In [1]:
```python
import numpy as np
import pandas as pd
import datetime as dt
import matplotlib.pyplot as plt
import seaborn as sns
import os
os.chdir('/Users/aarsh/Documents/Applied Machine Learning/ Sales Project/rossmann-store-sales')
```

In [2]:
```python
store=pd.read_csv('Store.csv',parse_dates=True)
train=pd.read_csv('train.csv',parse_dates=[2])
test=pd.read_csv('test.csv',parse_dates=[3])
```

```
/Applications/anaconda3/lib/python3.7/site-packages/IPython/core/interactiveshell.py:3063: DtypeWarning: Columns (7) have mixed types.Specify dtype option on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

In [3]:
```python
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1017209 entries, 0 to 1017208
Data columns (total 9 columns):
 #   Column         Non-Null Count    Dtype
---  ------         --------------    -----
 0   Store          1017209 non-null  int64
 1   DayOfWeek      1017209 non-null  int64
 2   Date           1017209 non-null  datetime64[ns]
 3   Sales          1017209 non-null  int64
 4   Customers      1017209 non-null  int64
 5   Open           1017209 non-null  int64
 6   Promo          1017209 non-null  int64
 7   StateHoliday   1017209 non-null  object
 8   SchoolHoliday  1017209 non-null  int64
dtypes: datetime64[ns](1), int64(7), object(1)
memory usage: 69.8+ MB
```

In [4]:
```python
store.isnull().any()
```

Out[4]:
```
Store                        False
StoreType                    False
Assortment                   False
CompetitionDistance           True
CompetitionOpenSinceMonth     True
CompetitionOpenSinceYear      True
Promo2                       False
Promo2SinceWeek               True
Promo2SinceYear               True
PromoInterval                 True
dtype: bool
```

In [5]:
```python
store.loc[store.CompetitionOpenSinceMonth.isnull(),"CompetitionOpenSinceMonth"]=store["CompetitionOpenSinceMonth"].mean()
store.loc[store.CompetitionOpenSinceYear.isnull(),"CompetitionOpenSinceYear"]=store["CompetitionOpenSinceYear"].mean()
store.fillna(0,inplace=True)
```

In [6]:
```python
train.isnull().any()
```

Out[6]:
```
Store            False
DayOfWeek        False
Date             False
Sales            False
Customers        False
Open             False
Promo            False
StateHoliday     False
SchoolHoliday    False
dtype: bool
```

In [7]:
```python
test.isnull().sum()
```

Out[7]:
```
Id                0
Store             0
DayOfWeek         0
Date              0
Open             11
Promo             0
StateHoliday      0
SchoolHoliday     0
dtype: int64
```

In [8]:
```python
test[test['Open'].isnull()]
```

Out[8]:

	Id	Store	DayOfWeek	Date	Open	Promo	StateHoliday	SchoolHoliday
479	480	622	4	2015-09-17	NaN	1	0	0
1335	1336	622	3	2015-09-16	NaN	1	0	0
2191	2192	622	2	2015-09-15	NaN	1	0	0
3047	3048	622	1	2015-09-14	NaN	1	0	0
4759	4760	622	6	2015-09-12	NaN	0	0	0
5615	5616	622	5	2015-09-11	NaN	0	0	0
6471	6472	622	4	2015-09-10	NaN	0	0	0
7327	7328	622	3	2015-09-09	NaN	0	0	0
8183	8184	622	2	2015-09-08	NaN	0	0	0
9039	9040	622	1	2015-09-07	NaN	0	0	0
10751	10752	622	6	2015-09-05	NaN	0	0	0

In [9]:
```python
test.fillna(1,inplace=True)
```

In [10]:
```python
np.sum([train["Sales"]==0])
```

Out[10]: 172871

In [11]:
```python
data=pd.merge(train,store,on='Store')
test_data=pd.merge(test,store,on='Store')
data=data[(data.Open!=0) & (data.Sales>0)]
test_data=test_data[test_data.Open==1]
```

In [12]:
```python
def data_processing(data):
    mappings = {'0':0, 'a':1, 'b':2, 'c':3, 'd':4}
    data.StoreType.replace(mappings, inplace=True)
    data.Assortment.replace(mappings, inplace=True)
    data.StateHoliday.replace(mappings, inplace=True)

    data['Month'] = data.Date.dt.month
    data['Year'] = data.Date.dt.year
    data['Day'] = data.Date.dt.day
    data['WeekOfYear'] = data.Date.dt.weekofyear


#competitor open time in months
    data['CompetitionOpen'] = 12 * (data.Year - data.CompetitionOpenSinceYear) + \
        (data.Month - data.CompetitionOpenSinceMonth)
    data['CompetitionOpen'] = data['CompetitionOpen'].apply(lambda x: x if x > 0 else 0)
#promo2 open time in months
    data['PromoOpen'] = 12 * (data.Year - data.Promo2SinceYear) + \
        (data.WeekOfYear - data.Promo2SinceWeek) / 4.0
    data['PromoOpen'] = data['PromoOpen'].apply(lambda x: x if x > 0 else 0)
 # Indicate whether the month is in promo interval
    month2str = {1:'Jan', 2:'Feb', 3:'Mar', 4:'Apr', 5:'May', 6:'Jun', \
             7:'Jul', 8:'Aug', 9:'Sept', 10:'Oct', 11:'Nov', 12:'Dec'}
    data['month_str'] = data.Month.map(month2str)

    def check(row):
        if isinstance(row['PromoInterval'],str) and row['month_str'] in row['PromoInterval']:
            return 1
        else:
            return 0

    data['IsPromoMonth'] =  data.apply(lambda row: check(row),axis=1)
    return data
data=data_processing(data)
test_data=data_processing(test_data)
```

In [13]:
```python
test_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 35104 entries, 0 to 41087
Data columns (total 25 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Id                         35104 non-null  int64
 1   Store                      35104 non-null  int64
 2   DayOfWeek                  35104 non-null  int64
 3   Date                       35104 non-null  datetime64[ns]
 4   Open                       35104 non-null  float64
 5   Promo                      35104 non-null  int64
 6   StateHoliday               35104 non-null  int64
 7   SchoolHoliday              35104 non-null  int64
 8   StoreType                  35104 non-null  int64
 9   Assortment                 35104 non-null  int64
 10  CompetitionDistance        35104 non-null  float64
 11  CompetitionOpenSinceMonth  35104 non-null  float64
 12  CompetitionOpenSinceYear   35104 non-null  float64
 13  Promo2                     35104 non-null  int64
 14  Promo2SinceWeek            35104 non-null  float64
 15  Promo2SinceYear            35104 non-null  float64
 16  PromoInterval              35104 non-null  object
 17  Month                      35104 non-null  int64
 18  Year                       35104 non-null  int64
 19  Day                        35104 non-null  int64
 20  WeekOfYear                 35104 non-null  int64
 21  CompetitionOpen            35104 non-null  float64
 22  PromoOpen                  35104 non-null  float64
 23  month_str                  35104 non-null  object
 24  IsPromoMonth               35104 non-null  int64
dtypes: datetime64[ns](1), float64(8), int64(14), object(2)
memory usage: 7.0+ MB
```

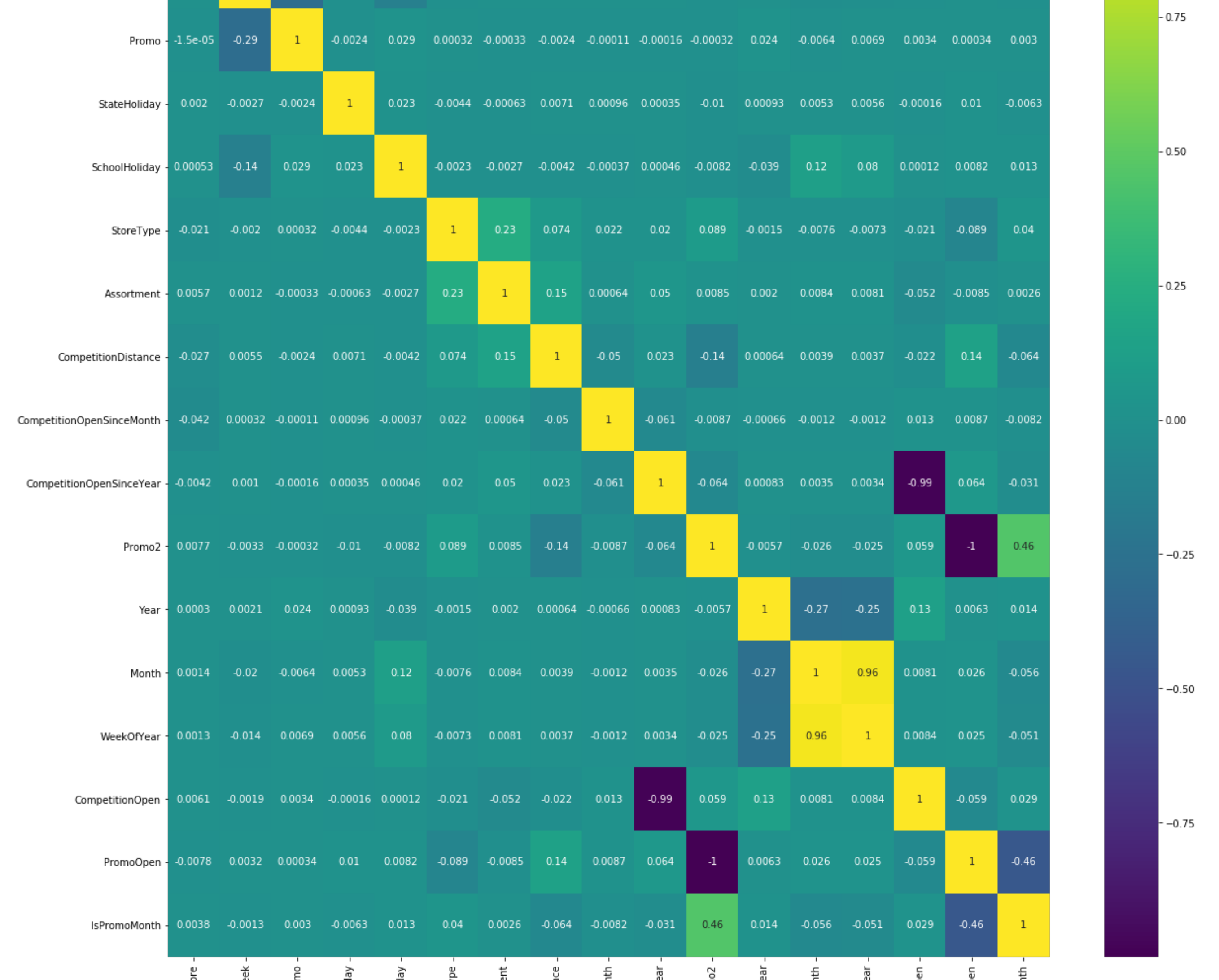
In [14]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 844338 entries, 0 to 1017207
Data columns (total 26 columns):
 #   Column                     Non-Null Count   Dtype
---  ------                     --------------   -----
 0   Store                      844338 non-null  int64
 1   DayOfWeek                  844338 non-null  int64
 2   Date                       844338 non-null  datetime64[ns]
 3   Sales                      844338 non-null  int64
 4   Customers                  844338 non-null  int64
 5   Open                       844338 non-null  int64
 6   Promo                      844338 non-null  int64
 7   StateHoliday               844338 non-null  int64
 8   SchoolHoliday              844338 non-null  int64
 9   StoreType                  844338 non-null  int64
 10  Assortment                 844338 non-null  int64
 11  CompetitionDistance        844338 non-null  float64
 12  CompetitionOpenSinceMonth  844338 non-null  float64
 13  CompetitionOpenSinceYear   844338 non-null  float64
 14  Promo2                     844338 non-null  int64
 15  Promo2SinceWeek            844338 non-null  float64
 16  Promo2SinceYear            844338 non-null  float64
 17  PromoInterval              844338 non-null  object
 18  Month                      844338 non-null  int64
 19  Year                       844338 non-null  int64
 20  Day                        844338 non-null  int64
 21  WeekOfYear                 844338 non-null  int64
 22  CompetitionOpen            844338 non-null  float64
 23  PromoOpen                  844338 non-null  float64
 24  month_str                  844338 non-null  object
 25  IsPromoMonth               844338 non-null  int64
dtypes: datetime64[ns](1), float64(7), int64(16), object(2)
memory usage: 173.9+ MB
```

In [ ]:
```python
features = ['Store', 'DayOfWeek', 'Promo', 'StateHoliday', 'SchoolHoliday',
       'StoreType', 'Assortment', 'CompetitionDistance',
       'CompetitionOpenSinceMonth', 'CompetitionOpenSinceYear', 'Promo2', 'Year', 'Month',
       'WeekOfYear', 'CompetitionOpen', 'PromoOpen','IsPromoMonth']
target='Sales'
```

Checking correlation between features

In [16]:
```python
k=20
cols=data[features].corr()
plt.figure(figsize=(20,20))
sns.heatmap(cols,annot=True,cmap='viridis')
plt.show()
```



Applying log transformation to the target variable

as it was right-skewed, the transformation normalizes the values so that the data distribution follows a bell curve. This helps our regression model to converge better.

In [17]:
```python
X=data[features]
y=np.log(data["Sales"]+1)

from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,y,random_state=0)

X_train.shape,X_test.shape,y_train.shape,y_test.shape
```

Out[17]: ((633253, 17), (211085, 17), (633253,), (211085,))

Defining Evaluation metrics

In [18]:
```python
def evaluation(model,X_test,y_test):
    from sklearn.metrics import mean_squared_error,r2_score as MSE,r2_score
    y_pred=model.predict(X_test)
    y_pred=np.exp(y_pred)-1
    y_test_c=np.exp(y_test)-1
    RMSE=MSE(y_test_c,y_pred)**1/2
    rmspe = (np.sqrt(np.mean(np.square((y_test_c - y_pred) / y_test_c)))) * 100
    r2_score=r2_score(y_test_c,y_pred)
    return (RMSE,r2_score,rmspe)
```

Creating a baseline model using Random Forest

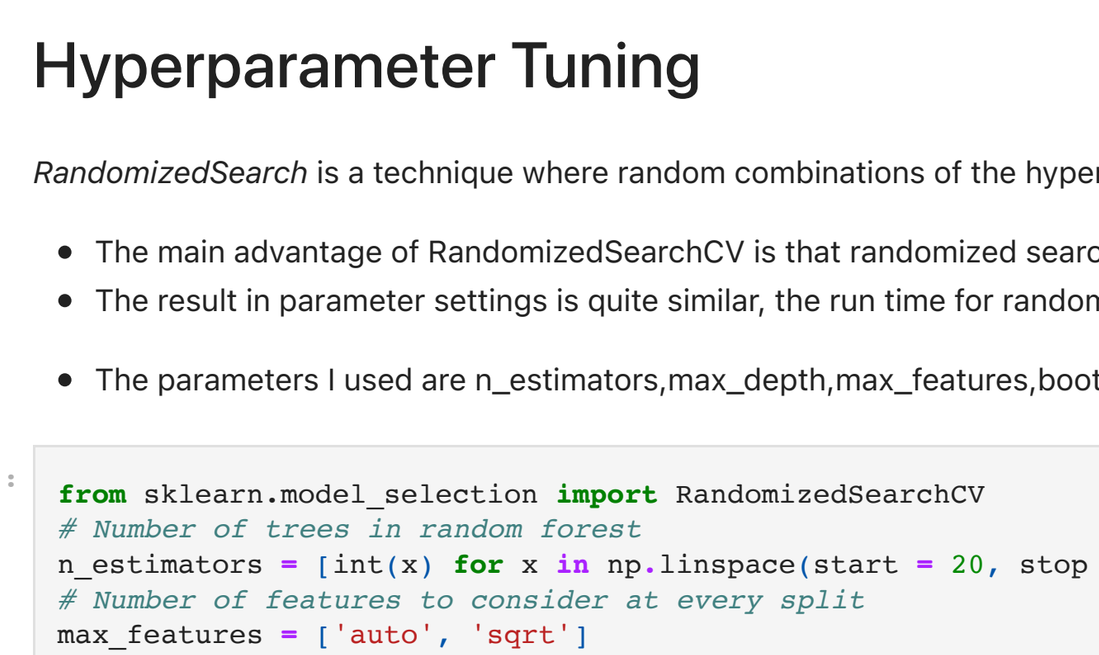
Random forests are bagged decision tree models that split on a subset of features on each split.One advantage which i had using this model was, not a lot of pre-processing had to be done , aslo the data didn't have to scaled/normalized.Random Forest works in the following way:-

