COMP5360 Spring 2022: Final Project

Optical-Spectroscopic Object Classification

Your Data

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Project Description

Our project in summary is the classification of astronomical objects using Python. The ultimate goal of the project is to be able to pass in specific astronomical data and have our Python model return what type of astronomical object it is. The classifications of astronomical objects we chose to have is: Galaxy, Star and Quasar. When passing in the specific data points, our model should return to us what exactly the astronomical object is out of those three classifications. With this in mind, we also hope to try our model out when it is complete with other data to see if it can accurately return the correct classification of the astronomical object.

We are using data from https://www.sdss.org/dr17/data_access/bulk and http://skyserver.sdss.org/dr17 to use for our data model. This data includes numerous data points, including right ascension angle, declination angle, ultraviolet filter, green filter, red filter, etc. With this data we can construct the classification system we need to determine the final object.

We plan to use dimensionality reduction, such as PCA/t-SNE, as well as cross-validated classification/clustering methods – such as SVM (Support Vector Machine) and K-means – for our analysis methods on this data and to build our model.

In summary, the question we are trying to answer – our hypothesis – is, what astronomical objects do we have based on the data we have been given?

Data Acquisition

Assessment of possible data sources

Data Description

Our data set contains numerous data points including right ascension angle, declination angle, ultraviolet filter, green filter, red filter, etc

Flexible Image Transport System (FITS)

Our first process for acquiring the data from https://www.sdss.org/dr17/data_access/bulk involved researching and locating .fits files (Flexible Image Transport System – defines digital file format useful for storage). However, with this process, we were unable to determine exactly what the .fits files contained. For example, we were unsure with our initial data processing if one .fits file represented one data object or multiple.

Source in our Repository: "comp5360_final\EDA\Python\Read.py"

In [155…

```
# #conda install astropy
# import astropy
# from astropy.io import fits
# from astropy.table import Table

# with fits.open('spec-10000-57346-0001.fits') as hdul:
#     print(hdul.info())
#     print(hdul[1].header)
#     print(hdul[1].data)
```

Web Scraping

Our second process for acquiring data from https://www.sdss.org/dr17/data_access/bulk involved web scraping. Since we knew the data was stored here we were able to locate the specific astronomical objects here: http://skyserver.sdss.org/dr17/VisualTools .

Upon accessing this page, we noticed there were individual links to the “PhotoObj” (imaging) and the “SpecObj” (spectra)

 Spec  Image

When we followed these links, we saw that the data was constructed as HTML tables.  HTML

So, we decided we would web scrape our data using these HTML tables, store the information and write it all out to a CSV using Python.

However, we did run into some issues:

Issue#1: We first checked to see if we could web scrape this website and when we noticed they had a specific API, we continued with our process. The first issue we noticed is that we could not ping the website too much, so we set up a timer to wait a second or two before querying the website again. One person queried spectral data; the other person queried image data. Once all our data had been queried, we would merge both CSVs together to have one large dataset of both the image and spectral data.

Issue#2: After querying a few of the HTML pages, we noticed if we programmatically accessed the webpage, it would not return the correct data. Even typing in the URL by hand resulted in incorrect data. For example, where there should have been a value a "0" was always returned. At this point, we determined we had to change our course for acquiring the data again.

Source in our Repository: "comp5360_final\data_acquisition\Python\web_scraping_optical_spectra_and_imagi

In [156…

```
# #%% imports
# from bs4 import BeautifulSoup
# from selenium import webdriver
# import time
# from os import listdir
# from os import chdir
# import pandas as pd


# #%% SWITCHES

# #folder containing repo root
# repo_path = r'C:\Users\Bob\Desktop\U\comp5360_final'
# #repo_path = r'/Users/roannarague/Documents/BMI_6106_Final'

# #
# web_driver_path = 'C:/Users/Bob/Downloads/chromedriver_win32/chromedriver.exe'
# #web_driver_path = '/Users/roannarague/Downloads/chromedriver_win32/chromedriver.exe'

# # set FALSE for imaging data
# #want_optical_spectra = True
# want_optical_spectra = False


# #%% working directory
# chdir(repo_path)
# chdir('.\data_acquisition\Python')

# #%% data temp/out dirs
# web_scraping_dir = '../../data/web_scraping'
# data_folder = 'optical_spectra_data' if want_optical_spectra else 'imaging_data'
# data_out_dir = f'{web_scraping_dir}/{data_folder}'
# temp_html_dir = f'{web_scraping_dir}/temp_html'

# #%% out file
# data_type = 'optical_spectra' if want_optical_spectra else 'imaging_data'
# out_csv = f'{data_out_dir}/{data_type}_first_10000.csv'

# #%% read in reference data
```

```
# df = pd.read_csv('../../data/star_classification.csv')

# #%% scrape table from each spec_obj_ID's page in 1 second intervals and write to file
# optical_spectra_url = 'http://skyserver.sdss.org/dr17/VisualTools/explore/displayresu
# imaging_url = 'https://skyserver.sdss.org/dr17/VisualTools/explore/displayresults?nam
# spec_obj_ID_param = '&spec=' # common parameter
# obj_ID_param = '&id=' # imaging parameter

# abort = False
# no_data = []
# with webdriver.Chrome(web_driver_path) as driver:
#     for ids in df.loc[0:10000,['spec_obj_ID','obj_ID']].to_numpy():
#         specObjId = int(ids[0])
#         objId = int(ids[1])
#         query = ''
#         if want_optical_spectra:
#             query = f'{optical_spectra_url}{spec_obj_ID_param}{specObjId}'
#         else:
#             query = f'{imaging_url}{obj_ID_param}{objId}{spec_obj_ID_param}{specObjId
#         try:
#             driver.get(query)
#             table = driver.find_element_by_xpath('//table/..')
#             table_html = table.get_attribute('innerHTML')
#             with open(f'{temp_html_dir}/{specObjId}.html', 'w') as new_file:
#                 new_file.write(table_html)
#         except:
#             no_data.append(specObjId)
#         time.sleep(1)
#         if not abort:
#             continue
#         break


#     with open(f'{data_out_dir}/no_data_spec_Obj_Ids_first_10000.txt','w') as nd_file:
#         nd_file.write(f'{no_data}')


# #%% list all files in saved HTML directory
# pages = []
# for file in listdir(temp_html_dir):
#     with open(f'{temp_html_dir}/{file}', encoding='utf-8') as f:
#         pages.append(BeautifulSoup(f.read(), 'html.parser'))


# #%% hacky way to visualize first page contents
# len(pages)
# pg = pages[0]
# pg.text.replace('\n',' ').replace('   ',',')[2:3424].replace(' ',': ').split(',') # r


# #%% extract key/value pairs from each page into list of dicts
# spec_obj_dictionaries = []
# pg_idx = 0
# for page in pages:
#     try:
#         pdict = {}
#         for row in page.select('tr'):
#             field = row.select('tr > th > span')[0].text
#             value = row.select('tr > td')[0].text
#             if field == 'img':
```

```
#                 break
#             pdict[field]=value
#         spec_obj_dictionaries.append(pdict)
#     except Exception as e:
#         print(f'Broke on page index {pg_idx} due to {str(e)}')
#     pg_idx += 1


# #%% check successful scrapes weren't all GALAXY
# sdf = pd.DataFrame(spec_obj_dictionaries)
# #print(sdf['class'].value_counts()) not all team members' scrape designations have cl
# #sdf['spec_obj_ID']...

# # TODO: RO PR -> df.iloc[0] =>
# # obj_ID         1237660961327743232.0
# # alpha                     135.689107
# # delta                      32.494632
# # u                          23.87882
# # g                           22.2753
# # r                          20.39501
# # i                          19.16573
# # z                          18.79371
# # run_ID                         3606
# # rerun_ID                        301
# # cam_col                           2
# # field_ID                         79
# # spec_obj_ID    6543777369295181824.0
# # class                        GALAXY
# # redshift                   0.634794
# # plate                          5812
# # MJD                           56354
# # fiber_ID                        171

# # 6543777369295181824.html written to disk has specObjID of 0
# #
# # fortunately, the file name has this ID and in memory list of soup,
# # but I am concerned about the values
# # (e.g. 'u'='23.87882' (above) vs sdf.iloc[0].u=='23.78062')
# # in cases where we get this specObjId

# #%% save to disk for team merge
# sdf.to_csv(out_csv)

# #%% check
# test = pd.read_csv(out_csv)
```

Web Querying

Finally our third process for acquiring data from https://www.sdss.org/dr17/data_access/bulk, involved using a special tool on the website: https://skyserver.sdss.org/dr17/CrossMatchTools/ObjectCrossID. This tool allowed us to query the data directly on the website using SQL. We were able to check the correct search types we needed and write the data out as a final CSV file.

 CrossID

However, we also ran into some issues:

Issue#1: The data returned resulted in massive files, so we had to do 10 runs of this query to get all our data. Then we merged all the CSV files together

Issue#2: When we had our final dataset, we noticed there were only two classifications: stars and galaxies. But no quasars. For this database, these were the only two classifications. To fix this issue, we used: https://skyserver.sdss.org/dr17/SearchTools/sql# to write a direct SQL query for Quasars. This returned a CSV file of just quasars where we then matched the "spec_obj_id" with the "spec_obj_id" in our initial dataset (with just galaxies and stars) and re-classified any of them that had a matching "spec_obj_id" in the quasar CSV.

 SQL

Source in our Repository: "comp5360_final\data_acquisition\Python\web_query_file_builder.py"

In [157…

```
# #%% Imports

# import numpy as np
# import pandas as pd
# from os import chdir


# #%% working directory

# #folder containing repo root
# repo_path = r'C:\Users\Bob\Desktop\U\comp5360_final'
# #repo_path = r'/Users/roannarague/Documents/BMI_6106_Final'

# chdir(repo_path)

# chdir('./data_acquisition/Python')


# #%% read in reference data
# df = pd.read_csv('../../data/star_classification.csv')


# #%%% build
# out_dir = '../../data/skyserver_querying'

# num_chunks = 10
# num_objs = df.shape[0]
# chunk_size = int(num_objs / num_chunks)

# for i in range(num_chunks):
#     ra_dec = []
#     ra_dec.append('  name  ra         dec\n')
#     idx = 0
#     start = chunk_size * i
#     end = start + chunk_size - 1
#     if num_chunks == i + 1:
#         end += 1
#     for ids in df.loc[start:end,['alpha', 'delta']].values:
#         idx += 1
```

```
#         xname = hex(idx)[2:]
#         ra_dec.append(f'  {xname:<4}  {ids[0]:<19}  {ids[1]}\n')

#     with open(f'{out_dir}/ra_dec_{start}-{end}.txt','w') as f:
#         f.writelines(ra_dec)
```

Clean up concatenated Web Query data

Check data for issues

Source in our Repository: "comp5360_final\data_acquisition\Python\clean_and_compare_ref_vs_final_combine

In [158…

```
# #%% Imports

# import numpy as np
# import pandas as pd
# from os import chdir


# #%% working directory

# #folder containing repo root
# repo_path = r'C:\Users\Bob\Desktop\U\comp5360_final'
# #repo_path = r'/Users/roannarague/Documents/BMI_6106_Final'

# chdir(repo_path)

# chdir('./data_acquisition/Python')


# #%% read in reference data
# df = pd.read_csv('../../data/star_classification.csv')


# #%% clean up join of queries

# def FreshValDf():
#     t = pd.read_csv('../../data/skyserver_querying/final_combined.csv', skiprows=1)

#     cols = t.columns.to_numpy()
#     # ['name', 'objID', 'ra', 'dec', 'run', 'rerun', 'camcol', 'field','type', ...

#     # drop 'name' per artifact of query
#     t = t.drop('name', axis=1)

#     cols = t.columns.to_numpy()
#     # ['objID', 'ra', 'dec', 'run', 'rerun', 'camcol', 'field','type', 'modelMag_u',
#         'modelMag_i', 'modelMag_z', 'specObjID', 'plate', 'mjd', 'fiberID']
```

```
#     len(t.specObjID.unique())
#     #126598

#     t.shape
#     #(128429, 19)

#     t.shape[0] - len(t.specObjID.unique())
#     #1831

#     val_cnts = t.specObjID.value_counts()
#     val_cnts.reset_index().iloc[0]
#     # index        specObjID
#     # specObjID            9

#     #remove header rows (from joining queries)
#     rows_to_drop_idx = t[t['specObjID']=='specObjID'].index
#     t = t.drop(rows_to_drop_idx)

#     #check ref and val data for matching spec_obj_IDs

#     # all duplicated specObjID rows have sames values in all columns
#     t.duplicated().sum()
#     # 1823 (doesn't include first occurrence)
#     len(t) - t.duplicated().sum()
#     # 128420 - 1823 = 126597

#     t = t.drop(t.loc[t.duplicated()].index)

#     len(t)
#     # 126597
#     len(t['specObjID'].unique())
#     # 126597
#     return t


# tdf = FreshValDf()


# #%% subset ref and val data by matching spec_obj_IDs

# ref_spec_obj_ids = df['spec_obj_ID'].to_numpy()
# val_spec_obj_ids = tdf['specObjID'].astype(float).to_numpy()

# spec_obj_ids_from_val_in_ref = val_spec_obj_ids[np.in1d(val_spec_obj_ids, ref_spec_ob
# len(spec_obj_ids_from_val_in_ref)
# #71155

# ref_spec_obj_ids = df['spec_obj_ID'].apply(lambda x: str(int(x))).to_numpy()
# val_spec_obj_ids = tdf['specObjID'].to_numpy()

# spec_obj_ids_from_val_in_ref = val_spec_obj_ids[np.in1d(val_spec_obj_ids, ref_spec_ob
# len(spec_obj_ids_from_val_in_ref)
# #71155

# # subset queried data (common soi w/ref data)
# df_val_subset = tdf[tdf['specObjID'].isin(spec_obj_ids_from_val_in_ref)]
# df_val_subset.shape

# # subset ref data
# soi_float = spec_obj_ids_from_val_in_ref.astype(float)
```

```
# df_ref_subset = df[df['spec_obj_ID'].isin(soi_float)]
# df_ref_subset.shape


# #%% look at data types/values to decide what makes sense

# def prnt(df):
#     print()
#     idx = df.dtypes.index
#     dt = df.dtypes
#     val = df.iloc[0]
#     for i in range(len(val)):
#         typ = str(dt[i])
#         print(f'{typ:<10}  {idx[i]:<15}{val[i]:>24}')
#     print()

# prnt(df_ref_subset)
# # float64     obj_ID           1.2376609613277432e+18
# # float64     alpha                    135.6891066036
# # float64     delta                   32.4946318397087
# # float64     u                              23.87882
# # float64     g                               22.2753
# # float64     r                              20.39501
# # float64     i                              19.16573
# # float64     z                              18.79371
# # int64       run_ID                             3606
# # int64       rerun_ID                            301
# # int64       cam_col                               2
# # int64       field_ID                             79
# # float64     spec_obj_ID       6.543777369295182e+18
# # object      class                            GALAXY
# # float64     redshift                      0.6347936
# # int64       plate                              5812
# # int64       MJD                               56354
# # int64       fiber_ID                            171

# prnt(df_val_subset)
# # object      objID                1237660961327743273
# # object      ra                       135.6891066036
# # object      dec                     32.4946318397087
# # object      run                                3606
# # object      rerun                               301
# # object      camcol                                2
# # object      field                                79
# # object      type                             GALAXY
# # object      modelMag_u                     23.87882
# # object      modelMag_g                      22.2753
# # object      modelMag_r                     20.39501
# # object      modelMag_i                     19.16573
# # object      modelMag_z                     18.79371
# # object      specObjID           6543777369295181824
# # object      plate                              5812
# # object      mjd                               56354
# # object      fiberID                             171
# # object      z                                0.6347936

# modelMag ~ (de Vaucouleurs magnitude fit || Exponential fit magnitude), better of DeV

# #%% match up
# def ConvertToMatchRef(d):
```

```
#     d['redshift'] = d['z']
#     d['class'] = d['type']
#     d['spec_obj_ID'] = d['specObjID']
#     d['obj_ID'] = d['objID']
#     d['alpha'] = d['ra'].astype(float)
#     d['delta'] = d['dec'].astype(float)
#     d['u'] = d['modelMag_u'].astype(float)
#     d['g'] = d['modelMag_g'].astype(float)
#     d['r'] = d['modelMag_r'].astype(float)
#     d['i'] = d['modelMag_i'].astype(float)
#     d['z'] = d['modelMag_z'].astype(float)


#     d = d.drop(['type'], axis=1)
#     d = d.drop(['ra'], axis=1)
#     d = d.drop(['dec'], axis=1)
#     d = d.drop(['modelMag_u'], axis=1)
#     d = d.drop(['modelMag_g'], axis=1)
#     d = d.drop(['modelMag_r'], axis=1)
#     d = d.drop(['modelMag_i'], axis=1)
#     d = d.drop(['modelMag_z'], axis=1)

#     d['run_ID'] = d['run'].astype(int)
#     d['rerun_ID'] = d['rerun'].astype(int)
#     d['cam_col'] = d['camcol'].astype(int)
#     d['field_ID'] = d['field'].astype(int)
#     d['plate'] = d['plate'].astype(int)
#     d['MJD'] = d['mjd'].astype(int)
#     d['fiber_ID'] = d['fiberID'].astype(int)

#     d = d.drop(['objID','specObjID', 'run',
#                 'rerun', 'camcol', 'field',
#                 'mjd', 'fiberID'], axis=1)
#     return d

# #%%
# df_val_subset = ConvertToMatchRef(df_val_subset)

# #%% check
# prnt(df_val_subset)
# prnt(df_ref_subset)
# print(df_val_subset.shape)
# print(df_ref_subset.shape)

# #%% write
# df_val_subset.to_csv('final_combined_clean_subset_matching_ref.csv')



# #%% NO QUASARS?
# df_val_subset['class'].value_counts()


# #%%
# print(df['class'].value_counts())

# #%% YUP, NO QUASARS!

# df_val = FreshValDf()
# df_val['type'].value_counts()
```

```
# df_val = df_val.drop(df_val[df_val.isna().any(axis=1)].index)
# ddd = ConvertToMatchRef(df_val)
# prnt(ddd)
# print(ddd['class'].value_counts())

# t = pd.read_csv('../../data/skyserver_querying/final_combined.csv', skiprows=1)
# t['type'].value_counts()
```

Found that we had no Quasar data

Peer Review verified no Quasar data

Queried https://skyserver.sdss.org/dr17/CrossMatchTools/ObjectCrossID for only Quasars ("Quasars2.csv")

Matched `spec_obj_ID` to previously queried astronomical objects (Quasars mostly over-generalized as `STAR`)

Source in our Repository: "comp5360_final\data_acquisition\Python\SetQuasars.py"

In [159…

```
# ## Part 1a: Read in initial final combined csv (the one with no Quasars)

# # imports and setup
# import pandas as pd
# import numpy as np
# import os


# #set working directory
# os.chdir('/Users/roannarague/Downloads')
# #os.chdir('/Users/Bob/Desktop/u/comp5360_final/data_acquisition/Python/')

# #read in the final_combined csv (with no quasars)
# # renamed final_combined_clean_subset_matching_ref.csv to shorten
# df_combined = pd.read_csv('/Users/roannarague/Downloads/final_combined_3.csv')
# #df_combined = pd.read_csv('./final_combined_3.csv')

# #print a few lines
# #df_combined.head()

# #check out all our spec ob IDs
# #print(df_combined['spec_obj_ID'])


# ## PART 1b: Read in our ALL Quasar CSV data

# #read in the final_combined csv (with no quasars)
# df_qso = pd.read_csv('/Users/roannarague/Downloads/Quasars2.csv')
# #df_qso = pd.read_csv('./Quasars2.csv')

# #print a few lines
# #df_qso.head()

# #print columns
# #print(df_qso.columns.tolist())
```

```
# #create new dataframe of just spec obj ids
# df_specs = pd.DataFrame().assign(specObjID=df_qso['specObjID'])

# #df_specs.head()

# #create a numpy array out of this new dataframe
# specID_array = df_specs.to_numpy()

# #print(specID_array)


# # PART 2: Iterate through our final_combined_3.csv to find specObjIDs that match our

# ## PART 2a: iterate through our df_combined dataframe and start comparing specObjIDs

# #iterate through our df_combined dataframe

# #create a variable to store our first quasar spec id we find so we can validate later
# firstQSOSpecID = 0

# #print("================= SpecObjID ========== Class ======")
# for index, row in df_combined.iterrows():
#     #print("index: " , index, " --> ", row['spec_obj_ID'], " " ,row['class'])
#     #print(row['spec_obj_ID'])
#     if row['spec_obj_ID'] in specID_array:
#         firstQSOSpecID = row['spec_obj_ID']

#         #print our old row
#         #print("==================== ROW ====================")
#         #print("OLD Row: ", "index: ", index, "Row: ", row['spec_obj_ID'], " CLASS: "

#         #so now we have to change the class type from whatever it was to QSO == Quasa
#         df_combined.at[index,'class']='QSO'

#         #print our new row
#         #print("NEW Row: ", "index: ", index, "Row: ", row['spec_obj_ID'], " CLASS: "

# #DOUBLE CHECKING DOWN HERE to make sure that it actually was in the quasar numpy arra
# #for i in specID_array:
#     #if i == firstQSOSpecID:
#         #print("Successful Test #1!")
#         #print(i, " == ", firstQSOSpecID)


# # PART 3: Write to a new final_combined_QSO.csv file

# ## PART 3a: Write a new csv file with Quasars in it

# #first let's take a look at our dataframe head again:
# #for index, row in df_combined.iterrows():
#     #if row['class'] == 'QSO':
#         #print("index: " , index, " --> ", row['spec_obj_ID'], " " ,row['class'])


# #Write to a csv file
# df_combined.to_csv('/Users/roannarague/Downloads/final_combined_QSO_1.csv')
# #df_combined.to_csv('./final_combined_QSO_1.csv')
```

```
# # PART 4: re-read in our new combined csv file with quasars

# #read in the final_combined csv (with quasars)
# df_combined_QSO = pd.read_csv('/Users/roannarague/Downloads/final_combined_QSO_1.csv'
# #df_combined_QSO = pd.read_csv('./final_combined_QSO_1.csv')

# #print a few lines
# #df_combined_QSO.head()
# print(df_combined_QSO.groupby('class').count())


# df_combined['class'].value_counts()
```

Remove index columns and exclude in output CSV

Query 100,000 Optical Spectroscopic Objects for Test

Lastly, we queried 100,000 objects with a fair degree of similarity--ensuring GALAXY/STAR/QUASAR--to our train objects for model test.

Source in our Repository: "comp5360_final\data\star_classification_test_readme.txt"

In [160…

```
# source:
# https://skyserver.sdss.org/dr17/SearchTools/sql

# SQL:
# -- This query does a table JOIN between the imaging (PhotoObj) and spectra
# --(SpecObj) tables and includes the necessary columns in the SELECT to upload
# --the results to the SAS(Science Archive Server) for FITS file retrieval.
# SELECT TOP 100000
# p.objid,p.ra,p.dec,p.u,p.g,p.r,p.i,p.z,
# p.run, p.rerun, p.camcol, p.field,
# s.specobjid, s.class, s.z as redshift,
# s.plate, s.mjd, s.fiberid
# FROM PhotoObj AS p
# JOIN SpecObj AS s ON s.bestobjid = p.objid
# WHERE
#   p.u BETWEEN 10.99 AND 32.8
#   AND g BETWEEN 10.49 AND 31.61
#   AND p.i BETWEEN 9.45 AND 32.15
#   AND p.z BETWEEN 9.6 AND 29.39
#   AND s.z BETWEEN -0.0099 AND 7.012
#   AND s.mjd BETWEEN 51607 AND 58933

# SELECT TOP 500000
# p.objid,p.ra,p.dec,p.u,p.g,p.r,p.i,p.z,
# p.run, p.rerun, p.camcol, p.field,
# s.specobjid, s.class, s.z as redshift,
# s.plate, s.mjd, s.fiberid
# FROM PhotoObj AS p
# JOIN SpecObj AS s ON s.bestobjid = p.objid
# WHERE
#   p.u BETWEEN 10.99 AND 32.8
#   AND g BETWEEN 10.49 AND 31.61
#   AND p.i BETWEEN 9.45 AND 32.15
```

```
#   AND p.z BETWEEN 9.6 AND 29.39
#   AND s.z BETWEEN -0.0099 AND 7.012
#   AND s.mjd BETWEEN 51607 AND 58933
```

Source in our Repository: "comp5360_final\data\star_classification_test.csv"

Source in our Repository: "comp5360_final\data\star_classification_test_500000.csv"

Final notes: After our process of acquiring data, we finally retrieved a usable dataset of ~100,000 objects to use for building our Python model.

Ethical Data Concerns

Something to consider would be why some of the data was classified as a quasar and then as a galaxy/star? As mentioned above, the classification rules change over time. Get a percentage of how many astronomical objects were later classified as quasar instead of a star/galaxy.

Methods

For our model, we are going to use Python and we are going to utilize the following methods:

- Dimensionality reduction – PCA/LDA
- Cross validated classification/clustering -- SVM and K-means

---

Dimensionality Reduction

Dimensionality reduciton is important to visualize and understand high dimensional data. For example, we have up to 17 dimensions to potentionally use to predict our 1 dimension of `class`. Additionally, dimensionality reduction can help with feature selection by clustering the reduced dimensions.

In [161…

```
# imports and setup

import numpy as np

import pandas as pd
pd.set_option('display.notebook_repr_html', False)

from sklearn.decomposition import PCA
from sklearn.manifold import TSNE
from sklearn.preprocessing import scale
```

```
from sklearn.preprocessing import LabelEncoder
from sklearn.cluster import KMeans, AgglomerativeClustering
from sklearn.metrics import homogeneity_score, v_measure_score, classification_report,
from sklearn.feature_selection import mutual_info_classif
from sklearn.neighbors import LocalOutlierFactor
from sklearn.model_selection import train_test_split, cross_val_score, cross_validate
from sklearn import svm, metrics
from sklearn.ensemble import RandomForestClassifier

from imblearn.over_sampling import SMOTE

import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap
cmap_bold = ListedColormap(['#FF0000', '#00FF00', '#0000FF'], 'GALAXY, QSO, STAR')
from mpl_toolkits.mplot3d import Axes3D
%matplotlib inline
plt.rcParams['figure.figsize'] = (10, 6)
plt.style.use('ggplot')

import seaborn as sns

import plotly.express as px
```

Load Data

In [162…

```
df = pd.read_csv('data/star_classification.csv')
```

In [163…

```
df.columns.values
```

Out[163…

```
array(['obj_ID', 'alpha', 'delta', 'u', 'g', 'r', 'i', 'z', 'run_ID',
       'rerun_ID', 'cam_col', 'field_ID', 'spec_obj_ID', 'class',
       'redshift', 'plate', 'MJD', 'fiber_ID'], dtype=object)
```

Variables

- `obj_ID`
  - unique identifier for the object in the image catalog used by CAS (Catalog Archive Server)
- `alpha`
  - right ascension angle (similar to longitude)
- `delta`
  - declination angle (similar to latitude)
- `u`
  - ultraviolet filter (photometric system)
- `g`
  - green filter (photometric system)
- `r`
  - red filter (photometric system)
- `i`
  - near infrared filter (photometric system)

- `z`
  - infrared filter (photometric system)
- `run_ID`
  - identifier for the specific scan
- `rereun_ID`
  - identifier specifying how the image was processed
- `cam_col`
  - camera column (identifies the scanline within run)
- `field_ID`
  - identifier specifying each field
- `spec_obj_ID`
  - unique optical spectroscopic object identifier
- `class`
  - class of optical spectroscopic object (e.g. GALAXY, STAR, QUASAR)
- `redshift`
  - based on the increase in wavelength
- `plate`
  - identifier of plate in SDSS
- `MJD`
  - modified julian date (date of observation)
- `fiber_ID`
  - identifier of the fiber pointing light at the focal plane (for observation)

What Variables May Contain Information

In [164…

```
df.describe()
```

Out[164…

```
            obj_ID          alpha          delta              u  \
count  1.000000e+05  100000.000000  100000.000000  100000.000000
mean   1.237665e+18     177.629117      24.135305      21.980468
std    8.438560e+12      96.502241      19.644665      31.769291
min    1.237646e+18       0.005528     -18.785328   -9999.000000
25%    1.237659e+18     127.518222       5.146771      20.352353
50%    1.237663e+18     180.900700      23.645922      22.179135
75%    1.237668e+18     233.895005      39.901550      23.687440
max    1.237681e+18     359.999810      83.000519      32.781390

                   g              r              i              z  \
count  100000.000000  100000.000000  100000.000000  100000.000000
mean       20.531387      19.645762      19.084854      18.668810
std        31.750292       1.854760       1.757895      31.728152
min     -9999.000000       9.822070       9.469903   -9999.000000
25%        18.965230      18.135828      17.732285      17.460677
50%        21.099835      20.125290      19.405145      19.004595
75%        22.123767      21.044785      20.396495      19.921120
max        31.602240      29.571860      32.141470      29.383740

              run_ID  rerun_ID        cam_col       field_ID   spec_obj_ID  \
count  100000.000000  100000.0  100000.000000  100000.000000  1.000000e+05
mean     4481.366060     301.0       3.511610     186.130520  5.783882e+18
```

```
std      1964.764593       0.0       1.586912     149.011073  3.324016e+18
min       109.000000     301.0       1.000000      11.000000  2.995191e+17
25%      3187.000000     301.0       2.000000      82.000000  2.844138e+18
50%      4188.000000     301.0       4.000000     146.000000  5.614883e+18
75%      5326.000000     301.0       5.000000     241.000000  8.332144e+18
max      8162.000000     301.0       6.000000     989.000000  1.412694e+19

            redshift          plate            MJD       fiber_ID
count  100000.000000  100000.000000  100000.000000  100000.000000
mean        0.576661    5137.009660   55588.647500     449.312740
std         0.730707    2952.303351    1808.484233     272.498404
min        -0.009971     266.000000   51608.000000       1.000000
25%         0.054517    2526.000000   54234.000000     221.000000
50%         0.424173    4987.000000   55868.500000     433.000000
75%         0.704154    7400.250000   56777.000000     645.000000
max         7.011245   12547.000000   58932.000000    1000.000000
```

`rerun_ID` is constant (`std == 0`) and can thereby be removed

`obj_ID` & `spec_obj_ID` , aside from having high Standard Deviation (`std`) are assigned to specific parent objects and spectroscopic objects for identification. These values are arbitrary and do not contain observable information about the underlying object being observed. Additionally, they may have some relation to the class of the object and thereby have the potential to confound downstream analyses/predictions and should therefore be dropped.

In [165…

```
df = df.drop('rerun_ID', axis=1)
df = df.drop('obj_ID', axis=1)
df = df.drop('spec_obj_ID', axis=1)
```

Univariate Outlier Detection

In [166…

```
df.describe()
```

Out[166…

```
              alpha          delta              u              g  \
count  100000.000000  100000.000000  100000.000000  100000.000000
mean      177.629117      24.135305      21.980468      20.531387
std        96.502241      19.644665      31.769291      31.750292
min         0.005528     -18.785328   -9999.000000   -9999.000000
25%       127.518222       5.146771      20.352353      18.965230
50%       180.900700      23.645922      22.179135      21.099835
75%       233.895005      39.901550      23.687440      22.123767
max       359.999810      83.000519      32.781390      31.602240

                  r              i              z         run_ID  \
count  100000.000000  100000.000000  100000.000000  100000.000000
mean       19.645762      19.084854      18.668810    4481.366060
std         1.854760       1.757895      31.728152    1964.764593
min         9.822070       9.469903   -9999.000000     109.000000
25%        18.135828      17.732285      17.460677    3187.000000
50%        20.125290      19.405145      19.004595    4188.000000
75%        21.044785      20.396495      19.921120    5326.000000
max        29.571860      32.141470      29.383740    8162.000000

             cam_col       field_ID       redshift          plate  \
count  100000.000000  100000.000000  100000.000000  100000.000000
```

```
mean        3.511610     186.130520       0.576661    5137.009660
std         1.586912     149.011073       0.730707    2952.303351
min         1.000000      11.000000      -0.009971     266.000000
25%         2.000000      82.000000       0.054517    2526.000000
50%         4.000000     146.000000       0.424173    4987.000000
75%         5.000000     241.000000       0.704154    7400.250000
max         6.000000     989.000000       7.011245   12547.000000

                MJD       fiber_ID
count  100000.000000  100000.000000
mean    55588.647500     449.312740
std      1808.484233     272.498404
min     51608.000000       1.000000
25%     54234.000000     221.000000
50%     55868.500000     433.000000
75%     56777.000000     645.000000
max     58932.000000    1000.000000
```

u , g , and z have an outstanding min of -9999 , investigate how prevalent

In [167…

```
df[((df.u==-9999) | (df.g==-9999) | (df.z==-9999))]
```

Out[167…

```
           alpha     delta       u       g        r         i       z  \
79543  224.006526 -0.624304 -9999.0 -9999.0  18.1656  18.01675 -9999.0

       run_ID  cam_col  field_ID class  redshift  plate    MJD  fiber_ID
79543     752        2       537  STAR  0.000089   3314  54970       162
```

It appears there is a single outlier, which will heavily impact a variety of parametric methods (e.g. PCA).

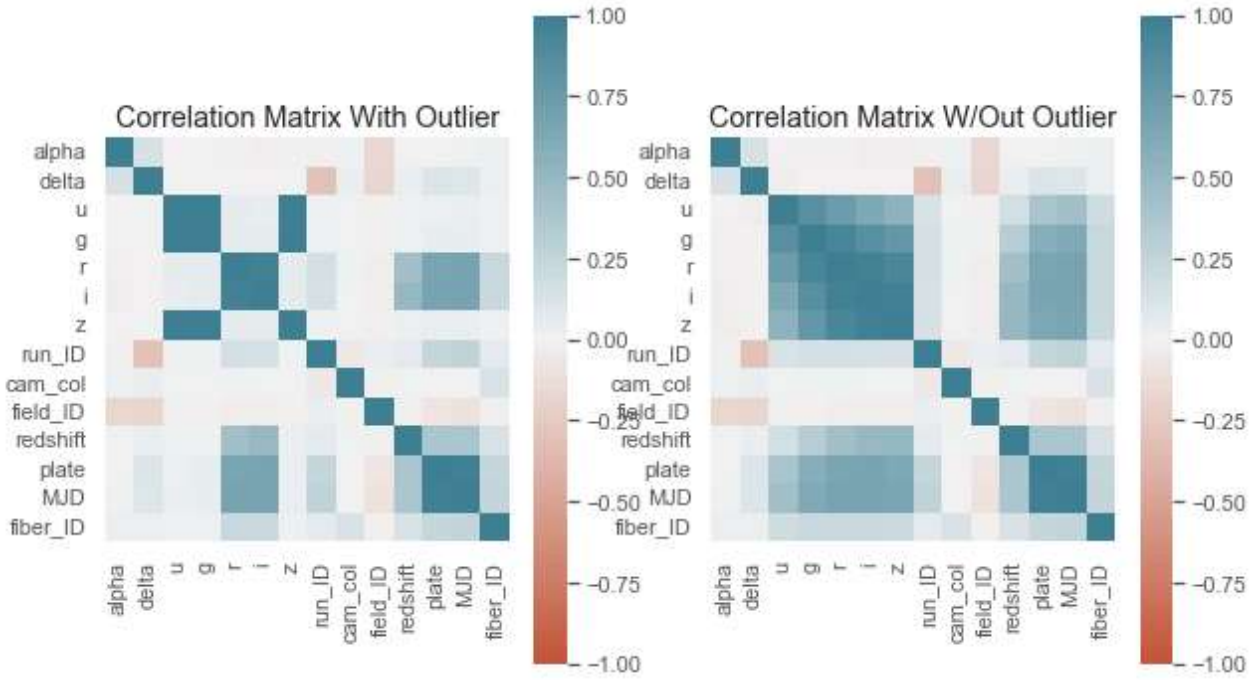
What type of effect is the having on the relationship of the variables? Should we drop the outlier?

Correlation Matrix with and without Outlier

In [168…

```
rb_diverging = sns.diverging_palette(20,220, n=200)
fig,axs = plt.subplots(1,2)

sns.heatmap(df.corr(),
            center=0,
            vmin=-1,
            vmax=1,
            square=True,
            cmap=rb_diverging,
            ax=axs[0]).set_title('Correlation Matrix With Outlier')
sns.heatmap(df.drop(79543).corr(),
            center=0,
            vmin=-1,
            vmax=1,
            square=True,
            cmap=rb_diverging,
```

```
            ax=axs[1]).set_title('Correlation Matrix W/Out Outlier')
print()
```



We can see that the outlier is having a significant impact on the relationship among variables and should be dropped

---

In [169…

```
df = df.drop(79543)
df.describe()
```

Out[169…

	alpha	delta	u	g	r
count	99999.000000	99999.000000	99999.000000	99999.000000	99999.000000
mean	177.628653	24.135552	22.080679	20.631583	19.645777
std	96.502612	19.644608	2.251068	2.037384	1.854763
min	0.005528	-18.785328	10.996230	10.498200	9.822070
25%	127.517698	5.147477	20.352410	18.965240	18.135795
50%	180.900527	23.646462	22.179140	21.099930	20.125310
75%	233.895005	39.901582	23.687480	22.123775	21.044790
max	359.999810	83.000519	32.781390	31.602240	29.571860

	i	z	run_ID	cam_col	field_ID
count	99999.000000	99999.000000	99999.000000	99999.000000	99999.000000
mean	19.084865	18.768988	4481.403354	3.511625	186.127011
std	1.757900	1.765982	1964.739021	1.586913	149.007687
min	9.469903	9.612333	109.000000	1.000000	11.000000
25%	17.732280	17.460830	3187.000000	2.000000	82.000000
50%	19.405150	19.004600	4188.000000	4.000000	146.000000
75%	20.396510	19.921120	5326.000000	5.000000	241.000000
max	32.141470	29.383740	8162.000000	6.000000	989.000000

	redshift	plate	MJD	fiber_ID
count	99999.000000	99999.000000	99999.000000	99999.000000
mean	0.576667	5137.027890	55588.653687	449.315613
std	0.730709	2952.312485	1808.492217	272.498252

```
min       -0.009971    266.000000  51608.000000      1.000000
25%        0.054522   2526.000000  54234.000000    221.000000
50%        0.424176   4987.000000  55869.000000    433.000000
75%        0.704172   7400.500000  56777.000000    645.000000
max        7.011245  12547.000000  58932.000000   1000.000000
```

Split `y` (response) and `X` (predictors)

In [170…

```
y = df['class']
X = df.drop(['class'], axis=1)
X.columns.values
```

Out[170…

```
array(['alpha', 'delta', 'u', 'g', 'r', 'i', 'z', 'run_ID', 'cam_col',
       'field_ID', 'redshift', 'plate', 'MJD', 'fiber_ID'], dtype=object)
```

What Classes are present

In [171…

```
print(y.value_counts().index.values)
```

```
['GALAXY' 'STAR' 'QSO']
```

The dataset contains 14 features (attributes) corresponding to 3 different types of Optical-Spectroscopic Object.

Features (attributes):

- alpha
- delta
- u
- g
- r
- i
- z
- run_ID
- cam_col
- field_ID
- redshift
- plate
- MJD
- fiber_ID

Classes:

- GALAXY
- STAR
- QSO (QUASAR)

Center/Scale the Data

In [172…

```
X_df = pd.DataFrame(X).apply(scale)
X = scale(X)
```

Encode Class

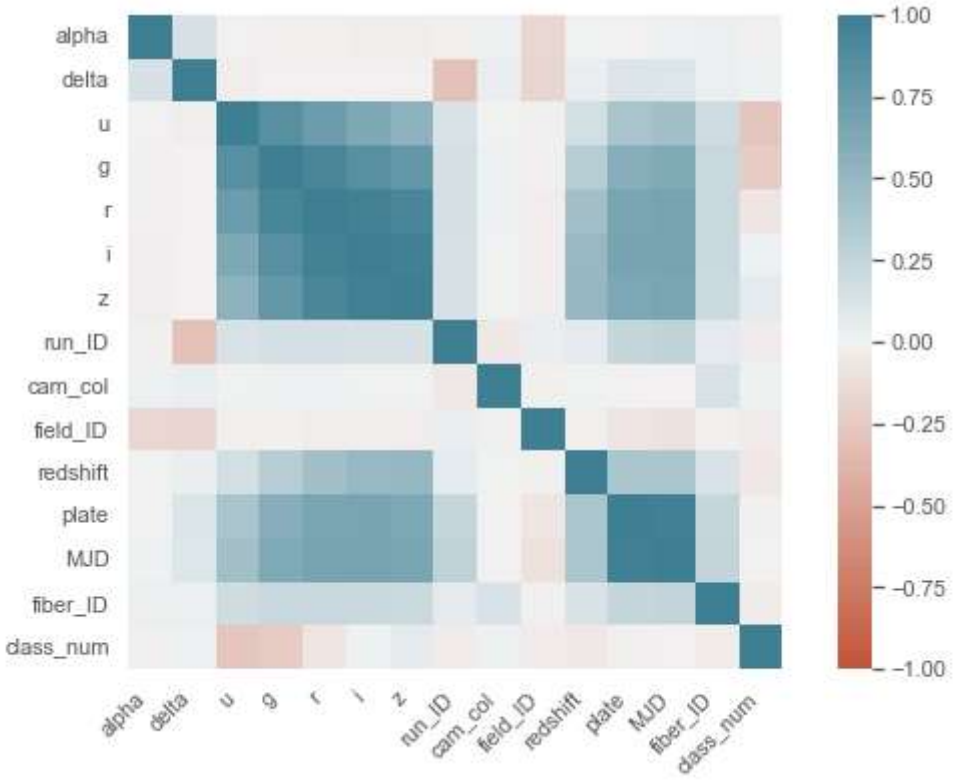
In [173…

```
# hold on to le to allow easy decoding as needed
le = LabelEncoder().fit(y)
y_num = le.transform(y)
```

Check Correlation Matrix Prior to PCA

In [174…

```
X_df['class_num'] = y_num
ax = sns.heatmap(X_df.corr(), center=0, vmin=-1, vmax=1, square=True, cmap=rb_diverging
ax.set_xticklabels(ax.get_xticklabels(), horizontalalignment='right', rotation=45)
X_df = X_df.drop('class_num', axis=1)
print()
```



Remove correlated variables believed to represent same underlying trend, if any, before PCA per will amplify variance and dominate PC1

PCA

Principal Component Analysis (PCA) is an often-used tool in astronomy and stellar classification. It

helps with the trial-and-error process, meaning it finds the most interesting linear coreelations of the variables. Can do either 2D or 3D plots.

Need to select correct amount of scaled components

In [175…

```
pca_scaled_1 = PCA(n_components = 0.95)
pca_scaled_1.fit(X)
reduced_data = pca_scaled_1.transform(X)
print('Original Dimensions: ',X.shape)
print('Reduced Dimensions: ',reduced_data.shape)
```

```
Original Dimensions:  (99999, 14)
Reduced Dimensions:  (99999, 9)
```

So what this means is that 95% of variance is observed by 9 dimensions

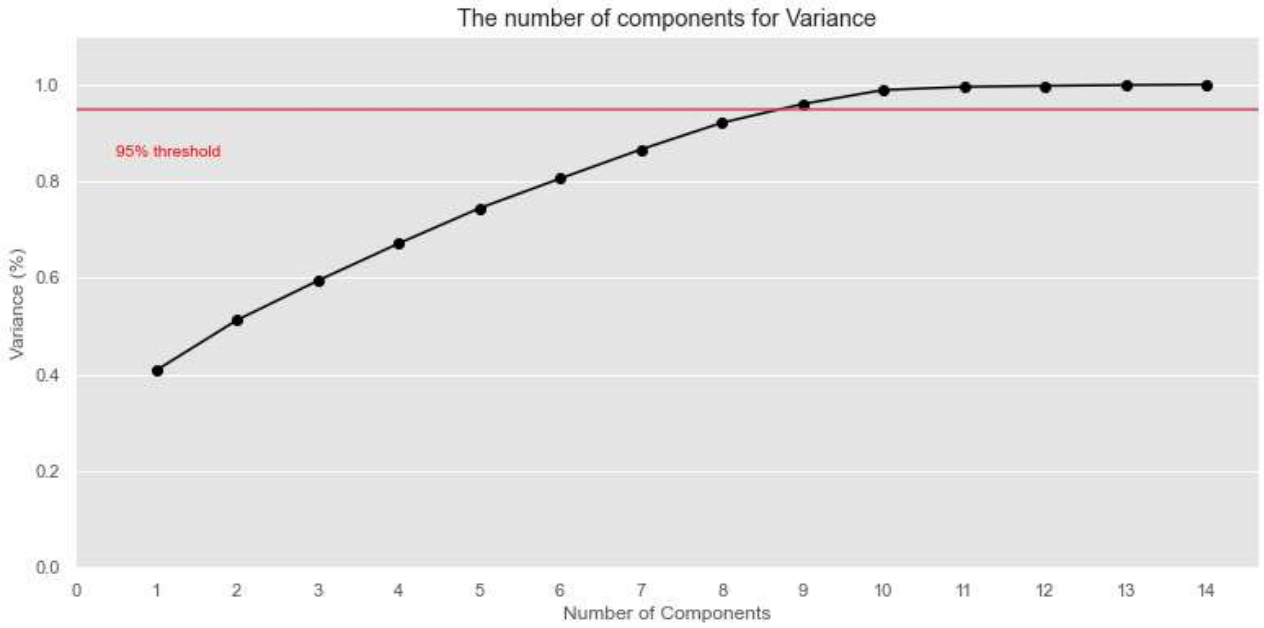
Now we can select the correct amount of components

So let's create a plot to visualize this data, basically I want to see the component cutoff point by creating a plot with our 95% threhold line, and wherever our 'component line' crosses is the amount of components we should choose

Cumulative Variance Plot

In [176…

```
pca_2_plot = PCA().fit(X)
plt.rcParams["figure.figsize"] = (13,6)
fig, ax = plt.subplots()
plt.ylim(0.0,1.1)
plt.plot(np.arange(1, 15, step=1), np.cumsum(pca_2_plot.explained_variance_ratio_), mar
plt.xlabel('Number of Components')
plt.xticks(np.arange(0, 15, step=1)) #change to 1 based
plt.ylabel('Variance (%)')
plt.title('The number of components for Variance')
plt.axhline(y=0.95, color='r', linestyle='-')
plt.text(0.5, 0.85, '95% threshold', color = 'red', fontsize=10)
ax.grid(axis='x')
plt.show()
```



Create our PCA on our scaled data

In [177…

```
pca = PCA(n_components=9, random_state=37)
X_pca_nine = pca.fit_transform(X)
```

Create a Scree Plot

The scree plot will show us how much variance each component has on the data. This way we can see which components we actually need for our final PCA. Whatever components don't capture most of the information then we can ignore them.

In [178…

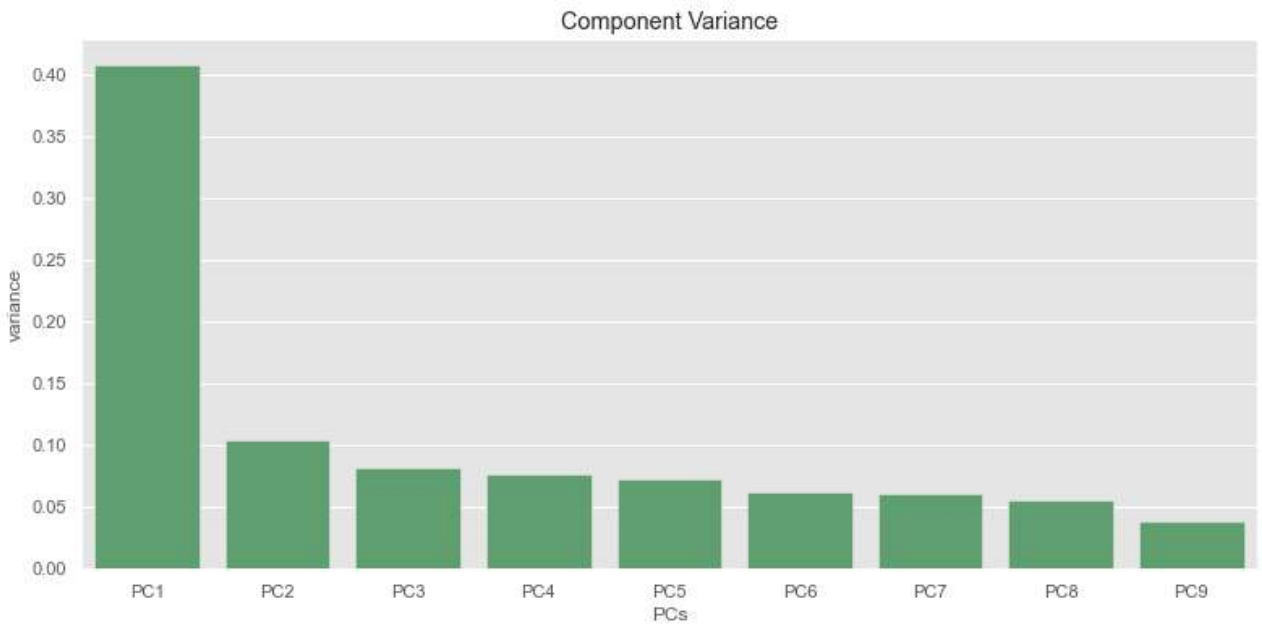
```
#print our variance
print('----- VARIANCE ----')
print(pca.explained_variance_)

#now print the ratio
print('----- RATIO -----')
print(pca.explained_variance_ratio_)
```

```
----- VARIANCE ----
[5.71484359 1.45721281 1.14195913 1.08035967 1.02027689 0.86192915
 0.84450327 0.7722561  0.54279451]
----- RATIO -----
[0.40819903 0.10408559 0.08156769 0.07716778 0.07287619 0.06156575
 0.06032106 0.0551606  0.03877065]
```

SCREE PLOT

In [179…

```
scree_plot = pd.DataFrame({'variance':pca.explained_variance_ratio_,'PCs':['PC1','PC2',
sns.barplot(x='PCs',y="variance",data=scree_plot, color="g").set_title('Component Varia
```



Interpretation of Scree Plot:

This shows that it looks like the first 3 components contain the most valuable information of our data.

Take a look at the correlations between the original data and each component

In [180…

```
#create a new data farme with our PCA
pc_rem = pd.DataFrame(data = X_pca_nine,
                      columns = ['pc1','pc2','pc3','pc4','pc5',
                                 'pc6','pc7','pc8','pc9'])

#drop the components we established above that we do not need
pc_rem=pc_rem.drop(['pc4'],axis=1)
pc_rem=pc_rem.drop(['pc5'],axis=1)
pc_rem=pc_rem.drop(['pc6'],axis=1)
pc_rem=pc_rem.drop(['pc7'],axis=1)
pc_rem=pc_rem.drop(['pc8'],axis=1)
pc_rem=pc_rem.drop(['pc9'],axis=1)


pc_col = pd.concat([pc_rem, X_df], axis=1)
pc_col
corrMat = pd.DataFrame.cov(pc_col)
sns.set(rc={'figure.figsize':(16,6)})
sns.heatmap(corrMat, annot=True, fmt='.2f')
plt.figure(figsize=(28,28))
plt.show()
```


```
<Figure size 2016x2016 with 0 Axes>
```

Explain the Components observed

PC1 *— The first component is negatively correlated with eight of the original variables. It decreases with MJD , plate , red-shift , z , i , r , g , u*

PC2 *— The second component increases with two of the original varaibles. It increases with field_ID , run_ID*

PC3 *— The third component increases with only one of the values, increasing on run_ID*

Create a new dataframe for our new PCA

In [181…

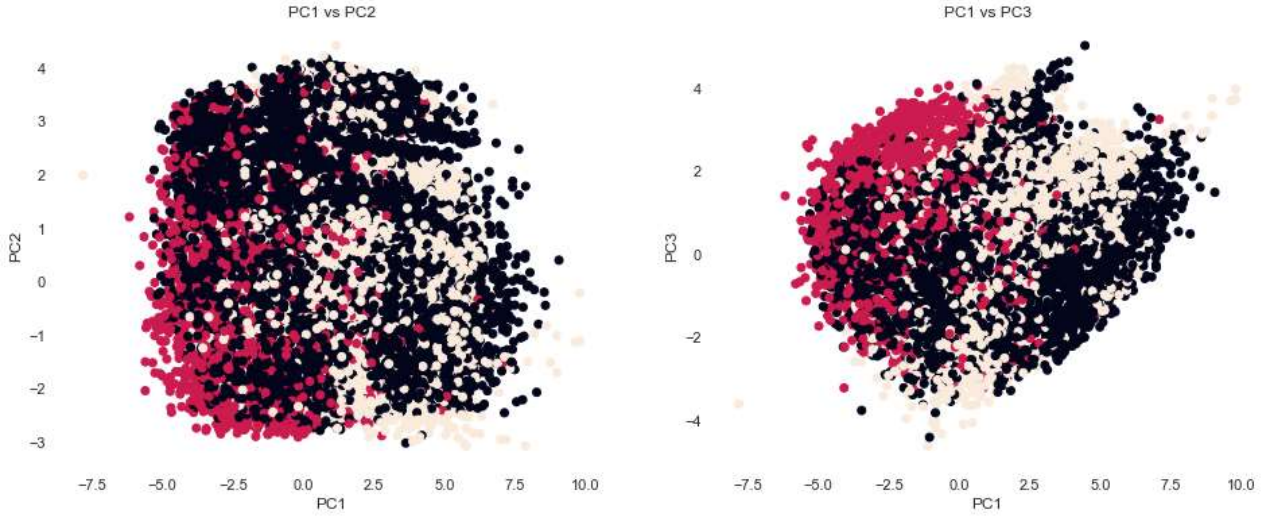
```
df_pca_au = pd.DataFrame()
df_pca_au['pca-1'] = X_pca_nine[:,0]
```

```
df_pca_au['pca-2'] = X_pca_nine[:,1]
df_pca_au['y_num'] = y_num
```

Scatter plot (PC1 vs PC2 or PC1 vs PC3)

In [182…

```
fig = plt.figure()
ax1 = fig.add_subplot(121)
ax2 = fig.add_subplot(122)

ax1.scatter(X_pca_nine[:,0],X_pca_nine[:,1], c=y_num)
ax1.set_xlabel("PC1")
ax1.set_ylabel("PC2")
ax1.set_frame_on(False)
ax1.grid(True)
ax1.set_title('PC1 vs PC2')

ax2.scatter(X_pca_nine[:,0],X_pca_nine[:,2], c=y_num)
ax2.set_xlabel("PC1")
ax2.set_ylabel("PC3")
ax2.set_title('PC1 vs PC3')
ax2.grid(True)
ax2.set_frame_on(False)
```



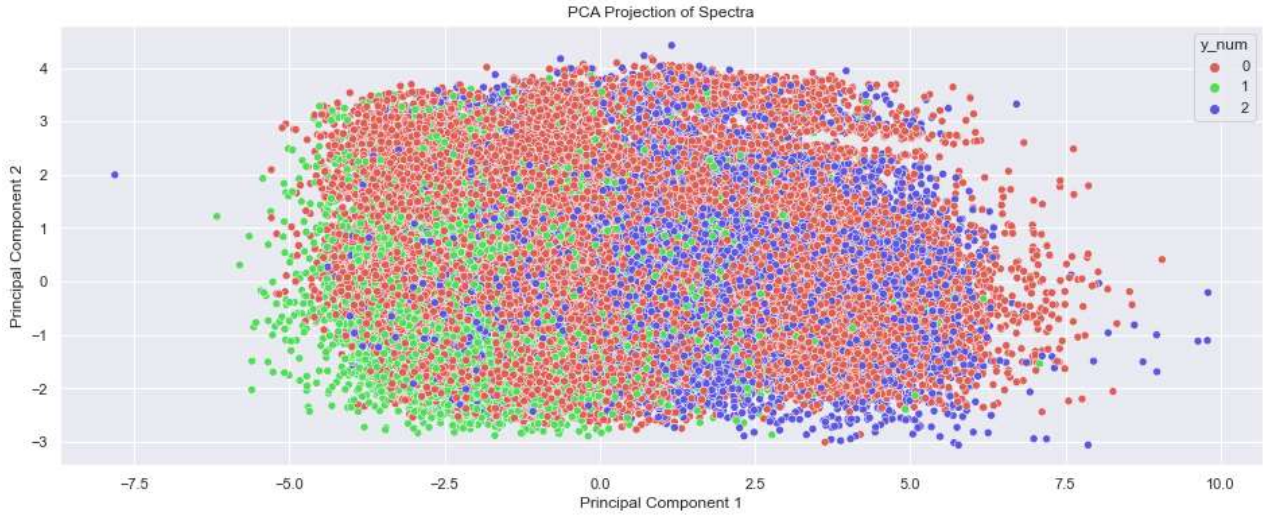
We can see from the above Principal Component Scatter Plots that our classes are not forming a cohesive structure. Let's look further.

Plot our PCA as a scatter plot with Auxilary Data

In [183…

```
sns.scatterplot(x='pca-1',
                y='pca-2',
                hue='y_num',
                data=df_pca_au,
                palette=sns.color_palette('hls',3)).set_title('PCA Projection of Spectr
print(le.classes_)

plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.show()
```

```
['GALAXY' 'QSO' 'STAR']
```



Interpretation of Principal Component Scatter Plots:

We can see from the above Principal Component Scatter Plots that our classes are not forming a cohesive structure and something may that does not correspond to the underlying classes may be dominating the variance--particularly in PC1 and PC2

PCA BiPlot with Auxilary Data

Let's take a look at what the BiPlot would be wiht all the auxilary data

In [304…

```
features = ['alpha', 'delta','u','g','r','i','z','run_id','cam-col',
            'field_id','red-shift','plate','MJD','fiber_id']
loadings = pca.components_.T * np.sqrt(pca.explained_variance_)
fig = px.scatter(df_pca_au, x='pca-1', y='pca-2', title='Biplot of PC1 & PC2', opacity=
for i, feature in enumerate(features):
    fig.add_shape(
        type='line',
        x0=0, y0=0,
        x1=loadings[i, 0]*4.5,
        y1=loadings[i, 1]*4.5
    )
    fig.add_annotation(
        x=loadings[i, 0]*5.5,
        y=loadings[i, 1]*5.5,
        ax=0, ay=0,
        xanchor="center",
        yanchor="bottom",
        text=feature,
    )
fig.show()
```

Interpretation of Bi-Plot with Auxilary Data

- *The orientation of our vectors with respect to our first Principal Component (PC1) shows that u, z, r, red_shift, fiber_id, MJD, plate, and i contributes more to PC1.*
- *The orientation of our vectors with respect to our second Principal Component (PC2) shows that run_id, field_id, cam_col, alpha and delta contributes more to PC2.*
- *The length of r, i, z, MJD, and plate, seem to represent that there might be more variability of these variables.*
- *The angles of r, i , z, MJD, plate, u, red_shift and fiber_id, seem to imply that there is a high positive correlation between them.*
- *The angles of alpha and delta appear to imply that there is a high positive correlation between them.*
- *The angles of field_id and g, u, i, r, z, MJD, plate, red_shift, and fiber_id imply there is NO correlation between them.*
- *And the angles between field_id, run_id AND cam_col, alpha and delta imply a strong negative correlation between the variables.*

Investigate Correlations and Potential PCA Variance Inflation

In [185…

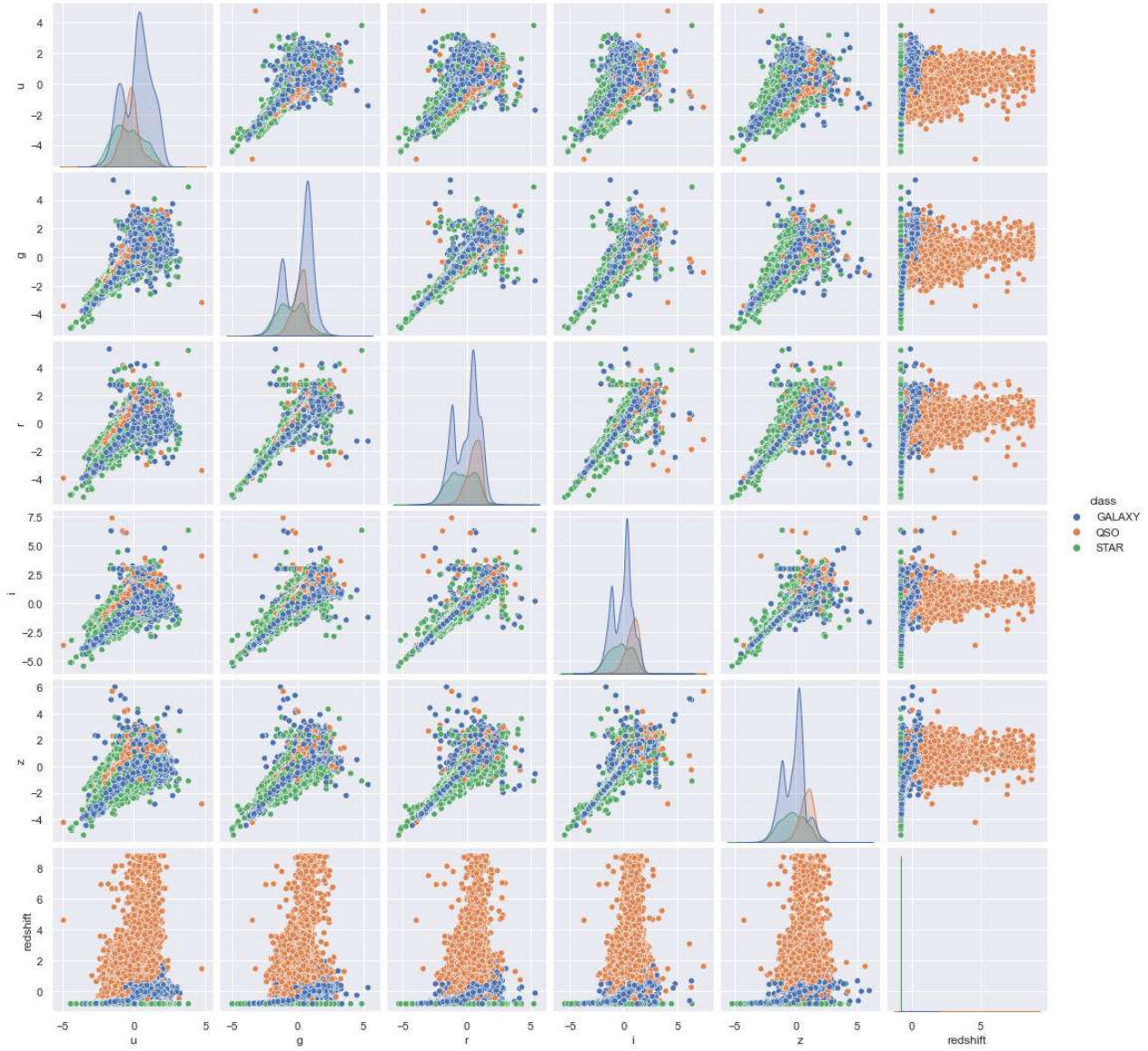
```
X_df['class'] = y
```

In [186…
```
sns.pairplot(X_df, hue='class')
print()
```

Based on the Biplot and Pairplot, we can clearly see a lot of variables do not provide distinguishing, characteristic information about any of our classes.

We explore this in depth in our t-SNE section (further below), but for now, let's look at the places we see linear combinations that relate to our classes.

In [187…
```
sns.pairplot(pd.merge(X_df.loc[:,['u','g','r','i','z','redshift']],
                      y,
                      on=X_df.index).drop('key_0', axis=1),
             hue='class')
print()
```



We can clearly see much cleaner separation of our classes among the relationships of these variables.

Let's see how this changes the results of our PCA

Without Auxilary Columns

In [188…

```
pca_scaled_1 = PCA(n_components = 0.95, random_state=37)
pca_scaled_1.fit(X_df.loc[:,['u','g','r','i','z','redshift']])
reduced_data = pca_scaled_1.transform(X_df.loc[:,['u','g','r','i','z','redshift']])
print('Original Dimensions: ',X.shape)
print('Reduced Dimensions: ',reduced_data.shape)
```

```
Original Dimensions:  (99999, 14)
Reduced Dimensions:  (99999, 3)
```

So what this means is that 95% of variance is observed by 3 dimensions

Now we can select the correct amount of components

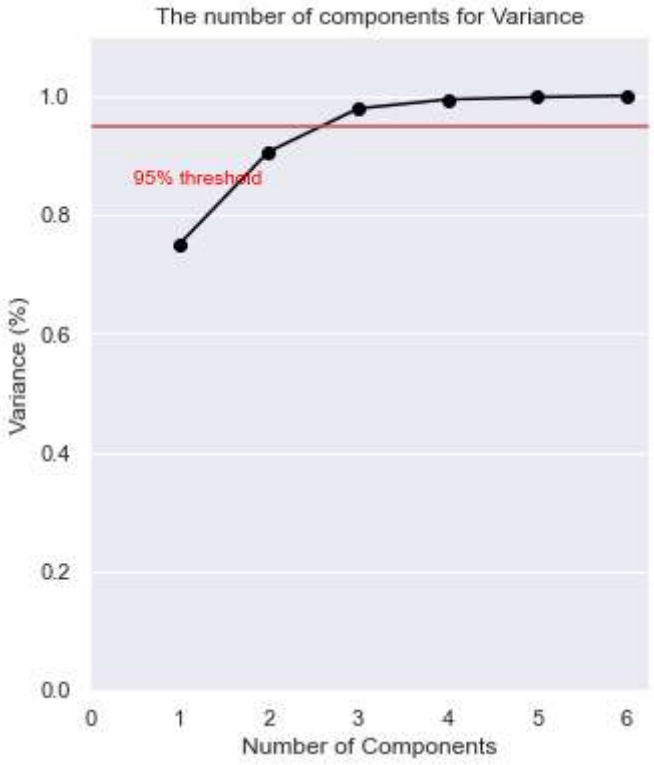
So let's create a plot to visualize this data, basically I want to see the component cutoff point by creating a plot with our 95% threhold line, and wherever our 'component line' crosses is the

amount of components we should choose

Cumulative Variance Plot

In [189…

```
pca_3_plot = PCA().fit(X_df.loc[:,['u','g','r','i','z','redshift']])
plt.rcParams["figure.figsize"] = (5,6)
fig, ax = plt.subplots()
plt.ylim(0.0,1.1)
plt.plot(np.arange(1, 7, step=1), np.cumsum(pca_3_plot.explained_variance_ratio_), mark
plt.xlabel('Number of Components')
plt.xticks(np.arange(0, 7, step=1)) #change to 1 based
plt.ylabel('Variance (%)')
plt.title('The number of components for Variance')
plt.axhline(y=0.95, color='r', linestyle='-')
plt.text(0.5, 0.85, '95% threshold', color = 'red', fontsize=10)
ax.grid(axis='x')
plt.show()
```



After looking at our Scree Plot, it seems that actually 95% of variance is explained by 3 dimensions

Create our PCA on our scaled data without Auxilary Columns

In [190…

```
pca_3 = PCA(n_components=3)
X_pca_three = pca_3.fit_transform(X_df.loc[:,['u','g','r','i','z','redshift']])
```

Create a Scree Plot without Auxliary Columns

The scree plot will show us how much variance each component has on the data. This way we can see which components we actually need for our final PCA. Whatever components don't capture most of the information then we can ignore them.

In [191…

```
#print our variance
```

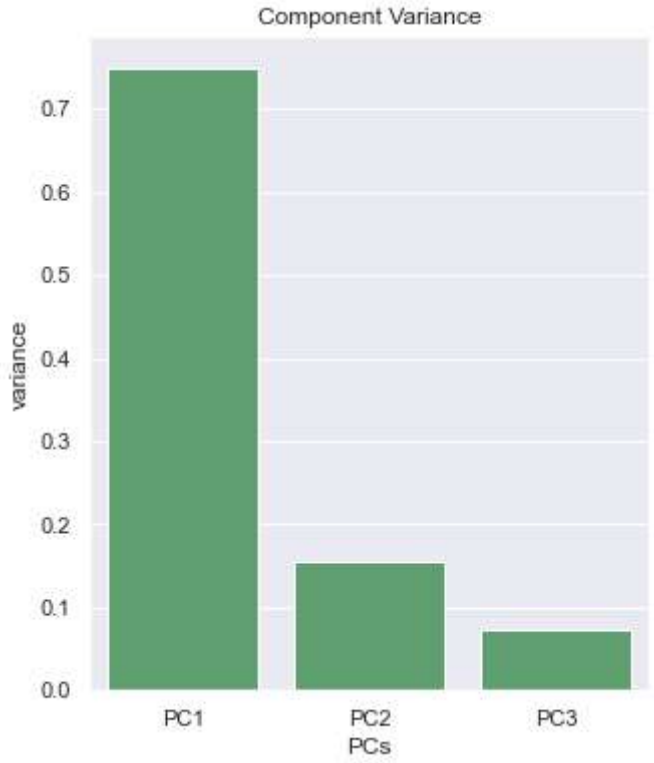
```
print('----- VARIANCE ----')
print(pca_3.explained_variance_)

#now print the ratio
print('----- RATIO -----')
print(pca_3.explained_variance_ratio_)
```

```
----- VARIANCE ----
[4.49809045 0.9373612  0.43547947]
----- RATIO -----
[0.74967425 0.15622531 0.07257919]
```

SCREE PLOT

In [192…

```
scree_plot = pd.DataFrame({'variance':pca_3.explained_variance_ratio_,'PCs':['PC1','PC2
sns.barplot(x='PCs',y="variance",data=scree_plot, color="g").set_title('Component Varia
```



Interpretation of Scree Plot:

This shows that it looks like the first 2 components contain the most valuable information of our data.

Take a look at the correlations between the original data and each component

In [193…

```
#create a new data farme with our PCA
pc_rem_3 = pd.DataFrame(data = X_pca_three, columns = ['pc1','pc2','pc3'])
#drop the components we established above that we do not need
pc_rem_3=pc_rem_3.drop(['pc3'],axis=1)

pc_col_3 = pd.concat([pc_rem_3, X_df], axis=1)
pc_col_3
corrMat = pd.DataFrame.cov(pc_col_3)
sns.set(rc={'figure.figsize':(16,6)})
sns.heatmap(corrMat, annot=True, fmt='.2f')
```

```
plt.figure(figsize=(28,28))
plt.show()
```


```
<Figure size 2016x2016 with 0 Axes>
```

Explain the Components observed without Auxilary columns

PC1 *— The first component is negatively correlated with eight of the original variables. It decreases with MJD , plate , red-shift , z , i , r , g , u*

PC2 *— The second component increases with one of the original varaibles. It increases with red-shift*

Create a new dataframe for our new PCA

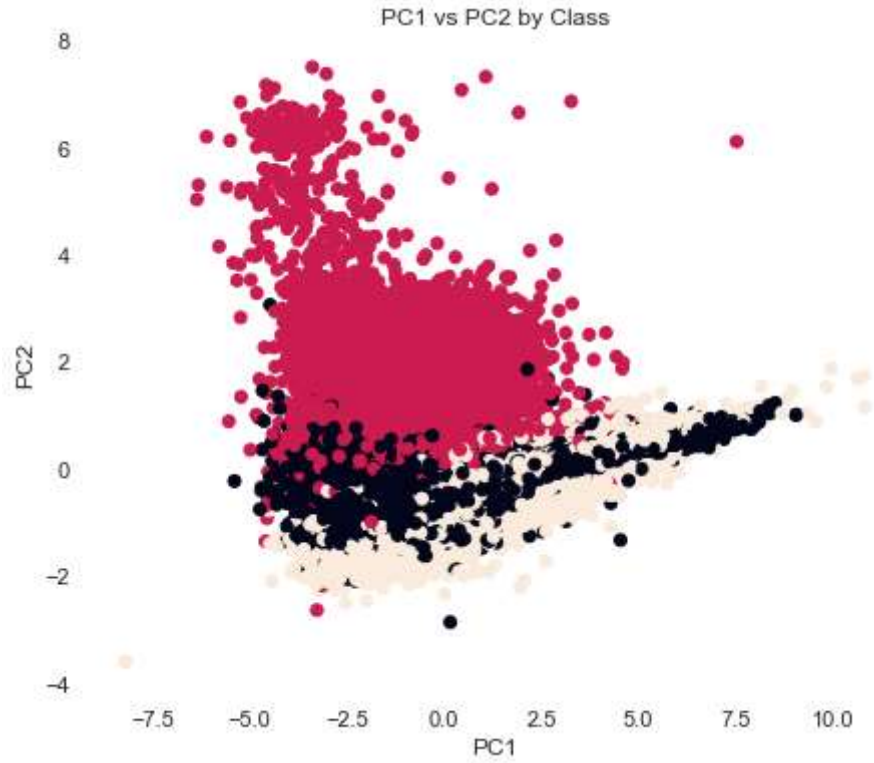
In [194…

```
df_pca_wout_au = pd.DataFrame()
df_pca_wout_au['pca-1'] = X_pca_three[:,0]
df_pca_wout_au['pca-2'] = X_pca_three[:,1]
df_pca_wout_au['pca-3'] = X_pca_three[:,2]
df_pca_wout_au['y_num'] = y_num
```

Scatter plot (PC1 vs PC2 or PC1 vs PC3)

In [195…

```
fig = plt.figure()
ax1 = fig.add_subplot(121)

ax1.scatter(X_pca_three[:,0],X_pca_three[:,1], c=y_num)
ax1.set_xlabel("PC1")
ax1.set_ylabel("PC2")
ax1.set_frame_on(False)
ax1.grid(True)
ax1.set_title('PC1 vs PC2 by Class')
print()
```



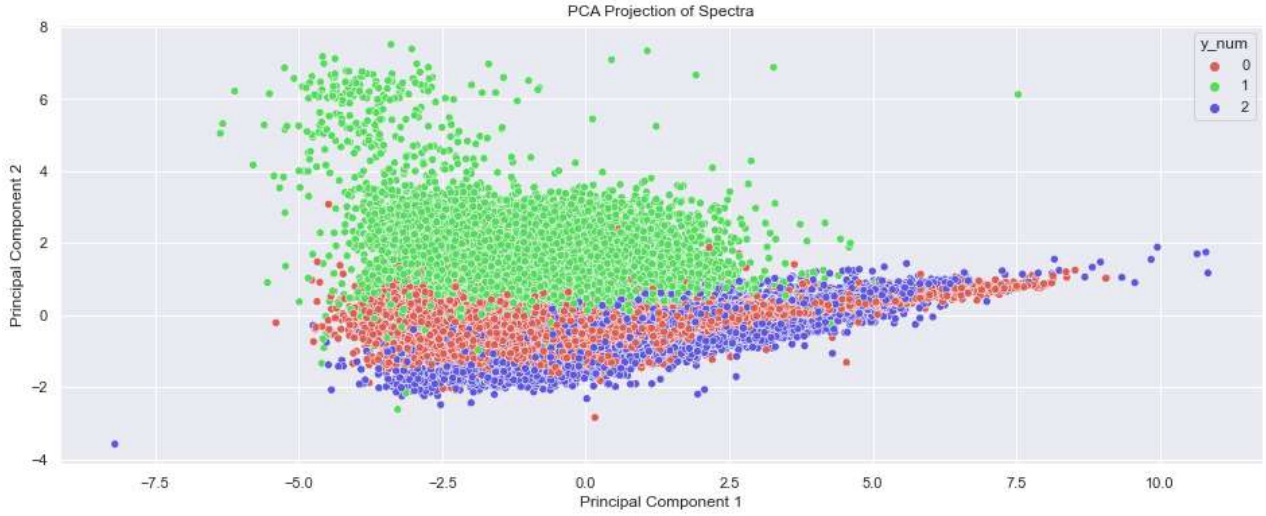
We can see from the above Principal Component Scatter Plots that our classes are now forming a cohesive structure. Let's look further.

Plot our PCA as a scatter plot without Auxilary Columns

In [196…

```
sns.scatterplot(x='pca-1',
                y='pca-2',
                hue='y_num',
                data=df_pca_wout_au,
                palette=sns.color_palette('hls',3)).set_title('PCA Projection of Spectr
print(le.classes_)

plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.show()
```

```
['GALAXY' 'QSO' 'STAR']
```



Interpretation of Principal Component Scatter Plots without Auxilary data:

We can see from the above Principal Component Scatter Plots that our classes are now forming a cohesive structure and that the additional auxilary data was potentially dominating the variance.

PCA BiPlot without Auxilary Data

Now let's take a look at our BiPlot without the additional Auxilary Data

In [197…

```
features = ['u','g','r','i','z','redshift']
loadings = pca_3.components_.T * np.sqrt(pca_3.explained_variance_)
fig = px.scatter(df_pca_wout_au, x='pca-1', y='pca-2', title='Biplot of PC1 & PC2', opa
for i, feature in enumerate(features):
    fig.add_shape(
        type='line',
        x0=0, y0=0,
        x1=loadings[i, 0]*4.5,
        y1=loadings[i, 1]*4.5
    )
    fig.add_annotation(
        x=loadings[i, 0]*5.5,
        y=loadings[i, 1]*5.5,
        ax=0, ay=0,
        xanchor="center",
        yanchor="bottom",
        text=feature,
    )
fig.show()
```

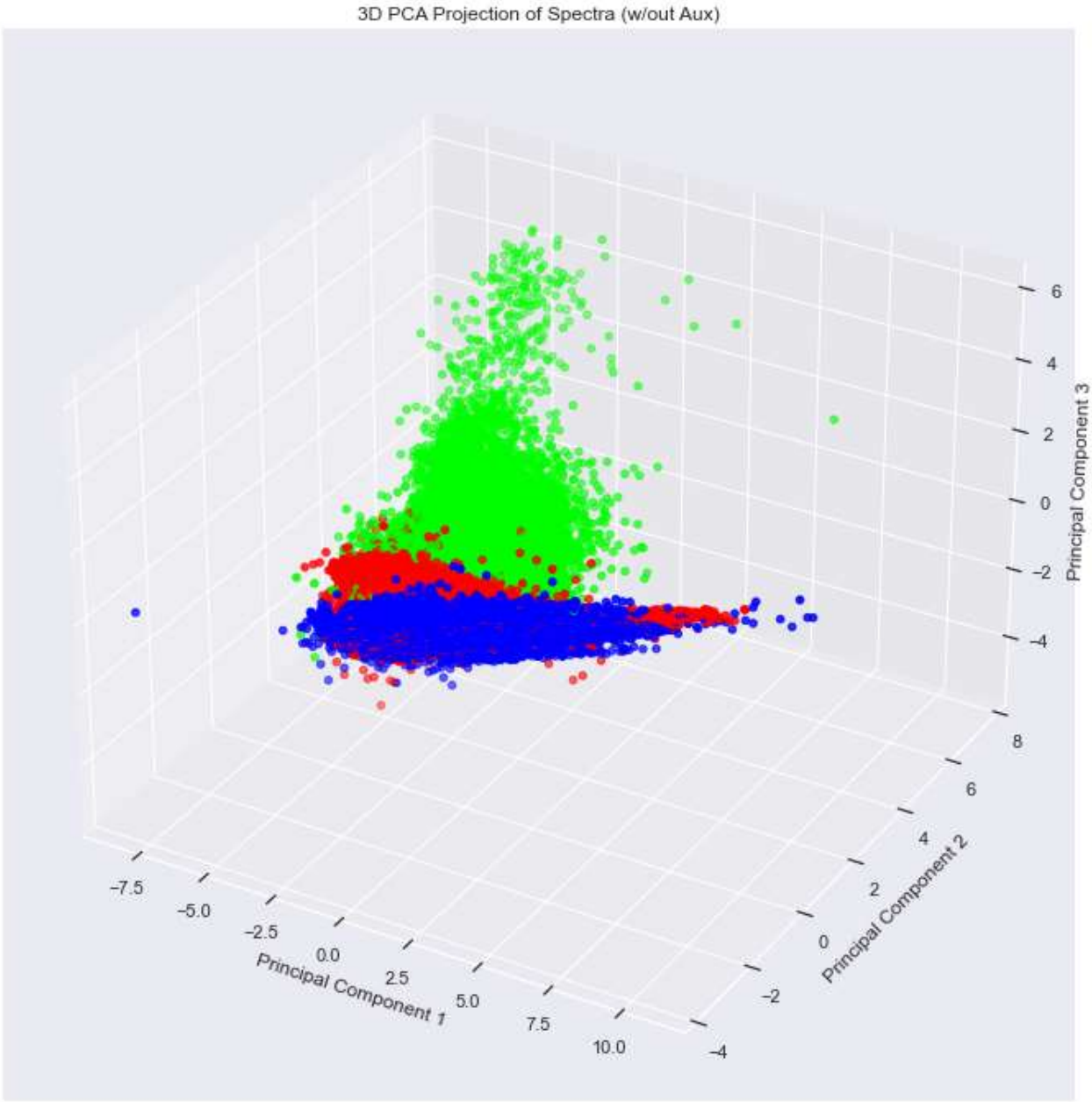
Interpretation of biplot without Auxiliary Data

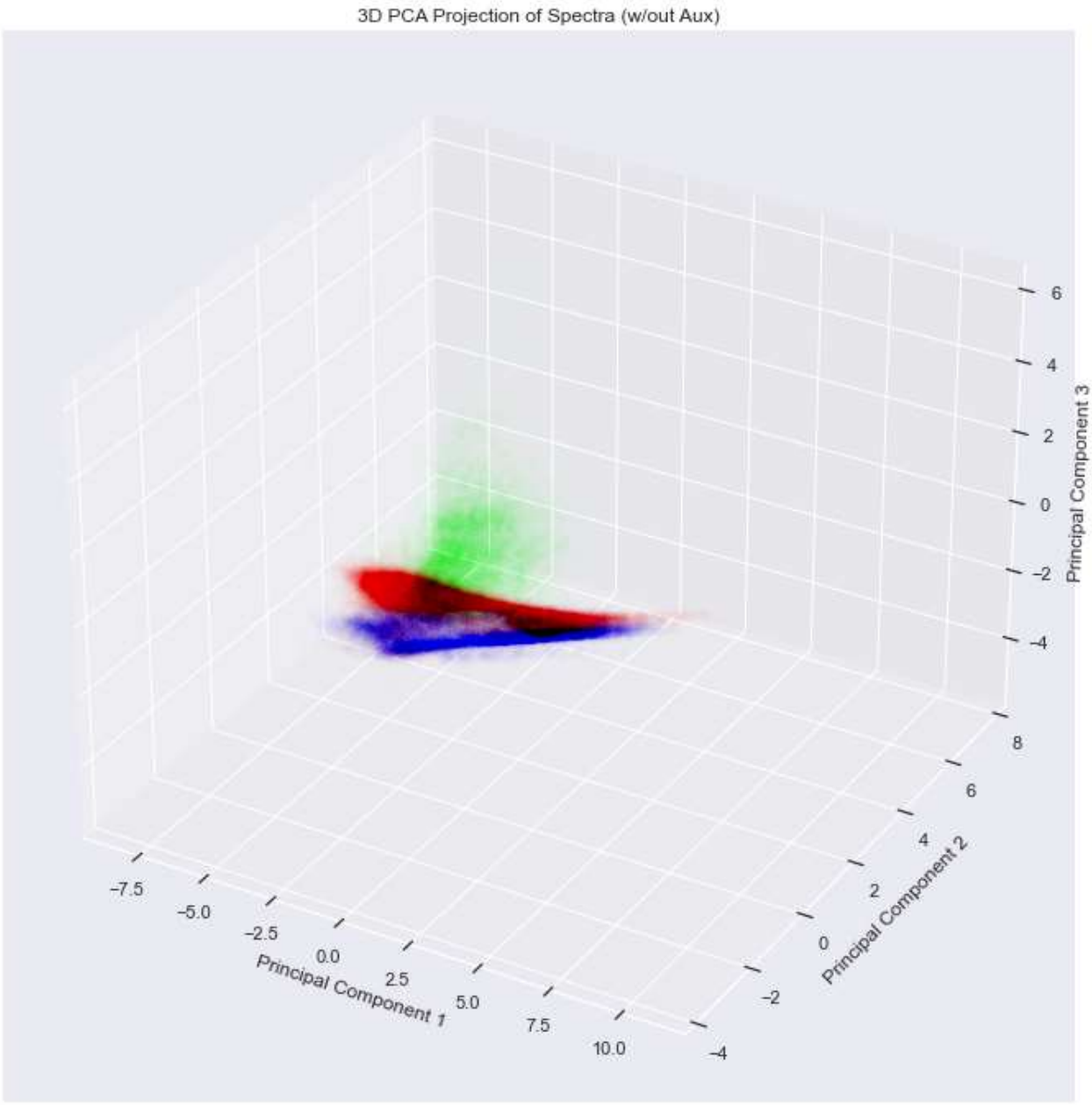
- *The orientation of our vectors with respect to our first Principal Component (PC1) shows that z, r, and i contributes more to PC1. The magnitude of g making it a significant contributor as well.*
- *The orientation of our vectors with respect to our second Principal Component (PC2) shows that redshift, g, and u contribute more to PC2.*
- *The length/magnitude of r, i, and z seem to represent that these variables contribute a significant amount of variance to Principle Component 1.*
- *The angles of r, i , and z seem to imply that there is a high positive correlation between them.*
- *The angles of g and u to imply that there is a high positive correlation between them.*

3D PCA Scatter Plot

In [198…

```
fig = plt.figure(figsize=(12,12))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(df_pca_wout_au['pca-1'],
           df_pca_wout_au['pca-2'],
           zs=df_pca_wout_au['pca-3'],
           c=y_num,
           cmap=cmap_bold)
ax.set_xlabel('Principal Component 1')
ax.set_ylabel('Principal Component 2')
ax.set_zlabel('Principal Component 3')
ax.set_title('3D PCA Projection of Spectra (w/out Aux)')
plt.show()

fig = plt.figure(figsize=(12,12))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(df_pca_wout_au['pca-1'],
           df_pca_wout_au['pca-2'],
           zs=df_pca_wout_au['pca-3'],
           c=y_num,
           cmap=cmap_bold, alpha=0.002)
ax.set_xlabel('Principal Component 1')
ax.set_ylabel('Principal Component 2')
ax.set_zlabel('Principal Component 3')
ax.set_title('3D PCA Projection of Spectra (w/out Aux)')
plt.show()
```


3D PCA Projection of Spectra (w/out Aux)
Principal Component 1
Principal Component 2
Principal Component 3
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5
10.0
−4
−2
0
2
4
6
8
−4
−2
0
2
4
6



We can clearly see that our classes are forming cohesive structures among the first three dimensions of our PCA with variables `u`, `g`, `r`, `i`, `z`, *and* `redshift` *--particularly in comparison to our PCA that also included* `alpha`, `delta`, `run_id`, `cam_col`, `field_id`, `plate`, `MJD`, `fiber_id`.

---

t-SNE

Calculate 2D t-SNE (with Auxiliary Columns)

In [199…

```
tsne_2_aux = TSNE(n_components=2, verbose=1, random_state=37)
tsne_2d_aux = tsne_2_aux.fit_transform(X)
```

```
[t-SNE] Computing 91 nearest neighbors...
[t-SNE] Indexed 99999 samples in 0.375s...
[t-SNE] Computed neighbors for 99999 samples in 93.203s...
[t-SNE] Computed conditional probabilities for sample 1000 / 99999
[t-SNE] Computed conditional probabilities for sample 2000 / 99999
[t-SNE] Computed conditional probabilities for sample 3000 / 99999
[t-SNE] Computed conditional probabilities for sample 4000 / 99999
[t-SNE] Computed conditional probabilities for sample 5000 / 99999
[t-SNE] Computed conditional probabilities for sample 6000 / 99999
[t-SNE] Computed conditional probabilities for sample 7000 / 99999
[t-SNE] Computed conditional probabilities for sample 8000 / 99999
[t-SNE] Computed conditional probabilities for sample 9000 / 99999
[t-SNE] Computed conditional probabilities for sample 10000 / 99999
[t-SNE] Computed conditional probabilities for sample 11000 / 99999
[t-SNE] Computed conditional probabilities for sample 12000 / 99999
[t-SNE] Computed conditional probabilities for sample 13000 / 99999
[t-SNE] Computed conditional probabilities for sample 14000 / 99999
[t-SNE] Computed conditional probabilities for sample 15000 / 99999
[t-SNE] Computed conditional probabilities for sample 16000 / 99999
[t-SNE] Computed conditional probabilities for sample 17000 / 99999
[t-SNE] Computed conditional probabilities for sample 18000 / 99999
[t-SNE] Computed conditional probabilities for sample 19000 / 99999
[t-SNE] Computed conditional probabilities for sample 20000 / 99999
[t-SNE] Computed conditional probabilities for sample 21000 / 99999
[t-SNE] Computed conditional probabilities for sample 22000 / 99999
[t-SNE] Computed conditional probabilities for sample 23000 / 99999
[t-SNE] Computed conditional probabilities for sample 24000 / 99999
[t-SNE] Computed conditional probabilities for sample 25000 / 99999
[t-SNE] Computed conditional probabilities for sample 26000 / 99999
[t-SNE] Computed conditional probabilities for sample 27000 / 99999
[t-SNE] Computed conditional probabilities for sample 28000 / 99999
[t-SNE] Computed conditional probabilities for sample 29000 / 99999
[t-SNE] Computed conditional probabilities for sample 30000 / 99999
[t-SNE] Computed conditional probabilities for sample 31000 / 99999
[t-SNE] Computed conditional probabilities for sample 32000 / 99999
[t-SNE] Computed conditional probabilities for sample 33000 / 99999
[t-SNE] Computed conditional probabilities for sample 34000 / 99999
[t-SNE] Computed conditional probabilities for sample 35000 / 99999
[t-SNE] Computed conditional probabilities for sample 36000 / 99999
[t-SNE] Computed conditional probabilities for sample 37000 / 99999
[t-SNE] Computed conditional probabilities for sample 38000 / 99999
[t-SNE] Computed conditional probabilities for sample 39000 / 99999
[t-SNE] Computed conditional probabilities for sample 40000 / 99999
[t-SNE] Computed conditional probabilities for sample 41000 / 99999
[t-SNE] Computed conditional probabilities for sample 42000 / 99999
[t-SNE] Computed conditional probabilities for sample 43000 / 99999
[t-SNE] Computed conditional probabilities for sample 44000 / 99999
[t-SNE] Computed conditional probabilities for sample 45000 / 99999
[t-SNE] Computed conditional probabilities for sample 46000 / 99999
[t-SNE] Computed conditional probabilities for sample 47000 / 99999
[t-SNE] Computed conditional probabilities for sample 48000 / 99999
[t-SNE] Computed conditional probabilities for sample 49000 / 99999
[t-SNE] Computed conditional probabilities for sample 50000 / 99999
[t-SNE] Computed conditional probabilities for sample 51000 / 99999
[t-SNE] Computed conditional probabilities for sample 52000 / 99999
[t-SNE] Computed conditional probabilities for sample 53000 / 99999
[t-SNE] Computed conditional probabilities for sample 54000 / 99999
[t-SNE] Computed conditional probabilities for sample 55000 / 99999
[t-SNE] Computed conditional probabilities for sample 56000 / 99999
[t-SNE] Computed conditional probabilities for sample 57000 / 99999
```

```
[t-SNE] Computed conditional probabilities for sample 58000 / 99999
[t-SNE] Computed conditional probabilities for sample 59000 / 99999
[t-SNE] Computed conditional probabilities for sample 60000 / 99999
[t-SNE] Computed conditional probabilities for sample 61000 / 99999
[t-SNE] Computed conditional probabilities for sample 62000 / 99999
[t-SNE] Computed conditional probabilities for sample 63000 / 99999
[t-SNE] Computed conditional probabilities for sample 64000 / 99999
[t-SNE] Computed conditional probabilities for sample 65000 / 99999
[t-SNE] Computed conditional probabilities for sample 66000 / 99999
[t-SNE] Computed conditional probabilities for sample 67000 / 99999
[t-SNE] Computed conditional probabilities for sample 68000 / 99999
[t-SNE] Computed conditional probabilities for sample 69000 / 99999
[t-SNE] Computed conditional probabilities for sample 70000 / 99999
[t-SNE] Computed conditional probabilities for sample 71000 / 99999
[t-SNE] Computed conditional probabilities for sample 72000 / 99999
[t-SNE] Computed conditional probabilities for sample 73000 / 99999
[t-SNE] Computed conditional probabilities for sample 74000 / 99999
[t-SNE] Computed conditional probabilities for sample 75000 / 99999
[t-SNE] Computed conditional probabilities for sample 76000 / 99999
[t-SNE] Computed conditional probabilities for sample 77000 / 99999
[t-SNE] Computed conditional probabilities for sample 78000 / 99999
[t-SNE] Computed conditional probabilities for sample 79000 / 99999
[t-SNE] Computed conditional probabilities for sample 80000 / 99999
[t-SNE] Computed conditional probabilities for sample 81000 / 99999
[t-SNE] Computed conditional probabilities for sample 82000 / 99999
[t-SNE] Computed conditional probabilities for sample 83000 / 99999
[t-SNE] Computed conditional probabilities for sample 84000 / 99999
[t-SNE] Computed conditional probabilities for sample 85000 / 99999
[t-SNE] Computed conditional probabilities for sample 86000 / 99999
[t-SNE] Computed conditional probabilities for sample 87000 / 99999
[t-SNE] Computed conditional probabilities for sample 88000 / 99999
[t-SNE] Computed conditional probabilities for sample 89000 / 99999
[t-SNE] Computed conditional probabilities for sample 90000 / 99999
[t-SNE] Computed conditional probabilities for sample 91000 / 99999
[t-SNE] Computed conditional probabilities for sample 92000 / 99999
[t-SNE] Computed conditional probabilities for sample 93000 / 99999
[t-SNE] Computed conditional probabilities for sample 94000 / 99999
[t-SNE] Computed conditional probabilities for sample 95000 / 99999
[t-SNE] Computed conditional probabilities for sample 96000 / 99999
[t-SNE] Computed conditional probabilities for sample 97000 / 99999
[t-SNE] Computed conditional probabilities for sample 98000 / 99999
[t-SNE] Computed conditional probabilities for sample 99000 / 99999
[t-SNE] Computed conditional probabilities for sample 99999 / 99999
[t-SNE] Mean sigma: 0.538113
[t-SNE] KL divergence after 250 iterations with early exaggeration: 103.694984
[t-SNE] KL divergence after 1000 iterations: 3.134697
```

Create 2D t-SNE Data Frame (with Auxiliary Columns)

In [200…

```
df_tsne_2d_aux = pd.DataFrame()
df_tsne_2d_aux['tsne-2d-1'] = tsne_2d_aux[:,0]
df_tsne_2d_aux['tsne-2d-2'] = tsne_2d_aux[:,1]
df_tsne_2d_aux['y_num'] = y_num
```

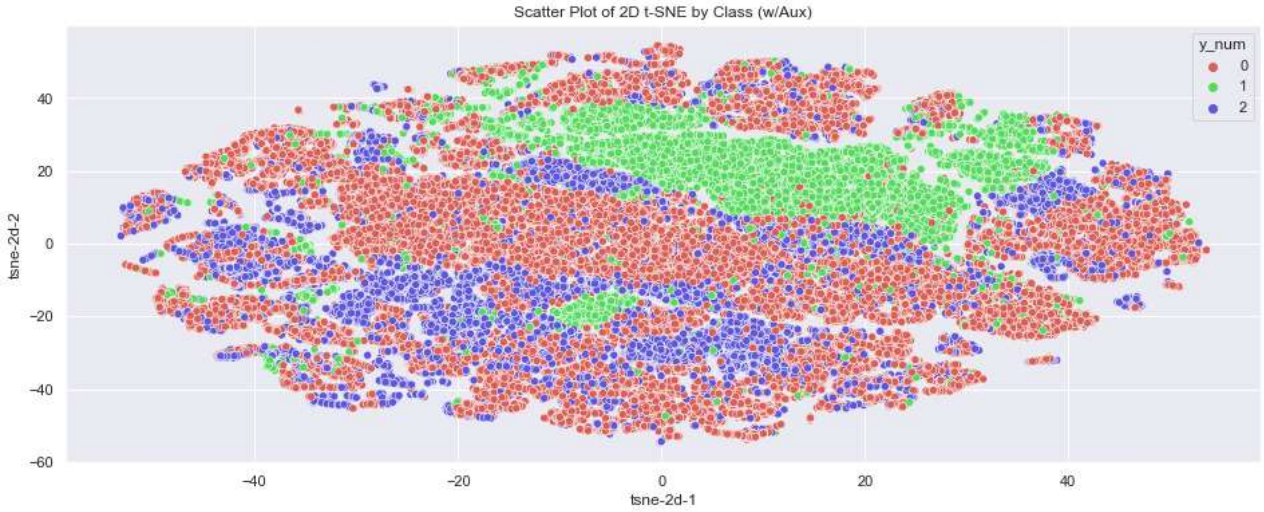
Scatter Plot 2D t-SNE by Class (with Auxiliary Columns)

In [201…

```
sns.scatterplot(x='tsne-2d-1',
```

```
                y='tsne-2d-2',
                hue='y_num',
                data=df_tsne_2d_aux,
                palette=sns.color_palette('hls',3)).set_title('Scatter Plot of 2D t-SNE
print(le.classes_)
```

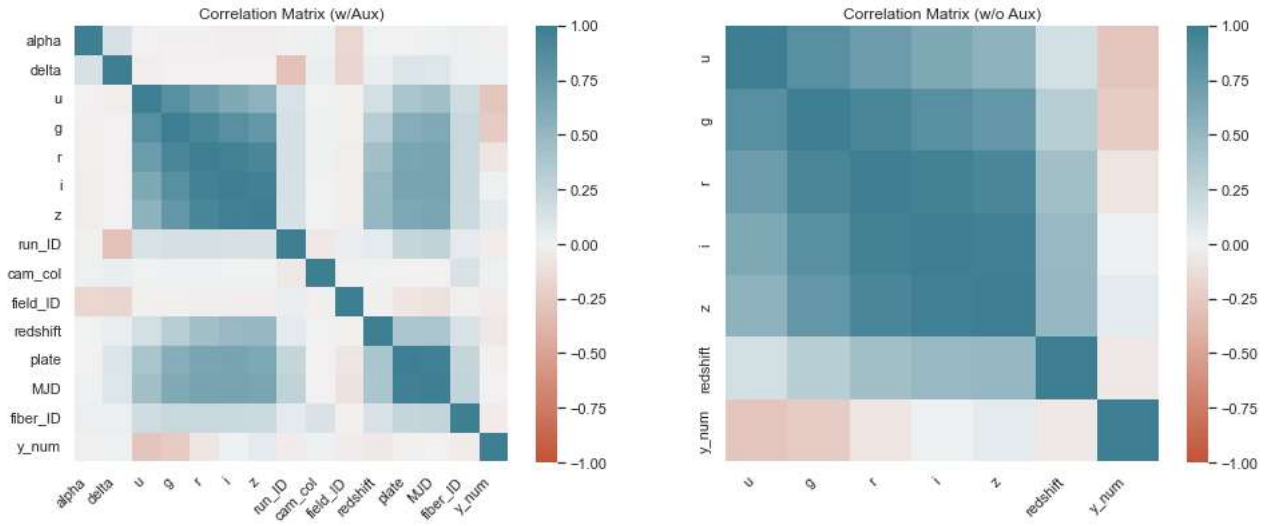
```
['GALAXY' 'QSO' 'STAR']
```



Correlation Matrix With/Without Auxiliary Columns

In [202…

```
fig,axs = plt.subplots(1,2)
X_df['y_num'] = y_num

ax = sns.heatmap(X_df.corr(), center=0, vmin=-1, vmax=1, square=True, cmap=rb_diverging
ax.set_xticklabels(ax.get_xticklabels(), horizontalalignment='right', rotation=45)
ax.set_title('Correlation Matrix (w/Aux)')

ax = sns.heatmap(X_df.drop(['alpha',
                            'delta',
                            'cam_col',
                            'plate',
                            'field_ID',
                            'run_ID',
                            'MJD',
                            'fiber_ID'], axis=1).corr(),
                 center=0,
                 vmin=-1,
                 vmax=1,
                 square=True,
                 cmap=rb_diverging,
                 ax=axs[1])
ax.set_xticklabels(ax.get_xticklabels(), horizontalalignment='right', rotation=45)
ax.set_title('Correlation Matrix (w/o Aux)')

X_df = X_df.drop('y_num', axis=1)
print()
```



`plate` & `MJD` are moderately correlated with `u`, `g`, `r`, `i`, `z`, and `reshift`. The same can be said for `fiber_ID`, to a lesser degree. In addition, `alpha` and `delta` represent the location on the celestial sphere (sky), which may have a relationship with the classes of astronomical objects present, but is not an observable charateristic of the object itself. Similarly, `run_id` is the identifier of the run, which may have implications on classes observed in that run, but is not directly an attribute of the object--and likewise for `cam_col` / `field_ID`.

As we saw with the single outlier that shaped our correlation matrix, added varaince that does not represent the underlying silhouette we are trying to capture can lead us astray--particularly when contained in a variable that has a significant correlation with a variable that does represent what we are trying to capture.

Let's examine what happens to our t-SNE dimensions when we remove these variables.

Calculate 2D t-SNE (without Auxiliary Columns)

In [203…

```
X_df
```

Out[203…

```
          alpha     delta         u         g         r         i         z  \
0     -0.434597  0.425517  0.798798  0.806782  0.403953  0.046001  0.013999
1     -0.339915  0.363391  1.198064  1.079967  1.584395  1.185087  1.611170
2     -0.367244  0.582702  1.413732  0.997513  0.519736  0.150012  0.101520
3      1.669522 -1.249122  0.024940  1.543642  1.059894  0.807601  0.272435
4      1.737308 -0.150255 -1.174337 -1.497665 -1.697426 -1.767888 -1.825836
...         ...       ...       ...       ...       ...       ...       ...
99995 -1.430103 -1.360667  0.038609  1.150636  1.217554  1.263226  1.113665
99996 -1.535042 -0.220758  0.271206  0.861254  0.433617  0.382689  0.365958
99997  0.486608 -0.429374 -0.404929 -0.668318 -0.777190 -0.793294 -0.802265
99998  0.358955  1.146621  1.452522  0.493766  0.144538 -0.007011 -0.081637
99999  0.199658  1.289373  0.240345  0.572240  0.515094  0.526042  0.289790

          run_ID   cam_col  field_ID  redshift     plate       MJD  fiber_ID  \
0     -0.445559 -0.952562 -0.718940  0.079549  0.228626  0.423198 -1.021353
1      0.018627  0.937911 -0.450496  0.277088  1.797912  1.420719 -0.081893
2     -0.445559 -0.952562 -0.443785  0.092415 -0.190031  0.001850 -0.551623
3     -0.147299 -0.322404  0.187058  0.486761  1.358932  1.354918  1.195186
```

```
4      1.842797 -0.322404 -0.329696 -0.630273  0.333290  0.330855  1.441060
...         ...       ...       ...       ...       ...       ...       ...
99995  1.677889 -0.952562  2.650031 -0.789192  1.435144  1.194563 -0.041526
99996  1.748636 -1.582719  0.690391 -0.235076  0.843063  0.743909  1.529134
99997  0.423772  0.307753  0.817901 -0.592990 -0.803790 -0.582617 -1.377321
99998 -0.423164  0.307753 -0.369963 -0.166452  0.546683  0.430939  0.075907
99999 -0.423164  0.307753 -0.846451 -0.046150  0.769899  0.837910  1.474088

        class
0      GALAXY
1      GALAXY
2      GALAXY
3      GALAXY
4      GALAXY
...       ...
99995  GALAXY
99996  GALAXY
99997  GALAXY
99998  GALAXY
99999  GALAXY

[99999 rows x 15 columns]
```

In [204…

```
tsne_2 = TSNE(n_components=2, verbose=1, random_state=37)
tsne_2d = tsne_2.fit_transform(
    X_df.drop(['alpha',
               'delta',
               'cam_col',
               'plate',
               'field_ID',
               'run_ID',
               'MJD',
               'fiber_ID',
               'class'], axis=1).to_numpy())
```

```
[t-SNE] Computing 91 nearest neighbors...
[t-SNE] Indexed 99999 samples in 0.265s...
[t-SNE] Computed neighbors for 99999 samples in 7.626s...
[t-SNE] Computed conditional probabilities for sample 1000 / 99999
[t-SNE] Computed conditional probabilities for sample 2000 / 99999
[t-SNE] Computed conditional probabilities for sample 3000 / 99999
[t-SNE] Computed conditional probabilities for sample 4000 / 99999
[t-SNE] Computed conditional probabilities for sample 5000 / 99999
[t-SNE] Computed conditional probabilities for sample 6000 / 99999
[t-SNE] Computed conditional probabilities for sample 7000 / 99999
[t-SNE] Computed conditional probabilities for sample 8000 / 99999
[t-SNE] Computed conditional probabilities for sample 9000 / 99999
[t-SNE] Computed conditional probabilities for sample 10000 / 99999
[t-SNE] Computed conditional probabilities for sample 11000 / 99999
[t-SNE] Computed conditional probabilities for sample 12000 / 99999
[t-SNE] Computed conditional probabilities for sample 13000 / 99999
[t-SNE] Computed conditional probabilities for sample 14000 / 99999
[t-SNE] Computed conditional probabilities for sample 15000 / 99999
[t-SNE] Computed conditional probabilities for sample 16000 / 99999
[t-SNE] Computed conditional probabilities for sample 17000 / 99999
[t-SNE] Computed conditional probabilities for sample 18000 / 99999
[t-SNE] Computed conditional probabilities for sample 19000 / 99999
[t-SNE] Computed conditional probabilities for sample 20000 / 99999
[t-SNE] Computed conditional probabilities for sample 21000 / 99999
```

```
[t-SNE] Computed conditional probabilities for sample 22000 / 99999
[t-SNE] Computed conditional probabilities for sample 23000 / 99999
[t-SNE] Computed conditional probabilities for sample 24000 / 99999
[t-SNE] Computed conditional probabilities for sample 25000 / 99999
[t-SNE] Computed conditional probabilities for sample 26000 / 99999
[t-SNE] Computed conditional probabilities for sample 27000 / 99999
[t-SNE] Computed conditional probabilities for sample 28000 / 99999
[t-SNE] Computed conditional probabilities for sample 29000 / 99999
[t-SNE] Computed conditional probabilities for sample 30000 / 99999
[t-SNE] Computed conditional probabilities for sample 31000 / 99999
[t-SNE] Computed conditional probabilities for sample 32000 / 99999
[t-SNE] Computed conditional probabilities for sample 33000 / 99999
[t-SNE] Computed conditional probabilities for sample 34000 / 99999
[t-SNE] Computed conditional probabilities for sample 35000 / 99999
[t-SNE] Computed conditional probabilities for sample 36000 / 99999
[t-SNE] Computed conditional probabilities for sample 37000 / 99999
[t-SNE] Computed conditional probabilities for sample 38000 / 99999
[t-SNE] Computed conditional probabilities for sample 39000 / 99999
[t-SNE] Computed conditional probabilities for sample 40000 / 99999
[t-SNE] Computed conditional probabilities for sample 41000 / 99999
[t-SNE] Computed conditional probabilities for sample 42000 / 99999
[t-SNE] Computed conditional probabilities for sample 43000 / 99999
[t-SNE] Computed conditional probabilities for sample 44000 / 99999
[t-SNE] Computed conditional probabilities for sample 45000 / 99999
[t-SNE] Computed conditional probabilities for sample 46000 / 99999
[t-SNE] Computed conditional probabilities for sample 47000 / 99999
[t-SNE] Computed conditional probabilities for sample 48000 / 99999
[t-SNE] Computed conditional probabilities for sample 49000 / 99999
[t-SNE] Computed conditional probabilities for sample 50000 / 99999
[t-SNE] Computed conditional probabilities for sample 51000 / 99999
[t-SNE] Computed conditional probabilities for sample 52000 / 99999
[t-SNE] Computed conditional probabilities for sample 53000 / 99999
[t-SNE] Computed conditional probabilities for sample 54000 / 99999
[t-SNE] Computed conditional probabilities for sample 55000 / 99999
[t-SNE] Computed conditional probabilities for sample 56000 / 99999
[t-SNE] Computed conditional probabilities for sample 57000 / 99999
[t-SNE] Computed conditional probabilities for sample 58000 / 99999
[t-SNE] Computed conditional probabilities for sample 59000 / 99999
[t-SNE] Computed conditional probabilities for sample 60000 / 99999
[t-SNE] Computed conditional probabilities for sample 61000 / 99999
[t-SNE] Computed conditional probabilities for sample 62000 / 99999
[t-SNE] Computed conditional probabilities for sample 63000 / 99999
[t-SNE] Computed conditional probabilities for sample 64000 / 99999
[t-SNE] Computed conditional probabilities for sample 65000 / 99999
[t-SNE] Computed conditional probabilities for sample 66000 / 99999
[t-SNE] Computed conditional probabilities for sample 67000 / 99999
[t-SNE] Computed conditional probabilities for sample 68000 / 99999
[t-SNE] Computed conditional probabilities for sample 69000 / 99999
[t-SNE] Computed conditional probabilities for sample 70000 / 99999
[t-SNE] Computed conditional probabilities for sample 71000 / 99999
[t-SNE] Computed conditional probabilities for sample 72000 / 99999
[t-SNE] Computed conditional probabilities for sample 73000 / 99999
[t-SNE] Computed conditional probabilities for sample 74000 / 99999
[t-SNE] Computed conditional probabilities for sample 75000 / 99999
[t-SNE] Computed conditional probabilities for sample 76000 / 99999
[t-SNE] Computed conditional probabilities for sample 77000 / 99999
[t-SNE] Computed conditional probabilities for sample 78000 / 99999
[t-SNE] Computed conditional probabilities for sample 79000 / 99999
[t-SNE] Computed conditional probabilities for sample 80000 / 99999
[t-SNE] Computed conditional probabilities for sample 81000 / 99999
```

```
[t-SNE] Computed conditional probabilities for sample 82000 / 99999
[t-SNE] Computed conditional probabilities for sample 83000 / 99999
[t-SNE] Computed conditional probabilities for sample 84000 / 99999
[t-SNE] Computed conditional probabilities for sample 85000 / 99999
[t-SNE] Computed conditional probabilities for sample 86000 / 99999
[t-SNE] Computed conditional probabilities for sample 87000 / 99999
[t-SNE] Computed conditional probabilities for sample 88000 / 99999
[t-SNE] Computed conditional probabilities for sample 89000 / 99999
[t-SNE] Computed conditional probabilities for sample 90000 / 99999
[t-SNE] Computed conditional probabilities for sample 91000 / 99999
[t-SNE] Computed conditional probabilities for sample 92000 / 99999
[t-SNE] Computed conditional probabilities for sample 93000 / 99999
[t-SNE] Computed conditional probabilities for sample 94000 / 99999
[t-SNE] Computed conditional probabilities for sample 95000 / 99999
[t-SNE] Computed conditional probabilities for sample 96000 / 99999
[t-SNE] Computed conditional probabilities for sample 97000 / 99999
[t-SNE] Computed conditional probabilities for sample 98000 / 99999
[t-SNE] Computed conditional probabilities for sample 99000 / 99999
[t-SNE] Computed conditional probabilities for sample 99999 / 99999
[t-SNE] Mean sigma: 0.060146
[t-SNE] KL divergence after 250 iterations with early exaggeration: 97.411530
[t-SNE] KL divergence after 1000 iterations: 2.827295
```

Create 2D t-SNE Data Frame (without Auxiliary Columns)

In [205…

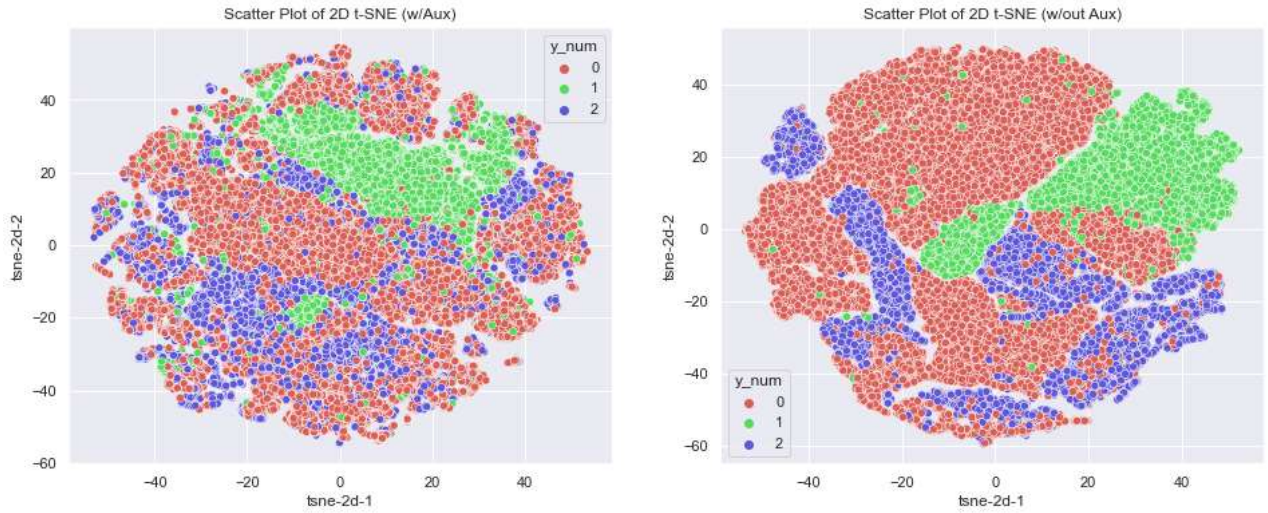
```
df_tsne_2d = pd.DataFrame()
df_tsne_2d['tsne-2d-1'] = tsne_2d[:,0]
df_tsne_2d['tsne-2d-2'] = tsne_2d[:,1]
df_tsne_2d['y_num'] = y_num
```

Scatter Plot 2D t-SNE by Class (with/without Auxiliary Columns)

In [206…

```
fig,axs = plt.subplots(1,2)

sns.scatterplot(x='tsne-2d-1',
                y='tsne-2d-2',
                hue='y_num',
                data=df_tsne_2d_aux,
                palette=sns.color_palette('hls',3),
                ax=axs[0]).set_title('Scatter Plot of 2D t-SNE (w/Aux)')

sns.scatterplot(x='tsne-2d-1',
                y='tsne-2d-2',
                hue='y_num',
                data=df_tsne_2d,
                palette=sns.color_palette('hls',3),
                ax=axs[1]).set_title('Scatter Plot of 2D t-SNE (w/out Aux)')

print(le.classes_)
```

```
['GALAXY' 'QSO' 'STAR']
```



Clearly the difference is a much more coherent DImensionality Reduction, given the insight from coloring based on `class`

Let's validate that the variables we are considering removing/keeping.

In [207…

```
X_df['class_num'] = y_num
X_df['class_num'] = X_df['class_num'].astype(int)

def KdePlot(colmn, log=False):
    for num_class in range(3):
        dat=X_df[X_df['class_num']==num_class][colmn]
        if log:
            dat=np.log(dat)
        sns.kdeplot(data=dat,
                    label = le.inverse_transform([num_class]))
    sns.kdeplot(data=X_df[colmn],
                label = ['ALL'])
    plt.legend();
```

Variable vs Class Density Plots

Let's validate that the variables we are considering removing do not appear to categorize or distinguish any of our classes

Conversly, let's validate that the variables we are considering keeping do appear to categorize or distinguish one or more classes

---

In [208…

```
y.value_counts()
```

Out[208…

```
GALAXY    59445
STAR      21593
QSO       18961
Name: class, dtype: int64
```

*One thing to keep in mind, before we proceed, is that we have **Class Imbalance** among our classes*

(GALAXY , STAR , QSO).

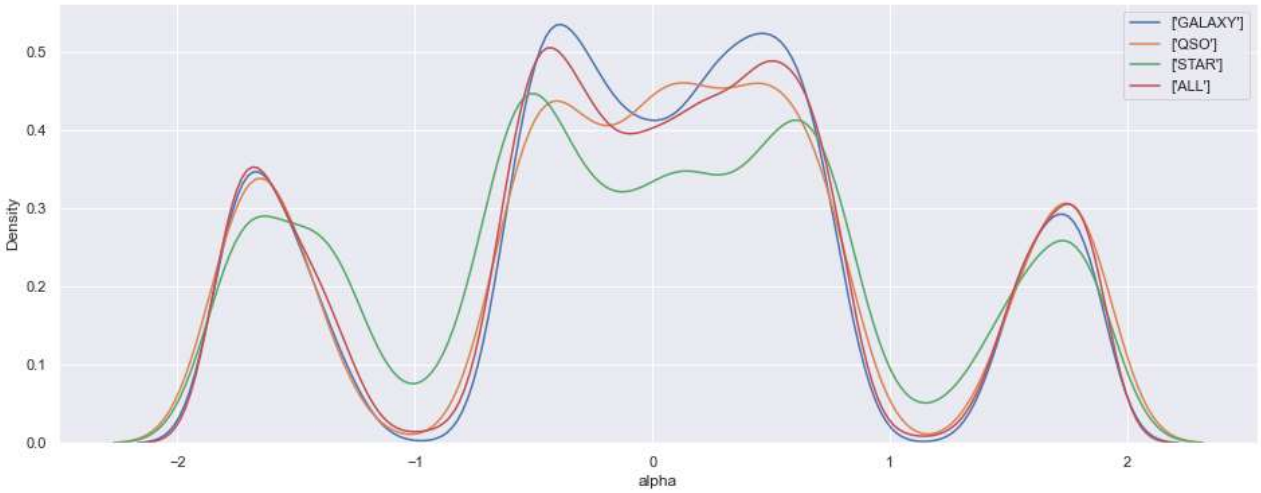
This means that we should interpret the below density plots with that in mind.

In our case, GALAXY has a significantly higher sample size and will therefore dominate the distribution of the ALL density plot.

Right Ascension (similar to longitude)

In [209…

```
KdePlot('alpha')
```



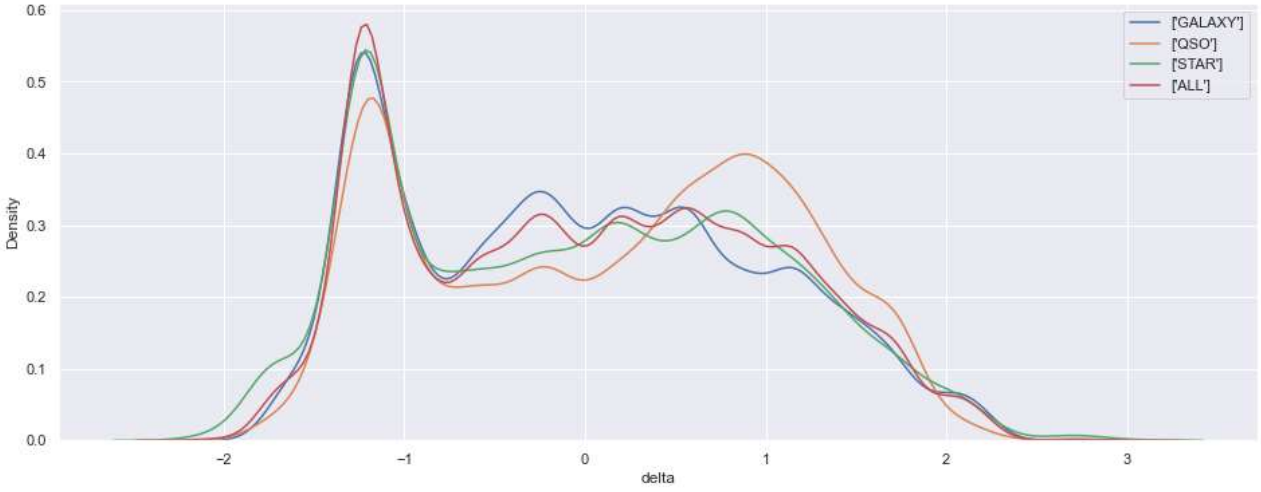
Though not highly significant, STAR distinctly stands out relative to the other classes

---

Declination (similar to latitude)

In [210…

```
KdePlot('delta')
```



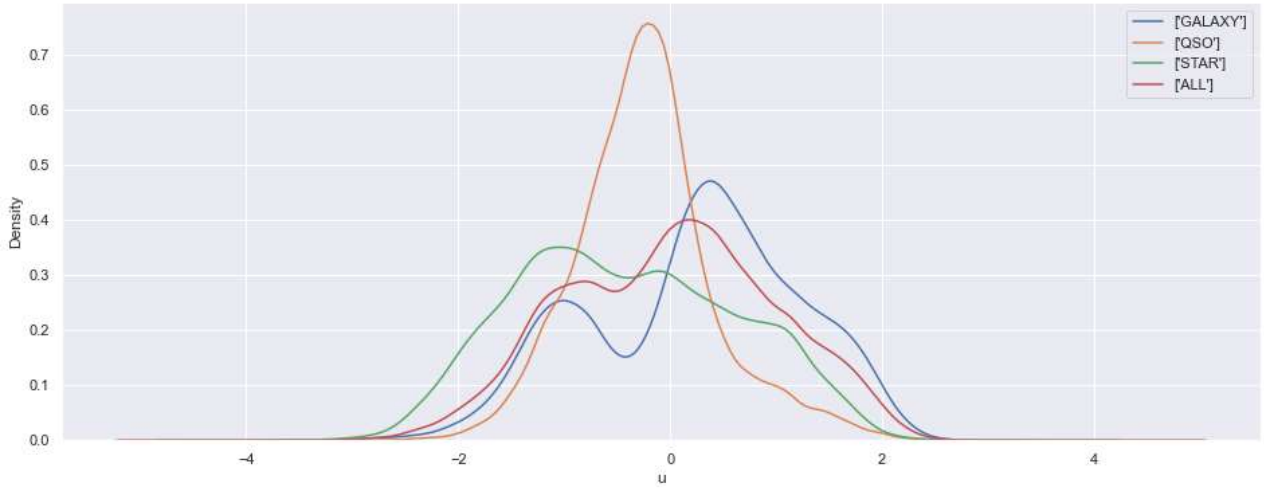
QSO has a distinct profile on the rigth half of the density graph

---

Ultraviolet Photometric Filter

In [211…

```
KdePlot('u')
```

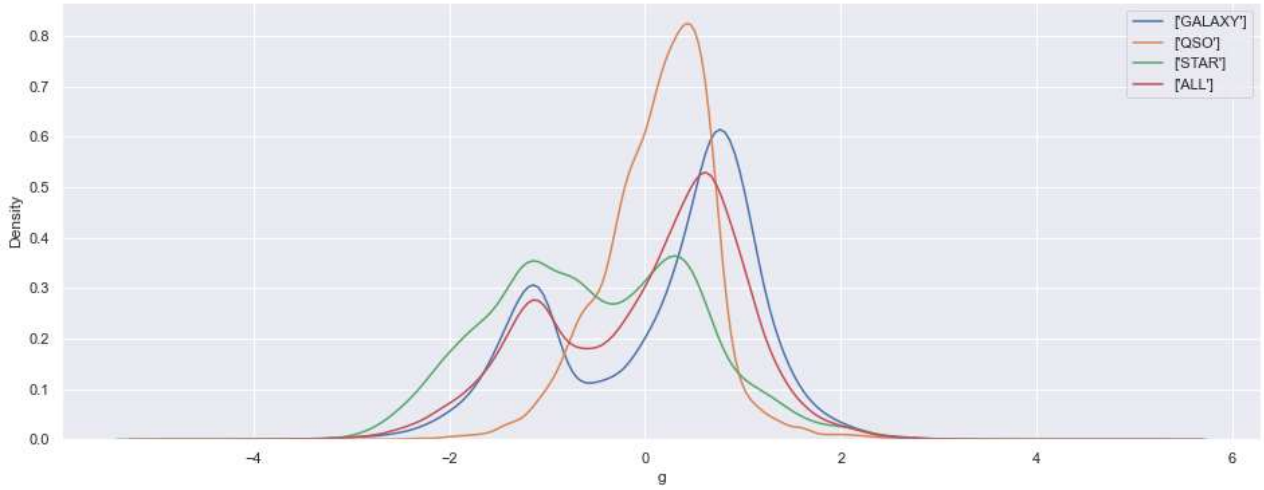


QSO has a distinct profile and GALAXY / STAR --though not significant--may be somewhat distinguishable as well

Green Photometric Filter

In [212…

```
KdePlot('g')
```

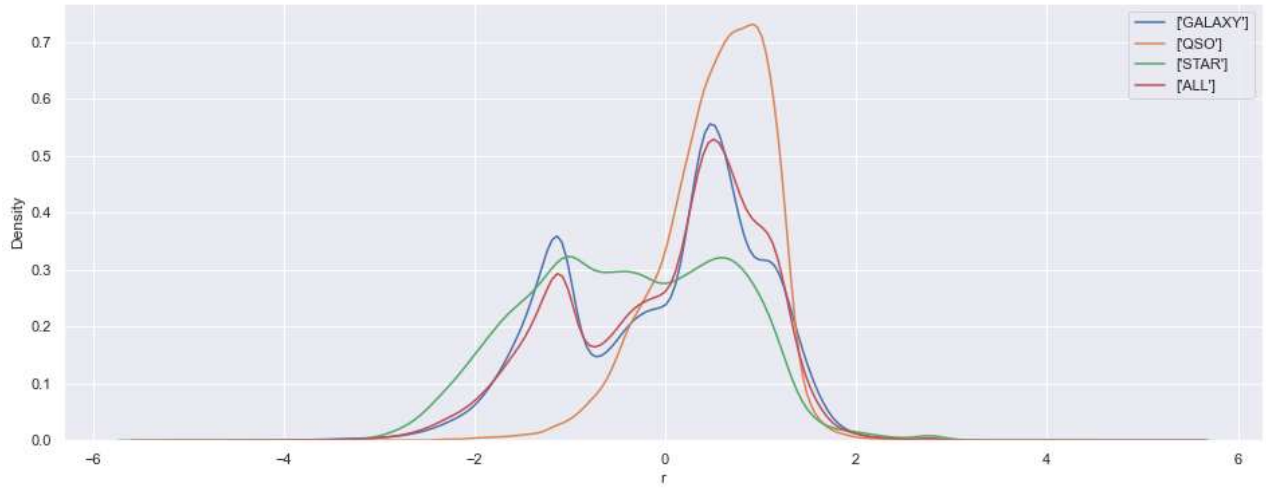


QSO has a distinct profile and GALAXY / STAR --though not significant--may be somewhat distinguishable as well

Red Photometric Filter

In [213…

```
KdePlot('r')
```



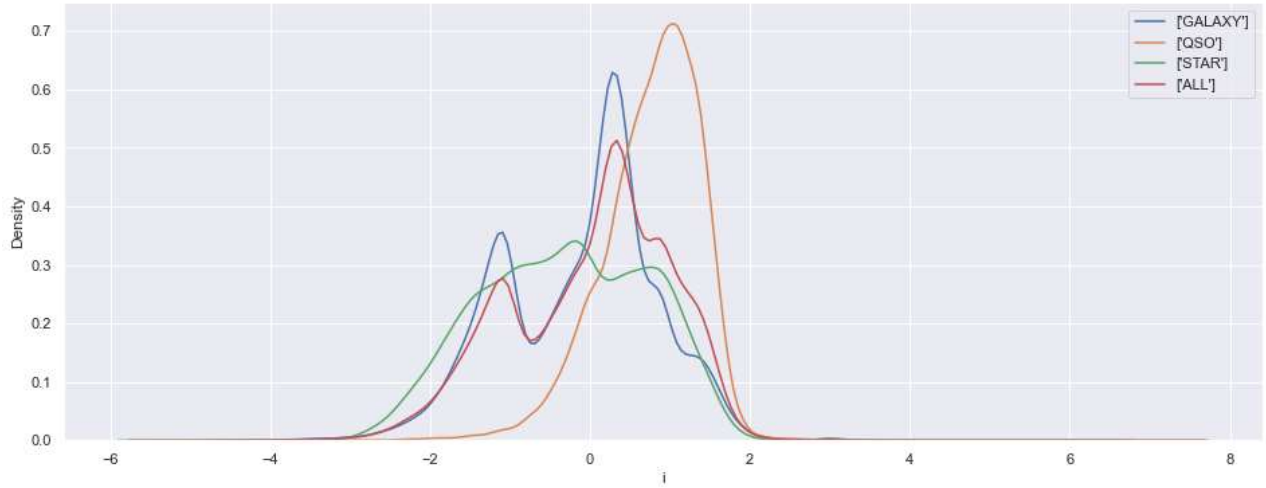
QSO again has a distinct profile and GALAXY / STAR are more distinct than in the last two plots for g and u

---

Near Infrared Photometric Filter

In [214…

```
KdePlot('i')
```



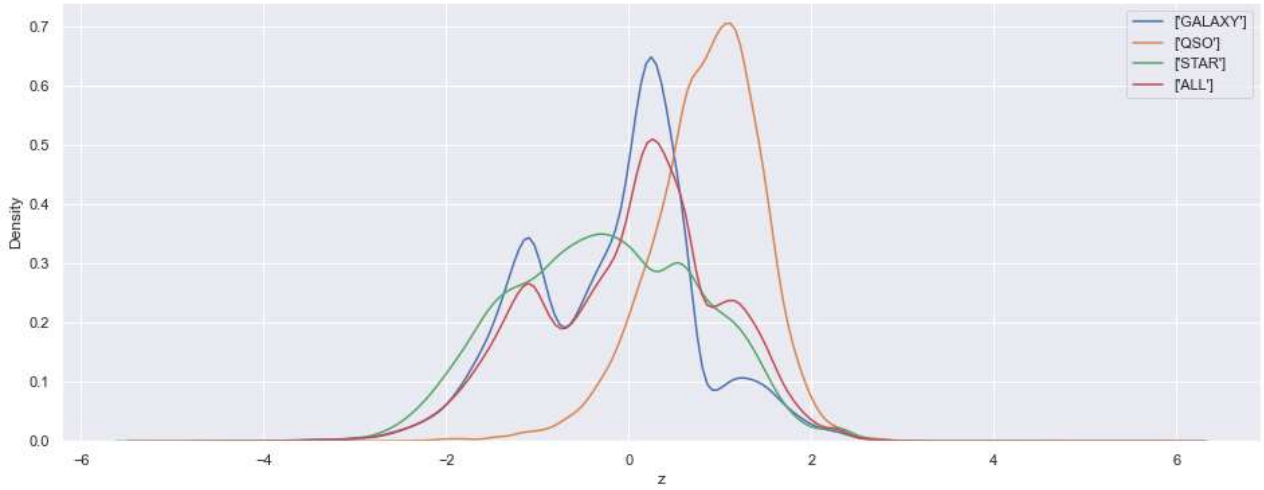
QSO continues to have the high unimodal peak; however, STAR is close to unimodal--in constrast to the last two plots for g and r

---

Infrared Photometric Filter

In [215…

```
KdePlot('z')
```



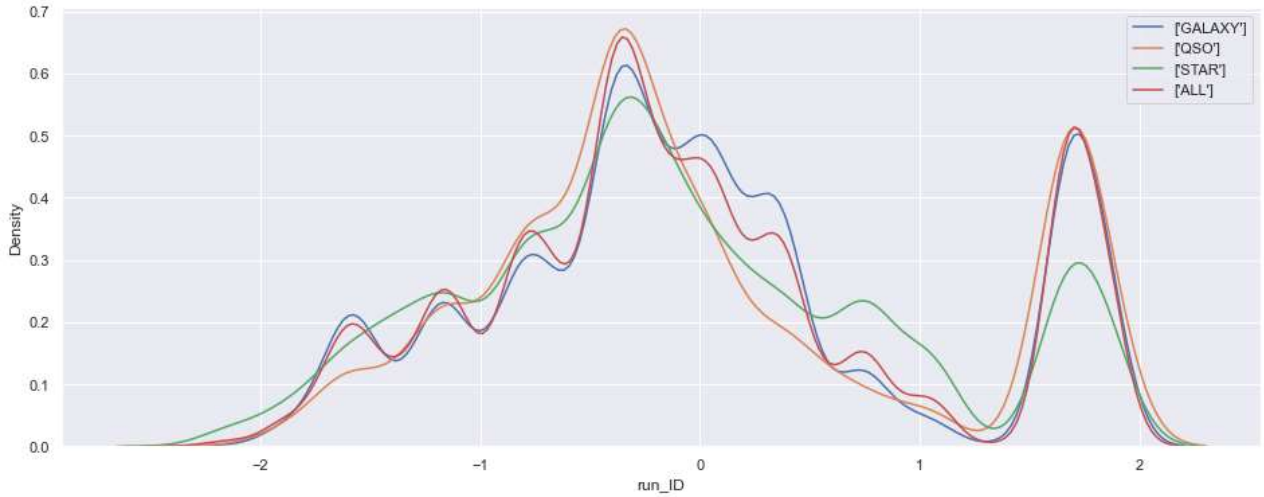
QSO continues to have the high unimodal peak and STAR is closer to unimodal than in the higher photometric frequencies

---

Run Identifier for the Specific Scan

In [216...

```
KdePlot('run_ID')
```



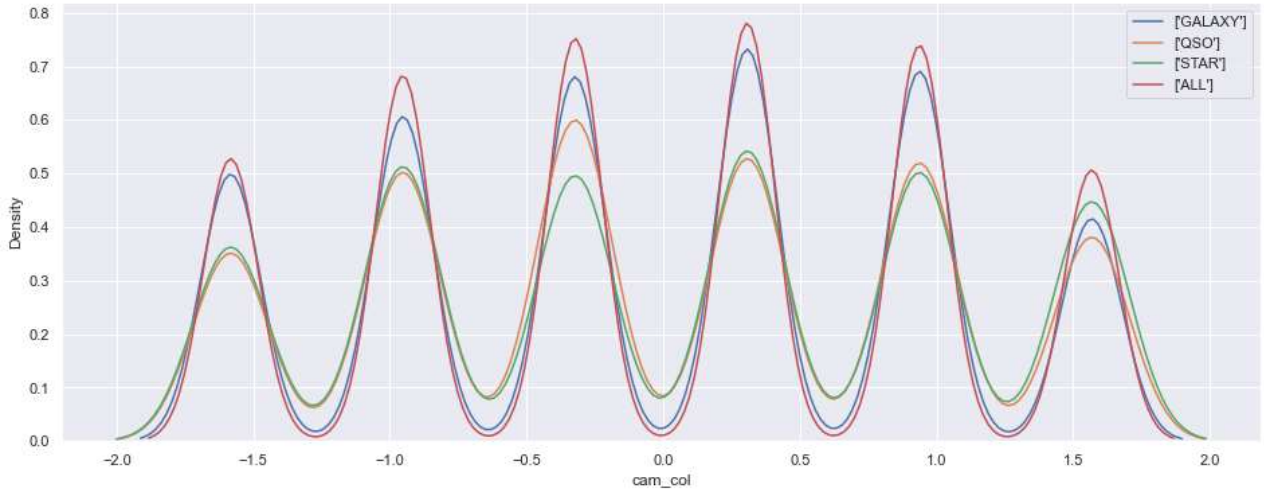
There is no significant distinction here and this variable should be removed

---

Camera Column (identifies the scanline within run)

In [217...

```
KdePlot('cam_col')
```



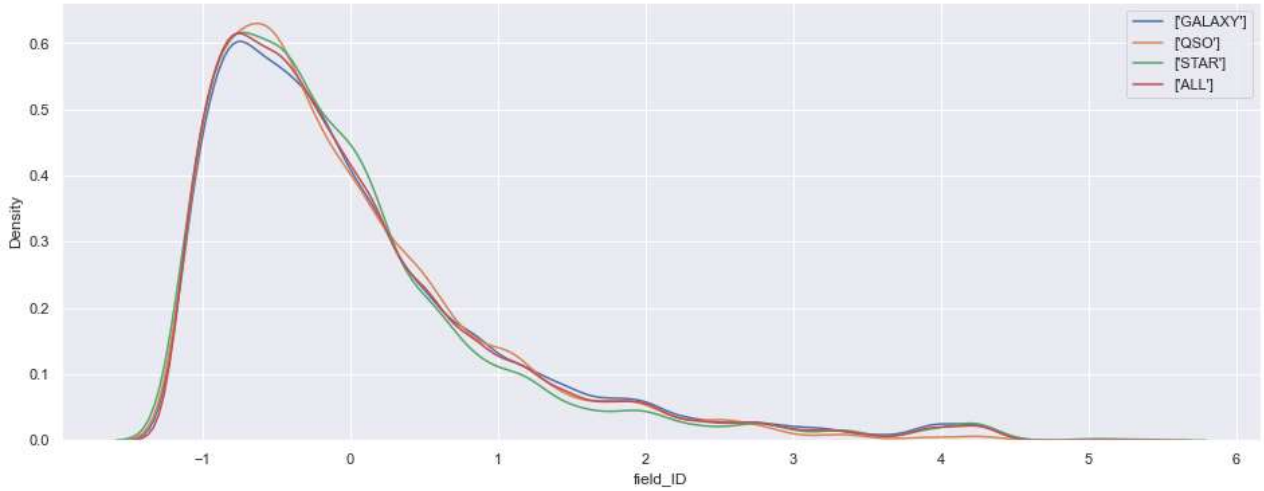
There is no significant distinction here and this variable should be removed

---

Field ID (identifier specifying each field)

In [218…

```
KdePlot('field_ID')
```



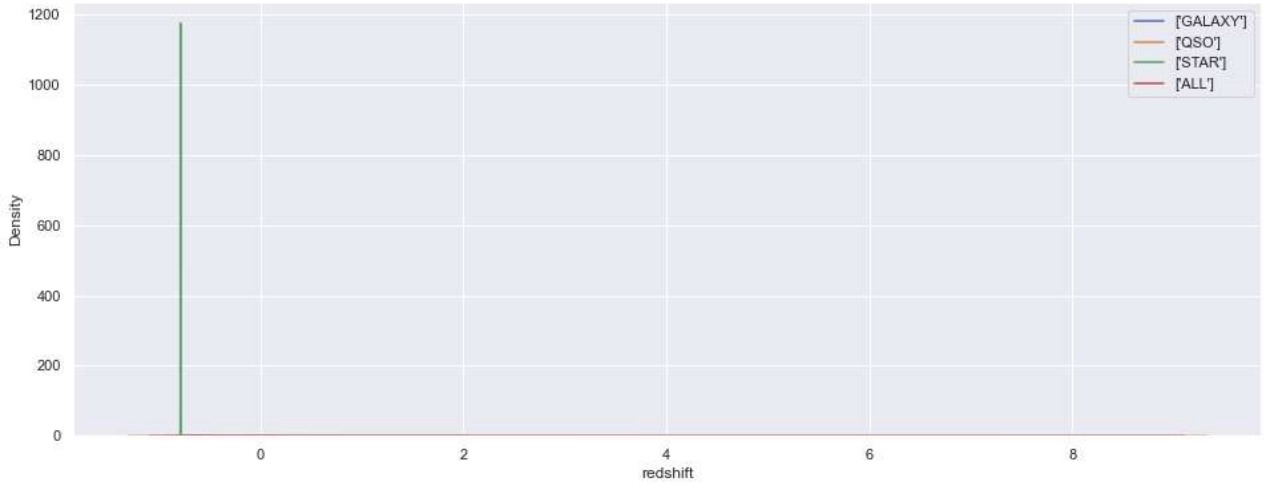
There is no significant distinction here and this variable should be removed

---

Redshift (based on the increase in wavelength)

In [219…

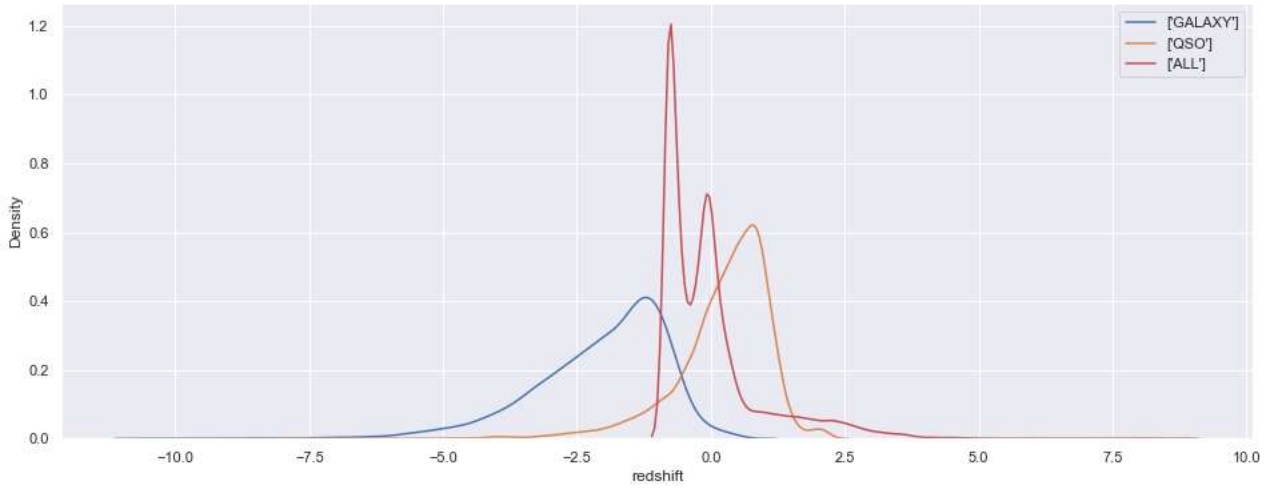
```
KdePlot('redshift')
```



In [220…

```
KdePlot('redshift', log=True)
```

```
C:\Users\Bob\anaconda3\envs\imblearn-clone\lib\site-packages\pandas\core\arraylike.py:364: RuntimeWarning:

invalid value encountered in log

C:\Users\Bob\anaconda3\envs\imblearn-clone\lib\site-packages\pandas\core\arraylike.py:364: RuntimeWarning:

invalid value encountered in log

C:\Users\Bob\anaconda3\envs\imblearn-clone\lib\site-packages\pandas\core\arraylike.py:364: RuntimeWarning:

invalid value encountered in log

C:\Users\Bob\anaconda3\envs\imblearn-clone\lib\site-packages\seaborn\distributions.py:316: UserWarning:

Dataset has 0 variance; skipping density estimate. Pass `warn_singular=False` to disable this warning.
```



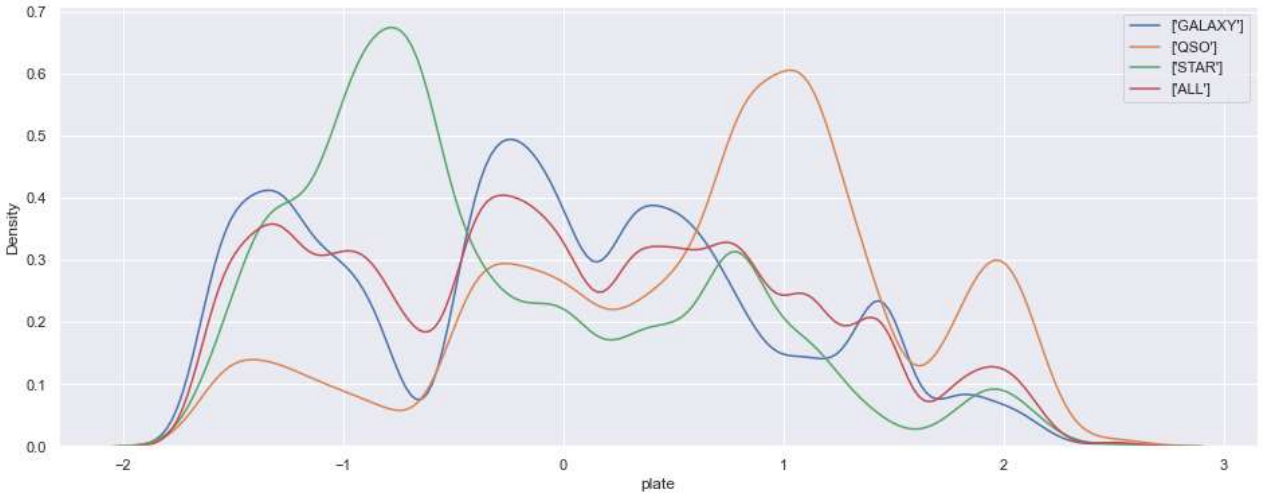
We can see that a warning was thrown and `STAR` does not appear on the log-transformed graph. This may be in part because we are dealing with the data in its already scaled form; however, ***we can***

clearly see that $redsh$ if t ***distinctly characterized all three classes.***

Plate (identifier of plate in SDSS)

In [221…

```
KdePlot('plate')
```

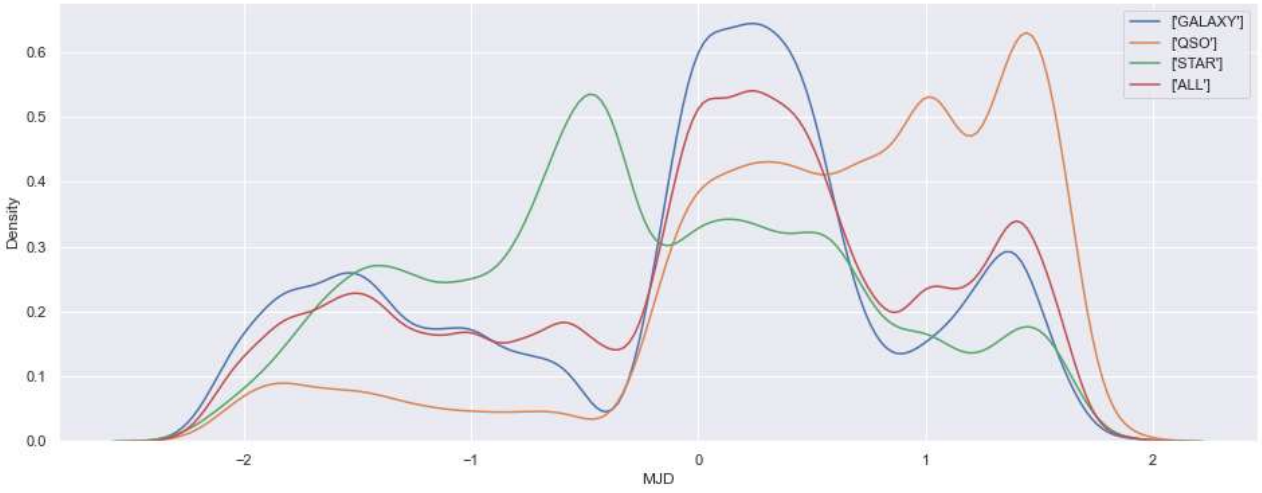


We can see that `QSO` *has a distinct profile--particularly on the right of the graph--and* `STAR / GALAXY` *on the left half of the graph.*

MJD (Modified Julian Date of observation)

In [222…

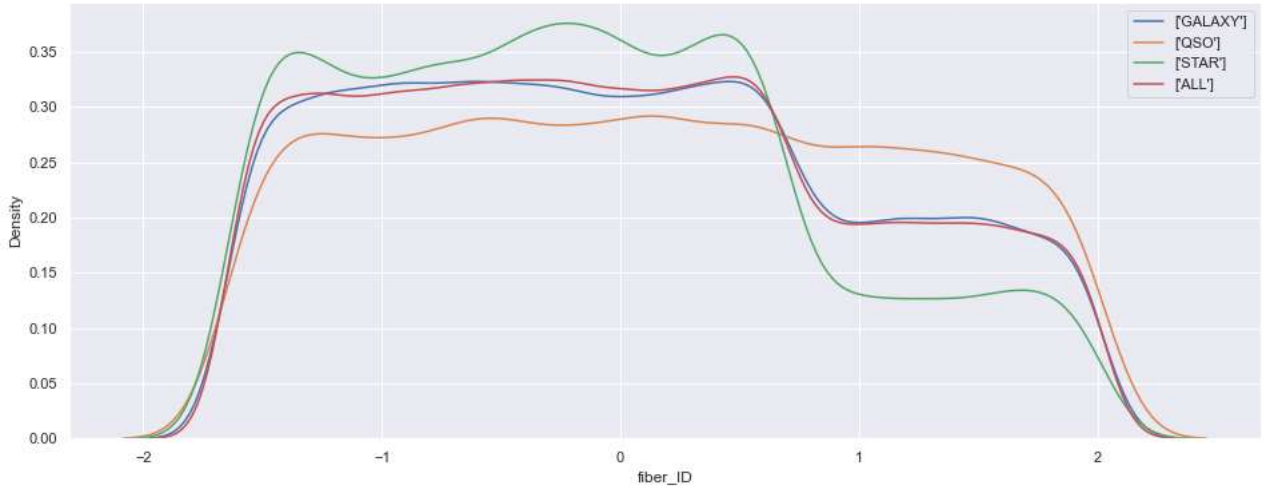
```
KdePlot('MJD')
```



The distribution for `MJD` *distinctly characterizes each of the classes.*

- Fiber ID (identifies the fiber pointing the light at the focal plane for the observation)

In [223...
```
KdePlot('fiber_ID')
```



There is no significant distinction here and this variable should be removed

---

Based on the above, we have validated the inclusion of all the variables we were not considering removing.

We will proceed with dimensionality reduction using these variables, as well as perform the same dimensionality reduction where we include the other outstanding variables from above and compare the results.

In [224...
```
X_df_aux = X_df.drop(['fiber_ID', 'field_ID', 'cam_col', 'run_ID', 'class_num'], axis=1
X_aux = X_df_aux.to_numpy()
X_df_no_aux = X_df.drop(['alpha', 'delta', 'cam_col', 'plate', 'field_ID',
                         'run_ID', 'MJD', 'fiber_ID', 'class_num'], axis=1
                )
X_no_aux = X_df_no_aux.to_numpy()
```

Switch to explicit for clarity

In [225...
```
X_df_aux = X_df_aux.loc[:,['u','g','r','i','z','redshift','alpha','delta','plate','MJD'
X_aux = X_df_aux.to_numpy()
X_df_no_aux = X_df_no_aux.loc[:,['u','g','r','i','z','redshift']]
X_no_aux = X_df_no_aux.to_numpy()
```

Calculate 3D t-SNE (with Auxiliary Columns)

In [226...
```
tsne_3_aux = TSNE(n_components=3, verbose=1, random_state=37)
tsne_3d_aux = tsne_3_aux.fit_transform(X_aux)
```

```
[t-SNE] Computing 91 nearest neighbors...
[t-SNE] Indexed 99999 samples in 0.326s...
[t-SNE] Computed neighbors for 99999 samples in 23.309s...
[t-SNE] Computed conditional probabilities for sample 1000 / 99999
[t-SNE] Computed conditional probabilities for sample 2000 / 99999
[t-SNE] Computed conditional probabilities for sample 3000 / 99999
[t-SNE] Computed conditional probabilities for sample 4000 / 99999
```

```
[t-SNE] Computed conditional probabilities for sample 5000 / 99999
[t-SNE] Computed conditional probabilities for sample 6000 / 99999
[t-SNE] Computed conditional probabilities for sample 7000 / 99999
[t-SNE] Computed conditional probabilities for sample 8000 / 99999
[t-SNE] Computed conditional probabilities for sample 9000 / 99999
[t-SNE] Computed conditional probabilities for sample 10000 / 99999
[t-SNE] Computed conditional probabilities for sample 11000 / 99999
[t-SNE] Computed conditional probabilities for sample 12000 / 99999
[t-SNE] Computed conditional probabilities for sample 13000 / 99999
[t-SNE] Computed conditional probabilities for sample 14000 / 99999
[t-SNE] Computed conditional probabilities for sample 15000 / 99999
[t-SNE] Computed conditional probabilities for sample 16000 / 99999
[t-SNE] Computed conditional probabilities for sample 17000 / 99999
[t-SNE] Computed conditional probabilities for sample 18000 / 99999
[t-SNE] Computed conditional probabilities for sample 19000 / 99999
[t-SNE] Computed conditional probabilities for sample 20000 / 99999
[t-SNE] Computed conditional probabilities for sample 21000 / 99999
[t-SNE] Computed conditional probabilities for sample 22000 / 99999
[t-SNE] Computed conditional probabilities for sample 23000 / 99999
[t-SNE] Computed conditional probabilities for sample 24000 / 99999
[t-SNE] Computed conditional probabilities for sample 25000 / 99999
[t-SNE] Computed conditional probabilities for sample 26000 / 99999
[t-SNE] Computed conditional probabilities for sample 27000 / 99999
[t-SNE] Computed conditional probabilities for sample 28000 / 99999
[t-SNE] Computed conditional probabilities for sample 29000 / 99999
[t-SNE] Computed conditional probabilities for sample 30000 / 99999
[t-SNE] Computed conditional probabilities for sample 31000 / 99999
[t-SNE] Computed conditional probabilities for sample 32000 / 99999
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[t-SNE] Computed conditional probabilities for sample 39000 / 99999
[t-SNE] Computed conditional probabilities for sample 40000 / 99999
[t-SNE] Computed conditional probabilities for sample 41000 / 99999
[t-SNE] Computed conditional probabilities for sample 42000 / 99999
[t-SNE] Computed conditional probabilities for sample 43000 / 99999
[t-SNE] Computed conditional probabilities for sample 44000 / 99999
[t-SNE] Computed conditional probabilities for sample 45000 / 99999
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[t-SNE] Computed conditional probabilities for sample 49000 / 99999
[t-SNE] Computed conditional probabilities for sample 50000 / 99999
[t-SNE] Computed conditional probabilities for sample 51000 / 99999
[t-SNE] Computed conditional probabilities for sample 52000 / 99999
[t-SNE] Computed conditional probabilities for sample 53000 / 99999
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[t-SNE] Computed conditional probabilities for sample 57000 / 99999
[t-SNE] Computed conditional probabilities for sample 58000 / 99999
[t-SNE] Computed conditional probabilities for sample 59000 / 99999
[t-SNE] Computed conditional probabilities for sample 60000 / 99999
[t-SNE] Computed conditional probabilities for sample 61000 / 99999
[t-SNE] Computed conditional probabilities for sample 62000 / 99999
[t-SNE] Computed conditional probabilities for sample 63000 / 99999
[t-SNE] Computed conditional probabilities for sample 64000 / 99999
```

```
[t-SNE] Computed conditional probabilities for sample 65000 / 99999
[t-SNE] Computed conditional probabilities for sample 66000 / 99999
[t-SNE] Computed conditional probabilities for sample 67000 / 99999
[t-SNE] Computed conditional probabilities for sample 68000 / 99999
[t-SNE] Computed conditional probabilities for sample 69000 / 99999
[t-SNE] Computed conditional probabilities for sample 70000 / 99999
[t-SNE] Computed conditional probabilities for sample 71000 / 99999
[t-SNE] Computed conditional probabilities for sample 72000 / 99999
[t-SNE] Computed conditional probabilities for sample 73000 / 99999
[t-SNE] Computed conditional probabilities for sample 74000 / 99999
[t-SNE] Computed conditional probabilities for sample 75000 / 99999
[t-SNE] Computed conditional probabilities for sample 76000 / 99999
[t-SNE] Computed conditional probabilities for sample 77000 / 99999
[t-SNE] Computed conditional probabilities for sample 78000 / 99999
[t-SNE] Computed conditional probabilities for sample 79000 / 99999
[t-SNE] Computed conditional probabilities for sample 80000 / 99999
[t-SNE] Computed conditional probabilities for sample 81000 / 99999
[t-SNE] Computed conditional probabilities for sample 82000 / 99999
[t-SNE] Computed conditional probabilities for sample 83000 / 99999
[t-SNE] Computed conditional probabilities for sample 84000 / 99999
[t-SNE] Computed conditional probabilities for sample 85000 / 99999
[t-SNE] Computed conditional probabilities for sample 86000 / 99999
[t-SNE] Computed conditional probabilities for sample 87000 / 99999
[t-SNE] Computed conditional probabilities for sample 88000 / 99999
[t-SNE] Computed conditional probabilities for sample 89000 / 99999
[t-SNE] Computed conditional probabilities for sample 90000 / 99999
[t-SNE] Computed conditional probabilities for sample 91000 / 99999
[t-SNE] Computed conditional probabilities for sample 92000 / 99999
[t-SNE] Computed conditional probabilities for sample 93000 / 99999
[t-SNE] Computed conditional probabilities for sample 94000 / 99999
[t-SNE] Computed conditional probabilities for sample 95000 / 99999
[t-SNE] Computed conditional probabilities for sample 96000 / 99999
[t-SNE] Computed conditional probabilities for sample 97000 / 99999
[t-SNE] Computed conditional probabilities for sample 98000 / 99999
[t-SNE] Computed conditional probabilities for sample 99000 / 99999
[t-SNE] Computed conditional probabilities for sample 99999 / 99999
[t-SNE] Mean sigma: 0.237256
[t-SNE] KL divergence after 250 iterations with early exaggeration: 94.544510
[t-SNE] KL divergence after 1000 iterations: 2.222878
```

Create 3D t-SNE Data Frame (with Auxiliary Columns)

In [227…

```
df_tsne_3d_aux = pd.DataFrame()
df_tsne_3d_aux['tsne-3d-1'] = tsne_3d_aux[:,0]
df_tsne_3d_aux['tsne-3d-2'] = tsne_3d_aux[:,1]
df_tsne_3d_aux['tsne-3d-3'] = tsne_3d_aux[:,2]
df_tsne_3d_aux['y_num'] = y_num
```

Calculate 3D t-SNE (without Auxiliary Columns)

In [228…

```
tsne_3 = TSNE(n_components=3, verbose=1, random_state=37)
tsne_3d = tsne_3.fit_transform(X_no_aux)
```

```
[t-SNE] Computing 91 nearest neighbors...
[t-SNE] Indexed 99999 samples in 0.313s...
```

```
[t-SNE] Computed neighbors for 99999 samples in 7.672s...
[t-SNE] Computed conditional probabilities for sample 1000 / 99999
[t-SNE] Computed conditional probabilities for sample 2000 / 99999
[t-SNE] Computed conditional probabilities for sample 3000 / 99999
[t-SNE] Computed conditional probabilities for sample 4000 / 99999
[t-SNE] Computed conditional probabilities for sample 5000 / 99999
[t-SNE] Computed conditional probabilities for sample 6000 / 99999
[t-SNE] Computed conditional probabilities for sample 7000 / 99999
[t-SNE] Computed conditional probabilities for sample 8000 / 99999
[t-SNE] Computed conditional probabilities for sample 9000 / 99999
[t-SNE] Computed conditional probabilities for sample 10000 / 99999
[t-SNE] Computed conditional probabilities for sample 11000 / 99999
[t-SNE] Computed conditional probabilities for sample 12000 / 99999
[t-SNE] Computed conditional probabilities for sample 13000 / 99999
[t-SNE] Computed conditional probabilities for sample 14000 / 99999
[t-SNE] Computed conditional probabilities for sample 15000 / 99999
[t-SNE] Computed conditional probabilities for sample 16000 / 99999
[t-SNE] Computed conditional probabilities for sample 17000 / 99999
[t-SNE] Computed conditional probabilities for sample 18000 / 99999
[t-SNE] Computed conditional probabilities for sample 19000 / 99999
[t-SNE] Computed conditional probabilities for sample 20000 / 99999
[t-SNE] Computed conditional probabilities for sample 21000 / 99999
[t-SNE] Computed conditional probabilities for sample 22000 / 99999
[t-SNE] Computed conditional probabilities for sample 23000 / 99999
[t-SNE] Computed conditional probabilities for sample 24000 / 99999
[t-SNE] Computed conditional probabilities for sample 25000 / 99999
[t-SNE] Computed conditional probabilities for sample 26000 / 99999
[t-SNE] Computed conditional probabilities for sample 27000 / 99999
[t-SNE] Computed conditional probabilities for sample 28000 / 99999
[t-SNE] Computed conditional probabilities for sample 29000 / 99999
[t-SNE] Computed conditional probabilities for sample 30000 / 99999
[t-SNE] Computed conditional probabilities for sample 31000 / 99999
[t-SNE] Computed conditional probabilities for sample 32000 / 99999
[t-SNE] Computed conditional probabilities for sample 33000 / 99999
[t-SNE] Computed conditional probabilities for sample 34000 / 99999
[t-SNE] Computed conditional probabilities for sample 35000 / 99999
[t-SNE] Computed conditional probabilities for sample 36000 / 99999
[t-SNE] Computed conditional probabilities for sample 37000 / 99999
[t-SNE] Computed conditional probabilities for sample 38000 / 99999
[t-SNE] Computed conditional probabilities for sample 39000 / 99999
[t-SNE] Computed conditional probabilities for sample 40000 / 99999
[t-SNE] Computed conditional probabilities for sample 41000 / 99999
[t-SNE] Computed conditional probabilities for sample 42000 / 99999
[t-SNE] Computed conditional probabilities for sample 43000 / 99999
[t-SNE] Computed conditional probabilities for sample 44000 / 99999
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[t-SNE] Computed conditional probabilities for sample 47000 / 99999
[t-SNE] Computed conditional probabilities for sample 48000 / 99999
[t-SNE] Computed conditional probabilities for sample 49000 / 99999
[t-SNE] Computed conditional probabilities for sample 50000 / 99999
[t-SNE] Computed conditional probabilities for sample 51000 / 99999
[t-SNE] Computed conditional probabilities for sample 52000 / 99999
[t-SNE] Computed conditional probabilities for sample 53000 / 99999
[t-SNE] Computed conditional probabilities for sample 54000 / 99999
[t-SNE] Computed conditional probabilities for sample 55000 / 99999
[t-SNE] Computed conditional probabilities for sample 56000 / 99999
[t-SNE] Computed conditional probabilities for sample 57000 / 99999
[t-SNE] Computed conditional probabilities for sample 58000 / 99999
[t-SNE] Computed conditional probabilities for sample 59000 / 99999
```

```
[t-SNE] Computed conditional probabilities for sample 60000 / 99999
[t-SNE] Computed conditional probabilities for sample 61000 / 99999
[t-SNE] Computed conditional probabilities for sample 62000 / 99999
[t-SNE] Computed conditional probabilities for sample 63000 / 99999
[t-SNE] Computed conditional probabilities for sample 64000 / 99999
[t-SNE] Computed conditional probabilities for sample 65000 / 99999
[t-SNE] Computed conditional probabilities for sample 66000 / 99999
[t-SNE] Computed conditional probabilities for sample 67000 / 99999
[t-SNE] Computed conditional probabilities for sample 68000 / 99999
[t-SNE] Computed conditional probabilities for sample 69000 / 99999
[t-SNE] Computed conditional probabilities for sample 70000 / 99999
[t-SNE] Computed conditional probabilities for sample 71000 / 99999
[t-SNE] Computed conditional probabilities for sample 72000 / 99999
[t-SNE] Computed conditional probabilities for sample 73000 / 99999
[t-SNE] Computed conditional probabilities for sample 74000 / 99999
[t-SNE] Computed conditional probabilities for sample 75000 / 99999
[t-SNE] Computed conditional probabilities for sample 76000 / 99999
[t-SNE] Computed conditional probabilities for sample 77000 / 99999
[t-SNE] Computed conditional probabilities for sample 78000 / 99999
[t-SNE] Computed conditional probabilities for sample 79000 / 99999
[t-SNE] Computed conditional probabilities for sample 80000 / 99999
[t-SNE] Computed conditional probabilities for sample 81000 / 99999
[t-SNE] Computed conditional probabilities for sample 82000 / 99999
[t-SNE] Computed conditional probabilities for sample 83000 / 99999
[t-SNE] Computed conditional probabilities for sample 84000 / 99999
[t-SNE] Computed conditional probabilities for sample 85000 / 99999
[t-SNE] Computed conditional probabilities for sample 86000 / 99999
[t-SNE] Computed conditional probabilities for sample 87000 / 99999
[t-SNE] Computed conditional probabilities for sample 88000 / 99999
[t-SNE] Computed conditional probabilities for sample 89000 / 99999
[t-SNE] Computed conditional probabilities for sample 90000 / 99999
[t-SNE] Computed conditional probabilities for sample 91000 / 99999
[t-SNE] Computed conditional probabilities for sample 92000 / 99999
[t-SNE] Computed conditional probabilities for sample 93000 / 99999
[t-SNE] Computed conditional probabilities for sample 94000 / 99999
[t-SNE] Computed conditional probabilities for sample 95000 / 99999
[t-SNE] Computed conditional probabilities for sample 96000 / 99999
[t-SNE] Computed conditional probabilities for sample 97000 / 99999
[t-SNE] Computed conditional probabilities for sample 98000 / 99999
[t-SNE] Computed conditional probabilities for sample 99000 / 99999
[t-SNE] Computed conditional probabilities for sample 99999 / 99999
[t-SNE] Mean sigma: 0.060146
[t-SNE] KL divergence after 250 iterations with early exaggeration: 94.144081
[t-SNE] KL divergence after 1000 iterations: 2.273288
```

Create 3D t-SNE Data Frame (without Auxiliary Columns)

In [229…

```
df_tsne_3d = pd.DataFrame()
df_tsne_3d['tsne-3d-1'] = tsne_3d[:,0]
df_tsne_3d['tsne-3d-2'] = tsne_3d[:,1]
df_tsne_3d['tsne-3d-3'] = tsne_3d[:,2]
df_tsne_3d['y_num'] = y_num
```

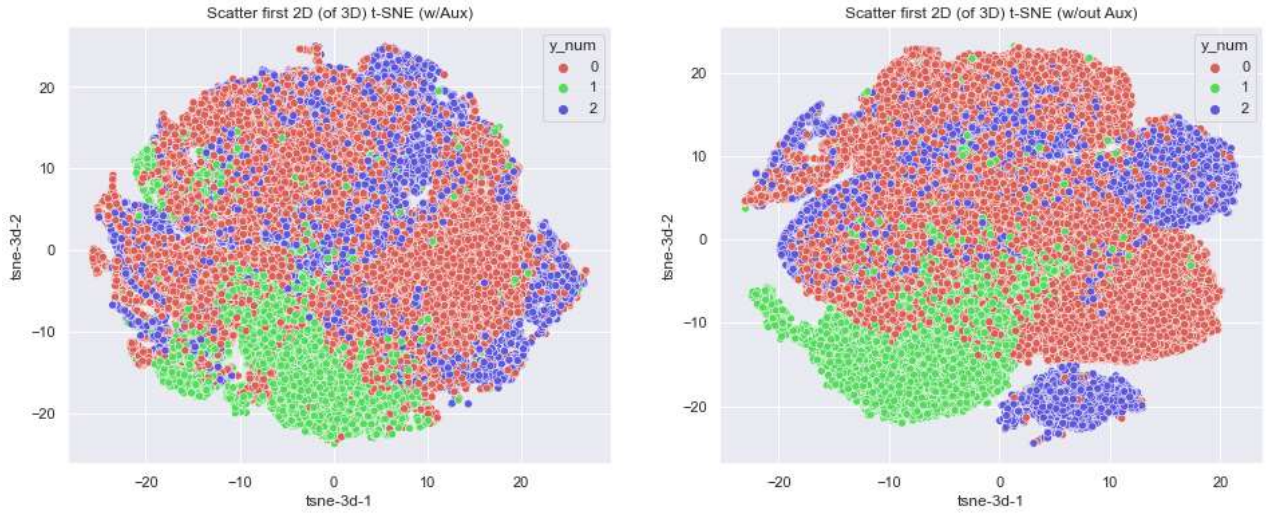
Scatter Plot First 2D of 3D t-SNE by Class (with/without Auxiliary Columns)

In [230…

```
fig,axs = plt.subplots(1,2)
```

```
sns.scatterplot(x='tsne-3d-1',
                y='tsne-3d-2',
                hue='y_num',
                data=df_tsne_3d_aux,
                palette=sns.color_palette('hls',3),
                ax=axs[0]).set_title('Scatter first 2D (of 3D) t-SNE (w/Aux)')

sns.scatterplot(x='tsne-3d-1',
                y='tsne-3d-2',
                hue='y_num',
                data=df_tsne_3d,
                palette=sns.color_palette('hls',3),
                ax=axs[1]).set_title('Scatter first 2D (of 3D) t-SNE (w/out Aux)')

print(le.classes_)
```

```
['GALAXY' 'QSO' 'STAR']
```



Based on the first two dimensions of the 3D t-SNE's, we can clearly see a more cohesive structure in the plot on the right (without auxiliary columns).

Let's see if this trend carries over to all three dimensions of the 3D t-SNE's.

In [231…

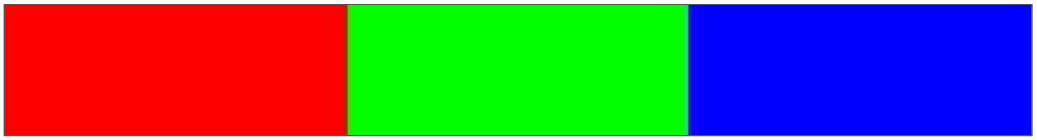
```
#
# 3D scatter plot of 3D t-SNE (100% vs 10% alpha)
#
def Plot3DtSNE_df(ttle='title', df1=None, azm=-60, elv=30):
    fig = plt.figure()
    ax = fig.add_subplot(121, projection='3d')
    ax.scatter(df1['tsne-3d-1'],
               df1['tsne-3d-2'],
               zs=df1['tsne-3d-3'],
               c=df1['y_num'],
               cmap=cmap_bold,
               label=le.inverse_transform,
               s=1
              )
    plt.title(ttle)
    plt.legend(le.classes_) # TODO
    ax.set_xlabel('Dimension 1')
    ax.set_ylabel('Dimension 2')
```

```
    ax.set_zlabel('Dimension 3')
    ax.azim = azm
    ax.elev = elv

    ax = fig.add_subplot(122, projection='3d')
    ax.scatter(df1['tsne-3d-1'],
               df1['tsne-3d-2'],
               zs=df1['tsne-3d-3'],
               c=df1['y_num'],
               cmap=cmap_bold,
               label=le.inverse_transform,
               s=1,
               alpha=0.1
              )
    plt.title(ttle)
    plt.legend(le.classes_) # TODO
    ax.set_xlabel('Dimension 1')
    ax.set_ylabel('Dimension 2')
    ax.set_zlabel('Dimension 3')
    ax.azim = azm
    ax.elev = elv
    return ax
```

In [232…

```
cmap_bold
```

Out[232… ***GALAXY, QSO, STAR***



☐ under bad ☐ over ☐

In [233…

```
#      GALAXY                  QSO                    STAR
```

3D Scatter Plot w/Aux

---

alpha, delta, u, g, r, i, z, redshift, plate, MJD

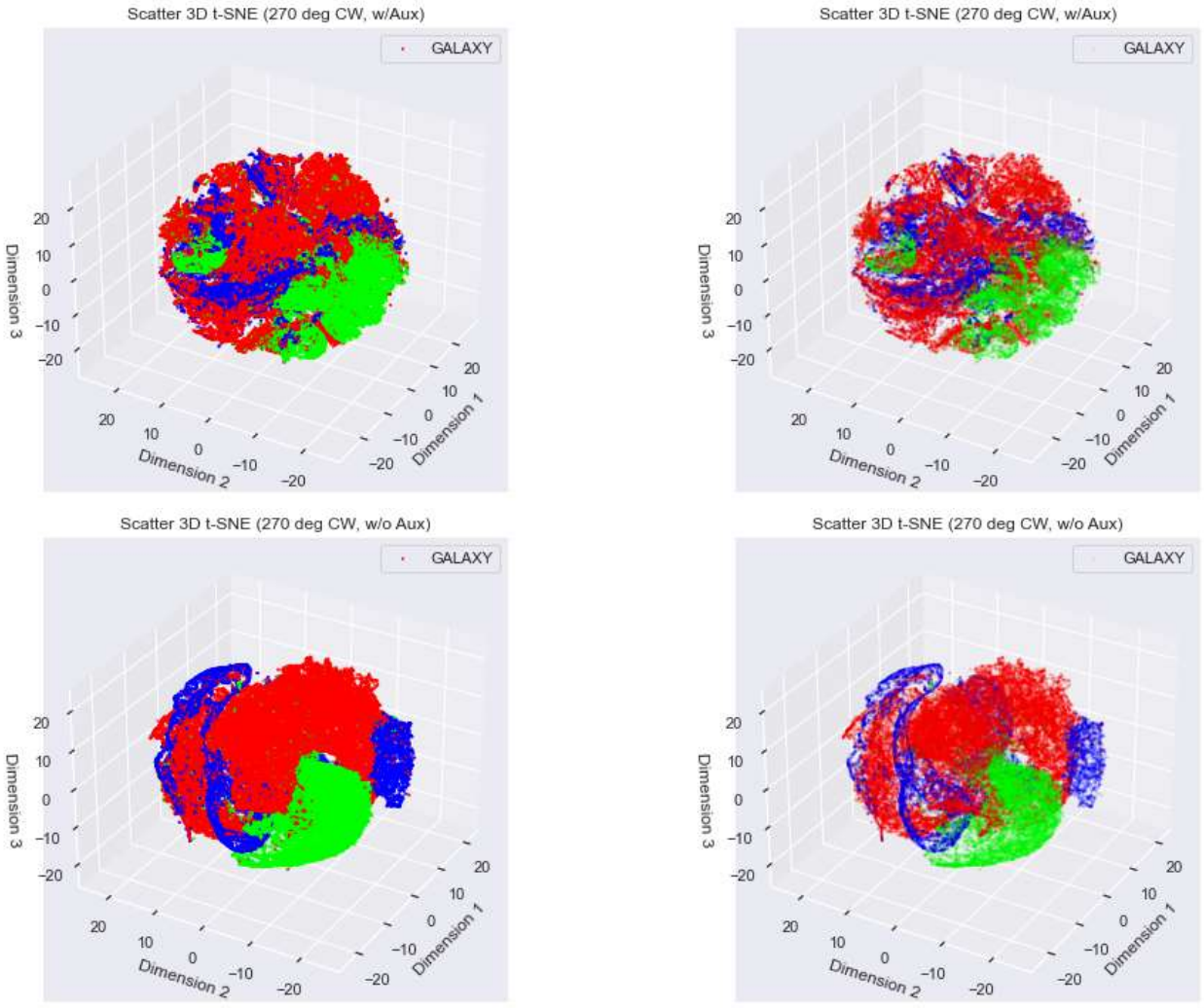
3D Scatter Plot w/o Aux

---

u, g, r, i, z, redshift

In [234…

```
Plot3DtSNE_df('Scatter 3D t-SNE (270 deg CW, w/Aux)', df_tsne_3d_aux, 210)
Plot3DtSNE_df('Scatter 3D t-SNE (270 deg CW, w/o Aux)', df_tsne_3d, 210)
print()
```



We can see, particularly for the blue points (STAR), in the top two graphs, that the added variance/noise appears to prevent a cohesive structure from forming.

This is in contrast to the bottom two graphs, where you can clearly see a cohesive structure.

Below, we can follow the blue structure through the rotations of the 3D t-SNE.

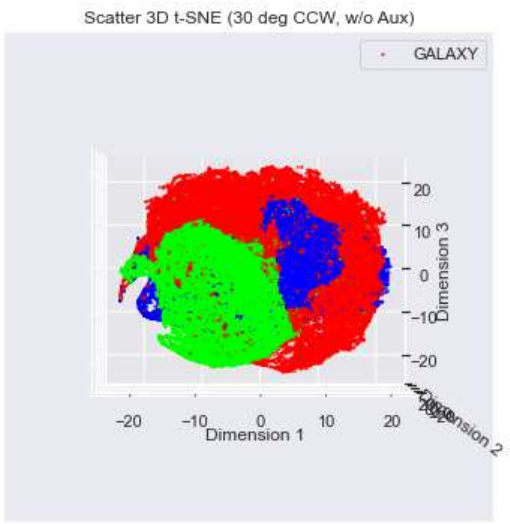
3D Scatter Plot w/o Aux

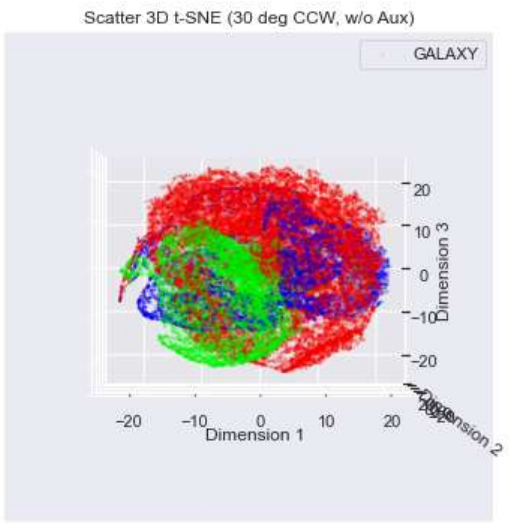
---

u, g, r, i, z, redshift

In [235…

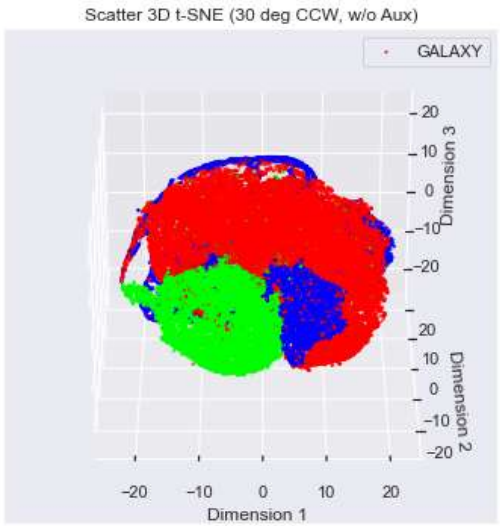
```
Plot3DtSNE_df('Scatter 3D t-SNE (30 deg CCW, w/o Aux)', df_tsne_3d, -90,0)
print()
```

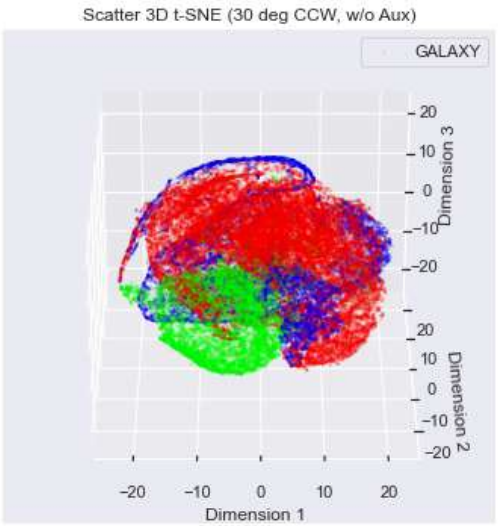




In [236…

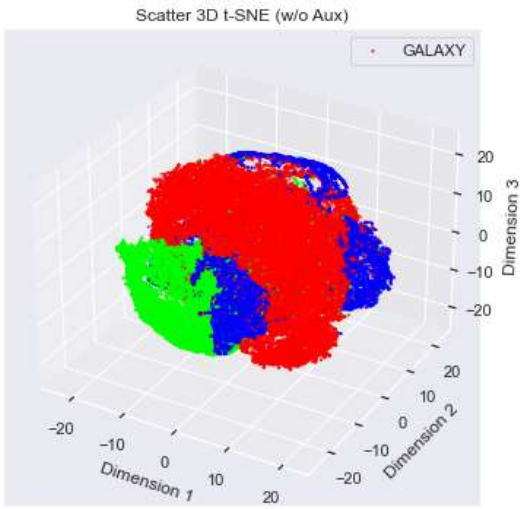
```
Plot3DtSNE_df('Scatter 3D t-SNE (30 deg CCW, w/o Aux)', df_tsne_3d, -90)
print()
```

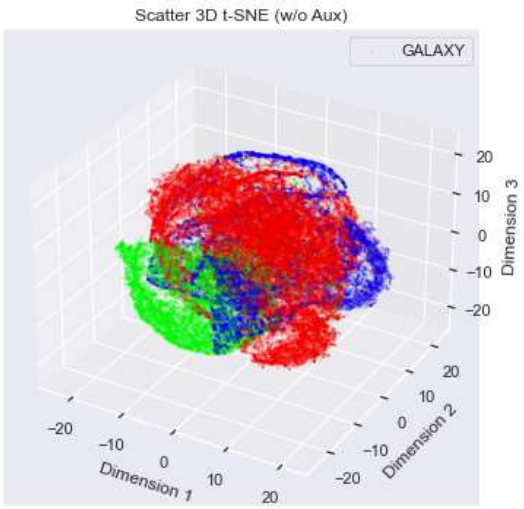




In [237…

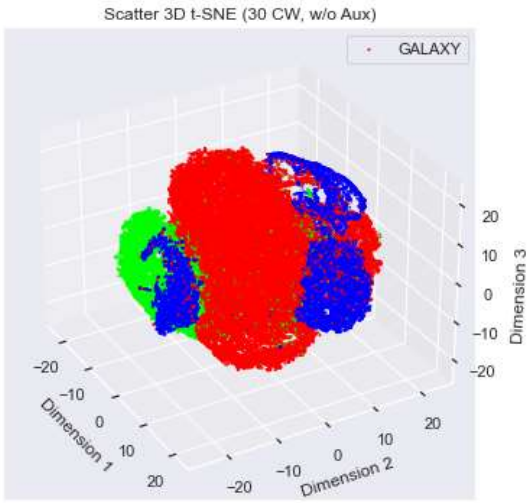
```
Plot3DtSNE_df('Scatter 3D t-SNE (w/o Aux)', df_tsne_3d)
print()
```

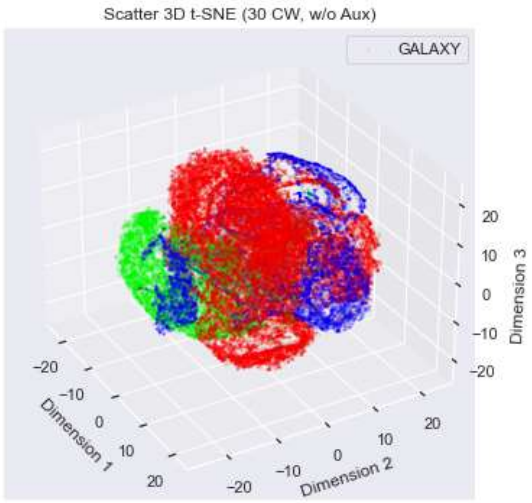




In [238…

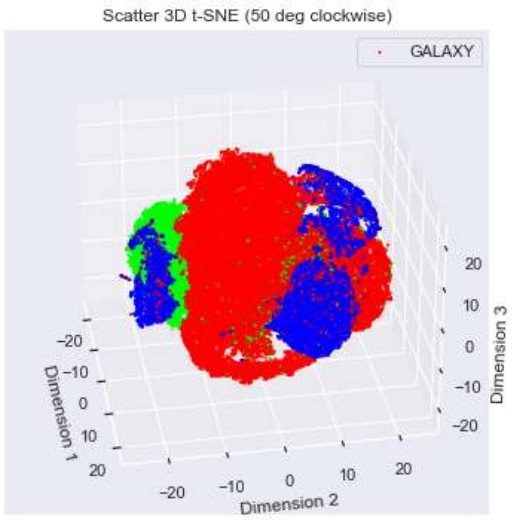
```
Plot3DtSNE_df('Scatter 3D t-SNE (30 CW, w/o Aux)', df_tsne_3d, -30)
print()
```

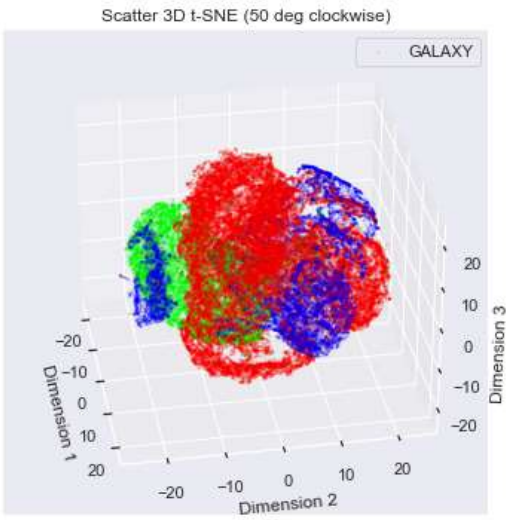




In [239…

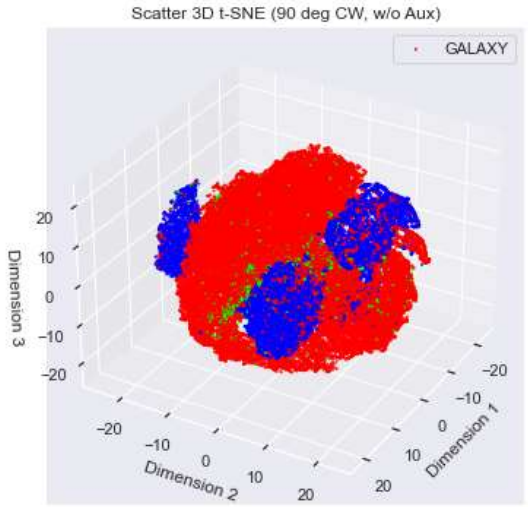
```
Plot3DtSNE_df('Scatter 3D t-SNE (50 deg clockwise)', df_tsne_3d, -10)
print()
```

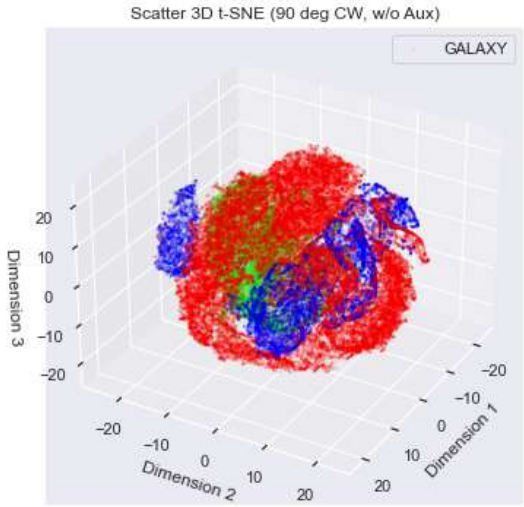




In [240…

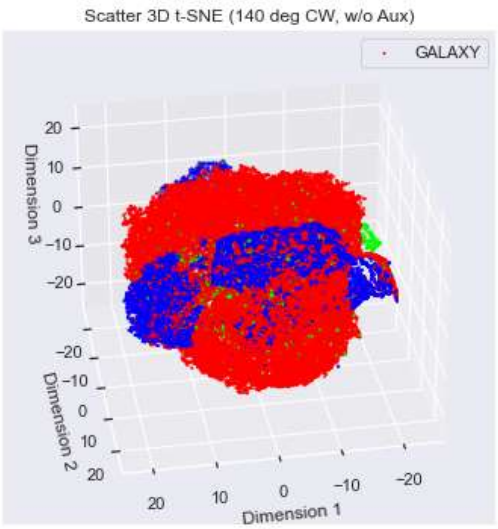
```
Plot3DtSNE_df('Scatter 3D t-SNE (90 deg CW, w/o Aux)', df_tsne_3d, 30)
print()
```

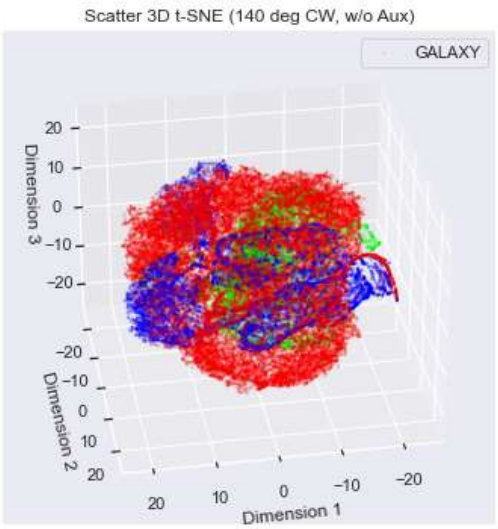




In [241…

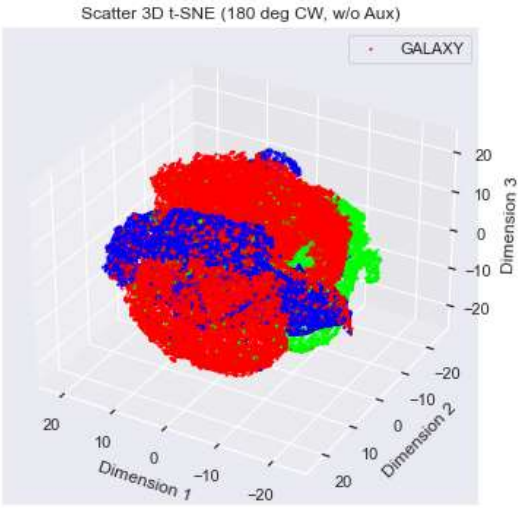
```
Plot3DtSNE_df('Scatter 3D t-SNE (140 deg CW, w/o Aux)', df_tsne_3d, 80)
print()
```

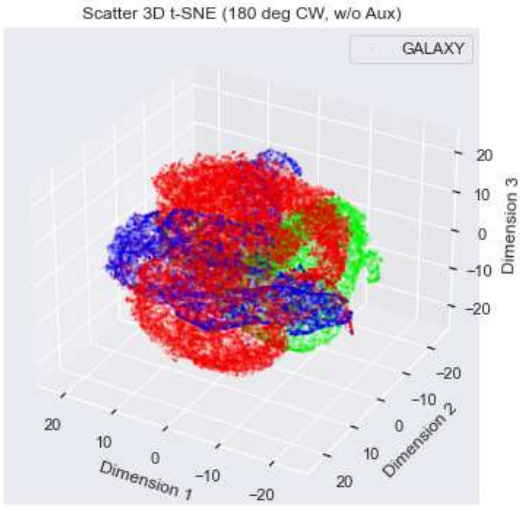




In [242…

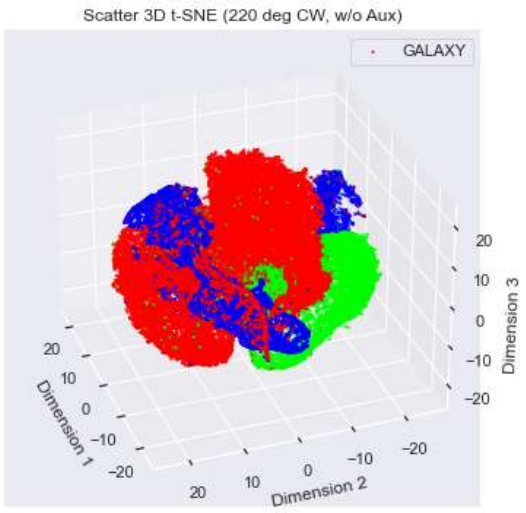
```
Plot3DtSNE_df('Scatter 3D t-SNE (180 deg CW, w/o Aux)', df_tsne_3d, 120)
print()
```

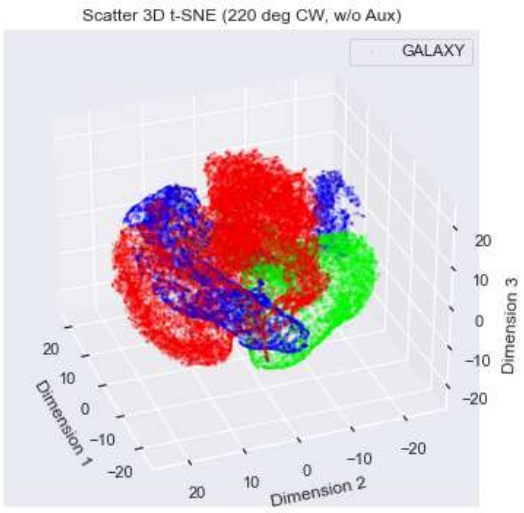




In [243…

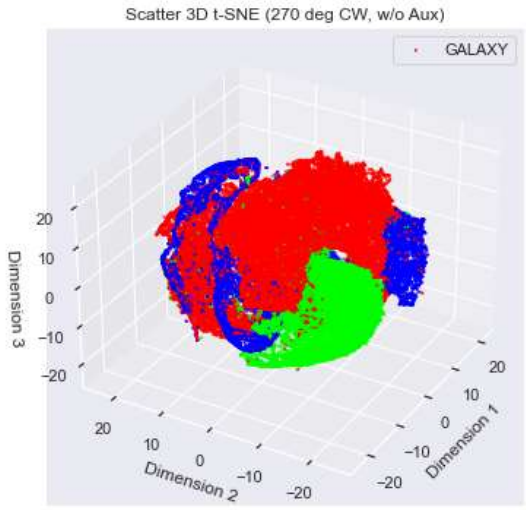
```
Plot3DtSNE_df('Scatter 3D t-SNE (220 deg CW, w/o Aux)', df_tsne_3d, 160)
print()
```

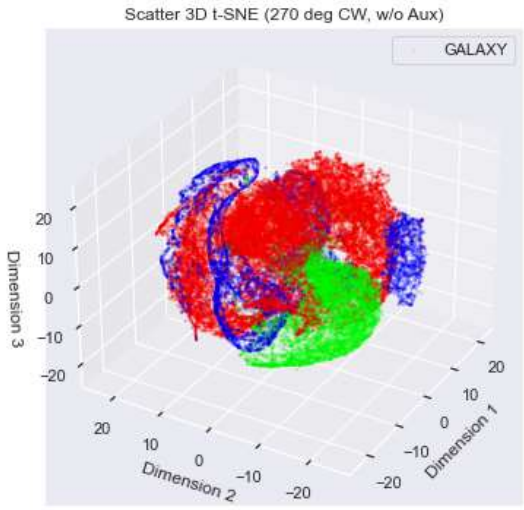




In [244…

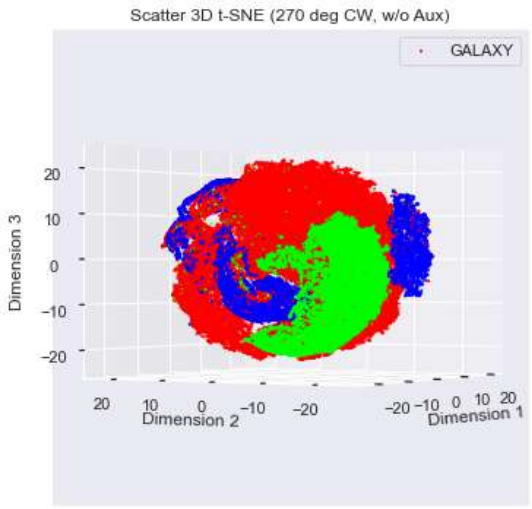
```
Plot3DtSNE_df('Scatter 3D t-SNE (270 deg CW, w/o Aux)', df_tsne_3d, 210)
print()
```

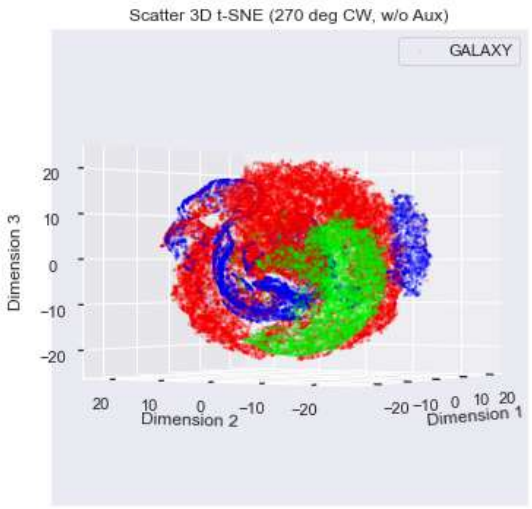




In [245…

```
Plot3DtSNE_df('Scatter 3D t-SNE (270 deg CW, w/o Aux)', df_tsne_3d, 210, 0)
print()
```





In [246…
```
cmap_bold
```

Out[246… ***GALAXY, QSO, STAR***

☐ *under* *bad* ☐ *over* ☐

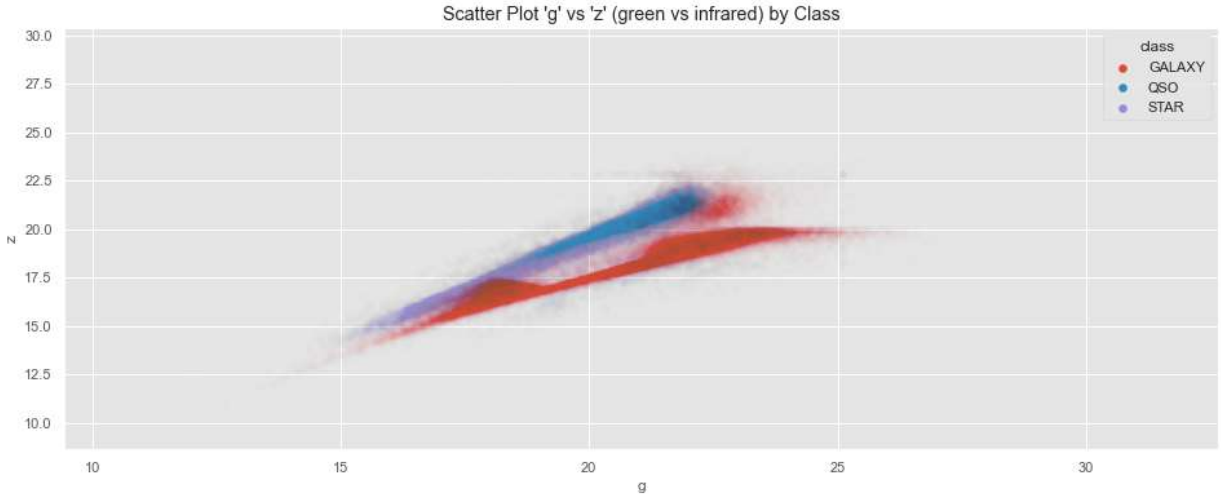
In [247…
```
#       GALAXY                  QSO                     STAR
```

The `u`, `g`, `r`, `i`, `z`, `redshift` t-SNE clearly has a more cohesive structure than the t-SNE that included `alpha`, `delta`, `plate`, and `MJD` in addition the photometric/redshift variables.

This is particularly true for the entity corresponding to `STAR`, as well as `QSO`.

We can see in the `g` vs `z` scatter plot ***below*** *that $STAR$* ***and*** *QSO* ***have a particular relationship****, in some dimensions, that would become harder to distinguish as more dimensions/variance is added through variables that do not directly correspond to the true underlying trend.*

In [248…
```
plt.style.use('ggplot')
sns.scatterplot(x='g',
                y='z',
                data=df,
                hue=df['class'],
                alpha=.002).set_title('Scatter Plot \'g\' vs \'z\' (green vs infrare
print()
```



Notice the ring of *STAR* ***around the*** *QSO* ***cluster*** (mentioned above)

---

t-SNE from First 3 Principle Components

Calculate 3D t-SNE from 3D PCA

In [249...

```
tsne_3_pca = TSNE(n_components=3, verbose=1, random_state=37)
tsne_3d_pca = tsne_3_pca.fit_transform(df_pca_wout_au.drop('y_num', axis=1))
```

```
[t-SNE] Computing 91 nearest neighbors...
[t-SNE] Indexed 99999 samples in 0.102s...
[t-SNE] Computed neighbors for 99999 samples in 2.680s...
[t-SNE] Computed conditional probabilities for sample 1000 / 99999
[t-SNE] Computed conditional probabilities for sample 2000 / 99999
[t-SNE] Computed conditional probabilities for sample 3000 / 99999
[t-SNE] Computed conditional probabilities for sample 4000 / 99999
[t-SNE] Computed conditional probabilities for sample 5000 / 99999
[t-SNE] Computed conditional probabilities for sample 6000 / 99999
[t-SNE] Computed conditional probabilities for sample 7000 / 99999
[t-SNE] Computed conditional probabilities for sample 8000 / 99999
[t-SNE] Computed conditional probabilities for sample 9000 / 99999
[t-SNE] Computed conditional probabilities for sample 10000 / 99999
[t-SNE] Computed conditional probabilities for sample 11000 / 99999
[t-SNE] Computed conditional probabilities for sample 12000 / 99999
[t-SNE] Computed conditional probabilities for sample 13000 / 99999
[t-SNE] Computed conditional probabilities for sample 14000 / 99999
[t-SNE] Computed conditional probabilities for sample 15000 / 99999
[t-SNE] Computed conditional probabilities for sample 16000 / 99999
[t-SNE] Computed conditional probabilities for sample 17000 / 99999
[t-SNE] Computed conditional probabilities for sample 18000 / 99999
[t-SNE] Computed conditional probabilities for sample 19000 / 99999
[t-SNE] Computed conditional probabilities for sample 20000 / 99999
[t-SNE] Computed conditional probabilities for sample 21000 / 99999
[t-SNE] Computed conditional probabilities for sample 22000 / 99999
[t-SNE] Computed conditional probabilities for sample 23000 / 99999
[t-SNE] Computed conditional probabilities for sample 24000 / 99999
[t-SNE] Computed conditional probabilities for sample 25000 / 99999
[t-SNE] Computed conditional probabilities for sample 26000 / 99999
[t-SNE] Computed conditional probabilities for sample 27000 / 99999
```

```
[t-SNE] Computed conditional probabilities for sample 28000 / 99999
[t-SNE] Computed conditional probabilities for sample 29000 / 99999
[t-SNE] Computed conditional probabilities for sample 30000 / 99999
[t-SNE] Computed conditional probabilities for sample 31000 / 99999
[t-SNE] Computed conditional probabilities for sample 32000 / 99999
[t-SNE] Computed conditional probabilities for sample 33000 / 99999
[t-SNE] Computed conditional probabilities for sample 34000 / 99999
[t-SNE] Computed conditional probabilities for sample 35000 / 99999
[t-SNE] Computed conditional probabilities for sample 36000 / 99999
[t-SNE] Computed conditional probabilities for sample 37000 / 99999
[t-SNE] Computed conditional probabilities for sample 38000 / 99999
[t-SNE] Computed conditional probabilities for sample 39000 / 99999
[t-SNE] Computed conditional probabilities for sample 40000 / 99999
[t-SNE] Computed conditional probabilities for sample 41000 / 99999
[t-SNE] Computed conditional probabilities for sample 42000 / 99999
[t-SNE] Computed conditional probabilities for sample 43000 / 99999
[t-SNE] Computed conditional probabilities for sample 44000 / 99999
[t-SNE] Computed conditional probabilities for sample 45000 / 99999
[t-SNE] Computed conditional probabilities for sample 46000 / 99999
[t-SNE] Computed conditional probabilities for sample 47000 / 99999
[t-SNE] Computed conditional probabilities for sample 48000 / 99999
[t-SNE] Computed conditional probabilities for sample 49000 / 99999
[t-SNE] Computed conditional probabilities for sample 50000 / 99999
[t-SNE] Computed conditional probabilities for sample 51000 / 99999
[t-SNE] Computed conditional probabilities for sample 52000 / 99999
[t-SNE] Computed conditional probabilities for sample 53000 / 99999
[t-SNE] Computed conditional probabilities for sample 54000 / 99999
[t-SNE] Computed conditional probabilities for sample 55000 / 99999
[t-SNE] Computed conditional probabilities for sample 56000 / 99999
[t-SNE] Computed conditional probabilities for sample 57000 / 99999
[t-SNE] Computed conditional probabilities for sample 58000 / 99999
[t-SNE] Computed conditional probabilities for sample 59000 / 99999
[t-SNE] Computed conditional probabilities for sample 60000 / 99999
[t-SNE] Computed conditional probabilities for sample 61000 / 99999
[t-SNE] Computed conditional probabilities for sample 62000 / 99999
[t-SNE] Computed conditional probabilities for sample 63000 / 99999
[t-SNE] Computed conditional probabilities for sample 64000 / 99999
[t-SNE] Computed conditional probabilities for sample 65000 / 99999
[t-SNE] Computed conditional probabilities for sample 66000 / 99999
[t-SNE] Computed conditional probabilities for sample 67000 / 99999
[t-SNE] Computed conditional probabilities for sample 68000 / 99999
[t-SNE] Computed conditional probabilities for sample 69000 / 99999
[t-SNE] Computed conditional probabilities for sample 70000 / 99999
[t-SNE] Computed conditional probabilities for sample 71000 / 99999
[t-SNE] Computed conditional probabilities for sample 72000 / 99999
[t-SNE] Computed conditional probabilities for sample 73000 / 99999
[t-SNE] Computed conditional probabilities for sample 74000 / 99999
[t-SNE] Computed conditional probabilities for sample 75000 / 99999
[t-SNE] Computed conditional probabilities for sample 76000 / 99999
[t-SNE] Computed conditional probabilities for sample 77000 / 99999
[t-SNE] Computed conditional probabilities for sample 78000 / 99999
[t-SNE] Computed conditional probabilities for sample 79000 / 99999
[t-SNE] Computed conditional probabilities for sample 80000 / 99999
[t-SNE] Computed conditional probabilities for sample 81000 / 99999
[t-SNE] Computed conditional probabilities for sample 82000 / 99999
[t-SNE] Computed conditional probabilities for sample 83000 / 99999
[t-SNE] Computed conditional probabilities for sample 84000 / 99999
[t-SNE] Computed conditional probabilities for sample 85000 / 99999
[t-SNE] Computed conditional probabilities for sample 86000 / 99999
[t-SNE] Computed conditional probabilities for sample 87000 / 99999
```

```
[t-SNE] Computed conditional probabilities for sample 88000 / 99999
[t-SNE] Computed conditional probabilities for sample 89000 / 99999
[t-SNE] Computed conditional probabilities for sample 90000 / 99999
[t-SNE] Computed conditional probabilities for sample 91000 / 99999
[t-SNE] Computed conditional probabilities for sample 92000 / 99999
[t-SNE] Computed conditional probabilities for sample 93000 / 99999
[t-SNE] Computed conditional probabilities for sample 94000 / 99999
[t-SNE] Computed conditional probabilities for sample 95000 / 99999
[t-SNE] Computed conditional probabilities for sample 96000 / 99999
[t-SNE] Computed conditional probabilities for sample 97000 / 99999
[t-SNE] Computed conditional probabilities for sample 98000 / 99999
[t-SNE] Computed conditional probabilities for sample 99000 / 99999
[t-SNE] Computed conditional probabilities for sample 99999 / 99999
[t-SNE] Mean sigma: 0.043916
[t-SNE] KL divergence after 250 iterations with early exaggeration: 91.936081
[t-SNE] KL divergence after 1000 iterations: 2.008830
```

Create Data Frame for 3D t-SNE from 3D PCA

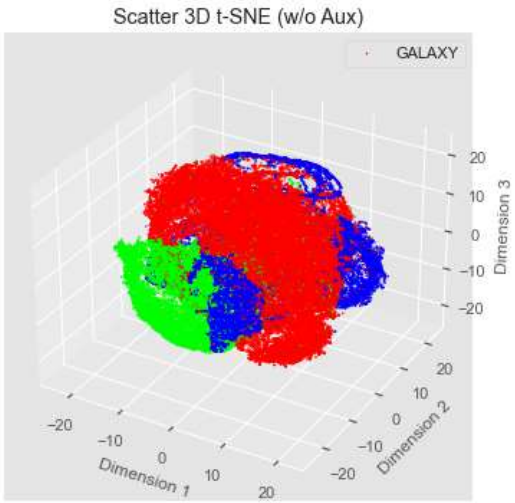
In [250…

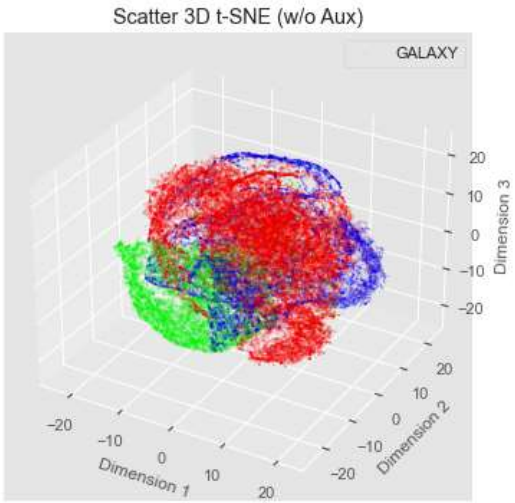
```
df_tsne_3d_pca = pd.DataFrame()
df_tsne_3d_pca['tsne-3d-1'] = tsne_3d_pca[:,0]
df_tsne_3d_pca['tsne-3d-2'] = tsne_3d_pca[:,1]
df_tsne_3d_pca['tsne-3d-3'] = tsne_3d_pca[:,2]
df_tsne_3d_pca['y_num'] = y_num
```

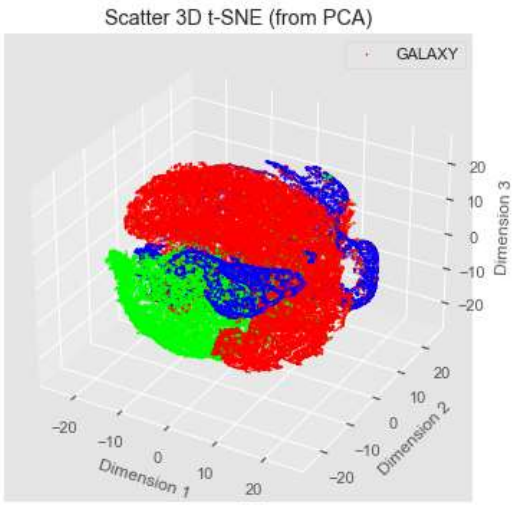
Compare 3D t-SNE (from 3D PCA) vs 3D t-SNE (from Scaled `r,g,u,i,z,redshift`)

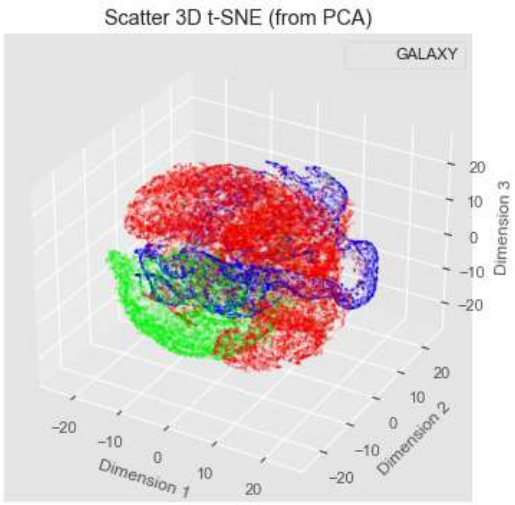
In [251…

```
Plot3DtSNE_df('Scatter 3D t-SNE (w/o Aux)', df_tsne_3d)
Plot3DtSNE_df('Scatter 3D t-SNE (from PCA)', df_tsne_3d_pca)
print()
```







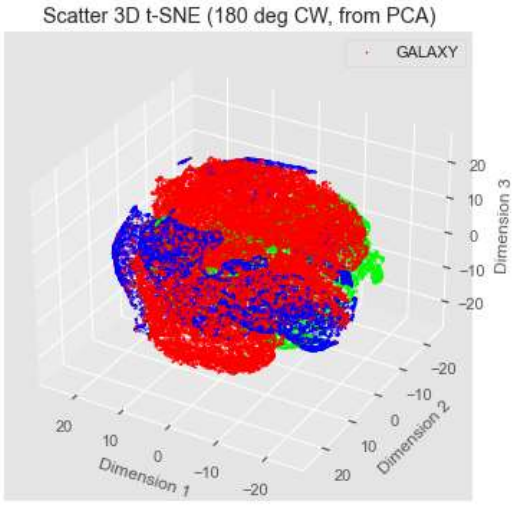


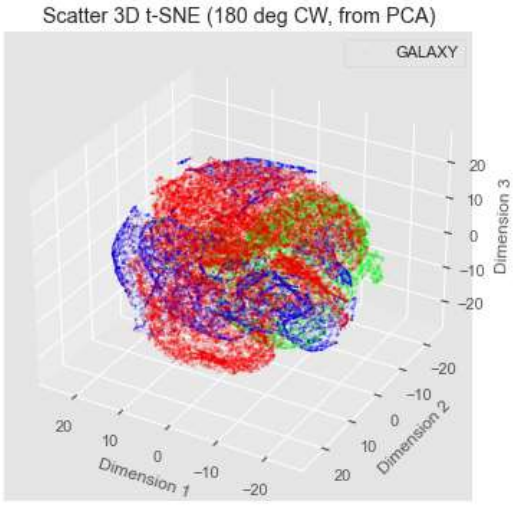
We can clearly see that there is potentially a more cohesive structure in the results of our 3D t-SNE from our first three principle components.

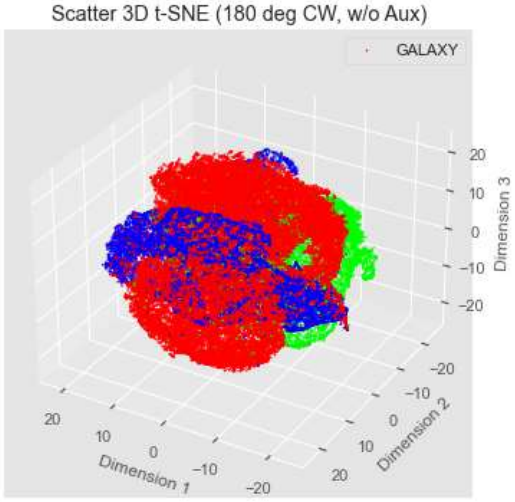
Let's look at the other side of our 3D scatter plot.

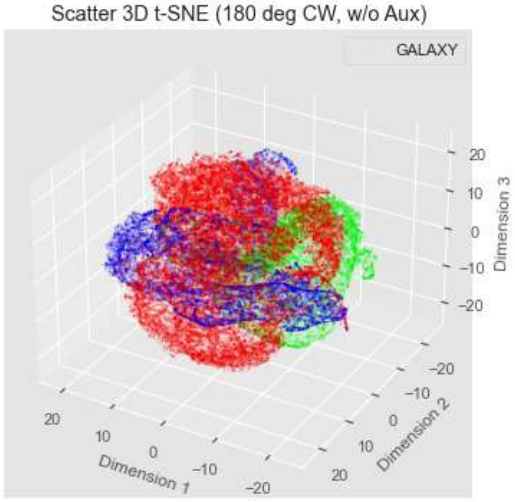
In [252…

```
Plot3DtSNE_df('Scatter 3D t-SNE (180 deg CW, from PCA)', df_tsne_3d_pca, 120)
Plot3DtSNE_df('Scatter 3D t-SNE (180 deg CW, w/o Aux)', df_tsne_3d, 120)
print()
```









It is less clear whether our 3D t-SNE from `u`, `g`, `r`, `i`, `z`, `redshift` has a more cohesive structure than our PCA based t-SNE, from this angle.

It is worth noting that we may be able to achieve clearer results if we did not constrain our PCA to three principal components and provide all of them to t-SNE. However, we have sufficiently validated the variables selected above.

Clustering

Cluster PCA

Cluster t-SNE

Cluster t-SNE on PCA

Compare with Base-Truth

In [253…

```
def KMeans3K(X_, y_):
    kmeans_model = KMeans(init='k-means++', n_clusters=3, n_init=10, random_state=37
    kmeans_model.fit(X_)
    y_pred = kmeans_model.predict(X_)
    print('V-Measure Score: ', metrics.v_measure_score(labels_true=y_, labels_pred=k
    print('Accuracy Score: ', metrics.accuracy_score(y_, y_pred))
    return kmeans_model
```

KMeans

Sorted by V-Measure Score

- *3D PCA*
- *X_no_aux*
- *3D t-SNE*
- *9D PCA*
- *2D t-SNE*
- *X_aux*
- *3D t-SNE on 3D PCA*
- *2D t-SNE w/Aux*
- *3D t-SNE w/Aux*

3D PCA

In [254…
```
KMeans3K(X_pca_three, y_num)
```

```
V-Measure Score:  0.30902198483780396
Accuracy Score:  0.22155221552215523
KMeans(n_clusters=3, random_state=37)
```
Out[254…

X Scaled w/out Aux

In [255…
```
KMeans3K(X_no_aux, y_num)
```

```
V-Measure Score:  0.30703665139691416
Accuracy Score:  0.44782447824478244
KMeans(n_clusters=3, random_state=37)
```
Out[255…

3D t-SNE

In [256…
```
KMeans3K(tsne_3d, y_num)
```

```
V-Measure Score:  0.16699460723575163
Accuracy Score:  0.26049260492604925
KMeans(n_clusters=3, random_state=37)
```
Out[256…

9D PCA

In [257…
```
KMeans3K(X_pca_nine, y_num)
```

```
V-Measure Score:  0.14926208343033856
Accuracy Score:  0.5525955259552595
KMeans(n_clusters=3, random_state=37)
```
Out[257…

2D t-SNE

In [258…
```
KMeans3K(tsne_2d, y_num)
```

```
V-Measure Score:  0.14884707165058883
Accuracy Score:  0.3103331033310333
KMeans(n_clusters=3, random_state=37)
```
Out[258…

X Scaled w/Aux

In [259…
```
KMeans3K(X_aux, y_num)
```

```
V-Measure Score:  0.1482924637078717
Accuracy Score:  0.4248142481424814
KMeans(n_clusters=3, random_state=37)
```
Out[259…

3D t-SNE on PCA

In [260…
```
KMeans3K(df_tsne_3d_pca.drop('y_num', axis=1) , y_num)
```

```
V-Measure Score:  0.09576087505968077
```

```
Accuracy Score:  0.3100431004310043
KMeans(n_clusters=3, random_state=37)
```
Out[260…

2D t-SNE (w/Aux)

In [261…
```
KMeans3K(tsne_2d_aux, y_num)
```

```
V-Measure Score:  0.05277012708157446
Accuracy Score:  0.25211252112521126
KMeans(n_clusters=3, random_state=37)
```
Out[261…

3D t-SNE (w/Aux)

In [262…
```
KMeans3K(tsne_3d_aux, y_num)
```

```
V-Measure Score:  0.005559777477021477
Accuracy Score:  0.3012030120301203
KMeans(n_clusters=3, random_state=37)
```
Out[262…

Based on the above V-Measure Scores, it appears that the scaled values of `u`, `g`, `r`, `i`, `z`, `redshift` *and a 3D PCA from the variables perform the best, with a V-Measure Score of 0.307 (in both cases).*

Given that a variety of parameters have been tried on KMeans with little difference and that our best V-Measure Score is low indicates that something else may be causing issue. Additionally, the fact that this is the case for KMeans clustering on our data and variations of our data in reduced dimensions indicates that we need to take other considerations, such as validating our feature selection, looking for multivariate outliers, mitigating class imbalance, and any other aspects that may be causing such poor results.

Univariate Feature Selection

In [263…
```
df = pd.read_csv('data/star_classification.csv').drop(['obj_ID', 'spec_obj_ID','reru
df = df.drop(df[df.z < -999].index)
```

In [264…
```
X_df_all = df.drop('class', axis=1)
```

In [265…
```
# encode any categorecal variables to discrete integers (excluding response variable
for column_name in X_df_all.select_dtypes('object'):
    X_df_all[column_name], _ = X_df_all[column_name].factorize()
```

Calculate Mutual Information between variables (0 means variables are independent)

`sklearn.feature_selection.f_classif` *is parametric and uses F-test to estimate linear dependency between two random variables.*

`sklearn.feature_selection.mutual_info_classif` is nonparametric and can capture any kind of statistical dependency--though requiring larger sample sizes for accurate estimates.

Univariate Feature Selection

In [266...
```
mutual_info_scores = mutual_info_classif(X_df_all, y, discrete_features = X_df_all.d
mutual_info_scores = pd.Series(mutual_info_scores, index=X_df_all.columns, name='MI
mutual_info_scores = mutual_info_scores.sort_values(ascending=False)
mutual_info_scores
```

Out[266...
```
redshift    0.801814
plate       0.275445
MJD         0.192275
z           0.145658
run_ID      0.143826
g           0.120600
i           0.109588
u           0.100328
r           0.075618
fiber_ID    0.051621
delta       0.044373
alpha       0.040456
field_ID    0.006539
cam_col     0.001044
Name: MI Scores, dtype: float64
```

Based on the above, it looks like removing `alpha` and `delta`, as well as adding `run_ID` may be worth trying.

With Auxiliary Columns == `alpha`, `delta`, `u`, `g`, `r`, `i`, `z`, `redshift`, `plate`, `MJD`

Without Auxiliary Columns == `u`, `g`, `r`, `i`, `z`, `redshift`

Proposed Columns == `u`, `g`, `r`, `i`, `z`, `redshift`, `plate`, `MJD`, `run_ID`

In [267...
```
X_mi = X_df_all.loc[:,['u','g','r','i','z','run_ID','redshift','plate','MJD']].apply
```

In [268...
```
KMeans3K(X_mi, y_num)
```

```
V-Measure Score:  0.15018334565259933
Accuracy Score:  0.4248142481424814
```

Out[268...
```
KMeans(n_clusters=3, random_state=37)
```

This is better than with Auxiliary Columns (V-Score 0.148), but not with out Auxiliary Columns (V-Score 0.307)

In [269...
```
mi_tsne_3 = TSNE(n_components=3, verbose=1, random_state=37)
mi_tsne_3d = mi_tsne_3.fit_transform(X_mi)
```

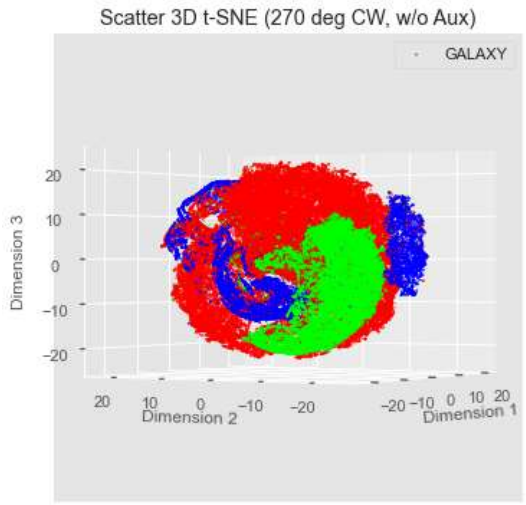
```
[t-SNE] Computing 91 nearest neighbors...
[t-SNE] Indexed 99999 samples in 0.359s...
[t-SNE] Computed neighbors for 99999 samples in 18.017s...
[t-SNE] Computed conditional probabilities for sample 1000 / 99999
[t-SNE] Computed conditional probabilities for sample 2000 / 99999
```

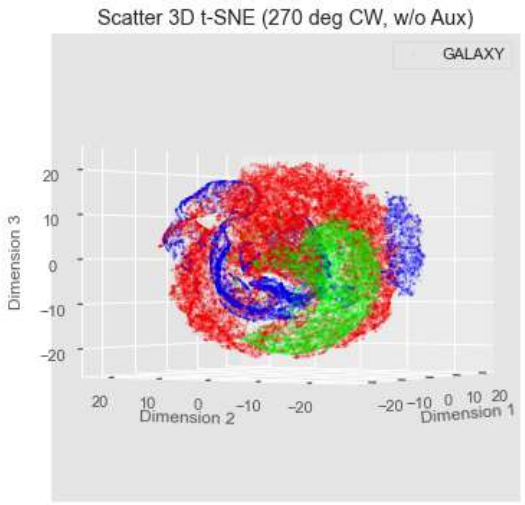
```
[t-SNE] Computed conditional probabilities for sample 3000 / 99999
[t-SNE] Computed conditional probabilities for sample 4000 / 99999
[t-SNE] Computed conditional probabilities for sample 5000 / 99999
[t-SNE] Computed conditional probabilities for sample 6000 / 99999
[t-SNE] Computed conditional probabilities for sample 7000 / 99999
[t-SNE] Computed conditional probabilities for sample 8000 / 99999
[t-SNE] Computed conditional probabilities for sample 9000 / 99999
[t-SNE] Computed conditional probabilities for sample 10000 / 99999
[t-SNE] Computed conditional probabilities for sample 11000 / 99999
[t-SNE] Computed conditional probabilities for sample 12000 / 99999
[t-SNE] Computed conditional probabilities for sample 13000 / 99999
[t-SNE] Computed conditional probabilities for sample 14000 / 99999
[t-SNE] Computed conditional probabilities for sample 15000 / 99999
[t-SNE] Computed conditional probabilities for sample 16000 / 99999
[t-SNE] Computed conditional probabilities for sample 17000 / 99999
[t-SNE] Computed conditional probabilities for sample 18000 / 99999
[t-SNE] Computed conditional probabilities for sample 19000 / 99999
[t-SNE] Computed conditional probabilities for sample 20000 / 99999
[t-SNE] Computed conditional probabilities for sample 21000 / 99999
[t-SNE] Computed conditional probabilities for sample 22000 / 99999
[t-SNE] Computed conditional probabilities for sample 23000 / 99999
[t-SNE] Computed conditional probabilities for sample 24000 / 99999
[t-SNE] Computed conditional probabilities for sample 25000 / 99999
[t-SNE] Computed conditional probabilities for sample 26000 / 99999
[t-SNE] Computed conditional probabilities for sample 27000 / 99999
[t-SNE] Computed conditional probabilities for sample 28000 / 99999
[t-SNE] Computed conditional probabilities for sample 29000 / 99999
[t-SNE] Computed conditional probabilities for sample 30000 / 99999
[t-SNE] Computed conditional probabilities for sample 31000 / 99999
[t-SNE] Computed conditional probabilities for sample 32000 / 99999
[t-SNE] Computed conditional probabilities for sample 33000 / 99999
[t-SNE] Computed conditional probabilities for sample 34000 / 99999
[t-SNE] Computed conditional probabilities for sample 35000 / 99999
[t-SNE] Computed conditional probabilities for sample 36000 / 99999
[t-SNE] Computed conditional probabilities for sample 37000 / 99999
[t-SNE] Computed conditional probabilities for sample 38000 / 99999
[t-SNE] Computed conditional probabilities for sample 39000 / 99999
[t-SNE] Computed conditional probabilities for sample 40000 / 99999
[t-SNE] Computed conditional probabilities for sample 41000 / 99999
[t-SNE] Computed conditional probabilities for sample 42000 / 99999
[t-SNE] Computed conditional probabilities for sample 43000 / 99999
[t-SNE] Computed conditional probabilities for sample 44000 / 99999
[t-SNE] Computed conditional probabilities for sample 45000 / 99999
[t-SNE] Computed conditional probabilities for sample 46000 / 99999
[t-SNE] Computed conditional probabilities for sample 47000 / 99999
[t-SNE] Computed conditional probabilities for sample 48000 / 99999
[t-SNE] Computed conditional probabilities for sample 49000 / 99999
[t-SNE] Computed conditional probabilities for sample 50000 / 99999
[t-SNE] Computed conditional probabilities for sample 51000 / 99999
[t-SNE] Computed conditional probabilities for sample 52000 / 99999
[t-SNE] Computed conditional probabilities for sample 53000 / 99999
[t-SNE] Computed conditional probabilities for sample 54000 / 99999
[t-SNE] Computed conditional probabilities for sample 55000 / 99999
[t-SNE] Computed conditional probabilities for sample 56000 / 99999
[t-SNE] Computed conditional probabilities for sample 57000 / 99999
[t-SNE] Computed conditional probabilities for sample 58000 / 99999
[t-SNE] Computed conditional probabilities for sample 59000 / 99999
[t-SNE] Computed conditional probabilities for sample 60000 / 99999
[t-SNE] Computed conditional probabilities for sample 61000 / 99999
[t-SNE] Computed conditional probabilities for sample 62000 / 99999
```

```
[t-SNE] Computed conditional probabilities for sample 63000 / 99999
[t-SNE] Computed conditional probabilities for sample 64000 / 99999
[t-SNE] Computed conditional probabilities for sample 65000 / 99999
[t-SNE] Computed conditional probabilities for sample 66000 / 99999
[t-SNE] Computed conditional probabilities for sample 67000 / 99999
[t-SNE] Computed conditional probabilities for sample 68000 / 99999
[t-SNE] Computed conditional probabilities for sample 69000 / 99999
[t-SNE] Computed conditional probabilities for sample 70000 / 99999
[t-SNE] Computed conditional probabilities for sample 71000 / 99999
[t-SNE] Computed conditional probabilities for sample 72000 / 99999
[t-SNE] Computed conditional probabilities for sample 73000 / 99999
[t-SNE] Computed conditional probabilities for sample 74000 / 99999
[t-SNE] Computed conditional probabilities for sample 75000 / 99999
[t-SNE] Computed conditional probabilities for sample 76000 / 99999
[t-SNE] Computed conditional probabilities for sample 77000 / 99999
[t-SNE] Computed conditional probabilities for sample 78000 / 99999
[t-SNE] Computed conditional probabilities for sample 79000 / 99999
[t-SNE] Computed conditional probabilities for sample 80000 / 99999
[t-SNE] Computed conditional probabilities for sample 81000 / 99999
[t-SNE] Computed conditional probabilities for sample 82000 / 99999
[t-SNE] Computed conditional probabilities for sample 83000 / 99999
[t-SNE] Computed conditional probabilities for sample 84000 / 99999
[t-SNE] Computed conditional probabilities for sample 85000 / 99999
[t-SNE] Computed conditional probabilities for sample 86000 / 99999
[t-SNE] Computed conditional probabilities for sample 87000 / 99999
[t-SNE] Computed conditional probabilities for sample 88000 / 99999
[t-SNE] Computed conditional probabilities for sample 89000 / 99999
[t-SNE] Computed conditional probabilities for sample 90000 / 99999
[t-SNE] Computed conditional probabilities for sample 91000 / 99999
[t-SNE] Computed conditional probabilities for sample 92000 / 99999
[t-SNE] Computed conditional probabilities for sample 93000 / 99999
[t-SNE] Computed conditional probabilities for sample 94000 / 99999
[t-SNE] Computed conditional probabilities for sample 95000 / 99999
[t-SNE] Computed conditional probabilities for sample 96000 / 99999
[t-SNE] Computed conditional probabilities for sample 97000 / 99999
[t-SNE] Computed conditional probabilities for sample 98000 / 99999
[t-SNE] Computed conditional probabilities for sample 99000 / 99999
[t-SNE] Computed conditional probabilities for sample 99999 / 99999
[t-SNE] Mean sigma: 0.176875
[t-SNE] KL divergence after 250 iterations with early exaggeration: 96.042648
[t-SNE] KL divergence after 1000 iterations: 2.264761
```

In [270…

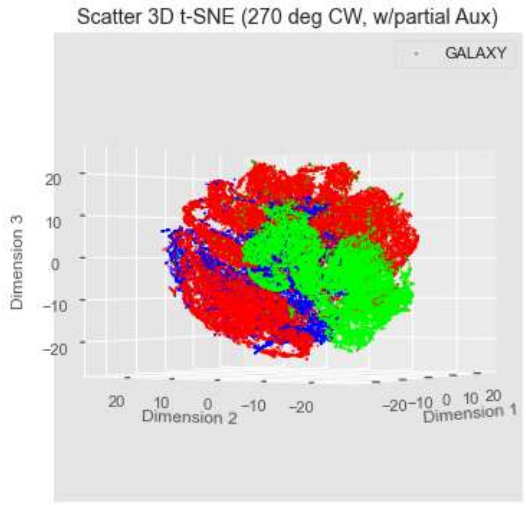
```
Plot3DtSNE_df('Scatter 3D t-SNE (270 deg CW, w/o Aux)', df_tsne_3d, 210, 0)
print()
```

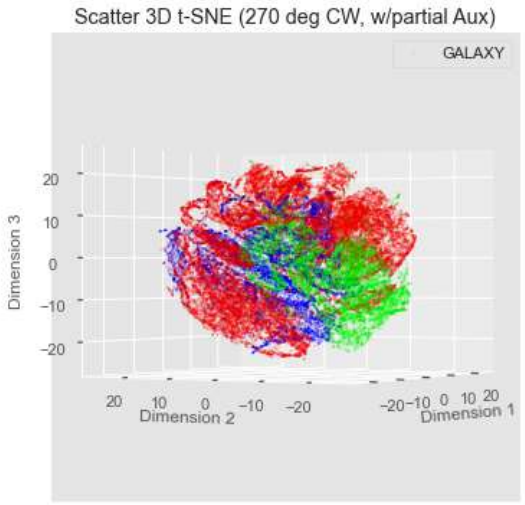




In [271…

```
df_mi_tsne_3d = pd.DataFrame()
df_mi_tsne_3d['tsne-3d-1'] = mi_tsne_3d[:,0]
df_mi_tsne_3d['tsne-3d-2'] = mi_tsne_3d[:,1]
df_mi_tsne_3d['tsne-3d-3'] = mi_tsne_3d[:,2]
df_mi_tsne_3d['y_num'] = y_num
Plot3DtSNE_df('Scatter 3D t-SNE (270 deg CW, w/partial Aux)', df_mi_tsne_3d, 210, 0)
print()
```





Based on the above KMeans scores being lower and the 3D t-SNE being less cohesive, our selection of features has been validated and includes:

`u, g, r, i, z, and redshift.`

Multivariate Outlier Detection

In [272…

```
df_features = df.loc[:,['u','g','r','i','z','redshift','class']]
```

In [273…

```
clf = LocalOutlierFactor()
```

```
y_lof = clf.fit_predict(df_features.drop('class',axis=1).apply(scale))
```

In [274…

```
lof_score = pd.DataFrame()
lof_score['score'] = clf.negative_outlier_factor_
```

In [275…

```
lof_score.describe()
```

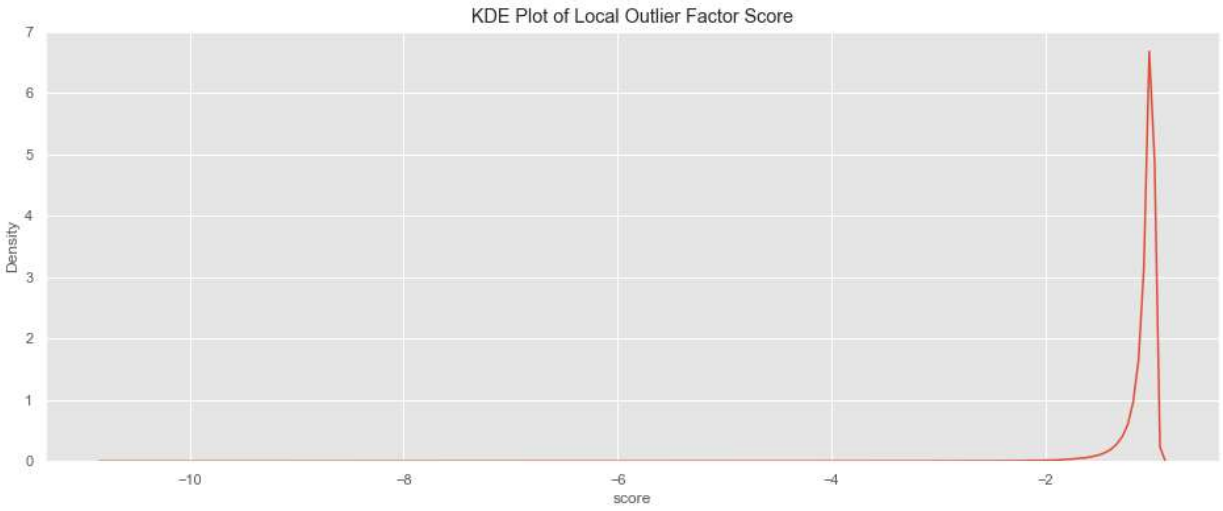
Out[275…

	score
count	99999.000000
mean	-1.090468
std	0.238155
min	-10.780989
25%	-1.098164
50%	-1.030006
75%	-0.999547
max	-0.946417

KDE Plot Local Outlier Factor to Pick Cutoff

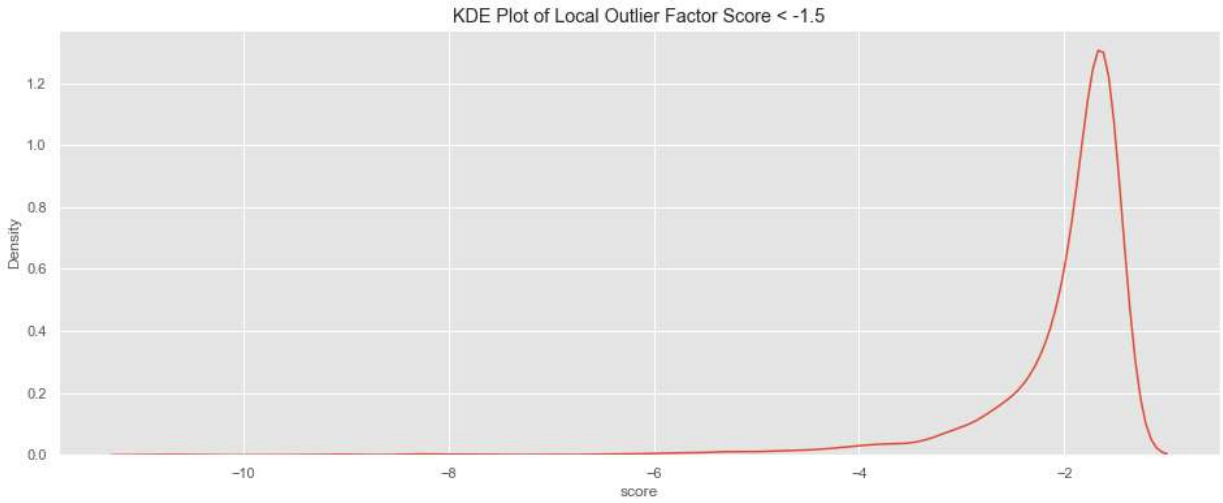
In [276…

```
sns.kdeplot(lof_score['score']).set_title('KDE Plot of Local Outlier Factor Score')
print()
```



In [277…

```
sns.kdeplot(lof_score[lof_score < -1.5]['score']).set_title('KDE Plot of Local Outli
print()
```



Based on the mean Local Outlier Factor Score of -1.1 and the KDE Plot of all observations, as well as observations with a score less than -1.5, it appears that -1.5 is a reasonable cutoff for multivariate outliers.

In [278…
```
df_features['class'].value_counts()
```

Out[278…
```
GALAXY    59445
STAR      21593
QSO       18961
Name: class, dtype: int64
```

Drop Outliers

In [279…
```
lof_mask = lof_score['score'] < -1.5
outlier_indices = lof_score[lof_mask].index.tolist()
```

In [280…
```
df_minus_outliers = df.drop(outlier_indices)
df_minus_outliers.head(2)
```

Out[280…

	alpha	delta	u	g	r	i	z	run_ID	cam_col	field_ID	class	redshift	plate	MJD	fiber_ID
0	135.689107	32.494632	23.87882	22.27530	20.39501	19.16573	18.79371	3606	2	79	GALAXY	0.634794	5812	56354	171
1	144.826101	31.274185	24.77759	22.83188	22.58444	21.16812	21.61427	4518	5	119	GALAXY	0.779136	10445	58158	427

In [281…
```
X_minus_outliers = df_minus_outliers.loc[:,['u', 'g', 'r', 'i', 'z', 'redshift',
                                            'alpha', 'delta','plate', 'MJD']]
X_minus_outliers = X_minus_outliers.apply(scale)
X = X_minus_outliers
X.head(2)
```

Out[281…

	u	g	r	i	z	redshift	alpha	delta	plate	MJD
0	0.799158	0.808477	0.404009	0.044719	0.012991	0.075173	-0.434848			
1	1.200633	1.083452	1.592221	1.191412	1.619845	0.273055	-0.340128			

```
0  0.423587  0.225722  0.420492
1  0.361469  1.797902  1.420449
```

In [282…

```
y_minus_outliers = df_minus_outliers['class']
y_minus_outliers.value_counts()
```

Out[282…

```
GALAXY    57824
STAR      20698
QSO       18464
Name: class, dtype: int64
```

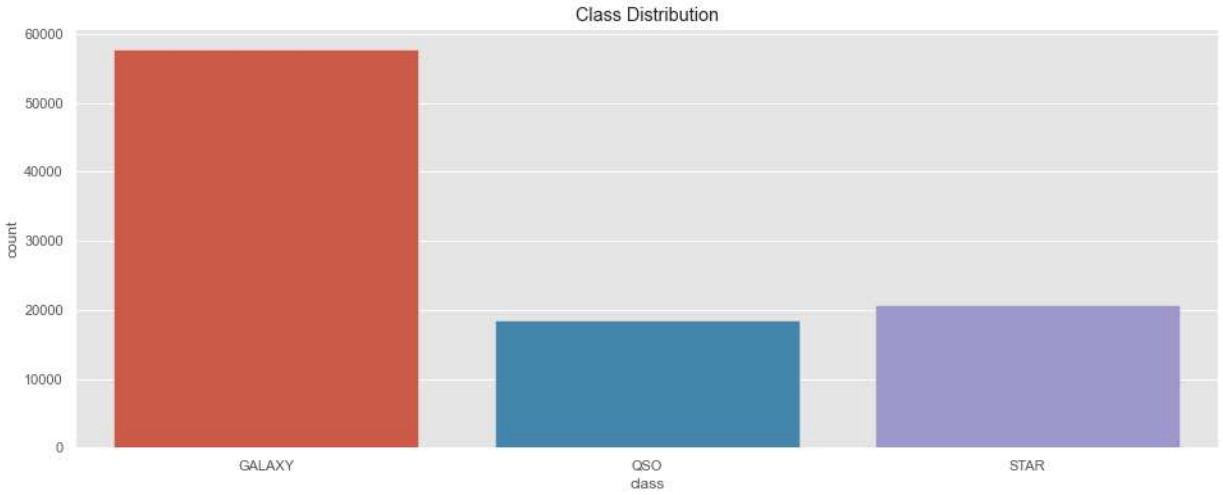
It appears that `GALAXY` accounted for a good portion of the outliers, which makes sense, as `GALAXY` is quite a broad range of observable objects--although so is `STAR` and this is reflected by the proportion of `STAR` outlier vs `QSO` outliers.

Class Imbalance

In [283…

```
sns.countplot(df_minus_outliers['class']).set_title('Class Distribution')
print()
```

```
C:\Users\Bob\anaconda3\envs\imblearn-clone\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:

Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
```



In [284…

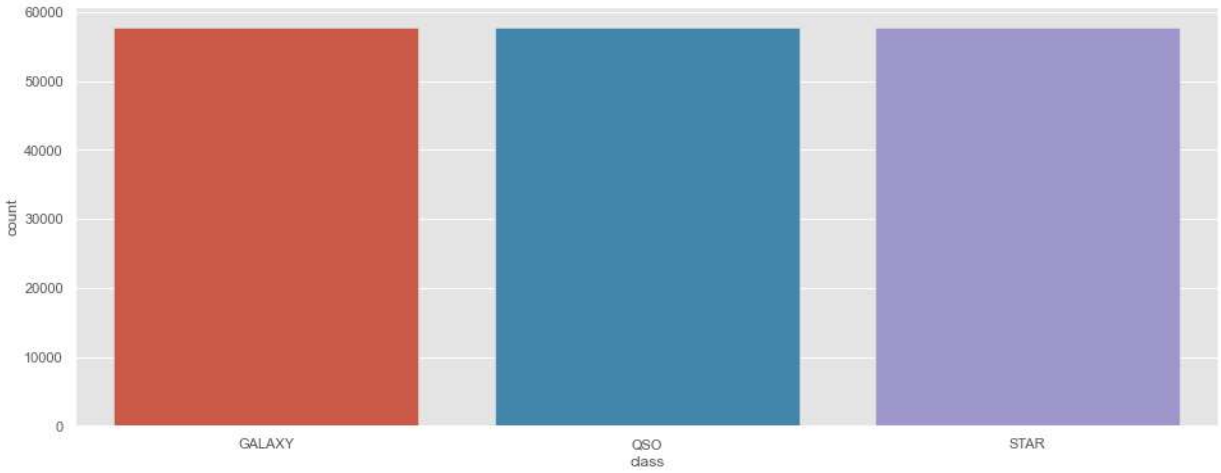
```
smt = SMOTE(random_state=37)
X_balanced, y_balanced = smt.fit_resample(X_minus_outliers, y_minus_outliers)
```

In [285…

```
sns.countplot(y_balanced)
print()
```

```
C:\Users\Bob\anaconda3\envs\imblearn-clone\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
```

```
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
```



In [286…
```
X_balanced.count()
```

Out[286…
```
u            173472
g            173472
r            173472
i            173472
z            173472
redshift     173472
alpha        173472
delta        173472
plate        173472
MJD          173472
dtype: int64
```

In [287…
```
y_balanced.value_counts()
```

Out[287…
```
GALAXY    57824
QSO       57824
STAR      57824
Name: class, dtype: int64
```

In [288…
```
leo = LabelEncoder().fit(y_balanced)
y_num = leo.transform(y_balanced)
y_num[0:10]
```

Out[288…
```
array([0, 0, 0, 0, 0, 1, 1, 0, 0, 2])
```

Random Forest

Random Forest WITHOUT Aux Data

Create a function to run our random forest classifier

In [289…
```
def rForestMethod(x_train, y_train, x_test, y_test):
```

```
    r_forest = RandomForestClassifier()
    r_forest_model = r_forest.fit(x_train,y_train)
    predicted = r_forest.predict(x_test)
    score = r_forest.score(x_test, y_test)
    rf_score_ = np.mean(score)

    print('Accuracy : %.3f' % (rf_score_))
    print('-------- Classification Report ---------')
    print(classification_report(y_test, predicted))
    return r_forest_model, r_forest
```

Test / Train our data for our Random Forest classifier

In [290…

```
#run on our scaled data WITHOUT Aux Data
x3 = X_balanced.loc[:,['u','g','r','i','z','redshift']]
y3 = y_num

x3_train, x3_test, y3_train, y3_test = train_test_split(x3, y3, test_size = 0.30, ra
```

Run our Random Forest Model

In [291…

```
rf_wout_aux, rf_wout_aux_clf = rForestMethod(x3_train, y3_train, x3_test, y3_test)
```

```
Accuracy : 0.980
-------- Classification Report ---------
              precision    recall  f1-score   support

           0       0.96      0.98      0.97     17328
           1       0.98      0.96      0.97     17349
           2       1.00      1.00      1.00     17365

    accuracy                           0.98     52042
   macro avg       0.98      0.98      0.98     52042
weighted avg       0.98      0.98      0.98     52042
```

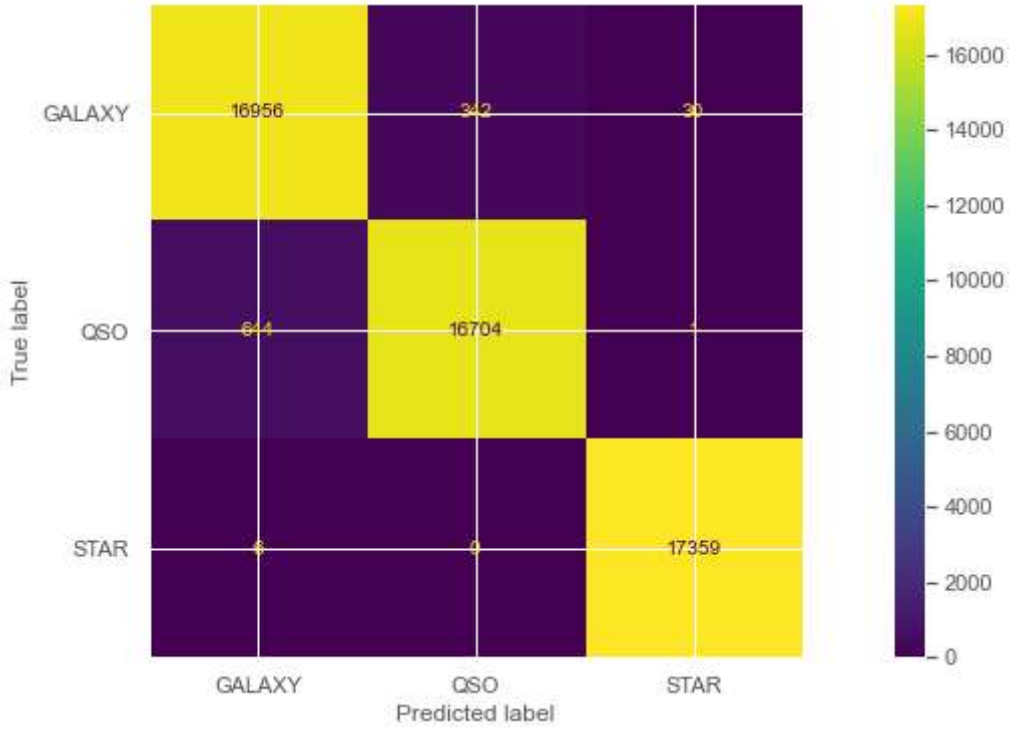
Confusion Matrix for Random Forest WITHOUT Aux Data

In [292…

```
def plot_confusion_matrix(mod, xtest, ytest):
    cm = confusion_matrix(ytest, mod.predict(xtest), labels=mod.classes_)
    disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=leo.classes_)
    disp.plot()
```

In [293…

```
plot_confusion_matrix(rf_wout_aux, x3_test, y3_test)
plt.show()
```



Random Forest Classifier WITH AUX Data

Test / Train our data for our Random Forest classifier

In [294...

```
#run on our scaled data WITHOUT Aux Data
x4 = X_balanced.loc[:,['u', 'g', 'r', 'i', 'z', 'redshift', 'alpha', 'delta','plate'
y4 = y_num


x4_train, x4_test, y4_train, y4_test = train_test_split(x4, y4, test_size = 0.30, ra
```

Run our Random Forest Model

In [295...

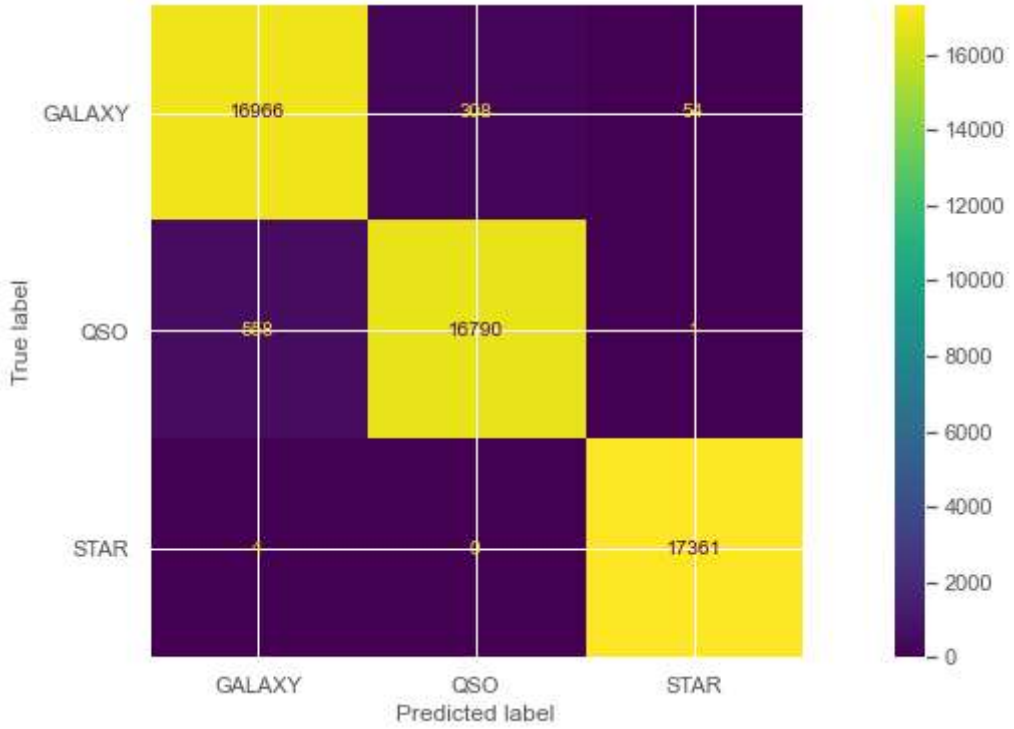
```
rf_w_aux, rf_w_aux_clf = rForestMethod(x4_train, y4_train, x4_test, y4_test)
```

```
Accuracy : 0.982
-------- Classification Report ---------
              precision    recall  f1-score   support

           0       0.97      0.98      0.97     17328
           1       0.98      0.97      0.97     17349
           2       1.00      1.00      1.00     17365

    accuracy                           0.98     52042
   macro avg       0.98      0.98      0.98     52042
weighted avg       0.98      0.98      0.98     52042
```

Confusion Matrix for Random Forest WITHAux Data

In [296...

```
plot_confusion_matrix(rf_w_aux, x4_test, y4_test)
plt.show()
```



SVM Classifier

SVM Classifier without Aux Data

Create our Test and Training datasets

In [297...

```
def svmMethod(x_train, y_train, x_test, y_test):
    svm_clf = svm.SVC(kernel='rbf', C=1, random_state=0,probability=True)
    svm_model = svm_clf.fit(x_train,y_train)
    predicted = svm_clf.predict(x_test)
    score = svm_clf.score(x_test, y_test)
    svm_score_ = np.mean(score)

    print('Accuracy : %.3f' % (svm_score_))
    print('-------- Classification Report ---------')
    print(classification_report(y_test, predicted))
    return svm_model, svm_clf
```

In [298...

```
#run on our scaled data WITHOUT Aux Data
x1 = X_balanced.loc[:,['u','g','r','i','z','redshift']]
y1 = y_num

x_train, x_test, y_train, y_test = train_test_split(x1, y1, test_size = 0.30, random_
```

Run our SVM and fit our test and training sets

In [299...

```
svm_wout_aux, svm_wout_aux_clf = svmMethod(x_train, y_train, x_test, y_test)
```

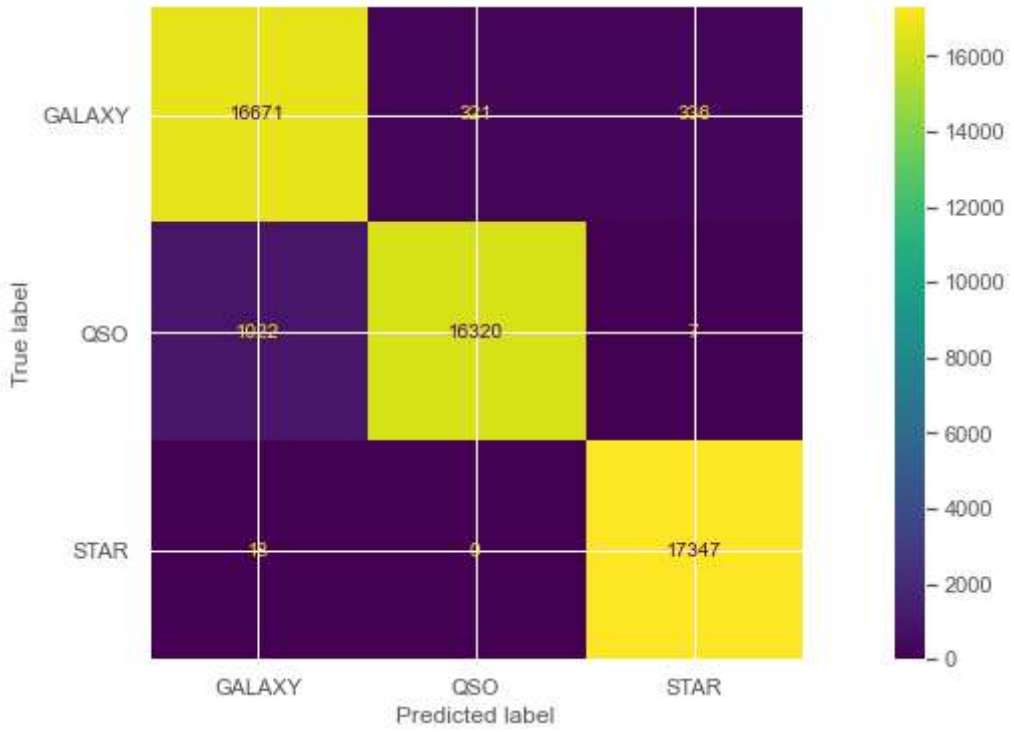
```
Accuracy : 0.967
-------- Classification Report ---------
```

	precision	recall	f1-score	support
0	0.94	0.96	0.95	17328
1	0.98	0.94	0.96	17349
2	0.98	1.00	0.99	17365
accuracy			0.97	52042
macro avg	0.97	0.97	0.97	52042
weighted avg	0.97	0.97	0.97	52042

Confusion Matrix without Aux Data

In [300…

```
plot_confusion_matrix(svm_wout_aux, x_test, y_test)
plt.show()
```



SVM Classifier with Aux Data

Run our SVM on our scaled data with Aux Data

Test/Train split with AUX

In [301…

```
#run on our scaled data WITH Aux Data
x2 = X_balanced.loc[:,['u', 'g', 'r', 'i', 'z', 'redshift', 'alpha', 'delta','plate'
y2 = y_num

x2_train, x2_test, y2_train, y2_test = train_test_split(x2, y2, test_size = 0.30, ra
```

Run our SVM and fit our test and training sets

In [302…

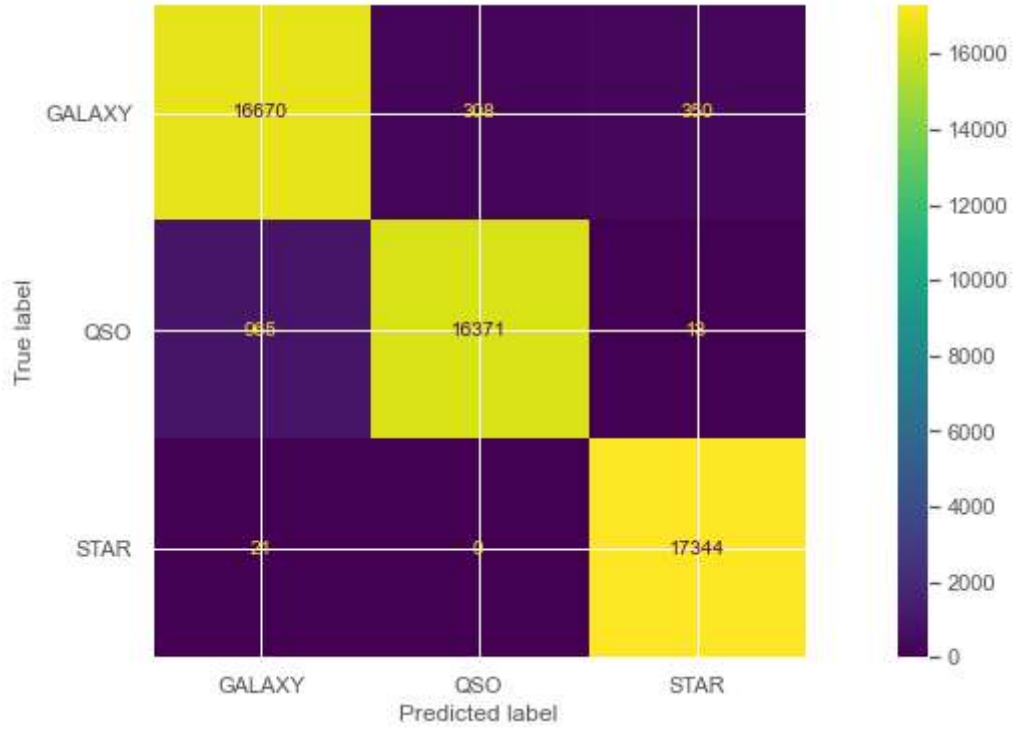
```
svm_w_aux, svm_w_aux_clf = svmMethod(x2_train, y2_train, x2_test, y2_test)
```

```
Accuracy : 0.968
-------- Classification Report ---------
              precision    recall  f1-score   support

           0       0.94      0.96      0.95     17328
           1       0.98      0.94      0.96     17349
           2       0.98      1.00      0.99     17365

    accuracy                           0.97     52042
   macro avg       0.97      0.97      0.97     52042
weighted avg       0.97      0.97      0.97     52042
```

Confusion Matrix with Aux Data

In [303…

```
plot_confusion_matrix(svm_w_aux, x2_test, y2_test)
plt.show()
```



500,000 Optical-Spectroscopic Object Test

In [305…

```
df_500K_test = pd.read_csv('data/star_classification_test_500000.csv')
df_500K_test.head()
```

Out[305…

	objid	ra	dec	u	g	r	\
0	1237660961327743273	135.689107	32.494632	23.87882	22.27530	20.39501	
1	1237664879951151463	144.826101	31.274185	24.77759	22.83188	22.58444	

```
2  1237660961330430096  142.188790  35.582444  25.26307  22.66389  20.60976
3  1237663478724298013  338.741038  -0.402828  22.13682  23.77656  21.61162
4  1237680272041377978  345.282593  21.183866  19.43718  17.58028  16.49747

          i         z   run  rerun  camcol  field             specobjid  \
0  19.16573  18.79371  3606    301       2     79   6543777369295181824
1  21.16812  21.61427  4518    301       5    119  11760142036707334144
2  19.34857  18.94827  3606    301       2    120   5152200256025548800
3  20.50454  19.25010  4192    301       3    214  10301071412954421248
4  15.97711  15.54461  8102    301       3    137   6891864880783316992

    class  redshift  plate    mjd  fiberid
0  GALAXY  0.634794   5812  56354      171
1  GALAXY  0.779136  10445  58158      427
2  GALAXY  0.644195   4576  55592      299
3  GALAXY  0.932346   9149  58039      775
4  GALAXY  0.116123   6121  56187      842
```

Random Forest Without Aux

In [309…
```
rf_pred = rf_wout_aux_clf.predict(df_500K_test.loc[:,['u','g','r','i','z','redshift'
```

In [313…
```
metrics.accuracy_score(leo.transform(df_500K_test['class']), rf_pred)
```

Out[313…
```
0.97109
```

97.1%

Random Forest With Aux

In [316…
```
rf_pred_aux = rf_w_aux_clf.predict(df_500K_test.loc[:,['u', 'g', 'r', 'i', 'z', 'red
                                                       'ra', 'dec','plate', 'mjd']].
```

In [317…
```
metrics.accuracy_score(leo.transform(df_500K_test['class']), rf_pred_aux)
```

Out[317…
```
0.974266
```

97.4%

SVM Without Aux

In [318…
```
svm_pred = svm_wout_aux_clf.predict(df_500K_test.loc[:,['u','g','r','i','z','redshif
```

In [319…
```
metrics.accuracy_score(leo.transform(df_500K_test['class']), svm_pred)
```

Out[319…
```
0.964396
```

96.4%

SVM With Aux

In [320…
```
svm_pred_aux = svm_w_aux_clf.predict(df_500K_test.loc[:,['u', 'g', 'r', 'i', 'z', 'r
                                                         'ra', 'dec','plate', 'mjd']].
```

In [321…
```
metrics.accuracy_score(leo.transform(df_500K_test['class']), svm_pred_aux)
```

Out[321…
```
0.963658
```

96.3%

Final Results Summary

As our final results, and in summary, our model was able to determine the correct classes of stellar objects by: After our initial steps of data acquisition that involved:

- *parsing through FITS files*
- *Web scraping*
- *An initial Web Query using the Cross Match Tools on the SDSS dr17 database*
- *Injecting the necessary Quasar and data*
- *Until finally running the final query using the Search Tools on the SDSS dr17 website to give us ~100,000 objects of data.*

We were then able to massage the data accordingly, checking for any outliers, and any class imbalance before performing the following methods on the final, cleaned data set:

- *PCA*
- *t-SNE*
- *Random Forest*
- *SVM*
- *and initially some K-Means clustering*

We determined that when comparing both models, one model containing auxliary data and another model without that there were differences in the model's capability of determining the correct class for the stellar object.

Dimensionality Reduction

- *PCA: for our PCA dimensionality reduction method/model ->*
  - *The difference between data WITH our auxiliary resulted in a model with indiscriminate clusters, it was hard to tell and there was not cohesive structure forming within our PC1*

and PC2 models. This implied that there was possibly some variables dominating the variance.

- *The difference between data WITHOUT our auxiliary resulted in a model with discriminate clusters, it was a lot easier to tell and there WAS a somewhat cohesive structure forming within our PC1 and PC2 models.*

- *t-SNE:*

  - *With t-SNE, we noticed the same behavior with some of the variables, for example --> plate & MJD are moderately correlated with u, g, r, i, z, and redshift. The same can be said for fiber_ID, to a lesser degree. In addition, alpha and delta represent the location on the celestial sphere (sky), which may have a relationship with the classes of astronomical objects present, but is not an observable charateristic of the object itself. Similarly, run_id is the identifier of the run, which may have implications on classes observed in that run, but is not directly an attribute of the object--and likewise for cam_col/field_ID.*

  - *As we saw with the single outlier that shaped our correlation matrix, added varaince that does not represent the underlying silhouette we are trying to capture can lead us astray--particularly when contained in a variable that has a significant correlation with a variable that does represent what we are trying to capture.*

Let's examine what happens to our t-SNE dimensions when we remove these variables.

Classifiers / Clustering

- *Random Forest:*

  - *WITHOUT the Auxilary data, Random Forest had about a 98% accuracy score*
    - *97.1% on 500,000 Optical-Spectroscopic Object Test*
  - *WITH Auxilary data we were unable to run*
    - *97.4% on 500,000 Optical-Spectroscopic Object Test*
- *SVM:*

  - *WITHOUT the Auxilary data, SVM had about a 96.4% accuracy score*
    - *96.4% on 500,000 Optical-Spectroscopic Object Test*
  - *WITH the Auxilary data, was about a 96.8%*
    - *96.3% on 500,000 Optical-Spectroscopic Object Test*
- *K-Means:*

  - *WITHOUT the Auxilary data, K-means had about a 44% accuracy score*
  - *WITH the Auxilary, K-means. had about a 42% accuracy score*

FINAL NOTES *In summary for the Classifiers and Clustering Random Forest did do a much better job at classifying the data with a 98% accuracy score compared to 96% on SVM WITHOUT Auxliary data also compared with 44% by K-Means WITHOUT Auxliary data.*

As final, our model with the combination of proper data acquisition, data massaging/cleaning, dimensionality reduction using multiple methods and then clustering/classifying using multiple methods on the data to determine that certain data was causing some dominance in the variance and once we removed depending on which classifier/model we decided to use we had to about 98% accuracy in classifying our astronomical data.

In [ ]:
```
END
```

Preliminary Results

Exploratory clustering as an initial pass over our data, but we have not done qualifying clustering yet. We have not checked for outliers; we have not mitigated any class imbalance or dimensionality reduction to remove unimportant variables that might cause noise, and we have not cross validated yet.

In [3]:
```
import numpy as np

from sklearn.cluster import KMeans
from sklearn import metrics
from sklearn.metrics import silhouette_samples, silhouette_score

import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.cm as cm
%matplotlib inline
plt.rcParams['figure.figsize'] = (10, 6)
plt.style.use('ggplot')
# Create color maps
from matplotlib.colors import ListedColormap
cmap = ListedColormap(["#e41a1c","#984ea3","#a65628","#377eb8","#ffff33","#4daf4a","
```

How do you choose K? *Ideas:*

1. *Visual comparison.*
2. *Looking for at which k the total intra-cluster distance tapers off.*
3. *Silhouette analysis*

The first method is useful when the feature vectors are lower dimensional, but it's difficult to visualize data in higher dimensions. Let's consider the other two ideas.

Analyzing Change in Intra-Cluster Distance

We can run K-Means for different Ks and plot the intra-cluster distance.

In [285…
```
import pandas as pd
```

In [390…
```
df = pd.read_csv('./data_acquisition/Python/final_combined_QSO_1.csv')
df = df.loc[:,'plate':'fiber_ID']
df.head(1)
```

Out[390…

	plate	z	redshift	class	spec_obj_ID	obj_ID	alpha	d
0	5812	18.79371	0.634794	GALAXY	6543777369295181824	1237660961327743273	135.689107	32.49

Are there any NaN's

In [298…
```
df.isna().sum()
```

Out[298…
```
plate          0
z              0
redshift       0
class          0
spec_obj_ID    0
obj_ID         0
alpha          0
delta          0
u              0
g              0
r              0
i              0
run_ID         0
rerun_ID       0
cam_col        0
field_ID       0
MJD            0
fiber_ID       0
dtype: int64
```

Check data types

In [389…
```
df.dtypes
```

Out[389…
```
plate          int64
z            float64
redshift     float64
alpha        float64
delta        float64
u            float64
g            float64
r            float64
i            float64
class_num      int32
class         object
dtype: object
```

Encode `class`

In [392…
```
le = LabelEncoder().fit(df['class'])
df['class_num'] = le.transform(df['class'])
df.tail().loc[:,['class','class_num']]
```

Out[392…

	class	class_num
71150	GALAXY	0
71151	QSO	1
71152	GALAXY	0
71153	GALAXY	0
71154	GALAXY	0

Look at other variables

In [139…
```
df.dtypes
```

Out[139…
```
plate           int64
z             float64
redshift      float64
class          object
spec_obj_ID    uint64
obj_ID          int64
alpha         float64
delta         float64
u             float64
g             float64
r             float64
i             float64
run_ID          int64
rerun_ID        int64
cam_col         int64
field_ID        int64
MJD             int64
fiber_ID        int64
```

```
class_num        int32
dtype: object
```

Modified Julian Date (MJD)

In [140…
```
df.MJD.min()
```

Out[140…
```
51608
```

In [141…
```
march_2000 = 51603  #https://core2.gsfc.nasa.gov/time/mjd2000.html
```

In [142…
```
(df.MJD.max() - df.MJD.min()) / 365.25
```

Out[142…
```
20.05201916495551
```

Roughly March 2000 through Mid-2020

Drop for now to simplifiy exploratory clustering

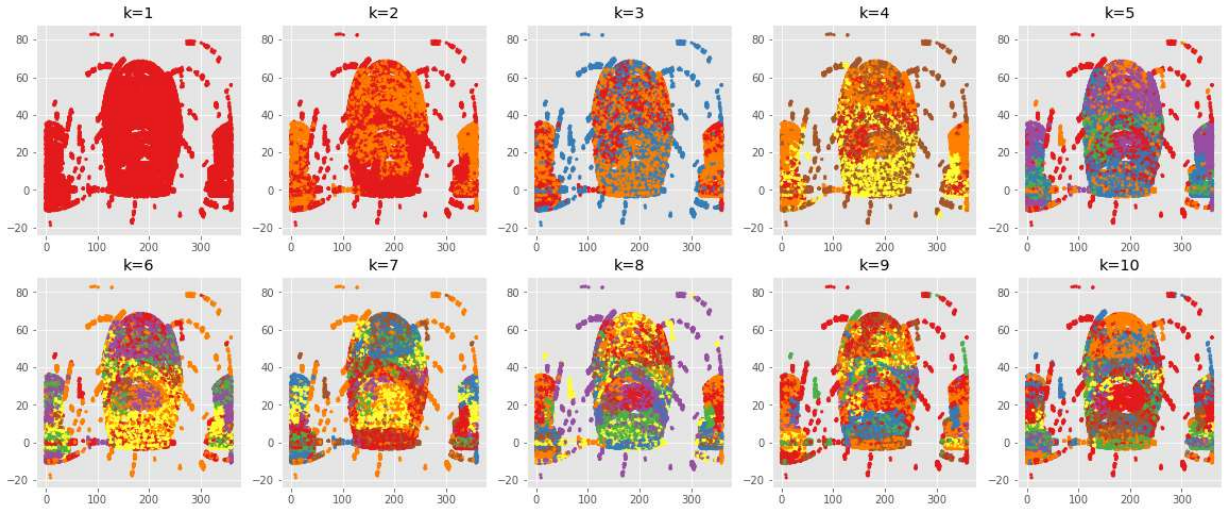
In [143…
```
df = df.drop(['class', 'spec_obj_ID', 'obj_ID', 'MJD'], axis=1)
df.dtypes
```

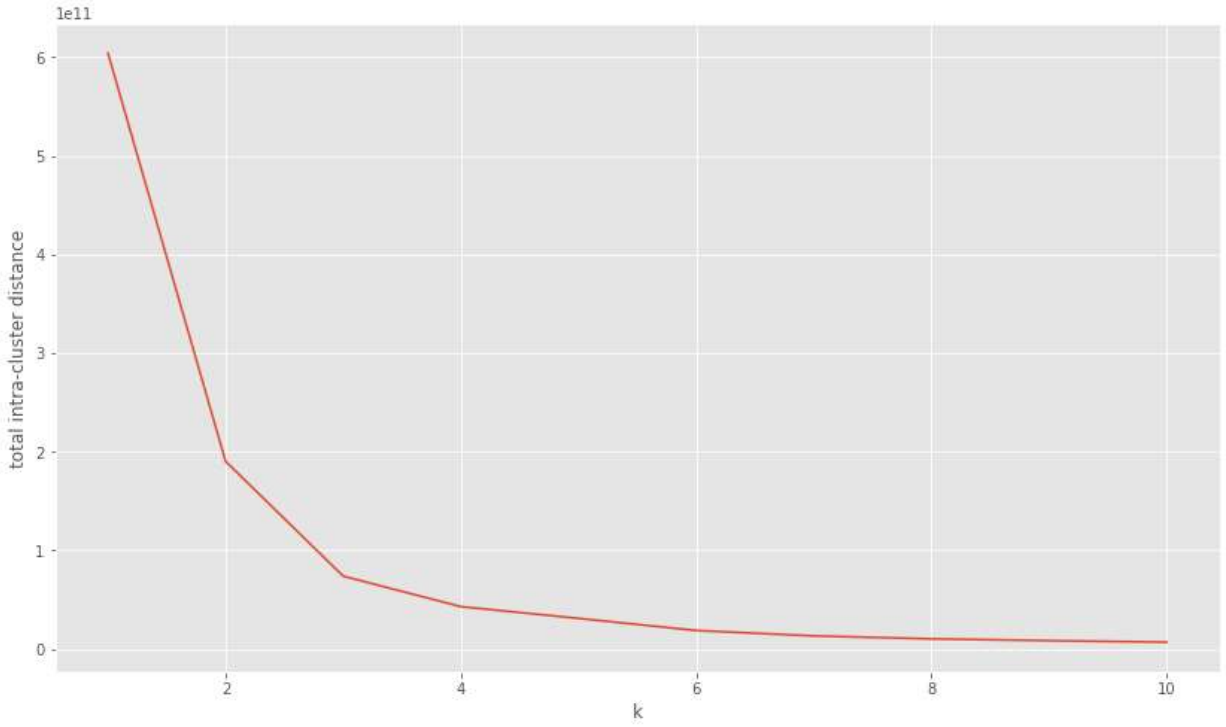
Out[143…
```
plate          int64
z            float64
redshift     float64
alpha        float64
delta        float64
u            float64
g            float64
r            float64
i            float64
run_ID         int64
rerun_ID       int64
cam_col        int64
field_ID       int64
fiber_ID       int64
class_num      int32
dtype: object
```

k-means

In [184…
```
# clustering for k = 1 to k = 10
ks = range(1,11)
scores = []

fig, axs = plt.subplots(2,5, figsize=(20, 8))
# fig, axs = plt.subplots(1,1)

for k in ks:
```

```
    model = KMeans(n_clusters=k)
    y_pred = model.fit_predict(df.drop(['class_num'],axis=1).values)
    scores.append(-model.score(df.drop(['class_num'],axis=1)))

    subplot = axs[int((k-1)/5)][(k-1)%5]
    subplot.scatter(x='alpha', y='delta', c=y_pred, data=df,  marker="o", cmap=cmap,
    subplot.set_title("k="+str(k))


fig = plt.figure(figsize=(14, 8))
plt.plot(ks, scores)
plt.ylabel('total intra-cluster distance')
plt.xlabel('k')
plt.show()
```





Base-Truth is k=3, elbow appears to be 3 or 4

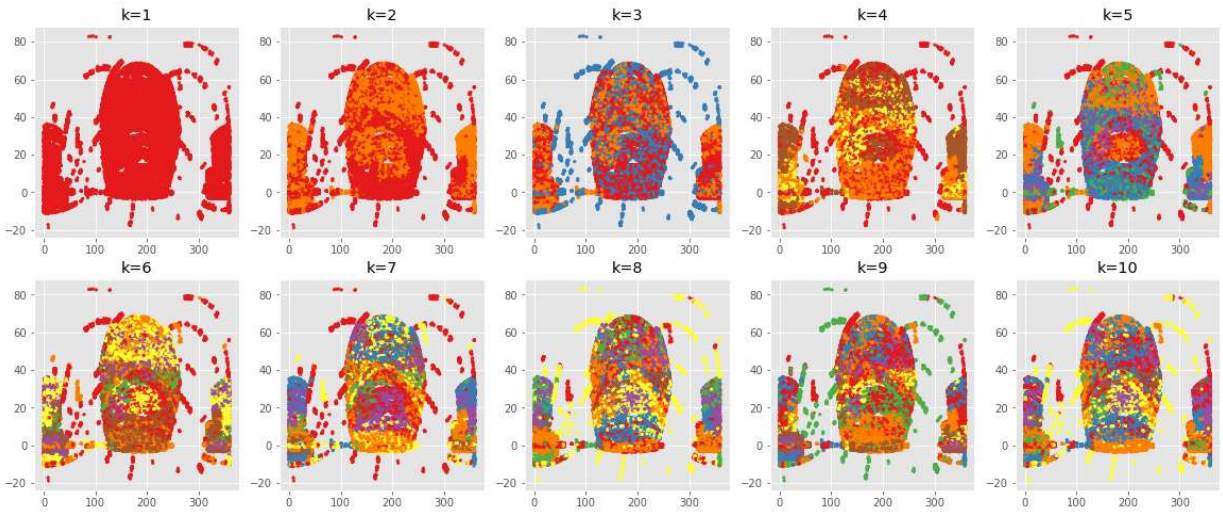
Rerun with less columns

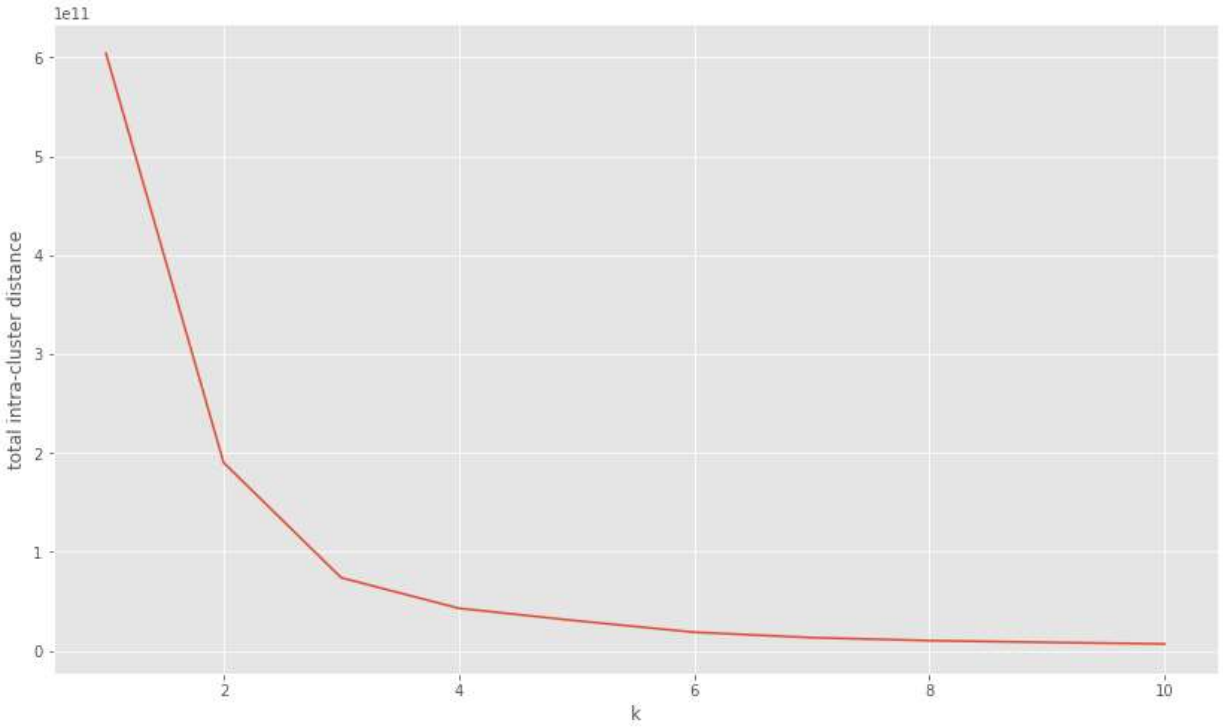
In [145…
```
df.columns
```

Out[145…
```
Index(['plate', 'z', 'redshift', 'alpha', 'delta', 'u', 'g', 'r', 'i',
       'run_ID', 'rerun_ID', 'cam_col', 'field_ID', 'fiber_ID', 'class_num'],
      dtype='object')
```

k-means

In [146…
```
# clustering for k = 1 to k = 10
ks = range(1,11)
scores = []

fig, axs = plt.subplots(2,5, figsize=(20, 8))
# fig, axs = plt.subplots(1,1)

for k in ks:
    model = KMeans(n_clusters=k)
    y_pred = model.fit_predict(df.drop(['run_ID', 'rerun_ID',
                                        'cam_col', 'field_ID',
                                        'fiber_ID', 'class_num'],axis=1).values)
    scores.append(-model.score(df.drop(['run_ID', 'rerun_ID',
                                        'cam_col', 'field_ID',
                                        'fiber_ID', 'class_num'],axis=1)))

    subplot = axs[int((k-1)/5)][(k-1)%5]
    subplot.scatter(x='alpha', y='delta', c=y_pred, data=df,  marker="o", cmap=cmap,
    subplot.set_title("k="+str(k))


fig = plt.figure(figsize=(14, 8))
plt.plot(ks, scores)
plt.ylabel('total intra-cluster distance')
plt.xlabel('k')
plt.show()
```





Elbow is more distinctly k=3 (Base-Truth)

Removed variables resulted in ~ order of magnitude less intra-cluster distance at k=3 than before

In [147…

```
df = df.drop(['run_ID', 'rerun_ID', 'cam_col', 'field_ID', 'fiber_ID'],axis=1)
df.head(1)
```

Out[147…

	plate	z	redshift	alpha	delta	u	g	r	i	class_nun
0	5812	18.79371	0.634794	135.689107	32.494632	23.87882	22.2753	20.39501	19.16573	

Silhouette plot

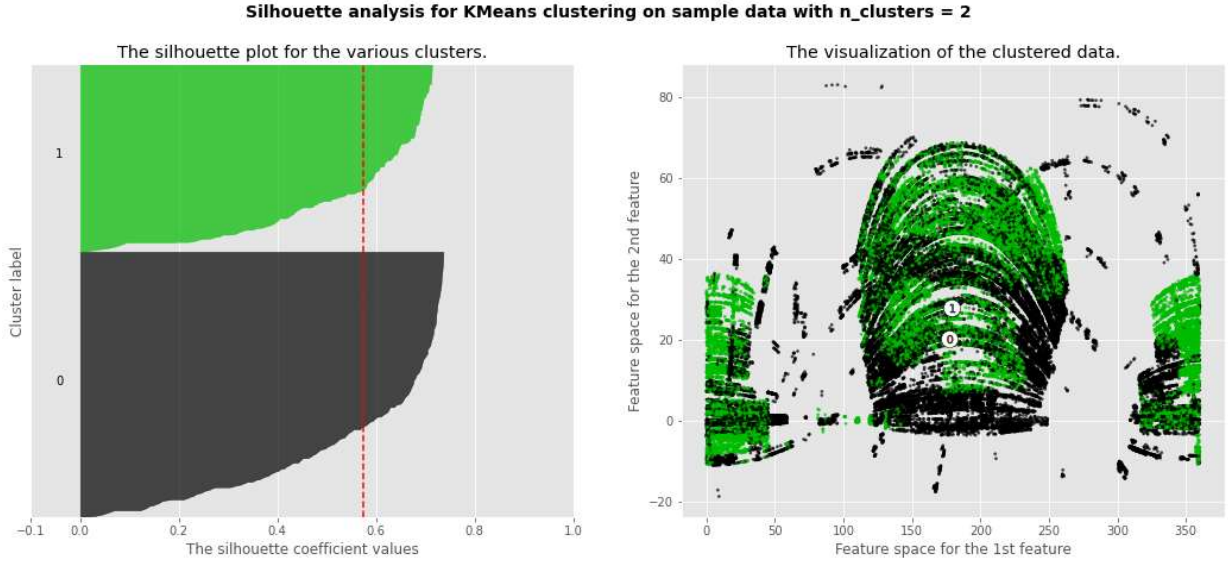
In [202…

```
d = df.drop('class_num', axis=1).values
range_n_clusters = [2, 3, 4, 5, 6, 7]

for n_clusters in range_n_clusters:
    # Create a subplot with 1 row and 2 columns
    fig, (ax1, ax2) = plt.subplots(1, 2)
    fig.set_size_inches(18, 7)

    # The 1st subplot is the silhouette plot
    # The silhouette coefficient can range from -1, 1 but in this example all
    # lie within [-0.1, 1]
    ax1.set_xlim([-0.1, 1])
    # The (n_clusters+1)*10 is for inserting blank space between silhouette
```

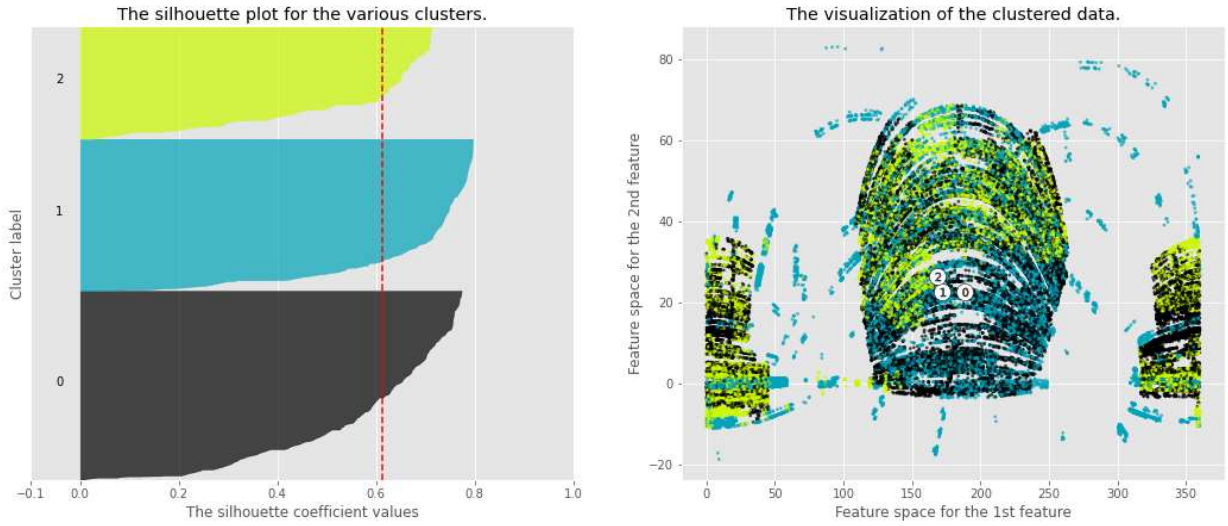
```
    # plots of individual clusters, to demarcate them clearly.
    ax1.set_ylim([0, len(d) + (n_clusters + 1) * 10])

    # Initialize the clusterer with n_clusters value and a random generator
    # seed of 10 for reproducibility.
    clusterer = KMeans(n_clusters=n_clusters, random_state=10)
    cluster_labels = clusterer.fit_predict(d)

    # The silhouette_score gives the average value for all the samples.
    # This gives a perspective into the density and separation of the formed
    # clusters
    silhouette_avg = silhouette_score(d, cluster_labels)
    print("For n_clusters =", n_clusters,
          "The silhouette_score is :", silhouette_avg)

    # Compute the silhouette scores for each sample
    sample_silhouette_values = silhouette_samples(d, cluster_labels)

    y_lower = 10
    for i in range(n_clusters):
        # Aggregate the silhouette scores for samples belonging to
        # cluster i, and sort them
        ith_cluster_silhouette_values = \
            sample_silhouette_values[cluster_labels == i]

        ith_cluster_silhouette_values.sort()

        size_cluster_i = ith_cluster_silhouette_values.shape[0]
        y_upper = y_lower + size_cluster_i

        color = cm.nipy_spectral(float(i) / n_clusters)
        ax1.fill_betweenx(np.arange(y_lower, y_upper),
                          0, ith_cluster_silhouette_values,
                          facecolor=color, edgecolor=color, alpha=0.7)

        # Label the silhouette plots with their cluster numbers at the middle
        ax1.text(-0.05, y_lower + 0.5 * size_cluster_i, str(i))

        # Compute the new y_lower for next plot
        y_lower = y_upper + 10  # 10 for the 0 samples

    ax1.set_title("The silhouette plot for the various clusters.")
    ax1.set_xlabel("The silhouette coefficient values")
    ax1.set_ylabel("Cluster label")

    # The vertical line for average silhouette coefficient of all the values
    ax1.axvline(x=silhouette_avg, color="red", linestyle="--")

    ax1.set_yticks([])  # Clear the yaxis labels / ticks
    ax1.set_xticks([-0.1, 0, 0.2, 0.4, 0.6, 0.8, 1])

    # 2nd Plot showing the actual clusters formed
    colors = cm.nipy_spectral(cluster_labels.astype(float) / n_clusters)
    ax2.scatter(d[:, 3], d[:, 4], marker='.', s=30, lw=0, alpha=0.7,
                c=colors, edgecolor='k')

    # Labeling the clusters
    centers = clusterer.cluster_centers_
    # Draw white circles at cluster centers
    ax2.scatter(centers[:, 3], centers[:, 4], marker='o',
```

```
                c="white", alpha=1, s=200, edgecolor='k')

    for i, c in enumerate(centers):
        ax2.scatter(c[3], c[4], marker='$%d$' % i, alpha=1,
                    s=50, edgecolor='k')

    ax2.set_title("The visualization of the clustered data.")
    ax2.set_xlabel("Feature space for the 1st feature")
    ax2.set_ylabel("Feature space for the 2nd feature")

    plt.suptitle(("Silhouette analysis for KMeans clustering on sample data "
                  "with n_clusters = %d" % n_clusters),
                 fontsize=14, fontweight='bold')

    plt.show()
```

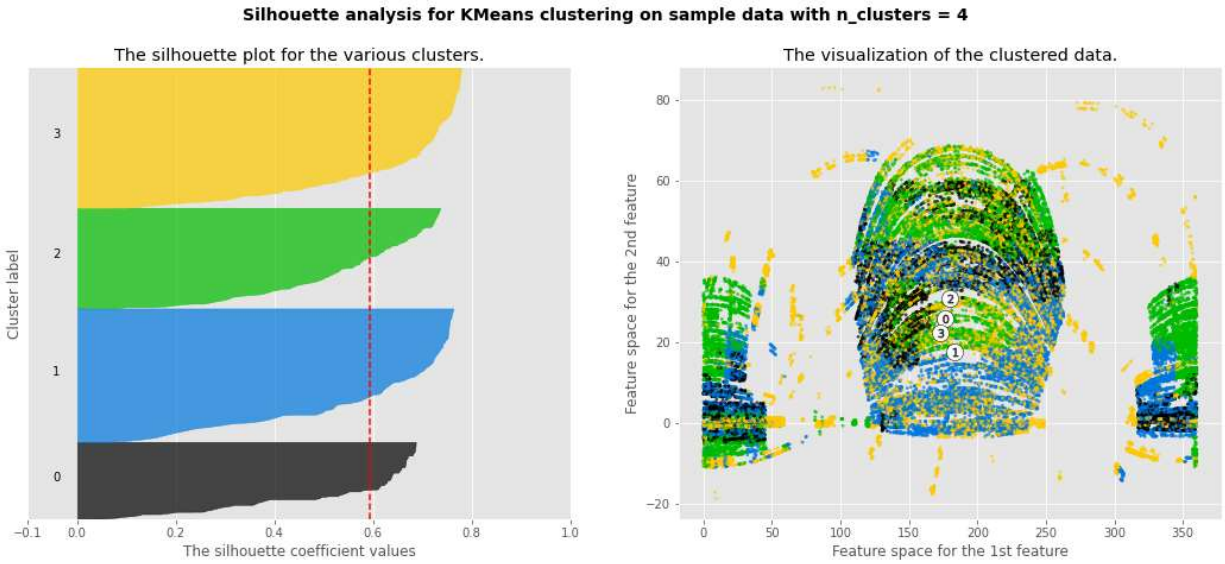
```
For n_clusters = 2 The silhouette_score is : 0.5738599509906098
```



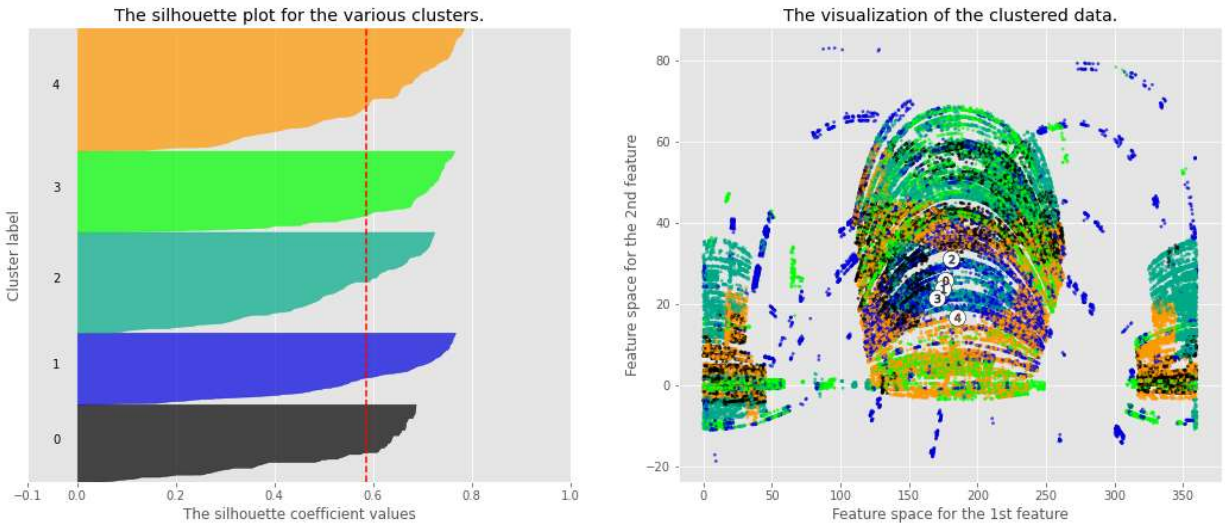

```
For n_clusters = 3 The silhouette_score is : 0.6119220136140294
```



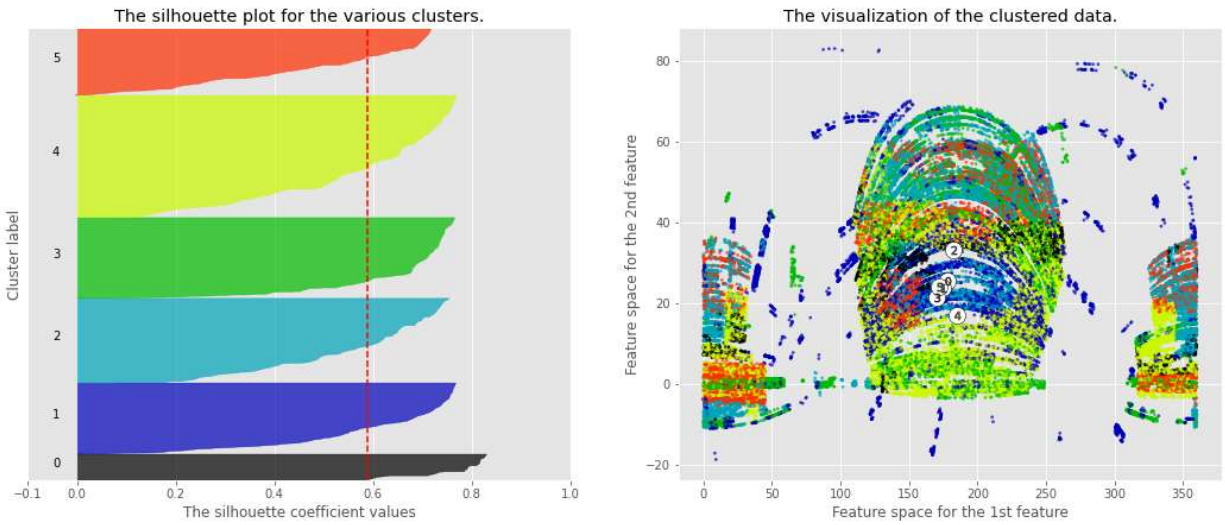

```
For n_clusters = 4 The silhouette_score is : 0.593575621783908
```



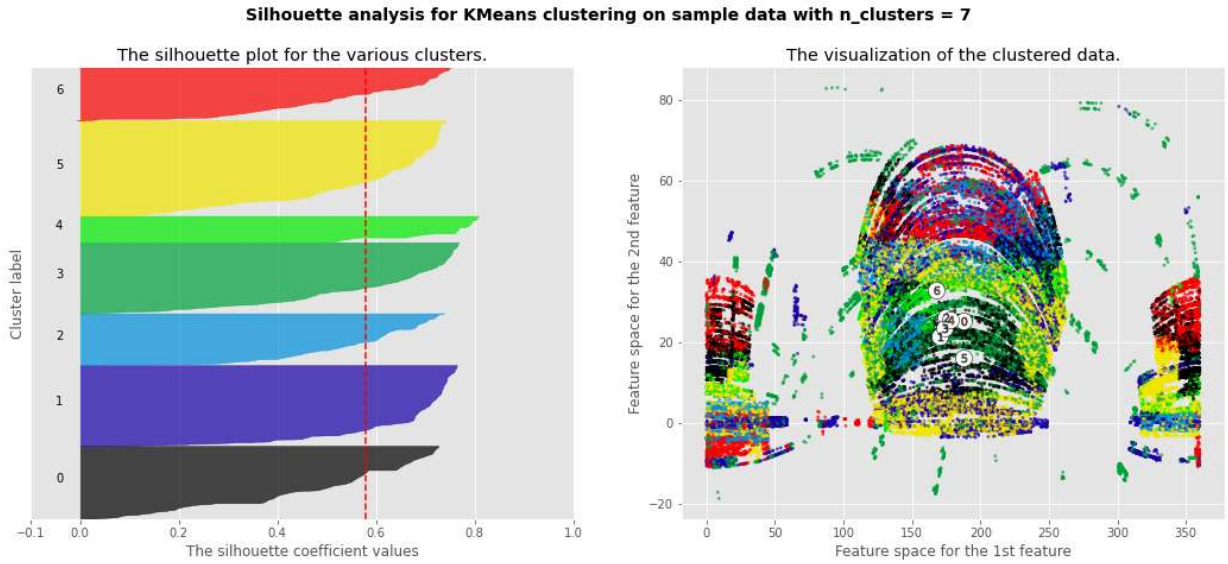
For n_clusters = 5 The silhouette_score is : 0.5857406457568644



For n_clusters = 6 The silhouette_score is : 0.5890318221073857



For n_clusters = 7 The silhouette_score is : 0.5791386409248354



Peer Feedback

Our peer feedback answered the following questions:

Are the objectives interesting and suitable for a class project? ***-- yes***

Is the scope of the project appropriate? If not, suggest improvements. ***-- yes. It was mentioned that we should consider data classifications changing over time given that over time there have been higher resolution telescopes/cameras, better technology that could change the outcome classification of an astronomical object. If we were to create this model now how accurate would it be in the future?***

Is the split between optional and must-have features appropriate? Why? ***-- yes***

Is the stakeholder analysis comprehensive? Are there specific ethical issues? ***-- something to consider is why some data is classified as a quasar and then as a galaxy/star. As mentioned above, the classification rules change over time. Get a percentage of how many astronomical objects were later classified as quasar instead of a star/galaxy.***

Data Acquisition and Cleanup

Is data acquisition realistic? ***-- with .fits files it was not realistic, with web-scraping we got closer with acquiring the data and finally with using SDSS's query/crossmatch/SQL tools we were able to realistically retrieve the data.***

Is the data acquisition trivial (e.g., downloading an existing dataset). Does the rest of the project compensate? ***-- not it was not trivial, and the rest of the project does compensate.***

What is the plan for cleanup? Is cleanup that goes beyond what was taught in class necessary?

The cleanup plan involves combining CSVs, adjusting some of the classifications from galaxy/star to quasar if the "spec_obj_id" aligns with the quasar dataset. Removing duplicate header rows and validating we have balanced data.

Is there enough data to accomplish the stated objectives?

Yes. Instructor (Bei Wang) indicated that ~100,000 data points is a sufficient starting point

If needed, more data points can be acquired using the same methods we used to acquire our working dataset.

Are there other variables that are not being modeled that have a strong effect on the problem? ***-- at this moment in time, this is unknown. The hope is our model might be able to tell us which variables have a strong effect on the problem.***

Analysis Methodology

Does the analysis methodology work for the data? E.g., for supervised learning - is the data labeled?

Yes, supervised learning with labeled data

Would other analysis methods be appropriate?

Yes, Bayesian Models could also be appropriate

--Instructor (Haoyu Chen) feedback was to optionally consider adding methods from Bayesian Models for Astrophysical Data by Hilbe, Souza, and Ishida *Yes, t-SNE may be appropriate for Dimensionality Reduction/Visualization***

--Instructor (Bei Wang) feedback

"Visualization in Astrophysics: Developing New Methods, Discovering Our Universe, and Educating the Earth" - Bei Wang, et al

CNN could also be a potential option, as "Kim and Brunner [KB16] performed star-galaxy classification using CNNs"

Is the scale of the dataset sufficient for the analysis methodology?

Yes. Instructor (Bei Wang) indicated that ~100,000 data points is a sufficient starting point. More data points can be acquired as needed.

Completed Milestones

- *Determining the proper method for retrieving our dataset*

- *Acquiring our dataset (retrieving 100,000 objects)*
- *Validating our dataset had at least a portion of our three classification types: Galaxy, Star, Quasar*
- *Getting a final, useable CSV file to perform and build our model with*
- *Initial data analysis of the final dataset (clustering)*

Upcoming Milestones

- *Check for class imbalance and outliers*
- *Perform the rest of the analysis methods on the data:*
- *Classification (SVM, K-means)*
- *Dimensionality Reduction (PCA/LDA)*

Potential Modificaiton to the Project

How do we check if our data is linear? So first we should do some kind check to verify whether our data is linear or nonlinear. If the data is nonlinear, we will have to switch our methods from LDA and PCA to t-SNE and UMAP. We originally planned to mitigate outliers before dimensionality reduction, we are now of the opinion it would be best to run dimensionality reduction with and without outliers and then compare the results of both. Along these same lines, we originally planned to center/scale the data before clustering, but now we are going to center/scale and then cluster and then not center/scale and compare the results.

Project Summary:

Overall, our project is on track, and we have followed our original milestones that we set at the beginning of the class. We initially ran into some roadblocks at the start when trying to acquire the appropriate data and acquiring in a way that made sense and was not so cumbersome. Once those roadblocks were surpassed, we are now able to view and understand our final dataset to perform our final data analysis and all the methods we listed to create a model to accurately predict an astronomical object based on the data we feed into it.

Assessment

Is our project on track: ***yes***

Final Results Summary

As our final results, and in summary, our model was able to determine the correct classes of stellar objects by: After our initial steps of data acquisition that involved:

- *parsing through FITS files*
- *Web scraping*
- *An initial Web Query using the Cross Match Tools on the SDSS dr17 database*
- *Injecting the necessary Quasar and data*
- *Until finally running the final query using the Search Tools on the SDSS dr17 website to give us ~100,000 objects of data.*

We were then able to massage the data accordingly, checking for any outliers, and any class imbalance before performing the following methods on the final, cleaned data set:

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- PCA
- t-SNE
- Random Forest
- SVM
- and initially some K-Means clustering
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We determined that when comparing both models, one model containing auxliary data and another model without that there were differences in the model's capability of determining the correct class for the stellar object.

Dimensionality Reduction

- *PCA: for our PCA dimensionality reduction method/model ->*
  - *The difference between data WITH our auxiliary resulted in a model with indiscriminate clusters, it was hard to tell and there was not cohesive structure forming within our PC1 and PC2 models. This implied that there was possibly some variables dominating the variance.*
  - *The difference between data WITHOUT our auxiliary resulted in a model with discriminate clusters, it was a lot easier to tell and there WAS a somewhat cohesive structure forming within our PC1 and PC2 models.*

- *t-SNE:*

- *With t-SNE, we noticed the same behavior with some of the variables, for example --> plate & MJD are moderately correlated with u, g, r, i, z, and redshift. The same can be said for fiber_ID, to a lesser degree. In addition, alpha and delta represent the location on the celestial sphere (sky), which may have a relationship with the classes of astronomical objects present, but is not an observable charateristic of the object itself. Similarly, run_id is the identifier of the run, which may have implications on classes observed in that run, but is not directly an attribute of the object--and likewise for cam_col/field_ID.*

- *As we saw with the single outlier that shaped our correlation matrix, added varaince that does not represent the underlying silhouette we are trying to capture can lead us astray--particularly when contained in a variable that has a significant correlation with a variable that does represent what we are trying to capture.*

Let's examine what happens to our t-SNE dimensions when we remove these variables.

Classifiers / Clustering

- *Random Forest:*
  - *WITHOUT the Auxilary data, Random Forest had about a 98% accuracy score*
    - *97.1% on 500,000 Optical-Spectroscopic Object Test*
  - *WITH Auxilary data we were unable to run*
    - *97.4% on 500,000 Optical-Spectroscopic Object Test*
- *SVM:*
  - *WITHOUT the Auxilary data, SVM had about a 96.4% accuracy score*
    - *96.4% on 500,000 Optical-Spectroscopic Object Test*
  - *WITH the Auxilary data, was about a 96.8%*
    - *96.3% on 500,000 Optical-Spectroscopic Object Test*
- *K-Means:*
  - *WITHOUT the Auxilary data, K-means had about a 44% accuracy score*
  - *WITH the Auxilary, K-means. had about a 42% accuracy score*

FINAL NOTES *In summary for the Classifiers and Clustering Random Forest did do a much better job at classifying the data with a 98% accuracy score compared to 96% on SVM WITHOUT Auxliary data also compared with 44% by K-Means WITHOUT Auxliary data.*

As final, our model with the combination of proper data acquisition, data massaging/cleaning, dimensionality reduction using multiple methods and then clustering/classifying using multiple methods on the data to determine that certain data was causing some dominance in the variance and once we removed depending on which classifier/model we decided to use we had to about 98% accuracy in classifying our astronomical data.