

Learn Bayes

2024-11-07

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Quarto <http://allendowney.github.io/ThinkBayes2>

Chapter 1

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

Penguins

```
import pandas as pd
import numpy as np
```

```
df = pd.read_csv("https://raw.githubusercontent.com/mwaskom/seaborn-data/master/penguins.csv")
df = df.dropna()
df.head()
```

| | species | island | bill_length_mm | bill_depth_mm | flipper_length_mm | body_mass_g | sex |
|---|---------|-----------|----------------|---------------|-------------------|-------------|--------|
| 0 | Adelie | Torgersen | 39.1 | 18.7 | 181.0 | 3750.0 | MALE |
| 1 | Adelie | Torgersen | 39.5 | 17.4 | 186.0 | 3800.0 | FEMALE |
| 2 | Adelie | Torgersen | 40.3 | 18.0 | 195.0 | 3250.0 | FEMALE |
| 4 | Adelie | Torgersen | 36.7 | 19.3 | 193.0 | 3450.0 | FEMALE |
| 5 | Adelie | Torgersen | 39.3 | 20.6 | 190.0 | 3650.0 | MALE |

```
df.shape
```

(333, 7)

```
set(df.species), set(df.island), set(df.sex)
```

```
({'Adelie', 'Chinstrap', 'Gentoo'},
 {'Biscoe', 'Dream', 'Torgersen'},
 {'FEMALE', 'MALE'})
```

(‘Adelie’, ‘Chinstrap’, ‘Gentoo’) (‘FEMALE’, ‘MALE’)

A FEMALE B Adelie

1.1 A & B

$P(A \& B)$:

```
def prob_sex_and_species(df, sex_str, species_str):
    subset = df[(df['sex'] == sex_str) & (df['species'] == species_str)]
    return len(subset) / len(df)
```

```
prob_sex_and_species(df, sex_str='FEMALE', species_str='Adelie')
```

0.21921921921921922

1.2 A|B

$P(A|B)$ P(Female|Adelie):

```
def prob_sex_given_species(df, sex_str, species_str):
    species_subset = df[df.species == species_str]
    sex_subset_within_species_subset = species_subset[species_subset.sex == sex_str]
    return len(sex_subset_within_species_subset)/len(species_subset)
```

```
prob_sex_given_species(df, 'FEMALE', 'Adelie')
```

0.5

1.3

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

```
def prob_species(df, species_str):
    subset = df[df.species == species_str]
    return len(subset)/len(df)
```

```
prob_species(df, 'Adelie')
```

```
0.43843843843843844
```

```
prob_sex_given_species(
    df, 'FEMALE', 'Adelie') == prob_sex_and_species(
    df, 'FEMALE', 'Adelie')/prob_species(df, 'Adelie')
```

```
True
```

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

$$P(A \& B) = P(A|B)P(B)$$

$$P(B \& A) = P(B|A)P(A)$$

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

Chapter 2

2.1

| | | |
|---|----|----|
| 1 | 30 | 10 |
| 2 | 20 | 20 |

$$\frac{30}{30 + 20} = \frac{3}{5}$$

$$P(h_1|d) = \frac{P(h_1)P(d|h_1)}{P(d)} = \frac{\frac{1}{2} \cdot \frac{3}{4}}{\frac{5}{8}} = \frac{3}{5}$$

$$P(h|d) = \frac{P(h)P(d|h)}{P(d)}$$

h hypothesis d posterior.
 $P(h)$ prior () $P(d|h)$ likelihood () $P(h|d)$

- hypothesis:
- data:

- $P(h)$ (Prior) h hypothesis $P() = 0.5$
- $P(d|h)$ (Likelihood) $P(|) = 0.75$
- $P(d)$

$$P() = P(_1)P(| _1) + P(_2)P(| _2)$$

$$P() = \frac{1}{2} \cdot \frac{3}{4} + \frac{1}{2} \cdot \frac{1}{2} = \frac{5}{8}$$

- posterior: $P(h|d)$

$$P(_1 |) = \frac{P(_1)P(| _1)}{P()}$$

$$P(_1 |) = \frac{\frac{1}{2} \cdot \frac{3}{4}}{\frac{5}{8}} = \frac{3}{5}$$

2.2

```
import pandas as pd
table = pd.DataFrame(index = [" 1", " 2"])

table['prior'] = 1/2, 1/2
table
```

| prior | |
|-------|-----|
| 1 | 0.5 |
| 2 | 0.5 |

$p(_1 |)$ hypothesis data prior $p(_1)$ likelihood $p(| _1)$ posterior

```
table['likelihood'] = 3/4, 1/2
table
```

| | prior | likelihood |
|---|-------|------------|
| 1 | 0.5 | 0.75 |
| 2 | 0.5 | 0.50 |

$prior * likelihood = P(d_1)P(d_2 | d_1):$

```
table['unnorm'] = table['prior'] * table['likelihood']
table
## unnorm      unnormalized posteriors
```

| | prior | likelihood | unnorm |
|---|-------|------------|--------|
| 1 | 0.5 | 0.75 | 0.375 |
| 2 | 0.5 | 0.50 | 0.250 |

$p(d) = p(d_1) = \frac{5}{8}$

```
table['posterior'] = table['unnorm'] / (5/8)
table
```

| | prior | likelihood | unnorm | posterior |
|---|-------|------------|--------|-----------|
| 1 | 0.5 | 0.75 | 0.375 | 0.6 |
| 2 | 0.5 | 0.50 | 0.250 | 0.4 |

$3/5 \quad p(d_2 | d_1) = \frac{2}{5}$

unnorm posterior unnorm unnorm

```
table['posterior_again'] = table['unnorm'] / table['unnorm'].sum()
table
```

| | prior | likelihood | unnorm | posterior | posterior_again |
|---|-------|------------|--------|-----------|-----------------|
| 1 | 0.5 | 0.75 | 0.375 | 0.6 | 0.6 |
| 2 | 0.5 | 0.50 | 0.250 | 0.4 | 0.4 |

2.3

6 8 12 A 1 A B 6

$$p(\text{dice} = 6 | \text{number} = 1)$$

- prior: $p(\text{dice} = 6)$
- likelihood: $p(\text{number} = 1 | \text{dice} = 6)$
- data: $p(\text{number} = 1)$
- posterior: $p(\text{dice} = 6 | \text{number} = 1)$

```
table2 = pd.DataFrame(index = [6, 8, 12])
from fractions import Fraction
table2['prior'] = Fraction(1,3)
table2['likelihood'] = Fraction(1,6), Fraction(1,8), Fraction(1, 12)
table2
```

| | prior | likelihood |
|----|-------|------------|
| 6 | 1/3 | 1/6 |
| 8 | 1/3 | 1/8 |
| 12 | 1/3 | 1/12 |

```
table2['unnorm'] = table2['prior'] * table2['likelihood']
table2
```

| | prior | likelihood | unnorm |
|----|-------|------------|--------|
| 6 | 1/3 | 1/6 | 1/18 |
| 8 | 1/3 | 1/8 | 1/24 |
| 12 | 1/3 | 1/12 | 1/36 |

