

# Week 2 Questions

Q1

a) There are  $6 \times 6 \times 6$  elements in the sample space, because each roll of the die can land on any of the 6 sides.  $6 \times 6 \times 6 = \mathbf{216}$

b) There is one outcome where they are all twos. There are  $(1 \times 5 \times 5) \times 3$  possible outcomes for one two being rolled and there are  $(1 \times 1 \times 5) \times 3$  possible outcomes for two twos. Therefore there are  $1 + 75 + 15 = 91$  outcomes containing *at least one* two. So the probability is  $91/216 = \mathbf{0.42}$

c)

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count = 0;

for i = 1:100000

    threeRolls = randi(6, 3, 1);
    if ismember(2, threeRolls)
        count = count + 1;
    end;

end;

result = count / 100000;
disp(result);
```

d) There must be two sixes and a five for the sum to be 17, therefore there is only one possible outcome.  $1/216 = \mathbf{0.0046}$

e) The number of possibilities that the first roll is a one is  $1 \times 6 \times 6 = 36$ . For the sum to be 12, the next two rolls must be either (5,6) or (6,5).  $2/36 = \mathbf{0.055}$

Q2

a) E is the second roll is a 5. F1 is the first roll is a 1 and F2 is the first roll is not a one.

$$P(E) = (1/6 \times 1/6) + (5/6 \times 1/20) = \mathbf{0.069}$$

b) E is now the second roll is a 15.  $P(E) = (1/6 \times 0/6) + (5/6 \times 1/20) = \mathbf{0.042}$

Q3

$P(G)$  is the probability that suspect is guilty,  $P(C)$  is the probability that the suspect has the characteristic. Using Bayes Theorem, the probability that the suspect is guilty, given they have the characteristic, is  $P(G|C) = P(C|G) \times P(G) / P(C)$ .  $P(C|G)$  is 1, because we know the criminal has this characteristic. We can use marginalization to find  $P(C) \rightarrow$

$$P(C|G) \times P(G) + P(C|G') \times P(G'). \quad P(G') = 1 - P(G) = 0.4. \quad P(C) = 1 \times 0.6 + 0.2 \times 0.4 = 0.68.$$

Therefore,  $P(G|C) = 0.6/0.68 = \mathbf{0.882}$

Q4

We use Bayes Theorem again.  $P(O)$  is the probability of observing two bars of signal, and  $P(L)$  is the probability of being in location  $L$ .  $P(L|O) = P(O|L) \times P(L) / P(O)$ . We use marginalization to find  $P(O) \rightarrow P(O|L1)P(L1) + P(O|L2)P(L2) + P(O|L3)P(L3) + \dots + P(O|L16)P(L16)$ .  $0.05 \times 0.75 + 0.1 \times 0.95 + 0.05 \times 0.75 + 0.05 \times 0.05 + 0.05 \times 0.05 + 0.1 \times 0.75 + 0.05 \times 0.95 + 0.05 \times 0.75 + 0.05 \times 0.01 + 0.05 \times 0.05 + 0.1 \times 0.75 + 0.05 \times 0.95 + 0.05 \times 0.01 + 0.05 \times 0.01 + 0.1 \times 0.05 + 0.05 \times 0.75 = P(O) = 0.504$ .

$$P(L1|O) = 0.05 \times 0.75 / 0.504 = \mathbf{0.0744}$$

$$P(L2|O) = 0.1 \times 0.95 / 0.504 = \mathbf{0.1885}$$

$$P(L3|O) = 0.05 \times 0.75 / 0.504 = \mathbf{0.0744}$$

$$P(L4|O) = 0.05 \times 0.05 / 0.504 = \mathbf{0.00496}$$

$$P(L5|O) = 0.05 \times 0.05 / 0.504 = \mathbf{0.00496}$$

$$P(L6|O) = 0.1 \times 0.75 / 0.504 = \mathbf{0.1488}$$

$$P(L7|O) = 0.05 \times 0.95 / 0.504 = \mathbf{0.0942}$$

$$P(L8|O) = 0.05 \times 0.75 / 0.504 = \mathbf{0.0744}$$

$$P(L9|O) = 0.05 \times 0.01 / 0.504 = \mathbf{0.00099}$$

$$P(L10|O) = 0.05 \times 0.05 / 0.504 = \mathbf{0.00496}$$

$$P(L11|O) = 0.1 \times 0.75 / 0.504 = \mathbf{0.1488}$$

$$P(L12|O) = 0.05 \times 0.95 / 0.504 = \mathbf{0.0942}$$

$$P(L13|O) = 0.05 \times 0.01 / 0.504 = \mathbf{0.00099}$$

$$P(L14|O) = 0.05 \times 0.01 / 0.504 = \mathbf{0.00099}$$

$$P(L15|O) = 0.1 \times 0.05 / 0.504 = \mathbf{0.0099}$$

$$P(L16|O) = 0.05 \times 0.75 / 0.504 = \mathbf{0.0744}$$

```
priors = [  
    0.05, 0.1, 0.05, 0.05;  
    0.05, 0.1, 0.05, 0.05;  
    0.05, 0.05, 0.1, 0.05;  
    0.05, 0.05, 0.1, 0.05  
];  
  
likelihoods = [  
    0.75, 0.95, 0.75, 0.05;  
    0.05, 0.75, 0.95, 0.75;  
    0.01, 0.05, 0.75, 0.95;  
    0.01, 0.01, 0.05, 0.75  
];  
  
evidence = 0;
```

```
for i = 1:16
    temp = priors(i) * likelihoods(i);
    evidence = evidence + temp;
end

posteriors = zeros(4,4);

for i = 1:16
    posteriors(i) = priors(i) * likelihoods(i) / evidence;
end

disp(posteriors)
```

I start by declaring the two matrices *priors* and *likelihoods*, then iterate over them in order to calculate the *evidence*. Then I just declare the posteriors matrix as a 4x4 of zeros, and again iterate through, storing each result in the respective spot. It could probably be more efficient if I stored the result of  $\text{priors}(i) * \text{likelihoods}(i)$ , rather than calculating it twice, but the way I have it seems easier to read for me.