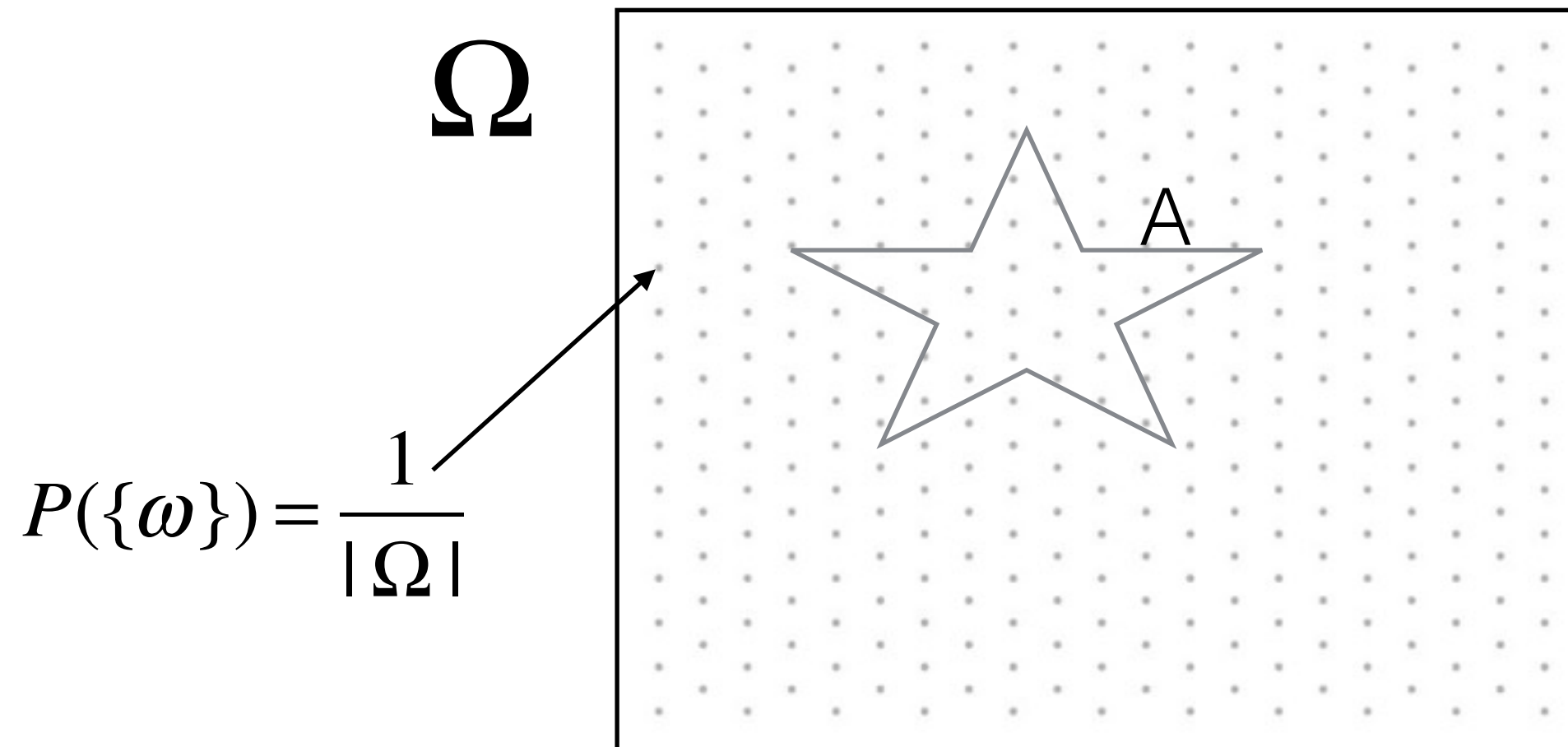


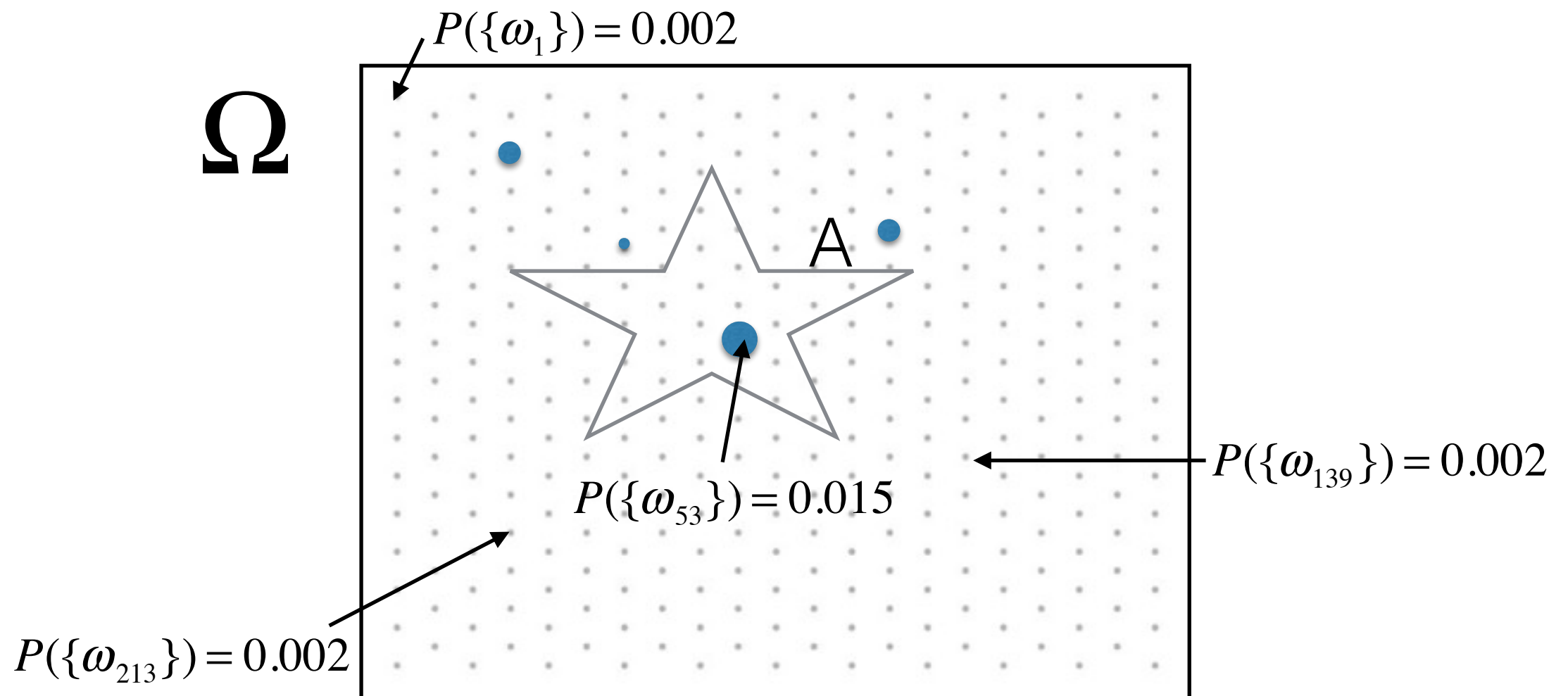
# General finite distributions Conditional Probabilities and independence

# Uniform Dist. over finite outcome space spaces



$$P(A) = \frac{|A|}{|\Omega|}$$

# Non-Uniform Dist. over finite outcome space spaces



Constraints: 1.  $\forall \omega \in \Omega \quad 0 \leq P(\{\omega\}) \leq 1$

$$2. \sum_{\omega \in \Omega} P(\{\omega\}) = 1$$

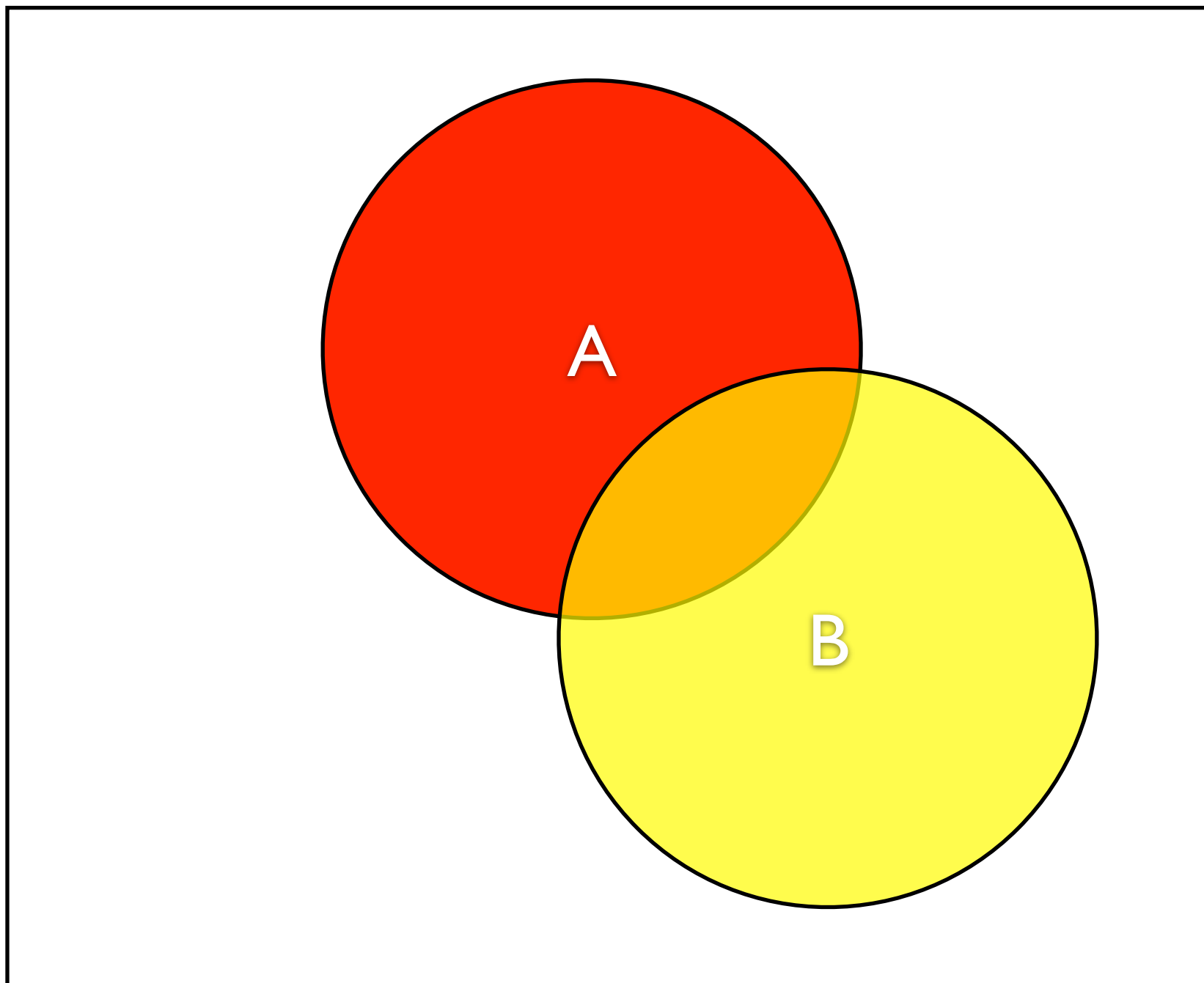
Probability Calculation:  $P(A) = \sum_{\omega \in A} P(\{\omega\})$

# Example: Biased coin

- Outcome space= {Head,Tail}
- $P(\{\text{Head}\})=0.3$
- $P(\{\text{Tail}\}) + P(\{\text{Head}\})=1$
- Therefore  $P(\{\text{Tail}\})=1-0.3=0.7$

# Events

Sample Space  $\Omega$

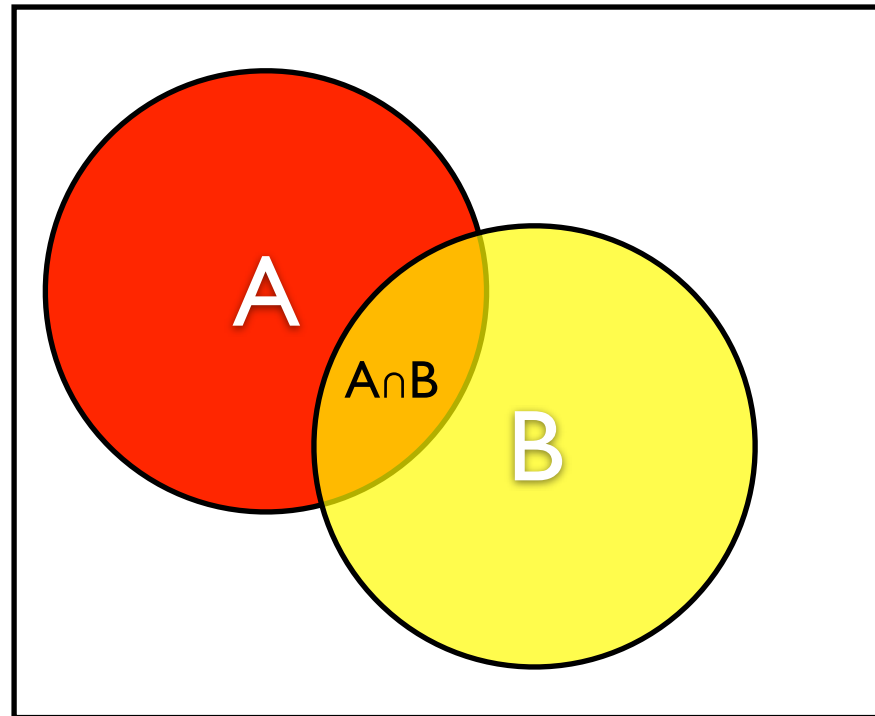


# Summation rules

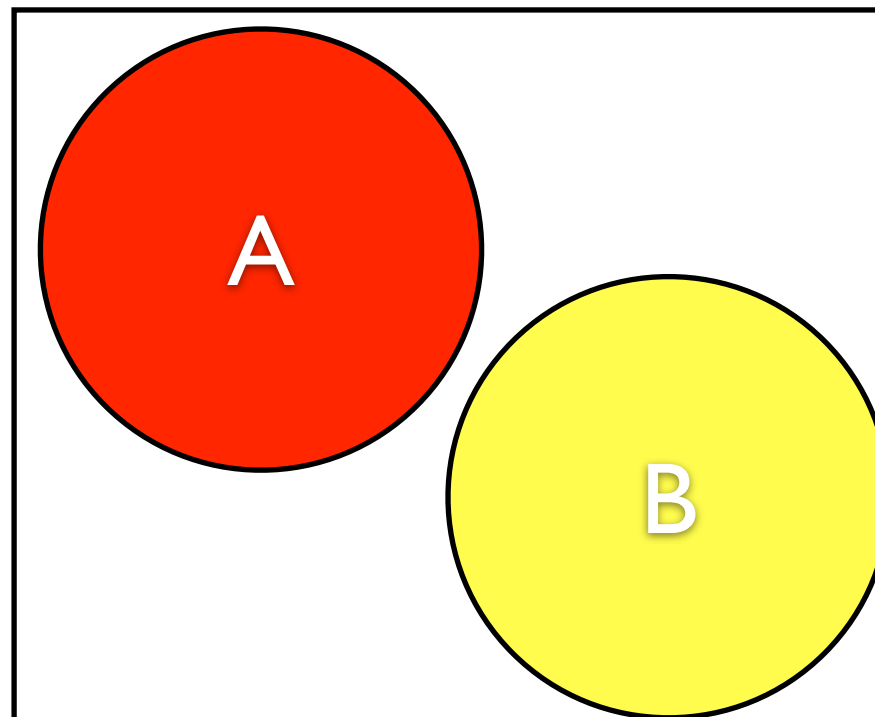
True always:

