	17 500 110 363.30 0.041473 8.062980e-02 A 18 500 110 557.70 0.063664 1.115460e-01 A 19 500 110 849.30 0.096952 1.494010e-01 A 20 500 110 1140.90 0.130240 1.813200e-01 A 21 500 110 1432.50 0.163527 2.088780e-01 B 22 500 110 1724.10 0.196815 2.331050e-01 B 23 500 110 2161.50 0.246747 2.639680e-01 B 24 500 110 2778.46 0.317176 2.999710e-01 B 25 500 110 3395.42 0.387605 3.306070e-01 B
	26 500 110 4012.38 0.458034 3.572330e-01 B 27 500 110 4629.34 0.528463 3.807590e-01 B 28 500 110 5554.78 0.634107 4.108870e-01 C
	28 500 110 5554.78 0.634107 4.108870e-01 C 29 500 110 6942.95 0.792574 4.480900e-01 C 1210 100 70 164685.00 18.799658 9.205660e-02 A 1211 100 70 245289.00 28.001027 1.166300e-01 A 1212 100 70 262800.00 30.00000 1.216990e-01 A 1213 100 60 0.00 0.000000 0.000000e+00 A 1214 100 60 0.05 0.000011 2.930000e+10 A 1215 100 60 0.15 0.000017 5.850000e-14 A 1216 100 60 0.20 0.000023 8.780000e-14 A 1218 100 60 0.30 0.000034 1.460000e-13 A 1219 100 60 0.50
	1219 100 60 0.50 0.000067 2.630000e-13 A 1220 100 60 0.90 0.000103 4.980000e-13 A 1221 100 60 1.70 0.000194 9.660000e-13 A 1222 100 60 3.30 0.000377 1.900000e-12 A 1223 100 60 6.50 0.000742 3.780000e-12 A 1224 100 60 12.90 0.001473 7.520000e-12 A 1225 100 60 25.70 0.002934 1.500000e-11 A 1226 100 60 51.30 0.005856 3.000000e-11 A 1228 100 60 102.50 0.011701 6.000000e-11 A 1229 100 60 409.70 0.046769 2.400000e-10 A 1230 100 60 819.30 0.093527 4.800000e-10 A
	1231 100 60 1638.50 0.187043 9.590000e-10 A 1232 100 60 3276.90 0.374075 1.920000e-09 A 1233 100 60 6553.70 0.748139 3.840000e-09 A 1234 100 60 13107.30 1.496267 7.670000e-09 A 1235 100 60 26214.50 2.992523 1.530000e-08 A 1236 100 60 52428.90 5.985034 3.070000e-08 A 1237 100 60 104858.00 11.970091 6.140000e-08 A 1238 100 60 209715.00 23.940068 1.230000e-07 A 1239 100 60 262800.00 30.000000 1.540000e-07 A
[74]: t[74]: [75]: t[75]:	Analysing the Data Set The creep data set has 1240 rows and 6 columns creep.shape (1240, 6) creep.columns Index(['Temperature', 'Load', 'Time Period(Hour)', 'Time Period(Year)', 'CEEQ', 'Category'], dtype='object') # check the types of data stored under each column
t[76]:	Temperature int64 Load int64 Time Period(Hour) float64 Time Period(Year) float64 CEEQ float64 Category object Simulations were run for 5 different temperatures in degree celsius print(creep.Temperature.unique()) [500 400 300 200 100]
[79]:	<pre>print(creep.Temperature.value_counts()) 500</pre>
[81]:	110 249 100 222 90 198 80 172 70 152 60 139 50 108 Name: Load, dtype: int64 There is no missing values in the data set Creep.isnull().sum() Temperature 0 Load 0
[82]: [82]:	Time Period(Hour) 0 Time Period(Year) 0 CEEQ 0 Category 0 dtype: int64 creep.Category.describe() count 1240 unique 6 top A freq 912 Name: Category, dtype: object The highest simulated creep value is 1.21 mm for the node shows the maximum creep value at a temperature of 500 degree Celcius, 110 MPa load when the simulation was run for 262800 hours.
[83]:	The whole data set is divided into 6 categories according to creep values. Category CEEQ(mm) A
[84]:	C 96 D 58 E 32 F 6 Name: Category, dtype: int64 # Let's sort the data set according to CEEQ value descending creep.sort_values('CEEQ', ascending=False).head(20) Temperature Load Time Period(Hour) Time Period(Year) CEEQ Category 52 500 110 262800.0 30.000000 1.210420 F 51 500 110 246570.0 28.147260 1.191960 F 50 500 110 214567.0 24.493950 1.153700 F 49 500 110 182565.0 20.840753 1.111160 F
	48 500 110 150562.0 17.187443 1.063000 F 47 500 110 127900.0 14.600457 1.023460 F 314 400 110 262800.0 30.000000 0.995481 E 46 500 110 112793.0 12.875913 0.993444 E 565 300 110 262800.0 30.000000 0.977253 E 313 400 110 239107.0 27.295320 0.973326 E 564 300 110 244231.0 27.880251 0.960213 E 45 500 110 97685.4 11.151301 0.960164 E 816 200 110 262800.0 30.000000 0.941316 E 312 400 110 199899.0 22.819521 0.933747 E 1066 100 110 262800.0 30.000000 0.925458 E
[85]:	### 815
[86]:	49 500 110 182565.0 20.840753 1.11116 F 50 500 110 214567.0 24.493950 1.15370 F 51 500 110 246570.0 28.147260 1.19196 F 52 500 110 262800.0 30.000000 1.21042 F So there are six values and let's put them into a graph to see the relation with increasing time period import matplotlib.pyplot as plt a=severe_creep['Time Period(Hour)'] b=severe_creep['CEEQ('] plt.plot(a,b, color='b', linestyle='', marker='o') plt.xlabel('Time Perioid(Hour)') plt.xlabel('CEEQ(mm)') plt.title('CEEQ(greater than 1mm ') plt.grid('True')
	1200 1175 1100 11075 1050 1
