4DIn12D

In [1]:

```
import numpy as np
import pandas as pd
import sklearn.cluster as sc
import matplotlib.pyplot as mp

df=pd.read_csv("4DIn12D.csv")
df.head()
```

Out[1]:

	labels	dim2	dim6	dim7	dim8	Name3Class
0	r155	0.314345	0.393007	0.044667	0.118493	3
1	r156	0.327695	0.410825	0.033796	0.070825	3
2	r157	0.316753	0.433747	0.054407	0.122989	3
3	r158	0.363791	0.399353	0.070283	0.097313	3
4	r159	0.320207	0.416929	0.066920	0.081252	3

In [2]:

```
x=df.iloc[:,1:-1]
y=df.iloc[:,-1]
```

In [3]:

```
# 均值漂移实现聚类划分

bw = sc.estimate_bandwidth(x, n_samples=len(x), quantile=0.2)
model = sc.MeanShift(bandwidth=bw)

model.fit(x)
centers = model.cluster_centers_
print(centers)
pred_y = model.predict(x)
```

```
[[0.33446171 0.39758833 0.07444329 0.07910476]
 [0.60301562 0.22273784 0.74762566 0.78930791]
 [0.91000036 0.80055592 0.07362254 0.08346961]
 [0.72607341 0.00129898 0.7066516  0.75453659]
 [0.21081142 0.01988992 0.74553331 0.82203023]
 [0.1981935  0.29306436 0.76030567 0.90897026]]
```

In [4]:

```
x["pred_y"]=pred_y
```

In [5]:

```
x=pd.merge(x,pd.get_dummies(x["pred_y"], prefix="expand"), left_index=True, right_index=True)
x=(x-x.min())/(x.max()-x.min())
x
```

Out[5]:

	dim2	dim6	dim7	dim8	pred_y	expand_0	expand_1	expand_2	expan
0	0.157172	0.476087	0.028182	0.119516	0.0	1.0	0.0	0.0	
1	0.175236	0.497742	0.016887	0.071436	0.0	1.0	0.0	0.0	
2	0.160430	0.525603	0.038303	0.124051	0.0	1.0	0.0	0.0	
3	0.224080	0.483800	0.054799	0.098153	0.0	1.0	0.0	0.0	
4	0.165104	0.505161	0.051304	0.081954	0.0	1.0	0.0	0.0	
...	...	...	...	...	...	...	...	...	
345	0.602898	0.281886	0.773255	0.813337	0.2	0.0	1.0	0.0	
346	0.589123	0.291132	0.824056	0.844943	0.2	0.0	1.0	0.0	
347	0.601757	0.290078	0.936338	0.728159	0.2	0.0	1.0	0.0	
348	0.544596	0.313879	0.724606	0.800907	0.2	0.0	1.0	0.0	
349	0.586442	0.287920	0.767719	0.752964	0.2	0.0	1.0	0.0	

