In [1]: In [2]: Out[2]:	NAME : SOUMIK SAHA REG NO:21BCE7048 MAIL ID :soumik.21bce7048@vitapstudent.ac.in SLOT: MORNING
	IMPORT SEABORN  import seaborn as sns import matplotlib.pyplot as plt
	dset=sns.load_dataset("car_crashes")           total         speeding         alcohol         not_distracted         no_previous         ins_premium         ins_losses         abbrev           0         18.8         7.332         5.640         18.048         15.040         784.55         145.08         AL           1         18.1         7.421         4.525         16.290         17.014         1053.48         133.93         AK           2         18.6         6.510         5.208         15.624         17.856         899.47         110.35         AZ           3         22.4         4.032         5.824         21.056         21.280         827.34         142.39         AR
	3         22.4         4.032         5.824         21.056         21.280         827.34         142.39         AR           4         12.0         4.200         3.360         10.920         10.680         878.41         165.63         CA           5         13.6         5.032         3.808         10.744         12.920         835.50         139.91         CO           6         10.8         4.968         3.888         9.396         8.856         1068.73         167.02         CT           7         16.2         6.156         4.860         14.094         16.038         1137.87         151.48         DE           8         5.9         2.006         1.593         5.900         5.900         1273.89         136.05         DC           9         17.9         3.759         5.191         16.468         16.826         1160.13         144.18         FL
	10       15.6       2.964       3.900       14.820       14.508       913.15       142.80       GA         11       17.5       9.450       7.175       14.350       15.225       861.18       120.92       HI         12       15.3       5.508       4.437       13.005       14.994       641.96       82.75       ID         13       12.8       4.608       4.352       12.032       12.288       803.11       139.15       IL         14       14.5       3.625       4.205       13.775       710.46       108.92       IN         15       15.7       2.669       3.925       15.229       13.659       649.06       114.47       IA
	16       17.8       4.806       4.272       13.706       15.130       780.45       133.80       KS         17       21.4       4.066       4.922       16.692       16.264       872.51       137.13       KY         18       20.5       7.175       6.765       14.965       20.090       1281.55       194.78       LA         19       15.1       5.738       4.530       13.137       12.684       661.88       96.57       ME         20       12.5       4.250       4.000       8.875       12.375       1048.78       192.70       MD         21       8.2       1.886       2.870       7.134       6.560       1011.14       135.63       MA         22       14.1       3.384       3.948       13.395       10.857       1110.61       152.26       MI
	23       9.6       2.208       2.784       8.448       8.448       777.18       133.35       MN         24       17.6       2.640       5.456       1.760       17.600       896.07       155.77       MS         25       16.1       6.923       5.474       14.812       13.524       790.32       144.45       MO         26       21.4       8.346       9.416       17.976       18.190       816.21       85.15       MT         27       14.9       1.937       5.215       13.857       13.410       732.28       114.82       NE         28       14.7       5.439       4.704       13.965       14.553       1029.87       138.71       NV         29       11.6       4.060       3.480       10.092       9.628       746.54       120.21       NH
	30 11.2 1.792 3.136 9.632 8.736 1301.52 159.85 NJ 31 18.4 3.496 4.968 12.328 18.032 869.85 120.75 NM 32 12.3 3.936 3.567 10.824 9.840 1234.31 150.01 NY 33 16.8 6.552 5.208 15.792 13.608 708.24 127.82 NC 34 23.9 5.497 10.038 23.661 20.554 688.75 109.72 ND 35 14.1 3.948 4.794 13.959 11.562 697.73 133.52 OH
	36         19.9         6.368         5.771         18.308         18.706         881.51         178.86         OK           37         12.8         4.224         3.328         8.576         11.520         804.71         104.61         OR           38         18.2         9.100         5.642         17.472         16.016         905.99         153.86         PA           39         11.1         3.774         4.218         10.212         8.769         1148.99         148.58         RI           40         23.9         9.082         9.799         22.944         19.359         858.97         116.29         SC           41         19.4         6.014         6.402         19.012         16.684         669.31         96.87         SD           42         19.5         4.095         5.655         15.990         15.795         767.91         155.57         TN
	43         19.4         7.760         7.372         17.654         16.878         1004.75         156.83         TX           44         11.3         4.859         1.808         9.944         10.848         809.38         109.48         UT           45         13.6         4.080         4.080         13.056         12.920         716.20         109.61         VT           46         12.7         2.413         3.429         11.049         11.176         768.95         153.72         VA           47         10.6         4.452         3.498         8.692         9.116         890.03         111.62         WA           48         23.8         8.092         6.664         23.086         20.706         992.61         152.56         WV           49         13.8         4.968         4.554         5.382         11.592         670.31         106.62         WI
In [3]:	50 17.4 7.308 5.568 14.094 15.660 791.14 122.04 WY  dset.info() <class 'pandas.core.frame.dataframe'=""> RangeIndex: 51 entries, 0 to 50 Data columns (total 8 columns): # Column Non-Null Count Dtype</class>
	0 total 51 non-null float64 1 speeding 51 non-null float64 2 alcohol 51 non-null float64 3 not_distracted 51 non-null float64 4 no_previous 51 non-null float64 5 ins_premium 51 non-null float64 6 ins_losses 51 non-null float64 7 abbrev 51 non-null object dtypes: float64(7), object(1) memory usage: 3.3+ KB
In [4]: Out[4]:	0       18.8       7.332       5.640       18.048       15.040       784.55       145.08       AL         1       18.1       7.421       4.525       16.290       17.014       1053.48       133.93       AK         2       18.6       6.510       5.208       15.624       17.856       899.47       110.35       AZ         3       22.4       4.032       5.824       21.056       21.280       827.34       142.39       AR
In [5]: Out[5]:	dset.tail()         total       speeding       alcohol       not_distracted       no_previous       ins_premium       ins_losses       abbrev         46       12.7       2.413       3.429       11.049       11.176       768.95       153.72       VA         47       10.6       4.452       3.498       8.692       9.116       890.03       111.62       WA         48       23.8       8.092       6.664       23.086       20.706       992.61       152.56       WV
In [6]:	49 13.8 4.968 4.554 5.382 11.592 670.31 106.62 WI 50 17.4 7.308 5.568 14.094 15.660 791.14 122.04 WY  HEAT MAP  corr=dset.corr()
Out[6]:	<pre>corr <ipython-input-6-dc92a5ab8bf7>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.</ipython-input-6-dc92a5ab8bf7></pre>
In [7]:	not_distracted         0.827560         0.588010         0.732816         1.000000         0.747307         -0.174856         -0.075970           no_previous         0.956179         0.571976         0.783520         0.747307         1.000000         -0.156895         -0.006359           ins_premium         -0.199702         -0.077675         -0.170612         -0.174856         -0.156895         1.000000         0.623116           ins_losses         -0.036011         -0.065928         -0.112547         -0.075970         -0.006359         0.623116         1.000000   Sns.heatmap(corr,annot=True)
Out[7]:	total - 1
	not_distracted - 0.83
	ins_losses0.036 -0.066 -0.11 -0.076 -0.0064 0.62 1  - losses0.036 -0.066 -0.11 -0.0064 0.62 1  - losses0.036 -0.066 0.62 1  - losses0.036 0.62 1
In [8]: Out[8]:	<pre>total False speeding False alcohol False not_distracted False no_previous False ins_premium False ins_losses False abbrev False dtype: bool</pre>
	dset.isnull().sum()  total 0 speeding 0 alcohol 0 not_distracted 0 no_previous 0 ins_premium 0 ins_losses 0 abbrev 0
	<pre>srs.scatterplot(x="alcohol", y="total", data=dset) plt.title("Scatterplot: Alcohol vs Total Crashes") plt.xlabel("Alcohol Consumption") plt.ylabel("Total Crashes")</pre> Text(0, 0.5, 'Total Crashes')
Out[10]:	Scatterplot: Alcohol vs Total Crashes  22.5 -  20.0 -
	17.5 - E 15.0 - E 12.5 - 10.0 -
-	7.5 - 5.0 2 4 6 8 10  Alcohol Consumption  Inference: Positive correlation between alcohol consumption and total crashes from the above plot, i.e as the alcohol consumption increases the total crashes increases.  sns.scatterplot(x="speeding", y="total", data=dset)
In [11]: Out[11]:	sns.scatterplot(x="speeding", y="total", data=dset) plt.title("Scatterplot: Speeding vs Total Crashes") plt.xlabel("Speeding") plt.ylabel("Total Crashes")  Text(0, 0.5, 'Total Crashes')  Scatterplot: Speeding vs Total Crashes  22.5 -
	22.5 - 20.0 -  17.5 -  15.0 -  10.5 -
	10.0 - 10.0 - 7.5 - 5.0 - 2 3 4 5 6 7 8 9 Speeding
In [12]:	Inference: Speeding doesn't show a clear linear trend with total crashes.  LINE PLOT  sns.lineplot(x="alcohol", y="total", data=dset) plt.title("Lineplot: Alcohol vs Total Crashes")
Out[12]:	plt.xlabel("Alcohol Consumption") plt.ylabel("Total Crashes")  Text(0, 0.5, 'Total Crashes')  Lineplot: Alcohol vs Total Crashes  22.5
	20.0 - 17.5 - 15.0 - 12.5 -
	10.0 - 7.5 - 5.0 2 4 6 8 10  Alcohol Consumption
In [13]: Out[13]:	Inference: No obvious linear trend in the relationship between alcohol consumption and total crashes.  sns.lineplot(x="speeding", y="total", data=dset) plt.title("Lineplot: Speeding vs Total Crashes") plt.xlabel("Speeding") plt.ylabel("Total Crashes")  Text(0, 0.5, 'Total Crashes')  Lineplot: Speeding vs Total Crashes
	22.5 - 20.0 -
	17.5 - 15.0 - 10.0 - 7.5 - 10.0 - 10.
	5.0 2 3 4 5 6 7 8 9  Inference: Speeding doesn't exhibit a consistent linear relationship with total crashes.  DISTRIBUTION PLOT
In [14]: Out[14]:	<pre>sns.histplot(dset["not_distracted"], kde=True) plt.title("Distplot: Not Distracted") plt.xlabel("Not Distracted")  Text(0.5, 0, 'Not Distracted')  Distplot: Not Distracted  16 -</pre>
	14 - 12 - 10 - 10 -
In [15]: Out[15]:	Inference: The distribution of "not_distracted" values is right-skewed  sns.histplot(dset["alcohol"], kde=True) plt.title("Distplot: Alcohol Consumption") plt.xlabel("Alcohol Consumption")  Text(0.5, 0, 'Alcohol Consumption')
out[13].	Distplot: Alcohol Consumption  12 - 10 -
	8 - 4 - 4 - 4 - 4 - 4 - 4 - 4 - 4 - 4 -
	Inference: The distribution of alcohol consumption appears to be right-skewed as well
<pre>In [16]: Out[16]:</pre>	sns.boxplot(x="alcohol", y="total", data=dset) plt.title("Boxplot: Alcohol vs Total Crashes") plt.xlabel("Alcohol Consumption") plt.ylabel("Total Crashes")  Text(0, 0.5, 'Total Crashes')
	22.5 -
In [17]:	1.5930GGWAN 300 Alcohol Consumption  Inference: The boxplot shows the distribution of total crashes for different levels of alcohol consumption. The lines indicates the outliers  sns.boxplot(x="speeding", y="total", data=dset) plt.title("Boxplot: Speeding vs Total Crashes") plt.xlabel("Speeding")
Out[17]:	plt.ylabel("Total Crashes")  Text(0, 0.5, 'Total Crashes')  Boxplot: Speeding vs Total Crashes
	17.5
	1.79.09900000000000000000000000000000000
In [18]: Out[18]:	<pre>sns.barplot(x="alcohol", y="total", data=dset) plt.title("Barplot: Alcohol vs Total Crashes") plt.xlabel("Alcohol Consumption") plt.ylabel("Total Crashes")</pre> Text(0, 0.5, 'Total Crashes')
	Barplot: Alcohol vs Total Crashes
	15 - P
In [19]:	Alcohol Consumption  Inference: The barplot displays the mean total crashes for different levels of alcohol consumption. So, if the alcohol consumption is high, then total crashes are also high.  sns.barplot(x="speeding", y="total", data=dset) plt.title("Barplot: Speeding vs Total Crashes")
<pre>In [19]: Out[19]:</pre>	Alcohol Consumption  Inference: The barplot displays the mean total crashes for different levels of alcohol consumption. So, if the alcohol consumption is high, then total crashes are also high.  sns.barplot(x="speeding", y="total", data=dset) plt.title("Barplot: Speeding vs Total Crashes") plt.ylabel("Speeding") plt.ylabel("Total Crashes")  Text(0, 0.5, 'Total Crashes')  Barplot: Speeding vs Total Crashes
	Alcohol Consumption  Inference: The barplot displays the mean total crashes for different levels of alcohol consumption. So, if the alcohol consumption is high, then total crashes are also high.  sns.barplot(x="speeding", y="total", data=dset) plt.title("Barplot: Speeding vs Total Crashes") plt.xlabel("Speeding") plt.ylabel("Total Crashes")  Text(0, 0.5, 'Total Crashes')  Barplot: Speeding vs Total Crashes
	Inference: The barplot displays the mean total crashes for different levels of alcohol consumption. So, if the alcohol consumption is high, then total crashes are also high.  Sins. barplot (x="speeding", y="total", data=dset) plt: title("darplot: speeding vs Total Crashes") plt: vitle("darplot: speeding vs Total Crashes")  Text(e, e.5. "Total Crashes")  Text(e, e.5. "Total Crashes")  Barplot: Speeding vs Total Crashes  1.78 1937 Poscous 4-2-2-2-2-2-2-2-2-2-2-2-2-2-2-2-2-2-2-2
Out[19]:	Interence: The barplot displays the mean total crashes for different levels of alcohol consumption. So, if the alcohol consumption is high, then total crashes are also high.  Sns. barplot (x="speeding", y="total", data=dsct) plit.itile("Barplot: Speeding vs Total Crashes") plit.vjabel("Total Crashes") plit.vjabel("Total Crashes")  Text(e, e.s., 'Total Crashes')  Text(e, b.s., 'Total Crashes')  1.7119999991111000061111000000000000000000
Out[19]:	Alcohol Consumption  informace The bargist displays the mount made to allow the rest of alcohol consumption. Stu, if the absolute consumption is high, then coal concluss one above high.  stock bar Conference in the street of the coal concluss one above high.  stock of Conference in the street of the coal conclusion of the coal coal coal coal coal coal coal coal
Out[19]:	Inference The baselot dispassy the man locate for different levels of accord consumption 5c. ("the above consumption in high, then look creatives are size high."  The consumption of the consumption of the consumption of high, then look creatives are size high.  The consumption of the consumption of the consumption of high, then look creatives are size high.  The consumption of the consumption of the consumption of high, then look creatives are size high.  The consumption of the consumption of the consumption of high, then look creatives are size high.  The consumption of the consumption of the consumption of high, then look creatives are size high.  The consumption of the consumption of the consumption of high, then look creatives are size high.  The consumption of the consumption of the consumption of high, then look creatives are size high.  The consumption of the consumption of the consumption of high, then look creatives are size high.  The consumption of the consumption of the consumption of high then look creatives are size high.  The consumption of the c
Out[19]:	Accobal Consequence of the page of page time in the consequence of page of pag
Out[19]:	Acceled Communities  ### Acceled Communities
Out[19]:  In [20]:  Out[20]:	Accided Consumption  Accided C
Out[19]: In [20]: Out[20]:	Activation Consumption  Activation Consumption  Activation Consumption  Activation Consumption  Activation Consumption  Activation  Activation Consumption  Activation  Activa
Out[19]: In [20]: Out[20]:	And the control of th
Out[19]: In [20]: Out[20]:	The control of the co
<pre>In [20]: Out[20]:  Out[21]:</pre>	The control for large displaced control contro
<pre>In [20]: Out[20]:  In [21]: Out[21]:</pre>	The continue of the continue o
<pre>In [20]: Out[20]:  In [21]: Out[21]:</pre>	The control of the co
<pre>In [20]: Out[20]:  In [21]: Out[21]:</pre>	Manufacture for the control of the c
<pre>In [20]: Out[20]:  In [21]: Out[22]:</pre>	THE THE PROPERTY OF THE PROPER
<pre>In [20]:</pre>	District Control of the Control of t
<pre>In [20]:</pre>	Additional and additional additional and additional
<pre>In [20]: Out[20]: Out[21]: Out[22]: Out[22]:</pre>	And control of the co
<pre>In [20]: Out[20]: Out[21]: Out[22]: Out[22]:</pre>	STATE AND ADDRESS OF THE STATE
<pre>In [24]:  In [24]:  In [22]:  Out [22]:  Out [23]: </pre>	The control of the co
<pre>In [24]:  In [24]:  In [22]:  Out [22]:  Out [23]: </pre>	The state of the s
In [24]: Out [21]: Out [22]: Out [23]:	The state of the s
In [24]: Out [21]: Out [22]: Out [23]:	The state of the control of the cont
In [24]: Out [21]: Out [22]: Out [23]:	The state of the s