In [2]:	<pre>import pandas as pd import numpy as np from sklearn import pr from IPython.display : import warnings warnings.filterwarning</pre>	import display,	HTML									
	# reading the data df = pd.read_csv('C:/l print(df.shape) df=df.rename(columns=1 cols=df.columns display(HTML(df.head(1 (100000, 36)) 0 42fb5e2ec009a05ff5143227 2 42fb5e2ec009a05ff5143227 3 42fb5e2ec009a05ff5143227 4 42fb5e2ec009a05ff5143227 5 42fb5e2ec009a05ff5143227	lambda x: x.str 10).to_html())) 7297074f1e9c6c3ebb9 7297074f1e9c6c3ebb9 7297074f1e9c6c3ebb9 7297074f1e9c6c3ebb9	ip()) 0c914e223349672eca7 0c914e223349672eca7 0c914e223349672eca7 0c914e223349672eca7 0c914e223349672eca7	hash millisecond c 19ad0 0 0 19ad0 1 0 19ad0 2 0 19ad0 3 0 19ad0 4 0 19ad0 5	malware CentOS malware Windows malware Mac malware Ubuntu malware Mac malware Windows	0 0 0 0	0 3069378560 0 3069378560 0 3069378560 0 3069378560 0 3069378560 0 3069378560	14274 14274 14274 14274 14274 14274	0 0 0 0 0 0 0 0 0 0	vm_pgoff vm_trunca 0 0 0 0 0 0	13173 13173 13173 13173 13173 13173	0 0 0 0 0
; n [15]:		7297074f1e9c6c3ebb9 7297074f1e9c6c3ebb9 7297074f1e9c6c3ebb9 7297074f1e9c6c3ebb9 7297074f1e9c6c3ebb9 7297074f1e9c6c3ebb9 7297074f1e9c6c3ebb9 7297074f1e9c6c3ebb9 7297074f1e9c6c3ebb9	0c914e223349672eca7 0c914e223349672eca7 0c914e223349672eca7 dme file s', 'usage_coun prio static_prio	9ad0 7 9ad0 8 9ad0 9 ter', 'prio', 'st	ogoff vm_truncate_count	0 0 0prio', 'vm_pg task_size map_e	count hiwater_r	ss total_vm	shared_vm exec_v	m reserved_vm nr_	13173 13173 13173 hiwater_rss', _ptes nvcsw niv	csw signal
; ; ;	 malware CentOS malware Windows malware Mac malware Ubuntu malware Windows malware Windows malware Ubuntu malware CentOS malware Mac 	0 306 0 306 0 306 0 306 0 306 0 306	69378560 1427 69378560 1427 69378560 1427 69378560 1427 69378560 1427 69378560 1427 69378560 1427 69378560 1427 69378560 1427 69378560 1427 69378560 1427 69378560 1427	1 0 0 1 1 0 1 1 0 1 1 0 1 1 1 0 1 1 1 1	0 13173 0 13173 0 13173 0 13173 0 13173 0 13173 0 13173 0 13173 0 13173 0 13173	0 0 0 0 0 0 0	6850 6850 6850 6850 6850 6850 6850 6850	0 150 0 150 0 150 0 150 0 150 0 150 0 150 0 150 0 150	120 12 120 12 120 12 120 12 120 12 120 12 120 12 120 12 120 12 120 12 120 12	24 210 24 210 24 210 24 210 24 210 24 210 24 210	0 341974 0 341974 0 341974 0 341974 0 341974 0 341974 0 341974 0 341974 0 341974	0 0 0 0 0 0 0 0
ut[16]: (1	os usage_counter prio static_prio normal_prio vm_pgoff vm_truncate_count	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	es									
t[17]:	<pre># convert all nominal df_num=df.copy(deep=Ti df_dummies=pd.get_dumm df_num=df_num.join(df_ # drop original column df_num=df_num.drop('os df_num.head() classification usage_cou malware</pre>	<pre>rue) mies(df_num['os _dummies) ns s',axis=1)</pre>	'],dtype=float)		truncate_count task_size	e map_count hiw	/ater_rss re: 0	served_vm nr_ 210	ptes nvcsw nivc	sw signal_nvcsw 0	CentOS Debian M	
; ; 5	<pre>malware malware malware malware malware malware malware rows × 23 columns # dropping the extra of df_num.drop('CentOS',</pre>		14274 14274 14274 14274	0 0 0 0 0 0 0 0	13173 (C	6850 6850 6850 6850 6850	0 0 0	210 210 210 210	0 341974 0 341974 0 341974 0 341974	0 0 0 0 0 0 0 0	0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0	1.0 0.0
