We read in the data

In [5]:
```
import matplotlib.pyplot as plt
%matplotlib inline
plt.rcParams['figure.figsize'] = 20, 10
import pandas as pd
import numpy as np
import math


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

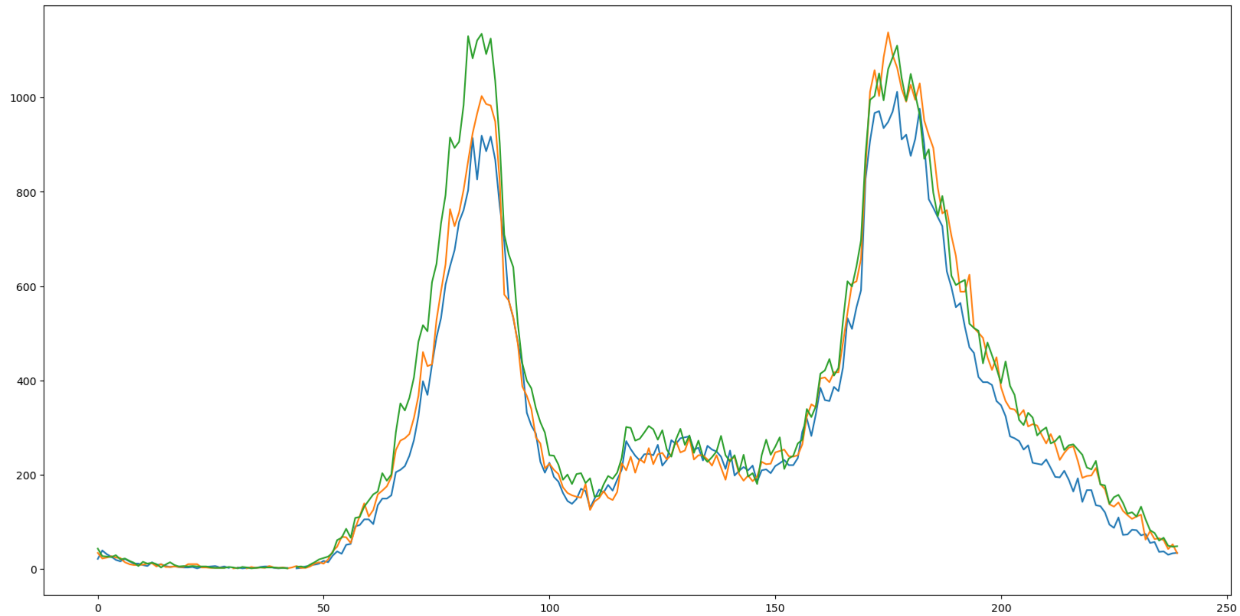
Out[5]:

	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 [6]:
```
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"])
```

Out[6]:
```
[<matplotlib.lines.Line2D at 0x7fa43d018a60>]
```



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 [7]:
```
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 [8]:
```
monday, tuesday, saturday, sunday
```

Out[8]:
```
(     hour  monday
 0     0.0    21.0
 1     0.1    39.0
 2     0.2    31.0
 3     0.3    26.0
 4     0.4    19.0
 ..    ...     ...
 235  23.5    36.0
 236  23.6    37.0
 237  23.7    30.0
 238  23.8    33.0
 239  23.9    34.0

 [240 rows x 2 columns],
      hour  tuesday
 0     0.0     34.0
 1     0.1     22.0
 2     0.2     24.0
 3     0.3     27.0
 4     0.4     24.0
 ..    ...      ...
 235  23.5     65.0
 236  23.6     61.0
 237  23.7     42.0
 238  23.8     52.0
 239  23.9     33.0

 [240 rows x 2 columns],
      hour  saturday
 0     0.0      89.0
 1     0.1      87.0
 2     0.2      98.0
 3     0.3      99.0
 4     0.4      98.0

 ..    ...       ...
```