350 rows × 11 columns

In [6]:

```
import numpy as np
from sklearn.preprocessing import LabelEncoder
from yellowbrick.features.radviz import RadViz
DIAMETER_METHODS = ['mean_cluster', 'farthest']
CLUSTER_DISTANCE_METHODS = ['nearest', 'farthest']

def inter_cluster_distances(labels, distances, method='nearest'):
    """Calculates the distances between the two nearest points of each cluster.
    :param labels: a list containing cluster labels for each of the n elements
    :param distances: an n x n numpy.array containing the pairwise distances between elements
    :param method: `nearest` for the distances between the two nearest points in each cluster, o
r `farthest`
    """
    if method not in CLUSTER_DISTANCE_METHODS:
        raise ValueError(
            'method must be one of {}'.format(CLUSTER_DISTANCE_METHODS))

    if method == 'nearest':
        return __cluster_distances_by_points(labels, distances)
    elif method == 'farthest':
        return __cluster_distances_by_points(labels, distances, farthest=True)


def __cluster_distances_by_points(labels, distances, farthest=False):
    n_unique_labels = len(np.unique(labels))
    cluster_distances = np.full((n_unique_labels, n_unique_labels),
                                float('inf') if not farthest else 0)

    np.fill_diagonal(cluster_distances, 0)

    for i in np.arange(0, len(labels) - 1):
        for ii in np.arange(i, len(labels)):
            if labels[i] != labels[ii] and (
                (not farthest and
                 distances[i, ii] < cluster_distances[labels[i], labels[ii]])
                    or
                (farthest and
                 distances[i, ii] > cluster_distances[labels[i], labels[ii]])):
                cluster_distances[labels[i], labels[ii]] = cluster_distances[
                    labels[ii], labels[i]] = distances[i, ii]
    return cluster_distances


def diameter(labels, distances, method='farthest'):
    """Calculates cluster diameters
    :param labels: a list containing cluster labels for each of the n elements
    :param distances: an n x n numpy.array containing the pairwise distances between elements
    :param method: either `mean_cluster` for the mean distance between all elements in each clus
ter, or `farthest` for the distance between the two points furthest from each other
    """
    if method not in DIAMETER_METHODS:
        raise ValueError('method must be one of {}'.format(DIAMETER_METHODS))

    n_clusters = len(np.unique(labels))
    diameters = np.zeros(n_clusters)

    if method == 'mean_cluster':
        for i in range(0, len(labels) - 1):
            for ii in range(i + 1, len(labels)):
```

```
                if labels[i] == labels[ii]:
                    diameters[labels[i]] += distances[i, ii]

        for i in range(len(diameters)):
            diameters[i] /= sum(labels == i)

    elif method == 'farthest':
        for i in range(0, len(labels) - 1):
            for ii in range(i + 1, len(labels)):
                if labels[i] == labels[ii] and distances[i, ii] > diameters[
                        labels[i]]:
                    diameters[labels[i]] = distances[i, ii]
    return diameters


def dunn(labels, distances, diameter_method='farthest',
         cdist_method='nearest'):
    """
    Dunn index for cluster validation (larger is better).

    .. math:: D = \\min_{i = 1 \\ldots n_c; j = i + 1\ldots n_c} \\left\\lbrace \\frac{d \\left( c_i,c_j \\right)}{\\max_{k = 1 \\ldots n_c} \\left(diam \\left(c_k \\right) \\right)} \\right\\rbrace

    where :math:`d(c_i,c_j)` represents the distance between
    clusters :math:`c_i` and :math:`c_j`, and :math:`diam(c_k)` is the diameter of cluster :math:`c_k`.
    Inter-cluster distance can be defined in many ways, such as the distance between cluster centroids or between their closest elements. Cluster diameter can be defined as the mean distance between all elements in the cluster, between all elements to the cluster centroid, or as the distance between the two furthest elements.
    The higher the value of the resulting Dunn index, the better the clustering
    result is considered, since higher values indicate that clusters are
    compact (small :math:`diam(c_k)`) and far apart (large :math:`d \\left( c_i,c_j \\right)`).
    :param labels: a list containing cluster labels for each of the n elements
    :param distances: an n x n numpy.array containing the pairwise distances between elements
    :param diameter_method: see :py:function:`diameter` `method` parameter
    :param cdist_method: see :py:function:`diameter` `method` parameter

    .. [Kovacs2005] Kovács, F., Legány, C., & Babos, A. (2005). Cluster validity measurement techniques. 6th International Symposium of Hungarian Researchers on Computational Intelligence.
    """

    labels = LabelEncoder().fit(labels).transform(labels)

    ic_distances = inter_cluster_distances(labels, distances, cdist_method)
    min_distance = min(ic_distances[ic_distances.nonzero()])
    max_diameter = max(diameter(labels, distances, diameter_method))

    return min_distance / max_diameter
```

原始计算

In [7]:

```
from sklearn.metrics.pairwise import euclidean_distances
from sklearn.metrics import *
from sklearn.datasets import load_iris
from sklearn.cluster import KMeans

kmeans = KMeans(n_clusters=3)
k = kmeans.fit_predict(x.iloc[:,0:4].values,y)
d = euclidean_distances(x.iloc[:,0:4].values)
dunk = dunn(k, d)
acc=accuracy_score(y,k)
```

In [8]:

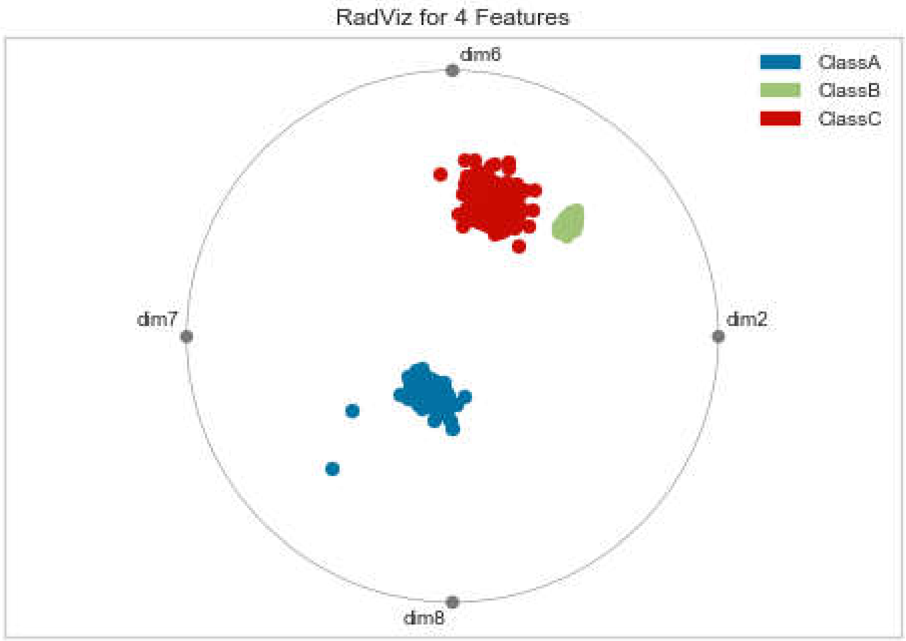
```
display(dunk)
display(acc)
```

0.9080528404189566

0.3971428571428571З

In [9]:

```
features=["dim2","dim6","dim7","dim8"]
classes=["ClassA","ClassB","ClassC"]
visualizer = RadViz(classes= classes, features= features)
# Fit the data to the visualizer
visualizer.fit(x.iloc[:,0:4].values, y.values)
# Transform the data
visualizer.transform(x.iloc[:,0:4])
# Draw/show/poof the data
visualizer.poof()
```



Out[9]:

