Exercise 3

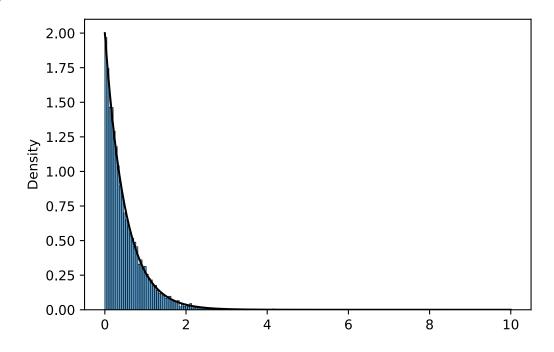
```
In []: %load_ext autoreload
%autoreload 2

In []: from src.my_random.gen import *
    from src.my_random.tests import chi2, kolmogorov, emperical_dist
    import matplotlib.pyplot as plt
    import seaborn as sns
    import scipy.stats as stats
    import pandas as pd
```

Exponential Distribution

```
In []: lmbda = 2
    exps = exponential(lmbda, 10_000)
    h = sns.histplot(exps, stat='density')
    x = np.linspace(0, 10, 1000)
    sns.lineplot(x=x, y=stats.expon.pdf(x, scale=1/lmbda), color='k')
    kolmogorov(exps, stats.expon())
```

Out[]: 79.10421538962612



Normal Distribution

```
In []: norms = norm_box_mueller(1000)
h = sns.histplot(norms, stat='density')
x=np.linspace(-10,10,1000)
sns.lineplot(x=x, y=stats.norm.pdf(x), color='k')
h.set(xlim=(-10, 10))
```

```
Out[]: [(-10.0, 10.0)]
```

```
0.4 -

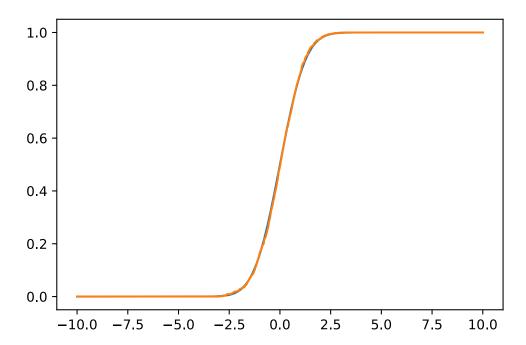
0.3 -

0.1 -

0.0 -7.5 -5.0 -2.5 0.0 2.5 5.0 7.5 10.0
```

```
In [ ]: sns.lineplot(x=x, y=stats.norm.cdf(x))
sns.lineplot(x=x, y=[emperical_dist(i, norms) for i in x])
kolmogorov(norms, stats.norm(), (-10, 10))
```

Out[]: (-62.65744413894945, -1.9736956037033961)



Pareto

```
In []: paretos = pareto(2.05, 1, 10)
h = sns.histplot(paretos, stat='density')
x=np.linspace(-10,10,1000)
sns.lineplot(x=x, y=stats.pareto.pdf(x, b=2.05, scale=1), color='k')
```

```
h.set(xlim=(1, 10))
         kolmogorov(paretos, dist=stats.pareto(b=1, scale=2.05), range=(1,1e4))
        6.842882392759879
Out[ ]:
           2.00
           1.75
           1.50
           1.25
         Density
           1.00
           0.75
           0.50
           0.25
           0.00
                             3
                                          5
                                                 6
                                                        7
                                                              8
                                                                     9
                                                                           10
In [ ]:
        sns.lineplot(x = x, y = [emperical_dist(i, paretos) for i in x])
         sns.lineplot(x=x, y=stats.pareto(b=2.05, scale=1).cdf(x))
        <AxesSubplot:>
Out[]:
         1.0
         8.0
         0.6
         0.4
         0.2
         0.0
                                         0.0
                                                2.5
                                                       5.0
                                                             7.5
             -10.0 -7.5
                          -5.0
                                 -2.5
                                                                   10.0
        ks = [2.05, 2.5, 3, 4]
In [ ]:
         df = pd.DataFrame({k: pareto(k, 1, 10) for k in ks})
In [ ]: obs_stats = df.aggregate(['mean', 'var'])
In [ ]:
        def mean_pareto(beta, k):
             return beta*k/(k-1)
```

```
def var pareto(beta, k):
             return beta**2*k/((k-1)**2 * (k-2))
         true_means = [mean_pareto(1, i) for i in ks]
         true vars = [var pareto(1, i) for i in ks]
         true_stats = pd.DataFrame({'mean': true_means, 'var': true_vars})
         true_stats.T
                     0
                                            3
Out[]:
                              1
                                   2
               1.952381 1.666667 1.50 1.333333
         mean
           var 37.188209 2.222222 0.75 0.222222
In [ ]:
         obs stats
Out[]:
                  2.05
                           2.50
                                    3.00
                                            4.00
         mean 1.797133 1.764837 1.329337 1.285407
           var 0.815427 1.253118 0.426290 0.073788
```

Comparing the means and vars, we see that the estimates are are more off the smaller k are. Furthermore, we notice that the estimates of the means are way better than the variance estimates.

```
In []: norms = np.stack([norm_box_mueller(10) for _ in range(100)])
    t = np.array(stats.t.interval(.95, 9))
    t_confs = np.stack([t*(row.std()/np.sqrt(10)) + row.mean() for row in norms])
    chi = np.array(stats.chi2.interval(.95, 9))
    chi_confs = np.stack([9*row.var() / chi[::-1] for row in norms])

conf = norms.mean(axis=1) + np.array([-1.96*norms.std(axis=1), 1.96*norms.std(
    mean_df = pd.DataFrame({'lwr': t_confs[:,0], 'mean':norms.mean(1), 'upr':t_con var_df = pd.DataFrame({'lwr': chi_confs[:,0], 'var':norms.var(1), 'upr':chi_co
In []: mean_df.describe()
```

lwr mean upr count 100.000000 100.000000 100.000000 -0.688873 -0.011229 0.666416 mean std 0.311284 0.261927 0.286284 min -1.368979 -0.804567 -0.250260 25% -0.925813 -0.183167 0.469010 50% -0.687262 -0.048167 0.658813 75% -0.493565 0.198056 0.850182 0.119087 max 0.665376 1.401509

Out[]:

Out[]:

	lwr	var	upr
count	100.000000	100.000000	100.000000
mean	0.443607	0.937625	3.124967
std	0.187871	0.397091	1.323446
min	0.120146	0.253945	0.846361
25%	0.328122	0.693532	2.311441
50%	0.407786	0.861913	2.872629
75%	0.551490	1.165652	3.884945
max	1.201059	2.538607	8.460802

We see that the confidence intervals vary quite a lot both for the mean and the variance. In the extreme case of the mean, 0 is not even in the confidence interval, which in a lot of experiments would mean we would have concluded a statistical signficant result, even though this is gaussian noise.\ The variance has non-symmetrical confidence intervals. We see that especially the upper bound of the variance has a high standard deviation. This is to be expected, since we only have 10 observations