“unnorm” posterior

```
table2['posterior'] = table2['unnorm']/table2['unnorm'].sum()
table2
```

| | prior | likelihood | unnorm | posterior |
|----|-------|------------|--------|-----------|
| 6 | 1/3 | 1/6 | 1/18 | 4/9 |
| 8 | 1/3 | 1/8 | 1/24 | 1/3 |
| 12 | 1/3 | 1/12 | 1/36 | 2/9 |

2.4

C A B A

- 1.
- 2.
- 3.

| A | B |
|---|-----|
| 1 | 1 |
| 1 | 2 |
| 1 | 3 |
| 1 | 4 |
| 1 | 5 |
| 1 | 6 |
| 1 | 7 |
| 1 | 8 |
| 1 | 9 |
| 1 | 10 |
| 1 | 11 |
| 1 | 12 |
| 1 | 13 |
| 1 | 14 |
| 1 | 15 |
| 1 | 16 |
| 1 | 17 |
| 1 | 18 |
| 1 | 19 |
| 1 | 20 |
| 1 | 21 |
| 1 | 22 |
| 1 | 23 |
| 1 | 24 |
| 1 | 25 |
| 1 | 26 |
| 1 | 27 |
| 1 | 28 |
| 1 | 29 |
| 1 | 30 |
| 1 | 31 |
| 1 | 32 |
| 1 | 33 |
| 1 | 34 |
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| 1 | 39 |
| 1 | 40 |
| 1 | 41 |
| 1 | 42 |
| 1 | 43 |
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| 1 | 50 |
| 1 | 51 |
| 1 | 52 |
| 1 | 53 |
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| 1 | 55 |
| 1 | 56 |
| 1 | 57 |
| 1 | 58 |
| 1 | 59 |
| 1 | 60 |
| 1 | 61 |
| 1 | 62 |
| 1 | 63 |
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| 1 | 85 |
| 1 | 86 |
| 1 | 87 |
| 1 | 88 |
| 1 | 89 |
| 1 | 90 |
| 1 | 91 |
| 1 | 92 |
| 1 | 93 |
| 1 | 94 |
| 1 | 95 |
| 1 | 96 |
| 1 | 97 |
| 1 | 98 |
| 1 | 99 |
| 1 | 100 |
| 2 | 1 |
| 2 | 2 |
| 2 | 3 |
| 2 | 4 |
| 2 | 5 |
| 2 | 6 |
| 2 | 7 |
| 2 | 8 |
| 2 | 9 |
| 2 | 10 |
| 2 | 11 |
| 2 | 12 |
| 2 | 13 |
| 2 | 14 |
| 2 | 15 |
| 2 | 16 |
| 2 | 17 |
| 2 | 18 |
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| 2 | 20 |
| 2 | 21 |
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| 2 | 24 |
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| 2 | 26 |
| 2 | 27 |
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| 2 | 30 |
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| 2 | 39 |
| 2 | 40 |
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| 2 | 72 |
| 2 | 73 |
| 2 | 74 |
| 2 | 75 |
| 2 | 76 |
| 2 | 77 |
| 2 | 78 |
| 2 | 79 |
| 2 | 80 |
| 2 | 81 |
| 2 | 82 |
| 2 | 83 |
| 2 | 84 |
| 2 | 85 |
| 2 | |

1/2

| | | | |
|------------|-------|------------|---------|
| hypothesis | prior | $p(\quad)$ | A, B, C |
|------------|-------|------------|---------|

Data: C

Likelihood $p(\text{Data}|h)$ Posterior $p(h|\text{Data})$

prior

```
table3 = pd.DataFrame(index = ['A', 'B', 'C'])
table3['prior'] = Fraction(1, 3)
table3
```

| | prior |
|---|-------|
| A | 1/3 |
| B | 1/3 |
| C | 1/3 |

| | Likelihood | Likelihood | hypothesis | data |
|------------|------------|------------|------------|----------|
| hypothesis | A, | C | 1/2 | |
| hypothesis | B | | A | C data 1 |
| hypothesis | C | C | 0 | |

```
table3['likelihood'] = Fraction(1, 2), 1, 0
table3['unnorm'] = table3['prior'] * table3['likelihood']
table3['posterior'] = table3['unnorm']/(table3['unnorm'].sum())
table3
```

| | prior | likelihood | unnorm | posterior |
|---|-------|------------|--------|-----------|
| A | 1/3 | 1/2 | 1/6 | 1/3 |
| B | 1/3 | 1 | 1/3 | 2/3 |
| C | 1/3 | 0 | 0 | 0 |

B

Chapter 3

3.1

Posterior distribution \propto Prior distribution \times Likelihood distribution

\propto proportional to a b prior likelihood posterior

Section 2.1

```
import numpy as np
import matplotlib.pyplot as plt
```

```
def normalize_array(arr):
    return np.array([i/sum(arr) for i in arr])
```

```
prior = np.array([0.5, 0.5])
prior
```

```
array([0.5, 0.5])
```

```
# Likelihood: hypothesis data
# hypothesis data
likelihood_red = np.array([0.75, 0.5])
posterior = normalize_array(prior * likelihood_red)
posterior
```

```
array([0.6, 0.4])
```

```

                                prior    likelihood
posterior
                                0.6      0.4
prior
                                prior    posterior    likelihood

```

```

posterior *= likelihood_red
posterior = normalize_array(posterior)
posterior

```

```
array([0.69230769, 0.30769231])
```

```

prior                posterior Likelihood    likelihood_white

```

```

likelihood_white = np.array([0.25, 0.5])
posterior *= likelihood_white
posterior = normalize_array(posterior)
posterior

```

```
array([0.52941176, 0.47058824])
```

3.2

```
101      0 100
```

- 0 0%
- 1 1%
- 2 2%
- ...
- 99 99%
- 100 100%

x 

- hypothesis: x
- data:
- prior: $p(h)$
- likelihood: $p(d|h)$
- posterior: $p(h|d)$

```

n = 101
# uniform prior:
all_ones = [1]*n
prior = normalize_array(all_ones)
# likelihood array:
likelihood_red = np.array([i/(n-1) for i in range(n)])
posterior = normalize_array(prior * likelihood_red)
posterior[0:5]

```

```

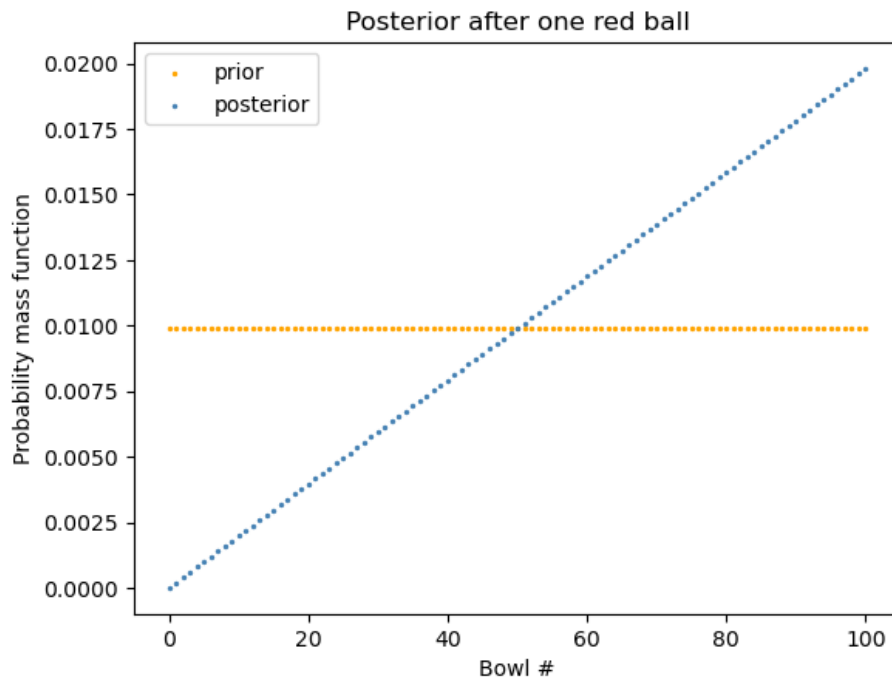
array([0.          , 0.00019802, 0.00039604, 0.00059406, 0.00079208])

```

```

x_axis = range(n)
plt.scatter(x = x_axis, y = prior,
            label="prior", color="orange", s = 2)
plt.scatter(x = x_axis, y = posterior,
            label="posterior", color="steelblue", s = 2)
plt.xlabel("Bowl #")
plt.ylabel("Probability mass function")
plt.legend()
plt.title("Posterior after one red ball")
plt.show()

```

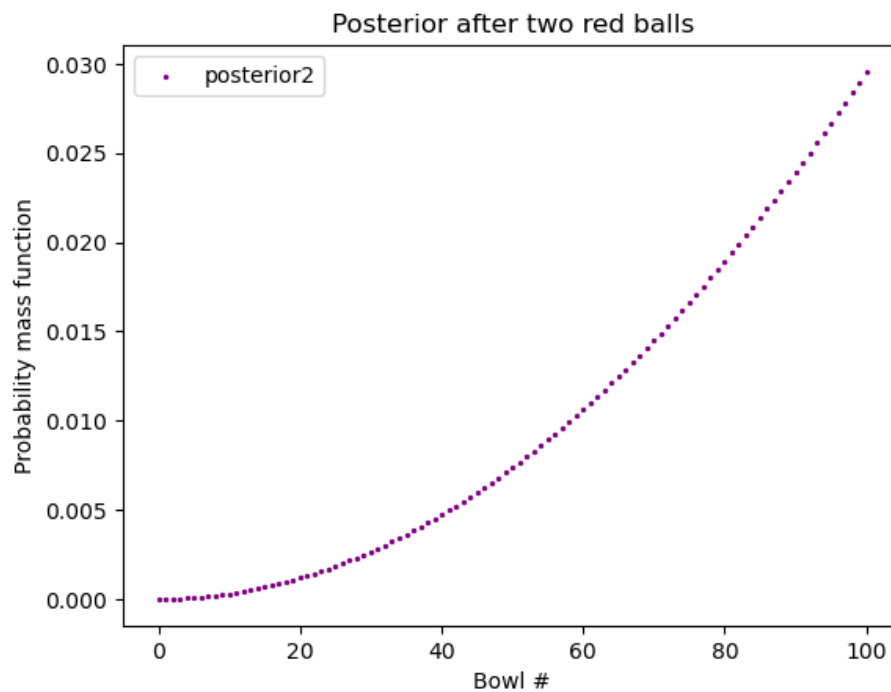


x

```

posterior2 = normalize_array(posterior * likelihood_red)
plt.scatter(x = x_axis, y = posterior2,
            label="posterior2", color="purple", s = 2)
plt.xlabel("Bowl #")
plt.ylabel("Probability mass function")
plt.legend()
plt.title("Posterior after two red balls")
plt.show()

```

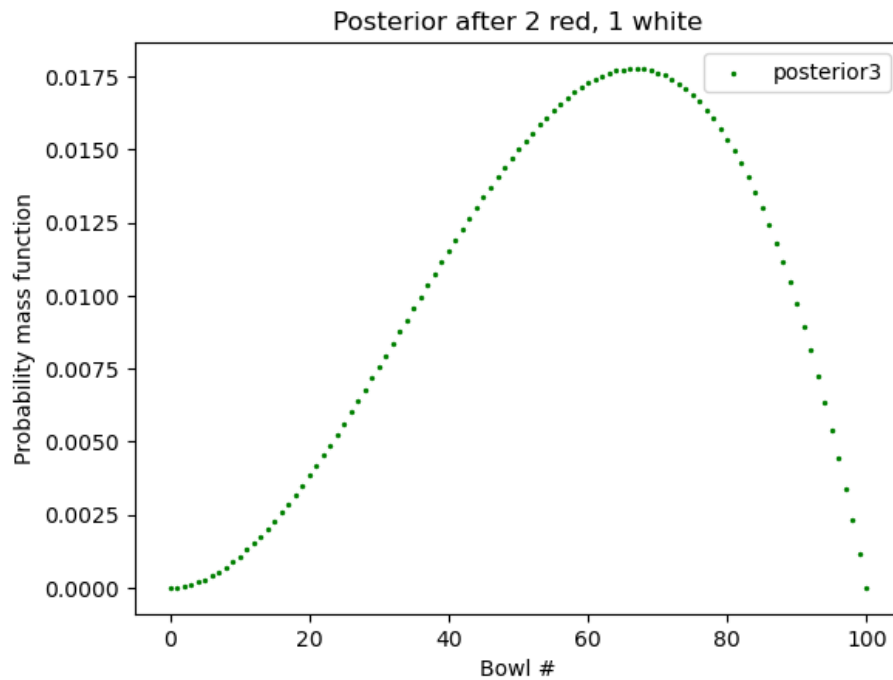

 x

prior

posterior

prior

```
likelihood_white = np.array([1 - x for x in likelihood_red])
posterior3 = normalize_array(posterior2 * likelihood_white)
plt.scatter(x = x_axis, y = posterior3,
            label="posterior3", color="green", s = 2)
plt.xlabel("Bowl #")
plt.ylabel("Probability mass function")
plt.legend()
plt.title("Posterior after 2 red, 1 white")
plt.show()
```



PMF (probability mass function) “maximum a posterior probability”
(MAP).

```
max_index = np.argmax(posterior3)
print("    #", max_index)
```

```
# 67
```

3.3

```
posterior3
```

```
all_ones = [1]*n
prior = normalize_array(all_ones)
posterior = normalize_array(prior * likelihood_red)
posterior2 = normalize_array(posterior * likelihood_red)
posterior3 = normalize_array(posterior2 * likelihood_white)
```

```
normalize_array()
```

```
all_ones = [1]*n
prior = normalize_array(all_ones)
```

```
prior, likelihood_red, likelihood_white, posterior (array)
```

```
-- --
```

```
posterior3
```

```
posterior3_new = all_ones * likelihood_white * likelihood_red * likelihood_red #
posterior3_new = normalize_array(posterior3_new) #
```

```
posterior3[0:5]
```

```
array([0.00000000e+00, 1.18811881e-05, 4.70447045e-05, 1.04770477e-04,
       1.84338434e-04])
```

```
posterior3_new = all_ones * likelihood_white * likelihood_red * likelihood_red
posterior3_new = normalize_array(posterior3_new)
posterior3_new[0:5]
```

```
array([0.00000000e+00, 1.18811881e-05, 4.70447045e-05, 1.04770477e-04,
       1.84338434e-04])
```

```
sum(np.isclose(posterior3, posterior3_new)) == len(prior)
```

```
True
```

```
-- -- --
```

