i i f f f i i i f	mport pandas as pd mport matplotlib.pyplot as plt mport seaborn as sn mport numpy as np from sklearn.cluster import AgglomerativeClustering from sklearn.preprocessing import StandardScaler from sklearn.preprocessing import StandardScaler from sklearn.cluster import KMeans mport os mport subprocess mport subprocess mport numpy as np from sklearn.cluster import KMeans mport os mport os mport subprocess mport subprocess mport numpy as nx from sklearn.preprocessing import subprocess mport subprocess mport subprocess mport subprocess mport numpy as nx from scipy.cluster import hierarchy from scipy.cluster import dendrogram
# d p d sh	Anpe of data AMD BABA NVDA ROKU U Date LOG/2021 82.58998 211.059998 184.272507 382.73011 107.889999 ROG/2021 83.82000 214.86001 190.572495 421.70012 112.959999
13 14 15 16 17 252	106/2021 86.09998 218.380005 192.054993 423.579987 113.760002 100.054993 423.579987 110.150002 100.054993 423.579987 110.150002 100.054993 423.579987 110.150002 100.054993 423.57998 430.940002 110.150002 100.054998 98.519997 156.47001 73.25000 34.349998 105.230003 158.360001 74.290001 33.759998 105.230003 108.02999 165.27004 83.00000 36.169998 105.20003 101.449997 156.00995 78.580002 32.849998 100.054999 100.05499 100.054999 100.05499 10
f r	returns = pd.DataFrame() for i in df: returns[i] = np.log(df[i]).diff() eturns.corr() AMD BABA NVDA ROKU U AMD 1.00000 0.356762 0.818748 0.46103 0.513069 ABA 0.356762 1.00000 0.327675 0.470825 0.414495 VDA 0.818748 0.327675 1.00000 0.497427 0.594451
: c ######	OKU 0.451033 0.470825 0.497427 1.00000 0.624803 U 0.513069 0.414495 0.594451 0.624803 1.00000 OUTMATRIX = returns.corr() If fig, ax = plt.subplots(figsize=(10,10))
U ROKU NVDA BABA AMD	- 0.36
p p	
	def preprocess(df): """Preprocess data for KMeans clustering""" df_log = np.log1p(df) scaler = StandardScaler() scaler.fit(df_log) df_norm = scaler.transform(df_log) return df_norm def elbow_plot(df): """Create elbow plot from normalized data"""
	<pre>df_norm = preprocess(df) sse = {} for k in range(1, 21): kmeans = KMeans(n_clusters=k, random_state=1) kmeans.fit(df_norm) sse[k] = kmeans.inertia_ plt.title('Elbow plot for K selection') plt.xlabel('k') plt.ylabel('SSE') sn.pointplot(x=list(sse.keys()), y=list(sse.values())) plt.show()</pre>
C: va	Albow_plot(df) Albow_plot(df)
d 1 p p	abels = agg_clustering.fit_predict(data) llt.figure(figsize = (8,5)) llt.scatter(data[labels == 0, 0], data[labels == 0, 1], c = 'red', label = 'Cluster 1') llt.scatter(data[labels == 1, 0], data[labels == 1, 1], c = 'blue', label = 'Cluster 2') llt.scatter(data[labels == 2, 0], data[labels == 2, 1], c = 'green', label = 'Cluster 3')
# # p	<pre>cplt.scatter(data[labels == 3 , 0] , data[labels == 3 , 1] , c = 'purple', label = 'Cluster 4') cplt.scatter(data[labels == 4 , 0] , data[labels == 4 , 1] , c = 'yellow', label = 'Cluster 5') clt.slepend(loc = 'upper right') cluster 1 cluster 2 cluster 3 cluster 3</pre>
: # Z p n d p	Dendrogramma ana hmera gia oles tis times kai twn 5 metoxwn = linkage(data, method = 'ward') plt.figure(figsize = (10,10)) names = df.index.to_list() lendrogramm(Z, labels = names) plt.title('Dendrogram')
Те	ext(0, 0.5, 'Euclidean Distance') Dendrogram 2500 - 2000 -
Euclidean Distan	1000 -
p n d	<pre>int figure(figsize = (8,6)) tames = df.columns.to_list() tendrogram = hierarchy.dendrogram(Z, labels = names) tlt.title('Dendrogram') tlt.title('Dendrogram') tlt.tylabel('Euclidean Distance')</pre>
Te	Dendrogram Dendrogram 15
C C	DOTTdf=df.corr() COTTdf=df.to_numpy() DATAd = 1
p n d p p p	<pre>inleques (corr, method = 'ward') inleques (figsize = (8,6)) tames = df.columns.to_list() tendrogram = hierarchy.dendrogram(Z, labels = names) tlt.title('Dendrogram') tlt.ylabel('Euclidean Distance') tlt.ylabel('Euclidean Distance') tlt.axhline(y=max_d, c='k') matplotlib.lines.Line2D at 0x1d22243d070> Dendrogram Dendrogram Dendrogram Dendrogram</pre>
Euclidean Distance	2.0 - 15 - 10 -
	n. clustermax(df, figsize = (10,10), cmap = 'Blues') reaborn.matrix.ClusterGrid at exid2220c7dx9> -000 -000 -000 -000 -000 -000 -000 -
]: d	-03/05/2022 -27/04/2022 -14/04
	<pre>else: fig, ax = plt.subplots(1, 2, figsize = (30,10)) fig.tight_layout() ax[0].bar(range(0, N), D) ax[0].set(xlabel = 'Data', ylabel = 'Degree', title = 'Value of Degree Network of Time Series') plt.grid() M = np.max(D) P_D = np.zeros(int(M+1)) for i in range(int(M+1)): P_D[i] = np.count_nonzero(D == i) my_sum = sum(P_D) P_D = P_D/my_sum ax[1].plot(P_D) ax[1].set(xlabel = 'Node Degree k', ylabel = 'Degree Distribution', title = 'Degree Distribution') if len(country) == 0: tit = 'Degree Distribution for Correlation Graph' else:</pre>
d	<pre>tit = 'Degree Distribution for {}'.format(country) plt.grid() fig.subplots_adjust(top=0.88) fig.suptitle(tit, size = 16) plt.show() return D, aver_D lef Degree_Distribution_Directed(x, labels = ''): N = len(x) k_in = np.zeros(N) k_out = np.zeros(N) for i in range(N): for j in range(i, N):</pre>
	<pre>k_in[j] += 1 else:</pre>
	<pre>fig, ax = plt.subplots(2, 2, figsize = (40,15)) ax[0,0].bar(range(0, N), k_in) ax[0,0].set(ylabel = 'Degree In') if labels != '': ax[0,0].set_xticks(ticks = range(N), labels = labels, rotation = 45) plt.grid() ax[0,1].loglog(P_in) ax[0,1].set(xlabel = 'Node Degree k_in', ylabel = 'Degree In Distribution') tit = 'Degree In Distribution for Correlation Graph' plt.grid() fig.subplots_adjust(top=0.88) fig.suptitle(tit, size = 16) ax[1,0].bar(range(0, N), k_out) ax[1,0].set(ylabel = 'Degree Out') if labels != '':</pre>
t p d	<pre>ax[1,0].set_xticks(ticks = range(N), labels = labels, rotation = 45) plt.grid() ax[1,1].loglog(P_out) ax[1,1].set(xlabel = 'Node Degree k_out', ylabel = 'Degree Out Distribution') tit = 'Degree Out Distribution for Correlation Graph' plt.grid() fig.subplots_adjust(top=0.88) fig.supptitle(tit, size = 16) plt.show() return k_in, k_out return k_in, k_out return k_in = 'Degree Distribution for Correlation Graph' it = 'Degree Distribution for Correlation Graph' ilt.show() if = pd.DataFrame(columns = ['Source', 'Target', 'Type', 'weight']) yp = 'Directed'</pre>
G C	<pre>for i in range(len(corr)): for j in range(i, len(corr)): w = corr[i,j] if w == 0: continue elif w > 0: source = corr_df.index[i] target = corr_df.columns[j] else: source = corr_df.index[j] target = corr_df.columns[i] w = abs(w) tmp_df = pd.DataFrame([[source, target, typ, w]], columns = ['Source', 'Target', 'Type', 'weight']) df = pd.concat([df, tmp_df], ignore_index = None) il = nx.from_pandas_edgelist(df, source = 'Source', target = 'Target', edge_attr = 'weight', create_using = nx.DiGraph()) continue elis = nx.get_edge_attributes(G1, 'weight')</pre>
# o o } f n t p t p p	<pre>if for key in widths: if widths[key] *= 4/3 iptions = {</pre>
pt ## p nt pp nt pp	<pre>it = 'Circular Correlation graph\nClustering: {}'.format(clus) it = 'Circular Correlation graph' if plt.show() it clf() x.draw_kamada_kawai(G1, **options) it = 'Kamada-Kawai path-length cost-function Correlation graph\nClustering: {}'.format(clus) it = 'Kamada-Kawai path-length cost-function Correlation graph' it : tamada-Kawai path-length cost-function Correlation graph' it : show() it.clf() x.draw_shell(G1, **options) it = 'Shell Correlation graph\nClustering: {}'.format(clus) itt.title(tit) it = 'Shell Correlation graph'</pre>
p	Degree Out Distribution for Correlation Graph 4 × 10 ⁻² 4 × 10 ⁻² 9 3 3 × 10 ⁻³
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	5 -
	Kamada-Kawai path-length cost-function Correlation graph Clustering: 0.5
	Shell Correlation graph Clustering: 0.5
]:	AND NO