pr(E | \bar{H})} = \underbrace{\frac{\Pr(H)}{\Pr(\bar{H})}}_{\text{Odds}} \frac{\Pr(E | H)}{\Pr(E | \bar{H})}$$

- After observing E, update odds by  $\frac{\Pr(E | H)}{\Pr(E | \bar{H})}$

## Lee Sedol vs AlphaGo

- Let H: Lee is better than AG
- Before the match,  $\Pr(H) = 0.9$   
 $\Pr(\bar{H}) = 0.1$



- If Lee is better than AG, then Lee wins game with 0.8 probability →  $\Pr(E | H) = 0.8$ ,  $\Pr(\bar{E} | H) = 0.2$
- If AG is better than Lee, then AG wins game with 0.9 probability →  $\Pr(E | \bar{H}) = 0.9$ ,  $\Pr(\bar{E} | \bar{H}) = 0.1$
- E: AG won a game
- What is updated odds after the game?  

$$\text{Odds} = \frac{\Pr(H)}{\Pr(\bar{H})} = \frac{0.9}{0.1} = 9$$

$$\frac{\Pr(E | H)}{\Pr(E | \bar{H})} = \frac{0.2}{0.9} = \frac{2}{9}$$

$$\Rightarrow 9 \times \frac{2}{9} = 2$$
- What if AG wins two games in a row?

## Coins & Urns



- An urn contains 2 coins: A and B
  - A comes up heads with probability  $\frac{1}{4}$
  - B comes up heads with probability  $\frac{3}{4}$
  - Pick coin randomly and flip it, and it comes up heads

$$Pr(A) = \frac{1}{2}$$

$$Pr(A | H) = \frac{\frac{1}{2} \cdot \frac{1}{4}}{\frac{1}{2} \cdot \frac{1}{4} + \frac{1}{2} \cdot \frac{3}{4}} = \frac{1}{4}$$

$$Pr(H) \rightarrow Pr(A|H) \\ \frac{1}{2} \quad \frac{1}{4} \quad \frac{1}{2} \cdot \frac{1}{4} \\ \text{increase}$$

- What are the odds that A was picked?
  - Before the experiment  $Pr(A) = Pr(\bar{A}) = Pr(B) = \frac{1}{2}$
  - $\frac{Pr(A)}{Pr(\bar{A})} = \frac{Pr(A)}{1 - Pr(A)} = 1$

$$\begin{aligned} \text{After the experiment} \\ \rightarrow \frac{Pr(A | \text{heads})}{Pr(\bar{A} | \text{heads})} &= \frac{Pr(A) Pr(\text{heads} | A)}{Pr(\bar{A}) Pr(\text{heads} | \bar{A})} \\ &= \frac{\frac{1}{2} \cdot \frac{1}{4}}{\frac{1}{2} \cdot \frac{3}{4}} = \frac{1}{3} \end{aligned}$$

## Verifying Matrix Multiplication



- Given three  $n \times n$  matrices **A**, **B**, and **C**
- Want to verify that **AB = C**
- **Complexity** of matrix multiplication
  - $\Theta(n^3)$
  - $\Theta(n^{2.37})$  (Best Algorithm)
- Randomized algorithm
  - Select a vector  $\vec{r} = (r_1, r_2, \dots, r_n) \in \{0, 1\}^n$
  - Compute **AB** $\vec{r}$  (First compute **B** $\vec{r}$  and then **A**(**B** $\vec{r}$ ), Complexity =  $\Theta(n^2)$ )
  - Compute **C** $\vec{r}$
  - Decision:
    - If **AB** $\vec{r} = \text{C}\vec{r} \rightarrow$  Conclude that **AB = C**
    - If **AB** $\vec{r} \neq \text{C}\vec{r} \rightarrow$  Conclude that **AB  $\neq$  C**

## Theorem



- If  $\mathbf{AB} \neq \mathbf{C}$  and if  $\bar{r}$  is chosen uniformly at random from  $\{0, 1\}^n$ , then  $\Pr(\mathbf{AB}\bar{r} = \mathbf{C}\bar{r}) \leq 1/2$
- Proof
  - First, note that selecting  $\bar{r}$  uniformly at random from  $\{0, 1\}^n$  is equivalent to select each  $r_i$  uniformly at random from  $\{0, 1\}$
  - Let  $\mathbf{D} = \mathbf{AB} - \mathbf{C} \neq \mathbf{0}$  *→ none zero elem.*
  - From  $\mathbf{AB}\bar{r} = \mathbf{C}\bar{r}$ , we know that  $\mathbf{D}\bar{r} = \mathbf{0}$
  - Because  $\mathbf{D} \neq \mathbf{0}$ , there must be some non-zero elements in  $\mathbf{D}$
  - Let a non-zero element is  $d_{11}$
  - $\sum_{j=1}^n d_{1j} \cdot r_j = 0$
  - $\rightarrow r_1 = -\frac{\sum_{j=2}^n d_{1j} \cdot r_j}{d_{11}} \quad (1)$
  - There is at most one choice of  $r_1$  that satisfies Eq 1.
  - Because  $r_1$  can be either 0 or 1, the probability that  $\mathbf{AB}\bar{r} = \mathbf{C}\bar{r}$  is at most  $1/2$

