Identification of Students with Similar Performance in Micro- Learning Programming Courses with Automatically Evaluated Student Assignments

Draft code for the paper.

Import required libarries.

In [1]:
```
import pandas as pd
import pycaret
import seaborn as sns
import matplotlib.pyplot as plt
```

Import dataset. Students with zero activity have been already removed.

In [2]:
```
dataset = pd.read_csv('data_java_21_aggregated_not_zero.csv', sep = ';')
```

Exploratory Data Analysis

In [3]:
```
dataset.shape
```

Out[3]:
```
(102, 27)
```

In [4]:
```
1 dataset.head()
```

Out[4]:

	intro	intro-VPL	methods	methods-VPL	encap	encap-VPL	constructors	constructors-VPL	classes1	classes1-VPL	...	polymorphism-VPL	intro-VPL.1	methods-VPL-f	encap-VPL-f	constructors-VPL-f	clas
0	110	60	160	630	148	100	110	165	80	0	...	45	60	630	100	165	
1	110	60	160	630	150	100	110	165	80	0	...	45	60	630	100	165	
2	110	60	160	630	150	100	110	165	80	0	...	45	60	630	100	165	
3	110	60	160	630	150	100	110	165	80	0	...	45	60	630	100	165	
4	110	60	160	630	150	100	110	157	80	0	...	45	60	630	100	157	

5 rows × 27 columns

In [5]:
```
1 dataset.tail(20)
```

Out[5]:

	intro	intro-VPL	methods	methods-VPL	encap	encap-VPL	constructors	constructors-VPL	classes1	classes1-VPL	...	polymorphism-VPL	intro-VPL.1	methods-VPL-f	encap-VPL-f	constructors-VPL-f	c
82	50	0	60	0	30	0	50	0	0	0	...	0	0	0	0	0	
83	97	20	0	100	10	70	0	124	0	0	...	0	20	100	70	124	
84	10	20	0	140	50	40	0	60	0	0	...	0	20	140	40	60	
85	10	20	0	140	50	40	0	60	0	0	...	0	20	140	40	60	
86	0	60	0	60	10	70	0	98	0	0	...	0	60	60	70	98	
87	71	60	93	183	0	0	0	0	0	0	...	0	60	183	0	0	
88	0	0	0	188	0	40	0	65	0	0	...	0	0	188	40	65	
89	85	0	128	80	26	34	0	0	0	0	...	0	0	80	34	0	
90	107	60	0	100	0	20	0	0	0	0	...	0	60	100	20	0	
91	106	60	50	40	0	0	0	0	0	0	...	0	60	40	0	0	
92	102	0	0	80	0	0	0	0	0	0	...	0	0	80	0	0	
93	71	0	30	40	20	0	0	0	0	0	...	0	0	40	0	0	
94	0	0	0	90	0	40	0	30	0	0	...	0	0	90	40	30	
95	97	60	0	0	0	0	0	0	0	0	...	0	60	0	0	0	
96	91	20	0	40	0	0	0	0	0	0	...	0	20	40	0	0	
97	40	0	0	97	0	10	0	0	0	0	...	0	0	97	10	0	
98	98	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
99	0	0	0	0	20	0	0	0	0	0	...	0	0	0	0	0	
100	20	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
101	0	20	0	0	0	0	0	0	0	0	...	0	20	0	0	0	

20 rows × 27 columns

In [6]:
```
1 dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 102 entries, 0 to 101
Data columns (total 27 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   intro               102 non-null    int64
 1   intro-VPL           102 non-null    int64
 2   methods             102 non-null    int64
 3   methods-VPL         102 non-null    int64
 4   encap               102 non-null    int64
 5   encap-VPL           102 non-null    int64
 6   constructors        102 non-null    int64
 7   constructors-VPL    102 non-null    int64
 8   classes1            102 non-null    int64
 9   classes1-VPL        102 non-null    int64
 10  classes2            102 non-null    int64
 11  classes2-VPL        102 non-null    int64
 12  static              102 non-null    int64
 13  static-VPL          102 non-null    int64
```

In [7]:
```
1 dataset.describe().T
```

Out[7]:

	count	mean	std	min	25%	50%	75%	max
intro	102.0	94.509804	30.101066	0.0	97.25	110.0	110.00	110.0
intro-VPL	102.0	46.196078	23.239621	0.0	40.00	60.0	60.00	60.0
methods	102.0	123.421569	59.649544	0.0	102.50	159.0	160.00	160.0
methods-VPL	102.0	348.843137	224.051875	0.0	107.50	346.0	584.50	630.0
encap	102.0	108.745098	58.633901	0.0	71.75	146.5	150.00	150.0
encap-VPL	102.0	71.598039	38.642115	0.0	40.00	100.0	100.00	100.0
constructors	102.0	79.117647	44.749533	0.0	51.00	105.5	110.00	110.0
constructors-VPL	102.0	112.637255	63.217179	0.0	60.00	139.0	165.00	165.0
classes1	102.0	52.401961	34.236007	0.0	0.00	73.0	80.00	80.0
classes1-VPL	102.0	0.000000	0.000000	0.0	0.00	0.0	0.00	0.0
classes2	102.0	109.450980	71.353482	0.0	32.50	150.0	169.75	170.0
classes2-VPL	102.0	54.166667	41.345462	0.0	0.00	65.0	95.00	95.0
static	102.0	57.362745	33.316303	0.0	40.00	77.0	80.00	80.0
static-VPL	102.0	147.950980	109.225027	0.0	38.00	170.0	270.00	270.0
inher	102.0	116.568627	75.730569	0.0	40.00	161.5	186.50	190.0
inher-VPL	102.0	139.941176	110.768944	0.0	27.00	158.5	270.00	270.0
polymorphism	102.0	45.107843	31.401238	0.0	0.00	69.0	70.00	70.0
polymorphism-VPL	102.0	26.647059	21.434518	0.0	0.00	45.0	45.00	45.0
intro-VPL.1	102.0	46.196078	23.239621	0.0	40.00	60.0	60.00	60.0
methods-VPL-f	102.0	348.843137	224.051875	0.0	107.50	346.0	584.50	630.0
encap-VPL-f	102.0	71.598039	38.642115	0.0	40.00	100.0	100.00	100.0
constructors-VPL-f	102.0	112.637255	63.217179	0.0	60.00	139.0	165.00	165.0
classes2-VPL-f	102.0	54.166667	41.345462	0.0	0.00	65.0	95.00	95.0
static-VPL-f	102.0	147.950980	109.225027	0.0	38.00	170.0	270.00	270.0
inher-VPL-f	102.0	139.941176	110.768944	0.0	27.00	158.5	270.00	270.0
polymorphism-VPL-f	102.0	26.647059	21.434518	0.0	0.00	45.0	45.00	45.0
sum_vpl	102.0	1734.666667	927.242140	20.0	969.00	2025.5	2570.50	2753.0

In [ ]:
```
1
```

Selection Attributes for Micro-learning Units with Quizzes and Programming Assignments

In [8]:
```
1 dataset_reduced = dataset[['intro','intro-VPL','methods','methods-VPL','encap','encap-VPL','constructors',
2                                                'constructors-VPL','classes1','classes2','classes2-VPL','static','static-VPL',
3                                                'inher', 'inher-VPL', 'polymorphism', 'polymorphism-VPL']]
```

In [9]:
```
1 dataset_reduced = dataset_reduced.astype(float)
```

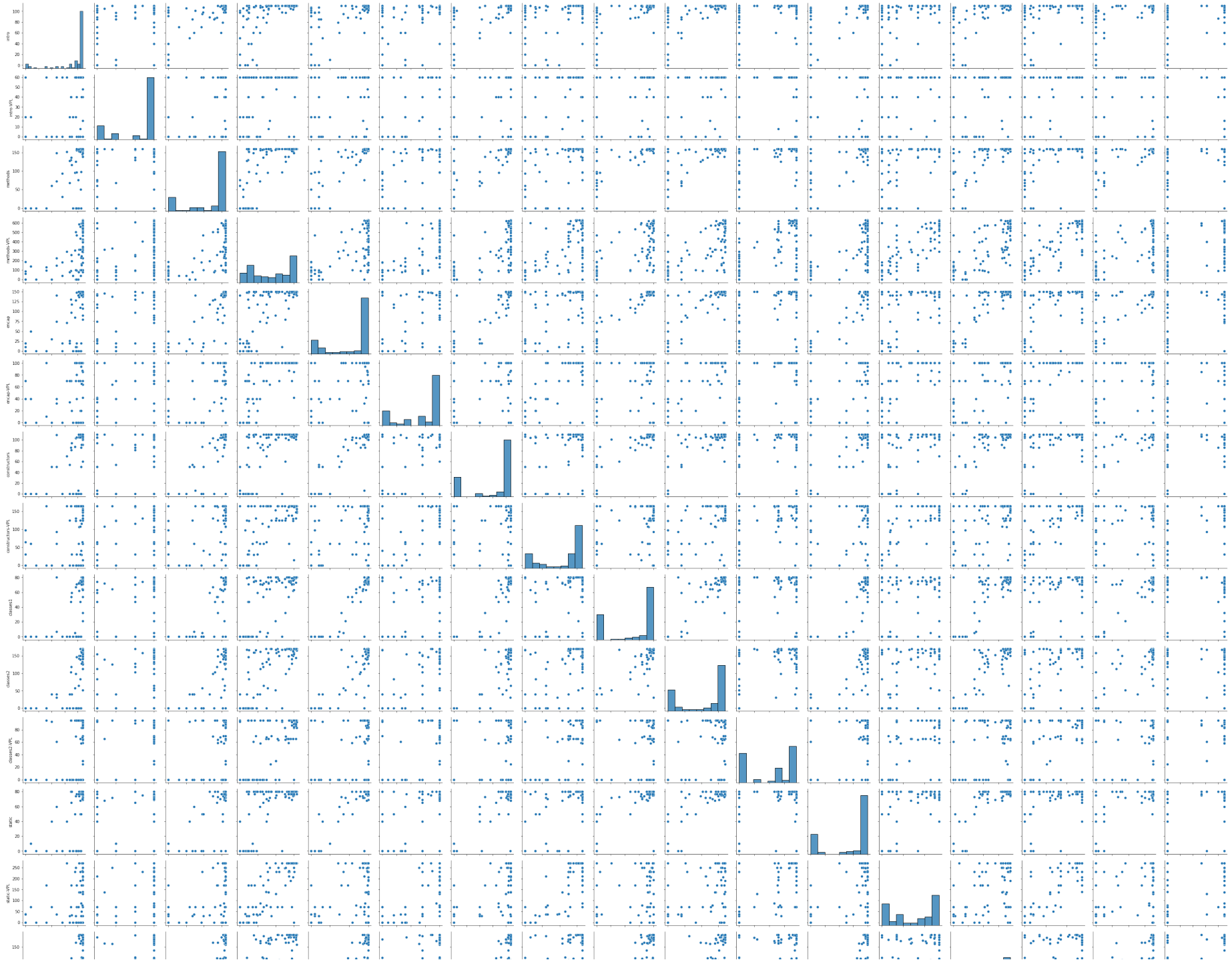
In [10]:
```
1 dataset_reduced.describe().T
```

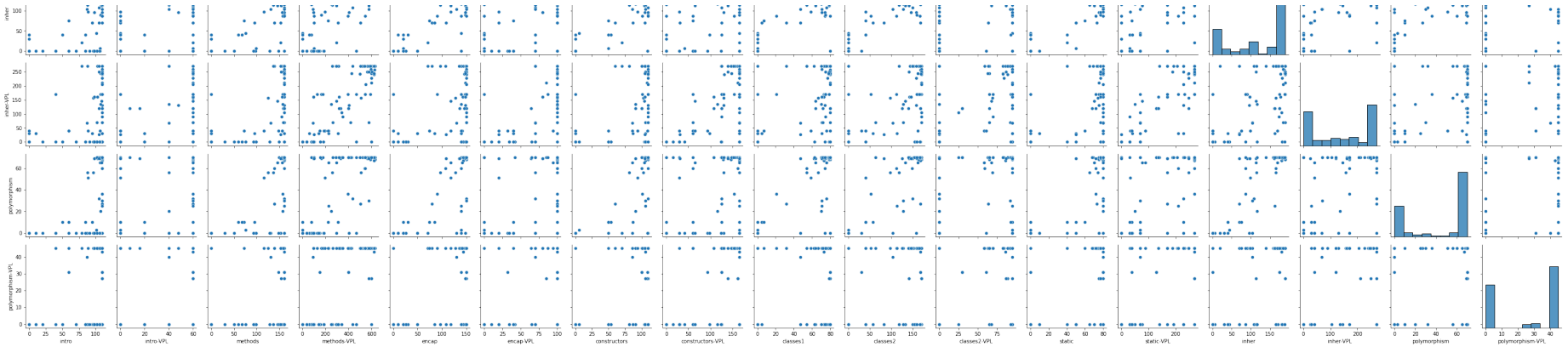
Out[10]:

	count	mean	std	min	25%	50%	75%	max
intro	102.0	94.509804	30.101066	0.0	97.25	110.0	110.00	110.0
intro-VPL	102.0	46.196078	23.239621	0.0	40.00	60.0	60.00	60.0
methods	102.0	123.421569	59.649544	0.0	102.50	159.0	160.00	160.0
methods-VPL	102.0	348.843137	224.051875	0.0	107.50	346.0	584.50	630.0
encap	102.0	108.745098	58.633901	0.0	71.75	146.5	150.00	150.0
encap-VPL	102.0	71.598039	38.642115	0.0	40.00	100.0	100.00	100.0
constructors	102.0	79.117647	44.749533	0.0	51.00	105.5	110.00	110.0
constructors-VPL	102.0	112.637255	63.217179	0.0	60.00	139.0	165.00	165.0
classes1	102.0	52.401961	34.236007	0.0	0.00	73.0	80.00	80.0
classes2	102.0	109.450980	71.353482	0.0	32.50	150.0	169.75	170.0
classes2-VPL	102.0	54.166667	41.345462	0.0	0.00	65.0	95.00	95.0

In [11]:
```
g = sns.PairGrid(dataset_reduced)
g.map_diag(sns.histplot)
g.map_offdiag(sns.scatterplot)
```

Out[11]: <seaborn.axisgrid.PairGrid at 0x166165bc908>

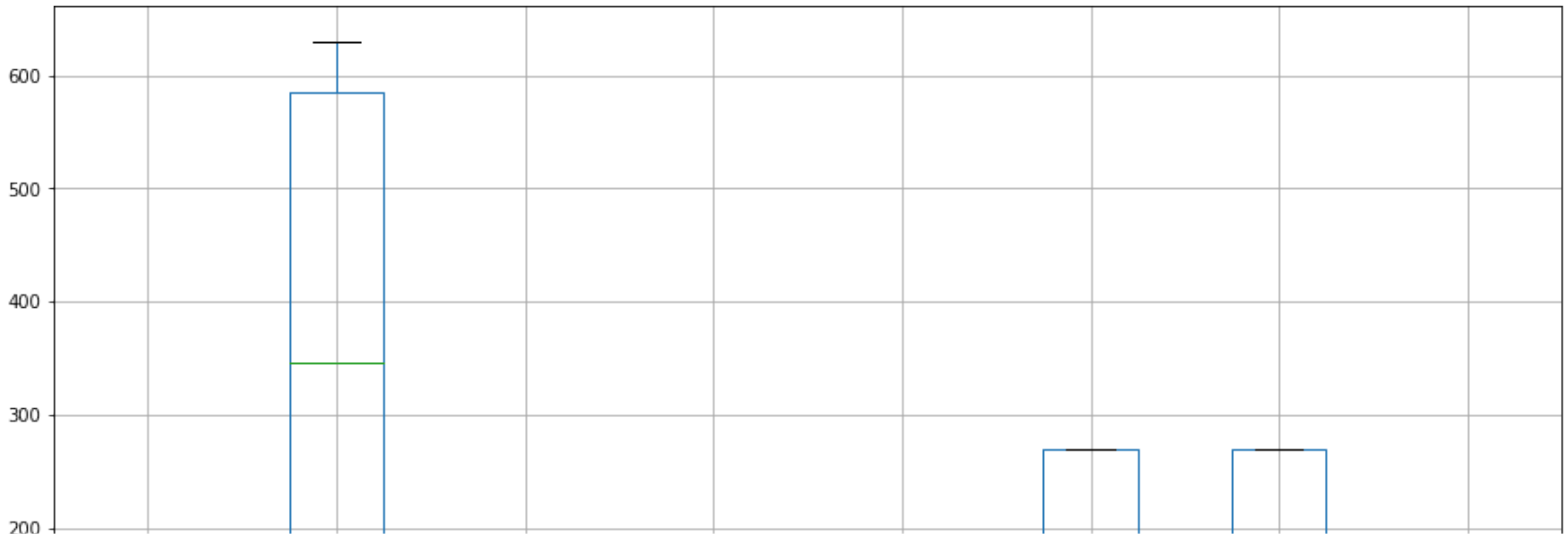

intro
intro-VPL
methods
methods-VPL
encap
encap-VPL
constructors
constructors-VPL
classes1
classes2
classes2-VPL
static
static-VPL



Description of Features with VPLs - Automatically Evaluated Programming Assignments

In [12]:
```
1 dataset_reduced.boxplot(column = ['intro-VPL','methods-VPL','encap-VPL','constructors-VPL','classes2-VPL','static-VPL',
2                                   'inher-VPL',  'polymorphism-VPL'],figsize=(15,8))
```

Out[12]: <AxesSubplot:>

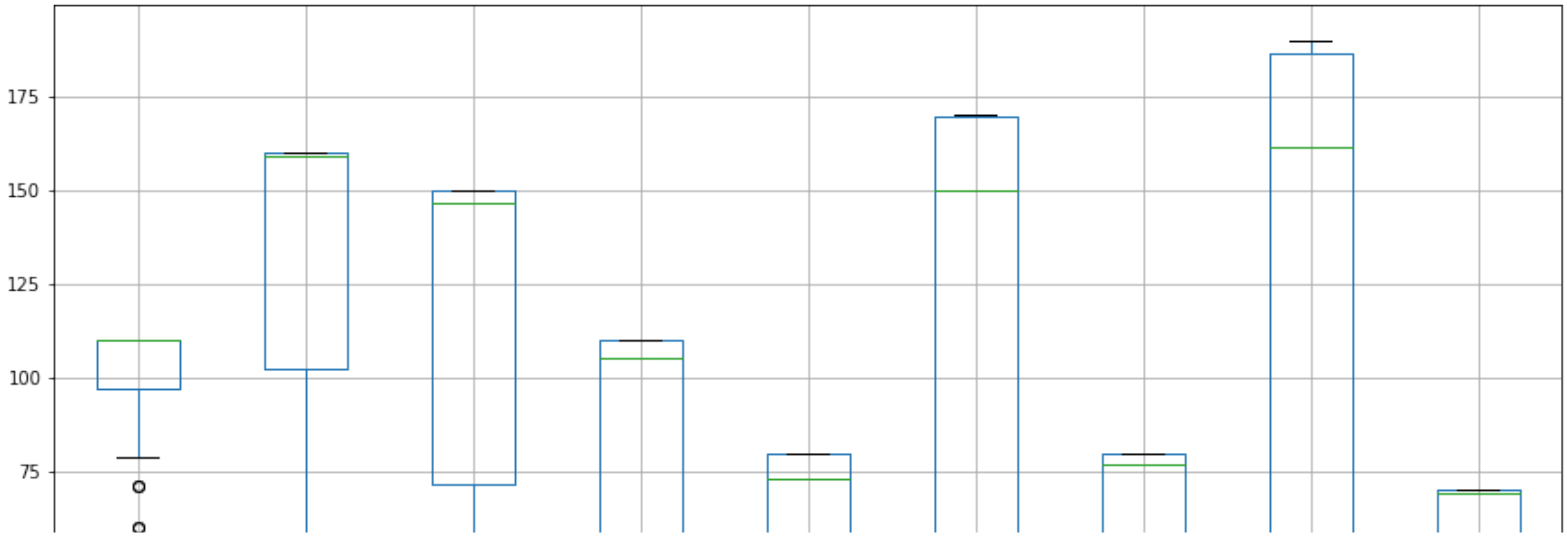


In [ ]:
```
1
```

Description of Features for Micro-learning Units with Quizzes

In [13]:
```
1 dataset_reduced.boxplot(column = ['intro','methods','encap','constructors','classes1','classes2','static', 'inher',  'polymorphis
```

