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1 Libraries

```
In [1]: import pandas as pd
        import numpy as np
        import seaborn as sns
        import matplotlib.pyplot as plt
        from sklearn.metrics import mean_squared_error

        sns.set_style("dark")
        sns.set_palette("bright", 10)
```

2 Read in data

```
In [2]: df = pd.read_csv('data.csv')
        df = df.sort_values(by='date')  # make sure the date column is in asscending order
        df.head()
```

```
Out[2]:          date day.of.week  car.count  weather cloud.indicator
        0  2010-01-01      Friday        101      0.1           clear
        1  2010-01-02    Saturday         34      0.2          cloudy
        2  2010-01-03      Sunday        113      0.4           clear
        3  2010-01-04      Monday          5      0.6          cloudy
        4  2010-01-05     Tuesday        124      0.1           clear
```

3 check if any null within the dataframe

```
In [3]: for i in range(df.shape[1]):
            if df.iloc[i].isnull().sum()==0:
                print('There is no null value in ', df.columns[i])
            else:
                print('There is null value in ', df.columns[i])
```

```
There is no null value in  date
There is no null value in  day.of.week
There is no null value in  car.count
There is no null value in  weather
There is no null value in  cloud.indicator
```

4 Feature Engineering

In [4]:
```
# create new column indicate the year and month of each row
df['year'] = pd.DatetimeIndex(df['date']).year
df['month'] = pd.DatetimeIndex(df['date']).month

df.head()
```

Out[4]:

	date	day.of.week	car.count	weather	cloud.indicator	year	month
0	2010-01-01	Friday	101	0.1	clear	2010	1
1	2010-01-02	Saturday	34	0.2	cloudy	2010	1
2	2010-01-03	Sunday	113	0.4	clear	2010	1
3	2010-01-04	Monday	5	0.6	cloudy	2010	1
4	2010-01-05	Tuesday	124	0.1	clear	2010	1

In [5]:
```
# convert the string day of week to numeric number
weekdays = {
    'Monday':1,
    'Tuesday':2,
    'Wednesday':3,
    'Thursday':4,
    'Friday':5,
    'Saturday':6,
    'Sunday':7
}

df['day.of.week'] = df['day.of.week'].map(lambda x: weekdays[x])
df.head()
```

Out[5]:

	date	day.of.week	car.count	weather	cloud.indicator	year	month
0	2010-01-01	5	101	0.1	clear	2010	1
1	2010-01-02	6	34	0.2	cloudy	2010	1
2	2010-01-03	7	113	0.4	clear	2010	1
3	2010-01-04	1	5	0.6	cloudy	2010	1
4	2010-01-05	2	124	0.1	clear	2010	1

In [6]:
```
# use label encoder to conver the categorical data to numerica label
df['cloud.indicator'] = df['cloud.indicator'].map(lambda x: 1 if x=='clear' else 0)

df.head()
```

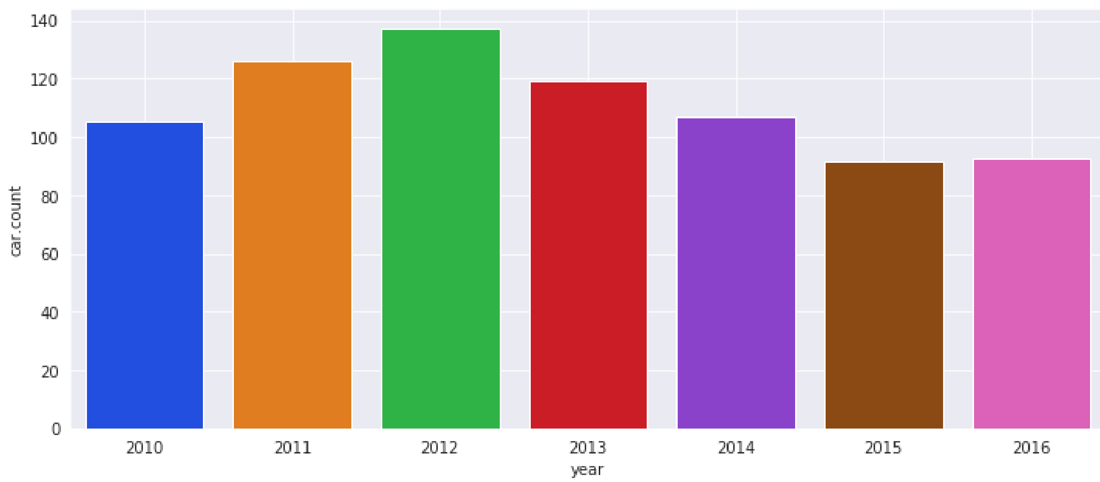
Out[6]:

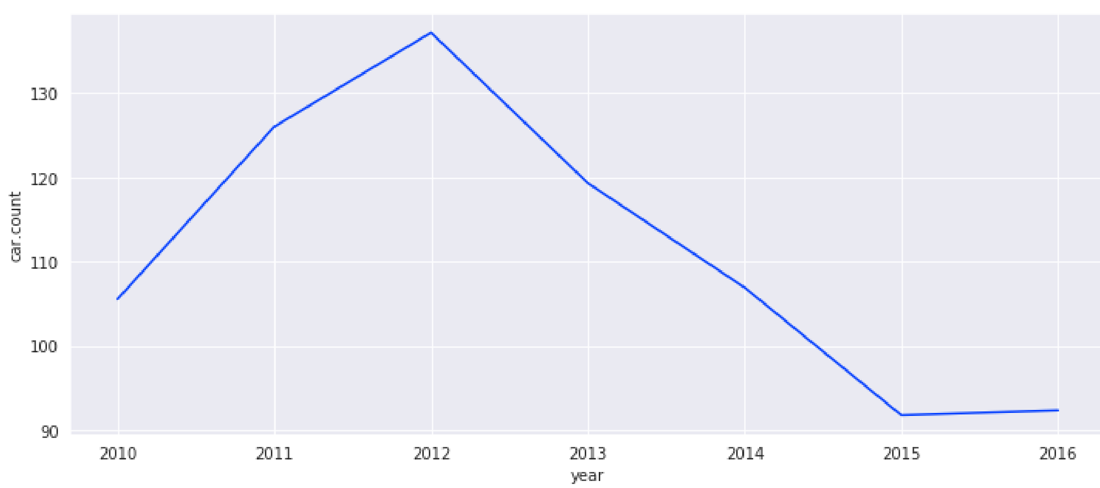
	date	day.of.week	car.count	weather	cloud.indicator	year	month
0	2010-01-01	5	101	0.1	1	2010	1
1	2010-01-02	6	34	0.2	0	2010	1
2	2010-01-03	7	113	0.4	1	2010	1
3	2010-01-04	1	5	0.6	0	2010	1
4	2010-01-05	2	124	0.1	1	2010	1

5 Exploratory data analysis

5.0.1 visualize the year factor which affects the car count

In [7]:
```
# plot the average car count in each year ---> shows the max car count in year 2012, m
plt.figure(figsize=(12,5))
sns.barplot(x=df.groupby(['year']).mean()['car.count'].index, y=df.groupby(['year']).me
plt.grid(True)
plt.show()

plt.figure(figsize=(12,5))
plt.plot(df.groupby(['year']).mean()['car.count'])
plt.xlabel('year')
plt.ylabel('car.count')
plt.grid(True)
plt.show()
```

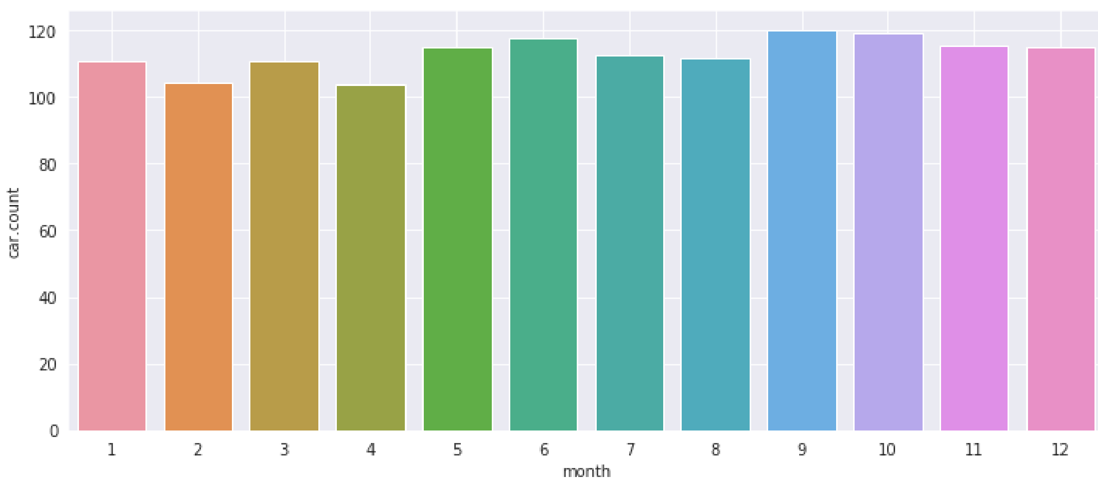


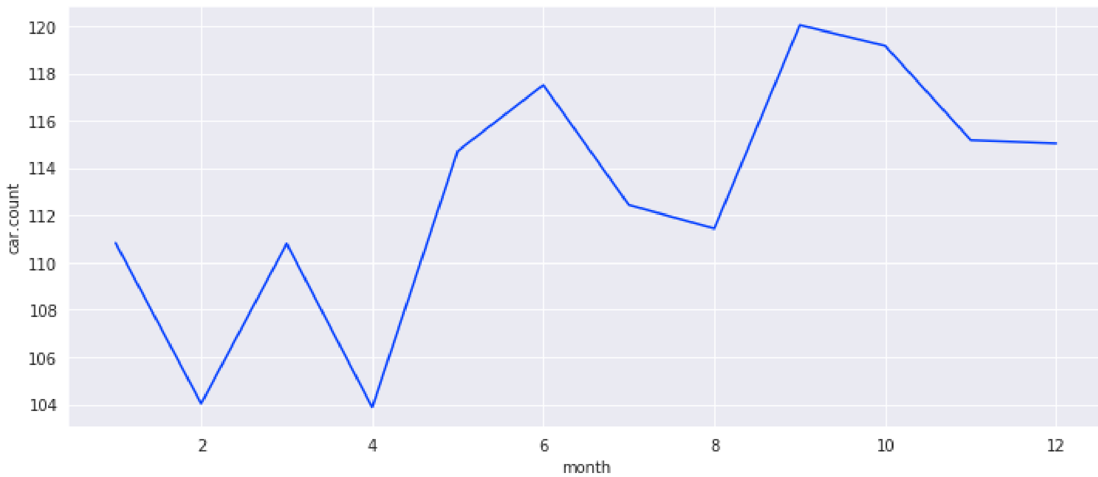


plots show that most number of cars occurs in year 2012, fewest year is in year 2015

5.0.2 visualize the month factor which affects the car count

```
In [8]: # plot the average car count in each month ---> shows the max car count in September, 
        plt.figure(figsize=(12,5))
        sns.barplot(x=df.groupby(['month']).mean()['car.count'].index, y=df.groupby(['month'])
        plt.grid(True)
        plt.show()

        plt.figure(figsize=(12,5))
        plt.plot(df.groupby(['month']).mean()['car.count'])
        plt.xlabel('month')
        plt.ylabel('car.count')
        plt.grid(True)
        plt.show()
```

