





# Conditional Probability

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SCONE Lab.

## Independence

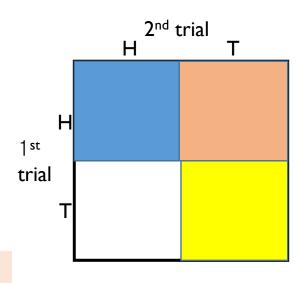
• Definition: Two events E and F are independent iff

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

- Example
  - Flip a coin twice
  - Event E: First trial is heads
  - Event F: Second trial is tails

- Pr(E) = 
$$\frac{1}{2}$$
, Pr(F) =  $\frac{1}{2}$  → Pr(E ∩ F) =  $\frac{1}{4}$ 

What if the coin is unfair?



 $\bullet$  Generally, If events  $E_1, E_2, \dots E_n$  are mutually independent iff

$$Pr(E_1 \cap E_2 \cap ... \cap E_n) = \prod_{i=1}^n Pr(E_i)$$

- Example
  - Baseball Matchup on a same day: Kia-Nx, Ss-LG, KT-SK, Hw-Do, NC-Lo
  - Prob. that Kia, Ss, KT, Do, NC win?

## Independence

- Roll two dice, yielding values D1 and D2
- Events
  - E: D1 = 1
  - F: D2 = 1
  - What is Pr(E), Pr(F), and  $Pr(E \cap F)$ ?
  - $Pr(E) = Pr(F) = 1/6, Pr(E \cap F) = 1/36$ 
    - $\rightarrow$  Pr(E  $\cap$  F) = Pr(E) Pr(F) Independent
- Another event G: D1+D2 = 5  $\rightarrow$  {(1,4), (2,3), (3,2), (4,1)}
  - What is Pr(E), Pr(G), and  $Pr(E \cap G)$ ?
  - $Pr(E) = 1/6, Pr(G) = 4/36, Pr(E \cap G) = 1/36$ 
    - $\rightarrow$  Pr(E \cap G) \neq Pr(E) Pr(G) Dependent

Expectation of sum of rolling two dice? Expectation of sum of rolling two dice given one is 1?

# Conditional Probability

#### Conditional probability, Pr(E|F)

- Probability that E occurs given that F has already occurred
- "Conditioning on F"
- Sample space,  $\Omega$ , shrinks to those elements in F (i.e.  $\Omega \rightarrow \Omega \cap F$ )
- Event space, E, reduced to those elements coincide with F

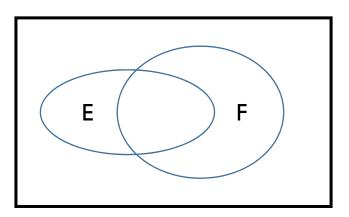
(i.e. 
$$E \cap F$$
)

• With equally likely outcomes:

$$Pr(E \mid F) = \frac{\# of \ outcomes \ in \ E \cap F}{\# of \ outcomes \ in \ F} = \frac{|E \cap F|}{|F|}$$



$$Pr(E|F) = \frac{Pr(E \cap F)}{Pr(F)}$$
 where  $Pr(F) > 0$ 



# Example

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

## Chain Rule

• From 
$$\Pr(E|F) = \frac{\Pr(E \cap F)}{\Pr(F)}$$
,  
we obtain  $\Pr(E \cap F) = \Pr(E \mid F) \cdot \Pr(F)$  Chain Rule

- If E and F are independent  $\rightarrow$  Pr(E|F) = Pr(E)
  - Example: Given the first coin flip is heads, the second coin flip is tails
- Generalized chain rule (Or Multiplication rule)

$$Pr(E_1 \cap E_2 \cap ... \cap E_n)$$

 $= Pr(E_1)Pr(E_2 \mid E_1)Pr(E_3 \mid E_1 \cap E_2)...Pr(E_n \mid E_1 \cap E_2 \cap ... \cap E_{n-1})$ 

## Properties of Conditional Probability

#### • Lemma:

- $-0 \le Pr(E \mid F) \le 1$
- $Pr(\Omega \mid F) = 1$
- For any sequence of pairwise mutually disjoint events  $E_1, E_2, \dots, E_n$  $Pr(\bigcup_{i=1}^n E_i \mid F) = \sum_{i=1}^n Pr(E_i \mid F)$

## 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  $\mathbf{R} = \{1, 2, ..., 100d\}$
- Return r<sub>i</sub> to **R** after the trial
- Let Fi be an event that i-th trial fails  $\rightarrow$  F(r<sub>i</sub>) = G(r<sub>i</sub>)
- $Pr(F_1) = Pr(F_2) = ... = Pr(F_k) \le 1/100$
- Pr(Randomized algorithm fails) = Pr(F<sub>1</sub>  $\cap$  F<sub>2</sub>  $\cap$  ...  $\cap$  F<sub>k</sub>)  $\leq (\frac{1}{100})^k$

## Polynomial Identities: Revisit

### Without replacement

- Discard ri after the i-th trial
- After the i-th trial, there are 100d-i elements in **R** and at most d-i roots in **R**

$$ightharpoonup \Pr(\mathsf{F}_{\mathsf{i}} \mid \mathsf{F}_{\mathsf{I}} \cap \mathsf{F}_{\mathsf{2}} \cap \ldots \cap \mathsf{F}_{\mathsf{i-1}}) \leq \frac{d - (i - 1)}{100d - (i - 1)}$$

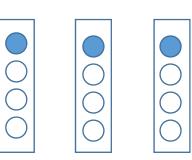
- Pr(Randomized algorithm fails)
  - $= \Pr(F_1 \cap F_2 \cap ... \cap F_k)$
  - $= Pr(F_1)Pr(F_2 \mid F_1)Pr(F_3 \mid F_1 \cap F_2)...Pr(F_k \mid F_1 \cap F_2 \cap ... \cap F_{k-1})$

$$\leq \prod_{i=1}^{k} \frac{d - (i-1)}{100d - (i-1)} < \left(\frac{1}{100}\right)^k$$

Only **SLIGHTLY** better than with replacement algorithm

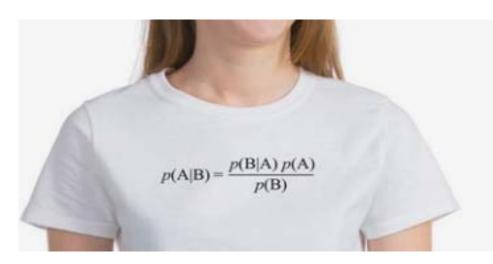
# Example: Project Team

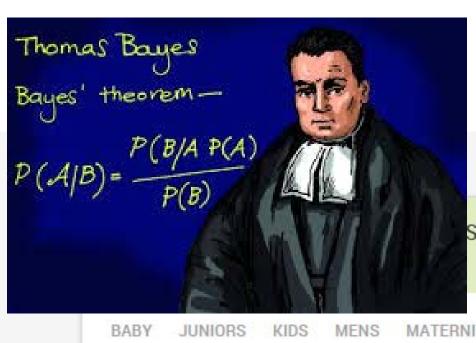
- With 12 students and make three project teams each of which consists of four randomly selected students
- Family name distribution: 3 Kim's (Let AKim, BKim, CKim) and 9 other surnames
- Probability that each team has exactly one Kim
- Solution
  - EI:AKim is in any one team
  - E2:AKim and BKim in different teams
  - E3:AKim, BKim and CKim in different teams
  - $Pr(E3 \mid E1 \cap E2) = 4/10$



# Bayses' Theorem (Law/Rule)

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





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# Bayes' Theorem

• E = (E
$$\cap$$
F) U (E $\cap$   $\overline{F}$ )

Note  $(E \cap F) \cap (E \cap \overline{F}) = \emptyset$ 

• 
$$Pr(E) = Pr(E \cap F) + Pr(E \cap \overline{F})$$
  
=  $Pr(E \mid F) Pr(F) + Pr(E \mid \overline{F}) Pr(\overline{F})$ 

### More generally,

- Let F<sub>1</sub>, F<sub>2</sub>, ... F<sub>n</sub> be mutually exclusive and exhaustive events
- Given E observed, want to determine which of F<sub>j</sub> also occurred

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

# Spam Email

- Frequently used words and phrases in spam email
  - "Dear Friend", "Prize", "Make Money Fast", "Hot", "Million", ...
- 60% of all email is spam
  - 50% of spam has MMF
  - 10% of non-spam has MMF
- An email has MMF. What is the probability that the email is spam?
  - E: Email has MMF
  - F: Email is spam

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

Learn: Naïve Bayesian Filtering (NBF)

## Another Example

#### • Three coins

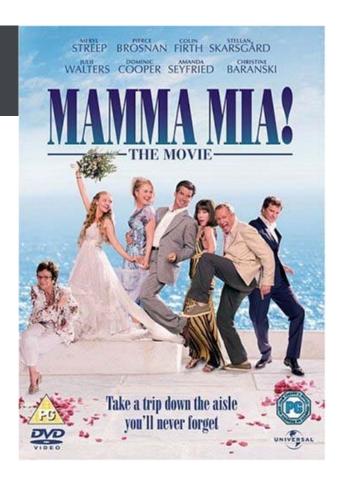
- Two of them are un-biased and one is biased such that Pr(heads) = 2/3
- Flip three coins in a random order and found that first and second coins are heads and third is tails
- Compute the probability that the first coin is the biased coin

#### Solution

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

### YAE: Mamma Mia

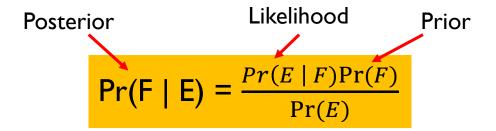
- Child is born with (A, a) gene pair (Event (A,a))
  - Mother has (A,A) gene pair
  - Two possible fathers:
    - Adam: (a,a), Bob: (A,a)
  - Mother's belief: Pr(Adam) = p, Pr(Bob) = (1-p)
  - What is probability that the father is Adam?
  - $Pr(Adam \mid (A,a)) = ?$



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# Probability Inference

• Bayes' Theorem



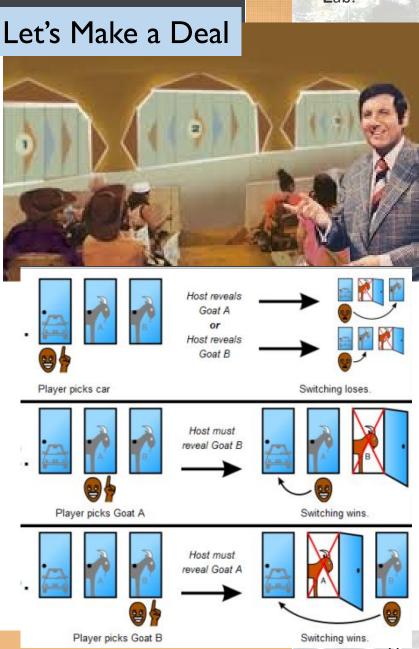
• Probability changes after evidences (E) are observed

## Monty Hall Problem

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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 pick door No. 2?" Is it to your advantage to switch your choice?

Marilyn Savant vs Erdos



# Monty Hall Problem

- Without loss of generality, assume the player picks door 1
- O Define events
  - C1: Car is behind door 1 (Similarly C2, C3) → Pr(C1) = 1/3
  - X1: Player pick door 1
  - H3: Host open door 3
  - $Pr(H3 \mid C1 \cap X1) = \frac{1}{2}$ ,  $Pr(H3 \mid C2 \cap X1) = 1$ ,  $Pr(H3 \mid C3 \cap X1) = 0$
- Probability of win after switching =  $Pr(C2 \mid H3 \cap X1)$ 
  - $\rightarrow$  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 nits are all 1's, followed by a single 0
- Pr(E)?
  - Pr(first n 1's) = Pr(Ist bit = 1)·Pr(2<sup>nd</sup> bit = 1) · · · · Pr(n-th bit = 1) =  $p^n$
  - $Pr(E) = Pr(first n 1's) \cdot Pr(n+1^{st} bit = 0)$ =  $p^n(1-p)$
- Let F: k out of n random bits are 1
  - Pr(First k bits are 1, then n-k 0's) =  $p^k(1-p)^{n-k}$
  - Pr(k out of n 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 most efficient and popular, yet simplest algorithm
    - Complexity = O(I)
- 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)

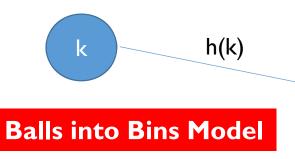
## Hash Table

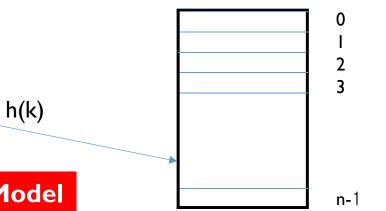
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Index

Lab.

• Key, Hash function, and Hash table





- Example: 주민번호
  - Each person has a unique key of 13 digits
    - Key space (K) =  $10^{13}$
  - There are  $< 10^8$  unique keys
- Hash function h:  $K \rightarrow (0, 1, ..., n-1)$ 
  - 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

## 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)?

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

#### Solution

- Fi: Key i not hashed to the first slot  $(0 \le i \le m)$
- Pr(Fi) = 1-1/n = (n-1)/n, for all  $0 \le i \le m$
- Pr(no keys hashed to the fist slot) =  $Pr(F_1 \cap F_2 \cap ... \cap F_m)$

$$- P(E) = 1-Pr(F_1 \cap F_2 \cap ... \cap F_m)$$
$$= 1 - \left(\frac{n-1}{n}\right)^m$$

### • Similar to 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

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

- 
$$Pr(E) = Pr(E1 \cup E2 \cup ... \cup Ek)$$
  
=  $1-Pr(\overline{E1} \cup E2 \cup ... \cup Ek)$   
=  $1-Pr(\overline{E1} \cap \overline{E2} \cap ... \cap \overline{Ek})$ 

### Ei & Ej independent?

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

## Odds

• Odds of an event (H) is defined as

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

Odds of H given evidence E

$$\frac{\Pr(H \mid E)}{\Pr(\overline{H} \mid E)} = \frac{\Pr(H) \Pr(E \mid H) / \Pr(E)}{\Pr(\overline{H}) \Pr(E \mid \overline{H}) / \Pr(E)}$$
$$= \frac{\Pr(H) \Pr(E \mid \overline{H})}{\Pr(\overline{H}) \Pr(E \mid \overline{H})}$$

• After observing E, update odds by  $\frac{\Pr(E \mid H)}{\Pr(E \mid \overline{H})}$ 

## Lee Sedol vs AlphaGo

SCONE Lab.

- Let H: Lee is better than AG
- Before the match, Pr(H) = 0.9



- If Lee is better than AG, then Lee wins game with 0.8 probability
- If AG is better than Lee, then AG wins game with 0.9 probability
- E: AG won a game
- What is updated odds after the game?
- What if AG wins two games in a row?

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## Coins & Urns

#### • An urn contains 2 coins: A and B

- A comes up heads with probability 1/4
- B comes up heads with probability <sup>3</sup>/<sub>4</sub>
- Pick coin randomly and flip it, and it comes up heads

### • What are the odds that A was picked?

- Before the experiment  $Pr(A) = Pr(\overline{A}) = Pr(B) = \frac{1}{2}$ 

After the experiment

# Verifying Matrix Multiplication

- o 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  $\bar{r} = (r_1, r_2, ..., r_n) \in \{0, 1\}^n$
  - Compute  $\mathbf{A}\mathbf{B}\bar{r}$  (First compute  $\mathbf{B}\bar{r}$  and then  $\mathbf{A}(\mathbf{B}\bar{r})$ , Complexity =  $\Theta(n^2)$ )
  - Compute  $\mathbf{C}\bar{r}$
  - Decision:
    - If  $AB\bar{r} = C\bar{r} \rightarrow Conclude$  that AB = C
    - If  $AB\bar{r} \neq C\bar{r} \Rightarrow$  Conclude that  $AB \neq C$

## Theorem

o If  $AB \neq C$  and if  $\bar{r}$  is chosen uniformly at random from  $\{0, 1\}^n$ , then  $Pr(AB\bar{r} = C\bar{r}) \leq \frac{1}{2}$ 

#### • 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  $D = AB C \neq 0$
- 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  $d_{11}$

$$-\sum_{j=1}^{n} d_{1j} \cdot r_{j} = 0$$

$$\Rightarrow r_{1} = -\frac{\sum_{j=2}^{n} d_{1j} \cdot r_{j}}{d_{11}}$$
 (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  $\frac{1}{2}$

# Randomized Algorithm

- Assume that  $AB \neq C$
- Repeat the test k times with  $\bar{r}$  selected uniformly at random from  $\{0,1\}^n$ .

