Satellite Data

Now use a statistical-based filter selection method to select the most discriminant feature.

Load the necessary libraries and the data

In [ ]:
```
# Step 1: Load and Preprocess Data
from ucimlrepo import fetch_ucirepo
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Fetch the dataset
statlog_landsat_satellite = fetch_ucirepo(id=146)

# data (as pandas dataframes)
X = statlog_landsat_satellite.data.features
y = statlog_landsat_satellite.data.targets
```

In [ ]:
```
df = X.assign(y=y)
```

Now, we report one-to other t-test p-values

In [ ]:
```
from scipy import stats

class_data = {}
for class_label in y["class"].unique():
    class_data[class_label] = df[df["y"] == class_label]

results = []
classes = list(class_data.keys())

for i in range(len(classes)):
    for j in range(i+1, len(classes)):
        class1 = class_data[classes[i]]
        class2 = class_data[classes[j]]
        for column in df.columns[:-1]:
```

```python
            t_statistic, p_value = stats.ttest_ind(class1[column], class2[column])
            results.append((column, classes[i], classes[j], t_statistic, p_value))

result_t_test = pd.DataFrame(results, columns = ['Feature', 'Class 1', 'Class2', 't-statisitc', 'p-value'])
result_t_test
#significane 0.05
#alpha = 0.05

#selected_features_t_test = result_t_test[result_t_test['p-value'] < alpha]

#print(selected_features_t_test)
```

Out[ ]:

	Feature	Class 1	Class2	t-statisitc	p-value
0	Attribute1	3	4	30.096091	3.281795e-164
1	Attribute2	3	4	29.127384	1.453090e-155
2	Attribute3	3	4	32.072758	3.645964e-182
3	Attribute4	3	4	30.919016	1.227980e-171
4	Attribute5	3	4	32.688717	7.787227e-188
...	...	...	...	...	...
535	Attribute32	2	1	44.236078	1.618743e-307
536	Attribute33	2	1	-36.648910	1.163164e-230
537	Attribute34	2	1	-79.278275	0.000000e+00
538	Attribute35	2	1	8.362560	1.065254e-16
539	Attribute36	2	1	41.741003	5.159350e-282

540 rows × 5 columns

Analogously, we performed the One-to-Other KS- p-values

In [ ]:

```python
ks_results = []
classes = list(class_data.keys())

for i in range(len(classes)):
    for j in range(i+1, len(classes)):
        class1 = class_data[classes[i]]
        class2 = class_data[classes[j]]
        for column in df.columns[:-1]:
            #ks
```

```
            ks_statistic, ks_p_value = stats.ks_2samp(class1[column], class2[column])
            ks_results.append((column, classes[i], classes[j], ks_statistic, ks_p_value))


result_ks_test = pd.DataFrame(ks_results, columns = ['Feature', 'Class 1', 'Class2', 't-statisitc', 'p-value'])
result_ks_test
```

Out[ ]:

	Feature	Class 1	Class2	t-statisitc	p-value
0	Attribute1	3	4	0.590553	1.081019e-139
1	Attribute2	3	4	0.618637	1.782161e-154
2	Attribute3	3	4	0.620436	1.980902e-155
3	Attribute4	3	4	0.596374	1.128059e-142
4	Attribute5	3	4	0.614752	2.349314e-152
...	...	...	...	...	...
535	Attribute32	2	1	0.781465	1.822375e-294
536	Attribute33	2	1	0.690157	3.951711e-221
537	Attribute34	2	1	0.865572	4.051338e-322
538	Attribute35	2	1	0.177414	9.829564e-14
539	Attribute36	2	1	0.762973	2.865326e-278

540 rows × 5 columns

Now using ROC AUC

In [ ]:

```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor
from sklearn.metrics import roc_auc_score

#separte in train and test datasets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

roc_auc_results = []

for feature in X_train.columns:
    clf = DecisionTreeClassifier()

    clf.fit(X_train[feature].fillna(0).to_frame(), y_train)
```

```python
    y_scored = clf.predict_proba(X_test[feature].to_frame())

    roc_auc_results.append(roc_auc_score(y_test, y_scored, multi_class='ovr'))

results_roc = pd.Series(roc_auc_results)

results_roc.index = X_train.columns

results_roc_df = pd.DataFrame({
    'Feature': results_roc.index,
    'roc_auc': results_roc.values
})

# Muestra el DataFrame
results_roc_df
```

Out[ ]:

	Feature	roc_auc
0	Attribute1	0.841729
1	Attribute2	0.841859
2	Attribute3	0.796173
3	Attribute4	0.827412
4	Attribute5	0.858386
5	Attribute6	0.851289
6	Attribute7	0.796095
7	Attribute8	0.827831
8	Attribute9	0.845229
9	Attribute10	0.837111
10	Attribute11	0.797725
11	Attribute12	0.820930
12	Attribute13	0.859329
13	Attribute14	0.853800
14	Attribute15	0.806963
15	Attribute16	0.842519
16	Attribute17	0.876212
17	Attribute18	0.878900
18	Attribute19	0.805027
19	Attribute20	0.845358
20	Attribute21	0.869825
21	Attribute22	0.861839
22	Attribute23	0.805540
23	Attribute24	0.835885
24	Attribute25	0.840513
25	Attribute26	0.834317
26	Attribute27	0.786526

	Feature	roc_auc
27	Attribute28	0.826860
28	Attribute29	0.855004
29	Attribute30	0.848189
30	Attribute31	0.797210
31	Attribute32	0.820969
32	Attribute33	0.853111
33	Attribute34	0.840684
34	Attribute35	0.792385
35	Attribute36	0.826401

Adjust the p_values for FDR

In [ ]:

```
from statsmodels.stats.multitest import fdrcorrection

# Adjust p-values for FDR (both t-test and KS-test)
t_test_p_values = result_t_test['p-value'].values
ks_p_values = result_ks_test['p-value'].values

t_test_adjusted = multipletests(t_test_p_values, method='fdr_bh')[1]
ks_adjusted = multipletests(ks_p_values, method='fdr_bh')[1]

result_t_test['FDR-adjusted p-value'] = t_test_adjusted
result_ks_test['FDR-adjusted p-value'] = ks_adjusted
```

Compare the ranking of the p-values for the three different methods.

First, we are going to calculate the mean of the corrected p values for each feature for the t-test and ks test.

In [ ]:

```
# ks
mean_p_values_ks = result_ks_test.groupby('Feature')['FDR-adjusted p-value'].mean().reset_index()
mean_p_values_ks.rename(columns={'p-value': 'FDR-adjusted p-value'}, inplace=True)
mean_p_values_df_ks = mean_p_values_ks

# t-test
mean_p_values_t_test = result_t_test.groupby('Feature')['FDR-adjusted p-value'].mean().reset_index()
mean_p_values_t_test.rename(columns={'p-value': 'FDR-adjusted p-value'}, inplace=True)
mean_p_values_df_t = mean_p_values_t_test
```

Now, we combined the results in a dataframe

In [ ]:
```
ranking_df = pd.merge(mean_p_values_df_t[['Feature', 'FDR-adjusted p-value']],
                      mean_p_values_df_ks[['Feature', 'FDR-adjusted p-value']],
                      on='Feature', suffixes=('_t_test', '_ks'))
ranking_df = pd.merge(ranking_df, results_roc_df, on='Feature')
```

In [ ]:
```
ranking_df
```

Out[ ]:

	Feature	FDR-adjusted p-value_t_test	FDR-adjusted p-value_ks	roc_auc
0	Attribute1	6.610641e-15	1.516973e-30	0.841729
1	Attribute10	6.834457e-26	1.164221e-46	0.837111
2	Attribute11	1.156428e-02	4.040214e-04	0.797725
3	Attribute12	2.865018e-10	4.172099e-23	0.820930
4	Attribute13	8.625106e-15	3.112649e-31	0.859329
5	Attribute14	6.338784e-15	8.703658e-44	0.853800
6	Attribute15	5.174310e-06	1.646539e-07	0.806963
7	Attribute16	1.464519e-05	9.195123e-30	0.842519
8	Attribute17	4.161674e-25	1.460148e-42	0.876212
9	Attribute18	4.891669e-16	4.130507e-51	0.878900
10	Attribute19	7.059655e-04	6.700984e-06	0.805027
11	Attribute2	1.095815e-16	1.029653e-38	0.841859
12	Attribute20	1.254657e-06	2.694846e-32	0.845358
13	Attribute21	6.702344e-20	1.783788e-43	0.869825
14	Attribute22	1.158223e-20	4.202383e-52	0.861839
15	Attribute23	2.418061e-04	1.764358e-05	0.805540
16	Attribute24	1.325681e-07	3.410477e-23	0.835885
17	Attribute25	2.869168e-06	3.574524e-24	0.840513
18	Attribute26	6.989594e-14	4.846886e-39	0.834317
19	Attribute27	1.456329e-09	1.064026e-11	0.786526
20	Attribute28	6.229255e-04	5.057471e-17	0.826860
21	Attribute29	1.638265e-12	2.536568e-35	0.855004
22	Attribute3	9.339383e-03	8.058272e-05	0.796173
23	Attribute30	6.638249e-18	2.059393e-45	0.848189
24	Attribute31	3.458041e-06	3.072608e-09	0.797210
25	Attribute32	1.596755e-06	1.752727e-20	0.820969
26	Attribute33	3.242728e-12	2.537384e-38	0.853111

