GCRidgeline (/github/anettszs/GCRidgeline/tree/main)
/ ridgeline.ipynb (/github/anettszs/GCRidgeline/tree/main/ridgeline.ipynb)

In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.nonparametric.smoothers_lowess import lowess
from scipy.interpolate import CubicSpline, interp1d
```

In [3]:
```
# --- Adjust parameters and Load Data---

lower_limit_G, upper_limit_G, color_index_upper_lim = 20, 10, 1.5  #hard limi
bprp, gmag = np.loadtxt("NGC6397.txt", unpack=True, skiprows=1)  #input data,
```

Data Preparation

In this section we search for the bluest point in the color-magnitude diagram (CMD), This is useful for example in isochrone fitting, where we need to know the position of the main sequence turn-off (MSTO) point. The LOWESS (Locally Weighted Scatterplot Smoothing) method is applied to determine the primary ridgeline of the CMD. Then the numerical derivative of the ridge line is calculated, which is used to determine the slope of the ridgeline. This slope is used to rotate the points in the CMD, so that the ridgeline is horizontal in the transformed coordinate system.

In [4]:

```
arr = np.column_stack((bprp, gmag))
arr = arr[(arr[:, 1] < lower_limit_G) & ~((arr[:, 0] < color_index_upper_lim)
df = pd.DataFrame(arr, columns=['bprp', 'gmag']).dropna().sort_values('gmag')
df[['ridge_bprp', 'ridge_gmag']] = lowess(df['bprp'], df['gmag'], frac=0.2)[:
blue_x, blue_y = df.loc[df['ridge_bprp'].idxmin(), ['ridge_bprp', 'ridge_gmag
#cut2_points_x, cut2_points_y = blue_x + 0.3, blue_y - 2


def numerical_derivative(x, y):
    x, y = np.asarray(x), np.asarray(y)
    d = np.zeros_like(y)
    d[0] = (y[1] - y[0]) / (x[1] - x[0])
    d[1:-1] = (y[2:] - y[:-2]) / (x[2:] - x[:-2])
    d[-1] = (y[-1] - y[-2]) / (x[-1] - x[-2])
    return d

def rotate_points(x, y, rx, ry, inverse=False):
    a = np.arctan(numerical_derivative(ry, rx))
    if inverse:
        a = -a
    c, s = np.cos(a), np.sin(a)
    x_rot = x * c - y * s
    y_rot = x * s + y * c
    if not inverse:
        y_rot += ry
    return x_rot, y_rot

# --- Rotation and Binning ---
df[['x_new', 'y_new']] = np.column_stack(
    rotate_points(df['bprp']-df['ridge_bprp'], df['gmag']-df['ridge_gmag'], d
)
df["x_new0"] = 0
df = df.sort_values(by='y_new')
```

We separate the datapoints into N number of bins along the Y axis. Then we calculate KDE (Kernel Density Estimate) values along the X axis of each bin and calculate the median values along the Y axis. The maximum values of the KDEs became the X coordinate and the median values became the Y coordinates of the N well-defined bin points. We connect these points with a cubic spline. Then we transform everything back into the original coordinate system where the interpolated cubic spline becomes the new ridgeline. This way, the new ridgeline now closely follows the turnoff point and the RGB.

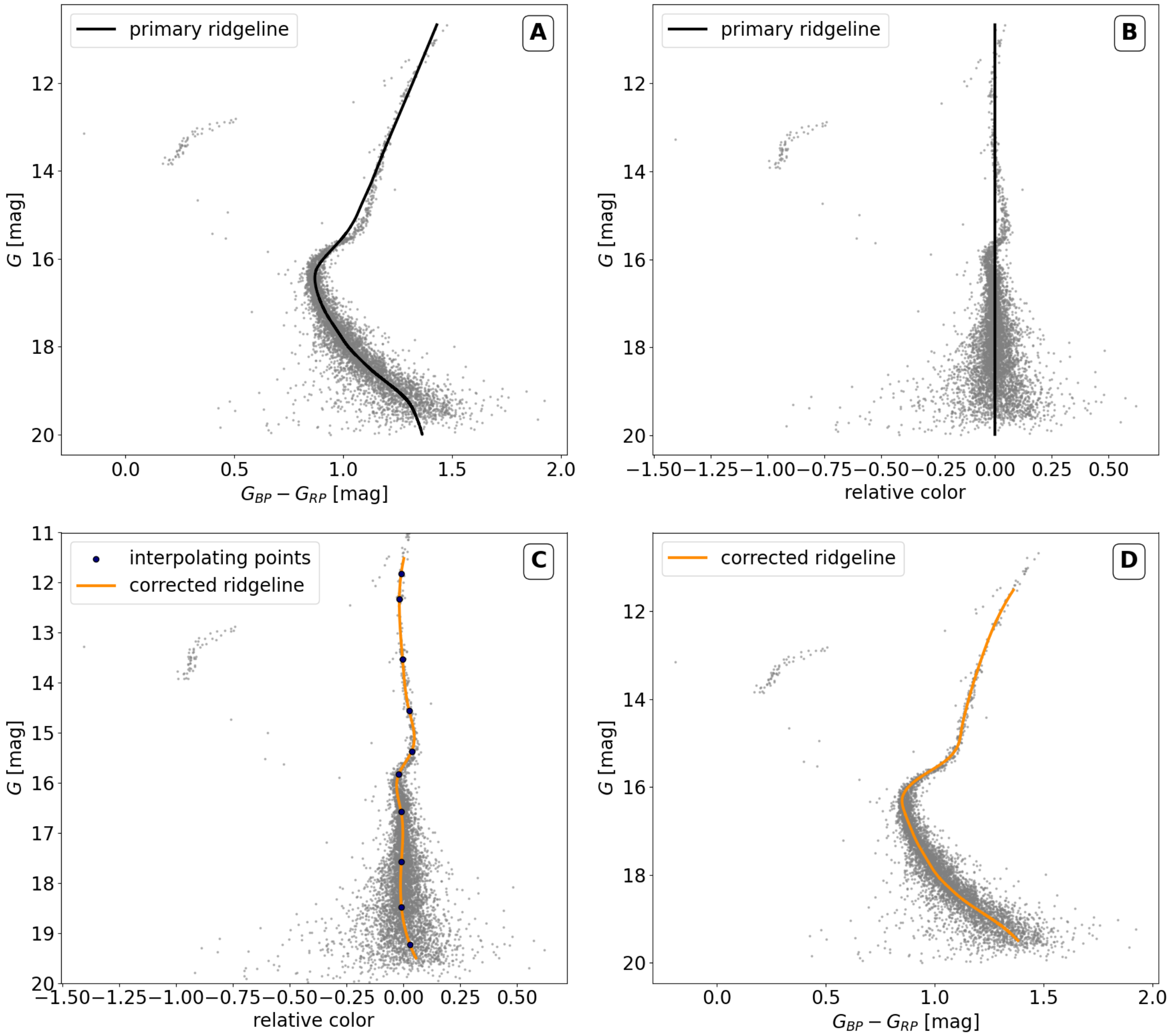
In [5]:
```python
bins = np.array([11.5,12,13,14,15,15.6,16,17,18,19,19.5]) #Adjust the bins as

bin_labels = [str(b) for b in bins[:-1]]
df['bin'] = pd.cut(df['y_new'], bins=bins, labels=bin_labels, right=False)

# --- KDE Calculation ---
def calculate_kde(df, column, y_column, bandwidth='scott'):
    results = []
    for bin_label, group in df.groupby('bin', observed=False):
        if group[column].empty:
            continue
        fig, ax = plt.subplots()
        kde_plot = sns.kdeplot(group[column], bw_method=bandwidth, ax=ax)
        xxx, yyy = kde_plot.lines[0].get_data()
        plt.close(fig)
        idx_max = pd.Series(yyy).idxmax()
        results.append({
            'bin': bin_label,
            'x_at_max_density': xxx[idx_max],
            'median_y': group[y_column].median()
        })
    return results

kde_results = calculate_kde(df, 'x_new', 'y_new')
results_df = pd.DataFrame(kde_results).sort_values(by='median_y')
y_sorted = results_df['median_y'].values
x_sorted = results_df['x_at_max_density'].values

# --- Interpolation and Inverse Rotation ---
cs = CubicSpline(y_sorted, x_sorted)
mask = (df['y_new'] >= bins[0]) & (df['y_new'] < bins[-1])
df.loc[mask, 'x_interpolate'] = cs(df.loc[mask, 'y_new'])
df.loc[~mask, 'x_interpolate'] = np.nan

df['x_back2'], df['y_back2'] = rotate_points(
    df['x_interpolate'], df['y_new'] - df['ridge_gmag'], df['ridge_bprp'], df
)
df['x_back2'] += df['ridge_bprp']
df['y_back2'] += df['ridge_gmag']

# --- Final Sorting and Linear Interpolation ---
df_sorted = df[['x_back2', 'y_back2']].sort_values(by='y_back2').dropna().res
x_sorted = df_sorted['x_back2'].values
y_sorted = df_sorted['y_back2'].values
linear_interp = interp1d(y_sorted, x_sorted, kind='linear', fill_value="extra
y_fine2 = np.linspace(y_sorted.min(), y_sorted.max(), 10000)
x_fine2 = linear_interp(y_fine2)
```

```
/tmp/ipykernel_3341/3890085491.py:13: RuntimeWarning: invalid value encounte
red in divide
  d[1:-1] = (y[2:] - y[:-2]) / (x[2:] - x[:-2])
```

Visualization

In [ ]:
```
# Set the font size and family for the plot
plt.rcParams.update({'font.size': 20})
#plt.rcParams["font.family"] = "Liberation Serif" ## specital font family, ca

# Set the point size and transparency
s = 3
alpha = 0.5

fig, axs = plt.subplots(2, 2, figsize=(18, 16))

# Top left: CMD with primary ridgeline
axs[0, 0].invert_yaxis()
#axs[0, 0].set_xlim(0.75, 1.5)
axs[0, 0].scatter(df['bprp'], df['gmag'], s=s, c='grey', alpha=alpha)
axs[0, 0].plot(df['ridge_bprp'], df["ridge_gmag"], c="black", lw=3, label="pr
axs[0, 0].set_xlabel('$G_{BP}-G_{RP}$ [mag]')
axs[0, 0].set_ylabel('$G$ [mag]')
axs[0, 0].legend(loc='upper left')

# Top right: Rotated CMD with primary ridgeline
axs[0, 1].invert_yaxis()
#axs[0, 1].set_xlim(-0.6, 0.4)
axs[0, 1].scatter(df['x_new'], df['y_new'], s=s, color='grey', alpha=alpha)
axs[0, 1].plot(df['x_new0'], df['y_new'], c="black", lw=3, label="primary rid
axs[0, 1].set_xlabel('relative color')
axs[0, 1].set_ylabel('$G$ [mag]')
axs[0, 1].legend(loc='upper left')

# Bottom left: Rotated CMD with KDE maxima and interpolated curve
axs[1, 0].invert_yaxis()
#axs[1, 0].set_xlim(-0.6, 0.4)
axs[1, 0].set_ylim(20, 11)
axs[1, 0].scatter(df['x_new'], df['y_new'], s=s, color='grey', alpha=alpha)
axs[1, 0].scatter(results_df['x_at_max_density'].values, results_df['median_y
axs[1, 0].plot(df['x_interpolate'], df['y_new'], c="darkorange", zorder=1, lw
axs[1, 0].set_xlabel('relative color')
axs[1, 0].set_ylabel('$G$ [mag]')
axs[1, 0].legend(loc='upper left')


# Bottom right: CMD with corrected ridgeline
axs[1, 1].invert_yaxis()
#axs[1, 1].set_xlim(0.75, 1.5)
axs[1, 1].scatter(df['bprp'], df['gmag'], s=s, color='grey', alpha=alpha)
axs[1, 1].plot(df['x_back2'], df['y_back2'], color='darkorange', lw=3, label=
axs[1, 1].set_xlabel('$G_{BP}-G_{RP}$ [mag]')
axs[1, 1].set_ylabel('$G$ [mag]')
axs[1, 1].legend()

## Add annotation for the panels a, b, c, d
axs[0, 0].annotate('A', xy=(0.96, 0.96), xycoords='axes fraction', fontsize=2
                  ha='right', va='top', bbox=dict(facecolor='white', edgecolo
axs[0, 1].annotate('B', xy=(0.96, 0.96), xycoords='axes fraction', fontsize=2
                  ha='right', va='top', bbox=dict(facecolor='white', edgecolo
axs[1, 0].annotate('C', xy=(0.96, 0.96), xycoords='axes fraction', fontsize=2
                  ha='right', va='top', bbox=dict(facecolor='white', edgecolo
```

```
axs[1, 1].annotate('D', xy=(0.96, 0.96), xycoords='axes fraction', fontsize=2
                   ha='right', va='top', bbox=dict(facecolor='white', edgecolo

plt.tight_layout()
#plt.savefig("ridgeline_analysis.png", dpi=300)
plt.show()
```



Supplementary features

Only the final ridgeline plot

In [20]:
```
fig = plt.figure(figsize=(8,8))
plt.gca().invert_yaxis()

## Adjust limits according to your data
plt.xlim(0.7,1.5)

plt.scatter(df['bprp'],df['gmag'], s=s, alpha=alpha, color='grey')
#plt.plot(df['ridge_bprp'], df["ridge_gmag"], c="darkorange", lw=2, label="pr
plt.plot(df['x_back2'], df['y_back2'],color='navy',lw=2, label="corrected rid

plt.xlabel('$G_{BP}-G_{RP}$ [mag]', fontsize=20)
plt.ylabel('$G$ [mag]', fontsize=20)
plt.legend()

#plt.savefig("ridge_NGC6379.png", dpi=300)
plt.show()
```