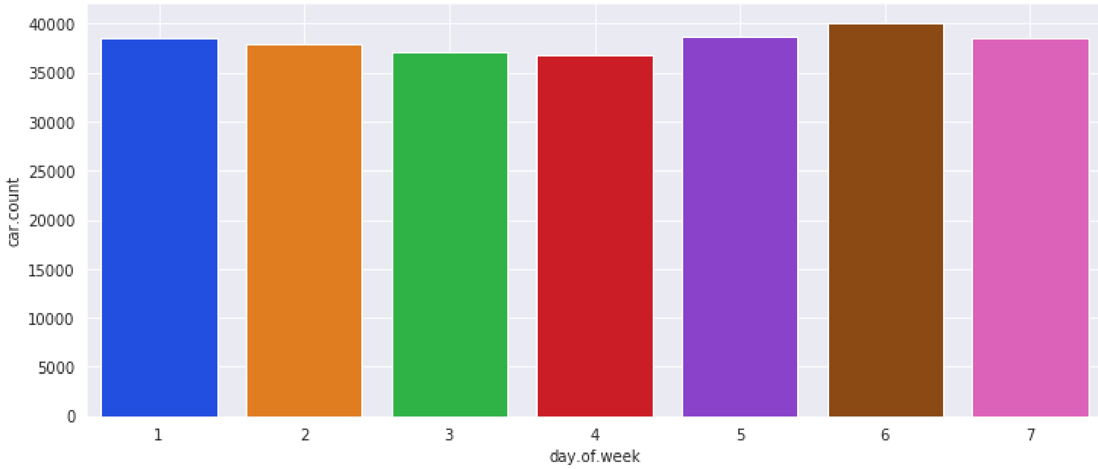


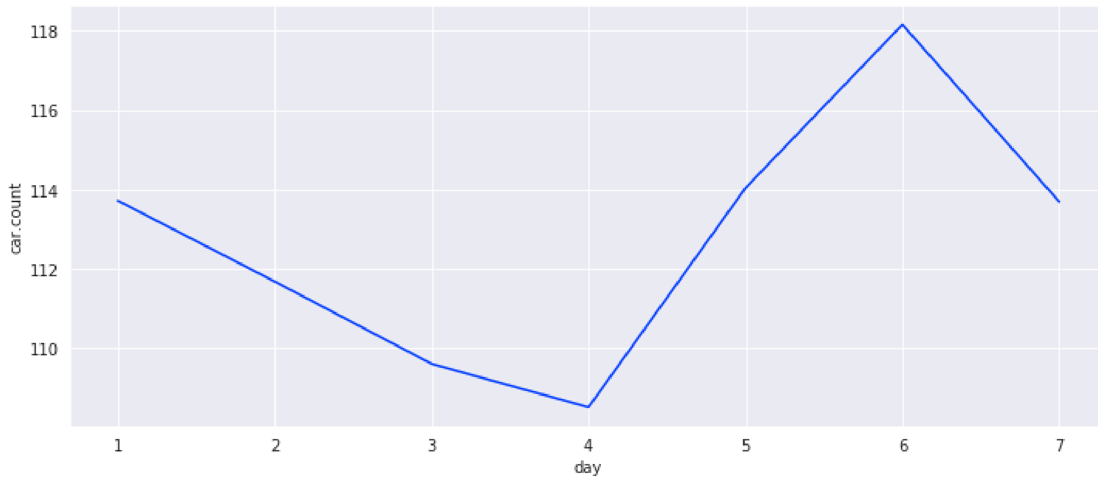


Summer time is the popular months--May to October

5.0.3 visualize the day of week factor which affects the car count

```
In [9]: # plot the average car count in each day in week ---> shows the max car count in Satur
        plt.figure(figsize=(12,5))
        sns.barplot(x=df.groupby(['day.of.week']).sum()['car.count'].index, y=df.groupby(['day
        plt.grid(True)
        plt.show()

        plt.figure(figsize=(12,5))
        plt.plot(df.groupby(['day.of.week']).mean()['car.count'])
        plt.xlabel('day')
        plt.ylabel('car.count')
        plt.grid(True)
        plt.show()
```

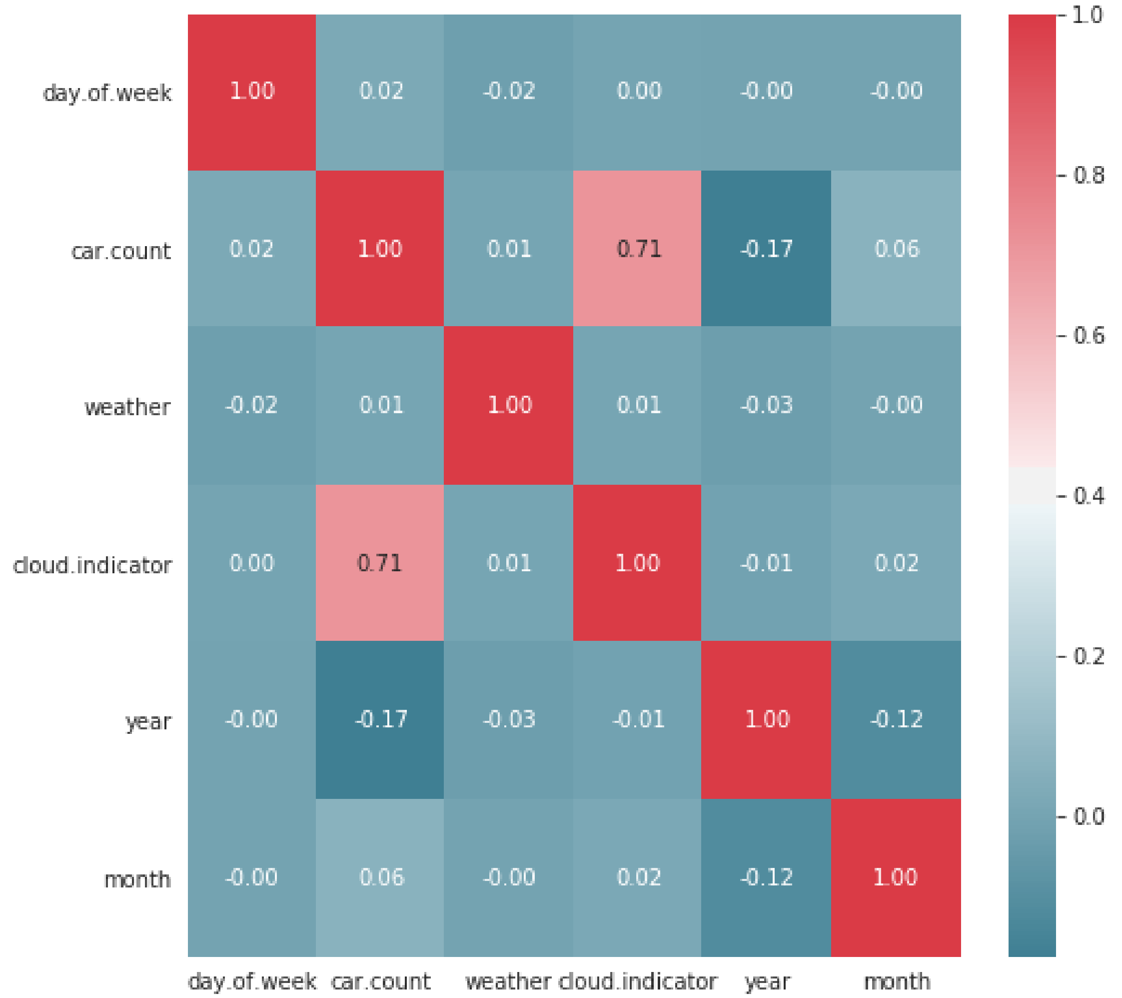




Saturday always has the most number of car, Thursday is the day with fewest car

5.0.4 correlation heatmap

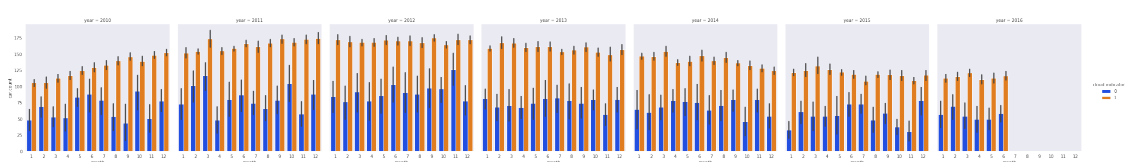
In [10]:
```
# create Correlation df
corr = df.corr(method='pearson')
# plot figsize
fig, ax = plt.subplots(figsize=(8, 8))

# generate Color Map, red & blue
colormap = sns.diverging_palette(220, 10, as_cmap=True)
# generate Heat Map, allow annotations and place floats in map
sns.heatmap(corr, cmap=colormap, annot=True, fmt=".2f")

# show plot
plt.show()
```



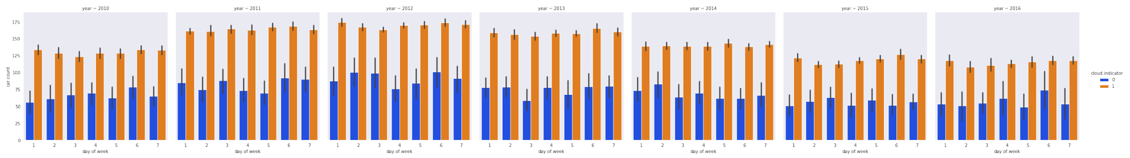
Cloud situation is mostly positively correlated to car count

5.0.5 visualize the cloud situation effects on month, year by year

```
In [11]: # detail lookup the car count in clear and cloudy cloud.indicator by month
         sns.catplot(x='month', y='car.count', hue='cloud.indicator',
                     col='year', data=df, kind="bar")
         plt.show()
```



```
In [12]: # detail lookup the car count in clear and cloudy cloud.indicator by day of week
         sns.catplot(x='day.of.week', y='car.count', hue='cloud.indicator',
                     col='year', data=df, kind="bar")
         plt.show()
```



```
In [13]: dff = df
```

6 SVR regression model to predict the car.count

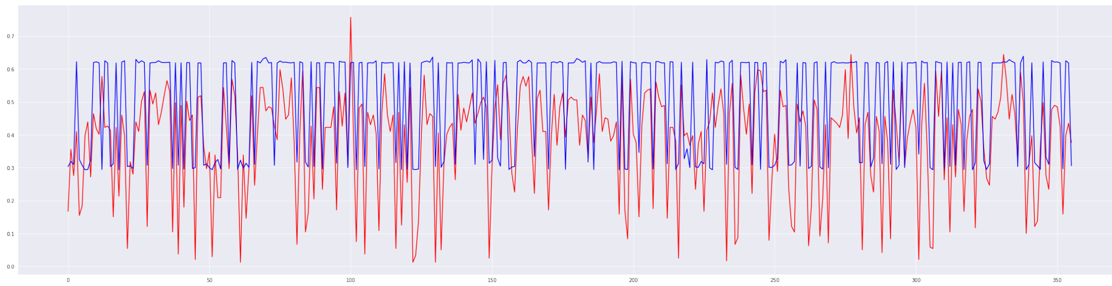
```
In [14]: df = df[['day.of.week', 'weather', 'cloud.indicator', 'car.count']]
         df.head()
```

Out[14]:

	day.of.week	weather	cloud.indicator	car.count
0	5	0.1	1	101
1	6	0.2	0	34
2	7	0.4	1	113
3	1	0.6	0	5
4	2	0.1	1	124

```
In [15]: # set X be the feature matrix, y be the response(predictor) vector
         X = df.iloc[:, 1:-1].values
         y = df.iloc[:, -1].values

In [16]: from sklearn.preprocessing import MinMaxScaler
         sc_X = MinMaxScaler()
         sc_y = MinMaxScaler()
         X = sc_X.fit_transform(X)
         y = sc_y.fit_transform([[i] for i in y])
         y = [i for j in y for i in j]

In [17]: train_idx = int(len(df) * .85)

In [18]: X_train, y_train, X_test, y_test = X[:train_idx], y[:train_idx], X[train_idx:], y[trai

In [19]: from sklearn.svm import SVR
         svr = SVR()
         svr.fit(X_train, y_train)
         y_pred = svr.predict(X_test)
```

```
In [20]: # Visualising the SVR results
         plt.figure(figsize=(40,10))
         plt.plot(y_test, color = 'red')
         plt.plot(svr.predict(X_test), color = 'blue')
         plt.grid(True)
         plt.show()
```



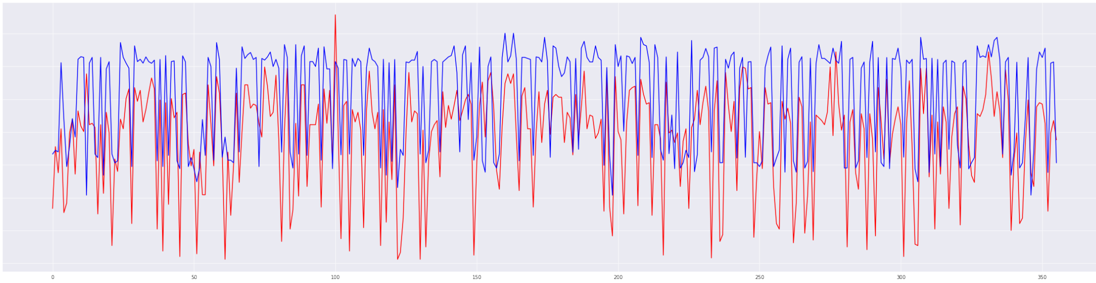

```
In [21]: # print out the mean square error between actual and predicted values
         from sklearn.metrics import mean_squared_error
         mean_squared_error(y_test, svr.predict(X_test))

Out[21]: 0.02492335819190767
```

this model prediction seems mostly greater than the actual value, so I believe it's great for predict the max car.count for future days

7 Random Forest Regression model to predict car.count

```
In [22]: from sklearn.ensemble import RandomForestRegressor
         regressor = RandomForestRegressor(n_estimators = 500, random_state = 42)
         regressor.fit(X_train, y_train)

         y_pred = regressor.predict(X_test)
```

```
In [23]: # Visualising the SVR results
         plt.figure(figsize=(40,10))

         plt.plot(y_test, color = 'red')
         plt.plot(y_pred, color = 'blue')
         plt.grid(True)
         plt.show()
```



```
In [24]: # print out the mean square error between actual and predicted values
         from sklearn.metrics import mean_squared_error
         mean_squared_error(y_test, svr.predict(X_test))

Out[24]: 0.02492335819190767
```

this model prediction seems mostly greater than the actual value, so I believe it's great for predict the max car.count for future days

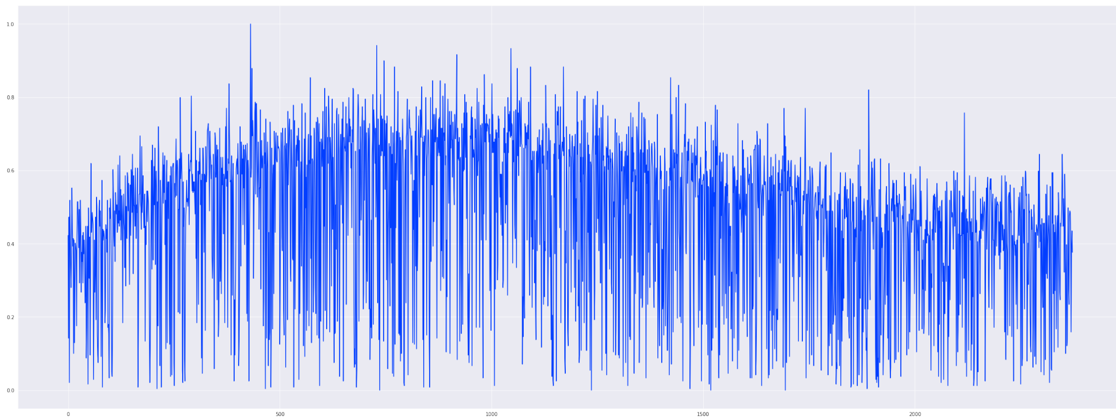
8 ARIMA model to predicting the car.count

```
In [25]: df = pd.read_csv('data.csv')
         df = df[['date', 'car.count']]
         df = df[['car.count']]

         from sklearn.preprocessing import MinMaxScaler
         scaler = MinMaxScaler()
         df = pd.DataFrame(scaler.fit_transform(df), columns=df.columns)
         df.head()
```

Out[25]:

	car.count
0	0.422594
1	0.142259
2	0.472803
3	0.020921
4	0.518828

```
In [26]: plt.figure(figsize=(40,15))
         plt.grid(True)
         plt.plot(df['car.count'].tolist())

Out[26]: [<matplotlib.lines.Line2D at 0x1a1f6596a0>]
```



In [27]:
```python
# Check stationarity
from statsmodels.tsa.stattools import adfuller

X = df['car.count'].values
result = adfuller(X)
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
print('Critical Values:')
for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))
```

```
ADF Statistic: -4.400166
p-value: 0.000297
Critical Values:
	1%: -3.433
	5%: -2.863
	10%: -2.567
```

since the ADF statistic is less than the critical value ==> reject the null hypothesis,say that the series is stationary!

In [28]:
```python
# visualize the seasonal decomposition
from statsmodels.tsa.seasonal import seasonal_decompose
res = seasonal_decompose(df['car.count'].values, freq=365)

fig, (ax1,ax2,ax3) = plt.subplots(3,1, figsize=(30,18))
ax1.plot(res.trend)
ax2.plot(res.resid)
ax3.plot(res.seasonal)
```

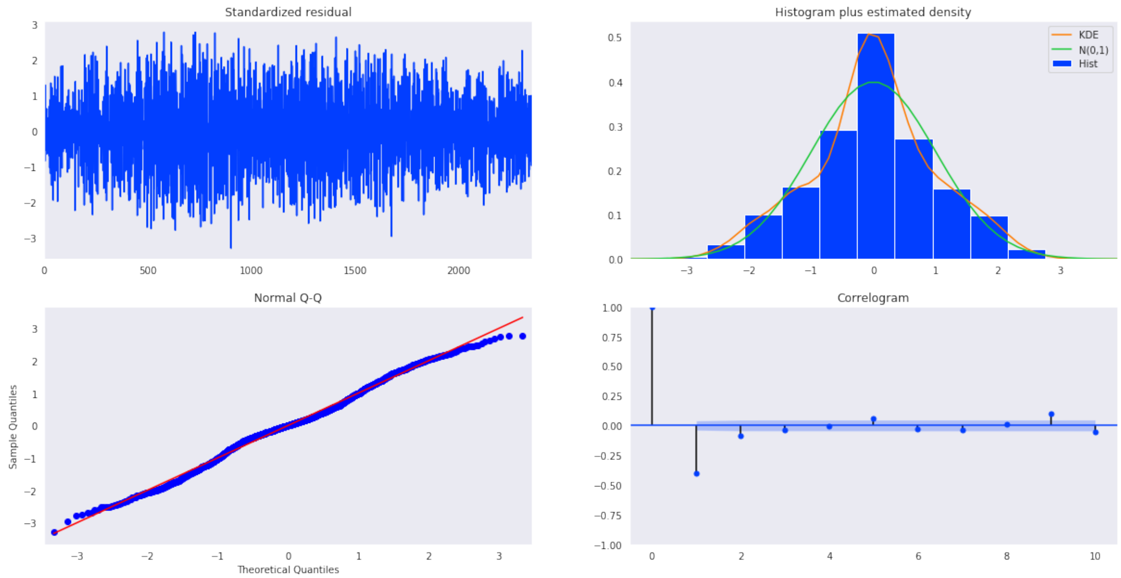
Out[28]:
```
[<matplotlib.lines.Line2D at 0x1a20ce4128>]
```

the data is sationarity, seasonal, and it is good to form ARIMA model

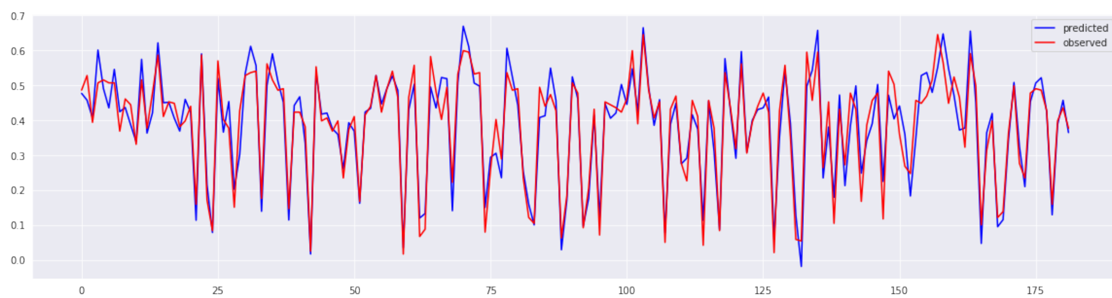
```
In [29]: import statsmodels.api as sm
         mod = sm.tsa.statespace.SARIMAX(X,order=(3,2,0),
                                         seasonal_order=(3,0,3,4),
                                         enforce_stationarity=False,
                                         enforce_invertibility=False)
         results = mod.fit()
         print('ARIMA{}x{} - AIC:{}'.format((0,2,1), (0,2,1,12), results.aic))
```

```
/anaconda3/lib/python3.6/site-packages/statsmodels/base/model.py:508: ConvergenceWarning: Maxi
  "Check mle_retvals", ConvergenceWarning)


ARIMA(0, 2, 1)x(0, 2, 1, 12) - AIC:586.833697671251
```

```
In [30]: results.plot_diagnostics(figsize=(20, 10))
         plt.show()
```




```
In [31]: # try the model to predict the 2016-1-1 to 2016-6-30 car count, and compare with the
         pred = results.get_prediction(start = 2192, end = 2373, dynamic=False)
         pred_ci = pred.conf_int()

         plt.figure(figsize=(20,5))
         plt.grid(True)
         plt.plot(pred.predicted_mean, color='blue', label='predicted')
         plt.plot(df.iloc[2191:2373, :].values, color='red', label='observed')
         plt.legend()
         plt.show()
```




```
In [32]: # print out the mean square error
         from sklearn.metrics import mean_squared_error
         mean_squared_error(df.iloc[2191:2373, :].values, pred.predicted_mean)
```

```
Out[32]: 0.0025080627939369176
```

9 Keras Model of binary classification

9.0.1 use the features of day.of.week, weather, and car.count to predict the cloud.indicator

In [33]:
```
df = dff[[ 'day.of.week', 'weather', 'car.count', 'cloud.indicator']]
df = pd.DataFrame(scaler.fit_transform(df), columns=df.columns)
df['cloud.indicator'] = df['cloud.indicator'].astype(int)

# set X be the feature matrix, y be the response(predictor) vector
X = df.iloc[:, :-1].values
y = df.iloc[:, -1].values
```

In [34]:
```
df.head()
```

Out[34]:

	day.of.week	weather	car.count	cloud.indicator
0	0.666667	0.440000	0.422594	1
1	0.833333	0.453333	0.142259	0
2	1.000000	0.480000	0.472803	1
3	0.000000	0.506667	0.020921	0
4	0.166667	0.440000	0.518828	1

In [35]:
```
# split the dataset into 80% training set, and 20% for testing
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_sta
```

In [36]:
```
# balance the dataset
from imblearn.over_sampling import SMOTE
smote = SMOTE(kind = "regular")

X_train, y_train = smote.fit_sample(X_train, y_train)
```

In [37]:
```
#importing the keras libraries and keras
import keras
from keras.models import Sequential
from keras.callbacks import BaseLogger, ModelCheckpoint, EarlyStopping, TensorBoard, 
from keras.layers import Dense, Activation, Flatten

model = Sequential()

model.add(Dense(units= 100, kernel_initializer ='glorot_uniform', bias_initializer ='
                activation = 'relu', input_dim = X.shape[1]))

# add hidden layers
for i in range(4):
    model.add(Dense(units= 120, kernel_initializer ='glorot_uniform', bias_initialize
                    activation = 'relu'))

# Adding the output layer
model.add(Dense(units = 2, kernel_initializer='glorot_uniform', bias_initializer='glo
```

```
                    activation ='sigmoid'))

baselogger = BaseLogger()

checkpointer = ModelCheckpoint(filepath ='weights.{epoch:02d}-{val_loss:.2f}.hdf5', mo
                               save_best_only = False, save_weights_only = False, mode

earlystopper = EarlyStopping(monitor ='val_acc', min_delta = 0, patience = 5, verbose

tensor_board = TensorBoard(log_dir ='./logs', histogram_freq = 0, batch_size = 10, wri
                           write_images = True, embeddings_freq = 0, embeddings_layer_
                           embeddings_metadata = None)

reduced_lr = ReduceLROnPlateau(monitor ='val_loss', factor = 0.25, patience = 1, verbo
                               cooldown = 0, min_lr = 0)

callbacks_list = [baselogger, checkpointer, earlystopper, tensor_board, reduced_lr]

model.compile(optimizer ='adam' , loss ='sparse_categorical_crossentropy', metrics =

history = model.fit(X_train, y_train, validation_split = 0.33,
                    batch_size = 100, epochs = 10,
                    verbose = 1, shuffle = True,
                    validation_data = (X_test, y_test),
                    callbacks = callbacks_list)
print(history)
```

```
/anaconda3/lib/python3.6/site-packages/h5py/__init__.py:36: FutureWarning: Conversion of the se
  from ._conv import register_converters as _register_converters
Using TensorFlow backend.


Train on 2146 samples, validate on 475 samples
Epoch 1/10
2146/2146 [==============================] - 0s 142us/step - loss: 0.6819 - acc: 0.5615 - val_l

Epoch 00001: saving model to weights.01-0.64.hdf5
Epoch 2/10
2146/2146 [==============================] - 0s 40us/step - loss: 0.5461 - acc: 0.7829 - val_lo

Epoch 00002: saving model to weights.02-0.43.hdf5
Epoch 3/10
2146/2146 [==============================] - 0s 32us/step - loss: 0.3788 - acc: 0.8243 - val_lo

Epoch 00003: saving model to weights.03-0.39.hdf5
Epoch 4/10
2146/2146 [==============================] - 0s 40us/step - loss: 0.3627 - acc: 0.8239 - val_lo
```

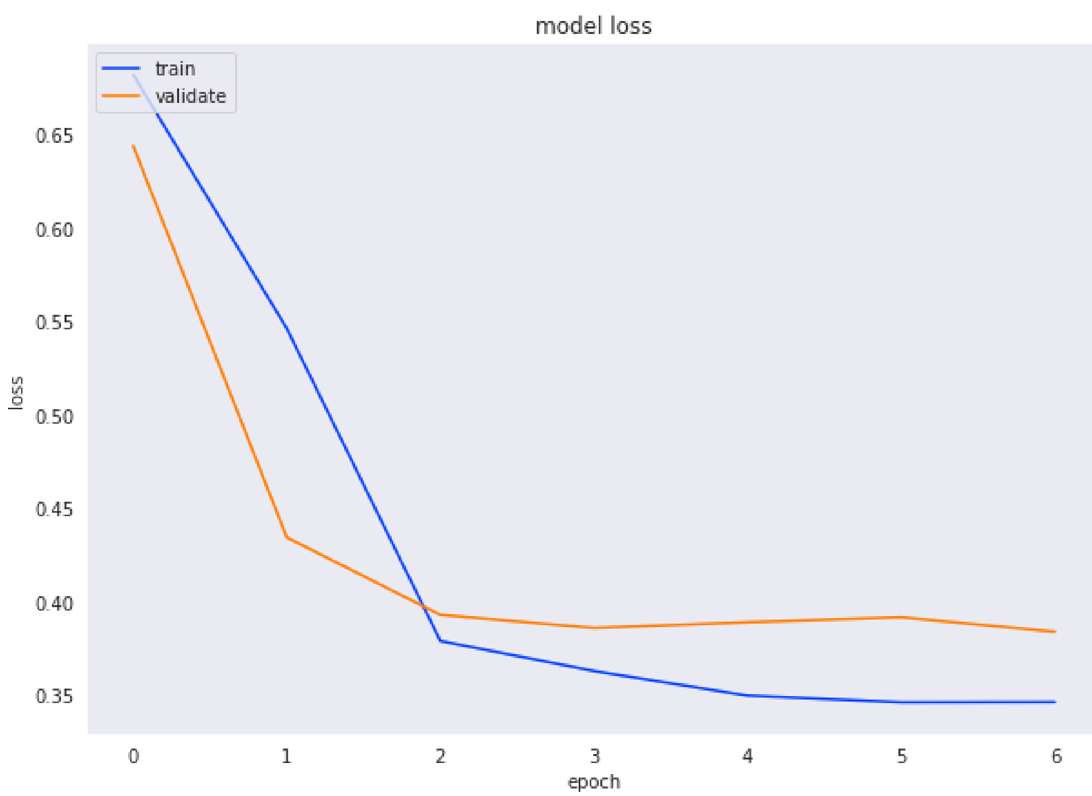
```
Epoch 00004: saving model to weights.04-0.39.hdf5
Epoch 5/10
2146/2146 [==============================] - 0s 40us/step - loss: 0.3495 - acc: 0.8313 - val_lo

Epoch 00005: saving model to weights.05-0.39.hdf5

Epoch 00005: ReduceLROnPlateau reducing learning rate to 0.0002500000118743628.
Epoch 6/10
2146/2146 [==============================] - 0s 53us/step - loss: 0.3460 - acc: 0.8360 - val_lo

Epoch 00006: saving model to weights.06-0.39.hdf5

Epoch 00006: ReduceLROnPlateau reducing learning rate to 6.25000029685907e-05.
Epoch 7/10
2146/2146 [==============================] - 0s 58us/step - loss: 0.3461 - acc: 0.8378 - val_lo

Epoch 00007: saving model to weights.07-0.38.hdf5
Epoch 00007: early stopping
<keras.callbacks.History object at 0x1c37782be0>
```

In [38]:
```
# model accuracy inprovement interval
score = model.evaluate(X_test, y_test, verbose=0)
score
```

Out[38]:
```
[0.38373624262056855, 0.8105263157894737]
```

In [39]:
```
# summarize history for accuracy
plt.figure(figsize=(10,7))
plt.plot(history.history['acc'])
plt.plot(history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'validate'], loc='upper left')
plt.show()

# summarize history for loss
plt.figure(figsize=(10,7))
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'validate'], loc='upper left')
plt.show()
```


model accuracy
train
validate
accuracy
epoch
0.85
0.80
0.75
0.70
0.65
0.60
0.55
0
1
2
3
4
5
6


model loss
train
validate
loss
epoch
0.65
0.60
0.55
0.50
0.45
0.40
0.35
0
1
2
3
4
5
6

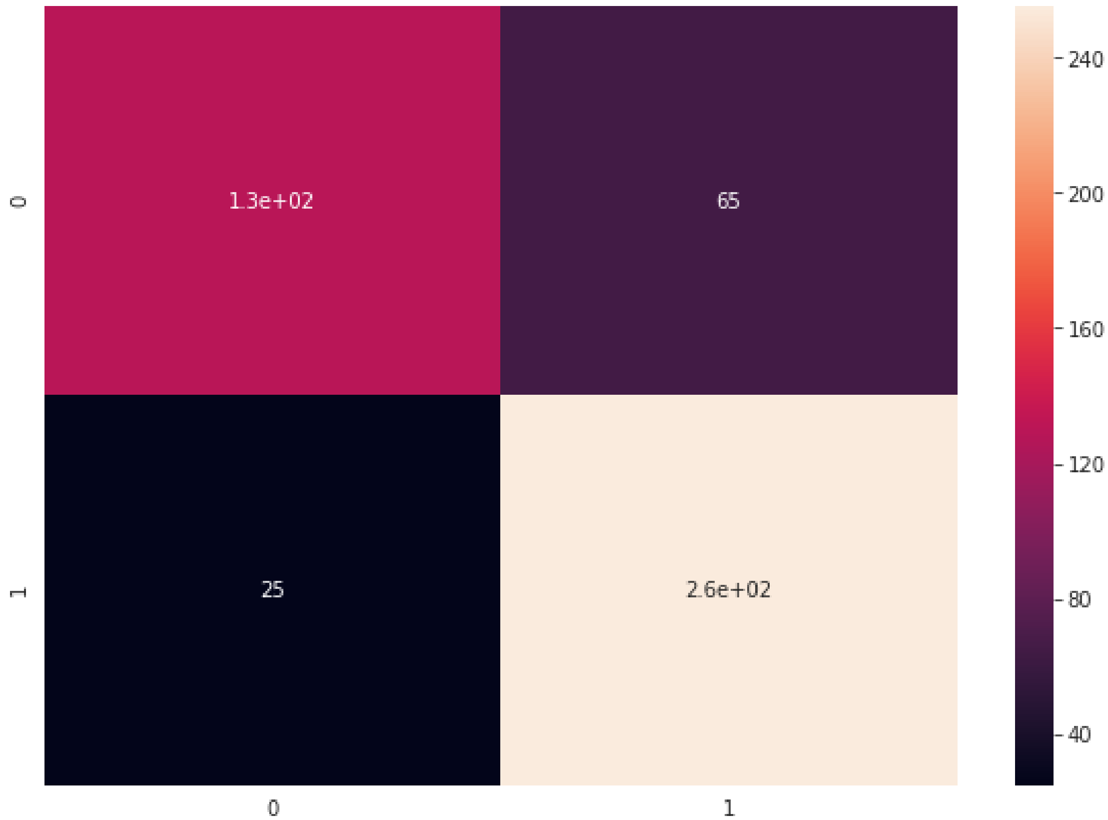
In [40]:
```
# Predicting the Test set results
y_pred = model.predict(X_test)
# conver the probability to actual prediction grade label
y_predict = [ np.argmax(a) for a in y_pred ]

y_test = np.asarray(y_test)
y_predict = np.asarray(y_predict)
```

In [41]:
```
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score, accuracy_score

print("precision = ", precision_score(y_test, y_predict, average='macro'))

print("recall = ", recall_score(y_test, y_predict, average='macro'))

print("f1_score = ", f1_score(y_test, y_predict, average='macro')  )

print("accuracy = ", accuracy_score(y_test, y_predict)  )
```

```
precision =  0.8177923387096775
recall =  0.7886904761904762
f1_score =  0.7964285714285714
accuracy =  0.8105263157894737
```

In [42]:
```
# heatmap visualization of the model performance
import seaborn as sn
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix

df_cm = pd.DataFrame(confusion_matrix(y_test, y_predict), index = [i for i in "01"],
                  columns = [i for i in "01"])
plt.figure(figsize = (10,7))
sn.heatmap(df_cm, annot=True)
```

Out[42]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1c397d2cc0>
```


1.3e+02
65
25
2.6e+02
0
1
0
1
240
200
160
120
80
40