## Randomized Algorithm



- Assume that  $\mathbf{AB} \neq \mathbf{C}$
  - Repeat the test k times with  $\bar{r}$  selected uniformly at random from  $\{0, 1\}^n$ .
- If all k test results are  $\mathbf{AB}\bar{r} = \mathbf{C}\bar{r}$ , then conclude that  $\mathbf{AB} = \mathbf{C}$

- Analysis
    - $F_i$ : Event that i-th test fails
    - $\Pr(F_1) = \Pr(F_2) = \dots = \Pr(F_k) \leq 1/2$
    - $\Pr(\text{Algorithm fails}) = \Pr(F_1 \cap F_2 \cap \dots \cap F_k) \leq 2^{-k}$
- $\Downarrow$   
 $O(n^k)$

## Revisit: Matrix Multiplication Application of Bayes' Theorem



- E: Event that **AB** = C
- At the beginning, we do not know if it is true or false  
→ Prior knowledge  $\Pr(E) = \Pr(\bar{E}) = 1/2$
- B1: First test returns that the identity is correct
- $\Pr(E | B1) = \frac{\Pr(B1|E) \cdot \Pr(E)}{\Pr(B1|E) \cdot \Pr(E) + \Pr(B1|\bar{E}) \cdot \Pr(\bar{E})}$   
 $\geq 2/3$  (Handwritten:  $\frac{1}{2} \cdot \frac{1}{2} \geq \frac{1}{2} \cdot \frac{1}{2}$ )
- B2: Second test returns that the identity is correct
- $\Pr(E | B2) \geq \frac{2/3}{2/3 + 1/3 \cdot 1/2} \geq 4/5$
- Assume that after i-th test, our belief is that  $\Pr(E) \geq 2^i / (2^{i+1} + 1)$
- $\Pr(E | B_{i+1}) \geq \frac{2^{i+1}}{2^{i+1} + 1} = 1 - \frac{1}{2^{i+1} + 1}$

$B_2 \rightarrow B$   
 $\Pr(E | B1) \rightarrow \Pr(E)$

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## Advanced Conditional Probability



- Insurance companies have been using probabilities to make different yet proper charges to customers
  - For example, customers who are more probable to incur costs are charged more than customers with less risks
- Car insurance company problem
  - There are two types of drivers: Careful (0.6) and Careless (0.4)
  - Probabilities that careful and careless customers have accidents in one year are 0.2 and 0.4, respectively
  - Events to have accidents in each year are independent (Depends only on the driver types)
  - Given that a new customer has accidents in the first year, What is the probability that the customer have accidents in the second year?
- Note  $\Pr(E | F) = \Pr(E | G \cap F) \Pr(G | F) + \Pr(E | \bar{G} \cap F) \Pr(\bar{G} | F)$ 
  - $\Pr(E | F) = \Pr(E \cap G | F) + \Pr(E \cap \bar{G} | F)$   
 $= \Pr(E \cap G \cap F) / \Pr(F) + \Pr(E \cap \bar{G} \cap F) / \Pr(F)$   
 $= \Pr(E | G \cap F) \Pr(G \cap F) / \Pr(F) + \Pr(E | \bar{G} \cap F) \Pr(\bar{G} \cap F) / \Pr(F)$   
 $= \Pr(E | G \cap F) \Pr(G | F) \Pr(F) / \Pr(F)$   
 $+ \Pr(E | \bar{G} \cap F) \Pr(\bar{G} | F) \Pr(F) / \Pr(F)$

Handwritten notes for Car insurance problem:  
 $\Pr(C) = 0.6$   
 $\Pr(\bar{C}) = 0.4$   
 $\Pr(A|C) = 0.2$   
 $\Pr(A|\bar{C}) = 0.4$   
 $\Pr(A_2|C) = 0.2$   
 $\Pr(A_2|\bar{C}) = 0.4$   
 $\Pr(A_1 \cap A_2 | C) = (0.2) \cdot (0.2)$   
 $\Pr(A_1 \cap A_2 | \bar{C}) = (0.4) \cdot (0.4)$   
 $\Pr(A_1 \cap A_2) = \Pr(A_1 \cap A_2 | C) \Pr(C) + \Pr(A_1 \cap A_2 | \bar{C}) \Pr(\bar{C})$   
 $\Pr(A_1) = \Pr(A_1 | C) \Pr(C) + \Pr(A_1 | \bar{C}) \Pr(\bar{C})$

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## Advanced Conditional Probability



### • Solution

- A2: Event that the customer have accidents in the second year
- A1: Event that the customer have accidents in the first year
- C: Event that customer is careful ( $\bar{C}$  : Careless)
- $\Pr(E | F) = \Pr(E | G \cap F) \Pr(G | F) + \Pr(E | \bar{G} \cap F) \Pr(\bar{G} | F)$
- $E \leftarrow A2, F \leftarrow A1, G \leftarrow C$
- $\Pr(A2 | A1) = \Pr(A2 | A1 \cap C) \Pr(C | A1) + \Pr(A2 | A1 \cap \bar{C}) \Pr(\bar{C} | A1)$
- Compute  $\Pr(C | A1)$  using Bayes' Theorem
- $\Pr(A2 | A1 \cap C) ??$

- Suppose a customer have accidents in first and second years consecutively, what is the probability that the customer is a careful driver?

$$\rightarrow \Pr(C | A1 \cap A2)$$

$$= \frac{\Pr(A1 \cap A2 | C) \cdot \Pr(C)}{\Pr(A1 \cap A2)}$$

AlphaGo W/W/W/L

Pr(L|WWWL)

Sequential Information Update

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## Sequential Information Update



- A hypotheses H (such as a driver is careful driver) with an initial guess is given  $\Pr(H \text{ is True}) = p = 1 - \Pr(H \text{ is False})$
- After an Event E is occurred, the conditional probability that H is True (Let this be T) is given as

$$\Pr(T | E) = \frac{\Pr(E | T) \Pr(T)}{\Pr(E | T) \Pr(T) + \Pr(E | F) \Pr(F)}$$

- Now, suppose we observed two successive (independent) events E1 and E2

$$\Pr(T | E1 \cap E2) = \frac{\Pr(E1 \cap E2 | T) \Pr(T)}{\Pr(E1 \cap E2 | T) \Pr(T) + \Pr(E1 \cap E2 | F) \Pr(F)}$$

- Can we consider E2 as E and  $\Pr(T | E1)$  as  $\Pr(T)$ ?

### • Solution

- Yes, if E1 and E2 are conditionally independent given H
  - $\rightarrow \Pr(E1 \cap E2 | H) = \Pr(E2 | H) \Pr(E1 | H)$
- To show  $\Pr(T | E1 \cap E2) = \frac{\Pr(E2 | T) \Pr(T | E1)}{\Pr(E2 | T) \Pr(T | E1) + \Pr(E2 | F) \Pr(F | E1)}$

Bayes theory  $\rightarrow$

$$\Pr(A|B) = \frac{\Pr(B|A) \cdot \Pr(A)}{\Pr(B)}$$

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## Conditional Independence



- Events E and F are **conditionally Independent** given G iff

$$\Pr(E \cap F \mid G) = \Pr(E \mid G) \Pr(F \mid G)$$

$$\Pr(E \cap F) = \Pr(E) \cdot \Pr(F)$$

- Claim: If E and F are independent

→ E given G and F given G are independent

- No, Counter example

– Roll two dice yielding values D1 and D2

– E: D1=1  $\Pr(E) = \frac{1}{6}$

– F: D2=6  $\Pr(F) = \frac{1}{6}$

– G: D1+D2=7 (1,6), (2,5), ..., (6,1) → 6 outcomes  
 $= \Pr(E) \Pr(F) = \frac{1}{6} \times \frac{1}{6} = \frac{1}{36}$

– E and F are independent,  $\Pr(E \cap F) = 1/36$  and  $\Pr(E) = 1/6$ ,  $\Pr(F) = 1/6$

–  $\Pr(E \mid G) = 1/6$ ,  $\Pr(F \mid G) = 1/6$  and  $\Pr(E \cap F \mid G) = 1/6$  → not independent

↑  
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## Conditional Independence



- Claim: If E and F are conditionally independent given G

then  $\Pr(E \mid F \cap G) = \Pr(E \mid G)$

$$\hookrightarrow \Pr(E \cap F \mid G) = \Pr(E \mid G) \cdot \Pr(F \mid G)$$

- Proof

$$\begin{aligned} - \Pr(E \mid F \cap G) &= \frac{\Pr(E \cap F \cap G)}{\Pr(F \cap G)} \\ &= \frac{\Pr(E \cap F \mid G) \cdot \Pr(G)}{\Pr(F \cap G)} \\ &= \frac{\Pr(E \cap F \mid G)}{\Pr(G)} = \Pr(E \mid G) \end{aligned}$$

$$\frac{\Pr(E \mid G) \Pr(F \mid G) \cdot \Pr(G)}{\Pr(E \cap F)}$$

## Another Example



- 100 person in “The Class” Bldg
  - 30 are in AI Track (Either students or faculty)
  - 20 are Faculty
  - There are 6 AI Faculty
  - $\Pr(AI)=0.3$ ,  $\Pr(F)=0.2$   $\Pr(AI \cap F)=0.06 \rightarrow$  AI and F are independent
  - Only the persons in AI or Faculty can use the ServerRoom
  - AI given ServerRoom and F given ServerRoom are independent?
- Solution
  - D: ServerRoom users = AI U F
  - $|D| = 30 + 20 - 6 = 44$
  - $\Pr(AI|D) = 30/44$ ,  $\Pr(F|D) = 20/44$ ,  $\Pr(AI \cap F | D) = 6/44$
  - $\rightarrow$  **Conditionally Dependent**

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## Independence & Conditioning



- Conditioning can make dependent events to independent?
- Yes, Example
  - Sample space: {M, Tu, W, Th, F, Sa, Su} <sup>7 days</sup>
  - A: not Monday = {Tu, W, Th, F, Sa, Su}  $\rightarrow$  6 days
  - B: {Sa}
  - C: {Sa, Su}
  - $\Pr(A)=6/7$ ,  $\Pr(B)=1/7$  and  $\Pr(A \cap B)=1/7 \neq \Pr(A) \cdot \Pr(B)$   
 $\frac{6}{7} \times \frac{1}{7} = \frac{6}{49}$   
 $\rightarrow$  A and B are dependent
  - $\Pr(A|C)=1$ ,  $\Pr(B|C)=1/2$ ,  $\Pr(A \cap B|C)=1/2 = \Pr(A|C) \cdot \Pr(B|C)$   
 $1 \times \frac{1}{2}$   
 $\rightarrow$  A|C and B|C are independent

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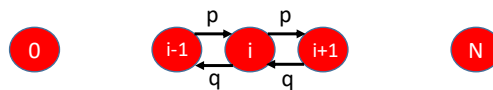
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## Gambler's Ruin Problem



### Game setting

- Gambler A and B
- Successive coin flips. If heads, A collect one unit from B. If tails, A give one unit to B
- $\Pr(\text{heads}) = p = 1 - \Pr(\text{tails})$
- A starts with  $i$  units and B starts with  $N-i$  units
- Game finishes when one of gamblers collects all
- Probability that A wins?



### Solution

- $E$ : A wins
- $H$ : first flip is heads
- $P_i = \Pr(E) = \Pr(E | H)\Pr(H) + \Pr(E | \bar{H})\Pr(\bar{H})$



## Gambler's Ruin Problem



### Solution

- $P_i = \Pr(E | H) \cdot p + \Pr(E | \bar{H}) \cdot (1-p)$   
 $= p \cdot P_{i+1} + q \cdot P_{i-1}$   
 $\rightarrow p \cdot P_i + q \cdot P_i = p \cdot P_{i+1} + q \cdot P_{i-1}$   
 $\rightarrow P_{i+1} - P_i = q/p (P_i - P_{i-1})$
- Obviously,  $P_0 = 0$  and  $P_N = 1$   
 $P_2 - P_1 = q/p (P_1 - P_0) = (q/p) P_1$   
 $P_3 - P_2 = q/p (P_2 - P_1) = (q/p)^2 P_1$   
 $\vdots$   
 $P_i - P_{i-1} = (q/p)^{i-1} P_1$   
 $\rightarrow P_i - P_1 = P_1 [ (q/p) + (q/p)^2 + \dots + (q/p)^{i-1} ]$   
 $\rightarrow P_i = \begin{cases} \frac{1-(q/p)^i}{1-(q/p)} \cdot P_1, & \text{if } p \neq 1/2 \\ i \cdot P_1, & \text{if } p = 1/2 \end{cases}$

## Gambler's Ruin Problem



### • Solution

– From  $P_N = 1$ , we obtain

$$P_1 = \begin{cases} \frac{1-(q/p)}{1-(q/p)^N}, & \text{if } p \neq 1/2 \\ \frac{1}{N}, & \text{if } p = 1/2 \end{cases}$$

$$\rightarrow P_i = \begin{cases} \frac{1-(q/p)^i}{1-(q/p)^N}, & \text{if } p \neq 1/2 \\ \frac{i}{N}, & \text{if } p = 1/2 \end{cases}$$