	Feature	FDR-adjusted p-value_t_test	FDR-adjusted p-value_ks	roc_auc
27	Attribute34	8.513060e-24	1.197893e-45	0.840684
28	Attribute35	1.936563e-05	5.499561e-08	0.792385
29	Attribute36	4.333297e-09	1.543257e-19	0.826401
30	Attribute4	1.002249e-10	2.849858e-25	0.827412
31	Attribute5	5.457235e-21	2.118687e-38	0.858386
32	Attribute6	1.381265e-19	8.581139e-44	0.851289
33	Attribute7	2.843596e-02	2.863931e-05	0.796095
34	Attribute8	1.330187e-10	4.516820e-20	0.827831
35	Attribute9	5.993331e-16	2.855948e-34	0.845229

In [ ]:

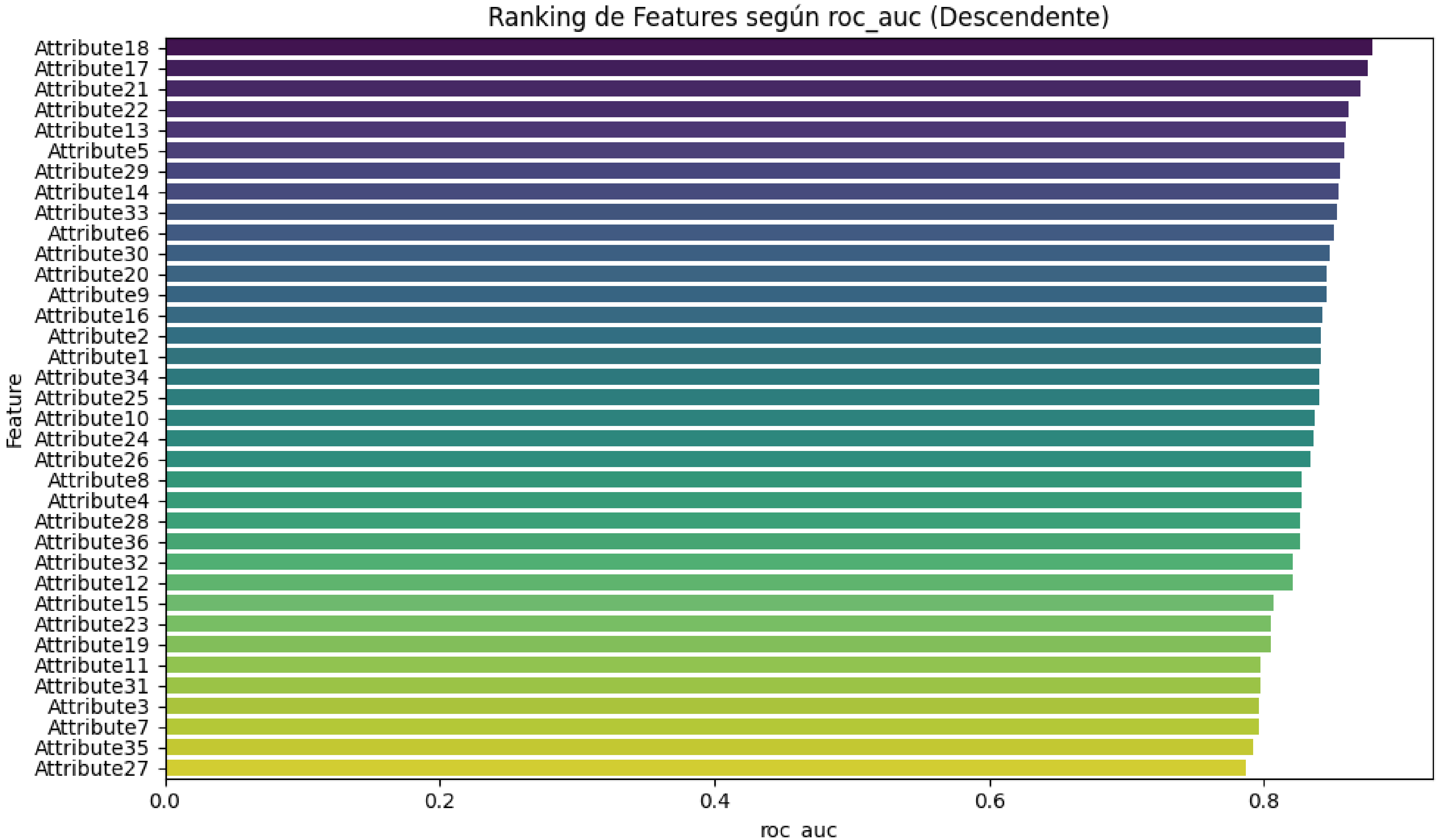
```
import matplotlib.pyplot as plt
import seaborn as sns

#SORTED BY AUC
plt.figure(figsize=(10, 6))
sns.barplot(x='roc_auc', y='Feature', data=ranking_df.sort_values('roc_auc', ascending=False), palette='viridis')
plt.title('Ranking de Features según roc_auc (Descendente)')
plt.xlabel('roc_auc')
plt.ylabel('Feature')
plt.tight_layout()
plt.show()
```

```
/var/folders/h4/v6kv36fs44lg2yrrlf2z2jyr0000gn/T/ipykernel_90249/1083825134.py:6: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue
` and set `legend=False` for the same effect.

  sns.barplot(x='roc_auc', y='Feature', data=ranking_df.sort_values('roc_auc', ascending=False), palette='viridis')
```



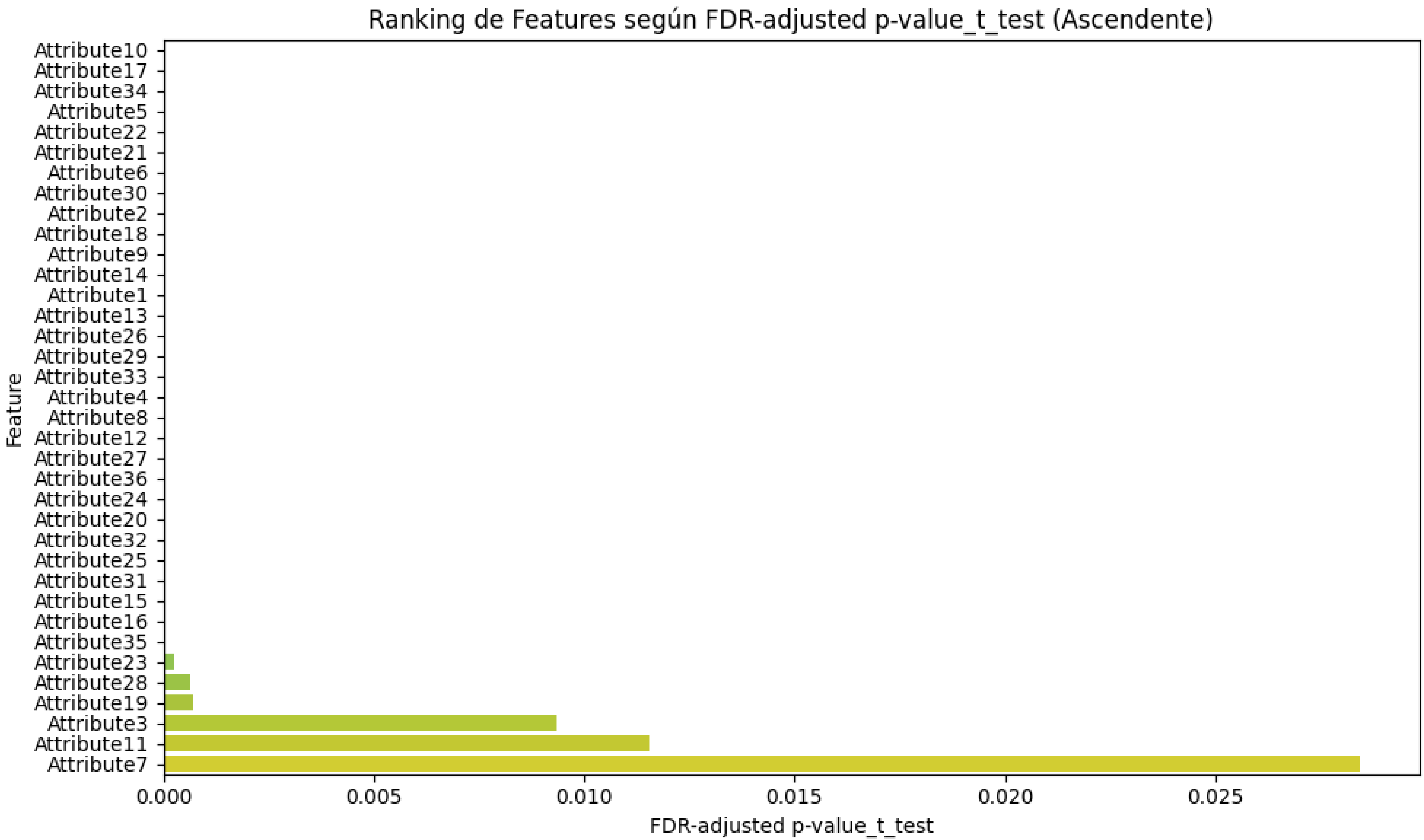
In [ ]:

```
#SORTED BY T-TEST
plt.figure(figsize=(10, 6))
sns.barplot(x='FDR-adjusted p-value_t_test', y='Feature', data=ranking_df.sort_values('FDR-adjusted p-value_t_test'), p
plt.title('Ranking de Features según FDR-adjusted p-value_t_test (Ascendente)')
plt.xlabel('FDR-adjusted p-value_t_test')
plt.ylabel('Feature')
plt.tight_layout()
plt.show()
```

```
/var/folders/h4/v6kv36fs44lg2yrrlf2z2jyr0000gn/T/ipykernel_90249/1207628925.py:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue
` and set `legend=False` for the same effect.

  sns.barplot(x='FDR-adjusted p-value_t_test', y='Feature', data=ranking_df.sort_values('FDR-adjusted p-value_t_test'),
palette='viridis')
```



