

Class 11 in-class problems, 18.05, Spring 2022

Concept questions

Concept question 1. Learning from experience

(a) Which treatment would you choose?

1. Treatment 1: cured 100% of patients in a trial.
2. Treatment 2: cured 95% of patients in a trial.
3. Treatment 3: cured 90% of patients in a trial.

Solution: No one correct answer.

(b) Which treatment would you choose?

1. Treatment 1: cured 3 out of 3 patients in a trial.
2. Treatment 2: cured 19 out of 20 patients treated in a trial.
3. Standard treatment: cured 90000 out of 100000 patients in clinical practice.

Solution: No one correct answer.

Board questions

Problem 1. Learning from data

- A certain disease has a prevalence of 0.005.
- A screening test has 2% false positives and 1% false negatives.

Suppose a random patient is screened and has a positive test.

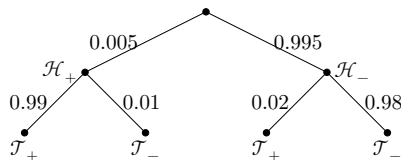
- Represent this information with a tree and use Bayes' theorem to compute the probabilities the patient does and doesn't have the disease.
- Identify the data, hypotheses, likelihoods, prior probabilities and posterior probabilities.
- Make a full likelihood table containing all hypotheses and possible test data.
- Redo the computation using a Bayesian update table. Match the terms in your table to the terms in your previous calculation.

Solution: (a) Tree based Bayes computation

Let \mathcal{H}_+ mean the patient has the disease and \mathcal{H}_- they don't.

Let \mathcal{T}_+ : they test positive and \mathcal{T}_- they test negative.

We can organize this in a tree:



Bayes' theorem says $P(\mathcal{H}_+ | \mathcal{T}_+) = \frac{P(\mathcal{T}_+ | \mathcal{H}_+)P(\mathcal{H}_+)}{P(\mathcal{T}_+)}$.

Using the tree, the total probability

$$\begin{aligned} P(\mathcal{T}_+) &= P(\mathcal{T}_+ | \mathcal{H}_+)P(\mathcal{H}_+) + P(\mathcal{T}_+ | \mathcal{H}_-)P(\mathcal{H}_-) \\ &= 0.99 \cdot 0.005 + 0.02 \cdot 0.995 = 0.02485 \end{aligned}$$

So,

$$\begin{aligned} P(\mathcal{H}_+ | \mathcal{T}_+) &= \frac{P(\mathcal{T}_+ | \mathcal{H}_+)P(\mathcal{H}_+)}{P(\mathcal{T}_+)} = \frac{0.99 \cdot 0.005}{0.02485} = 0.199 \\ P(\mathcal{H}_- | \mathcal{T}_+) &= \frac{P(\mathcal{T}_+ | \mathcal{H}_-)P(\mathcal{H}_-)}{P(\mathcal{T}_+)} = \frac{0.02 \cdot 0.995}{0.02485} = 0.801 \end{aligned}$$

The positive test greatly increases the probability of \mathcal{H}_+ , but it is still much less probable than \mathcal{H}_- .

(b) Terminology

Data: The data are the results of the experiment. In this case, the positive test.

Hypotheses: The hypotheses are the possible answers to the question being asked. In this case they are \mathcal{H}_+ the patient has the disease; \mathcal{H}_- they don't.

Likelihoods: The likelihood given a hypothesis is the probability of the data given that hypothesis. In this case there are two likelihoods, one for each hypothesis

$$P(\mathcal{T}_+ | \mathcal{H}_+) = 0.99 \quad \text{and} \quad P(\mathcal{T}_+ | \mathcal{H}_-) = 0.02.$$

We repeat: the likelihood is a probability **given** the hypothesis, **not** a probability of the hypothesis.

Prior probabilities of the hypotheses: The priors are the probabilities of the hypotheses prior to collecting data. In this case,

$$P(\mathcal{H}_+) = 0.005 \quad \text{and} \quad P(\mathcal{H}_-) = 0.995$$

Posterior probabilities of the hypotheses: The posteriors are the probabilities of the hypotheses **given** the data. In this case

$$P(\mathcal{H}_+ | \mathcal{T}_+) = 0.199 \quad \text{and} \quad P(\mathcal{H}_- | \mathcal{T}_+) = 0.801.$$

Posterior	Likelihood	Prior
↓	↓	↓
$P(\mathcal{H}_+ \mathcal{T}_+) = \frac{P(\mathcal{T}_+ \mathcal{H}_+) \cdot P(\mathcal{H}_+)}{P(\mathcal{T}_+)}$		
	↑	
Total probability of the data		

(c) Full likelihood table

The table holds likelihoods $P(\mathcal{D}|\mathcal{H})$ for every possible hypothesis and data combination.

hypothesis \mathcal{H}	likelihood $P(\mathcal{D} \mathcal{H})$	
disease state	$P(\mathcal{T}_+ \mathcal{H})$	$P(\mathcal{T}_- \mathcal{H})$
\mathcal{H}_+	0.99	0.01
\mathcal{H}_-	0.02	0.98

Notice in the table below that the $P(\mathcal{T}_+|\mathcal{H})$ column is exactly the likelihood column in the Bayesian update table.

(d) Calculation using a Bayesian update table

\mathcal{H} = hypothesis: \mathcal{H}_+ (patient has disease); \mathcal{H}_- (they don't).

Data: \mathcal{T}_+ (positive screening test).

hypothesis	prior	likelihood	Bayes numerator	posterior
\mathcal{H}	$P(\mathcal{H})$	$P(\mathcal{T}_+ \mathcal{H})$	$P(\mathcal{T}_+ \mathcal{H})P(\mathcal{H})$	$P(\mathcal{H} \mathcal{T}_+)$
\mathcal{H}_+	0.005	0.99	0.00495	0.199
\mathcal{H}_-	0.995	0.02	0.0199	0.801
total	1	NO SUM	$P(\mathcal{T}_+) = 0.02485$	1

Data $\mathcal{D} = \mathcal{T}_+$

Total probability: $P(\mathcal{T}_+) =$ sum of Bayes numerator column = 0.02485

Bayes' theorem: $P(\mathcal{H}|\mathcal{T}_+) = \frac{P(\mathcal{T}_+|\mathcal{H})P(\mathcal{H})}{P(\mathcal{T}_+)} = \frac{\text{likelihood} \times \text{prior}}{\text{total prob. of data}}$

Problem 2. Dice

I have five dice: 4-sided, 6-sided, 8-sided, 12-sided, 20-sided.

I pick one at random, roll it and report that the roll was a 13.

Goal: Find the probabilities the die is 4, 6, 8, 12 or 20 sided.

(a) Identify the hypotheses.

(b) Make a likelihood table with columns for the data 'rolled a 13', 'rolled a 5' and 'rolled a 9'.

(c) Make a Bayesian update table and compute the posterior probabilities that the chosen die is each of the five dice.

(d) Same question if I had reported a 5.

(e) Same question if I had reported a 9.



Solution: (a) The hypotheses are: \mathcal{H}_4 , the chosen die was 4-sided; \mathcal{H}_6 , the chosen die was 6-sided; Likewise \mathcal{H}_8 , \mathcal{H}_{12} , \mathcal{H}_{20} .

(b) The likelihoods for a roll of 5, 9 and 13 are

hypothesis \mathcal{H}	$P(5 \mathcal{H})$	$P(9 \mathcal{H})$	$P(13 \mathcal{H})$
\mathcal{H}_4	0	0	0
\mathcal{H}_6	1/6	0	0
\mathcal{H}_8	1/8	1/8	0
\mathcal{H}_{12}	1/12	1/12	0
\mathcal{H}_{20}	1/20	1/20	1/20

(c) \mathcal{D} = ‘rolled a 13’. So our likelihood column uses the $P(13|\mathcal{H})$ from part (b).

hypothesis	prior	likelihood	Bayes	
			numerator	posterior
\mathcal{H}	$P(\mathcal{H})$	$P(\mathcal{D} \mathcal{H})$	$P(\mathcal{D} \mathcal{H})P(\mathcal{H})$	$P(\mathcal{H} \mathcal{D})$
\mathcal{H}_4	1/5	0	0	0
\mathcal{H}_6	1/5	0	0	0
\mathcal{H}_8	1/5	0	0	0
\mathcal{H}_{12}	1/5	0	0	0
\mathcal{H}_{20}	1/5	1/20	1/100	1
total	1		1/100	1

The only possibility is the 20-sided die.

(d) \mathcal{D} = ‘rolled a 5’. So our likelihood column uses the $P(5|\mathcal{H})$ from part (b).

hypothesis	prior	likelihood	Bayes	
			numerator	posterior
\mathcal{H}	$P(\mathcal{H})$	$P(\mathcal{D} \mathcal{H})$	$P(\mathcal{D} \mathcal{H})P(\mathcal{H})$	$P(\mathcal{H} \mathcal{D})$
\mathcal{H}_4	1/5	0	0	0
\mathcal{H}_6	1/5	1/6	1/30	0.392
\mathcal{H}_8	1/5	1/8	1/40	0.294
\mathcal{H}_{12}	1/5	1/12	1/60	0.196
\mathcal{H}_{20}	1/5	1/20	1/100	0.118
total	1		0.085	1

\mathcal{H}_4 is impossible. The most probable hypothesis is \mathcal{H}_6 .

(e) \mathcal{D} = ‘rolled a 9’. So our likelihood column uses the $P(9|\mathcal{H})$ from part (b).

hypothesis	prior	likelihood	Bayes	
			numerator	posterior
\mathcal{H}	$P(\mathcal{H})$	$P(\mathcal{D} \mathcal{H})$	$P(\mathcal{D} \mathcal{H})P(\mathcal{H})$	$P(\mathcal{H} \mathcal{D})$
\mathcal{H}_4	1/5	0	0	0
\mathcal{H}_6	1/5	0	0	0
\mathcal{H}_8	1/5	0	0	0
\mathcal{H}_{12}	1/5	1/12	1/60	0.625
\mathcal{H}_{20}	1/5	1/20	1/100	0.375
total	1		0.0267	1

The most probable hypothesis is \mathcal{H}_{12} .

Problem 3. Iterated updates

Suppose I rolled a 9 and then a 5.

(a) *Do the Bayesian update in two steps:*

Step 1: First update for the 9.

Step 2: Then update the update for the 5.

(b) *Do the Bayesian update in one step.*

That is, the data is \mathcal{D} = ‘9 followed by 5’

Solution: (a) Tabular solution: two steps

$\mathcal{D}_1 = \text{'rolled a 9'}$, $\mathcal{D}_2 = \text{'rolled a 5'}$

Bayes numerator₁ = likelihood₁ × prior.

Bayes numerator₂ = likelihood₂ × Bayes numerator₁

hyp.	prior	Bayes			Bayes	
		likel. 1	num. 1	likel. 2	num. 2	posterior
\mathcal{H}	$P(\mathcal{H})$	$P(\mathcal{D}_1 \mathcal{H})$	***	$P(\mathcal{D}_2 \mathcal{H})$	***	$P(\mathcal{H} \mathcal{D}_1, \mathcal{D}_2)$
\mathcal{H}_4	1/5	0	0	0	0	0
\mathcal{H}_6	1/5	0	0	1/6	0	0
\mathcal{H}_8	1/5	0	0	1/8	0	0
\mathcal{H}_{12}	1/5	1/12	1/60	1/12	1/720	0.735
\mathcal{H}_{20}	1/5	1/20	1/100	1/20	1/2000	0.265
total	1				0.0019	1

(b) Tabular solution: one step

$\mathcal{D} = \text{'rolled a 9 then a 5'}$

hypothesis	prior	likelihood	Bayes	
			numerator	posterior
\mathcal{H}	$P(\mathcal{H})$	$P(\mathcal{D} \mathcal{H})$	$P(\mathcal{D} \mathcal{H})P(\mathcal{H})$	$P(\mathcal{H} \mathcal{D})$
\mathcal{H}_4	1/5	0	0	0
\mathcal{H}_6	1/5	0	0	0
\mathcal{H}_8	1/5	0	0	0
\mathcal{H}_{12}	1/5	1/144	1/720	0.735
\mathcal{H}_{20}	1/5	1/400	1/2000	0.265
total	1		0.0019	1

Problem 4. Probabilistic prediction (Probably won't get here till next time)

With the same setup as before let:

$\mathcal{D}_1 = \text{result of first roll}$, $\mathcal{D}_2 = \text{result of second roll}$

(a) Find $P(\mathcal{D}_1 = 5)$.

(b) Find $P(\mathcal{D}_2 = 4|\mathcal{D}_1 = 5)$.

Solution: $\mathcal{D}_1 = \text{'rolled a 5'}$, $\mathcal{D}_2 = \text{'rolled a 4'}$

hyp.	prior	Bayes				
		likel. 1	num. 1	post. 1	likel. 2	post. 1 × likel. 2
\mathcal{H}	$P(\mathcal{H})$	$P(\mathcal{D}_1 \mathcal{H})$	***	$P(\mathcal{H} \mathcal{D}_1)$	$P(\mathcal{D}_2 \mathcal{H}, \mathcal{D}_1)$	$P(\mathcal{D}_2 \mathcal{H}, \mathcal{D}_1)P(\mathcal{H} \mathcal{D}_1)$
\mathcal{H}_4	1/5	0	0	0	*	0
\mathcal{H}_6	1/5	1/6	1/30	0.392	1/6	0.392 · 1/6
\mathcal{H}_8	1/5	1/8	1/40	0.294	1/8	0.294 · 1/40
\mathcal{H}_{12}	1/5	1/12	1/60	0.196	1/12	0.196 · 1/12
\mathcal{H}_{20}	1/5	1/20	1/100	0.118	1/20	0.118 · 1/20
total	1		0.085	1		0.124

The law of total probability tells us $P(\mathcal{D}_1)$ is the sum of the Bayes numerator 1 column in the table: $P(\mathcal{D}_1) = 0.085$.

The law of total probability tells us $P(\mathcal{D}_2|\mathcal{D}_1)$ is the sum of the last column in the table:

$P(\mathcal{D}_2|\mathcal{D}_1) = 0.124$ **Solution:** $\mathcal{D}_1 = \text{'rolled a 5'}$, $\mathcal{D}_2 = \text{'rolled a 4'}$

Bayes						
hyp.	prior	likel. 1	num. 1	post. 1	likel. 2	post. 1 \times likel. 2
\mathcal{H}	$P(\mathcal{H})$	$P(\mathcal{D}_1 \mathcal{H})$	***	$P(\mathcal{H} \mathcal{D}_1)$	$P(\mathcal{D}_2 \mathcal{H}, \mathcal{D}_1)$	$P(\mathcal{D}_2 \mathcal{H}, \mathcal{D}_1)P(\mathcal{H} \mathcal{D}_1)$
\mathcal{H}_4	1/5	0	0	0	*	0
\mathcal{H}_6	1/5	1/6	1/30	0.392	1/6	0.392 \cdot 1/6
\mathcal{H}_8	1/5	1/8	1/40	0.294	1/8	0.294 \cdot 1/40
\mathcal{H}_{12}	1/5	1/12	1/60	0.196	1/12	0.196 \cdot 1/12
\mathcal{H}_{20}	1/5	1/20	1/100	0.118	1/20	0.118 \cdot 1/20
total	1		0.085	1		0.124

The law of total probability tells us $P(\mathcal{D}_1)$ is the sum of the Bayes numerator 1 column in the table: $P(\mathcal{D}_1) = 0.085$.

The law of total probability tells us $P(\mathcal{D}_2|\mathcal{D}_1)$ is the sum of the last column in the table: $P(\mathcal{D}_2|\mathcal{D}_1) = 0.124$

Extra problems

Extra 1. Bayesian updating: terminology, trees, tables

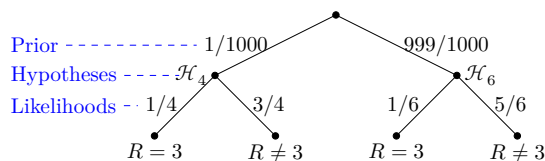
I have a bag with one 4-sided die and 999 6-sided dice. I pick one at random and roll it. Suppose I get a 3.

Goal: find the probabilities the chosen die was 4-sided or 6-sided.

- (a) Identify the hypotheses.
- (b) Use Bayes' theorem to compute the posterior probabilities. Organize the computation using trees.
- (c) Connect all the Bayesian updating terminology with the parts of the computation.
- (d) Redo the computation using a Bayesian updating table.