If all k test results are  $AB\bar{r} = C\bar{r}$ , then conclude that AB = C

### Analysis

- Fi: Event that i-th test fails
- $Pr(F_1) = Pr(F_2) = ... = Pr(F_k) \le 1/2$
- Pr(Algorithm fails) = Pr(F<sub>1</sub> ∩ F<sub>2</sub> ∩ ... ∩ F<sub>k</sub>) ≤  $2^{-k}$

# Application of Bayes' Theorem

- E: Event that AB = C
- At the beginning, we do not know if it is true or false
  - → Prior knowledge  $Pr(E) = Pr(\overline{E}) = \frac{1}{2}$
- B1: First test returns that the identity is correct

• Pr(E | B1) = 
$$\frac{\Pr(B1|E) \cdot \Pr(E)}{\Pr(B1|E) \cdot \Pr(E) + \Pr(B1|\bar{E}) \cdot \Pr(\bar{E})}$$
$$\geq 2/3$$

• B2: Second test returns that the identity is correct

• 
$$Pr(E \mid B2) \ge \frac{^2/_3}{^2/_3 + ^1/_3 \cdot ^1/_2} \ge 4/5$$

• Assume that after i-th test, our belief is that  $Pr(E) \ge 2^i / (2^{i+1})$ 

• 
$$Pr(E \mid Bi+1) \ge \frac{2^{i+1}}{2^{i+1}+1} = 1 - \frac{1}{2^{i}+1}$$

## 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 customer have accidents in a 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  $Pr(E \mid F) = Pr(E \mid G \cap F) Pr(G \mid F) + Pr(E \mid \overline{G} \cap F) Pr(\overline{G} \mid F)$ 
  - $Pr(E \mid F) = Pr(E \cap G \mid F) + Pr(E \cap \overline{G} \mid F)$ =  $Pr(E \cap G \cap F) / Pr(F) + Pr(E \cap \overline{G} \cap F) / Pr(F)$ =  $Pr(E \mid G \cap F) Pr(G \cap F) / Pr(F) + Pr(E \mid \overline{G} \cap F) Pr(\overline{G} \cap F) / Pr(F)$ =  $Pr(E \mid G \cap F) Pr(G \mid F) Pr(F) / Pr(F)$ +  $Pr(E \mid \overline{G} \cap F) Pr(\overline{G} \mid F) Pr(F) / Pr(F)$

## 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 ( $\overline{C}$ : Careless)
- $\Pr(E \mid F) = \Pr(E \mid G \cap F) \Pr(G \mid F) + \Pr(E \mid \overline{G} \cap F) \Pr(\overline{G} \mid F)$
- $E \leftarrow A2, F \leftarrow A1, G \leftarrow C$
- $\operatorname{Pr}(A2 \mid A1) = \operatorname{Pr}(A2 \mid A1 \cap C) \operatorname{Pr}(C \mid A1) + \operatorname{Pr}(A2 \mid A1 \cap \overline{C}) \operatorname{Pr}(\overline{C} \mid A1)$
- Compute Pr(C | A1) using Bayes' Theorem
- Pr(A2 | A1 ∩ C) ??
- Suppose a customer have accidents in first and second years consecutively, what is the probability that the customer is a careful driver?
  - **→** Pr (C | A1 ∩ A2)

AlphaGo W/W/W/L

**Sequential Information Update** 

## Sequential Information Update

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

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

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

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

- Can we consider E2 as E and  $Pr(T \mid E1)$  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 
$$Pr(T \mid E1 \cap E2) = \frac{Pr(E2 \mid T)Pr(T \mid E1)}{Pr(E2 \mid T)Pr(T \mid E1) + Pr(E2 \mid F)Pr(F \mid E1)}$$

# Conditional Independence

- Let E and F are independent
  - → E given G and F given G are independent also?
- No, Counter example
  - Roll two dice yielding values D1 and D2
  - E: D1=1
  - F: D2=6
  - G: D1+D2=7
  - E and F are independent,  $Pr(E \cap F) = 1/36$  and Pr(E) = 1/6, Pr(F) = 1/6
  - Pr(E | G)=1/6, Pr(F | G)=1/6 and  $Pr(E \cap F | G)=1/6$
- Events E and F are conditionally Independent given G iff  $Pr(E \cap F \mid G) = Pr(E \mid G) Pr(F \mid G)$
- Prove that if E and F are conditionally independent given G then  $Pr(E \mid F \cap G) = Pr(E \mid G)$

## Another Example

### • 100 person in Bldg 302

- 30 are in CS Dept. (Either students or faculty)
- 20 are Faculty
- There are 6 CS Faculty
- Pr(CS)=0.3, Pr(F)=0.2  $Pr(CS \cap F)=0.06$   $\rightarrow$  CS and F are independent
- Only the persons in CS Dept. or Faculty can use the DiningHall
- CS given DiningHall and F given DiningHall are independent?

#### Solution

- D: DiningHall users = CS U F
- |D| = 30 + 20 6 = 44
- $Pr(CS|D) = 30/44, Pr(F|D) = 20/44, Pr(CS \cap F \mid D) = 6/44$

#### Conditionally Dependent

# Independence & Conditioning

• Conditioning can make dependent events to independent?

### • Yes, Example

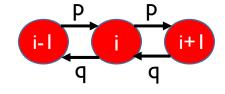
- Sample space: {M,Tu,W,Th, F, Sa, Su}
- A: not Monday =  $\{Tu, W, Th, F, Sa, Su\}$
- B: Sa
- C: {Sa, Su}
- Pr(A)=6/7, Pr(B)=1/7 and  $Pr(A \cap B)=1/7$ 
  - → A and B are dependent
- Pr(A|C)=1, Pr(B|C)=1/2,  $P(A \cap B|C)=1/2$ 
  - → A|C and B|C are independent

## 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(heads) = p = 1-Pr(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
- $Pi = Pr(E) = Pr(E \mid H)Pr(H) + Pr(E \mid \overline{H})Pr(\overline{H})$



## Gambler's Ruin Problem

#### Solution

- Pi = Pr(E | H)•p + Pr(E | 
$$\overline{H}$$
) •(1-p)  
= p•P<sub>i+1</sub> + q•P<sub>i-1</sub>  
 $\Rightarrow$  p•P<sub>i</sub> + q•P<sub>i</sub> = p•P<sub>i+1</sub> + q•P<sub>i-1</sub>  
 $\Rightarrow$  P<sub>i+1</sub> - P<sub>i</sub> = q/p (P<sub>i</sub> - P<sub>i-1</sub>)  
- Obviously, Po = 0 and P<sub>N</sub> = 1  
P<sub>2</sub> - P<sub>1</sub> = q/p (P<sub>1</sub> - P<sub>0</sub>) = (q/p) P<sub>1</sub>  
P<sub>3</sub> - P<sub>2</sub> = q/p (P<sub>2</sub> - P<sub>1</sub>) = (q/p)<sup>2</sup> P<sub>1</sub>  
 $\vdots$   
Pi - P<sub>i-1</sub> = (q/p)<sup>i-1</sup> P<sub>1</sub>  
 $\Rightarrow$  Pi - P<sub>1</sub> = P<sub>1</sub> [ (q/p) + (q/p)<sup>2</sup> +...+ (q/p)<sup>i-1</sup> ]  
 $\Rightarrow$  P<sub>i</sub> = 
$$\begin{cases} \frac{1-(q/p)^{i}}{1-(q/p)} \cdot P_{1}, & \text{if } p \neq 1/2\\ i \cdot P_{1}, & \text{if } p = 1/2 \end{cases}$$

## Gambler's Ruin Problem

#### Solution

- From  $P_N = 1$ , we obtain

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

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