<matplotlib.axes._subplots.AxesSubplot at 0x19880555388>

加一个维度计算

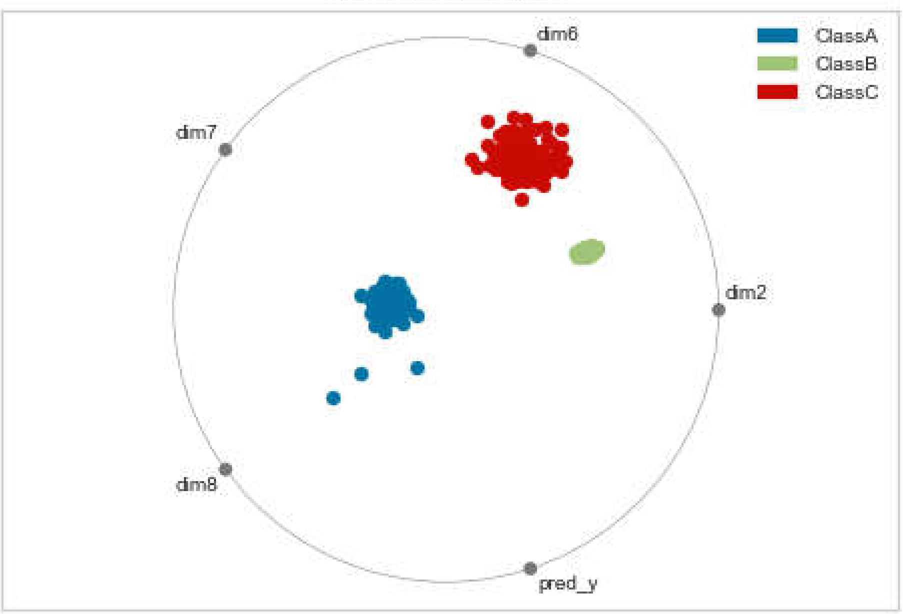
In [10]:

```
kmeans = KMeans(n_clusters=3)
k = kmeans.fit_predict(x.iloc[:,0:5].values)
d = euclidean_distances(x.iloc[:,0:5].values)
dunk = dunn(k, d)
acc=accuracy_score(y,k)
display(dunk)
display(acc)
features=["dim2","dim6","dim7","dim8","pred_y"]
classes=["ClassA","ClassB","ClassC"]
visualizer = RadViz(classes= classes, features= features)
# Fit the data to the visualizer
visualizer.fit(x.iloc[:,0:5].values, y.values)
# Transform the data
visualizer.transform(x.iloc[:,0:5])
# Draw/show/poof the data
visualizer.poof()
```

0.7294044389779202

0.3971428571428571 3

RadViz for 5 Features



Out[10]:

<matplotlib.axes._subplots.AxesSubplot at 0x198806362c8>

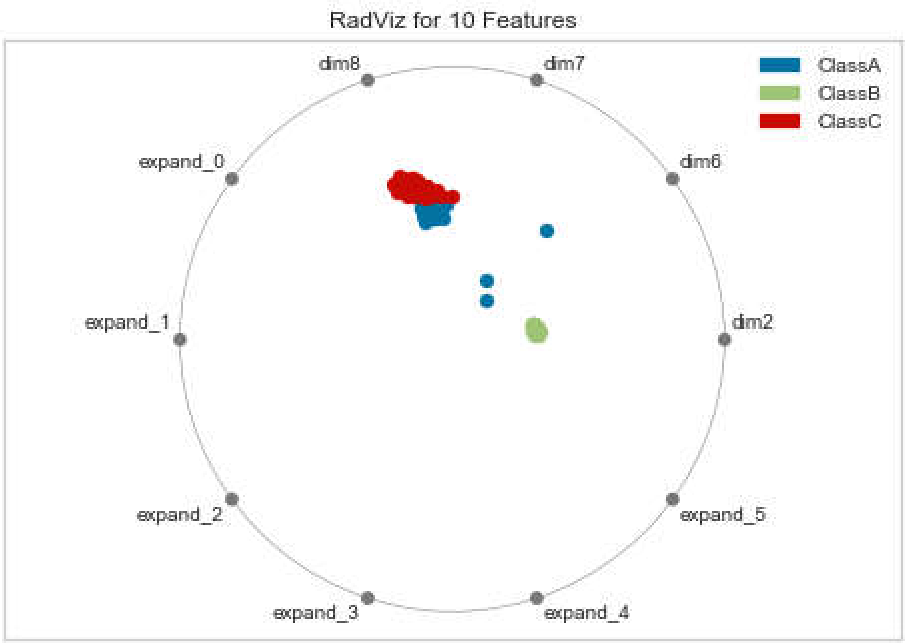
加二值化维度计算

In [11]:

```
kmeans = KMeans(n_clusters=3)
k = kmeans.fit_predict(x.drop(["pred_y"],axis=1).values)
d = euclidean_distances(x.drop(["pred_y"],axis=1).values)
dunk = dunn(k, d)
acc=accuracy_score(y,k)
display(dunk)
display(acc)
features=["dim2","dim6","dim7","dim8","expand_0","expand_1","expand_2","expand_3","expand_4","ex
pand_5"]
classes=["ClassA","ClassB","ClassC"]
visualizer = RadViz(classes= classes, features= features)
# Fit the data to the visualizer
visualizer.fit(x.drop(["pred_y"],axis=1).values, y.values)
# Transform the data
visualizer.transform(x.drop(["pred_y"],axis=1))
# Draw/show/poof the data
visualizer.poof()
```