Out[13]: <AxesSubplot:>

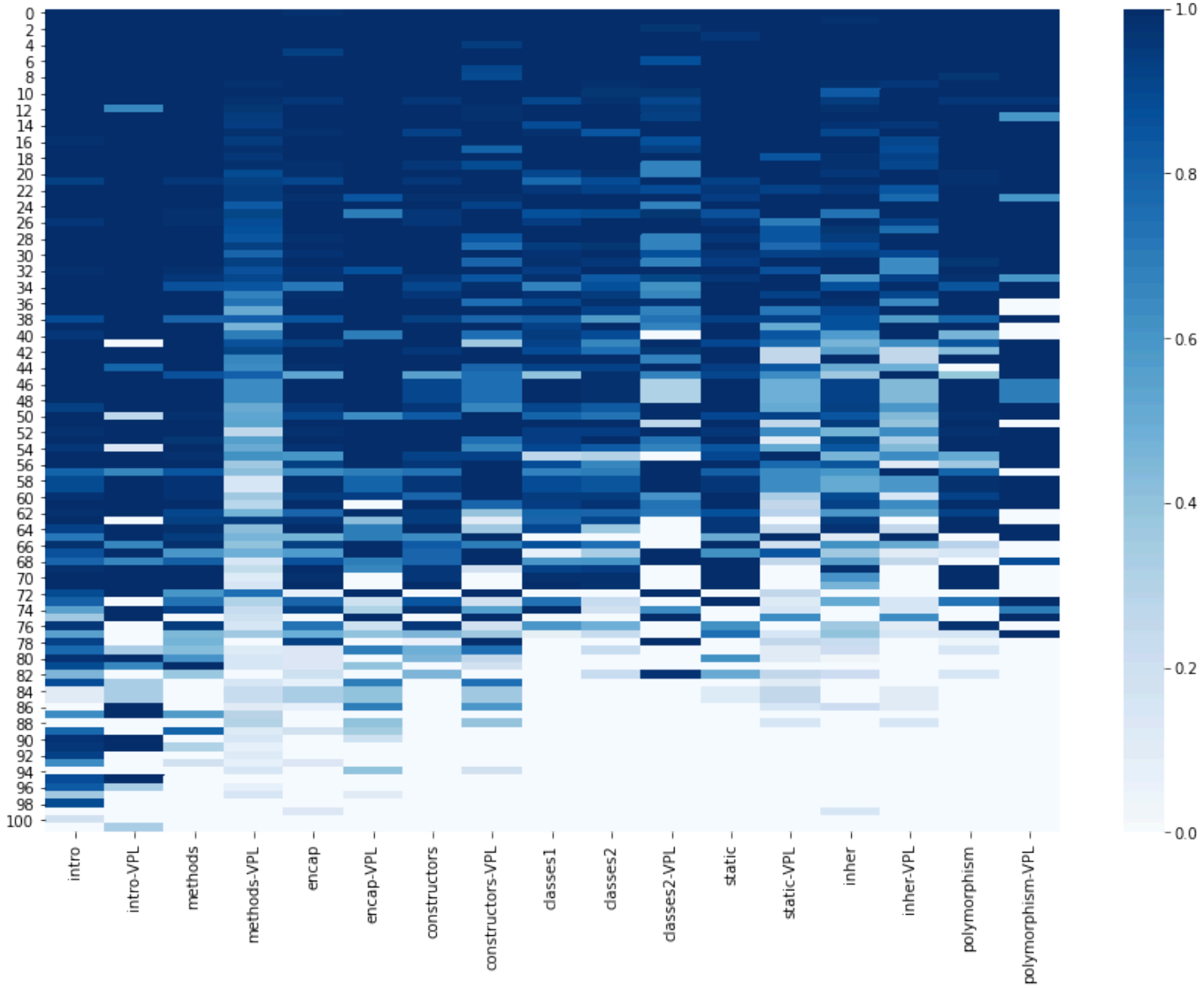


Dataset Normalization and Visualization of Grades Over Topics

In [14]:
```
1 # copy the data
2 dataset_reduced_min_max_scaled = dataset_reduced.copy()
3
4 # apply normalization techniques
5 for column in dataset_reduced_min_max_scaled.columns:
6     dataset_reduced_min_max_scaled[column] = (dataset_reduced_min_max_scaled[column] - dataset_reduced_min_max_scaled[column].min
7
```

In [15]:
```
1 fig, ax = plt.subplots(figsize=(15, 10))
2 sns.heatmap(dataset_reduced_min_max_scaled, cmap='Blues')
```

Out[15]: <AxesSubplot:>



In [16]:
```
1 dataset_reduced.corr(method='spearman')
```

Out[16]:

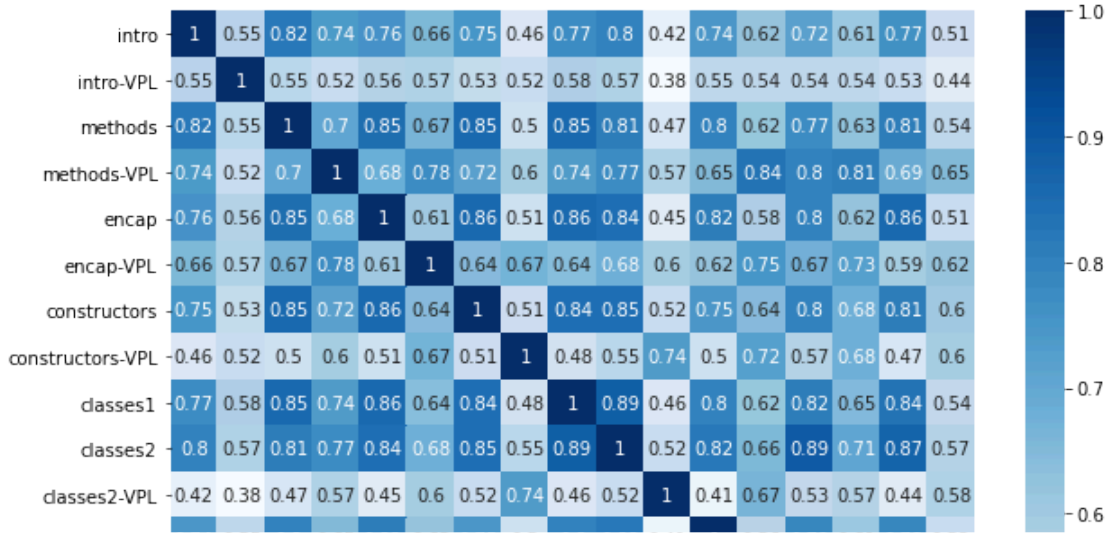
	intro	intro-VPL	methods	methods-VPL	encap	encap-VPL	constructors	constructors-VPL	classes1	classes2	classes2-VPL	static	static-VPL	inh
intro	1.000000	0.554696	0.823184	0.741630	0.756987	0.655632	0.750949	0.462903	0.769973	0.799437	0.422968	0.744914	0.617819	0.7194
intro-VPL	0.554696	1.000000	0.553167	0.521474	0.564133	0.570029	0.529508	0.519096	0.578190	0.573242	0.376203	0.548742	0.539914	0.5422
methods	0.823184	0.553167	1.000000	0.703647	0.850211	0.668541	0.854673	0.501322	0.854209	0.814883	0.471693	0.804898	0.615815	0.7744
methods-VPL	0.741630	0.521474	0.703647	1.000000	0.684170	0.780068	0.718098	0.597180	0.738520	0.771162	0.571024	0.651329	0.837327	0.8031
encap	0.756987	0.564133	0.850211	0.684170	1.000000	0.607419	0.862756	0.505264	0.862313	0.842227	0.446467	0.816903	0.576520	0.8018
encap-VPL	0.655632	0.570029	0.668541	0.780068	0.607419	1.000000	0.644660	0.669163	0.642104	0.681103	0.597559	0.620922	0.751434	0.6736
constructors	0.750949	0.529508	0.854673	0.718098	0.862756	0.644660	1.000000	0.512340	0.844933	0.845751	0.516844	0.748485	0.644834	0.7972
constructors-VPL	0.462903	0.519096	0.501322	0.597180	0.505264	0.669163	0.512340	1.000000	0.483317	0.551548	0.738707	0.502234	0.724223	0.5653
classes1	0.769973	0.578190	0.854209	0.738520	0.862313	0.642104	0.844933	0.483317	1.000000	0.886645	0.460544	0.797561	0.616972	0.8163
classes2	0.799437	0.573242	0.814883	0.771162	0.842227	0.681103	0.845751	0.551548	0.886645	1.000000	0.522603	0.820736	0.656609	0.8947

Correlation matrix for all features.

In [17]:

```
fig, ax = plt.subplots(figsize=(10, 8))
sns.heatmap(dataset_reduced.corr(method='spearman'),
        xticklabels=dataset_reduced.columns,
        yticklabels=dataset_reduced.columns, cmap='Blues', annot=True)
```

Out[17]: <AxesSubplot:>

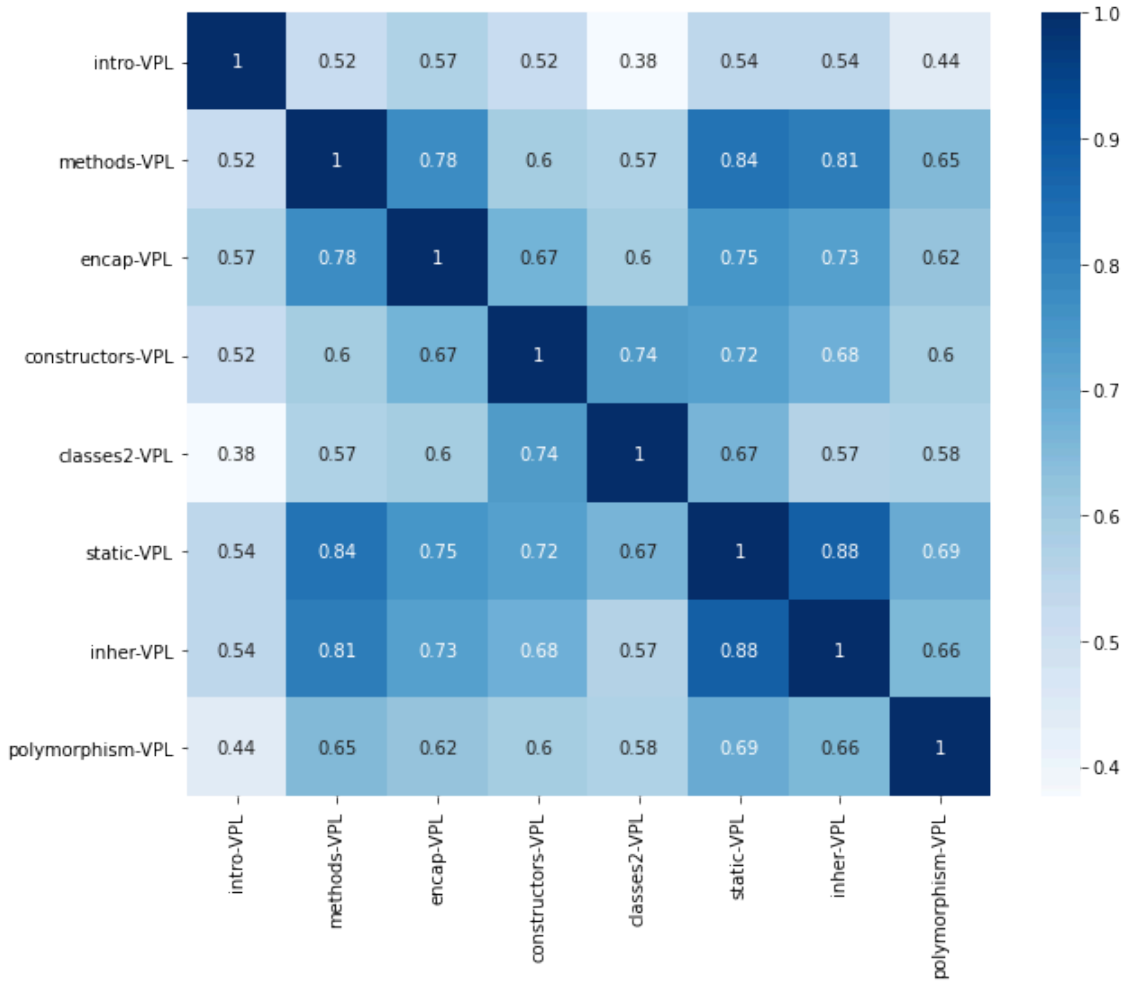


Correlation matrix for VPL-like features

In [18]:

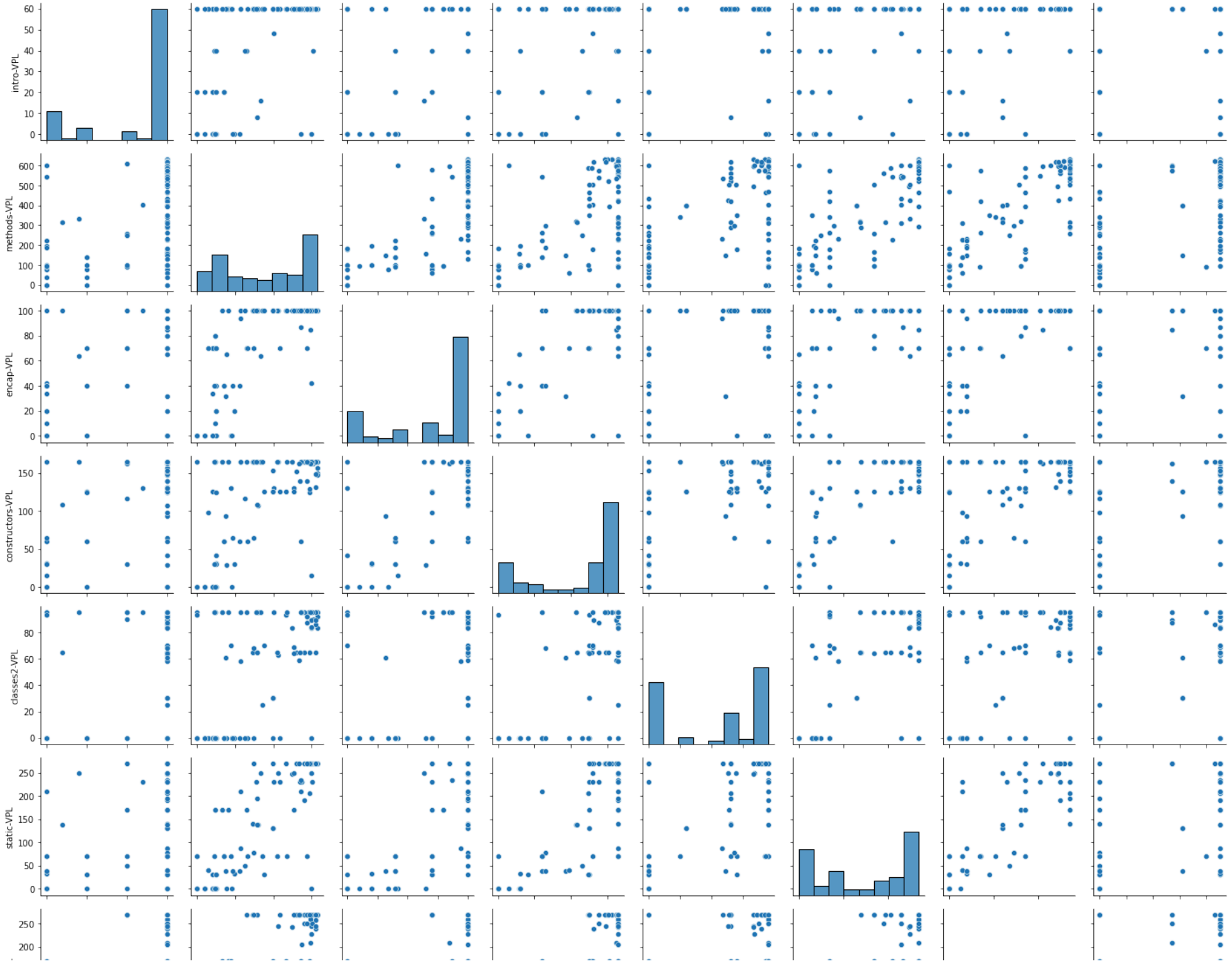
```
dataset_reduced_VPL = dataset_reduced[['intro-VPL','methods-VPL','encap-VPL','constructors-VPL','classes2-VPL','static-VPL',
                                       'inher-VPL',  'polymorphism-VPL']]
fig, ax = plt.subplots(figsize=(10, 8))
sns.heatmap(dataset_reduced_VPL.corr(method='spearman'),
        xticklabels=dataset_reduced_VPL.columns,
        yticklabels=dataset_reduced_VPL.columns, cmap='Blues', annot=True)
```

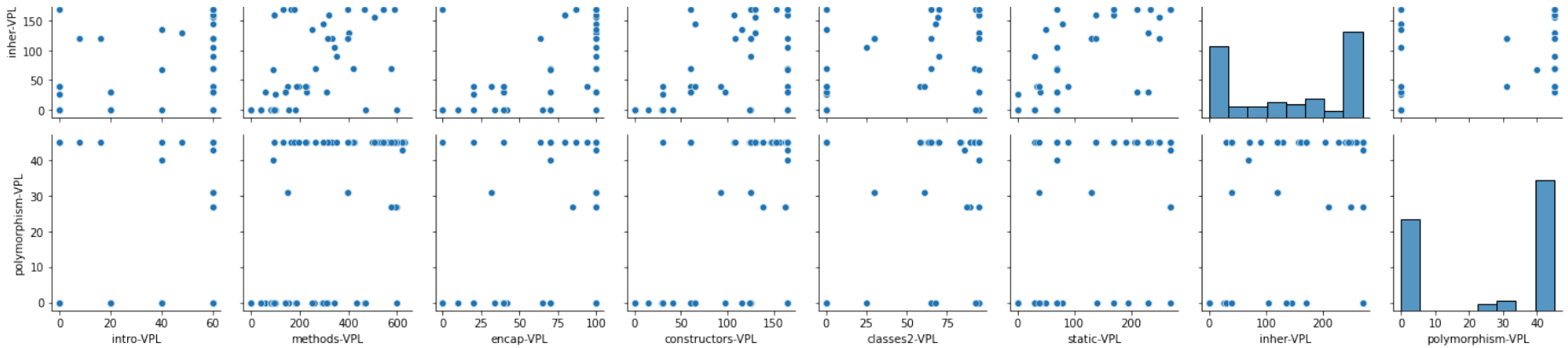
Out[18]: <AxesSubplot:>



In [19]:
```
g_vpl = sns.PairGrid(dataset_reduced_VPL)
g_vpl.map_diag(sns.histplot)
g_vpl.map_offdiag(sns.scatterplot)
```

Out[19]:
```
<seaborn.axisgrid.PairGrid at 0x166243b4c50>
```

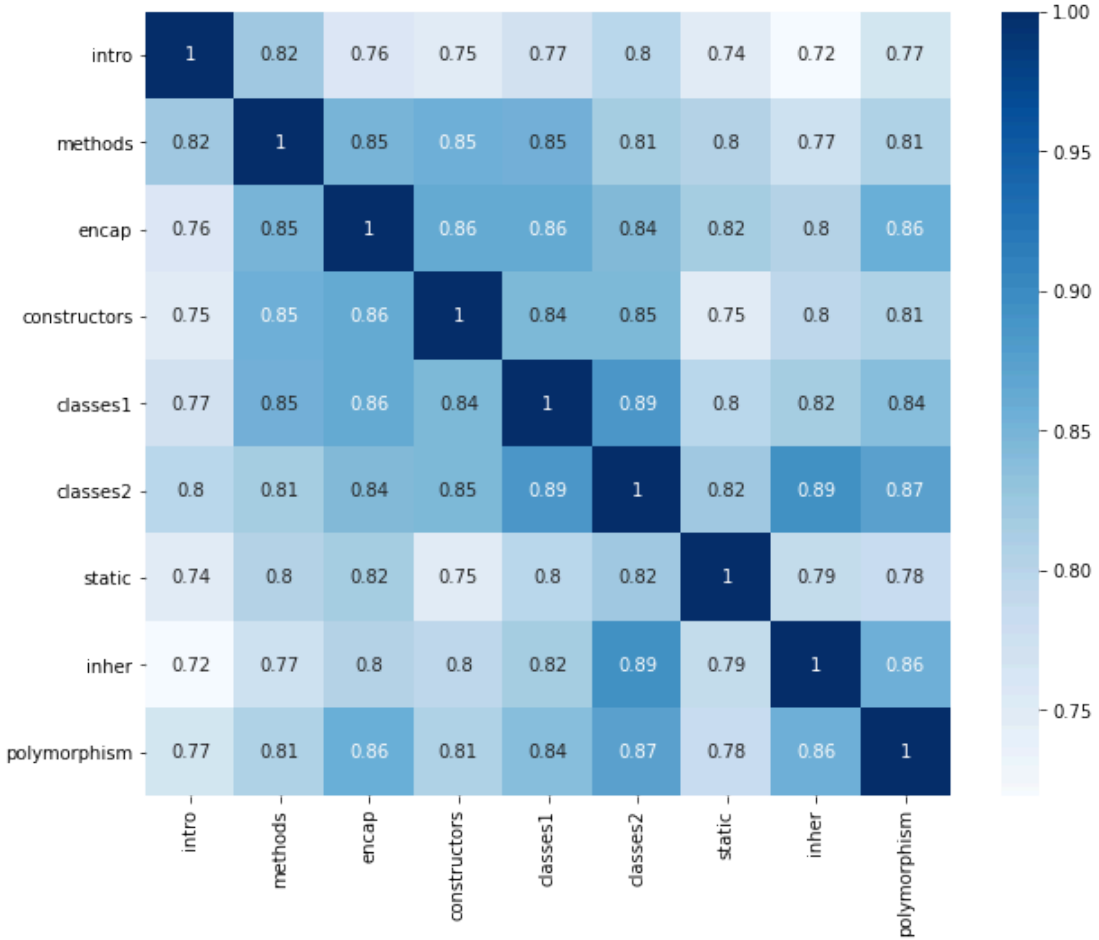

intro-VPL
methods-VPL
encap-VPL
constructors-VPL
classes2-VPL
static-VPL



Correlation matrix for Micro-learning units with Quizzes.

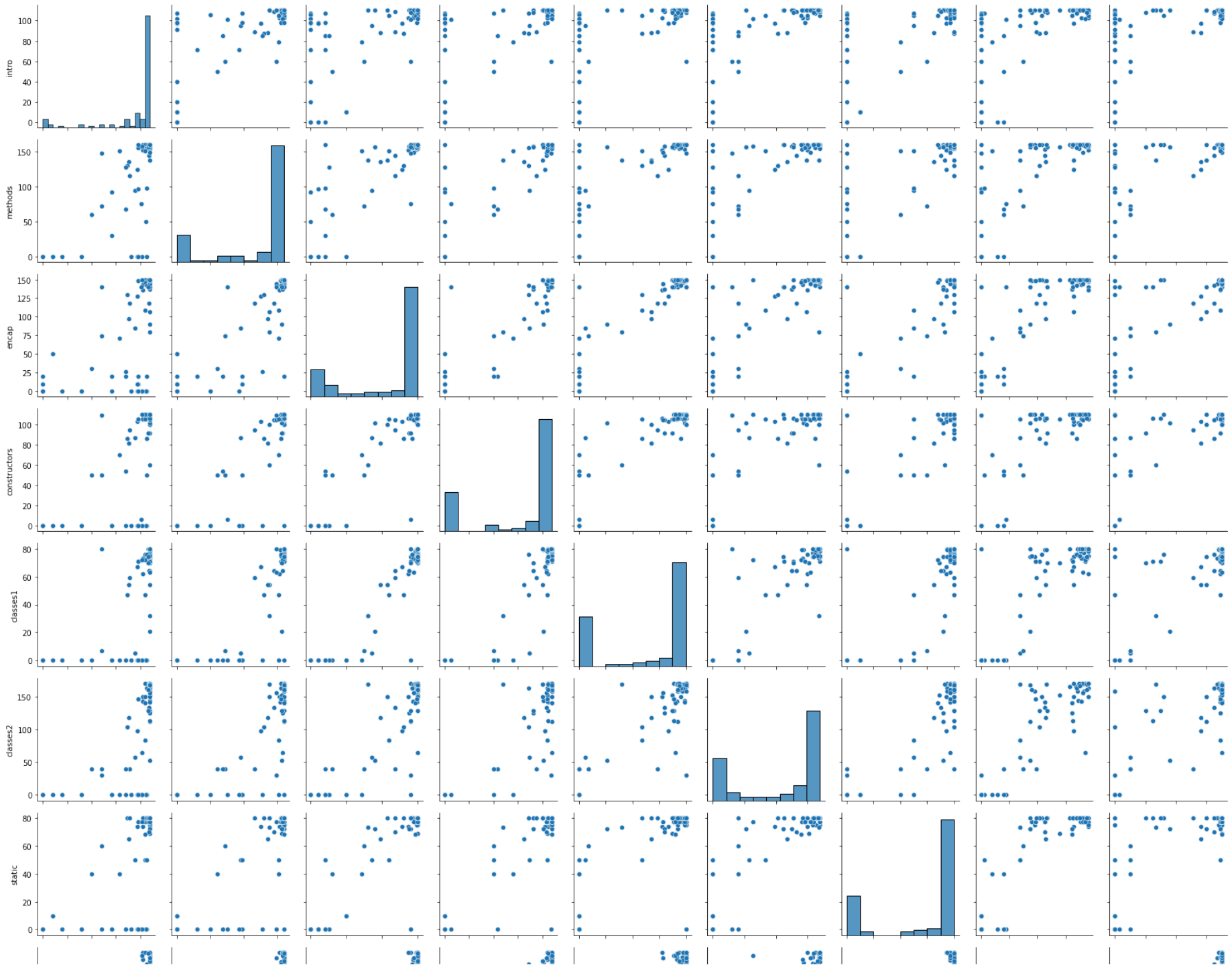
In [20]:
```
dataset_reduced_mc_lessons = dataset_reduced[['intro','methods','encap','constructors','classes1','classes2','static', 'inher',
fig, ax = plt.subplots(figsize=(10, 8))
sns.heatmap(dataset_reduced_mc_lessons.corr(method='spearman'),
        xticklabels=dataset_reduced_mc_lessons.columns,
        yticklabels=dataset_reduced_mc_lessons.columns, cmap='Blues', annot=True)
```

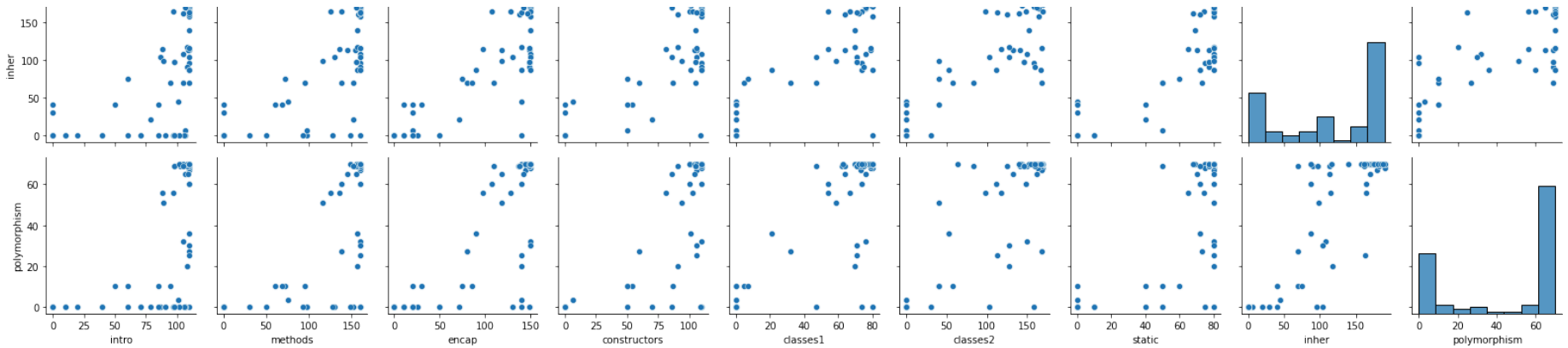
Out[20]: <AxesSubplot:>



In [21]:
```
g_mc = sns.PairGrid(dataset_reduced_mc_lessons)
g_mc.map_diag(sns.histplot)
g_mc.map_offdiag(sns.scatterplot)
```

Out[21]: <seaborn.axisgrid.PairGrid at 0x16628eac1d0>


intro
methods
encap
constructors
classes1
classes2
static



Creating Datasets for different Term Periods

In [22]:
```
dataset_T1 = dataset_reduced[['intro','intro-VPL','methods','methods-VPL']]
dataset_T2 = dataset_reduced[['encap','encap-VPL','constructors','constructors-VPL','classes1','classes2','classes2-VPL','static'
dataset_T3 = dataset_reduced[['inher','inher-VPL', 'polymorphism', 'polymorphism-VPL']]
```

In [23]:
```
dataset_T1 = dataset_T1.astype(float)
dataset_T2 = dataset_T2.astype(float)
dataset_T3 = dataset_T3.astype(float)
```

Modelling

Clustering of All Features

In [24]:

```
from pycaret.clustering import *

# input_dataset1 = setup(dataset_reduced, normalize = True, pca=True, pca_components=2,
 #                      numeric_features = ['intro-VPL','methods','methods-VPL','encap','encap-VPL','constructors','constructors-V
  #                    session_id = 123)

input_dataset1 = setup(dataset_reduced, normalize = True,
                 numeric_features = ['intro-VPL','methods','methods-VPL','encap','encap-VPL','constructors','constructors-VPL','cl
                 session_id = 123)
```

	Description	Value
0	session_id	123
1	Original Data	(102, 17)
2	Missing Values	False
3	Numeric Features	17
4	Categorical Features	0
5	Ordinal Features	False
6	High Cardinality Features	False
7	High Cardinality Method	None
8	Transformed Data	(102, 17)
9	CPU Jobs	-1
10	Use GPU	False
11	Log Experiment	False
12	Experiment Name	cluster-default-name
13	USI	680d
14	Imputation Type	simple
15	Iterative Imputation Iteration	None
16	Numeric Imputer	mean
17	Iterative Imputation Numeric Model	None
18	Categorical Imputer	mode
19	Iterative Imputation Categorical Model	None
20	Unknown Categoricals Handling	least_frequent
21	Normalize	True
22	Normalize Method	zscore
23	Transformation	False
24	Transformation Method	None
25	PCA	False
26	PCA Method	None
27	PCA Components	None

	Description	Value
28	Ignore Low Variance	False
29	Combine Rare Levels	False
30	Rare Level Threshold	None
31	Numeric Binning	False
32	Remove Outliers	False
33	Outliers Threshold	None
34	Remove Multicollinearity	False
35	Multicollinearity Threshold	None
36	Clustering	False
37	Clustering Iteration	None
38	Polynomial Features	False
39	Polynomial Degree	None
40	Trignometry Features	False
41	Polynomial Threshold	None
42	Group Features	False
43	Feature Selection	False
44	Feature Selection Method	classic
45	Features Selection Threshold	None
46	Feature Interaction	False
47	Feature Ratio	False
48	Interaction Threshold	None

Initial model with k=4.

In [25]:
```
1 kmeans = create_model('kmeans')
```

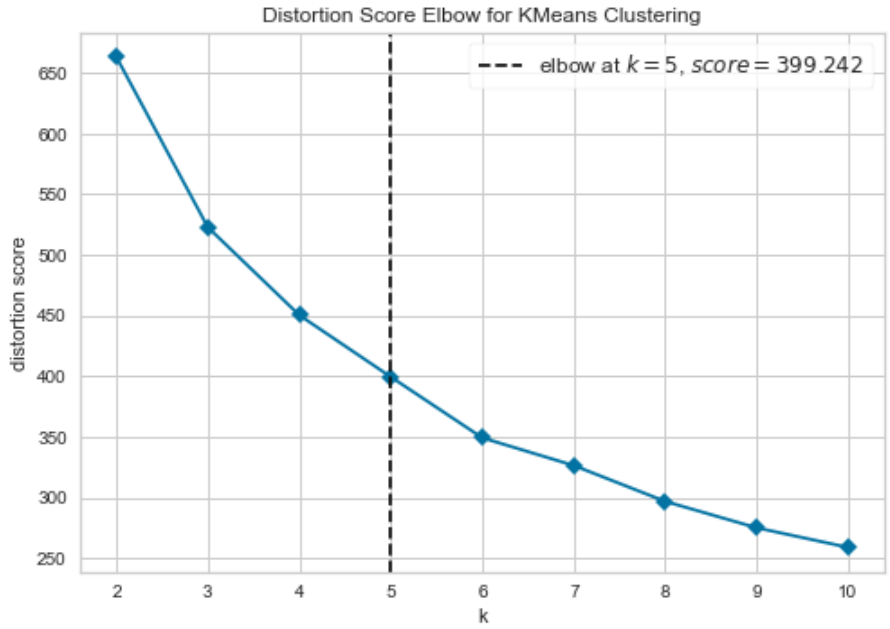
	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.3747	93.1811	1.3109	0	0	0

In [26]:
```
1 kmeans
```

Out[26]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=4, n_init=10, n_jobs=-1, precompute_distances='deprecated',
       random_state=123, tol=0.0001, verbose=0)
```

Elbow method.

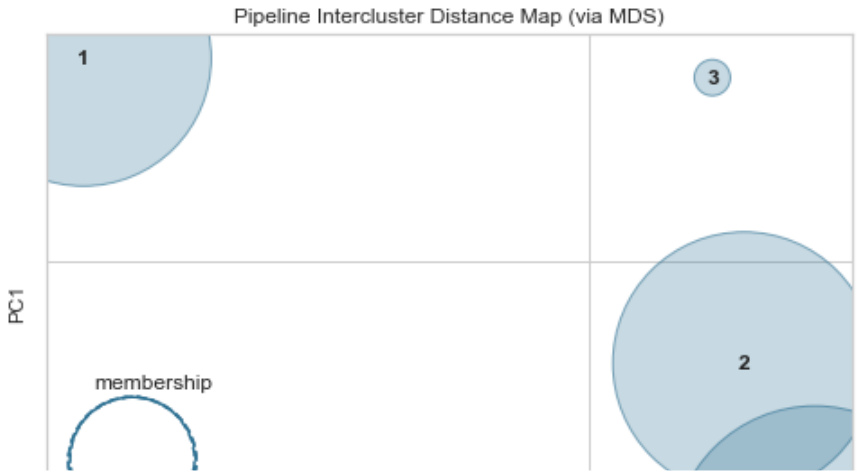
In [27]:
```
1 plot_model(kmeans, plot = 'elbow')
```



Model evaluation.

In [28]:
```
1 evaluate_model(kmeans)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution



K-Means Clustering with Different k

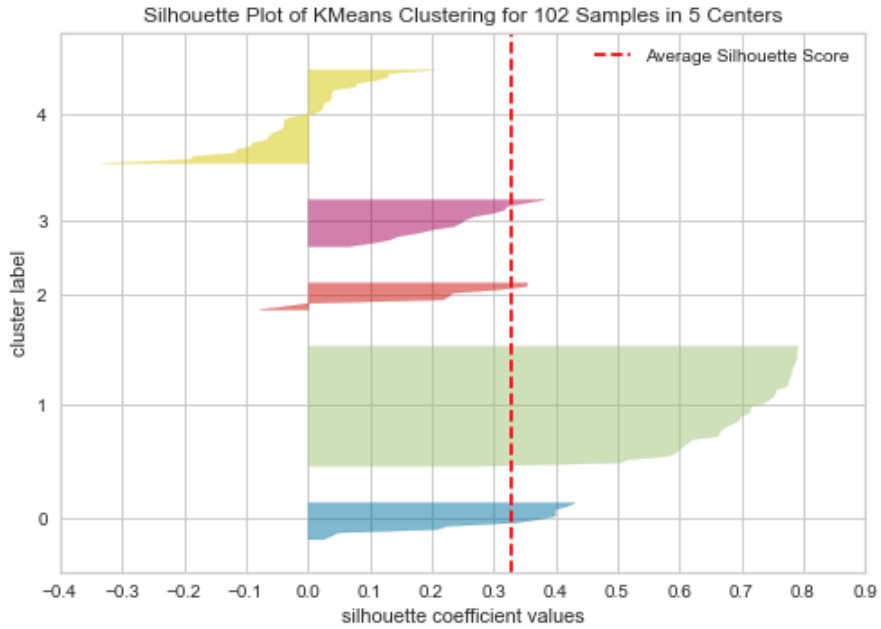
In [29]:
```
1 kmeans5 = create_model('kmeans', num_clusters = 5)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.3284	81.0733	1.483	0	0	0

In [30]:
```
1 kmeans5
```

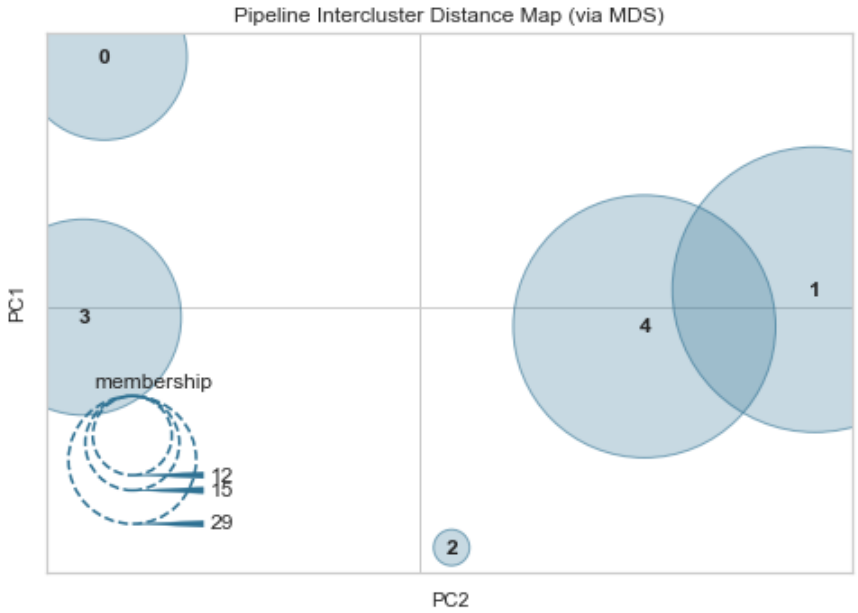
Out[30]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=5, n_init=10, n_jobs=-1, precompute_distances='deprecated',
       random_state=123, tol=0.0001, verbose=0)
```

In [31]:
```
1 plot_model(kmeans5, plot = 'silhouette')
```



In [32]:
```
1 evaluate_model(kmeans5)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution

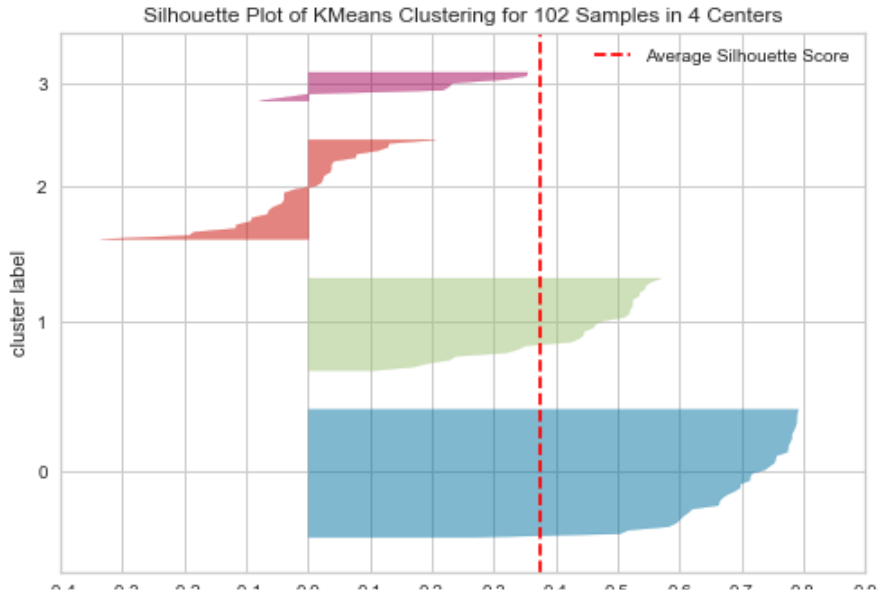


In [33]:
```
plot_model(kmeans5)
```

In [34]:
```
kmeans4 = create_model('kmeans', num_clusters = 4)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.3747	93.1811	1.3109	0	0	0

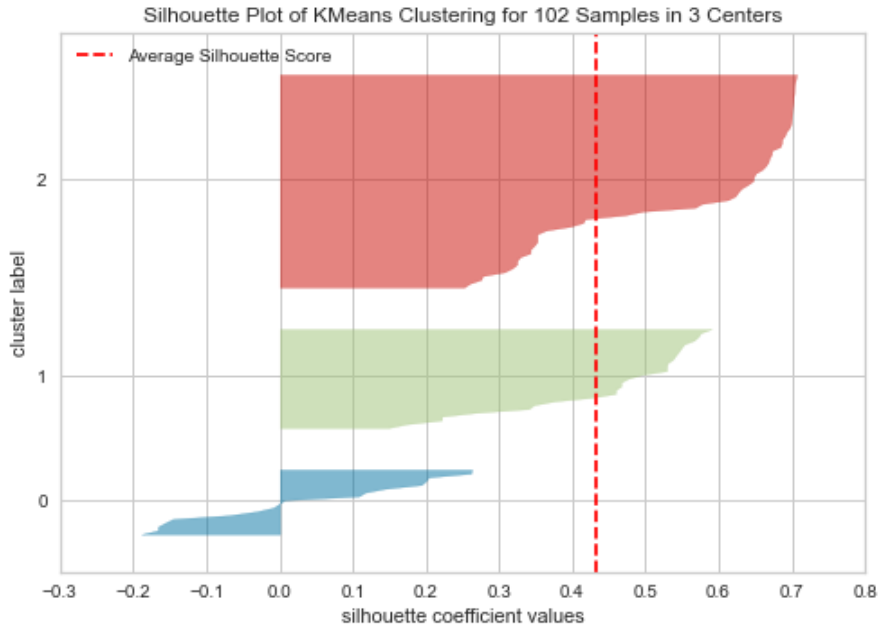
In [35]:
```
1 plot_model(kmeans4, plot = 'silhouette')
```



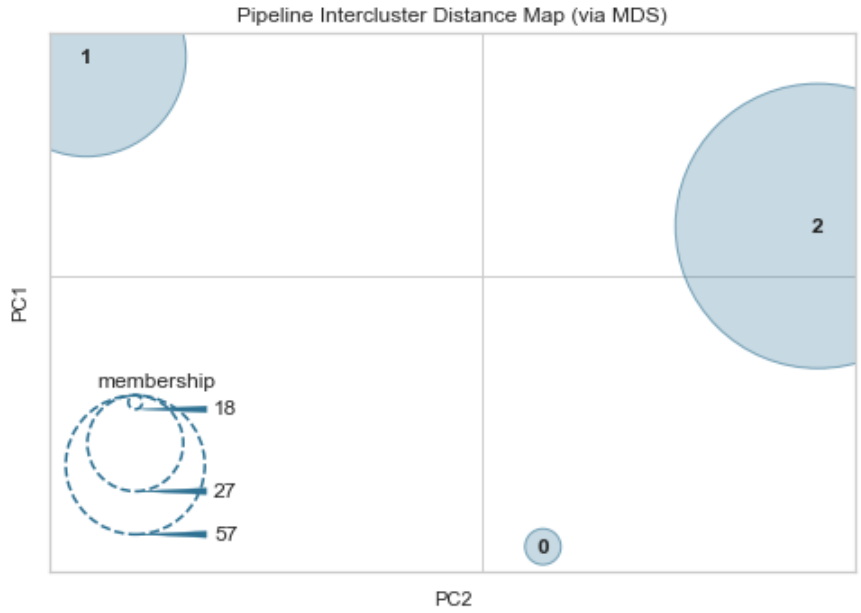
In [36]:
```
1 kmeans3 = create_model('kmeans', num_clusters = 3)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.4313	114.7803	1.2559	0	0	0

In [37]:
```
1 plot_model(kmeans3, plot = 'silhouette')
```



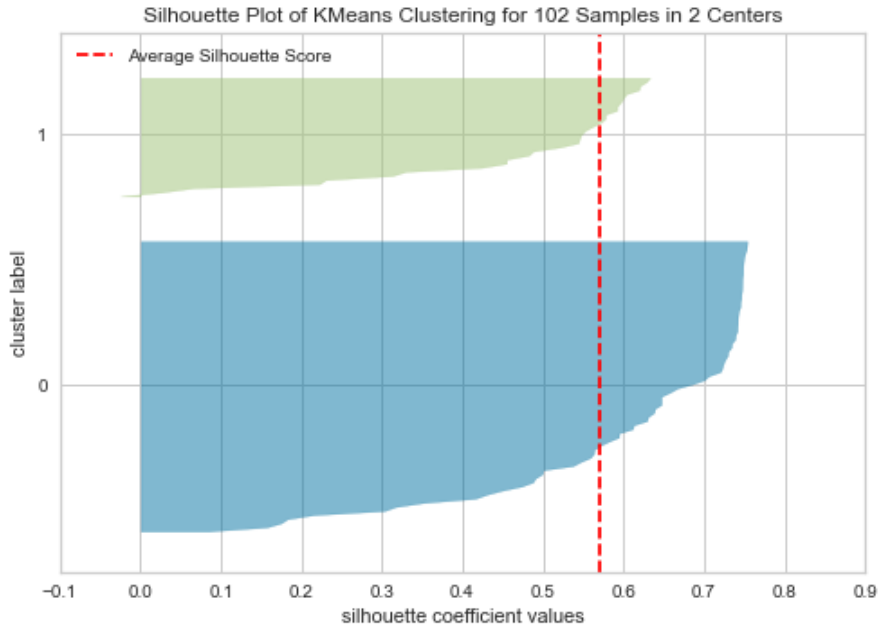
In [38]:
```
1 plot_model(kmeans3, plot = 'distance')
```



In [39]:
```
1 kmeans2 = create_model('kmeans', num_clusters = 2)
```

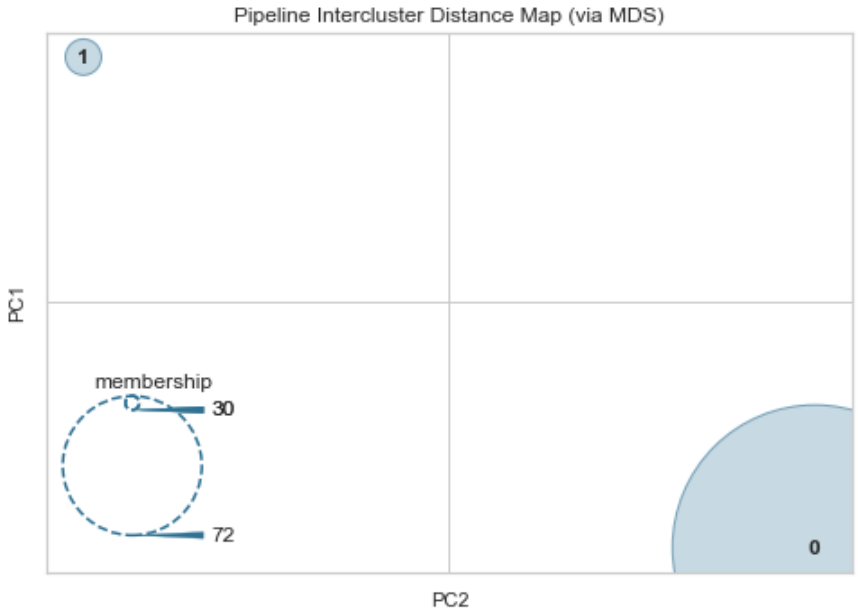
	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.57	161.6648	0.6984	0	0	0

In [40]:
```
1 plot_model(kmeans2, plot = 'silhouette')
```



In [41]:
```
1 evaluate_model(kmeans2)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution



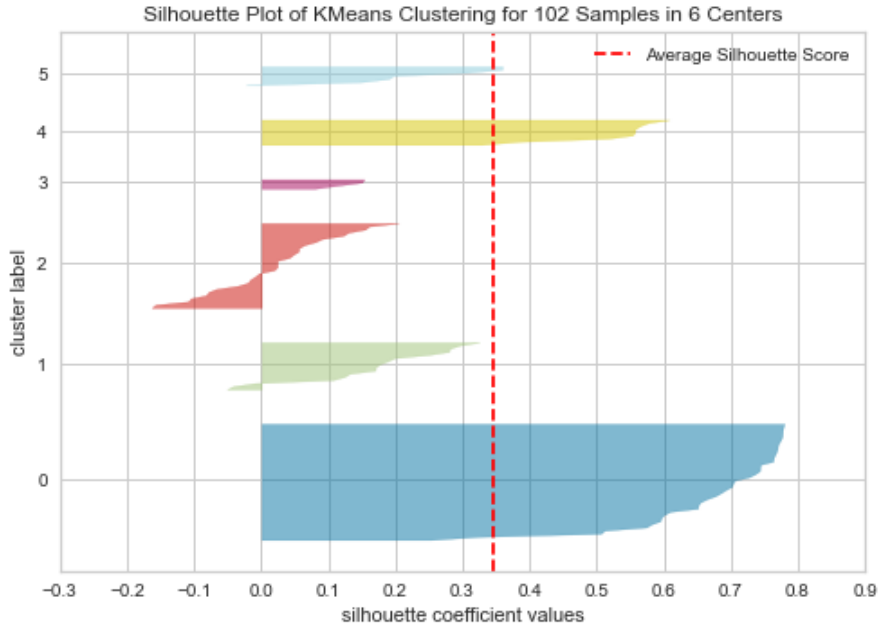
In [42]:
```
1 plot_model(kmeans2)
```

In [ ]:
```
1
```

In [43]:
```
1 kmeans6 = create_model('kmeans', num_clusters = 6)
```

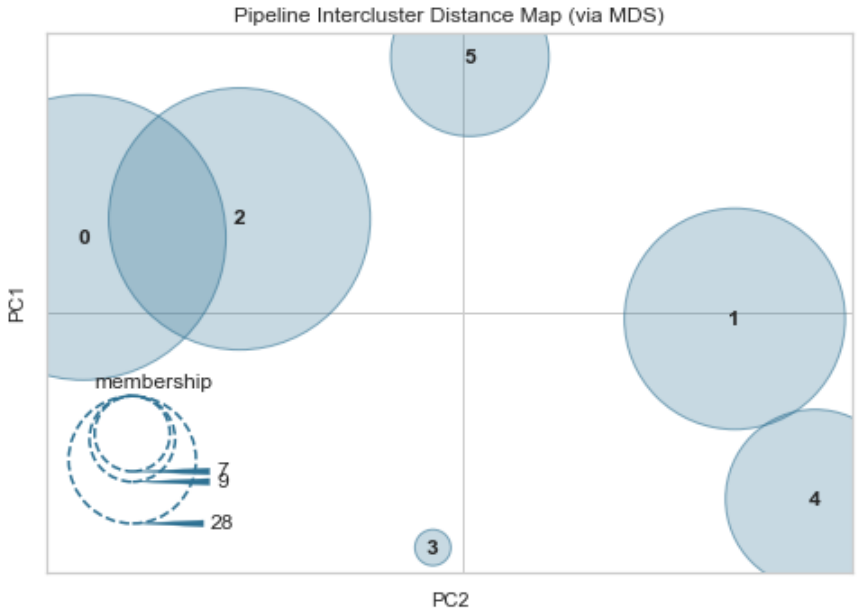
	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.3465	76.1701	1.2466	0	0	0

In [44]:
```
1 plot_model(kmeans6, plot = 'silhouette')
```



In [45]:
```
1 evaluate_model(kmeans6)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution



In [46]:
```
1 kmeans_df5 = assign_model(kmeans5)
```

In [47]:
```
1 kmeans_df5.head()
```

Out[47]:

	intro	intro-VPL	methods	methods-VPL	encap	encap-VPL	constructors	constructors-VPL	classes1	classes2	classes2-VPL	static	static-VPL	inher	inher-VPL	polymorphism	polymorp
0	110.0	60.0	160.0	630.0	148.0	100.0	110.0	165.0	80.0	170.0	95.0	80.0	270.0	190.0	270.0	70.0	
1	110.0	60.0	160.0	630.0	150.0	100.0	110.0	165.0	80.0	170.0	95.0	80.0	270.0	188.0	270.0	70.0	
2	110.0	60.0	160.0	630.0	150.0	100.0	110.0	165.0	80.0	170.0	92.0	80.0	270.0	190.0	270.0	70.0	
3	110.0	60.0	160.0	630.0	150.0	100.0	110.0	165.0	80.0	170.0	95.0	77.0	270.0	190.0	270.0	70.0	
4	110.0	60.0	160.0	630.0	150.0	100.0	110.0	157.0	80.0	170.0	95.0	80.0	270.0	190.0	270.0	70.0	

Clustering with Other Clustering Methods - DBSCAN

In [48]:
```
1 model_dbscan = create_model('dbscan')
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.0397	19.7449	1.0447	0	0	0

In [49]:
```
plot_model(model_dbscan)
```

In [50]:
```
model_dbscan2 = create_model('dbscan', eps = 0.7)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.1734	33.4757	1.0102	0	0	0

In [51]:
```
model_dbscan3 = create_model('dbscan', eps = 0.3)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	-0.0864	10.5508	1.0586	0	0	0

In [52]:
```
model_dbscan4 = create_model('dbscan', eps = 0.9)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.2354	42.3797	0.9726	0	0	0

In [53]:
```
1 model_dbscan5 = create_model('dbscan', eps = 2.0)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.3653	82.1147	1.2025	0	0	0

In [54]:
```
1 model_dbscan6 = create_model('dbscan', eps = 3.20)
```

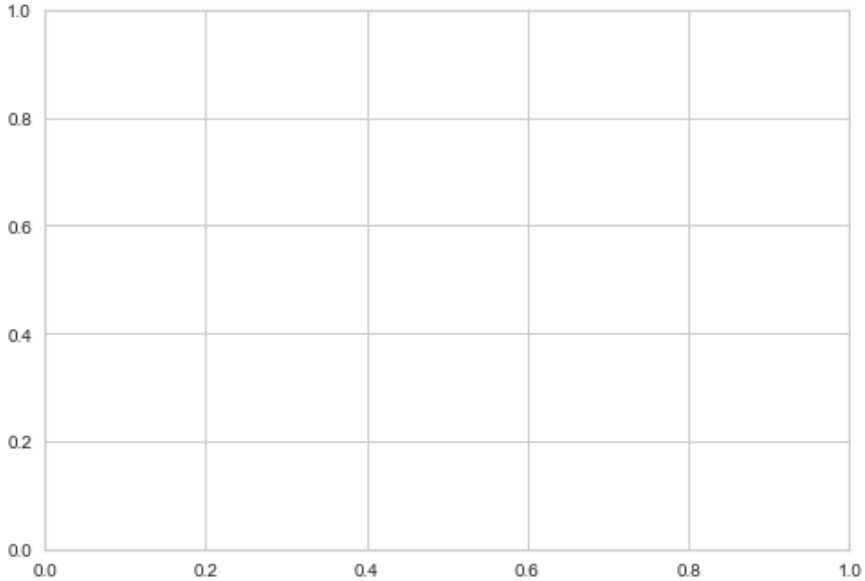
	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.4583	94.3754	1.4969	0	0	0

In [55]:
```
1 model_dbscan6
```

Out[55]:
```
DBSCAN(algorithm='auto', eps=3.2, leaf_size=30, metric='euclidean',
       metric_params=None, min_samples=5, n_jobs=-1, p=None)
```

In [56]:
```
1 evaluate_model(model_dbscan6)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution




```
<Figure size 576x396 with 0 Axes>
```

Clustering with Other Clustering Methods - OPTICS

In [57]:
```
1 model_optics = create_model('optics')
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	-0.0615	17.0579	1.3876	0	0	0

In [58]:

```
1 plot_model(model_optics)
```

Clustering with Other Clustering Methods - Affinity Propagation

In [59]:
```
1 model_ap = create_model('ap')
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.3662	57.6724	1.2593	0	0	0

In [60]:

```
1 plot_model(model_ap)
```

Clustering with Other Clustering Methods - Mean Shift

In [61]:
```
1 model_meanshift = create_model('meanshift')
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.3891	41.8296	0.7929	0	0	0

In [62]:
```
1 evaluate_model(model_meanshift)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution

Clustering with Other Clustering Methods - Hierarchical Clustering

In [63]:
```
1 model_hclust = create_model('hclust')
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.3688	85.9097	1.2241	0	0	0

In [64]:

```
1 plot_model(model_hclust)
```

Clustering with Other Clustering Methods - BIRCH

In [65]:
```
1 model_birch = create_model('birch')
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.4499	83.2682	1.0465	0	0	0

In [66]:

```
1 plot_model(model_birch)
```

In [67]:
```
1 get_metrics()
```

Out[67]:

ID	Name	Display Name	Score Function	Scorer	Target	Args	Greater is Better	Needs Ground Truth	Custom
silhouette	Silhouette	Silhouette	<function silhouette_score at 0x000001662E0C4730>	make_scorer(silhouette_score)	pred	{}	True	False	False
chs	Calinski-Harabasz	Calinski-Harabasz	<function calinski_harabasz_score at 0x0000016...	make_scorer(calinski_harabasz_score)	pred	{}	True	False	False
db	Davies-Bouldin	Davies-Bouldin	<function davies_bouldin_score at 0x000001662E...	make_scorer(davies_bouldin_score)	pred	{}	True	False	False
hs	Homogeneity Score	Homogeneity	<function homogeneity_score at 0x000001662E0A3...	make_scorer(homogeneity_score)	pred	{}	True	True	False
ari	Rand Index	Rand Index	<function adjusted_rand_score at 0x000001662E0...	make_scorer(adjusted_rand_score)	pred	{}	True	True	False
cs	Completeness Score	Completeness	<function completeness_score at 0x000001662E0A...	make_scorer(completeness_score)	pred	{}	True	True	False

In [ ]:
```
1
```

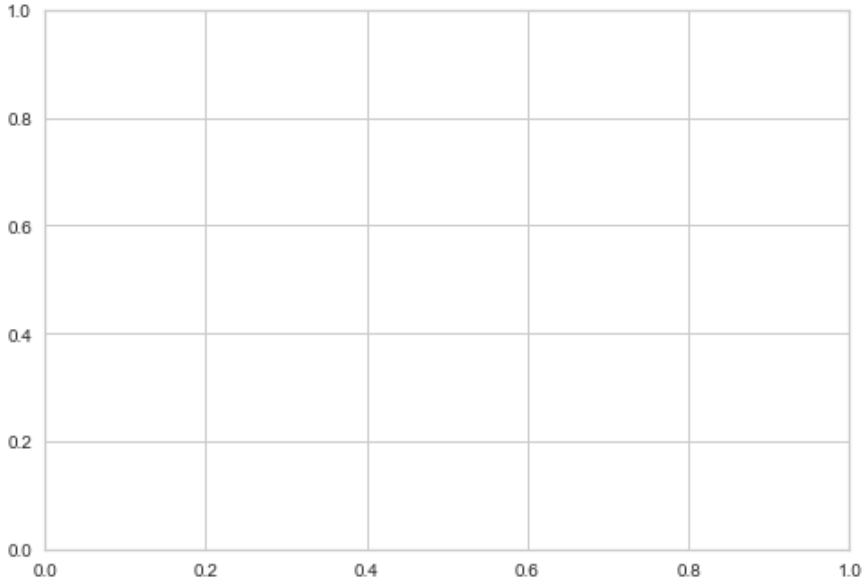
Aglomerative Clustering

In [68]:
```
1 model_aglomerative4 = create_model('hclust', n_clusters = 4)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.3688	85.9097	1.2241	0	0	0

In [69]:
```
1 evaluate_model(model_aglomerative4)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution



In [ ]:
```
1
```

Modelling Individual Term Periods with K-Means for Different k

The First Period

In [70]:

```
from pycaret.clustering import *

dataset_T1 = dataset_T1.astype(float)

input_dataset2 = setup(dataset_T1, normalize = True,
                       session_id = 123)
```

	Description	Value
0	session_id	123
1	Original Data	(102, 4)
2	Missing Values	False
3	Numeric Features	4
4	Categorical Features	0
5	Ordinal Features	False
6	High Cardinality Features	False
7	High Cardinality Method	None
8	Transformed Data	(102, 4)
9	CPU Jobs	-1
10	Use GPU	False
11	Log Experiment	False
12	Experiment Name	cluster-default-name
13	USI	bc74
14	Imputation Type	simple
15	Iterative Imputation Iteration	None
16	Numeric Imputer	mean
17	Iterative Imputation Numeric Model	None
18	Categorical Imputer	mode
19	Iterative Imputation Categorical Model	None
20	Unknown Categoricals Handling	least_frequent
21	Normalize	True
22	Normalize Method	zscore
23	Transformation	False
24	Transformation Method	None
25	PCA	False
26	PCA Method	None
27	PCA Components	None

	Description	Value
28	Ignore Low Variance	False
29	Combine Rare Levels	False
30	Rare Level Threshold	None
31	Numeric Binning	False
32	Remove Outliers	False
33	Outliers Threshold	None
34	Remove Multicollinearity	False
35	Multicollinearity Threshold	None
36	Clustering	False
37	Clustering Iteration	None
38	Polynomial Features	False
39	Polynomial Degree	None
40	Trignometry Features	False
41	Polynomial Threshold	None
42	Group Features	False
43	Feature Selection	False
44	Feature Selection Method	classic
45	Features Selection Threshold	None
46	Feature Interaction	False
47	Feature Ratio	False
48	Interaction Threshold	None

In [ ]:
```
1
```

In [71]:
```
1 kmeansT1 = create_model('kmeans')
```

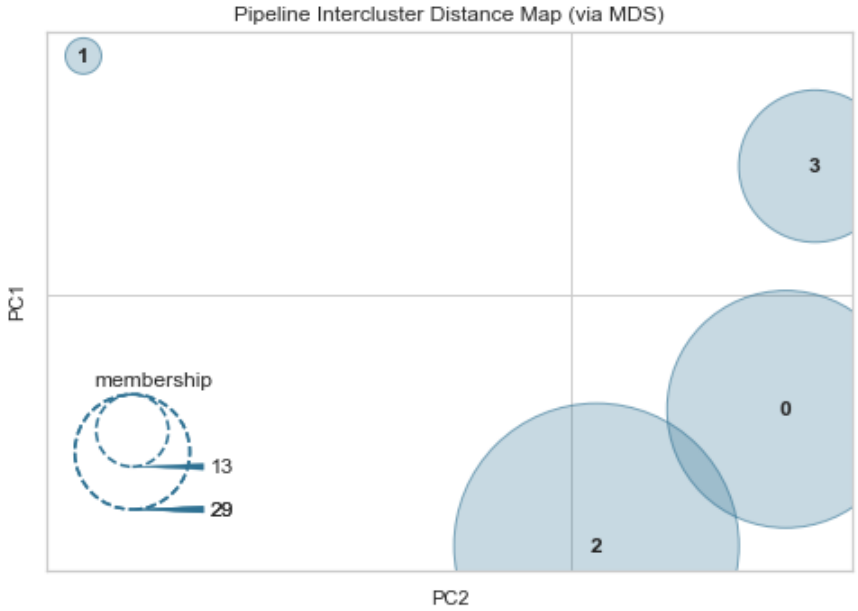
	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.4917	118.7943	0.8273	0	0	0

In [72]:
```
1 kmeansT1
```

Out[72]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=4, n_init=10, n_jobs=-1, precompute_distances='deprecated',
       random_state=123, tol=0.0001, verbose=0)
```

In [73]:
```
1 evaluate_model(kmeansT1)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution

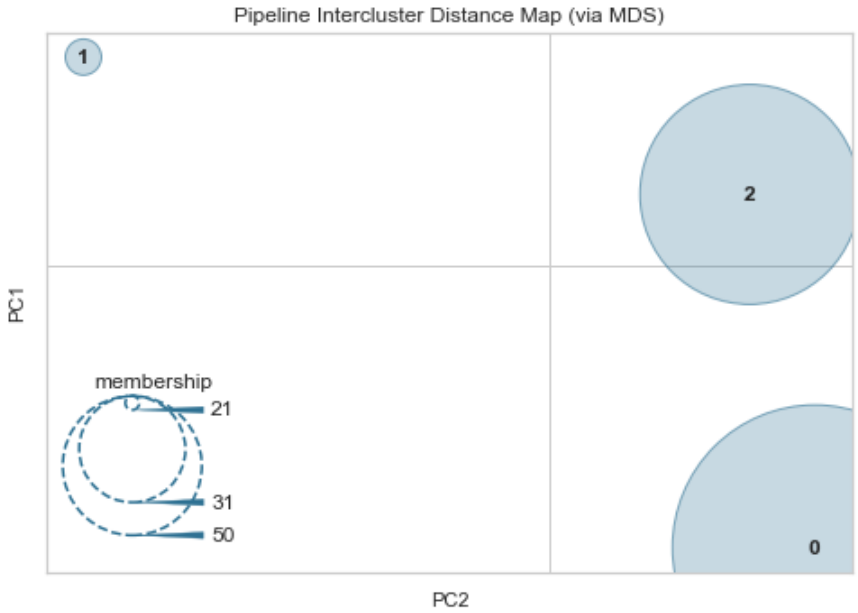


In [74]:
```
1 kmeansT1_3 = create_model('kmeans', num_clusters=3)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.4654	109.8245	0.8889	0	0	0

In [75]:
```
1 evaluate_model(kmeansT1_3)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution

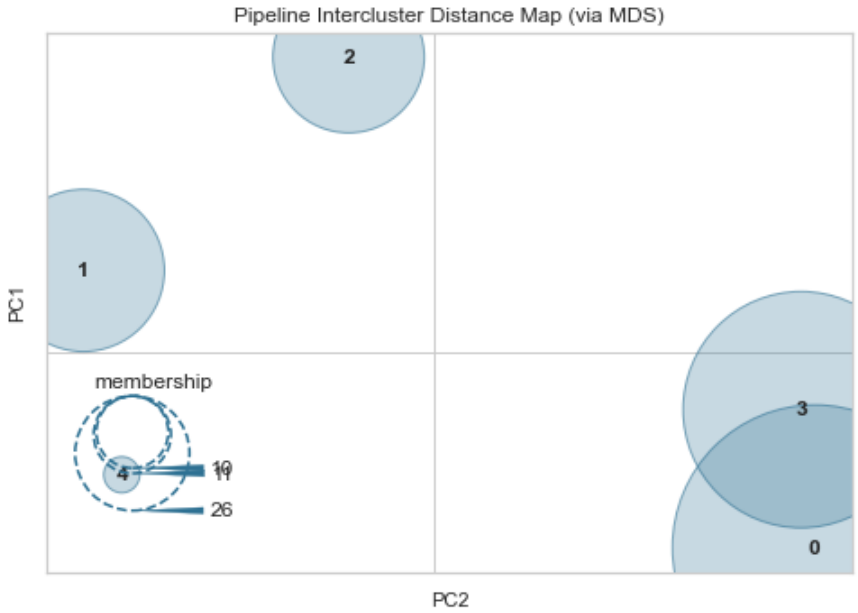


In [76]:
```
1 kmeansT1_5 = create_model('kmeans', num_clusters=5)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.5219	128.2155	0.8026	0	0	0

In [77]:
```
1 evaluate_model(kmeansT1_5)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution

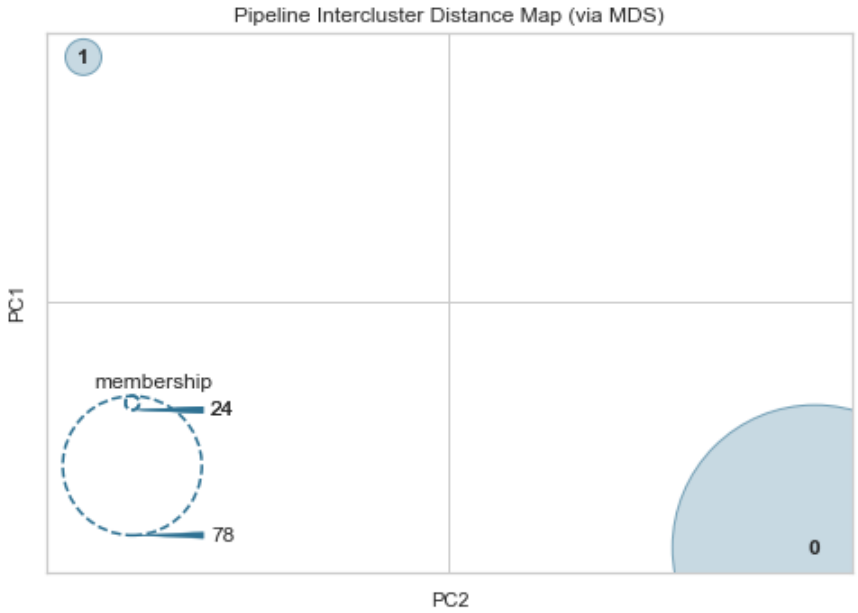


In [78]:
```
1 kmeansT1_2 = create_model('kmeans', num_clusters=2)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.5947	132.5591	0.7669	0	0	0

In [79]:
```
1 evaluate_model(kmeansT1_2)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution

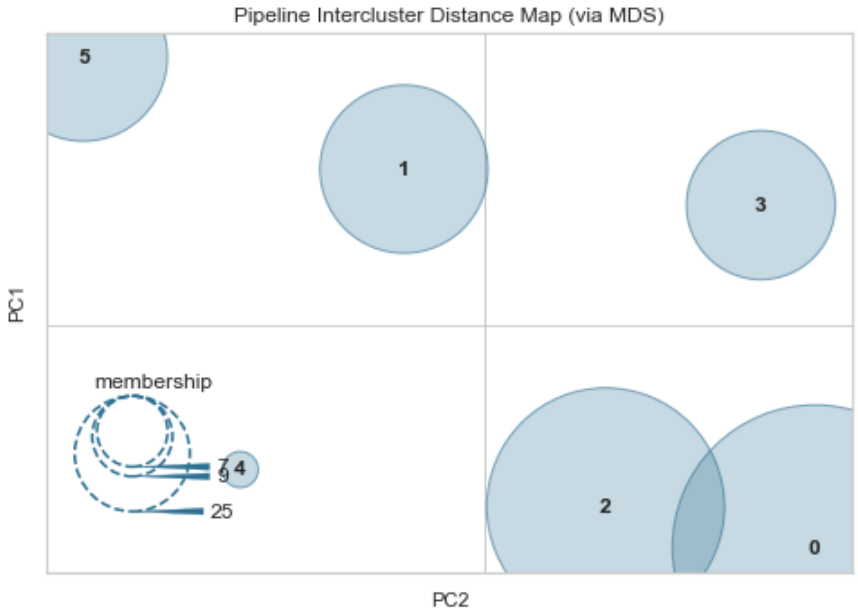


In [80]:
```
1 kmeansT1_6 = create_model('kmeans', num_clusters=6)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.5316	133.9519	0.7479	0	0	0

In [81]:
```
1 evaluate_model(kmeansT1_6)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution



Assignement of the results to the dataset values for cluster analysis results comparison.

In [82]:
```
1 kmeans_T1_4_assign = assign_model(kmeansT1)
```

In [83]:
```
1 kmeans_T1_6_assign = assign_model(kmeansT1_6)
```

In [84]:
```
1 kmeans_T1_2_assign = assign_model(kmeansT1_2)
```

In [85]:
```
1 kmeans_T1_6_assign.head()
```

Out[85]:

	intro	intro-VPL	methods	methods-VPL	Cluster
0	110.0	60.0	160.0	630.0	Cluster 0
1	110.0	60.0	160.0	630.0	Cluster 0
2	110.0	60.0	160.0	630.0	Cluster 0
3	110.0	60.0	160.0	630.0	Cluster 0
4	110.0	60.0	160.0	630.0	Cluster 0

In [86]:
```
1 kmeans_T1_2_assign.head()
```

Out[86]:

	intro	intro-VPL	methods	methods-VPL	Cluster
0	110.0	60.0	160.0	630.0	Cluster 0
1	110.0	60.0	160.0	630.0	Cluster 0
2	110.0	60.0	160.0	630.0	Cluster 0
3	110.0	60.0	160.0	630.0	Cluster 0
4	110.0	60.0	160.0	630.0	Cluster 0

In [87]:
```
1 clustersT = pd.DataFrame()
2 clustersTT = pd.DataFrame()
3 clustersTTT = pd.DataFrame()
```

In [88]:
```
1 clustersT['T1'] = kmeans_T1_6_assign['Cluster'] = kmeans_T1_6_assign['Cluster'].str.replace('\D+', '')
```

In [89]:
```
1 clustersTT = kmeans_T1_2_assign['Cluster']
```

In [90]:
```
1 clustersTT['T1'] = kmeans_T1_2_assign['Cluster'] = kmeans_T1_2_assign['Cluster'].str.replace('\D+', '')
```

In [91]:
```
1 clustersTTT['T1'] = kmeans_T1_4_assign['Cluster'] = kmeans_T1_4_assign['Cluster'].str.replace('\D+', '')
```

In [92]:
```
1 clustersTT['T1']
```

Out[92]:
```
0      0
1      0
2      0
3      0
4      0
      ..
97     1
98     1
99     1
100    1
101    1
Name: Cluster, Length: 102, dtype: object
```

The Second Period

In [93]:

```
from pycaret.clustering import *

input_dataset3 = setup(dataset_T2, normalize = True,
                       session_id = 123)
```

	Description	Value
0	session_id	123
1	Original Data	(102, 9)
2	Missing Values	False
3	Numeric Features	9
4	Categorical Features	0
5	Ordinal Features	False
6	High Cardinality Features	False
7	High Cardinality Method	None
8	Transformed Data	(102, 9)
9	CPU Jobs	-1
10	Use GPU	False
11	Log Experiment	False
12	Experiment Name	cluster-default-name
13	USI	df80
14	Imputation Type	simple
15	Iterative Imputation Iteration	None
16	Numeric Imputer	mean
17	Iterative Imputation Numeric Model	None
18	Categorical Imputer	mode
19	Iterative Imputation Categorical Model	None
20	Unknown Categoricals Handling	least_frequent
21	Normalize	True
22	Normalize Method	zscore
23	Transformation	False
24	Transformation Method	None
25	PCA	False
26	PCA Method	None
27	PCA Components	None

	Description	Value
28	Ignore Low Variance	False
29	Combine Rare Levels	False
30	Rare Level Threshold	None
31	Numeric Binning	False
32	Remove Outliers	False
33	Outliers Threshold	None
34	Remove Multicollinearity	False
35	Multicollinearity Threshold	None
36	Clustering	False
37	Clustering Iteration	None
38	Polynomial Features	False
39	Polynomial Degree	None
40	Trignometry Features	False
41	Polynomial Threshold	None
42	Group Features	False
43	Feature Selection	False
44	Feature Selection Method	classic
45	Features Selection Threshold	None
46	Feature Interaction	False
47	Feature Ratio	False
48	Interaction Threshold	None

In [94]:
```
1 kmeansT2_5 = create_model('kmeans', num_clusters=5)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.4677	133.5979	1.0457	0	0	0

In [95]:
```
kmeansT2_3 = create_model('kmeans', num_clusters=3)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.5643	167.2016	0.7829	0	0	0

In [96]:
```
kmeansT2_4 = create_model('kmeans', num_clusters=4)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.5701	144.1638	0.9049	0	0	0

In [97]:
```
kmeansT2_2 = create_model('kmeans', num_clusters=2)
```

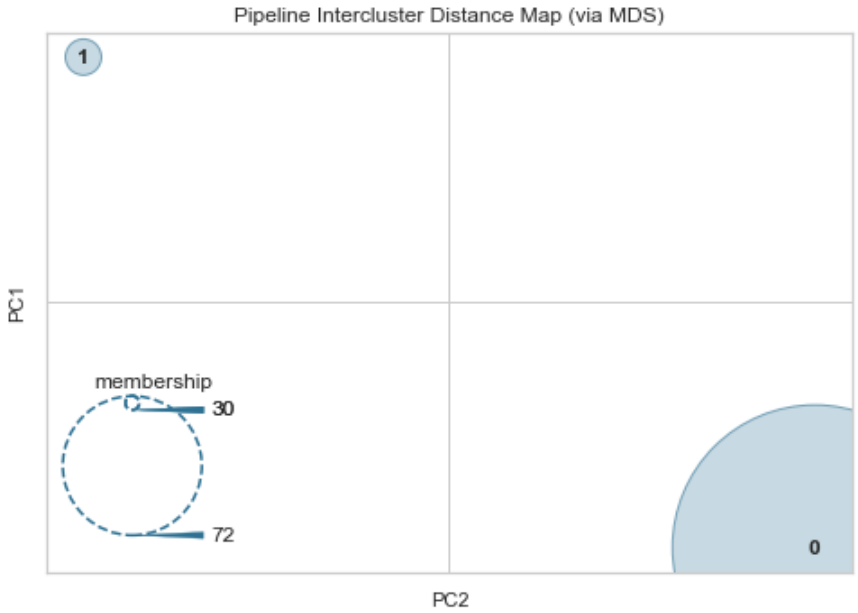
	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.6297	204.7539	0.5791	0	0	0

In [98]:
```
kmeansT2_6 = create_model('kmeans', num_clusters=6)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.4565	123.8955	1.0332	0	0	0

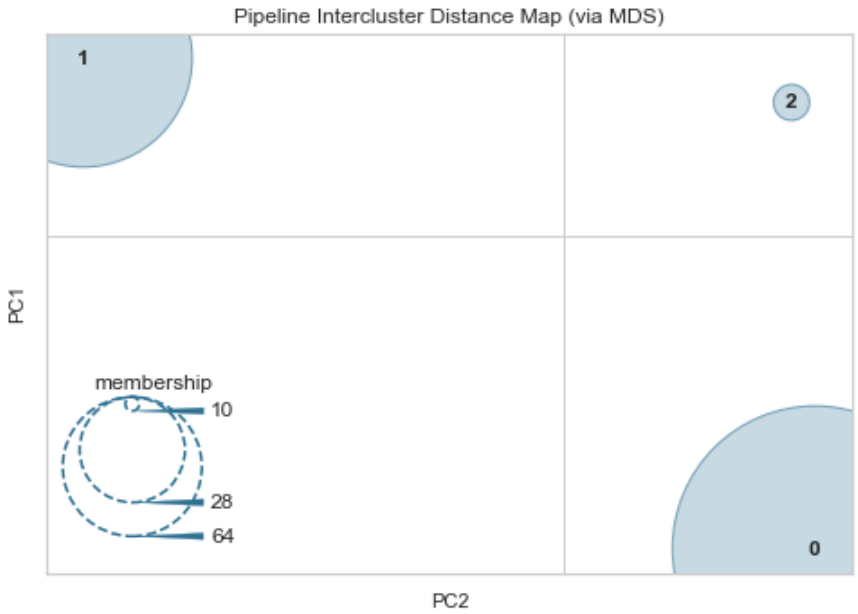
In [99]:
```
1 evaluate_model(kmeansT2_2)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution



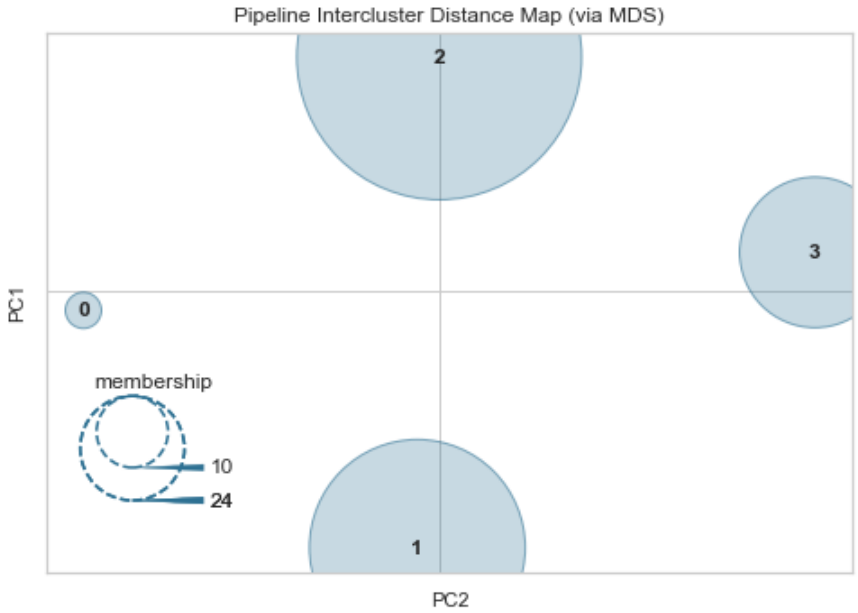
In [100]:
```
1 evaluate_model(kmeansT2_3)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution



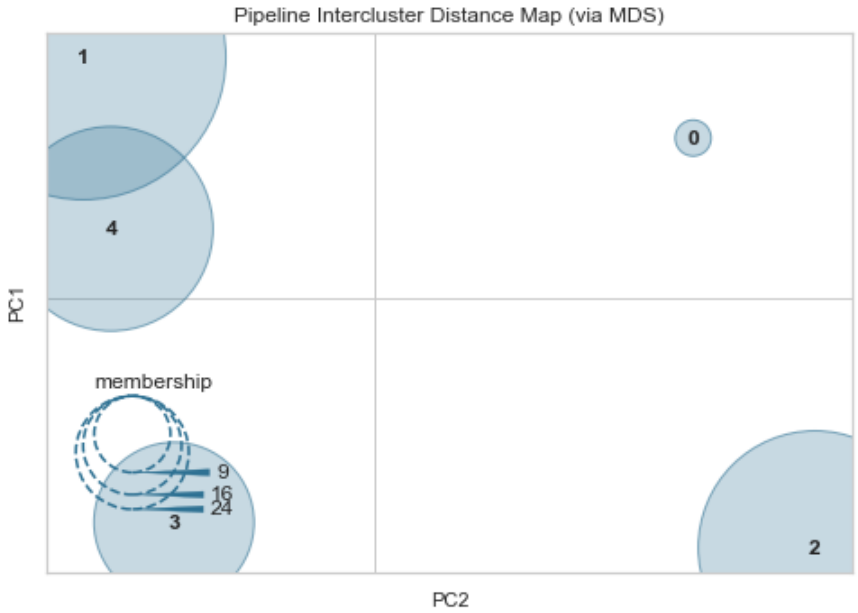
In [101]:
```
1 evaluate_model(kmeansT2_4)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution



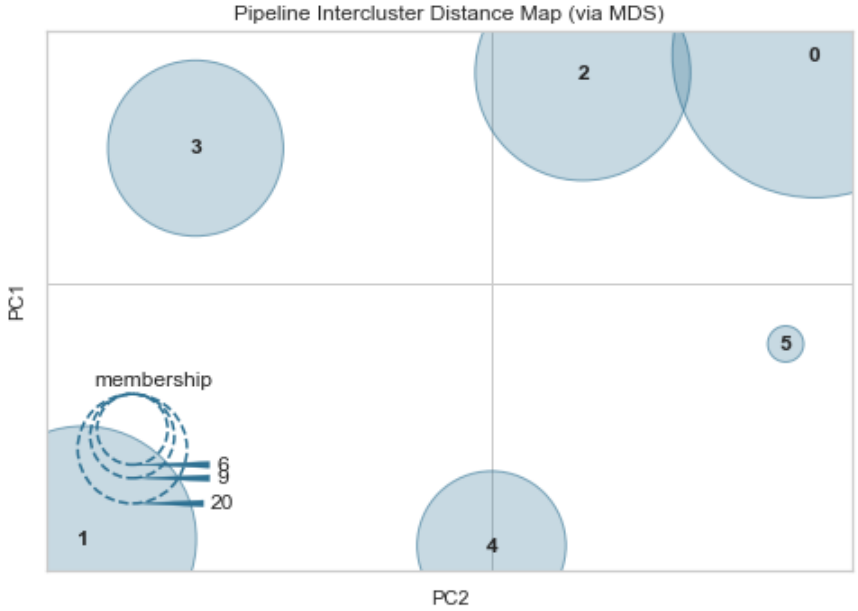
In [102]:
```
1 evaluate_model(kmeansT2_5)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution



In [103]:
```
1 evaluate_model(kmeansT2_6)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution



In [104]:
```
1 kmeans_T2_6_assign = assign_model(kmeansT2_6)
```

In [105]:
```
1 kmeans_T2_6_assign.head()
```

Out[105]:

	encap	encap-VPL	constructors	constructors-VPL	classes1	classes2	classes2-VPL	static	static-VPL	Cluster
0	148.0	100.0	110.0	165.0	80.0	170.0	95.0	80.0	270.0	Cluster 0
1	150.0	100.0	110.0	165.0	80.0	170.0	95.0	80.0	270.0	Cluster 0
2	150.0	100.0	110.0	165.0	80.0	170.0	92.0	80.0	270.0	Cluster 0
3	150.0	100.0	110.0	165.0	80.0	170.0	95.0	77.0	270.0	Cluster 0
4	150.0	100.0	110.0	157.0	80.0	170.0	95.0	80.0	270.0	Cluster 0

In [106]:
```
1 clustersT['T2'] = kmeans_T2_6_assign['Cluster'] = kmeans_T2_6_assign['Cluster'].str.replace('\D+', '')
```

In [107]:
```
1 clustersT['T2']
```

Out[107]:
```
0      0
1      0
2      0
3      0
4      0
      ..
97     1
98     1
99     1
100    1
101    1
Name: T2, Length: 102, dtype: object
```

In [108]:
```
1 kmeans_T2_2_assign = assign_model(kmeansT2_2)
```

In [109]:
```
1 clustersTT['T2'] = kmeans_T2_2_assign['Cluster'] = kmeans_T2_2_assign['Cluster'].str.replace('\D+', '')
```

In [110]:
```
1 clustersTT['T2']
```

Out[110]:
```
0      0
1      0
2      0
3      0
4      0
      ..
97     1
98     1
99     1
100    1
101    1
Name: Cluster, Length: 102, dtype: object
```

In [111]:
```
1 kmeans_T2_4_assign = assign_model(kmeansT2_4)
```

In [112]:
```
1 clustersTTT['T2'] = kmeans_T2_4_assign['Cluster'] = kmeans_T2_4_assign['Cluster'].str.replace('\D+', '')
```

In [ ]:
```
1
```

The Third Period

In [113]:
```
from pycaret.clustering import *

input_dataset4 = setup(dataset_T3, normalize = True,
                       session_id = 123)
```

	Description	Value
0	session_id	123
1	Original Data	(102, 4)
2	Missing Values	False
3	Numeric Features	4
4	Categorical Features	0
5	Ordinal Features	False
6	High Cardinality Features	False
7	High Cardinality Method	None
8	Transformed Data	(102, 4)
9	CPU Jobs	-1
10	Use GPU	False

In [114]:
```
kmeansT3_6 = create_model('kmeans', num_clusters=6)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.5948	187.3231	0.7725	0	0	0

In [115]:
```
kmeansT3_5 = create_model('kmeans', num_clusters=5)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.5775	177.7359	0.7942	0	0	0

In [116]:
```
kmeansT3_4 = create_model('kmeans', num_clusters=4)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.6057	167.6004	0.7765	0	0	0

In [117]:
```
1 kmeansT3_3 = create_model('kmeans', num_clusters=3)
```

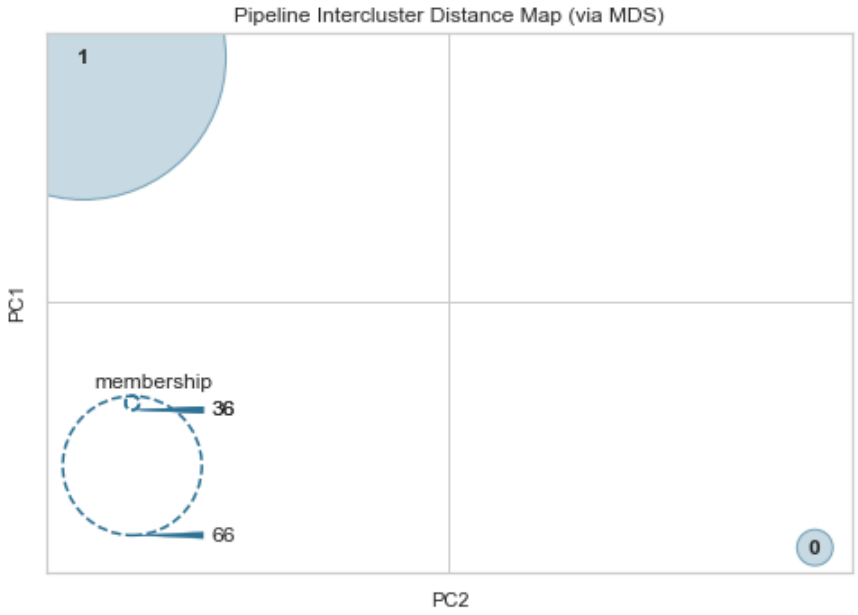
	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.5677	150.9572	0.8597	0	0	0

In [118]:
```
1 kmeansT3_2 = create_model('kmeans', num_clusters=2)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.5956	182.6024	0.6036	0	0	0

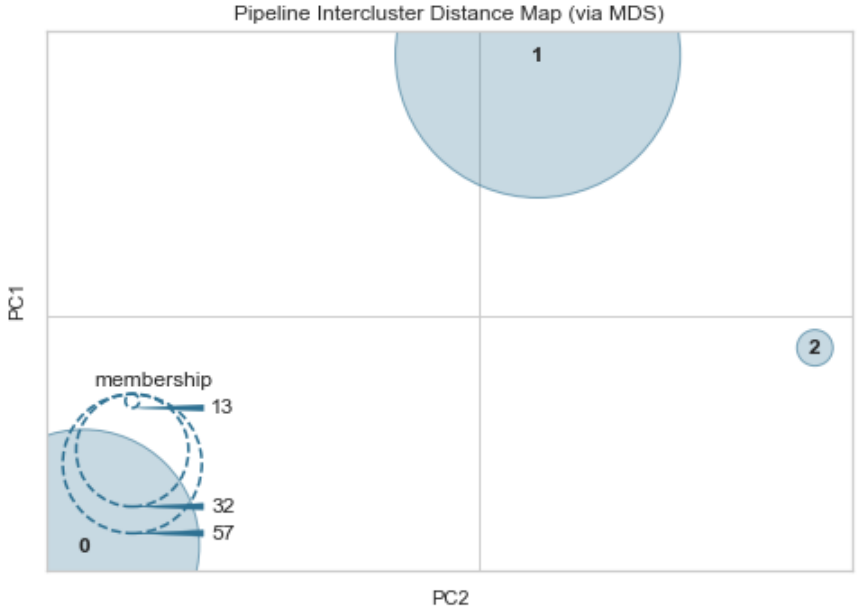
In [119]:
```
1 evaluate_model(kmeansT3_2)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution



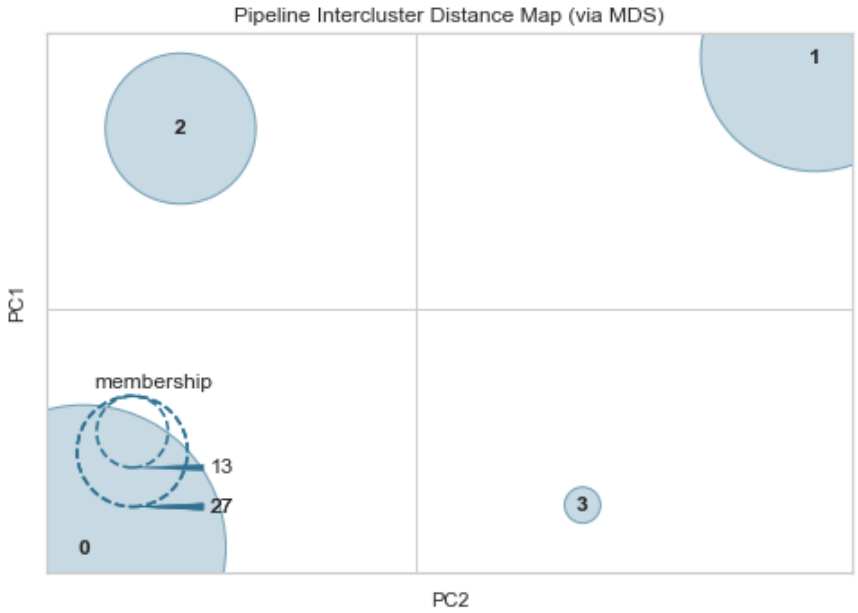
In [120]:
```
1 evaluate_model(kmeansT3_3)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution



In [121]:
```
1 evaluate_model(kmeansT3_4)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution

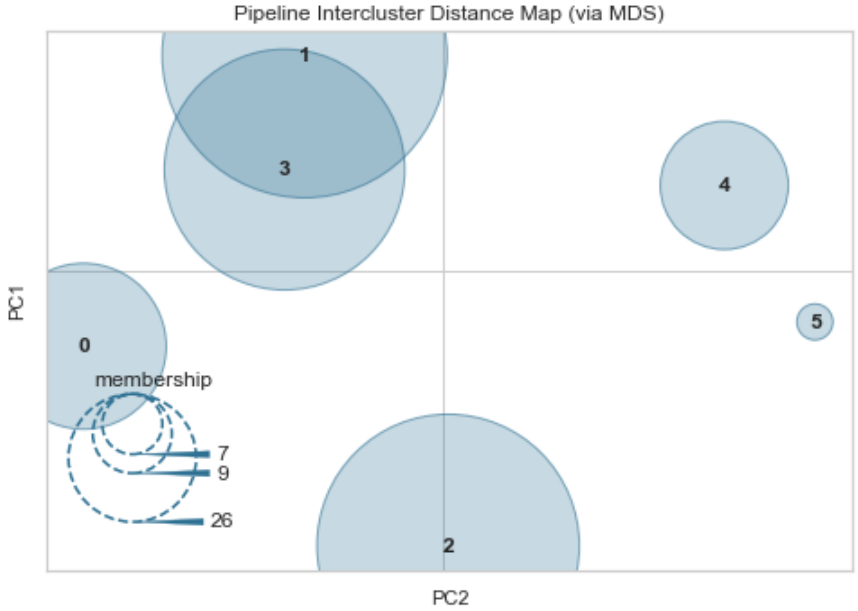


In [122]:
```
1 evaluate_model(kmeansT3_5)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution

In [123]:
```
1 evaluate_model(kmeansT3_6)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution



In [124]:
```
1 kmeans_T3_6_assign = assign_model(kmeansT3_6)
2 kmeans_T3_6_assign.head()
3 clustersT['T3'] = kmeans_T3_6_assign['Cluster'] = kmeans_T3_6_assign['Cluster'].str.replace('\D+', '')
```

In [125]:
```
1 clustersT['T3']
```

Out[125]:
```
0      1
1      1
2      1
3      1
4      1
      ..
97     2
98     2
99     2
100    2
101    2
Name: T3, Length: 102, dtype: object
```

In [126]:
```
1 kmeans_T3_2_assign = assign_model(kmeansT3_2)
```

In [127]:
```
1 clustersTT['T3'] = kmeans_T3_2_assign['Cluster'] = kmeans_T3_2_assign['Cluster'].str.replace('\D+', '')
```

In [128]:
```
1 clustersTT['T3']
```

Out[128]:
```
0      1
1      1
2      1
3      1
4      1
      ..
97     0
98     0
99     0
100    0
101    0
Name: Cluster, Length: 102, dtype: object
```

In [129]:
```
1 kmeans_T3_4_assign = assign_model(kmeansT3_4)
```

In [130]:
```
1 clustersTTT['T3'] = kmeans_T3_4_assign['Cluster'] = kmeans_T3_4_assign['Cluster'].str.replace('\D+', '')
```

VPL Features Custering

In [131]:
```
from pycaret.clustering import *

input_dataset5 = setup(dataset_reduced_VPL, normalize = True,
                       numeric_features = ['intro-VPL','methods-VPL','encap-VPL','constructors-VPL','classes2-VPL','static-VPL',
                                           'inher-VPL',  'polymorphism-VPL'],
                       session_id = 123)
```

	Description	Value
0	session_id	123
1	Original Data	(102, 8)
2	Missing Values	False
3	Numeric Features	8
4	Categorical Features	0
5	Ordinal Features	False
6	High Cardinality Features	False
7	High Cardinality Method	None
8	Transformed Data	(102, 8)
9	CPU Jobs	-1
10	Use GPU	False

In [132]:
```
kmeans_vpl2 = create_model('kmeans', num_clusters = 2)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.5482	162.3892	0.703	0	0	0

In [133]:
```
kmeans_vpl3 = create_model('kmeans', num_clusters = 3)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.4275	121.716	1.1015	0	0	0

In [134]:
```
1 kmeans_vpl4 = create_model('kmeans', num_clusters = 4)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.396	100.6032	1.0784	0	0	0

In [135]:
```
1 kmeans_vpl5 = create_model('kmeans', num_clusters = 5)
```

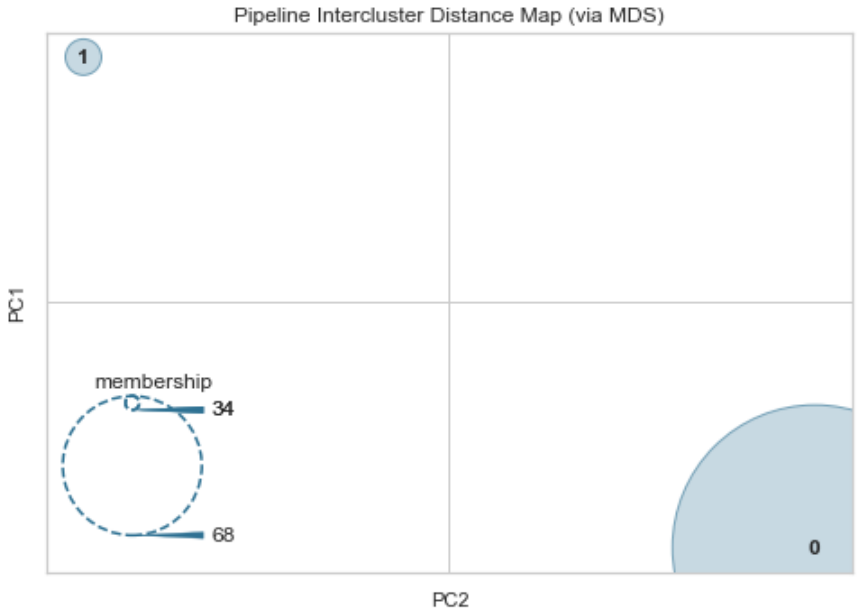
	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.4148	91.6369	1.18	0	0	0

In [136]:
```
1 kmeans_vpl6 = create_model('kmeans', num_clusters = 6)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.4228	81.6195	1.152	0	0	0

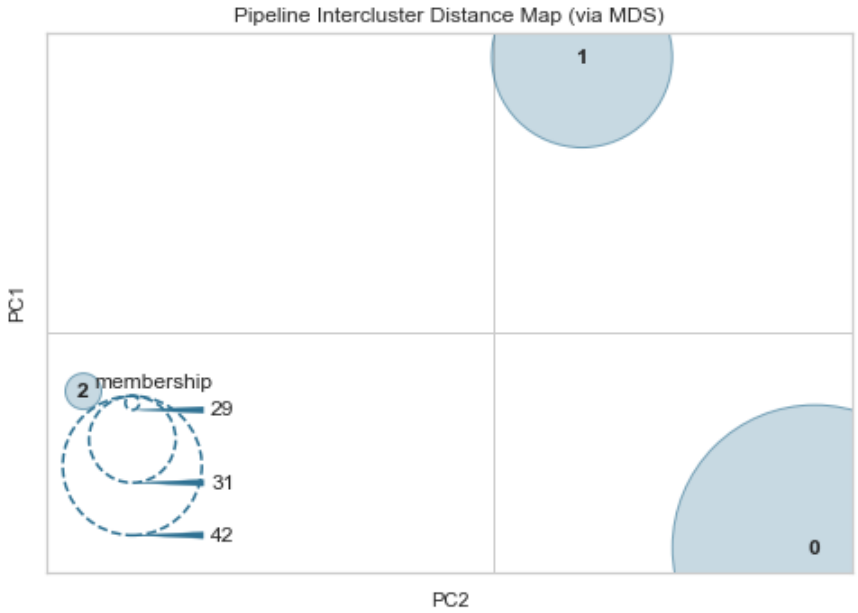
In [137]:
```
1 evaluate_model(kmeans_vpl2)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution



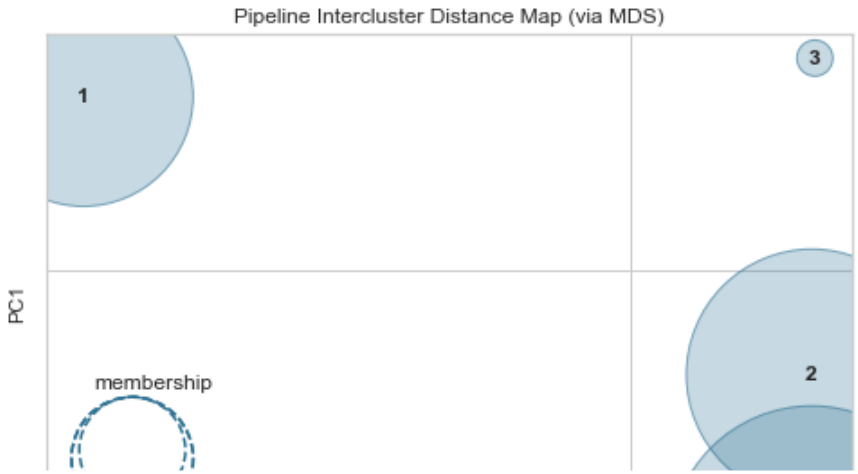
In [138]:
```
1 evaluate_model(kmeans_vpl3)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution



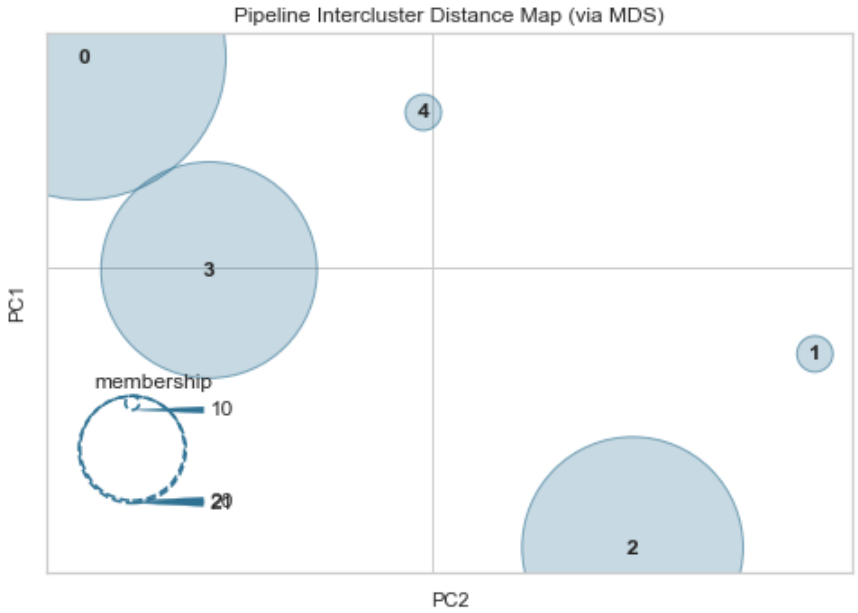
In [139]:
```
1 evaluate_model(kmeans_vpl4)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution



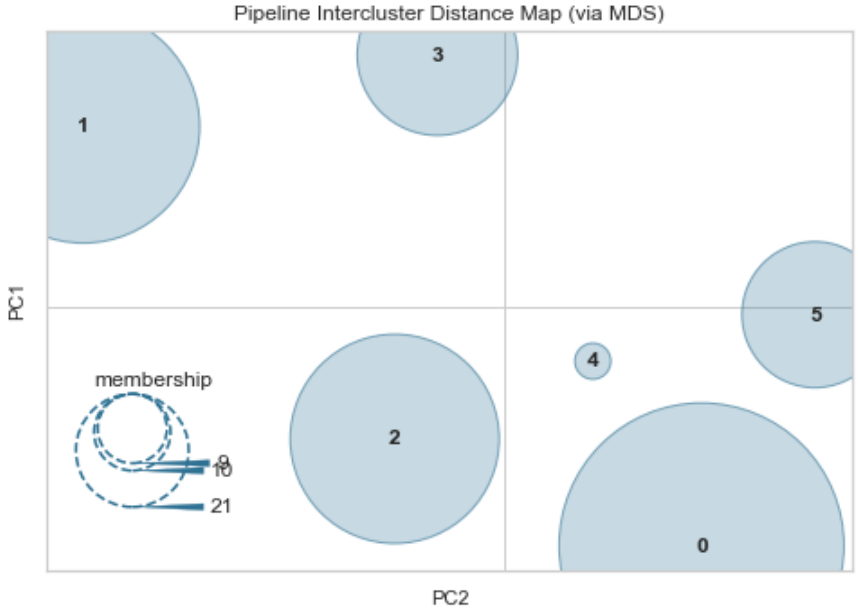
In [140]:
```
1 evaluate_model(kmeans_vpl5)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution



In [141]:
```
1 evaluate_model(kmeans_vpl6)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution



In [142]:
```
1 kmeans_VPL_2_assign = assign_model(kmeans_vpl2)
```

In [143]:
```
1 clustersVPL = pd.DataFrame()
```

In [144]:
```
1 clustersVPL['VPL'] = kmeans_VPL_2_assign['Cluster'] = kmeans_VPL_2_assign['Cluster'].str.replace('\D+', '')
```

In [145]:
```
1 clustersVPL.head()
```

Out[145]:

	VPL
0	0
1	0
2	0
3	0
4	0

In [ ]:
```
1
```

In [ ]:
```
1
```

In [ ]:
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In [ ]:
```
1
```

Micro-learning Units with Quizees Features Clusters

In [146]:

```
from pycaret.clustering import *

input_dataset6 = setup(dataset_reduced_mc_lessons, normalize = True,
                       numeric_features = ['intro','methods','encap','constructors','classes1','classes2','static', 'inher',  'pol
                       session_id = 123)
```

	Description	Value
0	session_id	123
1	Original Data	(102, 9)
2	Missing Values	False
3	Numeric Features	9
4	Categorical Features	0
5	Ordinal Features	False
6	High Cardinality Features	False
7	High Cardinality Method	None
8	Transformed Data	(102, 9)
9	CPU Jobs	-1
10	Use GPU	False
11	Log Experiment	False
12	Experiment Name	cluster-default-name
13	USI	a27e
14	Imputation Type	simple
15	Iterative Imputation Iteration	None
16	Numeric Imputer	mean
17	Iterative Imputation Numeric Model	None
18	Categorical Imputer	mode
19	Iterative Imputation Categorical Model	None
20	Unknown Categoricals Handling	least_frequent
21	Normalize	True
22	Normalize Method	zscore
23	Transformation	False
24	Transformation Method	None
25	PCA	False
26	PCA Method	None
27	PCA Components	None

	Description	Value
28	Ignore Low Variance	False
29	Combine Rare Levels	False
30	Rare Level Threshold	None
31	Numeric Binning	False
32	Remove Outliers	False
33	Outliers Threshold	None
34	Remove Multicollinearity	False
35	Multicollinearity Threshold	None
36	Clustering	False
37	Clustering Iteration	None
38	Polynomial Features	False
39	Polynomial Degree	None
40	Trignometry Features	False
41	Polynomial Threshold	None
42	Group Features	False
43	Feature Selection	False
44	Feature Selection Method	classic
45	Features Selection Threshold	None
46	Feature Interaction	False
47	Feature Ratio	False
48	Interaction Threshold	None

In [147]:
```
1 kmeans_mc_2 = create_model('kmeans', num_clusters = 2)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.7363	383.3815	0.4624	0	0	0

In [148]:
```
1 kmeans_mc_3 = create_model('kmeans', num_clusters = 3)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.6896	286.8699	0.6816	0	0	0

In [149]:
```
1 kmeans_mc_4 = create_model('kmeans', num_clusters = 4)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.5769	274.3522	0.8355	0	0	0

In [150]:
```
1 kmeans_mc_5 = create_model('kmeans', num_clusters = 5)
```

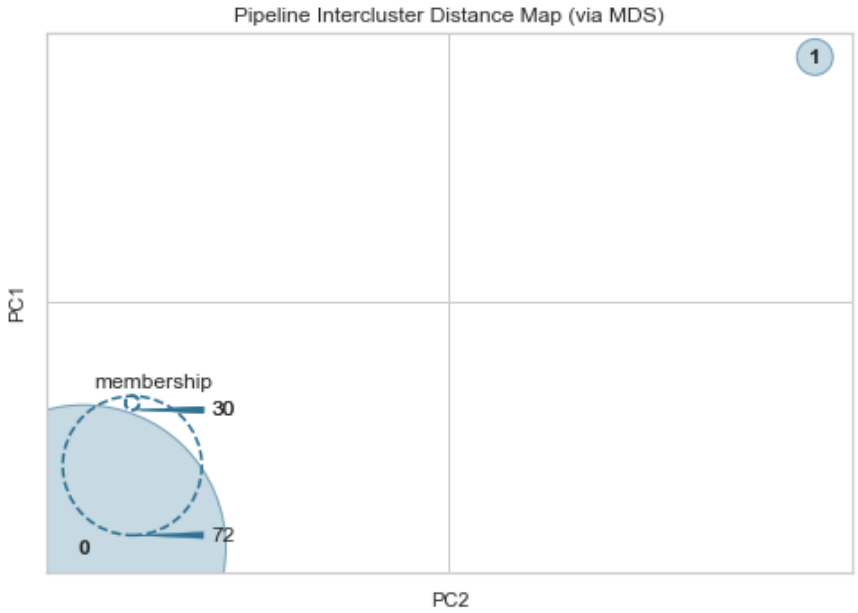
	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.5605	262.406	0.9686	0	0	0

In [151]:
```
1 kmeans_mc_6 = create_model('kmeans', num_clusters = 6)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.5601	241.889	0.9954	0	0	0

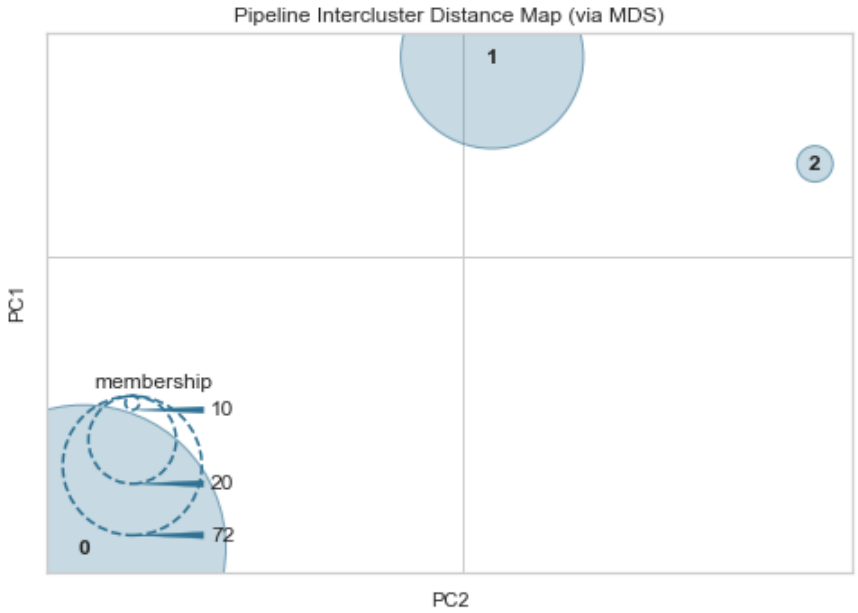
In [152]:
```
1 evaluate_model(kmeans_mc_2)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution



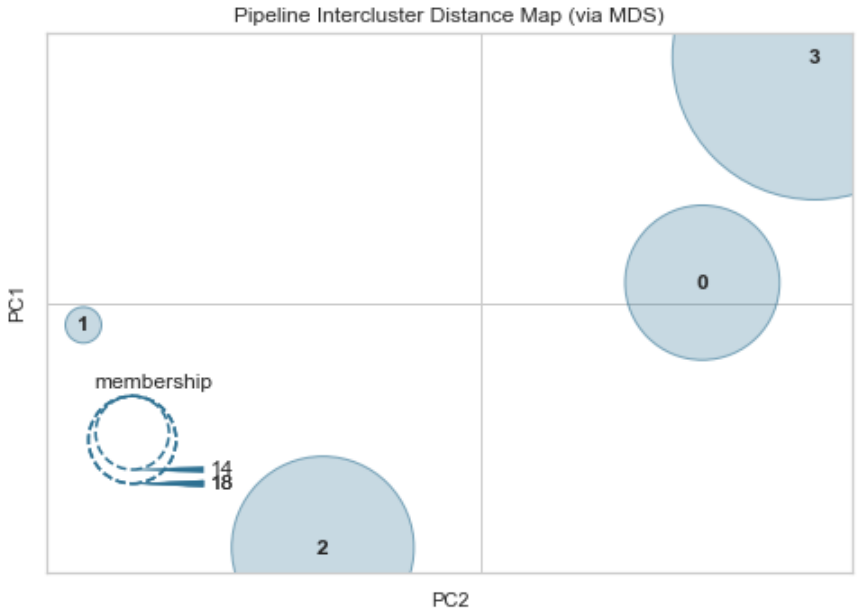
In [153]:
```
1 evaluate_model(kmeans_mc_3)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution



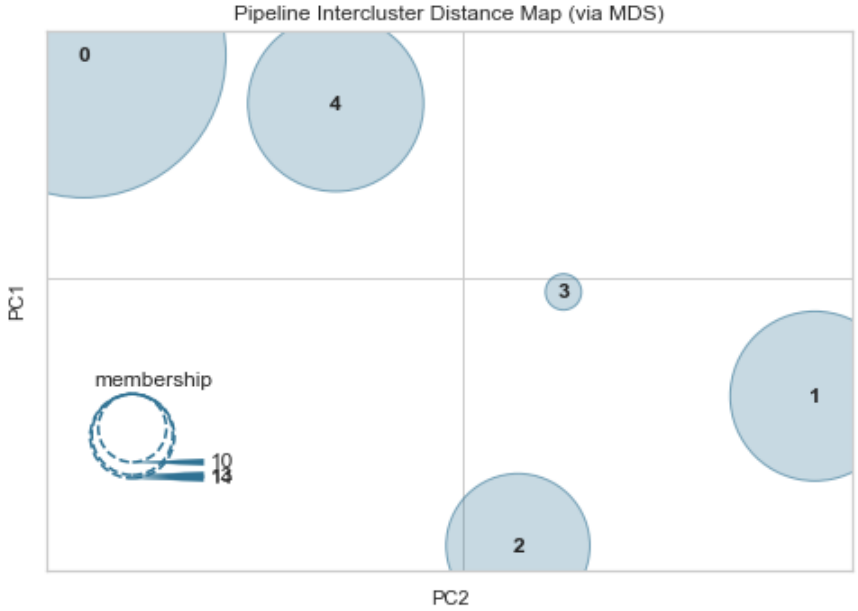
In [154]:
```
1 evaluate_model(kmeans_mc_4)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution



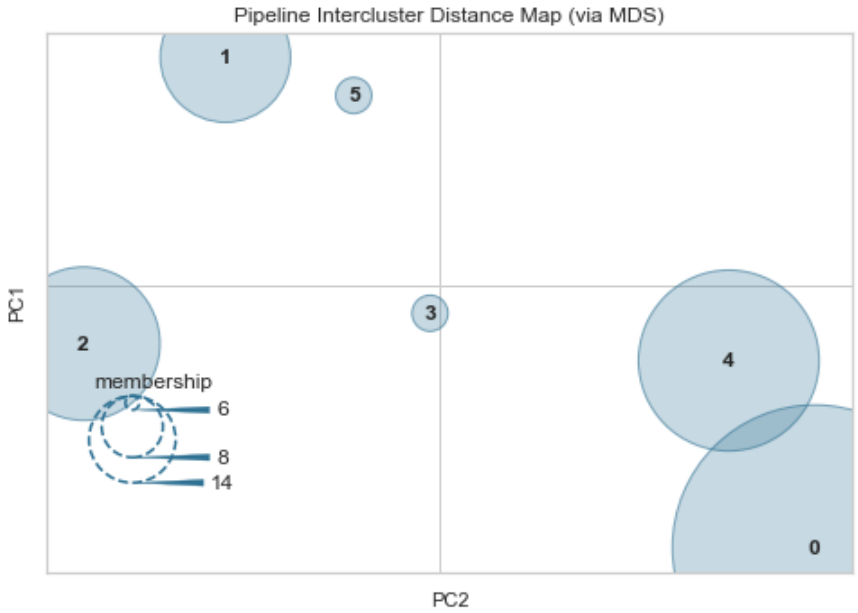
In [155]:
```
1 evaluate_model(kmeans_mc_5)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution



In [156]:
```
1 evaluate_model(kmeans_mc_6)
```

Plot Type: Cluster PCA Plot (2d) Cluster TSnE (3d) Elbow Silhouette Distance Distribution



In [157]:
```
1 kmeans_MC_2_assign = assign_model(kmeans_mc_2)
```

In [158]:
```
1 clustersMC = pd.DataFrame()
```

In [159]:
```
1 clustersMC['MC'] = kmeans_MC_2_assign['Cluster'] = kmeans_MC_2_assign['Cluster'].str.replace('\D+', '')
```

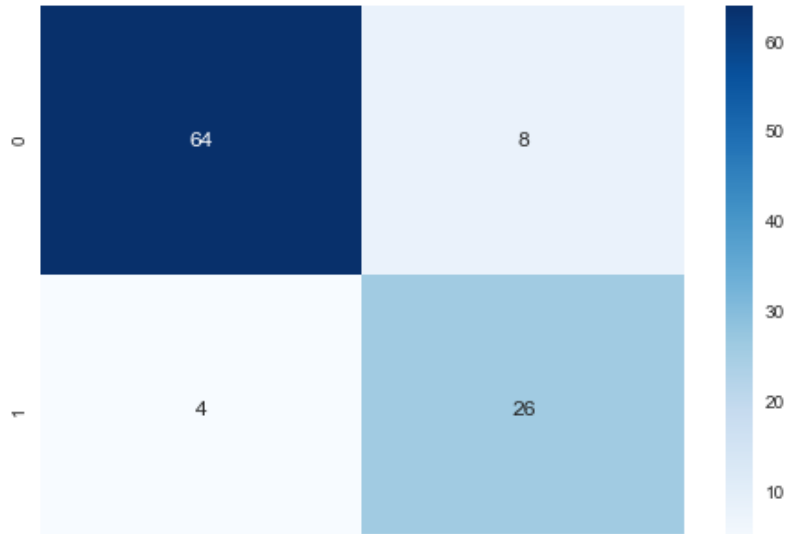
Calculation Changes Between Clusters

In [160]:
```
1 from sklearn.metrics.cluster import contingency_matrix
```

Differences Between Micro-learning Units Features and VPL Features for k = 2

In [161]:
```
1 sns.heatmap(contingency_matrix(clustersMC['MC'], clustersVPL['VPL']), annot=True,cmap='Blues')
```

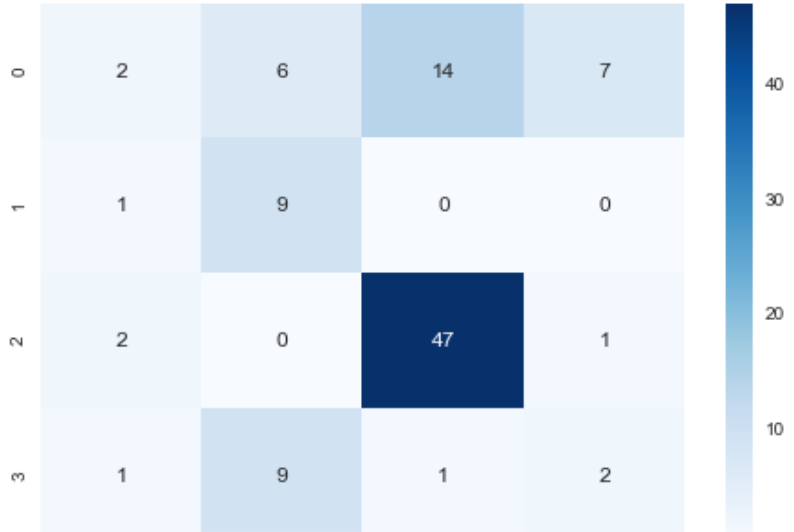
Out[161]: <AxesSubplot:>



Differences Between Different Term Periods

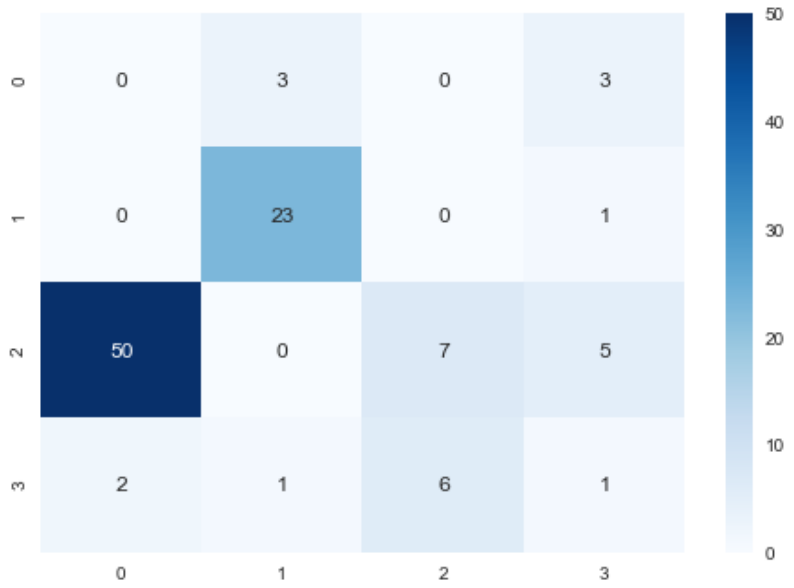
In [162]:
```
1 sns.heatmap(contingency_matrix(clustersTTT['T1'], clustersTTT['T2']), annot=True,cmap='Blues')
```

Out[162]: <AxesSubplot:>



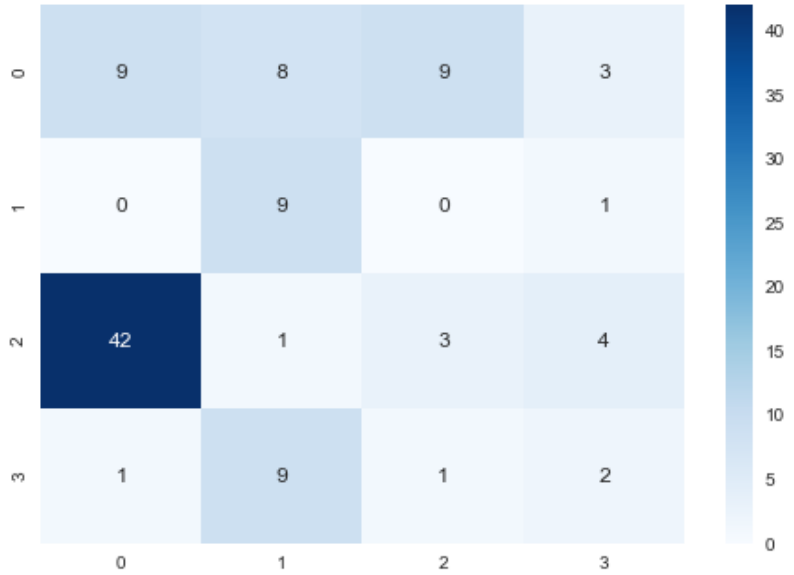
In [163]:
```
1 sns.heatmap(contingency_matrix(clustersTTT['T2'], clustersTTT['T3']), annot=True,cmap='Blues')
```

Out[163]: <AxesSubplot:>



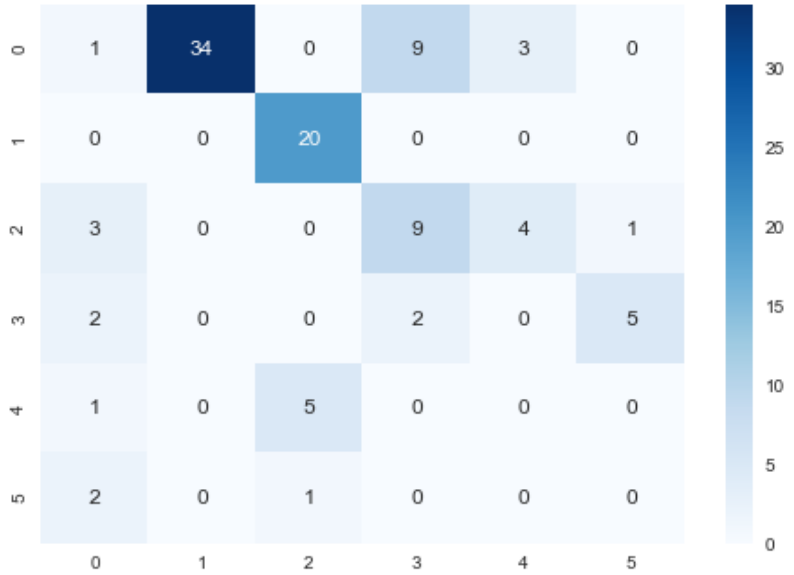
In [164]:
```
1 sns.heatmap(contingency_matrix(clustersTTT['T1'], clustersTTT['T3']), annot=True,cmap='Blues')
```