	We can filter data by multiple criteria. For example, here we see CEEQ values greater than .8mm at 400 degree
	311
[89]:	'50 MPa': pd.Series([1.50E-07,0.0053,0.0057,0.0052,0.0146],index=['100','200','300','400','500'])} df=pd.DataFrame(d) 110 MPa 100 MPa 90 MPa 80 MPa 70 MPa 60 MPa 50 MPa 100 0.9255
	<pre>d=df['90 MPa'] e=df['80 MPa'] f=df['70 MPa'] g=df['60 MPa'] h=df['50 MPa'] plt.plot(Temperature,b, color='b', linestyle='', marker='o',label='110 MPa') plt.plot(Temperature,c, color='g', linestyle='', marker='o') plt.plot(Temperature,d, color='r', linestyle='', marker='o') plt.plot(Temperature,e, color='c', linestyle='', marker='o') plt.plot(Temperature,f, color='m', linestyle='', marker='o') plt.plot(Temperature,g, color='y', linestyle='', marker='o') plt.plot(Temperature,h, color='k', linestyle='', marker='o') plt.grid('True') plt.xlabel('Temperature(C)') plt.ylabel('EEEQ(mm)') plt.title('Effects of load and temperature on creep strain(CEEQ) ') plt.legend(loc='upper left')</pre>
	Effects of load and temperature on creep strain(CEEQ) 12
[90]:	Cross Validation: Parameter Tuning Loading the data feature=creep[['Temperature','Load','Time Period(Hour)']] feature.head()
t[91]:	target.head() 0
[92]: [93]: [93]:	3 0 4 0 Name: Category, dtype: int64 # store feature matrix in "X" X=feature # store response vector in "y" y=target feature.dtypes Temperature int64 Load int64 Time Period(Hour) float64 dtype: object
[94]: [95]:	target.dtypes dtype('int64') Select the best tuning parameters (aka "hyperparameters") for KNN on the creep dataset from sklearn.model_selection import cross_val_score from sklearn.neighbors import KNeighborsClassifier k_range=list(range(1,31)) k_scores=[] for k in k_range: knn=KNeighborsClassifier(n_neighbors=k) scores=cross_val_score(knn,X,y,cv=10, scoring='accuracy') k_scores.append(scores.mean()) print(k_scores) [0.8143923822284712, 0.8063742590840283, 0.7949414677182423, 0.7763450459628735, 0.7706576835394561, 0.7674263628576032, 0.769851112720787, 0.743945674536772, 0.732513336087184, 0.7332333563
[97]: [98]:	996170205049, 0.7560944822149229, 0.7479380038340622, 0.7462851112720787, 0.7430454674536772, 0.7325132360487184, 0.733293563 75708, 0.7228517207940798, 0.7204781670750715, 0.7196575450694324, 0.7261162619067684, 0.7237301097625632, 0.724482741919826, 0.7261691544687519, 0.7270291207366861, 0.7301384328991121, 0.7236726423558253, 0.7277774776053008, 0.7390629402797351, 0.735 09975922432, 0.733404223442399, 0.7390503418545382, 0.7398445175791856, 0.7422183708543004] import matplotlib.pyplot as plt %matplotlib inline plt.plot(k_range,k_scores) plt.xlabel('value of K for KNN') plt.ylabel('Cross-validated accuracy') Text(0, 0.5, 'Cross-validated accuracy')
	0.78 0.78 0.72 0.72 0.72 0.72 0.72 0.72 0.72 0.72
[99]:	Compare the best KNN model with logistic regression on the iris dataset # 10-fold cross-validation with the best KNN model knn=KNeighborsClassifier(n_neighbors=1) print(cross_val_score(knn,X,y,cv=10,scoring='accuracy').mean()) 0.8143923822284712 # 10-fold cross-validation with logistic regression from sklearn.linear_model import LogisticRegression logreg=LogisticRegression() print(cross_val_score(logreg,X,y,cv=10,scoring='accuracy').mean()) 0.7194758698381779
[101]:	Training a machine learning model with scikit-learn K-nearest neighbors (KNN) classification knn=KNeighborsClassifier(n_neighbors=1) print(knn) knn.fit(X,y) KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
[102]:	<pre>print(knn.predict([[500,70,262800]])) print(knn.predict([[500,60,262800]])) print(knn.predict([[500,50,262800]]))</pre>
[102]:	<pre>d = {'110 MPa' : pd.Series([1.21,'F',5,5], index=['Simulated CEEQ(mm)','Category','Assinged Values','Predicted knn values']), '100 MPa' : pd.Series([.8843,'E',4,4],index=['Simulated CEEQ(mm)','Category','Assinged Values','Predicted knn values']), '90 MPa' : pd.Series([.6176,'D',3,3],index=['Simulated CEEQ(mm)','Category','Assinged Values','Predicted knn values']), '80 MPa' : pd.Series([.3912,'B',1,1],index=['Simulated CEEQ(mm)','Category','Assinged Values','Predicted knn values']), '70 MPa' : pd.Series([.2023,'B',1,1],index=['Simulated CEEQ(mm)','Category','Assinged Values','Predicted knn values']), '60 MPa' : pd.Series([.0719,'A',0,0],index=['Simulated CEEQ(mm)','Category','Assinged Values','Predicted knn values']), '50 MPa' : pd.Series([.0146,'A',0,0],index=['Simulated CEEQ(mm)','Category','Assinged Values','Predicted knn values'])} df=pd.DataFrame(d) df [5] [6] [7] [8] [9] [9]</pre>

[4] [3]

[2] [1] [0]

[0]

110 MPa 100 MPa

Category

Assinged Values

Predicted knn values

80 MPa

70 MPa

0

60 MPa

0

50 MPa

0

90 MPa

Simulated CEEQ(mm) 0.994581 0.71458 0.481047 0.286982 0.124644 0.0348307 0.00522387

2

D

3

Out[103]:

Creep Data Analysis

creep=pd.read_csv('creepdata.csv')

500

500

500

500

500

500

500

500

500

110

110

110

110

110

110

110

110

110

110

500 110

500 110

Temperature Load Time Period(Hour) Time Period(Year)

0.00

0.05

0.10

0.15

0.20

0.30

0.50

0.90

1.70

3.30

6.50

12.90

In [71]: import warnings
 warnings.filterwarnings('ignore')

import pandas as pd

In [72]: import numpy as np

In [73]: # print the creep data

0

1

2

3

5

7

8

9

10

11

Out[73]:

Importing creep data as comma separated value(csv) file

CEEQ Category

Α

Α

Α

Α

Α

0.000000 0.000000e+00

0.000011 1.460000e-05

0.000017 2.922200e-05

0.000023 4.380000e-05

0.000034 7.300000e-05

0.000057 1.314700e-04

0.000103 2.482770e-04

0.000194 4.817410e-04

0.000377 9.480650e-04

0.000742 1.878310e-03

0.001473 3.729230e-03