,	KMC Weather Aust Import Libraries
In [1]:	<pre>import pandas as pd from geopy.geocoders import Nominatim from progressbar import ProgressBar import time from sklearn.cluster import KMeans import matplotlib.pyplot as plt import plotly.graph_objects as go import warnings warnings.filterwarnings('ignore')</pre>
In [2]: Out[2]:	Import the dataset df=pd.read_csv('weatherAUS_84.csv') df.head() Date Location MinTemp MaxTemp Rainfall Evaporation Sunshine WindGustDir WindGustSpeed WindDir9am Humidity9am Humidity3pm Pressure9am Pressure3pm Cloud9am Cloud3pm
·	0 2008-12-01 Albury 13.4 22.9 0.6 NaN NaN W 44.0 W 71.0 22.0 1007.7 1007.1 8.0 NaN 1 2008-12-02 Albury 7.4 25.1 0.0 NaN NaN WW 44.0 NNW 44.0 25.0 1010.6 1007.8 NaN NaN 2 2008-12-03 Albury 12.9 25.7 0.0 NaN NaN WW 46.0 W 38.0 30.0 1007.6 1008.7 NaN NaN NaN 2 2008-12-03 Albury 9.2 28.0 0.0 NaN NaN NE 24.0 SE 45.0 16.0 1017.6 1012.8 NaN NaN 4 2008-12-05 Albury 17.5 32.3 1.0 NaN NaN W 41.0 ENE 82.0 33.0 1010.8 1006.0 7.0 8.0
In [3]: In [4]:	<pre>Data Analysis & Pre-processing # Drop records where target RainTomorrow=NaN df = df[pd.isnull(df['RainTomorrow'])==False] # For other columns with missing values, fill them in with column mean df = df.fillna(df.mean())</pre>
In [5]: In [6]:	<pre># Add spaces between multiple words in location names df['Location2']=df['Location'].str.replace(r"([A-Z])", r" \1").str.strip() # Update Location for Pearce RAAF so it can be found by geolocator df['Location2']=df['Location2'].apply(lambda x: 'Pearce, Bullsbrook' if x=='Pearce R A A F' else x)</pre>
In [7]: In [8]:	# Create a flag for RainToday and RainTomorrow, note RainTomorrowFlag can be used as target variable fro classification df['RainTodayFlag']=df['RainToday'].apply(lambda x: 1 if x=='Yes' else 0) df['RainTomorrowFlag']=df['RainTomorrow'].apply(lambda x: 1 if x=='Yes' else 0) df.head()
	Part
In [9]:	# Create a list of unique locations (cities) loc_list=list(df.Location2.unique()) geolocator = Nominatim(user_agent="add-your-agent-name") country ="Australia" loc_res=[] pbar=ProgressBar() # This will help us to show the progress of our iteration for city in pbar(loc_list):
Out[10]:	<pre>loc = geolocator.geocode(city+','+ country) res = [city, loc.latitude, loc.longitude] loc_res = loc_res + [res] time.sleep(1) # sleep for 1 second before submitting the next query # Add locations to a dataframe df_loc=pd.DataFrame(loc_res, columns=['Loc', 'Latitude', 'Longitude']) # Show data df_loc</pre> 100% ##################################
out[10]:	0 Albury -36.080477 146.916280 1 Badgerys Creek -33.881667 150.744163 2 Cobar -31.498333 145.834444 3 Coffs Harbour -30.296241 153.113529 4 Moree -29.461720 149.840715
	5 Newcastle -32.919295 151.779535 6 Norah Head -33.281667 151.567778 7 Norfolk Island -29.028958 167.958729 8 Penrith -33.751195 150.694171 9 Richmond -37.820395 145.002515 10 Sydney -33.869844 151.208285
	11 Sydney Airport -33.935309 151.165582 12 Wagga Wagga -35.115000 147.367778 13 Williamtown -32.815000 151.842778 14 Wollongong -34.427808 150.893054 15 Canberra -35.297591 149.101268 16 Tuggeranong -35.42097 149.092134
	17 Mount Ginini -35.52974 148.772540 18 Ballarat -37.562303 143.860565 19 Bendigo -36.758877 144.282593 20 Sale -38.10503 147.064790 21 Melbourne Airport -37.814218 144.963161
	23 Mildura -34.184726 142.162497 24 Nhii -35.432528 141.283319 25 Portland -38.345623 141.604230 26 Watsonia -37.711002 145.083635 27 Dartmoor -27.996162 115.189218
	29 Cairns -16.92066 145.772185 30 Gold Coast -28.002373 153.414599 31 Townsville -19.256939 146.823954 32 Adelaide -34.92818 138.599931 33 Mount Gambier -37.824670 140.782007
	34 Nuriootpa -34.469335 138.993901 35 Woomea -31.19914 136.825353 36 Albany -35.024782 117.883608 37 Witchcliffe -34.026335 115.100477 38 Pearce, Bullsbrook -31.67390 116.017544 39 Perth Airport -31.94061 115.967608
	40 Perth -31.95589 115.860580 41 Salmon Gums -32.981535 121.643942 42 Walpole -34.977680 116.731006 43 Hobart -42.882590 147.328123 44 Launceston -41.434081 147.137350 45 Alice Springs -23.698388 133.881289 46 Darwin -12.46040 310.841047 47 Katherine -14.46461 312.263599 48 Ulum -25.345554 313.036961
In [11]:	<pre>fig = go.Figure(data=go.Scattergeo(lat=df_loc['Latitude'], lon=df_loc['Longitude'], hovertext=df_loc['Loc'], mode = 'markers', marker_color = 'black',))</pre>
In [12]:	<pre>fig.update_layout(title = 'Mapping Australian cities', width=1000, height=600, margin={"r":10,"t":30,"l":0,"b":0}, geo = dict(scope='world', projection_type='miller', landcolor = "rgb(250, 250, 250)", center=dict(lat=-23.69839, lon=133.8813), # focus point</pre>
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	Use elbow method to find optimal number of clusters
In [13]:	<pre># Identify the number of clusters using Elbow method (WCSS) WCSS = [] K=range(1,10) for k in K: kmod = KMeans(n_clusters=k) kmod.fit(df_loc[['Latitude', 'Longitude']])</pre>
In [14]:	<pre># Plot elbow graph plt.plot(K, WCSS, 'bo-', color='black') plt.xlabel('k') plt.ylabel('WCSS') plt.title('Identify the number of clusters using Elbow method (WCSS)') plt.show()</pre>
	Identify the number of clusters using Elbow method (WCSS) 8000 - 6000 -
	2000 - 20
In [15]:	<pre># Model Building with K=3 & 4 # Select data for clustering model X = df_loc[['Latitude', 'Longitude']] # Set the model and its parameters - 3 clusters model3 = KMeans(n clusters=3.</pre>
	<pre>model3 = KMeans(n_clusters=3,</pre>
	<pre>n_init=10, # Number of time the k-means algorithm will be run with different max_iter=100, # maximum number of iterations to run default=300) # Fit the model (3 and 4 clusters) clust3 = model3.fit(X) clust4 = model4.fit(X) # Print model summary print('************************************</pre>
	<pre>print('************************************</pre>
	********** 3 Cluster Model ************ Cluster centers: [[-34.74921474 147.54680922] [-32.57211995 116.79924778] [-18.69110057 136.76983921]] Inertia (WCSS): 1994.7309795181147 No. of iterations: 3 ************* 4 Cluster Model ************************************
	[-32.4617723 152.13827238] [-18.69110057 136.76983921] [-36.67548207 143.68031393]] Inertia (WCSS): 1219.1626081918919 No. of iterations: 4 Cluster visualization
In [16]:	<pre># Attach cluster labels to the original dataset df_loc['Clust3']=clust3.labels_ df_loc['Clust4']=clust4.labels_ # Plot cluster on the map fig = go.Figure(data=go.Scattergeo(lat=df_loc['Latitude'], lon=df_loc['Longitude'], howertayt=df_loc[Flustall]</pre>
In [18]:	<pre>hovertext=df_loc[['Loc', 'Clust3']], mode = 'markers', marker=dict(colorscale=['blue', 'red', '#34eb34']), marker_color = df_loc['Clust3'],)) # Add traces fig.add_trace(go.Scattergeo(lat=model3.cluster_centers_[:,0], lon=model3.cluster_centers_[:,1],</pre>
	mode='markers', marker_symbol='x', marker_size=12, marker_color='lock', marker_line_color='black', marker_line_width=1))
	• trace 0 ★ trace 1
In [19]:	<pre>fig.update_layout(title = 'Mapping Australian cities', title_font_color='black', showlegend=False, width=1000, height=600, margin={"r":10, "t":30, "l":0, "b":0}, geo = dict(scope='world',</pre>
	Mapping Australian cities
In []:	