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  - ▶ Union:  $A \cup B$
  - ▶ Intersection:  $A \cap B$
  - **Complement**:  $A^c$ ,  $\overline{A}$  or A'
  - ► Set Difference: *A* \ *B*

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- Set with no elements: Ø
- Don't disrespect the Venn Diagram!

# Mathematical Operations Used in Probability

- Factorial:  $n! = n \cdot (n-1) \cdot (n-2) \cdot ... \cdot 2 \cdot 1$ 
  - Example:  $5! = 5 \cdot 4 \cdot 3 \cdot 2 \cdot 1$

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- Exponents
  - $e \approx 2.17$  (used in growth and construction of key distributions)
  - ▶ Negative exponents are interpreted as reciprocals:  $x^{-2} = \frac{1}{x^2}$
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  - ▶ Other exponent rules:  $c^x \cdot c^y$ ,  $c^x/c^y$ ,  $(c^x)^y$

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- Logarithms
  - ▶  $\log_x(y) = ?$  ⇒ how many powers of x give you y?
  - $\triangleright$  Example:  $\log_{10}(100) = ?$
  - Natural logarithm is the inverse of the exponential, e.x.:  $ln(e^5) = e^{ln(5)} = 5$
  - ▶ Other log properties: ln(xy), ln(x/y),  $ln(x^2)$ , ln(x+y)

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- Some properties of summation notation:

  - $\sum_{i=1}^{n} x = nx$
  - Geometric sums  $\sum_{i=0}^{\infty} r^i = \frac{1}{1-r}$  as long as |r| < 1

## Product Notation (and More!)

Any linear operation can be generalized in this way:

$$\Pi_{i=1}^{n} x_{i} = x_{1} \cdot x_{2} \cdot \ldots \cdot x_{n}$$

$$\bigcap_{i=1}^{n} A_{i} = A_{1} \cap A_{2} \cap \ldots \cap A_{n}, \quad \bigcup_{i=1}^{n} A_{i} = A_{1} \cup A_{2} \cup \ldots \cup A_{n}$$

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- · Some properties of product notation:

  - $\prod_{i=1}^{n} e^{x_i} = e^{\sum_{i=1}^{n} x_i}$
  - ▶ Important! The log of products becomes summation

$$\ln (\Pi_{i=1}^{n} x_{i}) = \ln(x_{1} \cdot x_{2} \cdot ... \cdot x_{n})$$

$$= \ln(x_{1}) + \ln(x_{2}) + ... + \ln(x_{n})$$

$$= \sum_{i=1}^{n} \ln(x_{i})$$

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  - $f: \mathbb{R}^2 \to \mathbb{R}$  given by  $f(x, y) = x^2 + y^2$
  - $f: \ell^{\infty} \to \mathbb{R}$  given by  $U(c_1, c_2, ...) = \sum_{i=1}^{\infty} u(c_i)$

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Some things to review for other classes: continuity, injective/surjective/bijective. Not needed here.

#### Calculus: Derivatives

- Derivatives capture notions of rates of change or slope
  - In economics, critical for optimization
  - ► To solve  $\max_x f(x)$ , need a first-order condition (f'(x) = 0) and a second-order condition (f''(x) < 0)

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- Refresher on common derivatives:

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- Other derivative rules to know:
  - ▶ Product rule:  $\frac{d}{dx}[f(x)g(x)] = f(x)g'(x) + f'(x)g(x)$
  - ► Chain rule:  $\frac{d}{dx}[f(g(x))] = f'(g(x))g'(x)$
  - ▶ Quotient rule:  $\frac{d}{dx} [f(x)/g(x)] = \frac{g(x)f'(x)-f(x)g'(x)}{g(x)^2}$
  - $f^{(k)}(x)$  denotes the k-th derivative of f(x)

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## Useful tips:

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  - Induction
  - Contrapositive

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"Anything is possible when you fly on the wings of mathematics!"

# SECTION 2.1-2.3: BASICS OF PROBABILITY

Building blocks in the language of probability:

**1** Experiment: The action/process of uncertainty

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Building blocks in the language of probability:

- **1** Experiment: The action/process of uncertainty
- **2** Sample Space, S: The set of all possible outcomes
  - **3 Event**, E: Any subset of outcomes in S. Events are stored in a collection,  $E \in \mathcal{E}$
- 4 Assigning relative likelihood of events in S is probability (P)

A triple  $(S, \mathcal{E}, P)$  is a probability space

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- Flipping that coin 3 times  $\Rightarrow \ \mathcal{S} = \{\textit{HHH}, \textit{HHT}, \textit{HTT}, \textit{TTT}, \textit{TTH}, \textit{THH}, \textit{HTH}, \textit{THT}\}$

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- What about rolling dice?
- Two gas stations with 6 pumps each. We measure how many pumps are in use at each station at 9:17 am on a Saturday.
   What does the sample space look like?

# A Complicated Sample Space

First Station	Second Station						
	0	1	2	3	4	5	6
0	(0, 0)	(0, 1)	(0, 2)	(0, 3)	(0, 4)	(0, 5)	(0, 6)
1	(1, 0)	(1, 1)	(1, 2)	(1, 3)	(1, 4)	(1, 5)	(1, 6)
2	(2, 0)	(2, 1)	(2, 2)	(2, 3)	(2, 4)	(2, 5)	(2, 6)
3	(3, 0)	(3, 1)	(3, 2)	(3, 3)	(3, 4)	(3, 5)	(3, 6)
4	(4, 0)	(4, 1)	(4, 2)	(4, 3)	(4, 4)	(4, 5)	(4, 6)
5	(5, 0)	(5, 1)	(5, 2)	(5, 3)	(5, 4)	(5, 5)	(5, 6)
6	(6, 0)	(6, 1)	(6, 2)	(6, 3)	(6, 4)	(6, 5)	(6, 6)

#### **Events**

## Events are any subset of outcomes in ${\mathcal S}$

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An event can be simple (|E| = 1) or compound (|E| > 1).

The collection of all events,  $\mathcal{E}$ , is the power set of  $\mathcal{S}$  when the state space is discrete<sup>1</sup>

 $<sup>^1</sup>$ When  $\mathcal S$  is not discrete,  $\mathcal E$  needs to satisfy some special closure conditions, so that it is a  $\sigma$ -algebra.

The goal of probability is to map events to numbers in a way that conveys information about likelihoods

0 | 1

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#### Axioms of Probability

For an event A, denote the probability that A occurs by P(A)

A probability measure is a function  $p: S \to \mathbb{R}$  that satisfies 3 axioms (building blocks of theory):

- A1 For all  $A \in \mathcal{S}$ ,  $P(A) \geq 0$
- A2 P(S) = 1
- A3 For any **infinite** collection of **disjoint** events  $\{A_1, A_2, ...\}$ ,  $P\left(\bigcup_{i=1}^{\infty} A_i\right) = \sum_{i=1}^{\infty} P(A_i)$  (countable additivity)

Questions about the axioms: What do we think? Why don't we need finiteness in A3? Etc?

#### Consequences of These Axioms I: Null Events

#### Proposition: Null Events have 0 Probability

What we want to show:  $P(\emptyset) = 0$ 

**Proof**: Use Axiom 3, taking as our infinite collection  $\{\emptyset, \emptyset, ...\}$ .

Notice that  $\emptyset \cap \emptyset = \emptyset$ , so the events are **disjoint**.

Then, 
$$P(\bigcup_{i=1}^{\infty} \emptyset) = P(\emptyset) = \sum_{i=1}^{\infty} P(\emptyset)$$
.

But we can't have  $x = \sum_{i=1}^{\infty} x$  unless x = 0. Hence,  $P(\emptyset) = 0$ .



#### Consequences of These Axioms II: Finite Collections

#### Proposition: Axiom 3 holds for finite collections

What we want to show: If  $\{A_1, ..., A_k\}$  is a finite collection of disjoint events, then  $P\left(\bigcup_{i=1}^k A_i\right) = \sum_{i=1}^k P(A_i)$ .

**Proof**: Take a finite collection of events  $\{A_1, ..., A_k\}$ .

Make this an **infinite** collection by appending  $\emptyset$ 's!

That is,  $\{A_1, ..., A_k\} \Rightarrow \{A_1, A_2, ..., A_k, \emptyset, \emptyset, ...\}.$ 

Then the third axiom says

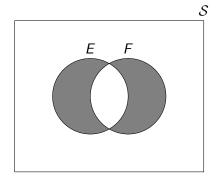
$$P\left(\bigcup_{i=1}^k A_i\right) = P\left(\bigcup_{i=1}^\infty A_i\right) = \sum_{i=1}^\infty P(A_i) = \sum_{i=1}^k P(A_i) + 0.$$



#### More Probability Properties

- 1 For all  $E \in \mathcal{E}$ ,  $P(E) = 1 P(\overline{E})$
- **2** For all  $E \in \mathcal{E}$ ,  $P(E) \leq 1$
- 3 For any two events E, F,  $P(E \cup F) = P(E) + P(F) P(E \cap F)$

#### Can you prove these?



This is something to watch out for!

#### Some examples

- If you flip a fair coin twice, what's the probability of getting at least one head?
- What's the probability of drawing either a spade or an ace from a deck of cards?

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When in doubt, list and count!

	Hrs Needed (day)   Hrs Needed (year)		Hours Left
			8760
Sleeping	8	2920	5840

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Commute	2	500	1731

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Holidays	5 days/yr	120	2231	
Commute	2	500	1731	
Working	8	2000	-269	

How to use this to your advantage: there are 8760 hours in a year. But you need time for...

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Commute	2	500	1731
Working	8	2000	-269

So you have to be about an hour late to work every day!

## SECTION 2.4: CONDITIONAL PROBABILITY

#### Dealing with Information

Suppose we're on a research team for the FDA. We're trying to evaluate Panacea<sup>TM</sup>, a new SSRI for depression

What questions can probability answer about Panacea? What would we like to know in order to approve it?

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- How likely is it that taking Panacea causes migraines?

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What happens when new information comes along?

- Patient started taking Panacea, has canceled 3 appointments
- Migraine patient has a history of headaches

How do we use this info to update desired probabilities?

#### Multiple Events

When we have two events A and B, it is helpful to distinguish:

- Marginal probabilities: P(A) and P(B)
- Joint probability:  $P(A \cap B)$
- Conditional probabilities: P(A|B), P(B|A)

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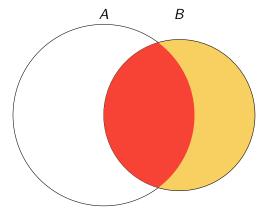
	Side Effects	
Symptom Repression	No	Yes
No	15	10
Yes	70	5

How effective is this drug? (What is P(SymptomRepression)?)

What if the patient is reporting side effects? (What is P(SR|SE)?)

#### A Formula for Conditional Probability

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



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You know that 70% of the restaurants in Boston sell french fries, and that 40% still make the cake you like. Googling tells you that 30% of restaurants do both.

If you go to a restaurant with french fries, what is the probability you can still have your cake?

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	C	$\overline{C}$	Marginal
FF	_		0.7
FF	_		0.3
Marginal	0.4	0.6	1

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### Example 1: Applying conditional probabilities

#### We know that:

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#### We know that:

- $P(A) + P(\overline{A}) = 1$
- $P(A \cap B) + P(A \cap \overline{B}) = P(A)$

#### Hence,

	C	$\overline{C}$	Marginal
FF	0.3	0.4	0.7
FF	0.1	0.2	0.3
Marginal	0.4	0.6	1

#### Example 1: Applying conditional probabilities

We know that:

• 
$$P(A) + P(\overline{A}) = 1$$

• 
$$P(A \cap B) + P(A \cap \overline{B}) = P(A)$$

Hence,

	C	$\overline{C}$	Marginal
FF	0.3	0.4	0.7
FF	0.1	0.2	0.3
Marginal	0.4	0.6	1

Hence, if you choose FF, then  $P(C|FF) = 3/7 \approx 0.49$ . Those odds are better than your marginal odds!

Check out this cool site for a visualization of conditional probability

# SECTION 2.5: INDEPDENDENCE

#### Indepdendence

Two events A and B are independent if P(A|B) = P(A). Otherwise, they are dependent.

Some consequences of independence:

- P(B|A) = P(B) (symmetry)
- $\overline{A}$  and B are independent
- B and  $\overline{A}$  are independent
- $\overline{A}$  and  $\overline{B}$  are independent

#### How do we know when events are independent?

If two events are independent:

$$P(A \cap B) \Leftrightarrow P(A|B)P(B) \Leftrightarrow P(A)P(B)$$

Hence, when the intersection of two events has the same probability as the product of the two events, they are independent

Q: What is the prob. of drawing a red card that is not an ace?

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	R	$\overline{R}$	
A	2/52	2/52	4/52
$\overline{A}$	24/52	24/52	48/52
	26/52	26/52	1

Q: What is the prob. of drawing a red card that is not an ace?

	R	$\overline{R}$	
A	1/26	1/26	1/13
$\overline{A}$	6/13	6/13	12/13
	1/2	1/2	1

Q: What is the prob. of drawing a red card that is not an ace?

$$\begin{array}{c|cccc} R & \overline{R} & \\ \hline A & 1/26 & 1/26 & 1/13 \\ \overline{A} & 6/13 & 6/13 & 12/13 \\ \hline & 1/2 & 1/2 & 1 \\ \hline \end{array}$$

**A**: Hence,  $P(\overline{A} \cap R) = 6/13$ .

Q: Are the events  $\overline{A}$ , R independent?

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A: Take product of the marginals:

$$P(\overline{A}) \cdot P(R) = \frac{12}{13} \frac{1}{2} = \frac{6}{13}$$

Q: Are the events  $\overline{A}$ , R independent?

A: Take product of the marginals:

$$P(\overline{A}) \cdot P(R) = \frac{12}{13} \frac{1}{2} = \frac{6}{13}$$

A: Hence, the two events are independent.

QUESTIONS?