$$P(A \cup B) \leq P(A) + P(B)$$

Sample Space  $\Omega$



Sample Space  $\Omega$

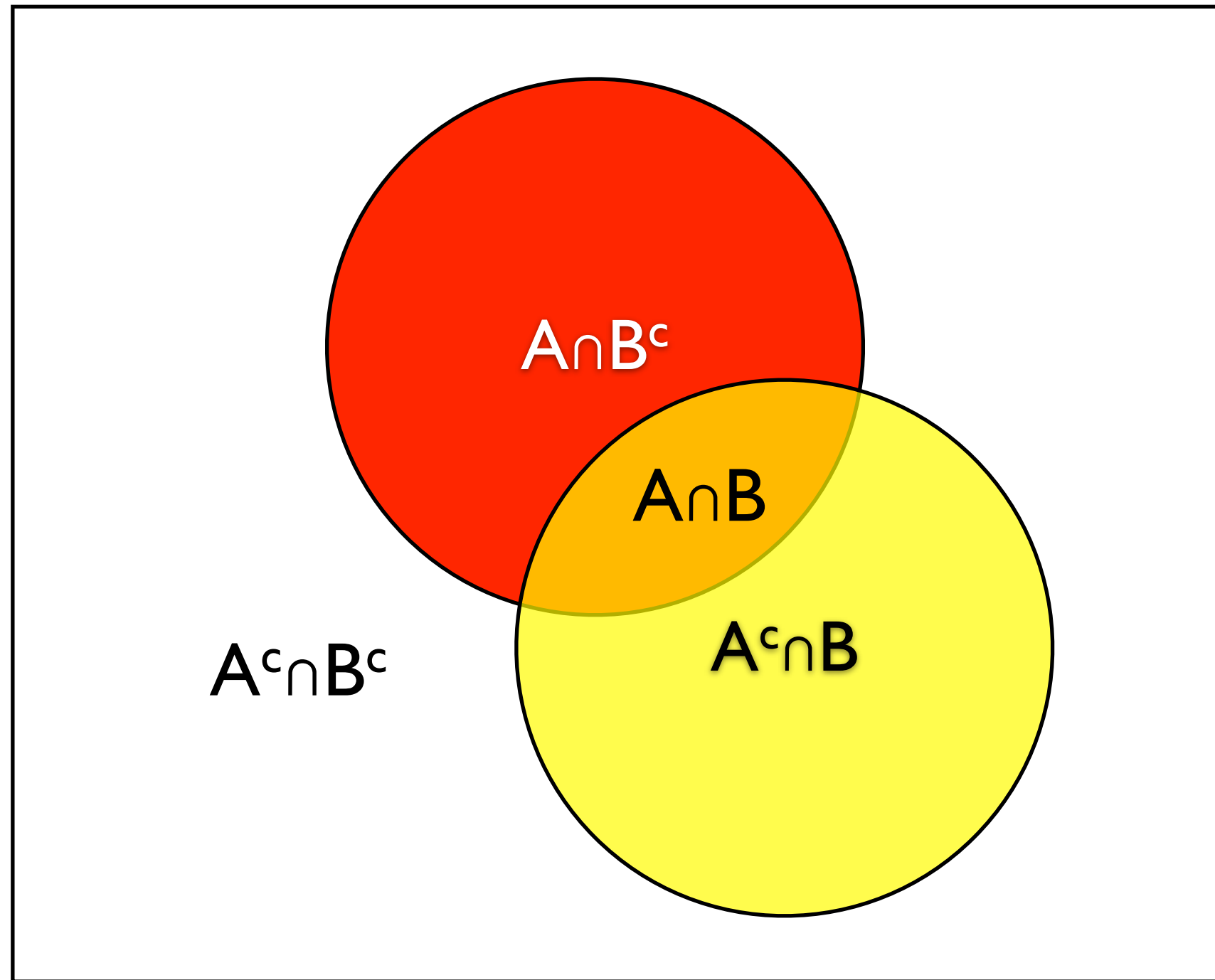


A and B are disjoint:  $A \cap B = \emptyset$

implies:  $P(A \cup B) = P(A) + P(B)$

# Partitioning into disjoint events

Sample Space  $\Omega$



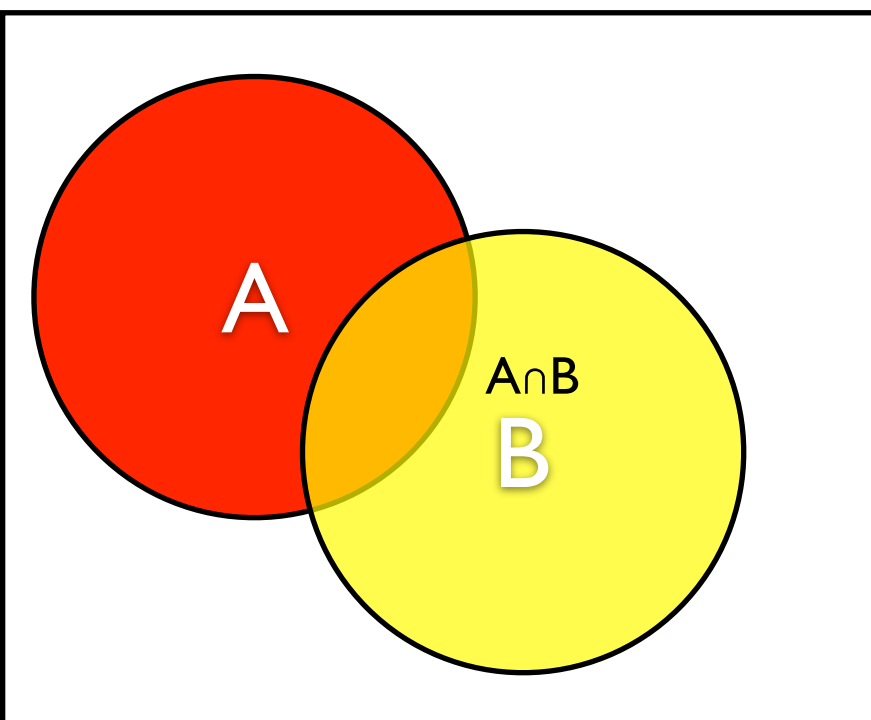
$$P(A \cup B) = P(A \cap B^c) + P(A^c \cap B) + P(A \cap B) = 1 - P(A^c \cap B^c)$$

What can we say about  $P(A \cap B)$ ?