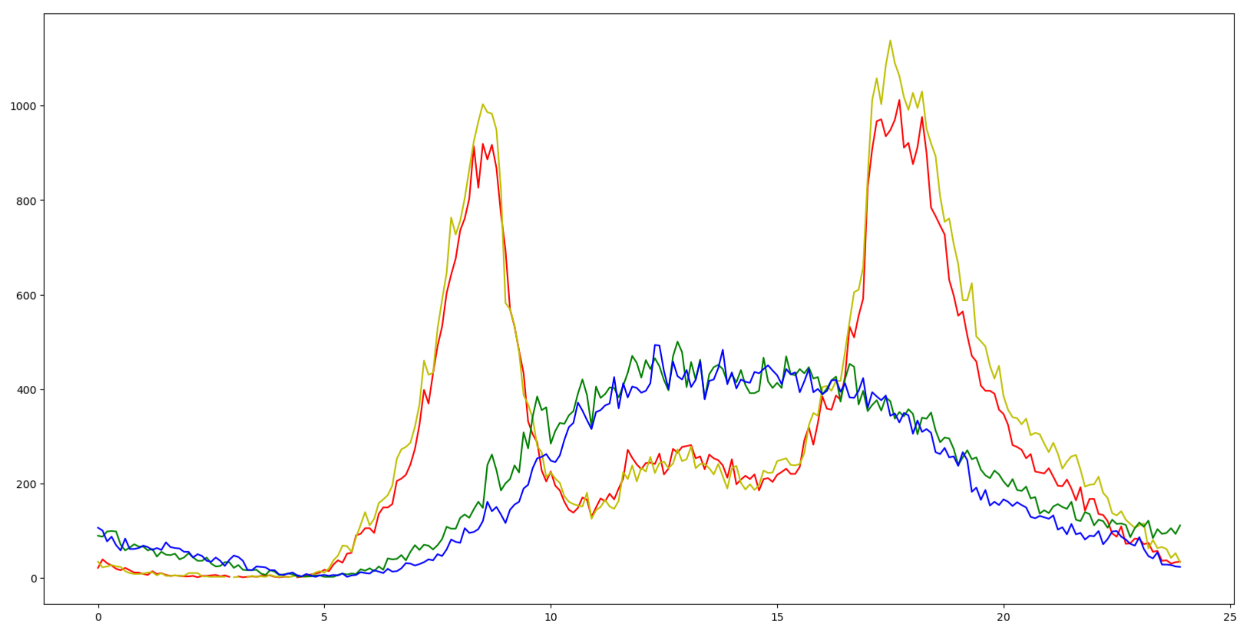
```
235  23.5      93.0
236  23.6      95.0
237  23.7     105.0
238  23.8      93.0
239  23.9     111.0

[240 rows x 2 columns],
     hour  sunday
0     0.0   106.0
1     0.1   100.0
2     0.2    77.0
3     0.3    87.0
4     0.4    69.0
..    ...     ...
235  23.5    28.0
236  23.6    28.0
237  23.7    27.0
238  23.8    24.0
239  23.9    23.0

[240 rows x 2 columns])
```

In [9]:

```
plt.figure(figsize=(20,10))
plt.plot(monday.hour, monday.monday, c = "r")
plt.plot(tuesday.hour, tuesday.tuesday, c = "y")
plt.plot(saturday.hour, saturday.saturday, c = "g")
plt.plot(sunday.hour, sunday.sunday, c = "b")
```

Out[9]:

```
[<matplotlib.lines.Line2D at 0x7fa43e373b20>]
```



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

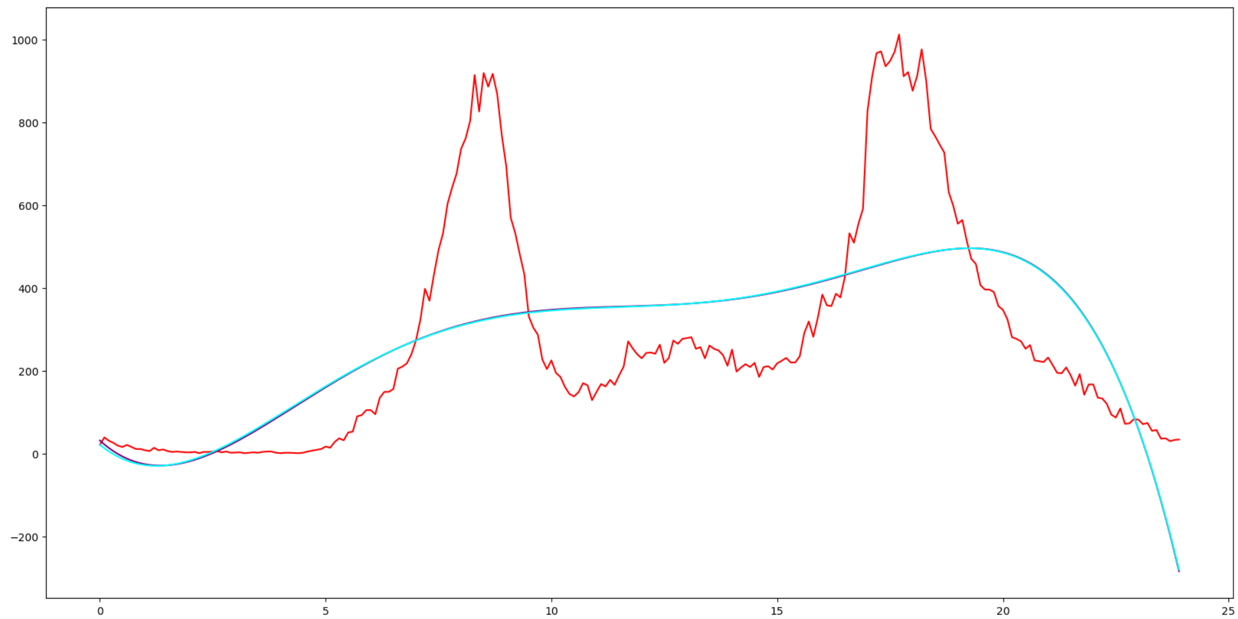
Plot all the results for each polynomial.

In [10]:
```
from sklearn import linear_model, metrics
from sklearn.preprocessing import PolynomialFeatures
from sklearn.model_selection import train_test_split

linear = linear_model.LinearRegression()

ridge = linear_model.Ridge()

n_5 = PolynomialFeatures(degree = 5)
n_15 = PolynomialFeatures(degree = 15)
n_20 = PolynomialFeatures(degree = 20)
```

In [11]:
```
# Monday

monday_clean = monday.dropna()

mon_x = monday_clean.hour

mon_y = monday_clean.monday
```

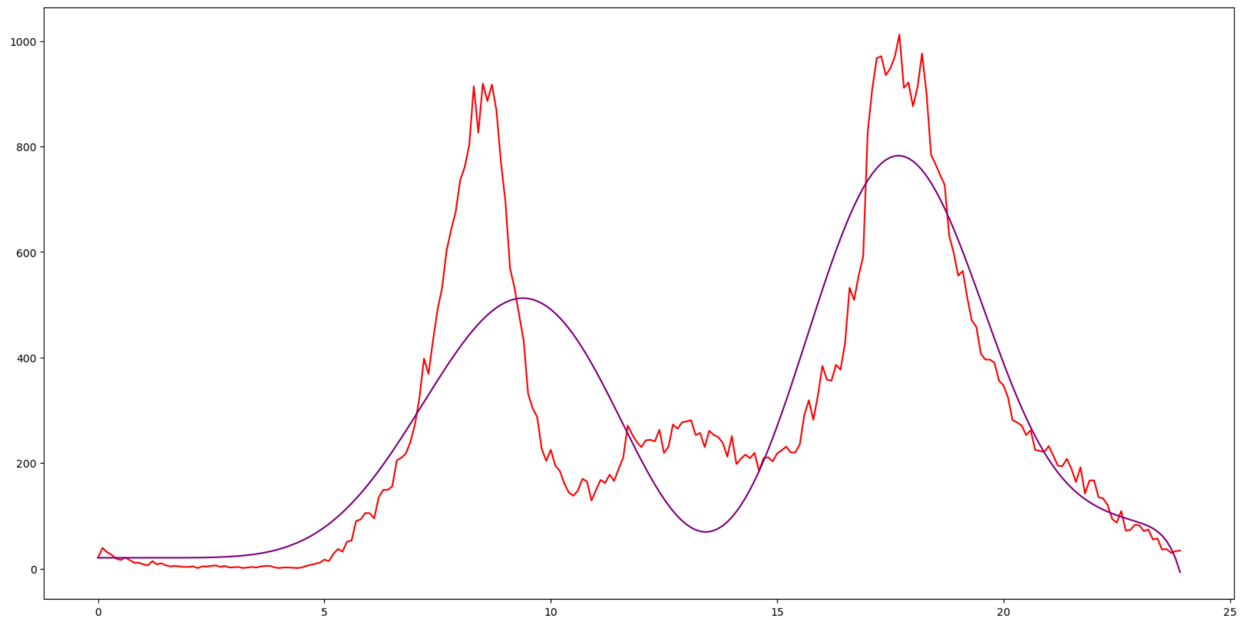
In [16]:
```
monday_5 = n_5.fit_transform(mon_x.values.reshape(-1,1))

linear.fit(monday_5, mon_y)

ridge.fit(monday_5, mon_y) #I tested ridge and it is extremely similar

plt.figure(figsize=(20,10))
plt.plot(mon_x, mon_y, c = "r")
plt.plot(mon_x, linear.predict(monday_5), c = "purple")
plt.plot(mon_x, ridge.predict(monday_5), c = "cyan")
```

Out[16]:
```
[<matplotlib.lines.Line2D at 0x7fa43fd2b5e0>]
```



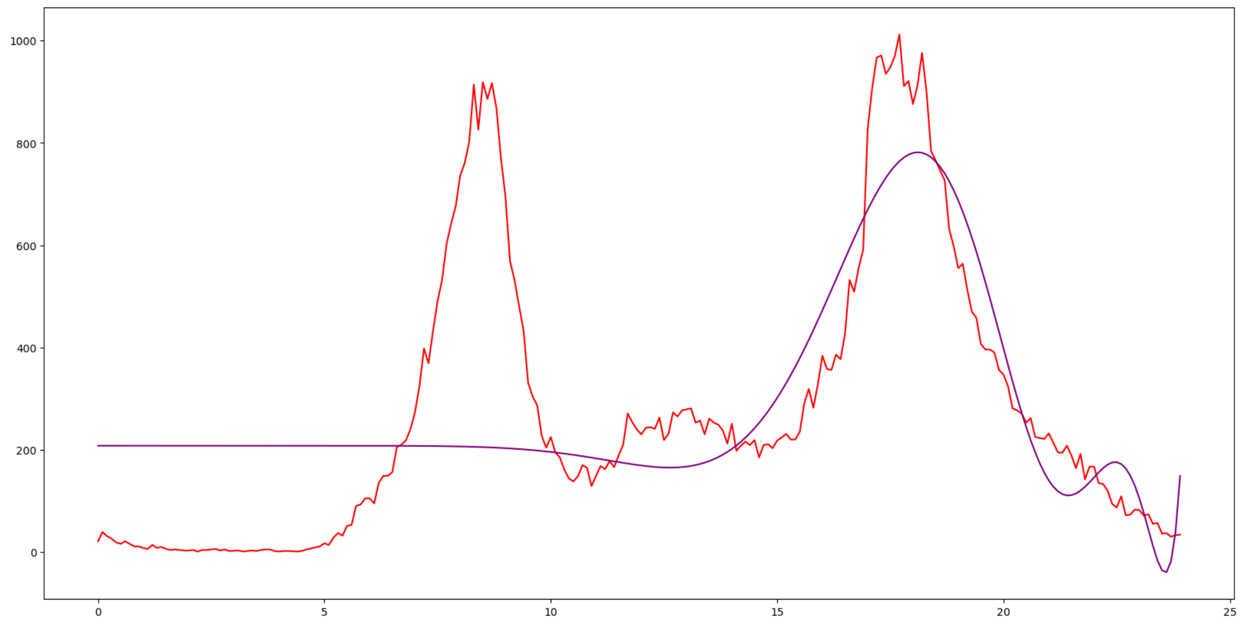
In [19]:
```
monday_15 = n_15.fit_transform(mon_x.values.reshape(-1,1)) #Probably b

linear.fit(monday_15, mon_y)

#ridge.fit(monday_15, mon_y) #I tested ridge and its significantly wor

plt.figure(figsize=(20,10))
plt.plot(mon_x, mon_y, c = "r")
plt.plot(mon_x, linear.predict(monday_15), c = "purple")
#plt.plot(mon_x, ridge.predict(monday_15), c = "cyan")
```

Out[19]:
```
[<matplotlib.lines.Line2D at 0x7fa440e0f310>]
```



In [20]:
```
monday_20 = n_20.fit_transform(mon_x.values.reshape(-1,1))

linear.fit(monday_20, mon_y)

#ridge.fit(monday_20, mon_y) I tested ridge and its significantly wors

plt.figure(figsize=(20,10))
plt.plot(mon_x, mon_y, c = "r")
plt.plot(mon_x, linear.predict(monday_20), c = "purple")
#plt.plot(mon_x, np.dot(monday_20, ridge.coef_) + ridge.intercept_, c
```

Out[20]: [<matplotlib.lines.Line2D at 0x7fa440ea8cd0>]

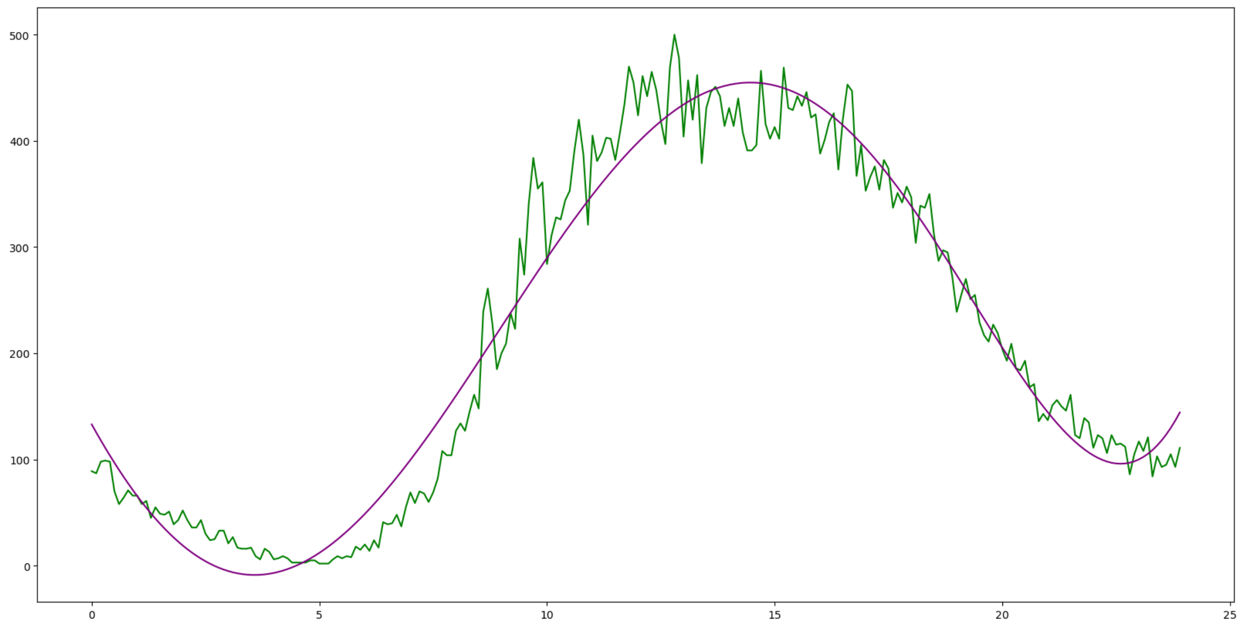


2b. Repeat 2a for saturday

In [22]:
```
# Saturday

saturday_clean = saturday.dropna()

sat_x = saturday_clean.hour

sat_y = saturday_clean.saturday
```

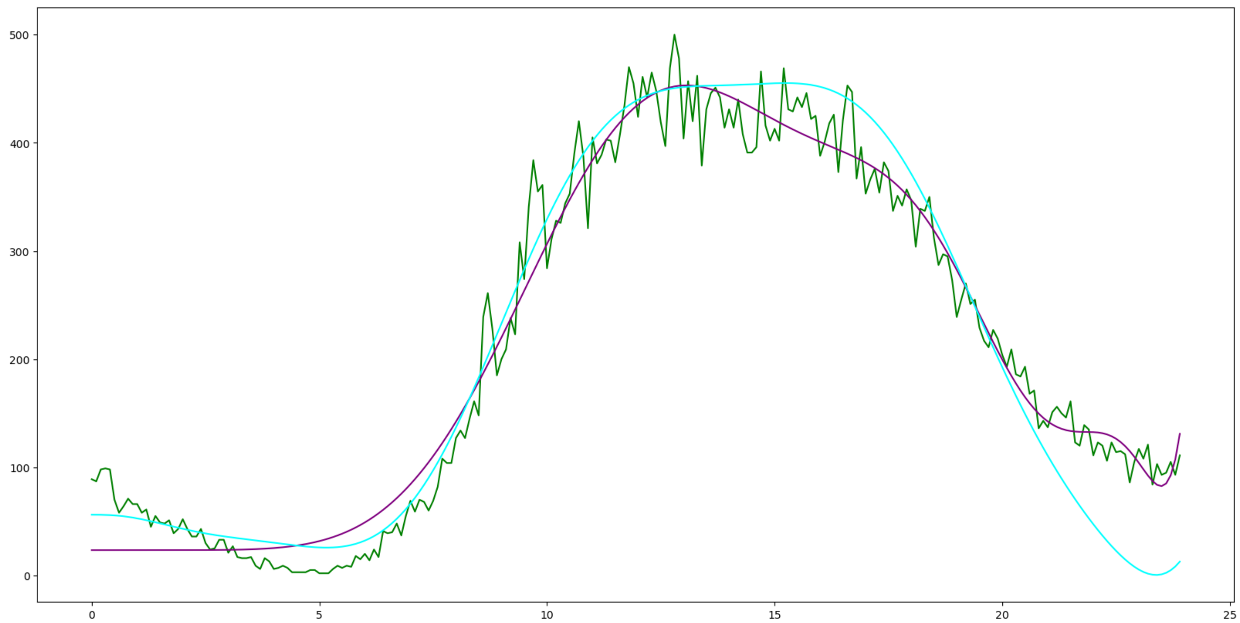
In [25]:
```
saturday_5 = n_5.fit_transform(sat_x.values.reshape(-1,1))

linear.fit(saturday_5, sat_y)

#ridge.fit(saturday_5, sat_y) #I tested ridge and it is extremely simi

plt.figure(figsize=(20,10))
plt.plot(sat_x, sat_y, c = "g")
plt.plot(sat_x, linear.predict(saturday_5), c = "purple")
#plt.plot(sat_x, ridge.predict(saturday_5), c = "cyan")
```

Out[25]:
```
[<matplotlib.lines.Line2D at 0x7fa442129450>]
```



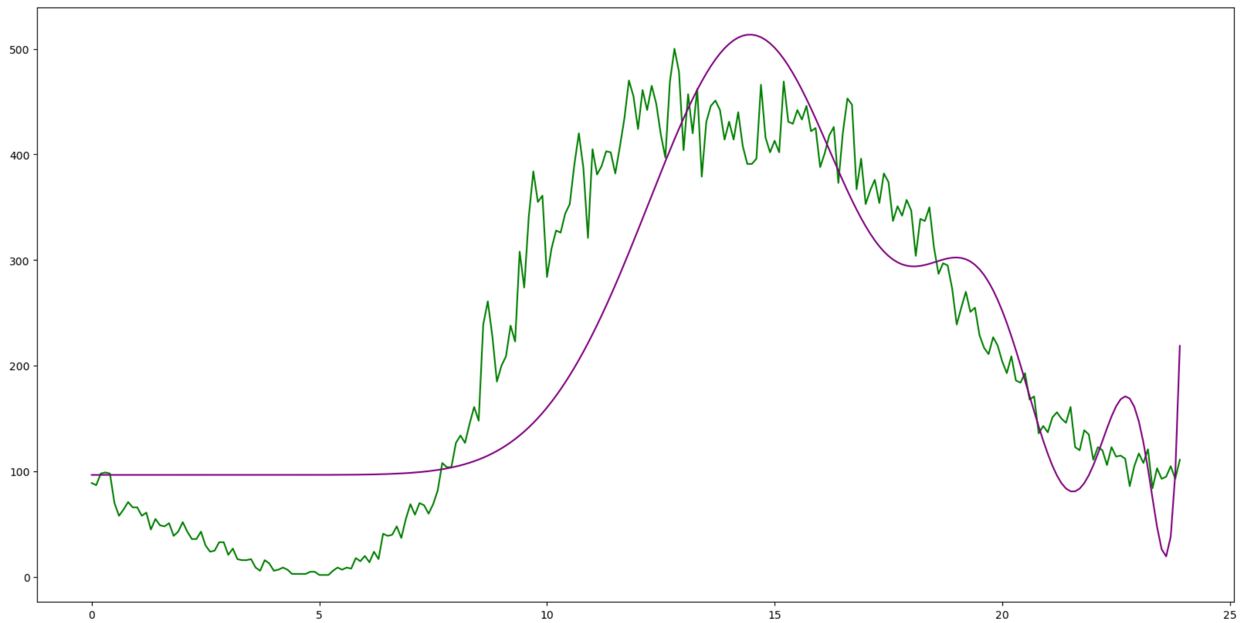
In [26]:
```
saturday_15 = n_15.fit_transform(sat_x.values.reshape(-1,1)) #Probably

linear.fit(saturday_15, sat_y)

ridge.fit(saturday_15, sat_y)

plt.figure(figsize=(20,10))
plt.plot(sat_x, sat_y, c = "g")
plt.plot(sat_x, linear.predict(saturday_15), c = "purple")
plt.plot(sat_x, ridge.predict(saturday_15), c = "cyan")
```

Out[26]:
```
[<matplotlib.lines.Line2D at 0x7fa43f782470>]
```



In [28]:
```
saturday_20 = n_20.fit_transform(sat_x.values.reshape(-1,1))

linear.fit(saturday_20, sat_y)

#ridge.fit(saturday_20, sat_y) #I tested ridge and it is significantly

plt.figure(figsize=(20,10))
plt.plot(sat_x, sat_y, c = "g")
plt.plot(sat_x, linear.predict(saturday_20), c = "purple")
#plt.plot(sat_x, ridge.predict(saturday_20), c = "cyan")
```

Out[28]:
```
[<matplotlib.lines.Line2D at 0x7fa43ebf1c90>]
```



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`

Of the three models for Monday, n equal to 5, 15, and 20, I assessed n equal to 15 to be the best predictor of y. This is visually apparent when plotted and backed up mathematically when comparing the MSE, MAE, and MAPE. The model n equal to 5 does not account for the peaks or troughs. The model n equal to 20 heavily biases towards the later peak. The model n equal to 15 is reasonably effective at predicting values of y but seems to under estimate peaks and over estimate troughs. This is a linear model as the ridge models had notable deviations from the values.

In [33]:
```
#Monday

linear_mon = linear_model.LinearRegression()

linear_mon.fit(monday_15, mon_y)

(
    metrics.mean_squared_error(mon_y, linear_mon.predict(monday_15)),
    metrics.mean_absolute_error(mon_y, linear_mon.predict(monday_15)),
    metrics.mean_absolute_percentage_error(mon_y, linear_mon.predict(m
)
```

Out[33]: (19403.939668165112, 98.159188823613, 1.9402673082566422)

The Monday model n equal to 15 is a reasonable predictor of Tuesday values. This is apparent when comparing Monday and Tuesday values plotted. It is also backed up mathematically when comparing the MSE, MAE, and MAPE.

In [36]:
```
#Tuesday

tuesday_clean = tuesday.dropna()

tues_y = tuesday_clean.tuesday

(
    metrics.mean_squared_error(tues_y, linear_mon.predict(monday_15)),
    metrics.mean_absolute_error(tues_y, linear_mon.predict(monday_15))
    metrics.mean_absolute_percentage_error(tues_y, linear_mon.predict(
)
```

Out[36]: (23858.51449183471, 105.84192260925452, 1.864778041172082)

Of the three models for Saturday, n equal to 5, 15, and 20, I assessed n equal to 15 to be the best predictor of y. Between n equal to 5 and n equal to 15 it is very close. Ultimately n equal to 15 has slightly better values of MSE, MAE, and MAPE and accounts for some of the peak values for Saturday. It does struggle with the early hour values for Saturday. The model n equal to 20 seems to overfit for the later times and significantly under fit for the earlier times. The model n equal to 15 is a linear model as the ridge model, while the best of the ridge model so far, has a significant drop off later in the day.

In [37]:
```
#Saturday

linear_sat = linear_model.LinearRegression()

linear_sat.fit(saturday_15, sat_y)

(
    metrics.mean_squared_error(sat_y, linear_sat.predict(saturday_15))
    metrics.mean_absolute_error(sat_y, linear_sat.predict(saturday_15)
    metrics.mean_absolute_percentage_error(sat_y, linear_sat.predict(s
)
```

Out[37]:
```
(809.0490983038588, 22.623668377460458, 0.7329285426915966)
```

The model for Saturday n equal to 15 is a reasonable predictor for Sunday. This is visually apparent when plotted and is mathematically supported by MSE, MAE, and MAPE.

In [38]:
```
#Sunday

sunday_clean = sunday.dropna()

sun_y = sunday_clean.sunday

(
    metrics.mean_squared_error(sun_y, linear_sat.predict(saturday_15))
    metrics.mean_absolute_error(sun_y, linear_sat.predict(saturday_15)
    metrics.mean_absolute_percentage_error(sun_y, linear_sat.predict(s
)
```

Out[38]:
```
(1638.719793550288, 34.64797283054569, 0.9311980840848827)
```

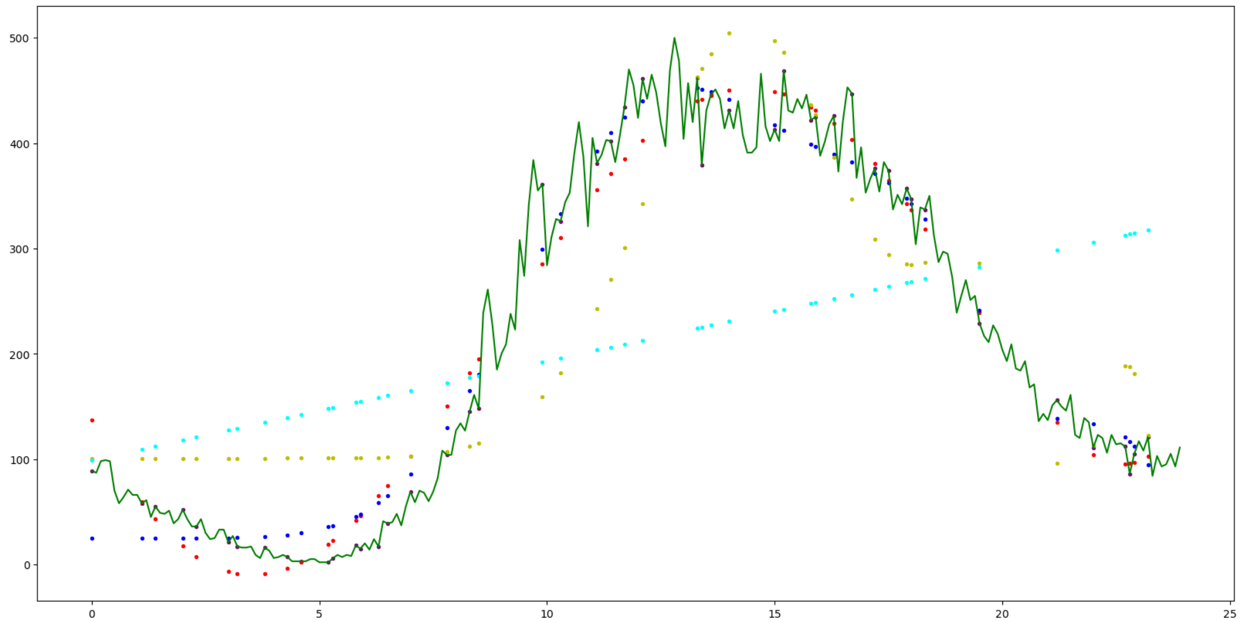
4. With `saturday`, use `train_test_split` to create training and test sets and build a model. Create predictions using the xtest from and determine the errors between these predictions and the ytest (MSE, MAE, MAPE).

repeat for `monday`

Based on the MSE, MAE, and MAPE values linear15, in blue, appears to have the least overall errors and seems to have reasonable estimates of y for Saturday. The points are also fairly close to the actual data values for Saturday.

In [196]:
```
#Saturday

sat_xtrain, sat_xtest, sat_ytrain, sat_ytest = train_test_split(sat_x,

linear = linear_model.LinearRegression().fit(sat_xtrain.values.reshape

sat_xtrain5 = PolynomialFeatures(degree=5).fit_transform(sat_xtrain.va
sat_xtest5 = PolynomialFeatures(degree=5).fit_transform(sat_xtest.valu

linear5 = linear_model.LinearRegression().fit(sat_xtrain5, sat_ytrain)

sat_xtrain15 = PolynomialFeatures(degree=15).fit_transform(sat_xtrain.
sat_xtest15 = PolynomialFeatures(degree=15).fit_transform(sat_xtest.va

linear15 = linear_model.LinearRegression().fit(sat_xtrain15, sat_ytrai

sat_xtrain20 = PolynomialFeatures(degree=20).fit_transform(sat_xtrain.
sat_xtest20 = PolynomialFeatures(degree=20).fit_transform(sat_xtest.va

linear20 = linear_model.LinearRegression().fit(sat_xtrain20, sat_ytrai

size = 8
plt.scatter(sat_xtest, sat_ytest, c = 'purple', s=size)
plt.plot(sat_x, sat_y, c = "g")
plt.scatter(sat_xtest, linear5.predict(sat_xtest5), c='r', s=size)
plt.scatter(sat_xtest, linear15.predict(sat_xtest15), c='b', s=size)
plt.scatter(sat_xtest, linear20.predict(sat_xtest20), c ='y', s=size)
plt.scatter(sat_xtest, linear.predict(sat_xtest.values.reshape(-1, 1))
```

Out[196]: <matplotlib.collections.PathCollection at 0x7fea85bda3e0>



In [197]:
```
#Saturday MSE
(
    metrics.mean_squared_error(sat_ytest, linear.predict(sat_xtest.val
    metrics.mean_squared_error(sat_ytest, linear5.predict(sat_xtest5))
    metrics.mean_squared_error(sat_ytest, linear15.predict(sat_xtest15
    metrics.mean_squared_error(sat_ytest, linear20.predict(sat_xtest20
)
```

Out[197]:
```
(23065.2703051803, 905.7097558268573, 839.1941372782458, 6509.8137456
70064)
```

In [198]:
```
#Saturday MAE
(
    metrics.mean_absolute_error(sat_ytest, linear.predict(sat_xtest.va
    metrics.mean_absolute_error(sat_ytest, linear5.predict(sat_xtest5)
    metrics.mean_absolute_error(sat_ytest, linear15.predict(sat_xtest1
    metrics.mean_absolute_error(sat_ytest, linear20.predict(sat_xtest2
)
```

Out[198]:
```
(139.32564971520176, 24.728582492281507, 23.257874920289463, 68.79431
006780094)
```

In [199]:
```
#Satuday MAPE
(
    metrics.mean_absolute_percentage_error(sat_ytest, linear.predict(s
    metrics.mean_absolute_percentage_error(sat_ytest, linear5.predict(
    metrics.mean_absolute_percentage_error(sat_ytest, linear15.predict
    metrics.mean_absolute_percentage_error(sat_ytest, linear20.predict
)
```

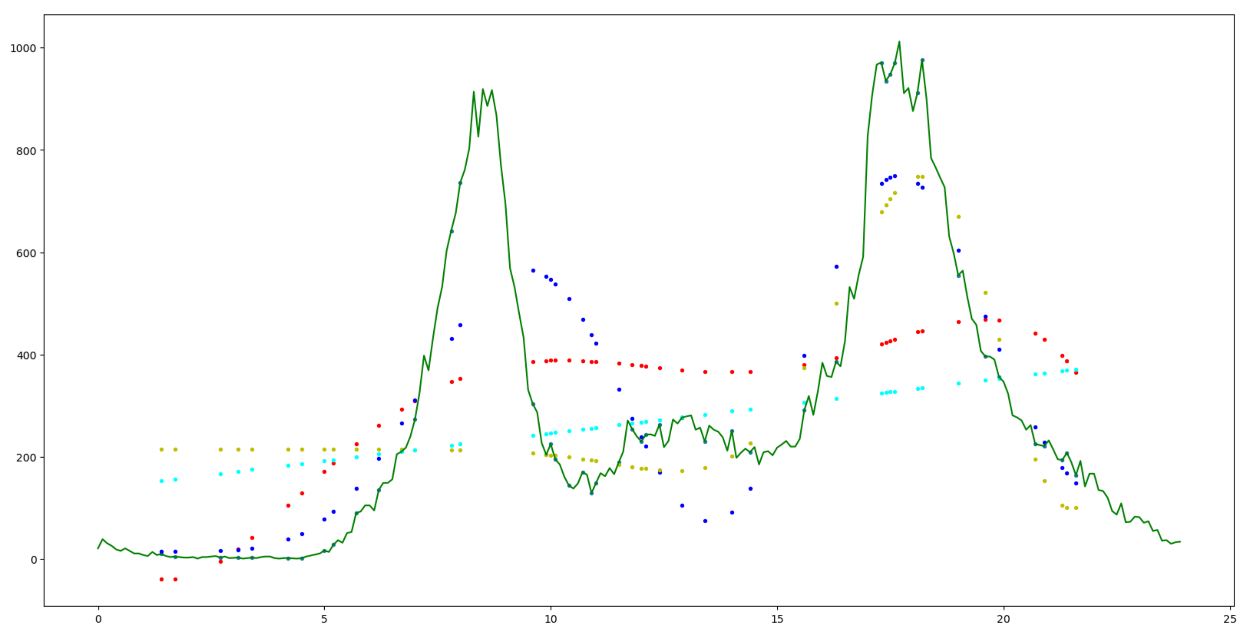
Out[199]:
```
(4.944195277429863, 0.632339983209748, 0.9955009244667496, 3.23268115
61478443)
```

Based on the MSE, MAE, and MAPE values linear15, in blue, appears to have the least overall errors and may have semi-reasonable estimates of y for Monday. The points are the closet of the models to estimating the two peaks in the Monday but seems to underestimate both peaks and the central trough as well.

In [200]:
```

```

```
#Monday
mon_xtrain, mon_xtest, mon_ytrain, mon_ytest = train_test_split(mon_x,

linear = linear_model.LinearRegression().fit(mon_xtrain.values.reshape

mon_xtrain5 = PolynomialFeatures(degree=5).fit_transform(mon_xtrain.va
mon_xtest5 = PolynomialFeatures(degree=5).fit_transform(mon_xtest.valu

linear5 = linear_model.LinearRegression().fit(mon_xtrain5, mon_ytrain)

mon_xtrain15 = PolynomialFeatures(degree=15).fit_transform(mon_xtrain.
mon_xtest15 = PolynomialFeatures(degree=15).fit_transform(mon_xtest.va

linear15 = linear_model.LinearRegression().fit(mon_xtrain15, mon_ytrai

mon_xtrain20 = PolynomialFeatures(degree=20).fit_transform(mon_xtrain.
mon_xtest20 = PolynomialFeatures(degree=20).fit_transform(mon_xtest.va

linear20 = linear_model.LinearRegression().fit(mon_xtrain20, mon_ytrai

size = 8
plt.scatter(mon_xtest, mon_ytest, s=size)
plt.plot(mon_x, mon_y, c = "g")
plt.scatter(mon_xtest, linear5.predict(mon_xtest5), c='r', s=size)
plt.scatter(mon_xtest, linear15.predict(mon_xtest15), c='b', s=size)
plt.scatter(mon_xtest, linear20.predict(mon_xtest20), c ='y', s=size)
plt.scatter(mon_xtest, linear.predict(mon_xtest.values.reshape(-1, 1))
```

Out[200]: <matplotlib.collections.PathCollection at 0x7fea85c5aaa0>



In [201]:
```
#Monday MSE
(
    metrics.mean_squared_error(mon_ytest, linear.predict(mon_xtest.val
    metrics.mean_squared_error(mon_ytest, linear5.predict(mon_xtest5))
    metrics.mean_squared_error(mon_ytest, linear15.predict(mon_xtest15
    metrics.mean_squared_error(mon_ytest, linear20.predict(mon_xtest20
)
```

Out[201]:
```
(68925.67191776562, 56851.792551018436, 29129.16352815497, 28180.2992
88658687)
```

In [202]:
```
#Monday MAE
(
    metrics.mean_absolute_error(mon_ytest, linear.predict(mon_xtest.va
    metrics.mean_absolute_error(mon_ytest, linear5.predict(mon_xtest5)
    metrics.mean_absolute_error(mon_ytest, linear15.predict(mon_xtest1
    metrics.mean_absolute_error(mon_ytest, linear20.predict(mon_xtest2
)
```

Out[202]:
```
(177.61003750483667, 188.67505600636116, 128.9651071108673, 128.98099
545130987)
```

In [203]:
```
#Monday MAPE
(
    metrics.mean_absolute_percentage_error(mon_ytest, linear.predict(m
    metrics.mean_absolute_percentage_error(mon_ytest, linear5.predict(
    metrics.mean_absolute_percentage_error(mon_ytest, linear15.predict
    metrics.mean_absolute_percentage_error(mon_ytest, linear20.predict
)
```

Out[203]:
```
(8.964683576327841, 4.023080080443859, 1.8679937801413182, 10.7606664
89302018)
```