## Call center data modeling

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In [1]: # import libraries
        import numpy as np
        from scipy import stats
        import matplotlib.pyplot as plt
        # load call center data set
        waiting times day = np.loadtxt('call center.csv')
In [3]: # data pre-processing
        current time = 0
        waiting times per hour = [[] for _ in range(24)] # Make 24 empty lists,
         one per hour
        for t in waiting times day:
            current_hour = int(current_time // 60)
            current time += t
            waiting times per hour[current hour].append(t)
        for hour, waiting times hour in enumerate(waiting times per hour):
            print('%02i:00-%02i:00 - %i calls' % (hour, hour + 1, len(waiting_ti
        mes hour)))
        00:00-01:00 - 7 calls
        01:00-02:00 - 5 calls
        02:00-03:00 - 8 calls
        03:00-04:00 - 7 calls
        04:00-05:00 - 21 calls
        05:00-06:00 - 42 calls
        06:00-07:00 - 96 calls
        07:00-08:00 - 189 calls
        08:00-09:00 - 274 calls
        09:00-10:00 - 344 calls
        10:00-11:00 - 487 calls
        11:00-12:00 - 892 calls
        12:00-13:00 - 869 calls
        13:00-14:00 - 401 calls
        14:00-15:00 - 206 calls
        15:00-16:00 - 169 calls
        16:00-17:00 - 261 calls
        17:00-18:00 - 430 calls
        18:00-19:00 - 579 calls
        19:00-20:00 - 383 calls
        20:00-21:00 - 136 calls
        21:00-22:00 - 45 calls
        22:00-23:00 - 28 calls
        23:00-24:00 - 12 calls
```

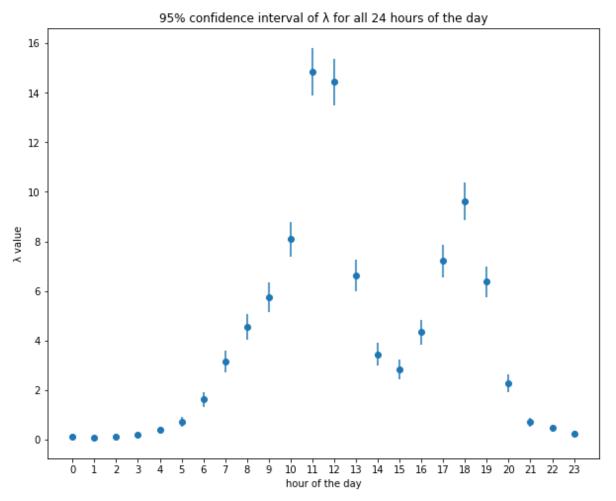
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In [18]: alpha per hour = []
         beta per hour = []
         posterior_per_hour = []
          for hour, waiting times hour in enumerate(waiting times per hour):
              # set prior hyperparameters
              alpha 0 = 1
              beta_0 = 0.25
              # calculate posterior hyperparameters
              alpha = alpha_0 + len(waiting_times_hour)
              beta = beta_0 + sum(waiting_times_hour)
              print("Posterior for hour \{:d\} is: \alpha = \{:.2f\}, \beta = \{:.2f\}".format(ho
         ur, alpha, beta))
              # create posterior distribution
              posterior = stats.gamma(a=alpha, scale=1/beta)
              print ("95% confidence interval over \lambda: [{:.2f}, {:.2f}]".format(post
          erior.ppf(0.025), posterior.ppf(0.975))
              print ("mean of \lambda: {:.2f}".format(posterior.mean()))
              # add data to set
              alpha per hour.append(alpha)
              beta_per_hour.append(beta)
              posterior_per_hour.append(posterior)
```

Posterior for hour 0 is:  $\alpha = 8.00$ ,  $\beta = 60.51$ 95% confidence interval over  $\lambda$ : [0.06, 0.24] mean of  $\lambda$ : 0.13 Posterior for hour 1 is:  $\alpha = 6.00$ ,  $\beta = 67.87$ 95% confidence interval over  $\lambda$ : [0.03, 0.17] mean of  $\lambda$ : 0.09 Posterior for hour 2 is:  $\alpha = 9.00$ ,  $\beta = 69.97$ 95% confidence interval over  $\lambda$ : [0.06, 0.23] mean of  $\lambda$ : 0.13 Posterior for hour 3 is:  $\alpha = 8.00$ ,  $\beta = 44.65$ 95% confidence interval over  $\lambda$ : [0.08, 0.32] mean of  $\lambda$ : 0.18 Posterior for hour 4 is:  $\alpha = 22.00$ ,  $\beta = 58.83$ 95% confidence interval over  $\lambda$ : [0.23, 0.55] mean of  $\lambda$ : 0.37 Posterior for hour 5 is:  $\alpha = 43.00$ ,  $\beta = 60.18$ 95% confidence interval over  $\lambda$ : [0.52, 0.94] mean of  $\lambda$ : 0.71 Posterior for hour 6 is:  $\alpha = 97.00$ ,  $\beta = 59.89$ 95% confidence interval over  $\lambda$ : [1.31, 1.96] mean of  $\lambda$ : 1.62 Posterior for hour 7 is:  $\alpha$  = 190.00,  $\beta$  = 60.18 95% confidence interval over  $\lambda$ : [2.72, 3.62] mean of  $\lambda$ : 3.16 Posterior for hour 8 is:  $\alpha = 275.00$ ,  $\beta = 60.50$ 95% confidence interval over  $\lambda$ : [4.02, 5.10] mean of  $\lambda$ : 4.55 Posterior for hour 9 is:  $\alpha = 345.00$ ,  $\beta = 60.06$ 95% confidence interval over  $\lambda$ : [5.15, 6.37] mean of  $\lambda$ : 5.74 Posterior for hour 10 is:  $\alpha = 488.00$ ,  $\beta = 60.28$ 95% confidence interval over  $\lambda$ : [7.39, 8.83] mean of  $\lambda$ : 8.10 Posterior for hour 11 is:  $\alpha$  = 893.00,  $\beta$  = 60.09 95% confidence interval over  $\lambda$ : [13.90, 15.85] mean of  $\lambda$ : 14.86 Posterior for hour 12 is:  $\alpha = 870.00$ ,  $\beta = 60.26$ 95% confidence interval over  $\lambda$ : [13.49, 15.41] mean of  $\lambda$ : 14.44 Posterior for hour 13 is:  $\alpha = 402.00$ ,  $\beta = 60.72$ 95% confidence interval over  $\lambda$ : [5.99, 7.28] mean of  $\lambda$ : 6.62 Posterior for hour 14 is:  $\alpha = 207.00$ ,  $\beta = 60.24$ 95% confidence interval over  $\lambda$ : [2.98, 3.92] mean of  $\lambda$ : 3.44 Posterior for hour 15 is:  $\alpha = 170.00$ ,  $\beta = 59.93$ 95% confidence interval over  $\lambda$ : [2.43, 3.28] mean of  $\lambda$ : 2.84 Posterior for hour 16 is:  $\alpha = 262.00$ ,  $\beta = 60.54$ 95% confidence interval over  $\lambda$ : [3.82, 4.87] mean of  $\lambda$ : 4.33 Posterior for hour 17 is:  $\alpha = 431.00$ ,  $\beta = 59.80$ 95% confidence interval over  $\lambda$ : [6.54, 7.90] mean of  $\lambda$ : 7.21 Posterior for hour 18 is:  $\alpha$  = 580.00,  $\beta$  = 60.25 95% confidence interval over  $\lambda$ : [8.86, 10.43] mean of  $\lambda$ : 9.63

Posterior for hour 19 is:  $\alpha$  = 384.00,  $\beta$  = 60.30 95% confidence interval over  $\lambda$ : [5.75, 7.02] mean of  $\lambda$ : 6.37 Posterior for hour 20 is:  $\alpha$  = 137.00,  $\beta$  = 60.24 95% confidence interval over  $\lambda$ : [1.91, 2.67] mean of  $\lambda$ : 2.27 Posterior for hour 21 is:  $\alpha$  = 46.00,  $\beta$  = 66.21 95% confidence interval over  $\lambda$ : [0.51, 0.91] mean of  $\lambda$ : 0.69 Posterior for hour 22 is:  $\alpha$  = 29.00,  $\beta$  = 63.24 95% confidence interval over  $\lambda$ : [0.31, 0.64] mean of  $\lambda$ : 0.46 Posterior for hour 23 is:  $\alpha$  = 13.00,  $\beta$  = 53.39 95% confidence interval over  $\lambda$ : [0.13, 0.39] mean of  $\lambda$ : 0.24

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In [42]: mean_per_hour = [post.mean() for post in posterior_per_hour]
    confidence_95_per_hour = [post.mean() - post.ppf(0.025) for post in post
    erior_per_hour]

plt.rcParams['figure.figsize'] = [10, 8]
    plt.errorbar(x=list(range(0, 24)), y=mean_per_hour, yerr=confidence_95_p
    er_hour, fmt='o')
    plt.title("95% confidence interval of λ for all 24 hours of the day")
    plt.xlabel("hour of the day")
    plt.xticks(list(range(0, 24)))
    plt.ylabel("λ value")
    plt.show()
```



This graph visually represents the estimated incoming call rate per minute in the 24 hours a day. The dot represents where the actual average number of phone calls per minute (population mean) is most likely to occur, and the line above and below the dot shows the range where we are 95% confidence that the accrual population mean is. In addition, by looking through the pattern by the hour, the number of call increase as noon, peaking at 10-11th hour, and there is another increase of call between 17-19th hour. By using Bayesian approach, the 95% confidence interval is obtained, and by supplying the handling capacity represented by the upper bound, it means at current demand there is 97.5% chance that there will be no wait time on the call service.