In [1]:
```
# Predict asteroid diameter values using 'Asteroid.csv' data set from Kaggle
 (contributed by Victor Basu)
# Model: XGBRegressor; in addition comparison with Linear Regression model wil
l be made
# Notes on data:
    # data is medium size comprising of 839736 entries and 27 columns
    # for a small portion of the data (~ 1/6) the asteroids diameters are know
n - this portion will be used to train the model
    # subsequently the model will be used to predict the diameters for the dat
a in which this information is missing
```

In [2]:
```
# import libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
sns.set(style="whitegrid", font_scale=1.5)
```

In [3]:
```
# read data

data = pd.read_csv('Asteroid.csv', low_memory = False)
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 839736 entries, 0 to 839735
Data columns (total 27 columns):
full_name         839736 non-null object
a                 839734 non-null float64
e                 839736 non-null float64
G                 119 non-null float64
i                 839736 non-null float64
om                839736 non-null float64
w                 839736 non-null float64
q                 839736 non-null float64
ad                839730 non-null float64
per_y             839735 non-null float64
data_arc          823947 non-null float64
condition_code    838743 non-null object
n_obs_used        839736 non-null int64
H                 837042 non-null float64
diameter          137681 non-null object
extent            18 non-null object
albedo            136452 non-null float64
rot_per           18796 non-null float64
GM                14 non-null float64
BV                1021 non-null float64
UB                979 non-null float64
IR                1 non-null float64
spec_B            1666 non-null object
spec_T            980 non-null object
neo               839730 non-null object
pha               822814 non-null object
moid              822814 non-null float64
dtypes: float64(18), int64(1), object(8)
memory usage: 173.0+ MB
```

In [4]:
```
data.columns
```

Out[4]:
```
Index(['full_name', 'a', 'e', 'G', 'i', 'om', 'w', 'q', 'ad', 'per_y',
       'data_arc', 'condition_code', 'n_obs_used', 'H', 'diameter', 'extent',
       'albedo', 'rot_per', 'GM', 'BV', 'UB', 'IR', 'spec_B', 'spec_T', 'ne
o',
       'pha', 'moid'],
      dtype='object')
```

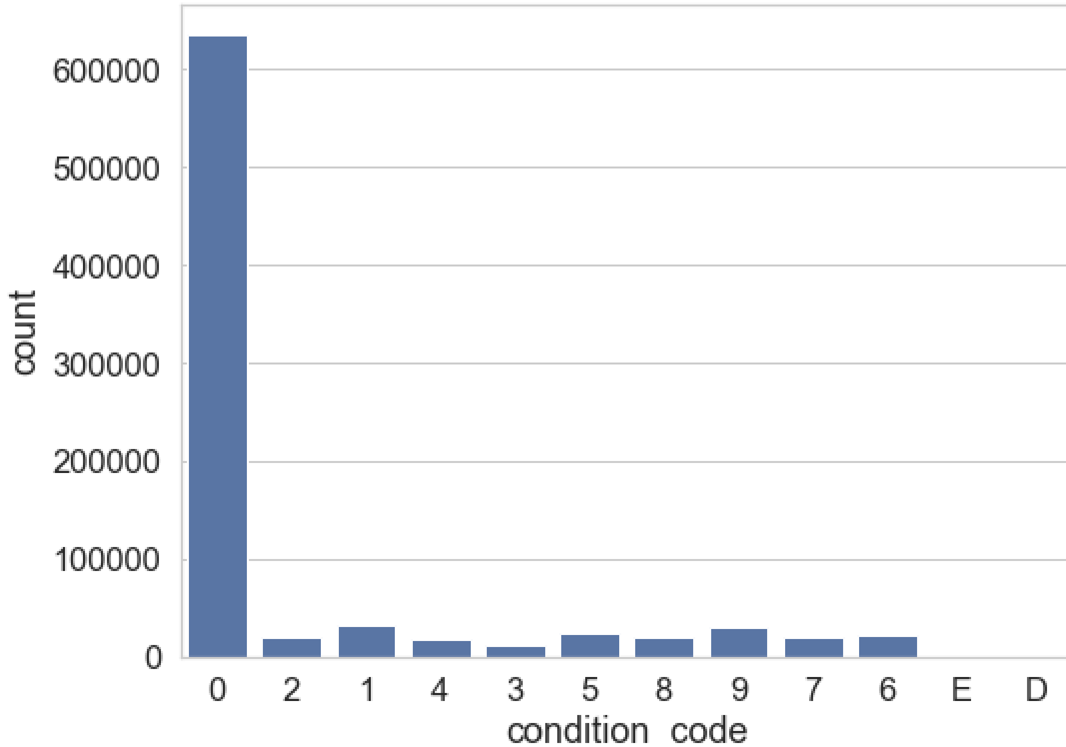
In [5]:
```
# select only features with a meaningful amount of non-null values
# drop 'full_name' and 'n_obs_used' which are not important for our problem
# place the target 'diameter' at the end for easier separation of features, X,
and target, y, later on

data = data[['a', 'e', 'i', 'om', 'w', 'q', 'ad', 'per_y', 'data_arc', 'condit
ion_code',
             'H', 'albedo', 'neo', 'pha', 'moid', 'diameter']]
data.head(10)
```

Out[5]:

	a	e	i	om	w	q	ad	per_y	data_ar
0	2.769165	0.076009	10.594067	80.305532	73.597694	2.558684	2.979647	4.608202	8822.
1	2.772466	0.230337	34.836234	173.080063	310.048857	2.133865	3.411067	4.616444	72318.
2	2.669150	0.256942	12.988919	169.852760	248.138626	1.983332	3.354967	4.360814	72684.
3	2.361418	0.088721	7.141771	103.810804	150.728541	2.151909	2.570926	3.628837	24288.
4	2.574249	0.191095	5.366988	141.576604	358.687608	2.082324	3.066174	4.130323	63431.
5	2.425160	0.203007	14.737901	138.640203	239.807490	1.932835	2.917485	3.776755	62329.
6	2.385334	0.231206	5.523651	259.563231	145.265106	1.833831	2.936837	3.684105	62452.
7	2.201764	0.156499	5.886955	110.889330	285.287462	1.857190	2.546339	3.267115	62655.
8	2.385637	0.123114	5.576816	68.908577	6.417369	2.091931	2.679342	3.684806	61821.
9	3.141539	0.112461	3.831560	283.202167	312.315206	2.788240	3.494839	5.568291	62175.

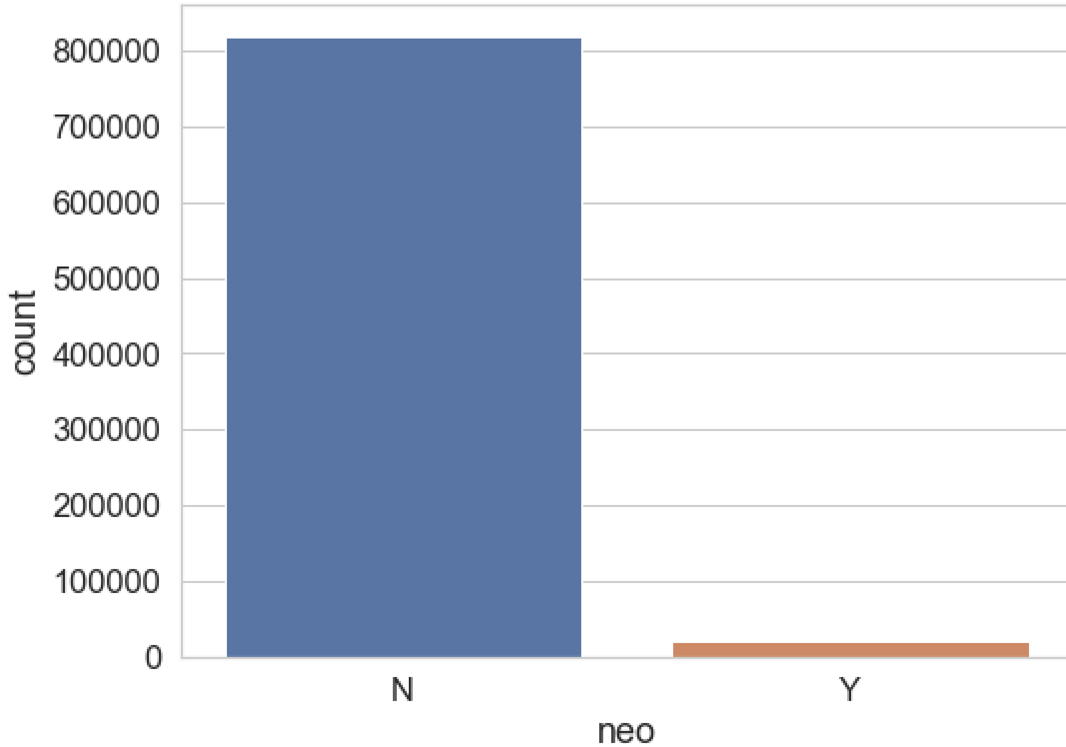
In [6]:
```
# EDA - looking into some of the features
```

In [7]:
```
# look at 'condition_code'

plt.figure(figsize = (8, 6))
sns.countplot(data['condition_code'], color = 'b')
plt.show()
```



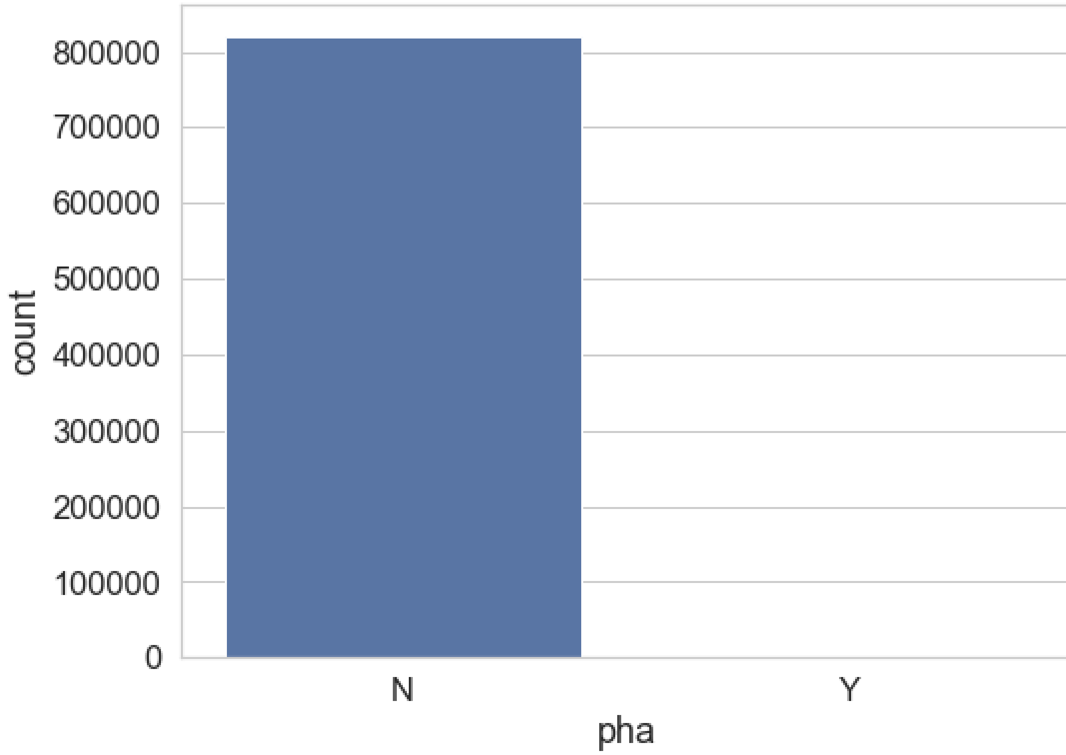
In [8]:
```
# overwhelming majority of data points are with condition_code = 0
# interesting that the condition_code notation includes numbers and letters
```

In [9]:
```
# look at 'neo'

plt.figure(figsize = (8, 6))
sns.countplot(data['neo'])
plt.show()
```



In [10]:
```
# overwhelming majority of data points = N
```

In [11]:
```
# look at 'pha'

plt.figure(figsize = (8, 6))
sns.countplot(data['pha'])
plt.show()
```



In [12]:
```
# overwhelming majority of data points = N
```

In [13]:
```
# data cleaning and preparation
```

In [14]:
```
# all three of the above features are strongly unbalanced, thus, we will remov
e them from data

data.columns
```

Out[14]:
```
Index(['a', 'e', 'i', 'om', 'w', 'q', 'ad', 'per_y', 'data_arc',
       'condition_code', 'H', 'albedo', 'neo', 'pha', 'moid', 'diameter'],
      dtype='object')
```

In [15]:
```
data = data[['a', 'e', 'i', 'om', 'w', 'q', 'ad', 'per_y', 'data_arc', 'H', 'a
lbedo', 'moid', 'diameter']]
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 839736 entries, 0 to 839735
Data columns (total 13 columns):
a           839734 non-null float64
e           839736 non-null float64
i           839736 non-null float64
om          839736 non-null float64
w           839736 non-null float64
q           839736 non-null float64
ad          839730 non-null float64
per_y       839735 non-null float64
data_arc    823947 non-null float64
H           837042 non-null float64
albedo      136452 non-null float64
moid        822814 non-null float64
diameter    137681 non-null object
dtypes: float64(12), object(1)
memory usage: 83.3+ MB
```

In [16]:
```
# although 'diameter' is supposed to have numerical values, it appears that it
is in string format
# convert data to numeric format

data = data.astype('float64')

data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 839736 entries, 0 to 839735
Data columns (total 13 columns):
a           839734 non-null float64
e           839736 non-null float64
i           839736 non-null float64
om          839736 non-null float64
w           839736 non-null float64
q           839736 non-null float64
ad          839730 non-null float64
per_y       839735 non-null float64
data_arc    823947 non-null float64
H           837042 non-null float64
albedo      136452 non-null float64
moid        822814 non-null float64
diameter    137681 non-null float64
dtypes: float64(13)
memory usage: 83.3 MB
```

In [17]:
```
# replace all missing values with 0s which is the sparse value expected by XGB
oost

data.fillna(0, inplace = True)
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 839736 entries, 0 to 839735
Data columns (total 13 columns):
a           839736 non-null float64
e           839736 non-null float64
i           839736 non-null float64
om          839736 non-null float64
w           839736 non-null float64
q           839736 non-null float64
ad          839736 non-null float64
per_y       839736 non-null float64
data_arc    839736 non-null float64
H           839736 non-null float64
albedo      839736 non-null float64
moid        839736 non-null float64
diameter    839736 non-null float64
dtypes: float64(13)
memory usage: 83.3 MB
```

In [18]:
```
# all nulls a filled
```

In [19]:
```
# create data set, data_1, where diameter is known

data_1 = data[data['diameter'] > 0] # 0 values represent data with unknown dia
meter
data_1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 137681 entries, 0 to 810411
Data columns (total 13 columns):
a           137681 non-null float64
e           137681 non-null float64
i           137681 non-null float64
om          137681 non-null float64
w           137681 non-null float64
q           137681 non-null float64
ad          137681 non-null float64
per_y       137681 non-null float64
data_arc    137681 non-null float64
H           137681 non-null float64
albedo      137681 non-null float64
moid        137681 non-null float64
diameter    137681 non-null float64
dtypes: float64(13)
memory usage: 14.7 MB
```

In [20]:
```
# data with known asteroid diameter have total of 137681 entries
```

In [21]:
```
# create data set, data_2, where diameter is unknown

data_2 = data[data['diameter'] < data_1['diameter'].min()] # this leaves only
 0 values which represent unknown diameter
data_2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 702055 entries, 681 to 839735
Data columns (total 13 columns):
a           702055 non-null float64
e           702055 non-null float64
i           702055 non-null float64
om          702055 non-null float64
w           702055 non-null float64
q           702055 non-null float64
ad          702055 non-null float64
per_y       702055 non-null float64
data_arc    702055 non-null float64
H           702055 non-null float64
albedo      702055 non-null float64
moid        702055 non-null float64
diameter    702055 non-null float64
dtypes: float64(13)
memory usage: 75.0 MB
```

In [22]:
```
# data with unknown asteroid diameter have total of 702055 entries (more than
 5 x that of data_1)
```

In [23]:
```
# check data_1
data_1.head(10)
```

Out[23]:

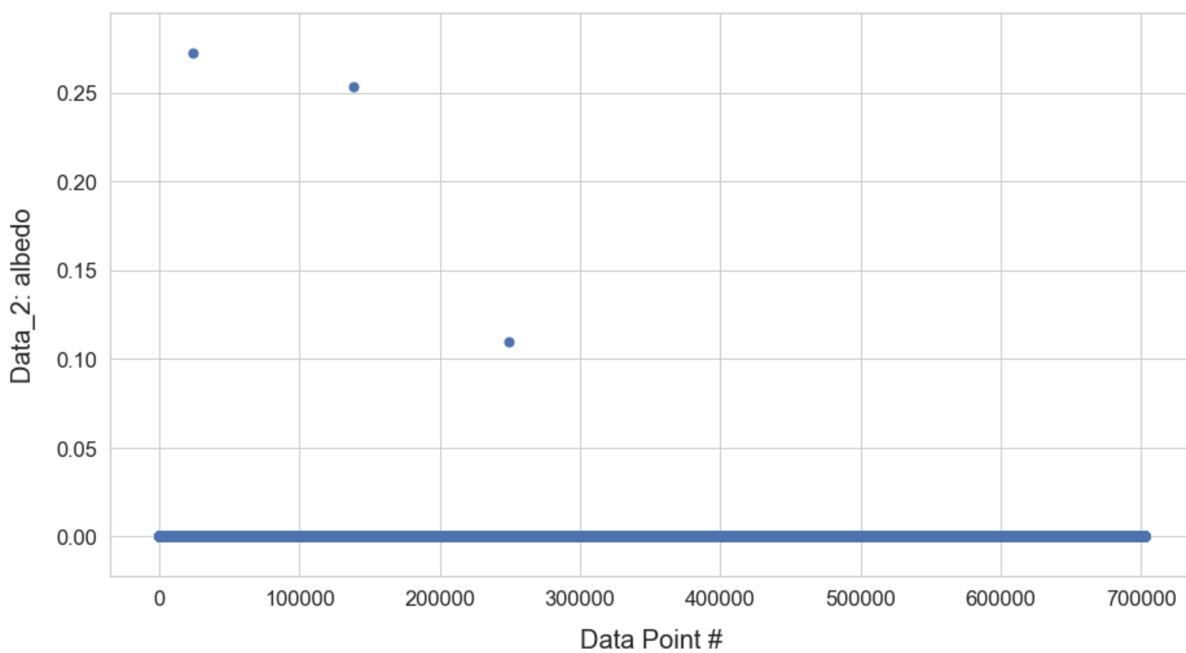
	a	e	i	om	w	q	ad	per_y	data_ar
0	2.769165	0.076009	10.594067	80.305532	73.597694	2.558684	2.979647	4.608202	8822.
1	2.772466	0.230337	34.836234	173.080063	310.048857	2.133865	3.411067	4.616444	72318.
2	2.669150	0.256942	12.988919	169.852760	248.138626	1.983332	3.354967	4.360814	72684.
3	2.361418	0.088721	7.141771	103.810804	150.728541	2.151909	2.570926	3.628837	24288.
4	2.574249	0.191095	5.366988	141.576604	358.687608	2.082324	3.066174	4.130323	63431.
5	2.425160	0.203007	14.737901	138.640203	239.807490	1.932835	2.917485	3.776755	62329.
6	2.385334	0.231206	5.523651	259.563231	145.265106	1.833831	2.936837	3.684105	62452.
7	2.201764	0.156499	5.886955	110.889330	285.287462	1.857190	2.546339	3.267115	62655.
8	2.385637	0.123114	5.576816	68.908577	6.417369	2.091931	2.679342	3.684806	61821.
9	3.141539	0.112461	3.831560	283.202167	312.315206	2.788240	3.494839	5.568291	62175.

In [24]:
```
# check data_2
data_2.head(10)
```

Out[24]:

	a	e	i	om	w	q	ad	per_y	data
681	2.654040	0.171983	11.505648	190.799958	104.993826	2.197591	3.110489	4.323837	40(
698	2.610998	0.410284	15.299180	242.551766	91.399514	1.539746	3.682249	4.219081	42!
718	2.638780	0.546301	11.564845	183.887287	156.163668	1.197212	4.080348	4.286601	39‹
729	2.243362	0.177505	4.234895	95.073806	123.549777	1.845154	2.641570	3.360139	39'
842	2.279598	0.209766	7.997717	4.071363	316.957206	1.801415	2.757780	3.441878	37!
961	2.908998	0.097329	2.602636	145.481660	223.473847	2.625868	3.192128	4.961619	37‹
984	2.299979	0.277462	4.056565	290.307048	59.553605	1.661822	2.938137	3.488142	35:
1008	2.625175	0.455500	15.769676	229.461495	186.428747	1.429408	3.820942	4.253492	34(
1010	2.391976	0.350864	5.494744	132.525452	353.279770	1.552718	3.231235	3.699504	34(
1064	2.360276	0.297141	8.362855	330.324142	353.652287	1.658942	3.061610	3.626205	33(

In [25]:
```
# it appears 'albedo' is also unknown in data_2

# check by plotting data_2['albedo']

plt.figure(figsize = (15, 8))
plt.scatter(np.arange(1, len(data_2) + 1), data_2['albedo'], s = 50, c = 'b')
plt.xlabel('Data Point #', fontsize = 20, labelpad = 15)
plt.ylabel('Data_2: albedo', fontsize = 20, labelpad = 15)
plt.show()
```



In [26]:
```
# indeed almost all of the albedo data points in data_2 are 0s and it cannot b
e used in predictions
# because of this we will remove albedo from both data_1 and data_2

data_1.columns
```

Out[26]:
```
Index(['a', 'e', 'i', 'om', 'w', 'q', 'ad', 'per_y', 'data_arc', 'H', 'albed
o',
       'moid', 'diameter'],
      dtype='object')
```

In [27]:
```
data_1 = data_1[['a', 'e', 'i', 'om', 'w', 'q', 'ad', 'per_y', 'data_arc', 'H'
, 'moid', 'diameter']]

data_1.head(10)
```

Out[27]:

	a	e	i	om	w	q	ad	per_y	data_ar
0	2.769165	0.076009	10.594067	80.305532	73.597694	2.558684	2.979647	4.608202	8822.
1	2.772466	0.230337	34.836234	173.080063	310.048857	2.133865	3.411067	4.616444	72318.
2	2.669150	0.256942	12.988919	169.852760	248.138626	1.983332	3.354967	4.360814	72684.
3	2.361418	0.088721	7.141771	103.810804	150.728541	2.151909	2.570926	3.628837	24288.
4	2.574249	0.191095	5.366988	141.576604	358.687608	2.082324	3.066174	4.130323	63431.
5	2.425160	0.203007	14.737901	138.640203	239.807490	1.932835	2.917485	3.776755	62329.
6	2.385334	0.231206	5.523651	259.563231	145.265106	1.833831	2.936837	3.684105	62452.
7	2.201764	0.156499	5.886955	110.889330	285.287462	1.857190	2.546339	3.267115	62655.
8	2.385637	0.123114	5.576816	68.908577	6.417369	2.091931	2.679342	3.684806	61821.
9	3.141539	0.112461	3.831560	283.202167	312.315206	2.788240	3.494839	5.568291	62175.

In [28]:
```
# in data_2 we drop also the diameter which is unknown

data_2 = data_2[['a', 'e', 'i', 'om', 'w', 'q', 'ad', 'per_y', 'data_arc', 'H'
, 'moid']]

data_2.head(10)
```

Out[28]:

	a	e	i	om	w	q	ad	per_y	data
681	2.654040	0.171983	11.505648	190.799958	104.993826	2.197591	3.110489	4.323837	40(
698	2.610998	0.410284	15.299180	242.551766	91.399514	1.539746	3.682249	4.219081	42!
718	2.638780	0.546301	11.564845	183.887287	156.163668	1.197212	4.080348	4.286601	39/
729	2.243362	0.177505	4.234895	95.073806	123.549777	1.845154	2.641570	3.360139	39'
842	2.279598	0.209766	7.997717	4.071363	316.957206	1.801415	2.757780	3.441878	37!
961	2.908998	0.097329	2.602636	145.481660	223.473847	2.625868	3.192128	4.961619	37/
984	2.299979	0.277462	4.056565	290.307048	59.553605	1.661822	2.938137	3.488142	35:
1008	2.625175	0.455500	15.769676	229.461495	186.428747	1.429408	3.820942	4.253492	34!
1010	2.391976	0.350864	5.494744	132.525452	353.279770	1.552718	3.231235	3.699504	34!
1064	2.360276	0.297141	8.362855	330.324142	353.652287	1.658942	3.061610	3.626205	33(

In [29]:
```
# finally, we are left with 11 features and diameter as a target in data_1; da
ta_2 consists of features only
```

In [30]:
```
# separate features and target from data_1 which we will use with ML models

X_1 = data_1.iloc[:, :-1].values # all columns, but last
y_1 = data_1.iloc[:, -1].values # last column

X_2 = data_2.values # data_2 has only features
```

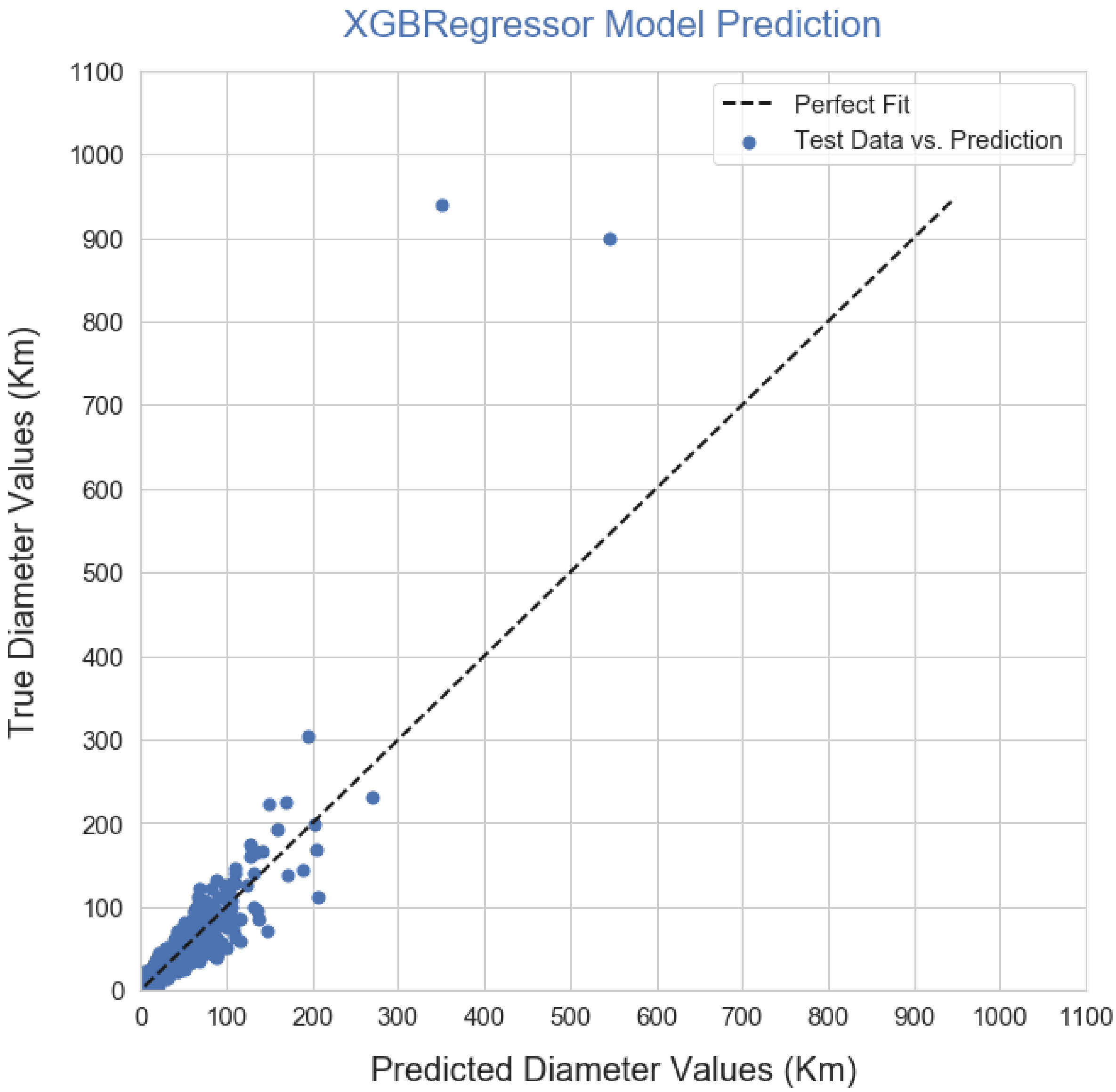
In [31]:
```
# apply XGBRegressor
```

In [32]:
```
# split X_1 and y_1 in train/test sets

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X_1, y_1, test_size = 0.2,
random_state = 0)
```

In [33]:
```
from xgboost import XGBRegressor

model_1 = XGBRegressor(objective = 'reg:squarederror')
```

In [34]:
```
model_1.fit(X_train, y_train)

y_pred_1 = model_1.predict(X_test)
```

In [35]:
```
# compare predictions, y_pred_1, to test values, y_test

# create line to represent perfect fit to data test values, y_test

y_line = np.arange(int(y_test.min()) - 10, int(y_test.max()) + 10)

# set axes limits - adjust if necessary
x_min = 0
x_max = y_test.max() + 100
d_x = 100

y_min = 0
y_max = y_test.max() + 100
d_y = 100

plt.figure(figsize = (10, 10))
ax = plt.axes()

ax.set_xlim(x_min, x_max)
ax.set_xticks(np.arange(x_min, x_max + d_x, d_x))

ax.set_ylim(y_min, y_max)
ax.set_yticks(np.arange(y_min, y_max + d_y, d_y))

plt.scatter(y_pred_1, y_test, s = 50, c = 'b', label = 'Test Data vs. Predicti
on')
plt.plot(y_line, y_line, 'k--', lw = 2, label = 'Perfect Fit')
plt.xlabel('Predicted Diameter Values (Km)', fontsize = 20, labelpad = 15)
plt.ylabel('True Diameter Values (Km)', fontsize = 20, labelpad = 15)
plt.title('XGBRegressor Model Prediction', fontsize = 22, c = 'b', pad = 20)
plt.legend(fontsize = 15)
plt.tick_params(labelsize = 15)
plt.show()
```



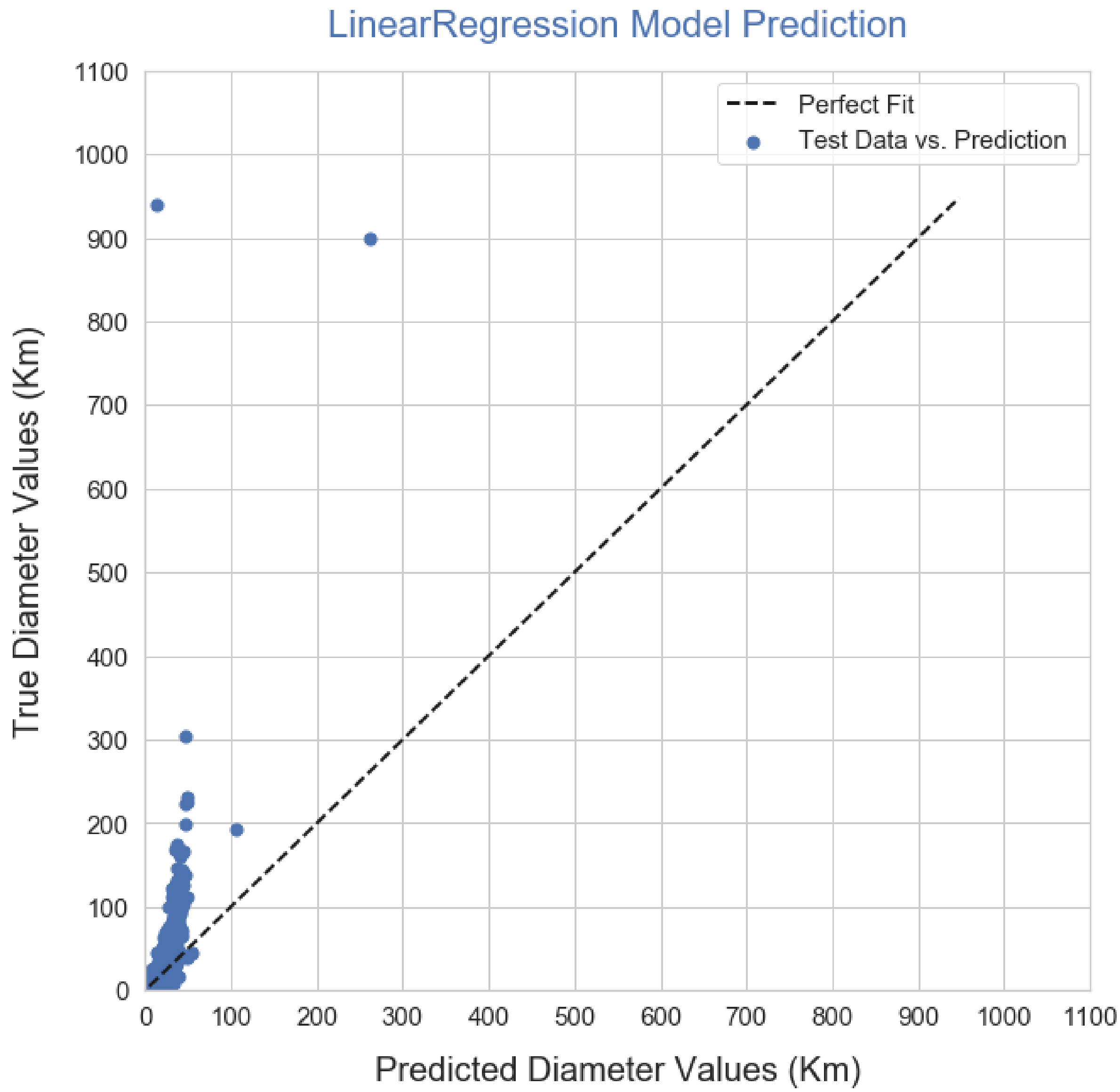
In [36]:
```
# except for two extreme data points, outliers, predictions are quite accurate
being closely grouped around the perfect fit line
```

In [37]:
```
# apply Linear Regression and compare results
```

In [38]:
```
from sklearn.linear_model import LinearRegression
model_2 = LinearRegression()
```

In [39]:
```
model_2.fit(X_train, y_train)

y_pred_2 = model_2.predict(X_test)
```

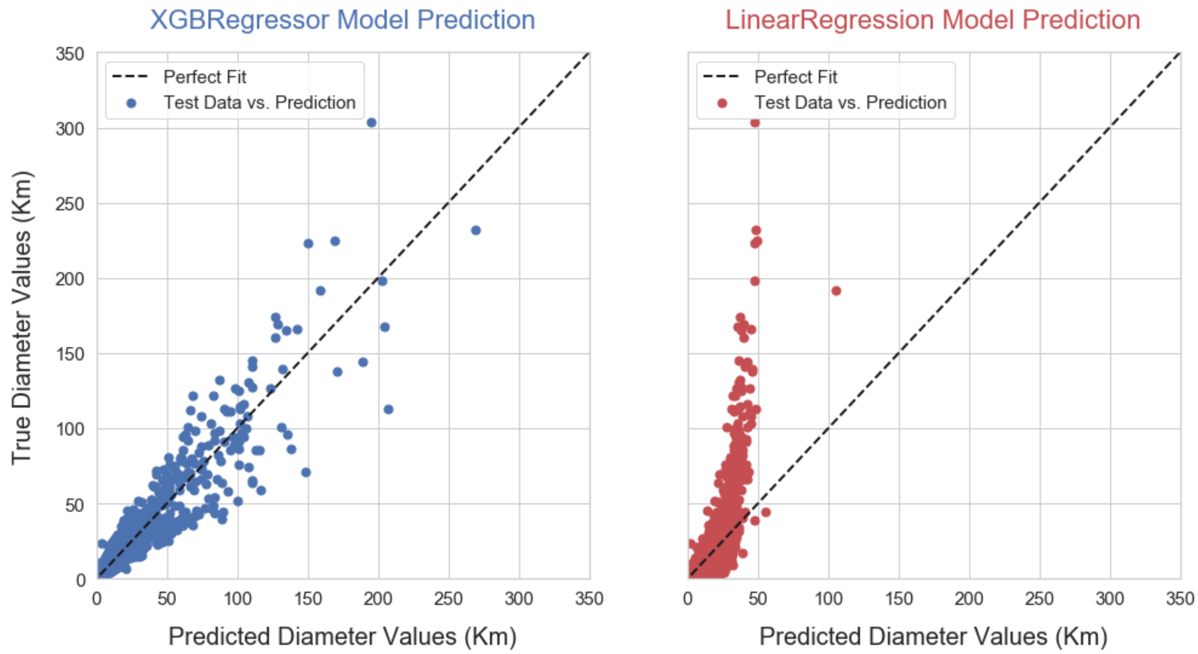
In [40]:
```
# compare predictions, y_pred_2, to test values, y_test

plt.figure(figsize = (10, 10))
ax = plt.axes()

ax.set_xlim(x_min, x_max)
ax.set_xticks(np.arange(x_min, x_max + d_x, d_x))

ax.set_ylim(y_min, y_max)
ax.set_yticks(np.arange(y_min, y_max + d_y, d_y))

plt.scatter(y_pred_2, y_test, s = 50, c = 'b', label = 'Test Data vs. Predicti
on')
plt.plot(y_line, y_line, 'k--', lw = 2, label = 'Perfect Fit')
plt.xlabel('Predicted Diameter Values (Km)', fontsize = 20, labelpad = 15)
plt.ylabel('True Diameter Values (Km)', fontsize = 20, labelpad = 15)
plt.title('LinearRegression Model Prediction', fontsize = 22, c = 'b', pad = 2
0)
plt.legend(fontsize = 15)
plt.tick_params(labelsize = 15)
plt.show()
```



In [41]:
```
# LinearRegression model predictions deviate significantly from the perfect fi
t line and the true data values
```

In [42]:
```
# let's plot the XGBRegressor and the Linear Regression models predictions nex
t to each other for better comparison
# also for better visibility we will exclude from the plots the two outliers w
ith very large diameter values
```

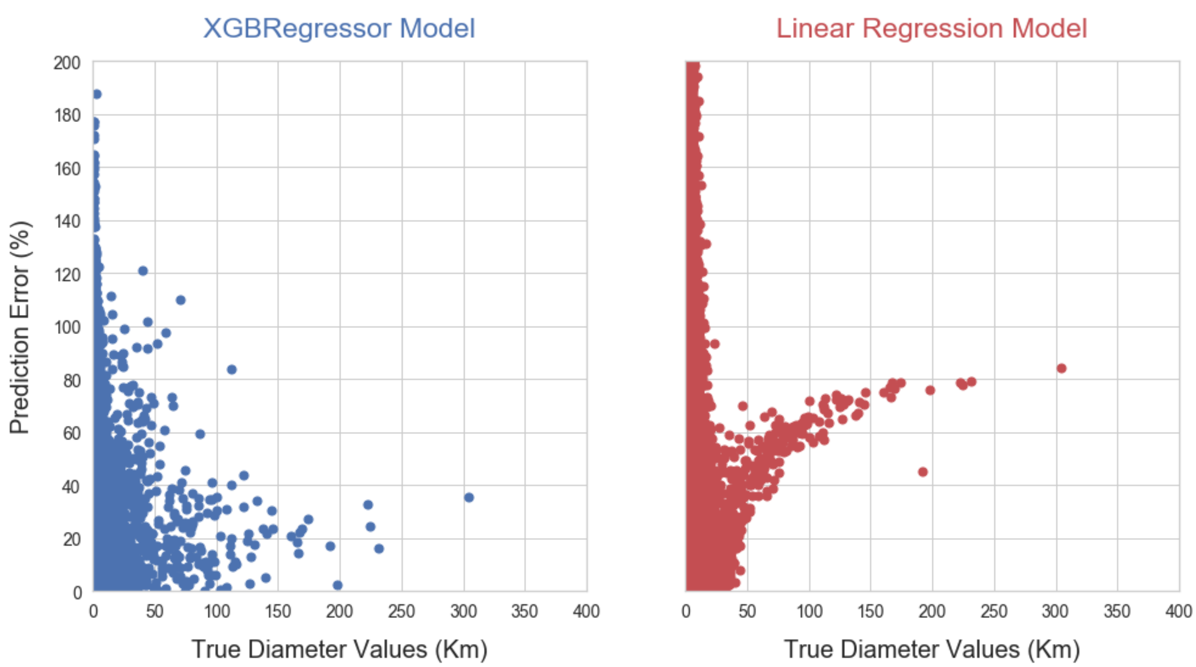
In [43]:
```
# set axes limits - adjust if necessary
x_min = 0
x_max = 350 # set threshold to exclude the outliers
d_x = 50

y_min = 0
y_max = 350 # set threshold to exclude the outliers
d_y = 50

fig, axes = plt.subplots(1, 2, sharey=True, figsize=(16,8))

# XGBRegressor
axes[0].scatter(y_pred_1, y_test, s = 50, c = 'b', label = 'Test Data vs. Pred
iction')
axes[0].plot(y_line, y_line, 'k--', lw = 2, label = 'Perfect Fit')
axes[0].set_xlabel('Predicted Diameter Values (Km)', fontsize = 20, labelpad =
15)
axes[0].set_ylabel('True Diameter Values (Km)', fontsize = 20, labelpad = 15)
axes[0].set_title('XGBRegressor Model Prediction', fontsize = 22, c = 'b', pad
= 20)
axes[0].legend(fontsize = 15)
axes[0].set_xlim(x_min, x_max)
axes[0].set_xticks(np.arange(x_min, x_max + d_x, d_x))
axes[0].set_ylim(y_min, y_max)
axes[0].set_yticks(np.arange(y_min, y_max + d_y, d_y))
axes[0].tick_params(labelsize = 15)


# Linear Regression
axes[1].scatter(y_pred_2, y_test, s = 50, c = 'r', label = 'Test Data vs. Pred
iction')
axes[1].plot(y_line, y_line, 'k--', lw = 2, label = 'Perfect Fit')
axes[1].set_xlabel('Predicted Diameter Values (Km)', fontsize = 20, labelpad =
15)
axes[1].set_title('LinearRegression Model Prediction', fontsize = 22, c = 'r',
pad = 20)
axes[1].legend(fontsize = 15)
axes[1].set_xlim(x_min, x_max)
axes[1].set_xticks(np.arange(x_min, x_max + d_x, d_x))
axes[1].set_ylim(y_min, y_max)
axes[1].set_yticks(np.arange(y_min, y_max + d_y, d_y))
axes[1].tick_params(labelsize = 15)

plt.show()
```



In [44]:
```
# comparison of the predictions next to each other shows dramatic difference i
n the predictions
# it is clear that XGBRegressor model outperforms the Linear Regression model
 in a significant way
```

In [45]:
```
# For more quantitative analysis let's plot the predictions absolute error in
 % from the two models

# XGBRegressor prediction error
error_1 = 100 * (np.absolute(y_pred_1 - y_test) / y_test) # absolute error in
 %


# LinearRegression prediction error
error_2 = 100 * (np.absolute(y_pred_2 - y_test) / y_test) # absolute error in
 %
```

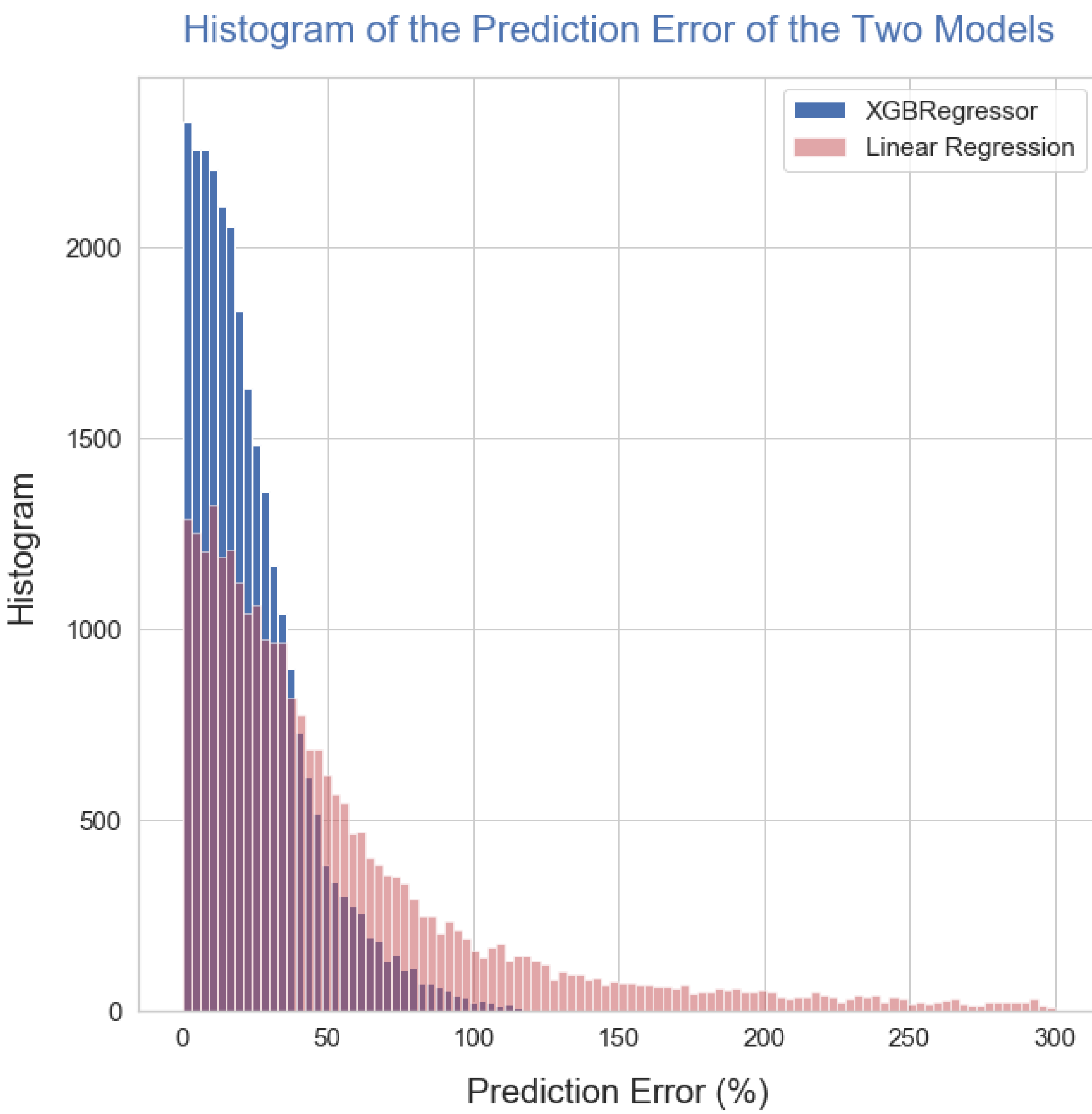
In [46]:
```
# set axes limits - adjust if necessary
x_min = 0
x_max = 400 # set threshold to exclude the outliers
d_x = 50

y_min = 0
y_max = 200 # limit y axis to include only errors <= 200 %  for better visuali
zation
d_y = 20

fig, axes = plt.subplots(1, 2, sharey=True, figsize=(16,8))

# XGBRegressor
axes[0].scatter(y_test, error_1, s = 50, c = 'b')
axes[0].set_title('XGBRegressor Model', fontsize = 23, c = 'b', pad = 20)
axes[0].set_xlabel('True Diameter Values (Km)', fontsize = 20, labelpad = 15)
axes[0].set_ylabel('Prediction Error (%)', fontsize = 20, labelpad = 15)
axes[0].set_xlim(x_min, x_max)
axes[0].set_xticks(np.arange(x_min, x_max + d_x, d_x))
axes[0].set_ylim(y_min, y_max)
axes[0].set_yticks(np.arange(y_min, y_max + d_y, d_y))
axes[0].tick_params(labelsize = 14)


# Linear Regression
axes[1].scatter(y_test, error_2, s = 50, c = 'r')
axes[1].set_title('Linear Regression Model', fontsize = 23, c = 'r', pad = 20)
axes[1].set_xlabel('True Diameter Values (Km)', fontsize = 20, labelpad = 15)
axes[1].set_xlim(x_min, x_max)
axes[1].set_xticks(np.arange(x_min, x_max + d_x, d_x))
axes[1].set_ylim(y_min, y_max)
axes[1].set_yticks(np.arange(y_min, y_max + d_y, d_y))
axes[1].tick_params(labelsize = 14)

plt.show()
```



In [47]:
```
# two main observations:
    # 1) asteroid diameters < 100 km
            # both models can make large errors, particularly for very small d
iameter values which is natural to expect
            # however, Linear Regression model has much more large errors, par
ticularly for these small diameter values
    # 2) asteroid diameters > 100 km,
            # XGBRegressor error drops below 40 %
            # Linear Regression error is above 60 % reaching up to 80 % (more
 than 2x that of XGBRegressor model)
```

In [48]:
```
# further analysis of the accuracy of the predictions --> obtain the histogram
s of the prediction errors

error_1 = error_1[error_1 < 300] # truncate at 300 % for better visualization
error_2 = error_2[error_2 < 300] # truncate at 300 % for better visualization
```

In [49]:
```
plt.figure(figsize = (10, 10))

plt.hist(error_1, bins = 100, color = 'b', label = 'XGBRegressor')
plt.hist(error_2, bins = 100, color = 'r', alpha = 0.5, label = 'Linear Regres
sion')
plt.xlabel('Prediction Error (%)', fontsize = 20, labelpad = 15)
plt.ylabel('Histogram', fontsize = 20, labelpad = 15)
plt.title('Histogram of the Prediction Error of the Two Models', fontsize = 22
, c = 'b', pad = 20)
plt.legend(fontsize = 15)
plt.tick_params(labelsize = 15)
plt.show()
```



In [50]:
```
# XGBRegressor model:
    # error values are confined mostly within ~ 40 %; very small number extend
s beyond 50 %
# Linear Regression model:
    # significant portion of error values spill well beyond the 50 % mark
    # the distribution tail reaches much further indicating reasonable probabi
lity of very large errors
```

In [51]:
```
# finally, compare the Mean and Standard Deviation of the error for the two mo
dels

print('XGBRegressor Mean Error: ', np.round(error_1.mean(), 1))
print('XGBRegressor Error Standard Deviation: ', np.round(error_1.std(), 1))
print('\n')
print('Linear Regression Mean Error: ', np.round(error_2.mean(), 1))
print('Linear Regression Error Standard Deviation: ', np.round(error_2.std(),
1))
```

```
XGBRegressor Mean Error:  23.8
XGBRegressor Error Standard Deviation:  20.9


Linear Regression Mean Error:  53.7
Linear Regression Error Standard Deviation:  55.9
```

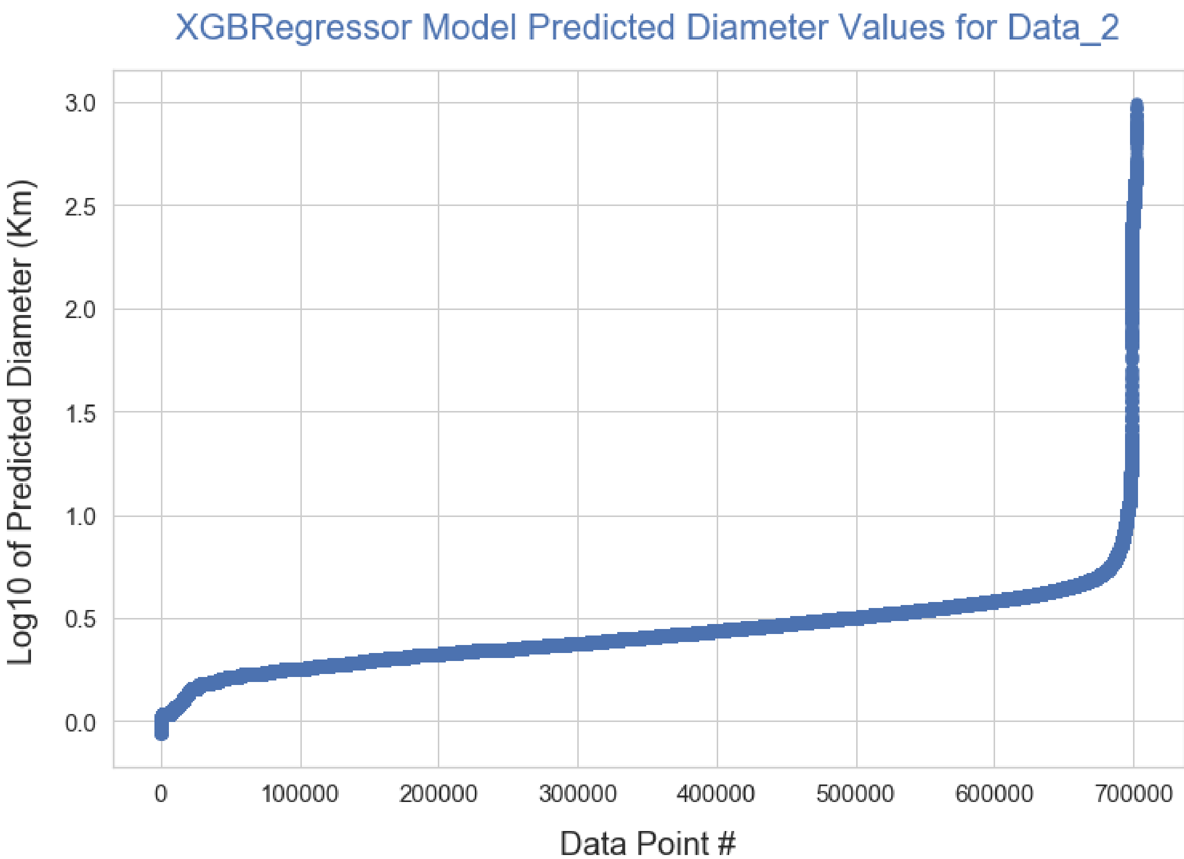
In [52]:
```
# Conclusion from the models comparison:
    # XGBRegressor model is much more accurate with error mean and std less th
an half of that for Linear Regression model
```

In [53]:
```
# Final step: Predict the asteroid diameter values for the asteroids with unkn
own diameter, data_2, using XGBRegressor model
```

In [54]:
```
# use XGBRegressor model_1 trained on the complete set of X_1 and y_1 to predi
ct diameter values from data_2 features, X_2

model_1.fit(X_1, y_1)

y_pred_1b = model_1.predict(X_2)
```

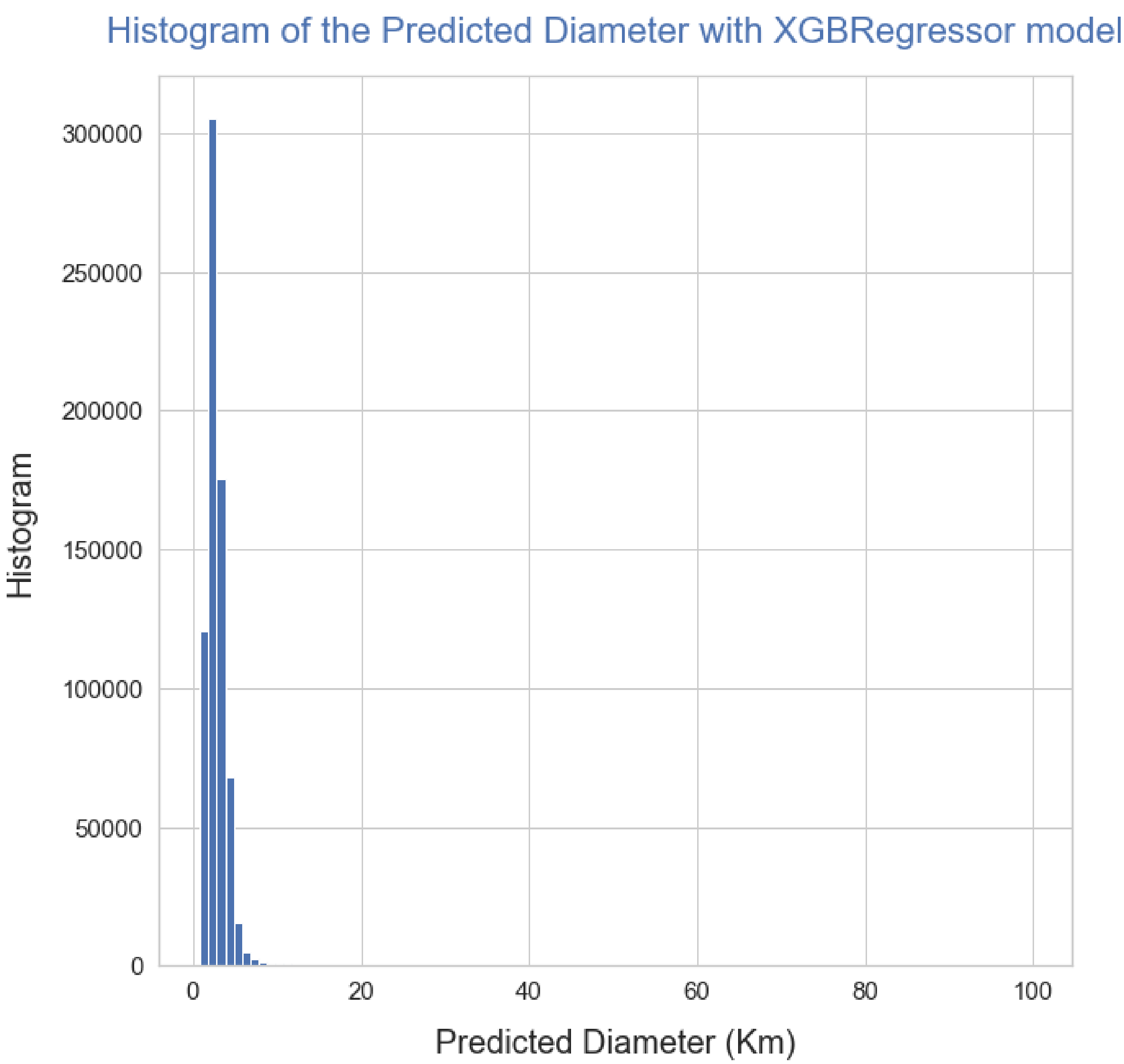
In [55]:
```
# we have nothing to compare to, so we will create some simple plots to examin
e the properties of the predicted values
```

In [56]:
```
# plot predicted diameter values in ascending order

plt.figure(figsize = (12, 8))

plt.scatter(np.arange(1, len(X_2) +1), np.sort(np.log10(y_pred_1b)), s = 50, c
olor = 'b')
# use log10 in order to see well all values

plt.xlabel('Data Point #', fontsize = 20, labelpad = 15)
plt.ylabel('Log10 of Predicted Diameter (Km)', fontsize = 20, labelpad = 15)
plt.title('XGBRegressor Model Predicted Diameter Values for Data_2', fontsize
= 22, c = 'b', pad = 20)
plt.tick_params(labelsize = 15)
plt.show()
```

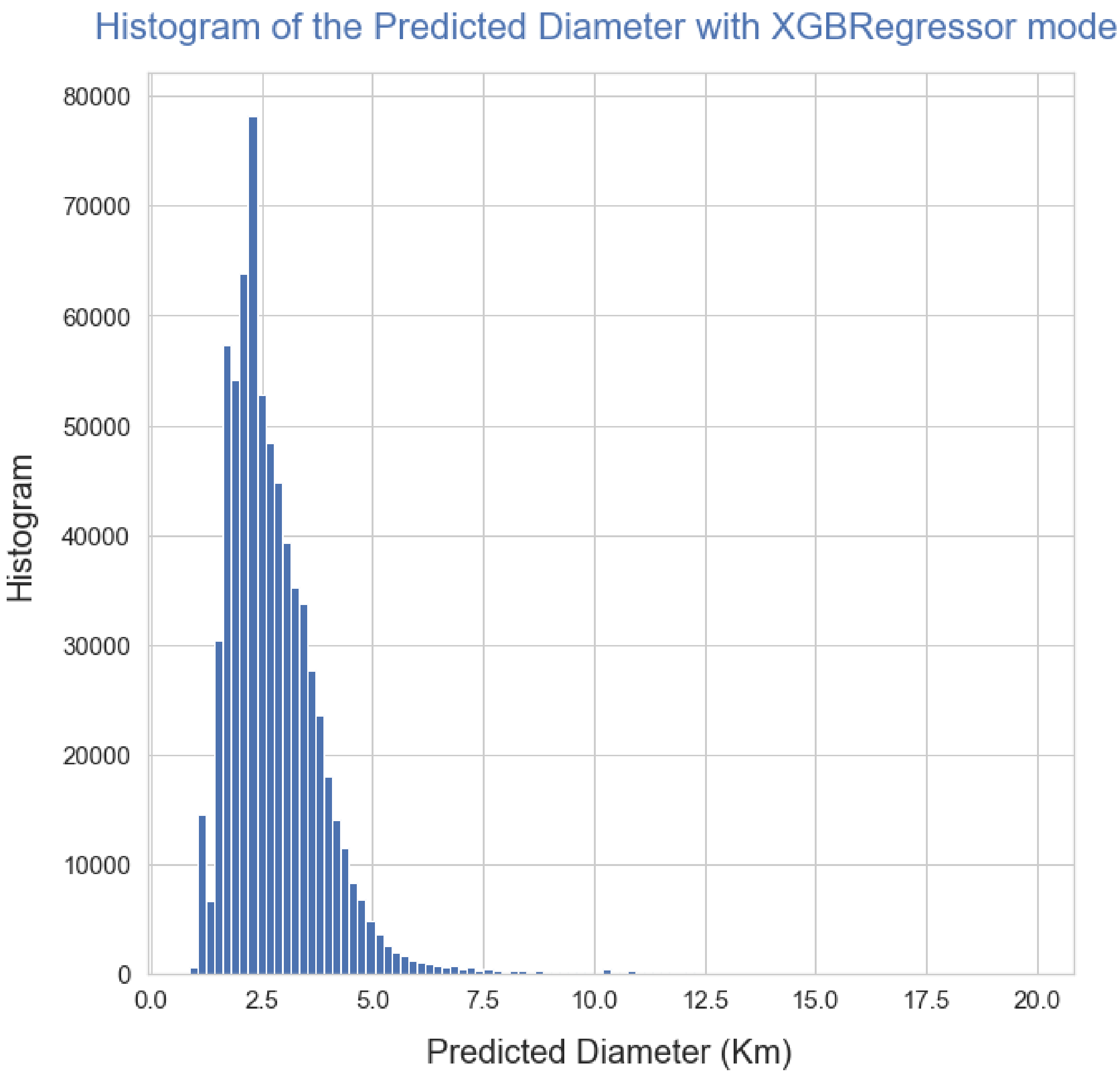


In [57]:
```
# Main observations from the plot
    # the negative values  obsereved indicate diameter values less than 1 km
    # the largest values reach 1000 km --> 10 ** 3
    # the plot shows that vast majority of the predicted values (~ 690000 poin
ts) are less than 10 Km (10 ** 1)
```

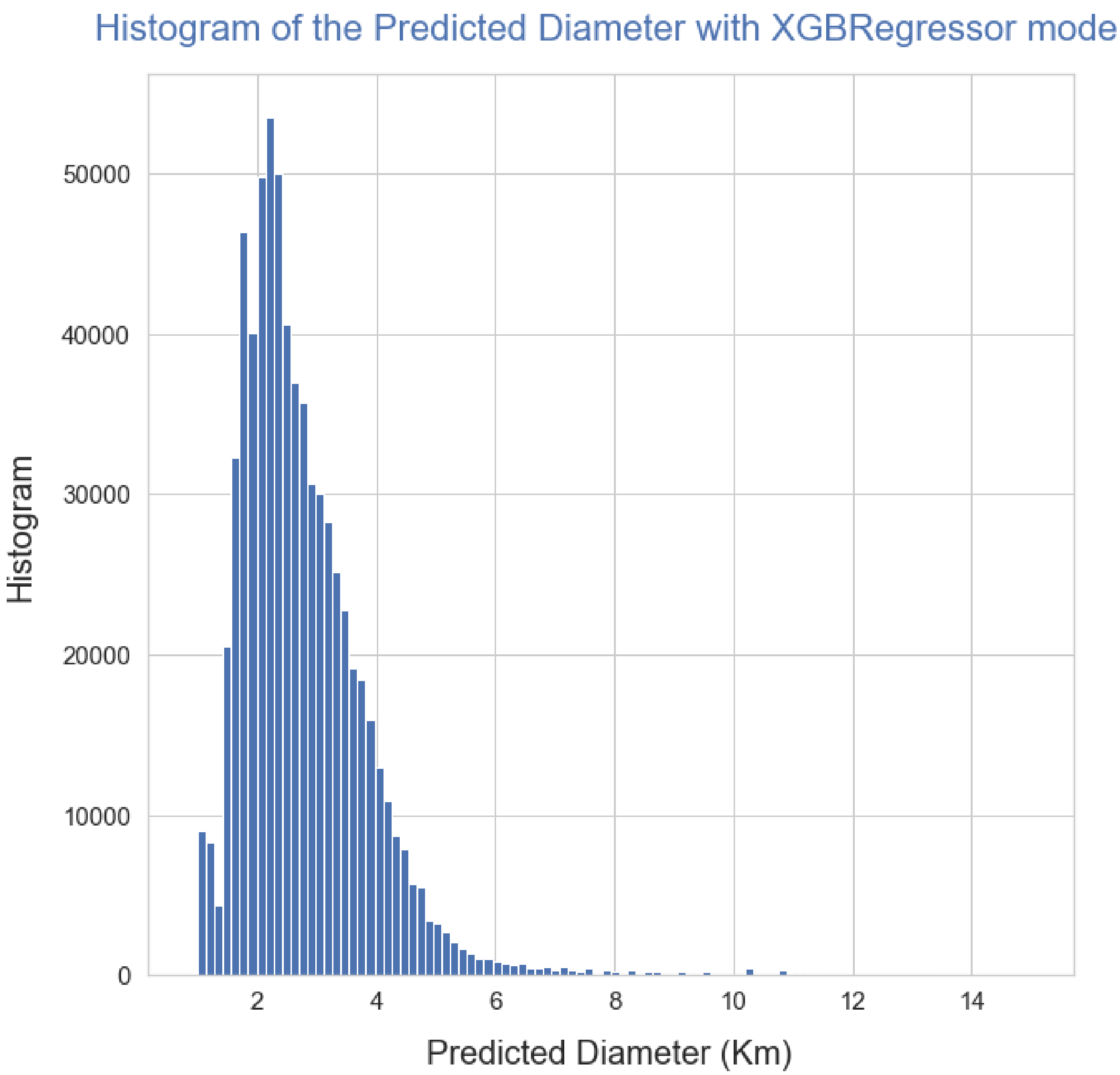
In [58]:
```
# plot histogram of the predicted diameter values
# as a first step, based on our observations above we will truncate the histog
ram to values below 100 Km

plt.figure(figsize = (10, 10))

plt.hist(y_pred_1b[y_pred_1b < 100], bins = 100, color = 'b') # truncate predi
ction values to 100 Km
plt.xlabel('Predicted Diameter (Km)', fontsize = 20, labelpad = 15)
plt.ylabel('Histogram', fontsize = 20, labelpad = 15)
plt.title('Histogram of the Predicted Diameter with XGBRegressor model', fonts
ize = 22, c = 'b', pad = 20)
plt.tick_params(labelsize = 15)
plt.show()
```



In [59]:
```
# majority of predicted diameter values are below 20 km --> use 20 Km as an up
per limit

plt.figure(figsize = (10, 10))

plt.hist(y_pred_1b[y_pred_1b < 20], bins = 100, color = 'b') # truncate predic
tion values to 20 Km
plt.xlabel('Predicted Diameter (Km)', fontsize = 20, labelpad = 15)
plt.ylabel('Histogram', fontsize = 20, labelpad = 15)
plt.title('Histogram of the Predicted Diameter with XGBRegressor model', fonts
ize = 22, c = 'b', pad = 20)
plt.tick_params(labelsize = 15)
plt.show()
```



In [60]:
```
# final plot with 15 Km as an upper limit

plt.figure(figsize = (10, 10))

plt.hist(y_pred_1b[y_pred_1b < 15], bins = 100, color = 'b') # truncate predic
tion values to 15 Km
plt.xlabel('Predicted Diameter (Km)', fontsize = 20, labelpad = 15)
plt.ylabel('Histogram', fontsize = 20, labelpad = 15)
plt.title('Histogram of the Predicted Diameter with XGBRegressor model', fonts
ize = 22, c = 'b', pad = 20)
plt.tick_params(labelsize = 15)
plt.show()
```



In [61]:
```
# predicted diameter values from data_2 have Poisson-like distribution
# due to lack of expertise in Astronomy and not being able to find definitive
 answers in the literature,
# we cannot confirm that this distribution matches expectations
# we would like to note also that it is not clear what kind of asteroids the d
ata has been collected for
# any feedback from experts in the field would be greatly appreciated!
```

In [62]:
```
# At the end, we combine the predicted diameter values with features data to c
omplete the data as our final delivarable

data_2.head(10)
```

Out[62]:

	a	e	i	om	w	q	ad	per_y	data
681	2.654040	0.171983	11.505648	190.799958	104.993826	2.197591	3.110489	4.323837	400
698	2.610998	0.410284	15.299180	242.551766	91.399514	1.539746	3.682249	4.219081	425
718	2.638780	0.546301	11.564845	183.887287	156.163668	1.197212	4.080348	4.286601	394
729	2.243362	0.177505	4.234895	95.073806	123.549777	1.845154	2.641570	3.360139	391
842	2.279598	0.209766	7.997717	4.071363	316.957206	1.801415	2.757780	3.441878	375
961	2.908998	0.097329	2.602636	145.481660	223.473847	2.625868	3.192128	4.961619	374
984	2.299979	0.277462	4.056565	290.307048	59.553605	1.661822	2.938137	3.488142	353
1008	2.625175	0.455500	15.769676	229.461495	186.428747	1.429408	3.820942	4.253492	349
1010	2.391976	0.350864	5.494744	132.525452	353.279770	1.552718	3.231235	3.699504	349
1064	2.360276	0.297141	8.362855	330.324142	353.652287	1.658942	3.061610	3.626205	338

In [63]:
```
# reset data_2 indices before adding the predicted diameter values

data_2 = data_2.reset_index(drop = True)

data_2.head(10)
```

Out[63]:

	a	e	i	om	w	q	ad	per_y	data_ar
0	2.654040	0.171983	11.505648	190.799958	104.993826	2.197591	3.110489	4.323837	40087.
1	2.610998	0.410284	15.299180	242.551766	91.399514	1.539746	3.682249	4.219081	42540.
2	2.638780	0.546301	11.564845	183.887287	156.163668	1.197212	4.080348	4.286601	39478.
3	2.243362	0.177505	4.234895	95.073806	123.549777	1.845154	2.641570	3.360139	39112.
4	2.279598	0.209766	7.997717	4.071363	316.957206	1.801415	2.757780	3.441878	37579.
5	2.908998	0.097329	2.602636	145.481660	223.473847	2.625868	3.192128	4.961619	37450.
6	2.299979	0.277462	4.056565	290.307048	59.553605	1.661822	2.938137	3.488142	35366.
7	2.625175	0.455500	15.769676	229.461495	186.428747	1.429408	3.820942	4.253492	34990.
8	2.391976	0.350864	5.494744	132.525452	353.279770	1.552718	3.231235	3.699504	34919.
9	2.360276	0.297141	8.362855	330.324142	353.652287	1.658942	3.061610	3.626205	33882.

In [64]:
```
# transfrom y_pred_1b array into series with name 'diameter'

y_pred_1b = pd.Series(y_pred_1b, name = 'diameter')
y_pred_1b.head(10)
```

Out[64]:
```
0    12.835646
1    15.836289
2     7.744624
3     6.937665
4     7.041404
5    16.612211
6     8.591853
7     7.688478
8     8.946400
9    11.652201
Name: diameter, dtype: float32
```

In [65]:
```
# finally, combine features with predicted diameter values

data_2 = pd.concat([data_2, y_pred_1b], axis = 1)
data_2.head(10)
```

Out[65]:

	a	e	i	om	w	q	ad	per_y	data_ar
0	2.654040	0.171983	11.505648	190.799958	104.993826	2.197591	3.110489	4.323837	40087.
1	2.610998	0.410284	15.299180	242.551766	91.399514	1.539746	3.682249	4.219081	42540.
2	2.638780	0.546301	11.564845	183.887287	156.163668	1.197212	4.080348	4.286601	39478.
3	2.243362	0.177505	4.234895	95.073806	123.549777	1.845154	2.641570	3.360139	39112.
4	2.279598	0.209766	7.997717	4.071363	316.957206	1.801415	2.757780	3.441878	37579.
5	2.908998	0.097329	2.602636	145.481660	223.473847	2.625868	3.192128	4.961619	37450.
6	2.299979	0.277462	4.056565	290.307048	59.553605	1.661822	2.938137	3.488142	35366.
7	2.625175	0.455500	15.769676	229.461495	186.428747	1.429408	3.820942	4.253492	34990.
8	2.391976	0.350864	5.494744	132.525452	353.279770	1.552718	3.231235	3.699504	34919.
9	2.360276	0.297141	8.362855	330.324142	353.652287	1.658942	3.061610	3.626205	33882.

In [66]:
```
# Data is complete, the predicted asteroid diameter values are included, and w
e have accomplished the project's objective.
```