# hw7

## April 21, 2022

### 0.1 Problem 3 Part C

from scipy.stats import norm

[1]: import numpy as np

```
[2]: num_trials = int(1e4)
    ps = [0.1, 0.3, 0.5]
    ns = [10, 40, 100]
    sims={}
    for p in ps:
        sims[str(p)] = {}
        for n in ns:
            sims[str(p)][n] = np.random.binomial(n, p, (num_trials))
    sims["0.3"][40]
[2]: array([17, 10, 16, ..., 15, 8, 12])
[3]: def get_part_a_interval(phats, p, n):
        z = norm.ppf(1-0.025)
        delta = np.sqrt(phats*(1-phats)/n) * z
        return phats - delta, phats + delta
    print("part A interval lower and upper: ", get_part_a_interval(np.array([0.11, __
    \rightarrow 0.12), 0.115, 1000))
    def get_part_b_interval(phats, p, n):
        z = norm.ppf(1-0.025)
        center = phats + z**2 / (2*n)
        delta = z * np.sqrt(phats*(1-phats)/n + z**2/(4*n**2))
        normalizer = 1 + z**2/n
        return (center-delta)/normalizer, (center+delta)/normalizer
```

```
print("part B interval lowers and uppers", get_part_b_interval(np.array([0.11,__
     \rightarrow 0.12), 0.115, 1000))
   part A interval lower and upper: (array([0.09060725, 0.09985905]),
   array([0.12939275, 0.14014095]))
   part B interval lowers and uppers (array([0.09207937, 0.10129926]),
   array([0.1309055 , 0.14160908]))
[4]: def report_coverage(sims, p, n, get_interval):
        phats = sims / n
        lower, upper = get_interval(phats, p, n)
        covered = np.logical_and(p > lower, p < upper).astype(int)</pre>
        return np.mean(covered)
[5]: for p in ps:
        for n in ns:
            a_coverage = report_coverage(sims[str(p)][n], p, n, get_part_a_interval)
            print(f"n={n}, p={p}, part a coverage: {a_coverage}",)
            b_coverage = report_coverage(sims[str(p)][n], p, n, get_part_b_interval)
            print(f"n={n}, p={p}, part b coverage: {b_coverage}",)
   n=10, p=0.1, part a coverage: 0.6427
   n=10, p=0.1, part b coverage: 0.9304
   n=40, p=0.1, part a coverage: 0.9129
   n=40, p=0.1, part b coverage: 0.9381
   n=100, p=0.1, part a coverage: 0.9314
   n=100, p=0.1, part b coverage: 0.9348
   n=10, p=0.3, part a coverage: 0.8462
   n=10, p=0.3, part b coverage: 0.9266
   n=40, p=0.3, part a coverage: 0.93
   n=40, p=0.3, part b coverage: 0.9461
   n=100, p=0.3, part a coverage: 0.9474
   n=100, p=0.3, part b coverage: 0.9356
   n=10, p=0.5, part a coverage: 0.8931
   n=10, p=0.5, part b coverage: 0.9782
   n=40, p=0.5, part a coverage: 0.9232
   n=40, p=0.5, part b coverage: 0.9647
   n=100, p=0.5, part a coverage: 0.9462
   n=100, p=0.5, part b coverage: 0.9462
```

The test from part (B) yields much better coverage for small values of n, especially when p is small

### 1 Problem 4

```
[6]: from scipy.special import gamma, digamma, polygamma from matplotlib import pyplot as plt from tqdm import tqdm
```

#### 1.1 Part A

Below we define the function  $f(\alpha)$  from lecture 13. This function has the property that  $f(\alpha) = 0$  iff  $\alpha$  is the MLE. We also define its derivative

$$f'(\alpha) = \frac{1}{\alpha} - \frac{\Gamma''(\alpha)\Gamma(\alpha) - \Gamma'(\alpha)^2}{\Gamma(\alpha)^2}$$

Note that polygamma(1, z) is the trigamma function.

```
[7]: def f(alpha, x):
    term_1 = np.log(alpha)
    term_2 = -digamma(alpha)
    term_3 = -np.log(np.mean(x))
    term_4 = np.mean(np.log(x))
    return term_1 + term_2 + term_3 + term_4

def f_prime(alpha):
    return 1/alpha - polygamma(1, alpha)
[8]: def update(alpha, x):
    return max(alpha - f(alpha, x)/f_prime(alpha), 1e-10)
```

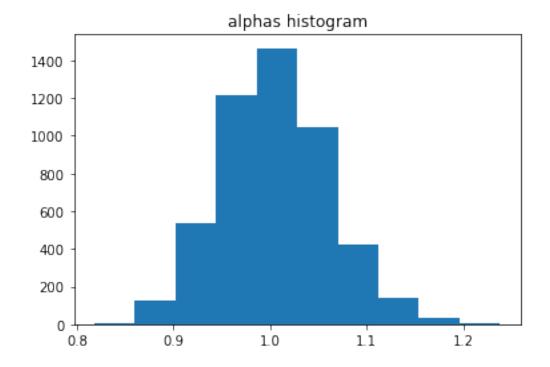
#### 1.2 Part B

```
[9]: # numpy's gamma distribution takes shape and scale parameters,
    # rather than shape and rate.
   alphas = []
   betas = []
   for _ in tqdm(range(5000)):
       x = np.random.gamma(1, 1/2, (500))
       x_bar = np.mean(x)
       alpha_init = x_bar**2 / np.mean((x-x_bar)**2)
       alpha = alpha_init
       for _ in range(100):
            alpha = update(alpha, x)
       alphas.append(alpha)
       betas.append(alpha/x_bar)
   print(f"alpha mean: {np.mean(alphas)}")
   print(f"alpha variance: {np.var(alphas)}")
   plt.cla()
```

```
plt.hist(alphas)
plt.title("alphas histogram")
plt.show()
print(f"beta mean: {np.mean(betas)}")
print(f"beta variance: {np.var(betas)}")
plt.hist(betas)
plt.title("betas histogram")
plt.show()
print(f"alpha and beta covariance: {np.cov(np.stack((alphas, betas)))[0,1]}")
```

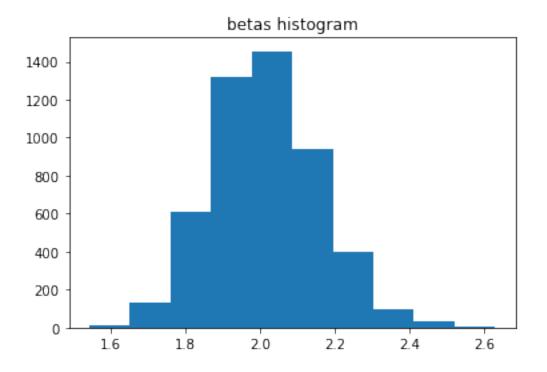
100%|| 5000/5000 [00:19<00:00, 259.54it/s]

alpha mean: 1.0053403088002046 alpha variance: 0.003136007404175372



beta mean: 2.014524881226936

beta variance: 0.020349896243377113



alpha and beta covariance: 0.006217366169198483

### 1.3 Part C

The value of  $\frac{1}{n}I(1,2)^{-1}$  is

```
[10]: alpha = 1
beta = 2
constant = 1/500 * 1/(alpha*polygamma(1,alpha)-1)
mat = np.array([[alpha, beta], [beta, beta**2*polygamma(1, alpha)]])
cov_matrix = constant * mat
print(cov_matrix)
```

```
[[0.00310109 0.00620218]
[0.00620218 0.02040437]]
```

Our simulations very closely match the approximate distribution of  $\mathcal{N}((1,2), \frac{1}{n}I(1,2)^{-1})$