

## Generating Synthetic Data

First, we'll simulate a dataset of counts from a Poisson distribution with a specified true rate parameter  $\lambda_{true}$ .

*Parameters:*

- True Rate ( $\lambda_{true}$ ): The actual rate at which events occur.
- Number of Observations ( $n$ ): The size of the dataset.

```
1 import numpy as np
2
3 # Set seed for reproducibility
4 np.random.seed(42)
5
6 # True rate parameter
7 lambda_true = 5
8
9 # Number of observations
10 n = 50
11
12 # Generate synthetic data from a Poisson distribution
13 synthetic_data = np.random.poisson(lam=lambda_true, size=n)
14
15 print("Synthetic Data:", synthetic_data)
16 print("Total Counts:", synthetic_data.sum())
```

```
➡ Synthetic Data: [ 5  4  4  5  5  3  5  4  6  7  2  5  5  6  4  6  6  1  7  2 11  4  3  8
   3  3  5  8  3  2  5  3  8 10  3  2  5  7  6  6  2  4  9  7 11  8  3  2
   3  4]
Total Counts: 250
```

## Defining the Gamma Prior

Next, we'll define the Gamma prior distribution for  $\lambda$  with initial parameters  $\alpha = 2$  and  $\beta = 2$ .

*Gamma Prior Parameters:*

Shape Parameter ( $\alpha$ ): Controls the shape of the distribution.

Rate Parameter ( $\beta$ ): Controls the rate at which events occur.

```
1 # Prior parameters
2 alpha_prior = 2
3 beta_prior = 2
4
5 print(f"Prior Gamma Parameters: alpha = {alpha_prior}, beta = {beta_prior}")
```

```
➡ Prior Gamma Parameters: alpha = 2, beta = 2
```

## Updating the Prior Parameters

```
1 # Sum of observed counts
2 sum_x = synthetic_data.sum()
3
4 # Update posterior parameters
5 alpha_post = alpha_prior + sum_x
6 beta_post = beta_prior + n
7
8 print(f"Posterior Gamma Parameters: alpha = {alpha_post}, beta = {beta_post}")
```

➡ Posterior Gamma Parameters: alpha = 252, beta = 52

## Python Function for Updating Posterior Parameters

```
1 def update_posterior_gamma_poisson(data, alpha_prior, beta_prior):
2     """
3     Updates the posterior Gamma distribution parameters for  $\lambda$  given Poisson-distributed data.
4
5     Parameters:
6     - data (array-like): Observed counts from a Poisson distribution.
7     - alpha_prior (float): Shape parameter of the Gamma prior.
8     - beta_prior (float): Rate parameter of the Gamma prior.
9
10    Returns:
11    - alpha_post (float): Updated shape parameter of the Gamma posterior.
12    - beta_post (float): Updated rate parameter of the Gamma posterior.
13    """
14    # Ensure data is a NumPy array for efficient computation
15    data = np.array(data)
16
17    # Number of observations
18    n = len(data)
19
20    # Sum of observed counts
21    sum_x = data.sum()
22
23    # Update posterior parameters
24    alpha_post = alpha_prior + sum_x
25    beta_post = beta_prior + n
26
27    return alpha_post, beta_post
28
```

## Using the Function

```
1 # Update posterior using the function
2 alpha_post_func, beta_post_func = update_posterior_gamma_poisson(
3     data=synthetic_data,
4     alpha_prior=alpha_prior,
5     beta_prior=beta_prior
6 )
7
8 print(f"Posterior Gamma Parameters (Function): alpha = {alpha_post_func}, beta = {beta_post_func}")
9
```

➡ Posterior Gamma Parameters (Function): alpha = 252, beta = 52

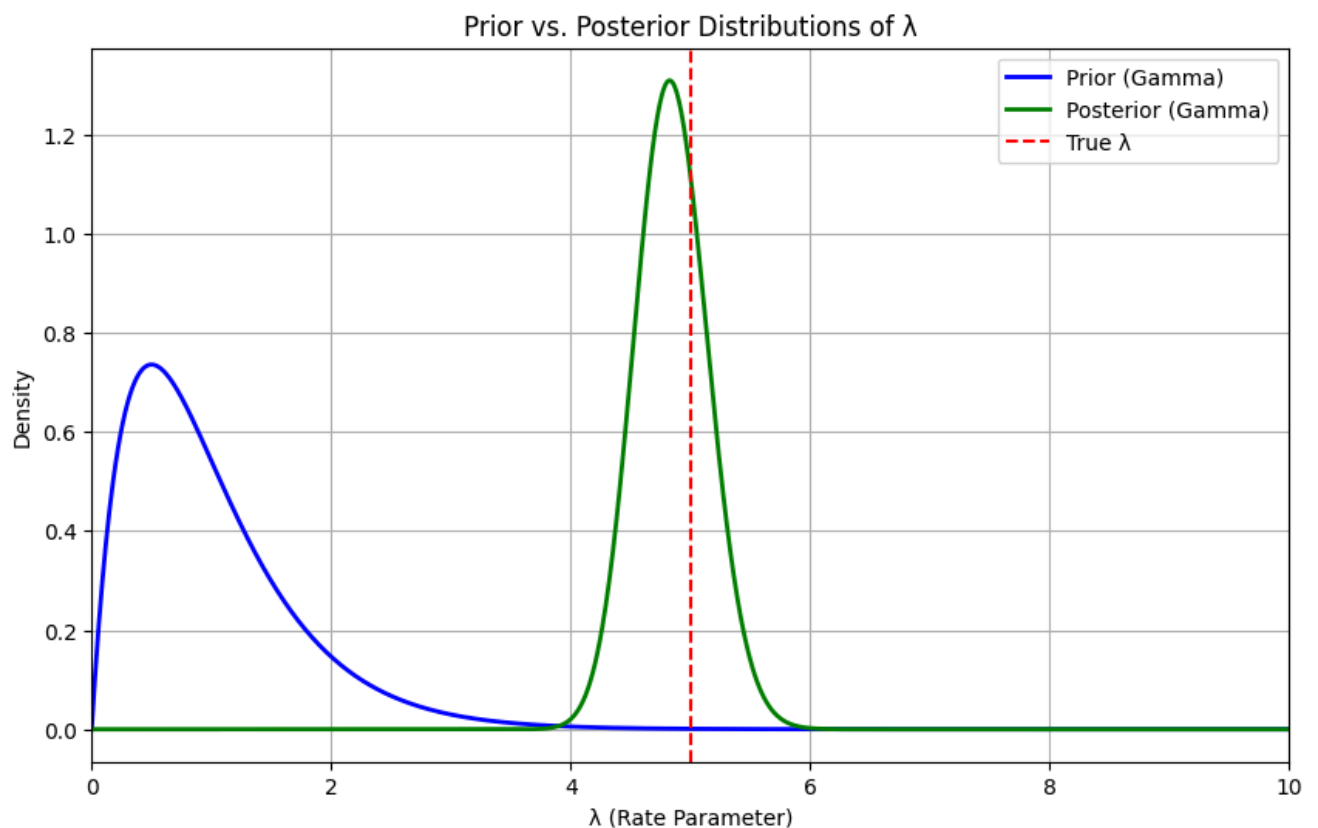
## Plotting Prior and Posterior Distributions

```
1 import numpy as np
2 import matplotlib.pyplot as plt
3 from scipy.stats import gamma
4
5 # Define the prior parameters
6 alpha_prior = 2
7 beta_prior = 2
8
9 # Define the posterior parameters from previous simulation
10 alpha_post = 252
```

```

11 beta_post = 52
12
13 # True lambda used to generate data
14 lambda_true = 5
15
16 # Generate a range of lambda values
17 lambda_values = np.linspace(0, 10, 1000)
18
19 # Compute the prior and posterior PDFs
20 prior_pdf = gamma.pdf(lambda_values, a=alpha_prior, scale=1/beta_prior)
21 posterior_pdf = gamma.pdf(lambda_values, a=alpha_post, scale=1/beta_post)
22
23 # Plotting
24 plt.figure(figsize=(10, 6))
25 plt.plot(lambda_values, prior_pdf, label='Prior (Gamma)', color='blue', lw=2)
26 plt.plot(lambda_values, posterior_pdf, label='Posterior (Gamma)', color='green', lw=2)
27 plt.axvline(lambda_true, color='red', linestyle='--', label='True  $\lambda$ ')
28 plt.title('Prior vs. Posterior Distributions of  $\lambda$ ')
29 plt.xlabel('λ (Rate Parameter)')
30 plt.ylabel('Density')
31 plt.xlim(0, 10)
32 plt.legend()
33 plt.grid(True)
34 plt.show()
35

```



### Posterior Concentration with Increasing Data

```

1 import numpy as np
2 import matplotlib.pyplot as plt
3 from scipy.stats import gamma
4
5 def update_posterior_gamma_poisson(data, alpha_prior, beta_prior):

```

```

6     """
7     Updates the posterior Gamma distribution parameters for  $\lambda$  given Poisson-distributed data.
8     """
9     data = np.array(data)
10    n = len(data)
11    sum_x = data.sum()
12    alpha_post = alpha_prior + sum_x
13    beta_post = beta_prior + n
14    return alpha_post, beta_post
15
16 # Set seed for reproducibility
17 np.random.seed(42)
18
19 # True rate parameter
20 lambda_true = 5
21
22 # Prior parameters
23 alpha_prior = 2
24 beta_prior = 2
25
26 # Define sample sizes to simulate
27 sample_sizes = [10, 50, 100, 500]
28
29 # Generate a range of lambda values for plotting
30 lambda_values = np.linspace(0, 10, 1000)
31
32 # Compute the prior PDF
33 prior_pdf = gamma.pdf(lambda_values, a=alpha_prior, scale=1/beta_prior)
34
35 # Initialize the plot
36 plt.figure(figsize=(12, 8))
37 plt.plot(lambda_values, prior_pdf, label='Prior (Gamma)', color='blue', lw=2)
38
39 # Colors for different sample sizes
40 colors = ['green', 'orange', 'purple', 'brown']
41
42 # Iterate over different sample sizes
43 for idx, n in enumerate(sample_sizes):
44     # Generate synthetic data
45     synthetic_data = np.random.poisson(lam=lambda_true, size=n)
46
47     # Update posterior parameters
48     alpha_post, beta_post = update_posterior_gamma_poisson(synthetic_data, alpha_prior, beta_prior)
49
50     # Compute posterior PDF
51     posterior_pdf = gamma.pdf(lambda_values, a=alpha_post, scale=1/beta_post)
52
53     # Plot posterior
54     plt.plot(lambda_values, posterior_pdf, label=f'Posterior n={n}', color=colors[idx], lw=2)
55
56 # Plot the true lambda
57 plt.axvline(lambda_true, color='red', linestyle='--', label='True  $\lambda$ ')
58
59 # Final plot adjustments
60 plt.title('Prior and Posterior Distributions of  $\lambda$  with Increasing Data')
61 plt.xlabel(' $\lambda$  (Rate Parameter)')
62 plt.ylabel('Density')
63 plt.xlim(0, 10)
64 plt.legend()
65 plt.grid(True)
66 plt.show()
67

```

