Astro Project

May 6, 2025

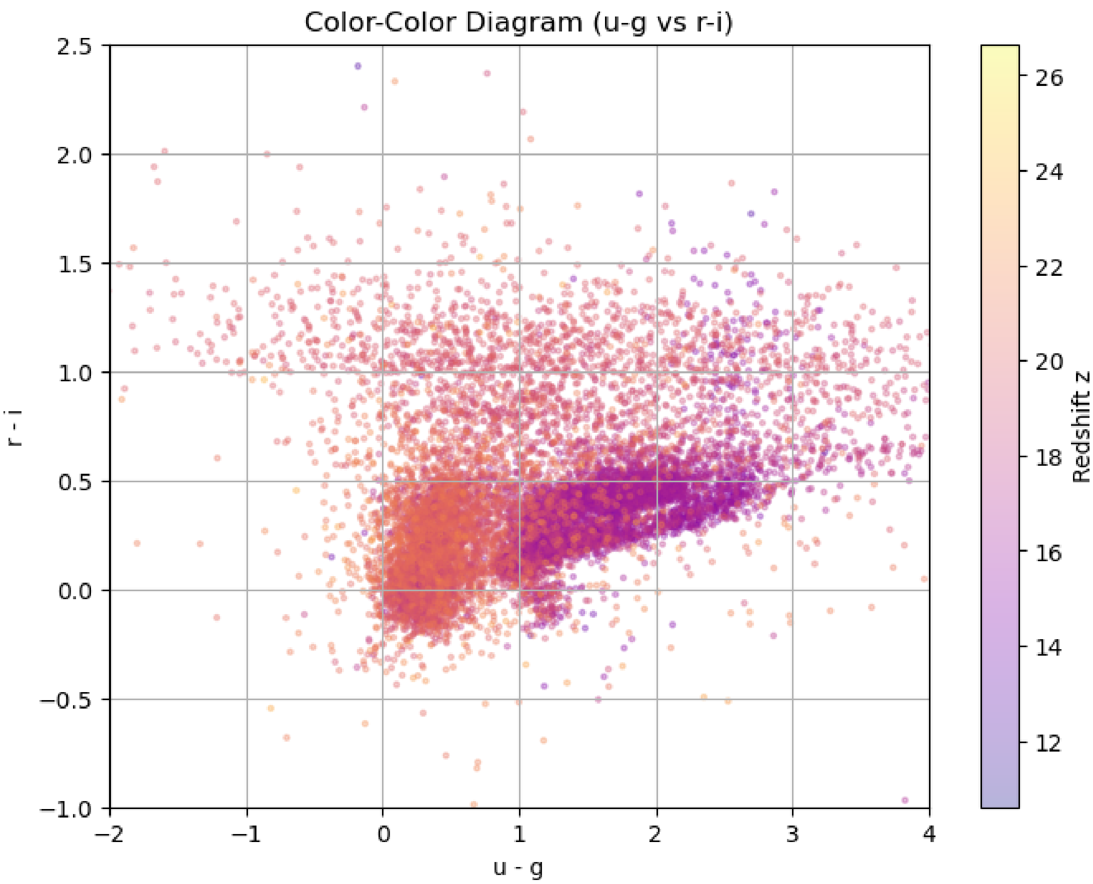
0.0.1 APPENDIX - CODE

[23]:
```
# Imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, confusion_matrix, classification_report
```

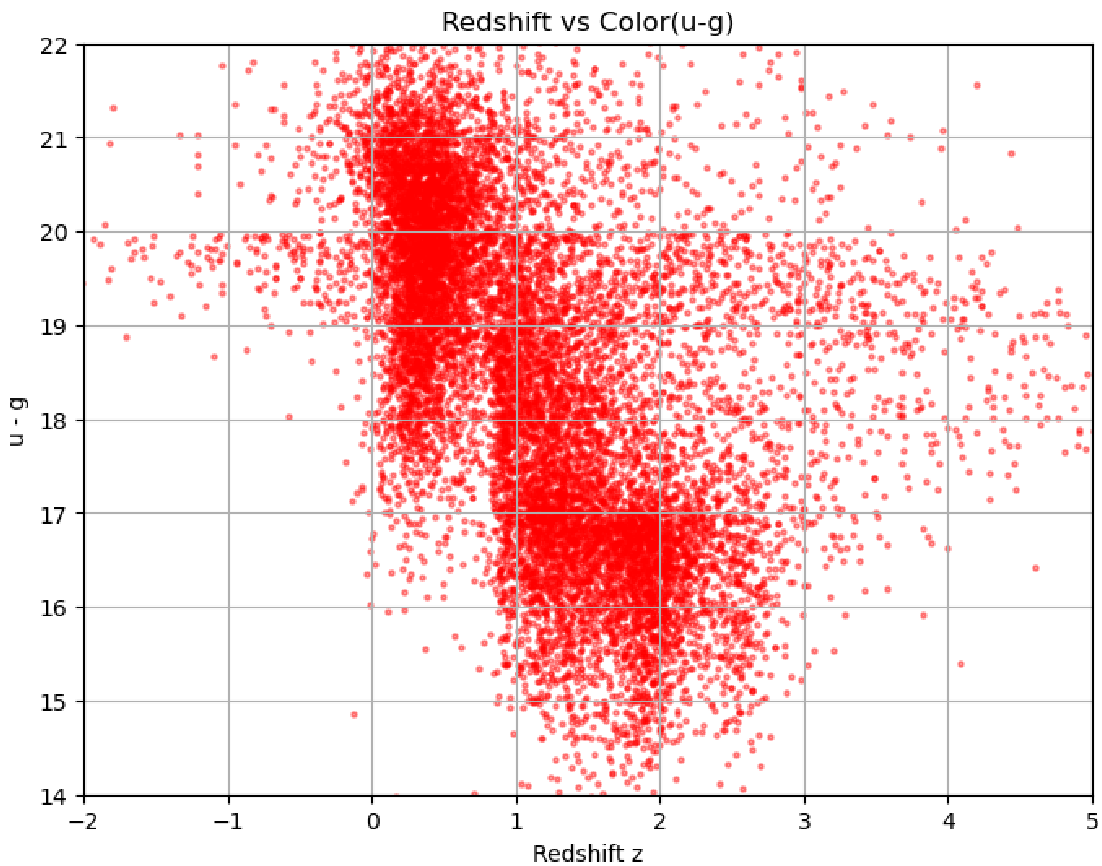
[24]:
```
# Step 1: Load Data
df = pd.read_csv('Data.csv')

# Step 2: Preprocessing
df = df.dropna(subset=['u', 'g', 'r', 'i', 'z', 'class'])

# Create color features
df['u-g'] = df['u'] - df['g']
df['g-r'] = df['g'] - df['r']
df['r-i'] = df['r'] - df['i']
df['i-z'] = df['i'] - df['z']

# Features and Labels
features = ['u', 'g', 'r', 'i', 'z', 'u-g', 'g-r', 'r-i', 'i-z']
X = df[features]
y = df['class']
```

[25]:
```
plt.figure(figsize=(8,6))
plt.scatter(df['u-g'], df['r-i'], c=df['z'], cmap='plasma', s=5, alpha=0.3)
plt.xlabel('u - g')
plt.ylabel('r - i')
```

```python
plt.xlim(-2,4)
plt.ylim(-1,2.5)
plt.title('Color-Color Diagram (u-g vs r-i)')
plt.colorbar(label='Redshift z')
plt.grid(True)
plt.show()
```



[26]:
```python
plt.figure(figsize=(8,6))
plt.scatter(df['u-g'], df['z'], alpha=0.4,color='red', s=5)
plt.xlabel('Redshift z')
plt.ylabel('u - g')
plt.ylim(14,22)
plt.xlim(-2,5)
plt.title('Redshift vs Color(u-g)')
plt.grid(True)
plt.show()
```



0.1 Classification (QSO vs Star vs Galaxy)

[27]:
```
# Split Data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42, stratify=y)

# Standardize features for SVM, KNN, Logistic Regression
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Step 3: Initialize Classifiers
classifiers = {
    "Random Forest": RandomForestClassifier(n_estimators=100, random_state=42),
    "SVM": SVC(kernel='rbf', probability=True, random_state=42),
    "KNN": KNeighborsClassifier(n_neighbors=5),
    "Logistic Regression": LogisticRegression(max_iter=1000, random_state=42),
    "Gradient Boosting": GradientBoostingClassifier(n_estimators=100,␣
 ↪random_state=42)
```

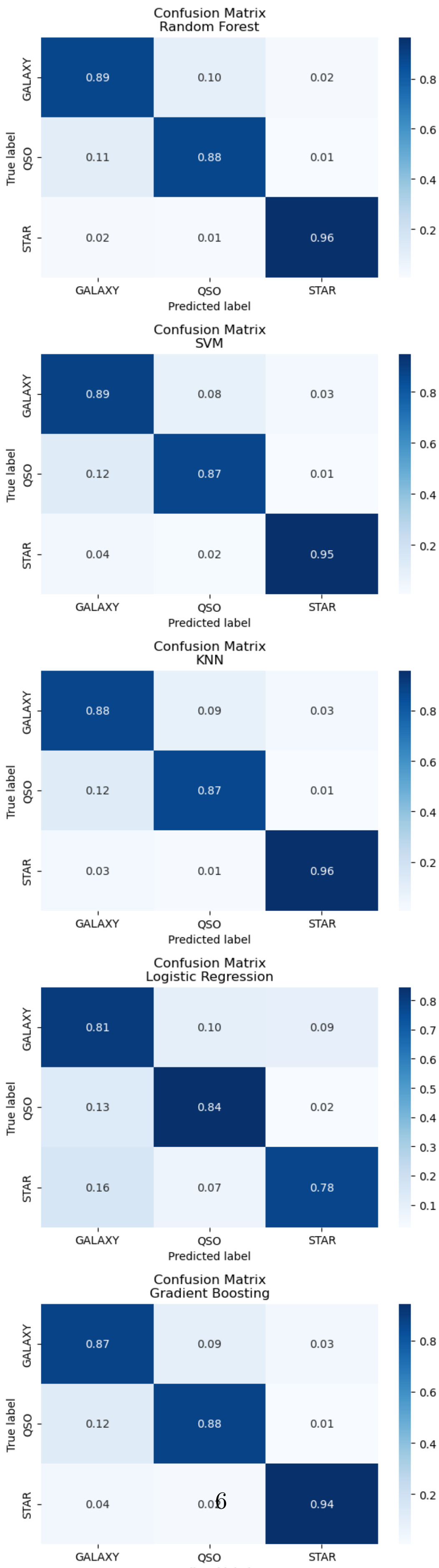
```
}

# Step 4: Train and Evaluate Classifiers
results = []

#fig, ax = plt.subplots(5, 1, figsize=(12, 5))

for name, clf in classifiers.items():
    if name in ["SVM", "KNN", "Logistic Regression"]:
        clf.fit(X_train_scaled, y_train)
        y_pred = clf.predict(X_test_scaled)
    else:
        clf.fit(X_train, y_train)
        y_pred = clf.predict(X_test)

    acc = accuracy_score(y_test, y_pred)
    prec = precision_score(y_test, y_pred, average='weighted')
    rec = recall_score(y_test, y_pred, average='weighted')
    f1 = f1_score(y_test, y_pred, average='weighted')

    results.append({
        'Classifier': name,
        'Accuracy': acc,
        'Precision': prec,
        'Recall': rec,
        'F1 Score': f1
    })


# Step 5: Compare Results
results_df = pd.DataFrame(results)
print(results_df)
```

```
            Classifier  Accuracy  Precision    Recall  F1 Score
0        Random Forest  0.902692   0.902624  0.902692  0.902634
1                  SVM  0.895385   0.895671  0.895385  0.895379
2                  KNN  0.896923   0.897053  0.896923  0.896824
3  Logistic Regression  0.815000   0.815573  0.815000  0.815142
4    Gradient Boosting  0.890769   0.890885  0.890769  0.890775
```

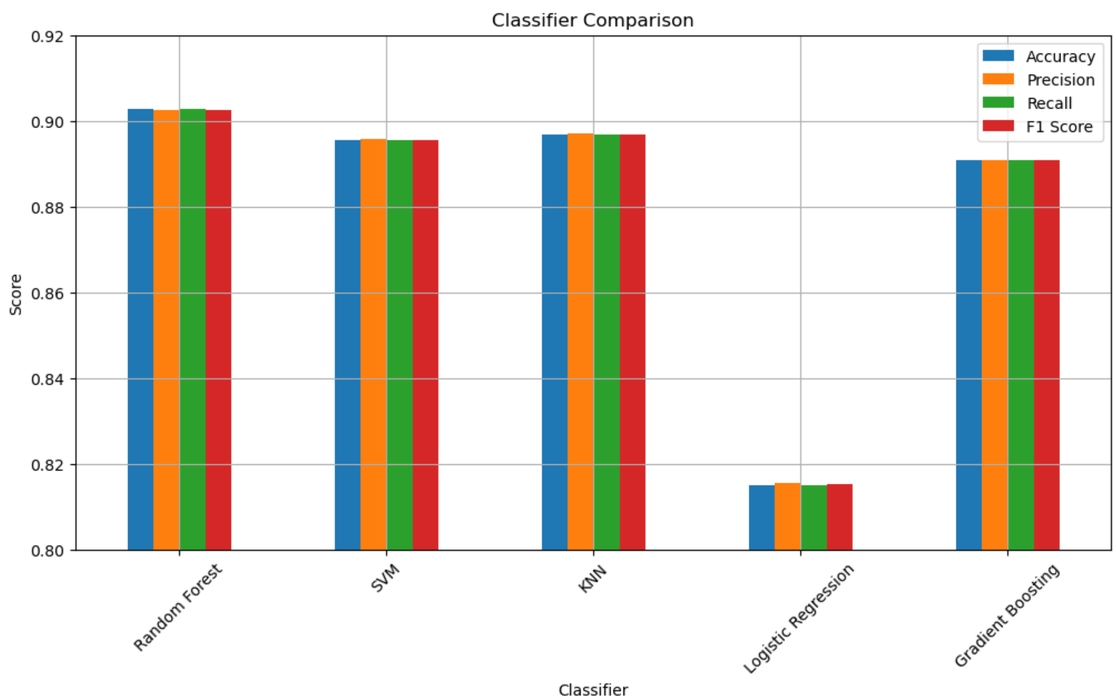
[28]:

```
# Specify the two models you want to compare
model_names = ['Random Forest', 'SVM','KNN','Logistic Regression','Gradient␣
↪Boosting']  # change these to the exact keys you used

# True labels
labels = np.unique(y_test)  # e.g. ['GALAXY','QSO']
```

```python
# Create subplots
fig, axes = plt.subplots(5, 1, figsize=(6, 20))

classifiers = {
    "Random Forest": RandomForestClassifier(n_estimators=100, random_state=42),
    "SVM": SVC(kernel='rbf', probability=True, random_state=42),
    "KNN": KNeighborsClassifier(n_neighbors=5),
    "Logistic Regression": LogisticRegression(max_iter=1000, random_state=42),
    "Gradient Boosting": GradientBoostingClassifier(n_estimators=100,
 ↪random_state=42)
}

for ax, name in zip(axes, model_names):
    model = classifiers[name]

    # Choose the correct feature set for each model
    if name in ["SVM", "KNN", "Logistic Regression"]:
        model.fit(X_train_scaled, y_train)
        y_pred = model.predict(X_test_scaled)
    else:
        model.fit(X_train, y_train)
        y_pred = model.predict(X_test)

    # Compute confusion matrix
    cm = confusion_matrix(y_test, y_pred, labels=labels,normalize='true')

    # Plot
    sns.heatmap(
        cm,
        annot=True,
        fmt='.2f',
        cmap='Blues',
        xticklabels=labels,
        yticklabels=labels,
        ax=ax
    )
    ax.set_title(f'Confusion Matrix\n{name}')
    ax.set_xlabel('Predicted label')
    ax.set_ylabel('True label')

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


Confusion Matrix
Random Forest
True label
GALAXY
QSO
STAR
0.89 0.10 0.02
0.11 0.88 0.01
0.02 0.01 0.96
GALAXY QSO STAR
Predicted label
0.8 0.6 0.4 0.2
Confusion Matrix
SVM
0.89 0.08 0.03
0.12 0.87 0.01
0.04 0.02 0.95
Confusion Matrix
KNN
0.88 0.09 0.03
0.12 0.87 0.01
0.03 0.01 0.96
Confusion Matrix
Logistic Regression
0.81 0.10 0.09
0.13 0.84 0.02
0.16 0.07 0.78
0.8 0.7 0.6 0.5 0.4 0.3 0.2 0.1
Confusion Matrix
Gradient Boosting
0.87 0.09 0.03
0.12 0.88 0.01
0.04 0.02 0.94

[29]:
```
# Step 6: Optional: Visualize
results_df.set_index('Classifier')[['Accuracy', 'Precision', 'Recall', 'F1␣
↪Score']].plot(kind='bar', figsize=(12,6))
plt.title('Classifier Comparison')
plt.ylabel('Score')
plt.ylim(0,1)
plt.ylim(0.8,0.92)
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```



0.2 Regression (Given spectral data predicting the redshift)

[30]:
```
# Imports
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.linear_model import LinearRegression
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
import pandas as pd
```

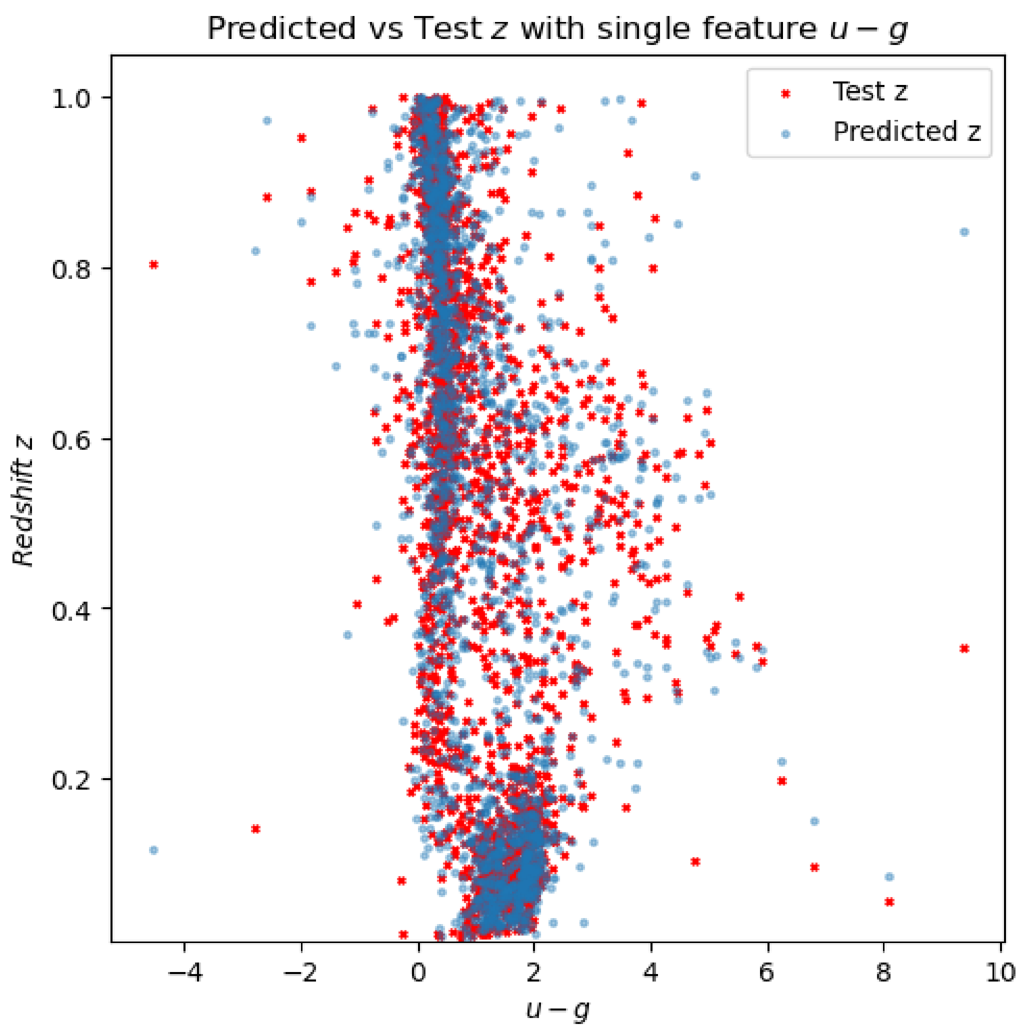
```python
import matplotlib.pyplot as plt
import numpy as np

# Step 1: Preprocessing (already done)
# Assuming df has features: u, g, r, i, z, u-g, g-r, r-i, i-z
# and target: redshift

X = df[['u', 'g', 'r', 'i', 'z', 'u-g', 'g-r', 'r-i', 'i-z']]
y = df['redshift']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
 ↪random_state=42)

# Step 2: Initialize Regressors
regressors = {
    "Random Forest": RandomForestRegressor(n_estimators=100, random_state=42),
    "Gradient Boosting": GradientBoostingRegressor(n_estimators=100,
 ↪random_state=42),
    "Linear Regression": LinearRegression(),
    "Support Vector Regressor": SVR(kernel='rbf'),
    "K-Nearest Neighbors": KNeighborsRegressor(n_neighbors=5),
    "Decision Tree": DecisionTreeRegressor(random_state=42)
}

# Step 3: Train, Predict and Evaluate
results = []

for name, reg in regressors.items():
    reg.fit(X_train, y_train)
    y_pred = reg.predict(X_test)

    rmse = np.sqrt(mean_squared_error(y_test, y_pred))
    mae = mean_absolute_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)

    results.append({
        'Regressor': name,
        'RMSE': rmse,
        'MAE': mae,
        'R2 Score': r2
    })

# Step 4: Compare Results
results_df = pd.DataFrame(results)
print(results_df)
```

```
                 Regressor      RMSE       MAE  R2 Score
```

0	Random Forest	0.124821	0.065574	0.865289
1	Gradient Boosting	0.131422	0.082329	0.850664
2	Linear Regression	0.208280	0.158639	0.624919
3	Support Vector Regressor	0.187481	0.131786	0.696089
4	K-Nearest Neighbors	0.131909	0.069795	0.849555
5	Decision Tree	0.173111	0.086549	0.740891

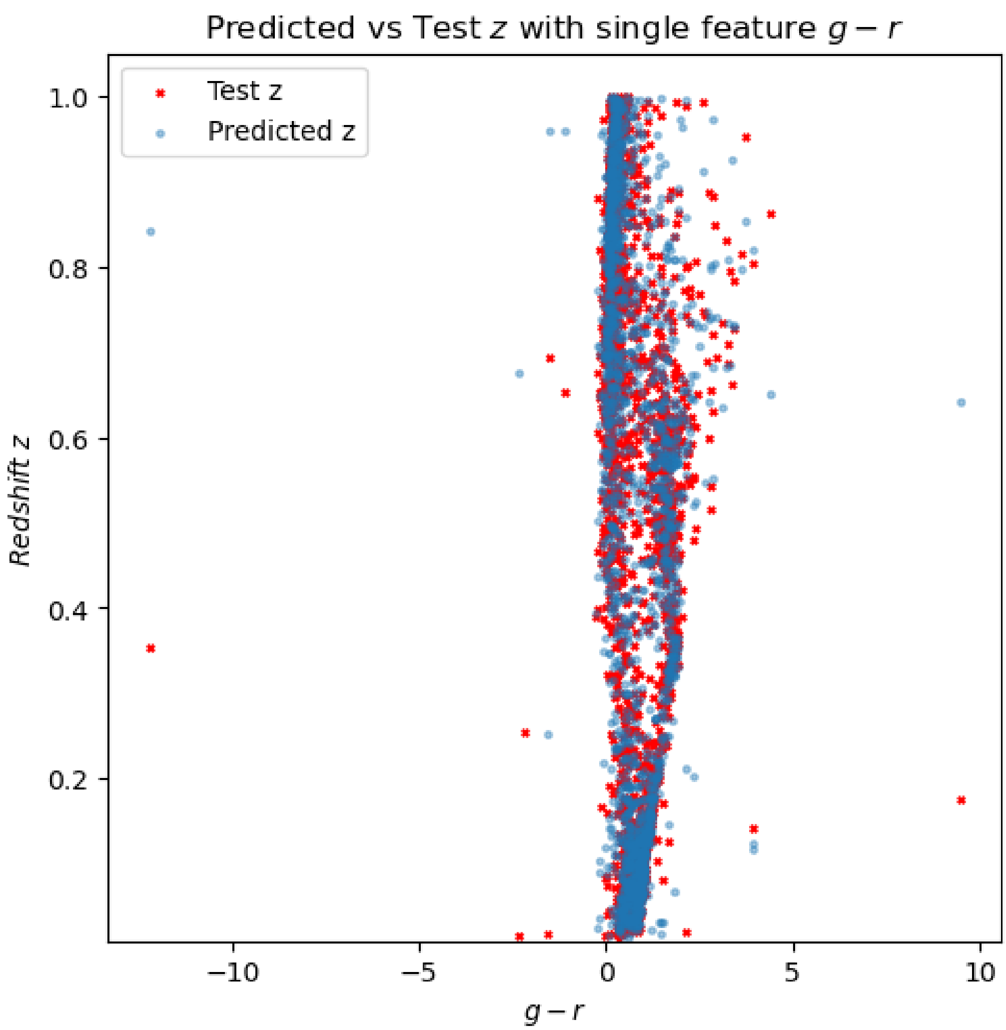
[31]:
```
x=X_test[['u-g']]
plt.rcParams["figure.figsize"] = (6,6)
plt.scatter(x,y_test,s=6,label='Test z',alpha=1,color='red',marker='x')
plt.scatter(x,y_pred,s=6,label='Predicted z',alpha=0.4,marker='o')
plt.xlabel('$u-g$')
plt.ylabel('$Redshift$ $z$')
plt.ylim(0.01)
plt.legend()
plt.title('Predicted vs Test $z$ with single feature $u-g$')
```

[31]: Text(0.5, 1.0, 'Predicted vs Test z with single feature $u-g$')



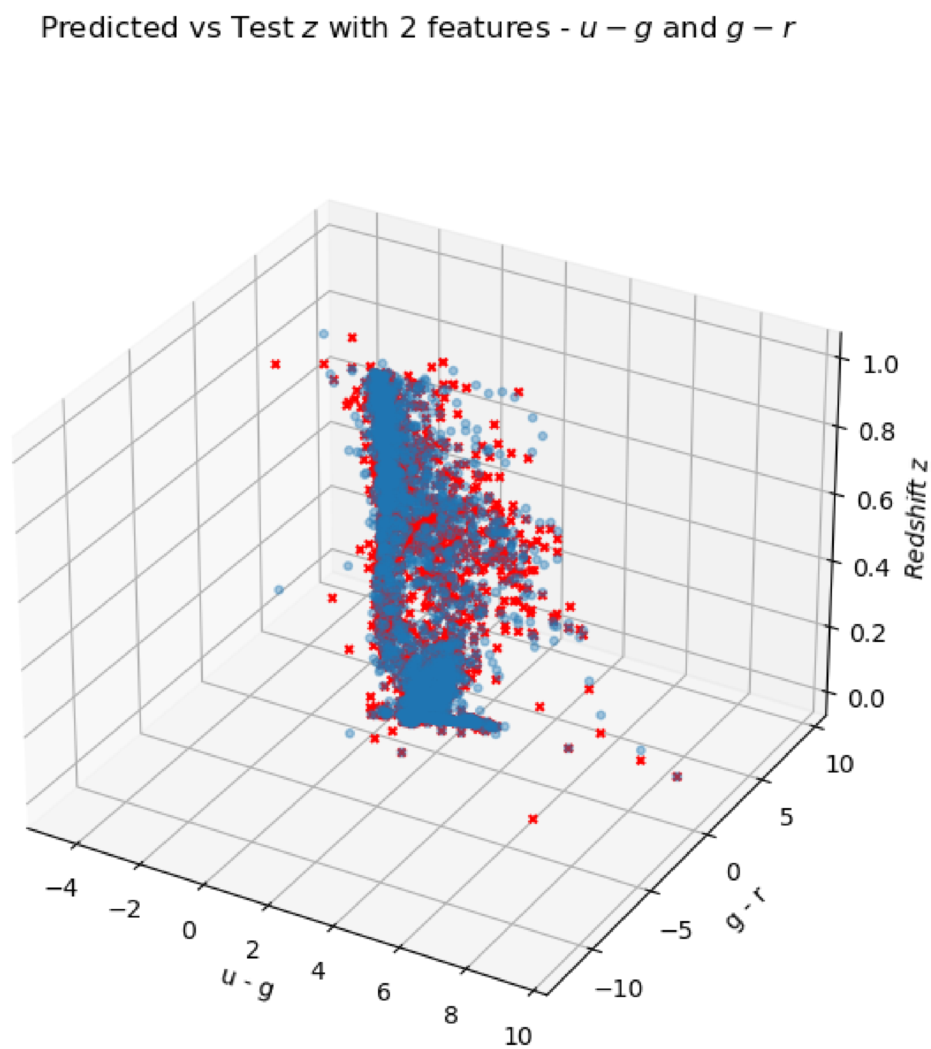
[32]:
```
x=X_test[['g-r']]
plt.rcParams["figure.figsize"] = (6,6)
plt.scatter(x,y_test,s=6,label='Test z',alpha=1,color='red',marker='x')
plt.scatter(x,y_pred,s=6,label='Predicted z',alpha=0.4,marker='o')
plt.xlabel('$g-r$')
plt.ylabel('$Redshift$ $z$')
plt.ylim(0.01)
plt.legend()
plt.title('Predicted vs Test $z$ with single feature $g-r$')
```

[32]:
```
Text(0.5, 1.0, 'Predicted vs Test $z$ with single feature $g-r$')
```



[33]:

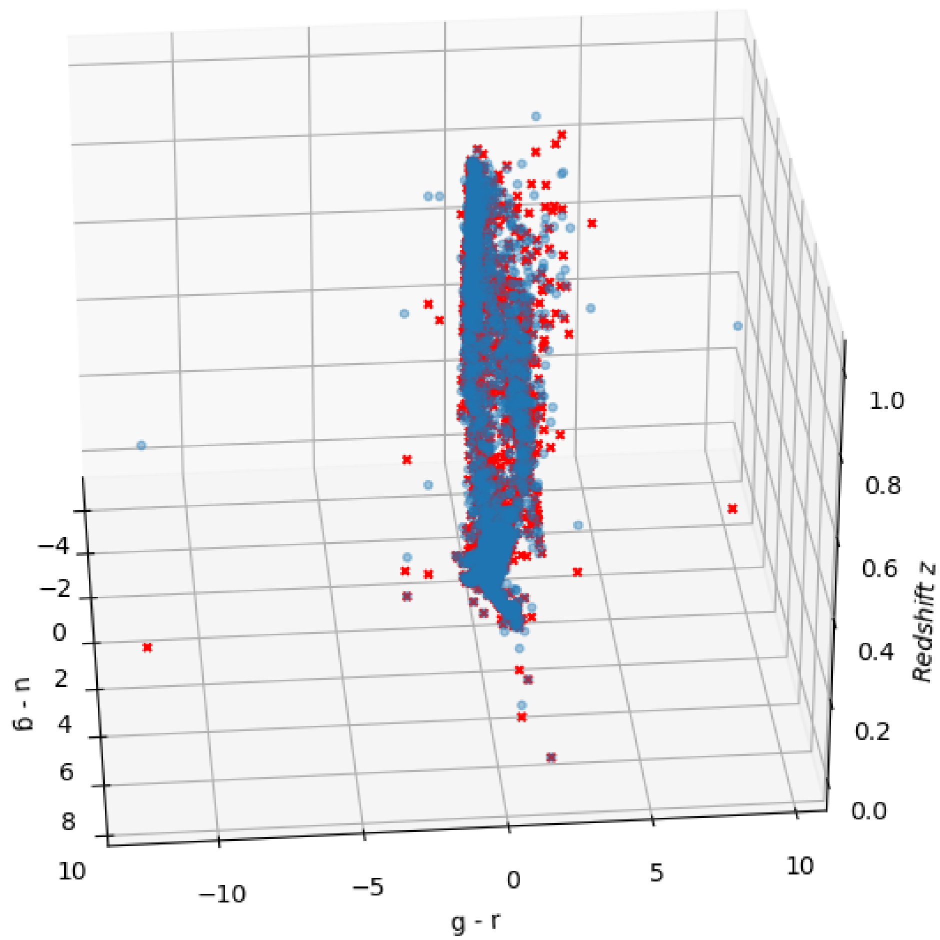
```
x1=X_test[['u-g']]
x2=X_test[['g-r']]

fig = plt.figure(figsize=(8, 8))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(x1, x2, y_test, s=10, alpha=1,color='red',marker='x')
ax.scatter(x1, x2, y_pred, s=10, alpha=0.4,marker='o')


# Labels and title
ax.set_xlabel('u - g')
ax.set_ylabel('g - r')
ax.set_zlabel('$Redshift$ $z$')
ax.set_title('Predicted vs Test $z$ with 2 features - $u-g$ and $g-r$')
ax.set_box_aspect(None, zoom=0.85)
#plt.tight_layout()
plt.show()
```



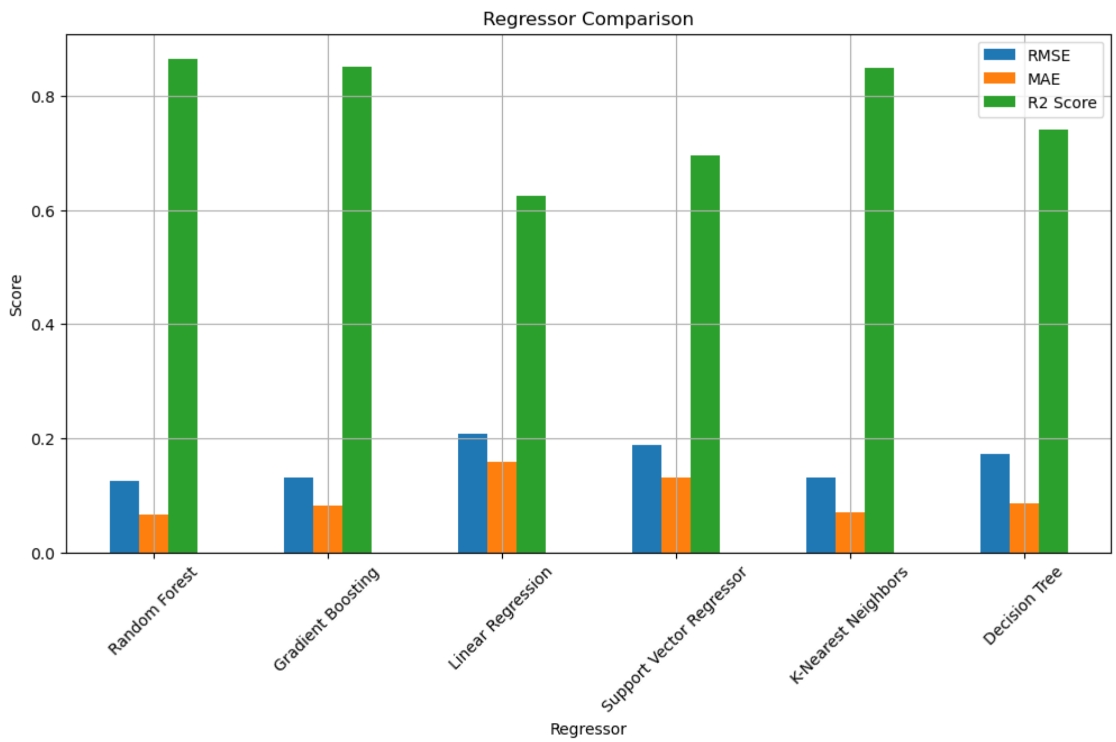
[49]:
```
# import matplotlib.pyplot as plt
# from mpl_toolkits.mplot3d import Axes3D
# import numpy as np
# import pandas as pd
# from PIL import Image

# # Create figure and 3D axes
# x1=X_test[['u-g']]
# x2=X_test[['g-r']]

# fig = plt.figure(figsize=(8, 8))
```

```
# ax = fig.add_subplot(111, projection='3d')
# ax.scatter(x1, x2, y_test, s=10, alpha=1,color='red',marker='x')
# ax.scatter(x1, x2, y_pred, s=10, alpha=0.4,marker='o')


# # Labels and title
# ax.set_xlabel('u - g')
# ax.set_ylabel('g - r')
# ax.set_zlabel('$Redshift$ $z$')
# ax.set_title('Predicted vs Test $z$ with 2 features - $u-g$ and $g-r$')

# # Generate frames for each angle
# frames = []
# for angle in range(0, 360, 5):
#     ax.view_init(elev=30, azim=angle)
#     fig.canvas.draw()
#     img_data = np.frombuffer(fig.canvas.tostring_rgb(), dtype='uint8')
#     w, h = fig.canvas.get_width_height()
#     img_data = img_data.reshape(h, w, 3)
#     frames.append(Image.fromarray(img_data))

# #Save frames as an animated GIF
# gif_path = '3d_scatter_rotate.gif'
# frames[0].save(gif_path, save_all=True, append_images=frames[1:],
 ↪duration=100, loop=0)

# #plt.close(fig)
```

Predicted vs Test z with 2 features - $u-g$ and $g-r$



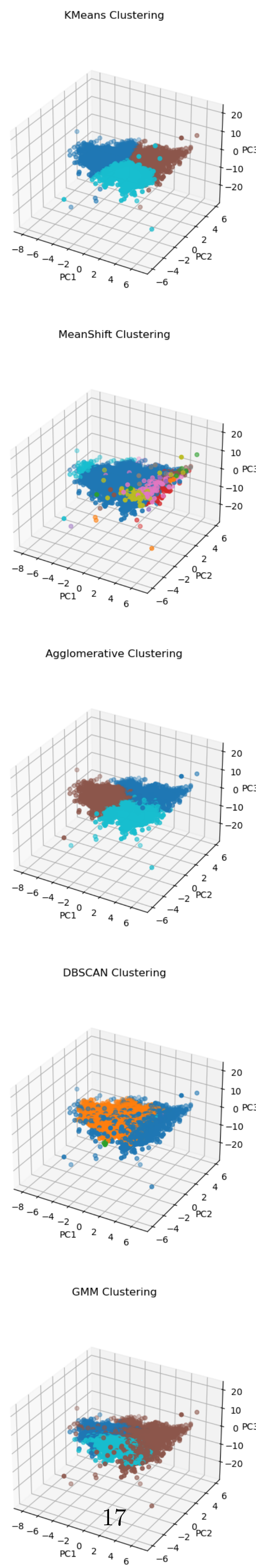
[35]:
```
# Step 5: Optional Visualization
results_df.set_index('Regressor')[['RMSE', 'MAE', 'R2 Score']].plot(kind='bar',␣
 ↪figsize=(12,6))
plt.title('Regressor Comparison')
plt.ylabel('Score')
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```



0.3 Clustering

[45]:
```
# Imports
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans, MeanShift, AgglomerativeClustering, DBSCAN
from sklearn.mixture import GaussianMixture
from sklearn.metrics import adjusted_rand_score, silhouette_score
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
import seaborn as sns
import numpy as np
import pandas as pd

# Step 1: Standardize Features
X = df[['u', 'g', 'r', 'i', 'z', 'u-g', 'g-r', 'r-i', 'i-z']]
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Step 2: Reduce to 3D with PCA
pca = PCA(n_components=3)
X_pca = pca.fit_transform(X_scaled)
```

```python
# Step 3: Initialize Clustering Models
cluster_models = {
    'KMeans': KMeans(n_clusters=3, random_state=42),
    'MeanShift': MeanShift(),
    'Agglomerative': AgglomerativeClustering(n_clusters=3),
    'DBSCAN': DBSCAN(eps=0.5, min_samples=5),
    'GMM': GaussianMixture(n_components=3, random_state=42)
}

cluster_labels = {}

# Step 4: Fit Models and Assign Labels
for name, model in cluster_models.items():
    if name == 'GMM':
        model.fit(X_scaled)
        labels = model.predict(X_scaled)
    else:
        labels = model.fit_predict(X_scaled)
    cluster_labels[name] = labels

# Step 5: 3D Visualization for Each Model
fig = plt.figure(figsize=(30, 25))

for idx, (name, labels) in enumerate(cluster_labels.items(), start=1):
    ax = fig.add_subplot(5, 1, idx, projection='3d')
    ax.scatter(X_pca[:, 0], X_pca[:, 1], X_pca[:, 2], c=labels, cmap='tab10',␣
 ↪s=20)
    ax.set_title(f'{name} Clustering', fontsize=12)
    ax.set_xlabel('PC1')
    ax.set_ylabel('PC2')
    ax.set_zlabel('PC3')
    ax.set_box_aspect(None, zoom=0.80)
plt.tight_layout()
plt.show()
```


KMeans Clustering
PC1
PC2
PC3
MeanShift Clustering
PC1
PC2
PC3
Agglomerative Clustering
PC1
PC2
PC3
DBSCAN Clustering
PC1
PC2
PC3
GMM Clustering
PC1
PC2
PC3

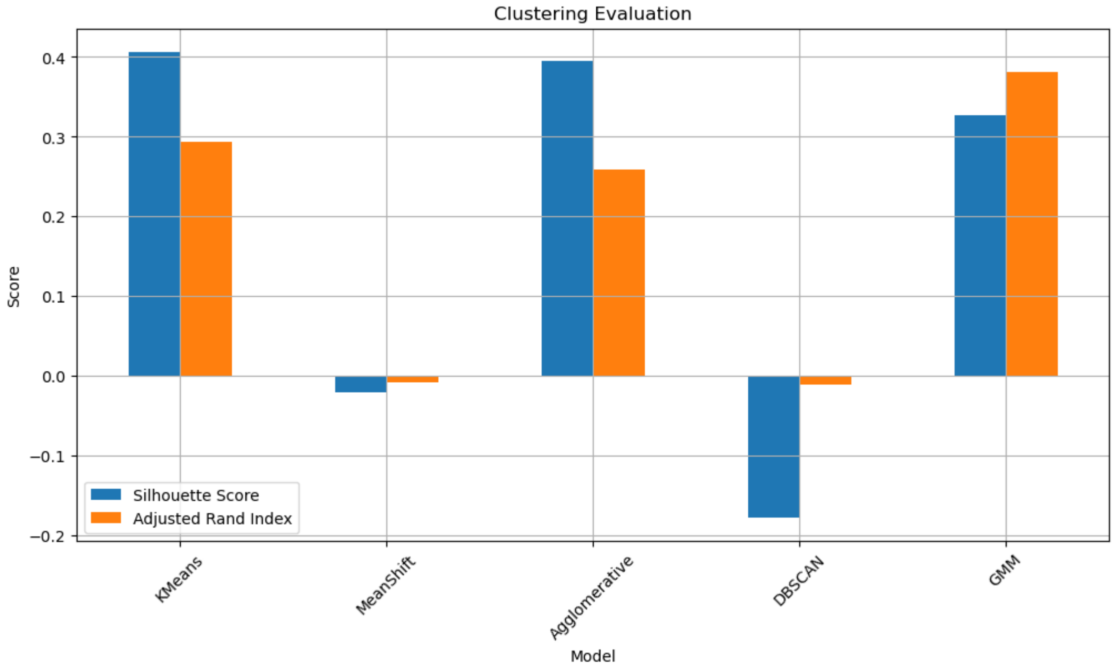
[37]:

```
# Step 6: Evaluate Clustering
results = []

for name, labels in cluster_labels.items():
    # Silhouette score only works if > 1 cluster
    if len(np.unique(labels)) > 1:
        sil_score = silhouette_score(X_scaled, labels)
    else:
        sil_score = np.nan

    # Adjusted Rand Index if true labels exist
    if 'class' in df.columns:
        true_labels = df['class'].values
        ari_score = adjusted_rand_score(true_labels, labels)
    else:
        ari_score = np.nan

    results.append({
        'Model': name,
        'Silhouette Score': sil_score,
        'Adjusted Rand Index': ari_score
    })
```

[38]:

```
# Step 7: Show Evaluation Results
results_df = pd.DataFrame(results)
print(results_df)

# Optional: Plot Evaluation
results_df.set_index('Model')[['Silhouette Score', 'Adjusted Rand Index']].
 ↪plot(kind='bar', figsize=(12,6))
plt.title('Clustering Evaluation')
plt.ylabel('Score')
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```

```
           Model  Silhouette Score  Adjusted Rand Index
0         KMeans          0.406598             0.293919
1      MeanShift         -0.020525            -0.007614
2  Agglomerative          0.395141             0.258972
3         DBSCAN         -0.177372            -0.011440
4            GMM          0.326114             0.380983
```



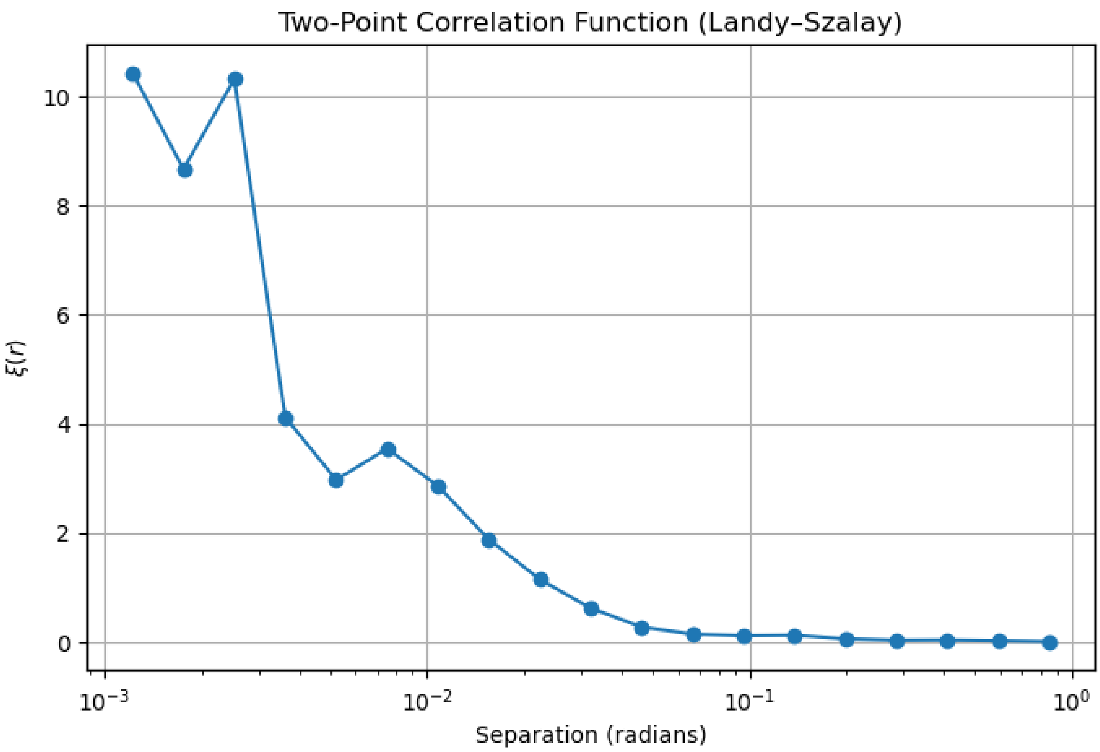
0.4 2-Point Correlation Function

[39]:
```
# Imports
import numpy as np
import matplotlib.pyplot as plt
from sklearn.neighbors import KDTree

# Step 1: Preprocessing
# Use existing 'ra', 'dec', and 'redshift' columns from df
# Filter galaxies in a redshift bin (optional)
# Preprocessing (as before)
z_min, z_max = 0.1, 0.3
df_filtered = df[(df['redshift'] >= z_min) & (df['redshift'] <= z_max)]
ra = np.deg2rad(df_filtered['ra'].values)
dec = np.deg2rad(df_filtered['dec'].values)
x = np.cos(dec) * np.cos(ra)
y = np.cos(dec) * np.sin(ra)
z = np.sin(dec)
positions = np.vstack((x, y, z)).T

# Build the KDTree for your data
from sklearn.neighbors import KDTree
tree_data = KDTree(positions)

# Define your bin edges and centers
```

```
r_bins = np.logspace(-3, 0, 20)      # 20 edges → 19 bins
r_bin_centers = 0.5 * (r_bins[1:] + r_bins[:-1])

# Compute cumulative data-data counts at each bin edge
cum_DD = tree_data.two_point_correlation(positions, r_bins)
# Then get just the counts in each bin:
DD_counts = np.diff(cum_DD)

# Generate a random catalog over the same footprint
n_random = len(positions)
ra_rand = np.random.uniform(df_filtered['ra'].min(), df_filtered['ra'].max(),␣
 ↪n_random)
dec_rand = np.random.uniform(df_filtered['dec'].min(), df_filtered['dec'].
 ↪max(), n_random)
ra_rand, dec_rand = np.deg2rad(ra_rand), np.deg2rad(dec_rand)
x_r, y_r, z_r = np.cos(dec_rand)*np.cos(ra_rand), np.cos(dec_rand)*np.
 ↪sin(ra_rand), np.sin(dec_rand)
positions_rand = np.vstack((x_r, y_r, z_r)).T

# Random-random counts
tree_rand = KDTree(positions_rand)
cum_RR = tree_rand.two_point_correlation(positions_rand, r_bins)
RR_counts = np.diff(cum_RR)

# Data-random cross counts
cum_DR = tree_data.two_point_correlation(positions_rand, r_bins)
DR_counts = np.diff(cum_DR)

# Landy-Szalay estimator
xi = (DD_counts - 2*DR_counts + RR_counts) / RR_counts
```

[40]:

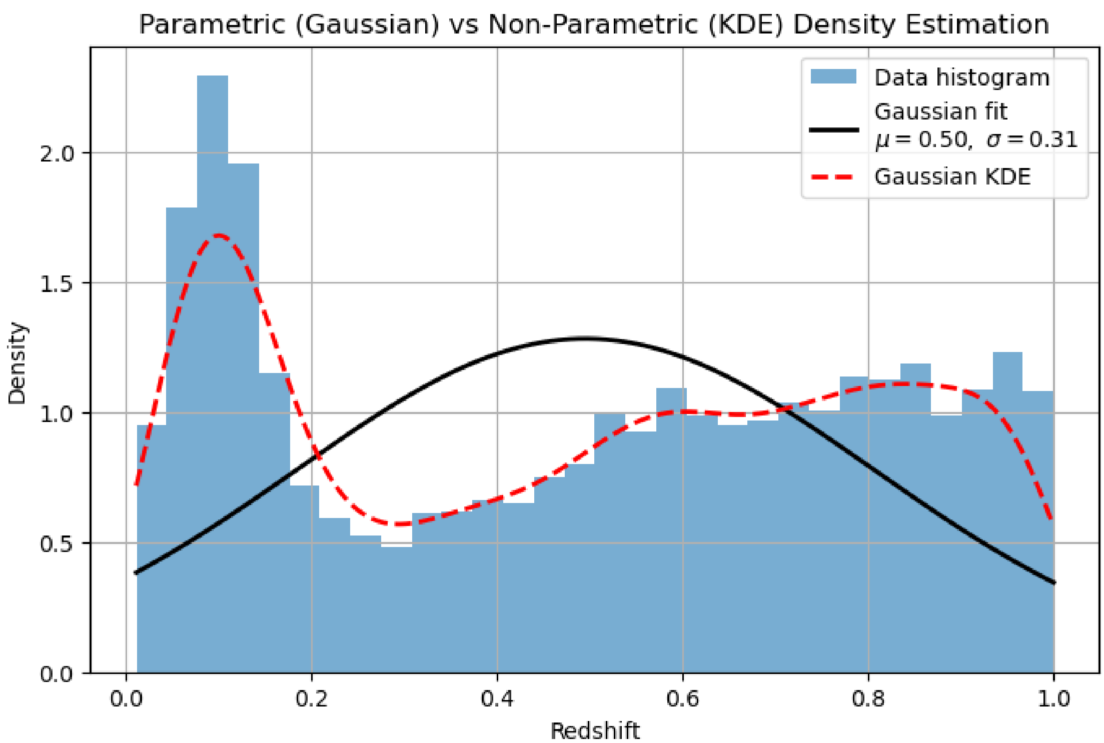
```
# Plot
import matplotlib.pyplot as plt

plt.figure(figsize=(8,5))
plt.plot(r_bin_centers, xi/30, marker='o', linestyle='-')
plt.xscale('log')
plt.xlabel('Separation (radians)')
plt.ylabel(r'$\xi(r)$')
plt.title('Two-Point Correlation Function (Landy-Szalay)')
plt.grid(True)
plt.show()
```



0.5 Parametric vs Non-Parametric

[41]:
```
# Imports (if not already imported)
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import norm, gaussian_kde

# Step 1: Filter out STAR class, keep only GALAXY and QSO
mask = df['class'].isin(['GALAXY', 'QSO'])
# Now pick your 1D variable on that subset (e.g., redshift or a color index)
data = df.loc[mask, 'redshift'].values  # or df.loc[mask, 'g-r'].values, etc.

# Step 2: Parametric Density Estimation (Gaussian fit)
# Fit a Gaussian to the data
mu, std = norm.fit(data)

# Create an array of x-values over the range of the data
x = np.linspace(data.min(), data.max(), 200)

# Compute the Gaussian PDF
pdf = norm.pdf(x, loc=mu, scale=std)
```

```
# Plot histogram and Gaussian fit
plt.figure(figsize=(8,5))
plt.hist(data, bins=30, density=True, alpha=0.6, label='Data histogram')
plt.plot(x, pdf, 'k-', lw=2, label=f'Gaussian fit\n$\mu={mu:.2f},\ \sigma={std:.
↪2f}$')

# Step 3: Non-Parametric Density Estimation (KDE)
kde = gaussian_kde(data)
kde_vals = kde(x)

# Overlay KDE curve
plt.plot(x, kde_vals, 'r--', lw=2, label='Gaussian KDE')

# Final touches
plt.xlabel('Redshift')
plt.ylabel('Density')
plt.title('Parametric (Gaussian) vs Non-Parametric (KDE) Density Estimation')
plt.legend()
plt.grid(True)
plt.show()
```



[42]:

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# Imports (if not already imported)
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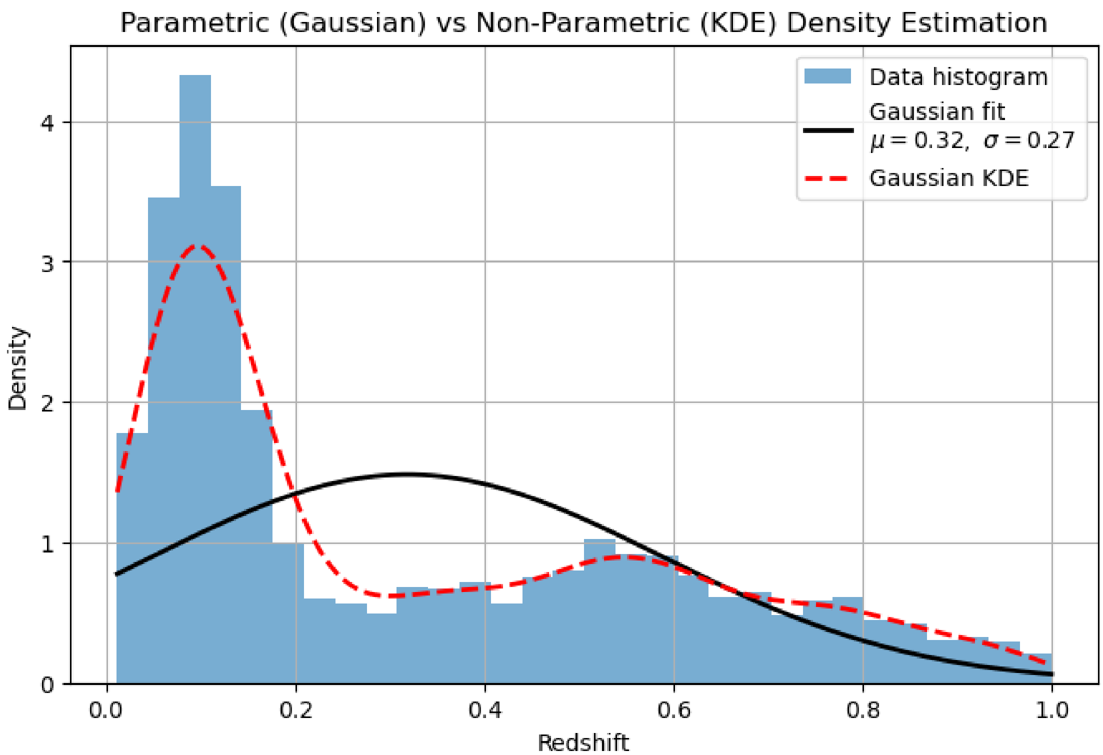

[43]:
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import matplotlib.pyplot as plt
from scipy.stats import norm, gaussian_kde

# Step 1: Filter out STAR class, keep only GALAXY and QSO
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# Now pick your 1D variable on that subset (e.g., redshift or a color index)
data = df.loc[mask, 'redshift'].values  # or df.loc[mask, 'g-r'].values, etc.

# Step 2: Parametric Density Estimation (Gaussian fit)
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mu, std = norm.fit(data)

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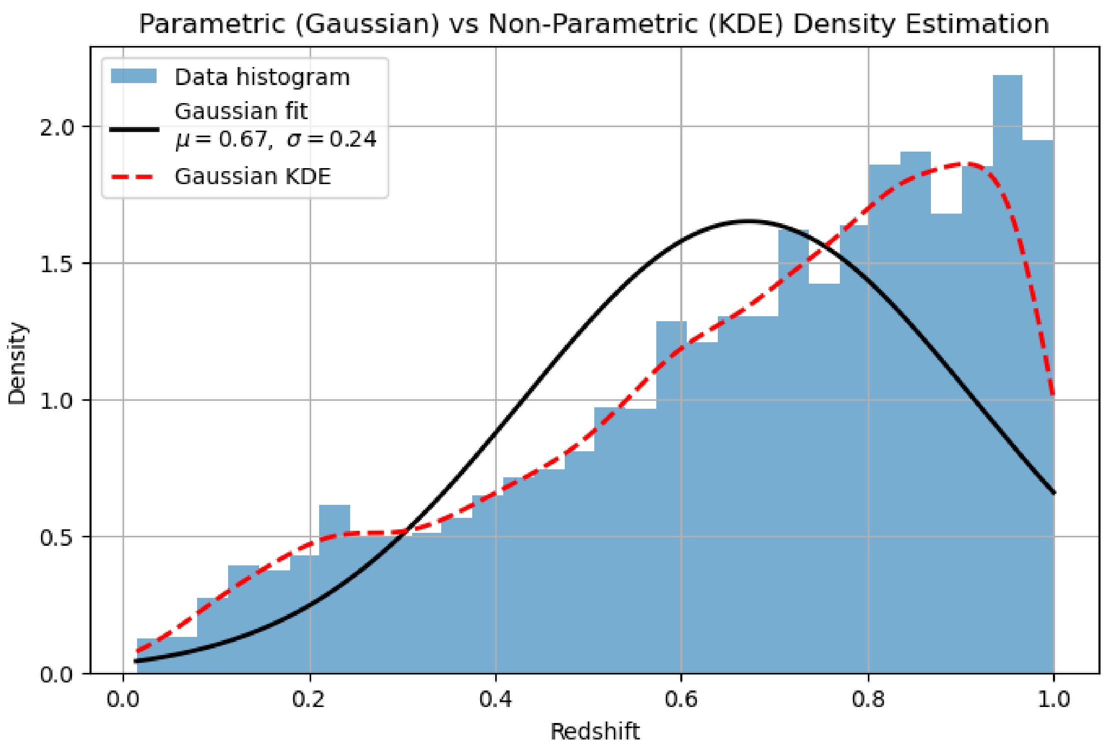

[ ]: