We read in the data

In [1]:
```
import matplotlib.pyplot as plt
%matplotlib inline
plt.rcParams['figure.figsize'] = 20, 10
import pandas as pd
import numpy as np


day_hour_count = pd.read_csv("bikeshare_hour_count.csv")
day_hour_count
```

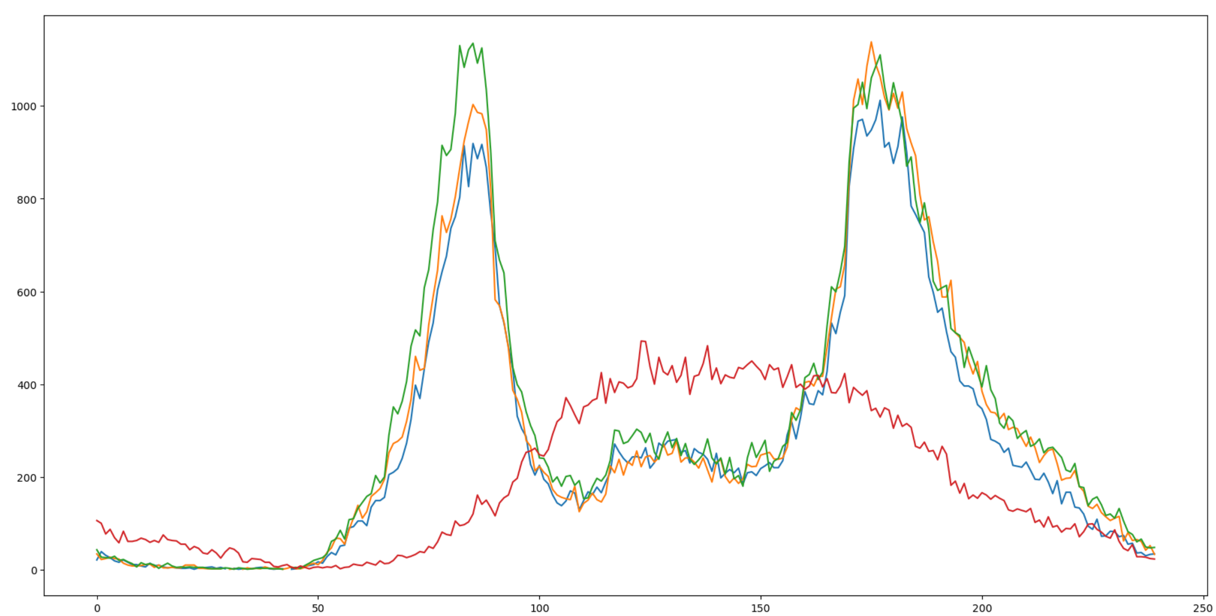
Out[1]:

	hour	monday	tuesday	wednesday	thursday	friday	saturday	sunday
0	0.0	21.0	34.0	43.0	47.0	51.0	89.0	106.0
1	0.1	39.0	22.0	27.0	37.0	56.0	87.0	100.0
2	0.2	31.0	24.0	26.0	42.0	50.0	98.0	77.0
3	0.3	26.0	27.0	25.0	29.0	52.0	99.0	87.0
4	0.4	19.0	24.0	29.0	29.0	50.0	98.0	69.0
...	...	...	...	...	...	...	...	...
235	23.5	36.0	65.0	60.0	94.0	80.0	93.0	28.0
236	23.6	37.0	61.0	66.0	100.0	81.0	95.0	28.0
237	23.7	30.0	42.0	49.0	80.0	101.0	105.0	27.0
238	23.8	33.0	52.0	47.0	79.0	91.0	93.0	24.0
239	23.9	34.0	33.0	48.0	65.0	105.0	111.0	23.0

240 rows × 8 columns

In [2]:
```
plt.figure(figsize=(20,10))
plt.plot(day_hour_count.index, day_hour_count["monday"])
plt.plot(day_hour_count.index, day_hour_count["tuesday"])
plt.plot(day_hour_count.index, day_hour_count["wednesday"])
plt.plot(day_hour_count.index, day_hour_count["sunday"])
```

Out[2]: [<matplotlib.lines.Line2D at 0x1d6a723d4d0>]



Assignment 4

Explain the results in a **paragraph + charts** of to describe which model you'd recommend. This means show the data and the model's line on the same chart. The paragraph is a simple justification and comparison of the several models you tried.