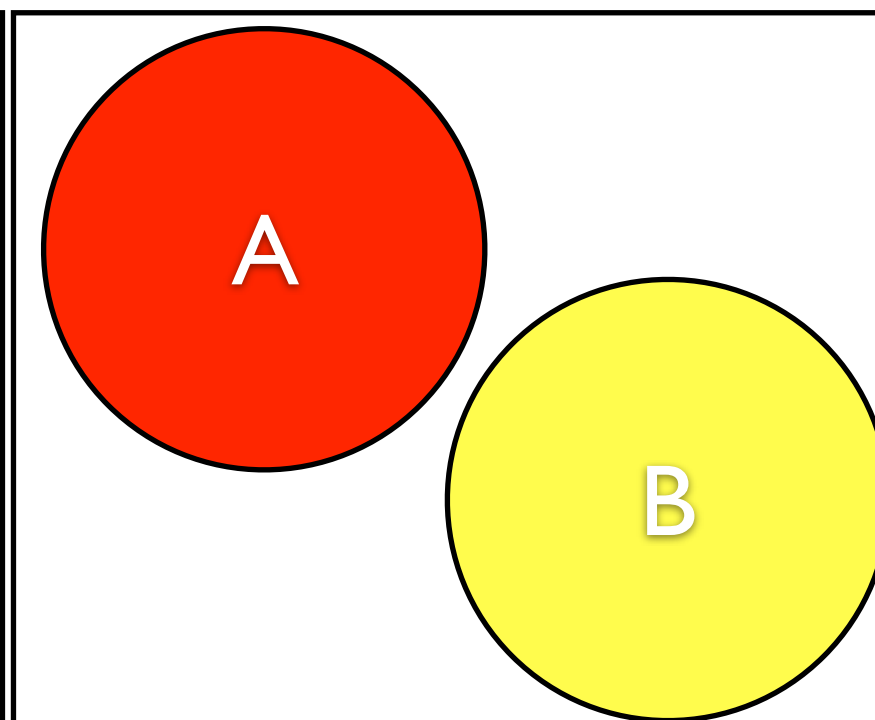
If  $A \cap B = \emptyset$  then  $P(A \cap B) = 0$  (other direction not quite - nonempty sets can have probability zero)

If  $A \subset B$  then  $P(A \cap B) = P(A)$  same as:  $x \in A$  implies  $x \in B$

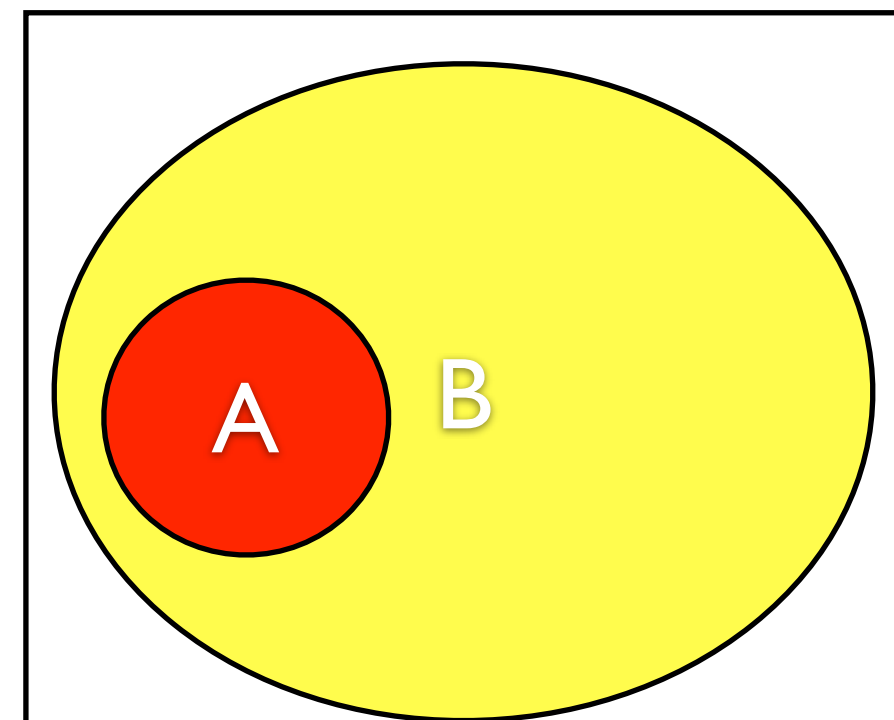
Sample Space  $\Omega$



Sample Space  $\Omega$



Sample Space  $\Omega$

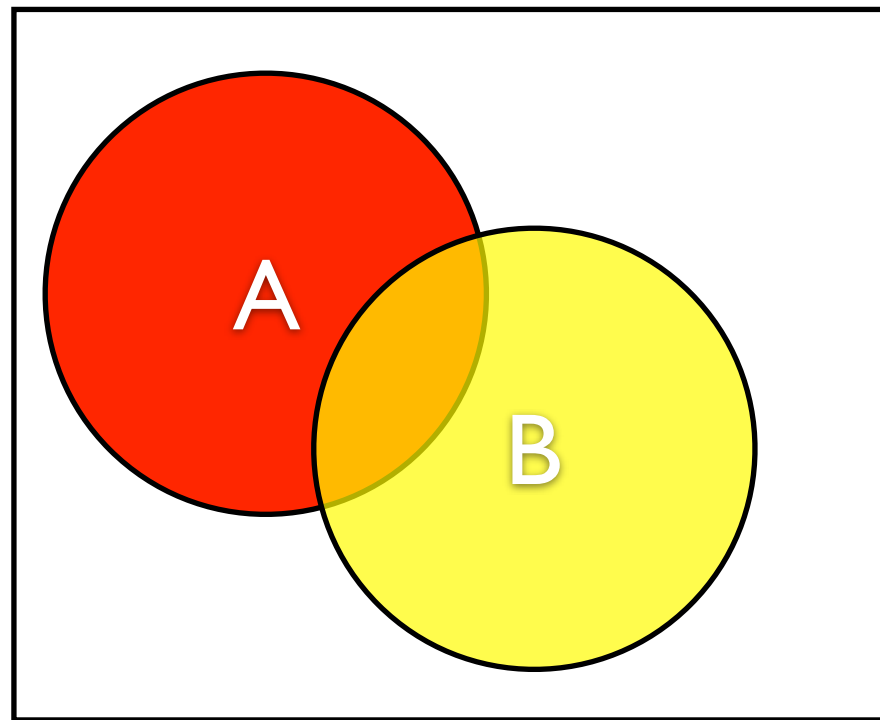




# Independence: Definition

$$P(A \cap B) = P(A) \times P(B) = P(A)P(B)$$

Sample Space  $\Omega$



# Example of Independence

Suppose we have a biased coin  $P(H) = 0.9$ ,  $P(T) = 0.1$

We flip the coin 10 times. What is the probability of

$H, T, H, H, H, T, H, H, H, H$  ?

The coin flips define independent events, therefore

$$P(H, T, H, H, H, T, H, H, H, H) =$$

$$= 0.9 \times 0.1 \times 0.9 \times 0.9 \times 0.9 \times 0.1 \times 0.9 \times 0.9 \times 0.9 \times 0.9$$

$$0.9^8 \times 0.1^2$$

# Binomial distribution for biased coins

$$(a + b)^n = \sum_{i=0}^n \binom{n}{i} a^{n-i} b^i$$

Fair  
Coin

Suppose  $a = b = \frac{1}{2}$  then we get:

$$1 = \left(\frac{1}{2} + \frac{1}{2}\right)^n = \sum_{i=0}^n \binom{n}{i} \left(\frac{1}{2}\right)^i \left(\frac{1}{2}\right)^{n-i} = \left(\frac{1}{2}\right)^n \sum_{i=0}^n \binom{n}{i}$$

$p$  = probability of heads

$q = 1 - p$  = probability of tails

Biased  
Coin

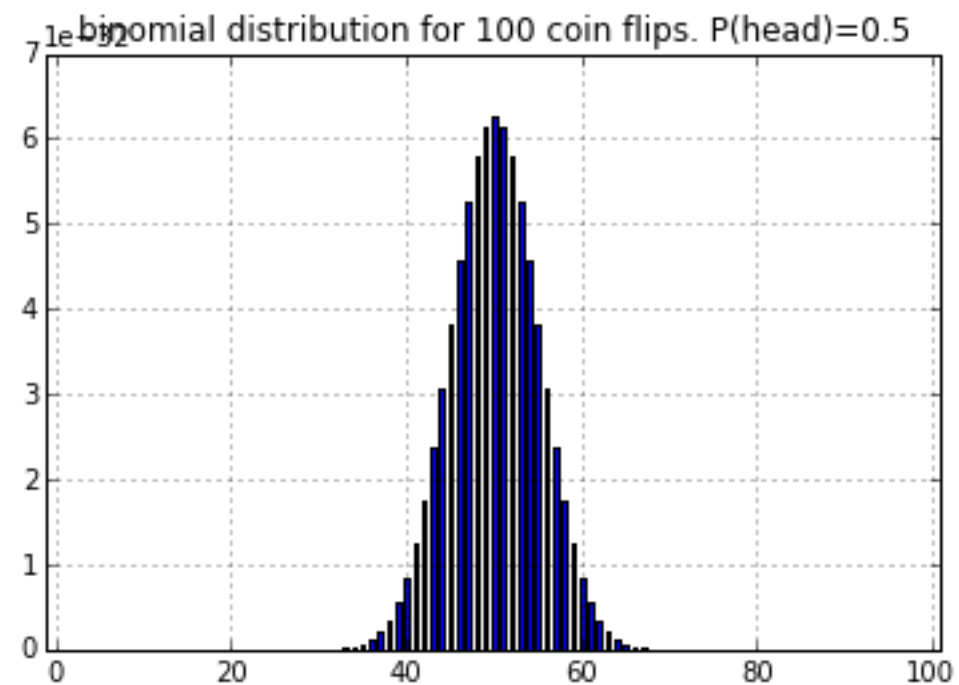
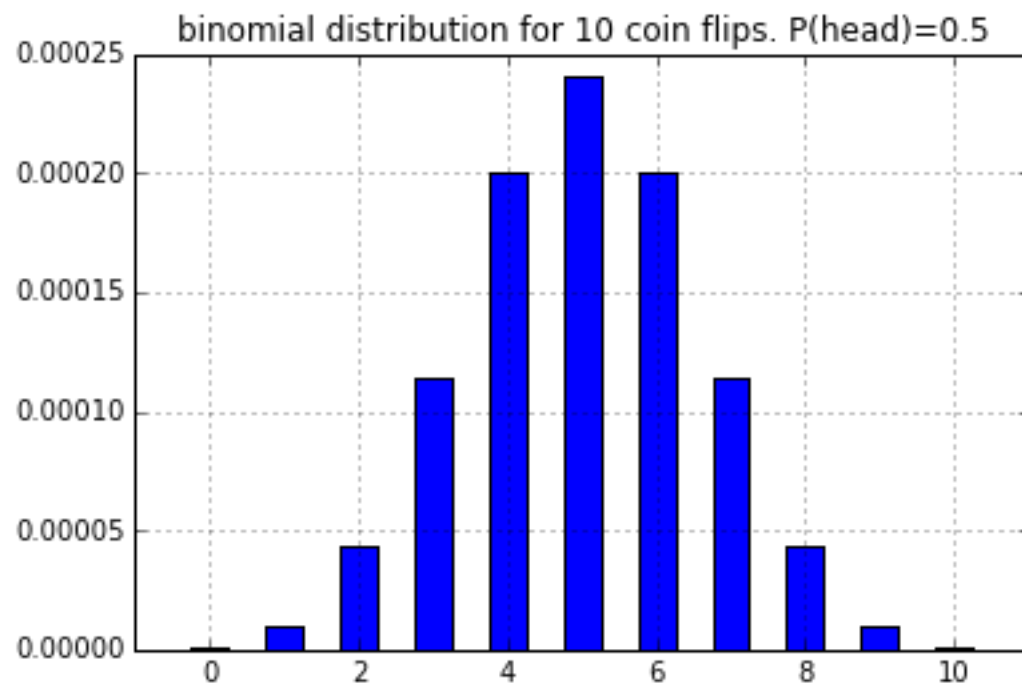
$$1 = (p + q)^n = \sum_{m=0}^n \binom{n}{m} p^m q^{n-m}$$

Probability of a sequence of length  $n$  having  $m$  heads and  $n - m$

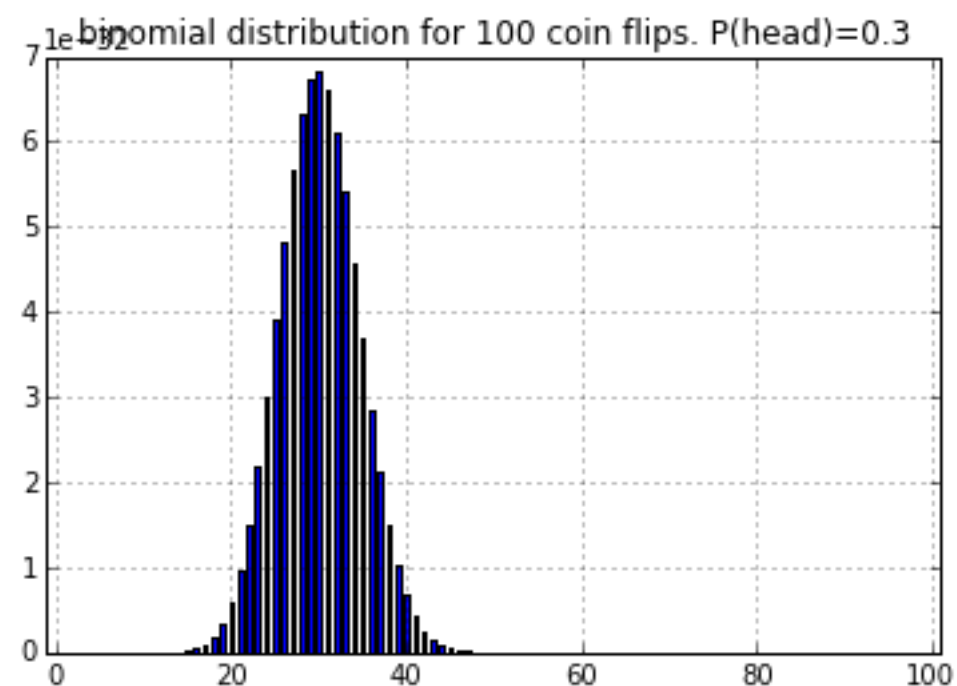
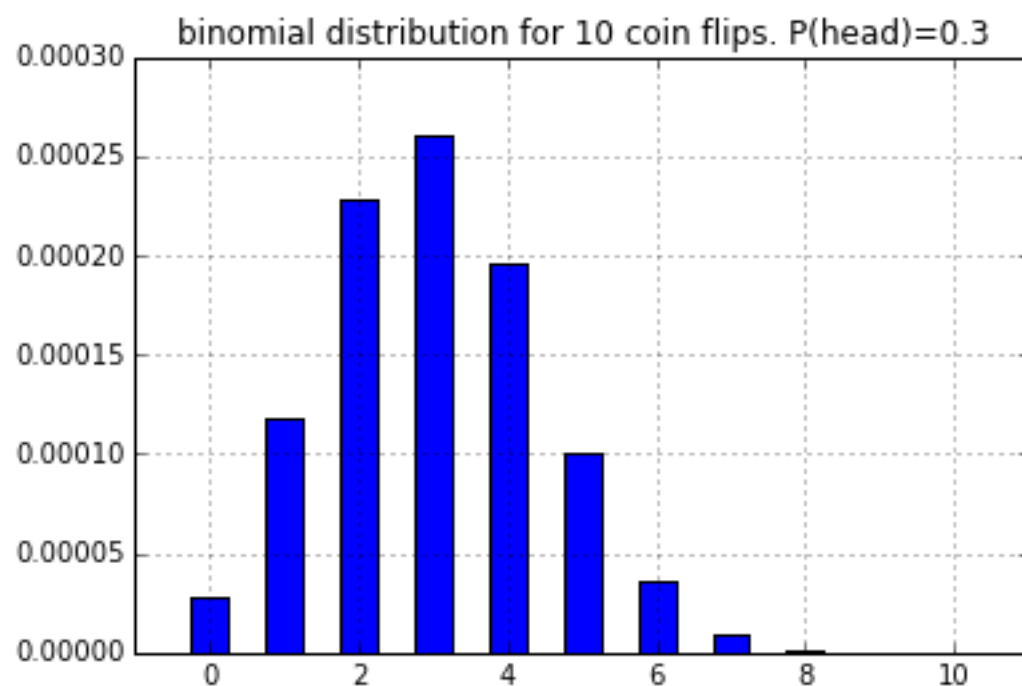
# General Binomial Distributions

$n=10$

$n=100$



$p=0.5$



$p=0.3$

# Dependence: Example

- Sample Space: all 22 year old men.
- Set A: men playing in the NBA
- Set B: men taller than 6' 5"
- $P(A \cap B) = P(\text{NBA players that are at least 6'5"}) \gg P(A)P(B)$

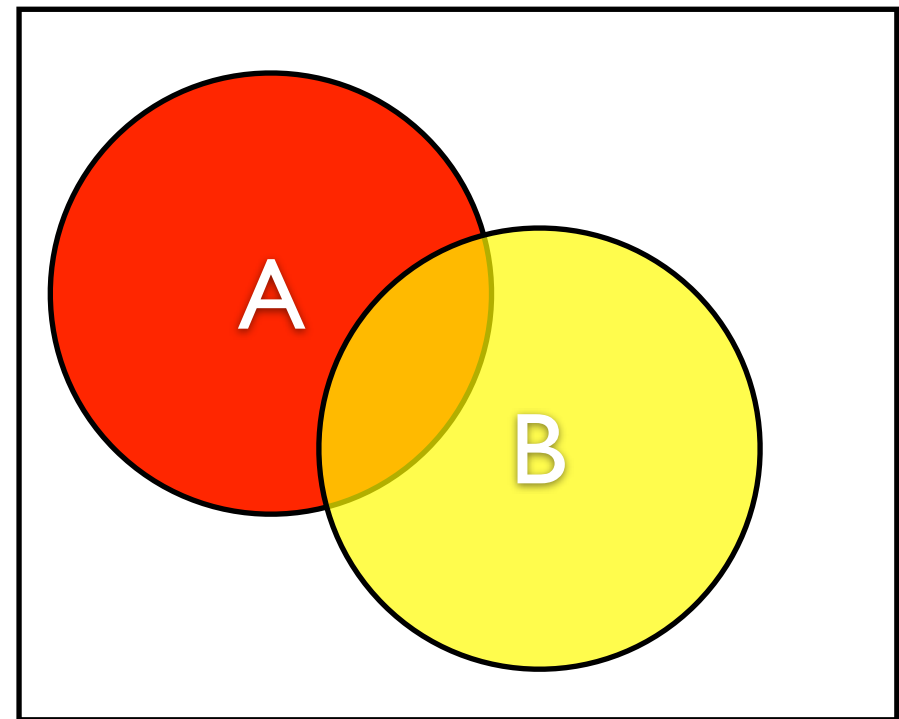
# Quantifying dependence: Conditional probability

The probability of  $A$  given  $B$  is:

$$P(A | B) \doteq \frac{P(A \cap B)}{P(B)}$$

$B$  replaces  $\Omega$

Sample Space  $\Omega$



# Dependence works both ways.

- If A depends on B then B depends on A
- Dependence/independence is **not** a directional relationship.
- Conditioning A on B rather than B on A is a decision of the observer - it is not inherent to the observed system.

# Expressing independence using conditional prob.

Definition of independence:  $P(A \cap B) = P(A)P(B)$

$$\text{Implication 1: } P(A | B) = \frac{P(A \cap B)}{P(B)} = \frac{P(A)P(B)}{P(B)} = P(A)$$

$$\text{Implication 2: } P(B | A) = \frac{P(A \cap B)}{P(A)} = \frac{P(A)P(B)}{P(A)} = P(B)$$

- Interpretation: If A and B are independent, knowing that A happened does not change the probability of B and vice versa
- Note: we are speaking of states of knowledge, NOT of causality.



# Conditional Prob. in Poker

- Suppose your private cards (hole) are Ace  $\heartsuit$ , 2  $\spadesuit$
- Suppose the community cards are 3  $\spadesuit$ , 4  $\spadesuit$ , 5  $\spadesuit$ , K  $\clubsuit$ , J  $\heartsuit$
- What is the probability that a particular opponent has a Straight Flush? (All cards of the same suit and sequential)
- $\Pr(\text{opponent's cards complete a straight flush} \mid \text{hole}=(\text{Ace } \heartsuit, 2 \spadesuit) \text{ and community}=(3 \spadesuit, 4 \spadesuit, 5 \spadesuit, K \clubsuit, J \heartsuit))$
- There are three combination the 2 cards of the opponent that would give her a straight flush: (1  $\spadesuit$ , 2  $\spadesuit$ ), (2  $\spadesuit$ , 6  $\spadesuit$ ), (6  $\spadesuit$ , 7  $\spadesuit$ ). However the first two pairs are impossible because you hold the 2  $\spadesuit$ .
- The conditional probability of a straight flush is therefor:  
 $\Pr(\text{opponent's cards complete a straight flush} \mid \text{hole}=(\text{Ace } \heartsuit, 2 \spadesuit) \text{ and community}=(3 \spadesuit, 4 \spadesuit, 5 \spadesuit, K \clubsuit, J \heartsuit)) = 1/C(52-7, 2)$

# independence in tabular form

|                  | marginal<br>on b | A            | A <sup>c</sup> |
|------------------|------------------|--------------|----------------|
| marginal<br>on A |                  | 4/12<br>=1/3 | 8/12<br>=2/3   |
| B                | 3/12<br>=1/4     | 1/12         | 2/12           |
| B <sup>c</sup>   | 9/12<br>=3/4     | 3/12         | 6/12           |

$$P(A \cap B) = 1/12$$

$$P(A) = 1/3$$

$$P(B) = 1/4$$

$$P(A \cap B) = P(A)P(B)$$

- A and B are independent
- Are A and B<sup>c</sup> Independent?

# Are $A$ and $B^c$ Independent?

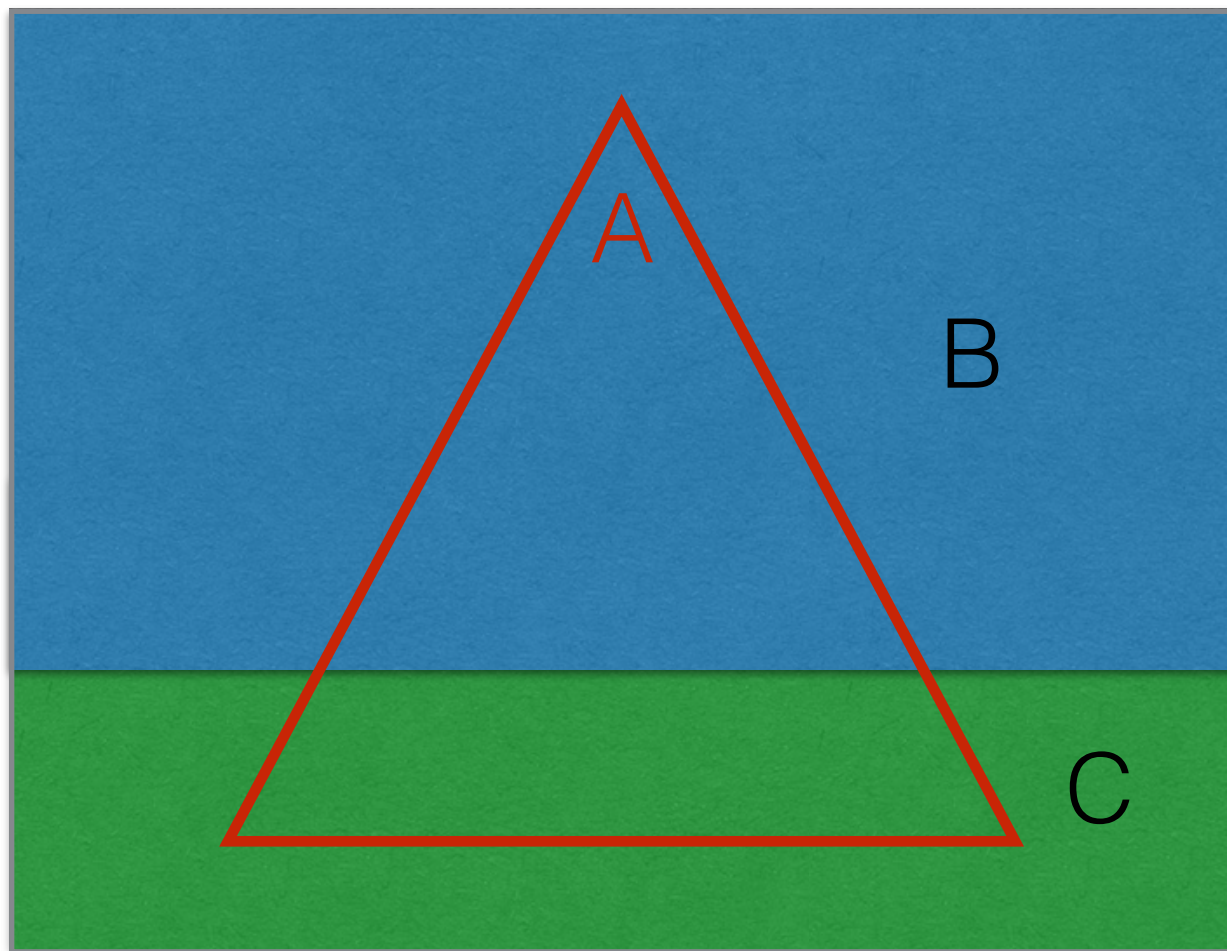
- Yes, because

$$\begin{aligned} P(A \cap B^c) &= P(A) - P(A \cap B) = \\ &= P(A) - P(A)P(B) = P(A)(1 - P(B)) = P(A)P(B^c) \end{aligned}$$

- Same for:  $A^c$  and  $B$  ,  $A^c$  and  $B^c$

# Conditional summation rule

$\Omega$



Standard summation rule

$$P(B) + P(C) = 1$$

Conditional summation rule

$$P(B|A) + P(C|A) = 1$$

Because:

$$P(B, A) + P(C, A) = P(A)$$

Dividing all by  $P(A)$  we get:

$$\frac{P(B, A)}{P(A)} + \frac{P(C, A)}{P(A)} = 1$$

# pair-wise vs complete independence

- Suppose we have three coins.
- We flip two of the coins to get HH, HT, TH, TT
- We chose the side of the third coin so that the number of Heads is even. (i.e. H if HT or TH. T otherwise)
- We have therefor a uniform distribution over 4 possibilities: HHT, HTH, THH, TTT.
- Focusing on any pair of coins, the outcomes of the coins are independent (Check!)
- However, consider the combination HHH
  - $P(HHH)=0$ , while  $P(H)P(H)P(H)=1/8$
- Even though each pair of coins are independent, the set of 3 coins are not independent!

# Bayesian Inference

# Bayesian Inference

- Who crashed the car?
- Suppose the only possible drivers are Rob or Sarah.
- We know the following probabilities.
  - $P(R \text{ rob drove})=10\%$ ,  $P(C \text{ crash} | R \text{ rob drove})=50\%$
  - $P(S \text{ Sarah drove})=90\%$ ,  $P(C \text{ crash} | S \text{ sarah drove})=1\%$

$$\begin{aligned} P(C) &= P(C, R) + P(C, S) = P(C | R)P(R) + P(C | S)P(S) \\ P(R | C) &= \frac{P(R, C)}{P(C)} = \frac{P(C | R)P(R)}{P(C)} = \frac{P(C | R)P(R)}{P(C | R)P(R) + P(C | S)P(S)} \\ &= \frac{0.1 \times 0.5}{0.1 \times 0.5 + 0.9 \times 0.01} = 0.85 \quad P(S | C) = 0.15 \end{aligned}$$

- Prior probabilities: Sarah drives the car 90% of the time, Rob 10% of the time.
- Posterior probabilities: given that there was an accident, the probability that the driver was Rob jumps to 85% because he is much more accident prone.

The following example is taken from *Probabilistic Reasoning in Intelligent Systems* by Judea Pearl:

You wake up in the middle of the night to the shrill sound of your burglar alarm. What is the chance that a burglary attempt has taken place?

The relevant facts are:

- There is a 95% chance that an attempted burglary attempt will trigger the alarm. That is,

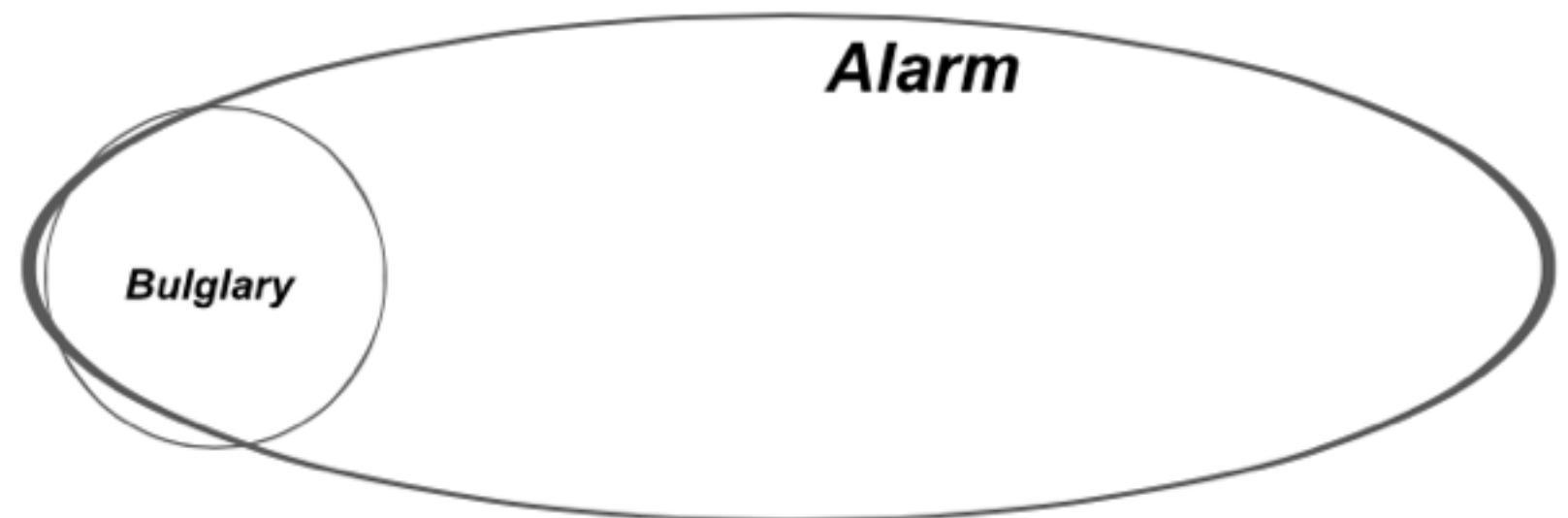
$$\Pr(\text{alarm}|\text{burglary}) = 0.95.$$

- There is a 1% chance of a false alarm.

$$\Pr(\text{alarm}|\text{no burglary}) = 0.01.$$

- Based on local crime statistics, there is a one-in-10,000 chance that a house will be burglarized on a given night.

$$\Pr(\text{burglary}) = 10^{-4}.$$





We are interested in the chance of a burglary given that the alarm has sounded. We can use the conditional probability formula for this:

$$\Pr(\text{burglary}|\text{alarm}) = \frac{\Pr(\text{burglary, alarm})}{\Pr(\text{alarm})} = \frac{\Pr(\text{alarm}|\text{burglary})\Pr(\text{burglary})}{\Pr(\text{alarm})}.$$

The one term we don't immediately know is  $\Pr(\text{alarm})$ . By the summation rule,

$$\Pr(\text{alarm}) = \Pr(\text{alarm}|\text{burglary})\Pr(\text{burglary}) + \Pr(\text{alarm}|\text{no burglary})\Pr(\text{no burglary}).$$

Putting it all together,

$$\Pr(\text{burglary}|\text{alarm}) = \frac{0.95 \times 10^{-4}}{0.95 \times 10^{-4} + 0.01 \times (1 - 10^{-4})} = 0.00941,$$

about 0.94%. Thus our belief in a burglary has risen approximately a hundredfold from its default value of  $10^{-4}$ , on account of the alarm.

It is frequently the case, as in this example, that we wish to update the chances of an event  $H$  based on new evidence  $E$ . In other words, we wish to know  $\Pr(H|E)$ . The derivation above implicitly uses the following formula, called **Bayes' rule**:

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

***To calculate  $\Pr(E)$  we use the summation rule***

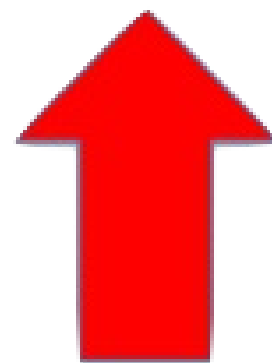
$$\Pr(H|E) = \frac{\Pr(E|H)\Pr(H)}{\Pr(E)} = \frac{\Pr(E|H)\Pr(H)}{\Pr(E|H)\Pr(H) + \Pr(E|H^c)\Pr(H^c)}$$

***To calculate  $\Pr(E)$  we use the summation rule***

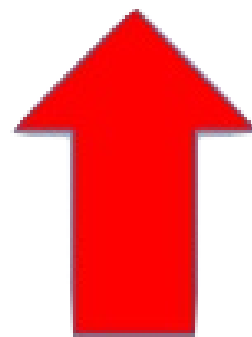
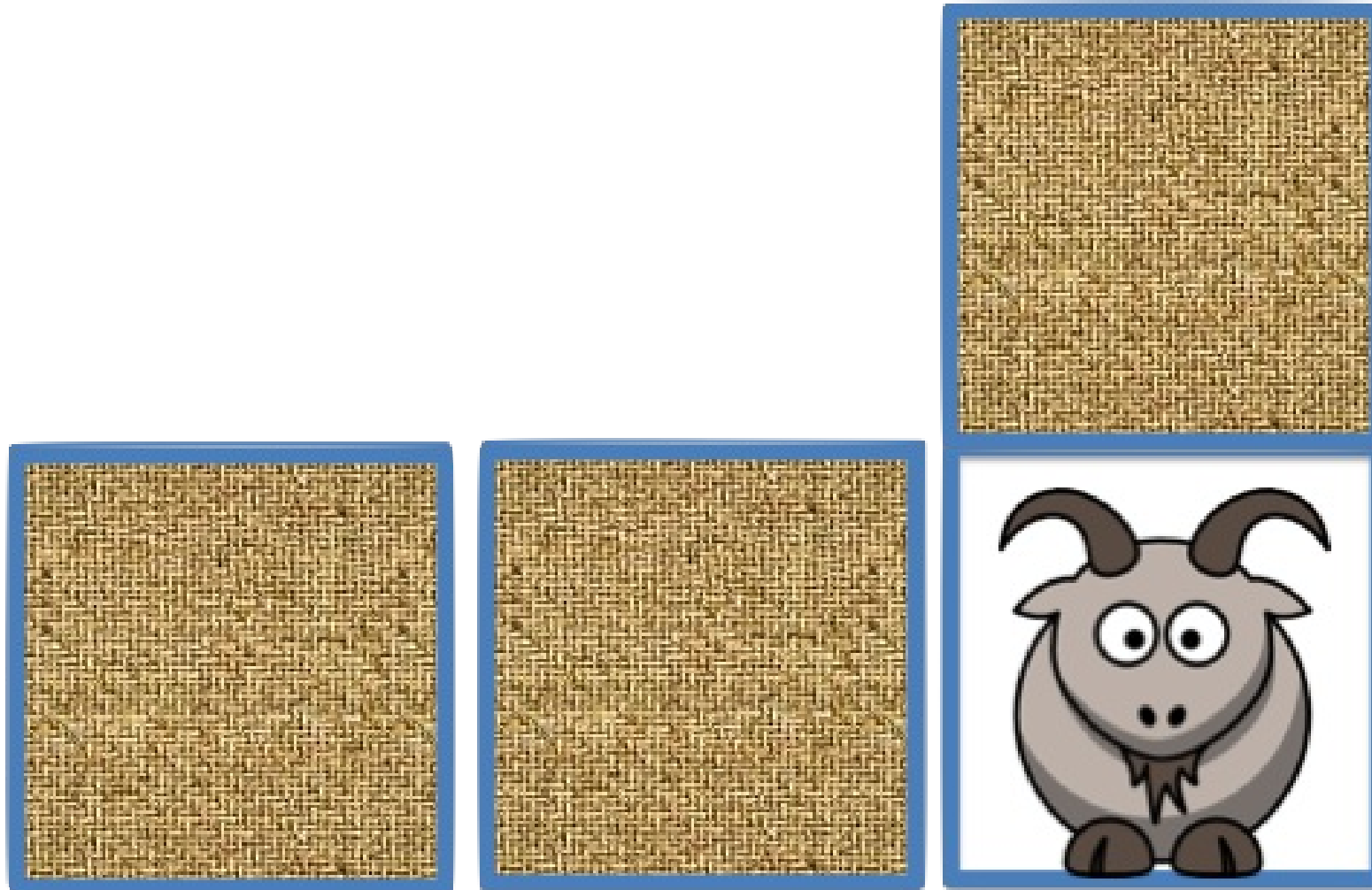
$$\Pr(H|E) = \frac{\Pr(E|H) \Pr(H)}{\Pr(E)} = \frac{\Pr(E|H) \Pr(H)}{\Pr(E|H) \Pr(H) + \Pr(E|H^c) \Pr(H^c)}$$

# The Monty Hall Puzzle

- Monty Hall was a variety show on TV.
- In one of the games there are three doors, one hiding a treasure, two hiding goats.
- Your goal is to select the door with the treasure.



*I am betting  
on this door*



*I am betting  
on this door*

*Monty opens  
this door*

*I am allowed to switch, should I?*

**Argument that it does not matter:**

***The chance that the treasure is behind each of the doors 50%.***

***As the probabilities are equal, it does not matter whether we switch or not.***

**Argument for choosing one of the two unopen doors at random.**

***Before I had to choose between 3 doors - my probability of success was 1/3***

***Now I am choosing between two doors, my probability of success is 1/2  
So random is better than staying on the same door.***

**Argument for Switching.**

***The probability that the treasure is behind the door I chose did not change.  
Therefore the probability that switching will put me on the treasure must be 2/3:***

$$1/2 * 1/3 + 1/2 * 2/3 = 1/2$$

**Arguments against switching:**

***I know already that one of the other doors has a goat behind it. So getting the information does not tell me anything new.***

*Analysis for always switching*

*prob 1/3*



*Initial bet*

*monty opens*



*I am betting on this door*



*Initial bet*



*I am betting on this door*

*monty opens*

*I lose*

*prob 1/3*



*I am betting on this door*



*Initial bet*

*monty opens*

*I win!*

*prob 1/3*



*I am betting on this door*

*monty opens*



*Initial bet*

*I win!*



***Hidden Assumption:*** *monty always opens a door to reveal a goat.*

***In fact, he might have his own goals:***

***If Monty wants us to lose:*** *open door only when we choose the treasure door.*

***If Monty wants us to win:*** *open door only when we choose a goat door.*

***For us the only SAFE thing to do is not to switch.***

***This is called the "Min-Max" strategy.***

***Min-Max is the strategy the guarantees us the best outcome in the worst case.***

***More on that - game theory.***