Лабораторная работа 0-1 по курсу "Машинное обучение"

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Группа	301

О датасете

Набор данных "Кеплер" предоставляет точные данных для проведения комплексного астеросейсмического анализа эволюционировавших звезд. В этой работе характерезуется подобные солнцу колебания и грануляцию для 16094 колеблющихся красных гигантов, используя данные о длительной частоте в конце миссии. Благодаря большому образцу красных гигантов выделяются звезды с ветвью красного гиганта (RGB) и звезды с гелиевым ядром (HeB) в совокупности отличаются распределением амплитуды колебаний, мощностью грануляции и шириной превышения мощности, что в основном связано с разницей масс. Необходимо составить классификатор для определения типа звезды. На проверку предоставлены параметры звезд без параметров фазы.

Содержание

Kpmag - видимая величина Кеплера

numax - Частота максимальной мощности колебаний

e_numax - Неопределенность

Delnu - Разделение акустических состояний по средней частоте

e_Delnu - Неопределенность in Delnu

A - Амплитуда колебаний в радиальном режиме

e_A - Неопределенность in A

Width - Ширина превышения мощности

e_Width - Неопределенность в ширине

Teff - Эффективная температура

e_Teff - Неопределенность в Teff

log(g) - Логарифмическая сила тяжести поверхности из этой работы

e_log(g) - Неопределенность в логарифме(g)

Fe/H - Металличность

e_Fe/H - Неопределенность в Fe/H

Gran - Мощность грануляции

e_Gran - Неопределенность in Gran

NoCorM - Корректирующее массовое решение

e_NoCorM - Неопределенность in NoCorM

NoCorR - Правка радиуса коррекции

e_NoCorR - Неопределенность in NoCorR

RGBcorM - RGB скорректированное массовое решение

e_RGBcorM - Неопределенность in RGBcorM

RGBcorR - GB решение с исправленным радиусом

e_RGBcorR - Неопределенность in RGBcorR

ClcorM - скорректированный массовый раствор

e_ClcorM - Неопределенность in ClcorM

ClcorR - Решение с исправленным радиусом

e_ClcorR - Неопределенность в ClcorR

Phase - Эволюционная фаза

Фазы следующим образом:

2 = Фаза HeB;

1 = Фаза RGB;

0 = неклассифицированная фаза

RGB (Red-Giant-Branch)

HeB (Helium Burning)

Загрузка данных

In [1]:
```
#Подключение библиотек
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.__version__
```

Out[1]:
```
'0.11.2'
```

In [2]:
```
df = pd.read_csv('Data_classified_phase_.csv')
```

```
df.shape
```

Out[2]:
```
(15388, 28)
```

In [3]:
```
df_un = pd.read_csv('Data_unclassified_phase_.csv')
df_un.shape
```

Out[3]:
```
(706, 28)
```

In [4]:
```
df.head(5)
```

Out[4]:

	Kpmag	numax	e_numax	Delnu	e_Delnu	A	e_A	Width	e_Width	Teff	...	e_No
0	9.20	29.99	0.60	3.399	0.011	104.9	4.6	12.3	1.5	4751	...	
1	13.23	29.48	0.48	3.962	0.116	149.7	8.3	12.0	3.9	5188	...	
2	12.58	41.39	0.54	4.311	0.013	86.1	4.6	15.3	1.6	4728	...	
3	12.14	41.17	0.90	4.414	0.061	63.8	2.9	24.8	2.7	5072	...	
4	11.74	36.91	0.71	3.991	0.064	116.1	9.6	14.0	2.4	4718	...	

5 rows × 28 columns

In [5]:
```
df.columns
```

Out[5]:
```
Index(['Kpmag', 'numax', 'e_numax', 'Delnu', 'e_Delnu', 'A', 'e_A', 'Widt
h',
       'e_Width', 'Teff', 'e_Teff', 'log(g)', 'e_log(g)', '[Fe/H]', 'e_[F
e/H]',
       'NoCorM', 'e_NoCorM', 'NoCorR', 'e_NoCorR', 'RGBcorM', 'e_RGBcor
M',
       'RGBcorR', 'e_RGBcorR', 'ClcorM', 'e_ClcorM', 'ClcorR', 'e_Clcor
R',
       'Phase'],
      dtype='object')
```

In [6]:
```
df_un.columns
```

Out[6]:
```
Index(['Kpmag', 'numax', 'e_numax', 'Delnu', 'e_Delnu', 'A', 'e_A', 'Widt
h',
       'e_Width', 'Teff', 'e_Teff', 'log(g)', 'e_log(g)', '[Fe/H]', 'e_[F
e/H]',
       'NoCorM', 'e_NoCorM', 'NoCorR', 'e_NoCorR', 'RGBcorM', 'e_RGBcor
M',
       'RGBcorR', 'e_RGBcorR', 'ClcorM', 'e_ClcorM', 'ClcorR', 'e_Clcor
R',
       'Phase'],
      dtype='object')
```

In [7]:
```
df.index
```

Out[7]:
```
RangeIndex(start=0, stop=15388, step=1)
```

In [8]:
```
df_un.index
```

Out[8]:
```
RangeIndex(start=0, stop=706, step=1)
```

In [9]:
```
df.dtypes
```

Out[9]:
```
Kpmag        float64
numax        float64
e_numax      float64
Delnu        float64
e_Delnu      float64
A             object
e_A           object
Width         object
e_Width       object
Teff           int64
e_Teff         int64
log(g)       float64
e_log(g)     float64
[Fe/H]       float64
e_[Fe/H]     float64
NoCorM       float64
e_NoCorM     float64
NoCorR       float64
e_NoCorR     float64
RGBcorM      float64
e_RGBcorM    float64
RGBcorR      float64
e_RGBcorR    float64
ClcorM       float64
e_ClcorM     float64
ClcorR       float64
e_ClcorR     float64
Phase          int64
dtype: object
```

In [10]:
```
df_un.dtypes
```

Out[10]:
```
Kpmag        float64
numax        float64
e_numax      float64
Delnu        float64
e_Delnu      float64
A            float64
e_A          float64
Width        float64
e_Width      float64
Teff           int64
e_Teff         int64
log(g)       float64
e_log(g)     float64
[Fe/H]       float64
e_[Fe/H]     float64
NoCorM       float64
e_NoCorM     float64
NoCorR       float64
e_NoCorR     float64
RGBcorM      float64
e_RGBcorM    float64
RGBcorR      float64
e_RGBcorR    float64
ClcorM       float64
e_ClcorM     float64
```

```
ClcorR       float64
e_ClcorR     float64
Phase          int64
dtype: object
```

Все параметры в пердставленном датасете - численные

Подготовка данных

Как видно, что некотрый тип данных на тестовых и тренировочных выборках не схожы. Необходимо перевести к одному типу. Удобнее Object => float64

In [11]:
```
arr = []
for column in df.columns:
    if df.dtypes[column] == 'object':
        arr.append(column)
print(arr)
```

```
['A', 'e_A', 'Width', 'e_Width']
```

Убрать пробелы данных на nan

In [12]:
```
for i in range(1, 20):
    df[df == i*' '] = np.nan
    df_un[df == i*' '] = np.nan
```

In [13]:
```
for i in arr:
    df[i] = pd.to_numeric(df[i])
```

Результат после преведения типов

In [14]:
```
df.dtypes
```

Out[14]:
```
Kpmag        float64
numax        float64
e_numax      float64
Delnu        float64
e_Delnu      float64
A            float64
e_A          float64
Width        float64
e_Width      float64
Teff           int64
e_Teff         int64
log(g)       float64
e_log(g)     float64
[Fe/H]       float64
e_[Fe/H]     float64
NoCorM       float64
e_NoCorM     float64
NoCorR       float64
e_NoCorR     float64
RGBcorM      float64
e_RGBcorM    float64
RGBcorR      float64
e_RGBcorR    float64
ClcorM       float64
e_ClcorM     float64
```

```
ClcorR       float64
e_ClcorR     float64
Phase          int64
dtype: object
```

In [15]:
```
df.describe()
```

Out[15]:

	Kpmag	numax	e_numax	Delnu	e_Delnu	A
count	15388.000000	15388.000000	15388.000000	15388.00000	15388.000000	14851.000000
mean	12.632402	64.673195	0.903276	6.16765	0.047327	95.059174
std	1.211778	50.958690	0.891080	3.56072	0.069763	51.897428
min	6.240000	3.970000	0.040000	0.74700	0.008000	10.700000
25%	11.900000	31.680000	0.560000	3.97675	0.017000	59.900000
50%	12.850000	42.260000	0.720000	4.54050	0.028000	90.800000
75%	13.510000	79.522500	1.000000	7.27000	0.050000	120.900000
max	16.850000	273.160000	70.270000	19.29400	1.338000	745.200000

8 rows × 28 columns

Работаем с потерями

Здесь мы видим, какие данные были утерены. Это необходимо исправить

In [16]:
```
#Для df
for i in df.columns:
    a = df[i].isnull().sum()
    if a > 0:
        print(i, '-', a)
print('end')
```

```
A - 537
e_A - 537
Width - 537
e_Width - 537
end
```

In [17]:
```
for i in df_un.columns:
    a = df_un[i].isnull().sum()
    if a > 0:
        print(i, '-', a)
print('end')
```

```
end
```

Выделим подтаблицу с параметрами в которых нет некоторых значений

In [18]:
```
df_nan = df[df.isna().any(axis=1)]
df_nan
```

Out[18]:

	Kpmag	numax	e_numax	Delnu	e_Delnu	A	e_A	Width	e_Width	Teff	...	e
33	13.537	234.61	3.17	16.733	0.070	NaN	NaN	NaN	NaN	5018	...	
69	12.931	212.06	2.91	15.984	0.035	NaN	NaN	NaN	NaN	4979	...	

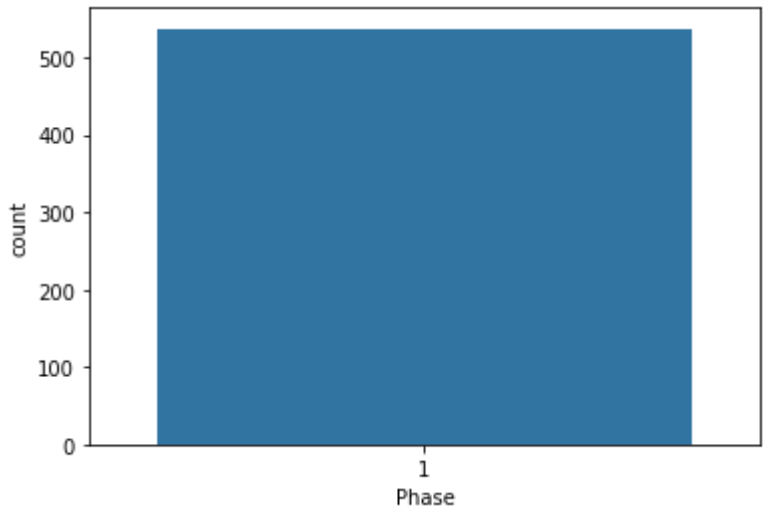
102	12.688	215.81	3.19	16.108	0.023	NaN	NaN	NaN	NaN	5008	...
124	12.381	224.38	1.56	16.205	0.041	NaN	NaN	NaN	NaN	4908	...
222	13.875	225.74	2.64	17.622	0.050	NaN	NaN	NaN	NaN	4893	...
...	...	...	...	...	...	...	...	...	...	...	...
15207	13.109	200.05	2.28	15.573	0.056	NaN	NaN	NaN	NaN	5035	...
15239	13.842	259.05	9.97	18.603	0.104	NaN	NaN	NaN	NaN	5080	...
15259	13.785	211.95	1.26	16.658	0.048	NaN	NaN	NaN	NaN	5098	...
15351	13.227	214.32	1.73	16.808	0.045	NaN	NaN	NaN	NaN	5049	...
15379	13.785	249.27	4.08	19.004	0.128	NaN	NaN	NaN	NaN	4996	...

