clustering-coping

May 29, 2024

1 K-Means Clustering for Brief COPE Questionnaire

In this project, we apply the k-means clustering algorithm to cluster the coping strategies. The goal is to identify distinct groups of **coping strategies** that influence `resilience`. To do this, we first use different feature selection methods to extract important strategies that influence `resilience`. Then, we employ k-means clustering to cluster these coping strategies. Finally, by comparing the obtained clusters, strategies that can improve resilience are introduced.

[2]:
```
# Imports

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

from sklearn.datasets import make_blobs
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from mpl_toolkits.mplot3d import Axes3D
import seaborn as sns
import pyreadstat
import warnings
warnings.filterwarnings('ignore')
```

[33]:
```
df, meta=pyreadstat.read_sav('konzas2.sav')
```

[34]:
```
df.head(3)
```

[34]:
```
   wb1  wb2  wb3  wb4  wb5  wb6  wb7  wb8  wb9  wb10  …  \
0  2.0  2.0  3.0  3.0  3.0  2.0  3.0  4.0  2.0   3.0  …
1  4.0  5.0  4.0  5.0  4.0  3.0  4.0  4.0  4.0   3.0  …
2  3.0  3.0  3.0  3.0  3.0  3.0  3.0  3.0  3.0   3.0  …

   Behavioral_disengagement  Venting  Positive_reframing  Planning  Humor  \
0                       2.0      4.0                 4.0       4.0    4.0
1                       3.0      5.0                 3.0       1.0    3.0
2                       3.0      2.0                 3.0       3.0    1.0
```

```
   Acceptance  Religion  Self_blame   res  well
0         4.0       3.0         4.0  62.0  42.0
1         4.0       4.0         3.0  80.0  56.0
2         4.0       2.0         2.0  68.0  44.0

[3 rows x 74 columns]
```