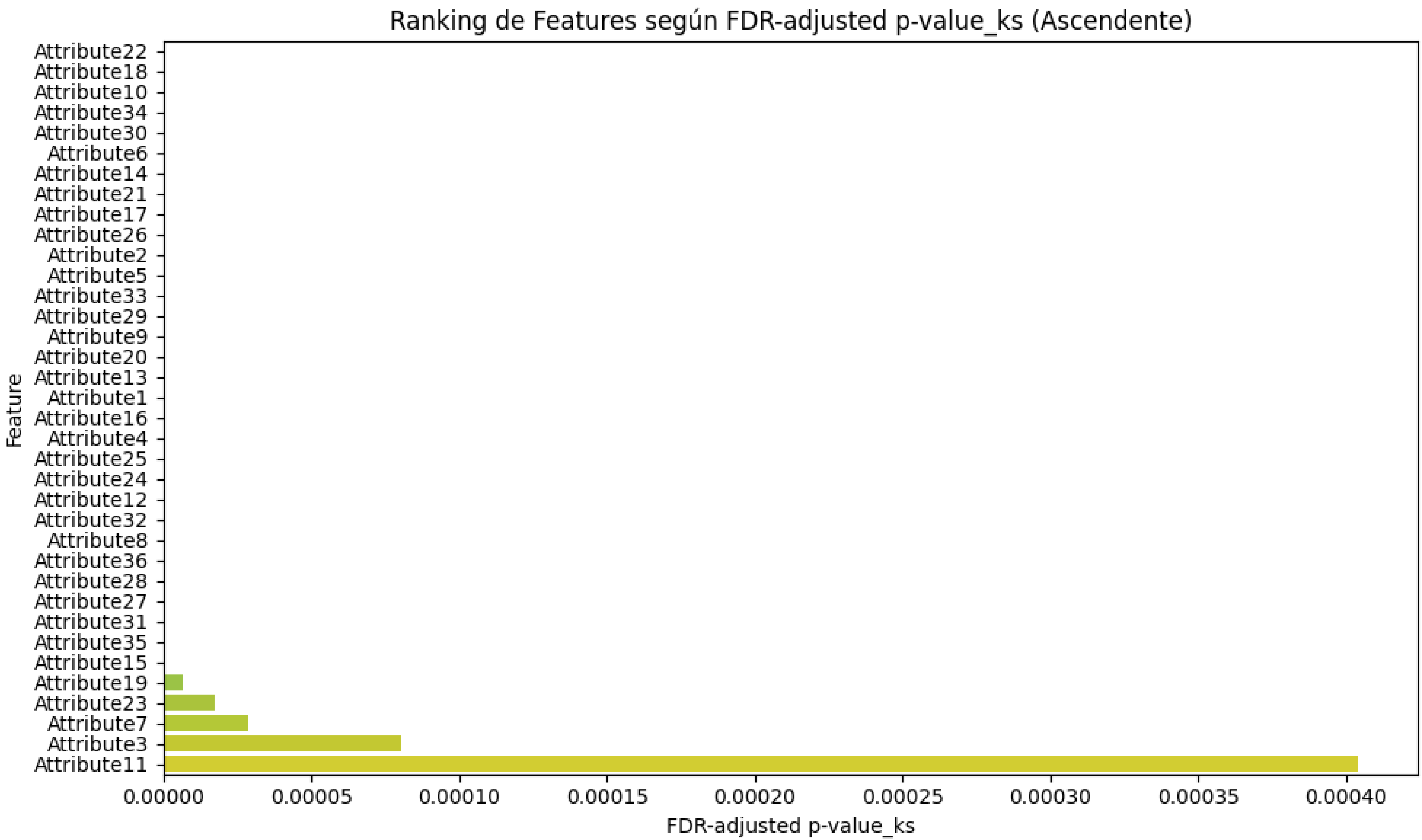
In [ ]:
```python
#sorted by ks
plt.figure(figsize=(10, 6))
sns.barplot(x='FDR-adjusted p-value_ks', y='Feature', data=ranking_df.sort_values('FDR-adjusted p-value_ks'), palette='
plt.title('Ranking de Features según FDR-adjusted p-value_ks (Ascendente)')
plt.xlabel('FDR-adjusted p-value_ks')
plt.ylabel('Feature')
```

```
plt.tight_layout()
plt.show()
```

```
/var/folders/h4/v6kv36fs44lg2yrrlf2z2jyr0000gn/T/ipykernel_90249/2410965441.py:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue
` and set `legend=False` for the same effect.

  sns.barplot(x='FDR-adjusted p-value_ks', y='Feature', data=ranking_df.sort_values('FDR-adjusted p-value_ks'), palette
='viridis')
```



Select any heuristic feature selection method. Compare the ranking to the statistical methods. We are going to use the Chi-Square Test method

In [ ]:
```
import sklearn.feature_selection as FS

chi_values, p_values = FS.chi2(X, y)

indices_chi = np.argsort(chi_values)[::-1]

chi_df = pd.DataFrame({
    'Feature': X.columns[indices_chi],  # Use the indices to sort the feature names
    'chi': chi_values[indices_chi]      # Use the sorted chi values
})

print(chi_df)
```

	Feature	chi
0	Attribute18	31767.095869
1	Attribute22	30510.985521
2	Attribute14	29725.448977
3	Attribute6	29233.716925
4	Attribute30	29215.811159
5	Attribute34	28780.786126
6	Attribute2	28208.488641
7	Attribute10	27851.344253
8	Attribute26	27238.571806
9	Attribute20	20208.148464
10	Attribute16	19385.145654
11	Attribute24	19358.263583
12	Attribute32	18444.822271
13	Attribute8	18371.176465
14	Attribute28	18054.859025
15	Attribute12	17974.249954
16	Attribute36	17596.603313
17	Attribute4	17555.029307
18	Attribute17	13296.630900
19	Attribute21	12813.377998
20	Attribute13	12542.874406
21	Attribute5	12336.219215
22	Attribute29	12323.142085
23	Attribute33	11974.142740
24	Attribute1	11856.141364
25	Attribute9	11853.039207
26	Attribute25	11772.071611
27	Attribute19	11144.625537
28	Attribute15	10698.193478
29	Attribute23	10574.750434
30	Attribute31	10202.998419
31	Attribute7	10199.845914
32	Attribute27	10008.605838
33	Attribute11	9896.457428
34	Attribute3	9793.304309
35	Attribute35	9683.338290

In [ ]:

```
ranking_df = pd.merge(ranking_df, chi_df, on='Feature')
ranking_df
```

Out[ ]:

