Assignment 5.2

Exercises 5 - 1, 5 - 2, and 6 - 1

In [1]:
```
# Imports
import brfss
import thinkstats2
import scipy.stats as stats
import numpy as np
import matplotlib.pyplot as plt
from empiricaldist import Cdf
from statsmodels.distributions.empirical_distribution import ECDF
```

Exercise 5 - 1

In the BRFSS, the distribution of heights is roughly normal with parameters μ = 178cm and σ = 7.7 cm for men, and μ = 163 cm and σ = 7.3cm for women

In order to join Blue Man Group, you have to be male and between 5'10" and 6'1" tall.

What percentage of the US male population is in this range?

In [2]:
```
df = brfss.ReadBrfss()
df.head()
```

Out[2]:

	age	sex	wtyrago	finalwt	wtkg2	htm3
0	82.0	2	76.363636	185.870345	70.91	157.0
1	65.0	2	72.727273	126.603027	72.73	163.0
2	48.0	2	NaN	181.063210	NaN	165.0
3	61.0	1	73.636364	517.926275	73.64	170.0
4	26.0	1	88.636364	1252.624630	88.64	185.0

In [8]:
```
# Get the normal distribution with parameters: mean = 178 and Standard Dev
mu = 178
sigma = 7.7

sample = stats.norm(loc = mu, scale = sigma)
sample
```

Out[8]:
```
<scipy.stats._distn_infrastructure.rv_frozen at 0x229e9d7cf40>
```

In [9]:
```
# Convert inches to cm
min_height = ((5 * 12) + 10) * 2.54
max_height = ((6 * 12) + 1) * 2.54

# Percentage of men under 5' 10"
men_min_height = sample.cdf(min_height)

# Percentage of men under 6' 1"
men_max_height = sample.cdf(max_height)

# Percentage of men between 5' 10" and 6' 1"
men_within_range = men_max_height - men_min_height

print(f"Men at 5' 10\": {round(men_min_height, 2) * 100}%")
print(f"Men at 6' 1\": {round(men_max_height, 2) * 100}%")
print(f"Men within range: {round(men_within_range, 2) * 100}%")
```

```
Men at 5' 10": 49.0%
Men at 6' 1": 83.0%
Men within range: 34.0%
```

Within the US population for men approximately 34% of them would qualify to be in the Blue Mar

Exercise 5 - 2

To get a feel for the Pareto distribution, lets see how different the world would be if the distrbution human height were Pareto. With the parameters x_{m} = 1 m and α = 1.7, we get a dis with a reasonable minimum, 1 m, and median, 1.5 m

Plot this distribution

In [10]:
```
alpha = 1.7
xmin = 1

dist = stats.pareto(b = alpha, scale = xmin)
dist
```

Out[10]:
```
<scipy.stats._distn_infrastructure.rv_frozen at 0x229e9d9b160>
```

What is the mean human height in Pareto world?

In [12]:
```
mean_height = dist.mean()
print(f"Mean height (m): {mean_height}")
print(f"Mean height (ft): {mean_height * 3.281}")
```

```
Mean height (m): 2.428571428571429
Mean height (ft): 7.968142857142858
```

The mean height in a Pareto world is 2.4 meters or about 8 feet tall

What fraction of the population is shorter than the mean?

In [7]:
```
percent_shorter = dist.cdf(mean_height)
percent_shorter
```

Out[7]: 0.778739697565288

About 77% of the people are shorter than 2.4 meters

If there are 7 billion people in Pareto world, now many do we expect to be taller than 1 km?

In [8]:
```
amt_shorter = dist.cdf(1000)
amt_taller = 1 - amt_shorter

total_pop_taller = amt_taller * 7000000000
total_pop_taller
```

Out[8]: 55602.976430479954

About 55,603 people wouldbe taller than 1 km

How tall do we expect the tallest person to be?

In [15]:
```
tallest_person = dist.ppf( 1 - (1 / 7000000000))
print(f"Tallest person (km) : {tallest_person}")
print(f"Tallest person (ft) : {tallest_person * 3281}")
```

```
Tallest person (km) : 618349.6106759505
Tallest person (ft) : 2028805072.6277938
1.0525455861201714
```

The tallest person would be 618,350 km or 2,028,805,072 ft

Exercise 6 - 1

The distribution of income is famously skewed to the right. In this exercise, we'll measure how st skew is.

The Current Population Survey (CPS) is a joint effort of the Bureau of Labor Statistics and the Ce Bureau to study income and related variables. Data collected in 2013 is available from http://www.census.gov/hhes/www/cpstables/032013/hhinc/toc.htm.

The dataset is in the form of a series of income ranges and the number of respondents who fell i range. The lowest range includes respondents who reported annual household income "Under \$ The highest range includes respondents who made "\$ 250,000 or more."

To estimate the mean and other statistics from these data, we have to make some assumptions a the lower and upper bounds, and how the values are distributed in each range.