t[18]: 	df_num.head() classification usage_cou malware malware malware malware malware malware malware conditions a series of the series of t			prio vm_pgoff vm_ 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	13173	6850 6850 6850 6850	vater_rss ex 0 0 0 0 0	ec_vm reserve 124 124 124 124 124 124	210 0 34 210 0 34 210 0 34 210 0 34 210 0 34 210 0 34	1974 0 1974 0 1974 0 1974 0	Debian 0 0.0 0 0.0 0 0.0 0 0.0 0 0.0 0 0.0	0.0 (0.0 (0.0 (0.0 (0.0 (0.0 (0.0 (0.0
[22]: [1] t[22]: [2] : [22]: [2]	df_num.drop('classifictols_to_norm = df_num df_num[cols_to_norm] : df_num.head() usage_counter	.columns.to_lis = df_num[cols_t	t() o_norm].apply(1	· · · · · · · · · · · · · · · · · · ·	min()) / (x.max() - sk_size map_count hiw NaN		 0.307692 0.307692 0.307692 0.307692	0.249311 0.249311 0.249311 0.249311 0.249311	NaN 0.091519 NaN 0.091519 NaN 0.091519 NaN 0.091519 NaN 0.091519 NaN 0.091519	nivcsw signal_nvcsv 0.0 Nal 0.0 Nal 0.0 Nal 0.0 Nal 0.0 Nal	N 0.0 0.0 N 0.0 0.0 N 0.0 1.0 N 0.0 0.0	Jbuntu W 0.0 0.0 0.0 1.0 0.0
t[23]:	usage_counter	0.00.00000 100000. 0.499762 0. 0.287065 0. 0.000000 0. 0.248016 0. 0.492063 0. 0.743056 0.		0.0 100 NaN NaN NaN NaN NaN NaN NaN NaN	0000.000000 0.0 1 0.321712 NaN 0.186489 NaN 0.000000 NaN 0.169110 NaN 0.317833 NaN 0.456305 NaN 1.000000 NaN	map_count hiwa 000000.000000 0.241567 0.147887 0.000000 0.150023 0.206165 0.316299 1.0000000	0.0 1000000 NaN 0	otal_vm	0.0000.00000 10000 0.343059 0.214211 0.000000 0.192308 0.336538 0.442308	0.000000 0.0 0.242872 NaN 0.155259 NaN 0.000000 NaN 0.114325 NaN 0.225895 NaN 0.336088 NaN 1.000000 NaN	nvcsw 100000.000000 100 0.226876 0.194690 0.000000 0.091519 0.204049 0.298492 1.000000	nivest 0000.00000 0.09038 0.14446 0.00000 0.00274 0.02465 0.12602 1.00000
[27]: [32]:	# dropping the Nan as df_num.drop(['usage_cd df_num.head()) prio static_prio vm_ 0 0.18254 0.016007 1 0.18254 0.016007 2 0.18254 0.016007 3 0.18254 0.016007 4 0.18254 0.016007 df_kmeans = df_num.copy(df_kmeans) df_knn = df_num.copy(df_kmeans) from sklearn.cluster : kmeans=KMeans(n_cluster) kmeans=KMeans(n_cluster) kmeans.fit(df_kmeans) y_pred=kmeans.predicter plt.scatter(df_kmeans) # get the cluster labe opt=kmeans.labels_	_truncate_count ma _truncate_count ma _0.199175 _0.199175 _0.199175 _0.199175 _0.199175 	<pre>l_prio', 'vm_pg ap_count total_vm 0.16651 0.052031 0.16651 0.052031 0.16651 0.052031 0.16651 0.052031 0.16651 0.052031 Colormap tate=1, max_iter ans['vm_truncat</pre>	shared_vm exec_vi 1.0 0.30769 1.0 0.30769 1.0 0.30769 1.0 0.30769 1.0 0.30769	m reserved_vm nvcsv 2 0.249311 0.09151 2 0.249311 0.09151 2 0.249311 0.09151 2 0.249311 0.09151 2 0.249311 0.09151	w nivcsw Debian 9 0.0 0.0 9 0.0 0.0 9 0.0 0.0 9 0.0 0.0			lace=True)			
