

# Exploratory analysis

March 18, 2021

```
[91]: %reload_ext autoreload
      %autoreload 2
      default_figsize=(14,12)
```

```
[92]: import datasets
      import numpy as np
      import pandas as pd
      import seaborn as sn
      import matplotlib.pyplot as plt
      import matplotlib
      matplotlib.rcParams['figure.figsize'] = (14, 12)

      dataset_name = "mcswain"
      dataset_module = datasets.datasets_by_name_all[dataset_name]
      x,y,metadata = dataset_module.load(dropna=True,verbose=True)
      y = datasets.map_y_em(y,dataset_name)

      # generate dataframe with both x and y
      xy = pd.concat([x,y],axis=1)
      xy.describe()
```

Warning loading data from McSwain2005-2009\_VPHAS-2MASS.csv:  
Dropped 2313 rows with missing values.  
Rows (original): 5455  
Rows (after drop): 3142

```
[92]:
```

	umag	gmag	rmag	imag	Hamag	\
count	3142.000000	3142.000000	3142.000000	3142.000000	3142.000000	
mean	16.304806	15.668695	14.651512	14.076811	14.398883	
std	1.572447	1.225343	1.047182	1.035455	1.041201	
min	12.260000	12.530000	11.990000	11.450000	11.690000	
25%	15.150000	14.722500	13.842500	13.260000	13.580000	
50%	16.445000	15.740000	14.700000	14.100000	14.435000	
75%	17.337500	16.650000	15.510000	14.900000	15.250000	
max	20.840000	19.050000	17.500000	17.090000	17.170000	

	Jmag	Hmag	Kmag	em
count	3142.000000	3142.000000	3142.000000	3142.000000

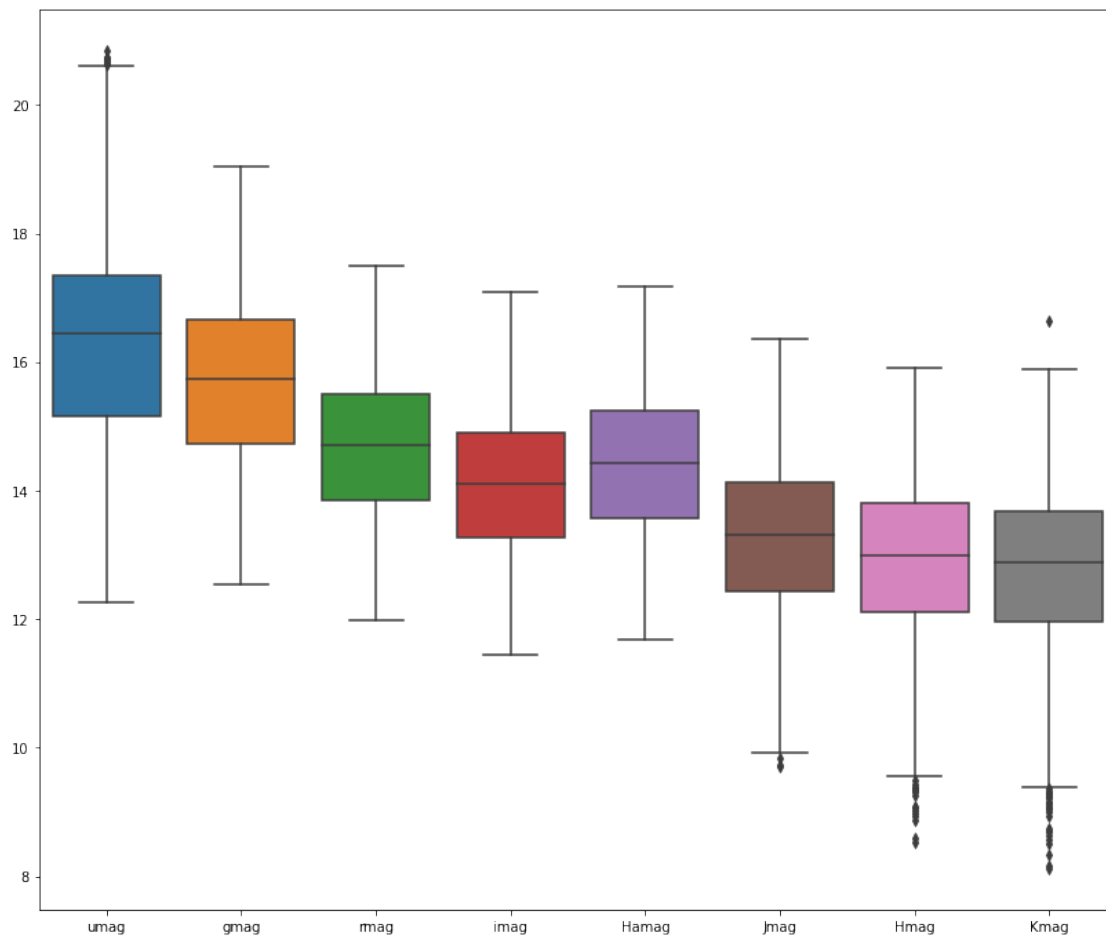
mean	13.248104	12.876838	12.739313	0.001591
std	1.128721	1.221364	1.259059	0.039866
min	9.700000	8.521000	8.118000	0.000000
25%	12.434000	12.101000	11.957000	0.000000
50%	13.306000	13.000000	12.876000	0.000000
75%	14.126750	13.801000	13.682000	0.000000
max	16.368000	15.912000	16.631000	1.000000

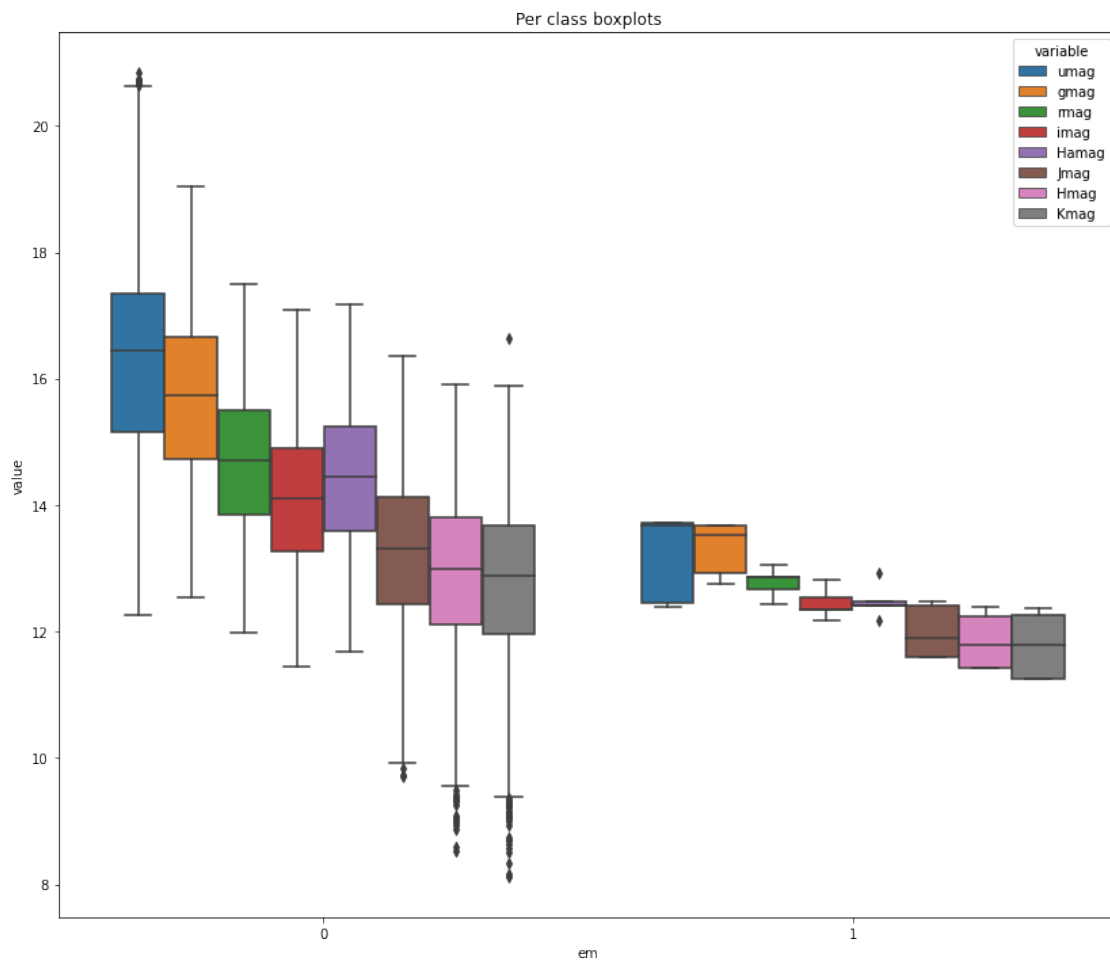
## 1 Variable visualization

```
[93]: sn.boxplot(data=x)

plt.figure()
xy_long = pd.melt(xy, id_vars='em')
sn.boxplot(x='em', y='value', hue='variable', data=xy_long)
plt.title("Per class boxplots")
```

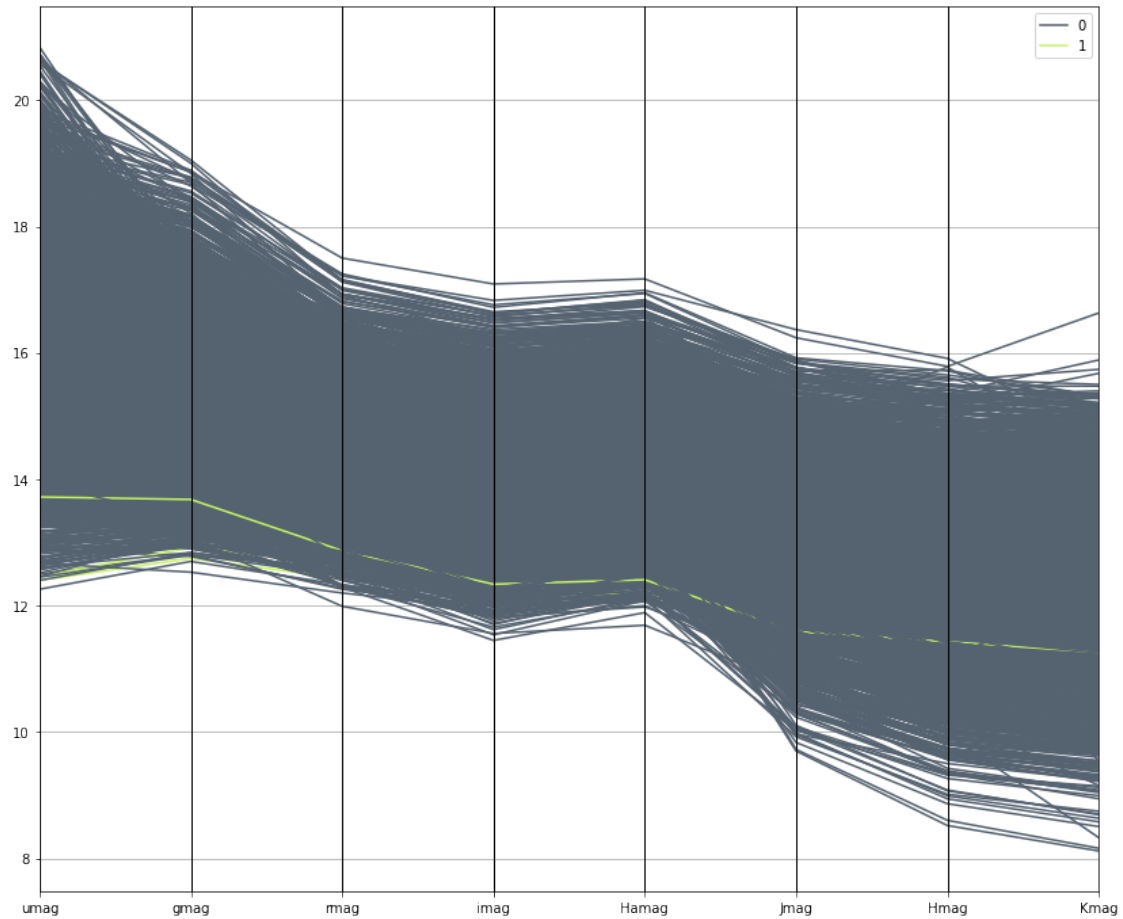
[93]: Text(0.5, 1.0, 'Per class boxplots')





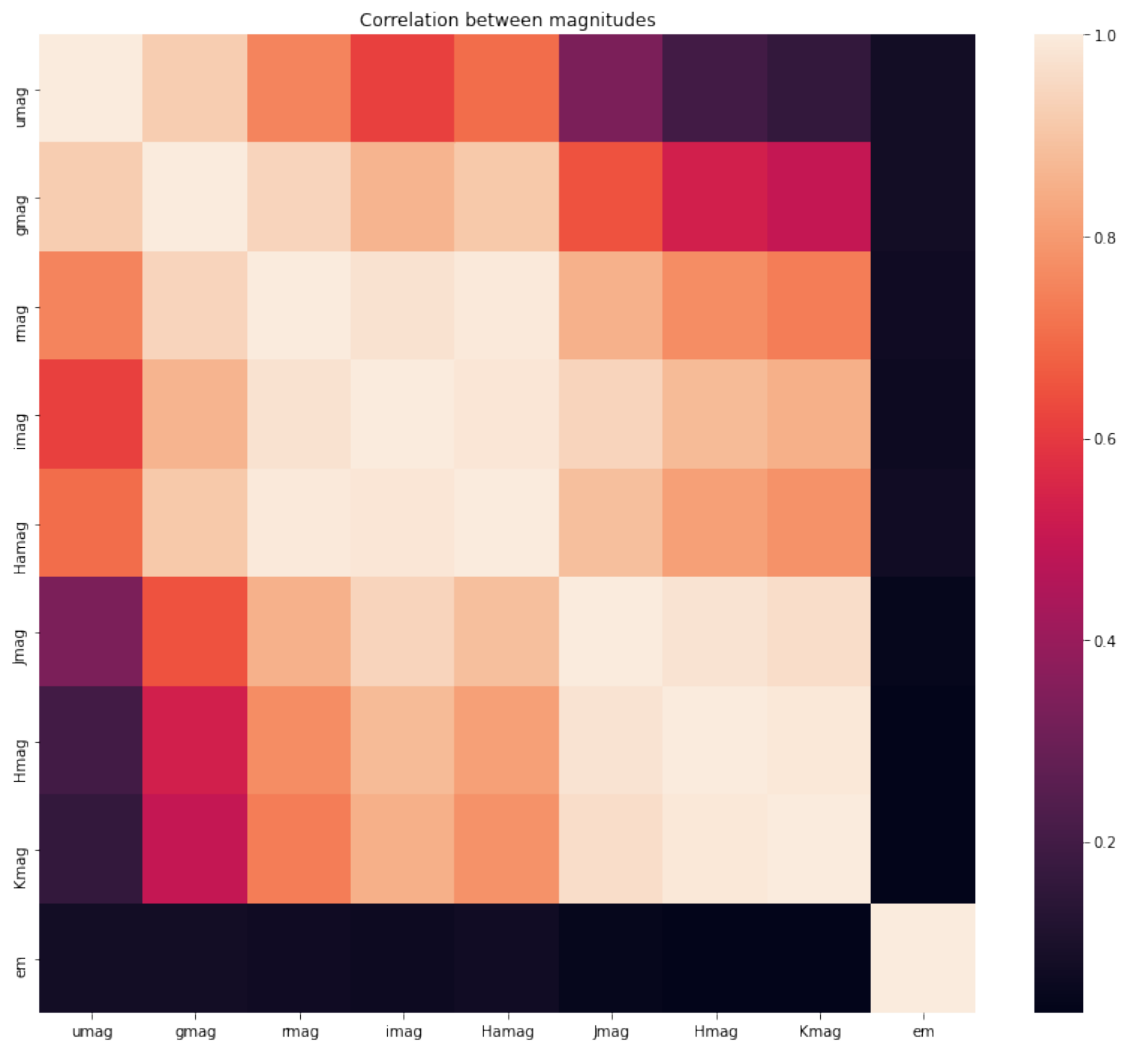
```
[94]: pd.plotting.parallel_coordinates(xy,"em",color=('#556270','#C7F464'))
```

```
[94]: <AxesSubplot:>
```

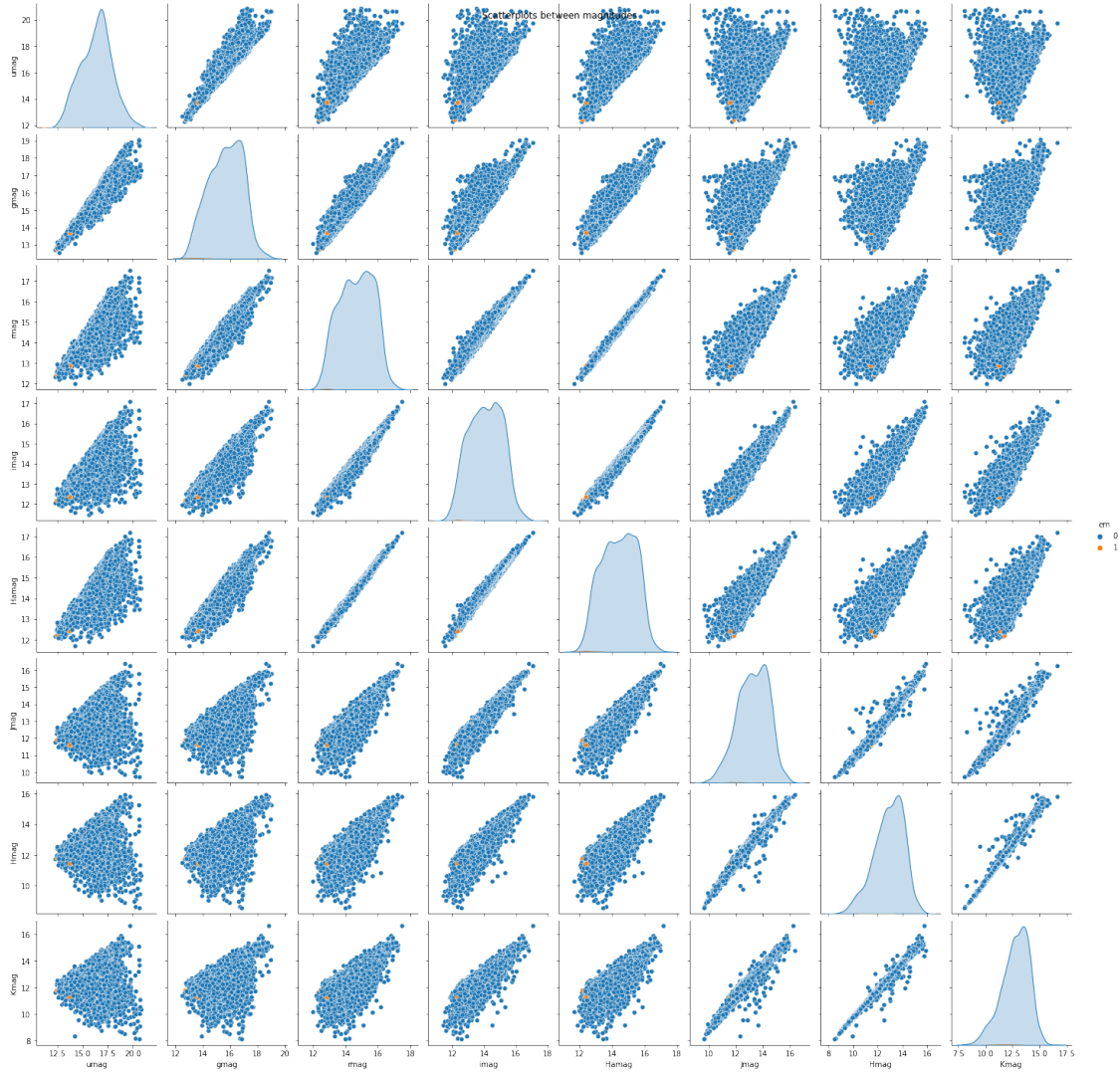


```
[95]: sn.heatmap(xy.corr().abs())
plt.title("Correlation between magnitudes")
plt.show()

sn.pairplot(xy,hue="em")
plt.suptitle("Scatterplots between magnitudes")
# axes=pd.plotting.scatter_matrix(x,c=y["em"],alpha=0.
  ↳9,grid=False,figsize=(14,12))
```



[95]: Text(0.5, 0.98, 'Scatterplots between magnitudes')



## 2 Outlier detection via confidence interval

```
[96]: from scipy import stats
m = len(x.columns) # number of columns = number of hypothesis
confidence= 0.98
adjusted_confidence = 1- (1-confidence)/m # bonferroni-adjusted confidence
max_zscore = stats.norm.ppf(adjusted_confidence)
print(f"Confidence (desired): {confidence}")
print(f"Confidence (adjusted): {adjusted_confidence}")
print(f"Z-score (adjusted): {max_zscore}")

indices = (np.abs(stats.zscore(x-x.mean())) > max_zscore).any(axis=1)
outliers_x = x[indices]
```

```

if dataset_name != "all_em":
    outliers_metadata = metadata[indices]
    outliers_x = outliers_x.
    ↪merge(outliers_metadata,left_index=True,right_index=True)
outliers_x

```

Confidence (desired): 0.98  
 Confidence (adjusted): 0.9975  
 Z-score (adjusted): 2.807033768343811

[96]:

	umag	gmag	rmag	imag	Hamag	Jmag	Hmag	Kmag	Rad	\
240	19.72	18.86	17.50	17.09	17.17	16.239	15.786	16.631	NaN	
1272	16.87	14.44	12.51	11.62	12.13	9.924	9.015	8.747	NaN	
1345	18.19	15.56	13.42	12.18	12.96	10.290	9.387	9.042	NaN	
1462	19.19	15.99	13.72	12.08	13.14	9.836	8.866	8.505	NaN	
1533	20.84	17.27	14.97	13.54	14.47	11.570	10.644	10.342	NaN	
1539	20.73	17.59	15.46	14.16	15.01	12.216	11.319	11.070	NaN	
1570	16.64	14.45	12.64	11.76	12.22	10.061	9.265	8.993	NaN	
1836	20.73	17.62	15.27	13.97	14.77	11.809	10.792	10.536	NaN	
1967	20.71	16.97	14.51	12.96	13.92	10.553	9.426	9.080	NaN	
1994	18.69	15.60	13.52	12.09	13.01	10.053	9.082	8.692	NaN	
2163	20.27	16.75	14.24	12.35	13.66	9.725	8.603	8.161	NaN	
2415	15.63	13.97	12.29	11.45	11.89	10.025	9.318	9.145	NaN	
2437	17.55	14.91	12.91	11.91	12.47	10.235	9.362	9.122	NaN	
2463	16.69	14.61	12.67	11.70	12.25	10.084	9.333	9.075	NaN	
2483	14.21	13.95	13.34	12.93	13.15	12.348	9.971	8.329	NaN	
2661	18.26	15.52	13.27	12.22	12.79	10.289	9.340	9.070	NaN	
2678	15.84	14.97	13.10	11.84	12.66	9.967	9.502	9.238	NaN	
2683	18.88	15.78	13.35	12.23	12.90	9.957	8.990	8.636	NaN	
2699	16.36	16.05	15.11	14.53	14.80	13.671	10.260	9.155	NaN	
2718	20.66	16.88	14.00	12.59	13.46	9.700	8.521	8.118	NaN	
3015	20.29	16.89	14.10	12.64	13.60	10.106	9.070	8.703	NaN	
3028	20.14	16.66	14.01	12.48	13.43	9.984	8.943	8.580	NaN	
3102	20.42	16.94	14.25	12.54	13.67	10.398	9.341	8.945	NaN	

	_DEJ2000	...	Cluster	vsini	e_Hmag	e_rmag	e_Rad	e_y-Ha	\
240	-25.483167	...	Haffner 16	NaN	0.126	0.05	NaN	0.115	
1272	-57.660417	...	IC 2581	NaN	0.022	0.00	NaN	0.073	
1345	-5.765472	...	Basel 1	NaN	0.022	0.00	NaN	0.064	
1462	-5.966361	...	Basel 1	NaN	0.042	0.00	NaN	0.065	
1533	-5.886528	...	Basel 1	NaN	0.026	0.01	NaN	0.088	
1539	-5.854250	...	Basel 1	NaN	0.023	0.01	NaN	0.092	
1570	-58.287500	...	NGC 3293	NaN	0.023	0.00	NaN	0.064	
1836	-60.696194	...	Trumpler 20	NaN	0.021	0.00	NaN	0.101	
1967	-60.611472	...	Trumpler 20	NaN	0.022	0.00	NaN	0.075	
1994	-60.631167	...	Trumpler 20	NaN	0.025	0.01	NaN	0.067	
2163	-60.574639	...	Trumpler 20	NaN	0.018	0.01	NaN	0.072	

2415	-47.466806	...	NGC 6200	NaN	0.024	0.00	NaN	0.050
2437	-47.544444	...	NGC 6200	NaN	0.024	0.00	NaN	0.061
2463	-47.478972	...	NGC 6200	NaN	0.026	0.00	NaN	0.058
2483	-46.933944	...	NGC 6204	NaN	NaN	0.01	NaN	0.102
2661	-44.725972	...	NGC 6249	NaN	0.023	0.00	NaN	0.057
2678	-33.431944	...	Trumpler 27	NaN	0.024	0.00	NaN	0.092
2683	-32.467667	...	Trumpler 28	NaN	0.029	0.00	NaN	0.081
2699	-32.420083	...	Trumpler 28	NaN	NaN	0.00	NaN	0.091
2718	-32.443972	...	Trumpler 28	NaN	0.034	0.00	NaN	0.098
3015	-8.509889	...	Trumpler 34	NaN	0.023	0.00	NaN	0.047
3028	-8.389750	...	Trumpler 34	NaN	0.023	0.00	NaN	0.078
3102	-5.930500	...	Basel 1	NaN	0.022	0.01	NaN	0.084

	e_Kmag	_RAJ2000	SB?	e_gmag
240	NaN	117.481417	NaN	0.01
1272	0.021	157.007667	NaN	0.01
1345	0.024	282.029125	NaN	0.00
1462	0.021	282.104792	NaN	0.00
1533	0.025	282.153042	NaN	0.01
1539	0.023	282.156125	NaN	0.01
1570	0.019	158.856375	NaN	0.00
1836	0.023	189.831292	NaN	0.02
1967	0.020	189.910875	NaN	0.01
1994	0.018	189.925042	NaN	0.01
2163	0.029	190.020042	NaN	0.01
2415	0.025	250.958125	NaN	0.00
2437	0.023	251.046333	NaN	0.00
2463	0.023	251.131750	NaN	0.01
2483	NaN	251.693333	NaN	0.01
2661	0.020	254.576000	NaN	0.00
2678	0.023	264.084292	NaN	0.00
2683	0.026	264.121042	NaN	0.00
2699	NaN	264.186458	NaN	0.01
2718	0.031	264.235167	NaN	0.01
3015	0.020	280.074042	NaN	0.00
3028	0.023	280.084833	NaN	0.01
3102	0.021	281.981750	NaN	0.01

[23 rows x 43 columns]

### 3 Outlier detection via IQR

```
[97]: iqr_factor=1.5
      q25,q75=x.quantile(0.25),x.quantile(0.75)
      iqr=q75-q25
      min_values = q25-iqr_factor*iqr
```



```

max_values = q75+iqr_factor*iqr
# ou
indices = (np.logical_or(x<min_values,x>max_values)).any(axis=1)
outliers_x = x[indices]
if dataset_name != "all_em":
    outliers_metadata = metadata[indices]
    outliers_x = outliers_x.
    ↪merge(outliers_metadata,left_index=True,right_index=True)
outliers_x

```

```

[97]:
      umag  gmag  rmag  imag  Hamag  Jmag  Hmag  Kmag  Rad  \
165   19.95  16.73  14.29  12.98  13.77  10.709  9.637  9.278  NaN
235   18.90  16.00  13.75  12.54  13.20  10.597  9.569  9.236  NaN
240   19.72  18.86  17.50  17.09  17.17  16.239  15.786  16.631  NaN
256   20.66  18.69  16.47  15.72  16.01  14.595  13.883  13.670  NaN
470   20.62  19.00  16.91  16.25  16.49  15.197  14.309  14.071  NaN
906   20.11  16.77  14.16  12.97  13.82  10.665  9.660  9.270  NaN
1272  16.87  14.44  12.51  11.62  12.13  9.924  9.015  8.747  NaN
1345  18.19  15.56  13.42  12.18  12.96  10.290  9.387  9.042  NaN
1395  19.78  16.67  14.23  12.84  13.77  10.572  9.561  9.217  NaN
1405  19.27  16.12  13.86  12.60  13.40  10.574  9.658  9.369  NaN
1462  19.19  15.99  13.72  12.08  13.14  9.836  8.866  8.505  NaN
1533  20.84  17.27  14.97  13.54  14.47  11.570  10.644  10.342  NaN
1539  20.73  17.59  15.46  14.16  15.01  12.216  11.319  11.070  NaN
1570  16.64  14.45  12.64  11.76  12.22  10.061  9.265  8.993  NaN
1577  15.15  14.38  12.88  12.04  12.51  10.323  9.570  9.301  NaN
1836  20.73  17.62  15.27  13.97  14.77  11.809  10.792  10.536  NaN
1967  20.71  16.97  14.51  12.96  13.92  10.553  9.426  9.080  NaN
1994  18.69  15.60  13.52  12.09  13.01  10.053  9.082  8.692  NaN
2163  20.27  16.75  14.24  12.35  13.66  9.725  8.603  8.161  NaN
2415  15.63  13.97  12.29  11.45  11.89  10.025  9.318  9.145  NaN
2437  17.55  14.91  12.91  11.91  12.47  10.235  9.362  9.122  NaN
2463  16.69  14.61  12.67  11.70  12.25  10.084  9.333  9.075  NaN
2483  14.21  13.95  13.34  12.93  13.15  12.348  9.971  8.329  NaN
2661  18.26  15.52  13.27  12.22  12.79  10.289  9.340  9.070  NaN
2674  16.20  14.57  12.89  11.99  12.51  10.388  9.647  9.247  NaN
2678  15.84  14.97  13.10  11.84  12.66  9.967  9.502  9.238  NaN
2683  18.88  15.78  13.35  12.23  12.90  9.957  8.990  8.636  NaN
2699  16.36  16.05  15.11  14.53  14.80  13.671  10.260  9.155  NaN
2713  16.57  14.70  12.85  12.04  12.47  10.359  9.581  9.304  NaN
2718  20.66  16.88  14.00  12.59  13.46  9.700  8.521  8.118  NaN
2750  18.60  15.82  13.67  12.50  13.21  10.497  9.607  9.329  NaN
3015  20.29  16.89  14.10  12.64  13.60  10.106  9.070  8.703  NaN
3027  20.69  17.51  14.94  13.62  14.48  11.284  10.356  10.017  NaN
3028  20.14  16.66  14.01  12.48  13.43  9.984  8.943  8.580  NaN
3102  20.42  16.94  14.25  12.54  13.67  10.398  9.341  8.945  NaN

```

	_DEJ2000	...	Cluster	vsini	e_Hmag	e_rmag	e_Rad	e_y-Ha	\
165	-20.711139	...	NGC 2421	NaN	0.022	0.00	NaN	0.069	
235	-20.649944	...	NGC 2421	NaN	0.024	0.00	NaN	0.064	
240	-25.483167	...	Haffner 16	NaN	0.126	0.05	NaN	0.115	
256	-25.517722	...	Haffner 16	NaN	0.022	0.01	NaN	0.089	
470	-25.544778	...	Haffner 16	NaN	NaN	0.01	NaN	0.099	
906	-53.920361	...	Ruprecht 79	NaN	0.022	0.00	NaN	0.077	
1272	-57.660417	...	IC 2581	NaN	0.022	0.00	NaN	0.073	
1345	-5.765472	...	Basel 1	NaN	0.022	0.00	NaN	0.064	
1395	-5.913583	...	Basel 1	NaN	0.027	0.01	NaN	0.073	
1405	-5.772222	...	Basel 1	NaN	0.021	0.00	NaN	0.071	
1462	-5.966361	...	Basel 1	NaN	0.042	0.00	NaN	0.065	
1533	-5.886528	...	Basel 1	NaN	0.026	0.01	NaN	0.088	
1539	-5.854250	...	Basel 1	NaN	0.023	0.01	NaN	0.092	
1570	-58.287500	...	NGC 3293	NaN	0.023	0.00	NaN	0.064	
1577	-58.192194	...	NGC 3293	NaN	0.028	0.00	NaN	0.057	
1836	-60.696194	...	Trumpler 20	NaN	0.021	0.00	NaN	0.101	
1967	-60.611472	...	Trumpler 20	NaN	0.022	0.00	NaN	0.075	
1994	-60.631167	...	Trumpler 20	NaN	0.025	0.01	NaN	0.067	
2163	-60.574639	...	Trumpler 20	NaN	0.018	0.01	NaN	0.072	
2415	-47.466806	...	NGC 6200	NaN	0.024	0.00	NaN	0.050	
2437	-47.544444	...	NGC 6200	NaN	0.024	0.00	NaN	0.061	
2463	-47.478972	...	NGC 6200	NaN	0.026	0.00	NaN	0.058	
2483	-46.933944	...	NGC 6204	NaN	NaN	0.01	NaN	0.102	
2661	-44.725972	...	NGC 6249	NaN	0.023	0.00	NaN	0.057	
2674	-35.635611	...	Bochum 13	NaN	0.030	0.00	NaN	0.093	
2678	-33.431944	...	Trumpler 27	NaN	0.024	0.00	NaN	0.092	
2683	-32.467667	...	Trumpler 28	NaN	0.029	0.00	NaN	0.081	
2699	-32.420083	...	Trumpler 28	NaN	NaN	0.00	NaN	0.091	
2713	-32.481056	...	Trumpler 28	NaN	0.026	0.00	NaN	0.060	
2718	-32.443972	...	Trumpler 28	NaN	0.034	0.00	NaN	0.098	
2750	-32.552806	...	Trumpler 28	NaN	0.025	0.00	NaN	0.068	
3015	-8.509889	...	Trumpler 34	NaN	0.023	0.00	NaN	0.047	
3027	-8.526639	...	Trumpler 34	NaN	0.024	0.00	NaN	0.065	
3028	-8.389750	...	Trumpler 34	NaN	0.023	0.00	NaN	0.078	
3102	-5.930500	...	Basel 1	NaN	0.022	0.01	NaN	0.084	

	e_Kmag	_RAJ2000	SB?	e_gmag
165	0.021	114.083458	NaN	0.00
235	0.019	114.173500	NaN	0.00
240	NaN	117.481417	NaN	0.01
256	0.043	117.495292	NaN	0.01
470	NaN	117.722875	NaN	0.01
906	0.023	145.126708	NaN	0.01
1272	0.021	157.007667	NaN	0.01
1345	0.024	282.029125	NaN	0.00
1395	0.021	282.059333	NaN	0.01

1405	0.019	282.067375	NaN	0.00
1462	0.021	282.104792	NaN	0.00
1533	0.025	282.153042	NaN	0.01
1539	0.023	282.156125	NaN	0.01
1570	0.019	158.856375	NaN	0.00
1577	0.026	159.009542	NaN	0.00
1836	0.023	189.831292	NaN	0.02
1967	0.020	189.910875	NaN	0.01
1994	0.018	189.925042	NaN	0.01
2163	0.029	190.020042	NaN	0.01
2415	0.025	250.958125	NaN	0.00
2437	0.023	251.046333	NaN	0.00
2463	0.023	251.131750	NaN	0.01
2483	NaN	251.693333	NaN	0.01
2661	0.020	254.576000	NaN	0.00
2674	0.027	259.347000	NaN	0.00
2678	0.023	264.084292	NaN	0.00
2683	0.026	264.121042	NaN	0.00
2699	NaN	264.186458	NaN	0.01
2713	0.023	264.221958	NaN	0.00
2718	0.031	264.235167	NaN	0.01
2750	0.023	264.319042	NaN	0.00
3015	0.020	280.074042	NaN	0.00
3027	0.023	280.084708	NaN	0.01
3028	0.023	280.084833	NaN	0.01
3102	0.021	281.981750	NaN	0.01

[35 rows x 43 columns]

## 4 Analysis of q-features ( $q_3$ ) (all magnitudes)

```
[98]: x_np=x.to_numpy()
import qfeatures
coefficients = dataset_module.coefficients
systems = dataset_module.systems
coefficients_np = np.array([coefficients[k] for k in x.columns])
systems = [systems[k] for k in x.columns]
q=qfeatures.calculate(x_np,coefficients_np,x.columns,systems,combination_size=3)
m = q.magnitudes

q_df = pd.DataFrame(m, columns = q.column_names)
q_df.describe()
```

```
[98]:          umag_gmag_rmag  umag_gmag_imag  umag_gmag_Hmag  umag_gmag_Jmag  \
count          3142.000000          3142.000000          3142.000000          3142.000000
mean             0.156141           -0.378599           -0.010663           -3.028395
```

std	0.477268	0.333868	0.437317	0.940956
min	-0.759654	-1.321813	-0.903692	-7.115069
25%	-0.126526	-0.615351	-0.282897	-3.564993
50%	0.016104	-0.469503	-0.131121	-2.951368
75%	0.231807	-0.232851	0.094217	-2.415524
max	2.579221	1.192398	2.186495	-0.466389

	umag_gmag_Hmag	umag_gmag_Kmag	umag_rmag_imag	umag_rmag_Hmag	\
count	3142.000000	3142.000000	3142.000000	3142.000000	
mean	-5.979377	-9.798617	0.954243	1.407748	
std	2.229224	3.864487	0.827491	0.977587	
min	-16.027196	-27.431046	-0.711111	-0.596636	
25%	-7.162250	-11.795907	0.425526	0.813995	
50%	-5.624293	-9.041667	0.664269	1.106449	
75%	-4.540071	-7.278962	1.343070	1.737780	
max	-0.952413	-1.686405	4.944912	6.135140	

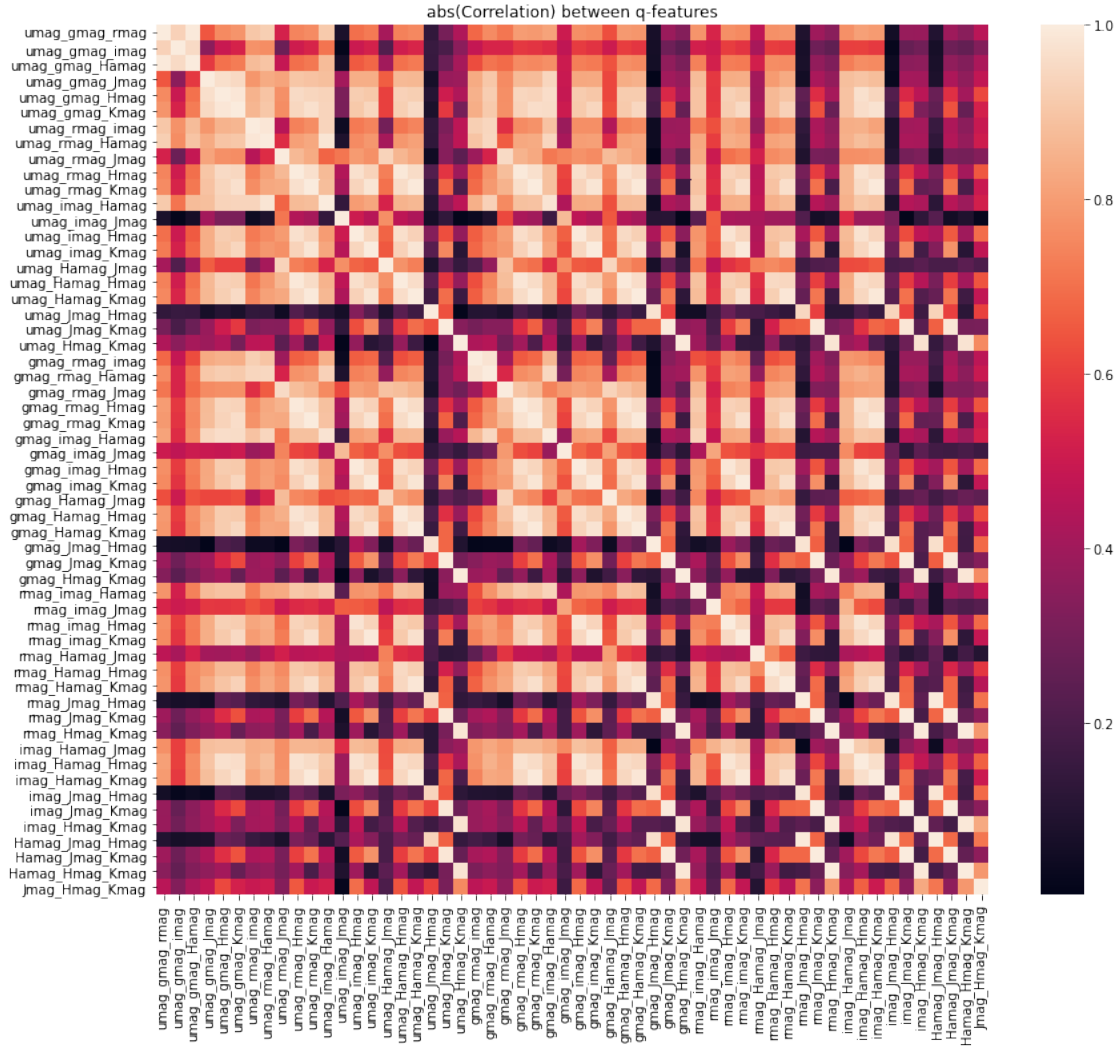
	umag_rmag_Jmag	umag_rmag_Hmag	...	imag_Hmag_Jmag	imag_Hmag_Hmag	\
count	3142.000000	3142.000000	...	3142.000000	3142.000000	
mean	-2.400995	-6.371318	...	0.365199	1.100709	
std	0.870262	2.649514	...	0.184691	0.539457	
min	-7.689333	-21.841478	...	-0.028903	0.046913	
25%	-2.914667	-7.681826	...	0.241431	0.755772	
50%	-2.415333	-5.949609	...	0.319889	0.973728	
75%	-1.835278	-4.581130	...	0.463094	1.322918	
max	0.383778	-0.032348	...	1.375556	4.200283	

	imag_Hmag_Kmag	imag_Jmag_Hmag	imag_Jmag_Kmag	imag_Hmag_Kmag	\
count	3142.000000	3142.000000	3142.000000	3142.000000	
mean	2.010004	0.029678	-0.817382	0.638187	
std	0.976299	0.406704	0.884542	0.772481	
min	0.031895	-6.482065	-13.751588	-11.218902	
25%	1.366315	-0.095897	-1.125529	0.350629	
50%	1.780310	0.037130	-0.677735	0.625464	
75%	2.436038	0.174163	-0.364721	0.986067	
max	7.662516	4.936783	4.142765	7.507065	

	Hamag_Jmag_Hmag	Hamag_Jmag_Kmag	Hamag_Hmag_Kmag	Jmag_Hmag_Kmag	
count	3142.000000	3142.000000	3142.000000	3142.000000	
mean	0.004697	-1.210278	0.767005	0.254415	
std	0.581073	1.279983	1.001007	0.264408	
min	-9.400609	-19.827601	-15.024588	-2.622131	
25%	-0.192011	-1.668518	0.427647	0.119691	
50%	0.027500	-0.991654	0.778657	0.231033	
75%	0.236761	-0.543185	1.206074	0.380542	
max	6.374304	5.383026	9.521608	2.715843	

[8 rows x 56 columns]

```
[99]: sn.heatmap(q_df.corr().abs())  
plt.title("abs(Correlation) between q-features")  
plt.show()
```



## 5 Analysis of q-features ( $q_3$ ) (calculated by system)

```
[100]: x_np=x.to_numpy()  
import qfeatures  
coefficients = dataset_module.coefficients  
systems = dataset_module.systems  
coefficients_np = np.array([coefficients[k] for k in x.columns])  
systems = [systems[k] for k in x.columns]
```

```

q= qfeatures.calculate(x_np,coefficients_np,x.
↳columns,systems,combination_size=3,by_system=True)

m = q.magnitudes

q_df = pd.DataFrame(m, columns = q.column_names)
q_df.describe()

```

```

[100]:
      umag_gmag_rmag  umag_gmag_imag  umag_gmag_Hmag  umag_rmag_imag  \
count      3142.000000      3142.000000      3142.000000      3142.000000
mean         0.156141       -0.378599       -0.010663         0.954243
std          0.477268         0.333868         0.437317         0.827491
min         -0.759654       -1.321813       -0.903692       -0.711111
25%         -0.126526       -0.615351       -0.282897         0.425526
50%          0.016104       -0.469503       -0.131121         0.664269
75%          0.231807       -0.232851         0.094217         1.343070
max          2.579221         1.192398         2.186495         4.944912

      umag_rmag_Hmag  umag_imag_Hmag  gmag_rmag_imag  gmag_rmag_Hmag  \
count      3142.000000      3142.000000      3142.000000      3142.000000
mean         1.407748         2.631337         0.684462         0.900313
std          0.977587         1.403822         0.334951         0.397890
min         -0.596636       -0.202336         0.068421         0.117617
25%          0.813995         1.770654         0.461711         0.643785
50%          1.106449         2.298271         0.602632         0.812547
75%          1.737780         3.101028         0.885789         1.145245
max          6.135140         9.560561         2.063684         2.630187

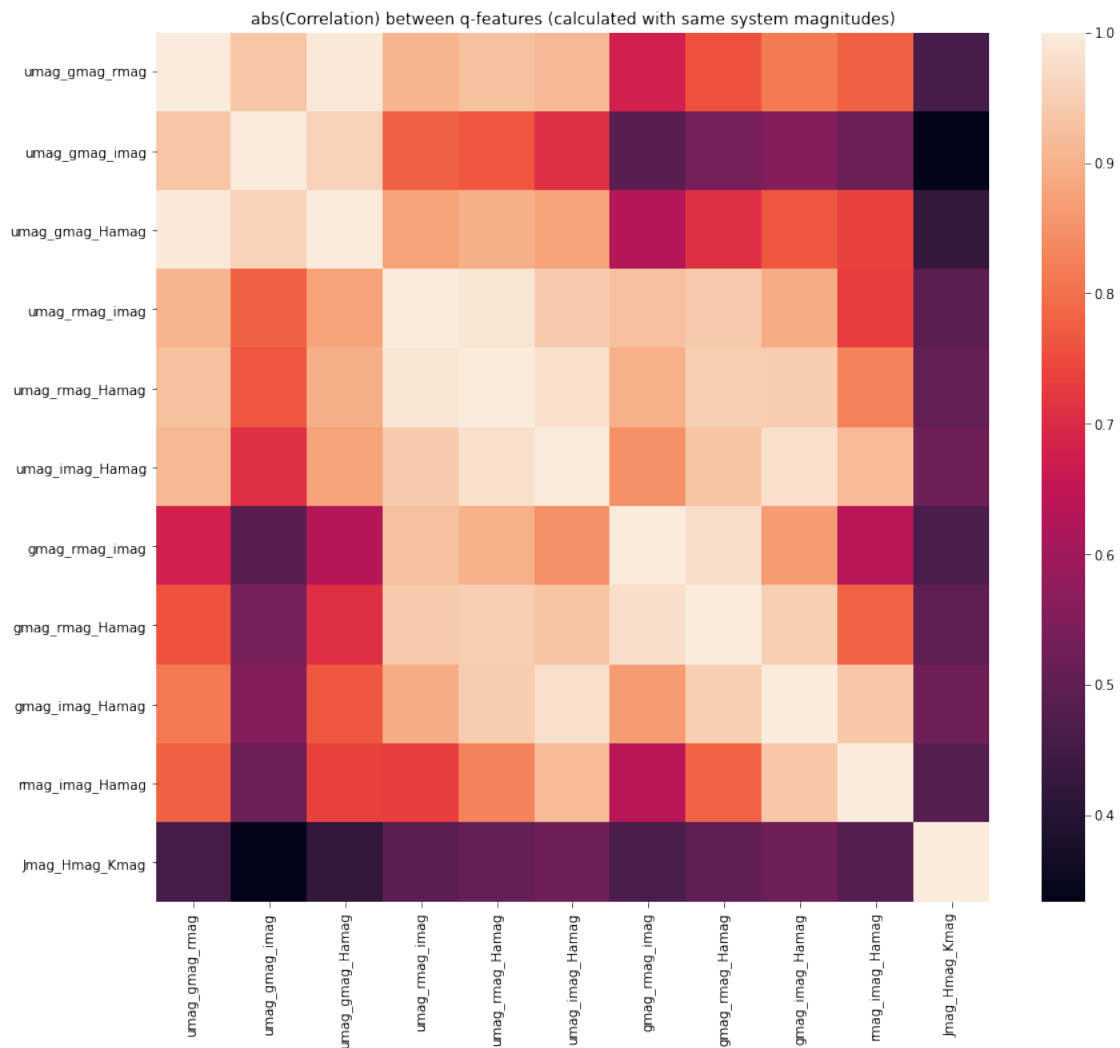
      gmag_imag_Hmag  rmag_imag_Hmag  Jmag_Hmag_Kmag
count      3142.000000      3142.000000      3142.000000
mean         1.831181         0.665001         0.254415
std          0.723852         0.265588         0.264408
min          0.310000         0.073178        -2.622131
25%          1.364100         0.474112         0.119691
50%          1.712173         0.636916         0.231033
75%          2.188703         0.817757         0.380542
max          5.373318         2.257290         2.715843

```

```

[101]: sn.heatmap(q_df.corr().abs())
plt.title("abs(Correlation) between q-features (calculated with same system_
↳magnitudes)")
plt.show()
q_dfy=pd.concat([q_df,y],axis=1)
sn.pairplot(q_dfy,hue="em")
plt.suptitle("Scatter plots between q-features (calculated with same system_
↳magnitudes)")

```



[101]: Text(0.5, 0.98, 'Scatter plots between q-features (calculated with same system magnitudes)')