537 rows × 28 columns

In [19]:
```
df_nan.shape
```

Out[19]:
```
(537, 28)
```

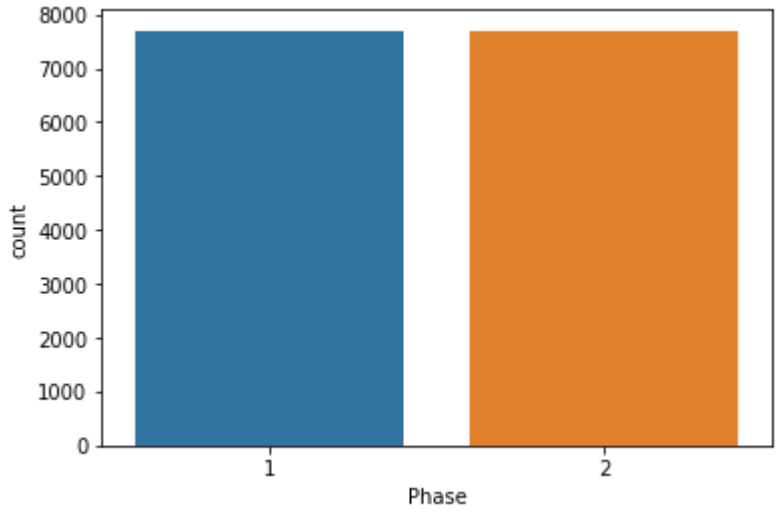
In [20]:
```
sns.countplot(x='Phase',data=df_nan)
pass
```



Как видно, все выпавшие варианты представляют 1 фазу

Выведем соотношение числа фаз

In [21]:
```
sns.countplot(x='Phase',data=df)
pass
```



In [22]:

```
df_new = df.copy()
df_new["A"] = df_new["A"].fillna(df_new["e_A"].median())
df_new["e_A"] = df_new["e_A"].fillna(df_new["e_Width"].median())
df_new["Width"] = df_new["Width"].fillna(df_new["e_A"].median())
df_new["e_Width"] = df_new["e_Width"].fillna(df_new["e_Width"].median())
print(df.shape, df_new.shape)
```

```
(15388, 28) (15388, 28)
```

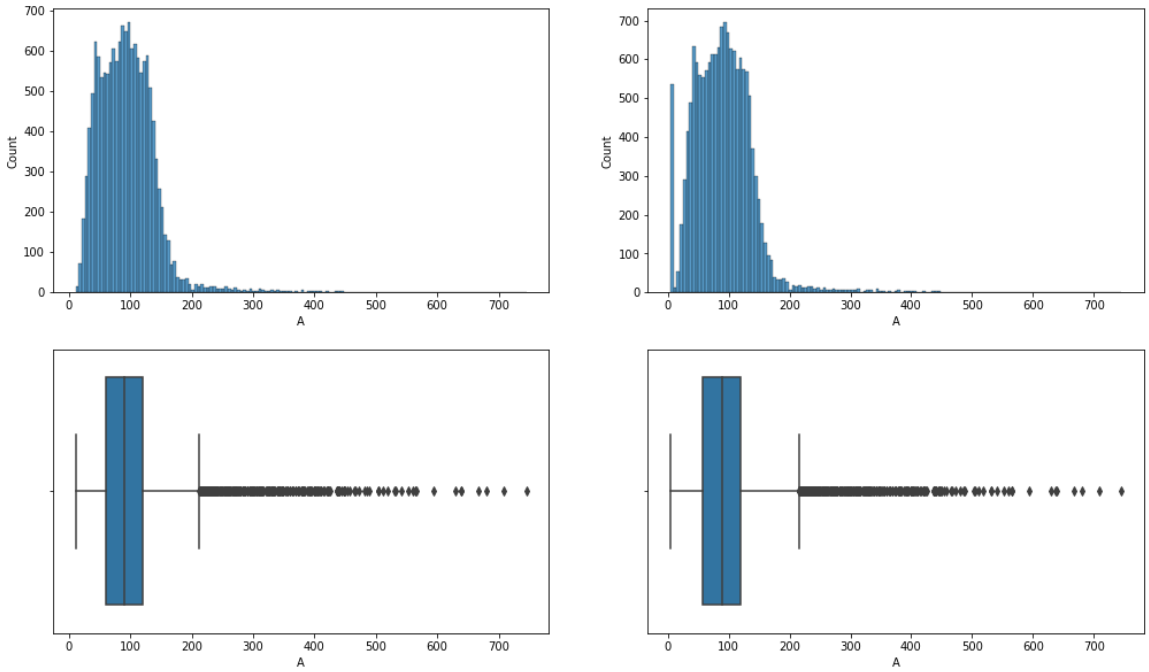
In [23]:

```
f, axes = plt.subplots(2, 2, figsize = (17,10))
sns.histplot(df['A'], ax = axes[0][0])
sns.histplot(df_new['A'], ax = axes[0][1])
sns.boxplot(df['A'], ax = axes[1][0])
sns.boxplot(df_new['A'], ax = axes[1][1])
```

```
C:\Users\itsyk\Python\lib\site-packages\seaborn\_decorators.py:36: Future
Warning: 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 misinter
pretation.
  warnings.warn(
C:\Users\itsyk\Python\lib\site-packages\seaborn\_decorators.py:36: Future
Warning: 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 misinter
pretation.
  warnings.warn(
```

Out[23]:

```
<AxesSubplot:xlabel='A'>
```



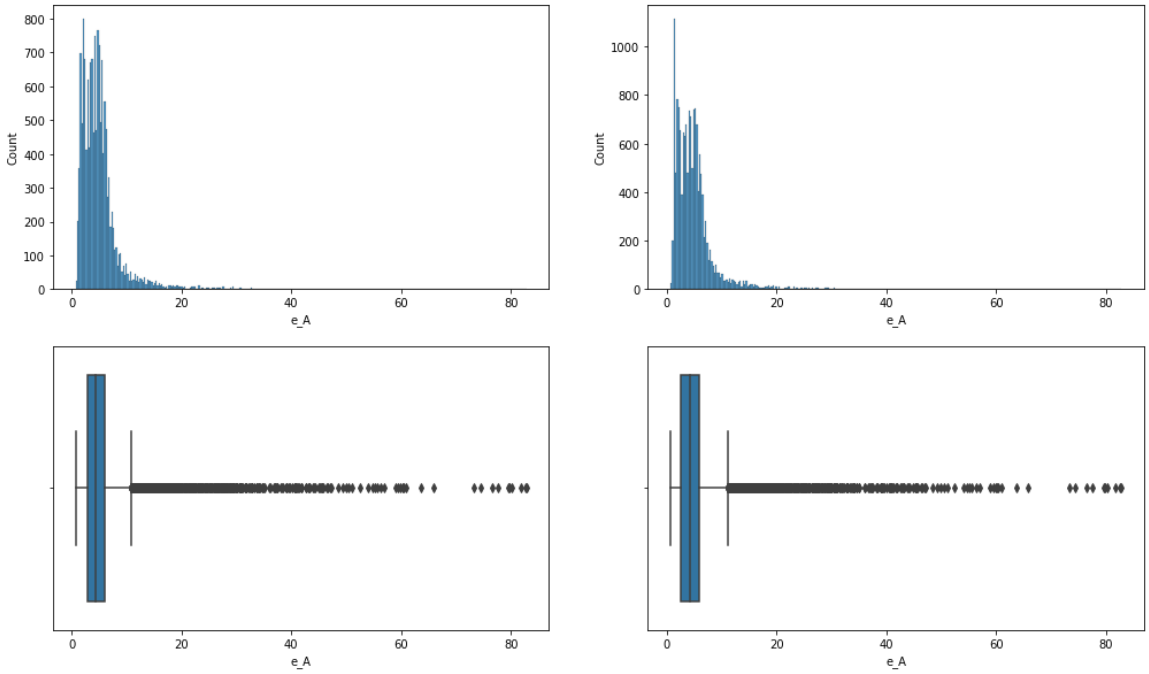
In [24]:

```
f, axes = plt.subplots(2, 2, figsize = (17,10))
sns.histplot(df['e_A'], ax = axes[0][0])
sns.histplot(df_new['e_A'], ax = axes[0][1])
sns.boxplot(df['e_A'], ax = axes[1][0])
sns.boxplot(df_new['e_A'], ax = axes[1][1])
```

```
C:\Users\itsyk\Python\lib\site-packages\seaborn\_decorators.py:36: Future
Warning: 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 misinter
pretation.
  warnings.warn(
C:\Users\itsyk\Python\lib\site-packages\seaborn\_decorators.py:36: Future
Warning: 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 misinter
pretation.
  warnings.warn(
```

Out[24]:

```
<AxesSubplot:xlabel='e_A'>
```



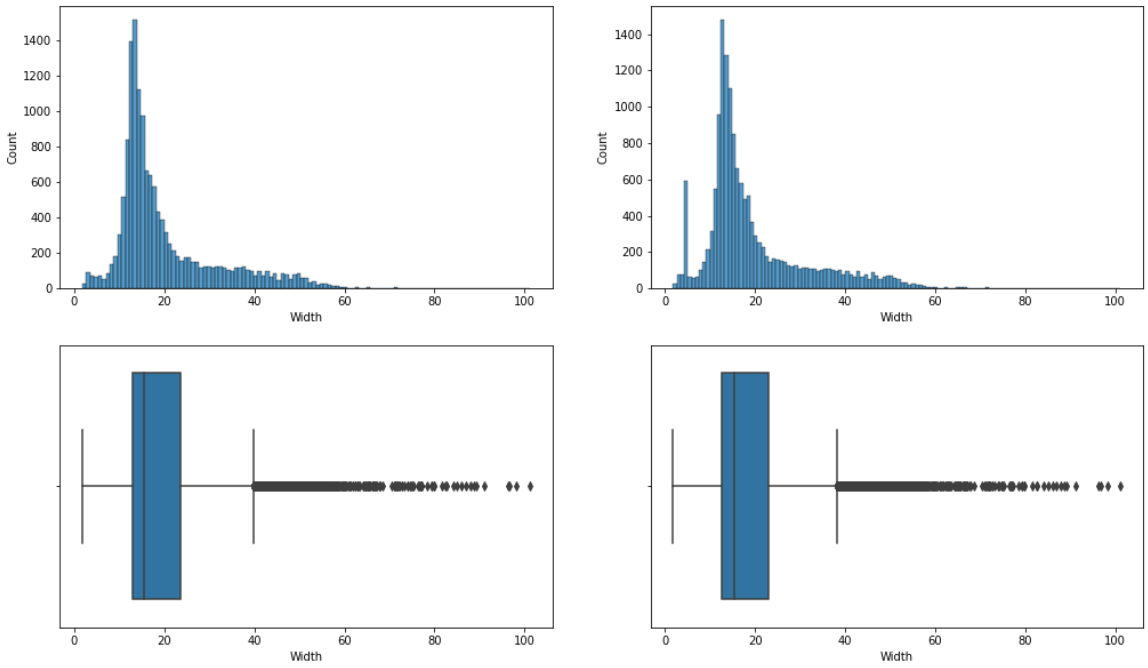
In [25]:

```
f, axes = plt.subplots(2, 2, figsize = (17,10))
sns.histplot(df['Width'], ax = axes[0][0])
sns.histplot(df_new['Width'], ax = axes[0][1])
sns.boxplot(df['Width'], ax = axes[1][0])
sns.boxplot(df_new['Width'], ax = axes[1][1])
```

```
C:\Users\itsyk\Python\lib\site-packages\seaborn\_decorators.py:36: Future
Warning: 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 misinter
pretation.
  warnings.warn(
C:\Users\itsyk\Python\lib\site-packages\seaborn\_decorators.py:36: Future
Warning: 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 misinter
pretation.
  warnings.warn(
```

Out[25]:

```
<AxesSubplot:xlabel='Width'>
```



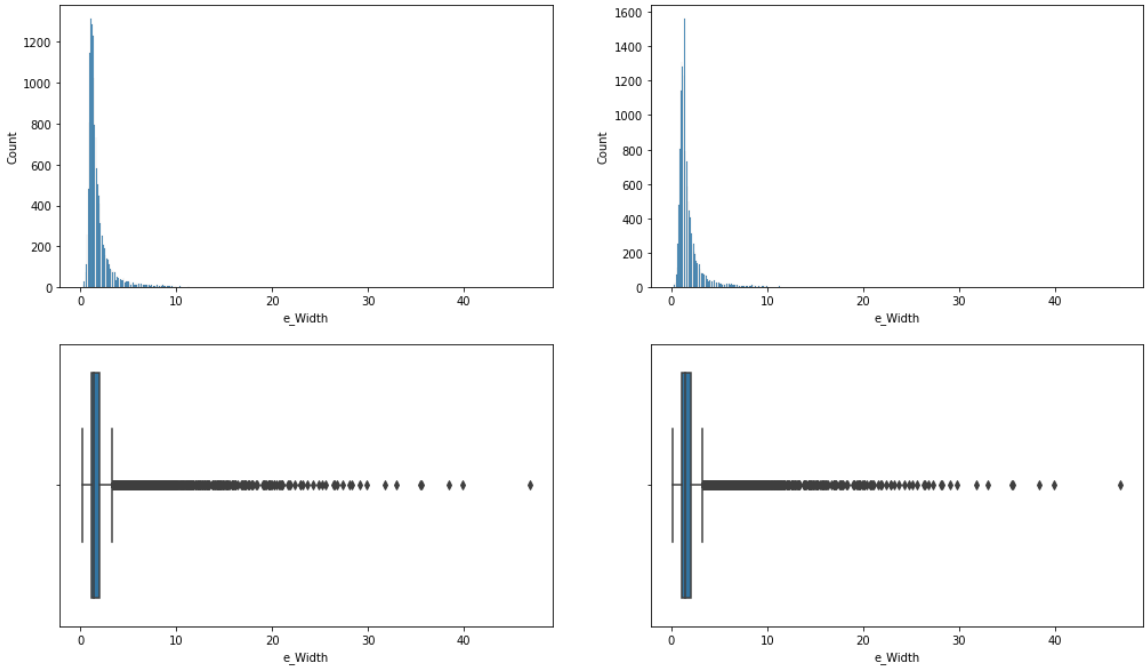
In [26]:

```
f, axes = plt.subplots(2, 2, figsize = (17,10))
sns.histplot(df['e_Width'], ax = axes[0][0])
sns.histplot(df_new['e_Width'], ax = axes[0][1])
sns.boxplot(df['e_Width'], ax = axes[1][0])
sns.boxplot(df_new['e_Width'], ax = axes[1][1])
```

```
C:\Users\itsyk\Python\lib\site-packages\seaborn\_decorators.py:36: Future
Warning: 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 misinter
pretation.
  warnings.warn(
C:\Users\itsyk\Python\lib\site-packages\seaborn\_decorators.py:36: Future
Warning: 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 misinter
pretation.
  warnings.warn(
```

Out[26]:

```
<AxesSubplot:xlabel='e_Width'>
```



Здесь я попробывал вместо nan значений написать усредненные, но некоторые знаения сильна выбиваются. Думаю, что лучше просто от них отказаться, так как данных достаточно.

In [27]:
```
df = df[df['A'].notna()]
df.shape
```

Out[27]:
```
(14851, 28)
```

In [28]:
```
for i in df.columns:
    a = df[i].isnull().sum()
    if a > 0:
        print(i, '-', a)
print('end')
```

```
end
```

In [29]:
```
df.head()
```

Out[29]:

	Kpmag	numax	e_numax	Delnu	e_Delnu	A	e_A	Width	e_Width	Teff	...	e_No
0	9.20	29.99	0.60	3.399	0.011	104.9	4.6	12.3	1.5	4751	...	
1	13.23	29.48	0.48	3.962	0.116	149.7	8.3	12.0	3.9	5188	...	
2	12.58	41.39	0.54	4.311	0.013	86.1	4.6	15.3	1.6	4728	...	
3	12.14	41.17	0.90	4.414	0.061	63.8	2.9	24.8	2.7	5072	...	
4	11.74	36.91	0.71	3.991	0.064	116.1	9.6	14.0	2.4	4718	...	

5 rows × 28 columns

In [30]:
```
df.describe()
```

Out[30]:

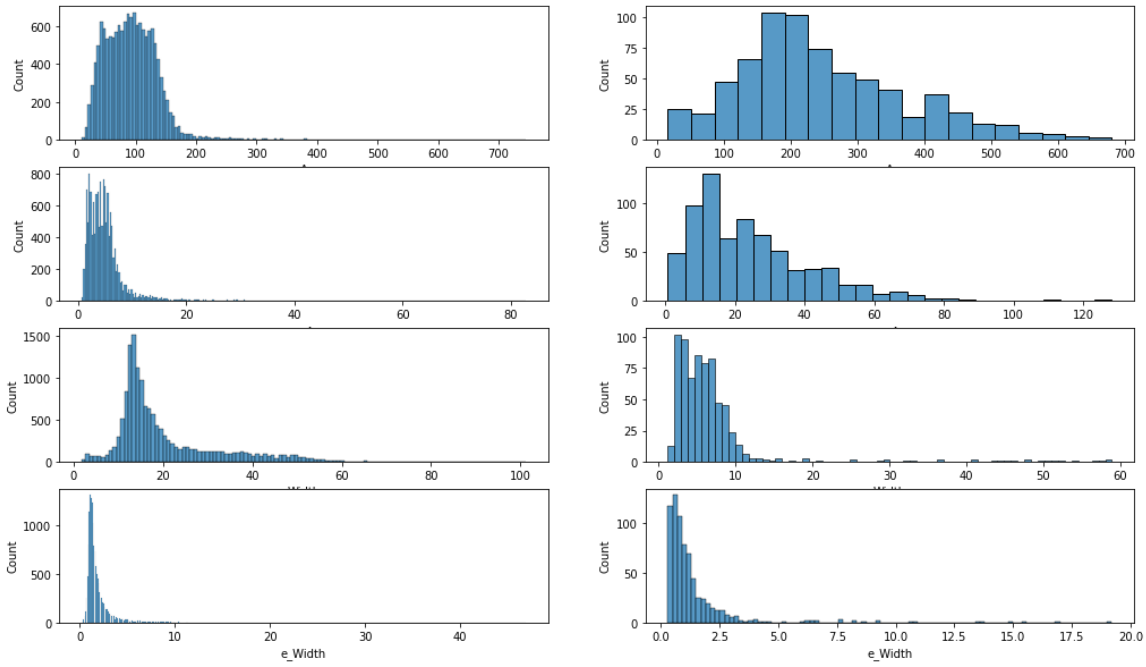
	Kpmag	numax	e_numax	Delnu	e_Delnu	A

count	14851.000000	14851.000000	14851.000000	14851.000000	14851.000000	14851.000000
mean	12.619928	58.995670	0.856245	5.783544	0.047270	95.059174
std	1.216108	41.937888	0.613275	2.979246	0.070172	51.897428
min	6.240000	3.970000	0.040000	0.747000	0.008000	10.700000
25%	11.880000	31.500000	0.550000	3.961000	0.016000	59.900000
50%	12.840000	40.960000	0.710000	4.457000	0.027000	90.800000
75%	13.500000	72.070000	0.960000	6.711500	0.050000	120.900000
max	16.850000	200.000000	25.370000	16.745000	1.338000	745.200000

8 rows × 28 columns

In [31]:
```
f, axes = plt.subplots(4, 2, figsize = (17,10))
sns.histplot(df['A'], ax = axes[0][0])
sns.histplot(df_un['A'], ax = axes[0][1])
sns.histplot(df['e_A'], ax = axes[1][0])
sns.histplot(df_un['e_A'], ax = axes[1][1])
sns.histplot(df['Width'], ax = axes[2][0])
sns.histplot(df_un['Width'], ax = axes[2][1])
sns.histplot(df['e_Width'], ax = axes[3][0])
sns.histplot(df_un['e_Width'], ax = axes[3][1])
```

Out[31]:
```
<AxesSubplot:xlabel='e_Width', ylabel='Count'>
```

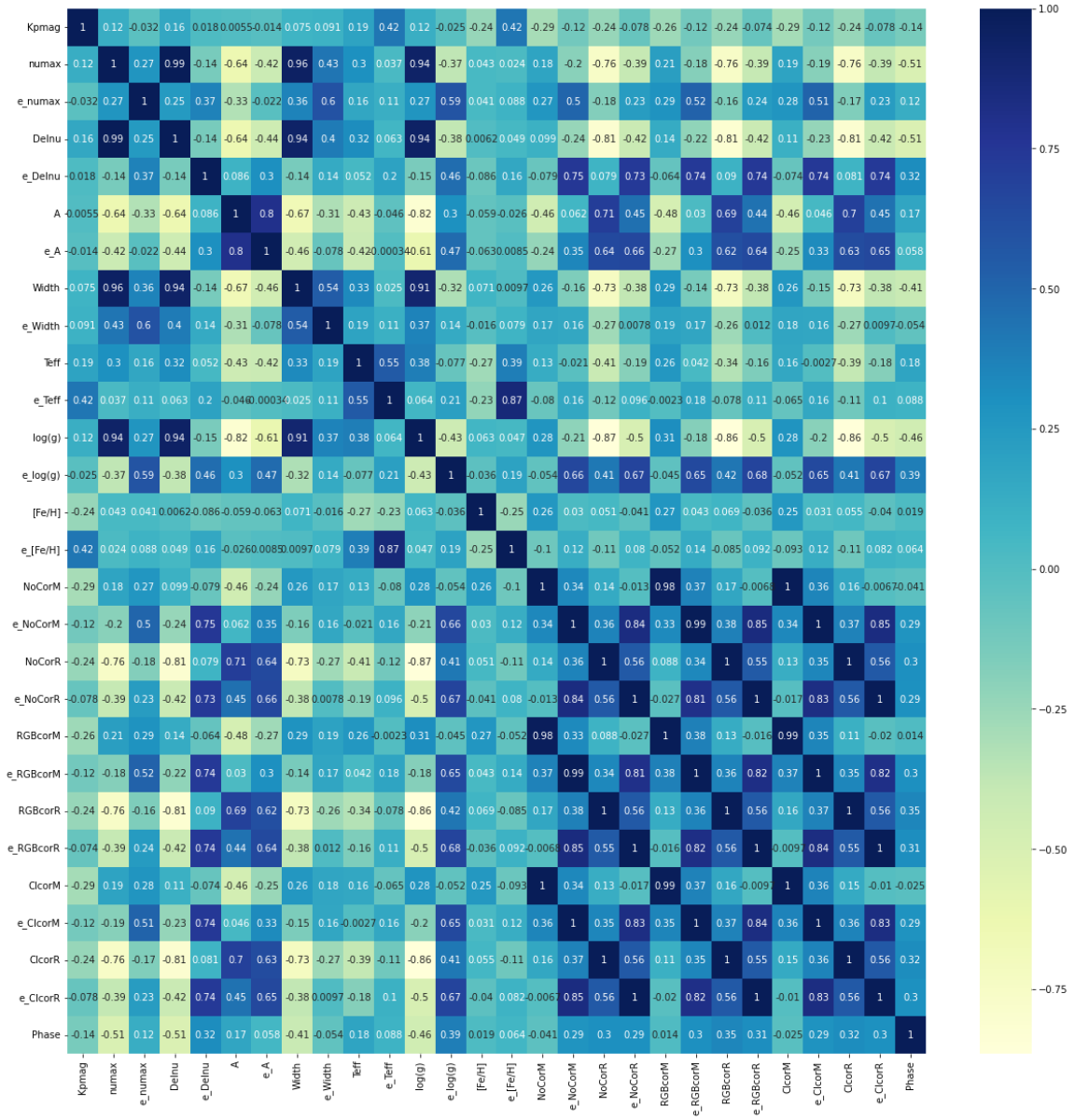


Как можно отметить, данных достаточно, чтобы определить фазы на неопределенных данных

Матрица корреляции

In [32]:
```
plt.figure(figsize = (20, 20))
corr_matrix = df.corr()
sns.heatmap(corr_matrix, annot=True, cmap="YlGnBu")
```

Out[32]:
```
<AxesSubplot:>
```



In [33]:

```
df_corr = df.corr().unstack().reset_index()
df_corr
```

Out[33]:

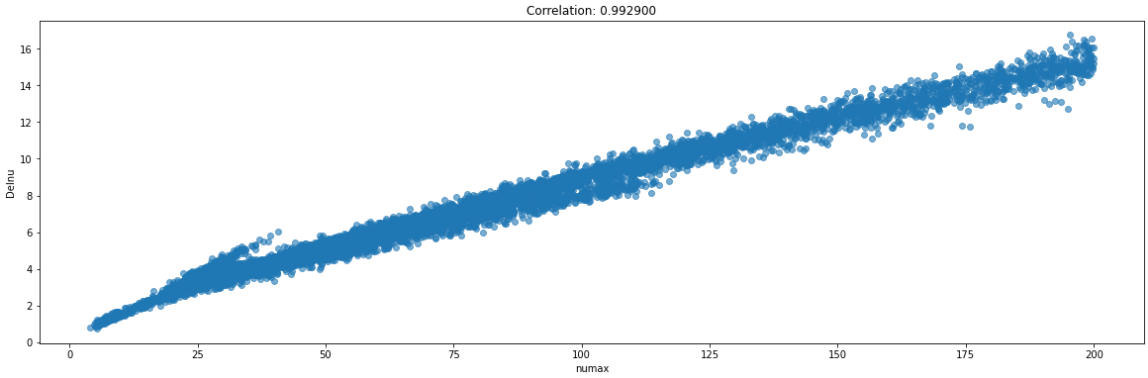
	level_0	level_1	0
0	Kpmag	Kpmag	1.000000
1	Kpmag	numax	0.118883
2	Kpmag	e_numax	-0.031973
3	Kpmag	Delnu	0.158125
4	Kpmag	e_Delnu	0.018239
...	...	...	...
779	Phase	ClcorM	-0.024521
780	Phase	e_ClcorM	0.288437
781	Phase	ClcorR	0.315257
782	Phase	e_ClcorR	0.299135
783	Phase	Phase	1.000000

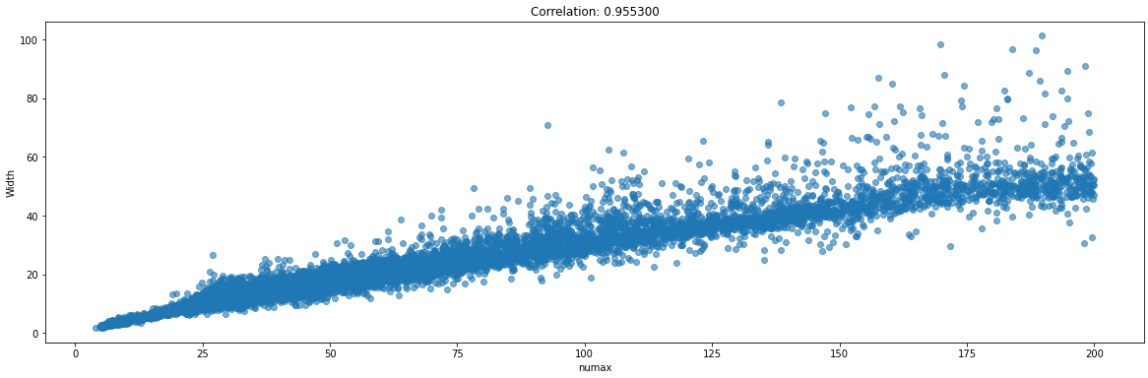
784 rows × 3 columns

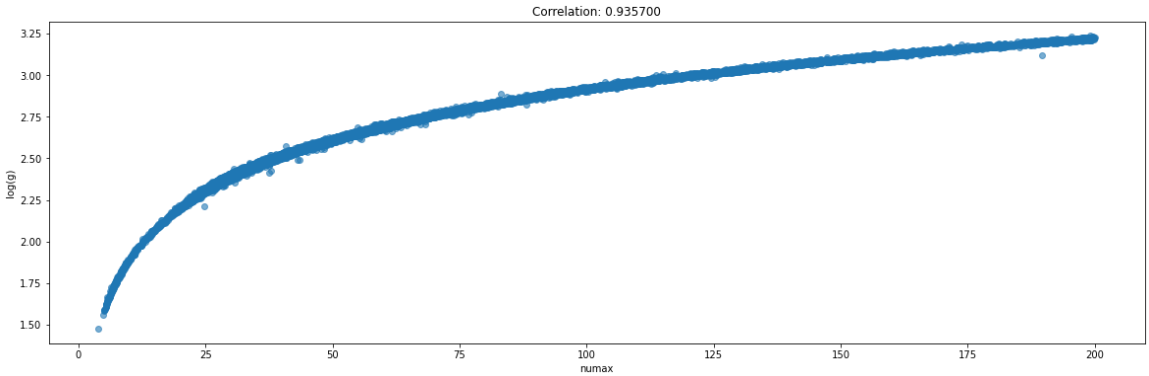
In [34]:
```
high_corr_features = []
for i in range(len(df_corr)):
    if df_corr[0][i] > 0.9 and df_corr['level_0'][i] != df_corr['level_1
        high_corr_features.append([df_corr['level_0'][i], df_corr['level_
high_corr_features
```

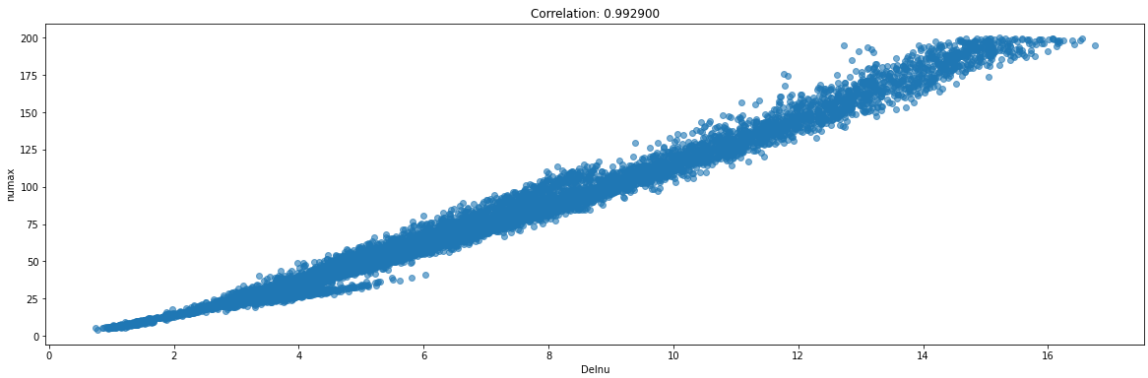
Out[34]:
```
[['numax', 'Delnu', 0.9929377587760945],
 ['numax', 'Width', 0.9552979711189871],
 ['numax', 'log(g)', 0.935695230273852],
 ['Delnu', 'numax', 0.9929377587760945],
 ['Delnu', 'Width', 0.9396805418304727],
 ['Delnu', 'log(g)', 0.942644750007283],
 ['Width', 'numax', 0.9552979711189871],
 ['Width', 'Delnu', 0.9396805418304727],
 ['Width', 'log(g)', 0.9112383054900803],
 ['log(g)', 'numax', 0.935695230273852],
 ['log(g)', 'Delnu', 0.942644750007283],
 ['log(g)', 'Width', 0.9112383054900803],
 ['NoCorM', 'RGBcorM', 0.9839076557216867],
 ['NoCorM', 'ClcorM', 0.9972906059411837],
 ['e_NoCorM', 'e_RGBcorM', 0.9935568667387731],
 ['e_NoCorM', 'e_ClcorM', 0.9982558829325169],
 ['NoCorR', 'RGBcorR', 0.995156784951965],
 ['NoCorR', 'ClcorR', 0.9992449435255716],
 ['e_NoCorR', 'e_RGBcorR', 0.998362812237733],
 ['e_NoCorR', 'e_ClcorR', 0.9996361917355046],
 ['RGBcorM', 'NoCorM', 0.9839076557216867],
 ['RGBcorM', 'ClcorM', 0.9899052085865482],
 ['e_RGBcorM', 'e_NoCorM', 0.9935568667387731],
 ['e_RGBcorM', 'e_ClcorM', 0.99623587429077],
 ['RGBcorR', 'NoCorR', 0.995156784951965],
 ['RGBcorR', 'ClcorR', 0.9969752898077152],
 ['e_RGBcorR', 'e_NoCorR', 0.998362812237733],
 ['e_RGBcorR', 'e_ClcorR', 0.9990123064794945],
 ['ClcorM', 'NoCorM', 0.9972906059411837],
 ['ClcorM', 'RGBcorM', 0.9899052085865482],
 ['e_ClcorM', 'e_NoCorM', 0.9982558829325169],
 ['e_ClcorM', 'e_RGBcorM', 0.99623587429077],
 ['ClcorR', 'NoCorR', 0.9992449435255716],
 ['ClcorR', 'RGBcorR', 0.9969752898077152],
 ['e_ClcorR', 'e_NoCorR', 0.9996361917355046],
 ['e_ClcorR', 'e_RGBcorR', 0.9990123064794945]]
```

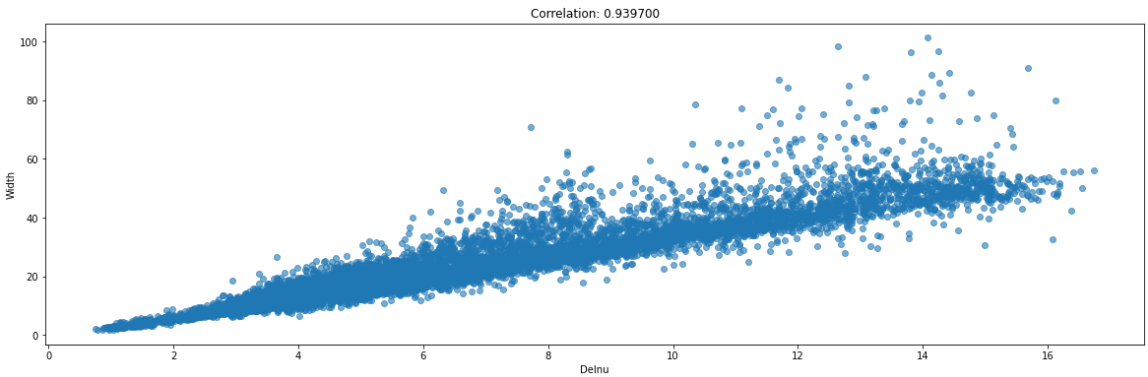
In [35]:
```
for i in  high_corr_features:
    plt.figure(figsize = (20, 6))
    plt.plot(df[i[0]], df[i[1]], 'o', alpha = 0.6)
    plt.title('Correlation: %f' % round(i[2], 4))
    plt.xlabel(i[0])
    plt.ylabel(i[1])
    plt.show()
```

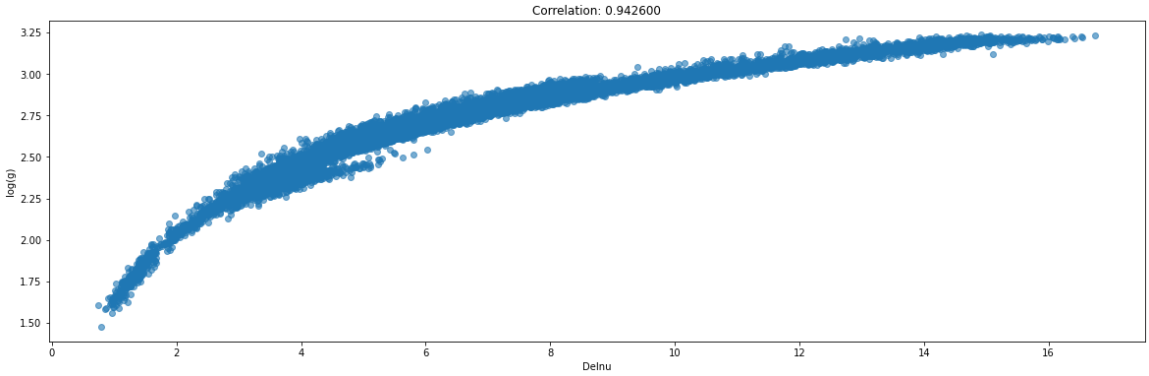

Correlation: 0.992900
Delnu
numax

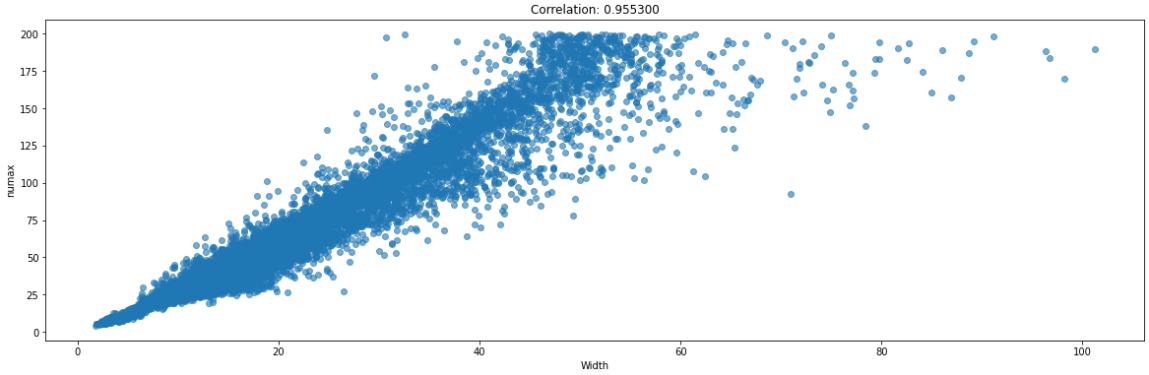

Correlation: 0.955300
Width
numax

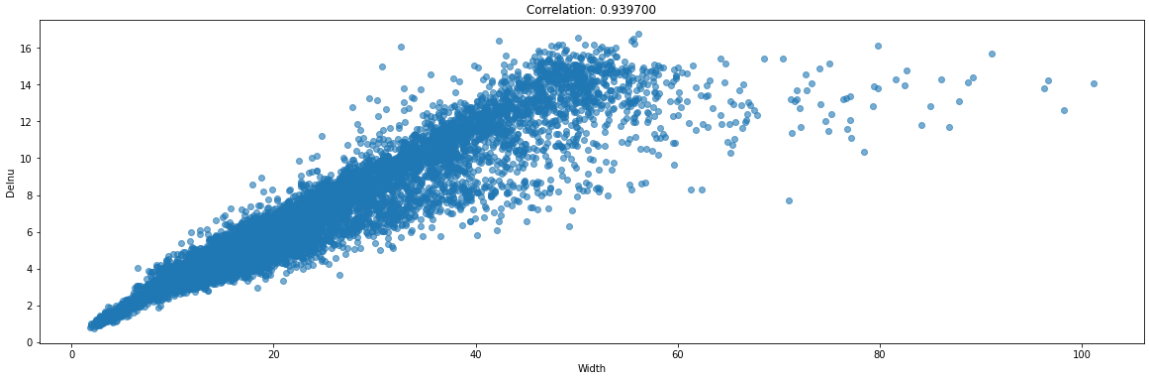

Correlation: 0.935700
log(g)
numax

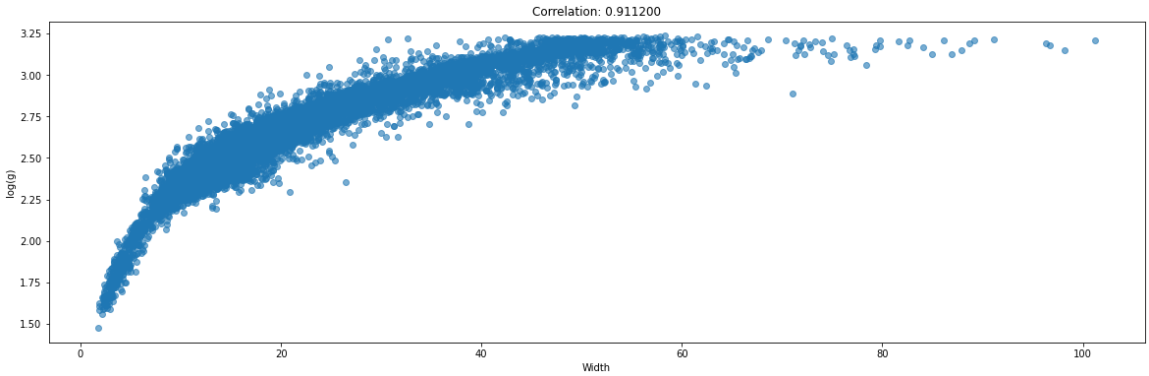

Correlation: 0.992900
numax
Delnu

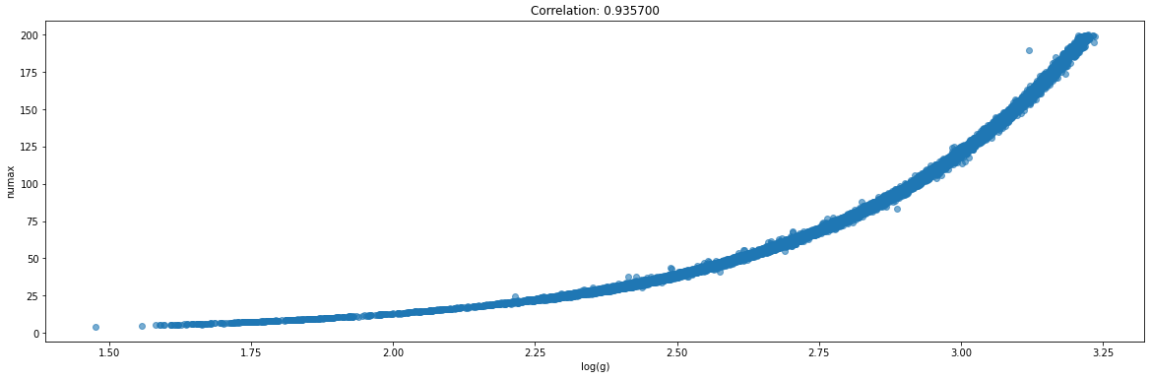

Correlation: 0.939700
Width
Delnu

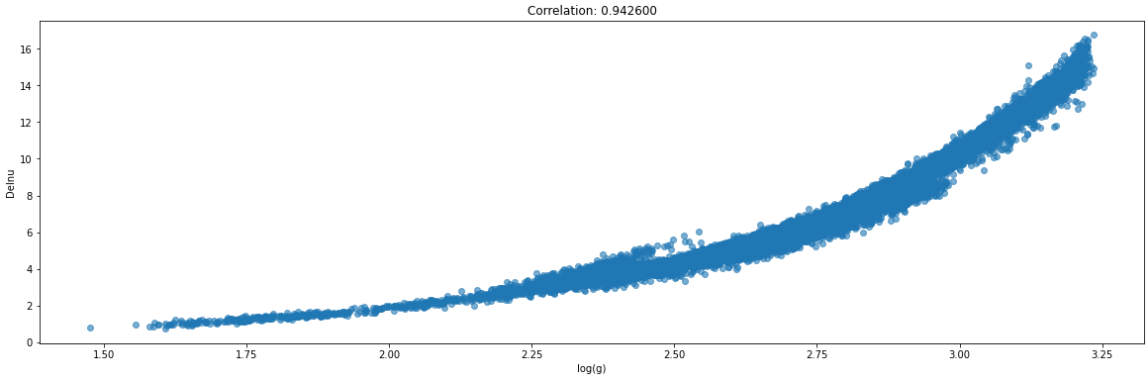

Correlation: 0.942600
log(g)
Delnu

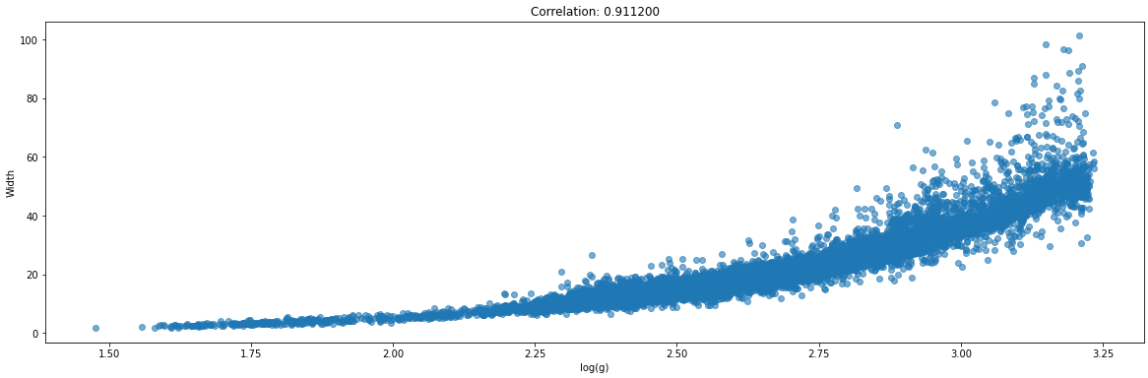

Correlation: 0.955300
numax
Width

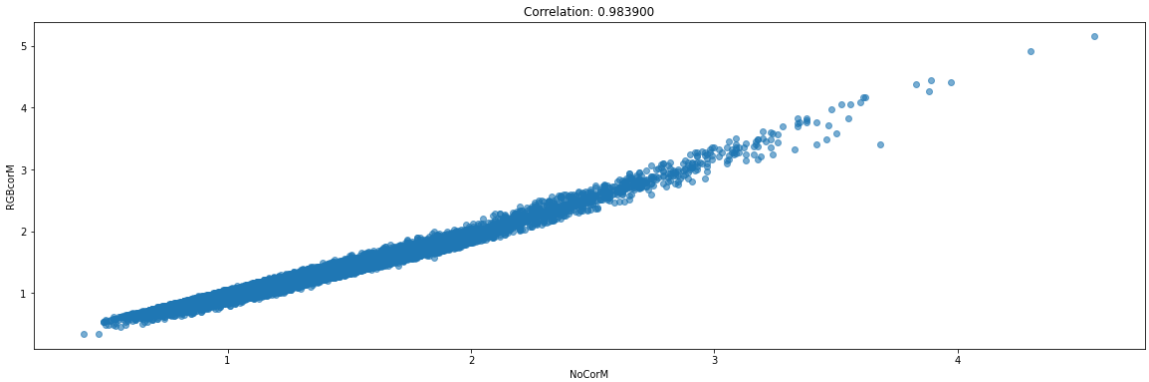

Correlation: 0.939700
Delnu
Width

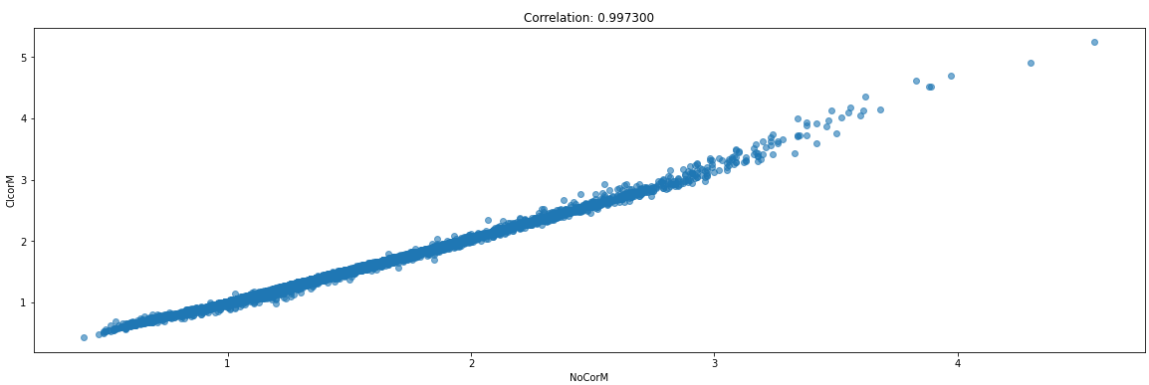

Correlation: 0.911200
log(g)
Width

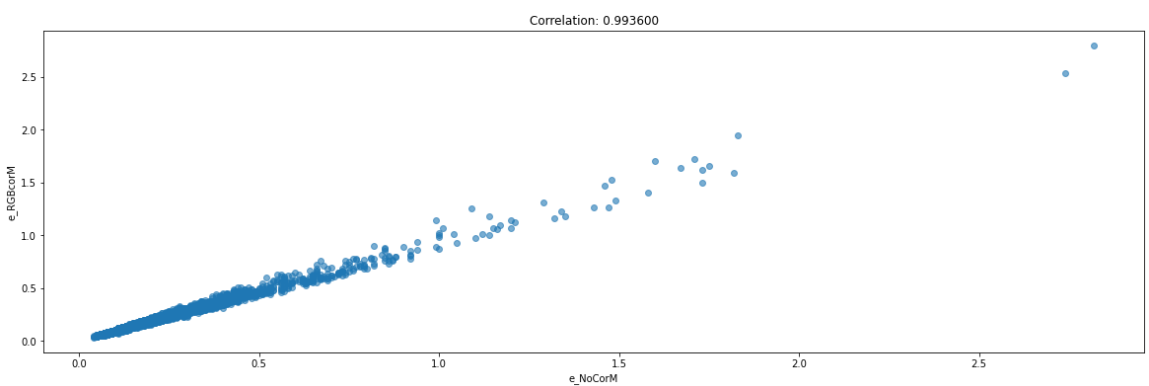

Correlation: 0.935700
numax
log(g)

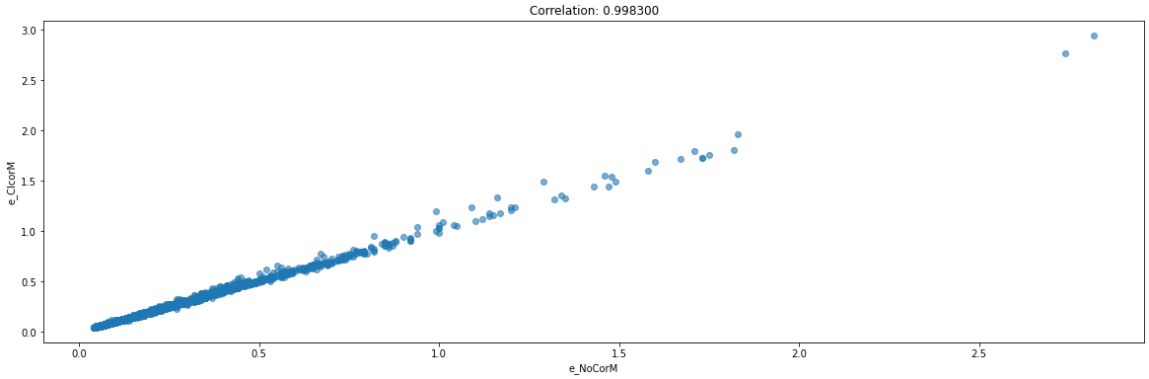

Correlation: 0.942600
Delnu
log(g)

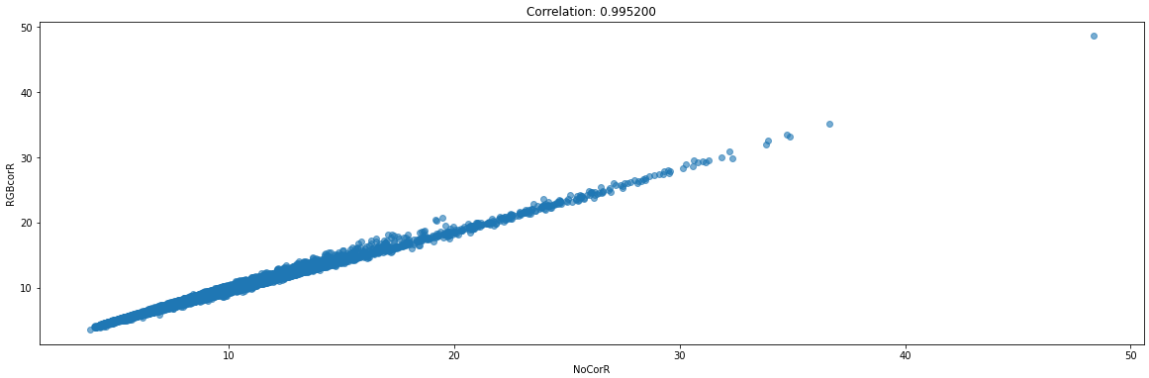

Correlation: 0.911200
Width
log(g)

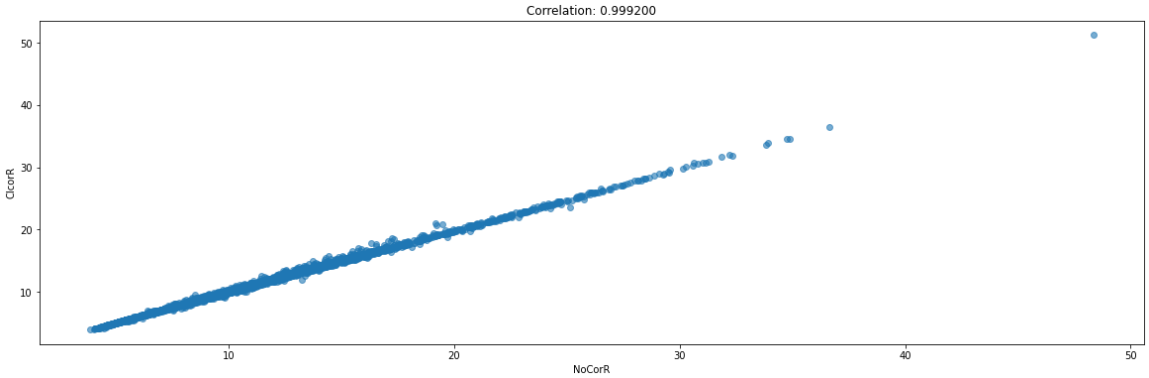

Correlation: 0.983900
RGBcorM
NoCorM

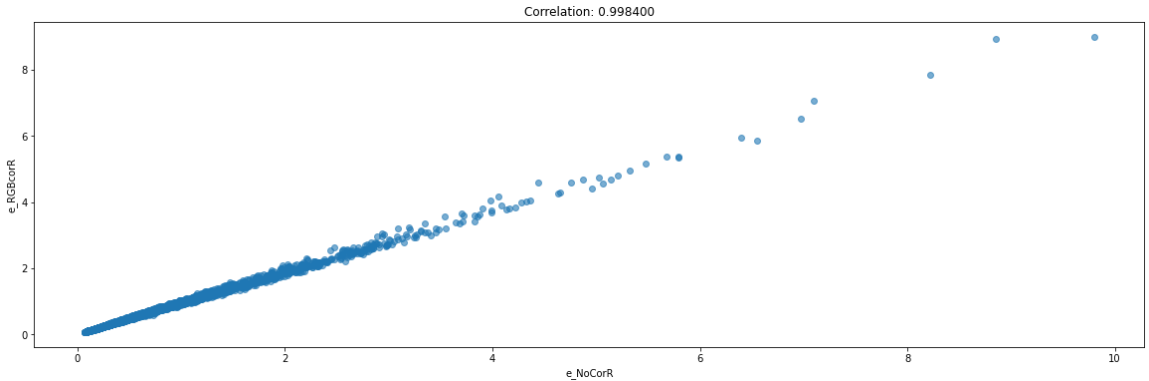

Correlation: 0.997300
CIcorM
NoCorM

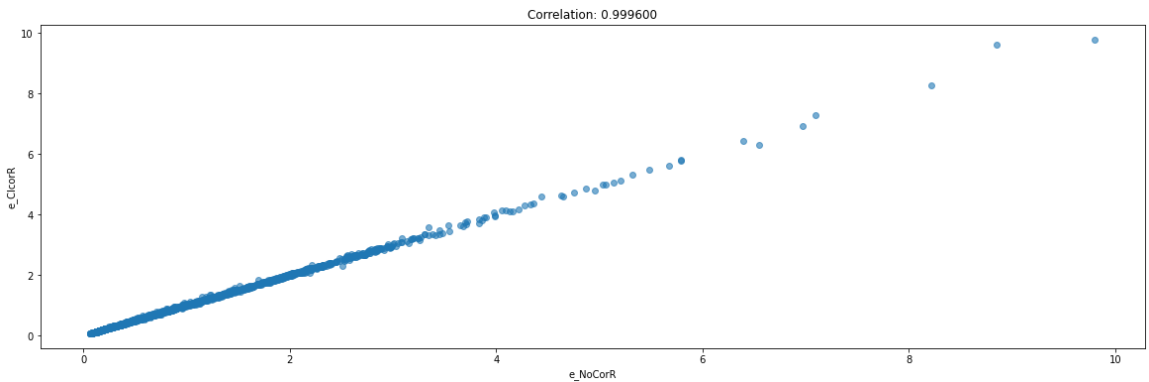

Correlation: 0.993600
e_RGBcorM
e_NoCorM

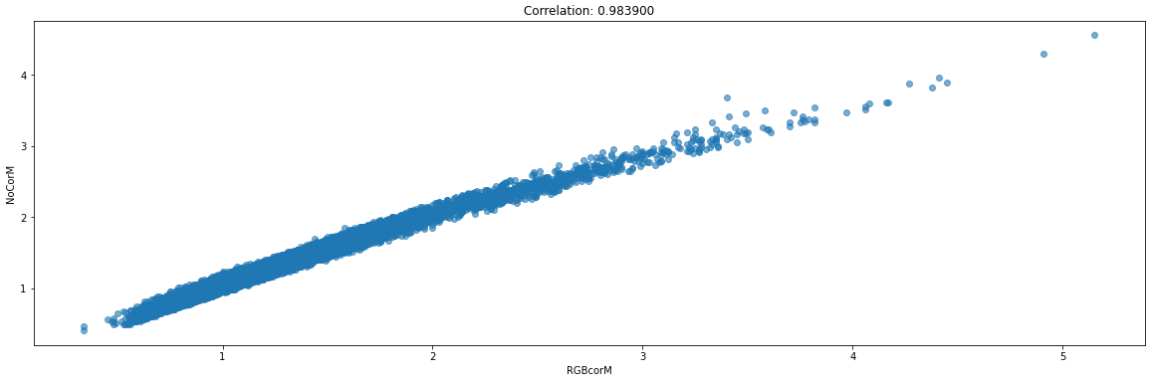

Correlation: 0.998300
e_ClcorM
e_NoCorM

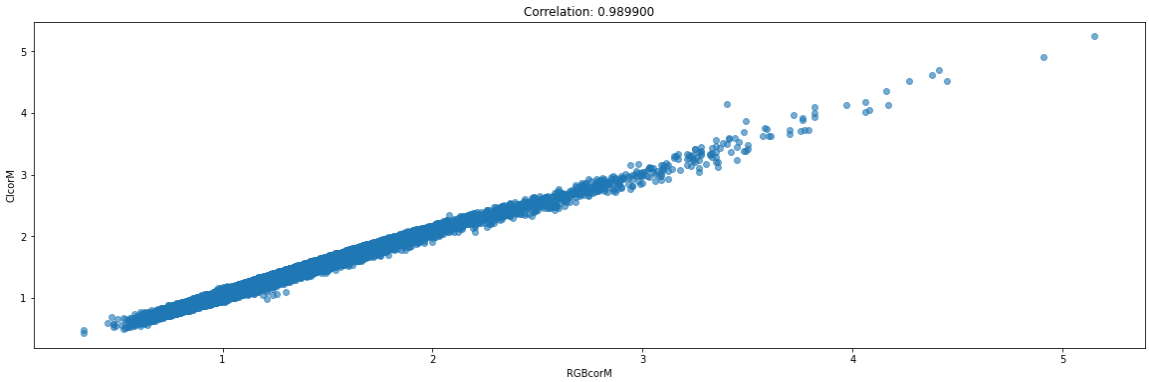

Correlation: 0.995200
RGBcorR
NoCorR

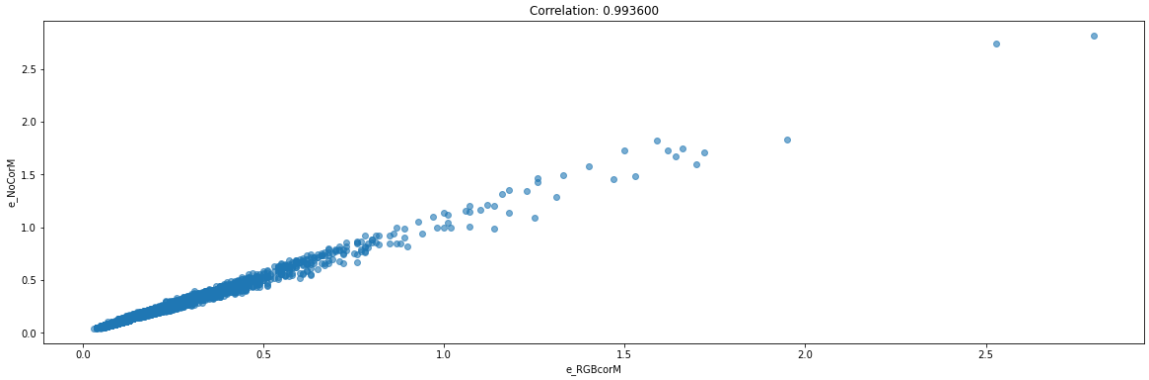

Correlation: 0.999200
ClcorR
NoCorR

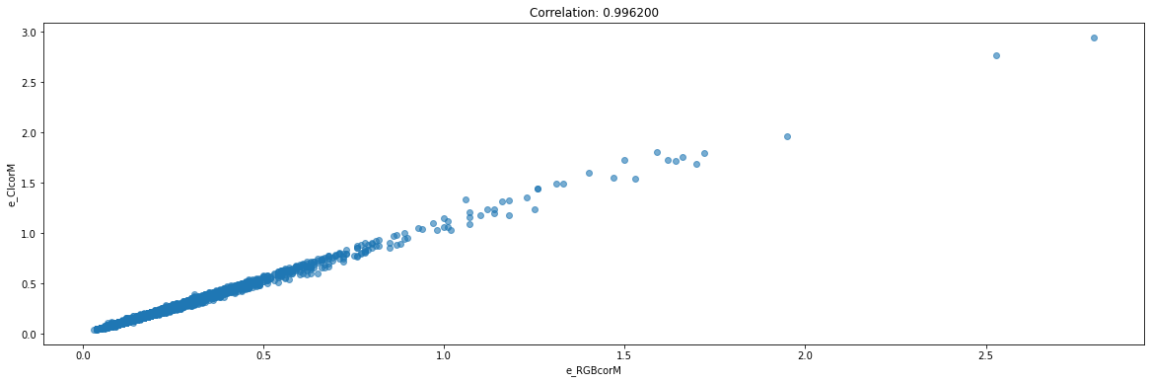

Correlation: 0.998400
e_RGBcorR
e_NoCorR

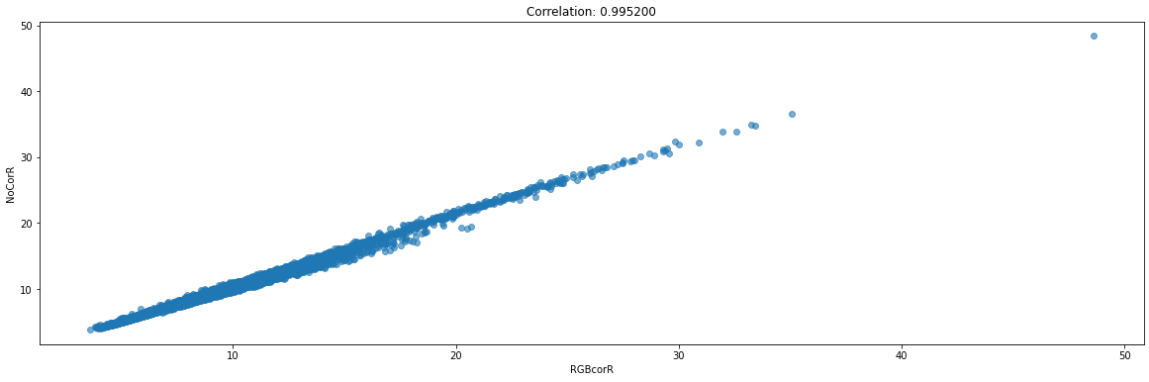

Correlation: 0.999600
e_ClcorR
e_NoCorR

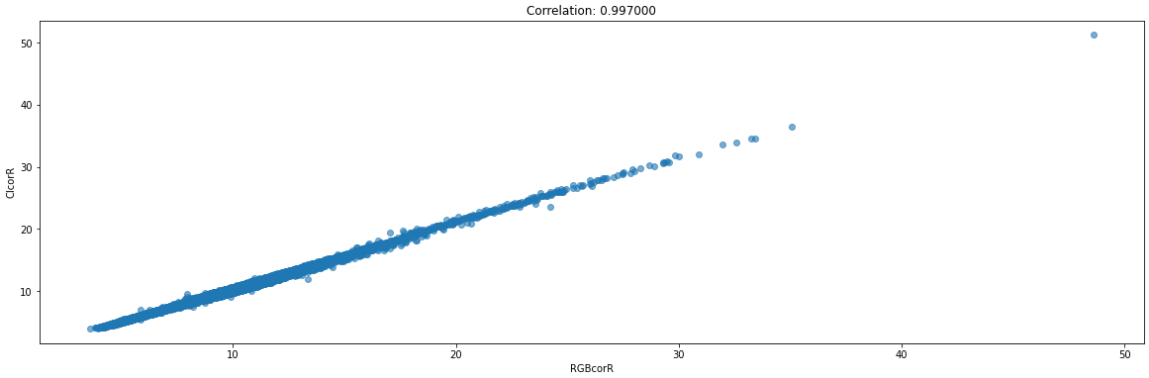

Correlation: 0.983900
NoCorrM
RGBcorrM

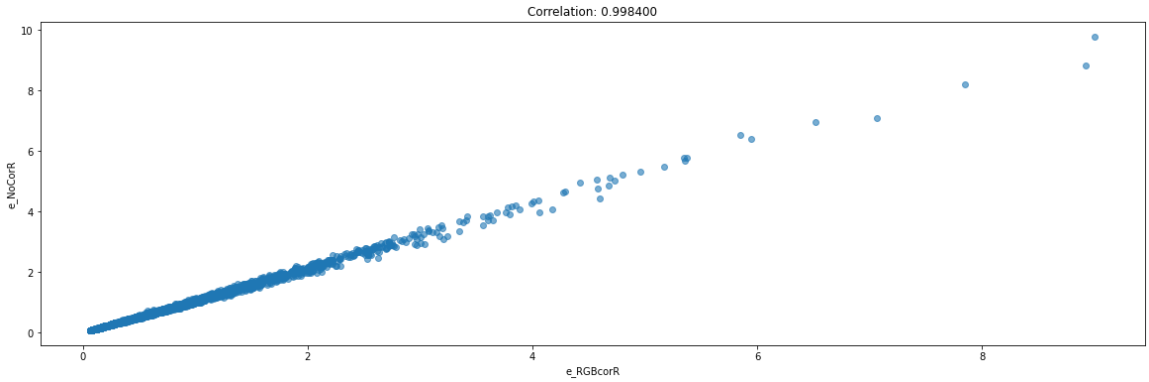

Correlation: 0.989900
CIcorrM
RGBcorrM

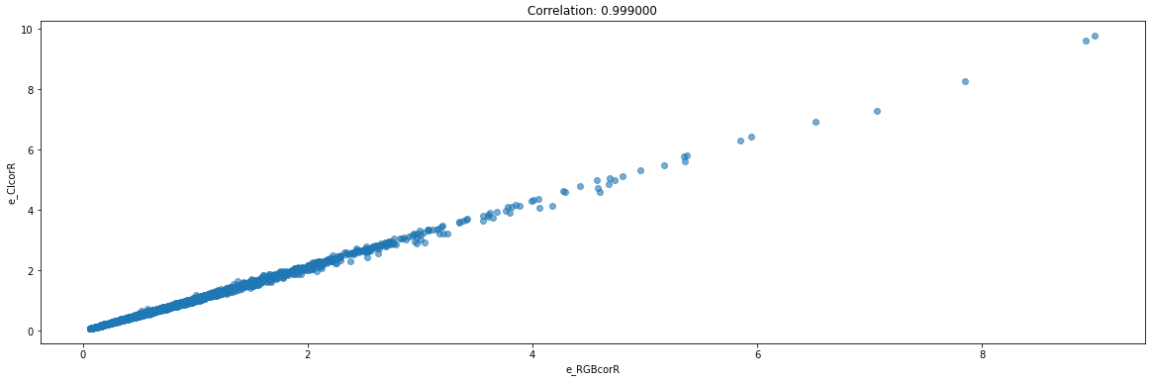

Correlation: 0.993600
e_NoCorrM
e_RGBcorrM

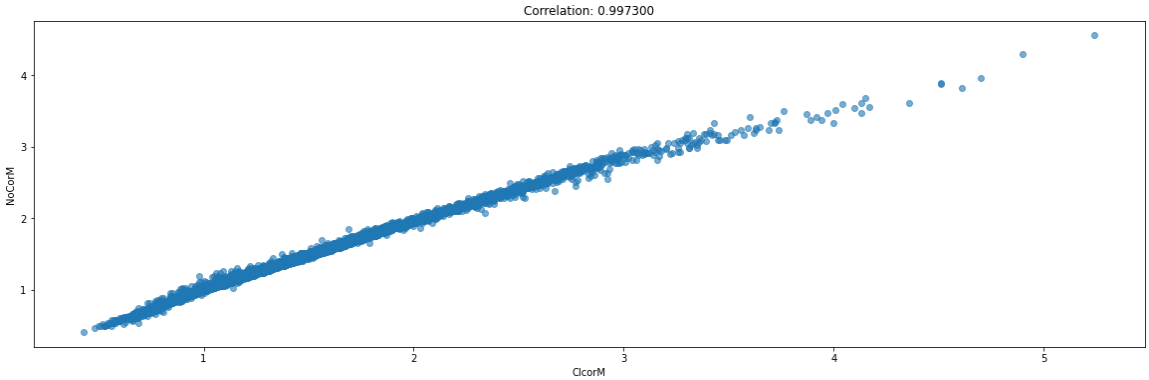

Correlation: 0.996200
e_CIcorrM
e_RGBcorrM

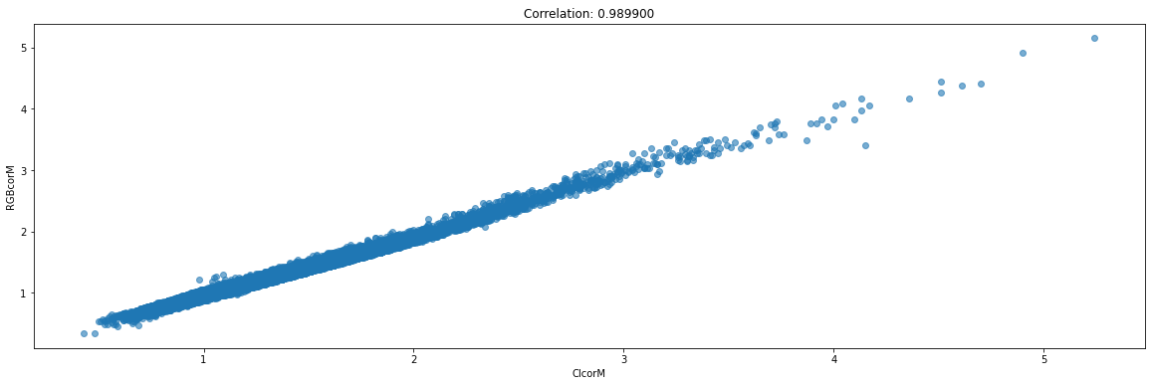

Correlation: 0.995200
NoCorrR
RGBcorrR

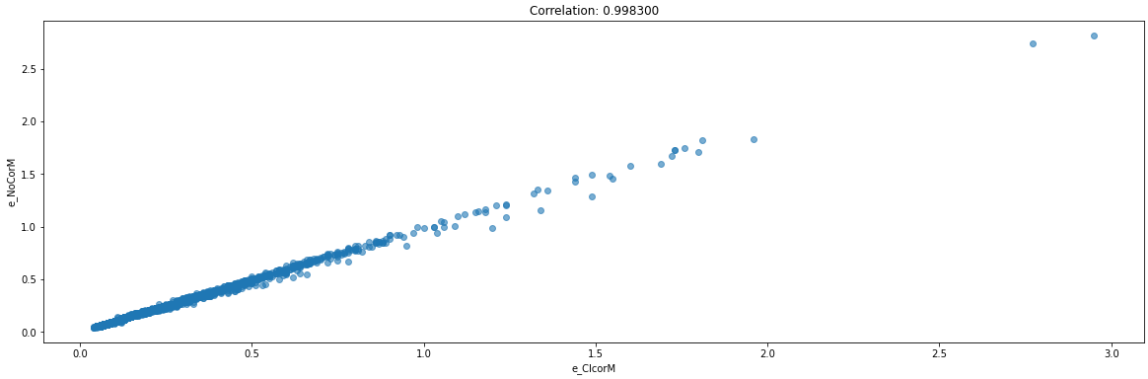

Correlation: 0.997000
ClcorR
RGBcorR

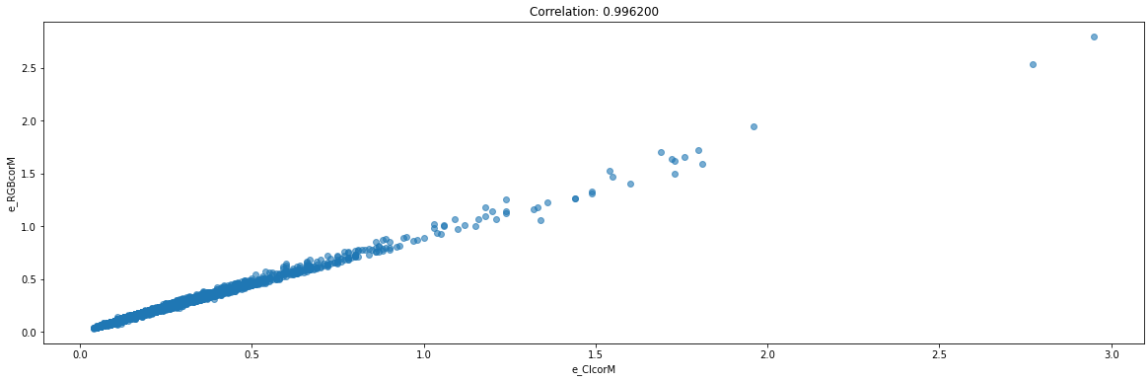

Correlation: 0.998400
e_NoCorR
e_RGBcorR

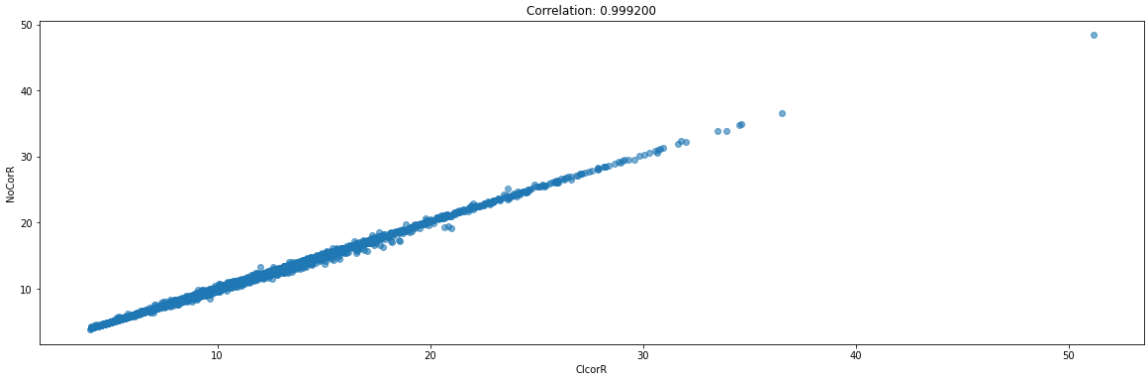

Correlation: 0.999000
e_ClcorR
e_RGBcorR

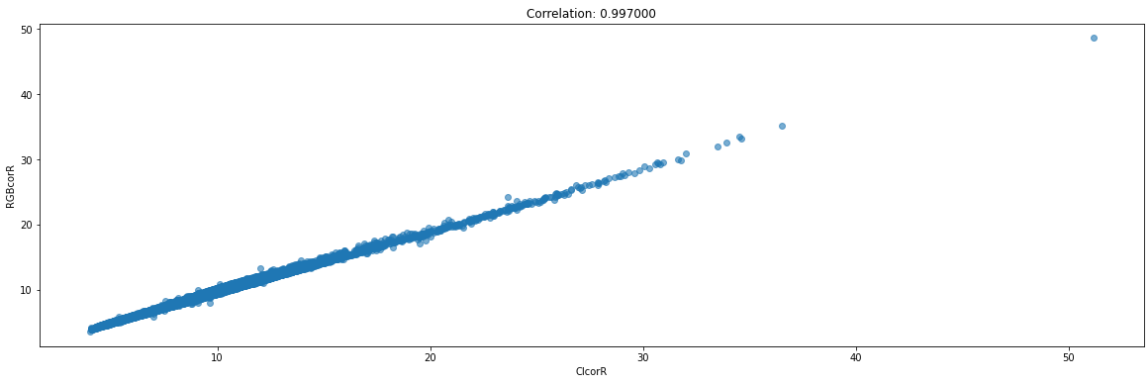

Correlation: 0.997300
NoCorM
ClcorM

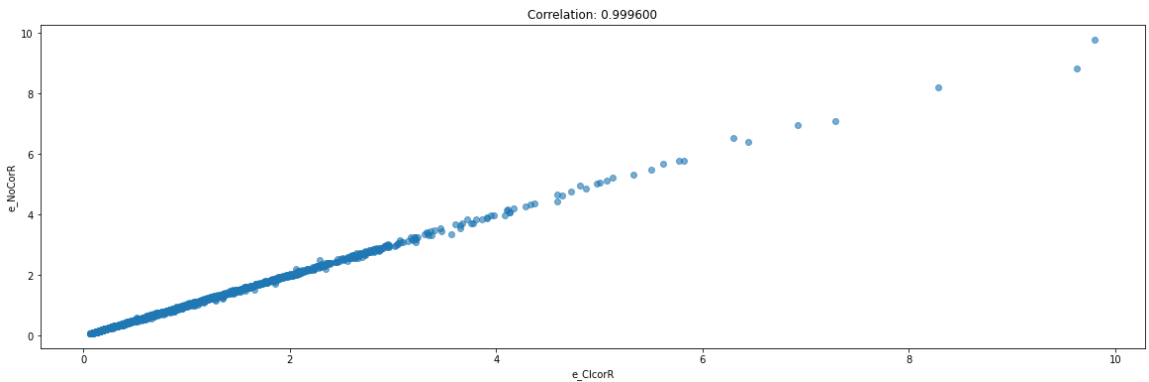

Correlation: 0.989900
RGBcorM
ClcorM

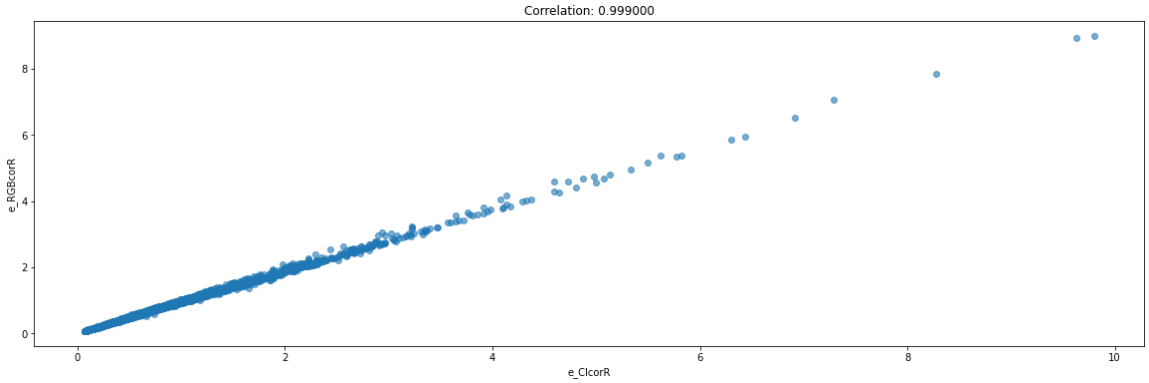

Correlation: 0.998300
e_NoCorM
e_ClcorM


Correlation: 0.996200
e_RGBcorM
e_ClcorM


Correlation: 0.999200
NoCorR
ClcorR


Correlation: 0.997000
RGBcorR
ClcorR


Correlation: 0.999600
e_NoCorR
e_ClcorR



Из полученной матрицы корреляции и графиков коррелиции можно выявить, что есть параметры которые можно отбросить, cor[A, B] которых = 1

In [36]:
```
par = ["NoCorM", "e_NoCorM", "NoCorR", "e_NoCorR",  "RGBcorM", "e_RGBcorI
par
```

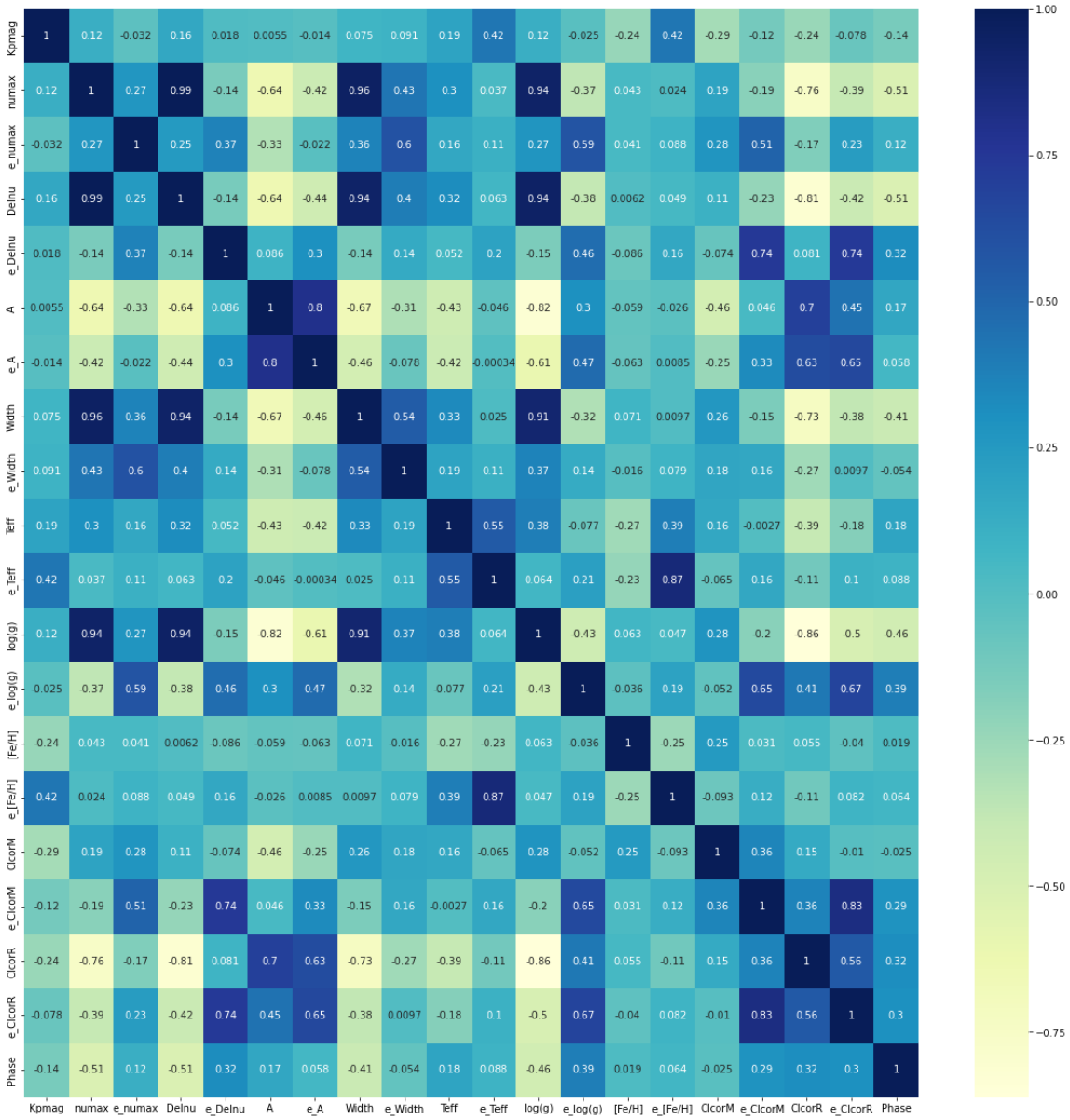
Out[36]:
```
['NoCorM',
 'e_NoCorM',
 'NoCorR',
 'e_NoCorR',
 'RGBcorM',
 'e_RGBcorM',
 'RGBcorR',
 'e_RGBcorR']
```

In [37]:
```
df = df.drop(par, axis = 1)
df_un = df_un.drop(par, axis = 1)
print(df.shape, df_un.shape)
```

```
(14851, 20) (706, 20)
```

In [38]:
```
plt.figure(figsize = (20, 20))
corr_matrix = df.corr()
sns.heatmap(corr_matrix, annot=True, cmap="YlGnBu")
```

Out[38]:
```
<AxesSubplot:>
```



Вывод по 0 части

В данной части лабораторной работы мной был найден датасет для определения фазы эволюционировавших звезд (Фаза HeB, Фаза RGB). В задании требуется по полученным данным для звезд, у которых не определена фаза, определить ее. В этой работе мной был реализован эта PRE-PROCESSING для подготовки данных к задачам машинного обучения. Я подготовил данные для решения задачи классификации по параметрам.