Exploratory analysis

March 18, 2021

[102]:
```
%reload_ext autoreload
%autoreload 2
default_figsize=(14,12)
```

[103]:
```
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 = "mohr_smith"
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 Mohr-Smith_2017.csv:
Dropped 38 rows with missing values.
Rows (original):   5915
Rows (after drop): 5877
```

[103]:

	umag	gmag	rmag	imag	Hamag
count	5877.000000	5877.000000	5877.000000	5877.000000	5877.000000
mean	17.216993	16.980114	15.609820	14.803716	15.268086
std	2.328989	1.966562	1.659154	1.527776	1.620235
min	12.143000	13.004000	11.957000	11.081000	11.620000
25%	15.378000	15.410000	14.243000	13.561000	13.940000
50%	17.371000	17.121000	15.716000	14.847000	15.362000
75%	19.272000	18.684000	16.989000	16.049000	16.606000
max	21.260000	19.998000	18.669000	17.864000	18.737000

	Jmag	Hmag	Kmag	em
count	5877.00000	5877.000000	5877.000000	5877.000000

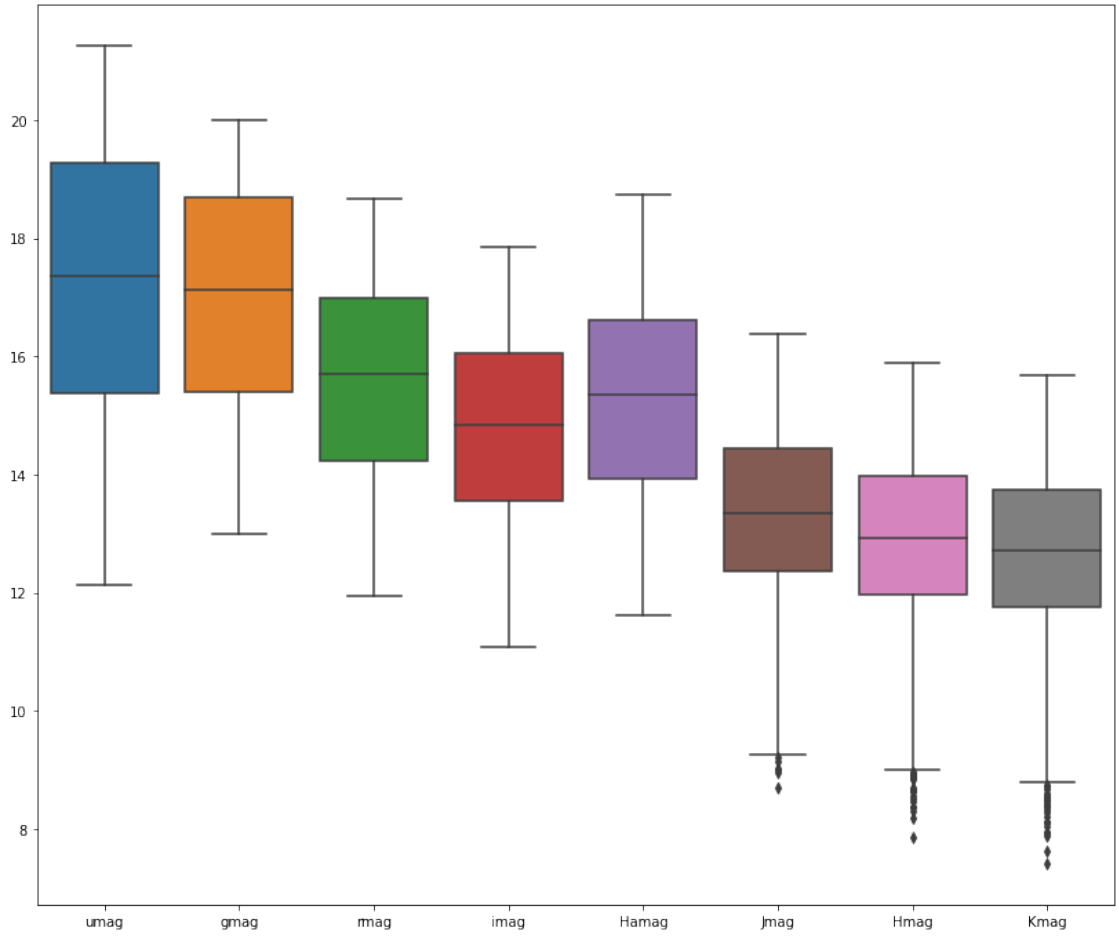
mean	13.37808	12.937877	12.713908	0.055470
std	1.39622	1.373603	1.387794	0.228916
min	8.69300	7.870000	7.414000	0.000000
25%	12.35800	11.977000	11.765000	0.000000
50%	13.34900	12.930000	12.710000	0.000000
75%	14.44600	13.976000	13.742000	0.000000
max	16.38600	15.896000	15.691000	1.000000

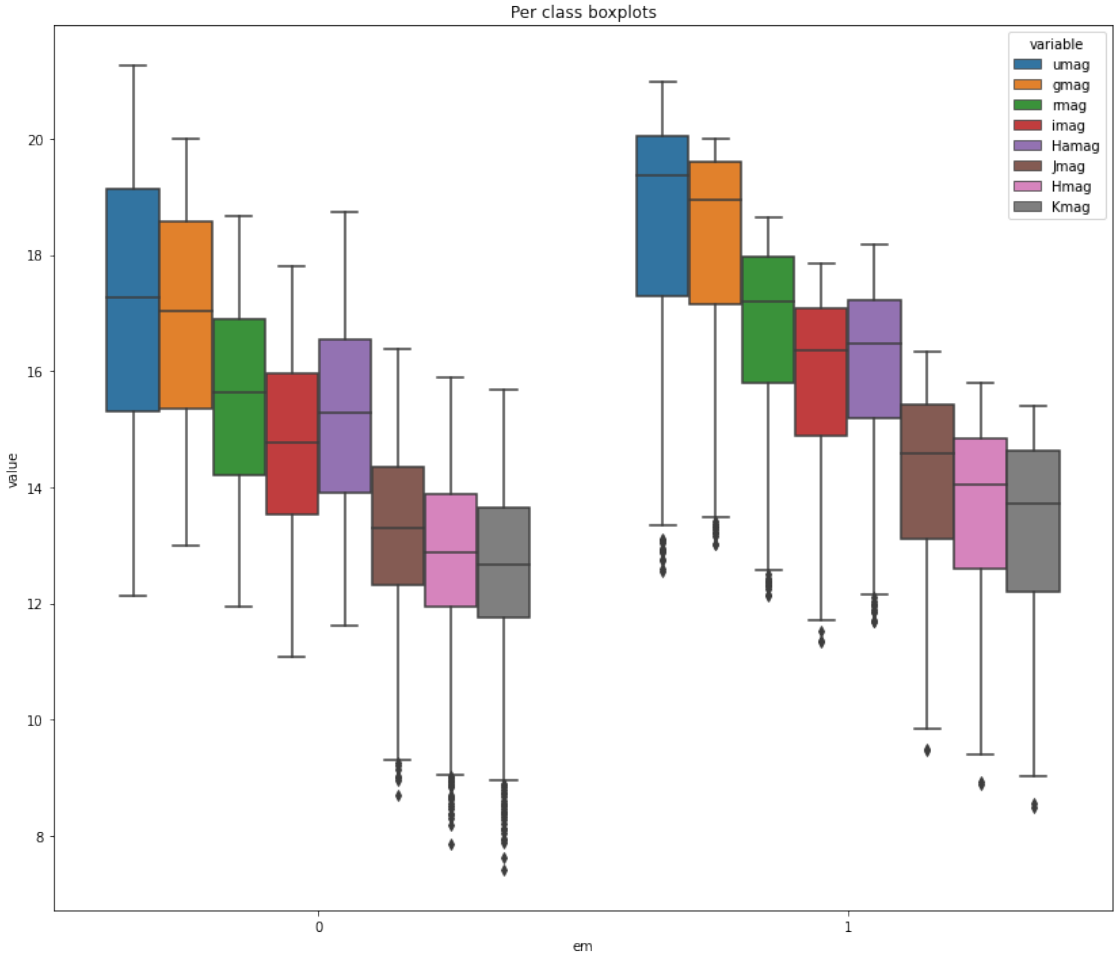
1 Variable visualization

[104]:
```
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")
```

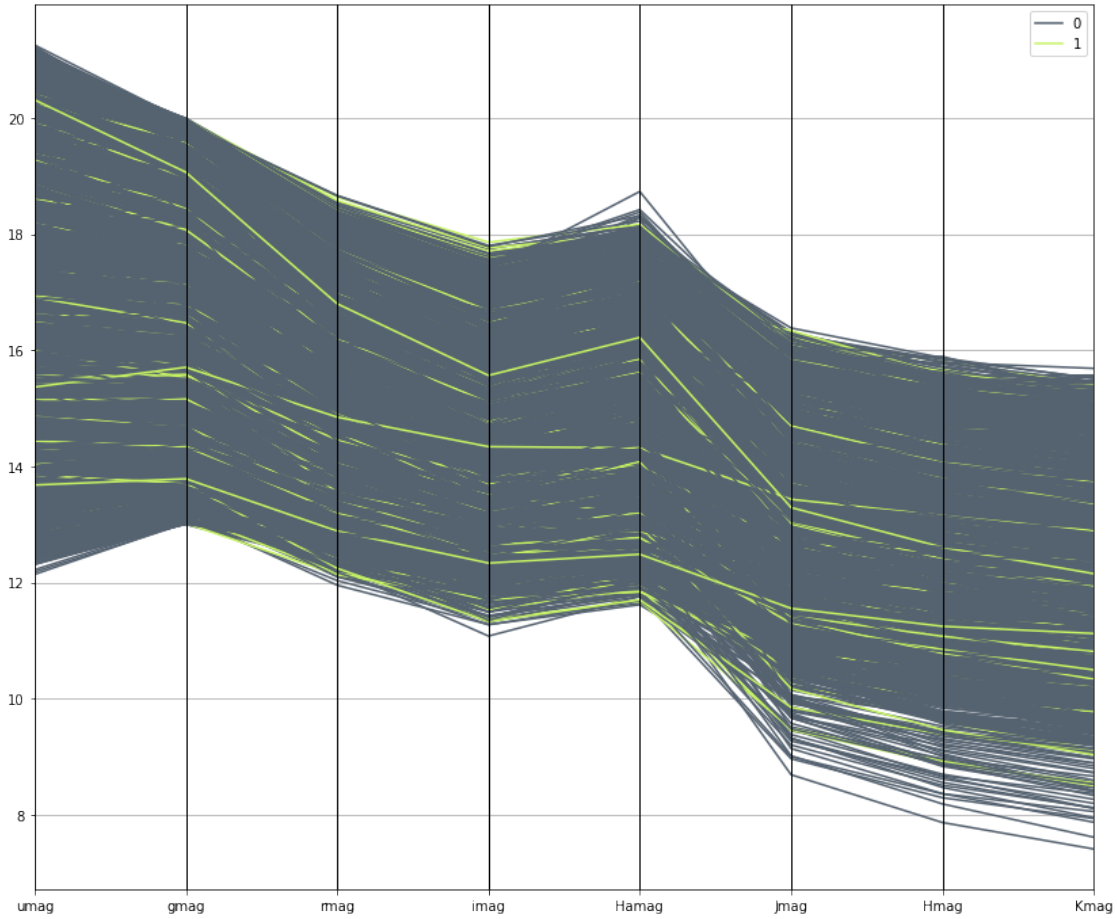
[104]: Text(0.5, 1.0, 'Per class boxplots')





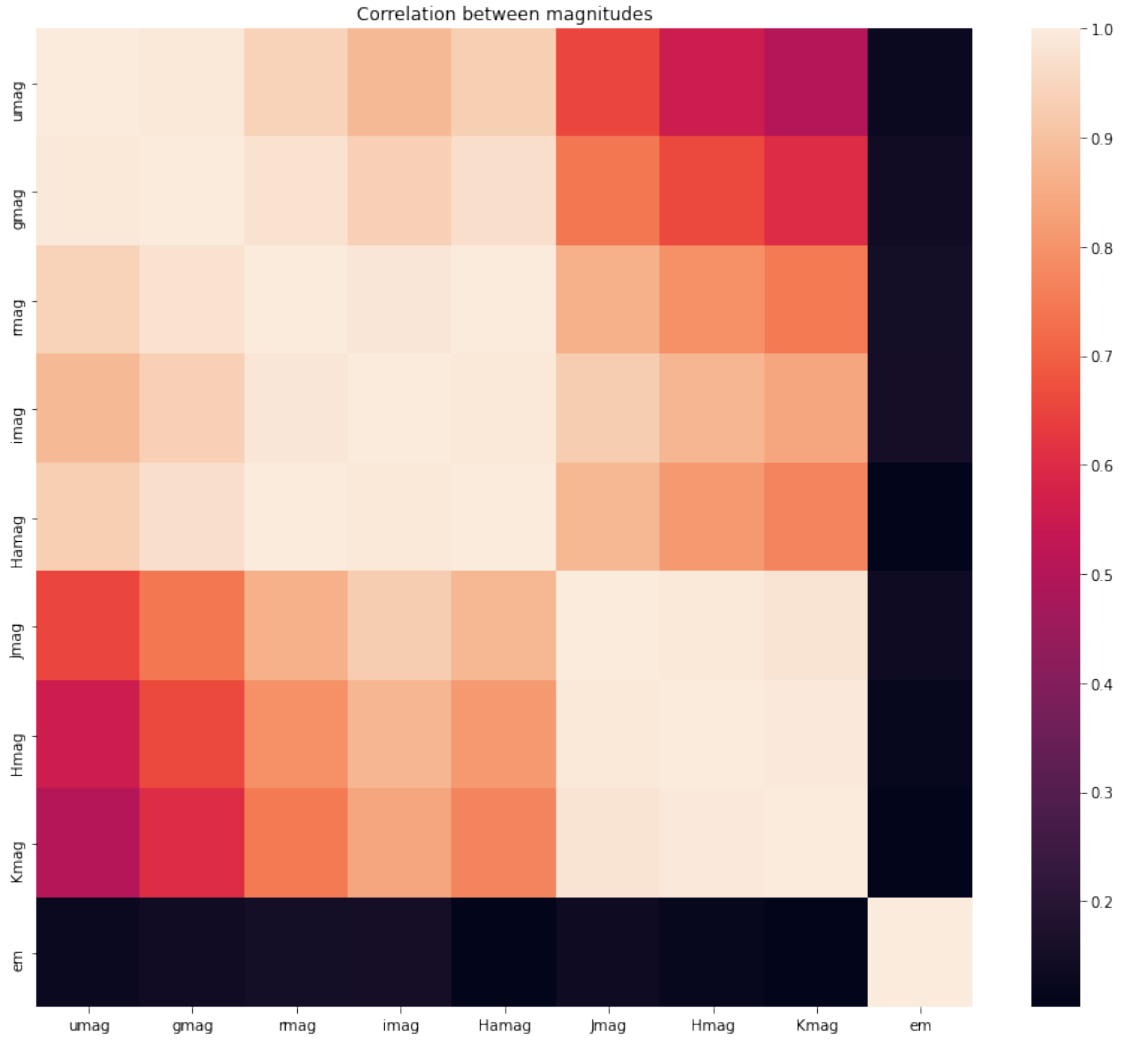
[105]:
```
pd.plotting.parallel_coordinates(xy,"em",color=('#556270','#C7F464'))
```

[105]: <AxesSubplot:>



[106]:
```
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))
```



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

2 Outlier detection via confidence interval

[107]:
```
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
```

[107]:

	umag	gmag	rmag	imag	Hamag	Jmag	Hmag	Kmag	A0	\
33	17.230	15.975	13.523	12.100	13.031	9.670	8.930	8.536	7.852	
40	17.566	15.969	13.405	11.925	12.928	9.317	8.560	8.115	7.995	
46	17.929	16.214	13.487	11.917	12.970	9.144	8.367	7.875	8.524	
57	17.728	16.367	13.978	12.543	13.478	10.023	9.224	8.802	7.826	
98	16.304	15.184	12.878	11.698	12.404	9.383	8.702	8.270	7.143	
131	16.936	15.480	12.953	11.486	12.341	8.693	7.870	7.414	8.350	
152	20.597	18.508	15.374	13.514	14.826	10.056	9.057	8.424	10.406	
185	16.588	15.619	13.410	12.131	12.934	9.722	9.025	8.567	7.475	
241	17.558	16.161	13.570	12.095	13.049	9.327	8.474	7.953	8.544	
301	14.975	14.257	12.236	11.081	11.762	8.968	8.297	7.940	6.844	
306	14.794	14.270	12.475	11.404	12.034	9.516	8.969	8.667	6.190	
437	19.141	17.146	14.245	12.551	13.746	9.479	8.656	8.113	9.147	
455	15.700	14.928	12.883	11.681	12.432	9.315	8.620	8.200	7.261	
469	17.844	16.488	14.034	12.574	13.513	9.870	9.100	8.600	8.195	
549	14.600	14.320	12.575	11.566	12.225	9.273	8.673	8.371	6.772	
558	14.593	14.293	12.563	11.542	12.169	9.450	8.950	8.520	6.496	
1120	14.979	14.243	12.437	11.366	11.680	9.488	8.925	8.498	6.007	
1713	15.168	14.395	12.444	11.318	11.885	9.005	8.365	8.059	6.855	
1783	14.353	13.961	12.394	11.538	11.903	9.465	8.881	8.555	5.901	
1937	17.744	16.371	13.813	12.309	13.302	9.674	8.837	8.406	8.375	
2245	16.736	16.161	13.962	12.592	13.489	9.756	8.880	8.334	8.616	
2361	15.297	14.605	12.680	11.556	12.232	9.689	9.120	8.725	6.294	
4753	16.710	15.442	13.140	11.778	12.642	9.577	8.856	8.469	7.189	
5170	16.262	15.748	13.700	12.411	13.154	9.975	9.167	8.738	7.747	
5359	16.351	15.423	13.115	11.700	12.603	9.018	8.190	7.617	8.415	
5563	14.949	14.260	12.473	11.405	12.035	9.485	8.892	8.531	6.086	
5605	15.297	14.487	12.594	11.352	12.067	9.205	8.511	8.126	6.790	
5722	20.484	18.317	15.149	13.372	14.604	9.970	9.007	8.402	10.121	

	DEJ2000	Rv	r2mag	RAJ2000	VPHAS-OB1	mu	chi2	logTeff
33	-57.331160	3.525	13.512	152.448798	85	10.64	1.60	4.507
40	-57.545887	3.538	13.394	152.325021	109	8.41	1.57	4.324
46	-57.463467	3.528	13.506	152.598693	130	8.49	2.09	4.366
57	-56.957887	3.698	13.955	153.389629	157	9.24	3.14	4.343
98	-57.016295	3.638	12.880	153.926987	261	8.89	3.60	4.352
131	-57.407289	3.794	12.942	153.668178	331	7.76	1.83	4.341

152	-57.090546	3.769	15.327	154.220685	376	9.29	4.29	4.417
185	-57.348754	3.836	13.438	154.072129	444	9.80	1.52	4.423
241	-57.546570	3.787	13.571	154.177204	559	8.89	0.54	4.404
301	-57.917252	3.769	12.251	154.224633	708	9.91	0.28	4.488
306	-58.156718	3.722	12.432	153.990057	724	10.92	1.75	4.509
437	-57.159384	3.589	14.247	156.036587	1006	8.19	4.96	4.315
455	-58.052421	4.026	12.882	155.131682	1041	9.43	0.84	4.424
469	-57.769781	3.791	14.009	155.582926	1069	9.21	3.05	4.366
549	-57.758620	4.400	12.582	156.004990	1216	10.69	4.69	4.530
558	-57.759795	4.159	12.569	156.009539	1226	11.33	2.25	4.562
1120	-58.818031	3.785	12.286	158.143987	2881	8.94	6.16	4.316
1713	-59.199053	4.013	12.356	160.281809	4755	8.68	6.44	4.363
1783	-59.454645	4.484	12.401	160.248764	4980	8.76	6.84	4.300
1937	-58.782316	3.647	13.814	161.481177	5468	10.03	2.12	4.470
2245	-59.783881	4.526	13.954	161.403107	6480	11.66	3.46	4.624
2361	-59.220889	3.607	12.676	162.343201	6880	10.38	5.33	4.449
4753	-60.884853	3.479	13.127	167.855369	12768	9.22	4.68	4.365
5170	-61.242734	4.254	13.696	168.747828	13501	12.28	3.22	4.632
5359	-61.330502	4.098	13.109	168.918911	13765	10.10	3.48	4.548
5563	-61.559307	3.835	12.517	169.582737	14153	9.12	1.34	4.338
5605	-61.469052	3.954	12.545	169.767548	14229	8.81	7.18	4.360
5722	-61.949044	3.680	15.143	170.078909	14506	8.86	1.96	4.369

3 Outlier detection via IQR

[108]:
```
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
```

[108]:

	umag	gmag	rmag	imag	Hamag	Jmag	Hmag	Kmag	A0	\
33	17.230	15.975	13.523	12.100	13.031	9.670	8.930	8.536	7.852	
40	17.566	15.969	13.405	11.925	12.928	9.317	8.560	8.115	7.995	
46	17.929	16.214	13.487	11.917	12.970	9.144	8.367	7.875	8.524	
98	16.304	15.184	12.878	11.698	12.404	9.383	8.702	8.270	7.143	
131	16.936	15.480	12.953	11.486	12.341	8.693	7.870	7.414	8.350	
152	20.597	18.508	15.374	13.514	14.826	10.056	9.057	8.424	10.406	

185	16.588	15.619	13.410	12.131	12.934	9.722	9.025	8.567	7.475
241	17.558	16.161	13.570	12.095	13.049	9.327	8.474	7.953	8.544
301	14.975	14.257	12.236	11.081	11.762	8.968	8.297	7.940	6.844
306	14.794	14.270	12.475	11.404	12.034	9.516	8.969	8.667	6.190
437	19.141	17.146	14.245	12.551	13.746	9.479	8.656	8.113	9.147
455	15.700	14.928	12.883	11.681	12.432	9.315	8.620	8.200	7.261
469	17.844	16.488	14.034	12.574	13.513	9.870	9.100	8.600	8.195
549	14.600	14.320	12.575	11.566	12.225	9.273	8.673	8.371	6.772
558	14.593	14.293	12.563	11.542	12.169	9.450	8.950	8.520	6.496
1120	14.979	14.243	12.437	11.366	11.680	9.488	8.925	8.498	6.007
1713	15.168	14.395	12.444	11.318	11.885	9.005	8.365	8.059	6.855
1783	14.353	13.961	12.394	11.538	11.903	9.465	8.881	8.555	5.901
1937	17.744	16.371	13.813	12.309	13.302	9.674	8.837	8.406	8.375
2245	16.736	16.161	13.962	12.592	13.489	9.756	8.880	8.334	8.616
2361	15.297	14.605	12.680	11.556	12.232	9.689	9.120	8.725	6.294
4753	16.710	15.442	13.140	11.778	12.642	9.577	8.856	8.469	7.189
5170	16.262	15.748	13.700	12.411	13.154	9.975	9.167	8.738	7.747
5359	16.351	15.423	13.115	11.700	12.603	9.018	8.190	7.617	8.415
5563	14.949	14.260	12.473	11.405	12.035	9.485	8.892	8.531	6.086
5605	15.297	14.487	12.594	11.352	12.067	9.205	8.511	8.126	6.790
5722	20.484	18.317	15.149	13.372	14.604	9.970	9.007	8.402	10.121

	DEJ2000	Rv	r2mag	RAJ2000	VPHAS-OB1	mu	chi2	logTeff
33	-57.331160	3.525	13.512	152.448798	85	10.64	1.60	4.507
40	-57.545887	3.538	13.394	152.325021	109	8.41	1.57	4.324
46	-57.463467	3.528	13.506	152.598693	130	8.49	2.09	4.366
98	-57.016295	3.638	12.880	153.926987	261	8.89	3.60	4.352
131	-57.407289	3.794	12.942	153.668178	331	7.76	1.83	4.341
152	-57.090546	3.769	15.327	154.220685	376	9.29	4.29	4.417
185	-57.348754	3.836	13.438	154.072129	444	9.80	1.52	4.423
241	-57.546570	3.787	13.571	154.177204	559	8.89	0.54	4.404
301	-57.917252	3.769	12.251	154.224633	708	9.91	0.28	4.488
306	-58.156718	3.722	12.432	153.990057	724	10.92	1.75	4.509
437	-57.159384	3.589	14.247	156.036587	1006	8.19	4.96	4.315
455	-58.052421	4.026	12.882	155.131682	1041	9.43	0.84	4.424
469	-57.769781	3.791	14.009	155.582926	1069	9.21	3.05	4.366
549	-57.758620	4.400	12.582	156.004990	1216	10.69	4.69	4.530
558	-57.759795	4.159	12.569	156.009539	1226	11.33	2.25	4.562
1120	-58.818031	3.785	12.286	158.143987	2881	8.94	6.16	4.316
1713	-59.199053	4.013	12.356	160.281809	4755	8.68	6.44	4.363
1783	-59.454645	4.484	12.401	160.248764	4980	8.76	6.84	4.300
1937	-58.782316	3.647	13.814	161.481177	5468	10.03	2.12	4.470
2245	-59.783881	4.526	13.954	161.403107	6480	11.66	3.46	4.624
2361	-59.220889	3.607	12.676	162.343201	6880	10.38	5.33	4.449
4753	-60.884853	3.479	13.127	167.855369	12768	9.22	4.68	4.365
5170	-61.242734	4.254	13.696	168.747828	13501	12.28	3.22	4.632
5359	-61.330502	4.098	13.109	168.918911	13765	10.10	3.48	4.548

```
5563 -61.559307  3.835  12.517  169.582737      14153   9.12  1.34    4.338
5605 -61.469052  3.954  12.545  169.767548      14229   8.81  7.18    4.360
5722 -61.949044  3.680  15.143  170.078909      14506   8.86  1.96    4.369
```

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

[109]:
```
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()
```

[109]:

	umag_gmag_rmag	umag_gmag_imag	umag_gmag_Hamag	umag_gmag_Jmag	\
count	5877.000000	5877.000000	5877.000000	5877.000000	
mean	-0.409710	-1.150416	-0.635135	-5.216200	
std	0.258130	0.130671	0.224254	1.549386	
min	-1.183961	-2.091596	-1.406519	-10.758042	
25%	-0.599502	-1.227567	-0.791967	-6.291792	
50%	-0.426035	-1.124708	-0.651668	-5.218694	
75%	-0.227082	-1.053386	-0.482411	-4.125556	
max	0.672143	-0.832544	0.275799	-0.477486	

	umag_gmag_Hmag	umag_gmag_Kmag	umag_rmag_imag	umag_rmag_Hamag	\
count	5877.000000	5877.000000	5877.000000	5877.000000	
mean	-9.341466	-14.959737	0.626648	1.275020	
std	3.078338	5.187979	0.614700	0.885778	
min	-20.305761	-33.831131	-1.319994	-1.448589	
25%	-11.489065	-18.563993	0.177035	0.620065	
50%	-9.338935	-14.950752	0.605485	1.244047	
75%	-7.134609	-11.265647	1.063117	1.900215	
max	0.201065	1.158850	3.173503	4.805280	

	umag_rmag_Jmag	umag_rmag_Hmag	…	imag_Hamag_Jmag	imag_Hamag_Hmag	\
count	5877.000000	5877.000000	…	5877.000000	5877.000000	
mean	-4.840076	-10.474658	…	0.664383	1.713869	
std	1.527176	3.667144	…	0.260581	0.676747	
min	-11.826778	-25.465348	…	-0.156500	-0.411696	
25%	-5.907778	-13.052304	…	0.482347	1.232391	
50%	-4.782889	-10.416435	…	0.657583	1.705935	
75%	-3.768000	-7.872522	…	0.844611	2.190152	

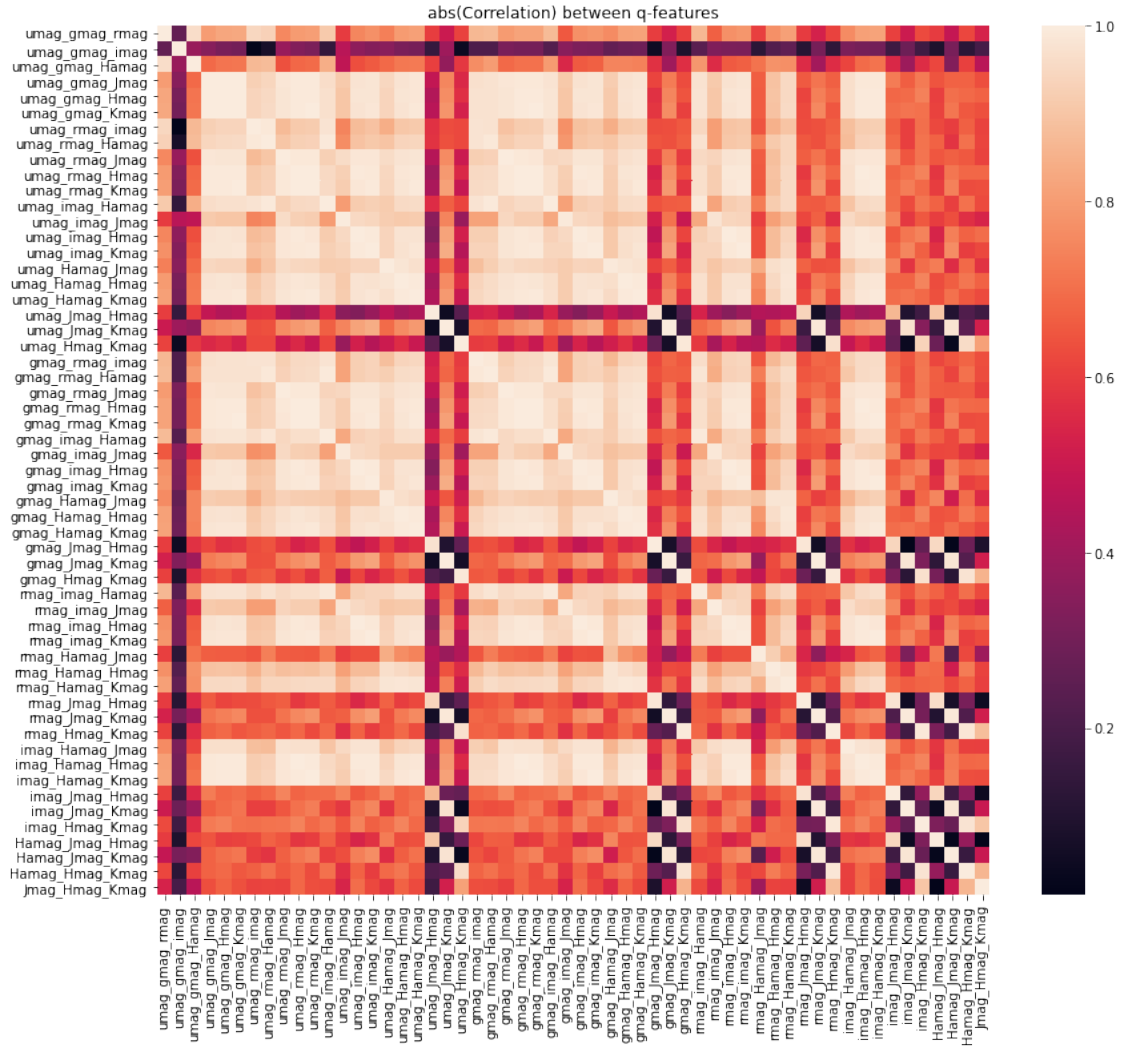
```
max         -0.261444        0.832565  …         1.753681         4.289304

       imag_Hamag_Kmag  imag_Jmag_Hmag  imag_Jmag_Kmag  imag_Hmag_Kmag  \
count      5877.000000     5877.000000     5877.000000     5877.000000
mean          3.124834        0.478241       -0.723156        0.950934
std           1.254977        0.269327        0.442834        0.476000
min          -0.772131       -0.953239       -2.635706       -2.127608
25%           2.239379        0.305826       -0.988647        0.630033
50%           3.103575        0.482783       -0.677353        0.932301
75%           4.002680        0.661935       -0.413118        1.275706
max           7.736477        1.935283        0.788412        2.847046

       Hamag_Jmag_Hmag  Hamag_Jmag_Kmag  Hamag_Hmag_Kmag  Jmag_Hmag_Kmag
count      5877.000000      5877.000000      5877.000000     5877.000000
mean          0.531117        -1.192100         1.100577        0.249903
std           0.376616         0.683245         0.618342        0.141120
min          -1.730391        -4.544699        -2.820353       -0.617078
25%           0.302348        -1.585222         0.691098        0.154026
50%           0.538217        -1.109229         1.080824        0.240222
75%           0.786391        -0.722118         1.519471        0.338431
max           2.403304         0.906758         3.560882        1.061144

[8 rows x 56 columns]
```

[110]:
```
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)

[111]:
```
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()
```

[111]:

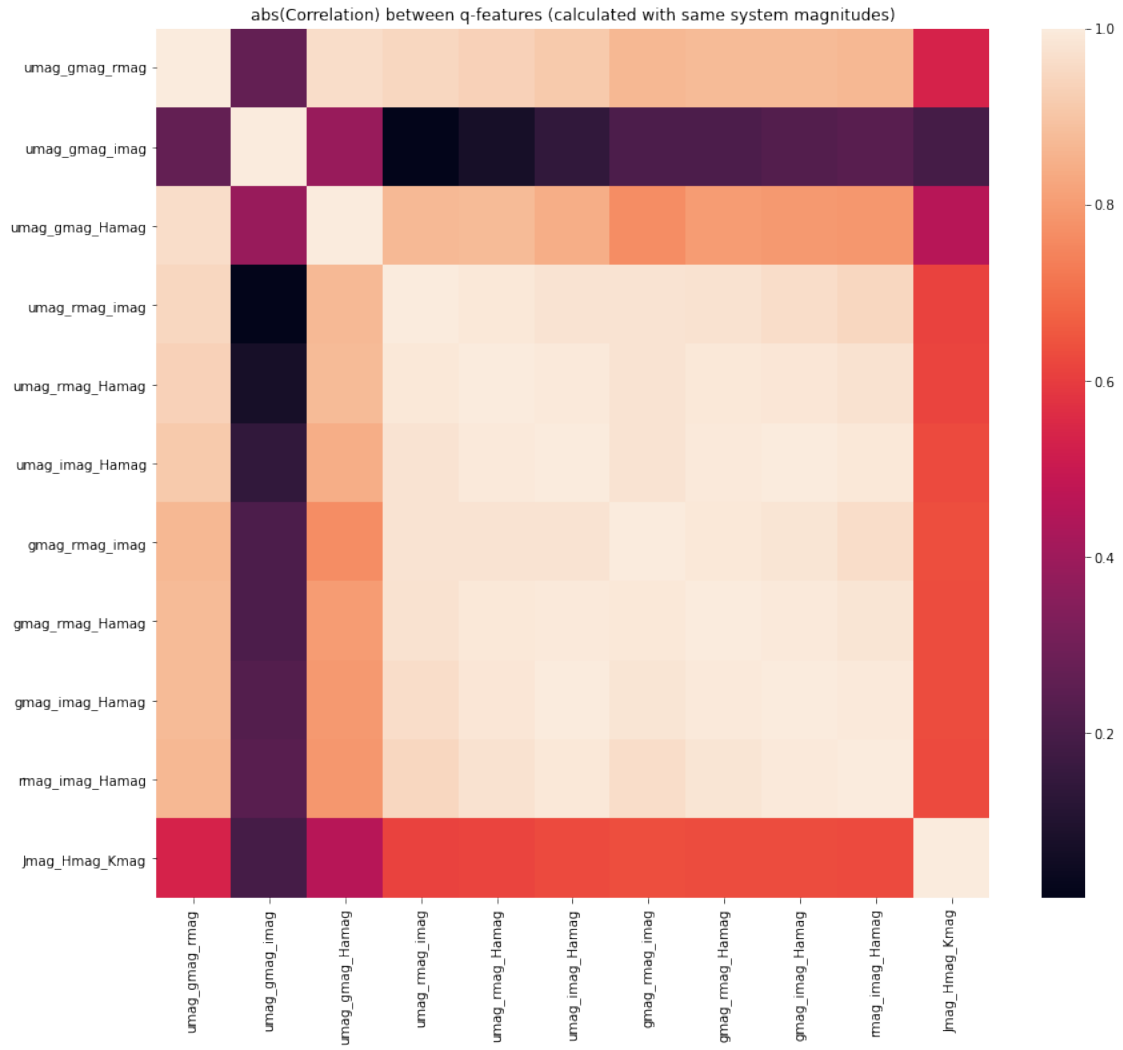
	umag_gmag_rmag	umag_gmag_imag	umag_gmag_Hamag	umag_rmag_imag
count	5877.000000	5877.000000	5877.000000	5877.000000
mean	-0.409710	-1.150416	-0.635135	0.626648
std	0.258130	0.130671	0.224254	0.614700
min	-1.183961	-2.091596	-1.406519	-1.319994
25%	-0.599502	-1.227567	-0.791967	0.177035
50%	-0.426035	-1.124708	-0.651668	0.605485
75%	-0.227082	-1.053386	-0.482411	1.063117
max	0.672143	-0.832544	0.275799	3.173503

	umag_rmag_Hamag	umag_imag_Hamag	gmag_rmag_imag	gmag_rmag_Hamag
count	5877.000000	5877.000000	5877.000000	5877.000000
mean	1.275020	2.994825	0.903602	1.212202
std	0.885778	1.486126	0.323645	0.453192
min	-1.448589	-1.556037	-0.101579	-0.162785
25%	0.620065	1.906206	0.676158	0.892037
50%	1.244047	2.951140	0.904684	1.206126
75%	1.900215	4.049458	1.132737	1.533299
max	4.805280	8.726065	2.139211	2.915874

	gmag_imag_Hamag	rmag_imag_Hamag	Jmag_Hmag_Kmag
count	5877.000000	5877.000000	5877.000000
mean	2.521421	0.936302	0.249903
std	0.917666	0.339618	0.141120
min	-0.251388	-0.071486	-0.617078
25%	1.853561	0.689159	0.154026
50%	2.506949	0.927701	0.240222
75%	3.170589	1.175449	0.338431
max	5.968804	2.227850	1.061144

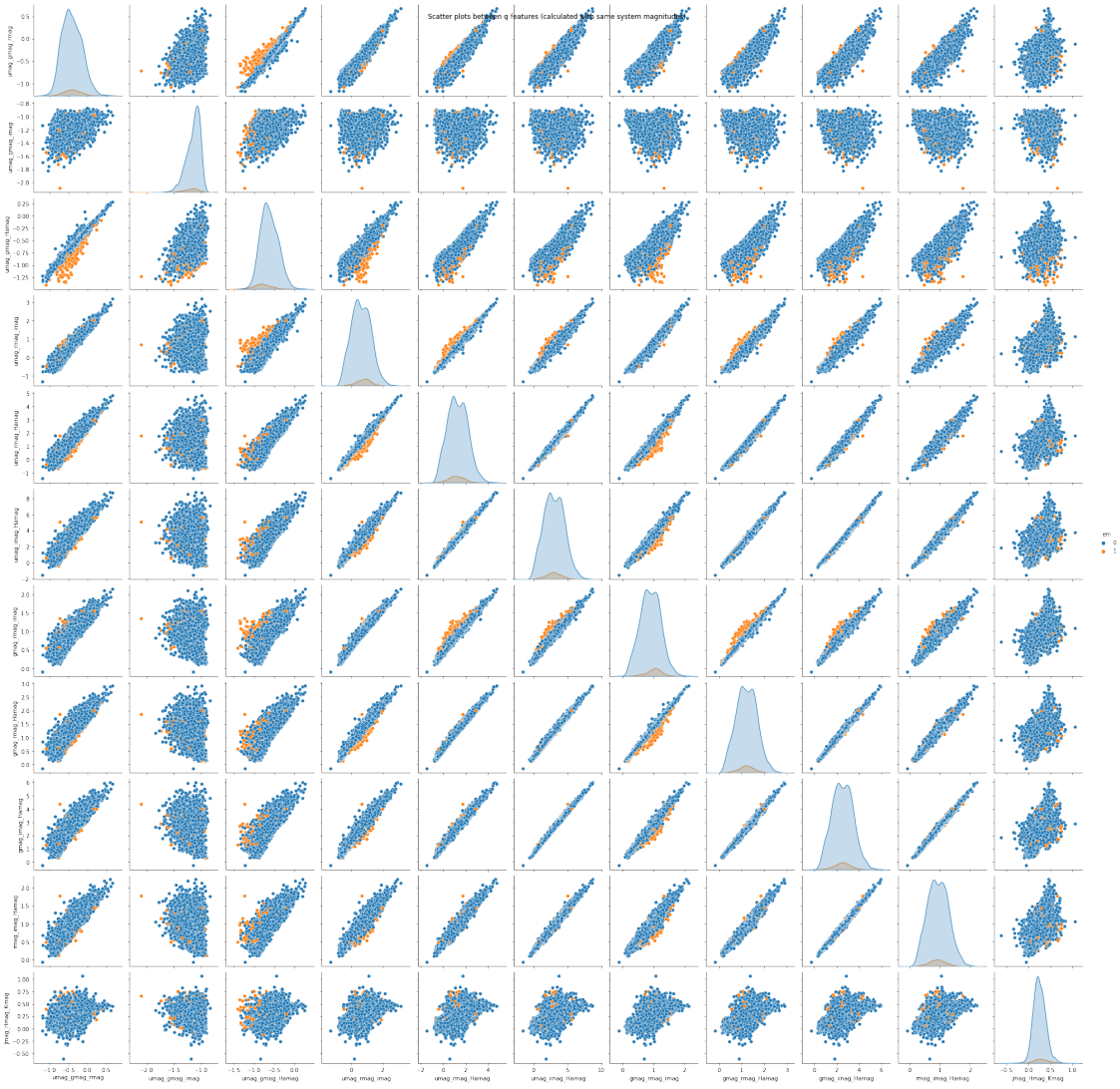
[115]:
```
sn.heatmap(q_df.corr().abs())
plt.title("abs(Correlation) between q-features (calculated with same system␣
 ↪magnitudes)")
```

[115]:
```
Text(0.5, 1.0, 'abs(Correlation) between q-features (calculated with same system
magnitudes)')
```



[114]:
```
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)")
```

[114]:
```
Text(0.5, 0.98, 'Scatter plots between q-features (calculated with same system
magnitudes)')
```


Scatter plots between q features (calculated from same system magnitudes)
umag_gmag_rmag
umag_gmag_imag
umag_gmag_ilamag
umag_rmag_imag
umag_rmag_ilamag
umag_imag_ilamag
gmag_rmag_imag
gmag_rmag_ilamag
gmag_imag_ilamag
rmag_imag_ilamag
imag_ilmag_Kmag
cm
0
1