3.4

$n + 1$

- 0 0/n
- 1 1/n

- $\frac{2}{n}$
- $\frac{n}{n}$

T

m r w

T

```
def update_bowls_pmf(n, r, w):
    """
    n:
    r:
    w:
    """
    priors = np.array([1]*n)
    priors = normalize_array(priors)
    likelihood_red = np.array([i/(n-1) for i in range(n)])
    likelihood_white = np.array([1- i for i in likelihood_red])
    likelihood = {
        "red": likelihood_red,
        "white": likelihood_white
    }
    dataset = ["red"]*r + ["white"]*w
    for data in dataset:
        priors *= likelihood[data]

    posterior = normalize_array(priors)
    return posterior

new_posterior = update_bowls_pmf(n=101, r=2, w=1)
new_posterior[0:5]

array([0.00000000e+00, 1.18811881e-05, 4.70447045e-05, 1.04770477e-04,
       1.84338434e-04])

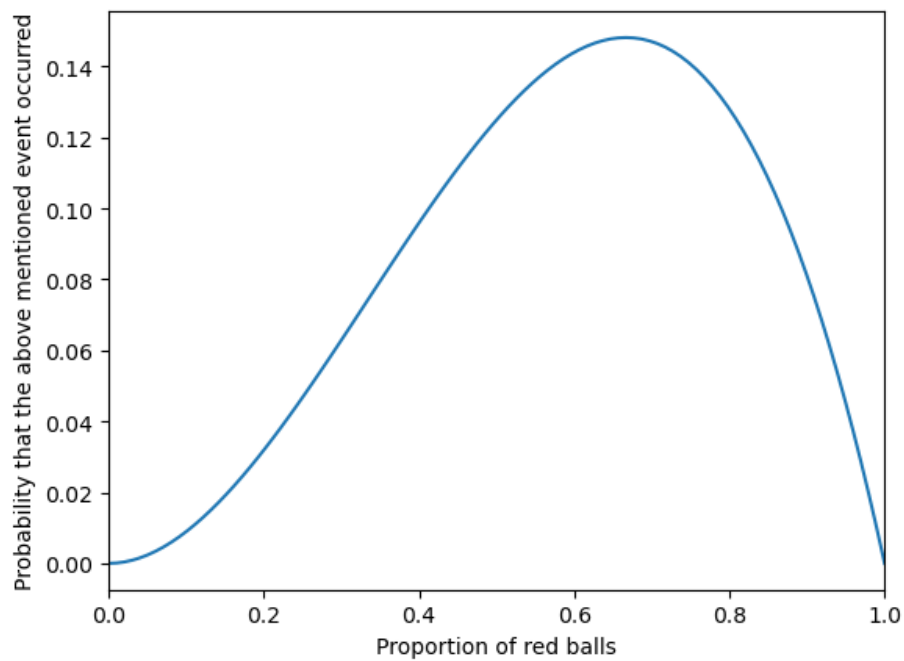
# - -
new_posterior = update_bowls_pmf(n=101, r=2, w=1)
sum(np.isclose(new_posterior, posterior3_new)) == len(prior)
```

True

3.5

```
def y(x):  
    #      x  
    return x**2*(1-x)
```

```
x = np.linspace(0, 1, 100)  
plt.plot(x, y(x))  
plt.xlabel("Proportion of red balls")  
plt.ylabel("Probability that the above mentioned event occurred")  
plt.xlim(0, 1)  
plt.show()
```



```

from scipy.optimize import minimize_scalar
def y(x):
    return -x**2*(1-x)
result = minimize_scalar(y, bounds=(0,1), method="bounded")
result

```

```

message: Solution found.
success: True
status: 0
fun: -0.14814814814787028
x: 0.666666139518174
nit: 10
nfev: 10

```

```

#
max_value = -result.fun
optimal_x = result.x
optimal_x, max_value

```

```

(0.666666139518174, 0.14814814814787028)

```

| | | |
|-------|---------------|-----|
| 66.7% | $\frac{2}{3}$ | |
| 67% | 67 | 67% |

Chapter 4

Prior Distributions

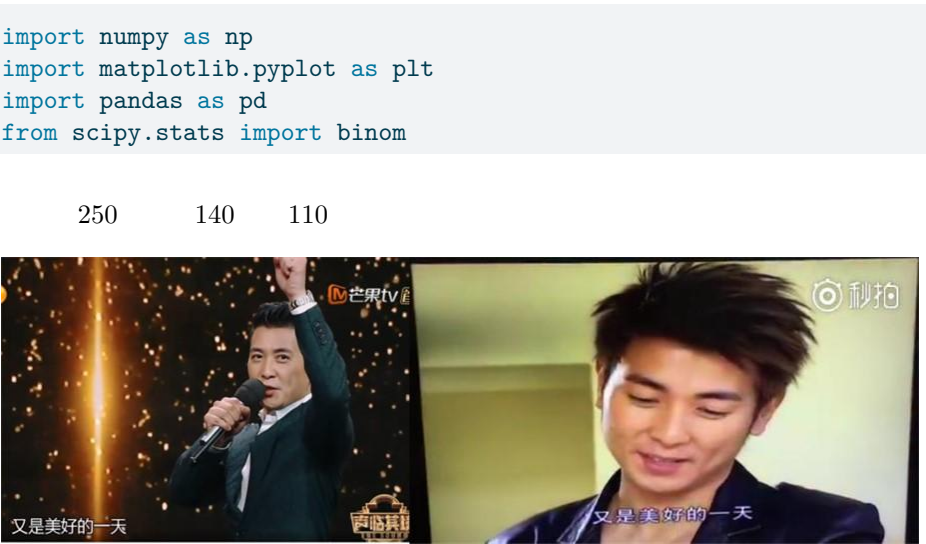


Figure 4.1:

Chapter 3

- $n + 1$
- 0 0/n
 - 1 1/n

- 2 2/n
- ...
- n n/n

250 140 110

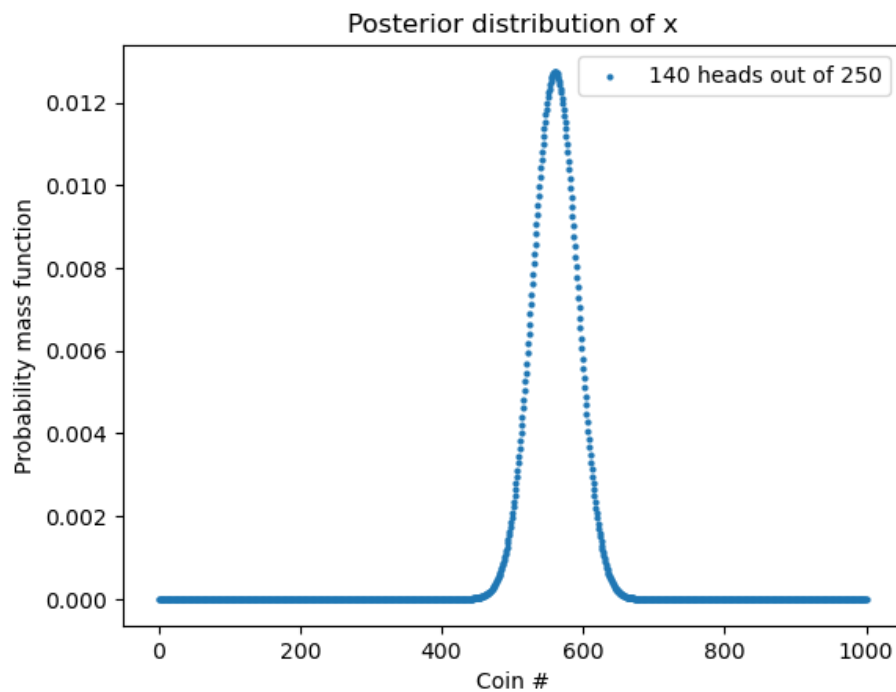
uniform prior

```
def normalize_array(arr):
    return np.array([i/sum(arr) for i in arr])

# update_bowls_pmf
def update_coins_pmf(n, h, t):
    """
    n:
    h:
    t:
    """
    prior = np.array([1]*n)
    prior = normalize_array(prior)
    likelihood_head = np.array([i/(n-1) for i in range(n)])
    likelihood_tail = np.array([1- i for i in likelihood_head])
    likelihood = {
        "head": likelihood_head,
        "tail": likelihood_tail
    }
    dataset = ["head"]*h + ["tail"]*t
    posterior = prior.copy()
    for data in dataset:
        posterior *= likelihood[data]
    return normalize_array(posterior)
```

```
posterior = update_coins_pmf(1001, 140, 110)
```

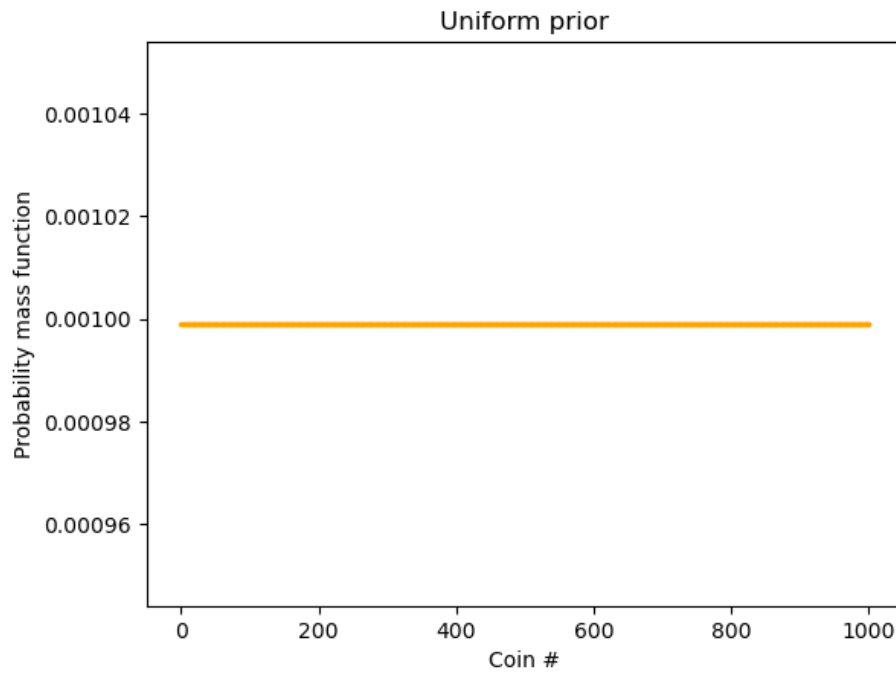
```
df = pd.DataFrame(posterior, columns=['probs'])
df = df.reset_index(names = "Coin #")
df.plot.scatter(x = "Coin #", y="probs",
                s = 4,
                label = "140 heads out of 250")
plt.ylabel("Probability mass function")
plt.legend()
plt.title("Posterior distribution of x")
plt.show()
```



4.1 Prior Distributions

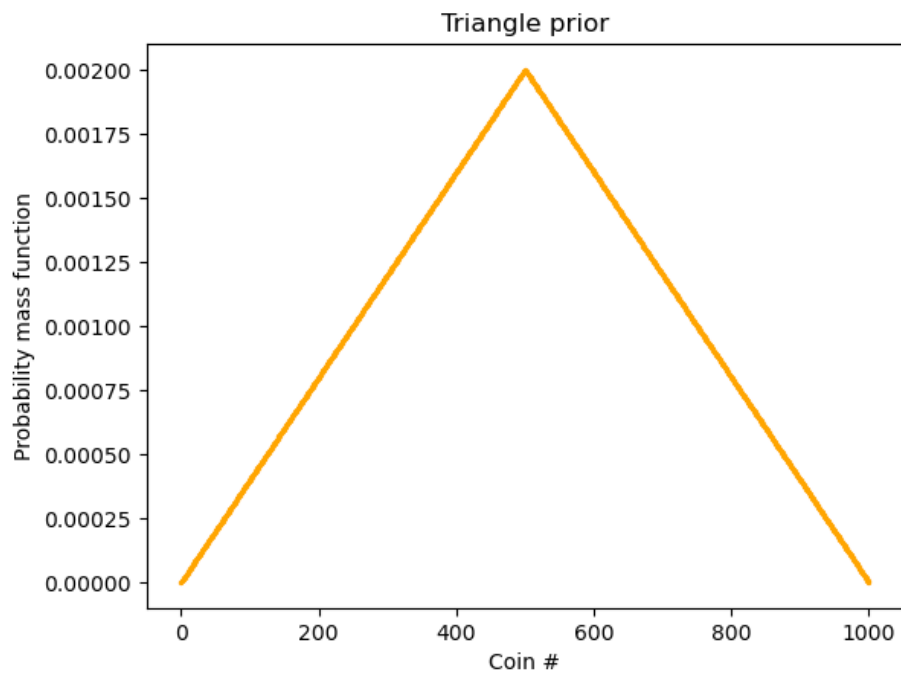
uniform prior

```
n = 1001
prior = np.array([1]*n)
uniform = normalize_array(prior)
x_axis = range(n)
plt.scatter(x = x_axis, y = uniform,
            label="prior", color="orange", s = 2)
plt.xlabel("Coin #")
plt.ylabel("Probability mass function")
plt.title("Uniform prior")
plt.show()
```



prior uniform

```
ramp_up = np.arange(500)
ramp_down = np.arange(500, -1, -1)
prior = np.append(ramp_up, ramp_down)
triangle = normalize_array(prior)
plt.scatter(x = x_axis, y = triangle,
            label="prior", color="orange", s = 2)
plt.xlabel("Coin #")
plt.ylabel("Probability mass function")
plt.title("Triangle prior")
plt.show()
```



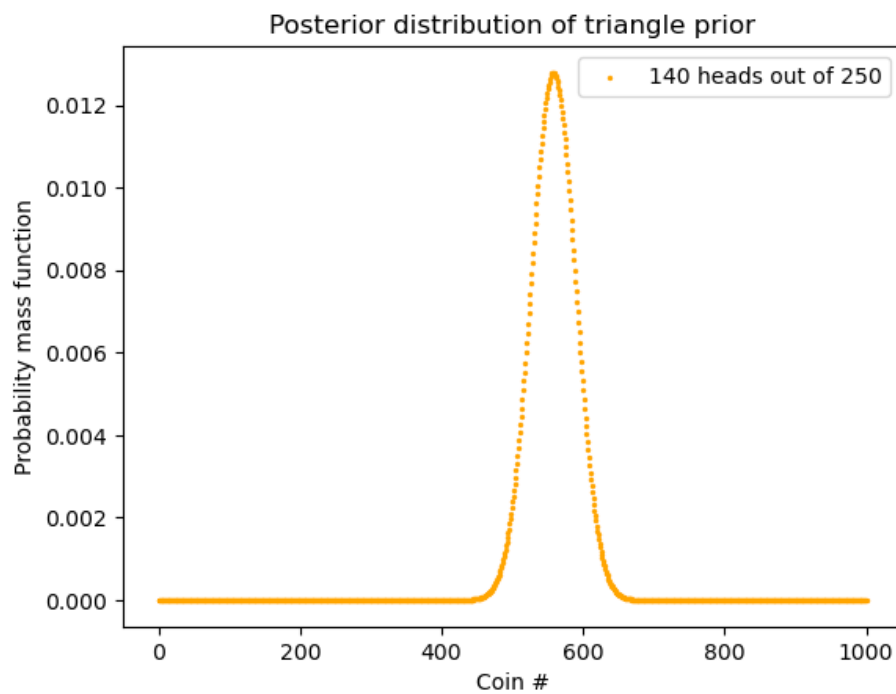
prior

```
# update_coins_pmf prior
def update_coins_pmf(n, h, t, prior):
    """
    n:
    h:
    t:
    prior: a normalized array
    """
    likelihood_head = np.array([i/(n-1) for i in range(n)])
    likelihood_tail = np.array([1-i for i in likelihood_head])
    likelihood = {
        "head": likelihood_head,
        "tail": likelihood_tail
    }
    dataset = ["head"]*h + ["tail"]*t
    posterior = prior.copy()
    for data in dataset:
        posterior *= likelihood[data]
    return normalize_array(posterior)
```

```
n = 1001
h = 140
t = 110
ramp_up = np.arange(500)
ramp_down = np.arange(500, -1, -1)
prior = np.append(ramp_up, ramp_down)
prior = normalize_array(prior)

posterior = update_coins_pmf(n, h, t, prior)

plt.scatter(x = x_axis, y = posterior,
            label="140 heads out of 250", color="orange", s = 2)
plt.xlabel("Coin #")
plt.ylabel("Probability mass function")
plt.title("Posterior distribution of triangle prior")
plt.legend()
plt.show()
```



```
max_index = np.argmax(posterior)
print("    Coin #", max_index)
```

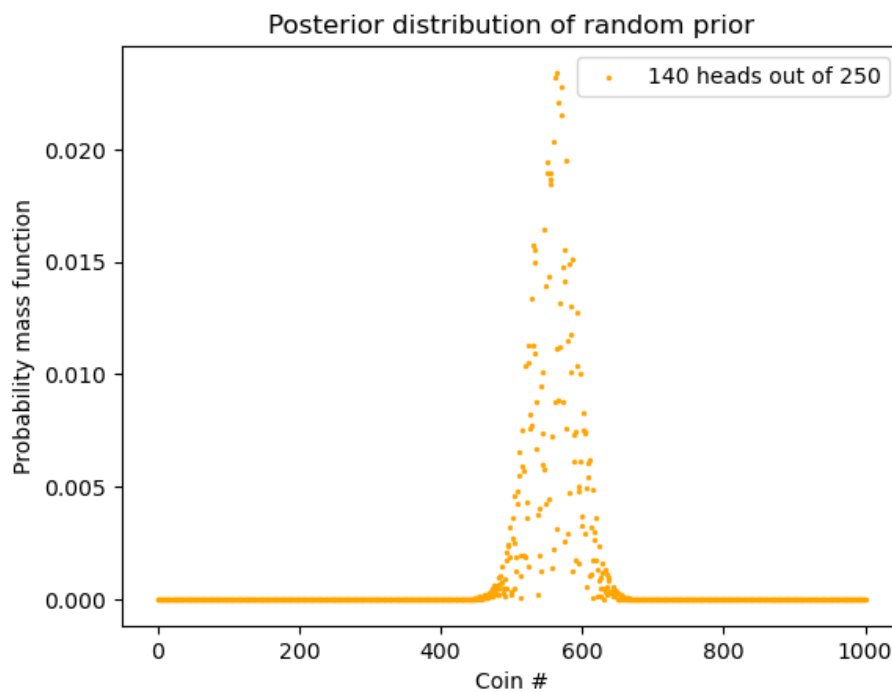
Coin # 558

uniform prior prior posterior
 prior

```
random_prior_values = np.random.rand(n)
random_prior = normalize_array(random_prior_values)

posterior = update_coins_pmf(n, h, t, prior=random_prior)
```

```
plt.scatter(x = x_axis, y = posterior,
            label="140 heads out of 250", color="orange", s = 2)
plt.xlabel("Coin #")
plt.ylabel("Probability mass function")
plt.title("Posterior distribution of random prior")
plt.legend()
plt.show()
```



```
max_index = np.argmax(posterior)
print("    Coin #", max_index)
```

Coin # 565

prior posterior

4.2 Batch updating

posterior

```
for data in dataset:
    posterior *= likelihood[data]
```

250 140 110 Data

- hypothesis:
- data: 250 140 110
- prior: $p(h)$
- likelihood: $p(d|h)$
- posterior: $p(h|d)$

prior likelihood posterior Prior uniform prior triangle
prior (array) Likelihood binomial distribution

$$P(X = k) = \binom{n}{k} p^k (1-p)^{n-k}$$

`scipy.stats.binom`

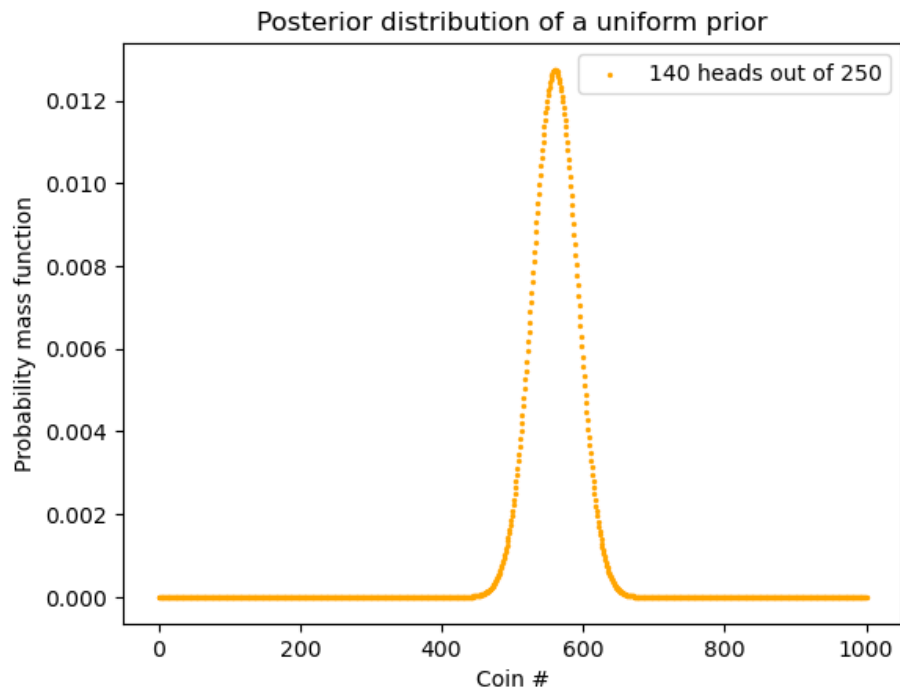
`scipy.stats.binom.pmf(k, n, p)`

k n p p p p
p prior

```
def update_binom(n, heads, tosses, prior):
    """
    heads: number of heads
    tosses: total tosses
    prior: prior distribution; should be a empiricaldist.pmf object (a Series)
    """
    # 0/n, 1/n, 2/n ...
    likelihood_head = np.array([i/(n-1) for i in range(n)])
    coin_head_probabilities = likelihood_head
    likelihood = binom.pmf(k = heads, n = tosses, p = coin_head_probabilities)
    posterior = prior.copy()
    posterior *= likelihood
    return normalize_array(posterior)
```

```
# n: number of coins
n = 1001
tosses = 250
# number of heads out of 250 tosses
heads = 140
prior = np.array([1]*n)
uniform = normalize_array(prior)
posterior = update_binom(n, heads, tosses, uniform)

plt.scatter(x = x_axis, y = posterior,
            label="140 heads out of 250", color="orange", s = 2)
plt.xlabel("Coin #")
plt.ylabel("Probability mass function")
plt.title("Posterior distribution of a uniform prior")
plt.legend()
plt.show()
```



Chapter 5

1 n 60



Figure 5.1:

1 n 1 1 2 2 n n 60

- hypothesis:
- data: 60
- prior: $p(h)$
- likelihood: $p(d|h)$
- posterior: $p(h|d)$

prior 1000 uniform probabilities

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```
def normalize_array(arr):
    return np.array([i/sum(arr) for i in arr])
```

```
n = 1000
prior = np.array([1]*n)
prior = normalize_array(prior)
```

```
def update_posterior(n, prior, data):
    '''to upate posterior in this example
    prior: empiricaldist.Pmf object
    data: e.g., 60
    '''
    # likelihood is 1/hypos because, say num 60 is only 1/100 chance in dice #100
    hypos = np.arange(1, n+1)
    likelihood = 1 / hypos
    # dice #1 to dice #data are impossible
    likelihood[data > hypos] = 0
    posterior = prior.copy()
    posterior *= likelihood
    return normalize_array(posterior)
```

```
posterior = update_posterior(n, prior, data = 60)
```

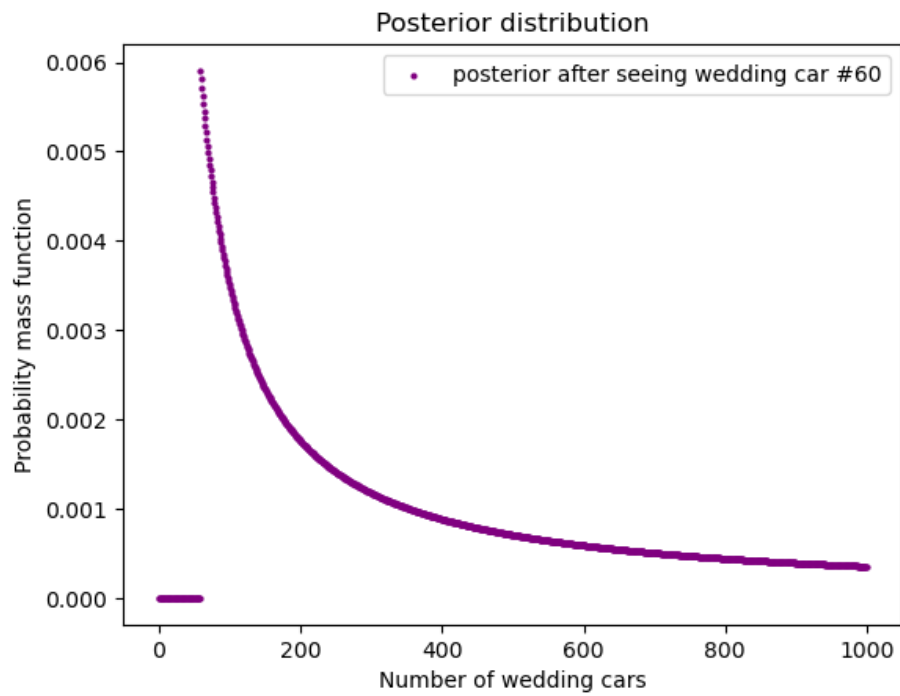
```
def draw_posterior(posterior, xlabel, c, legend_text, s=4):
    """
    posterior: posterior, a empiricaldist.Pmf object
    xlabel: xlabel you want to see in the plot
    c: color of the dots
    legend_text: text for the legend
    s: size of the dots
    """
    df = pd.DataFrame(posterior, columns=['probs'])
    df = df.reset_index(names = xlabel)
    df.plot.scatter(
        x = xlabel,
        y = 'probs',
        color = c,
        s = s,
```

```

        label = legend_text
    )
    plt.ylabel("Probability mass function")
    plt.legend()
    plt.title("Posterior distribution")
    plt.show()

draw_posterior(
    posterior, 'Number of wedding cars',
    c = 'purple', legend_text="posterior after seeing wedding car #60")

```



```

max_index = np.argmax(posterior)
print("    Wedding car #", max_index + 1)

```

Wedding car # 60

5.1 prior

prior

```

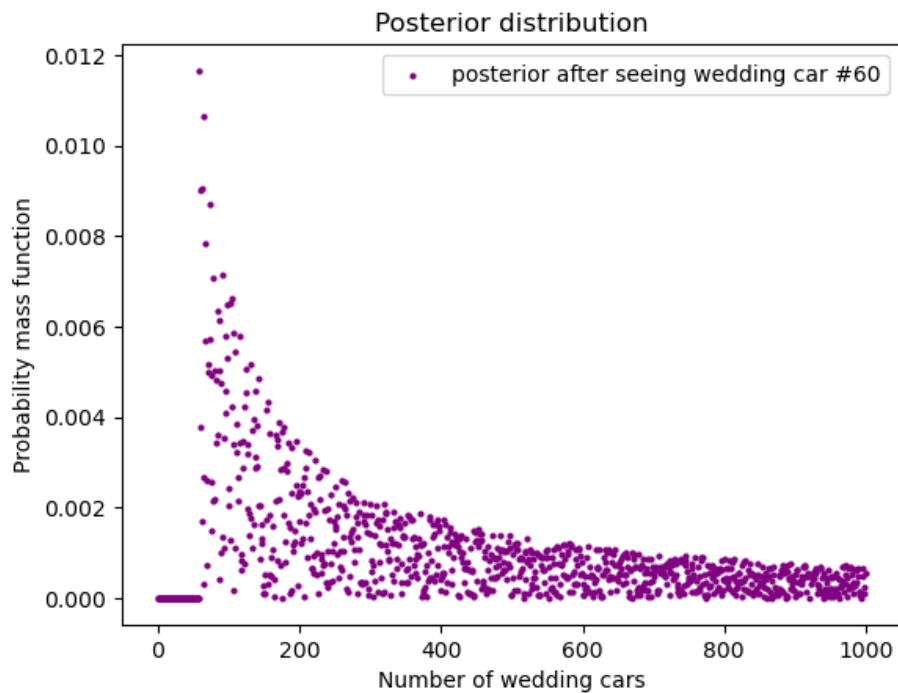
random_prior_values = np.random.rand(n)
random_prior = normalize_array(random_prior_values)
posterior = update_posterior(n, random_prior, data = 60)

```

```

draw_posterior(
    posterior, 'Number of wedding cars',
    c = 'purple', legend_text="posterior after seeing wedding car #60")

```



prior posterior

5.2

90 60 30 90 60 30
 posterior prior posterior likelihood
 prior posterior

```

dataset = [60, 30, 90]
posterior = prior.copy()
for data in dataset:

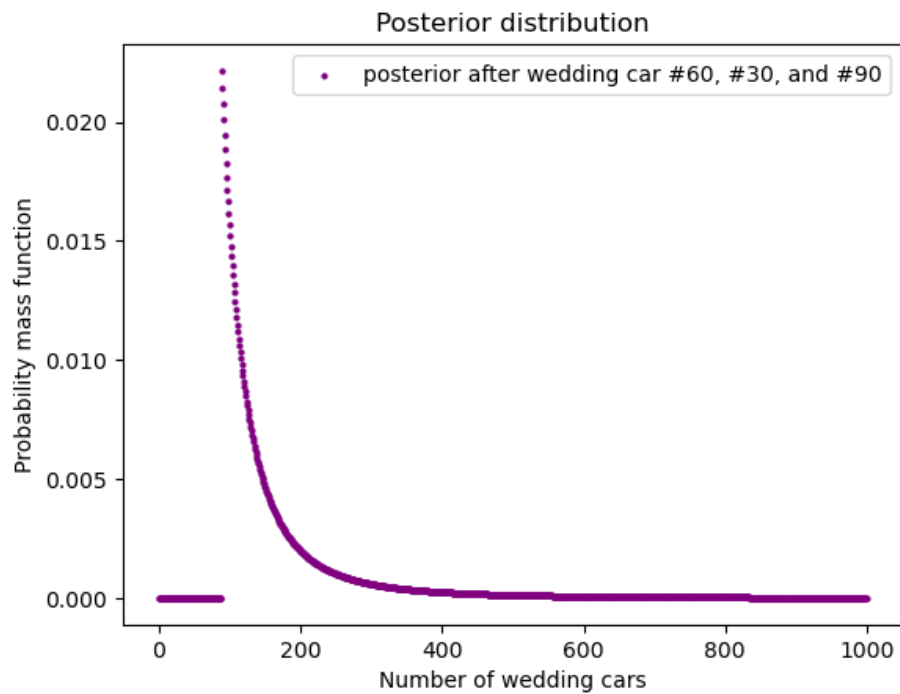
```



```

    posterior = update_posterior(n, posterior, data=data)
draw_posterior(
    posterior, 'Number of wedding cars',
    c = 'purple', legend_text="posterior after wedding car #60, #30, and #90")

```

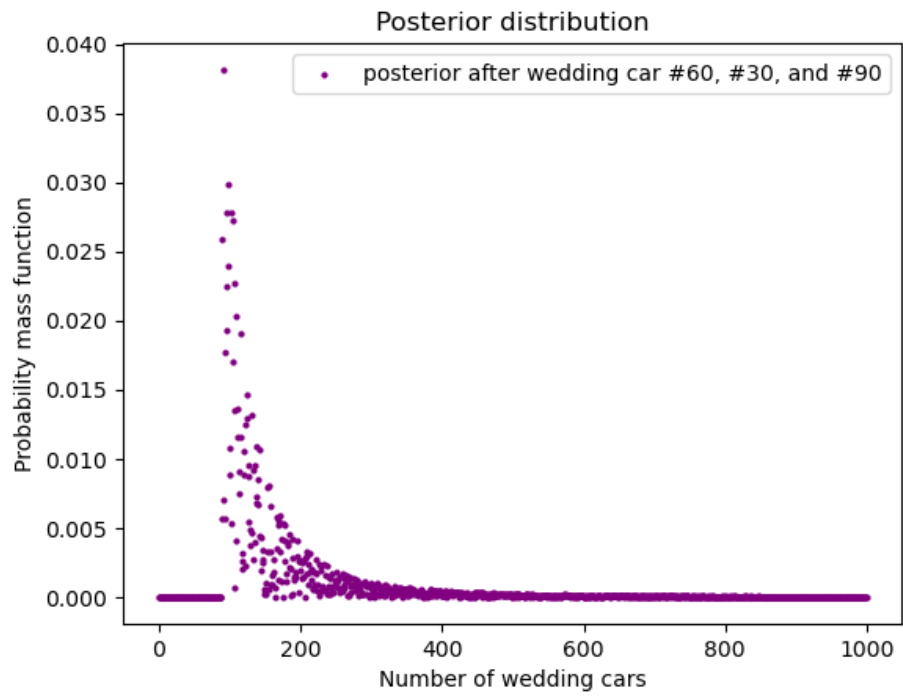


prior

```

dataset = [60, 30, 90]
posterior = random_prior.copy()
for data in dataset:
    posterior = update_posterior(n, posterior, data=data)
draw_posterior(
    posterior, 'Number of wedding cars',
    c = 'purple', legend_text="posterior after wedding car #60, #30, and #90")

```



(60) uniform prior

Chapter 6

Minimum, Maximum, and Mixture

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from scipy.stats import binom
```

Cumulative Distribution Function (CDF) Chapter 4

```
def normalize_array(arr):
    return np.array([i/sum(arr) for i in arr])

def update_binom(heads, tosses, prior):
    """
    heads: number of heads
    tosses: total tosses
    prior: prior distribution; should be a empiricaldist.pmf object (a Series)
    """
    # 0/n, 1/n, 2/n ...
    likelihood_head = np.array([i/(n-1) for i in range(n)])
    coin_head_probabilities = likelihood_head
    likelihood = binom.pmf(k = heads, n = tosses, p = coin_head_probabilities)
    posterior = prior.copy()
    posterior *= likelihood
    return normalize_array(posterior)

# n: number of coins
```

```

n = 1001
x_axis = range(n)
tosses = 250
# number of heads out of 250 tosses
heads = 140
prior = np.array([1]*n)
uniform = normalize_array(prior)
posterior = update_binom(heads, tosses, uniform)

```

```

def get_cdf(arr):
    """Get cumulative distribution function
    """
    total_sum = np.sum(arr)
    res = []
    sum = 0
    for x in arr:
        sum += x
        # normalize to make sure the max in res is 1
        res.append(sum/total_sum)
    return res

```

```

cdf = get_cdf(posterior)

```

```

plt.step(x=x_axis, y=cdf, label="CDF", color='orange', where='post')
# plt.scatter(x=x_axis, y = cdf, label="CDF", color = 'orange', s = 2)
plt.scatter(x = x_axis, y = posterior,
            label="PMF", color="steelblue", s = 2)
plt.xlabel("Coin #")
plt.ylabel("Probability mass function")
plt.title("CDF and PMF of posterior distribution of a uniform prior")
plt.legend()
plt.show()

```

