Forecasting Retail Sales of 45 Stores Using Time Series Model

Table of Contents

In [3]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

1. Introduction

Revenue plays an important role in retail companies. Currently, with the high growth rate of online sales, forecasting sales becomes a key issue for retail companies, which allows them to properly make short term planning such as managing commodity classification, controlling stock quantity and so on.

This paper builds AR(p) model with linear regression to quantify influence of temperature, holiday and other indicators on sales, and predict weekly sales. First, we build a general model using average sales data for all stores. Based on that, we then select the best performing store and build a new forecast model for it.

By establishing models, we are able to give some suggestions for the company to predict sales and make short term plans such as managing commodity classification, controlling stock quantity and so on.

2. Data

1. Data source

Data Source: Features data set.csv; sales data-set.csv; stores data-set.csv

[https://www.kaggle.com/manjeetsingh/retaildataset (https://www.kaggle.com/manjeetsingh/retaildataset)](https://www.kaggle.com/manjeetsingh/retaildataset)

2. Data description

The dataset provides us with historical sales data for 45 stores attached to one company and located in different regions - each store contains a number of departments.

During some special holidays such as Thanksgiving, Black Friday and Christmas Day, the company's sales in that week would increase dramatically, so we introduce IsHoliday dummy variable to explain the holiday effects.

The company also runs several promotional markdown events throughout the year. These markdowns precede prominent holidays, the four largest of which are the Super Bowl, Labor Day, Thanksgiving, and Christmas.

There are three csv documents, Stores, Features and Sales. **Stores** contains anonymized information about the 45 stores, indicating the type and size of store; **Features** contains additional data related to the store, department, and regional activity for the given dates; **Sales** includes historical weekly sales data, which covers to 2010-02-05 to 2012-11-01.

Our objects are as follows:

1. Help company distinguish the best performing types of stores in terms of sales, which allows them to adjust their plans accordingly.
2. Model the effects of markdowns, temperature and other indicators on weekly sales
3. Build forecast models for stores, based on which they are able to predict sales in the future.

In [4]:

```
features=pd.read_csv('Features data set.csv')
sales=pd.read_csv('sales data-set.csv')
stores=pd.read_csv('stores data-set.csv')
```

In [5]:

```
features
```

Out[5]:

	Store	Date	Temperature	Fuel_Price	MarkDown1	MarkDown2	MarkDown3	MarkDow
0	1	2/5/10	42.31	2.572	NaN	NaN	NaN	Na
1	1	2/12/10	38.51	2.548	NaN	NaN	NaN	Na
2	1	2/19/10	39.93	2.514	NaN	NaN	NaN	Na
3	1	2/26/10	46.63	2.561	NaN	NaN	NaN	Na
4	1	3/5/10	46.50	2.625	NaN	NaN	NaN	Na
...	...	...	...	...	...	...	...	
8185	45	6/28/13	76.05	3.639	4842.29	975.03	3.00	2449.
8186	45	7/5/13	77.50	3.614	9090.48	2268.58	582.74	5797.
8187	45	7/12/13	79.37	3.614	3789.94	1827.31	85.72	744.
8188	45	7/19/13	82.84	3.737	2961.49	1047.07	204.19	363.
8189	45	7/26/13	76.06	3.804	212.02	851.73	2.06	10.

8190 rows × 12 columns

In [6]:

```
sales
```

Out[6]:

	Store	Dept	Date	Weekly_Sales	IsHoliday
0	1	1	02/05/2010	24924.50	False
1	1	1	02/12/2010	46039.49	True
2	1	1	02/19/2010	41595.55	False
3	1	1	02/26/2010	19403.54	False
4	1	1	03/05/2010	21827.90	False
...	...	...	...	...	...
421565	45	98	09/28/2012	508.37	False
421566	45	98	10/05/2012	628.10	False
421567	45	98	10/12/2012	1061.02	False
421568	45	98	10/19/2012	760.01	False
421569	45	98	10/26/2012	1076.80	False

421570 rows × 5 columns

In [7]:

```
stores
```

Out[7]:

	Store	Type	Size
0	1	A	151315
1	2	A	202307
2	3	B	37392
3	4	A	205863
4	5	B	34875
5	6	A	202505
6	7	B	70713
7	8	A	155078
8	9	B	125833
9	10	B	126512
10	11	A	207499
11	12	B	112238
12	13	A	219622
13	14	A	200898
14	15	B	123737
15	16	B	57197
16	17	B	93188
17	18	B	120653
18	19	A	203819
19	20	A	203742
20	21	B	140167
21	22	B	119557
22	23	B	114533
23	24	A	203819
24	25	B	128107
25	26	A	152513
26	27	A	204184
27	28	A	206302
28	29	B	93638
29	30	C	42988
30	31	A	203750
31	32	A	203007
32	33	A	39690
33	34	A	158114
34	35	B	103681

	Store	Type	Size
35	36	A	39910
36	37	C	39910
37	38	C	39690
38	39	A	184109
39	40	A	155083
40	41	A	196321
41	42	C	39690
42	43	C	41062
43	44	C	39910
44	45	B	118221

3. Key Variable Definitions

MarkDown1-5: Anonymized data related to promotional markdowns. MarkDown data is only available after Nov 2011, and is not available for all stores all the time. Any missing value is marked with an NA.

IsHoliday: Dummy variable, whether the week is a special holiday week.

Store: The store number

Dept: The department number

4. Data Analysis

In [8]:

```
features['Date'] = pd.to_datetime(features['Date'])
sales['Date'] = pd.to_datetime(sales['Date'])
features
```

Out[8]:

	Store	Date	Temperature	Fuel_Price	MarkDown1	MarkDown2	MarkDown3	MarkDown4
0	1	2010-02-05	42.31	2.572	NaN	NaN	NaN	NaN
1	1	2010-02-12	38.51	2.548	NaN	NaN	NaN	NaN
2	1	2010-02-19	39.93	2.514	NaN	NaN	NaN	NaN
3	1	2010-02-26	46.63	2.561	NaN	NaN	NaN	NaN
4	1	2010-03-05	46.50	2.625	NaN	NaN	NaN	NaN
...	...	...	...	...	...	...	...	..
8185	45	2013-06-28	76.05	3.639	4842.29	975.03	3.00	2449.97
8186	45	2013-07-05	77.50	3.614	9090.48	2268.58	582.74	5797.47
8187	45	2013-07-12	79.37	3.614	3789.94	1827.31	85.72	744.84
8188	45	2013-07-19	82.84	3.737	2961.49	1047.07	204.19	363.00
8189	45	2013-07-26	76.06	3.804	212.02	851.73	2.06	10.88

8190 rows × 12 columns

Merge three tabs in a unique DataFrame.

In [9]:

```
df=pd.merge(sales,features, on=['Store','Date', 'IsHoliday'], how='left')
df=pd.merge(df,stores, on=['Store'], how='left')
df
```

Out[9]:

	Store	Dept	Date	Weekly_Sales	IsHoliday	Temperature	Fuel_Price	MarkDown1	MarkDown2	MarkD
0	1	1	2010-02-05	24924.50	False	42.31	2.572	NaN	NaN	
1	1	1	2010-02-12	46039.49	True	38.51	2.548	NaN	NaN	
2	1	1	2010-02-19	41595.55	False	39.93	2.514	NaN	NaN	
3	1	1	2010-02-26	19403.54	False	46.63	2.561	NaN	NaN	
4	1	1	2010-03-05	21827.90	False	46.50	2.625	NaN	NaN	
...	...	...	...	...	...	...	...	...	...	
421565	45	98	2012-09-28	508.37	False	64.88	3.997	4556.61	20.64	

Replace NaN with 0.

In [10]:

```
df.isna().sum()
```

Out[10]:

```
Store                0
Dept                 0
Date                 0
Weekly_Sales         0
IsHoliday            0
Temperature          0
Fuel_Price           0
MarkDown1       270889
MarkDown2       310322
MarkDown3       284479
MarkDown4       286603
MarkDown5       270138
CPI                  0
Unemployment         0
Type                 0
Size                 0
dtype: int64
```

There are a lot of missing values for MarkDown 1-5. Because markdown data is almost only available after Nov 2011 for each store.

In [11]:

```
df=df.fillna(0)
```

Transfer '*type*' value from letters A, B, C to numbers 0, 1, 2 respectively

Transfer '*IsHoliday*' value from True, False to numbers 1, 0 respectively

In [12]:

```
# transfer 'type' and  'IsHoliday' to a series of numbers
types_encoded, types =df['Type'].factorize()
df['Type'] = types_encoded

types_encoded, IsHoliday =df['IsHoliday'].factorize()
df['IsHoliday'] = types_encoded

df.head()
```

Out[12]:

	Store	Dept	Date	Weekly_Sales	IsHoliday	Temperature	Fuel_Price	MarkDown1	MarkDow
0	1	1	2010-02-05	24924.50	0	42.31	2.572	0.0	(
1	1	1	2010-02-12	46039.49	1	38.51	2.548	0.0	(
2	1	1	2010-02-19	41595.55	0	39.93	2.514	0.0	(
3	1	1	2010-02-26	19403.54	0	46.63	2.561	0.0	(
4	1	1	2010-03-05	21827.90	0	46.50	2.625	0.0	(

Check if the DataFrame has duplicated rows.

In [13]:

```
print('Duplicated Data:{}'.format(df.duplicated().sum()))
```

```
Duplicated Data:0
```

The result shows that there is no duplicated data.

Data description

In [14]:

```
df.describe()
```

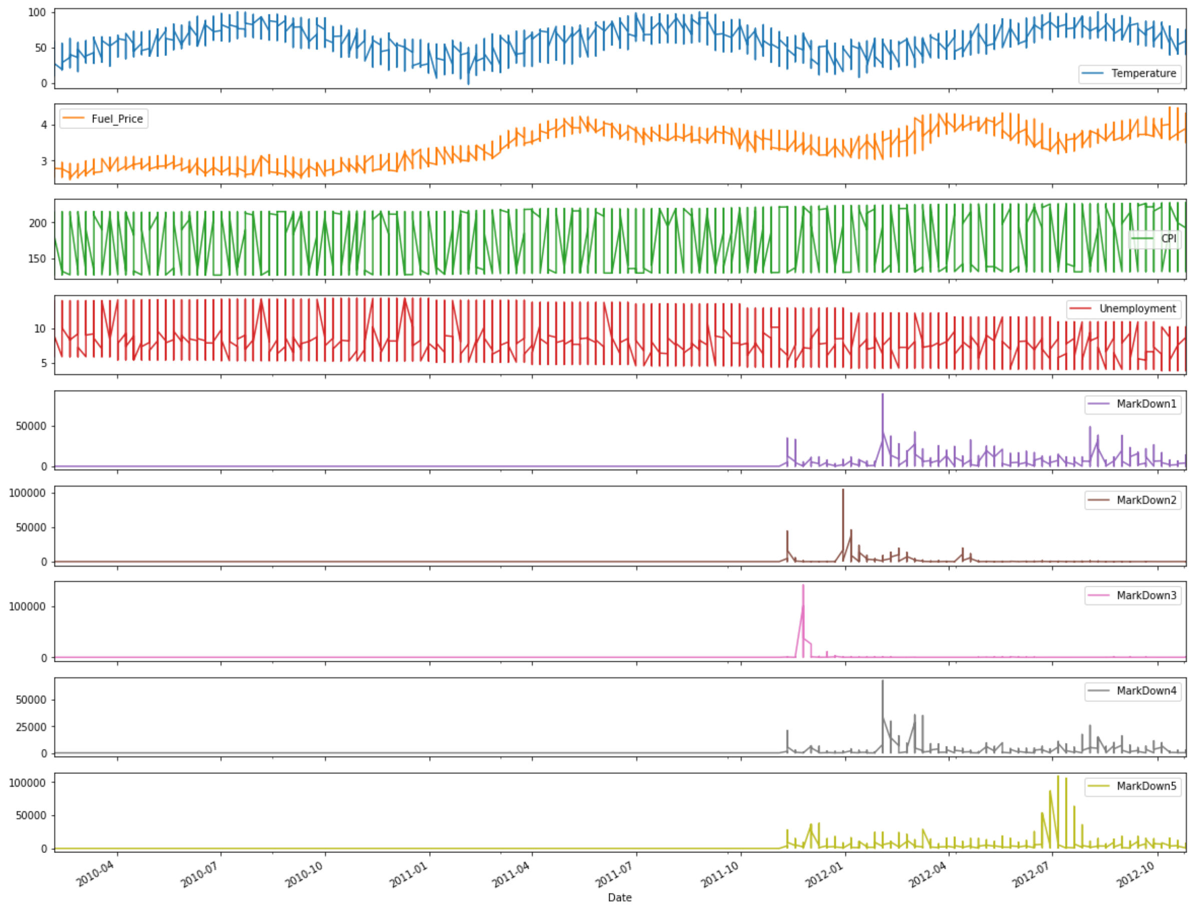
Out[14]:

	Store	Dept	Weekly_Sales	IsHoliday	Temperature	Fuel_Pri
count	421570.000000	421570.000000	421570.000000	421570.000000	421570.000000	421570.0000
mean	22.200546	44.260317	15981.258123	0.070358	60.090059	3.3610
std	12.785297	30.492054	22711.183519	0.255750	18.447931	0.4585
min	1.000000	1.000000	-4988.940000	0.000000	-2.060000	2.4720
25%	11.000000	18.000000	2079.650000	0.000000	46.680000	2.9330
50%	22.000000	37.000000	7612.030000	0.000000	62.090000	3.4520
75%	33.000000	74.000000	20205.852500	0.000000	74.280000	3.7380
max	45.000000	99.000000	693099.360000	1.000000	100.140000	4.4680

5. Data Visualization

In [15]:

```
df[['Date', 'Temperature', 'Fuel_Price', 'CPI', 'Unemployment',
    'MarkDown1', 'MarkDown2', 'MarkDown3', 'MarkDown4', 'MarkDown5']].plot(x='Date',
plt.show()
```



Here we average 45 stores' sale and rank mean weekly sales by date.

In [16]:

```
df_average_sales_week = df.groupby(by=['Date'], as_index=False)['Weekly_Sales'].mea
df_average_sales = df_average_sales_week.sort_values('Weekly_Sales', ascending=False
df_average_sales
```

Out[16]:

	Date	Weekly_Sales
46	2010-12-24	27378.692693
98	2011-12-23	25437.146122
42	2010-11-26	22403.336705
94	2011-11-25	22043.563476
45	2010-12-17	20892.463619
...	...	...
50	2011-01-21	13932.367385
49	2011-01-14	13891.283484
47	2010-12-31	13738.538566
51	2011-01-28	13566.239462
103	2012-01-27	13494.232612

143 rows × 2 columns

In [17]:

```
tsish = df.groupby(by=['Date'], as_index=False)['IsHoliday'].mean()
tsish
```

Out[17]:

	Date	IsHoliday
0	2010-02-05	0
1	2010-02-12	1
2	2010-02-19	0
3	2010-02-26	0
4	2010-03-05	0
...	...	...
138	2012-09-28	0
139	2012-10-05	0
140	2012-10-12	0
141	2012-10-19	0
142	2012-10-26	0

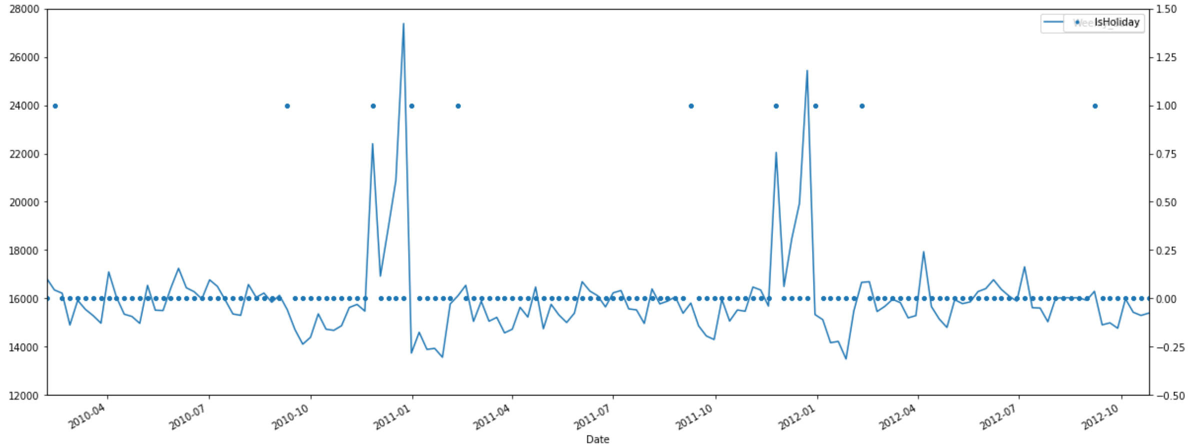
143 rows × 2 columns

In [18]:

```
fig,ax1=plt.subplots(figsize=(20,8))
ax2=ax1.twinx()
df_average_sales.plot(x='Date',ax=ax1,ylim=(12000,28000))
df.plot('Date','IsHoliday',ax=ax2,ylim=(-0.5,1.5),style='.')
```

Out[18]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x11ff4d6d0>
```



By comparing holidays time with the high sales periods, we are able to assume that these spikes of sales are probably due to the those big special festivals.

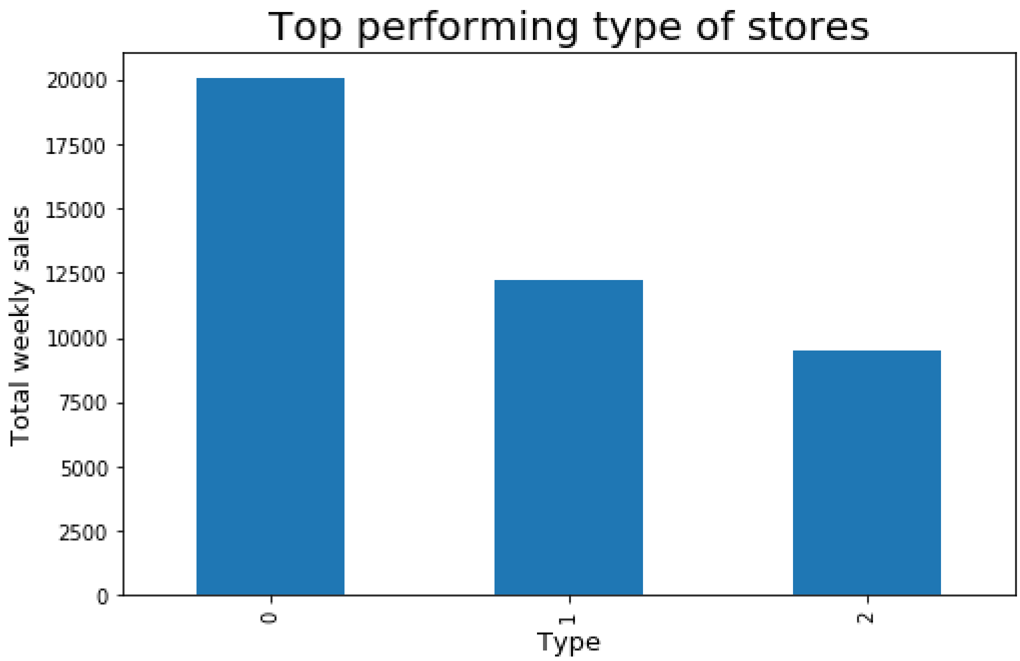
Top performing type of stores in term of sales

In [19]:

```
df_top_stores = df.groupby(by=['Type'], as_index=False)['Weekly_Sales'].mean().sort_
fig,ax = plt.subplots()
df_top_stores['Weekly_Sales'].plot.bar(figsize=(8,5))
ax.set_title('Top performing type of stores',size=20)
ax.set_xlabel('Type',size=13)
ax.set_ylabel('Total weekly sales',size=13)
```

Out[19]:

```
Text(0, 0.5, 'Total weekly sales')
```



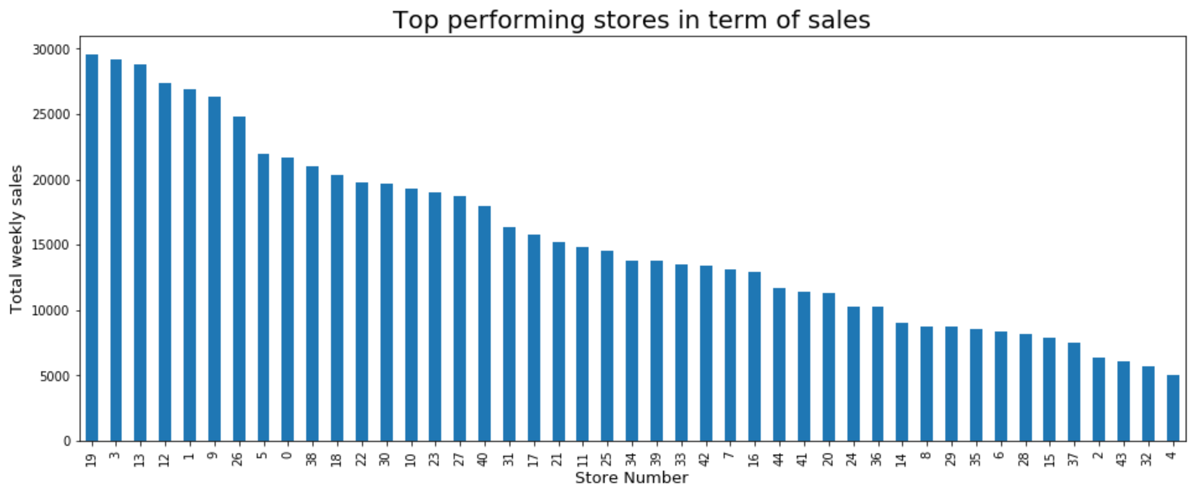
Top performing stores in term of sales

In [20]:

```
df_top_stores = df.groupby(by=['Store'], as_index=False)['Weekly_Sales'].mean().sort
fig,ax = plt.subplots()
df_top_stores['Weekly_Sales'].plot.bar(figsize=(16,6))
ax.set_title('Top performing stores in term of sales',size=20)
ax.set_xlabel('Store Number',size=13)
ax.set_ylabel('Total weekly sales',size=13)
```

Out[20]:

```
Text(0, 0.5, 'Total weekly sales')
```



From plot, we are able to see that the top 3 performing stores are No.19, No.3 and No.13

3. Forecast Model

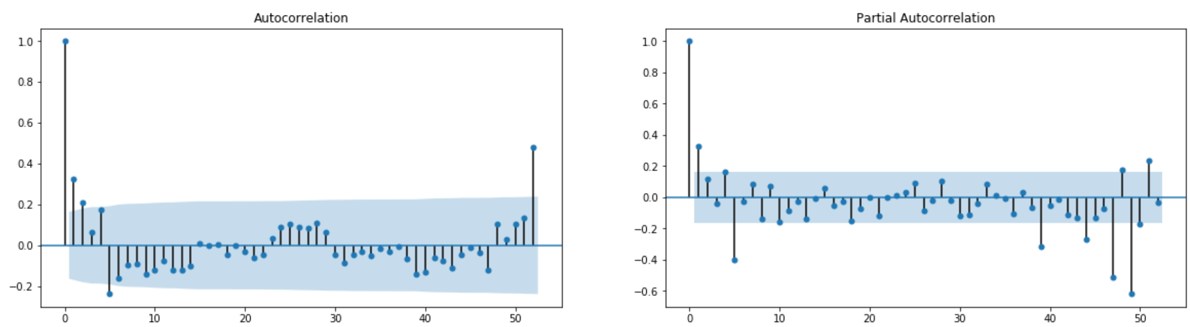
1. General forecast model for all stores

In [21]:

```
ts = df_average_sales_week.set_index('Date')
```

In [22]:

```
from statsmodels.graphics.tsaplots import acf, pacf, plot_acf, plot_pacf

fig, axes = plt.subplots(1,2,figsize=(20,5))
plot_acf(ts, lags=52, ax=axes[0])
plot_pacf(ts, lags=52, ax=axes[1])
plt.show()
```



To forecast the mean sales of stores with AR model, we analyze the correlation between current week and lagged weeks by PACF. Therefore, we our model contains lagged variables 1, 5, 39, 44, 47, 49 and 51 weeks, which are out of the confidence interval.

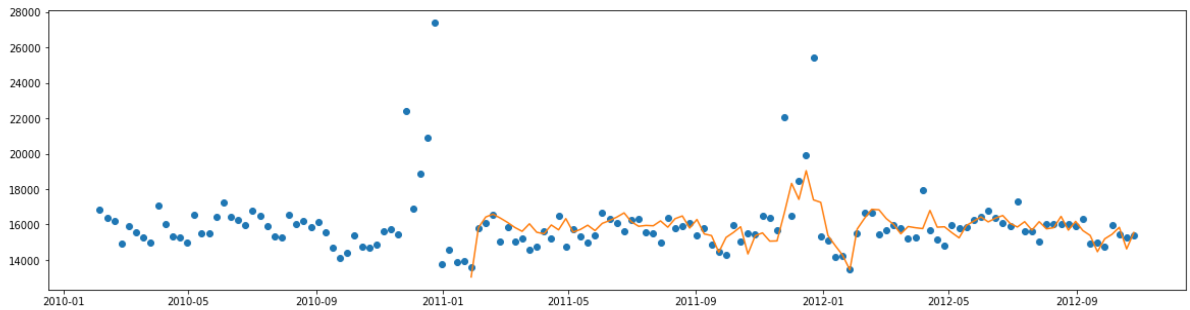
In [23]:

```
from sklearn.linear_model import LinearRegression

def fit_ar_model(ts, orders):

    X=np.array([ ts.values[(i-orders)].squeeze() if i >= np.max(orders) else np.arra

    mask = ~np.isnan(X[:,:1]).squeeze()

    Y= ts.values

    lin_reg=LinearRegression()

    lin_reg.fit(X[mask],Y[mask])

    print(lin_reg.coef_, lin_reg.intercept_)

    print('Score factor: %.2f' % lin_reg.score(X[mask],Y[mask]))

    return lin_reg.coef_, lin_reg.intercept_
def predict_ar_model(ts, orders, coef, intercept):
    return np.array([np.sum(np.dot(coef, ts.values[(i-orders)].squeeze())) + interce
```

In [24]:

```
orders=np.array([1,5,39,44,47,49,51])
coef, intercept = fit_ar_model(ts,orders)
pred=pd.DataFrame(index=ts.index, data=predict_ar_model(ts, orders, coef, intercept)
plt.figure(figsize=(20,5))
plt.plot(ts, 'o')
plt.plot(pred)
plt.show()
```

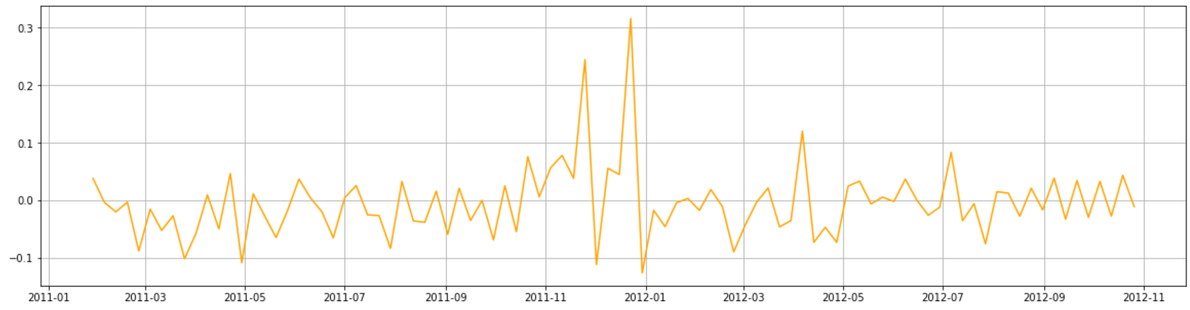
```
[[ 0.28047243 -0.23258453 -0.10810286 -0.07217166 -0.19948972 -0.03426
537
   0.17240587]] [19031.76542506]
Score factor: 0.30
```



In [25]:

```
diff=(ts['Weekly_Sales']-pred[0])/ts['Weekly_Sales']

print('AR Residuals: avg %.2f, std %.2f' % (diff.mean(), diff.std()))

plt.figure(figsize=(20,5))
plt.plot(diff, c='orange')
plt.grid()
plt.show()
```

```
AR Residuals: avg -0.00, std 0.06
```



Adding variable 'IsHoliday' to the AR model for a better prediction as it may relate the sales volumn.

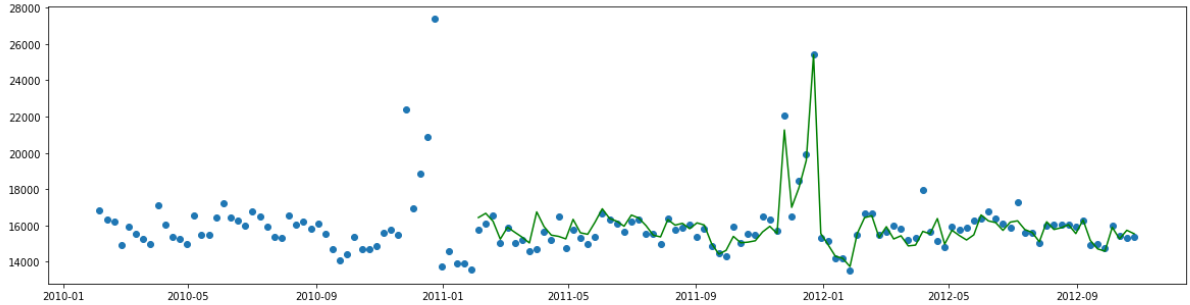
In [26]:

```
def fit_ar_model_ish(ts, orders,ish):

    X=np.array([ ts.values[(i-orders)].squeeze() if i >= np.max(orders) else np.arra

    X = np.append(X, ish.values, axis=1)

    mask = ~np.isnan(X[:,:1]).squeeze()

    Y= ts.values

    lin_reg=LinearRegression()

    lin_reg.fit(X[mask],Y[mask])

    print(lin_reg.coef_, lin_reg.intercept_)

    print('Score factor: %.2f' % lin_reg.score(X[mask],Y[mask]))

    return lin_reg.coef_, lin_reg.intercept_
def predict_ar_model_ish(ts, orders, ish, coef, intercept):

    X=np.array([ ts.values[(i-orders)].squeeze() if i >= np.max(orders) else np.arra

    X = np.append(X, ish.values, axis=1)

    return np.array( np.dot(X, coef.T) + intercept)
```

In [27]:

```
tsishe=tsish[['IsHoliday']]

orders=np.array([1, 5, 39, 44, 47, 49, 51, 52])
coef, intercept = fit_ar_model_ish(ts,orders,tsishe)
pred_ish=pd.DataFrame(index=ts.index, data=predict_ar_model_ish(ts, orders, tsishe,
plt.figure(figsize=(20,5))
plt.plot(ts, 'o')
plt.plot(pred_ish, c='green')
plt.show()
```

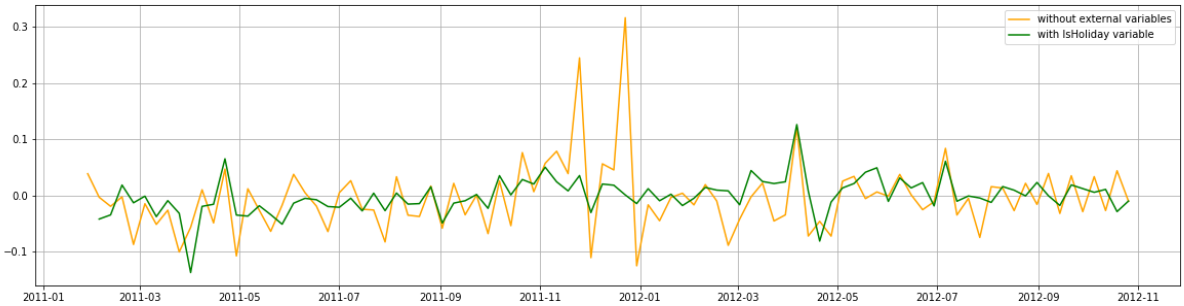
```
[[ 9.92746750e-02 -1.68669121e-02 -2.32465589e-03  2.47444589e-03
   2.16226339e-02 -1.48915731e-02 -4.16309545e-02  7.86631585e-01
   4.24685509e+02]] [2642.14666327]
Score factor: 0.88
```



In [28]:

```
diff=(ts['Weekly_Sales']-pred[0])/ts['Weekly_Sales']
diff_ish=(ts['Weekly_Sales']-pred_ish[0])/ts['Weekly_Sales']
print('AR Residuals: avg %.2f, std %.2f' % (diff.mean(), diff.std()))
print('AR wiht IsHoliday Residuals: avg %.2f, std %.2f' % (diff_ish.mean(), diff_ish

plt.figure(figsize=(20,5))
plt.plot(diff, c='orange', label='without external variables')
plt.plot(diff_ish, c='green', label='with IsHoliday variable')
plt.legend()
plt.grid()
plt.show()
```

```
AR Residuals: avg -0.00, std 0.06
AR wiht IsHoliday Residuals: avg -0.00, std 0.03
```



The coefficents of the dummy variable IsHoliday in the 2nd AR model is 4.247e^02, showing that stores tend to have a great higher sales volumn in holiday weeks. However, the coefficients of the lagged variables sharply drop in this model, indicating that 'IsHoliday' has larger influence on average and total sales volumn than sales history of the stores.

Moreover, by comparing the goodness-of-fitness between models w/ and w/o 'IsHoliday', we can see that IsHoiday greatly improves the degree of fitting and IsHoliday is significantly positively correlated to the value of sales of the stores.

2. Specific forecast model for the top store

From the calculation of top saling stores above, we know that the store with highest sales is No.19.

In [29]:

```
df19 = df.loc[df['Store']==19,:]
df19
```

Out[29]:

	Store	Dept	Date	Weekly_Sales	IsHoliday	Temperature	Fuel_Price	MarkDown1	MarkDown2	MarkD
177187	19	1	2010-02-05	21500.58	0	20.96	2.954	0.00	0.00	
177188	19	1	2010-02-12	40188.68	1	23.22	2.940	0.00	0.00	
177189	19	1	2010-02-19	32365.74	0	28.57	2.909	0.00	0.00	
177190	19	1	2010-02-26	15770.97	0	30.33	2.910	0.00	0.00	
177191	19	1	2010-03-05	18293.70	0	32.92	2.919	0.00	0.00	
...	...	...	...	...	...	...	...	...	...	
187330	19	99	2012-09-07	0.06	1	72.20	4.076	9053.47	27.41	

In [30]:

```
df19 = df19.groupby('Date',as_index=True).agg({'Weekly_Sales':'mean'})
df19
```

Out[30]:

Date	Weekly_Sales
2010-02-05	20939.405139
2010-02-12	21340.971528
2010-02-19	20213.014800
2010-02-26	19618.143714
2010-03-05	21068.233380
...	...
2012-09-28	19118.557429
2012-10-05	19555.779167
2012-10-12	19053.654930
2012-10-19	18872.890714
2012-10-26	18362.749444

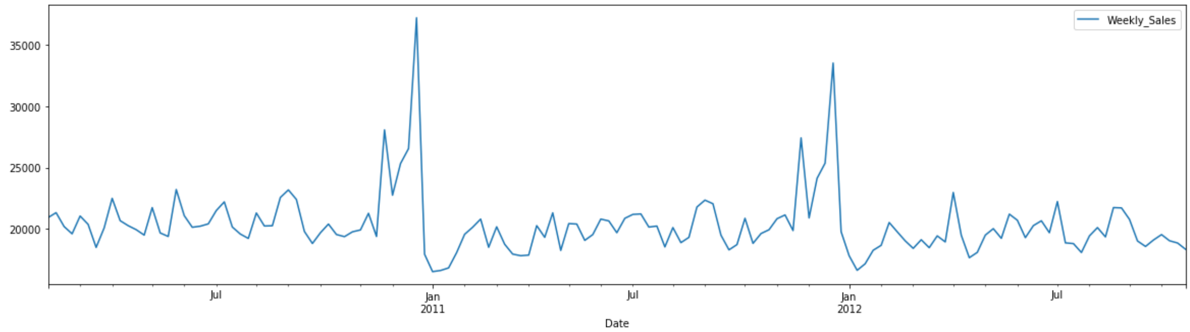
143 rows × 1 columns

In [31]:

```
df19.plot(figsize=(20,5))
```

Out[31]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x11f5f2850>
```

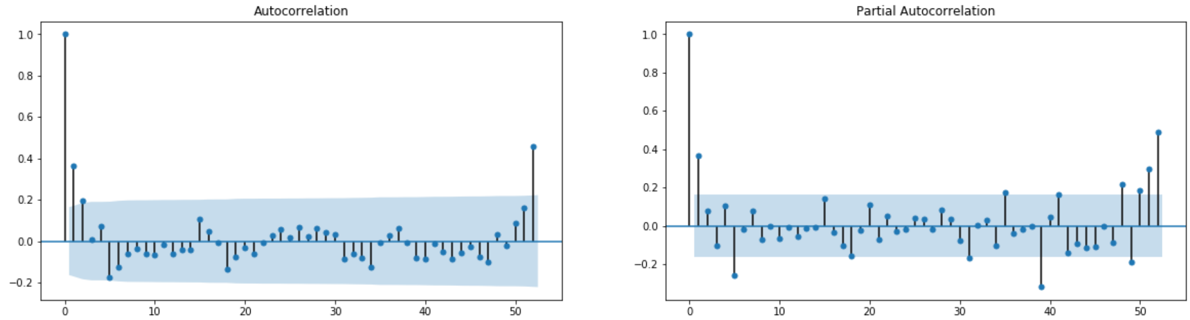


In [32]:

```
from statsmodels.graphics.tsaplots import acf, pacf, plot_acf, plot_pacf
```

In [33]:

```
fig, axes = plt.subplots(1,2, figsize=(20,5))
plot_acf(df19.values, lags=52, alpha=0.05, ax=axes[0])
plot_pacf(df19.values, lags=52, alpha=0.05, ax=axes[1])
plt.show()
```

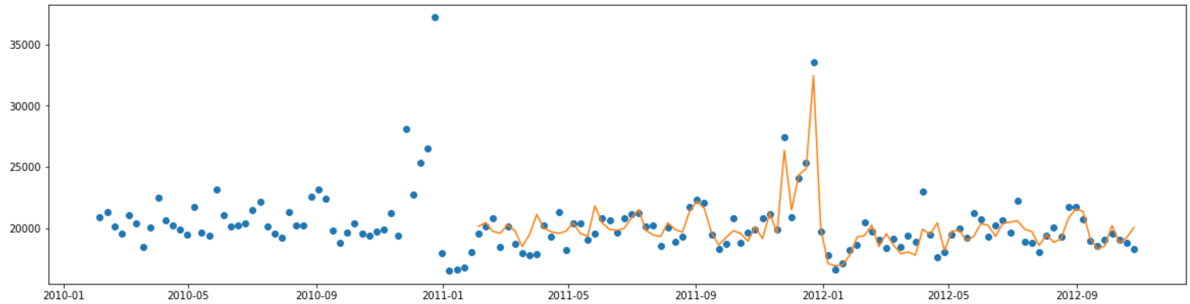


This particular store shows additional seasonalities from week 48, 50 and 52, which will be included in the AR model.

In [34]:

```
orders=np.array([1, 5, 39, 48, 49, 50, 51, 52])
coef, intercept = fit_ar_model(df19,orders)
pred=pd.DataFrame(index=df19.index,
                  data=predict_ar_model(df19, orders, coef, intercept))
plt.figure(figsize=(20,5))
plt.plot(df19, 'o')
plt.plot(pred)
plt.show()
```

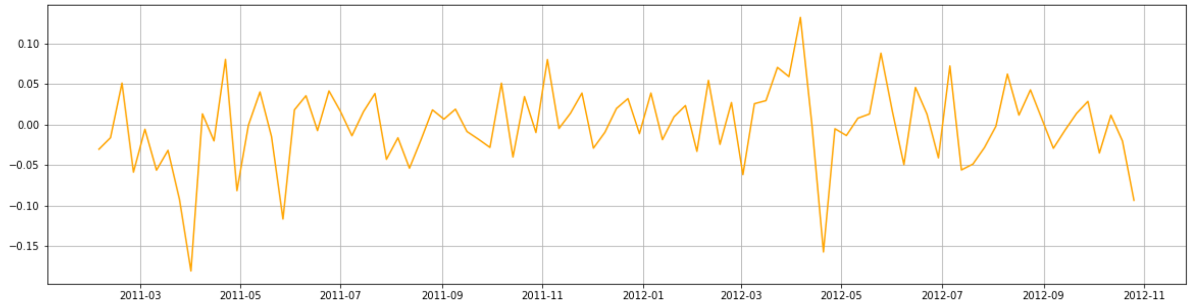
```
[[ 0.13400216  0.00421571 -0.0080964   0.06968813 -0.07535149  0.04919
529
   0.00323757  0.70823713]] [1972.34986697]
Score factor: 0.80
```



In [35]:

```
diff=(df19['Weekly_Sales']-pred[0])/df19['Weekly_Sales']

print('AR Residuals: avg %.2f, std %.2f' % (diff.mean(), diff.std()))

plt.figure(figsize=(20,5))
plt.plot(diff, c='orange')
plt.grid()
plt.show()
```

```
AR Residuals: avg -0.00, std 0.05
```



Look for predictive power from external variables

In [36]:

```
dfext = df.loc[df['Store']==19,:]
dfext = dfext.groupby(by=['Date'], as_index=True)[['Temperature', 'Fuel_Price', 'CPI
                                                   'MarkDown1', 'MarkDown2', 'MarkDow
dfext
```

Out[36]:

Date	Temperature	Fuel_Price	CPI	Unemployment	IsHoliday	MarkDown1	MarkDown2
2010-02-05	20.96	2.954	131.527903	8.350	0	0.00	0.00
2010-02-12	23.22	2.940	131.586613	8.350	1	0.00	0.00
2010-02-19	28.57	2.909	131.637000	8.350	0	0.00	0.00
2010-02-26	30.33	2.910	131.686000	8.350	0	0.00	0.00
2010-03-05	32.92	2.919	131.735000	8.350	0	0.00	0.00
...	...	...	...	...	...	...	...
2012-09-28	56.81	4.158	138.739500	8.193	0	2992.04	48.46
2012-10-05	59.86	4.151	138.825600	7.992	0	6971.59	0.00
2012-10-12	48.29	4.186	138.911700	7.992	0	2374.50	0.00
2012-10-19	53.44	4.153	138.833613	7.992	0	2948.25	0.00
2012-10-26	56.49	4.071	138.728161	7.992	0	5430.75	90.07

143 rows × 10 columns

In [37]:

```
dfext.describe()
```

Out[37]:

	Temperature	Fuel_Price	CPI	Unemployment	IsHoliday	MarkDown1	MarkDo
count	143.000000	143.000000	143.000000	143.000000	143.000000	143.000000	143.00
mean	52.295035	3.578294	135.092607	7.996252	0.069930	3744.799720	1324.17
std	16.611261	0.454128	2.378864	0.193968	0.255926	7331.242555	5383.87
min	20.660000	2.837000	131.527903	7.658000	0.000000	0.000000	-265.76
25%	39.065000	3.052000	132.756559	7.806000	0.000000	0.000000	0.00
50%	53.440000	3.722000	135.083733	8.067000	0.000000	0.000000	0.00
75%	67.985000	3.975500	137.299707	8.150000	0.000000	6122.550000	112.23
max	79.370000	4.211000	138.911700	8.350000	1.000000	51879.660000	50438.17

In [38]:

```
dfext['shifted_sales'] = df19.shift(-1)
dfext
```

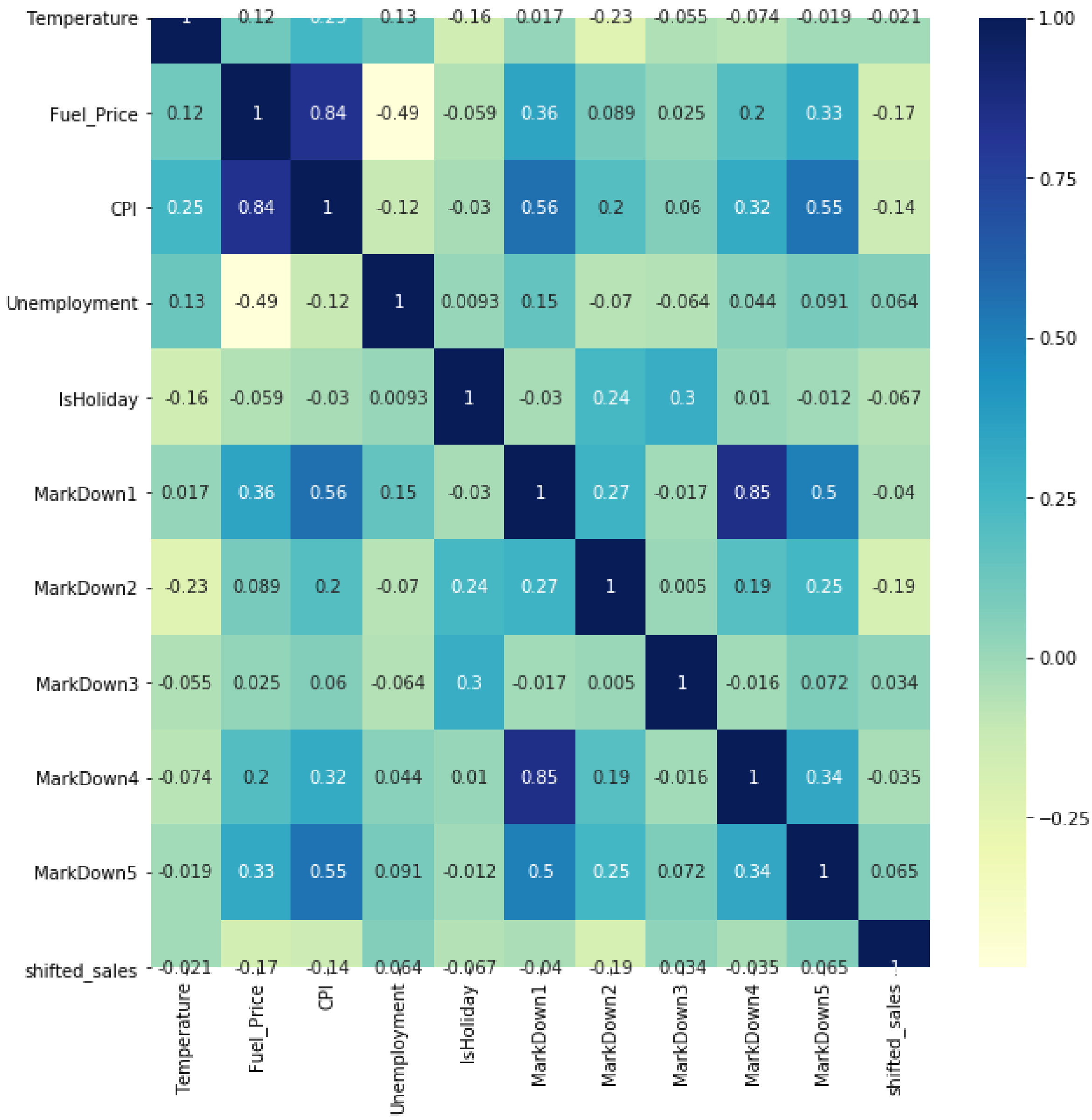
Out[38]:

	Temperature	Fuel_Price	CPI	Unemployment	IsHoliday	MarkDown1	MarkDown2
Date							
2010-02-05	20.96	2.954	131.527903	8.350	0	0.00	0.00
2010-02-12	23.22	2.940	131.586613	8.350	1	0.00	0.00
2010-02-19	28.57	2.909	131.637000	8.350	0	0.00	0.00
2010-02-26	30.33	2.910	131.686000	8.350	0	0.00	0.00
2010-03-05	32.92	2.919	131.735000	8.350	0	0.00	0.00
...	...	...	...	...	...	...	...
2012-09-28	56.81	4.158	138.739500	8.193	0	2992.04	48.46
2012-10-05	59.86	4.151	138.825600	7.992	0	6971.59	0.00
2012-10-12	48.29	4.186	138.911700	7.992	0	2374.50	0.00
2012-10-19	53.44	4.153	138.833613	7.992	0	2948.25	0.00
2012-10-26	56.49	4.071	138.728161	7.992	0	5430.75	90.07

143 rows × 11 columns

In [39]:

```
import seaborn as sns
corr = dfext.corr()
plt.figure(figsize=(10,10))
sns.heatmap(corr, cmap="YlGnBu",
            annot=True,
            xticklabels=corr.columns.values,
            yticklabels=corr.columns.values)
plt.show()
```



In [40]:

```
corr['shifted_sales'].sort_values(ascending=False)
```

Out[40]:

```
shifted_sales     1.000000
MarkDown5         0.064570
Unemployment      0.063831
MarkDown3         0.034011
Temperature      -0.020678
MarkDown4        -0.034691
MarkDown1        -0.040291
IsHoliday        -0.066735
CPI              -0.139821
Fuel_Price       -0.170241
MarkDown2        -0.185359
Name: shifted_sales, dtype: float64
```

The external variables available have some correlation with the 1-week lagged sales time series. This means that they have some degree of predictive power at 1 week and can be used to improve our model. The 'MarkDown' and the 'Temperature' being the most correlated and anti-correlate variables respectively

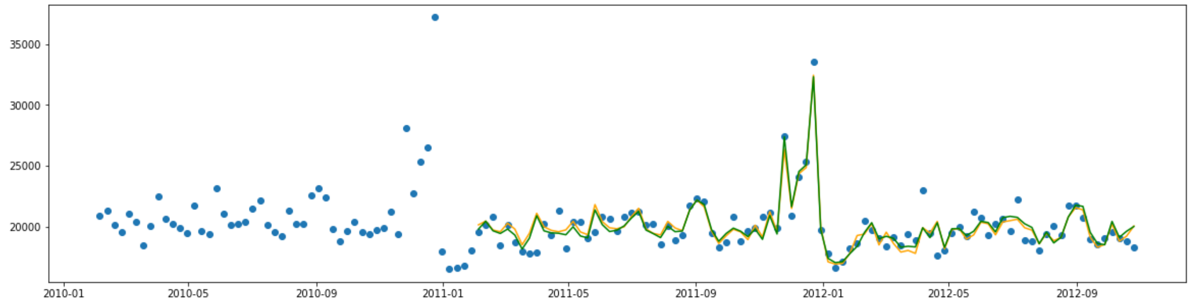
In [41]:

```
def fit_ar_model_ext(ts, orders, ext, fitter=LinearRegression()):

    X=np.array([ ts.values[(i-orders)].squeeze() if i >= np.max(orders) else np.arra

    X = np.append(X, ext.values, axis=1)

    mask = ~np.isnan(X[:,:1]).squeeze()

    Y= ts.values

    fitter.fit(X[mask],Y[mask].ravel())

    print(fitter.coef_, fitter.intercept_)

    print('Score factor: %.2f' % fitter.score(X[mask],Y[mask]))

    return fitter.coef_, fitter.intercept_

def predict_ar_model_ext(ts, orders, ext, coef, intercept):

    X=np.array([ ts.values[(i-orders)].squeeze() if i >= np.max(orders) else np.arra

    X = np.append(X, ext.values, axis=1)

    return np.array( np.dot(X, coef.T) + intercept)
```

In [42]:

```
dfexte=dfext[['Unemployment','Fuel_Price','CPI','Temperature', 'IsHoliday',
              'MarkDown1', 'MarkDown2', 'MarkDown3', 'MarkDown4', 'MarkDown5']]

orders=np.array([1, 5, 39, 48, 49, 50, 51, 52])
coef, intercept = fit_ar_model_ext(df19,orders,dfexte)
pred_ext=pd.DataFrame(index=df19.index, data=predict_ar_model_ext(df19, orders, dfe>
plt.figure(figsize=(20,5))
plt.plot(df19, 'o')
plt.plot(pred, c='orange')
plt.plot(pred_ext, c='green')
plt.show()
```

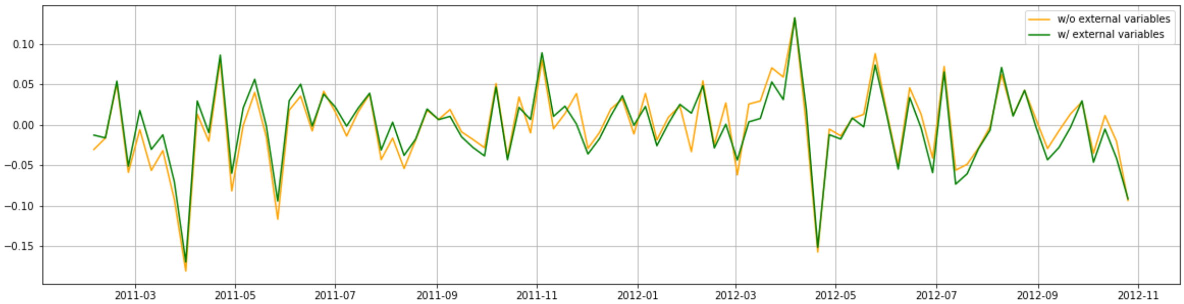
```
[ 1.23254851e-01 -2.92578328e-02 -1.36205480e-02 -1.21861033e-03
 -9.93198755e-02  4.31202377e-02 -5.50789281e-03  6.57626908e-01
 -1.57478106e+03 -6.52343646e+02  2.48104371e+02  6.50006705e-01
  2.85286847e+02  2.61502873e-02 -1.81384867e-02  2.64724582e-02
 -4.57060184e-02  1.03626229e-02] -12728.320192190546
Score factor: 0.82
```



In [43]:

```
diff=(df19['Weekly_Sales']-pred[0])/df19['Weekly_Sales']
diff_ext=(df19['Weekly_Sales']-pred_ext[0])/df19['Weekly_Sales']

print('AR Residuals: avg %.2f, std %.2f' % (diff.mean(), diff.std()))
print('AR wiht Ext Residuals: avg %.2f, std %.2f' % (diff_ext.mean(), diff_ext.std(

plt.figure(figsize=(20,5))
plt.plot(diff, c='orange', label='w/o external variables')
plt.plot(diff_ext, c='green', label='w/ external variables')
plt.legend()
plt.grid()
plt.show()
```

```
AR Residuals: avg -0.00, std 0.05
AR wiht Ext Residuals: avg -0.00, std 0.05
```



As adding external variables does not bring much extra benefits to the prediction, we can infer that the model only containing lagged variables has predicted the model quite well.

At the same time, the little improvement after adding external variables reveals that current and future sales volumn of one specific store is closely related to its past performance in sales. However, in the average sales case, we find out that the correlation is weak. This is mainly because for single store, sales is determined by its own features, which can be seen in past sales.

4. Conclusion

1. General Model

Summarzing models above, we can see that the lagged terms of week 1, 5, 39 ,51 or 52 are correlated to its current sales. Therefore, we are able to partly predict future average sales with sales volumn history. At the same time, hoildays will greatly stimulate consumption and increase the value of sales. Thus, the incoming holiday arrangements can alse helps us to forecast future sales in a macroscopic view.

2. Specific Model for Store 19

In this model, we can notice that the sales values from last week and one year ago affect the predicted sales most siginificantly. The reason is that the sales of specific stores is greatly decided by its own features like quality of goods or position and seasonality factors, which is embodied in -1 and -52 weeks. For the external variables, unemplyment, fuel price and temperature are negatively correlated to sales volumn while CPI and IsHoliday have positive correlation to sale. According to this, we can advise managers of stores to increase inventory when regional CPI raises or holiday is coming in preparation for ascending sales. Similarly, faced with higher unemployment rate or temperature, stores are supposed to cut down on their stock to avoid slow sale and unnecessary loss. Last but not least, as coefficients of dummy variables (0-1) markdowns are small, markdowns have tiny effect on stimulating sales of stores. Hence, markdowns seems not to be an effective method to raise sales volumn and managers need to think over other benefits from markdowns before decison making.

In [ ]:

```

```