Out[164]: <AxesSubplot:>



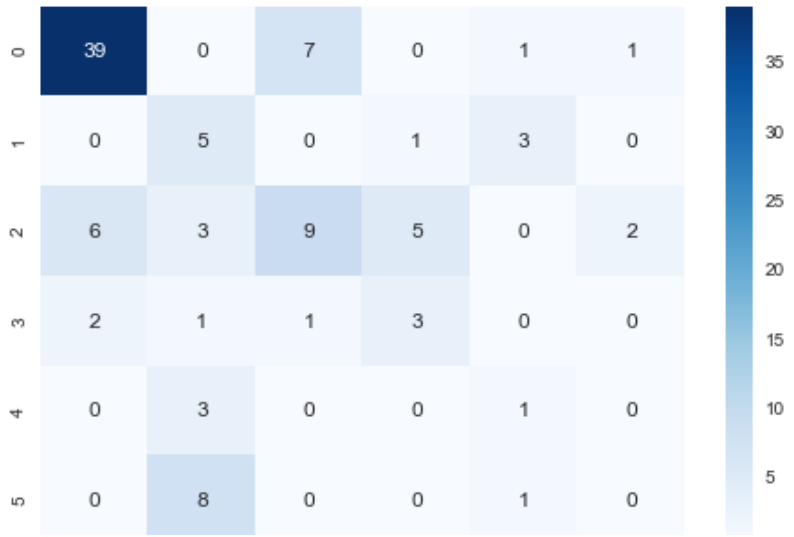
In [165]:
```
1 sns.heatmap(contingency_matrix(clustersT['T2'], clustersT['T3']), annot=True,cmap='Blues')
```

Out[165]: <AxesSubplot:>



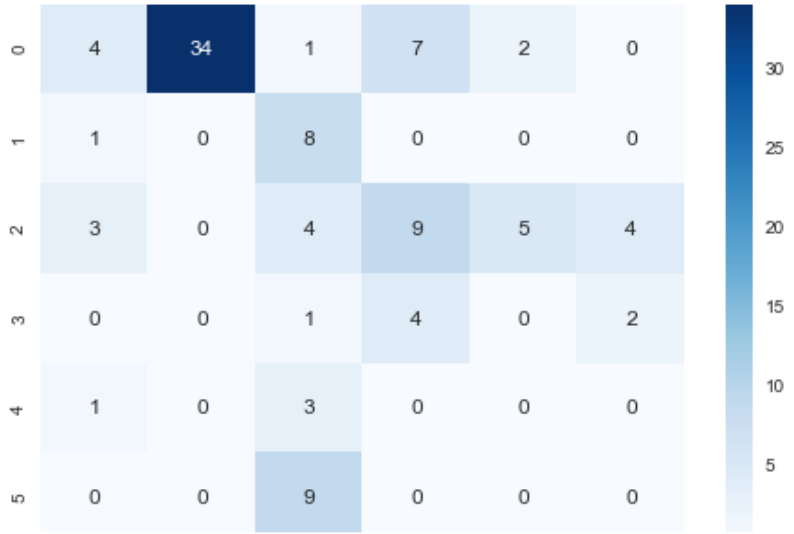
In [166]:
```
1 sns.heatmap(contingency_matrix(clustersT['T1'], clustersT['T2']), annot=True, cmap='Blues')
```

Out[166]: <AxesSubplot:>



In [167]:
```
1 sns.heatmap(contingency_matrix(clustersT['T1'], clustersT['T3']), annot=True, cmap='Blues')
```

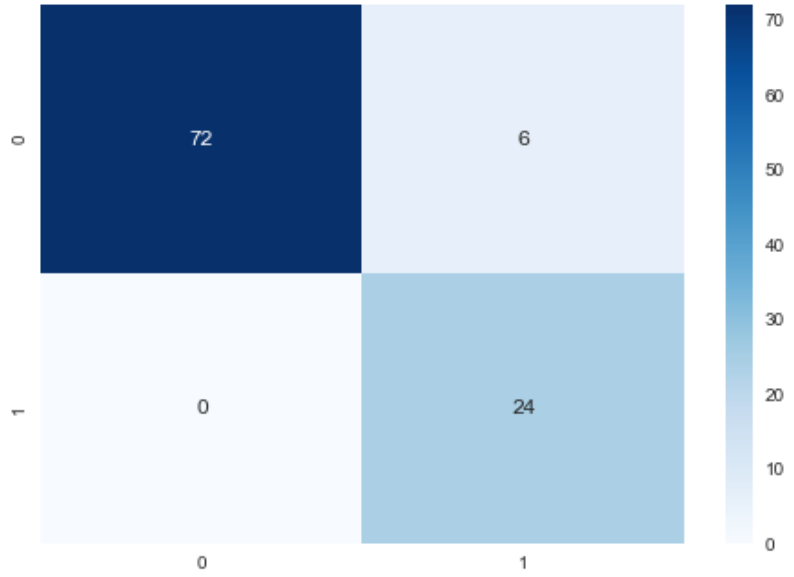
Out[167]: <AxesSubplot:>



In [ ]:
```
1
```

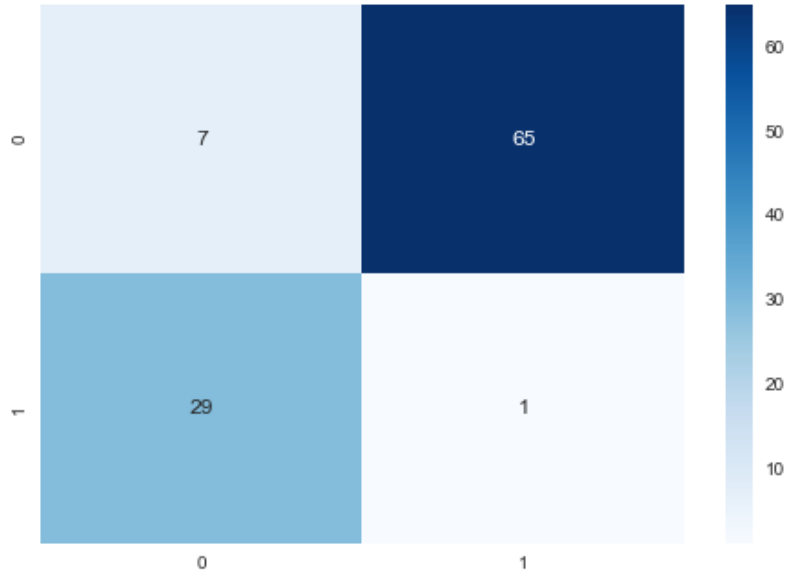
In [168]:
```
1 sns.heatmap(contingency_matrix(clustersTT['T1'], clustersTT['T2']), annot=True, cmap='Blues')
```

Out[168]: <AxesSubplot:>



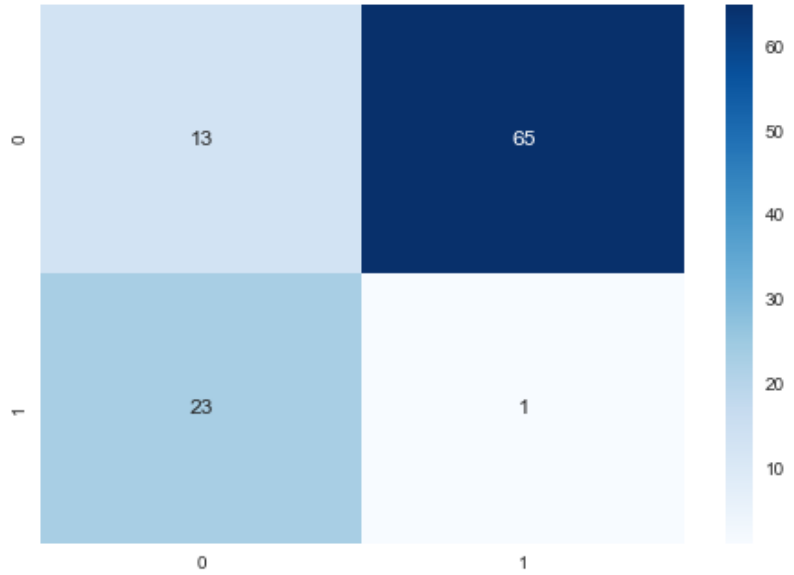
In [169]:
```
1 sns.heatmap(contingency_matrix(clustersTT['T2'], clustersTT['T3']), annot=True, cmap='Blues')
```

Out[169]: <AxesSubplot:>



In [170]:
```
1 sns.heatmap(contingency_matrix(clustersTT['T1'], clustersTT['T3']), annot=True, cmap='Blues')
```

Out[170]: <AxesSubplot:>



Calculation of Adjusted Rand Score

In [171]:
```
1 from sklearn.metrics.cluster import adjusted_rand_score
```

In [172]:
```
1 adjusted_rand_score(clustersMC['MC'], clustersVPL['VPL'])
```

Out[172]: 0.573626442352794

In [173]:
```
1 adjusted_rand_score(clustersT['T1'], clustersT['T2'])
```

Out[173]: 0.41652791113497356

In [174]:
```
1 adjusted_rand_score(clustersT['T2'], clustersT['T3'])
```

Out[174]: 0.5438701342049281

In [175]:
```
1 adjusted_rand_score(clustersT['T1'], clustersT['T3'])
```

Out[175]: 0.38476411751152273

In [176]:
```
1 adjusted_rand_score(clustersTT['T1'], clustersTT['T2'])
```

Out[176]: 0.7660444202207385

In [177]:
```
1 adjusted_rand_score(clustersTT['T2'], clustersTT['T3'])
```

Out[177]: 0.7043229112279911

In [178]:
```
1 adjusted_rand_score(clustersTT['T1'], clustersTT['T3'])
```

Out[178]: 0.5113062795825317

In [179]:
```
1 adjusted_rand_score(clustersTTT['T1'], clustersTTT['T2'])
```

Out[179]: 0.42580973489845253

In [180]:
```
1 adjusted_rand_score(clustersTTT['T2'], clustersTTT['T3'])
```

Out[180]: 0.6094009866667736

In [181]:
```
1 adjusted_rand_score(clustersTTT['T1'], clustersTTT['T3'])
```

Out[181]: 0.3720311461048107

PCA Calculation as an Alternative

In [182]:
```
1 from sklearn.decomposition import PCA
```

In [183]:
```
1 from sklearn.preprocessing import StandardScaler
```

In [184]:
```
1 scaler = StandardScaler()
```

In [185]:
```
1 dataset_reduced_std = scaler.fit_transform(dataset_reduced)
```

In [186]:
```
pca = PCA()
pca.fit(dataset_reduced_std)
```

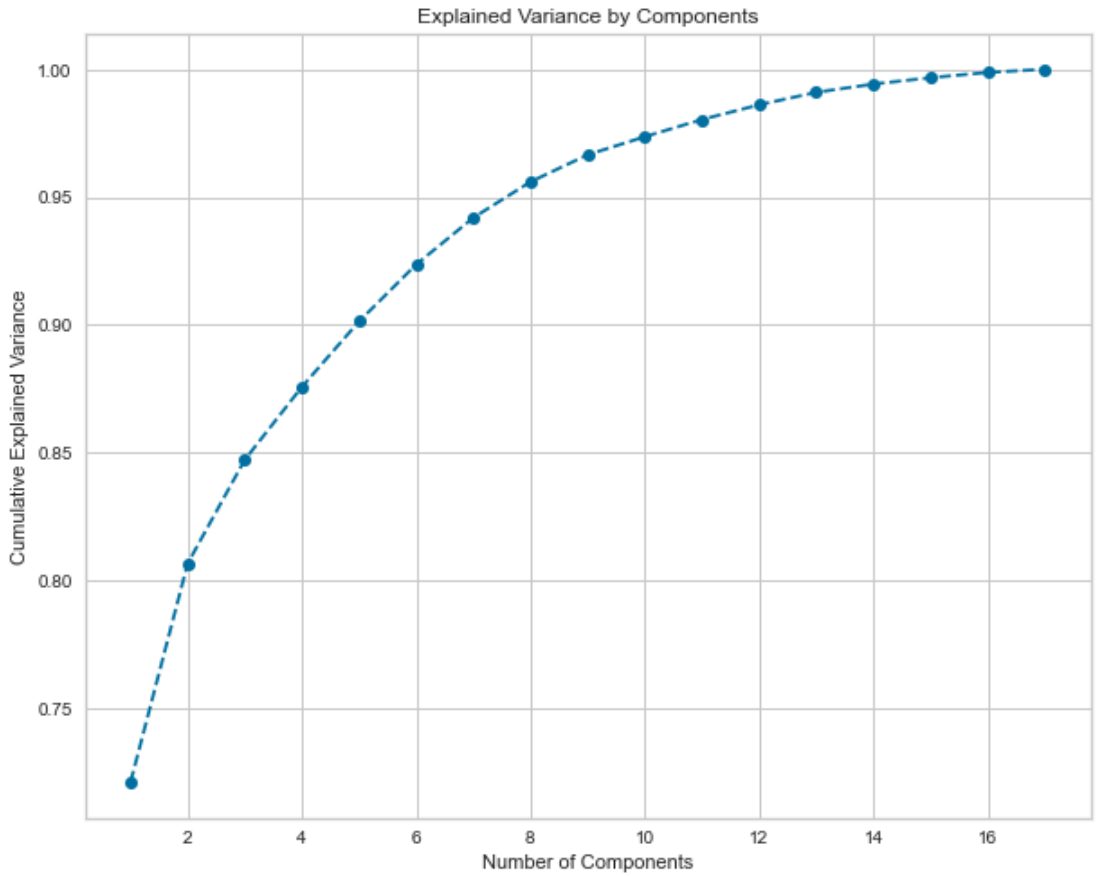
Out[186]:
```
PCA(copy=True, iterated_power='auto', n_components=None, random_state=None,
    svd_solver='auto', tol=0.0, whiten=False)
```

In [187]:
```
pca.explained_variance_ratio_
```

Out[187]:
```
array([0.7213091 , 0.08549269, 0.04057368, 0.02849862, 0.02558219,
       0.02225842, 0.01827447, 0.01402138, 0.01056267, 0.00706838,
       0.00671829, 0.00574404, 0.00488592, 0.00321943, 0.00249536,
       0.00206142, 0.00123395])
```

In [188]:
```
plt.figure(figsize = (10,8))
plt.plot(range(1,18), pca.explained_variance_ratio_.cumsum(),'bo', linestyle='--')
plt.title('Explained Variance by Components')
plt.xlabel('Number of Components')
plt.ylabel('Cumulative Explained Variance')
```

Out[188]:
```
Text(0, 0.5, 'Cumulative Explained Variance')
```



In [189]:
```
pca2 = PCA()
pca2.fit(dataset_reduced_min_max_scaled)

```

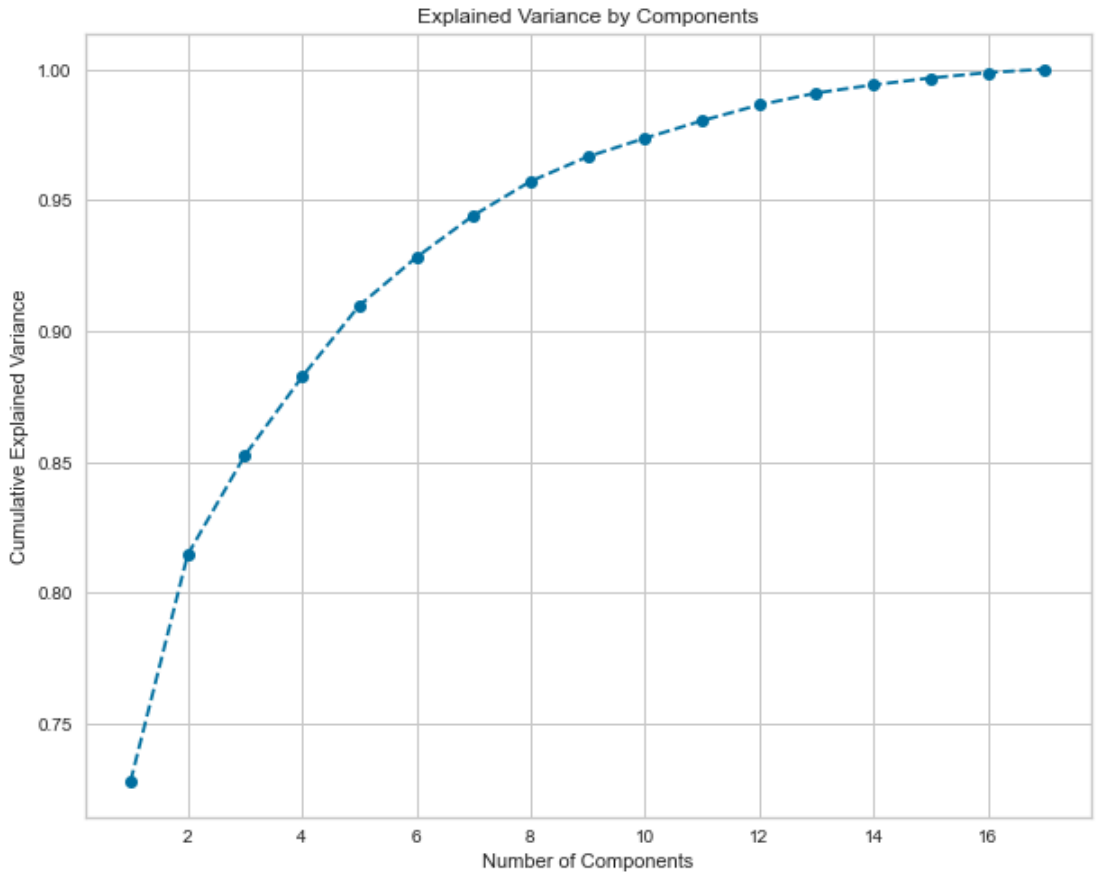
Out[189]:
```
PCA(copy=True, iterated_power='auto', n_components=None, random_state=None,
    svd_solver='auto', tol=0.0, whiten=False)
```

In [190]:
```
1 pca2.explained_variance_ratio_
```

Out[190]:
```
array([0.72795641, 0.08659105, 0.03790389, 0.02998272, 0.02722763,
       0.01842525, 0.01603878, 0.01304666, 0.00941073, 0.00704008,
       0.0066948 , 0.00603634, 0.00454973, 0.00312783, 0.00259642,
       0.00207652, 0.00129516])
```

In [191]:
```
1 plt.figure(figsize = (10,8))
2 plt.plot(range(1,18), pca2.explained_variance_ratio_.cumsum(),'bo', linestyle='--')
3 plt.title('Explained Variance by Components')
4 plt.xlabel('Number of Components')
5 plt.ylabel('Cumulative Explained Variance')
```

Out[191]:
```
Text(0, 0.5, 'Cumulative Explained Variance')
```



In [192]:
```
1 dataset_reduced_min_max_scaled.describe().T
```

Out[192]:

	count	mean	std	min	25%	50%	75%	max
intro	102.0	0.859180	0.273646	0.0	0.884091	1.000000	1.000000	1.0
intro-VPL	102.0	0.769935	0.387327	0.0	0.666667	1.000000	1.000000	1.0
methods	102.0	0.771385	0.372810	0.0	0.640625	0.993750	1.000000	1.0
methods-VPL	102.0	0.553719	0.355638	0.0	0.170635	0.549206	0.927778	1.0
encap	102.0	0.724967	0.390893	0.0	0.478333	0.976667	1.000000	1.0
encap-VPL	102.0	0.715980	0.386421	0.0	0.400000	1.000000	1.000000	1.0
constructors	102.0	0.719251	0.406814	0.0	0.463636	0.959091	1.000000	1.0
constructors-VPL	102.0	0.682650	0.383134	0.0	0.363636	0.842424	1.000000	1.0
classes1	102.0	0.655025	0.427950	0.0	0.000000	0.912500	1.000000	1.0
classes2	102.0	0.643829	0.419726	0.0	0.191176	0.882353	0.998529	1.0
classes2-VPL	102.0	0.570175	0.435215	0.0	0.000000	0.684211	1.000000	1.0
static	102.0	0.717034	0.416454	0.0	0.500000	0.962500	1.000000	1.0
static-VPL	102.0	0.547967	0.404537	0.0	0.140741	0.629630	1.000000	1.0
inher	102.0	0.613519	0.398582	0.0	0.210526	0.850000	0.981579	1.0
inher-VPL	102.0	0.518301	0.410255	0.0	0.100000	0.587037	1.000000	1.0
polymorphism	102.0	0.644398	0.448589	0.0	0.000000	0.985714	1.000000	1.0
polymorphism-VPL	102.0	0.592157	0.476323	0.0	0.000000	1.000000	1.000000	1.0

In [193]:
```
1 pca3 = PCA(n_components = 6)
```

In [194]:
```
1 pca3.fit(dataset_reduced_min_max_scaled)
```

Out[194]:
```
PCA(copy=True, iterated_power='auto', n_components=6, random_state=None,
    svd_solver='auto', tol=0.0, whiten=False)
```

In [195]:
```
1 pca3.explained_variance_ratio_
```

Out[195]:
```
array([0.72795641, 0.08659105, 0.03790389, 0.02998272, 0.02722763,
       0.01842525])
```

In [ ]:
```
1
```