[35]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 255 entries, 0 to 254
Data columns (total 74 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   wb1                        255 non-null    float64
 1   wb2                        253 non-null    float64
 2   wb3                        254 non-null    float64
 3   wb4                        254 non-null    float64
 4   wb5                        254 non-null    float64
 5   wb6                        253 non-null    float64
 6   wb7                        254 non-null    float64
 7   wb8                        254 non-null    float64
 8   wb9                        253 non-null    float64
 9   wb10                       254 non-null    float64
 10  wb11                       254 non-null    float64
 11  wb12                       254 non-null    float64
 12  wb13                       254 non-null    float64
 13  wb14                       254 non-null    float64
 14  rs1                        254 non-null    float64
 15  rs2                        254 non-null    float64
 16  rs3                        254 non-null    float64
 17  rs4                        254 non-null    float64
 18  rs5                        254 non-null    float64
 19  rs6                        254 non-null    float64
 20  rs7                        254 non-null    float64
 21  rs8                        254 non-null    float64
 22  rs9                        254 non-null    float64
 23  rs10                       254 non-null    float64
 24  rs11                       254 non-null    float64
 25  rs12                       254 non-null    float64
 26  rs13                       254 non-null    float64
 27  rs14                       254 non-null    float64
 28  coping1                    254 non-null    float64
 29  coping2                    254 non-null    float64
 30  coping3                    254 non-null    float64
 31  coping4                    254 non-null    float64
```

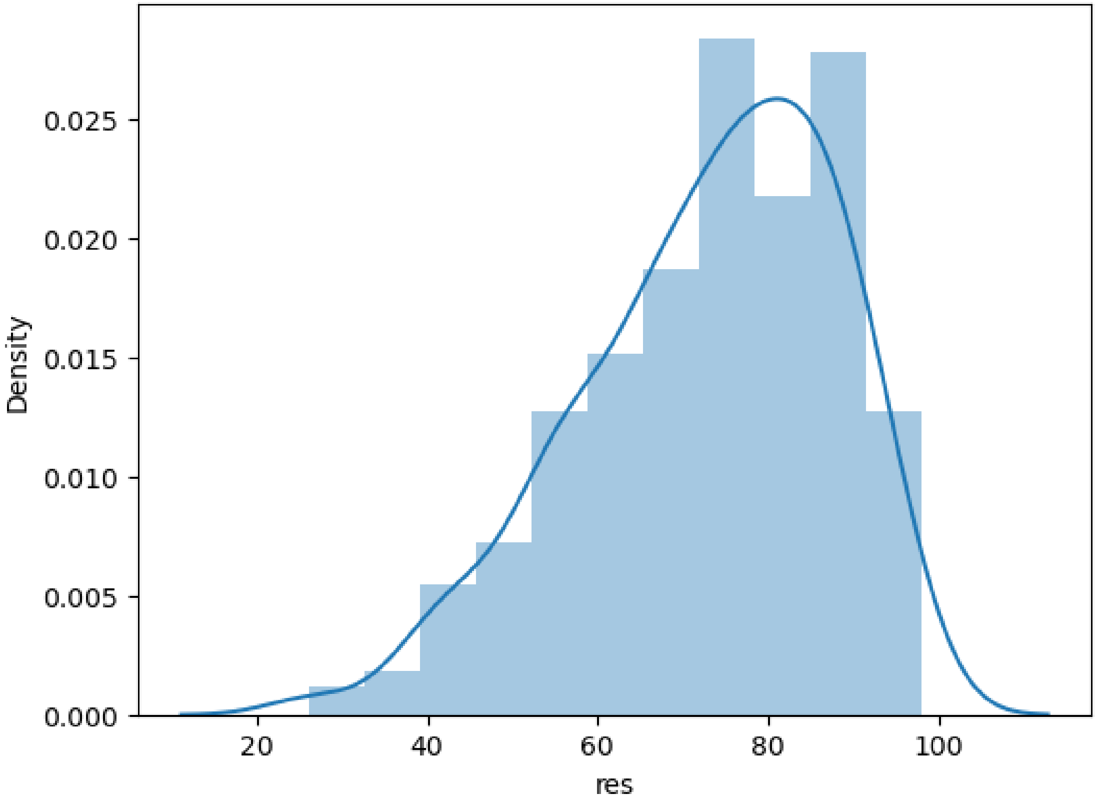
```
 32  coping5                    254 non-null    float64
 33  coping6                    254 non-null    float64
 34  coping7                    254 non-null    float64
 35  coping8                    254 non-null    float64
 36  coping9                    254 non-null    float64
 37  coping10                   254 non-null    float64
 38  coping11                   254 non-null    float64
 39  coping12                   254 non-null    float64
 40  coping13                   254 non-null    float64
 41  coping14                   254 non-null    float64
 42  coping15                   254 non-null    float64
 43  coping16                   254 non-null    float64
 44  coping17                   254 non-null    float64
 45  coping18                   254 non-null    float64
 46  coping19                   254 non-null    float64
 47  coping20                   254 non-null    float64
 48  coping21                   254 non-null    float64
 49  coping22                   254 non-null    float64
 50  coping23                   254 non-null    float64
 51  coping24                   254 non-null    float64
 52  coping25                   254 non-null    float64
 53  coping26                   254 non-null    float64
 54  coping27                   254 non-null    float64
 55  coping28                   254 non-null    float64
 56  sex                        254 non-null    float64
 57  age                        254 non-null    float64
 58  Self_distraction           254 non-null    float64
 59  Active_coping              254 non-null    float64
 60  Denial                     254 non-null    float64
 61  Substance_use              254 non-null    float64
 62  Emotional_support          254 non-null    float64
 63  UIS                        254 non-null    float64
 64  Behavioral_disengagement   254 non-null    float64
 65  Venting                    254 non-null    float64
 66  Positive_reframing         254 non-null    float64
 67  Planning                   254 non-null    float64
 68  Humor                      254 non-null    float64
 69  Acceptance                 254 non-null    float64
 70  Religion                   254 non-null    float64
 71  Self_blame                 254 non-null    float64
 72  res                        254 non-null    float64
 73  well                       254 non-null    float64
dtypes: float64(74)
memory usage: 147.6 KB
```

[36]:
```
df=df.dropna()
```

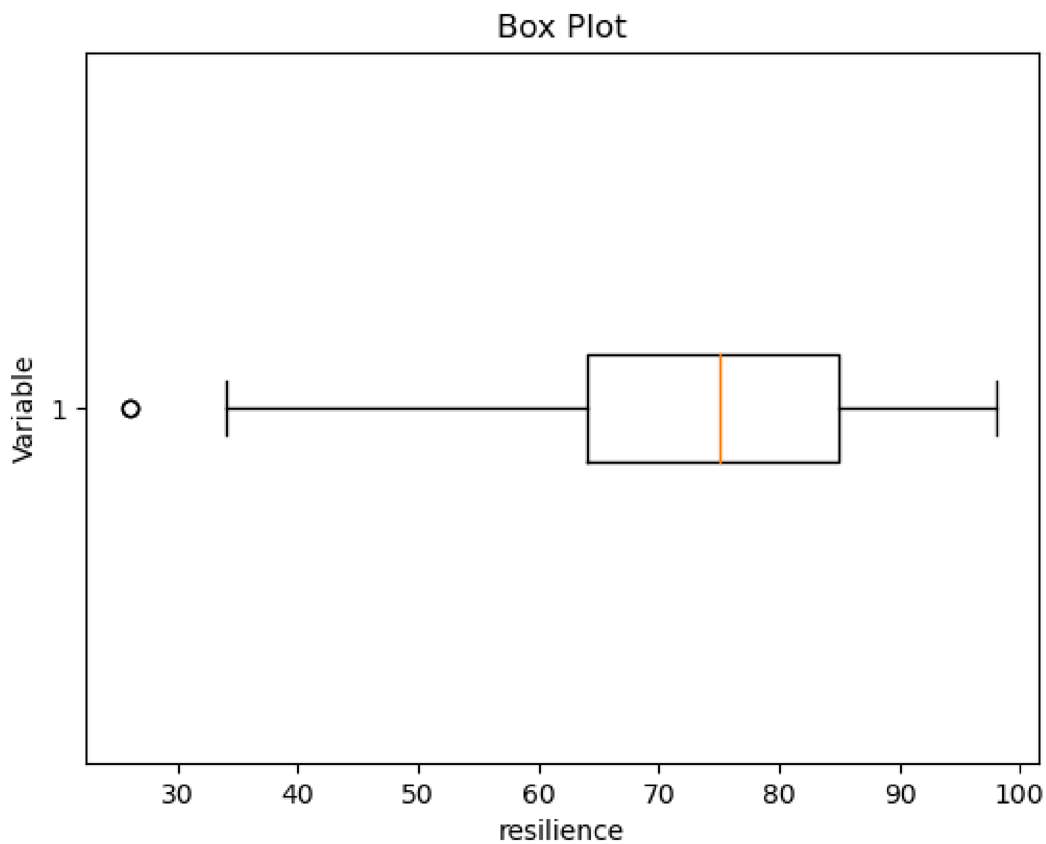
[37]:
```
y=df['res']
X=df[['Self_distraction','Active_coping','Denial','Substance_use','Emotional_support','UIS','E
```

[38]:
```
sns.distplot(y)
```

[38]: <Axes: xlabel='res', ylabel='Density'>



[39]:
```
plt.boxplot(y, vert=False)
plt.ylabel('Variable')
plt.xlabel('resilience')
plt.title('Box Plot')
plt.show()
```



[40]:
```
df1=df[['res','Self_distraction','Active_coping','Denial','Substance_use','Emotional_support',
df1.head(3)
```

[40]:
```
    res  Self_distraction  Active_coping  Denial  Substance_use  \
0  62.0               2.0            4.0     2.0            0.0
1  80.0               5.0            4.0     4.0            2.0
2  68.0               4.0            3.0     2.0            1.0

   Emotional_support  UIS  Behavioral_disengagement  Venting  \
0                4.0  4.0                       2.0      4.0
1                2.0  6.0                       3.0      5.0
2                4.0  3.0                       3.0      2.0

   Positive_reframing  Planning  Humor  Acceptance  Religion  Self_blame
0                 4.0       4.0    4.0         4.0       3.0         4.0
1                 3.0       1.0    3.0         4.0       4.0         3.0
2                 3.0       3.0    1.0         4.0       2.0         2.0
```

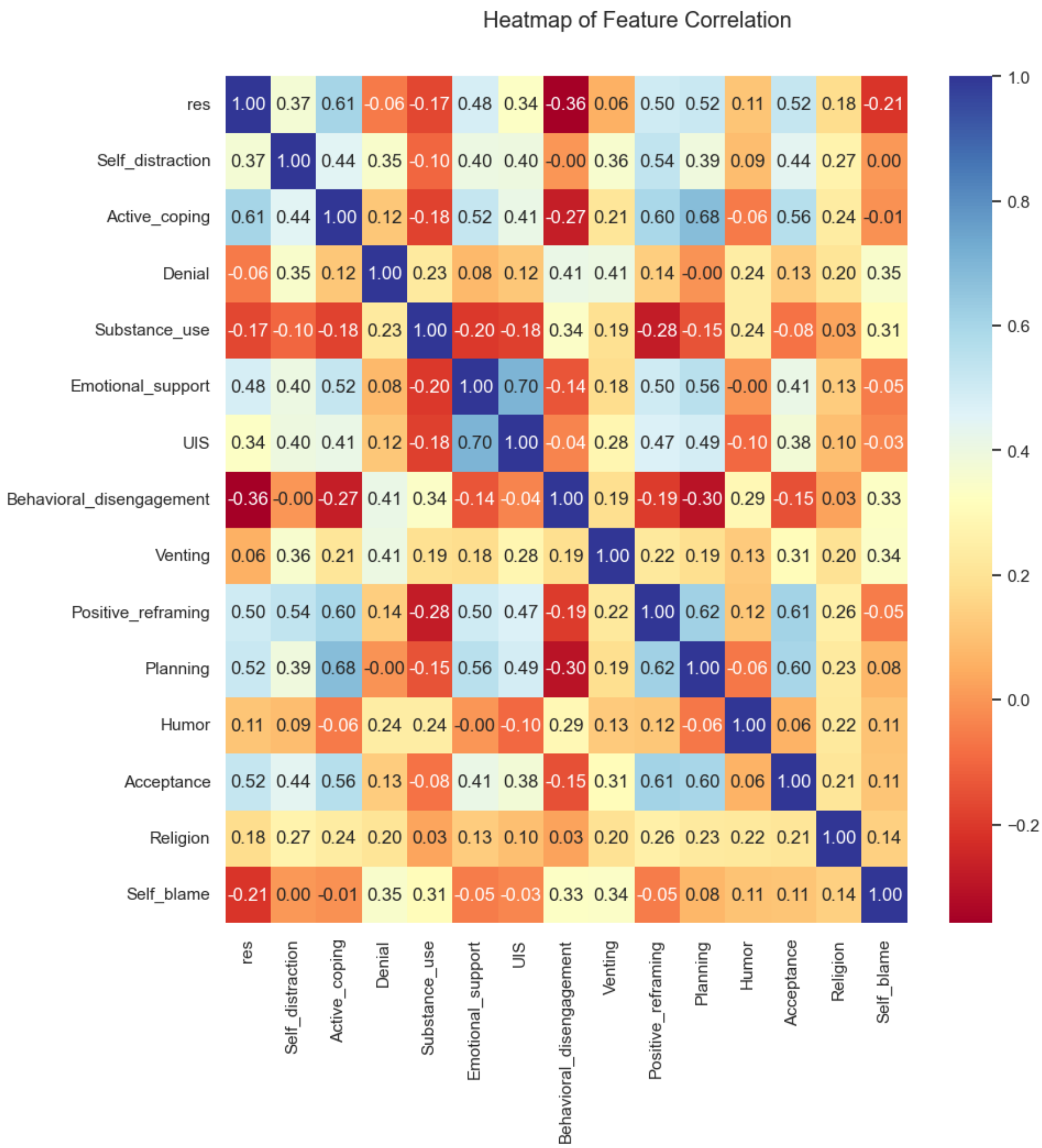
1.1 1. Feature selection

There are several feature selection methods commonly used in machine learning. Here, we employ a few popular ones in order to identify the most important features that can affect "resilience"

1.2 1.1: Correlations

Features that have high correlation with the target variable are considered important.

[41]:
```
sns.set_theme(style="whitegrid")
chart = 'Heatmap of Feature Correlation'

plt.figure(figsize=(10, 10))
plt.suptitle(f'{chart}', y=0.94)

# plotting a heatmap of feature correlation
sns.heatmap(df1.corr(), cmap='RdYlBu', annot=True, fmt='0.2f')
plt.show()
```



It is observed that the variables 'Self_distraction', 'Active_coping', 'Emotional_support', 'UIS', 'Behavioral_disengagement', 'Positive_reframing', 'Planning', 'Acceptance' have substantial correlation with "resilience".

1.3 1.2: L1 Regularization (Lasso)

L1 regularization can be used to induce sparsity in the model coefficients, effectively selecting a subset of features.

[42]:
```
from numpy import arange
from sklearn.model_selection import GridSearchCV
```

```
from sklearn.linear_model import Lasso
from sklearn.model_selection import RepeatedKFold
```

[43]:
```
model = Lasso()
# define model evaluation method
cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=10)
# define grid
grid = dict()
grid['alpha'] = arange(0, 1, 0.01)
# define search
search = GridSearchCV(model, grid, scoring='neg_mean_absolute_error', cv=cv,␣
↪n_jobs=-1)
# perform the search
results = search.fit(X, y)
# summarize
print('Config: %s' % results.best_params_)
```

```
Config: {'alpha': 0.43}
```

[26]:
```
model = Lasso(alpha=0.43)
model1=model.fit(X, y)
```

[27]:
```
pd.Series(model1.coef_, index = X.columns )
```

[27]:
```
Self_distraction             0.567773
Active_coping                3.325780
Denial                      -0.443956
Substance_use                0.053021
Emotional_support            1.465823
UIS                          0.000000
Behavioral_disengagement    -1.588137
Venting                     -0.305732
Positive_reframing           0.000000
Planning                     0.094181
Humor                        1.495374
Acceptance                   2.207096
Religion                     0.030261
Self_blame                  -1.285680
dtype: float64
```

The features whose coefficients in the Lasso regression model are far from zero are: 'Active_coping', 'Emotional_support', 'Behavioral_disengagement', 'Humor', 'Acceptance' and 'Self_blame'.

1.4 1.3: Recursive Feature Elimination (RFE)

RFE works by recursively eliminating the least important features based on model performance. It starts with all features, trains the model, and ranks the features by importance. Then, it removes the least important feature and repeats the process until a specified number of features remains.

[28]:
```python
from sklearn.feature_selection import RFE
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import KFold
```

[29]:
```python
# step-1: create a cross-validation scheme
folds = KFold(n_splits = 5, shuffle = True, random_state = 10)

# step-2: specify range of hyperparameters to tune
hyper_params = [{'n_features_to_select': list(range(1, 10))}]


# step-3: perform grid search
# 3.1 specify model
lm = RandomForestRegressor()
lm.fit(X, y)
rfe = RFE(lm)

# 3.2 call GridSearchCV()
model_cv = GridSearchCV(estimator = rfe,
                        param_grid = hyper_params,
                        scoring= 'r2',
                        cv = folds,
                        verbose = 1,
                        return_train_score=True)

# fit the model
model_cv.fit(X, y)
```

```
Fitting 5 folds for each of 9 candidates, totalling 45 fits
```

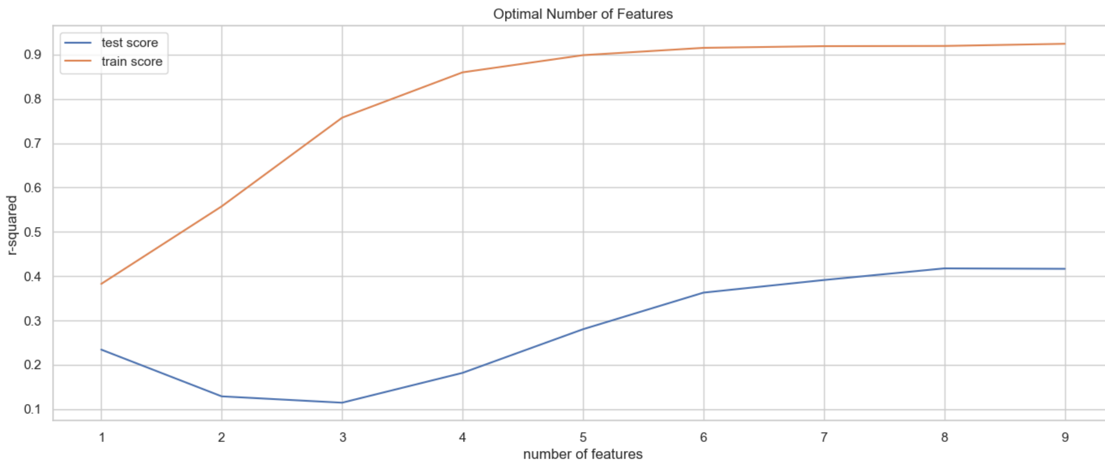
[29]:
```
GridSearchCV(cv=KFold(n_splits=5, random_state=10, shuffle=True),
             estimator=RFE(estimator=RandomForestRegressor()),
             param_grid=[{'n_features_to_select': [1, 2, 3, 4, 5, 6, 7, 8, 9]}],
             return_train_score=True, scoring='r2', verbose=1)
```

[31]:
```python
# cv results
cv_results = pd.DataFrame(model_cv.cv_results_)
```

[32]:
```python
# plotting cv results
plt.figure(figsize=(16,6))

plt.plot(cv_results["param_n_features_to_select"],␣
 ↪cv_results["mean_test_score"])
plt.plot(cv_results["param_n_features_to_select"],␣
 ↪cv_results["mean_train_score"])
plt.xlabel('number of features')
plt.ylabel('r-squared')
```

```
plt.title("Optimal Number of Features")
plt.legend(['test score', 'train score'], loc='upper left')
```

[32]: <matplotlib.legend.Legend at 0x19795bcf8d0>



The results recommend to select six features.

1.5 1.4: Feature Importance by Random Forest

This method ranks the features based on their importance derived from a specific model.

[33]:
```
from sklearn.metrics import r2_score
```

[34]:
```
# final model
n_features_optimal = 6

lm = RandomForestRegressor()
lm.fit(X, y)

rfe = RFE(lm, n_features_to_select=n_features_optimal)
rfe = rfe.fit(X, y)

# predict prices of X_test
y_pred = lm.predict(X)
r2 = r2_score(y, y_pred)
print(r2)
```

0.9254329587711181

[35]:
```
pd.Series(lm.feature_importances_, index = X.columns )
```

[35]:
```
Self_distraction            0.036410
Active_coping               0.228135
Denial                      0.031765
Substance_use               0.039899
Emotional_support           0.095199
UIS                         0.035931
Behavioral_disengagement    0.086747
Venting                     0.028020
Positive_reframing          0.112623
Planning                    0.083223
Humor                       0.042597
Acceptance                  0.082123
Religion                    0.027418
Self_blame                  0.069911
dtype: float64
```

Active_coping, Planning , Emotional_support, Positive_reframing, Behavioral_disengagement, Acceptance and Self_blame can be select by this method.

1.6 1.5: SelectFromModel

SelectFromModel is a meta-transformer that can be used with any estimator that has a coef_ or feature_importances_ attribute. It selects the features based on a specified threshold.

[36]:
```python
from sklearn.feature_selection import SelectFromModel
```

[37]:
```python
sel_ = SelectFromModel(RandomForestRegressor(random_state=10))
sel_.fit(X, y)
selected_feat = X.columns[(sel_.get_support())]
len(selected_feat)
```

[37]:
```
6
```

[38]:
```python
selected_feat
```

[38]:
```
Index(['Active_coping', 'Emotional_support', 'Behavioral_disengagement',
       'Positive_reframing', 'Planning', 'Acceptance'],
      dtype='object')
```

1.6.1 Visualizing lasso results

[39]:
```python
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
```

[40]:
```python
betas = []
penalties = [0.001, 0.01, 0.5, 1, 10]
```

```
for penalty in penalties:

    pipe = Pipeline([

        ("lasso", Lasso(alpha=penalty, random_state=10))
    ])

    pipe.fit(X, y)

    betas.append(pd.Series(pipe.named_steps["lasso"].coef_))

betas = pd.concat(betas, axis=1)
betas.columns = [f"{penalty}" for penalty in penalties]
betas.index = X.columns

betas.head()
```

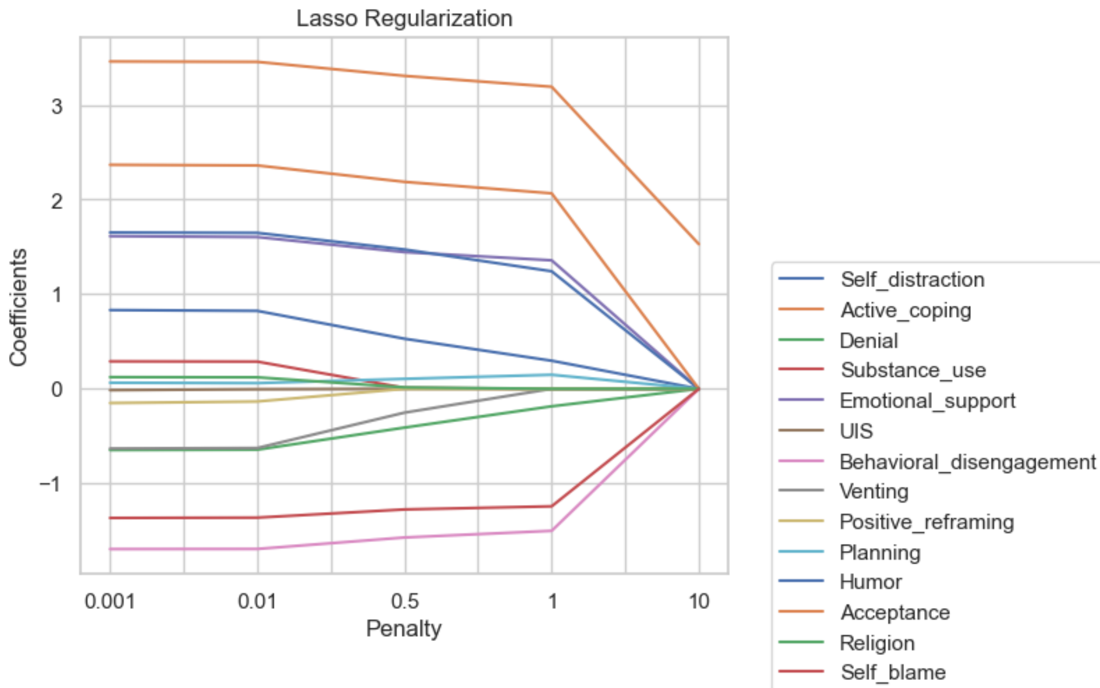
[40]:

	0.001	0.01	0.5	1	10
Self_distraction	0.832532	0.823992	0.529452	0.297074	0.000000
Active_coping	3.459603	3.455538	3.307433	3.192340	1.529051
Denial	-0.646760	-0.643246	-0.409725	-0.184660	-0.000000
Substance_use	0.290303	0.287816	0.010363	0.000000	-0.000000
Emotional_support	1.613288	1.603848	1.444680	1.358170	0.000000

[41]:

```
betas.T.plot(figsize=(6,5), legend=False)

plt.ylabel("Coefficients")
plt.xlabel("Penalty")
plt.title("Lasso Regularization")
# add legends and set its box position
plt.legend(X.columns,
           bbox_to_anchor = (1.05, 0.6))
```

[41]: <matplotlib.legend.Legend at 0x19795b49c50>



The features whose coefficients in the Lasso regression model are far from zero are: 'Active_coping', 'Emotional_support', 'Behavioral_disengagement', 'Humor', 'Acceptance' and 'Self_blame'.

Summary of feature selection: The main features that are particularly important in influencing resilience are: Active_coping, Planning , Emotional_support, Positive_reframing, Acceptance, Behavioral_disengagement, Humor, Self_blame

2 2: K-means clustering

Once the relevant coping strategies are identified, we utilize the k-means clustering algorithm to group them into distinct clusters based on their similarities.

[8]:
```
# dataframe of interested variables

df2=df[['sex', 'age',
       'Active_coping','Emotional_support', 'Behavioral_disengagement',
       'Positive_reframing','Planning','Humor','Acceptance','Self_blame','res']]
```

[9]:
```
# features
col_names = [ 'Active_coping', 'Emotional_support', 'Behavioral_disengagement',
       'Positive_reframing', 'Humor', 'Acceptance', 'Self_blame', 'Planning']
features = df2[col_names]
```

[44]:
```
features
```

[44]:

```
     Active_coping  Emotional_support  Behavioral_disengagement  \
0              4.0                4.0                       2.0
1              4.0                2.0                       3.0
2              3.0                4.0                       3.0
3              4.0                3.0                       3.0
4              4.0                3.0                       3.0
..             …                …                         …
248            3.0                4.0                       4.0
249            2.0                4.0                       3.0
250            3.0                2.0                       4.0
251            5.0                4.0                       2.0
252            6.0                4.0                       3.0

     Positive_reframing  Humor  Acceptance  Self_blame  Planning
0                   4.0    4.0         4.0         4.0       4.0
1                   3.0    3.0         4.0         3.0       1.0
2                   3.0    1.0         4.0         2.0       3.0
3                   4.0    5.0         4.0         2.0       3.0
4                   5.0    3.0         6.0         3.0       4.0
..                  …    …         …         …       …
248                 2.0    1.0         3.0         3.0       3.0
249                 3.0    6.0         5.0         6.0       3.0
250                 2.0    3.0         3.0         5.0       4.0
251                 2.0    3.0         6.0         3.0       4.0
252                 6.0    1.0         6.0         1.0       5.0

[253 rows x 8 columns]
```

2.1 2.1: Number of clusters

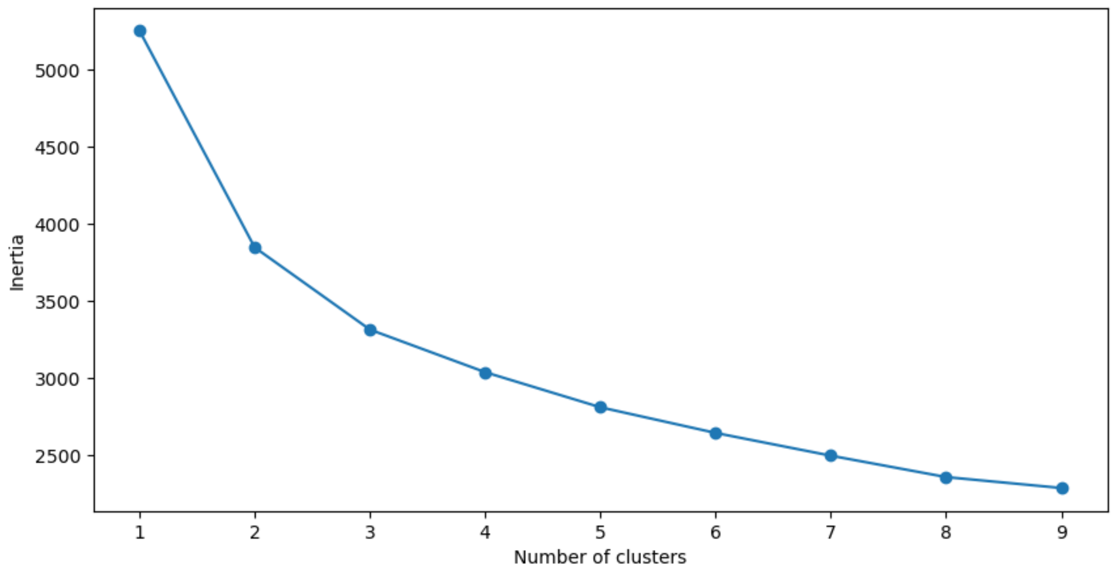
An important aspect of k-means algorithm is the selection of the desired number of clusters, denoted as **k**. Several methods and heuristics exist to estimate the optimal number of clusters, such as the *elbow method* or *silhouette analysis*. Here, The `elbow method` is utilized to examine different number of clusters.

[11]:

```
SSE = []

for cluster in range(1,10):
    kmeans = KMeans( n_clusters = cluster, init='k-means++')
    kmeans.fit(features)
    SSE.append(kmeans.inertia_)

# converting the results into a dataframe and plotting them

frame = pd.DataFrame({'Cluster':range(1,10), 'SSE':SSE})
plt.figure(figsize=(10,5))
plt.plot(frame['Cluster'], frame['SSE'], marker='o')
```

```
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')
```

[11]: Text(0, 0.5, 'Inertia')



The point on the plot where the WCSS (Interia) starts to decrease at a slower rate is considered the elbow of the plot. The corresponding value of k at this point is considered the optimal number of clusters. So, it is observed from the elbow plot that choosing three clusters is suitable.

2.2 2.2: Conduct k-means

[23]:
```
kmeans = KMeans( n_clusters = 3, init='k-means++')
kmeans.fit(features)
```

[23]: KMeans(n_clusters=3)

[24]:
```
clusters = kmeans.fit_predict(features.iloc[:,:])
df2["label"] = clusters
```

[25]:
```
df2.head(3)
```

[25]:
```
   sex   age  Active_coping  Emotional_support  Behavioral_disengagement  \
0  2.0  17.0            4.0                4.0                       2.0
1  2.0  16.0            4.0                2.0                       3.0
2  2.0  15.0            3.0                4.0                       3.0

   Positive_reframing  Planning  Humor  Acceptance  Self_blame   res  label
0                 4.0       4.0    4.0         4.0         4.0  62.0      2
```

```
1                  3.0       1.0    3.0         4.0         3.0  80.0      0
2                  3.0       3.0    1.0         4.0         2.0  68.0      0
```

[26]:
```
avg_df = df2.groupby(['label'], as_index=False).mean()
avg_df
```

[26]:
```
   label       sex        age  Active_coping  Emotional_support  \
0      0  1.718310  16.084507       2.718310           2.619718
1      1  1.629630  16.500000       5.120370           4.675926
2      2  1.716216  16.364865       4.486486           4.310811

   Behavioral_disengagement  Positive_reframing  Planning     Humor  \
0                  2.577465            2.070423  2.183099  2.253521
1                  0.740741            4.574074  4.842593  1.814815
2                  3.162162            4.432432  4.310811  3.797297

   Acceptance  Self_blame        res
0    2.732394    2.676056  58.788732
1    4.805556    1.962963  80.814815
2    4.716216    4.000000  74.824324
```

[18]:
```
# the mean of resilience for men(1) and women(2)
Sex=df2['sex']
df2['res'].groupby(df2['sex']).mean()
```

[18]:
```
sex
1.0    71.493827
2.0    73.534884
Name: res, dtype: float64
```

[19]:
```
# the mean of age in each cluster
df2['age'].groupby(df2['label']).mean()
```

[19]:
```
label
0    16.495146
1    16.054054
2    16.421053
Name: age, dtype: float64
```

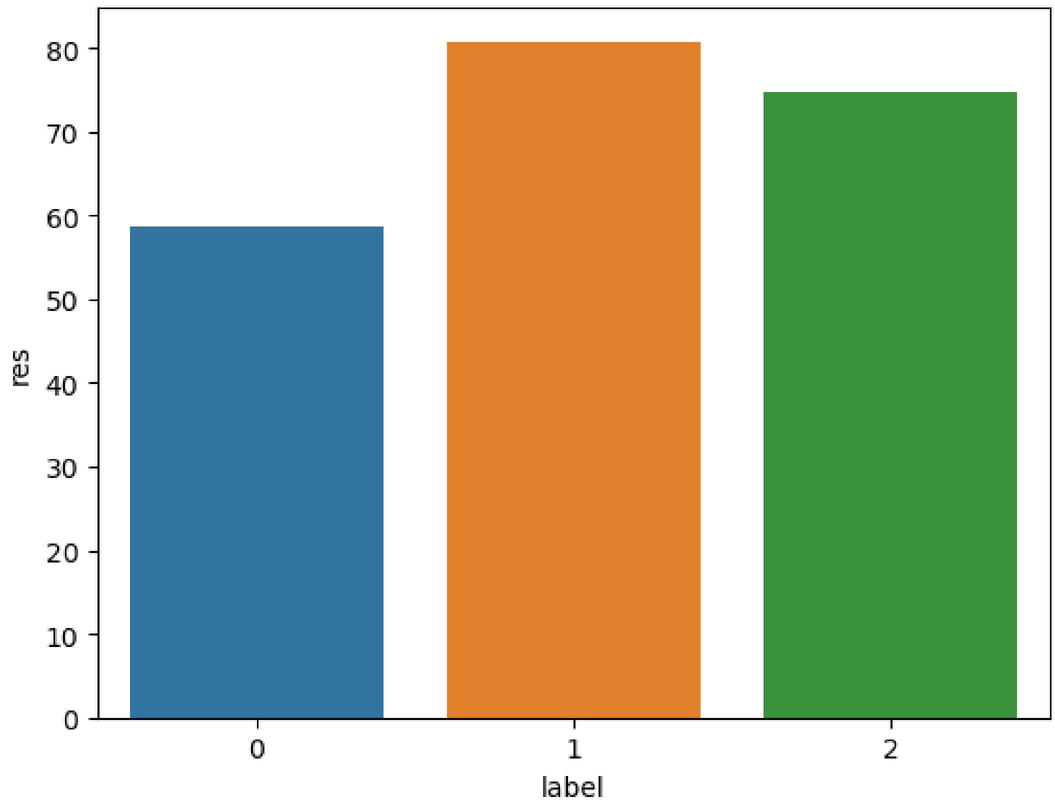
[20]:
```
# The numbers of men and women in each cluster
df3 = pd.DataFrame(df2.groupby(['label','sex'])['sex'].count())
df3.head()
```

[20]:
```
           sex
label sex
0     1.0   38
      2.0   65
```

```
1     1.0   21
      2.0   53
2     1.0   22
```

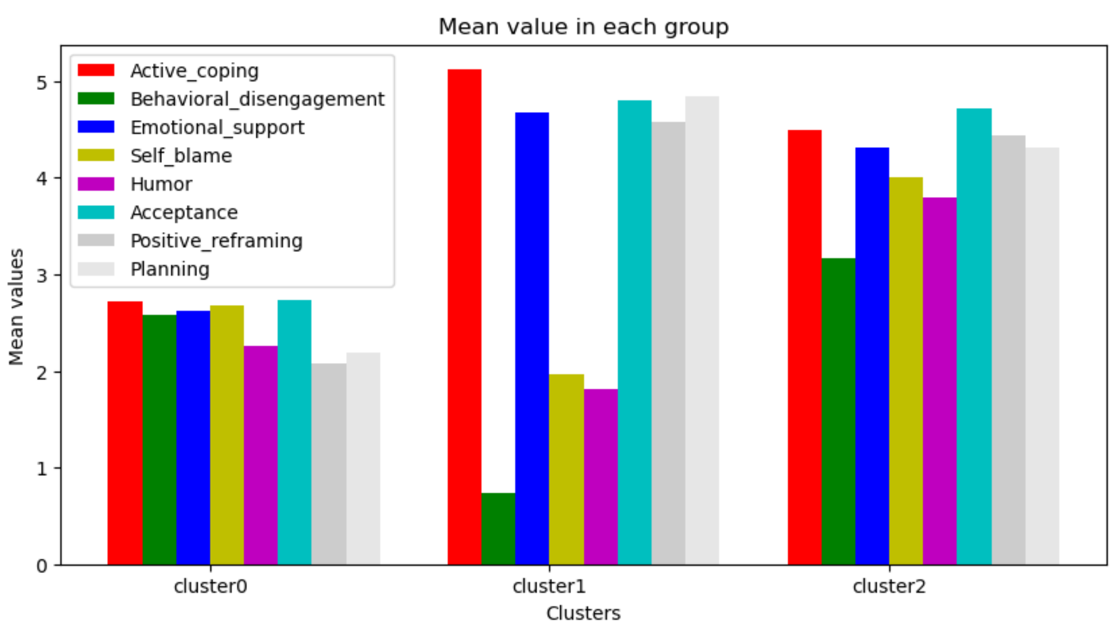
[27]:
```
# visualizing the mean of resilience in each cluster
sns.barplot(x='label',y='res', data=avg_df)
```

[27]: <Axes: xlabel='label', ylabel='res'>



[32]:
```
# visualizing the mean of features in each cluster

N = 3
ind = np.arange(3)
width = 0.25
plt.figure(figsize=(10,5))
xvals = avg_df["Active_coping"]
bar1 = plt.bar(ind, xvals, width=0.1, color = 'r')

yvals = avg_df["Behavioral_disengagement"]
bar2 = plt.bar(ind+0.1, yvals, width=0.1, color='g')
```

```
zvals = avg_df["Emotional_support"]
bar3 = plt.bar(ind+0.2, zvals, width=0.1, color = 'b')

wvals = avg_df["Self_blame"]
bar4 = plt.bar(ind+0.3, wvals, width=0.1, color = 'y')

tvals = avg_df["Humor"]
bar5 = plt.bar(ind+0.4, tvals, width=0.1, color = 'm')

svals = avg_df["Acceptance"]
bar6 = plt.bar(ind+0.5, svals, width=0.1, color = 'c')

bvals = avg_df["Positive_reframing"]
bar7 = plt.bar(ind+0.6, bvals, width=0.1, color = '0.8')

dvals = avg_df["Planning"]
bar8 = plt.bar(ind+0.7, dvals, width=0.1, color = '0.9')

plt.xlabel("Clusters")
plt.ylabel('Mean values')
plt.title("Mean value in each group")

plt.xticks(ind+width,['cluster0', 'cluster1', 'cluster2'])
plt.legend( (bar1, bar2, bar3, bar4, bar5, bar6, bar7,bar8), ('Active_coping',␣
 ↪'Behavioral_disengagement',
                                                                          ␣
 ↪'Emotional_support','Self_blame','Humor','Acceptance','Positive_reframing','Planning')␣
 ↪)
plt.show()
```



2.2.1 Main attributes of each cluster

Cluster 1: This cluster includes juveniles with the most resilience. They had high average for **Active_coping, Emotional_support, Acceptance, planning** and **Positive_reframing** and low average in *Behavioral_disengagement*, *Self_blame* and *Humor*.

Cluster 2: juveniles with the moderate resilience. This group had moderate average in almost all features and high average for *Active_coping* and *Acceptance*.

Cluster 0: This group had the lowest value of resilience characteristic. Active_coping, Emotional_support, Acceptance, planning and Positive_reframing were minimum for these juveniles.

2.2.2 Results

In this project, we used k-means clustering to identify different groups of coping strategies that can affect the resilience of juveniles. Our investigations revealed that juveniles with more **Active_coping, Emotional_support, Acceptance, planning** and **Positive_reframing** have more `resilience`. Further, *Behavioral_disengagement* and *Self_blame* negatively affected the resilience.