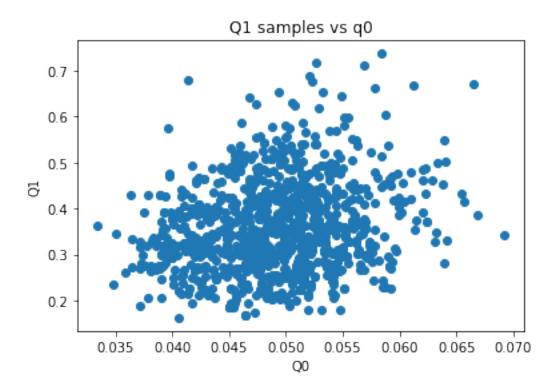
hw 02 code

October 2, 2021

```
[1]: !conda install mkl-service -y
    Collecting package metadata (current_repodata.json): done
    Solving environment: done
    # All requested packages already installed.
    Collaborators: Erica Zhu, Noah Kaminer, Alex Cui
[2]: import numpy as np
    %matplotlib inline
     import matplotlib.pyplot as plt
     import numpy as np
     import pandas as pd
     import seaborn as sns
     from scipy import stats
     from scipy.stats import multivariate_normal, norm, uniform, binom
     from ipywidgets import interact, interactive
     import pymc3 as pm
     from pymc3 import glm
     import statsmodels.api as sm
     import arviz
[3]: my_binary_array = np.array([0, 0, 1, 1, 0, 1])
     my real array = np.array([0.27, 0.34])
     print(my_real_array[my_binary_array])
    [0.27 0.27 0.34 0.34 0.27 0.34]
[4]: #her data
     np.random.seed(5)
     N = 100
    pi = 0.3
     q0 = 0.05
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q1 = 0.18
    n1 = int(N * pi)
    n0 = N - n1
    y_obs = np.zeros(N)
    y_obs[:n0] = np.random.geometric(q0, size=n0)
    y_obs[n0:] = np.random.geometric(q1, size=n1)
    print(y_obs)
    [5.40.5.49.14.19.29.15.7.5.2.27.12.4.42.7.11.7.
    20. 17. 18. 7. 7. 6. 8. 4. 4. 65. 63. 5. 1. 5. 24. 30. 1. 17.
      1. 15. 20. 83. 6. 32. 40. 50. 1. 13. 78. 10. 33. 16. 29. 13.
      3. 6. 66. 20. 34. 17. 20. 33. 51. 48. 34. 2. 9. 1. 16. 32. 1.
      3. 2. 8. 3. 6. 4. 5. 15. 15. 1. 10. 3. 1. 3. 4. 17. 3.
     10. 1. 4. 10. 4. 3. 9. 1. 5. 3.
[5]: #1D) Build PyMC3 model
    with pm.Model() as model:
        z = pm.Bernoulli('z', p=0.3, shape=len(y_obs))
        q_= pm.Beta('q', alpha = [1, 5], beta = [5, 1], shape=2)
        x_ = pm.Geometric('x', q_[z], observed=y_obs)
        trace = pm.sample(1000, chains = 1, return_inferencedata=True)
    Sequential sampling (1 chains in 1 job)
    CompoundStep
    >BinaryGibbsMetropolis: [z]
    >NUTS: [q]
    <IPython.core.display.HTML object>
    Sampling 1 chain for 1_000 tune and 1_000 draw iterations (1_000 + 1_000 draws
    total) took 20 seconds.
    Only one chain was sampled, this makes it impossible to run some convergence
    checks
[6]: # Obtain 1000 samples from the posterior distribution p(q0, q1/x1, ..., xn)
    # Generate a scatterplot (one point per sample)
    posterior = trace.posterior.q
    posterior
[6]: <xarray.DataArray 'q' (chain: 1, draw: 1000, q_dim_0: 2)>
    array([[[0.05893102, 0.53799438],
            [0.05012565, 0.55689909],
            [0.05144789, 0.46267003],
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[0.05124101, 0.32027099],
             [0.05693146, 0.29970642],
             [0.04722409, 0.17354984]]])
     Coordinates:
       * chain
                  (chain) int64 0
                  (draw) int64 0 1 2 3 4 5 6 7 8 ... 992 993 994 995 996 997 998 999
       * draw
       * q_dim_0 (q_dim_0) int64 0 1
[7]: post_DF = posterior[0].to_pandas()
     post_DF
[7]: q_dim_0
     draw
     0
              0.058931 0.537994
     1
              0.050126 0.556899
     2
              0.051448 0.462670
     3
              0.046782 0.446301
     4
              0.044357 0.491010
    995
              0.043824 0.402552
    996
              0.043824 0.402552
    997
              0.051241 0.320271
     998
              0.056931 0.299706
    999
              0.047224 0.173550
     [1000 rows x 2 columns]
[8]: #samples scatter plot
     plt.scatter(post_DF[0], post_DF[1])
     plt.xlabel("Q0")
     plt.ylabel("Q1")
     plt.title("Q1 samples vs q0");
```



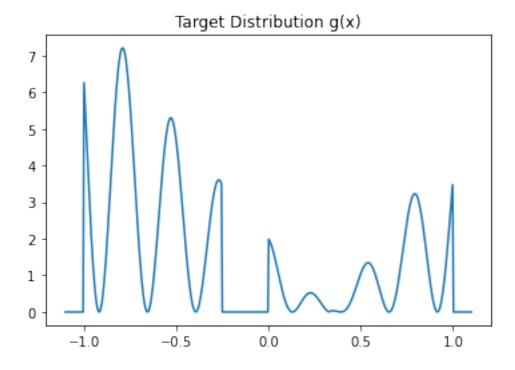
```
z_post = trace.posterior.z
      z_DF = z_post[0].to_pandas()
      #Mean of number of boxes that are from Factory 1 out of 100 sampled boxes
      #if Q1 > q0, sum of row must be greater than 50
      z_DF["sum"] = z_DF.sum(axis=1)
      z_DF[z_DF["sum"] > 50]
 [9]: Empty DataFrame
      Columns: [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19,
      20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39,
      40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59,
      60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79,
      80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99,
      ...]
      Index: []
      [0 rows x 101 columns]
[10]: #iii
      np.median(post_DF[0])
```

[9]: #*ii*

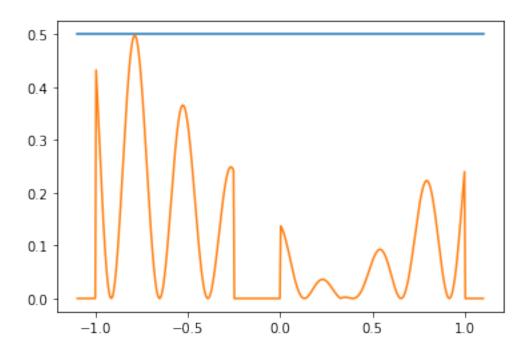
[10]: 0.04890866977616526

Short Answers i) Q0 and q1 appear independent under the posterior distribution. The points of Q0 and Q1 show minimal correlation. This is supported by the context of the question, where each factory's defect rate does not depend on the other's. ii) Approximatesly 100%. There are no rows where the number of boxes from Factory 1 is greater than Factory 0. iii) Median estimate of factory0's defect rate is 0.049.

```
[12]: #Plot g(x) over its domain: -1, 1
x = np.linspace(-1.1, 1.1, 500)
g_x = g(x)
plt.plot(x, g_x)
plt.title("Target Distribution g(x)");
```



```
[13]: proposal = plt.plot(x, np.ones(500)/2)
scaled = plt.plot(x, g_x* 0.069)
```



```
[14]: #Taking the rejection sample
      # Lab 4 Code modified
      def sample_1D_proposed_distribution(N):
          Produces N samples from the Uniform(-1,1) proposal distribution
          Inputs:
               N: int, desired number of samples
          Outputs:
               proposed\_samples : an 1d-array of size N which contains N independent_{\sqcup}
       \hookrightarrow samples from the proposal
           n n n
          proposed_samples = np.random.uniform(-1, 1, (N,))
          return(proposed_samples)
      # TODO: fill in
      @np.vectorize
      def compute_ratio_1D(proposed_sample, c):
           Computes the ratio between the scaled target density and proposal density_{\sqcup}
       \hookrightarrow evaluated at the
          proposed sample point
          Inputs:
```

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proposed_sample : float, proposed sample
        c : float, constant scaling factor that ensures that the proposal \sqcup
 → density is above the target density
    Outputs:
        ratio : float
    ratio = (g(proposed_sample) * c) / (1/2)
    assert(ratio <= 1)</pre>
    return(ratio)
# TODO: fill in
@np.vectorize
def accept_proposal(ratio):
    Accepts or rejects a proposal with probability equal to ratio
    Inputs:
        ratio: float, probability of acceptance
    Outputs:
        accept: True/False, if True, accept the proposal
    accept = bool(np.random.binomial(1, ratio))
    return(accept)
```

```
[15]: # TODO: complete the function
     @np.vectorize
     def get_1D_samples(N, c):
         Produces samples from target_1D_density
         Inputs:
            N: int, number of proposed_samples
             → density is above the target density
         Outputs:
             rejection\_samples: an 1d-array of which contains independent samples_{\sqcup}
      \hookrightarrow from the target
         proposed_samples = sample_1D_proposed_distribution(N)
         ratios = compute_ratio_1D(proposed_samples, c)
         accept_array = accept_proposal(ratios)
         rejection_samples = proposed_samples[accept_array]
         return(rejection_samples)
```

```
[16]: #Estimate c value
N = 10000
M = 0.069
rej_sample = get_1D_samples(N, M)
n = len(rej_sample)
c = M * N / n
c
```

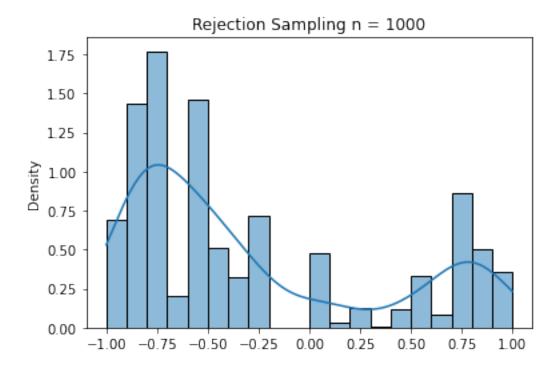
[16]: 0.33301158301158307

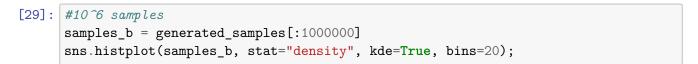
```
[17]: #2C: Use rejection sampling to generate a sample of size 10^3 from p(x)
@np.vectorize
def generate_sample(n, M):
    """
    Generate samples of size n
    Input: number of samples, int
    Output: array of samples
    """
    samples = np.array([])
    while len(samples) < n:
        sample = get_1D_samples(1, M)
        samples = np.append(samples, sample)

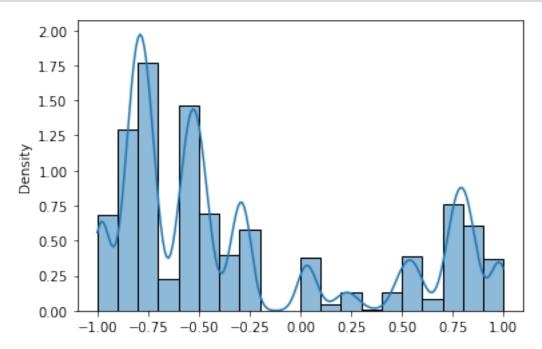
    return samples</pre>
```

```
[27]: generated_samples = get_1D_samples(5000000, 0.069)
```

```
[28]: #Generate 10^3 samples
samples_a = generated_samples[:1000]
sns.histplot(samples_a, stat="density", kde=True, bins=20)
plt.title("Rejection Sampling n = 1000");
```







[]:[