0.9779077599122492

0.21142857142857144



Out[11]:

<matplotlib.axes._subplots.AxesSubplot at 0x198806a9c48>

数据集iris

In [12]:

```
df=pd.read_csv("PaperData-软件学报-iris-normalization.csv")
df.head()
```

Out[12]:

	id	col1	col2	col3	col4	className	classId
0	1	0.722	0.523	0.145	0.04	Iris-setosa	1
1	2	0.696	0.455	0.159	0.04	Iris-setosa	1
2	3	0.734	0.523	0.174	0.04	Iris-setosa	1
3	4	0.684	0.545	0.174	0.04	Iris-setosa	1
4	5	0.696	0.545	0.188	0.04	Iris-setosa	1

In [13]:

```
df=df.drop(["id","className"],axis=1)
df.head()
```

Out[13]:

	col1	col2	col3	col4	classId
0	0.722	0.523	0.145	0.04	1
1	0.696	0.455	0.159	0.04	1
2	0.734	0.523	0.174	0.04	1
3	0.684	0.545	0.174	0.04	1
4	0.696	0.545	0.188	0.04	1

In [14]:

```
x=df.iloc[:,:-1]
y=df.iloc[:,-1]
```

In [15]:

```
# 均值漂移实现聚类划分

bw = sc.estimate_bandwidth(x, n_samples=len(x), quantile=0.2)
model = sc.MeanShift(bandwidth=bw)

model.fit(x)
centers = model.cluster_centers_
print(centers)
pred_y = model.predict(x)
x["pred_y"]=pred_y
x=pd.merge(x,pd.get_dummies(x["pred_y"], prefix="expand"), left_index=True, right_index=True)
x=(x-x.min())/(x.max()-x.min())
x
```

```
[[0.75920833 0.5894375  0.20997917 0.09333333]
 [0.74407143 0.69171429 0.62045238 0.52952381]
 [0.67017647 0.75544118 0.72082353 0.68117647]
 [0.8899     0.7682     0.8307     0.852     ]]
```

Out[15]:

	col1	col2	col3	col4	pred_y	expand_0	expand_1	expand_2	expan
0	0.390351	0.124771	0.000000	0.000000	0.0	1.0	0.0	0.0	
1	0.333333	0.000000	0.016374	0.000000	0.0	1.0	0.0	0.0	
2	0.416667	0.124771	0.033918	0.000000	0.0	1.0	0.0	0.0	
3	0.307018	0.165138	0.033918	0.000000	0.0	1.0	0.0	0.0	
4	0.333333	0.165138	0.050292	0.000000	0.0	1.0	0.0	0.0	
...	...	...	...	...	...	...	...	...	
145	0.945175	0.583486	0.915789	0.958333	1.0	0.0	0.0	0.0	
146	0.083333	0.666055	0.949708	0.958333	1.0	0.0	0.0	0.0	
147	0.140351	0.623853	0.966082	1.000000	1.0	0.0	0.0	0.0	
148	0.195175	0.708257	0.966082	1.000000	1.0	0.0	0.0	0.0	
149	0.721491	0.750459	1.000000	1.000000	1.0	0.0	0.0	0.0	