Solution: (a) The hypotheses are: \mathcal{H}_4 , the chosen die was 4-sided and \mathcal{H}_6 , the chosen die was 6-sided;

(b) Let R be the value of the roll. Here is the probability tree:



Bayes' theorem says $P(\mathcal{H}_4 | R = 3) = \frac{P(R = 3 | \mathcal{H}_4)P(\mathcal{H}_4)}{P(R = 3)}$. Likewise for \mathcal{H}_6

Using the tree, the total probability of $R = 3$.

$$P(R = 3) = P(R = 3 | \mathcal{H}_4)P(\mathcal{H}_4) + P(R = 3 | \mathcal{H}_6)P(\mathcal{H}_6) = 1/4000 + 999/6000 = 0.167$$

So,

$$P(\mathcal{H}_4 | R = 3) = \frac{P(R = 3 | \mathcal{H}_4)P(\mathcal{H}_4)}{P(R = 3)} = \frac{1/4000}{0.167} \approx 0.0015$$

$$P(\mathcal{H}_6 | R = 3) = \frac{P(R = 3 | \mathcal{H}_6)P(\mathcal{H}_6)}{P(R = 3)} = \frac{999/6000}{0.167} \approx 0.9985$$

The roll of 3 increases the probability of \mathcal{H}_4 , but it is still much less probable than \mathcal{H}_6 .

(c) Terminology

Data: The data are the results of the experiment. In this case, $R = 3$.

Hypotheses: The hypotheses are the possible answers to the question being asked. In this case they are \mathcal{H}_4 the die is 4-sided and \mathcal{H}_6 the die is 6-sided.

Likelihoods: The likelihood given a hypothesis is the probability of the data given that hypothesis. In this case there are two likelihoods, one for each hypothesis

$$P(R = 3 | \mathcal{H}_4) = 1/4 \quad \text{and} \quad P(R = 3 | \mathcal{H}_6) = 1/6.$$

We repeat: the likelihood is a probability **given** the hypothesis, **not** a probability of the hypothesis.

Prior probabilities of the hypotheses: The priors are the probabilities of the hypotheses prior to collecting data. In this case,

$$P(\mathcal{H}_4) = 1/1000 \quad \text{and} \quad P(\mathcal{H}_6) = 999/1000.$$

Posterior probabilities of the hypotheses: The posteriors are the probabilities of the hypotheses **given** the data. In this case

$$P(\mathcal{H}_4 | R = 3) \approx 0.0015 \quad \text{and} \quad P(\mathcal{H}_6 | R = 3) \approx 0.9985. \quad (\text{Computed below.})$$

Posterior	Likelihood	Prior
↓	↓	↓
$P(\mathcal{H}_4 R = 3) = \frac{P(R = 3 \mathcal{H}_4) \cdot P(\mathcal{H}_4)}{P(R = 3)}$		
	↗	
Total probability of the data		

(d) Calculation using a Bayesian update table

\mathcal{H} = hypothesis: \mathcal{H}_4 (4-sided die); \mathcal{H}_6 (6-sided die).

Data: $R = 3$ (roll of 3).

hypothesis	prior	likelihood	Bayes	
			numerator	posterior
\mathcal{H}	$P(\mathcal{H})$	$P(R = 3 \mathcal{H})$	$P(R = 3 \mathcal{H})P(\mathcal{H})$	$P(\mathcal{H} R = 3)$
\mathcal{H}_4	1/1000	1/4	1/4000	$\frac{1/4000}{0.167} \approx 0.0015$
\mathcal{H}_6	999/1000	1/6	999/6000	$\frac{999/6000}{0.167} \approx 0.9985$
total	1	NO SUM	$P(R = 3) = 0.167$	1

The Total probability of the data is $P(R = 3) = \text{sum of Bayes numerator column} = 0.167$.

$$\text{Bayes' theorem: } P(\mathcal{H}|R = 3) = \frac{P(R = 3|\mathcal{H})P(\mathcal{H})}{P(R = 3)} = \frac{\text{likelihood} \times \text{prior}}{\text{total prob. of data}}$$

The posterior probabilities are identical to those from the tree based calculation.

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18.05 Introduction to Probability and Statistics

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