1. Using the `day_hour_count` dataframe create 4 dataframes `monday`, `tuesday`, `saturday` and `sunday` that represent the data for those days. (hint: Monday is day=0)

In [3]:
```
#Create each dataframe
monday = day_hour_count[["hour","monday"]].copy()
tuesday = day_hour_count[["hour","tuesday"]].copy()
saturday = day_hour_count[["hour","saturday"]].copy()
sunday = day_hour_count[["hour","sunday"]].copy()
```

In [4]:
```
#drop the empty values
monday_d = monday.dropna(subset=["monday"])
tuesday_d = tuesday.dropna(subset=["tuesday"])
saturday_d = saturday.dropna(subset=["saturday"])
sunday_d = sunday.dropna(subset=["sunday"])
```

In [5]:
```
monday_d.shape, tuesday_d.shape, saturday_d.shape, sunday_d.shape
```

Out[5]:
```
((238, 2), (238, 2), (240, 2), (240, 2))
```

In [6]:
```
#transform into numpy array to apply models
x_mon = monday_d[["hour"]].to_numpy()
y_mon = monday_d[["monday"]].to_numpy()
x_tue = tuesday_d[["hour"]].to_numpy()
y_tue = tuesday_d[["tuesday"]].to_numpy()
x_sat = saturday_d[["hour"]].to_numpy()
y_sat = saturday_d[["saturday"]].to_numpy()
x_sun = sunday_d[["hour"]].to_numpy()
y_sun = sunday_d[["sunday"]].to_numpy()
```

2a. Create 3 models fit to (`x=hour` , `y=monday`) with varying polynomial degrees (choose from `n=5,15,20`). (Repeat for `saturday` below)

Plot all the results for each polynomial.

In [7]:
```
from sklearn.preprocessing import PolynomialFeatures
from sklearn import linear_model, metrics

#transform x values
poly5 = PolynomialFeatures(degree=5)
poly15 = PolynomialFeatures(degree=15)
poly20 = PolynomialFeatures(degree=20)

x_mon_5 = poly5.fit_transform(x_mon)
x_mon_15 = poly15.fit_transform(x_mon)
x_mon_20 = poly20.fit_transform(x_mon)

x_mon_5.shape, x_mon_15.shape, x_mon_20.shape, y_mon.shape
```

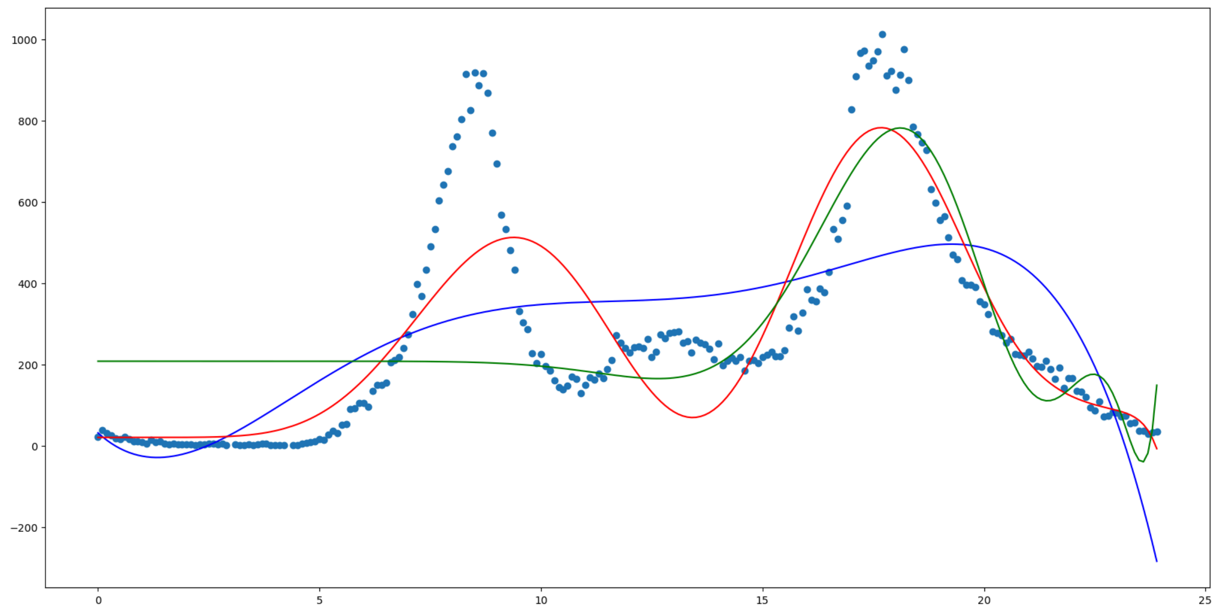
Out[7]:
```
((238, 6), (238, 16), (238, 21), (238, 1))
```

In [8]:
```
#fit each linear regression models
linear5_mon = linear_model.LinearRegression()
linear5_mon.fit(x_mon_5, y_mon)

linear15_mon = linear_model.LinearRegression()
linear15_mon.fit(x_mon_15, y_mon)

linear20_mon = linear_model.LinearRegression()
linear20_mon.fit(x_mon_20, y_mon)
```

Out[8]:
```
▾ LinearRegression (https://scikit-learn.org/1.4/modules/generated/sklearn.linear_model.LinearRegression.html)
LinearRegression()
```

In [9]:
```
#plot each prediction values

plt.scatter(x_mon, y_mon)
plt.plot(x_mon, linear5_mon.predict(x_mon_5), c = 'b')
plt.plot(x_mon, linear15_mon.predict(x_mon_15), c = 'r')
plt.plot(x_mon, linear20_mon.predict(x_mon_20), c = 'g')
```

Out[9]: [<matplotlib.lines.Line2D at 0x1d6b8513cd0>]



2b. Repeat 2a for saturday

In [10]:
```
#transform x values

x_sat_5 = poly5.fit_transform(x_sat)
x_sat_15 = poly15.fit_transform(x_sat)
x_sat_20 = poly20.fit_transform(x_sat)

x_sat_5.shape, x_sat_15.shape, x_sat_20.shape, y_sat.shape
```

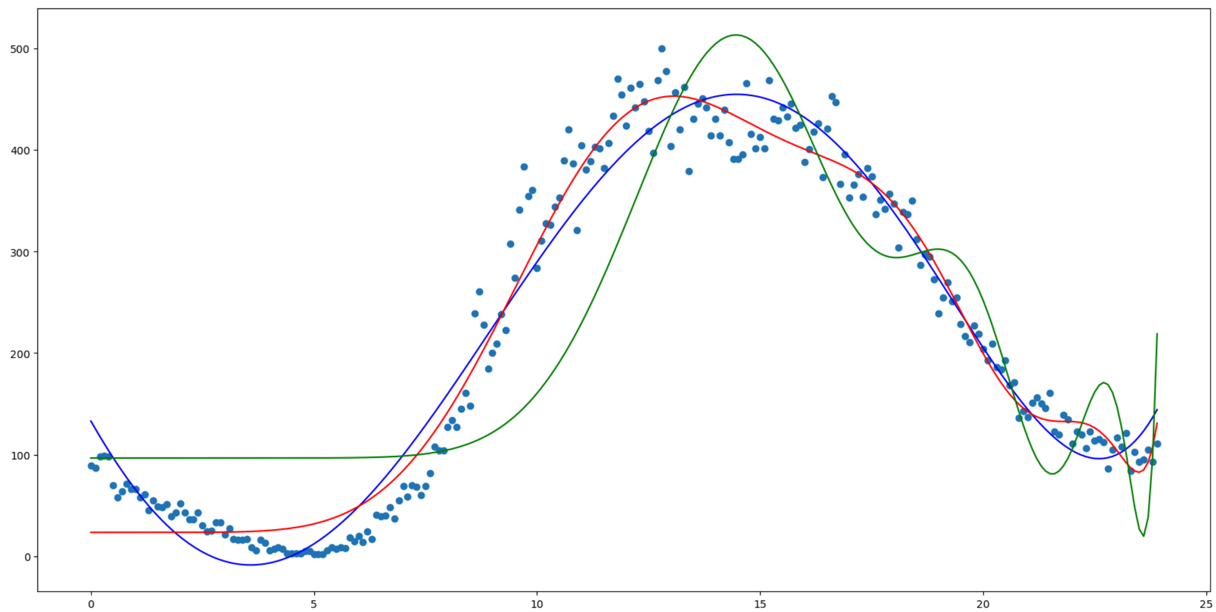
Out[10]: ((240, 6), (240, 16), (240, 21), (240, 1))

In [11]:
```
#fit each linear regression models

linear5_sat = linear_model.LinearRegression()
linear5_sat.fit(x_sat_5, y_sat)

linear15_sat = linear_model.LinearRegression()
linear15_sat.fit(x_sat_15, y_sat)

linear20_sat = linear_model.LinearRegression()
linear20_sat.fit(x_sat_20, y_sat)
```

Out[11]:
```
▾ LinearRegression
(https://scikit-learn.org/1.4/modules/generated/sklearn.linear_model.LinearRegression.html)

LinearRegression()
```

In [12]:
```
#plot each prediction values

plt.scatter(x_sat, y_sat)
plt.plot(x_sat, linear5_sat.predict(x_sat_5), c = 'b')
plt.plot(x_sat, linear15_sat.predict(x_sat_15), c = 'r')
plt.plot(x_sat, linear20_sat.predict(x_sat_20), c = 'g')
```

Out[12]: [<matplotlib.lines.Line2D at 0x1d6a4265b90>]



3. Using the best `monday` model's prediction, determine the errors (MSE, MAE, MAPE) between the prediction with the `monday` and `tuesday` datasets

Repeat for `saturday` / `sunday`

3-A. Monday/Tuesday

Step 1. Which model fits best with monday? Answer: polynomial 15

In [13]:
```
#MSE : polynomial 15 has the least error
(
    metrics.mean_squared_error(y_mon, linear5_mon.predict(x_mon_5)),
    metrics.mean_squared_error(y_mon, linear15_mon.predict(x_mon_15)),
    metrics.mean_squared_error(y_mon, linear20_mon.predict(x_mon_20))
)
```
Out[13]: (41987.445605897956, 19403.93577831465, 38378.3631392463)

In [14]:
```
#MAE : polynomial 15 has the least error
(
    metrics.mean_absolute_error(y_mon, linear5_mon.predict(x_mon_5)),
    metrics.mean_absolute_error(y_mon, linear15_mon.predict(x_mon_15)),
    metrics.mean_absolute_error(y_mon, linear20_mon.predict(x_mon_20))
)
```
Out[14]: (156.18451811204645, 98.15910929541432, 141.9853297373431)

In [15]:
```
#MAPE : polynomial 15 has the least error
(
    metrics.mean_absolute_percentage_error(y_mon, linear5_mon.predict(x_mon_5)),
    metrics.mean_absolute_percentage_error(y_mon, linear15_mon.predict(x_mon_15)),
    metrics.mean_absolute_percentage_error(y_mon, linear20_mon.predict(x_mon_20))
)
```
Out[15]: (3.959956065987383, 1.9413723475419873, 12.257657225600777)

Step 2. compare errors of monday and tuesday dataset with monday prediction model

Answer: MSE and MAE is lower in monday, but MAPE is lower in tuesday dataset

In [16]:
```
#MSE : error in monday data is lower
(
    metrics.mean_squared_error(y_mon, linear15_mon.predict(x_mon_15)),
    metrics.mean_squared_error(y_tue, linear15_mon.predict(x_mon_15)),
)
```
Out[16]: (19403.93577831465, 23858.84583062077)

In [17]:
```
#MAE : error in monday data is lower
(
    metrics.mean_absolute_error(y_mon, linear15_mon.predict(x_mon_15)),
    metrics.mean_absolute_error(y_tue, linear15_mon.predict(x_mon_15)),
)
```
Out[17]: (98.15910929541432, 105.85713546758706)

In [18]:
```
#MAPE : error in tuesday data is lower
(
    metrics.mean_absolute_percentage_error(y_mon, linear15_mon.predict(x_mon_15)),
    metrics.mean_absolute_percentage_error(y_tue, linear15_mon.predict(x_mon_15)),
)
```

Out[18]: (1.9413723475419873, 1.8661090206732218)

3-B. Saturday/Sunday

Step 1. Which model fits best with saturday?

Answer: Polynomial 15 for MSE and MAE, Polynomial 5 for MAPE

In [19]:
```
#MSE : polynomial 15 has the least error
(
    metrics.mean_squared_error(y_sat, linear5_sat.predict(x_sat_5)),
    metrics.mean_squared_error(y_sat, linear15_sat.predict(x_sat_15)),
    metrics.mean_squared_error(y_sat, linear20_sat.predict(x_sat_20))
)
```

Out[19]: (995.2167048171038, 809.0490991282165, 6297.7973844756625)

In [20]:
```
#MAE : polynomial 15 has the least error
(
    metrics.mean_absolute_error(y_sat, linear5_sat.predict(x_sat_5)),
    metrics.mean_absolute_error(y_sat, linear15_sat.predict(x_sat_15)),
    metrics.mean_absolute_error(y_sat, linear20_sat.predict(x_sat_20))
)
```

Out[20]: (25.347169800093255, 22.62367426115214, 65.02481417861516)

In [21]:
```
#MAPE : polynomial 5 has the least error
(
    metrics.mean_absolute_percentage_error(y_sat, linear5_sat.predict(x_sat_5)),
    metrics.mean_absolute_percentage_error(y_sat, linear15_sat.predict(x_sat_15)),
    metrics.mean_absolute_percentage_error(y_sat, linear20_sat.predict(x_sat_20))
)
```

Out[21]: (0.46989867265320395, 0.7329310568307361, 2.4339160967795337)

Step 2. errors of saturday and sunday dataset with monday prediction model

Answer: in all cases, error in saturday is lower than sunday

In [22]:
```
#MSE: error in saturday is lower
(
    metrics.mean_squared_error(y_sat, linear15_sat.predict(x_sat_15)),
    metrics.mean_squared_error(y_sun, linear15_sat.predict(x_sat_15)),
)
```

Out[22]: (809.0490991282165, 1638.7127680210274)

In [23]:
```
#MAE: error in saturday is lower
(
    metrics.mean_absolute_error(y_sat, linear15_sat.predict(x_sat_15)),
    metrics.mean_absolute_error(y_sun, linear15_sat.predict(x_sat_15)),
)
```

Out[23]: (22.62367426115214, 34.6479059578238)

In [24]:
```
#MAPE: error in saturday is lower
(
    metrics.mean_absolute_percentage_error(y_sat, linear5_sat.predict(x_sat_5)),
    metrics.mean_absolute_percentage_error(y_sun, linear5_sat.predict(x_sat_5)),
)
```

Out[24]:
```
(0.46989867265320395, 0.7723154684747456)
```

4. With `saturday`, use `train_test_split` to create training and test sets and build a model. Create predictions using the xtest from and determine the errors between these predictions and the ytest (MSE, MAE, MAPE).

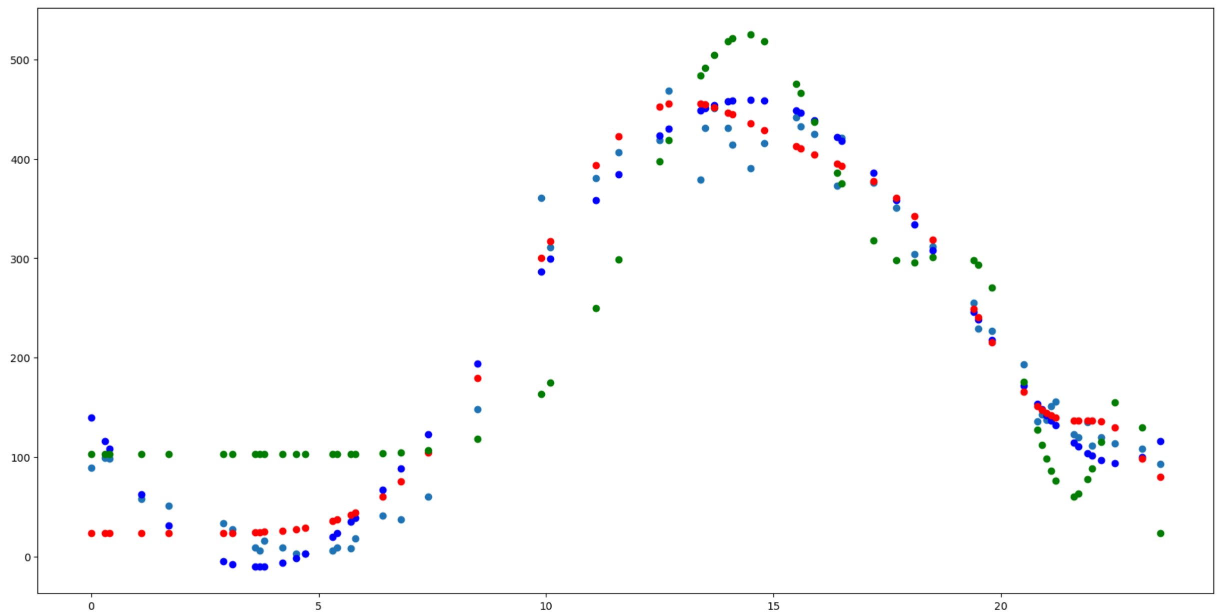
repeat for `monday`

4-A. Saturday

In [25]:
```
from sklearn.model_selection import train_test_split

#use train/test split for saturday data
xtrain_sat, xtest_sat, ytrain_sat, ytest_sat = train_test_split(x_sat, y_sat)
linear_sat = linear_model.LinearRegression().fit(xtrain_sat, ytrain_sat)

#build polynomial models for train and test set(n = 5, 15, 20)
xtrain5_sat = PolynomialFeatures(degree=5).fit_transform(xtrain_sat)
xtest5_sat = PolynomialFeatures(degree=5).fit_transform(xtest_sat)

linear5_sat_train = linear_model.LinearRegression().fit(xtrain5_sat, ytrain_sat)

xtrain15_sat = PolynomialFeatures(degree=15).fit_transform(xtrain_sat)
xtest15_sat = PolynomialFeatures(degree=15).fit_transform(xtest_sat)

linear15_sat_train = linear_model.LinearRegression().fit(xtrain15_sat, ytrain_sat)

xtrain20_sat = PolynomialFeatures(degree=20).fit_transform(xtrain_sat)
xtest20_sat = PolynomialFeatures(degree=20).fit_transform(xtest_sat)

linear20_sat_train = linear_model.LinearRegression().fit(xtrain20_sat, ytrain_sat)
```

In [26]:
```
#Plot prediction values

plt.scatter(xtest_sat, ytest_sat)
plt.scatter(xtest_sat, linear5_sat_train.predict(xtest5_sat), c='b')
plt.scatter(xtest_sat, linear15_sat_train.predict(xtest15_sat), c='r')
plt.scatter(xtest_sat, linear20_sat_train.predict(xtest20_sat), c='g')
```

Out[26]: <matplotlib.collections.PathCollection at 0x1d6a4284a10>



In [27]:
```
#MSE: Polynomial 15 has the least error
(
    metrics.mean_squared_error(ytest_sat, linear5_sat_train.predict(xtest5_sat)),
    metrics.mean_squared_error(ytest_sat, linear15_sat_train.predict(xtest15_sat)),
    metrics.mean_squared_error(ytest_sat, linear20_sat_train.predict(xtest20_sat))
)
```

Out[27]: (828.3942364798181, 862.7715913191707, 5352.183505537066)

In [28]:
```
#MAE : polynomial 15 has the least error
(
    metrics.mean_absolute_error(ytest_sat, linear5_sat.predict(xtest5_sat)),
    metrics.mean_absolute_error(ytest_sat, linear15_sat.predict(xtest15_sat)),
    metrics.mean_absolute_error(ytest_sat, linear20_sat.predict(xtest20_sat))
)
```

Out[28]: (21.347731605982265, 22.62669888873941, 56.62798776037457)

In [29]:
```
#MAPE : polynomial 5 has the least error
(
    metrics.mean_absolute_percentage_error(ytest_sat, linear5_sat.predict(xtest5_sat)),
    metrics.mean_absolute_percentage_error(ytest_sat, linear15_sat.predict(xtest15_sat)),
    metrics.mean_absolute_percentage_error(ytest_sat, linear20_sat.predict(xtest20_sat))
)
```

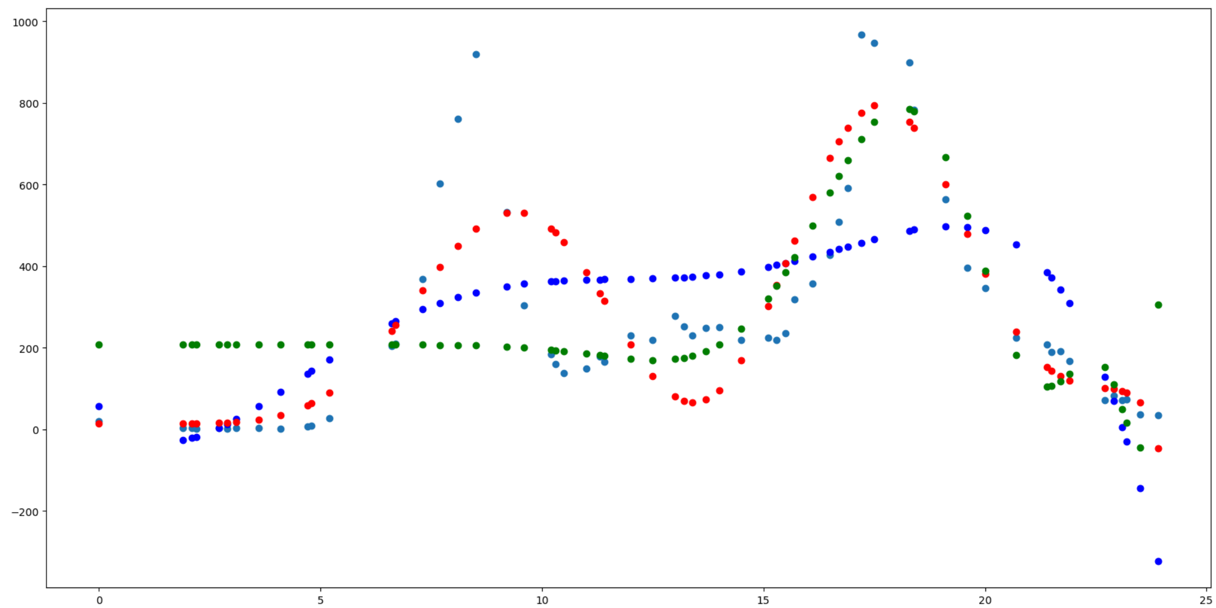
Out[29]: (0.4644772958620213, 0.7818309914378647, 2.6764788634421683)

4-B. Monday

In [30]:
```
#use train/test split for monday data
xtrain_mon, xtest_mon, ytrain_mon, ytest_mon = train_test_split(x_mon, y_mon)
linear_mon = linear_model.LinearRegression().fit(xtrain_mon, ytrain_mon)

#build polynomial models for train and test set(n = 5, 15, 20)
xtrain5_mon = PolynomialFeatures(degree=5).fit_transform(xtrain_mon)
xtest5_mon = PolynomialFeatures(degree=5).fit_transform(xtest_mon)

linear5_mon_train = linear_model.LinearRegression().fit(xtrain5_mon, ytrain_mon)

xtrain15_mon = PolynomialFeatures(degree=15).fit_transform(xtrain_mon)
xtest15_mon = PolynomialFeatures(degree=15).fit_transform(xtest_mon)

linear15_mon_train = linear_model.LinearRegression().fit(xtrain15_mon, ytrain_mon)

xtrain20_mon = PolynomialFeatures(degree=20).fit_transform(xtrain_mon)
xtest20_mon = PolynomialFeatures(degree=20).fit_transform(xtest_mon)

linear20_mon_train = linear_model.LinearRegression().fit(xtrain20_mon, ytrain_mon)
```

In [31]:
```
#Plot prediction values

plt.scatter(xtest_mon, ytest_mon)
plt.scatter(xtest_mon, linear5_mon_train.predict(xtest5_mon), c='b')
plt.scatter(xtest_mon, linear15_mon_train.predict(xtest15_mon), c='r')
plt.scatter(xtest_mon, linear20_mon_train.predict(xtest20_mon), c='g')
```

Out[31]: <matplotlib.collections.PathCollection at 0x1d6ba984790>



In [32]:
```
# MSE: polynomial 15 has the least error
(
    metrics.mean_squared_error(ytest_mon, linear5_mon_train.predict(xtest5_mon)),
    metrics.mean_squared_error(ytest_mon, linear15_mon_train.predict(xtest15_mon)),
    metrics.mean_squared_error(ytest_mon, linear20_mon_train.predict(xtest20_mon))
)
```

Out[32]: (39704.36537355736, 21769.81033890615, 33704.127256534244)

In [33]:
```
# MAE: polynomial 15 has the least error
(
    metrics.mean_absolute_error(ytest_mon, linear5_mon_train.predict(xtest5_mon)),
    metrics.mean_absolute_error(ytest_mon, linear15_mon_train.predict(xtest15_mon)),
    metrics.mean_absolute_error(ytest_mon, linear20_mon_train.predict(xtest20_mon))
)
```

Out[33]: (154.70033168727866, 109.0528563260089, 132.75904566898893)

In [34]:
```
# MAPE: polynomial 15 has the least error
(
    metrics.mean_absolute_percentage_error(ytest_mon, linear5_mon_train.predict(xtest5_mon)),
    metrics.mean_absolute_percentage_error(ytest_mon, linear15_mon_train.predict(xtest15_mon)),
    metrics.mean_absolute_percentage_error(ytest_mon, linear20_mon_train.predict(xtest20_mon))
)
```

Out[34]: (3.1785318035826577, 1.6972951809606711, 13.517158224190826)

Conclusion: the result of linear regression using train/test set (Assignment 4) is similar with linear regression using the whole data (Assignment 3)