	0 0.18254 0.016007 1 0.18254 0.016007 2 0.18254 0.016007 3 0.18254 0.016007 4 0.18254 0.016007 5 0.18254 0.016007 6 0.18254 0.016007 7 0.18254 0.016007 8 0.18254 0.016007 9 0.18254 0.016007	_truncate_count materials		shared_vm exec_vi 1.0 0.30769 1.0 0.30769 1.0 0.30769 1.0 0.30769 1.0 0.30769 1.0 0.30769 1.0 0.30769 1.0 0.30769 1.0 0.30769 1.0 0.30769 1.0 0.30769	0.249311 0.09151 0.249311 0.09151 0.249311 0.09151 0.249311 0.09151 0.249311 0.09151 0.249311 0.09151 0.249311 0.09151 0.249311 0.09151 0.249311 0.09151	9 0.0 0.0 9 0.0 0.0 9 0.0 0.0 9 0.0 0.0 9 0.0 0.0 9 0.0 0.0 9 0.0 0.0 9 0.0 0.0	Mac Ubuntu 0 0.0 0.0 1.0 0.0 1.0 0.0 1.0 0.0 0 0.0 1.0 0 0.0 0.0 1.0 0.0 0 0.0 0.0 0 0.0 0.0 1.0 0.0 1.0 0.0	Windows Clu 0.0 1.0 0.0 0.0 1.0 0.0 0.0 1.0 0.0 0.0 0.0 0.0	ster 1 1 3 4 3 1 4 3 1 3			
	0.8 - 0.6 - 0.4 - 0.2 - 0.0 0.2	0.4	0.6	0.8 1.0								
	<pre>import yellowbrick from yellowbrick.clust print(yellowbrickve km = KMeans(random_stavisualizer = KElbowVisvisualizer.fit(df_kmeavisualizer.show()) 1.5</pre>	ersion) ate=42,max_iter sualizer(km, k= ans) # F # Finalize	=500, algorithm (2,10), timings it the data to and render the	False , distance the visualizer		metric='disto	ortion')					
	90000 80000 70000 60000		!		score = 51452.223							
	50000 40000 30000 2 <axes: title="{'center'</td"><td>3 4 ': 'Distortion</td><td>5 k Score Elbow for</td><td>6 7 KMeans Clusterin</td><td>8 9 ng'}, xlabel='k', yl</td><td>abel='distorti</td><td>on score'></td><td></td><td></td><td></td><td></td><td></td></axes:>	3 4 ': 'Distortion	5 k Score Elbow for	6 7 KMeans Clusterin	8 9 ng'}, xlabel='k', yl	abel='distorti	on score'>					
[35]:	<pre># dividing into clusters km = KMeans(n_clusters km = km.fit(df_kmeans) opt=km.labels_ df_knn['Cluster']=opt display('Data:', HTML(d') 'Data:'</pre>	ering s=5)) df_knn.tail(10) o vm_truncate_cou	.to_html())) nt map_count tota	l_vm shared_vm ex	kec_vm reserved_vm nv	vcsw nivcsw De	ebian Mac Ubi					
· · · · · · · · · · · · · · · · · · ·	99990 0.928571 0.0 99991 0.928571 0.0 99992 0.928571 0.0 99993 0.928571 0.0 99994 0.928571 0.0 99995 0.928571 0.0 99996 0.928571 0.0 99997 0.928571 0.0 99998 0.928571 0.0 99999 0.928571 0.0	0.04071 0.04071 0.04071 0.04071 0.04071 0.04071 0.04071	0.04153 0.0 0.04153 0.0 0.04153 0.0 0.04153 0.0 0.04153 0.0 0.04153 0.0 0.04153 0.0 0.04153 0.0 0.04153 0.0 0.04153 0.0	1283 1.0 0. 1283 1.0 0. 1283 1.0 0. 1283 1.0 0. 1283 1.0 0. 1283 1.0 0. 1283 1.0 0. 1283 1.0 0. 1283 1.0 0.	048077 0.084022 048077 0.084022 048077 0.084022 048077 0.084022 048077 0.084022 048077 0.084022 048077 0.084022 048077 0.084022 048077 0.084022 048077 0.084022	0.0 0.005479 0.0 0.005479 0.0 0.005479 0.0 0.005479 0.0 0.005479 0.0 0.005479 0.0 0.005479 0.0 0.005479 0.0 0.005479	1.0 0.0 0.0 0.0 0.0 0.0 1.0 0.0 1.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 1.0	0.0 0.0 1.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 1.0 0.0 0.0 1.0 0.0 0.0 0.0	0 3 3 3 3 2 3 0			
[45]:	# Evaluating the clust from sklearn.metrics: silhouette = silhouett print("Silhouette Score: 0.33 from sklearn.metrics: db_index = davies_boul print("Davies Bouldin Davies Bouldin Score:	tering import silhouet te_score(df_num re:", silhouett 324821270873199 import davies_b ldin_score(df_n Score:", db_in	te_score , opt) e) 5 ouldin_score um, opt) dex)	0.				5.0				