150 rows × 9 columns

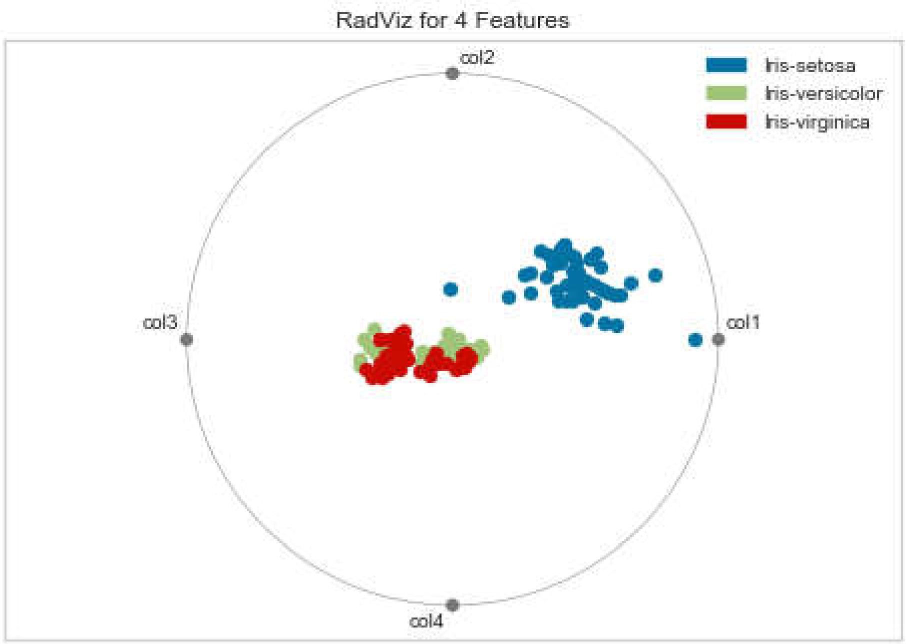
原始计算

In [16]:

```
kmeans = KMeans(n_clusters=3)
k = kmeans.fit_predict(x.iloc[:,0:4].values)
d = euclidean_distances(x.iloc[:,0:4].values)
dunk = dunn(k, d)
acc=accuracy_score(y,k)
display(dunk)
display(acc)
features=["col1","col2","col3","col4"]
classes=['Iris-setosa', 'Iris-versicolor', 'Iris-virginica']
visualizer = RadViz(classes= classes, features= features)
# Fit the data to the visualizer
visualizer.fit(x.iloc[:,0:4].values, y.values)
# Transform the data
visualizer.transform(x.iloc[:,0:4])
# Draw/show/poof the data
visualizer.poof()
```

0.142419234632111803

0.5666666666666667



Out[16]:

<matplotlib.axes._subplots.AxesSubplot at 0x19880689848>

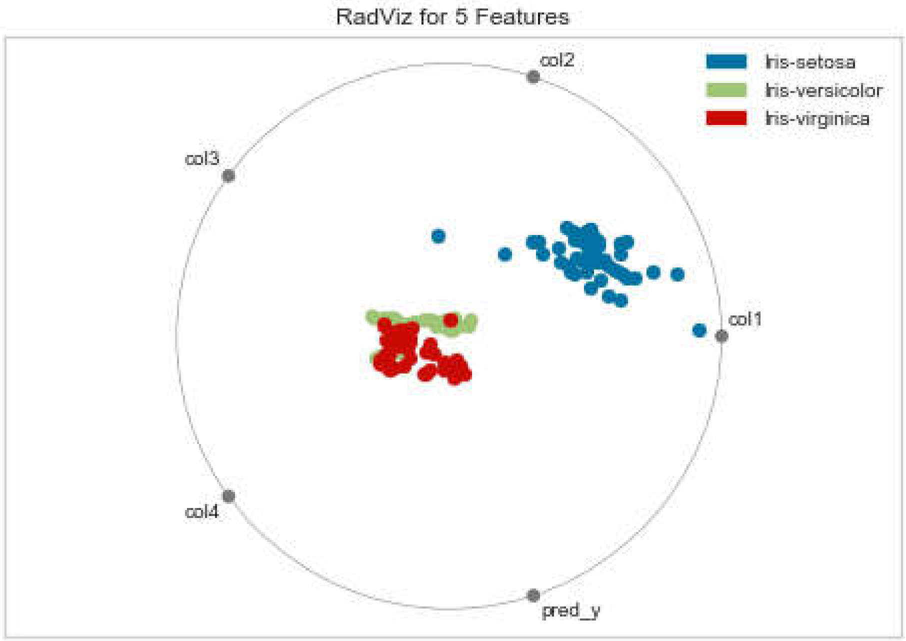
加一个维度计算

In [17]:

```
kmeans = KMeans(n_clusters=3)
k = kmeans.fit_predict(x.iloc[:,0:5].values)
d = euclidean_distances(x.iloc[:,0:5].values)
dunk = dunn(k, d)
acc=accuracy_score(y,k)
display(dunk)
display(acc)
features=["col1","col2","col3","col4","pred_y"]
classes=['Iris-setosa', 'Iris-versicolor', 'Iris-virginica']
visualizer = RadViz(classes= classes, features= features)
# Fit the data to the visualizer
visualizer.fit(x.iloc[:,0:5].values, y.values)
# Transform the data
visualizer.transform(x.iloc[:,0:5])
# Draw/show/poof the data
visualizer.poof()
```

0.308807437099932656

0.0



Out[17]:

<matplotlib.axes._subplots.AxesSubplot at 0x19880690688>

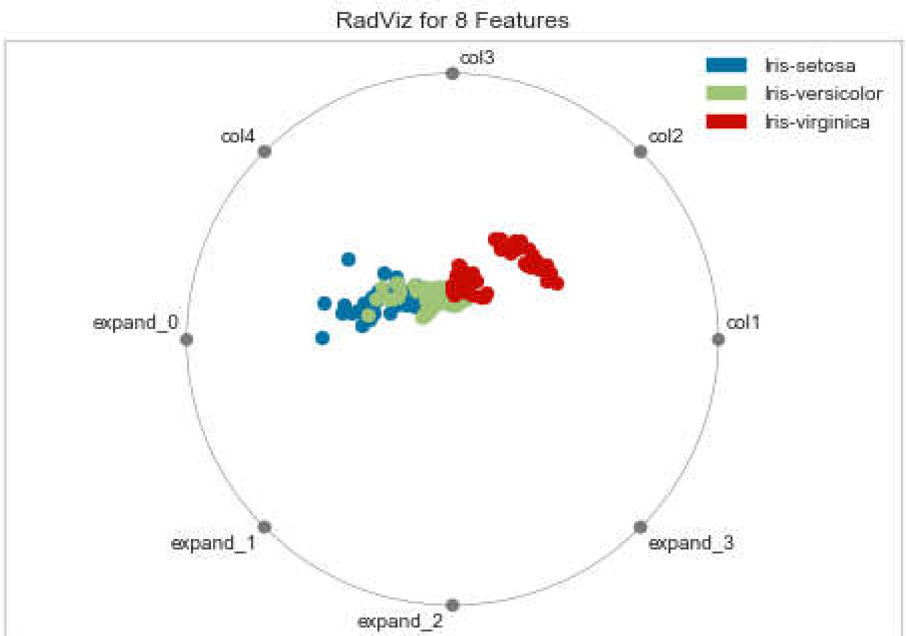
加二值化维度计算

In [18]:

```
kmeans = KMeans(n_clusters=3)
k = kmeans.fit_predict(x.drop(["pred_y"],axis=1).values)
d = euclidean_distances(x.drop(["pred_y"],axis=1).values)
dunk = dunn(k, d)
acc=accuracy_score(y,k)
display(dunk)
display(acc)
features=["col1","col2","col3","col4","expand_0","expand_1","expand_2","expand_3"]
classes=['Iris-setosa', 'Iris-versicolor', 'Iris-virginica']
visualizer = RadViz(classes= classes, features= features)
# Fit the data to the visualizer
visualizer.fit(x.drop(["pred_y"],axis=1).values, y.values)
# Transform the data
visualizer.transform(x.drop(["pred_y"],axis=1))
# Draw/show/poof the data
visualizer.poof()
```

0.7994737291087812

0.6266666666666667



Out[18]:

<matplotlib.axes._subplots.AxesSubplot at 0x1988081d148>

In [ ]: