## Probability and Random Processes ECS 315

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II. Events-Based Probability Theory


## Office Hours:

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5 Foundation of Probability Theory


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## Kolmogorov

- Andrey Nikolaevich Kolmogorov
- Soviet Russian mathematician
- Advanced various scientific fields
- probability theory
- topology
- classical mechanics

- computational complexity.

- 1922: Constructed a Fourier series that diverges almost everywhere, gaining international recognition.
- 1933: Published the book, Foundations of the Theory of Probability, laying the modern axiomatic foundations of probability theory and establishing his reputation as the world's leading living expert in this field. This book is available at


## I learned probability theory from



Eugene Dynkin


Philip Protter


Gennady Samorodnitsky


Terrence Fine



Toby Berger


## Not too far from Kolmogorov



You can be
the $4^{\text {th }}$-generation

probability theorists

# Probability and Random Processes ECS 315 

## Asst. Prof. Dr. Prapun Suksompong

prapun@siit.tu.ac.th<br>Event-Based Properties

## Probability space

- Mathematically, to talk about probability, we refer to probability space.
- Probability space has three components

1. Sample space $\Omega$
2. Collection of events

- Example: All subsets of $\Omega$. (Assume $\Omega$ is finite.)

3. Probability Measure

- A real-valued set function


## Kolmogorov's Axioms for Probability

Abstractly, a probability measure is a function that assigns real numbers to events, which satisfies the following assumptions:
P1 Nonnegativity: For any event $A$, This is called the

$$
P(A) \geq 0 .
$$ probability of the

## P2 Unit normalization:

 event $A$.$$
P(\Omega)=1
$$

P3 Countable Additivity: If $A_{1}, A_{2}, \ldots$, is a (countably-infinite) sequence of disjoint events, then

$$
P\left(\bigcup_{i=1}^{\infty} A_{i}\right)=\sum_{i=1}^{\infty} P\left(A_{i}\right)
$$

## Additivity

- Assumption: $A_{1}, A_{2}, \ldots$ are disjoint events.
[5.1 P3] - Countable Additivity: $P\left(\bigcup_{i=1}^{\infty} A_{i}\right)=\sum_{i=1}^{\infty} P\left(A_{i}\right)$
[5.4] $\bullet$ Finite Additivity: $P\left(\bigcup_{i=1}^{n} A_{i}\right)=\sum_{i=1}^{n} P\left(A_{i}\right)$
- The formula is quite intuitive when you visualize these events in a Venn diagram and think of their probabilities as areas.
- Example:

The "area" of the sample space is 1 .
[5.1 P2]


$$
P\left(A_{1} \cup A_{2} \cup A_{3}\right)=P\left(A_{1}\right)+P\left(A_{2}\right)+P\left(A_{3}\right)
$$

## ${ }^{[5.6]}$ Steps to find probability of an event that is defined by outcomes

1. Identify the sample space $\Omega$ and the probability $P(\{\omega\})$ for each outcome $\omega$.
2. Identify all the outcomes inside the event under consideration.
3. When the event is countable, its probability can be found by adding the probability $P(\{\omega\})$ of the outcomes from the previous step.

$$
P\left(\left\{a_{1}, a_{2}, \ldots, a_{n}\right\}\right)=\sum_{i=1}^{n} P\left(\left\{a_{i}\right\}\right) \quad P\left(\left\{a_{1}, a_{2}, \ldots\right\}\right)=\sum_{i=1}^{\infty} P\left(\left\{a_{i}\right\}\right)
$$

## Steps to Find Event-Based Probability

Step 1 Let $n$ be the number of events' names used in the question.

- For example, if the question only talks about $A$ and $B$, then $n=2$.

Step 2 Partition the sample space $(\Omega)$ into $2^{n}$ parts where each part is an intersection of the events or their complements.

- For example, when we have two events, the sample space can be partitioned into 4 parts:
(1) $A \cap B$,
(2) $A \cap B^{c}$,
(3) $A^{c} \cap B$, and
(4) $A^{c} \cap B^{c}$
as shown in the Venn diagram.


Step 3 Let $p_{i}$ be the probability of the $i^{\text {th }}$ part.

## Steps to Find Event-Based Probability

Step 4 Turn the given information into equation(s) of the $p_{i}$.

- For example, if you are given that $P(A \cup B)=0.3$, we see that $A \cup$ $B$ cover parts (1), © , and (3).Therefore, by finite additivity, the corresponding equation is $p_{1}+p_{2}+p_{3}=0.3$.
- It is easier to work with expression involving intersection than the one with union.
- Use de Morgan law [2.5] and complement rule [5.15]
- For example, suppose we are given that $P\left(A \cup B^{c}\right)=0.3$.
- By the complement rule, $P\left(\left(A \cup B^{c}\right)^{c}\right)=1-0.3=0.7$.
- By de Morgan law, $\left(A \cup B^{c}\right)^{c}=A^{c} \cap B$.
- Therefore, the provided information is equivalent to $P\left(A^{C} \cap B\right)=0.7$.
- The corresponding equation is $p_{3}=0.7$.
- Don't forget that we always have an extra piece of information:
$P(\Omega)=1$.
- With two events, this means $p_{1}+p_{2}+p_{3}+p_{4}=1$.


## Steps to Find Event-Based Probability

Step 5 Solve for the values of the $p_{i}$.

- Note that there are $n$ unknowns; so we will need $n$ equations to solve for the values of the $p_{i}$.
- If we don't have enough equations, you may be overlooking some given piece(s) of information or it is possible that you don't need to know the values of all the $p_{i}$ to find the final answer(s).
Step 6 The probability of any event can be found by adding the probabilities of the corresponding parts.


## Daniel Kahneman

- Daniel Kahneman
- Israeli-American psychologist
- 2002 Nobel laureate

- In Economics
- Hebrew University, Jerusalem, Israel.
'A lifetime’s worth of wisdom’
The International Bestseller

Thinking, Fast and Slow

- Professor emeritus of psychology and public affairs at Princeton University's Woodrow Wilson School.
- With Amos Tversky, Kahneman studied and clarified the kinds of misperceptions of randomness that fuel many of the common fallacies.


## K\&T: Q1

## 6. Judgments of and by representativeness

Amos Tversky and Daniel Kahneman

Several years ago, we presented an analysis of judgment under uncertainty hat related subjective probabilities and intuitive predictions to expectations and impressions about representativeness. Two distinct hypotheses incorporated this concept: (i) people expect samples to be highly similar to their parent population and also to represent the randomness of the sampling process (Tversky \& Kahneman, 1971, 2; 1974, 1); (ii) people often ely on representativeness as a heuristic for judgment and prediction The (irst
The first hypothesis was advanced to explain the common belief that hance processes are self-correcting, the exaggerated faith in the stability of results observed in small samples, the gambler's fallacy, and related
biases in judgments of randomness. We proposed that the lay conception of chance incorporates a belief in the law of small numbers, according to which even small samples are highly representative of their parent populations (Tversky \& Kahneman, 1971, 2). A similar hypothesis could also explain the common tendency to exaggerate the consistency and the predictive value of personality traits (Mischel, 1979) and to overestimate the correlations between similar variables (see Chap. 15) and behaviors (Shweder \& D'Andrade, 1980). People appear to believe in a hologram-like model of personality in which any fragment of behavior represents the actor's true character (Kahneman \& Tversky, 1973, 4).
The hypothesis that people expect samples to be highly representative of their parent populations is conceptually independent of the second hypothesis, that people often use the representativeness heuristic to make predictions and judge probabilities. That is, people often evaluate the probability of an uncertain event or a sample" "by the degree to which it is

This work was supported by the Office of Naval Research under Contract N00014-79-C-0077 o Stanford University.

Tversky, A., \& Kahneman, D. (1982). Judgments of and by representativeness. In D. Kahneman, P. Slovic, \& A. Tversky (Eds.), Judgment under Uncertainty: Heuristics and Biases (pp. 84-98). Cambridge: Cambridge University Press. doi:10.1017/CBO9780511809477.007

## 92 REPRESENTATIVENESS

Two brief personality sketches were constructed. Each participan encountered one of these sketches in the within-subjects treatment and the other in a between-subjects treatment. In the former, the personality sketch was followed by eight possible outcomes, including a representative outcome, an unrepresentative outcome, and the conjunction of the two. In the between-subjects treatment the list of outcomes included either he two crical single outcomes or their conjunction. The within-subjects are the mean ranks assigned to the various outcomes by the subjects who received this form.

Bill is 34 years old. He is intelligent, but unimaginative, compulsive, and generally lifeless. In school, he was strong in mathematics but weak in social studies and humanities.
Please rank order the following statements by their probability, using 1 for the most probable and 8 for the least probable.
(4.1) Bill is a physician who plays poker for a hobby
(1.8) Bill is an architect.
(6.2) Bill plays jazz for a hobby, (b)
(5.7) Bill surfs for a hobby.
(5.3) Bill is a reporter.
3.6) Bill is an accountant who plays jazz for a hobby. (A \& )
(5.4) Bill climbs mountains for a hobby

Linda is 31 years old, single, outspoken, and very bright. She majored in philosophy. As a student, she was deeply concerned with issues of discrimination and social justice, and also participated in anti-nuclear demonstrations.
Please rank the following statements by their probability, using 1 for the most (55) Lind is tee lest probable.
ry school.
(2.1) Linda is active in the feminist movement. (F)
(3.1) Linda is a psychiatric social worker.
(5.4) Linda is a member of the League of Women Voters.
(6.2) Linda is a bank teller. ( $T$ )
(6.4) Linda is an insurance salesperson.
(4.1) Linda is a bank teller and is active in the feminist movement. ( $T \& F$ )

As the reader has probably guessed, the description of Bill was constructed to be representative of an accountant (A) and unrepresentative of a person who plays jazz for a hobby (J). The description of Linda was constructed to be representative of an active feminist $(F)$ and unrepresentative of a bank teller ( $T$ ). In accord with psychological principles of similarity (Tversky, 1977) we expected that the compound targets, an accountant who plays jazz for a hobby ( $A \& / /$ ) and a bank teller who is active in the feminist movement ( $T \& F$ ), would fall between the respective simple targets. To test this prediction, we asked a group of 88

## K\&T: Q1

Imagine a woman named Linda, 31 years old, single, outspoken, and very bright. In college she majored in philosophy. While a student she was deeply concerned with discrimination and social justice and participated in antinuclear demonstrations.


- K\&T presented this description to a group of 88 subjects and asked them to rank the eight statements (shown on the next slide) on a scale of 1 to 8 according to their probability, with

1 representing the most probable and
8 representing the least probable.

## K\&T: Q1... Remarks

- The audiences who heard this description in the 1980s always laughed because they immediately knew that Linda had attended the University of California at Berkeley, which was famous at the time for its radical, politically engaged students.
- The League of Women Voters is no longer as prominent as it was, and the idea of a feminist "movement" sounds quaint, a testimonial to the change in the status of women over the last thirty years.
- Even in the Facebook era, however, it is still easy to guess the almost perfect consensus of judgments: Linda is a very good fit for an active feminist, a fairly good fit for someone who works in a bookstore and takes yoga classes-and a very poor fit for a bank teller or an insurance salesperson.


## K\&T: Q1 - Results

- Here are the results - from most to least probable

Statement
Average Probability Rank

Most probable
Linda is active in the feminist movement. 2.1

Linda is a psychiatric social worker. 3.1
Linda works in a bookstore and takes yoga classes.
Linda is a bank teller and is active in the feminist movement.
Linda is a teacher in an elementary school.
Linda is a member of the League of Women Voters. 5.4
Linda is a bank teller.
Least probable Linda is an insurance salesperson.

## K\&T: Q1 - Results (2)

- At first glance there may appear to be nothing unusual in these results: the description was in fact designed to be
- representative of an active feminist and
- unrepresentative of a bank teller or an insurance salesperson.

|  | Statement Average Probability Rank |  |  |
| :---: | :---: | :---: | :---: |
| Most probable | Linda is active in the feminist movement. | 2.1 |  |
|  | Linda is a psychiatric social worker. | 3.1 |  |
|  | Linda works in a bookstore and takes yoga classes. | 3.3 |  |
|  | Linda is a bank teller and is active in the feminist movement. | 4.1 | - |
|  | Linda is a teacher in an elementary school. | 5.2 |  |
|  | Linda is a member of the League of Women Voters. | 5.4 |  |
| $\downarrow$ | Linda is a bank teller. | 6.2 | $\longleftarrow$ |
| Least likely | Linda is an insurance salesperson. | 6.4 |  |

## K\&T: Q1 - Results (3)

- Let's focus on just three of the possibilities and their average ranks.
- This is the order in which 85 percent of the respondents ranked the three possibilities:

Statement
Average Probability Rank
More likely Linda is active in the feminist movement.
2.1

Linda is a bank teller and is active in the feminist movement.4.1

Less likely Linda is a bank teller.6.2

- If nothing about this looks strange, then K\&T have fooled you


## K\&T: Q1 - Contradiction

The probability that two events will both occur can never be greater than the probability that each will occur individually!

Statement
Average Probability Rank
Linda is active in the feminist movement. 2.1
Linda is a bank teller and is active in the feminist movement.
4.1

Linda is a bank teller.

## K\&T: Q2

- K\&T were not surprised by the result because they had given their subjects a large number of possibilities, and the connections among the three scenarios could easily have gotten lost in the shuffle.
- So they presented the description of Linda to another group, but this time they presented only three possibilities:
- Linda is active in the feminist movement.
- Linda is a bank teller and is active in the feminist movement.
- Linda is a bank teller.
- Is it now obvious that the middle one is the least likely?


## K\&T: Q2 - Results

- To their surprise, 87 percent of the subjects in this trial also incorrectly ranked the probability that "Linda is a bank teller and is active in the feminist movement" higher than the probability that "Linda is a bank teller".
- If the details we are given fit our mental picture of something, then the more details in a scenario, the more real it seems and hence the more probable we consider it to be
- even though any act of adding less-than-certain details to a conjecture makes the conjecture less probable.
- Even highly trained doctors make this error when analyzing symptoms.
- 91 percent of the doctors fall prey to the same bias.
[AmosTversky and Daniel Kahneman, "Extensional versus Intuitive Reasoning: The Conjunction Fallacy in Probability Judgment," Psychological Review 90, no. 4 (October 1983): 293-315.]


## Related Topic

BACK TO THE ABYSS What life is like eleven kilometres down rewscientist YOUR QUANTUM MIND
The deep connection between quantum theory and human thought

## LTTLE SECRETS <br> Why small words reveal your personality <br> VEGETARIAN MEAT <br> From lab to plate, <br> no animal required <br> Rewriting human evolution

- Page 34-37
- Tversky and Shafir @ Princeton University
Quantum minds

The fuzziness and weird ogic of the way particles behave applies surprisingly well to how humans think. Mark Buchanan finds the "you" in quantum

burgeoning field known as "quantum Interaction", whicc explores how quantum
theory can be seful in inas having nothing Oodowith physics, ranging from humal
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## K\&T: Q3

- Which is greater:
- the number of six-letter English words having "n" as their fifth letter or
- the number of six-letter English words ending in "-ing"?
- Most people choose the group of words ending in "ing". Why? Because words ending in "-ing" are easier to think of than generic six letter words having "n" as their fifth letter.
- Fact: The group of six-letter words having "n" as their fifth letter words includes all six-letter words ending in "-ing".
- Psychologists call this type of mistake the availability bias
- In reconstructing the past, we give unwarranted importance to memories that are most vivid and hence most available for retrieval.
[Amos Tversky and Daniel Kahneman, "Availability: A Heuristic for Judging Frequency and Probability," Cognitive Psychology 5 (1973): 207-32.]


## Misuse of probability in law

- It is not uncommon for experts in DNA analysis to testify at a criminal trial that a DNA sample taken from a crime scene matches that taken from a suspect.
- How certain are such matches?
- When DNA evidence was first introduced, a number of experts testified that false positives are impossible in DNA testing.
- Today DNA experts regularly testify that the odds of a random person's matching the crime sample are less than 1 in 1 million or 1 in 1 billion.
- In Oklahoma a court sentenced a man namedTimothy Durham to prison even though eleven witnesses had placed him in another state at the time of the crime.


## Tips for Finding Event-Based Probability

- Don't forget that we always have an extra piece of information: $P(\Omega)=1$.
- It is easier to work with expression involving intersection than the one with union.
- Use de Morgan law [2.5] and complement rule [5.15]
- For example, suppose we are given that $P\left(A \cup B^{c}\right)=0.3$.
- By the complement rule, $P\left(\left(A \cup B^{c}\right)^{c}\right)=1-0.3=0.7$.
- By de Morgan law, $\left(A \cup B^{c}\right)^{c}=A^{c} \cap B$.
- Therefore, the provided information is equivalent to $P\left(A^{c} \cap B\right)=0.7$.


## Tips for Finding Event-Based Probability

- Given $n$ events, the sample space $(\Omega)$ can be partitioned into $2^{n}$ parts where each part is an intersection of the events or their complements.
- For example, when we have two events, the sample space can be partitioned into 4 parts:
(1) $A \cap B$
(2) $A \cap B^{c}$
(3) $A^{c} \cap B$, and
(4) $A^{c} \cap B^{c}$
as shown in the Venn diagram.

- Any event can be written as a disjoint union of these parts. Therefore, if we can find the probabilities for these parts, then we can find the probability for any event by adding the probabilities of the corresponding parts.


## Tips for Finding Event-Based Probability

- If your aim is simply to find one working method to solve a problem (not trying to find the smart way to solve it), then the steps on the next slide will be helpful.
- It turns the problem into solving system of linear equations.


## Misuse of probability in law

- It is not uncommon for experts in DNA analysis to testify at a criminal trial that a DNA sample taken from a crime scene matches that taken from a suspect.
- How certain are such matches?
- When DNA evidence was first introduced, a number of experts testified that false positives are impossible in DNA testing.
- Today DNA experts regularly testify that the odds of a random person's matching the crime sample are less than 1 in 1 million or 1 in 1 billion.
- In Oklahoma, a court sentenced a man named Timothy Durham to more than 3,100 years in prison even though eleven witnesses had placed him in another state at the time of the crime.


## Misuse of probability in law



State: Oklahoma

Charge: Rape, Robbery

Conviction: Rape, Robbery

Sentence: 3,200 Years

Incident Date: 05/31/91

Conviction Date: 03/13/93

Exoneration Date: 12/09/97

Served: 4 years

## Lab Error

## (Human and Technical Errors)

- There is another statistic that is often not presented to the jury, one having to do with the fact that labs make errors, for instance, in collecting or handling a sample, by accidentally mixing or swapping samples, or by misinterpreting or incorrectly reporting results.
- Each of these errors is rare but not nearly as rare as a random match.
- The Philadelphia City Crime Laboratory admitted that it had swapped the reference sample of the defendant and the victim in a rape case
- A testing firm called Cellmark Diagnostics admitted a similar error.


## Timothy Durham's case

- It turned out that in the initial analysis the lab had failed to completely separate the DNA of the rapist and that of the victim in the fluid they tested, and the combination of the victim's and the rapist's DNA produced a positive result when compared with Durham's.
- A later retest turned up the error, and Durham was released after spending nearly four years in prison.


## DNA-Match Error + Lab Error

- Estimates of the error rate due to human causes vary, but many experts put it at around 1 percent.
- Most jurors assume that given the two types of error-the 1 in 1 billion accidental match and the 1 in 100 lab-error match-the overall error rate must be somewhere in between, say 1 in 500 million, which is still, for most jurors, beyond a reasonable doubt.


## Wait!...

- Even if the DNA match error was extremely accurate + Lab error is very small,
- there is also another probability concept that should be taken into account.
- More about this later.
- Right now, back to notes for more properties of probability measure.