	Feature	FDR-adjusted p-value_t_test	FDR-adjusted p-value_ks	roc_auc	chi
0	Attribute1	6.610641e-15	1.516973e-30	0.841729	11856.141364
1	Attribute10	6.834457e-26	1.164221e-46	0.837111	27851.344253
2	Attribute11	1.156428e-02	4.040214e-04	0.797725	9896.457428
3	Attribute12	2.865018e-10	4.172099e-23	0.820930	17974.249954
4	Attribute13	8.625106e-15	3.112649e-31	0.859329	12542.874406
5	Attribute14	6.338784e-15	8.703658e-44	0.853800	29725.448977
6	Attribute15	5.174310e-06	1.646539e-07	0.806963	10698.193478
7	Attribute16	1.464519e-05	9.195123e-30	0.842519	19385.145654
8	Attribute17	4.161674e-25	1.460148e-42	0.876212	13296.630900
9	Attribute18	4.891669e-16	4.130507e-51	0.878900	31767.095869
10	Attribute19	7.059655e-04	6.700984e-06	0.805027	11144.625537
11	Attribute2	1.095815e-16	1.029653e-38	0.841859	28208.488641
12	Attribute20	1.254657e-06	2.694846e-32	0.845358	20208.148464
13	Attribute21	6.702344e-20	1.783788e-43	0.869825	12813.377998
14	Attribute22	1.158223e-20	4.202383e-52	0.861839	30510.985521
15	Attribute23	2.418061e-04	1.764358e-05	0.805540	10574.750434
16	Attribute24	1.325681e-07	3.410477e-23	0.835885	19358.263583
17	Attribute25	2.869168e-06	3.574524e-24	0.840513	11772.071611
18	Attribute26	6.989594e-14	4.846886e-39	0.834317	27238.571806
19	Attribute27	1.456329e-09	1.064026e-11	0.786526	10008.605838
20	Attribute28	6.229255e-04	5.057471e-17	0.826860	18054.859025
21	Attribute29	1.638265e-12	2.536568e-35	0.855004	12323.142085
22	Attribute3	9.339383e-03	8.058272e-05	0.796173	9793.304309
23	Attribute30	6.638249e-18	2.059393e-45	0.848189	29215.811159
24	Attribute31	3.458041e-06	3.072608e-09	0.797210	10202.998419
25	Attribute32	1.596755e-06	1.752727e-20	0.820969	18444.822271
26	Attribute33	3.242728e-12	2.537384e-38	0.853111	11974.142740

	Feature	FDR-adjusted p-value_t_test	FDR-adjusted p-value_ks	roc_auc	chi
27	Attribute34	8.513060e-24	1.197893e-45	0.840684	28780.786126
28	Attribute35	1.936563e-05	5.499561e-08	0.792385	9683.338290
29	Attribute36	4.333297e-09	1.543257e-19	0.826401	17596.603313
30	Attribute4	1.002249e-10	2.849858e-25	0.827412	17555.029307
31	Attribute5	5.457235e-21	2.118687e-38	0.858386	12336.219215
32	Attribute6	1.381265e-19	8.581139e-44	0.851289	29233.716925
33	Attribute7	2.843596e-02	2.863931e-05	0.796095	10199.845914
34	Attribute8	1.330187e-10	4.516820e-20	0.827831	18371.176465
35	Attribute9	5.993331e-16	2.855948e-34	0.845229	11853.039207

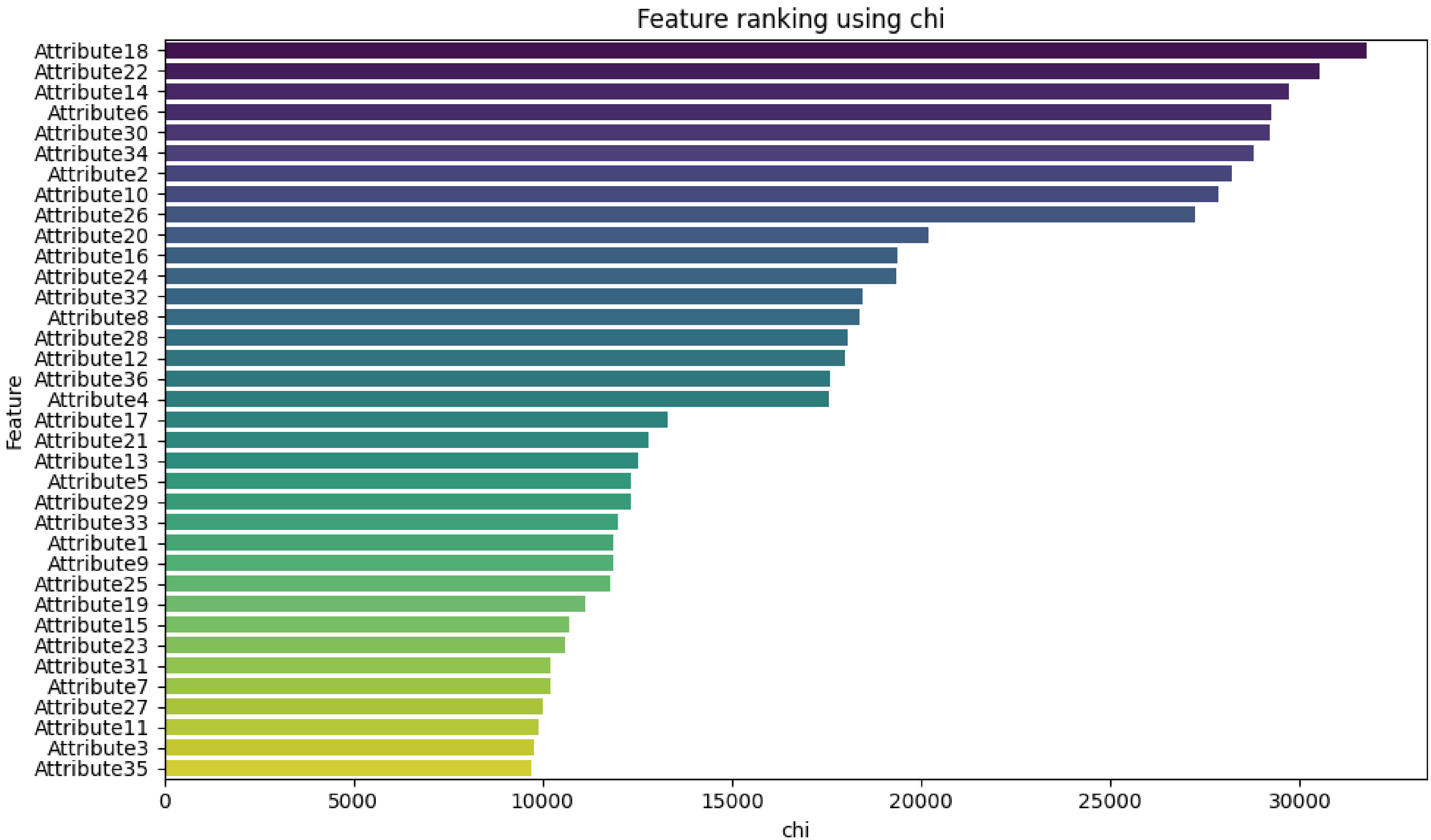
In [ ]:

```
#SORTED BY chi
plt.figure(figsize=(10, 6))
sns.barplot(x='chi', y='Feature', data=ranking_df.sort_values('chi', ascending=False), palette='viridis')
plt.title('Feature ranking using chi ')
plt.xlabel('chi')
plt.ylabel('Feature')
plt.tight_layout()
plt.show()
```

```
/var/folders/h4/v6kv36fs44lg2yrrlf2z2jyr0000gn/T/ipykernel_90249/668243646.py:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue
` and set `legend=False` for the same effect.

  sns.barplot(x='chi', y='Feature', data=ranking_df.sort_values('chi', ascending=False), palette='viridis')
```



As we can see each method ranked the features in a different order. Nevertheless we can observe that attributes 3, 11 and 25 are in the last places of the 4 rankings, while features 18, 22 and 17 are in the first places in most of the rankings.

Do a PCA transform on the data

In [ ]:
```
from sklearn.decomposition import PCA
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.model_selection import cross_val_score

# Step 1: Perform PCA on the data
scaler = StandardScaler()
```

```
X_scaled = scaler.fit_transform(X)

# Apply PCA
pca = PCA()
X_pca = pca.fit_transform(X_scaled)
```

Select the PCA components that explain 95% of the variance

In [ ]:
```
explained_variance_ratio = np.cumsum(pca.explained_variance_ratio_)
n_components = np.argmax(explained_variance_ratio >= 0.95) + 1
print(f"Number of PCA components selected: {n_components}")
```

```
Number of PCA components selected: 6
```

In [ ]:
```
X_pca_selected = X_pca[:, :n_components]
```

Perform Linear Discriminant Analysis (LDA)

In [ ]:
```
y_encoded = LabelEncoder().fit_transform(df['y'])

lda = LinearDiscriminantAnalysis()
lda.fit(X_pca_selected, y_encoded)
```

Out[ ]:
```
▾ LinearDiscriminantAnalysis
LinearDiscriminantAnalysis()
```

Report the performance of LDA

In [ ]:
```
lda_cv_score = cross_val_score(lda, X_pca_selected, y_encoded, cv=5)
print(f"Cross-validated accuracy score: {lda_cv_score.mean():.4f}")
```

```
Cross-validated accuracy score: 0.8107
```

In [ ]:
```
y_pred = lda.predict(X_pca_selected)
accuracy = accuracy_score(y_encoded, y_pred)
print(f"Accuracy: {accuracy:.4f}")
```

```
Accuracy: 0.8194
```