	Eventid Type Severity StartTime(UTC) EndTime(UTC) TimeZone AirportCode LocationLat LocationLng City County State ZipCode W-1 Snow Light 2016-01-06 23:14:00 2016-01-07 00:34:00 US/Mountain K04V 38.0972 -106.1689 Saguache Saguache CO 81149.0 W-2 Snow Light 2016-01-07 04:14:00 2016-01-07 04:54:00 US/Mountain K04V 38.0972 -106.1689 Saguache Saguache CO 81149.0 W-3 Snow Light 2016-01-07 05:54:00 2016-01-07 15:34:00 US/Mountain K04V 38.0972 -106.1689 Saguache Saguache CO 81149.0 W-4 Snow Light 2016-01-08 05:34:00 2016-01-08 05:54:00 US/Mountain K04V 38.0972 -106.1689 Saguache Saguache CO 81149.0 W-5 Snow Light 2016-01-08 13:54:00 2016-01-08 15:54:00 US/Mountain K04V 38.0972 -106.1689 Saguache Saguache CO 81149.0 df['Type'].value_counts()
1 3 0 1 3 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	Rain 3752341 Fog 1385264 Snow 827555 Cold 169182 Precipitation 96684 Storm 49553 Hail 2627 Name: Type, dtype: int64 df["Severity"].value_counts() Light 3820970 Severe 1167203 Moderate 1020399 Heavy 166323 UNK 96684 Other 2627
1 1 1 1 1	Name: Severity, dtype: int64 df["AirportCode"].value_counts() KSTH
	#Here we nor not interested in the records which consist "UNK(i.e. Unknown)" and "Other" in the severity column, #hence we are goining to discard those rows dataset = df[(df['Severity'] != 'UNK') & (df['Severity'] != 'Other')] dataset.head() Eventid Type Severity StartTime(UTC) EndTime(UTC) TimeZone AirportCode LocationLat LocationLng City County State ZipCode W-1 Snow Light 2016-01-06 23:14:00 2016-01-07 00:34:00 US/Mountain K04V 38.0972 -106.1689 Saguache Saguache CO 81149.0 W-2 Snow Light 2016-01-07 04:14:00 2016-01-07 04:54:00 US/Mountain K04V 38.0972 -106.1689 Saguache Saguache CO 81149.0
	2 W-3 Snow Light 2016-01-07 05:54:00 2016-01-07 15:34:00 US/Mountain KO4V 38.0972 -106.1689 Saguache Saguache CO 81149.0 3 W-4 Snow Light 2016-01-08 05:34:00 2016-01-08 05:54:00 US/Mountain KO4V 38.0972 -106.1689 Saguache Saguache CO 81149.0 4 W-5 Snow Light 2016-01-08 13:54:00 2016-01-08 15:54:00 US/Mountain KO4V 38.0972 -106.1689 Saguache Saguache CO 81149.0 dataset_types = dataset[['AirportCode', 'Type']] #create table which consists of given two column from main dataset AirportCode Type No KO4V Snow
	#group the airport_code as per occurrence occurrence of type of weather events #convert the categorical variables in column 'Type' into indicator/dummy variables types = pd.get_dummies(dataset_types['Type']) types['AirportCode'] = dataset_types['AirportCode'] types = types.groupby('AirportCode').sum().reset_index() types.head() AirportCode Cold Fog Rain Snow Storm
:	0 K01M 22.0 964.0 2507.0 58.0 0.0 1 K04V 20.0 67.0 1152.0 670.0 57.0 2 K04W 103.0 503.0 1717.0 946.0 1.0 3 K06D 612.0 763.0 848.0 1984.0 85.0 4 K08D 749.0 1214.0 701.0 1090.0 48.0 #k-means clustering codes =types[['AirportCode', axis=1, inplace=True)
	<pre>#import kmeans algorith from scikitlearn librsry from sklearn.cluster import KMeans from sklearn import datasets from sklearn.decomposition import PCA distortions = [] K = range(1, 20) for k in K: kmean = KMeans(n_clusters=k, random_state=0, n_init = 50, max_iter = 500) kmean.fit(types) distortions.append(kmean.inertia_)</pre>
	plt.figure(figsize=(10,5)) plt.plot(K, distortions, 'bx-') plt.xlabel('k') plt.ylabel('Distortion') plt.title('The Elbow Method') plt.show() The Elbow Method 25
	20 10 05 25 50 7.5 10.0 12.5 15.0 17.5 kmeans = KMeans(n_clusters=5, random_state=0).fit(types)
	codes['cluster'] = kmeans.labels_ codes.head() sipython-input-23-23da3e86526f>:3: SettingWithCopyWarning: A value is trying to be set on a copy of a slice from a DataFrame. Try using .loc[row_indexer, col_indexer] = value instead See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy codes['cluster'] = kmeans.labels_ AirportCode cluster O KOIM 2 1 KO4V 3
	<pre>2 K04W 0 3 K06D 0 4 K08D 3 pca = PCA().fit(types) pca_types = pca.transform(types) print("Variance explained by each component (%): ") for i in range(len(pca.explained_variance_ratio_)): print("\n",i*1,":", pca.explained_variance_ratio_[i]*100) print("Total sum (%): ",sum(pca.explained_variance_ratio_)*100) print("Explained variance of the first two components (%): ",sum(pca.explained_variance_ratio_[0:1])*100) Variance explained by each component (%):</pre>
-	1 : 65.44042945575798 2 : 20.029216969696844 3 : 12.850764249575597 4 : 1.176583866549171 5 : 0.5030054584204038 Total sum (%): 100.0 Explained variance of the first two components (%): 65.44042945575798 c0 = [] c1 = [] c2 = [] c3 = []
	<pre>c3 = [] c4 = [] for i in range(len(pca_types)): if kmeans.labels_[i] == 0: c0.append(pca_types[i]) if kmeans.labels_[i] == 1: c1.append(pca_types[i]) if kmeans.labels_[i] == 2: c2.append(pca_types[i]) if kmeans.labels_[i] == 3: c3.append(pca_types[i]) if kmeans.labels_[i] == 4: c4.append(pca_types[i])</pre>
	<pre>c0 = np.array(c0) c1 = np.array(c1) c2 = np.array(c2) c3 = np.array(c3) c4 = np.array(c4) plt.figure(figsize=(7,7)) plt.scatter(c0[:,0], c0[:,1], c='pink', label='Cluster 0') plt.scatter(c1[:,0], c1[:,1], c='purple', label='Cluster 1') plt.scatter(c2[:,0], c2[:,1], c='peren', label='Cluster 2') plt.scatter(c3[:,0], c3[:,1], c='orange', label='Cluster 3') plt.scatter(c4[:,0], c4[:,1], c='cyan', label='Cluster 4') plt.legend() plt.xlabel('PC1') plt.ylabel('PC2') plt.title('Low dimensional visualization (PCA) - Airports');</pre>
	Low dimensional visualization (PCA) - Airports 6000 -
	types['cluster'] = kmeans.labels_
	Cold Fog Rain Snow Storm cluster 0 22.0 964.0 2507.0 58.0 0.0 2 1 20.0 67.0 1152.0 670.0 57.0 3 2 103.0 503.0 1717.0 946.0 1.0 0 3 612.0 763.0 848.0 1984.0 85.0 0 4 749.0 1214.0 701.0 1090.0 48.0 3
	Cold Fog Rain Snow Storm cluster 0 99.634675 963.328173 1946.795666 1206.074303 19.040248 1 95.140496 306.239669 311.516529 53.082645 25.789256 2 64.562254 684.904325 2475.938401 180.039318 5.678899 3 88.291541 590.051360 1218.672205 413.315710 34.069486 4 78.325000 1085.037500 4402.962500 177.025000 15.937500 sns.catplot(x='cluster', y='Cold', data=types, kind='bar', color='#42b7bd');
	sns.catplot(x='cluster', y='Fog', data=types, kind='bar', color= '#42b7bd');
	1000 - 800 - 400 - 200 -
	o
	sns.catplot(x='cluster', y='Snow', data=types, kind='bar', color= '#42b7bd');
	1200 - 1000 - 800 - 800 -
	sns.catplot(x='cluster', y='Storm', data=types, kind='bar', color= '#42b7bd');
	latitude = 38.500000 longitude = -95.665 map_USA = folium.Map(location=[latitude, longitude], zoom_start=4) map_USA
	Ggfy General Country Cotava Ottava New York Washington The Bahamas Cotava Country General Country
(airports = df[['AirportCode', 'LocationLat', 'LocationLng', 'City', 'State']] airports.head() AirportCode
	number_of_occurences.reset_index(inplace=True) number_of_occurences.columns = ['AirportCode', 'Count'] number_of_occurences.head() AirportCode Count K3TH 11142 KMLP 10883 KHYW 9268 KSMCO 8242 KSMP 7996
(;	number_of_occurences = number_of_occurences.merge(airports.drop_duplicates()) number_of_occurences = number_of_occurences.merge(codes) number_of_occurences.head() AirportCode
	<pre>occurences = folium.map.FeatureGroup() n_mean = number_of_occurences['Count'].mean() for lat, lng, number, city, state in zip(number_of_occurences['LocationLat'],</pre>
	Golfe du Saint Luvent V Gull of Saints Lowvence Ottawa
	Unestate Pharais Los An es Pharais México La Habana® Ciudad