Problem 1-WS

August 1, 2025

0.1 Problem 1

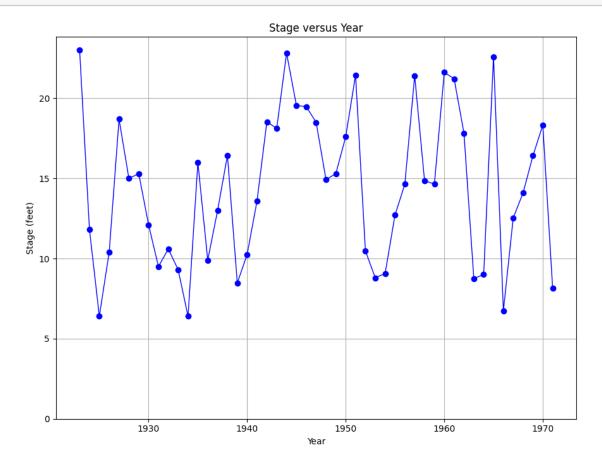
Figure 1 The following data represent gage height and annual peak discharge for some gaging station in Oklahoma. The stage is in feet and the discharge is in cubic feet per second. The data are sequential from 1923 through 1971. Use the data to: 1. Plot year versus stage (x-axis is year). 2. Plot year versus discharge (x-axis is year). 3. Plot the discharge versus stage. 4. Using the Weibull plotting position formula, determine the distribution parameters that fit the data for a log-normal distribution. 5. Using the Weibull plotting position formula, determine the distribution parameters that fit the data for a Gumbell distribution. 6. Using the Weibull plotting position formula, determine the distribution parameters that fit the data for a Gamma distribution. 7. Estimate the discharge associated with a 25-percent chance exceedence probability (i.e. the value that is equal to or exceeded with a 1 in 4 chance). 8. A resident claims that in the early 1900?s a flood corresponding to a stage of 30 feet occurred at the gage location. Estimate the exceedence probability (return period) of the flow associated with this event.

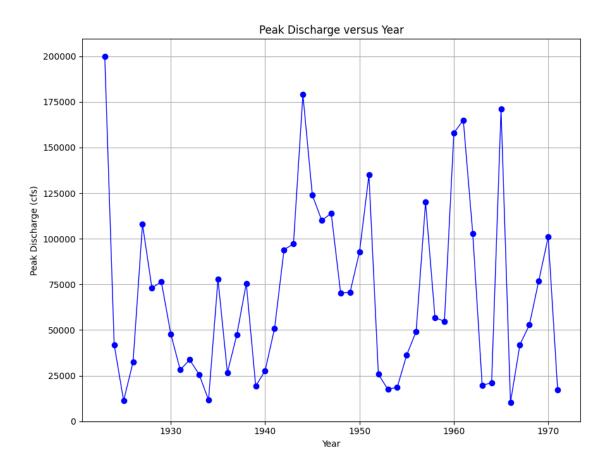
0.2 Solution(s) using ENGR-1330 methods

```
[235]: #=== Import Libraries ====#
       import matplotlib.pyplot # the python plotting library
      import math
                         # import math package
      import numpy
                         # import numpy package
      import pandas
                        # import pandas package
      import scipy.stats # import scipy stats package
       #=== Prototype Functions ====#
      def weibull_sorted(sample_length):
           # generate weibull plotting positions - sample is assumed already sorted
        ⇔(small to large)
          weibull_pp = [] # built a relative frequency approximation to probability,
        →assume each pick is equally likely
          for i in range(0,sample_length,1):
               weibull_pp.append((i+1)/(sample_length+1))
          return weibull_pp
      def loggit(x): # A prototype function to log transform x
          return(math.log(x))
      def \ antiloggit(logx): # A prototype function to transformed log(x)
          return(math.exp(logx))
```

```
def normdist(x,mu,sigma): # A prototype function to return density from normal ⊔
 \hookrightarrow distribution(s)
    argument = (x - mu)/(math.sqrt(2.0)*sigma)
    normdist = (1.0 + math.erf(argument))/2.0
    return normdist
def ev1dist(x,alpha,beta):
    argument = (x - alpha)/beta
    constant = 1.0/beta
    ev1dist = math.exp(-1.0*math.exp(-1.0*argument))
    return ev1dist
def gammacdf(x,tau,alpha,beta): # Gamma Cumulative Density function - with □
 →three parameter to one parameter convert
    xhat = x-tau
    lamda = 1.0/beta
    gammacdf = 1.0 - scipy.stats.gamma.cdf(lamda*xhat, alpha)
    return gammacdf
#==== Input Data ====#
database =[[1923,23,200000],
[1924,11.8,42000],
[1925, 6.4, 11300],
[1926,10.4,32400],
[1927,18.7,108000],
[1928, 15, 73000],
[1929, 15.3, 76500],
[1930,12.1,47800],
[1931,9.5,28200],
[1932,10.6,33700],
[1933,9.3,25700],
[1934,6.4,11700],
[1935,16,77800],
[1936,9.9,26600],
[1937,13,47500],
[1938,16.44,75600],
[1939,8.48,19200],
[1940,10.26,27800],
[1941,13.59,51000],
[1942,18.54,94000],
[1943,18.12,97200],
[1944,22.82,179000],
[1945,19.55,124000],
[1946,19.48,110000],
[1947,18.5,114000],
[1948,14.93,70200],
```

```
[1949,15.3,70700],
[1950,17.6,92800],
[1951,21.45,135000],
[1952,10.48,25800],
[1953,8.8,17500],
[1954,9.07,18700],
[1955,12.71,36300],
[1956,14.64,49200],
[1957,21.41,120000],
[1958,14.86,56800],
[1959,14.65,54800],
[1960,21.62,158000],
[1961,21.22,165000],
[1962,17.83,103000],
[1963,8.76,19700],
[1964,9,21100],
[1965,22.6,171000],
[1966,6.74,10400],
[1967,12.54,42000],
[1968,14.1,52800],
[1969,16.42,77000],
[1970,18.33,101000],
[1971,8.14,17100],
# extract annual peaks and stage
howmanyrows = len(database)
years=[0 for i in range(howmanyrows)]
stage=[0 for i in range(howmanyrows)]
peaks=[0 for i in range(howmanyrows)]
for i in range(howmanyrows):
    years[i]=database[i][0], #extract first entry each row of list database
    stage[i]=database[i][1] #extract second entry each row of list database
    peaks[i]=database[i][2] #extract third entry each row of list database
peaks_copy = list(peaks) # Copy the peaks list for making a rating curve later_
 \hookrightarrow on
```



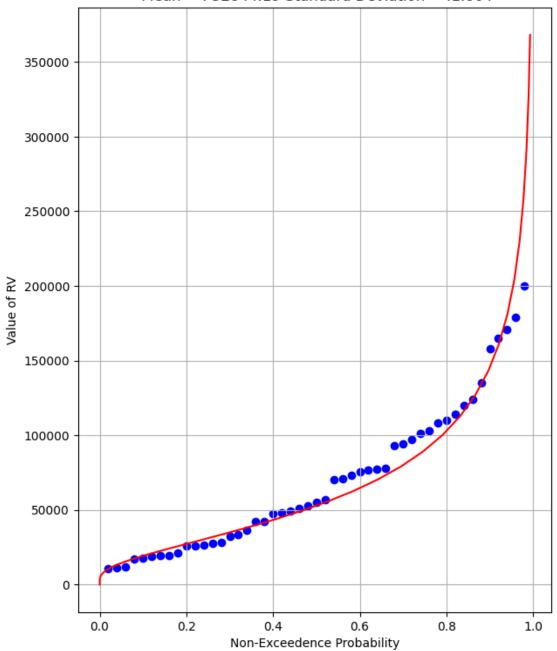


```
sample_length = len(peaks)
       weibull_pp = weibull_sorted(sample_length)
       peaks.sort() #sort in place
[239]: # Fit and plot lognormal
       peaks_array=pandas.Series(peaks)
       logsample = peaks_array.apply(loggit).tolist() # put the peaks into a list
       sample_mean = numpy.array(logsample).mean()
       sample_variance = numpy.array(logsample).std()**2
       logsample.sort() # sort the logsample in place!
       mu = sample_mean # Fitted Model in Log Space
       sigma = math.sqrt(sample_variance)
       x = []; ycdf = []
       xlow = 1; xhigh = 1.05*max(logsample) ; howMany = 100
       xstep = (xhigh - xlow)/howMany
       for i in range(0,howMany+1,1):
           x.append(antiloggit(xlow + i*xstep))
           yvalue = normdist(xlow + i*xstep,mu,sigma)
           ycdf.append(yvalue)
```

[238]: # generate plotting positions

Log Normal Data Model

Mean =: 52844.19 Standard Deviation =: 1.864



10.875102965825535 0.7890880443300708

```
[240]: from scipy.optimize import newton def f(x):
```

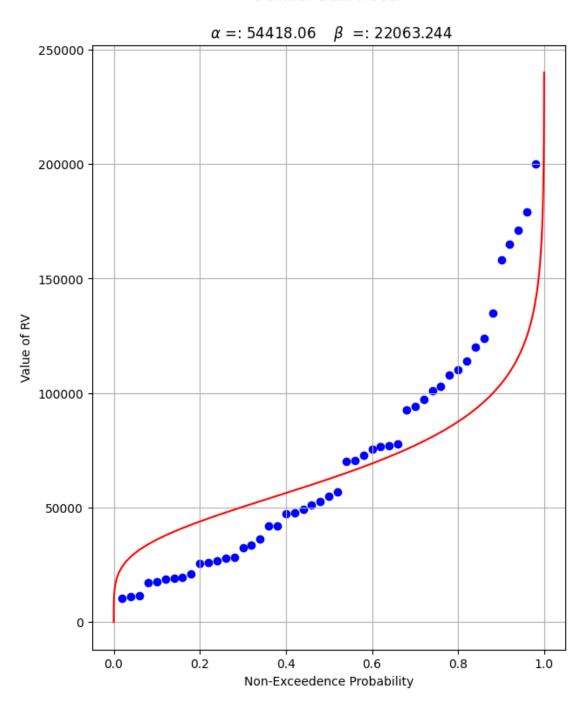
```
mu = 10.875102965825535
sigma = 0.7890880443300708
quantile = 0.75
argument = (loggit(x) - mu)/(math.sqrt(2.0)*sigma)
normdist = (1.0 + math.erf(argument))/2.0
return normdist - quantile

print("Log-Normal Fit \n 0.25 AEP (4-Year ARI) :", round(newton(f, □ ⇒20000), 2), "cfs")
```

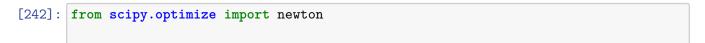
```
Log-Normal Fit
0.25 AEP (4-Year ARI) : 89979.29 cfs
```

```
[241]: # Fit and plot qumbell
       peaks_array=pandas.Series(peaks)
       sample mean = numpy.array(peaks array).mean()
       sample_variance = numpy.array(peaks_array).std()**2
       alpha_mom = sample_mean*math.sqrt(6)/math.pi
       beta_mom = math.sqrt(sample_variance) *0.45
       mu = sample_mean # Fitted Model
       sigma = math.sqrt(sample_variance)
       x = []; ycdf = []
       xlow = 0; xhigh = 1.2*max(peaks); howMany = 100
       xstep = (xhigh - xlow)/howMany
       for i in range(0,howMany+1,1):
           x.append(xlow + i*xstep)
           yvalue = ev1dist(xlow + i*xstep,alpha_mom,beta_mom)
           ycdf.append(yvalue)
       # Now plot the sample values and plotting position
       peaks.sort() #sort in place
       myfigure = matplotlib.pyplot.figure(figsize = (7,9)) # generate a object from
        → the figure class, set aspect ratio
       matplotlib.pyplot.scatter(weibull_pp, peaks ,color ='blue')
       matplotlib.pyplot.plot(ycdf, x, color ='red')
       matplotlib.pyplot.xlabel("Non-Exceedence Probability")
       matplotlib.pyplot.ylabel("Value of RV")
       mytitle = "Gumbell Data Model \n \n " + r"$\alpha$ =: " +11
        ⇒str(round((alpha_mom),2))+ r"
                                          $\beta$ =: " + str(round((beta_mom),3))
       matplotlib.pyplot.title(mytitle)
       matplotlib.pyplot.grid()
       matplotlib.pyplot.show()
       print(alpha_mom,beta_mom)
```

Gumbell Data Model



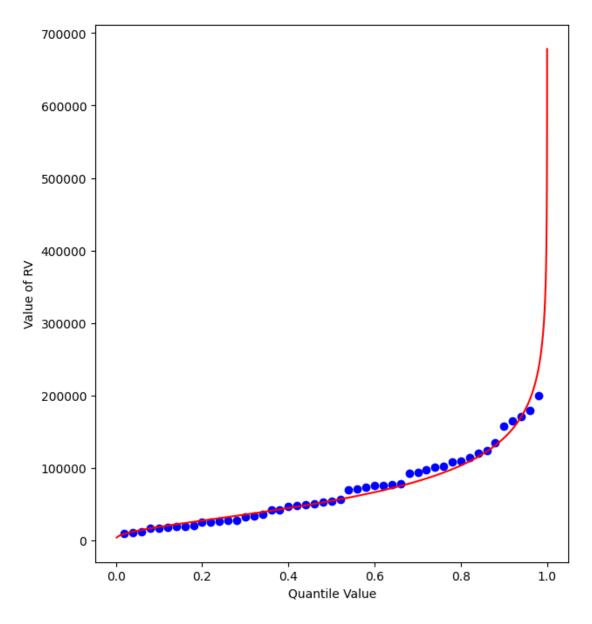
54418.063072225494 22063.243768147015



```
def f(x):
          alpha = 54418.063072225494
           beta = 22063.243768147015
          quantile = 0.75
          argument = (x - alpha)/beta
           constant = 1.0/beta
           ev1dist = math.exp(-1.0*math.exp(-1.0*argument))
          return ev1dist - quantile
      print("Gumbell Fit \n 0.25 AEP (4-Year ARI) :", round(newton(f, 70000),2),"cfs")
      Gumbell Fit
       0.25 AEP (4-Year ARI) : 81906.64 cfs
 []:
[243]: # Fit and plot Log-Pearson Type III (Gamma)
      logsample = peaks_array.apply(loggit).tolist() # put the peaks into a list
      sample_mean = numpy.array(logsample).mean()
      sample stdev = numpy.array(logsample).std()
      sample_skew = scipy.stats.skew(logsample)
      sample_alpha = 4.0/(sample_skew**2)
      sample beta = numpy.sign(sample skew)*math.sqrt(sample stdev**2/sample alpha)
      sample_tau = sample_mean - sample_alpha*sample_beta
      #==== Build Plot Data ====
      x = []; ycdf = []
      xlow = (0.9*min(logsample)); xhigh = (1.1*max(logsample)) ; howMany = 100
      xstep = (xhigh - xlow)/howMany
      for i in range(0,howMany+1,1):
          x.append(xlow + i*xstep)
          yvalue = gammacdf(xlow + i*xstep,sample_tau,sample_alpha,sample_beta)
          ycdf.append(yvalue)
       #=== Reverse Transform x ===
      for i in range(len(x)):
          x[i] = antiloggit(x[i])
      #=== Plot Result(s) ===
      peaks.sort()
      myfigure = matplotlib.pyplot.figure(figsize = (7,8)) # generate a object from
       ⇔the figure class, set aspect ratio
      matplotlib.pyplot.scatter(weibull_pp, peaks ,color ='blue')
      matplotlib.pyplot.plot(ycdf, x, color ='red')
      matplotlib.pyplot.xlabel("Quantile Value")
      matplotlib.pyplot.ylabel("Value of RV")
      mytitle = "Log Pearson Type III Distribution Data Model\n"
      mytitle += "Mean = " + str(antiloggit(sample_mean)) + "\n"
      mytitle += "SD = " + str(antiloggit(sample_stdev)) + "\n"
      mytitle += "Skew = " + str(antiloggit(sample_skew)) + "\n"
```

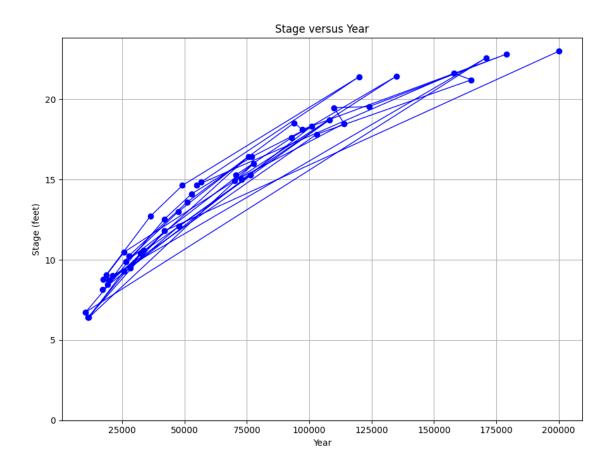
```
matplotlib.pyplot.title(mytitle)
matplotlib.pyplot.show()
print(sample_tau,sample_alpha,sample_beta)
```

Log Pearson Type III Distribution Data Model Mean = 52844.18547363883 SD = 2.20138794235525 Skew = 0.7573470348048779



16.55334964841315 51.78185270767057 -0.10965707841014505

```
[244]: from scipy.optimize import newton
       def f(x):
          sample_tau = 16.55334964841315
           sample_alpha = 51.78185270767057
           sample_beta = -0.10965707841014505
          quantile = 0.75
          argument = loggit(x)
          gammavalue = gammacdf(argument,sample_tau,sample_alpha,sample_beta)
          return gammavalue - quantile
       print("Log-Pearson (Gamma) Fit \n 0.25 AEP (4-Year ARI) :", round(newton(f, )
        →70000),2),"cfs")
      Log-Pearson (Gamma) Fit
       0.25 AEP (4-Year ARI) : 91615.5 cfs
[245]: # Plot Stage versus Q
       myfigure = matplotlib.pyplot.figure(figsize = (9,7)) # generate a object from_
       ⇔the figure class, set aspect ratio
       matplotlib.pyplot.plot(peaks_copy, stage ,color ='blue',marker='o',linewidth=1)
       matplotlib.pyplot.xlabel("Year")
       matplotlib.pyplot.ylabel("Stage (feet)")
       mytitle = "Stage versus Year"
       matplotlib.pyplot.title(mytitle)
       matplotlib.pyplot.grid() # Adjust rotation as needed
       matplotlib.pyplot.ylim(bottom=0) # Set y-axis to start at zero and auto-scale_
       ⇔upper bound
       matplotlib.pyplot.tight_layout() # Prevent label/title clipping
       matplotlib.pyplot.show()
```



```
[246]: # Generate a rating curve Power-law should work OK

# Convert lists to arrays
x = np.array(peaks_copy)
y = np.array(stage)

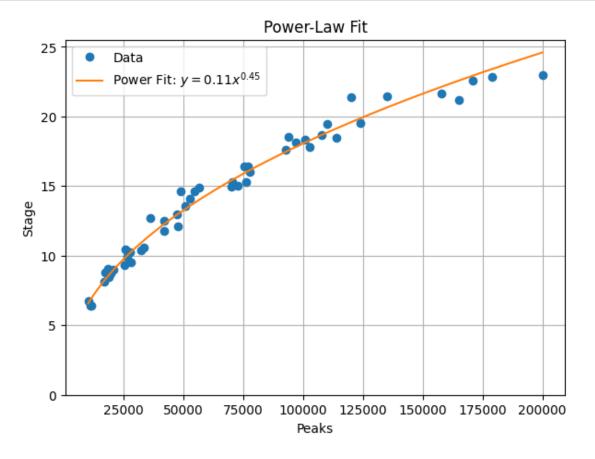
# Transform to log-log space
log_x = np.log(x)
log_y = np.log(y)

# Linear fit in log space
b, log_a = np.polyfit(log_x, log_y, deg=1)
a = np.exp(log_a)

# Power-law function: y = a * x^b
y_power = a * x_fit**b

# Plot
plt.figure(figsize=(7, 5))
plt.plot(x, y, 'o', label='Data')
```

```
plt.plot(x_fit, y_power, '-', label=fr'Power Fit: $y = {a:.2f}x^{{{b:.2f}}}$')
plt.xlabel("Peaks")
plt.ylabel("Stage")
plt.title("Power-Law Fit")
plt.legend()
plt.ylim(bottom=0)
plt.grid(True)
plt.show()
```



```
[247]: # Use newtons method to find Q for a given Stage
from scipy.optimize import newton

def f(x):
    stage = 30.0 #reported stage from old-timer
    constant=0.11
    exponent=0.45
    f=constant*(x**exponent)-stage
    return f

print("Estimated Discharge for Stage :", round(newton(f, 300000),0),"cfs")
```

Estimated Discharge for Stage : 258661.0 cfs

```
Log-Pearson (Gamma) Fit 0.014 AEP (71.4-Year ARI) : 258622.37 cfs
```