Original Dataset -> Randomized Bootstrap Copies -> Randomized Feature splits -> Ensemble Prediction

In [33]:
```python
from sklearn.ensemble import RandomForestRegressor
rf=RandomForestRegressor(n_estimators=8)
rf.fit(X_train,y_train)
```

Out[33]:
```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=None, max_features='auto', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      n_estimators=8, n_jobs=None, oob_score=False,
                      random_state=None, verbose=0, warm_start=False)
```

In [40]:
```python
#plotting feature importances
feat_importance = pd.Series(rf.feature_importances_, index=X_train.columns)
feat_importance.nlargest(10).sort_values(ascending = True).plot(kind='barh')
plt.xlabel('importance')
plt.title('Feature Importance')
plt.show()
```



In [38]:
```python
print("Root-mean-square-error,R2-error,Root-Mean-Squared-Percentage-error",evaluation(rf,X_test,y_test))
```

```
Root-mean-square-error,R2-error,Root-Mean-Squared-Percentage-error (0.4407601351606292, 0.8815202703212583, 15.527182332307982)
```

Hyperparameter Tuning

RandomizedSearch is a technique where random combinations of the hyperparameters are used to find the best solution for the built model.

- The main advantage of RandomizedSearchCV is that randomized search and the grid search explore exactly the same space of parameters.
- The result in parameter settings is quite similar, the run time for randomized search is drastically lower.
- The parameters I used are n_estimators,max_depth,max_features,bootstrap and performed 3 fold cross validation.

In [22]:
```python
from sklearn.model_selection import RandomizedSearchCV
# Number of trees in random forest
n_estimators = [int(x) for x in np.linspace(start = 20, stop = 50, num = 10)]
# Number of features to consider at every split
max_features = ['auto', 'sqrt']
# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(5, 15, num = 7)]
max_depth.append(None)
# Method of selecting samples for training each tree
bootstrap = [True, False]
# Create the random grid
random_grid = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'bootstrap': bootstrap}
rf_random = RandomizedSearchCV(estimator = rf, param_distributions = random_grid, n_iter = 10,
                               cv = 3, verbose=2,random_state=0,return_train_score=True
                               ,n_jobs = -1)
# Fit the random search model
rf_random.fit(X_train, y_train)
best_random = rf_random.best_estimator_
print(rf_random.best_params_)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done  23 out of  30 | elapsed:  4.4min remaining:  1.4min
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed:  5.0min finished
{'n_estimators': 40, 'max_features': 'sqrt', 'max_depth': None, 'bootstrap': True}
```

In [39]:
```python
print("Root-mean-square-error,R2-error,Root-mean-squared-percentage-error",evaluation(best_random,X_test,y_test))
```

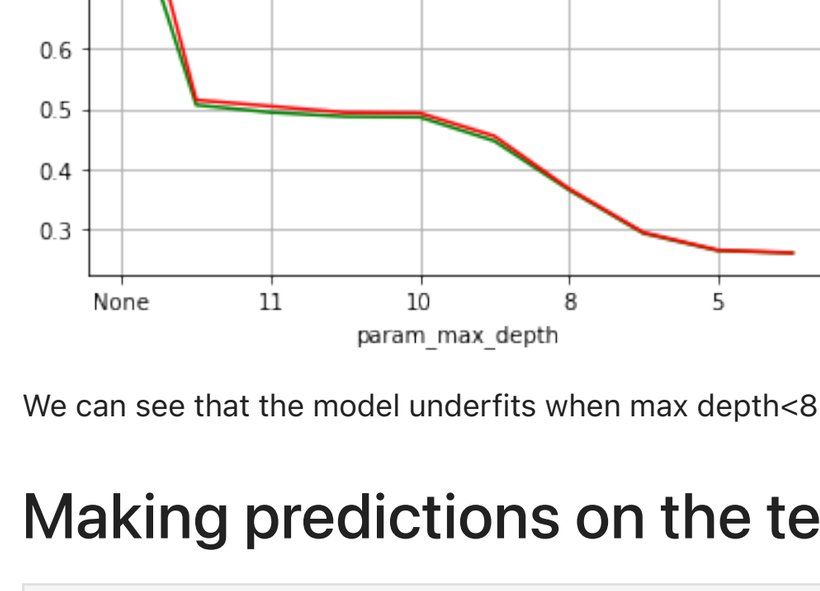
```
Root-mean-square-error,R2-error,Root-mean-squared-percentage-error (0.44346114260955793, 0.8869222852191159, 14.569761088899295)
```

In [24]:
```python
model_results = pd.DataFrame(rf_random.cv_results_).sort_values(by='mean_test_score' , ascending=False)
model_results
```

Out[24]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_n_estimators	param_max_features	param_max_depth	param_bootstrap	params	split0_test_score	split1_test_score	split2_test_score	mean_test_score	std_test_score	rank_
9	65.189207	0.219096	7.663637	0.090280	40	sqrt	None	True	{'n_estimators': 40, 'max_features': 'sqrt', '...	0.886999	0.888556	0.889229	0.888261	0.000934	
1	87.593739	0.081751	1.521246	0.014726	46	sqrt	11	False	{'n_estimators': 46, 'max_features': 'sqrt', '...	0.506412	0.504641	0.507487	0.506180	0.001174	
6	124.188464	0.094264	0.636102	0.006166	20	auto	11	False	{'n_estimators': 20, 'max_features': 'auto', '...	0.484806	0.493801	0.503095	0.493901	0.007467	
3	152.828889	0.207375	1.101602	0.018271	36	auto	10	True	{'n_estimators': 36, 'max_features': 'auto', '...	0.477132	0.492606	0.491102	0.486947	0.006967	
5	124.329907	0.248136	0.924791	0.049492	30	auto	10	True	{'n_estimators': 30, 'max_features': 'auto', '...	0.476632	0.491696	0.489918	0.486082	0.006722	
7	202.655150	0.104900	0.821921	0.017382	46	auto	10	False	{'n_estimators': 46, 'max_features': 'auto', '...	0.442153	0.443600	0.453883	0.446545	0.005222	
4	54.703350	0.190972	0.919870	0.025810	40	sqrt	8	False	{'n_estimators': 40, 'max_features': 'sqrt', '...	0.366693	0.362665	0.366876	0.365411	0.001943	
0	87.180902	0.066404	0.431281	0.012112	23	auto	6	False	{'n_estimators': 23, 'max_features': 'auto', '...	0.292885	0.295323	0.291683	0.293297	0.001515	
8	107.305092	0.231997	0.590265	0.047977	43	auto	5	False	{'n_estimators': 43, 'max_features': 'auto', '...	0.264765	0.263332	0.265736	0.264611	0.000987	
2	30.116592	0.047947	0.668517	0.008265	36	sqrt	5	True	{'n_estimators': 36, 'max_features': 'sqrt', '...	0.262657	0.258454	0.260751	0.260621	0.001718	

In [25]:
```python
model_results.set_index('param_max_depth')['mean_test_score'].plot(color='g',legend=True)
model_results.set_index('param_max_depth')['mean_train_score'].plot(color='r' , legend=True)
plt.grid(True)
plt.show()
```



We can see that the model underfits when max depth<8 and overfits when max depth>9, so we can set max depth=9.Also their is a change in percentage error.

Making predictions on the test data

In [26]:
```python
test_pred=best_random.predict(test_data[X_train.columns])
test_pred=np.exp(test_pred)-1
```

In [27]:
```python
test_pred
```

Out[27]:
```
array([ 4700.58301722,  4956.67684774,  4982.81408842, ...,
        7508.80512666, 10269.6437656 ,  7490.87280748])
```

In [32]:
```python
submission = pd.DataFrame({'Id' : test_data['Id'] , 'Sales' : test_pred})
submission['Sales'] = submission['Sales'].astype(int)
submission['Id']= submission.index
submission['Id'] = submission['Id']+1
submission.head()
```

Out[32]:

	Id	Sales
0	1	4700
1	2	4956
2	3	4982
3	4	5867
5	6	4221

In [37]:
```python
submission.to_csv('/Users/aarsh/Documents/Applied Machine Learning/ Sales Project/Submission.csv',index=False)
```

In [ ]: