cs107stargazers_Samia_Elena_Devin_Ali_Innocent

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1 Astronomical Data Science Library Demo

This Interactive Python Notebook (ipynb) file explains our library's functionalities, and includes a demonstration of how to execute required functions and handling of exceptions.

[2]:
```
# Install the library, which is distributed via Test PyPI
!python3 -m pip install --index-url https://test.pypi.org/simple/ 
 ↪--extra-index-url https://pypi.org/simple/ cs107stargazers
```

```
Looking in indexes: https://test.pypi.org/simple/, https://pypi.org/simple/
Collecting cs107stargazers
  Downloading https://test-files.pythonhosted.org/packages/9e/d0/b20c50aca6b3628
d31a1dc2c11629648463579879d1ff014b3ca4194c4d5/cs107stargazers-0.0.3-py3-none-
any.whl (15 kB)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages
(from cs107stargazers) (1.23.5)
Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages
(from cs107stargazers) (1.5.3)
Collecting differint (from cs107stargazers)
  Downloading differint-1.0.0-py3-none-any.whl (11 kB)
Collecting astroquery (from cs107stargazers)
  Downloading astroquery-0.4.6-py3-none-any.whl (4.5 MB)
                           4.5/4.5 MB
18.3 MB/s eta 0:00:00
Requirement already satisfied: scikit-learn in
/usr/local/lib/python3.10/dist-packages (from cs107stargazers) (1.2.2)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-
packages (from cs107stargazers) (3.7.1)
Requirement already satisfied: astropy>=4.0 in /usr/local/lib/python3.10/dist-
packages (from astroquery->cs107stargazers) (5.3.4)
Requirement already satisfied: requests>=2.4.3 in
/usr/local/lib/python3.10/dist-packages (from astroquery->cs107stargazers)
(2.31.0)
Requirement already satisfied: beautifulsoup4>=4.3.2 in
/usr/local/lib/python3.10/dist-packages (from astroquery->cs107stargazers)
(4.11.2)
Requirement already satisfied: html5lib>=0.999 in
/usr/local/lib/python3.10/dist-packages (from astroquery->cs107stargazers) (1.1)
```

```
Requirement already satisfied: keyring>=4.0 in /usr/lib/python3/dist-packages
(from astroquery->cs107stargazers) (23.5.0)
Collecting pyvo>=1.1 (from astroquery->cs107stargazers)
  Downloading pyvo-1.4.2-py3-none-any.whl (888 kB)
                           888.9/888.9

kB 36.1 MB/s eta 0:00:00
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->cs107stargazers)
(1.2.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-
packages (from matplotlib->cs107stargazers) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->cs107stargazers)
(4.46.0)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->cs107stargazers)
(1.4.5)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->cs107stargazers)
(23.2)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-
packages (from matplotlib->cs107stargazers) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->cs107stargazers)
(3.1.1)
Requirement already satisfied: python-dateutil>=2.7 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->cs107stargazers)
(2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-
packages (from pandas->cs107stargazers) (2023.3.post1)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.10/dist-
packages (from scikit-learn->cs107stargazers) (1.11.4)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-
packages (from scikit-learn->cs107stargazers) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn->cs107stargazers)
(3.2.0)
Requirement already satisfied: pyerfa>=2.0 in /usr/local/lib/python3.10/dist-
packages (from astropy>=4.0->astroquery->cs107stargazers) (2.0.1.1)
Requirement already satisfied: PyYAML>=3.13 in /usr/local/lib/python3.10/dist-
packages (from astropy>=4.0->astroquery->cs107stargazers) (6.0.1)
Requirement already satisfied: soupsieve>1.2 in /usr/local/lib/python3.10/dist-
packages (from beautifulsoup4>=4.3.2->astroquery->cs107stargazers) (2.5)
Requirement already satisfied: six>=1.9 in /usr/local/lib/python3.10/dist-
packages (from html5lib>=0.999->astroquery->cs107stargazers) (1.16.0)
Requirement already satisfied: webencodings in /usr/local/lib/python3.10/dist-
packages (from html5lib>=0.999->astroquery->cs107stargazers) (0.5.1)
```

```
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.10/dist-packages (from
requests>=2.4.3->astroquery->cs107stargazers) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-
packages (from requests>=2.4.3->astroquery->cs107stargazers) (3.6)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.10/dist-packages (from
requests>=2.4.3->astroquery->cs107stargazers) (2.0.7)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.10/dist-packages (from
requests>=2.4.3->astroquery->cs107stargazers) (2023.11.17)
Installing collected packages: differint, pyvo, astroquery, cs107stargazers
Successfully installed astroquery-0.4.6 cs107stargazers-0.0.3 differint-1.0.0
pyvo-1.4.2
```

[3]:
```
# Import the library
import cs107stargazers
```

1.1 Query Module

In the following theres an example of an ADQL query that when used as input into the Query() function returns an object with the following functionalities:

1. get_df
2. get_table (as in an astropy table)
3. print

[4]:
```
import pandas as pd # All our data is in Pandas DataFrame format, so we need␣
↪this
from astroquery.sdss import SDSS
import numpy as np
from sklearn.neighbors import KNeighborsRegressor
from cs107stargazers import query
```

[ ]:
```
#declaring my query
sample_query = """
SELECT
    TOP 10
    p.objID, p.ra, p.dec, p.u, p.g, p.r, p.i, p.z
FROM
    PhotoObj AS p
WHERE
    p.u BETWEEN 0 AND 19.6
"""

object = query.Query(sample_query)

#this stored a dataframe object into df
```

```
df = object.get_df()

#this stores a table type object into astropy_table
astropy_table = object.get_table()

#this prints out the data obtained by the query
object.print()
```

```
      objID               ra                dec         …    i        z
------------------- ---------------- ----------------- … -------- --------
1237678537416376475 319.855107255262  8.71000794986525 … 16.56604 16.40493
1237679321774096394 3.99012821084209 -6.11657839984856 … 16.92422 16.88132
1237679321774293108 4.47609980729239 -6.12668453451256 … 17.82319 17.79516
1237679321774293159 4.57646000102861 -6.07174662883298 … 16.50827 16.34224
1237679321776914474 10.4572497518612 -6.06263878936387 … 14.99698 14.80965
1237679321777242131 11.3042357027852 -6.22087295834064 … 17.31822  17.2555
1237679321777373209 11.5677943389135 -6.06065234786156 … 16.87575 16.81628
1237679321778683924 14.5942688944471 -6.01012145030255 … 16.57353  16.5056
1237679321779339268 16.0360177563126 -5.95854592578773 … 15.80109 15.75423
1237679321780715603 19.2787644208696  -5.9030590151752 … 17.21273 17.14535
```

1.2 Metadata Extraction

This module is used to extract metadata information. It work by first creating a `MetadataExctractor` object, by passing in the data (whether from the `query` step of our pipeline, or one that is directly provided by the user), and then can use the method `extract_metadata` to extract a list of several metadata information, or use `extract_specific_field` to extract a single metadata field. See the below for an example:

[5]:
```
# Import metadata exctraction module
from cs107stargazers import metadata_extraction
```

[ ]:
```
# Create metadata extractor object
metadata_extractor_object = metadata_extraction.MetadataExtractor(df)
```

[ ]:
```
# Extract `identifier` and `ra` (right ascension)
multiple_metadata = metadata_extractor_object.extract_metadata(["dec", "ra"])
multiple_metadata
```

[ ]:
```
        dec          ra
0  8.710008  319.855107
1 -6.116578    3.990128
2 -6.126685    4.476100
3 -6.071747    4.576460
4 -6.062639   10.457250
5 -6.220873   11.304236
6 -6.060652   11.567794
7 -6.010121   14.594269
```

```
8 -5.958546   16.036018
9 -5.903059   19.278764
```

[ ]:
```
# Extract `ra` specifically
specific_metadata = metadata_extractor_object.extract_specific_field("ra")
specific_metadata
```

[ ]:
```
0    319.855107
1      3.990128
2      4.476100
3      4.576460
4     10.457250
5     11.304236
6     11.567794
7     14.594269
8     16.036018
9     19.278764
Name: ra, dtype: float64
```

1.3 Preprocessing function

The following demonstrates how to create a preprocessing object and how to use its following functionalities:

1. normalize
2. rm_outlier
3. interpolate
4. get_redshift_corr

[6]:
```
from cs107stargazers import preprocessing
```

[ ]:
```
#normalize df declared before, making all columns except ID have range 0-1
pp = preprocessing.Preprocessing(df)
pp.normalize(replace = True)
pp.data.head()
```

[ ]:
```
                 objID        ra       dec         u         g         r  \
0  1237678537416376475  1.000000  1.000000  0.403671  0.459013  0.518441
1  1237679321774096394  0.000000  0.006985  0.537312  0.616918  0.674803
2  1237679321774293108  0.001539  0.006308  0.776977  1.000000  1.000000
3  1237679321774293159  0.001856  0.009988  1.000000  0.642794  0.570729
4  1237679321776914474  0.020474  0.010598  0.311592  0.000000  0.000000

          i         z
0  0.555182  0.534341
1  0.681917  0.693908
2  1.000000  1.000000
3  0.534741  0.513343
```

```
4  0.000000  0.000000
```

[ ]:
```python
#rm_oulier, you can see it removed an outlier in  RA!
pp = preprocessing.Preprocessing(df)
pp.rm_outlier(replace = True )
print(df.head())
pp.data.head()
```

```
                objID          ra       dec         u         g         r  \
0  1237678537416376475  319.855107  8.710008  18.35033  17.13285  16.66923
1  1237679321774096394    3.990128 -6.116578  18.59702  17.47490  17.07987
2  1237679321774293108    4.476100 -6.126685  19.03942  18.30472  17.93391
3  1237679321774293159    4.576460 -6.071747  19.45110  17.53095  16.80655
4  1237679321776914474   10.457250 -6.062639  18.18036  16.13855  15.30769

          i         z
0  16.56604  16.40493
1  16.92422  16.88132
2  17.82319  17.79516
3  16.50827  16.34224
4  14.99698  14.80965
```

[ ]:
```
                objID          ra       dec         u         g         r  \
1  1237679321774096394    3.990128 -6.116578  18.59702  17.47490  17.07987
2  1237679321774293108    4.476100 -6.126685  19.03942  18.30472  17.93391
3  1237679321774293159    4.576460 -6.071747  19.45110  17.53095  16.80655
4  1237679321776914474   10.457250 -6.062639  18.18036  16.13855  15.30769
5  1237679321777242131   11.304236 -6.220873  19.23810  18.04356  17.51633

          i         z
1  16.92422  16.88132
2  17.82319  17.79516
3  16.50827  16.34224
4  14.99698  14.80965
5  17.31822  17.25550
```

[ ]:
```python
#interpolated using kNN nearest neighbors regression!!!
pp = preprocessing.Preprocessing(df)
pp.interpolate([13, 14, 15], y_col = 'z', x_col='ra', replace =True)
pp.data.head()
```

[ ]:
```
                objID          ra       dec         u         g         r  \
0  1237678537416376475  319.855107  8.710008  18.35033  17.13285  16.66923
1  1237679321774096394    3.990128 -6.116578  18.59702  17.47490  17.07987
2  1237679321774293108    4.476100 -6.126685  19.03942  18.30472  17.93391
3  1237679321774293159    4.576460 -6.071747  19.45110  17.53095  16.80655
4  1237679321776914474   10.457250 -6.062639  18.18036  16.13855  15.30769
```

```
          i         z  ra_x_interpolate  z_y_interpolated
0  16.56604  16.40493              13.0         10.356576
1  16.92422  16.88132              14.0         10.356576
2  17.82319  17.79516              15.0         10.356576
3  16.50827  16.34224               NaN               NaN
4  14.99698  14.80965               NaN               NaN
```

[ ]:
```python
#get_redshift_corr with the redshift column, should mean corr = 1
corr = pp.get_redshift_corr(col = 'z')
print(corr)
```

```
1.0
```

1.4 Data Augmentation Differintegral/Fractional Derivative Module

[7]:
```python
from cs107stargazers import augment
```

[14]:
```python
mat = np.array([[ 1237678537416376475,  3.19855107e+02,  8.71000795e+00,
          1.83503300e+01,  1.71328500e+01,  1.66692300e+01,
          1.65660400e+01,  1.64049300e+01],
        [ 1237679321774096394,  3.99012821e+00, -6.11657840e+00,
          1.85970200e+01,  1.74749000e+01,  1.70798700e+01,
          1.69242200e+01,  1.68813200e+01],
        [ 1237679321774293108,  4.47609981e+00, -6.12668453e+00,
          1.90394200e+01,  1.83047200e+01,  1.79339100e+01,
          1.78231900e+01,  1.77951600e+01],
        [ 1237679321774293159,  4.57646000e+00, -6.07174663e+00,
          1.94511000e+01,  1.75309500e+01,  1.68065500e+01,
          1.65082700e+01,  1.63422400e+01],
        [ 1237679321776914474,  1.04572498e+01, -6.06263879e+00,
          1.81803600e+01,  1.61385500e+01,  1.53076900e+01,
          1.49969800e+01,  1.48096500e+01],
        [ 1237679321777242131,  1.13042357e+01, -6.22087296e+00,
          1.92381000e+01,  1.80435600e+01,  1.75163300e+01,
          1.73182200e+01,  1.72555000e+01],
        [ 1237679321777373209,  1.15677943e+01, -6.06065235e+00,
          1.86935600e+01,  1.74812300e+01,  1.70313800e+01,
          1.68757500e+01,  1.68162800e+01],
        [ 1237679321778683924,  1.45942689e+01, -6.01012145e+00,
          1.84718700e+01,  1.71846700e+01,  1.67297400e+01,
          1.65735300e+01,  1.65056000e+01],
        [ 1237679321779339268,  1.60360178e+01, -5.95854593e+00,
          1.76051900e+01,  1.64301900e+01,  1.59924300e+01,
          1.58010900e+01,  1.57542300e+01],
        [ 1237679321780715603,  1.92787644e+01, -5.90305902e+00,
          1.88168200e+01,  1.77291400e+01,  1.73524300e+01,
          1.72127300e+01,  1.71453500e+01]])
```

```
df = pd.DataFrame(mat, columns=["objID", "ra", "dec", "u", "g", "r", "i", "z"])

# Test class instantiation and data attribute
test1 = augment.Augment(df)

# Test derive() -- get derivatives of specified variables, using their vector␣
↪of values [i.e. emprical derivative, not analytical]
# all columns (vars)
test2 = test1.derive()
# notrun
test3 = test1.derive(notrun="objID")
# run
test4 = test1.derive(run="ra")

# Test fractional_derive() -- get differintegrals of a specified degree (ex: 0.
↪5) for specified variables, using their vector of vaues [i.e. empirical␣
↪differintegral, not analytical]
# all columns (vars)
test5 = test1.fractional_derive(0.5)
# notrun
test6 = test1.fractional_derive(0.5, notrun="objID")
# run
test7 = test1.fractional_derive(0.5, run="ra")
```

[12]:
```
# Augmented pandas dataframes are returned, with the specified derivatives␣
↪added as columns
print("test1")
test1.data.head  # pre-augmentation data
```

```
test1
```

[12]:
```
<bound method NDFrame.head of            objID          ra        dec         u
g          r          i  \
0  1.237679e+18  319.855107  8.710008  18.35033  17.13285  16.66923  16.56604
1  1.237679e+18    3.990128 -6.116578  18.59702  17.47490  17.07987  16.92422
2  1.237679e+18    4.476100 -6.126685  19.03942  18.30472  17.93391  17.82319
3  1.237679e+18    4.576460 -6.071747  19.45110  17.53095  16.80655  16.50827
4  1.237679e+18   10.457250 -6.062639  18.18036  16.13855  15.30769  14.99698
5  1.237679e+18   11.304236 -6.220873  19.23810  18.04356  17.51633  17.31822
6  1.237679e+18   11.567794 -6.060652  18.69356  17.48123  17.03138  16.87575
7  1.237679e+18   14.594269 -6.010121  18.47187  17.18467  16.72974  16.57353
8  1.237679e+18   16.036018 -5.958546  17.60519  16.43019  15.99243  15.80109
9  1.237679e+18   19.278764 -5.903059  18.81682  17.72914  17.35243  17.21273

          z
0  16.40493
```

```
1   16.88132
2   17.79516
3   16.34224
4   14.80965
5   17.25550
6   16.81628
7   16.50560
8   15.75423
9   17.14535   >
```

[13]:
```python
# Ex:
print("test7")
test7.head
# d_ra is now included in the augmented pd df, as per run="ra"
```

```
test7
```

[13]:
```
<bound method NDFrame.head of             objID          ra       dec         u
g         r         i  \
0  1.237679e+18  319.855107  8.710008  18.35033  17.13285  16.66923  16.56604
1  1.237679e+18    3.990128 -6.116578  18.59702  17.47490  17.07987  16.92422
2  1.237679e+18    4.476100 -6.126685  19.03942  18.30472  17.93391  17.82319
3  1.237679e+18    4.576460 -6.071747  19.45110  17.53095  16.80655  16.50827
4  1.237679e+18   10.457250 -6.062639  18.18036  16.13855  15.30769  14.99698
5  1.237679e+18   11.304236 -6.220873  19.23810  18.04356  17.51633  17.31822
6  1.237679e+18   11.567794 -6.060652  18.69356  17.48123  17.03138  16.87575
7  1.237679e+18   14.594269 -6.010121  18.47187  17.18467  16.72974  16.57353
8  1.237679e+18   16.036018 -5.958546  17.60519  16.43019  15.99243  15.80109
9  1.237679e+18   19.278764 -5.903059  18.81682  17.72914  17.35243  17.21273

          z       d_ra
0  16.40493   0.000000
1  16.88132   0.000000
2  17.79516   0.000000
3  16.34224 -76.638841
4  14.80965  51.931444
5  17.25550  19.288070
6  16.81628  28.254058
7  16.50560  17.641767
8  15.75423  15.412827
9  17.14535  21.392913   >
```

1.5 ML Classification Module

[21]:
```python
from cs107stargazers import ml_stargazer
```

[22]:
```python
query_string = """
SELECT TOP 100
```

```
  s.specobjid, s.ra, s.dec,
    s.z, s.zerr,
  s.plate, s.fiberID, s.mjd,
  p.petroMag_u, p.petroMag_g, p.petroMag_r, p.petroMag_i, p.petroMag_z
FROM
  specObj AS s
JOIN
  photoObj AS p ON s.bestobjid = p.objid
WHERE
  s.ra BETWEEN 150.0 AND 150.2
  AND s.dec BETWEEN 2.0 AND 2.2
"""

# Use astroquery to execute the query_string
result = SDSS.query_sql(query_string)

# Convert the result to a pandas DataFrame
df = result.to_pandas()

# go
vars_predict = ["s.ra", "s.dec"]
test1 = ml_stargazer.Ml_stargazer(df, vars_predict)

test1.fit()

# predict
test2 = test1.predict()
test3 = test1.predict("df")

# predict_proba
test4 = test1.predict_prob()
test5 = test1.predict_prob("df")
```

```
/usr/local/lib/python3.10/dist-packages/astroquery/sdss/core.py:874:
VisibleDeprecationWarning: Reading unicode strings without specifying the
encoding argument is deprecated. Set the encoding, use None for the system
default.
  arr = np.atleast_1d(np.genfromtxt(io.BytesIO(response.content),
```

[23]:
```
# prediction results as an array : classification predictions for each objid
test2
```

[23]:
```
array([2, 2, 1, 2, 2, 3, 1, 2, 2, 2, 1, 1, 1, 1])
```

[24]:
```
# same results as test2, but with "df" option, predict() returned an augmented␣
↪df with the predictions for each objid/row
test3.head
```

[24]:
```
<bound method NDFrame.head of                specobjid        ra       dec
z      zerr  plate  \
0   5333439080460951552  150.15146  2.114508  0.360811  0.000071   4737
1   5333441279484207104  150.15839  2.139557  1.806560  0.000217   4737
2   5333450350455136256  150.01425  2.123165  0.674894  0.000264   4737
3   5333440179972579328  150.10200  2.105460  2.288163  0.000201   4737
4   5333439355338858496  150.19896  2.132502  2.159098  0.000397   4737
5   3551219228948406272  150.03183  2.153030  0.000040  0.000013   3154
6   3551132367529811968  150.05767  2.103981  0.000143  0.000008   3154
7    564181993697339392  150.17974  2.110343  0.360109  0.000029    501
8    563102269235554304  150.19857  2.068522  0.185325  0.000033    500
9   5333439630216765440  150.19558  2.004407  1.918056  0.000742   4737
10   563102544113461248  150.09074  2.000002  0.219072  0.000039    500
11   563091274119276544  150.01336  2.029592  0.078522  0.000015    500
12   563102818991368192  150.05890  2.015155  2.497976  0.000200    500
13   564152581761296384  150.06041  2.006675  0.078554  0.000007    501

    fiberID    mjd  petroMag_u  petroMag_g  petroMag_r  petroMag_i  \
0       186  55630    22.26150    21.13026    19.32598    18.68287
1       194  55630    21.18538    20.74569    20.49621    20.63431
2       227  55630    22.87838    22.36625    21.39553    19.66856
3       190  55630    19.82726    19.30193    19.47647    19.50085
4       187  55630    19.79120    19.40157    19.36555    19.28410
5       476  54821    20.35766    19.18459    18.74906    18.61069
6       160  54821    20.78134    18.55424    17.71245    17.43136
7       386  52235    20.07983    19.64067    18.81063    18.55703
8       554  51994    20.36330    18.64462    17.48873    16.96234
9       188  55630    20.91766    20.55293    20.35970    20.42793
10      555  51994    29.04465    20.01676    17.57881    17.38373
11      514  51994    19.21918    16.86890    16.10585    15.63760
12      556  51994    20.57218    20.05057    19.76336    19.91281
13      279  52235    19.45869    18.24650    17.39133    17.07116

    petroMag_z  predict
0     18.17070        2
1     21.78856        2
2     19.30286        1
3     19.51974        2
4     18.83935        2
5     18.52880        3
6     17.28338        1
7     18.20124        2
8     16.50139        2
9     21.09297        2
10    18.27225        1
11    15.34091        1
12    19.57255        1
```

```
13    17.10035        1  >
```

[25]:
```python
# prediction results as an array : classification probabilities for each objid
test4
```

[25]:
```
array([[1.24459143e-07, 9.80114265e-01, 1.98856103e-02],
       [2.00232952e-09, 5.01031774e-01, 4.98968224e-01],
       [4.99892159e-01, 2.15697293e-04, 4.99892144e-01],
       [4.40243187e-02, 7.89101983e-01, 1.66873698e-01],
       [2.31155326e-13, 9.30136797e-01, 6.98632026e-02],
       [4.99707022e-01, 5.80700291e-04, 4.99712278e-01],
       [4.71573348e-01, 6.91180520e-02, 4.59308600e-01],
       [1.40967047e-10, 9.99891303e-01, 1.08697249e-04],
       [2.22506004e-11, 1.00000000e+00, 4.04687331e-13],
       [3.85885430e-09, 9.99999996e-01, 2.64438108e-24],
       [5.00323451e-01, 4.99676549e-01, 1.15247646e-19],
       [9.86721268e-01, 1.32787314e-02, 6.52808487e-10],
       [5.39345578e-01, 4.60654422e-01, 3.25737332e-15],
       [5.24498783e-01, 4.75501217e-01, 8.26990131e-17]])
```

[26]:
```python
# same results as test4, but as an augmented df (due to "df" option in␣
↪predict_proba())
test5.head
```

[26]:
```
<bound method NDFrame.head of                specobjid         ra       dec
z      zerr  plate  \
0   5333439080460951552  150.15146  2.114508  0.360811  0.000071   4737
1   5333441279484207104  150.15839  2.139557  1.806560  0.000217   4737
2   5333450350455136256  150.01425  2.123165  0.674894  0.000264   4737
3   5333440179972579328  150.10200  2.105460  2.288163  0.000201   4737
4   5333439355338858496  150.19896  2.132502  2.159098  0.000397   4737
5   3551219228948406272  150.03183  2.153030  0.000040  0.000013   3154
6   3551132367529811968  150.05767  2.103981  0.000143  0.000008   3154
7    564181993697339392  150.17974  2.110343  0.360109  0.000029    501
8    563102269235554304  150.19857  2.068522  0.185325  0.000033    500
9   5333439630216765440  150.19558  2.004407  1.918056  0.000742   4737
10   563102544113461248  150.09074  2.000002  0.219072  0.000039    500
11   563091274119276544  150.01336  2.029592  0.078522  0.000015    500
12   563102818991368192  150.05890  2.015155  2.497976  0.000200    500
13   564152581761296384  150.06041  2.006675  0.078554  0.000007    501

    fiberID    mjd  petroMag_u  petroMag_g  petroMag_r  petroMag_i  \
0       186  55630    22.26150    21.13026    19.32598    18.68287
1       194  55630    21.18538    20.74569    20.49621    20.63431
2       227  55630    22.87838    22.36625    21.39553    19.66856
3       190  55630    19.82726    19.30193    19.47647    19.50085
4       187  55630    19.79120    19.40157    19.36555    19.28410
```

```
5        476  54821    20.35766    19.18459    18.74906    18.61069
6        160  54821    20.78134    18.55424    17.71245    17.43136
7        386  52235    20.07983    19.64067    18.81063    18.55703
8        554  51994    20.36330    18.64462    17.48873    16.96234
9        188  55630    20.91766    20.55293    20.35970    20.42793
10       555  51994    29.04465    20.01676    17.57881    17.38373
11       514  51994    19.21918    16.86890    16.10585    15.63760
12       556  51994    20.57218    20.05057    19.76336    19.91281
13       279  52235    19.45869    18.24650    17.39133    17.07116

    petroMag_z        p_STAR  p_GALAXY         p_QSO
0     18.17070  1.244591e-07  0.980114  1.988561e-02
1     21.78856  2.002330e-09  0.501032  4.989682e-01
2     19.30286  4.998922e-01  0.000216  4.998921e-01
3     19.51974  4.402432e-02  0.789102  1.668737e-01
4     18.83935  2.311553e-13  0.930137  6.986320e-02
5     18.52880  4.997070e-01  0.000581  4.997123e-01
6     17.28338  4.715733e-01  0.069118  4.593086e-01
7     18.20124  1.409670e-10  0.999891  1.086972e-04
8     16.50139  2.225060e-11  1.000000  4.046873e-13
9     21.09297  3.858854e-09  1.000000  2.644381e-24
10    18.27225  5.003235e-01  0.499677  1.152476e-19
11    15.34091  9.867213e-01  0.013279  6.528085e-10
12    19.57255  5.393456e-01  0.460654  3.257373e-15
13    17.10035  5.244988e-01  0.475501  8.269901e-17  >
```

1.6 Spectrum Alignment Module

[ ]:
```python
from cs107stargazers.spectrumalignment import SpectrumAlignment
```

This module is used for aligning spectra based on their wavlength ranges.

get_df: Creates a nock datafarme using pandas.Dataframe with predefined values for Flux and Loglam columns.

test_common_range_creation: Tests the creation of common wavelength range. Creates a SpectrumAlignment instance using MockQuery. Defines mock dict spectra_data containing the wavelength and flux values for 2 spectra. Calls the _create_common_range with the mock data then asserts the common_range of the SpectrumAlignment instance is a np array with at least one element.

test_interpolate_spectrum: Tests the interpolation of a spectrum onto the common range. Creates SpectrumAlignment instances using MockQuery. Defines

[ ]:
```python
# Create a SpectrumAlignment object instance
spectral_alignment_object = SpectrumAlignment(df)

# Some spectra data
spectra_data = {
```

```
    'spectrum_1': {'wavelengths': np.array([400, 500, 600]), 'flux_values': np.
 ↪array([0.5, 0.8, 1.2])},
    'spectrum_2': {'wavelengths': np.array([410, 520, 630]), 'flux_values': np.
 ↪array([0.6, 0.9, 1.4])}
    # Add more spectra data as needed for testing
}
# Creation of a common range of wavelengths
spectral_alignment_object._create_common_range(spectra_data)

# Print the common range of wavelenghts
spectral_alignment_object.common_range
```

[ ]:
```
array([400, 401, 402, 403, 404, 405, 406, 407, 408, 409, 410, 411, 412,
       413, 414, 415, 416, 417, 418, 419, 420, 421, 422, 423, 424, 425,
       426, 427, 428, 429, 430, 431, 432, 433, 434, 435, 436, 437, 438,
       439, 440, 441, 442, 443, 444, 445, 446, 447, 448, 449, 450, 451,
       452, 453, 454, 455, 456, 457, 458, 459, 460, 461, 462, 463, 464,
       465, 466, 467, 468, 469, 470, 471, 472, 473, 474, 475, 476, 477,
       478, 479, 480, 481, 482, 483, 484, 485, 486, 487, 488, 489, 490,
       491, 492, 493, 494, 495, 496, 497, 498, 499, 500, 501, 502, 503,
       504, 505, 506, 507, 508, 509, 510, 511, 512, 513, 514, 515, 516,
       517, 518, 519, 520, 521, 522, 523, 524, 525, 526, 527, 528, 529,
       530, 531, 532, 533, 534, 535, 536, 537, 538, 539, 540, 541, 542,
       543, 544, 545, 546, 547, 548, 549, 550, 551, 552, 553, 554, 555,
       556, 557, 558, 559, 560, 561, 562, 563, 564, 565, 566, 567, 568,
       569, 570, 571, 572, 573, 574, 575, 576, 577, 578, 579, 580, 581,
       582, 583, 584, 585, 586, 587, 588, 589, 590, 591, 592, 593, 594,
       595, 596, 597, 598, 599, 600, 601, 602, 603, 604, 605, 606, 607,
       608, 609, 610, 611, 612, 613, 614, 615, 616, 617, 618, 619, 620,
       621, 622, 623, 624, 625, 626, 627, 628, 629, 630])
```

[ ]:
```
# Mock wavelengths and flux values
wavelengths = np.array([400, 500, 600])
flux_values = np.array([0.5, 0.8, 1.2])

# Spectrum interpolation
aligned_flux_values = spectral_alignment_object.
 ↪_interpolate_spectrum(wavelengths, flux_values)

# Print the aligned flux values
aligned_flux_values
```

[ ]:
```
array([0.5  , 0.503, 0.506, 0.509, 0.512, 0.515, 0.518, 0.521, 0.524,
       0.527, 0.53 , 0.533, 0.536, 0.539, 0.542, 0.545, 0.548, 0.551,
       0.554, 0.557, 0.56 , 0.563, 0.566, 0.569, 0.572, 0.575, 0.578,
       0.581, 0.584, 0.587, 0.59 , 0.593, 0.596, 0.599, 0.602, 0.605,
       0.608, 0.611, 0.614, 0.617, 0.62 , 0.623, 0.626, 0.629, 0.632,
```

```
0.635, 0.638, 0.641, 0.644, 0.647, 0.65 , 0.653, 0.656, 0.659,
0.662, 0.665, 0.668, 0.671, 0.674, 0.677, 0.68 , 0.683, 0.686,
0.689, 0.692, 0.695, 0.698, 0.701, 0.704, 0.707, 0.71 , 0.713,
0.716, 0.719, 0.722, 0.725, 0.728, 0.731, 0.734, 0.737, 0.74 ,
0.743, 0.746, 0.749, 0.752, 0.755, 0.758, 0.761, 0.764, 0.767,
0.77 , 0.773, 0.776, 0.779, 0.782, 0.785, 0.788, 0.791, 0.794,
0.797, 0.8  , 0.804, 0.808, 0.812, 0.816, 0.82 , 0.824, 0.828,
0.832, 0.836, 0.84 , 0.844, 0.848, 0.852, 0.856, 0.86 , 0.864,
0.868, 0.872, 0.876, 0.88 , 0.884, 0.888, 0.892, 0.896, 0.9  ,
0.904, 0.908, 0.912, 0.916, 0.92 , 0.924, 0.928, 0.932, 0.936,
0.94 , 0.944, 0.948, 0.952, 0.956, 0.96 , 0.964, 0.968, 0.972,
0.976, 0.98 , 0.984, 0.988, 0.992, 0.996, 1.   , 1.004, 1.008,
1.012, 1.016, 1.02 , 1.024, 1.028, 1.032, 1.036, 1.04 , 1.044,
1.048, 1.052, 1.056, 1.06 , 1.064, 1.068, 1.072, 1.076, 1.08 ,
1.084, 1.088, 1.092, 1.096, 1.1  , 1.104, 1.108, 1.112, 1.116,
1.12 , 1.124, 1.128, 1.132, 1.136, 1.14 , 1.144, 1.148, 1.152,
1.156, 1.16 , 1.164, 1.168, 1.172, 1.176, 1.18 , 1.184, 1.188,
1.192, 1.196, 1.2  , 1.2  , 1.2  , 1.2  , 1.2  , 1.2  , 1.2  ,
1.2  , 1.2  , 1.2  , 1.2  , 1.2  , 1.2  , 1.2  , 1.2  , 1.2  ,
1.2  , 1.2  , 1.2  , 1.2  , 1.2  , 1.2  , 1.2  , 1.2  , 1.2  ,
1.2  , 1.2  , 1.2  , 1.2  , 1.2  , 1.2  ])
```

1.7 Visualization Module

[ ]:
```python
from cs107stargazers import visualization
```

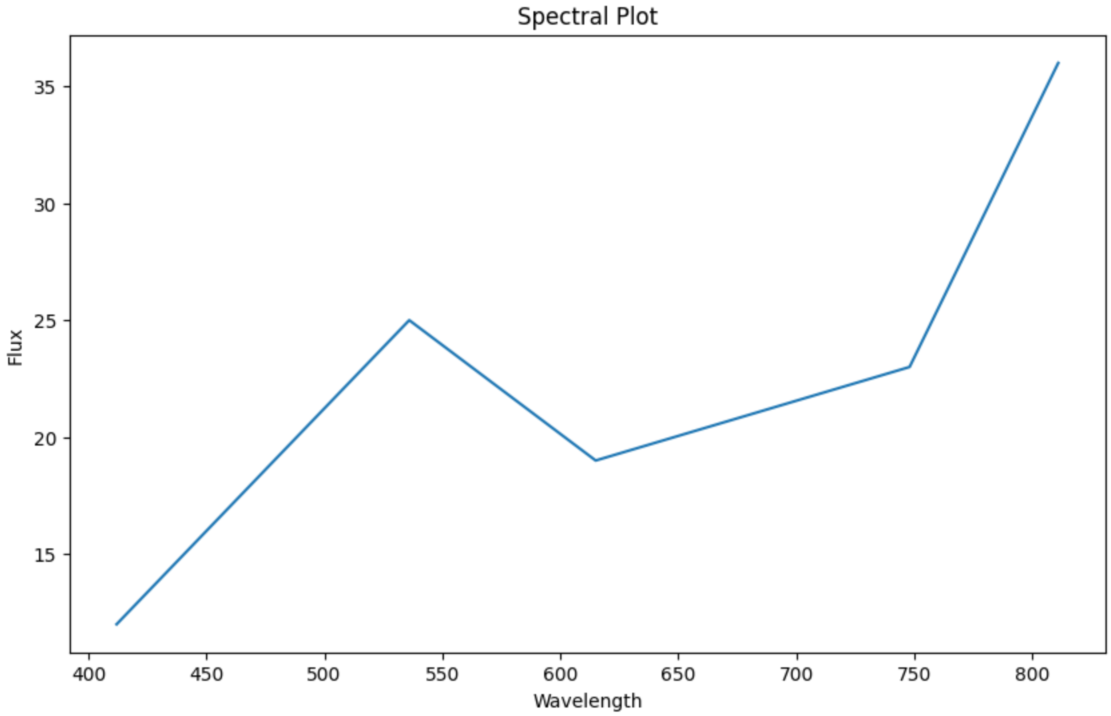
spectralplot method: We created a basic spectral plot using matplotlib. It assumes that the data passed to the class has ‘wavelength’ and ‘flux’ columns. The plt.figure(figsize=(10, 6)) line sets the size of the plot. The plt.plot(self.data[‘wavelength’], self.data[‘flux’]) line plots the spectral data. The remaining lines set labels and a title for the plot. plt.show() displays the plot.

ic_overlay method: This method creates a spectral plot with an overlay of an inferred continuum. It assumes the existence of an ‘inferred_continuum’ column in the data. Similar to spectralplot, it sets the size of the plot using plt.figure(figsize=(10, 6)). It then plots both the spectral data and the inferred continuum on the same plot using plt.plot. plt.show() is called to display the plot.

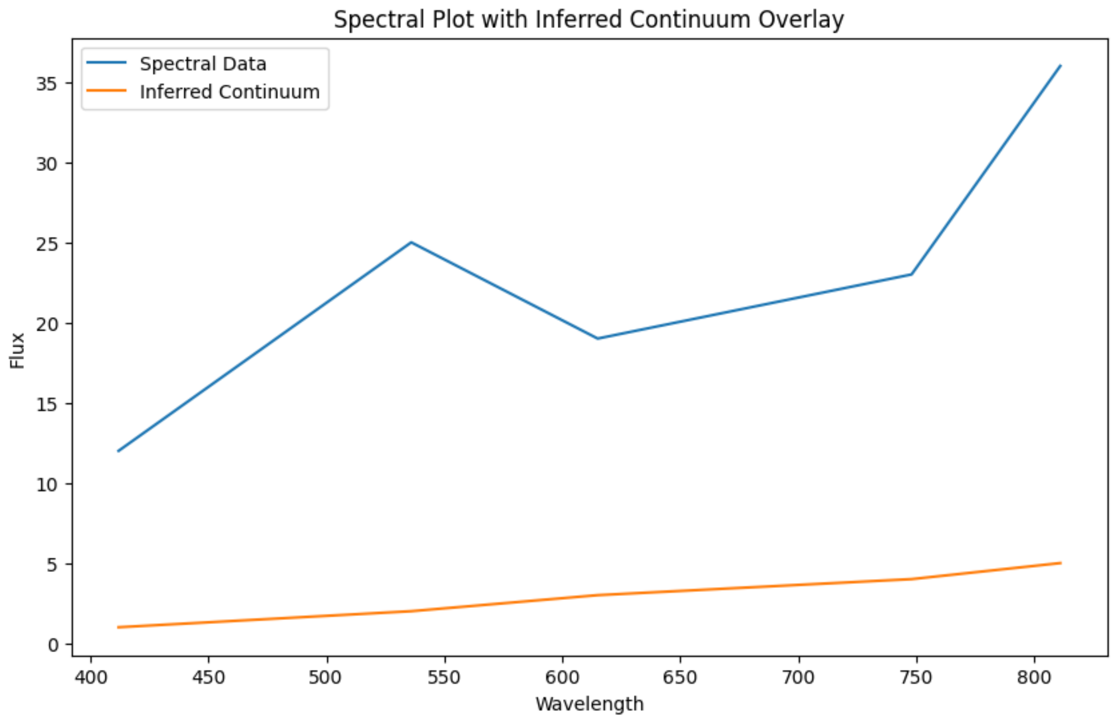
[ ]:
```python
# Sample data
df = pd.DataFrame({
        "wavelength": [412, 536, 615, 748, 811],
        "flux": [12, 25, 19, 23, 36],
        "inferred_continuum": [1, 2, 3, 4, 5]
    })


# Create instance of SDSSVis
visualization_object = visualization.SDSSVis(df)
```

[ ]:
```python
# Call `spectralplot` method
visualization_object.spectralplot()
```



[ ]:
```python
# Call `ic_overlay()` method
visualization_object.ic_overlay()
```


Spectral Plot with Inferred Continuum Overlay
Spectral Data
Inferred Continuum
Flux
Wavelength
0
5
10
15
20
25
30
35
400
450
500
550
600
650
700
750
800