In [5]:
```
import hinc
hinc_df = hinc.ReadData()
hinc_df.head()
```

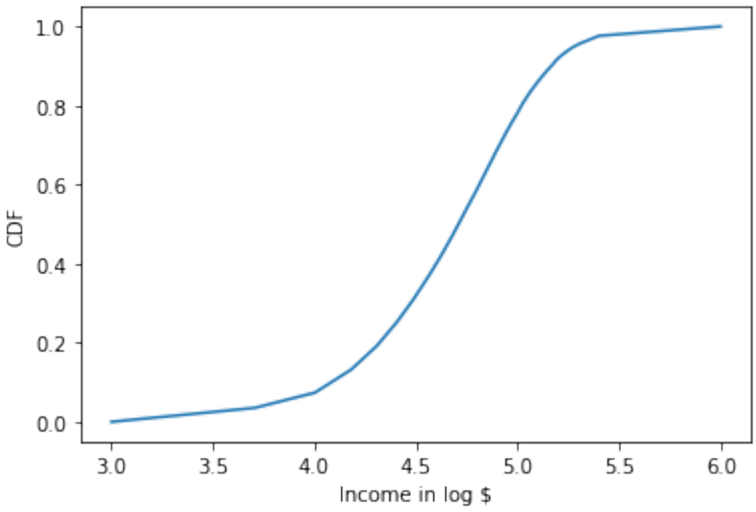
Out[5]:

	income	freq	cumsum	ps
0	4999.0	4204	4204	0.034330
1	9999.0	4729	8933	0.072947
2	14999.0	6982	15915	0.129963
3	19999.0	7157	23072	0.188407
4	24999.0	7131	30203	0.246640

In [6]:
```
def InterpolateSample(df, log_upper = 6.0):
    '''
    Makes a sample of log10 household income.

    Assumes that log10 income is uniform in each range.

    args:
        df (DataFrame): Dataframe with columns income and freq
        log_upper (float): log10 of the assumed upper bound for the highe

    returns:
        log_sample (array): NumPy array of log10 household income
    '''

    # compute the log10 of the upper bound for each range
    df['log_upper'] = np.log10(df.income)

    # get the lower bounds by shifting the upper bound and filling in
    # the first element
    df['log_lower'] = df.log_upper.shift(1)
    df.loc[0, 'log_lower'] = 3.0

    # plug in a value for the unknown upper bound of the highest range
    df.loc[41, 'log_upper'] = log_upper

    # use the freq column to generate the right number of values in
    # each range
    arrays = []
    for _, row in df.iterrows():
        vals = np.linspace(row.log_lower, row.log_upper, int(row.freq))
        arrays.append(vals)

    # collect the arrays into a single sample
    log_sample = np.concatenate(arrays)

    return log_sample
```

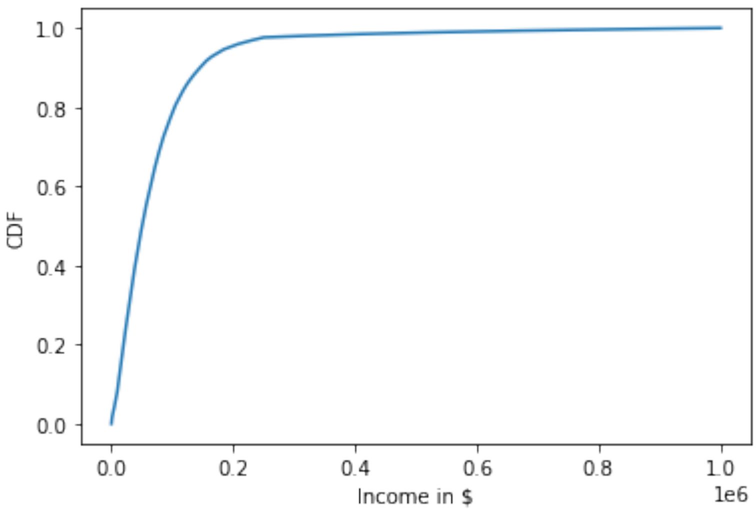
In [43]:
```
# Upper_log = 6 => represents the assumption that the largest income among
log_sample = InterpolateSample(hinc_df, log_upper = 6.0)
log_sample_cdf = Cdf.from_seq(log_sample)
log_sample_cdf.plot()
plt.xlabel('Income in log $')
plt.ylabel('CDF')
```

Out[43]: Text(0, 0.5, 'CDF')



In [44]:
```
sample = np.power(10, log_sample)
sample_cdf = Cdf.from_seq(sample)
sample_cdf.plot()
plt.xlabel('Income in $')
plt.ylabel('CDF')
```

Out[44]:
```
Text(0, 0.5, 'CDF')
```



Compute the median, mean, skewness and Pearson's skewness of the resulting sample.

In [61]:
```
# Mean income of the sample
income_mean = sample.mean()
print(f'The mean income is ${income_mean}')
```

```
The mean income is $74278.7075311872
```

In [60]:
```
# Median income of the sample
income_median = np.median(sample)
print(f'The median income is ${income_median}')
```

```
The median income is $51226.93306562372
```

In [59]:
```
# Skewness of the sample
income_skewness = stats.skew(sample)
print(f'The skewness is {income_skewness} indicating it is skewed right')
```

```
The skewness is 4.949920244429584 indicating it is skewed right
```

```
In [39]: # standard Deviation of the sample
         income_var = np.var(sample)
         income_stdDev = np.sqrt(income_var)
         income_stdDev
```

```
Out[39]: 93946.92996347835
```

```
In [58]: # Pearson's skewness of the sample
         income_pearson = 3 * (income_mean - income_median) / income_stdDev
         print(f"The Pearson's skewness is {income_pearson}")
```

```
The Pearson's skewness is 0.7361105192428792
```

What fraction of households reports a taxable income below the mean?

```
In [57]: # Calculate the Empirical Distribution of the sample
         ecdf = ECDF(sample)
         print(f'Probability that income less than the mean): {ecdf(income_mean)}'
```

```
Probability that income less than the mean): 0.6600058795668718
```

How do the results depend on the assumed upper bound?

In the example the highest income is not given so without it, we can only apply an educated gues
the results just depends on how we guess.