Exploratory Data Analysis on Walmart M5 Competition Data for building Forecasting Models

In the following kernel we would be performing EDA on M5 data. We use the insights gathered from EDA to forecast sales for 6 months after the last date in the dataset. The model made after this project will also be used for making forecast in PowerBI Dashboard.

Forecasting will be performed using HoltsWinter, ETS, SARIMAX and Fbprophet.

The dataset provides sales information about 10 stores which are located in 3 states. The number of quantity sold of each SKU at each store for all the dates from 29 January 2011 to 22 May 2016 is provided. More specifically the dataset involves init sales of 3049 products, classified in 3 Product Categories and 7 Products departments.

Dataset Files

- "calender.csv": Contains information about the dates the products are sold.
- "sell_prices.csv": Contains information about the dates the products are sold.
- "sales_train.csv": Contains the historical daily unit sales data per product and store.

Since it is a large dataset, I will be concentrating my analysis on stores in California.

Importing Libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import itertools
import datetime
import matplotlib.dates as mdates
from cycler import cycler


import statsmodels.api as sm
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.stats.diagnostic import acorr_ljungbox as ljung
from statsmodels.graphics.tsaplots import month_plot, seasonal_plot, plot_acf, p
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.tsa.arima_process import ArmaProcess
from statsmodels.tsa.holtwinters import ExponentialSmoothing, SimpleExpSmoothing
from statsmodels.tools.eval_measures import rmse
from scipy import signal
from scipy.stats import jarque_bera as jb
import pmdarima as pm
from pmdarima import ARIMA, auto_arima
from fbprophet import Prophet
```

```
import warnings
warnings.filterwarnings('ignore')
```

Importing Data

In [2]:
```
retail_data=pd.read_csv('sales_train_evaluation.csv')
calender=pd.read_csv("calendar.csv")
sell_prices=pd.read_csv("sell_prices.csv")
```

After importing all the data we will slice out the data of Califronia State and store in rd_ca variable.

In [3]:
```
rd_ca=retail_data[retail_data["state_id"]=="CA"].copy()
print("Missing Values:" +str(rd_ca.isna().sum().sum())) #To check whether we hav
rd_ca.head(5)
```

```
Missing Values:0
```

Out[3]:

	id	item_id	dept_id	cat_id	store_id	state_id	d_1
0	HOBBIES_1_001_CA_1_evaluation	HOBBIES_1_001	HOBBIES_1	HOBBIES	CA_1	CA	0
1	HOBBIES_1_002_CA_1_evaluation	HOBBIES_1_002	HOBBIES_1	HOBBIES	CA_1	CA	0
2	HOBBIES_1_003_CA_1_evaluation	HOBBIES_1_003	HOBBIES_1	HOBBIES	CA_1	CA	0
3	HOBBIES_1_004_CA_1_evaluation	HOBBIES_1_004	HOBBIES_1	HOBBIES	CA_1	CA	0
4	HOBBIES_1_005_CA_1_evaluation	HOBBIES_1_005	HOBBIES_1	HOBBIES	CA_1	CA	0

5 rows × 1947 columns

In the dataset we first have the columns ot identify the item,department, category, store and state. We have individual column for each day(d_1 to d_1941), which gives us the information regarding the quantity sold of the product on that given day.

In [4]:
```
sell_prices=sell_prices[sell_prices["store_id"].isin(["CA_1","CA_2","CA_3","CA_4
print("Missing Values: "+ str(sell_prices.isna().sum().sum())) #To check whether
sell_prices.head(5)
```

```
Missing Values: 0
```

Out[4]:

	store_id	item_id	wm_yr_wk	sell_price
0	CA_1	HOBBIES_1_001	11325	9.58
1	CA_1	HOBBIES_1_001	11326	9.58
2	CA_1	HOBBIES_1_001	11327	8.26
3	CA_1	HOBBIES_1_001	11328	8.26
4	CA_1	HOBBIES_1_001	11329	8.26

This dataframe provides us information regarding the sell prices of various products at different stores.The price of the items change weekly. The dataframe gives us the price of a each product in each store for each week. We have sliced out the data for stores in California.

After this we will also convert wide format dataframe 'rd_ca' to a long format dataframe, so that we can join the data from calender and sell_prices and have all the data in one dataframe.

In [5]:
```
rd_ca_melted=rd_ca.melt(id_vars=['id', 'item_id', 'dept_id', 'cat_id', 'store_ic
rd_ca_melted.rename({"variable":"Day","value":"Quantity"},axis=1,inplace=True)
rd_ca_melted.head(5)
#rd_ca_melted.to_csv("CA_sales.csv")
```

Out[5]:

	id	item_id	dept_id	cat_id	store_id	state_id	Day
0	HOBBIES_1_001_CA_1_evaluation	HOBBIES_1_001	HOBBIES_1	HOBBIES	CA_1	CA	d_1
1	HOBBIES_1_002_CA_1_evaluation	HOBBIES_1_002	HOBBIES_1	HOBBIES	CA_1	CA	d_1
2	HOBBIES_1_003_CA_1_evaluation	HOBBIES_1_003	HOBBIES_1	HOBBIES	CA_1	CA	d_1
3	HOBBIES_1_004_CA_1_evaluation	HOBBIES_1_004	HOBBIES_1	HOBBIES	CA_1	CA	d_1
4	HOBBIES_1_005_CA_1_evaluation	HOBBIES_1_005	HOBBIES_1	HOBBIES	CA_1	CA	d_1

Melting the dataset to use it in analysis.

Joining Various Datasets

In [6]:
```
ca_joined=pd.merge(calender,rd_ca_melted,how="right",left_on=("d"),right_on="Day
ca_joined=pd.merge(ca_joined,sell_prices,how="left",on=["store_id","item_id","wm
ca_joined.head(10)
```

Out[6]:

	date	wm_yr_wk	weekday	wday	month	year	d	event_name_1	event_type_1	event_
0	2011-01-29	11101	Saturday	1	1	2011	d_1	NaN	NaN	
1	2011-01-29	11101	Saturday	1	1	2011	d_1	NaN	NaN	
2	2011-01-29	11101	Saturday	1	1	2011	d_1	NaN	NaN	
3	2011-01-29	11101	Saturday	1	1	2011	d_1	NaN	NaN	
4	2011-01-29	11101	Saturday	1	1	2011	d_1	NaN	NaN	
5	2011-01-29	11101	Saturday	1	1	2011	d_1	NaN	NaN	
6	2011-01-29	11101	Saturday	1	1	2011	d_1	NaN	NaN	
7	2011-01-29	11101	Saturday	1	1	2011	d_1	NaN	NaN	
8	2011-01-29	11101	Saturday	1	1	2011	d_1	NaN	NaN	
9	2011-01-29	11101	Saturday	1	1	2011	d_1	NaN	NaN	

10 rows × 23 columns

Joined the sales dataset with Calender Dataset and also sell prices dataset.

In [7]:
```
ca_joined.drop(["snap_TX","snap_WI"],axis=1,inplace=True) #dropping columns not
ca_joined["total_sales"]=ca_joined["Quantity"]*ca_joined["sell_price"]
```

Calculating daily total sale value for each product at each store.

In [8]:
```
CA_store_daily=ca_joined.groupby(["store_id","date"],as_index=False).agg(Total_s
CA_store_daily["date"]=pd.to_datetime(CA_store_daily["date"])
CA_combined=CA_store_daily.pivot(index="date",columns="store_id",values="Total_s
CA1,CA2,CA3,CA4=[CA_store_daily[CA_store_daily["store_id"]==i].copy() for i in [
CA1.info()
CA_combined.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1941 entries, 0 to 1940
Data columns (total 3 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   store_id     1941 non-null   object
 1   date         1941 non-null   datetime64[ns]
 2   Total_sales  1941 non-null   float64
dtypes: datetime64[ns](1), float64(1), object(1)
memory usage: 60.7+ KB
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1941 entries, 2011-01-29 to 2016-05-22
Data columns (total 4 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   CA_1    1941 non-null   float64
 1   CA_2    1941 non-null   float64
 2   CA_3    1941 non-null   float64
 3   CA_4    1941 non-null   float64
dtypes: float64(4)
memory usage: 75.8 KB
```

Calculating daily total sales for each store and putting it in different dataframes. Also creating a new combined wideformat dataframe, where store_id are the columns, and cell contain daily total sale value for that store.

In [9]:
```
for i in [CA1,CA2,CA3,CA4]:
    i.set_index("date",inplace=True)
    i.index.freq="D"
```

Calculating Monthly sales for all stores.

In [10]:
```
CA_monthly=CA_combined.resample("MS").sum()
CA_monthly_ind=[]
for i in [CA1,CA2,CA3,CA4]:
    CA_monthly_ind.append(i["Total_sales"].resample("MS").sum())
CA_monthly_long=CA_store_daily.set_index("date").groupby(["store_id"])["Total_sa
```

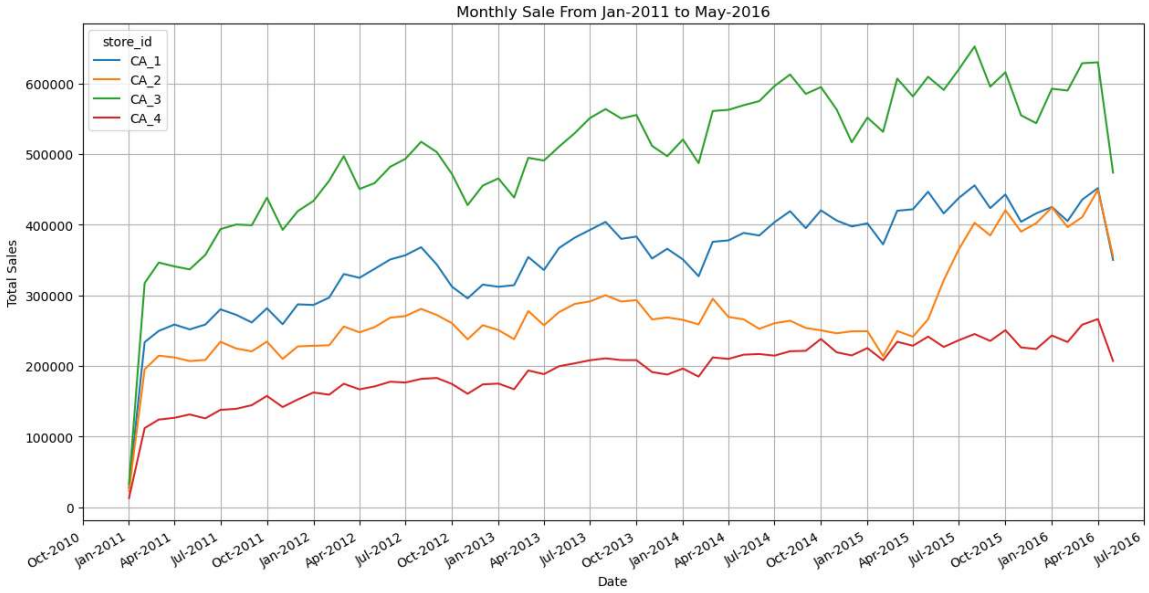
In [11]:
```
CA_monthly.to_excel("CA_monthly.xlsx")
CA1.to_excel("CA1.xlsx")
CA2.to_excel("CA2.xlsx")
CA3.to_excel("CA3.xlsx")
CA4.to_excel("CA4.xlsx")
CA_monthly_long.to_excel("CA_monthly_long.xlsx")
```

Exporting files to excel, so the above computing intensive data preparation steps can be skipped after data preparation is done for the first time.

In [12]:
```
CA_monthly.plot(legend=True,
                figsize=(15,8),
                xlim=[datetime.datetime(2010,10,1),datetime.datetime(2016,7,1)],
                grid=True,
                ylabel="Total Sales",
                xlabel="Date",
                x_compat=True)
ax = plt.gca()
ax.xaxis.set_major_locator(mdates.MonthLocator(interval=3))
```

```
ax.xaxis.set_major_formatter(mdates.DateFormatter('%b-%Y'))
ax.set_title("Monthly Sale From Jan-2011 to May-2016")
```

Out[12]:
```
Text(0.5, 1.0, 'Monthly Sale From Jan-2011 to May-2016')
```



From the graph we can infer few things

- There is sudden increase in sales between January 2011 and February 2011. This is an anomaly and when we inspect further, we will realize for January 2011 we only have sales data for 3 days. That's why sales for different stores in January is so close to zero.
- Similarly there is sudden drop in sales in May 2016 for all stores. This may be attributed to fact that dataset doesn't contain 8 days of data for the month May 2016. This is the reason for the sudden drop.
- To solve this issue, and to make sure these cases of incomplete data don't affect our models we will have to remove data for months of January 2011 and May 2016.
- For all the stores except CA2, total monthly sales is generally increasing year over year. The trend is upwards.
- The data is showing seasonality.
- For CA2, the trend is sideways till July-2015, after that is sudenly increases.

In [13]:
```
for i in range(4):
    CA_monthly_ind[i]=CA_monthly_ind[i].loc["02-2011":"04-2016"].copy()
CA_monthly=CA_monthly.loc["02-2011":"04-2016"].copy()
CA_monthly_long=CA_monthly_long.set_index("date").loc["02-2011":"04-2016"]
```

In [14]:
```
CA_monthly.to_excel("CA__monthly.xlsx")
for j,i in enumerate(CA_monthly_ind):
    i.to_excel("CA_"+str(j+1)+".xlsx")
CA_monthly_long.to_excel("CA__monthly_long.xlsx")
```

Exporting files to excel, so the above computing intensive data preparation steps can be skipped after data preparation is done for the first time.

In [15]:
```
print("Length of the full dataset:"+str(len(CA_monthly.index.unique())))
```

```
Length of the full dataset:63
```

Train Test Split

Before continuing further analysis it is necessary to split the dataset in train and test data. EDA, model fitting and selections would only be done using training data. Testing data will only be used after this to avoid any bias.

Typically we want atleast 3-4 full seasonal cycle for training. The testing data should be atleast equal to the forecast horizon. We have 63 months of data in our dataset. We want to forecast 6 months ahead after April 2016.

Also in a year there are 12 months, therefore, the length of one complete cycle is 12.

Keeping these things in mind we will have our trainig data as first 54 months which will have contain more than 4 seasonal cycles of data.Subsequently our testing data would be last 9 months of data.

In [16]:
```
CA_monthly_ind=[]
CA_monthly=pd.read_excel("CA__monthly.xlsx",parse_dates=True).set_index("date")
CA_monthly.index.freq="MS"
CA1=pd.read_excel("CA_1.xlsx",parse_dates=True).set_index("date")
CA2=pd.read_excel("CA_2.xlsx",parse_dates=True).set_index("date")
CA3=pd.read_excel("CA_3.xlsx",parse_dates=True).set_index("date")
CA4=pd.read_excel("CA_4.xlsx",parse_dates=True).set_index("date")
CA_monthly_long=pd.read_excel("CA__monthly_long.xlsx",parse_dates=True).set_inde
for i in [CA1,CA2,CA3,CA4]:
    CA_monthly_ind.append(i["Total_sales"])
```

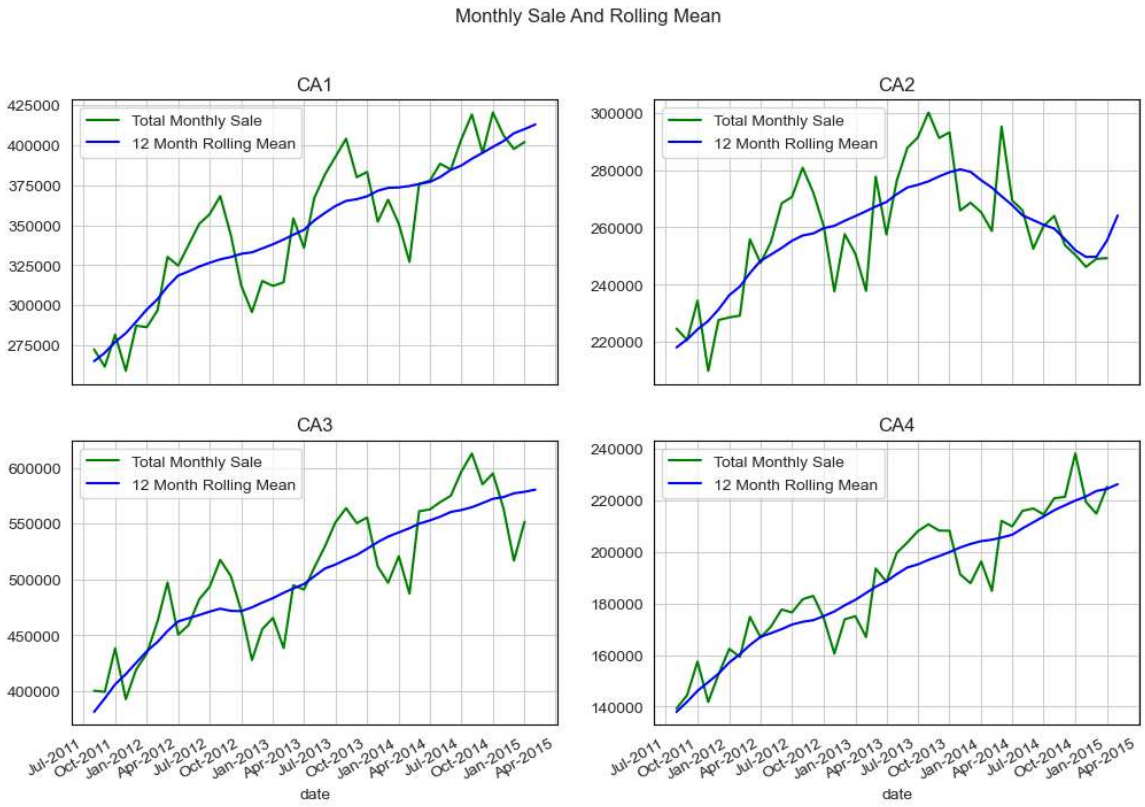
In [17]:
```
Train=CA_monthly[:-9]
Test=CA_monthly[-9:]
Train_ind=[i[:-9] for i in CA_monthly_ind]
Test_ind=[i[-9:] for i in CA_monthly_ind]
Train_long=CA_monthly_long.loc["02-2011":"07-2015"]
Test_long=CA_monthly_long.loc["08-2015":]
```

Exploratory Data Analysis

Rolling Mean and Sales

In [18]:
```
sns.set_style("whitegrid",{"axes.edgecolor": "black"})
fig, axes = plt.subplots(figsize=(12,8),nrows=2, ncols=2,sharex=True)
k=0;
for i in range(2):
    for y in range(2):
        Train_ind[k][6:-6].plot(legend=True,label="Total Monthly Sale",color="gr
        Train_ind[k].rolling(12,center=True).mean().plot(legend=True,color="blue
        axes[i][y].xaxis.set_major_locator(mdates.MonthLocator(interval=3))
        axes[i][y].xaxis.set_major_formatter(mdates.DateFormatter('%b-%Y'))
        k=k+1
fig.suptitle("Monthly Sale And Rolling Mean")
```

Out[18]:
```
Text(0.5, 0.98, 'Monthly Sale And Rolling Mean')
```

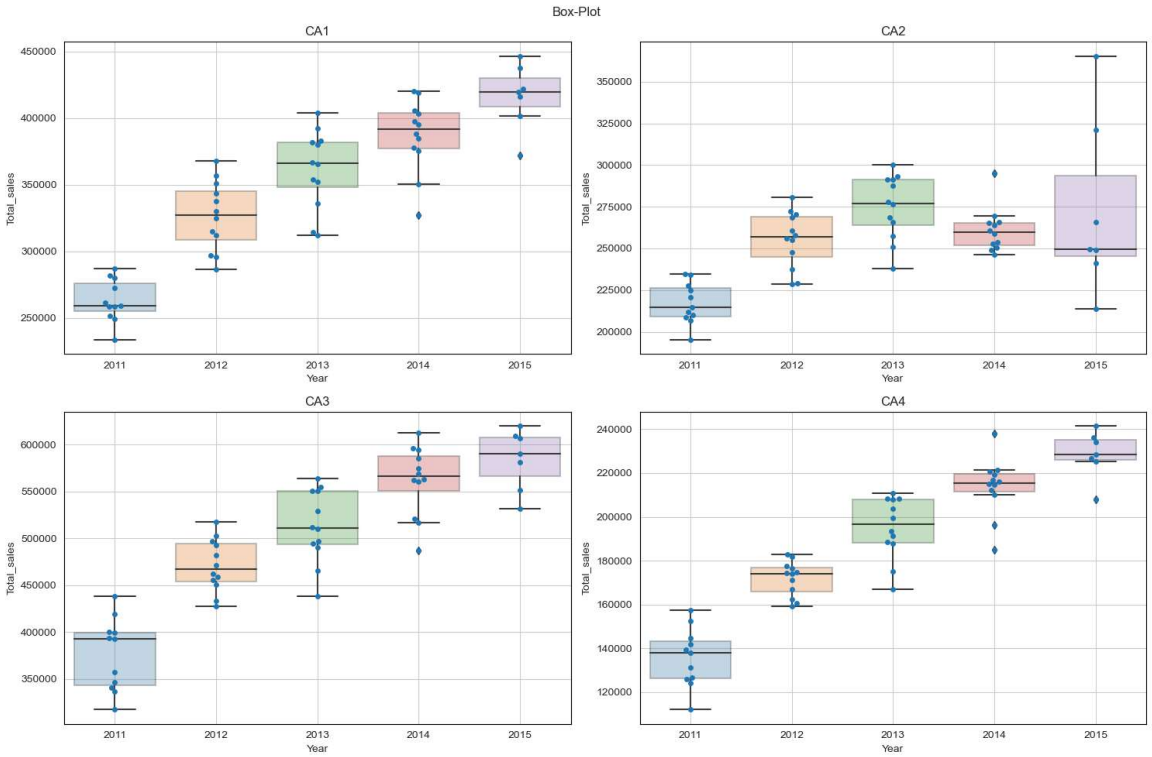


We can see some seasonal pattern, sale is peaking for CA1, CA3 and CA4 between July and October months for all years. For CA2, sales is more random and sales is peaking between july and october for 2 years, while peaking between jan and april for one year.

The trend is upwards for CA1, CA3 and CA4. For CA2, the trend is increasing till Dec-2013, and then we observe decreasing trend.

We are observing trend using Rolling Mean.

In [19]:
```
fig, ax = plt.subplots(figsize = (15,10),nrows=2,ncols=2)
for i in range(4):
    sns.boxplot(x=Train_ind[i].index.year.tolist(),y=Train_ind[i] ,ax=ax[int(i/2
    sns.swarmplot(y=Train_ind[i],ax=ax[int(i/2)][i%2] ,x=Train_ind[i].index.year
    ax[int(i/2)][i%2].set_title("CA"+str(i+1))
    ax[int(i/2)][i%2].grid(True)
    ax[int(i/2)][i%2].set_xlabel("Year")
fig.suptitle("Box-Plot")
fig.tight_layout()
```



Mean increases over the years for all stores except CA2. In the year 2014 there are outliers for all the stores. Other than that we dont find any outliers.

For CA1 and CA3 the distribution varies less over the years as the length of the box plot does not changes much between 2011 and 2015.

For CA2 the total monthly sale value varies significantly in 2015 and is more concentrated in in 2014. You can see this by seeing the side ways line for CA_2 store in graph titled "Monthly Sale From Jan-2011 to May-2016".

For CA4, the total monthly sale becomes more concentrated in the years 2014 and 2015.

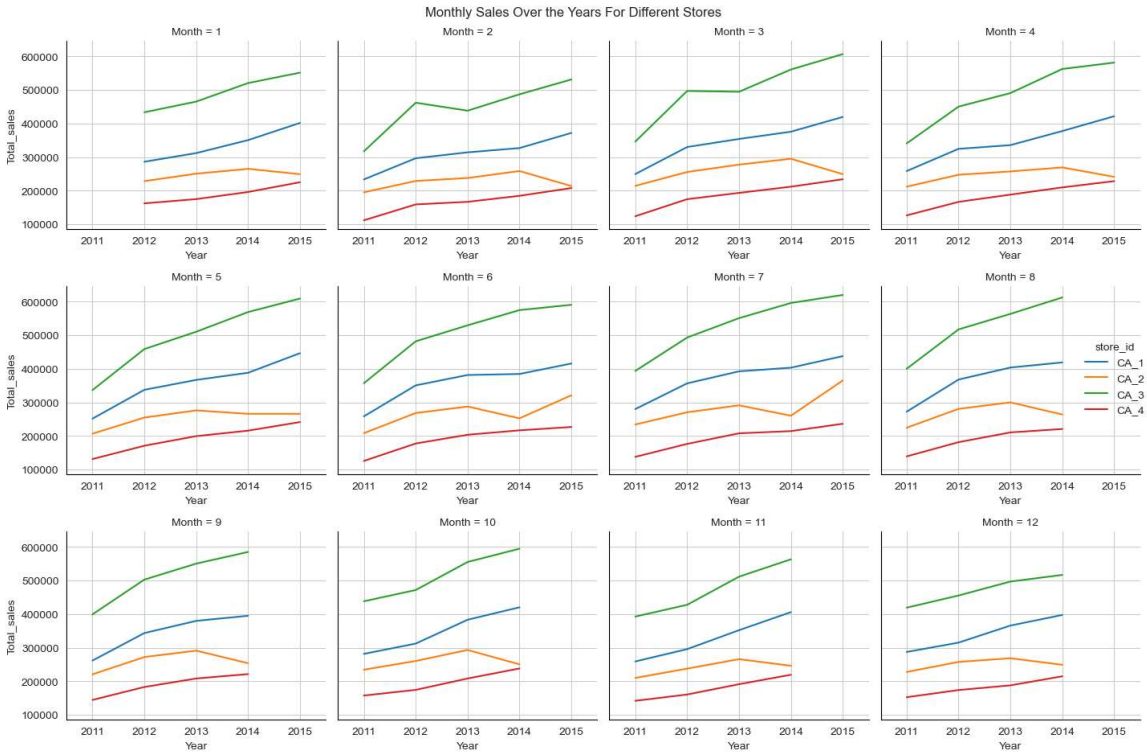
In [20]:
```
# iqr=(np.percentile(CA_monthly_ind[0]["2014"],75)-np.percentile(CA_monthly_ind[
# iqr1=iqr*1.5
# np.percentile(CA_monthly_ind[0]["2014"],25)-iqr1
```

Monthly trends & distrbution

Monthly Subseries Plot

In [21]:
```
Train_ss=Train_long.copy()
Train_ss["Year"]=Train_ss.index.year.tolist()
Train_ss["Month"]=Train_ss.index.month.tolist()
fg_grid=sns.relplot(data=Train_ss,
                    x="Year",
                    hue="store_id",
                    y="Total_sales",
                    col="Month",
                    kind="line",
                    col_wrap=4,
                    height=3.2,
                    aspect=1.06,
                    facet_kws={"sharex":False,"xlim":(2010.5,2015.5),"sharey":True}
```

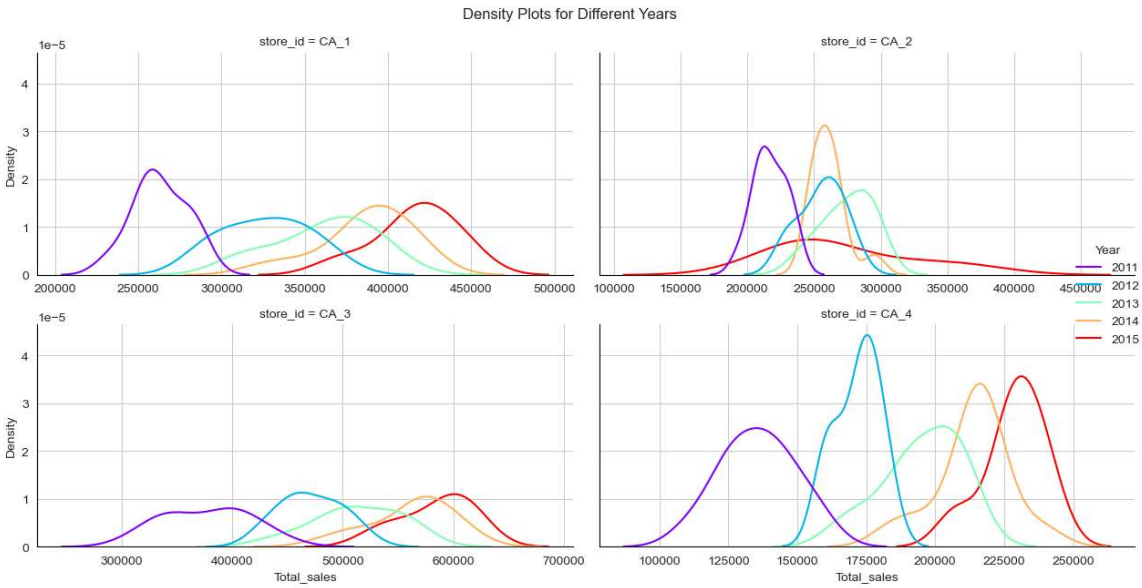
```
).figure.suptitle("Monthly Sales Over the Years For Different Stores")
fg_grid.figure.tight_layout()
```



Sale is increasing for different months year on year for all stores except CA2.

Distribution Plot

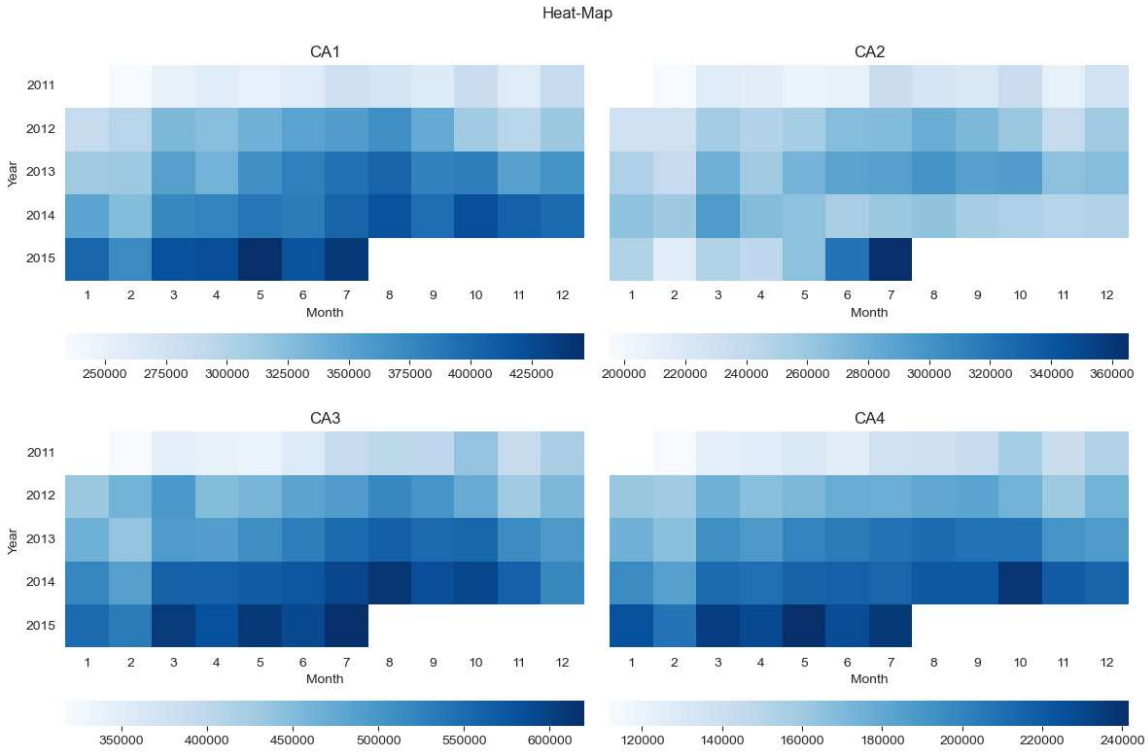
In [22]:
```
fg_grid=sns.displot(data=Train_ss,
            x="Total_sales",
            kind="kde",
            col="store_id",
            col_wrap=2,
            palette="rainbow",
            hue="Year",
            legend=True,
            facet_kws={"sharex":False},
            height=3.3,
            aspect=1.8,
            common_norm=False).figure.suptitle("Density Plots for Different Year
fg_grid.figure.tight_layout()
```



Kenel Density plot shows data looks normally distributed except for CA2 and CA3, bi-modal distribution could be there because of small sample size. Peaks shift right from 2011 to 2015 indicating increase in average.

Heat-Map

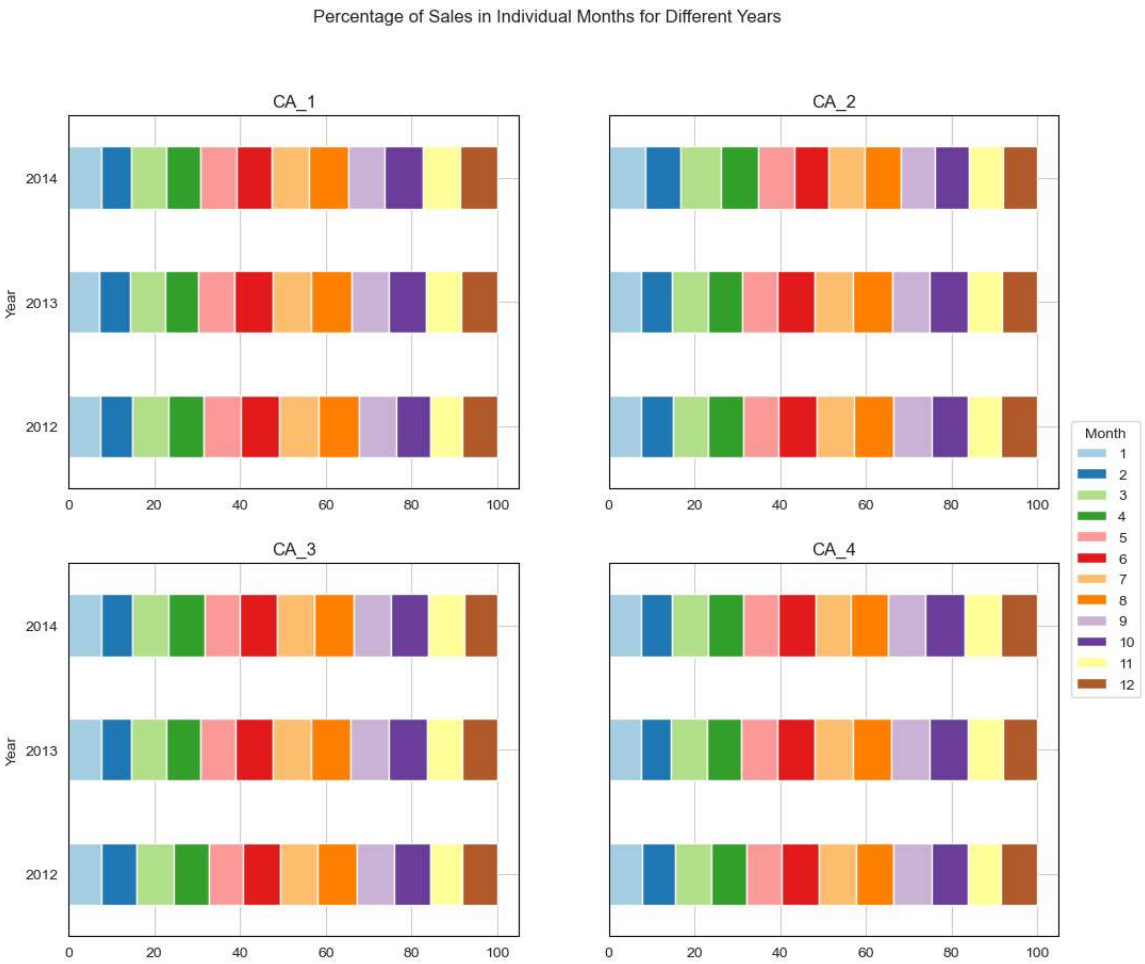
In [23]:
```
fig, axes = plt.subplots(figsize=(12,8),nrows=2, ncols=2,sharey=True)
p=pd.pivot_table(data=Train_ss[["store_id","Total_sales","Month","Year"]],
                 index=["store_id","Year"],
                 columns="Month",
                 values="Total_sales")
k=0;
for i in range(2):
    for y in range(2):
        k=k+1
        t=sns.heatmap(p.loc["CA_"+str(k)],
                      square=True,
                      cmap='Blues',
                      ax=axes[i][y],
                      cbar=True,
                      cbar_kws={"orientation":"horizontal"});
        axes[i][y].set_title("CA"+str(k))
        axes[i][y].tick_params('y', labelrotation=0)
        if y==1: axes[i][y].set_ylabel(None)
# mappable = t.get_children()[0]
# plt.colorbar(mappable, ax =[axes[2][0],axes[2][1]],use_gridspec=True,orientati
fig.suptitle("Heat-Map")
fig.tight_layout()
```



You can generally see that shade gets darker for all the years in months between 7th (July) and 10th (October). This confirms that sales peaks in monts between July and October, and then decreases slightly. There is also smaller peak in sales which comes in 3rd(March) month.

Stacked Bar Graph-Each Month Share in Total Sales

In [24]:
```
fig,ax=plt.subplots(figsize=(12,10),nrows=2,ncols=2,sharey=True)
for j in range(4):
        sum_of_years=p.loc["CA_"+str(j+1)].loc[2012:2014].sum(axis=1)
        p_percentage=p.loc["CA_"+str(j+1)].loc[2012:2014].divide(sum_of_years,ax
        p_percentage.plot(kind='barh', stacked=True, title="CA_"+str(j+1),ax=ax[
handles, labels = ax[0][0].get_legend_handles_labels()
fig.suptitle("Percentage of Sales in Individual Months for Different Years")
fig.legend(handles, labels,bbox_to_anchor=(0.97,0.6),title="Month")
plt.show()
```



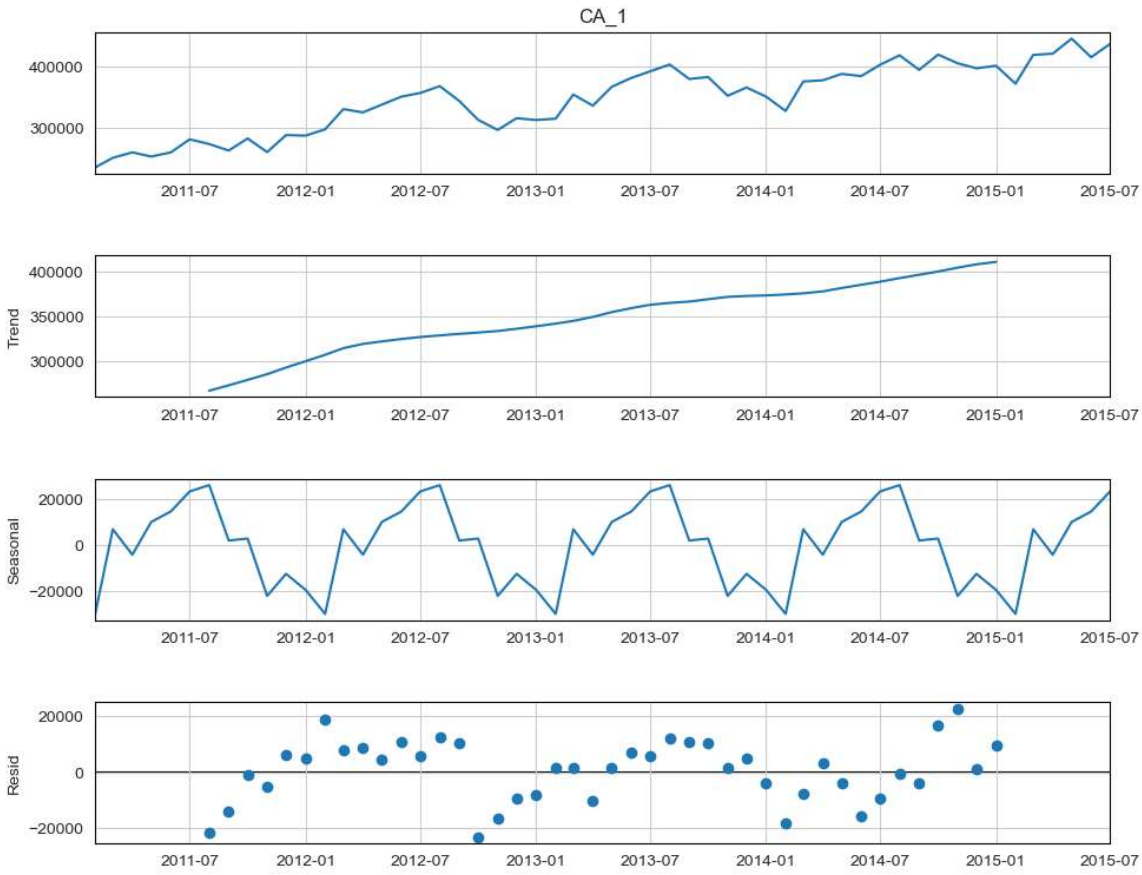
Percentage wise all months conribute roughly the same to total sales in the year. They all contribute 7.5% to 8.5% to total sales in year.

Decomposition

1. **CA1**

In [25]:
```
decompose_CA1 = seasonal_decompose(Train["CA_1"])
decompose_CA1.plot().set(figheight=8.1,figwidth=10.8)
```

Out[25]:
```
[None, None]
```



In [26]:
```
ljung_p=np.mean(ljung(decompose_CA1.resid.dropna(),lags=24,return_df=True)["lb_p
print("p-value :",ljung_p, "\nSince p < 0.05 =",str(ljung_p<0.05)+","
                      ,"The residuals are uncorelated" if ljung_p<0.05 else "The
```

```
p-value : 0.001411946194646062
Since p < 0.05 = True, The residuals are uncorelated
```

The trend is non-linear and upwards. Seasonal pattern is consistent.

Residuals are un-corelated. Residuals are the differences that are left between the values that is calculated after fitting the trend and seasonality, and the observed data. We want them to be uncorelated or i.i.d(Independent and Identically Distributed). If they show patterns, it means that there is some structural information that is left to be captured.

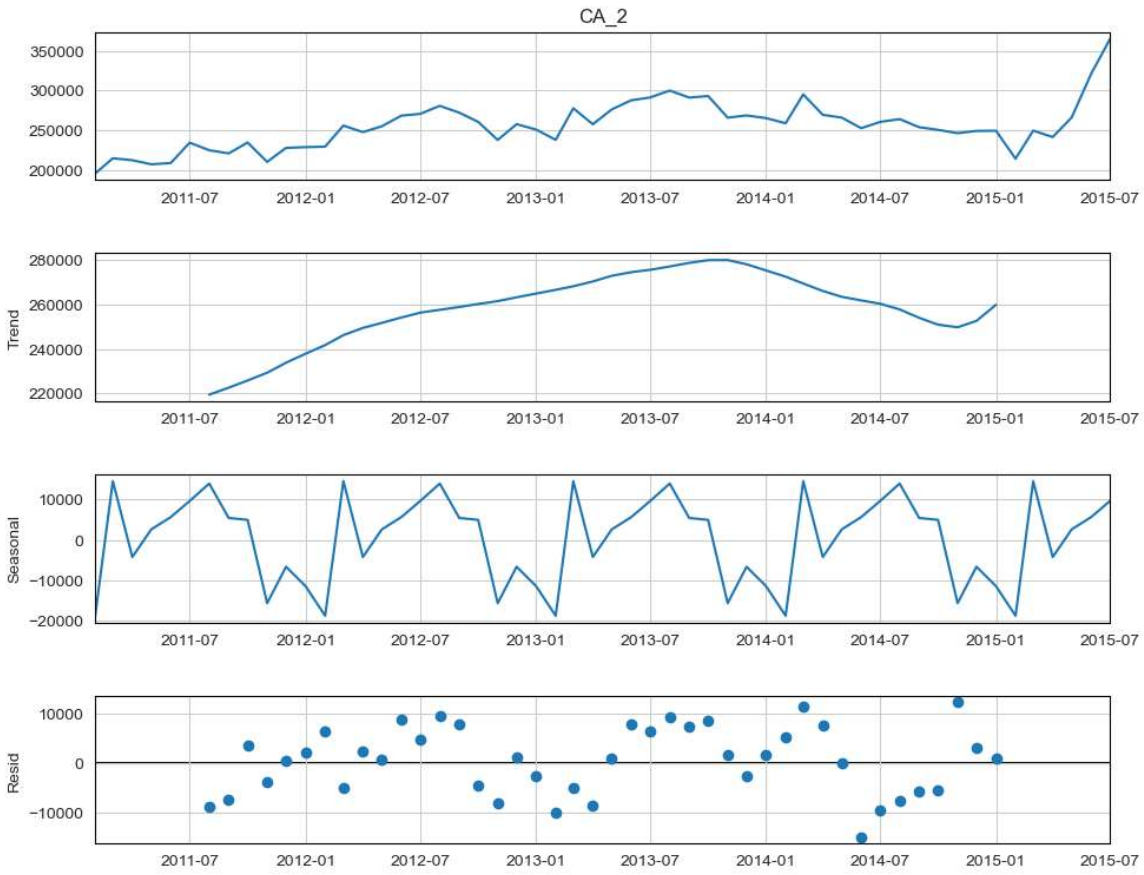
We have performed Ljung Box test to check whether they are i.i.d. Since the p-value < 0.05, We can say that residuals are uncorelated.

If the residuals are corelated, we may have to use external variable to explain that co relation.

2. **CA2**

In [27]:
```
decompose_CA2 = seasonal_decompose(Train["CA_2"])
decompose_CA2.plot().set(figheight=8.1,figwidth=10.8)
```

Out[27]:
```
[None, None]
```



In [28]:
```
ljung_p=np.mean(ljung(decompose_CA2.resid.dropna(),lags=24,return_df=True)["lb_p
print("p-value :",ljung_p, "\nSince p < 0.05 =",str(ljung_p<0.05)+","
                    ,"The residuals are uncorelated" if ljung_p<0.05 else "The
```

```
p-value : 0.0029624633711649493
Since p < 0.05 = True, The residuals are uncorelated
```

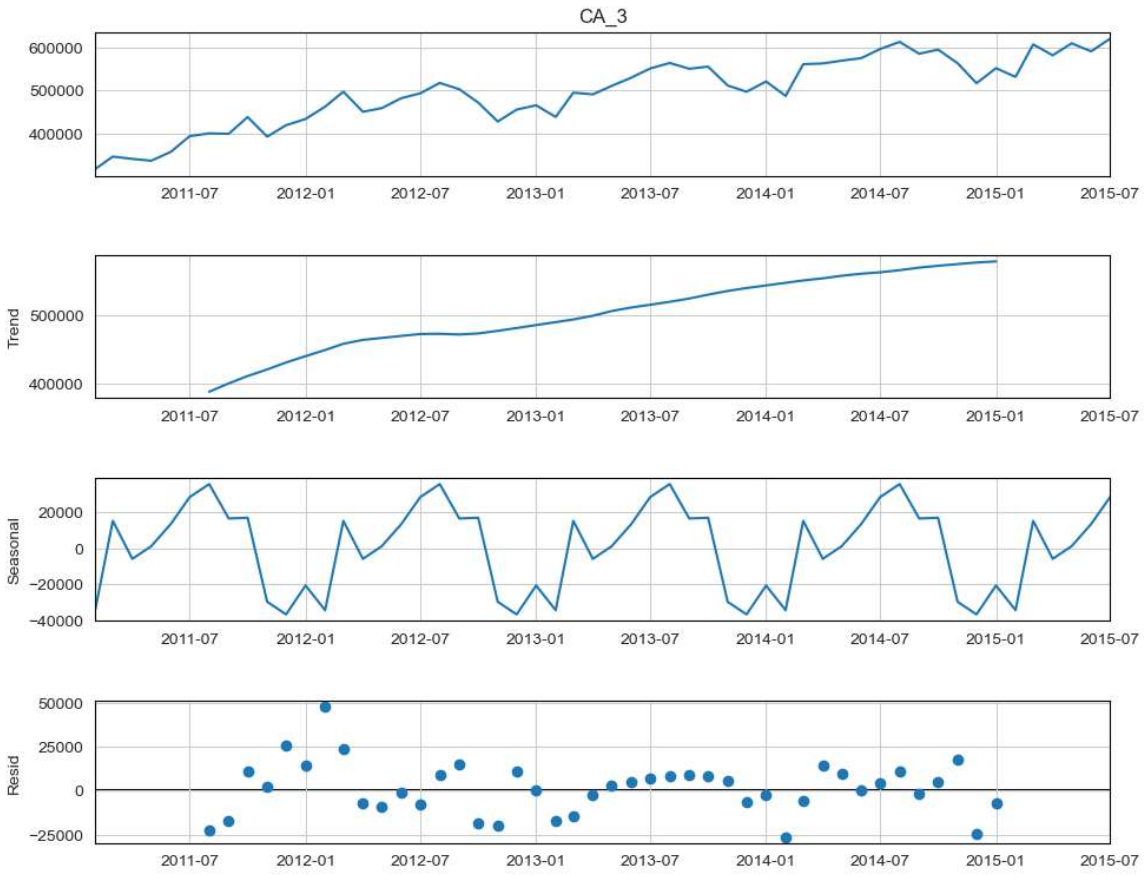
The trend is non-linear. The trend increases first few years and then decreases after 2014. This may indicate cyclic behaviour. Seasonal pattern is consistent.

Residuals are un-corelated.

3. **CA3**

In [29]:
```
decompose_CA3 = seasonal_decompose(Train["CA_3"])
decompose_CA3.plot().set(figheight=8.1,figwidth=10.8)
```

Out[29]:
```
[None, None]
```



In [30]:
```
ljung_p=np.mean(ljung(decompose_CA3.resid.dropna(),lags=24,return_df=True)["lb_p
print("p-value :",ljung_p, "\nSince p < 0.05 =",str(ljung_p<0.05)+","
                    ,"The residuals are uncorelated" if ljung_p<0.05 else "The
```

```
p-value : 0.3584778566044933
Since p < 0.05 = False, The resisuals are co-related
```

The trend is non-linear and upwards. Seasonal pattern is consistent.

Residuals are corelated. This is suggesting that we will have to use higher order models, or use external variable to explain the pattern in residuals

4. **CA4**

In [31]:
```
decompose_CA4 = seasonal_decompose(Train["CA_4"])
decompose_CA4.plot().set(figheight=8.1,figwidth=10.8)
```

Out[31]:
```
[None, None]
```

In [32]:
```
ljung_p=np.mean(ljung(decompose_CA4.resid.dropna(),lags=24,return_df=True)["lb_p
print("p-value :",ljung_p, "\nSince p < 0.05 =",str(ljung_p<0.05)+","
                    ,"The residuals are uncorelated" if ljung_p<0.05 else "The
```

```
p-value : 0.00389969832916549
Since p < 0.05 = True, The residuals are uncorelated
```

The trend is non-linear and upwards. Seasonal pattern is consistent.

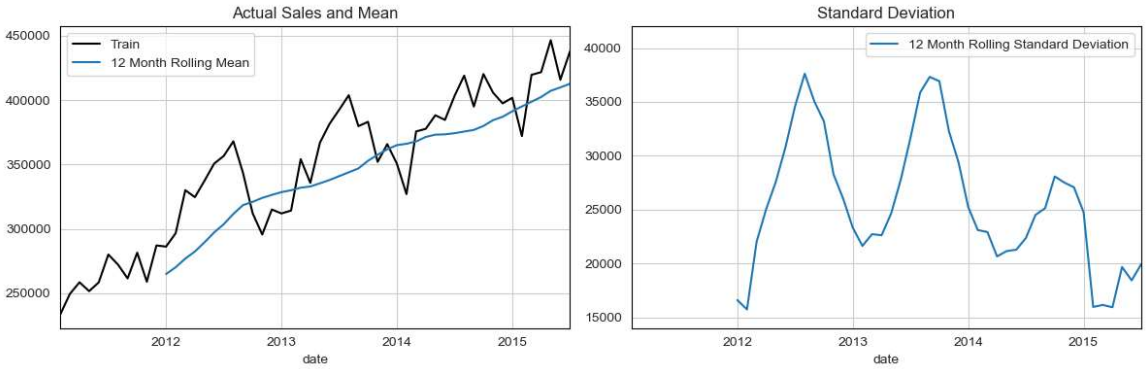
Residuals are un-corelated

Stationarity

1. **CA1**

In [33]:
```
fig,ax1=plt.subplots(figsize=(12,4),nrows=1,ncols=2)
Train["CA_1"].plot(ax=ax1[0],legend=True,label="Train",cmap="gray",title="Actual
Train["CA_1"].rolling(12,center=False).mean().plot(legend=True,ax=ax1[0],label="
Train["CA_1"].rolling(12,center=False).std().plot(ax=ax1[1],title="Standard Devi
fig.tight_layout()
print("Standard Deviation:",Train["CA_1"].std())
```

```
Standard Deviation: 56545.0596070229
```



Mean is increasing , but standard deviation is decreasing year over year. Increasing mean indicates that series is not stationary, also as we move foward in time, variation in the total monthly sale is decreasing which is indicated by reducing standard deviation year over year.

In [34]:
```
print("Coefficient of Variation:",Train["CA_1"].std()/Train["CA_1"].mean())
```

```
Coefficient of Variation: 0.1631393146301216
```

Coefficient of Variation: Coefficient of variation gives us an idea about the variability in the process, especially when looking at sales and demand. Note that this should be used for relative comparison and does not have a strict statistical defition. It's very common measure in demand planning and inventory analytics.

c.v = s.d/mean

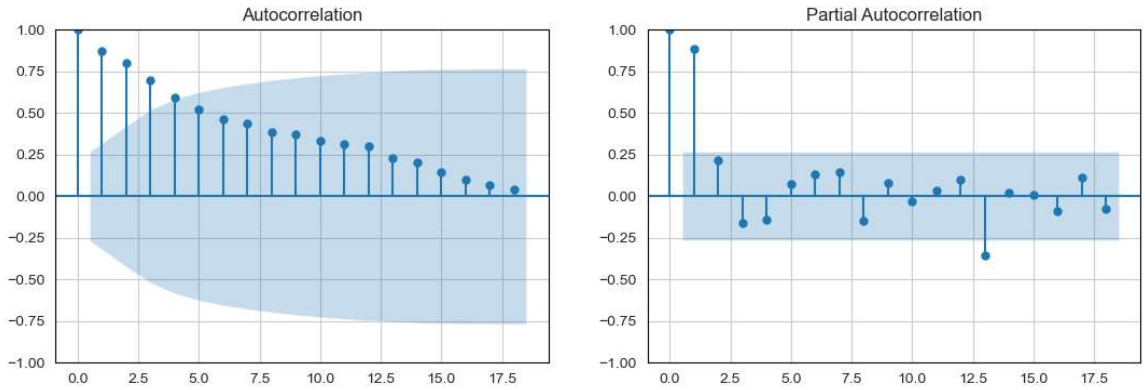
If C.V<0.75 => Low Variability

If 0.75<C.V<1.3 => Medium Variability

If C.V>1.3 => High Variability

This is over all a low variablility process.

In [35]:
```
fig,ax1=plt.subplots(figsize=(13,4),nrows=1,ncols=2)
plot_acf(Train["CA_1"],ax=ax1[0]);
plot_pacf(Train["CA_1"],ax=ax1[1]);
```



ACF(Auto Corelation Function) - It determines the correlation that is present between the current value and value at lag k. If the corelation values are outside the blue band,

means they are significant. We can see that sales in last 4 periods have significance in determining the sales in current period.

PACF(Partial Auto Corelation Function)- PACF gives us corelation between current value and value at lag k after removing the effects of lags<k. The pacf here cuts off after one lag. This means that after lag 1, the pacf values fall inside the blue band. The values that dall inside the blue band are considered not significant. There is only one value that is little above significant band at lag 13. We can ignore it.

The ACF model is also tapering down which in combination with PACF plot cutting off after a number of lags indicates an Auto Regressive Process.

These graph have significance in determining the order of ARIMA models. It requires much thorough study and experience to calculate ARIMA model parameters.

Luckily for us , there are built in functions available to us which calculates parameters for one of the best arima models based on the data. While building ARIMA models we will be using those functions.

In [36]:
```
adf = adfuller(Train["CA_1"])[1]
print(f"p value:{adf.round(4)}", ", Series is Stationary" if adf <0.05 else ", S
```

```
p value:0.2654 , Series is Non-Stationary
```

We have used adfuller test to test whether series is stationary or not. Based on upward trend we have already stated that series is non stationary, however, this will confirm this.

In [37]:
```
adf2 = adfuller(Train["CA_1"].diff(1).dropna())[1]
print(f"p value:{adf2.round(4)}", ", Series is Stationary" if adf2 <0.05 else ",
adf2 = adfuller(Train["CA_1"].diff(1).diff(1).dropna())[1]
print(f"p value:{adf2.round(4)}", ", Series is Stationary" if adf2 <0.05 else ",
```

```
p value:0.1305 , Series is Non-Stationary
p value:0.0 , Series is Stationary
```

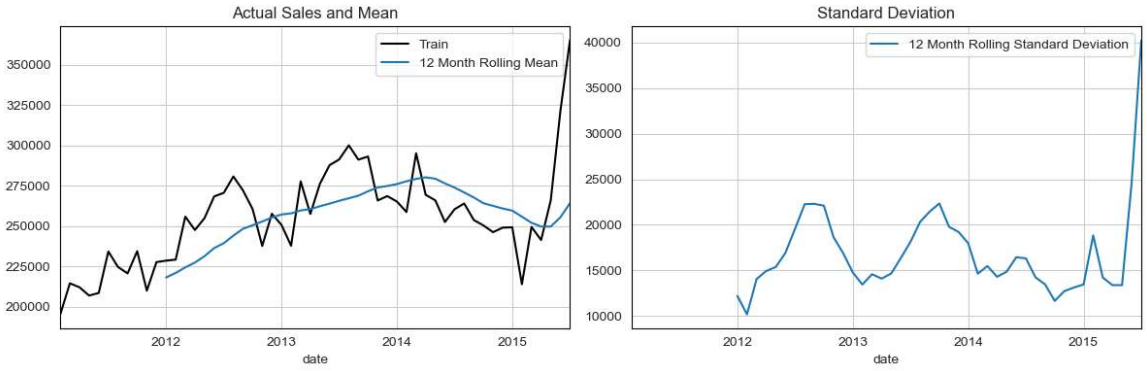
We can make series stationary by differencing the series i.e subracting each value with one before or after. We may have to do this one or more time to make it stationary.

Funfact- This would be the 'd' parameter of the 3 parameters of ARIMA model i.e p,d,q. More about it later

2. **CA2**

In [38]:
```
fig,ax1=plt.subplots(figsize=(12,4),nrows=1,ncols=2)
Train["CA_2"].plot(ax=ax1[0],legend=True,label="Train",cmap="gray",title="Actual
Train["CA_2"].rolling(12,center=False).mean().plot(legend=True,ax=ax1[0],label="
Train["CA_2"].rolling(12,center=False).std().plot(ax=ax1[1],title="Standard Devi
fig.tight_layout()
print("Standard Deviation:",Train["CA_2"].std())
```

```
Standard Deviation: 30762.858830483874
```



Mean is increasing initially but then starts to decrease.

Standard deviation is decreasing year over year, but at the very end there is spike in standard deviation.

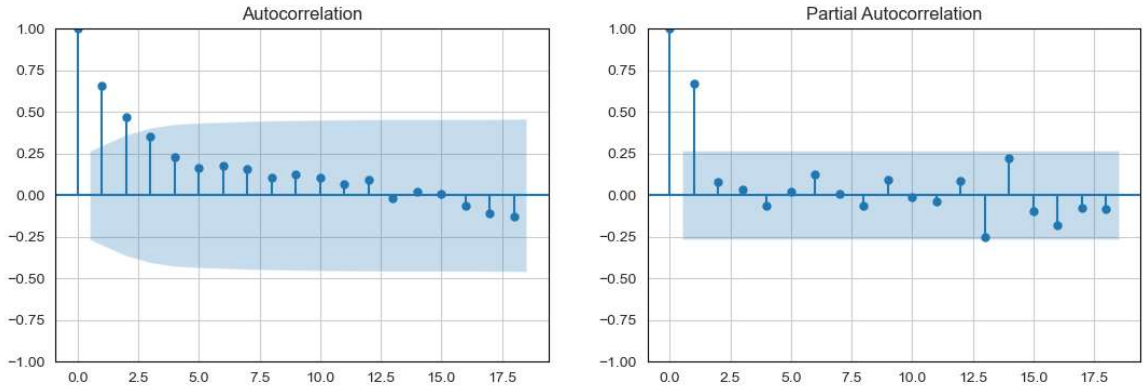
Non constant mean indicates that series is not stationary, also till 2015, variation in total monthly sale decreases, this changes after 2015 when there is sudden spike in Standard Deviation and total monthly sale varies much more. This can also be seen in the box plot of CA2.

In [39]:
```
print("Coefficient of Variation:",Train["CA_2"].std()/Train["CA_1"].mean())
```

```
Coefficient of Variation: 0.08875455681799314
```

This is a low variability process

In [40]:
```
fig,ax1=plt.subplots(figsize=(13,4),nrows=1,ncols=2)
plot_acf(Train["CA_2"],ax=ax1[0]);
plot_pacf(Train["CA_2"],ax=ax1[1]);
```



We can see that sales in last 2 periods have significance in determining the sales in current period.

The pacf here cuts off after one lag.

The ACF model is also tapering down which in combination with PACF plot cutting off after a number of lags indicates an Auto Regressive Process

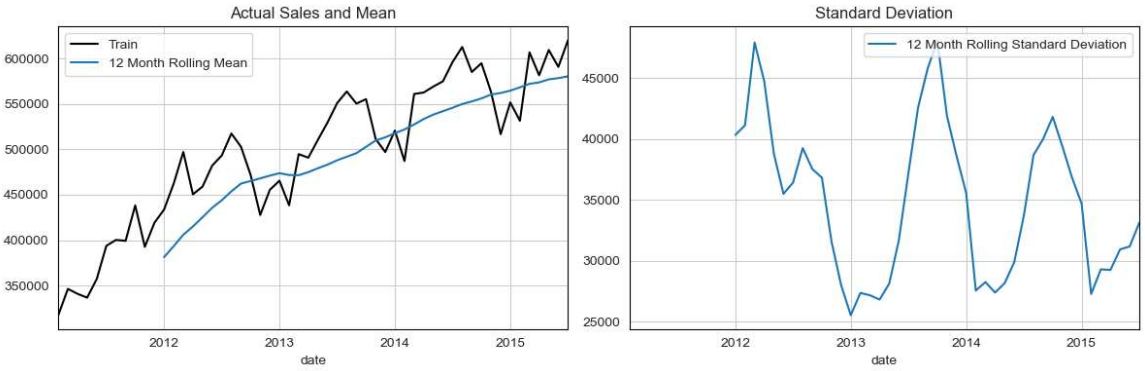
In [41]:
```
adf = adfuller(Train["CA_2"])[1]
print(f"p value:{adf.round(4)}", ", Series is Stationary" if adf <0.05 else ", S
```

```
p value:0.5276 , Series is Non-Stationary
```

2. **CA3**

In [42]:
```
fig,ax1=plt.subplots(figsize=(12,4),nrows=1,ncols=2)
Train["CA_3"].plot(ax=ax1[0],legend=True,label="Train",cmap="gray",title="Actual
Train["CA_3"].rolling(12,center=False).mean().plot(legend=True,ax=ax1[0],label="
Train["CA_3"].rolling(12,center=False).std().plot(ax=ax1[1],title="Standard Devi
fig.tight_layout()
print("Standard Deviation:",Train["CA_3"].std())
```

```
Standard Deviation: 79672.3647539057
```



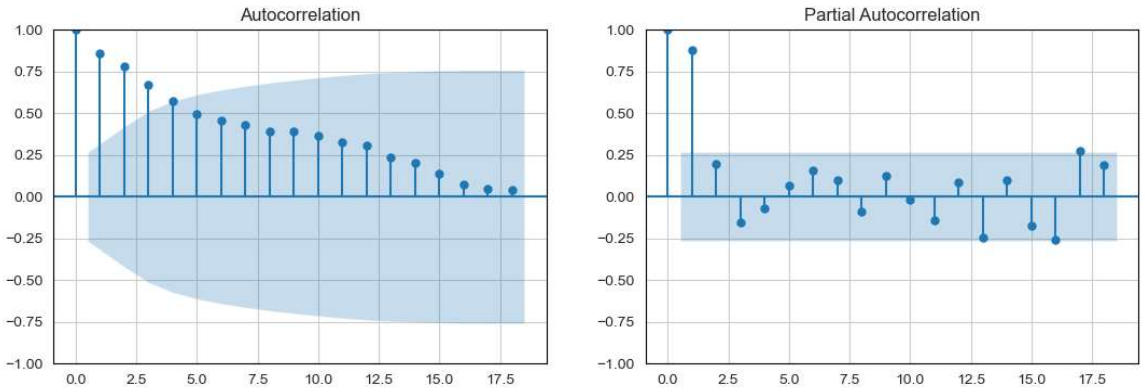
Mean is increasing , but standard deviation is decreasing year over year. Increasing mean indicates that series is not stationary, also as we move foward in time, variation in the total monthly sale is decreasing which is indicated by reducing standard deviation year over year.

In [43]:
```
print("Coefficient of Variation:",Train["CA_3"].std()/Train["CA_3"].mean())
```

```
Coefficient of Variation: 0.1605983240992905
```

This is a low variability process

In [44]:
```
fig,ax1=plt.subplots(figsize=(13,4),nrows=1,ncols=2)
plot_acf(Train["CA_3"],ax=ax1[0]);
plot_pacf(Train["CA_3"],ax=ax1[1]);
```



We can see that sales in the last 4 periods have significance in determining the sales in current period.

The pacf here cuts off after one lag.

The ACF model is also tapering down which in combination with PACF plot cutting off after a number of lags indicates an Auto Regressive Process

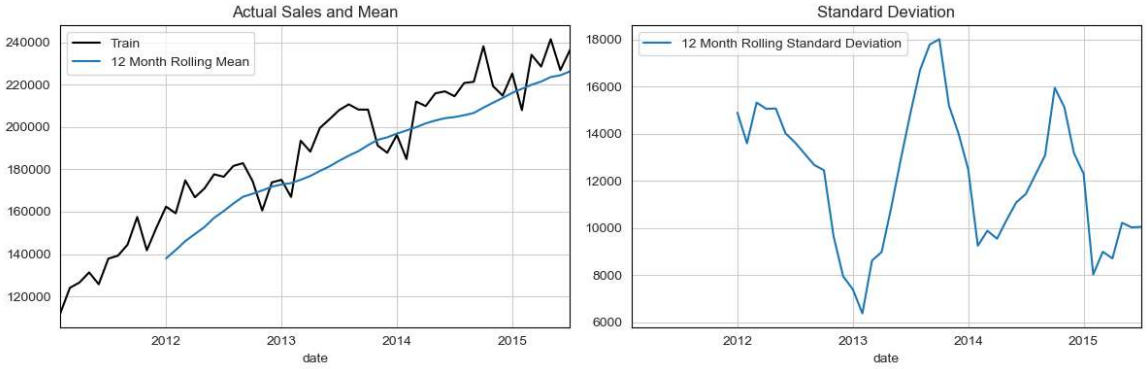
In [45]:
```
adf = adfuller(Train["CA_3"])[1]
print(f"p value:{adf.round(4)}", ", Series is Stationary" if adf <0.05 else ", S
```

```
p value:0.1219 , Series is Non-Stationary
```

2. **CA4**

In [46]:
```
fig,ax1=plt.subplots(figsize=(12,4),nrows=1,ncols=2)
Train["CA_4"].plot(ax=ax1[0],legend=True,label="Train",cmap="gray",title="Actual
Train["CA_4"].rolling(12,center=False).mean().plot(legend=True,ax=ax1[0],label="
Train["CA_4"].rolling(12,center=False).std().plot(ax=ax1[1],title="Standard Devi
fig.tight_layout()
print("Standard Deviation:",Train["CA_4"].std())
```

```
Standard Deviation: 33781.02481189229
```



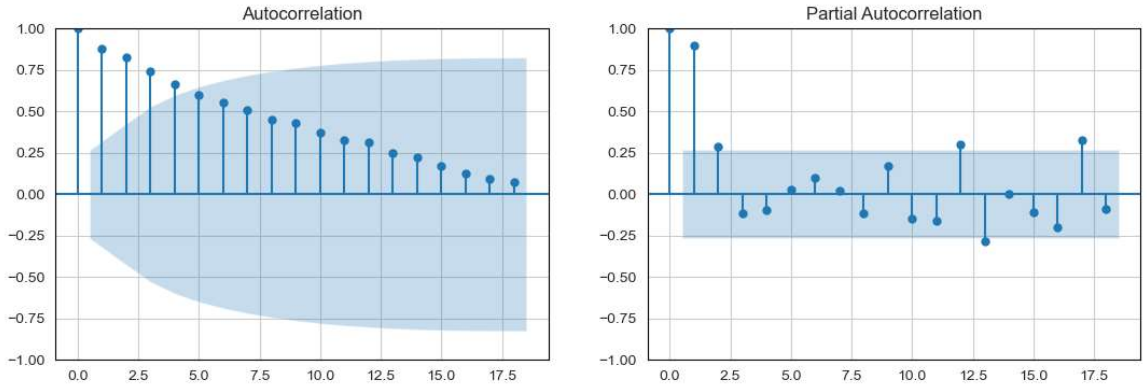
Mean is increasing , but standard deviation is decreasing year over year. Increasing mean indicates that series is not stationary, also as we move foward in time, variation in the total monthly sale is decreasing which is indicated by reducing standard deviation year over year.

In [47]:
```
print("Coefficient of Variation:",Train["CA_3"].std()/Train["CA_3"].mean())
```

```
Coefficient of Variation: 0.1605983240992905
```

This is a low variability process.

In [48]:
```
fig,ax1=plt.subplots(figsize=(13,4),nrows=1,ncols=2)
plot_acf(Train["CA_4"],ax=ax1[0]);
plot_pacf(Train["CA_4"],ax=ax1[1]);
```



We can see that last 4 periods have significance in determining the sales in current period.

The pacf here cuts off after one lag.

The ACF model is also tapering down which in combination with PACF plot cutting off after a number of lags indicates an Auto Regressive Process

In [49]:
```
adf = adfuller(Train["CA_4"])[1]
print(f"p value:{adf.round(4)}", ", Series is Stationary" if adf <0.05 else ", S
```

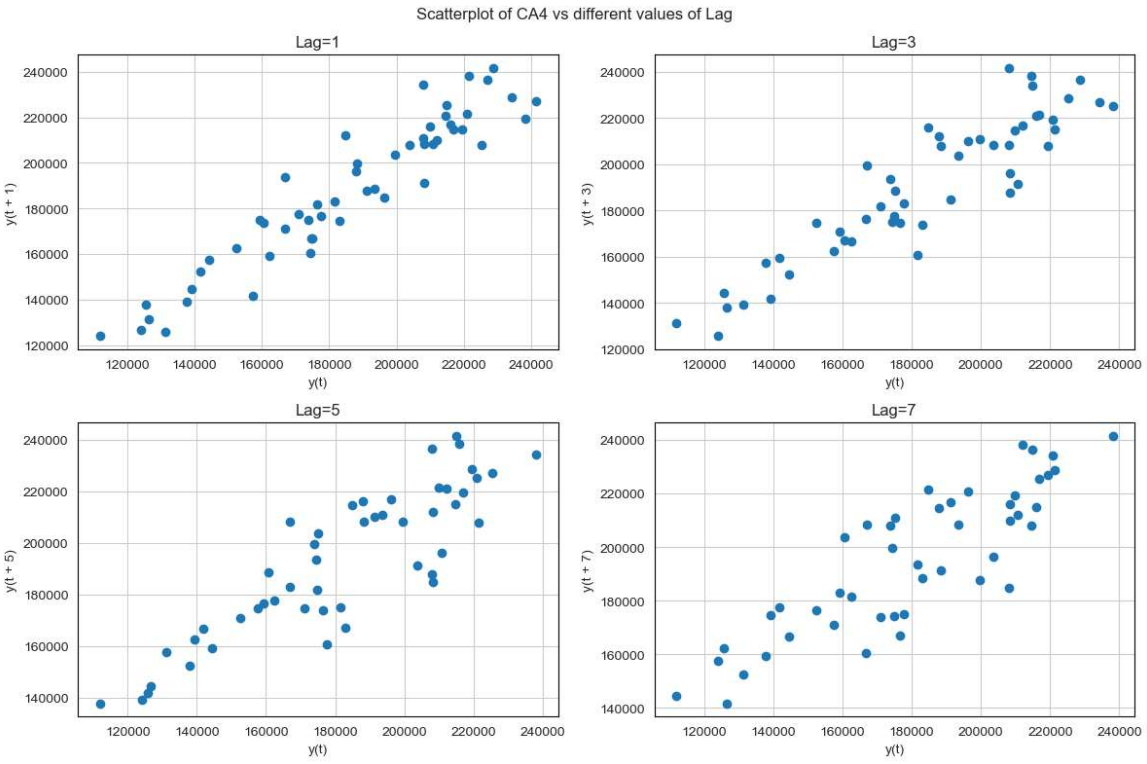
```
p value:0.2249 , Series is Non-Stationary
```

Lag Plot

Here we plot values in CA4 train dataset vs values at different lags. One thing you will observe is how the relationship gets weaker as number of lags increases.

This is also the finding of ACF plot that corelation between values decreases as lags increases for our time series data

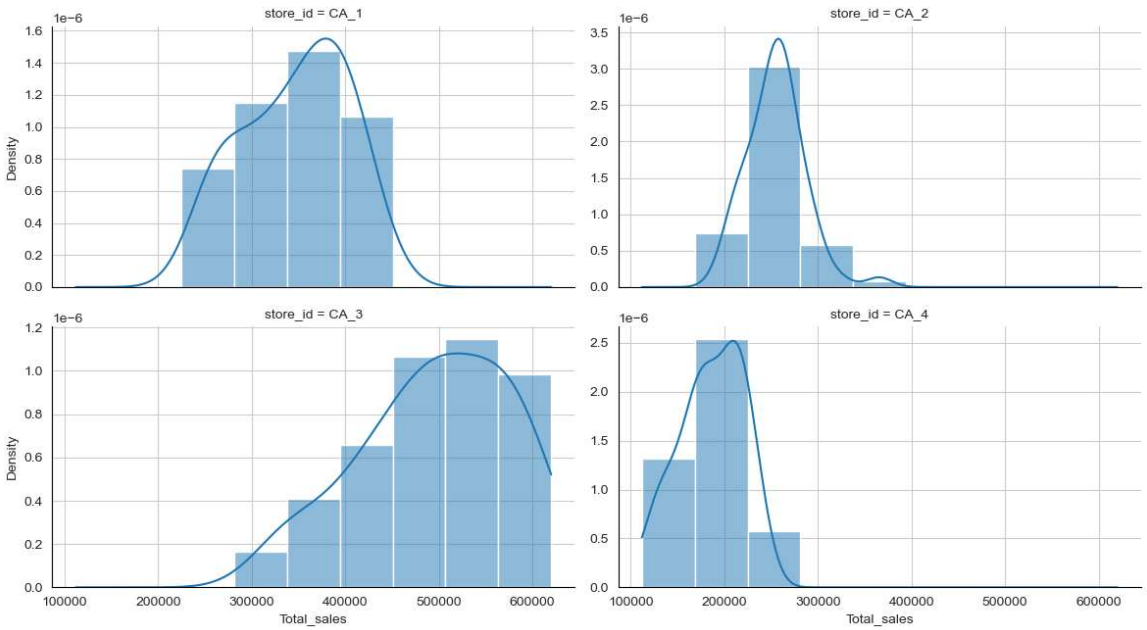
In [50]:
```
fig,ax=plt.subplots(figsize=(12,8),nrows=2,ncols=2)
fig.suptitle("Scatterplot of CA4 vs different values of Lag")
pd.plotting.lag_plot(Train["CA_4"],lag=1,ax=ax[0,0]).set_title("Lag=1")
pd.plotting.lag_plot(Train["CA_4"],lag=3,ax=ax[0,1]).set_title("Lag=3")
pd.plotting.lag_plot(Train["CA_4"],lag=5,ax=ax[1,0]).set_title("Lag=5")
pd.plotting.lag_plot(Train["CA_4"],lag=7,ax=ax[1,1]).set_title("Lag=7")
fig.tight_layout()
```



Distribution Plot - Is Our Series Normal ?

In [51]:
```
fg_obj=sns.displot(data=Train_ss[["store_id","Total_sales"]],
                   x="Total_sales",
                   kind="hist",
                   col="store_id",
                   col_wrap=2,
                   facet_kws={"sharex":True,"sharey":False},
```

```
            kde=True,
            stat="density",
            legend=True,
            height=3.3,
            aspect=1.8).tight_layout()
```



In [52]:
```
is_norm=pd.DataFrame(columns=["store_id","jb_p_value","Distribution"])
for i in ["CA_1","CA_2","CA_3","CA_4"]:
    p_value=jb(Train[i])[1]
    is_norm=pd.concat([is_norm,
                pd.DataFrame([{"store_id":i,
                               "jb_p_value":p_value,
                               "Distribution":"Normal" if p_value>0.05 else "Not
                             )],
                ignore_index=True)
is_norm
```

Out[52]:

	store_id	jb_p_value	Distribution
0	CA_1	0.228322	Normal
1	CA_2	0.003159	Not Normal
2	CA_3	0.255755	Normal
3	CA_4	0.266695	Normal

As mentioned above, series does not have to be Gaussian for accurate forecasting but if the data is highly skewed it can affect the model selection and forecast uncertainty.

We can use Box-Cox transformation to normalize our data.

Jarque Bera test shows the data if data is from normal distribution or not. p value of Jarque Bera test for CA1, CA3 and CA4 time series data show that they are normally distributed. Time Series data for store CA2 does not come from normal distribution according to Jarque Beta Test.

Model Fitting and Selection

Model Evaluation Functions

Different metrics to calculate accuracy MAPE(Mean Absolute Percent Error): This helps us to evaluates the accuracy of our model. The formula for this metric as follows:-

$$MAPE = \frac{\sum_{i=1}^{N} \frac{|ytrue_i - ypredicted_i|}{ytrue_i}}{N} * 100$$

RMSE(Root Mean Square Error): This is another metric we will be using to caculate accuracy. Formula for this metric is as follows:

$$RMSE = \sqrt{\sum_{i=1}^{n} (predicted_i - actual_i)^2}$$

Residual Evaluation

We will be checking whether residuals are normal, statinary, corelated using Jarque Bera Test, AdFuller Test, Ljung Box Test respectively.

We will also plot residuals, ACF and kde plot of residuals.

In [53]:
```
def MAPE(y_true,y_pred):
    ytrue,ypred=np.array(y_true),np.array(y_pred)
    accuracy_df=pd.DataFrame()
    MAPE1=np.round(np.mean(np.abs(ytrue-ypred)/ytrue)*100,1)
    return MAPE1

def accuracy(y_true,y_pred):
    ytrue,ypred=np.array(y_true),np.array(y_pred)
    MAPE1=MAPE(y_true,y_pred)
    rmse_r=np.round(rmse(ytrue,ypred),1)
    return pd.DataFrame({"RMSE":[rmse_r],"MAPE":[MAPE1]})

def residualcheck(residuals, lags):

    resid_mean=np.mean(residuals)
    ljp_valve=np.mean(ljung(x=residuals,lags=lags,return_df=False)[1])
    adfuller1=adfuller(residuals)[1]
    isnorm=jb(residuals)[1]

    fig = plt.figure(figsize=(8,6))
    layout = (2, 2)
    ts_ax = plt.subplot2grid(layout,(0,0),colspan=2)
    acf_ax = plt.subplot2grid(layout, (1, 0));
    kde_ax = plt.subplot2grid(layout, (1, 1));

    residuals.plot(ax=ts_ax)
    plot_acf(residuals, lags=lags, ax=acf_ax);
    sns.kdeplot(residuals,ax=kde_ax);
    sns.despine()
    plt.tight_layout();

    print("** Mean of the residuals: ", np.around(resid_mean,2))
```

```
    print("\n** Ljung Box Test, p-value:", ljp_valve, "(>0.05, Uncorrelated)" if

    print("\n** Jarque Bera Normality Test, p_value:", np.around(isnorm,3), "(>0

    print("\n** AD Fuller, p_value:", adfuller1, "(>0.05, Non-stationary)" if (a


    return ts_ax, acf_ax, kde_ax
```

Seasonal Naive Forecast

This is the simplest method available for forecasting.

In this forecasting technique, Forecast for a season in the current period would be equal to the value for same season in the last period. For e.g, The number of Ice Cream Baskin Robbins will be selling in May 2023 would be equal to the number of Ice Creams Baskin Robbins sold in May 2022.

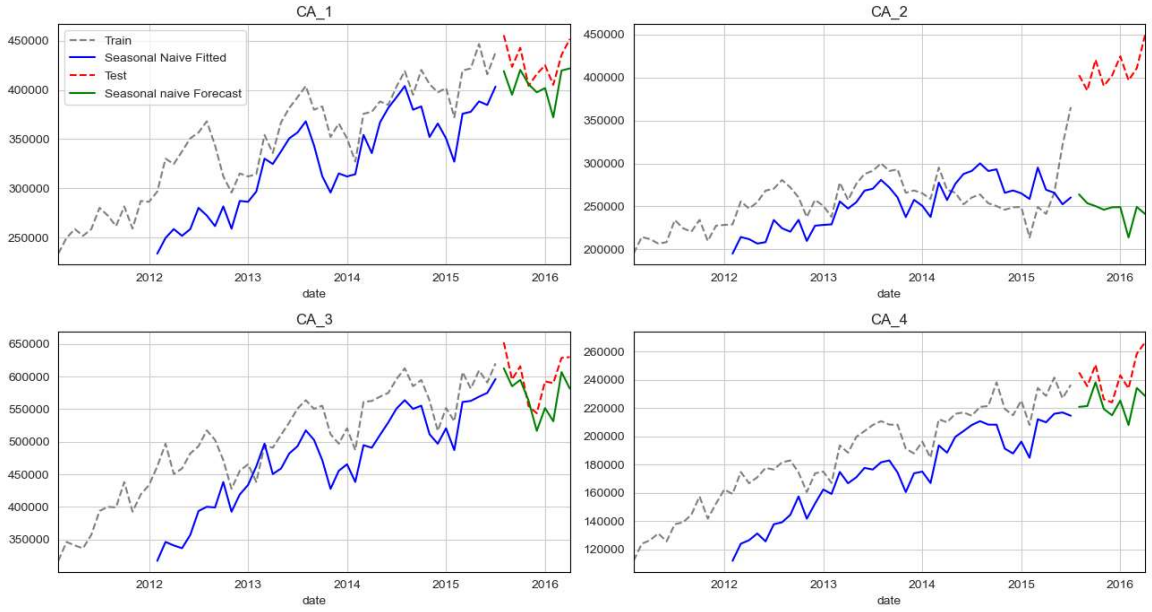
This is an different version of naive forecast where we directly use sale value in last period as forecast for next period.

In [54]:
```
Model_Performance=pd.DataFrame(columns=["store_id","Forecast Method","MAPE","RMS
store_list=["CA_1","CA_2","CA_3","CA_4"]
```

In [55]:
```
def snaive(train,seasons,forecast_horizon):
    if len(train)>forecast_horizon:
        last_season=train[-seasons:]
        reps=int(np.ceil(forecast_horizon/seasons))
        fc= np.tile(last_season,reps)
        forecast=fc[:forecast_horizon]
        fitted=train.shift(seasons)
        return forecast,fitted
    else:
        return "error"
```

In [56]:
```
predicted_naive=pd.DataFrame(columns=store_list)
fit_naive=pd.DataFrame(columns=store_list)
for i in store_list:
    forecast,fit=snaive(Train[i],12,9)
    predicted_naive[i]=forecast
    fit_naive[i]=fit
predicted_naive.set_index(Test.index,inplace=True)
fit_naive.set_index(Train.index,inplace=True)
```

In [57]:
```
fig,ax=plt.subplots(figsize=(13,7),nrows=2,ncols=2)
for i, axs in enumerate(ax.flat):
    Train["CA_"+str(i+1)].plot(style="--", color="gray",legend=(i==0), label="Tr
    fit_naive["CA_"+str(i+1)].dropna().plot(color="b",legend=(i==0) ,label="Seas
    Test["CA_"+str(i+1)].plot(style="--",color="r", legend=(i==0),label="Test",a
    predicted_naive["CA_"+str(i+1)].plot(color="g",legend=(i==0) ,label="Seasona
#handles, labels = ax[0,0].get_legend_handles_labels()
#fig.legend(handles, labels,bbox_to_anchor=(0.975,0.85,0.1,0.04))
fig.tight_layout()
```



In [58]:
```
for i in store_list:
    temp=pd.DataFrame({"store_id":i,
                       "Forecast Method":"Seasonal Naive",
                       "MAPE":accuracy(Test[i],predicted_naive[i]).MAPE,
                       "RMSE":accuracy(Test[i],predicted_naive[i]).RMSE})
    Model_Performance=pd.concat([Model_Performance,temp],axis=0,ignore_index=Tru
```

In [59]:
```
Model_Performance
```

Out[59]:

	store_id	Forecast Method	MAPE	RMSE
0	CA_1	Seasonal Naive	5.4	25314.8
1	CA_2	Seasonal Naive	39.6	164229.7
2	CA_3	Seasonal Naive	5.1	34676.5
3	CA_4	Seasonal Naive	7.8	21282.6

The forecast for CA1, CA3 and CA4 are able to catch the trend approximately. But for CA2 the error in forecast is quite large.

MAPE in the range of 5.4% to 7.1% is quite low when we consider the simplicity of this model.

For CA2 as there is sudden spike in sales, the model is not able to predict it

RMSE for CA1, CA3 and CA4 is less than the standard deviation of 56545.06, 79672.36 and 33781.02.

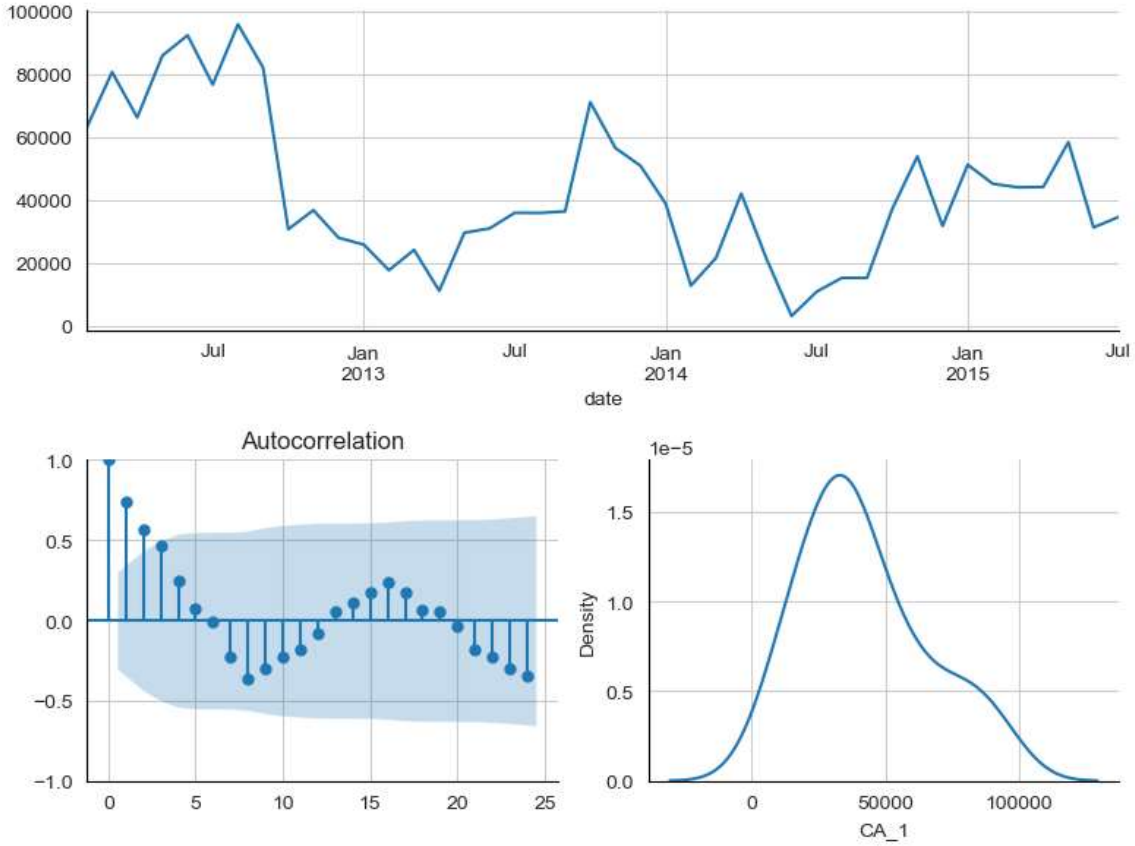
There is underfitting in prediction (Forecast being less than the actual value). However, that can be solved by adding the mean of error back to forecast.

In [60]:
```
residual_naive=[(Train[i]-fit_naive[i]).dropna() for i in store_list]
```

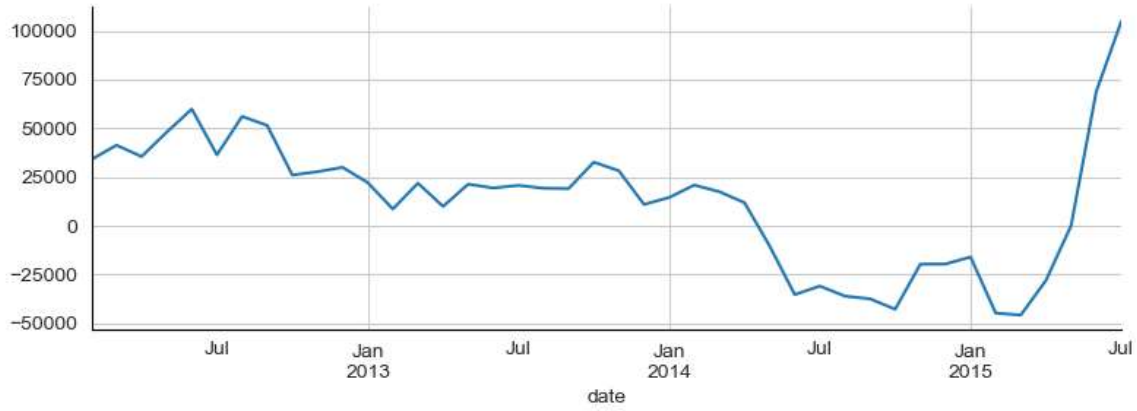
In [61]:
```
for i in range(len(store_list)):
    print("\n Store Name CA_"+str(i+1))
```

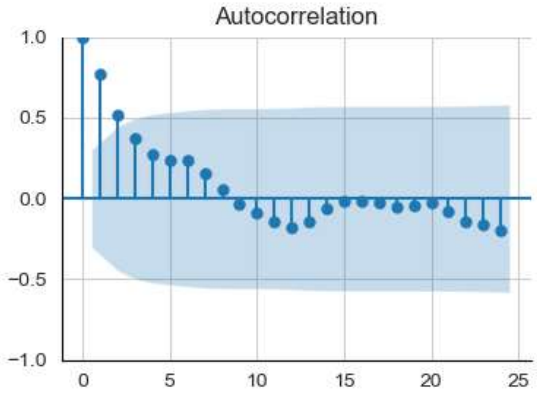
```
    residualcheck(residual_naive[i],24);
    plt.show()
```

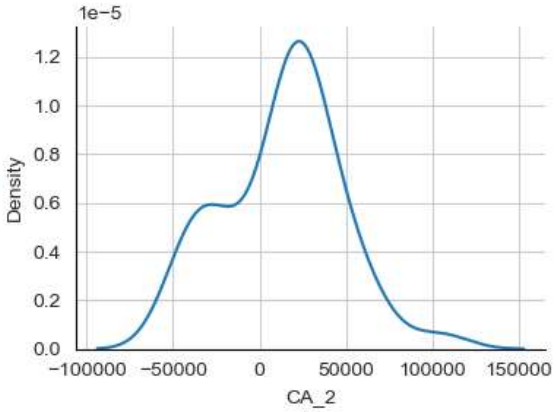
```
 Store Name CA_1
** Mean of the residuals:  42221.23

** Ljung Box Test, p-value: 2.5329639694110823e-08 (<0.05, Correlated)

** Jarque Bera Normality Test, p_value: 0.222 (>0.05, Normal)

** AD Fuller, p_value: 0.1333306043364812 (>0.05, Non-stationary)
```




```
 Store Name CA_2
** Mean of the residuals:  13164.13

** Ljung Box Test, p-value: 1.053449095990822e-06 (<0.05, Correlated)

** Jarque Bera Normality Test, p_value: 0.984 (>0.05, Normal)

** AD Fuller, p_value: 0.4753513194974987 (>0.05, Non-stationary)
```





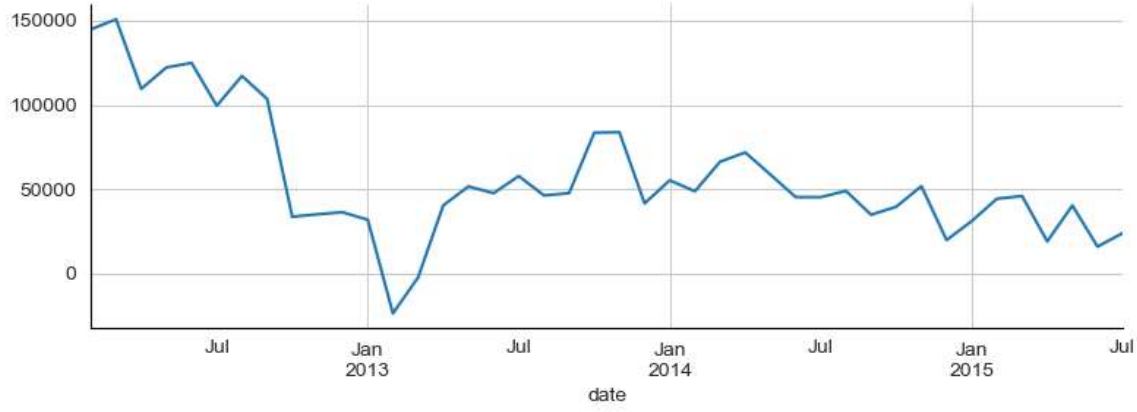


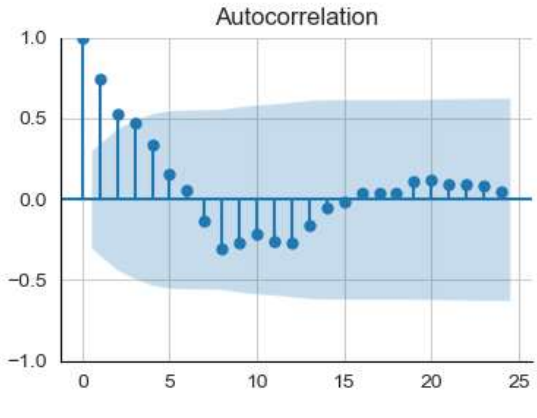
Store Name CA_3
** Mean of the residuals: 56885.09

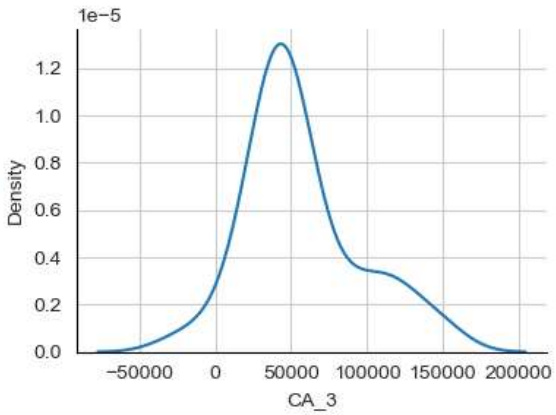
** Ljung Box Test, p-value: 2.7839058618955288e-08 (<0.05, Correlated)

** Jarque Bera Normality Test, p_value: 0.126 (>0.05, Normal)

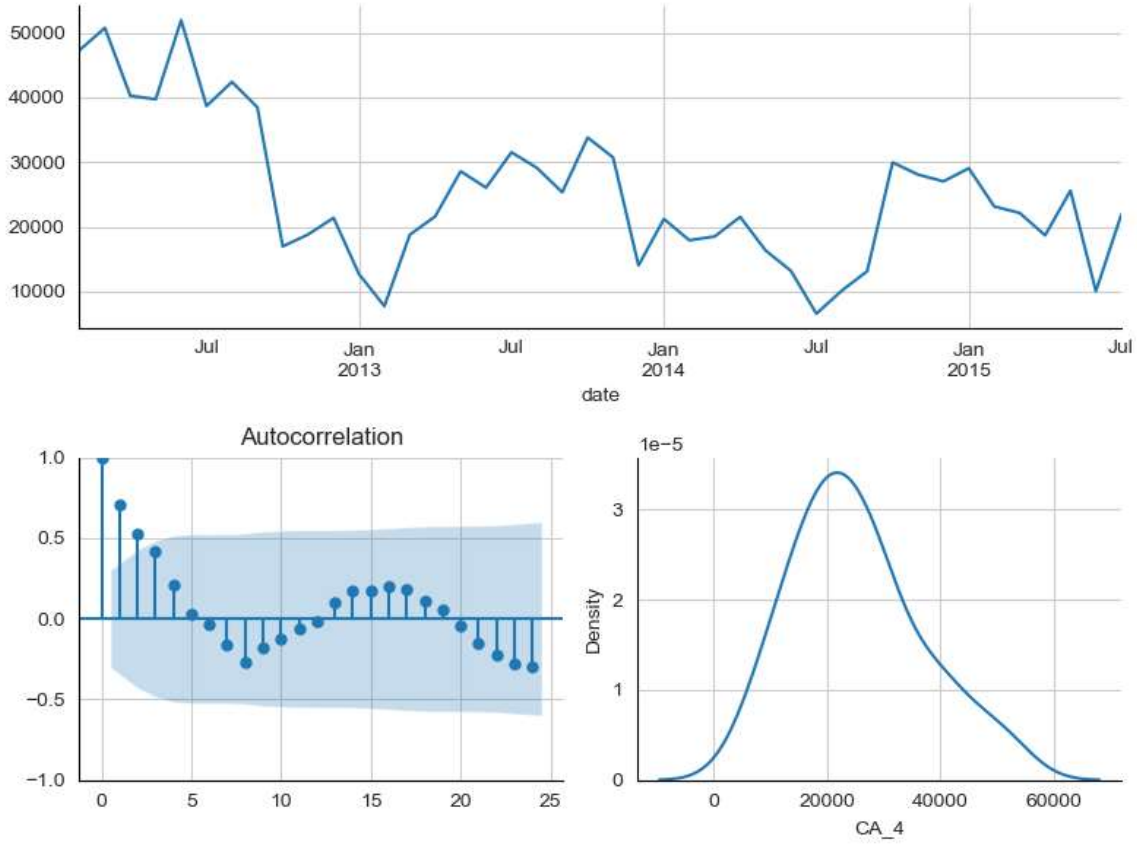
** AD Fuller, p_value: 0.06965858660922292 (>0.05, Non-stationary)







```
 Store Name CA_4
** Mean of the residuals:  25244.22

** Ljung Box Test, p-value: 3.000268725488574e-07 (<0.05, Correlated)

** Jarque Bera Normality Test, p_value: 0.287 (>0.05, Normal)

** AD Fuller, p_value: 0.05207218876434996 (>0.05, Non-stationary)
```



The residuals are Corelated, Non Stationary and Normal for all the stores.

This means that there is some structured information in the residuals which are not able to extract. The trend and seasonality has not been captured completely.

This is not a useful model on its own but we can use Seasonal Naive model in combination with other models to improve our accuracy.

HoltsWinter Exponential Smoothing Model

This is forecasting method that has been in used for decades. It still extensively used today. It is also called Triple Exponetial Smoothing method because it tries to estimate three smoothing parameters alpha,beta and gamma for three components of time series i.e Level,Trend and Seasonality.

- Level: Level is the average value around which time series varies in a full season. Alpha is the smoothing factor for level and tells the model how much of the past we have to give importance. It has value between 0 and 1. If the value of alpha is 1 then only last data point is used in caculating the forecast and if it is near 0 then all the past data points would have some effect on the forecast.

- Trend: Trend is the change in base level or average level over time. Trend can be additive or multiplicative. Additive trend means that base level increases linearly where as in multiplicative trend the base level increases exponentially. Beta is the smoothing factor for Trend, and it tells us how much of past trend in time series data model will be consider while making the forecast. If trend value is closer to 1 then only recent trend will be consider in making the forecast. We can also have damping parameter(phi) for trend which tells model to forget particular anount of recent trend.

- Seasonality: Seasonality is the number of periods in full season. For example, Monthly seasonality in Annual Data is 12, Weekly sesonality of annual data would be 52, Hourly seasonality for daily data is 24, Daily seasonality for weekly data would be 7. Gamma is the smoothing factor for seasonality. Seasonality can also be multiplicative or additive. - In additive seasonality, we will add the seasonal factor while making forecast, for e.g for a particular store in may month we usually get 300K worth extra sales as compared to average. So we will add 300K worth of extra sales to the average level. - In multiplicative seasonality we will multiply with seasonal factor, for e.g, for a particular store in july month we usually we get 15% less sale as compared to average. So we will multiply average sale with (1-0.15) while making forecast.

The Holts Winter Algorithm is based on the principle that future values can be calculated by studying the history.

We will be using ExponentialSmoothing() from statsmodels.tsa.holtwinters package for calculating the best values for these three smoothing parameters for our time series data and then building a model using those parameters.

A more thorough explanation for Holts Winter method can be found in this medium article.

In [62]:
```
def HoltsWinterGrid(train,test,seasonal_periods):
    trend=["add","mul"]
    seasonal=["add","mul"]
    damped=[False,True]
    use_boxcox=[True,False,"log"]

    params=itertools.product(trend,seasonal,damped,use_boxcox)
    result_df=pd.DataFrame(columns=["Trend","Seasonal","Damped","Box_Cox","AICc_
                                    "RMSE_Train","MAPE_Test","RMSE_Test","lj_resi
                                    "resid_mean"])

    for trend,seasonal,damped,boxcox in params:
        if boxcox!="log":
            model=ExponentialSmoothing(train,
                                       trend=trend,
                                       seasonal=seasonal,
                                       damped_trend=damped,
                                       seasonal_periods=seasonal_periods,
                                       use_boxcox=boxcox,
                                       initialization_method="heuristic",
                                       freq='MS').fit()
```

```
            MAPE_Train=MAPE(train,model.fittedvalues)
            rmse_train=rmse(train,model.fittedvalues)

            MAPE_Test=MAPE(test,model.forecast(len(test)))
            rmse_test=rmse(test,model.forecast(len(test)))
            resid=model.resid

        else:
            trainlog=np.log(train)
            model=ExponentialSmoothing(trainlog,
                                       trend=trend,
                                       seasonal=seasonal,
                                       damped_trend=damped,
                                       seasonal_periods=seasonal_periods,
                                       use_boxcox=False,
                                       initialization_method="heuristic",
                                       freq='MS').fit()

            MAPE_Train=MAPE(train,np.exp(model.fittedvalues))
            rmse_train=rmse(train,np.exp(model.fittedvalues))

            MAPE_Test=MAPE(test,np.exp(model.forecast(len(test))))
            rmse_test=rmse(test,np.exp(model.forecast(len(test))))
            resid=train-np.exp(model.fittedvalues)


        ljp_p_val=np.mean(ljung(resid,lags=20,return_df=False)[1])
        norm_p=jb(resid)[1]
        lj_residual="Uncorrelated" if ljp_p_val>0.05 else "Corelated"
        norm_p="Normal" if norm_p>0.05 else "Not Normal"

        Aicc=model.aicc.round(1)

        result_df = pd.concat([result_df,
                               pd.DataFrame({
                                   'Trend':[trend],
                                   'Seasonal': [seasonal],
                                   'Damped':[damped],
                                   'Box_Cox':[boxcox],
                                   'MAPE_Train':[np.round(MAPE_Train,2)],
                                   'RMSE_Train':[np.round(rmse_train,1)],
                                   'AICc_Train':[Aicc],
                                   'MAPE_Test':[np.round(MAPE_Test,2)],
                                   'RMSE_Test':[np.round(rmse_test,1)],
                                   'lj_residual' :[lj_residual],
                                   'jb_norm_residual':[norm_p],
                                   'resid_mean':[np.round(resid.mean(),1)]})] ,
                               ignore_index=True,
                               sort=False)

    return result_df.sort_values(by=["RMSE_Test","MAPE_Test","RMSE_Train","MAPE_
```

HWGrid:

We will loop through different combination of values that different arguements of ExponentialSmoothing function can take. For e.g Trend can be additive or multiplicative, we can use boxcox transformation for normalizing our data or we can also use log of our values to reduce the complexity of model(This results in less AICc and more efficient

model as you will observe when you read further),seasonal can also be additive or multiplicative.

We have prepared HWgrid function to loop through each combination and give the accuracy as well as AICc.

The AICc tries to give us the best model based on two parameters,i.e, fit of the model and the number of parameters. Lower the AICc for different models trained using the same dataset, more efficient the model is. **We are going to select the model with the lowest RMSE, but if two models have almost the same RMSE, then model with lower AIcc would be preferred.**

As model fits better AICc decreases but also as the number of parameters increases AICc also increases.

In [63]:
```
HW_model_all=pd.DataFrame()
HW_model_best=pd.DataFrame()
for i,j in enumerate(store_list):
    temp2=HoltsWinterGrid(Train[j], Test[j], seasonal_periods=12)
    temp2["store_id"]=j
    HW_model_all=pd.concat([HW_model_all,temp2],ignore_index=True)
    HW_model_best=pd.concat([HW_model_best,temp2.head(1)],ignore_index=True)
```

In [64]:
```
HW_model_all[HW_model_all["store_id"]=="CA_2"]
```

Out[64]:

	Trend	Seasonal	Damped	Box_Cox	AICc_Train	MAPE_Train	RMSE_Train	MAPE_Test
24	mul	add	False	True	1069.9	3.2	12451.8	1.190000e+01
25	mul	mul	True	log	-284.6	3.2	11276.1	1.000000e+01
26	add	mul	False	True	1063.7	3.3	11756.2	1.370000e+01
27	mul	add	False	log	-289.4	3.2	11272.1	1.400000e+01
28	add	mul	True	True	1068.9	3.4	11792.7	1.410000e+01
29	add	add	False	log	-289.4	3.2	11271.6	1.410000e+01
30	mul	mul	False	log	-289.5	3.2	11250.7	1.420000e+01
31	add	mul	False	log	-289.5	3.2	11249.7	1.430000e+01
32	mul	mul	False	True	1067.5	3.2	12176.3	1.420000e+01
33	add	add	False	True	1067.5	3.2	12174.2	1.420000e+01
34	add	add	True	log	-284.4	3.2	11297.4	1.480000e+01
35	add	mul	True	log	-284.6	3.2	11275.5	1.490000e+01
36	add	add	True	True	1070.1	3.2	11928.1	1.580000e+01
37	add	mul	True	False	1073.4	3.6	12301.6	3.200000e+01
38	add	mul	False	False	1068.8	3.6	12319.5	3.400000e+01
39	add	add	True	False	1076.0	3.7	12591.2	3.850000e+01
40	add	add	False	False	1071.3	3.7	12611.2	3.850000e+01
41	mul	mul	True	False	1071.7	3.5	12108.7	6.020000e+01
42	mul	mul	False	False	1067.1	3.5	12125.2	6.530000e+01
43	mul	add	False	False	1069.7	3.7	12418.5	7.980000e+01
44	mul	add	True	False	1074.4	3.7	12408.2	8.370000e+01
45	mul	add	True	log	23.0	108.2	276330.9	1.187737e+09
46	mul	mul	True	True	1070.2	3.2	11938.8	NaN
47	mul	add	True	True	NaN	NaN	NaN	NaN

Above are the results for models with different parameters for store CA2.

The RMSE of 54227 and MAPE Test of 11.9% is very less when compared to seasonal naive forecast which had an RMSE of 164229.7 and MAPE test of 39%. This shows that model was able to capture Trend and seasonality more precintly than seasonal naive model.

One more thing to observe here is the low AICC we get when we use log transformation. The RMSE Test only slightly increases for CA2 from 54227 to 57115. MAPE test is actually smaller. So we can give preference to this model because we get massive decrease in AICc score after trading sligthly for accuracy.

In [65]:
```
HW_model_best=HW_model_best.set_index("store_id")
```

```
HW_model_best
```

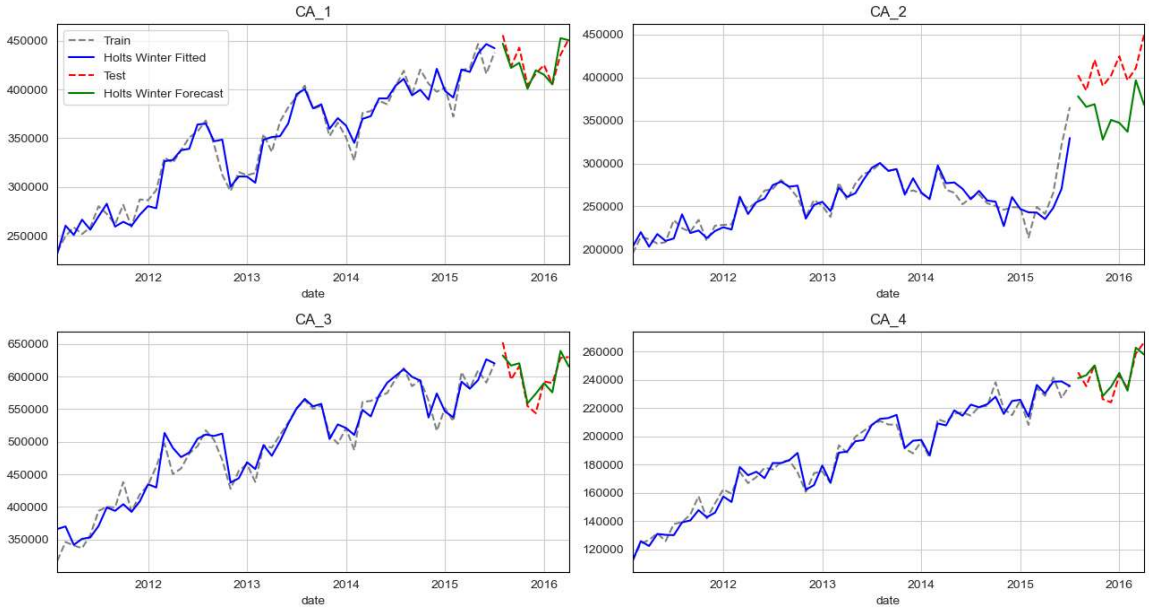
Out[65]:

store_id	Trend	Seasonal	Damped	Box_Cox	AICc_Train	MAPE_Train	RMSE_Train	MAPE_Tes
CA_1	mul	add	False	log	-312.1	2.6	11757.9	1.
CA_2	mul	add	False	True	1069.9	3.2	12451.8	11.
CA_3	mul	mul	False	False	1115.4	2.8	18960.7	2.
CA_4	add	mul	False	log	-332.2	2.2	5205.9	1.

These are the best Holts Winter Exponential smoothing model selected for each store based on RMSE Test values. We will predict the values using these Holts Winter model for each store. Then we will plot them to see how well they fit.

In [66]:
```
predicted_HW=pd.DataFrame(columns=store_list)
fit_HW=pd.DataFrame(columns=store_list)
for i in store_list:
    if HW_model_best.loc[i].Box_Cox!="log":
            model=ExponentialSmoothing(Train[i],
                                       trend=HW_model_best.loc[i].Trend,
                                       seasonal=HW_model_best.loc[i].Seasonal,
                                       damped_trend=HW_model_best.loc[i].Damped,
                                       seasonal_periods=12,
                                       use_boxcox=HW_model_best.loc[i].Box_Cox,
                                       initialization_method="heuristic",
                                       freq='MS').fit()

            fit_HW[i]=model.fittedvalues
            predicted_HW[i]=model.forecast(len(Test))

    else:
            model=ExponentialSmoothing(np.log(Train[i]),
                                       trend=HW_model_best.loc[i].Trend,
                                       seasonal=HW_model_best.loc[i].Seasonal,
                                       damped_trend=HW_model_best.loc[i].Damped,
                                       seasonal_periods=12,
                                       use_boxcox=False,
                                       initialization_method="heuristic",
                                       freq='MS').fit()
            fit_HW[i]=np.exp(model.fittedvalues)
            predicted_HW[i]=np.exp(model.forecast(len(Test)))
```

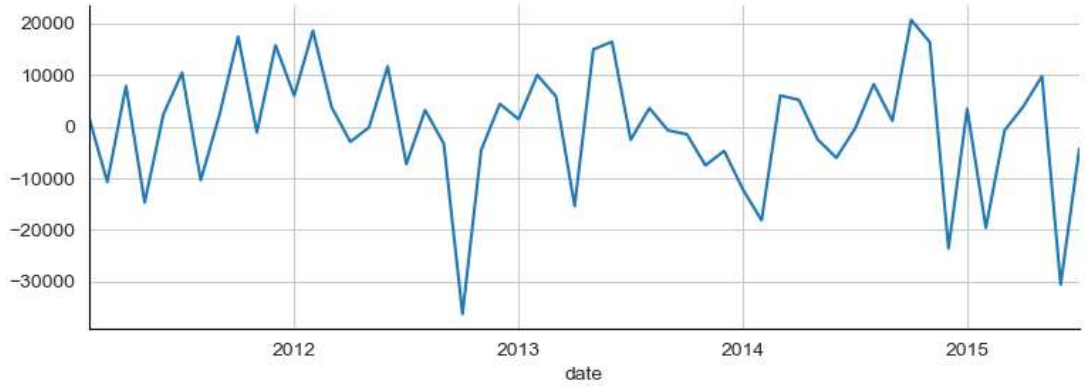
In [67]:
```
fig,ax=plt.subplots(figsize=(13,7),nrows=2,ncols=2)
for i, axs in enumerate(ax.flat):
    Train["CA_"+str(i+1)].plot(style="--", color="gray",legend=(i==0), label="Tr
    fit_HW["CA_"+str(i+1)].dropna().plot(color="b",legend=(i==0) ,label="Holts W
    Test["CA_"+str(i+1)].plot(style="--",color="r", legend=(i==0),label="Test",a
    predicted_HW["CA_"+str(i+1)].plot(color="g",legend=(i==0) ,label="Holts Wint
#handles, labels = ax[0,0].get_legend_handles_labels()
#fig.legend(handles, labels,bbox_to_anchor=(0.975,0.85,0.1,0.04))
fig.tight_layout()
```

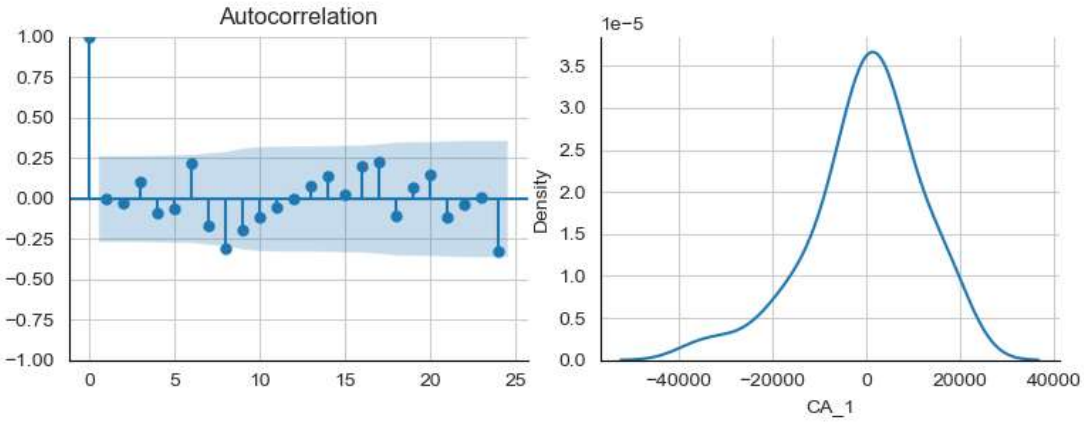


The seasonality and trend has been captured quite accurately for CA1, CA3 and CA4. For CA2, predicted values and test values are nearer to each but there is underfitting in data.

In [68]:
```
residual_HW=[(Train[i]-fit_HW[i]).dropna() for i in store_list]
for i in range(len(store_list)):
    print("\n Store Name CA_"+str(i+1))
    residualcheck(residual_HW[i],24);
    plt.show()
```

```
 Store Name CA_1
** Mean of the residuals:  -160.87

** Ljung Box Test, p-value: 0.3391165129820508 (>0.05, Uncorrelated)

** Jarque Bera Normality Test, p_value: 0.029 (<0.05, Not-normal)

** AD Fuller, p_value: 0.0011746043099081281 (<0.05, Stationary)
```



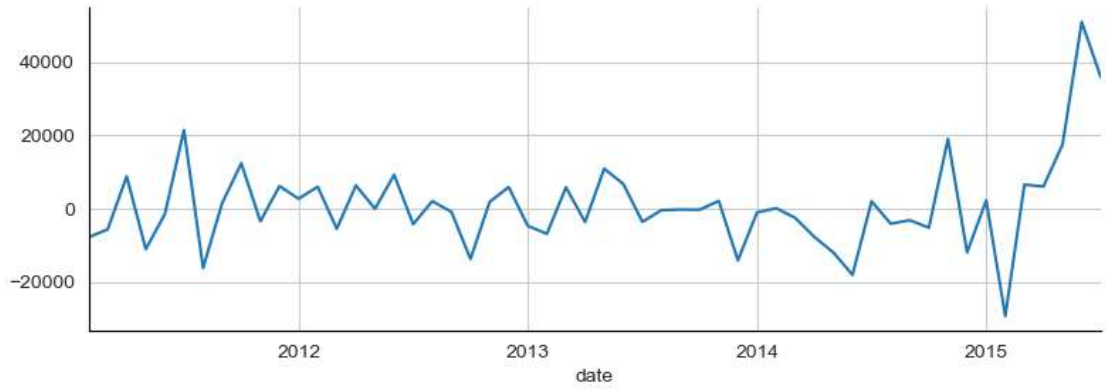


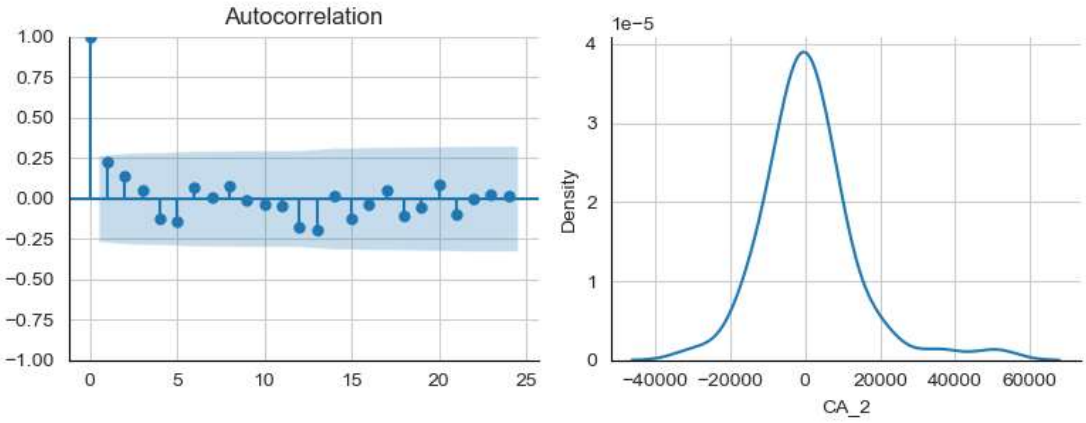
Store Name CA_2
** Mean of the residuals: 969.38

** Ljung Box Test, p-value: 0.5612631619287036 (>0.05, Uncorrelated)

** Jarque Bera Normality Test, p_value: 0.0 (<0.05, Not-normal)

** AD Fuller, p_value: 0.2605410198754875 (>0.05, Non-stationary)



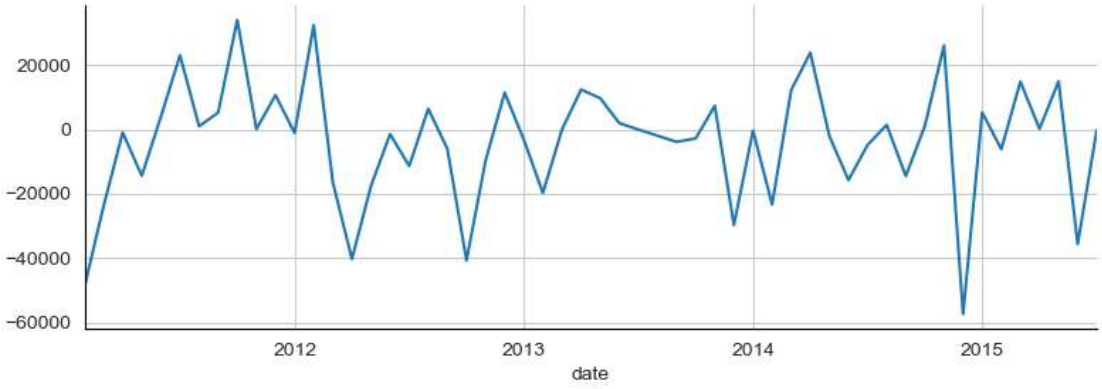


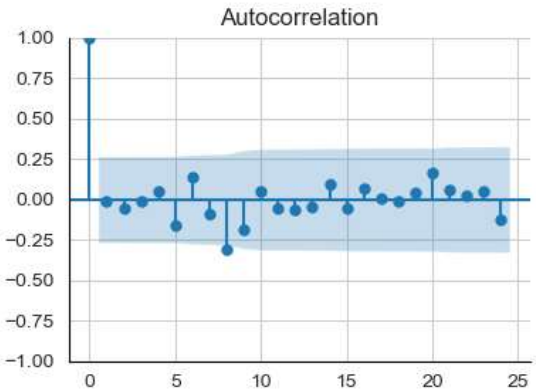
Store Name CA_3
** Mean of the residuals: -3600.42

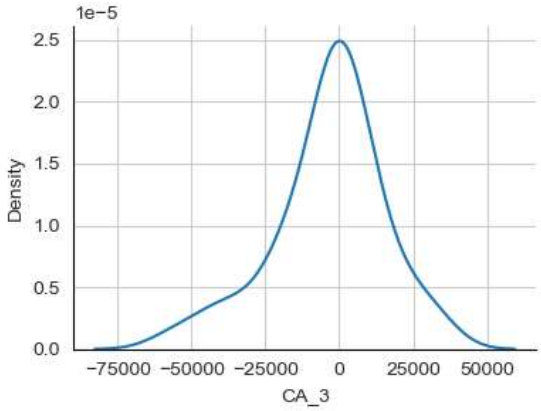
** Ljung Box Test, p-value: 0.6474385003166877 (>0.05, Uncorrelated)

** Jarque Bera Normality Test, p_value: 0.078 (>0.05, Normal)

** AD Fuller, p_value: 1.5026041884388735e-11 (<0.05, Stationary)





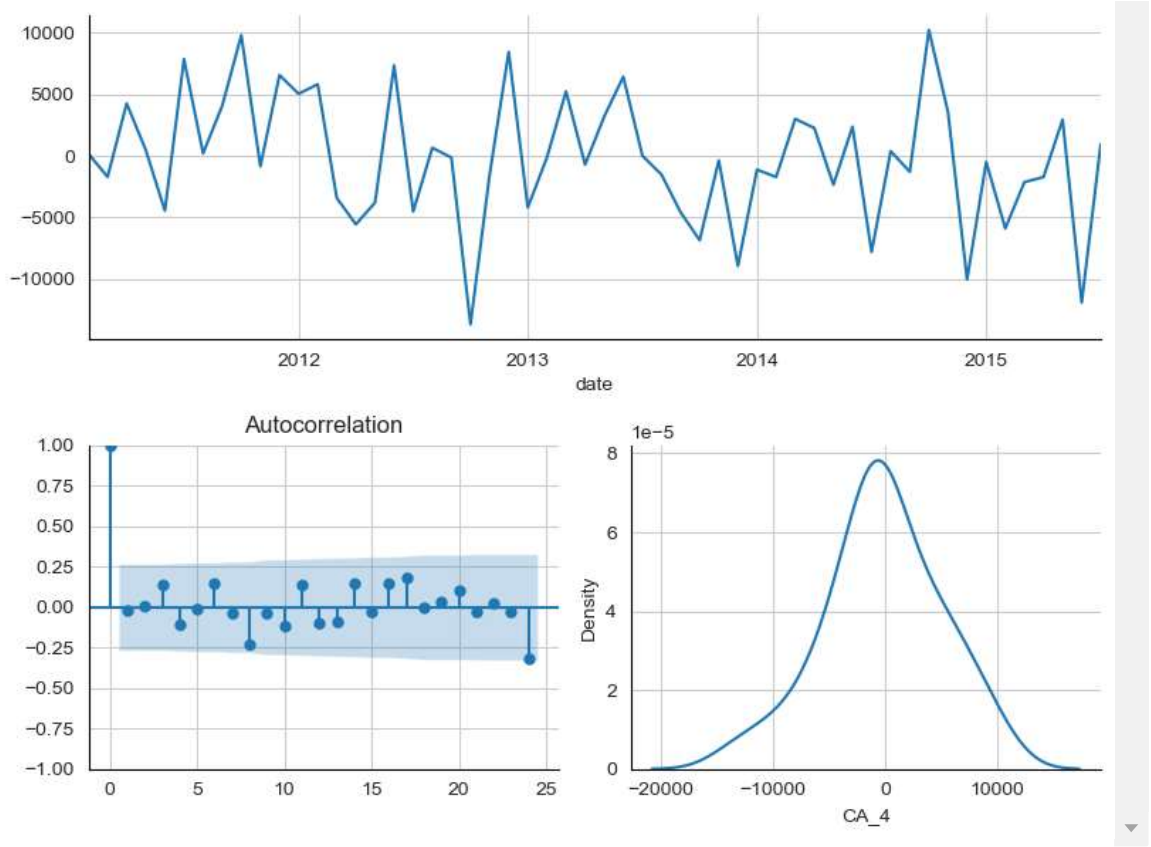


Store Name CA_4
** Mean of the residuals: -228.32

** Ljung Box Test, p-value: 0.6733261133680206 (>0.05, Uncorrelated)

** Jarque Bera Normality Test, p_value: 0.766 (>0.05, Normal)

** AD Fuller, p_value: 1.6937796180642248e-10 (<0.05, Stationary)



For CA1, residuals are Uncorelated, Not Normal and Stationary.

For CA2 residuals are uncorelated,not normal and non stationary. This may be due to the sudden increase in sale at the end.

For CA3 and CA4, residuals are uncorelated, normal and stationary.

In [69]:
```
for i in store_list:
    if HW_model_best.loc[i].Box_Cox=="log":
        model_name="Holts-Winter Log"
    elif HW_model_best.loc[i].Box_Cox==True:
        model_name="Holts-Winter Box-Cox"
    else:
        model_name="Holts-Winter"
    temp=pd.DataFrame({"store_id":i,
                  "Forecast Method":model_name,
                  "MAPE":accuracy(Test[i],predicted_HW[i]).MAPE,
                  "RMSE":accuracy(Test[i],predicted_HW[i]).RMSE})
    Model_Performance=pd.concat([Model_Performance,temp],axis=0,ignore_index=Tru
```

In [70]:
```
Model_Performance
```

Out[70]:

	store_id	Forecast Method	MAPE	RMSE
0	CA_1	Seasonal Naive	5.4	25314.8
1	CA_2	Seasonal Naive	39.6	164229.7
2	CA_3	Seasonal Naive	5.1	34676.5
3	CA_4	Seasonal Naive	7.8	21282.6
4	CA_1	Holts-Winter Log	1.6	9057.5
5	CA_2	Holts-Winter Box-Cox	11.9	54227.2
6	CA_3	Holts-Winter	2.3	16106.3
7	CA_4	Holts-Winter Log	1.9	5780.3

ETS Model Statespace Aproach Log

We will used ETS model which are similar to Holts Winter model but the difference lies in the framework they use identify the best parameters for the model.

ETS models decompose the time series into three components in 3 parts Error, Trend and Seasonality. It uses state space statistical framework to identify the statistical process and then make forecast.

Statsmodel statespace package has ExponentialSmoothing method we can use to make model for our time series data. We will first make model on log values.

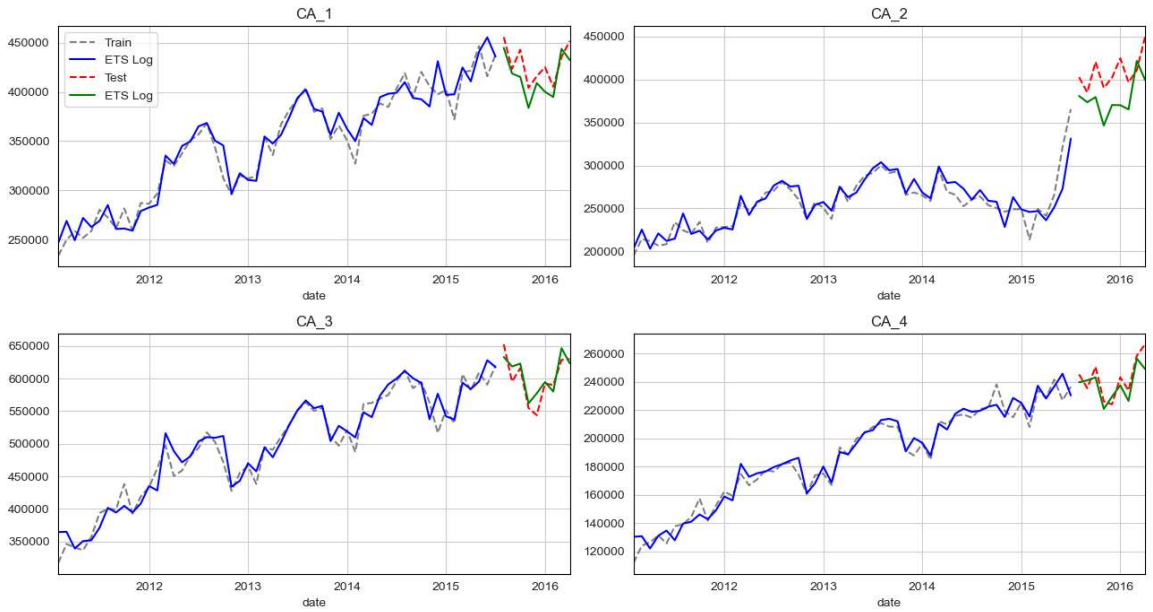
In ETS algorithms, different components can take following values Error(E): Additive(A) or Multiplicative(M) Trend(T): Additive(A), No Trend(N), Multiplicative(M), Damped(Ad) Seasonality: Null(N), Additive(A) or Multiplicative(M)

However, in statsmodel.tsa.statespace.ExponentialSmoothing only has Additive Error, Additive or Damped Trend Models.

In [71]:
```
predicted_ETSL=pd.DataFrame(columns=store_list)
fit_ETSL=pd.DataFrame(columns=store_list)
resid_ETSL=pd.DataFrame(columns=store_list)
ETSL_models=[]
for i in store_list:
    ets_LAdA=sm.tsa.statespace.ExponentialSmoothing(np.log(Train[i]),
                                                    trend=True,
                                                    initialization_method= 'heuristic
                                                    seasonal=12,
                                                    damped_trend=False).fit()

    predicted_ETSL[i] = np.exp(ets_LAdA.forecast(len(Test[i])))
    fit_ETSL[i]=np.exp(ets_LAdA.fittedvalues)
    resid_ETSL[i]=Train[i]-fit_ETSL[i]
    ETSL_models.append(ets_LAdA)
```

In [72]:
```
fig,ax=plt.subplots(figsize=(13,7),nrows=2,ncols=2)
for i, axs in enumerate(ax.flat):
    Train["CA_"+str(i+1)].plot(style="--", color="gray",legend=(i==0), label="Tr
    fit_ETSL["CA_"+str(i+1)].dropna().plot(color="b",legend=(i==0) ,label="ETS L
```

```
    Test["CA_"+str(i+1)].plot(style="--",color="r", legend=(i==0),label="Test",a
    predicted_ETSL["CA_"+str(i+1)].plot(color="g",legend=(i==0) ,label="ETS Log"
#handles, labels = ax[0,0].get_legend_handles_labels()
#fig.legend(handles, labels,bbox_to_anchor=(0.975,0.85,0.1,0.04))
fig.tight_layout()
```



In [73]:
```
for i in store_list:
    model_name="ETS Log"
    temp=pd.DataFrame({"store_id":i,
                       "Forecast Method":model_name,
                       "MAPE":accuracy(Test[i],predicted_ETSL[i]).MAPE,
                       "RMSE":accuracy(Test[i],predicted_ETSL[i]).RMSE})
    Model_Performance=pd.concat([Model_Performance,temp],axis=0,ignore_index=Tru
```

In [74]:
```
Model_Performance
```

Out[74]:

	store_id	Forecast Method	MAPE	RMSE
0	CA_1	Seasonal Naive	5.4	25314.8
1	CA_2	Seasonal Naive	39.6	164229.7
2	CA_3	Seasonal Naive	5.1	34676.5
3	CA_4	Seasonal Naive	7.8	21282.6
4	CA_1	Holts-Winter Log	1.6	9057.5
5	CA_2	Holts-Winter Box-Cox	11.9	54227.2
6	CA_3	Holts-Winter	2.3	16106.3
7	CA_4	Holts-Winter Log	1.9	5780.3
8	CA_1	ETS Log	3.5	16821.5
9	CA_2	ETS Log	8.0	36155.5
10	CA_3	ETS Log	2.4	16981.6
11	CA_4	ETS Log	2.8	7953.6

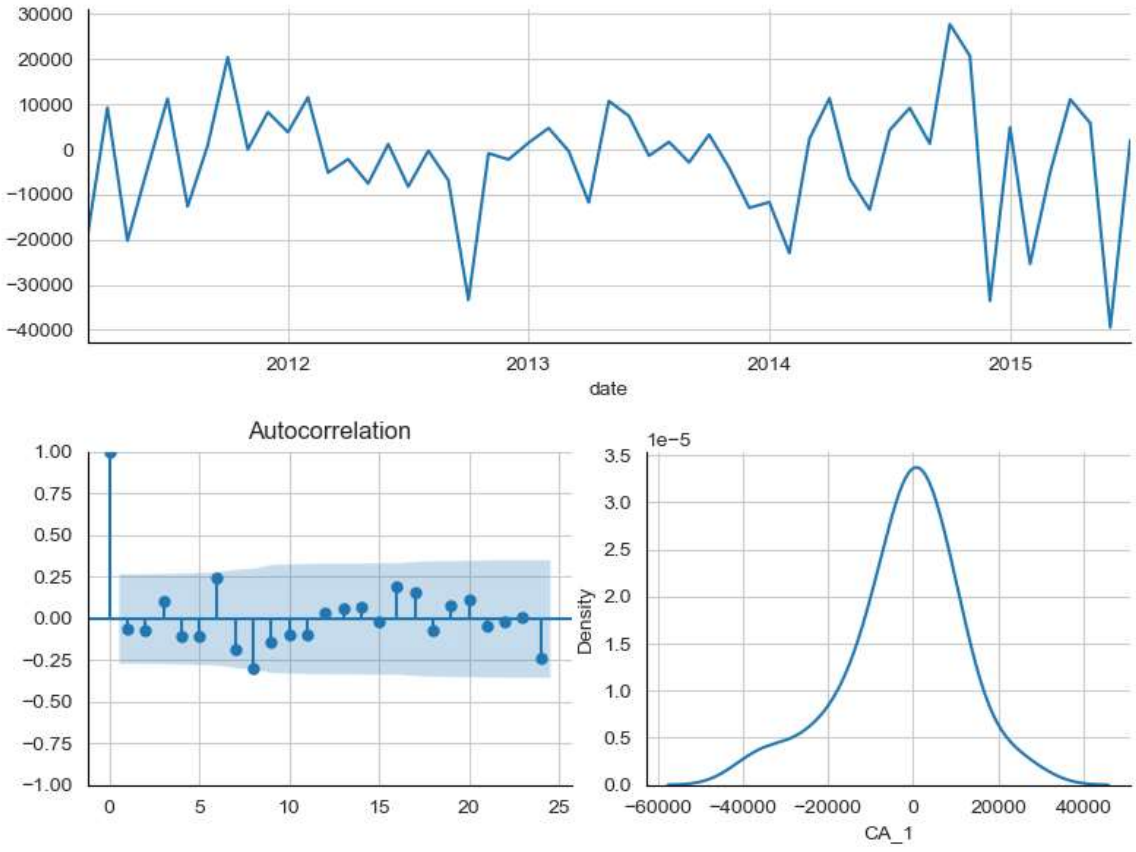
For CA1, CA3, and CA4 model captures trend and seasonality quite well, however they perform worse than their Holts Winter Counterpart.

However CA3, the difference in RMSE test in not that large and since ETS model will have lower AICc, we can consider that model over Holts Winter model.

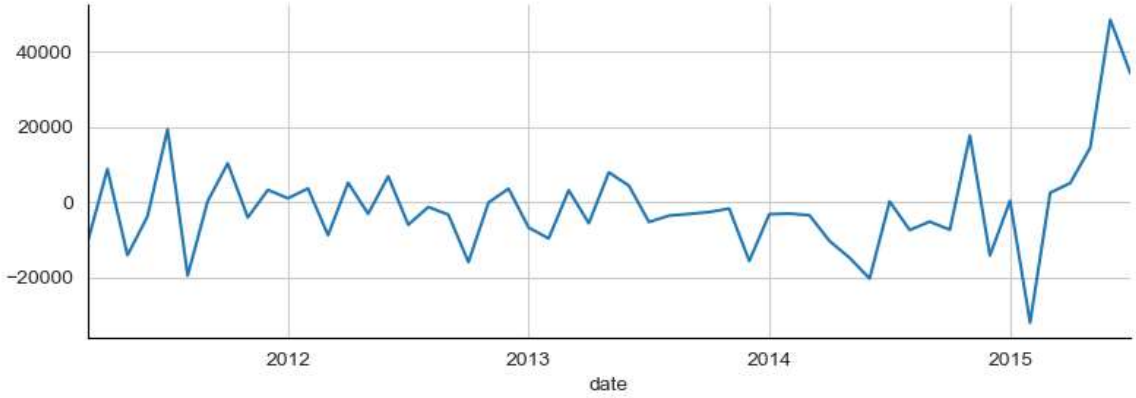
For CA2, model is performing better than Holts winter, which we can observe in the plot by looking at the improved fit and also by seeing lower RMSE test and MAPE test for the model.

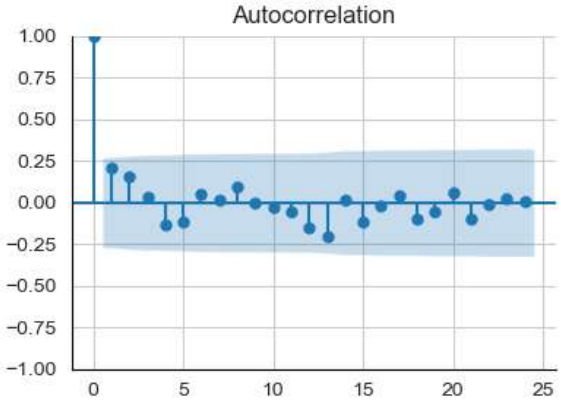
In [75]:
```
residual_ETSL=[(Train[i][1:]-fit_ETSL[i][1:]).dropna() for i in store_list]
for i in range(len(store_list)):
    print("\n Store Name CA_"+str(i+1))
    residualcheck(residual_ETSL[i],24);
    plt.show()
```

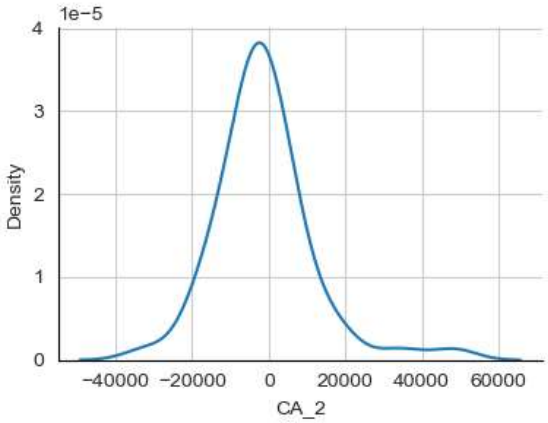
```
 Store Name CA_1
** Mean of the residuals:  -2225.43

** Ljung Box Test, p-value: 0.3232928805476591 (>0.05, Uncorrelated)

** Jarque Bera Normality Test, p_value: 0.075 (>0.05, Normal)

** AD Fuller, p_value: 0.000299732122087529 (<0.05, Stationary)
```




```
 Store Name CA_2
** Mean of the residuals:  -1249.26

** Ljung Box Test, p-value: 0.6254637997908613 (>0.05, Uncorrelated)

** Jarque Bera Normality Test, p_value: 0.0 (<0.05, Not-normal)

** AD Fuller, p_value: 0.32827827661110076 (>0.05, Non-stationary)
```





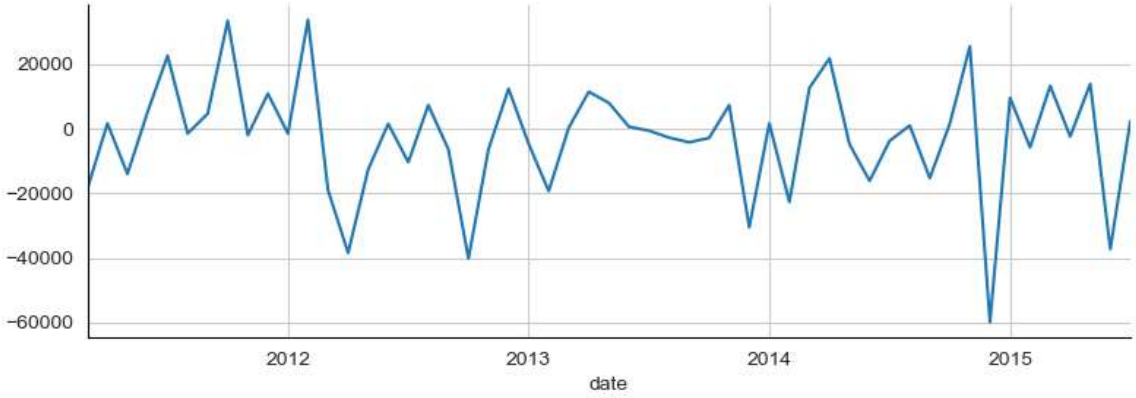


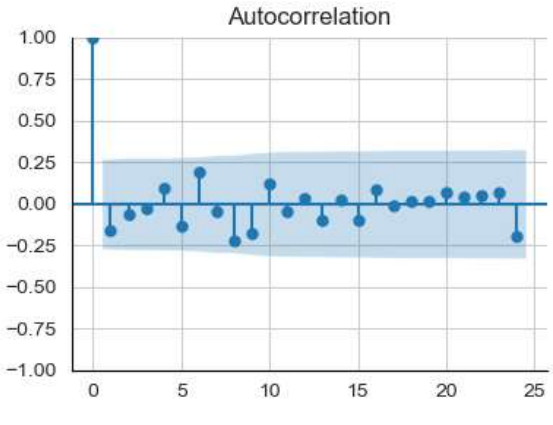
Store Name CA_3
** Mean of the residuals: -2607.21

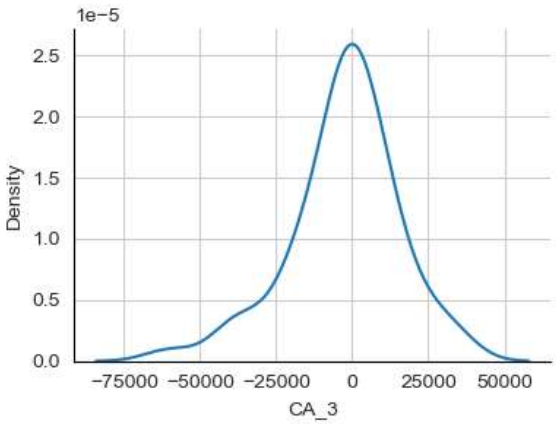
** Ljung Box Test, p-value: 0.5696067573583276 (>0.05, Uncorrelated)

** Jarque Bera Normality Test, p_value: 0.02 (<0.05, Not-normal)

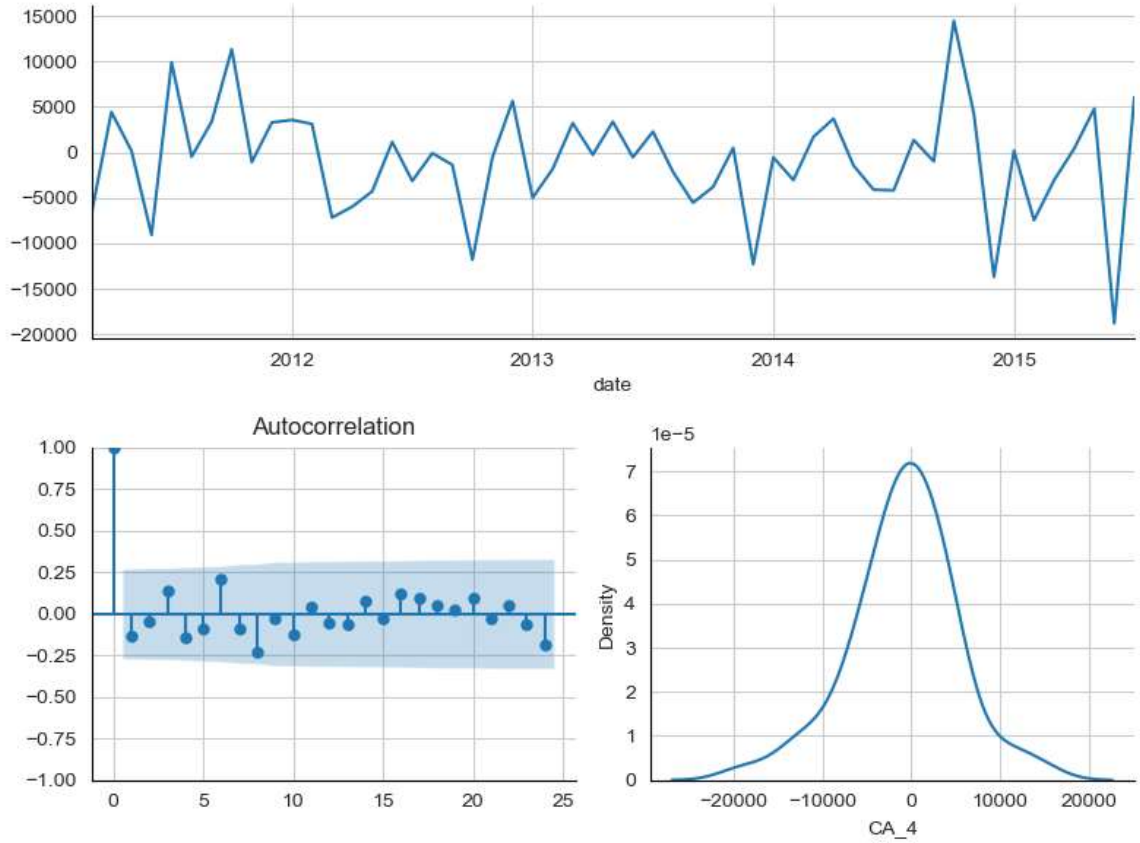
** AD Fuller, p_value: 0.003621473389802574 (<0.05, Stationary)







```
 Store Name CA_4
** Mean of the residuals:  -901.91

** Ljung Box Test, p-value: 0.5357758816786781 (>0.05, Uncorrelated)

** Jarque Bera Normality Test, p_value: 0.166 (>0.05, Normal)

** AD Fuller, p_value: 1.3764063135674395e-12 (<0.05, Stationary)
```



For CA1 and CA4, residuals are Uncorelated, Normal and Stationary.

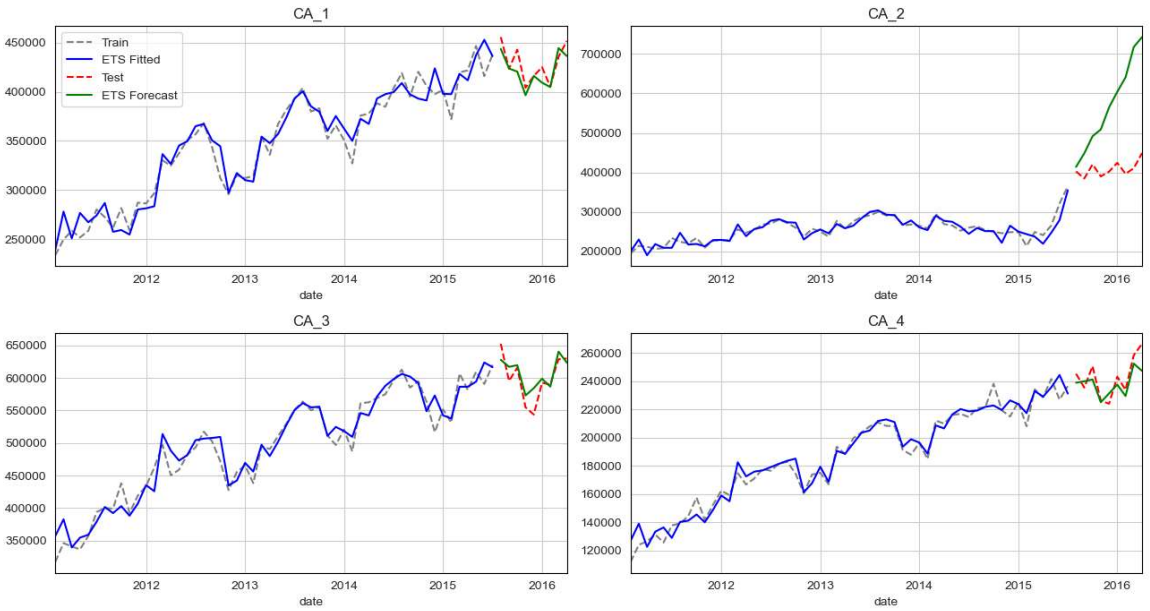
For CA2 residuals are uncorelated,not normal and non stationary. Non Stationarity may be due to the sudden increase in sale at the end.

For CA3, residuals are uncorelated, not normal and stationary.

ETS Model

In [76]:
```
predicted_ETS=pd.DataFrame(columns=store_list)
fit_ETS=pd.DataFrame(columns=store_list)
resid_ETS=pd.DataFrame(columns=store_list)
ETS_models=[]
for i in store_list:
    ets_AdA=sm.tsa.statespace.ExponentialSmoothing(Train[i],
                                                   trend=True,
                                                   initialization_method= 'heuristic
                                                   seasonal=12,
                                                   damped_trend=False).fit()

    predicted_ETS[i] = ets_AdA.forecast(len(Test[i]))
    fit_ETS[i]=ets_AdA.fittedvalues
    resid_ETS[i]=Train[i]-fit_ETS[i]
    ETS_models.append(ets_AdA)
```

In [77]:
```
fig,ax=plt.subplots(figsize=(13,7),nrows=2,ncols=2)
for i, axs in enumerate(ax.flat):
    Train["CA_"+str(i+1)].plot(style="--", color="gray",legend=(i==0), label="Tr
    fit_ETS["CA_"+str(i+1)].dropna().plot(color="b",legend=(i==0) ,label="ETS Fi
    Test["CA_"+str(i+1)].plot(style="--",color="r", legend=(i==0),label="Test",a
    predicted_ETS["CA_"+str(i+1)].plot(color="g",legend=(i==0) ,label="ETS Forec
#handles, labels = ax[0,0].get_legend_handles_labels()
#fig.legend(handles, labels,bbox_to_anchor=(0.975,0.85,0.1,0.04))
fig.tight_layout()
```



In [78]:
```
for i in store_list:
    model_name="ETS"
    temp=pd.DataFrame({"store_id":i,
                       "Forecast Method":model_name,
                       "MAPE":accuracy(Test[i],predicted_ETS[i]).MAPE,
                       "RMSE":accuracy(Test[i],predicted_ETS[i]).RMSE})
    Model_Performance=pd.concat([Model_Performance,temp],axis=0,ignore_index=Tru
```

In [79]:
```
Model_Performance
```

Out[79]:

	store_id	Forecast Method	MAPE	RMSE
0	CA_1	Seasonal Naive	5.4	25314.8
1	CA_2	Seasonal Naive	39.6	164229.7
2	CA_3	Seasonal Naive	5.1	34676.5
3	CA_4	Seasonal Naive	7.8	21282.6
4	CA_1	Holts-Winter Log	1.6	9057.5
5	CA_2	Holts-Winter Box-Cox	11.9	54227.2
6	CA_3	Holts-Winter	2.3	16106.3
7	CA_4	Holts-Winter Log	1.9	5780.3
8	CA_1	ETS Log	3.5	16821.5
9	CA_2	ETS Log	8.0	36155.5
10	CA_3	ETS Log	2.4	16981.6
11	CA_4	ETS Log	2.8	7953.6
12	CA_1	ETS	2.1	11887.0
13	CA_2	ETS	39.0	189053.3
14	CA_3	ETS	2.6	19131.5
15	CA_4	ETS	2.9	8546.3

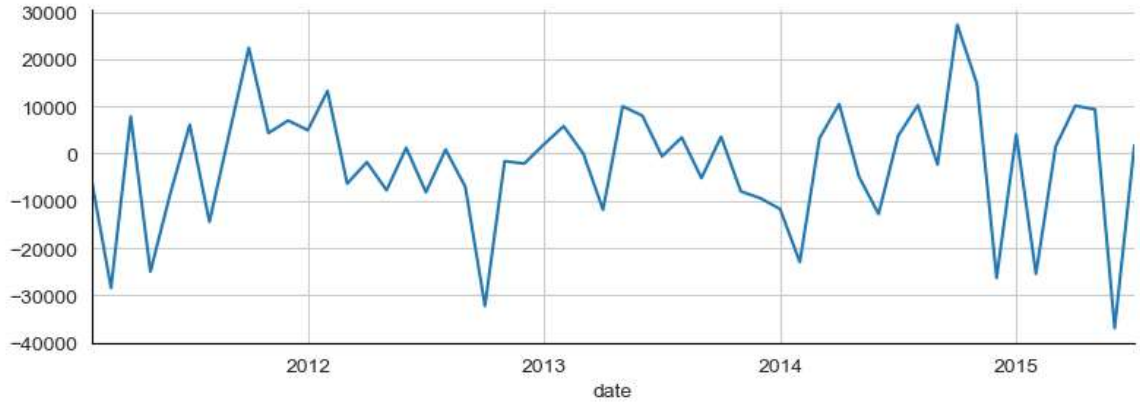
For CA1, ETS model perform better than the ETS log and Seasonal naive model, however, it perform worse than the Holts Winter model.

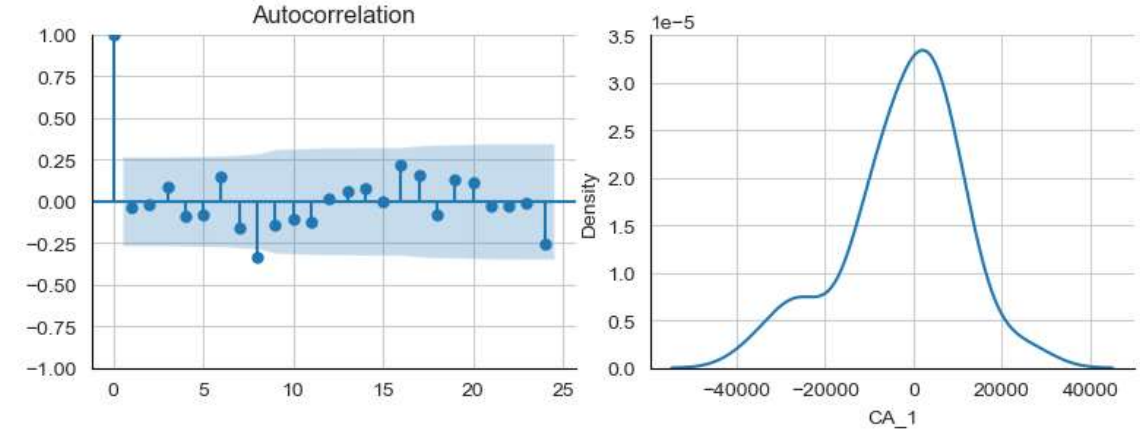
For CA2, ETS model is quite terrible and almost equal to seasonal naive model.

For CA3 and CA4, models catches trend and seasonality quite well but is not better than Holts Winter or ETS log models.

In [80]:
```
#residual_ETSL=[(Train[i][1:]-fit_ETSL[i][1:]).dropna() for i in store_list]
for i in range(len(store_list)):
    print("\n Store Name CA_"+str(i+1))
    residualcheck(resid_ETS["CA_"+str(i+1)],24);
    plt.show()
```

```
 Store Name CA_1
** Mean of the residuals:  -2336.81

** Ljung Box Test, p-value: 0.42762734396272367 (>0.05, Uncorrelated)

** Jarque Bera Normality Test, p_value: 0.152 (>0.05, Normal)

** AD Fuller, p_value: 0.00033648412573639283 (<0.05, Stationary)
```



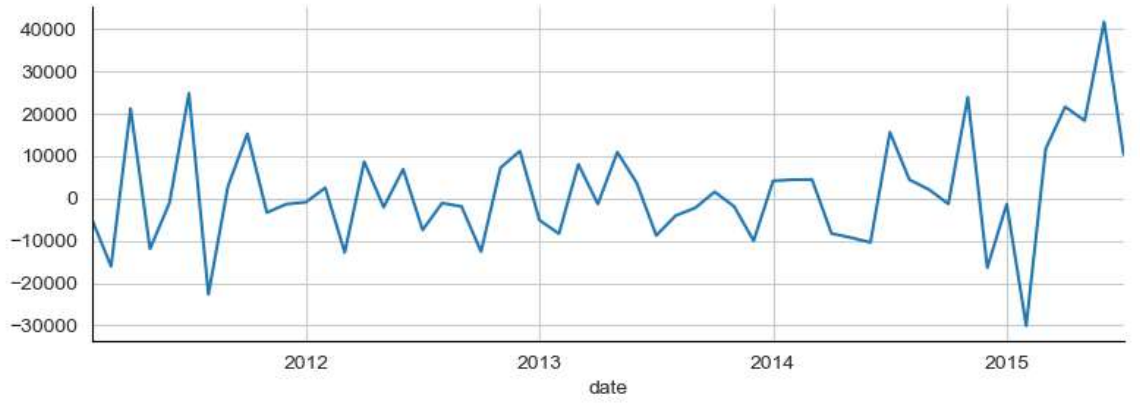


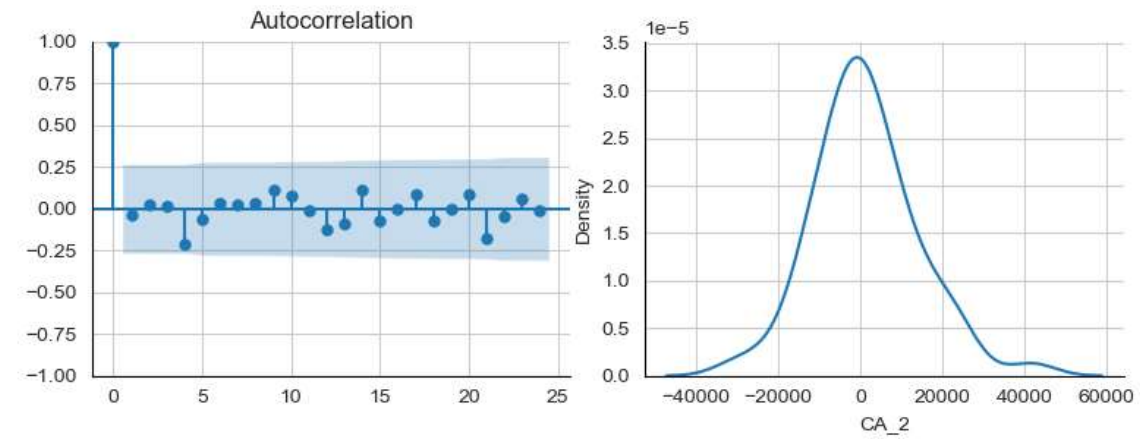
Store Name CA_2
** Mean of the residuals: 1301.44

** Ljung Box Test, p-value: 0.90564627512732 (>0.05, Uncorrelated)

** Jarque Bera Normality Test, p_value: 0.093 (>0.05, Normal)

** AD Fuller, p_value: 8.380714734792096e-11 (<0.05, Stationary)



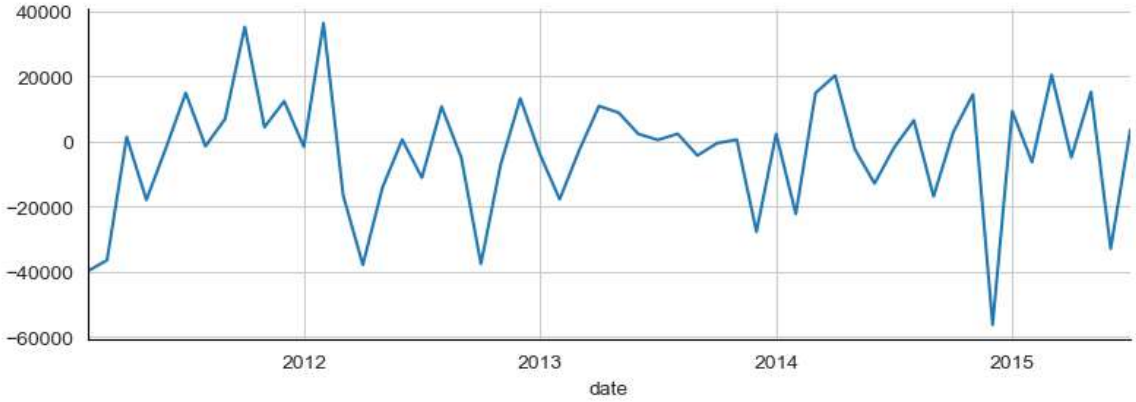


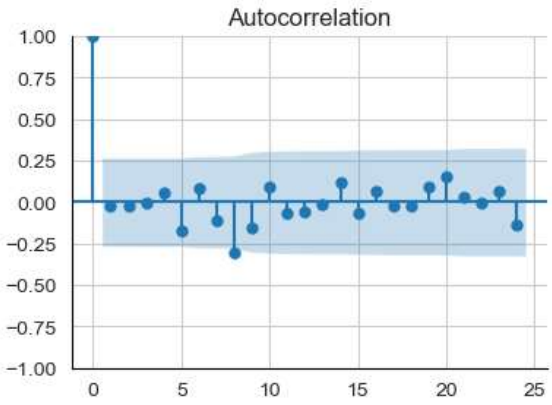
Store Name CA_3
** Mean of the residuals: -3204.89

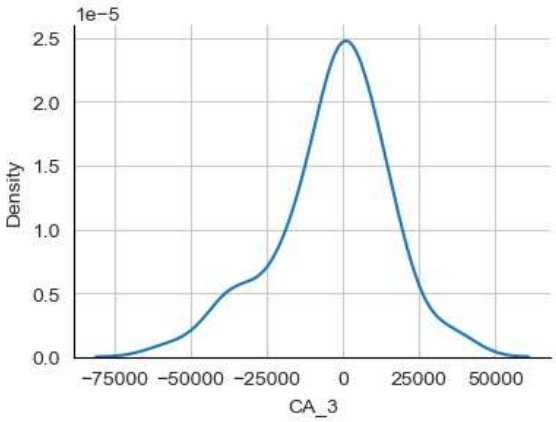
** Ljung Box Test, p-value: 0.6685569788254183 (>0.05, Uncorrelated)

** Jarque Bera Normality Test, p_value: 0.128 (>0.05, Normal)

** AD Fuller, p_value: 2.2944483039285072e-11 (<0.05, Stationary)





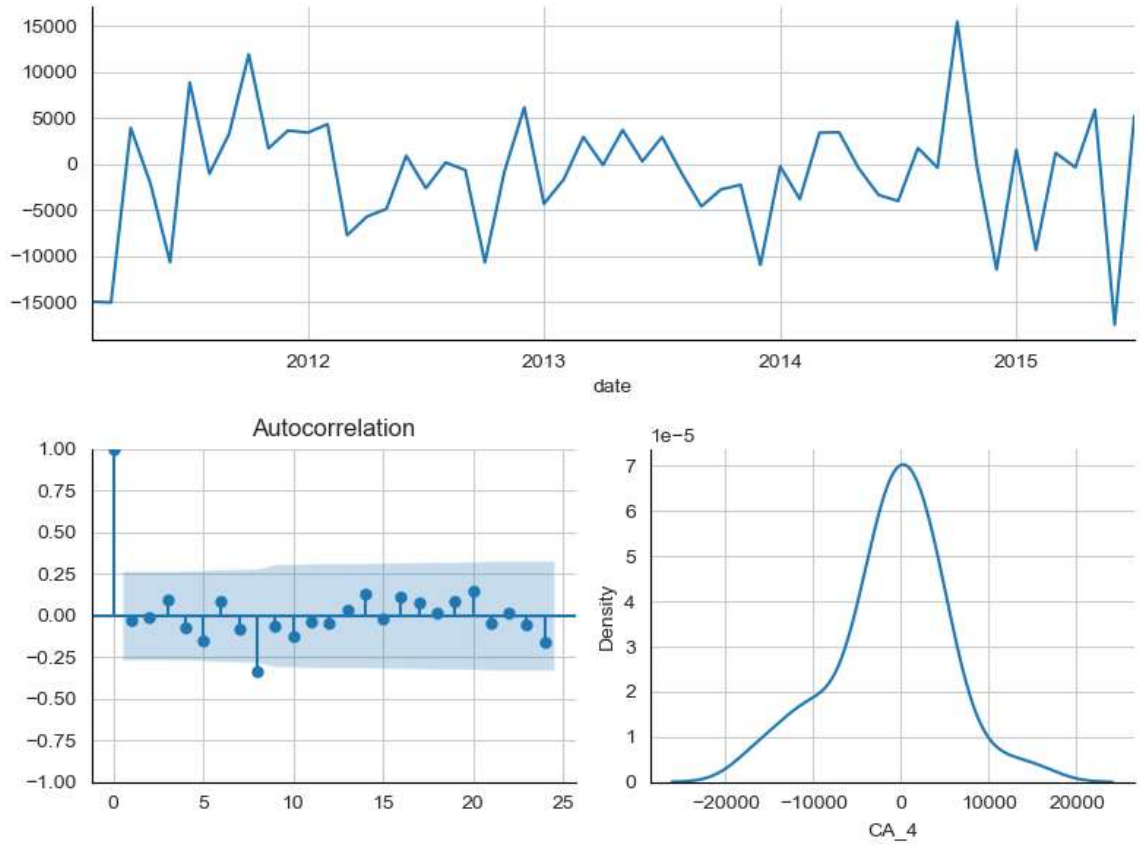


Store Name CA_4
** Mean of the residuals: -1107.95

** Ljung Box Test, p-value: 0.6209353282569073 (>0.05, Uncorrelated)

** Jarque Bera Normality Test, p_value: 0.378 (>0.05, Normal)

** AD Fuller, p_value: 0.000899610841629394 1 (<0.05, Stationary)



For all the stores, the residuals are Uncorelated, Normal and Stationary.

SARIMA Models

Sarima models are Seasonal ARIMA models. SARIMA is acronym for Seasonal Auto Regressive Integrated Moving Average.

Auto Regressive(AR) Moving Average(MA) Process states that current value of some series y depends linearly on its previous values plus a combination of current & previous values of error terms.

SARIMA models applies Regression on lag values and/or moving average on error terms.

The order of AR process is p. It tells us that how many past values we should consider while calculating the current value, The order of MA process is q. It tells us the number of past forecast error terms we should take in our weighted average. This weighted average is used by the model while calculating current value.

Since for ARIMA and SARIMA models, stationarity is a neccessary condition, we can tell model to difference our data with previous values in the data to make it stationary. The number of time the data values needs be differenced is the Integration component of ARIMA model. This is 'd' parameter of ARIMA model.

In the Seasonal Arima models we have 4 more parameters i.e. P,D,Q and number of periods in seasons. P,D and Q are counter parts of p,d and q for a seasonal process.

Finding these parameters require much study and knowledge, but in general p+d+q+P+D+Q <= 6. We will use auto_arima from pmdarima package to calculate the

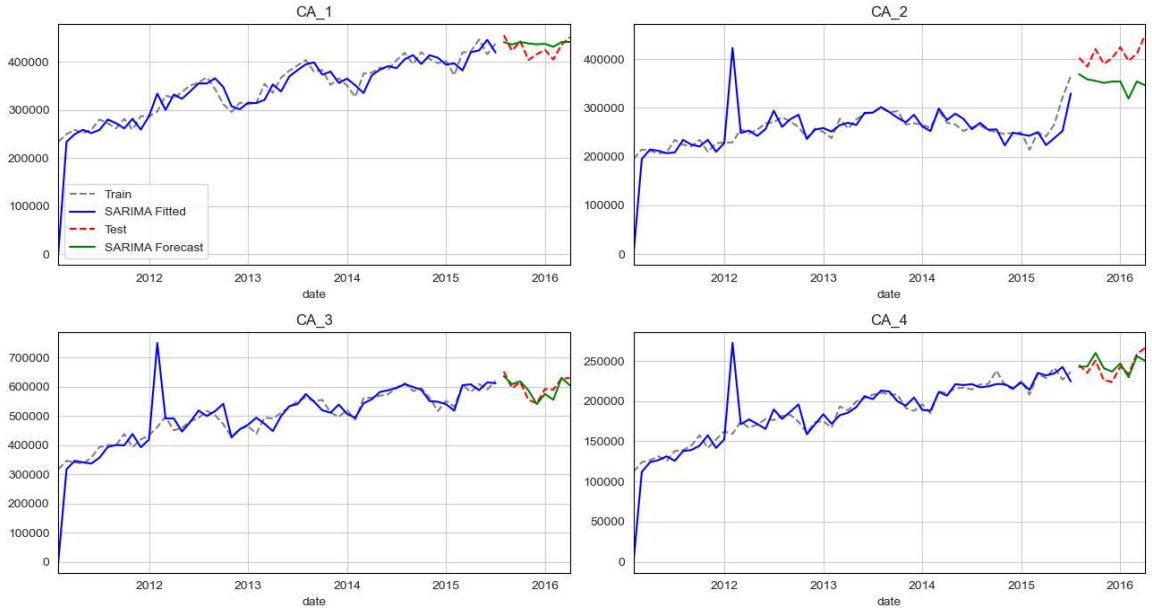
best parameters of SARIMA models for sales data of each store and then we will pass those parameters to statsmodel SARIMAX function.

We are going to use SARIMAX method from statsmodel library for building SARIMA model. X in SARIMAX stands for exogenous variable which we can give to this model if we want to supply model with external data. This gives us the functionality to not only use past data in building the model but also use external variable such as holidays, important events and days such as superbowl matches, worldcup matches or weather forecasts to explain any change in particular value on those days.

In [81]:
```
best_arima=[]
for i in store_list:
    best_arima.append(auto_arima(Train[i],
                                 seasonal=True,
                                 m=12,
                                 d=1,
                                 information_criterion='aicc'))
```

In [82]:
```
predicted_SARIMA=pd.DataFrame(columns=store_list)
fit_SARIMA=pd.DataFrame(columns=store_list)
resid_SARIMA=pd.DataFrame(columns=store_list)
for j,i in enumerate(store_list):
    sarima_model=SARIMAX(endog=Train[i],
                         **best_arima[j].get_params()
                        )
    sarima_fit=sarima_model.fit()
    start = len(Train)
    end = len(Train) +len(Test) -1
    fit_SARIMA[i] = sarima_fit.fittedvalues
    resid_SARIMA[i] = sarima_fit.resid[1:]
    predicted_SARIMA[i] = sarima_fit.predict(start, end, dynamic=False)
```

In [83]:
```
fig,ax=plt.subplots(figsize=(13,7),nrows=2,ncols=2)
for i, axs in enumerate(ax.flat):
    Train["CA_"+str(i+1)].plot(style="--", color="gray",legend=(i==0), label="Tr
    fit_SARIMA["CA_"+str(i+1)].dropna().plot(color="b",legend=(i==0) ,label="SAR
    Test["CA_"+str(i+1)].plot(style="--",color="r", legend=(i==0),label="Test",a
    predicted_SARIMA["CA_"+str(i+1)].plot(color="g",legend=(i==0) ,label="SARIMA
#handles, labels = ax[0,0].get_legend_handles_labels()
#fig.legend(handles, labels,bbox_to_anchor=(0.975,0.85,0.1,0.04))
fig.tight_layout()
```



In [84]:
```
for i in store_list:
    model_name="SARIMA"
    temp=pd.DataFrame({"store_id":i,
                       "Forecast Method":model_name,
                       "MAPE":accuracy(Test[i],predicted_SARIMA[i]).MAPE,
                       "RMSE":accuracy(Test[i],predicted_SARIMA[i]).RMSE})
    Model_Performance=pd.concat([Model_Performance,temp],axis=0,ignore_index=Tru
```

In [85]:
```
Model_Performance
```

Out[85]:

	store_id	Forecast Method	MAPE	RMSE
0	CA_1	Seasonal Naive	5.4	25314.8
1	CA_2	Seasonal Naive	39.6	164229.7
2	CA_3	Seasonal Naive	5.1	34676.5
3	CA_4	Seasonal Naive	7.8	21282.6
4	CA_1	Holts-Winter Log	1.6	9057.5
5	CA_2	Holts-Winter Box-Cox	11.9	54227.2
6	CA_3	Holts-Winter	2.3	16106.3
7	CA_4	Holts-Winter Log	1.9	5780.3
8	CA_1	ETS Log	3.5	16821.5
9	CA_2	ETS Log	8.0	36155.5
10	CA_3	ETS Log	2.4	16981.6
11	CA_4	ETS Log	2.8	7953.6
12	CA_1	ETS	2.1	11887.0
13	CA_2	ETS	39.0	189053.3
14	CA_3	ETS	2.6	19131.5
15	CA_4	ETS	2.9	8546.3
16	CA_1	SARIMA	3.7	18163.2
17	CA_2	SARIMA	13.9	62055.6
18	CA_3	SARIMA	2.7	19955.4
19	CA_4	SARIMA	3.4	9649.6

SARIMA model have performed well and they do catch the trend and season quite well. SARIMA models dont fit well in start of the time frame as we can observe from the plot. There are also some spikes we can observe.

From the Point of View of accuracy metrics, they are not the best models for any of the stores, but come in middle and perform substantially well than Seasonal Naive model.

In [86]:
```
best_arima[0].summary()
```

Out[86]:

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	54
Model:	SARIMAX(0, 1, 0)x(1, 0, 0, 12)	**Log Likelihood**	-597.926
Date:	Tue, 20 Dec 2022	**AIC**	1201.853
Time:	12:28:18	**BIC**	1207.763
Sample:	02-01-2011	**HQIC**	1204.126
	- 07-01-2015		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	3853.6875	3058.982	1.260	0.208	-2141.807	9849.182
ar.S.L12	0.1774	0.050	3.526	0.000	0.079	0.276
sigma2	4.094e+08	0.013	3.16e+10	0.000	4.09e+08	4.09e+08

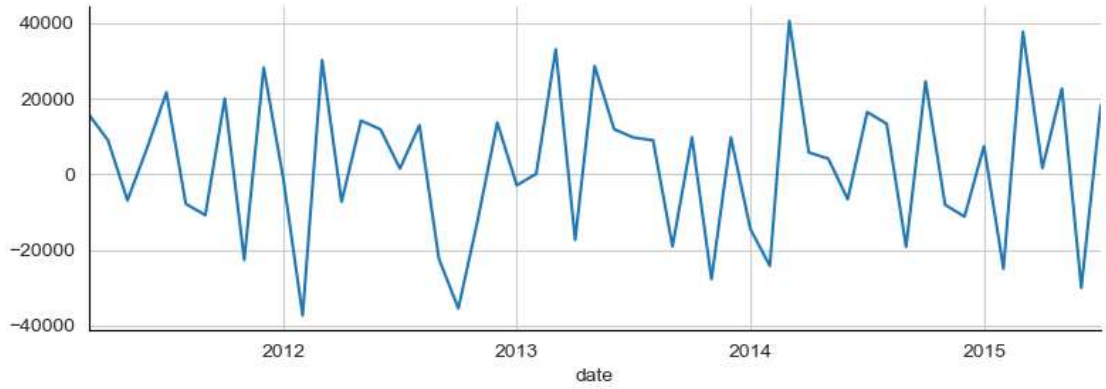
Ljung-Box (L1) (Q):	7.26	**Jarque-Bera (JB):**	1.36
Prob(Q):	0.01	**Prob(JB):**	0.51
Heteroskedasticity (H):	1.64	**Skew:**	-0.06
Prob(H) (two-sided):	0.30	**Kurtosis:**	2.23

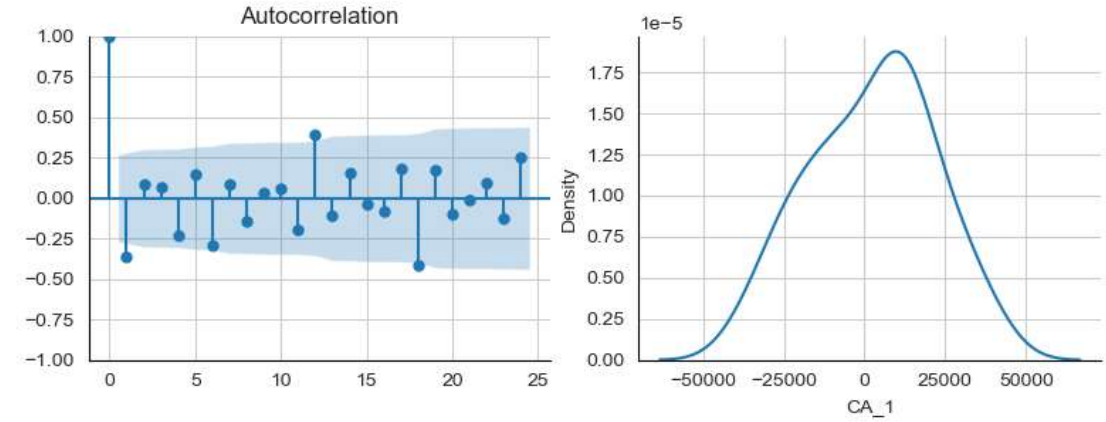
Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 6.67e+26. Standard errors may be unstable.

You can view the summary of arima model selected by auto_arima function on calling .summary() method. This will give us information such as order of (p,d,q), Ljung box, Jarque Bera test results on residuals, as well as various metrics for checking model quality such as AICC,BIC and HQIC.

In [87]:
```
for i in range(len(store_list)):
    print("\n Store Name CA_"+str(i+1))
    residualcheck(resid_SARIMA["CA_"+str(i+1)],24);
    plt.show()
```

```
 Store Name CA_1
** Mean of the residuals:  2297.92

** Ljung Box Test, p-value: 0.010185466391644794 (<0.05, Correlated)

** Jarque Bera Normality Test, p_value: 0.514 (>0.05, Normal)

** AD Fuller, p_value: 2.6757895247631787e-18 (<0.05, Stationary)
```



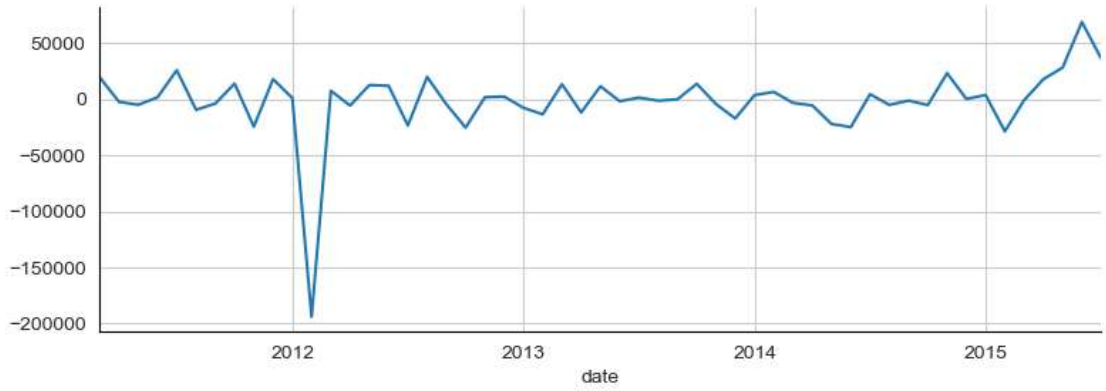


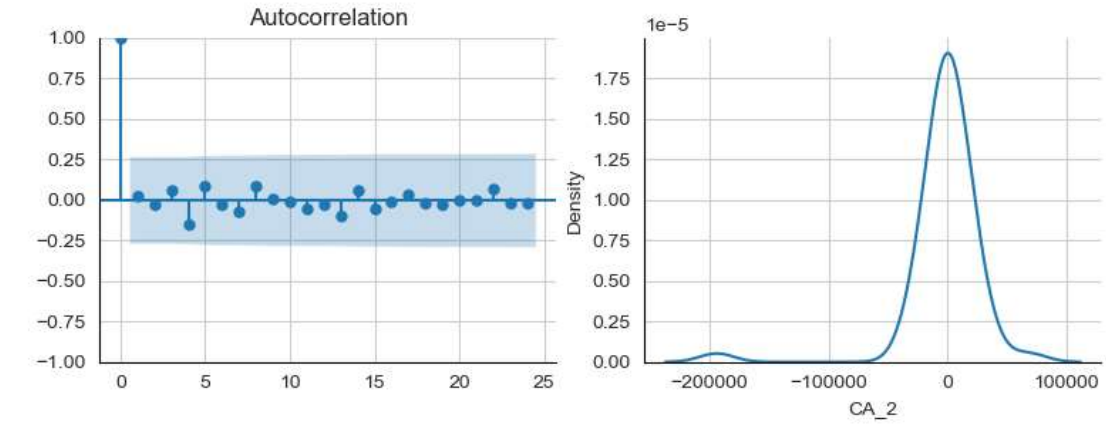
Store Name CA_2
** Mean of the residuals: -1691.06

** Ljung Box Test, p-value: 0.965162625450717 (>0.05, Uncorrelated)

** Jarque Bera Normality Test, p_value: 0.0 (<0.05, Not-normal)

** AD Fuller, p_value: 1.8123963465853475e-09 (<0.05, Stationary)



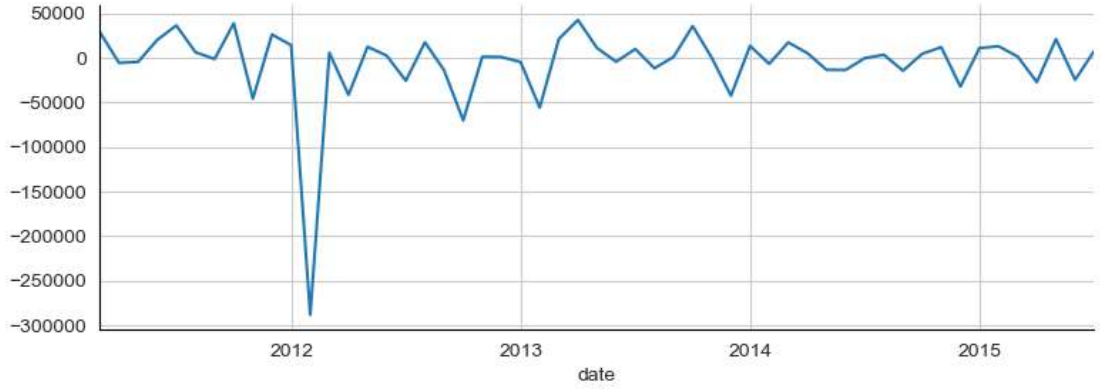


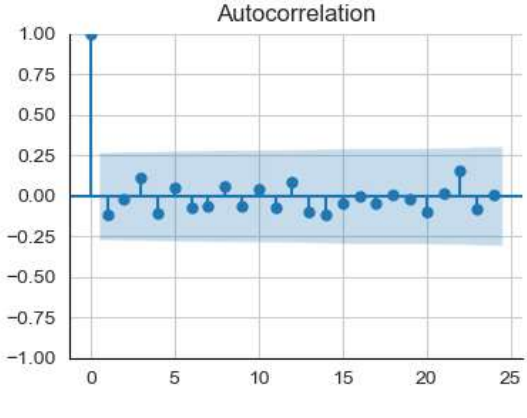
Store Name CA_3
** Mean of the residuals: -5523.66

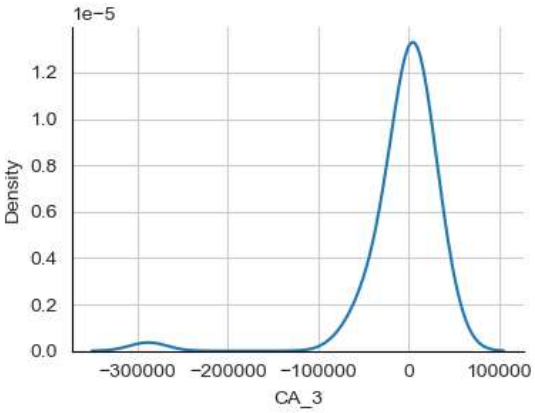
** Ljung Box Test, p-value: 0.9011233260220282 (>0.05, Uncorrelated)

** Jarque Bera Normality Test, p_value: 0.0 (<0.05, Not-normal)

** AD Fuller, p_value: 2.810040076127105e-12 (<0.05, Stationary)





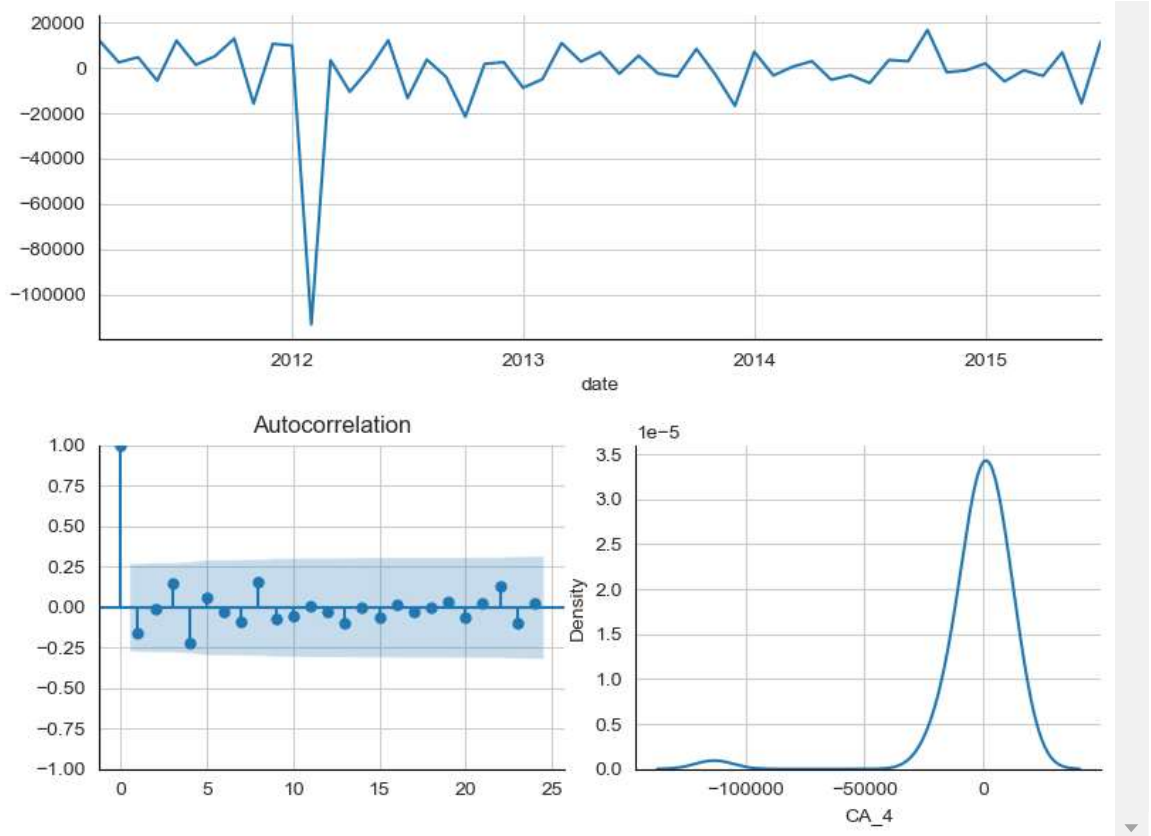


Store Name CA_4
** Mean of the residuals: -1665.17

** Ljung Box Test, p-value: 0.6831584834232732 (>0.05, Uncorrelated)

** Jarque Bera Normality Test, p_value: 0.0 (<0.05, Not-normal)

** AD Fuller, p_value: 3.4490302591008674e-13 (<0.05, Stationary)



For CA1, residuals are Corelated, Normal and Stationary. Presence of corelation means that thereis still some structured information remaining in the residuals.

For CA2,CA3 and CA4 residuals are uncorelated, not normal and stationary.

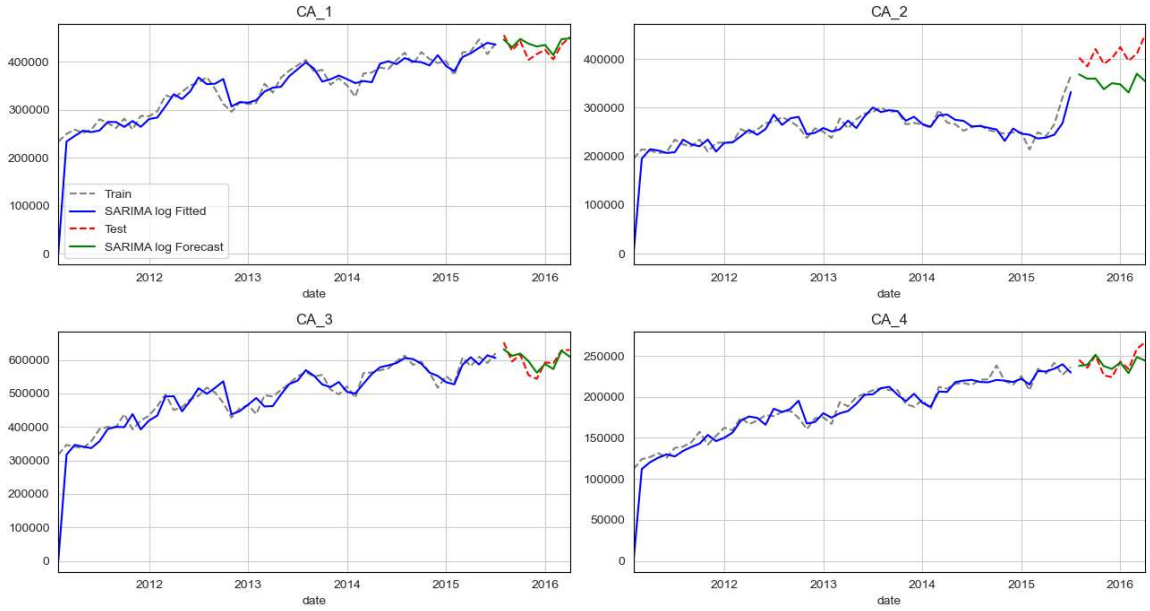
SARIMA Log Models

In [88]:
```
best_arimaL=[]
Trainlog=np.log(Train)
for i in store_list:
    best_arimaL.append(auto_arima(Trainlog[i],
                                  seasonal=True,
                                  m=12,
                                  d=1,
                                  information_criterion='aicc'))
```

In [89]:
```
predicted_SARIMAL=pd.DataFrame(columns=store_list)
fit_SARIMAL=pd.DataFrame(columns=store_list)
resid_SARIMAL=pd.DataFrame(columns=store_list)
for j,i in enumerate(store_list):
    sarima_model=SARIMAX(endog=Trainlog[i],
                         **best_arimaL[j].get_params()
                        )
    sarima_fit=sarima_model.fit()
    start = len(Train)
    end = len(Train) +len(Test) -1
    fit_SARIMAL[i] = np.exp(sarima_fit.fittedvalues)
    resid_SARIMAL[i] = Train[i][1:]-fit_SARIMAL[i][1:]
    predicted_SARIMAL[i] = np.exp(sarima_fit.predict(start, end, dynamic=False))
```

In [90]:
```
fig,ax=plt.subplots(figsize=(13,7),nrows=2,ncols=2)
for i, axs in enumerate(ax.flat):
```

```
    Train["CA_"+str(i+1)].plot(style="--", color="gray",legend=(i==0), label="Tr
    fit_SARIMAL["CA_"+str(i+1)].dropna().plot(color="b",legend=(i==0) ,label="SA
    Test["CA_"+str(i+1)].plot(style="--",color="r", legend=(i==0),label="Test",a
    predicted_SARIMAL["CA_"+str(i+1)].plot(color="g",legend=(i==0) ,label="SARIM
#handles, labels = ax[0,0].get_legend_handles_labels()
#fig.legend(handles, labels,bbox_to_anchor=(0.975,0.85,0.1,0.04))
fig.tight_layout()
```



In [91]:
```
for i in store_list:
    model_name="SARIMA Log"
    temp=pd.DataFrame({"store_id":i,
                       "Forecast Method":model_name,
                       "MAPE":accuracy(Test[i],predicted_SARIMAL[i]).MAPE,
                       "RMSE":accuracy(Test[i],predicted_SARIMAL[i]).RMSE})
    Model_Performance=pd.concat([Model_Performance,temp],axis=0,ignore_index=Tru
```

In [92]:
```
Model_Performance
```

Out[92]:

	store_id	Forecast Method	MAPE	RMSE
0	CA_1	Seasonal Naive	5.4	25314.8
1	CA_2	Seasonal Naive	39.6	164229.7
2	CA_3	Seasonal Naive	5.1	34676.5
3	CA_4	Seasonal Naive	7.8	21282.6
4	CA_1	Holts-Winter Log	1.6	9057.5
5	CA_2	Holts-Winter Box-Cox	11.9	54227.2
6	CA_3	Holts-Winter	2.3	16106.3
7	CA_4	Holts-Winter Log	1.9	5780.3
8	CA_1	ETS Log	3.5	16821.5
9	CA_2	ETS Log	8.0	36155.5
10	CA_3	ETS Log	2.4	16981.6
11	CA_4	ETS Log	2.8	7953.6
12	CA_1	ETS	2.1	11887.0
13	CA_2	ETS	39.0	189053.3
14	CA_3	ETS	2.6	19131.5
15	CA_4	ETS	2.9	8546.3
16	CA_1	SARIMA	3.7	18163.2
17	CA_2	SARIMA	13.9	62055.6
18	CA_3	SARIMA	2.7	19955.4
19	CA_4	SARIMA	3.4	9649.6
20	CA_1	SARIMA Log	2.8	14430.3
21	CA_2	SARIMA Log	13.5	59256.9
22	CA_3	SARIMA Log	2.7	19690.8
23	CA_4	SARIMA Log	3.2	10071.2

For CA1, there is considerable improvement in accuracy when we used log values in SARIMA model.

For CA2 and CA4, there is a slight improvement.

For CA3, there is not any improvement in accuracy.

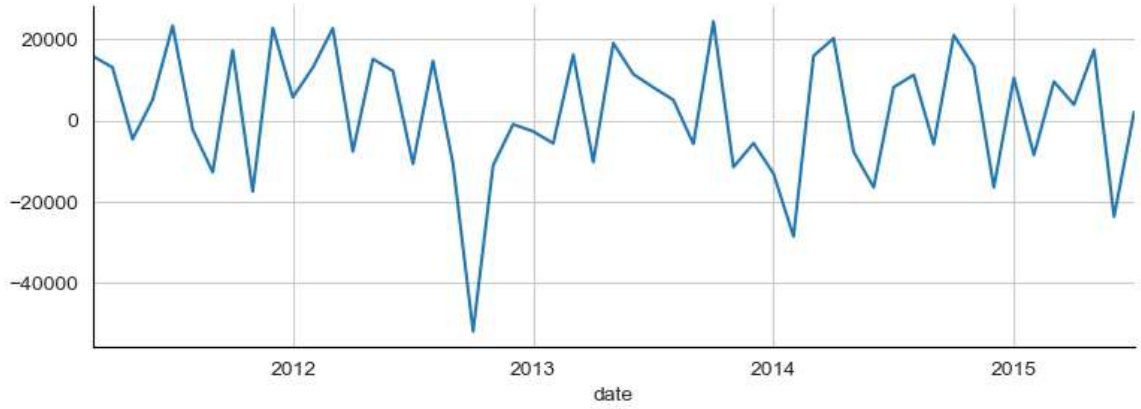
In [93]:
```
for i in range(len(store_list)):
    print("\n Store Name CA_"+str(i+1))
    residualcheck(resid_SARIMAL["CA_"+str(i+1)],24);
    plt.show()
```

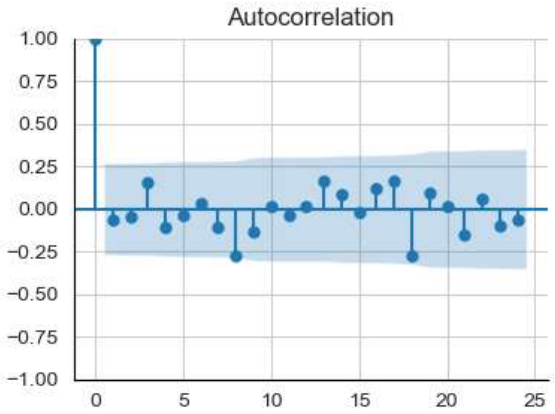
Store Name CA_1
** Mean of the residuals: 2048.61

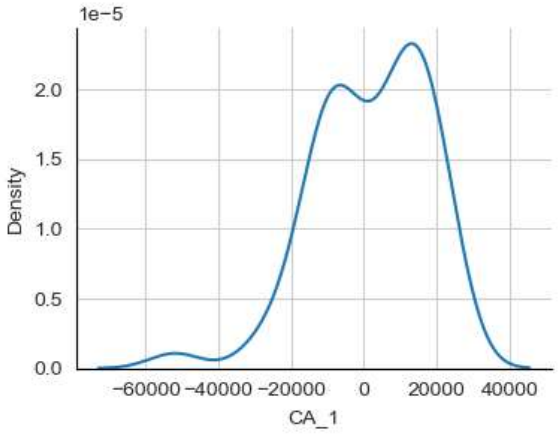
** Ljung Box Test, p-value: 0.5368636500651134 (>0.05, Uncorrelated)

** Jarque Bera Normality Test, p_value: 0.015 (<0.05, Not-normal)

** AD Fuller, p_value: 2.0631586774780955e-11 (<0.05, Stationary)





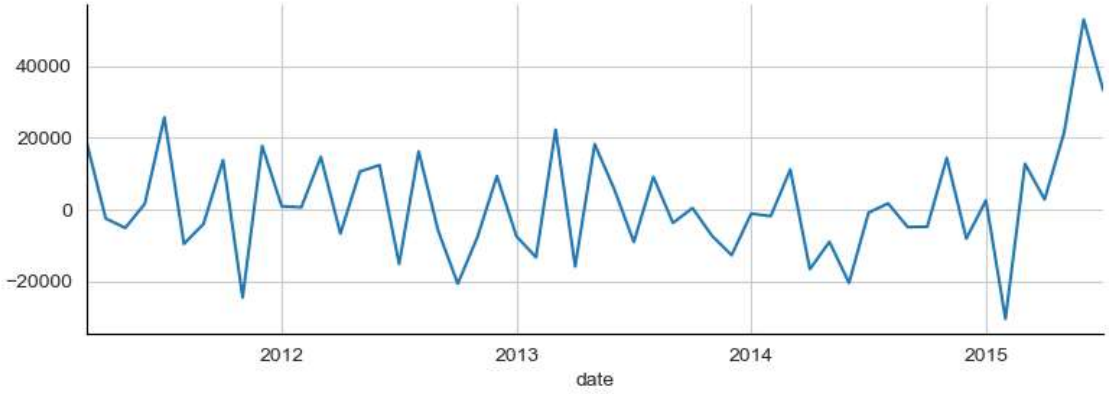


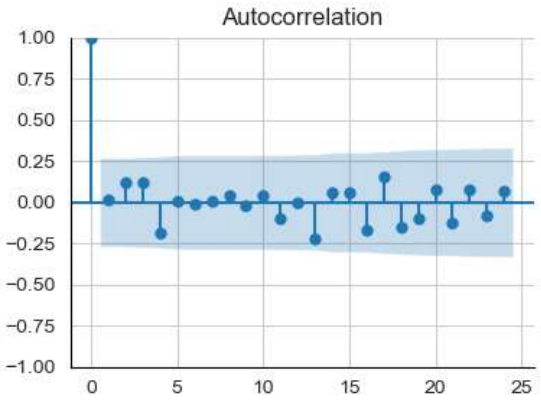
Store Name CA_2
** Mean of the residuals: 1553.59

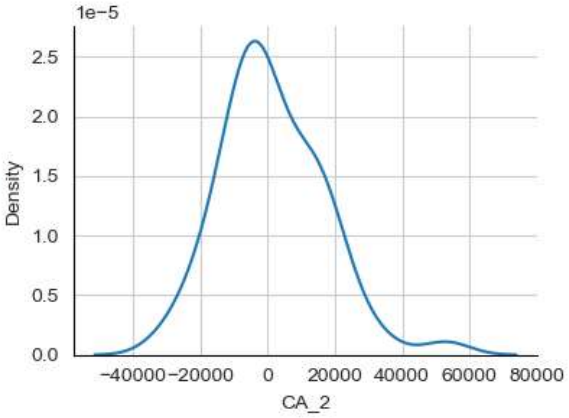
** Ljung Box Test, p-value: 0.7645779202348649 (>0.05, Uncorrelated)

** Jarque Bera Normality Test, p_value: 0.036 (<0.05, Not-normal)

** AD Fuller, p_value: 0.45751362229267967 (>0.05, Non-stationary)





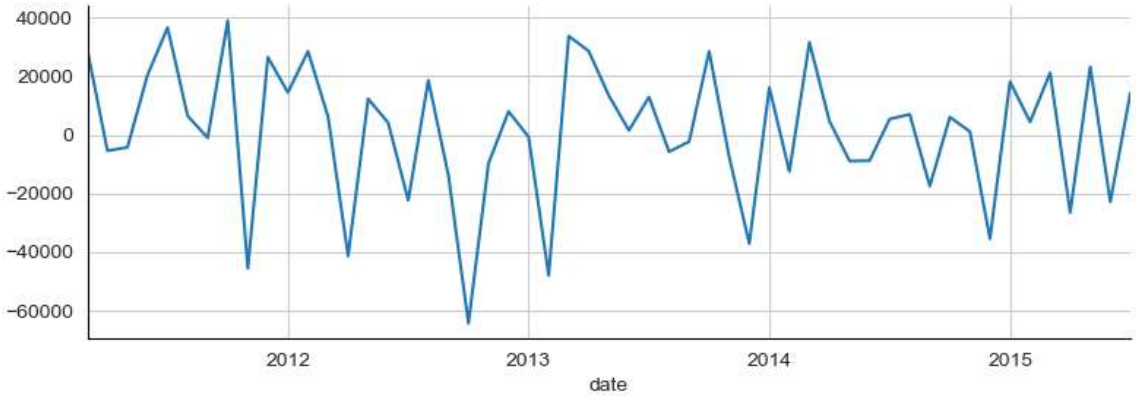


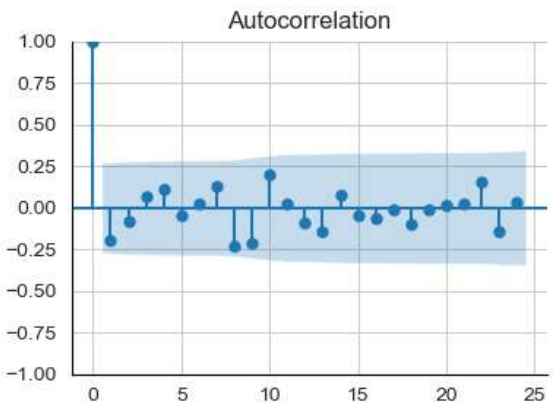
Store Name CA_3
** Mean of the residuals: 1525.45

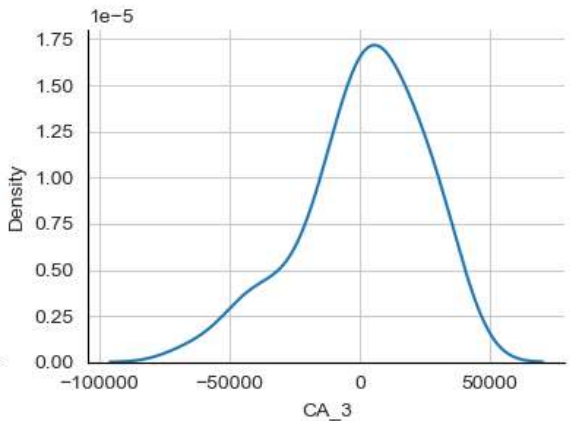
** Ljung Box Test, p-value: 0.43562441026587645 (>0.05, Uncorrelated)

** Jarque Bera Normality Test, p_value: 0.095 (>0.05, Normal)

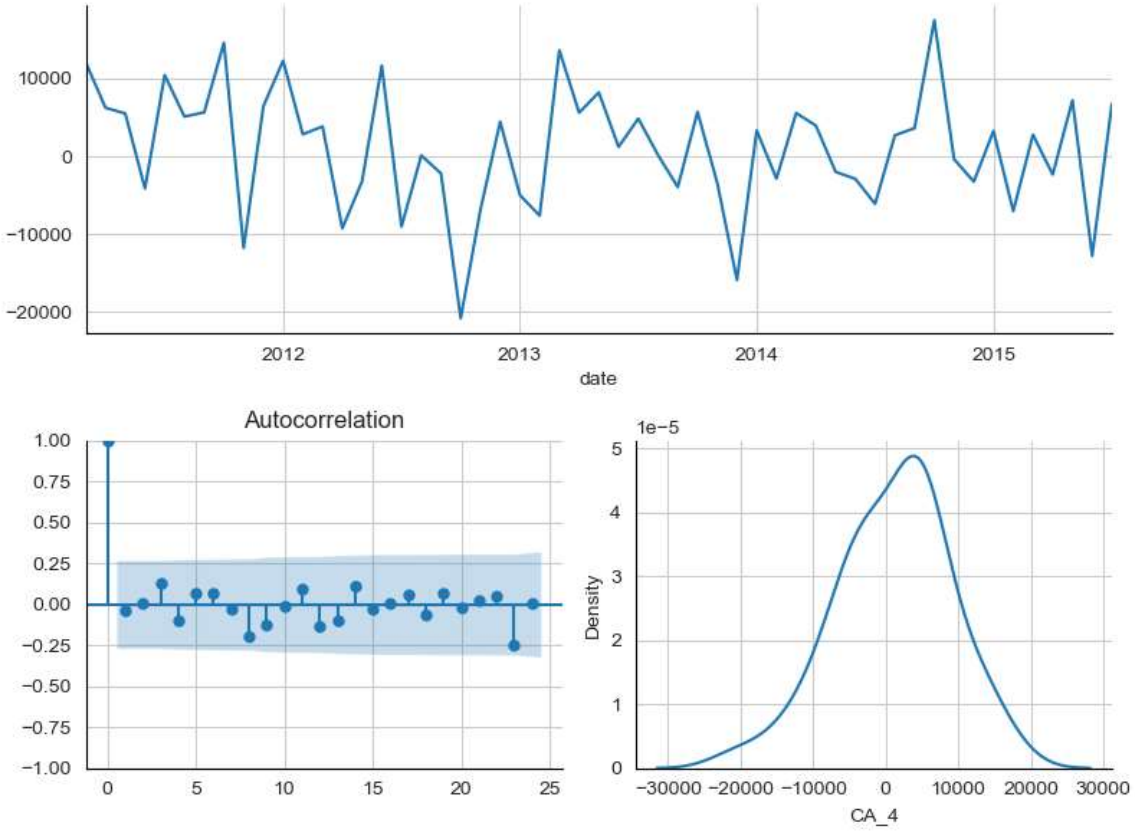
** AD Fuller, p_value: 3.4501371614470773e-14 (<0.05, Stationary)







```
 Store Name CA_4
** Mean of the residuals:  1029.08

** Ljung Box Test, p-value: 0.8659348160634135 (>0.05, Uncorrelated)

** Jarque Bera Normality Test, p_value: 0.527 (>0.05, Normal)

** AD Fuller, p_value: 5.2225110071778796e-11 (<0.05, Stationary)
```

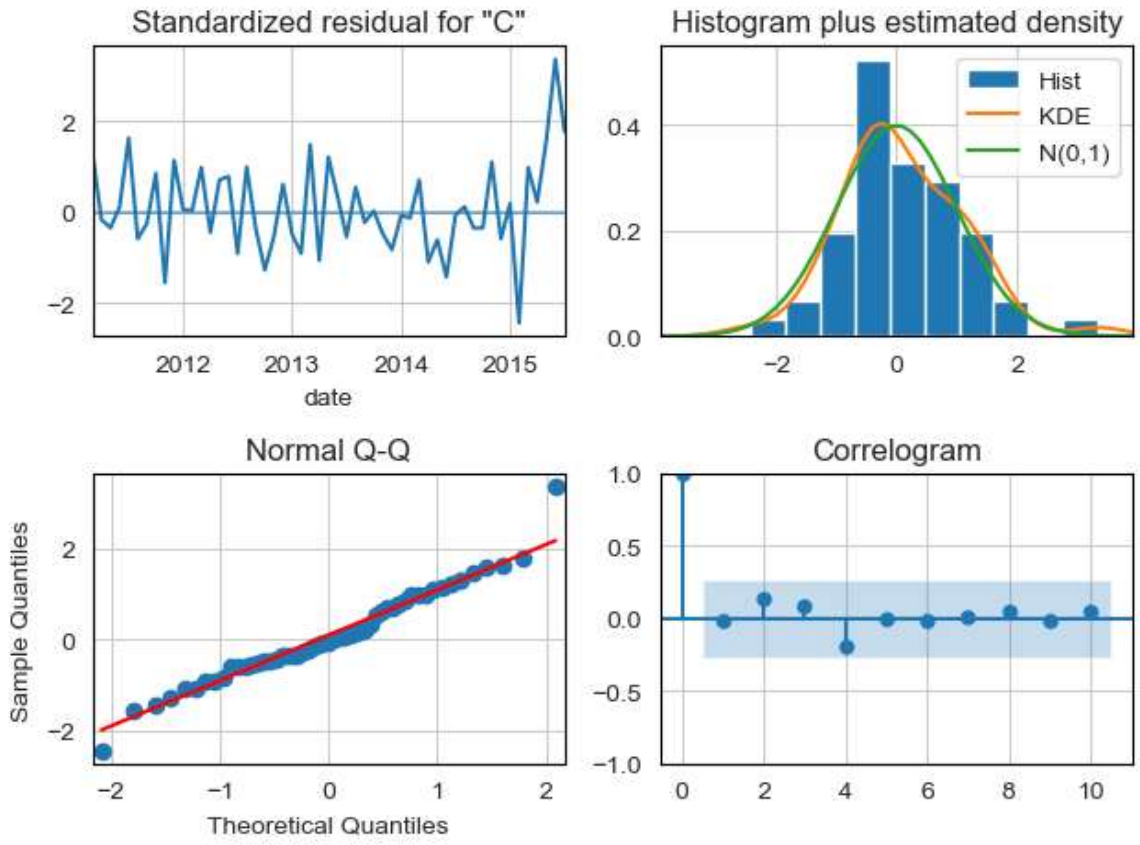


For CA1, Residuals are uncorelated, not normal and stationary.

For CA2, residuals are uncorelated, not normal and non stationary.

For CA3 and CA4, residuals are uncorelated, normal, stationary.

In [94]:
```
SARIMAX(endog=Trainlog["CA_2"],**best_arimaL[1].get_params()).fit().plot_diagnos
plt.tight_layout()
plt.show()
```



You can also use .plot_diagnostic() function on object that we get after fitting the SARIMAX model to analyze the residuals.

FB Prophet Model

FB Prophet Model is developed by Facebook. It is build in STAN.

Foundation of this model is Generalized Linear Model. This means that it has functions instead of coefficients for each variable of linear model. They are solved using backfill, method similar to back propogation.

This model is best for high frequency data such as hourly, or daily. FB prophet model can make a model even when there are multiple seasonalities in data, for e.g, Weekly seasonality, and monthly seasinality in annual daily sales data. This flexibility as well as easeness in making model makes FB prophet one of popular algorithm in Time Series Analysis.

A list of Holidays can be provided to this model.We can also add lower window and upper window to a holiday. This means that if holiday is on 26th then sales would be affected on 25th and 27th, if the lower window and upper window is 1.

We can tell Facebook Prophet model if we want to use logistic growth curve where we can add a changing cap over time.

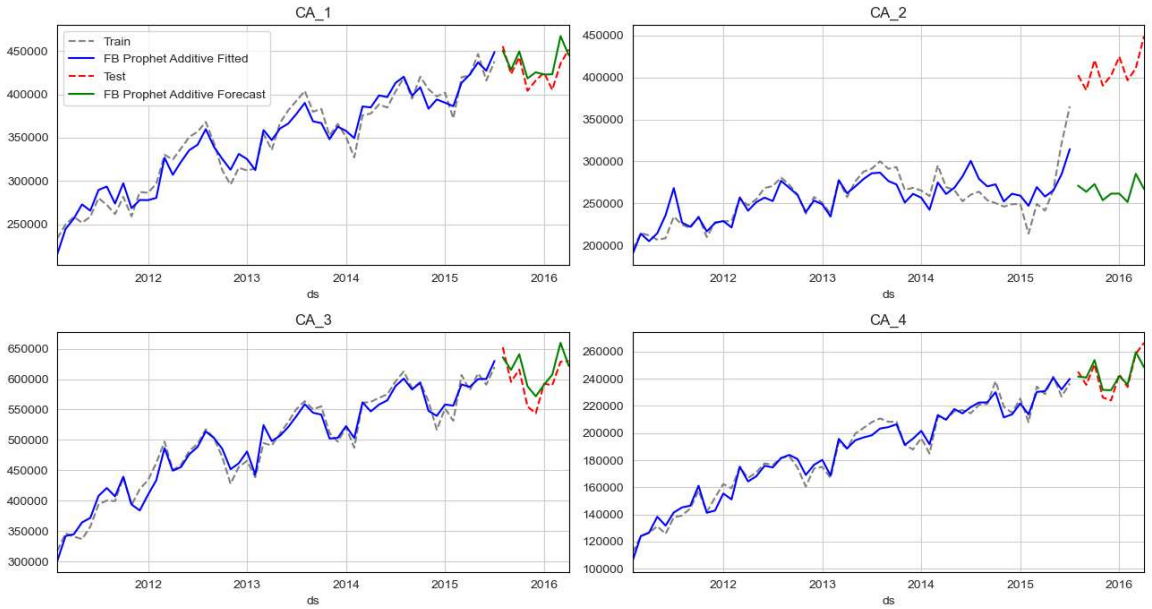
We will build model with both seasonality mode, Additive and Multiplicative

In [95]:
```
predicted_prophet_add=pd.DataFrame(columns=store_list)
fit_prophet_add=pd.DataFrame(columns=store_list)
```

```
resid_prophet_add=pd.DataFrame(columns=store_list)

predicted_prophet_mul=pd.DataFrame(columns=store_list)
fit_prophet_mul=pd.DataFrame(columns=store_list)
resid_prophet_mul=pd.DataFrame(columns=store_list)

prophetmodels=[]

for i in store_list:
    train_fb_prophet=Train[i].reset_index()
    train_fb_prophet.columns=["ds","y"]  ## Compulsary for prophet that datafram
    test_fb_prophet=Test[i].reset_index()
    test_fb_prophet.columns=["ds","y"]
    seasonality_mode=["multiplicative","additive"]
    for j in seasonality_mode:
        prophet_model=Prophet(weekly_seasonality=False,
                              daily_seasonality=False,
                              yearly_seasonality=True,
                              seasonality_mode=j).fit(train_fb_prophet)
        fb_dataframe=prophet_model.make_future_dataframe(len(Test),freq='MS',inc
        predicted_prophet=prophet_model.predict(fb_dataframe).set_index("ds")
        if j=="multiplicative":
            predicted_prophet_mul[i]=predicted_prophet[Test.index[0]:]["yhat"]
            fit_prophet_mul[i]=predicted_prophet[:Train.index[-1]]["yhat"]
            resid_prophet_mul[i]=Train[i]-fit_prophet_mul[i]
        else:
            predicted_prophet_add[i]=predicted_prophet[Test.index[0]:]["yhat"]
            fit_prophet_add[i]=predicted_prophet[:Train.index[-1]]["yhat"]
            resid_prophet_add[i]=Train[i]-fit_prophet_add[i]
            prophetmodels.append(prophet_model)
```

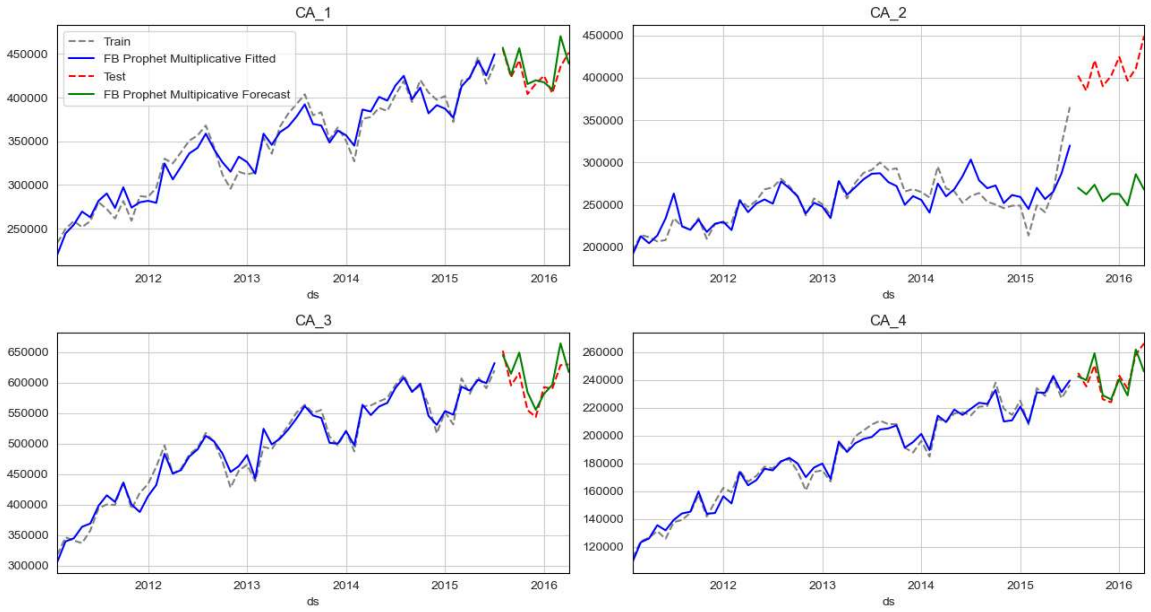
In [96]:

```
fig,ax=plt.subplots(figsize=(13,7),nrows=2,ncols=2)
for i, axs in enumerate(ax.flat):
    Train["CA_"+str(i+1)].plot(style="--", color="gray",legend=(i==0), label="Tr
    fit_prophet_add["CA_"+str(i+1)].dropna().plot(color="b",legend=(i==0) ,label
    Test["CA_"+str(i+1)].plot(style="--",color="r", legend=(i==0),label="Test",a
    predicted_prophet_add["CA_"+str(i+1)].plot(color="g",legend=(i==0) ,label="F
#handles, labels = ax[0,0].get_legend_handles_labels()
#fig.legend(handles, labels,bbox_to_anchor=(0.975,0.85,0.1,0.04))
fig.tight_layout()
```



In [97]:
```
for i in store_list:
    model_name="Prophet Additive"
    temp=pd.DataFrame({"store_id":i,
                       "Forecast Method":model_name,
                       "MAPE":accuracy(Test[i],predicted_prophet_add[i]).MAPE,
                       "RMSE":accuracy(Test[i],predicted_prophet_add[i]).RMSE})
    Model_Performance=pd.concat([Model_Performance,temp],axis=0,ignore_index=Tru
```

In [98]:
```
fig,ax=plt.subplots(figsize=(13,7),nrows=2,ncols=2)
for i, axs in enumerate(ax.flat):
    Train["CA_"+str(i+1)].plot(style="--", color="gray",legend=(i==0), label="Tr
    fit_prophet_mul["CA_"+str(i+1)].dropna().plot(color="b",legend=(i==0) ,label
    Test["CA_"+str(i+1)].plot(style="--",color="r", legend=(i==0),label="Test",a
    predicted_prophet_mul["CA_"+str(i+1)].plot(color="g",legend=(i==0) ,label="F
#handles, labels = ax[0,0].get_legend_handles_labels()
#fig.legend(handles, labels,bbox_to_anchor=(0.975,0.85,0.1,0.04))
fig.tight_layout()
```



In [99]:
```
for i in store_list:
    model_name="Prophet Multiplicative"
    temp=pd.DataFrame({"store_id":i,
                       "Forecast Method":model_name,
                       "MAPE":accuracy(Test[i],predicted_prophet_mul[i]).MAPE,
                       "RMSE":accuracy(Test[i],predicted_prophet_mul[i]).RMSE})
    Model_Performance=pd.concat([Model_Performance,temp],axis=0,ignore_index=Tru
```

In [100…
```
Model_Performance[Model_Performance["store_id"]=="CA_4"]
```

Out[100]:

	store_id	Forecast Method	MAPE	RMSE
3	CA_4	Seasonal Naive	7.8	21282.6
7	CA_4	Holts-Winter Log	1.9	5780.3
11	CA_4	ETS Log	2.8	7953.6
15	CA_4	ETS	2.9	8546.3
19	CA_4	SARIMA	3.4	9649.6
23	CA_4	SARIMA Log	3.2	10071.2
27	CA_4	Prophet Additive	2.1	7227.0
31	CA_4	Prophet Multiplicative	2.3	7947.3

FB Prophet model captures trend and seasonality quite well.

For CA4 it is the second best model.

For CA2, the model was not able to capture sudden increase and the accuracy is quite low.

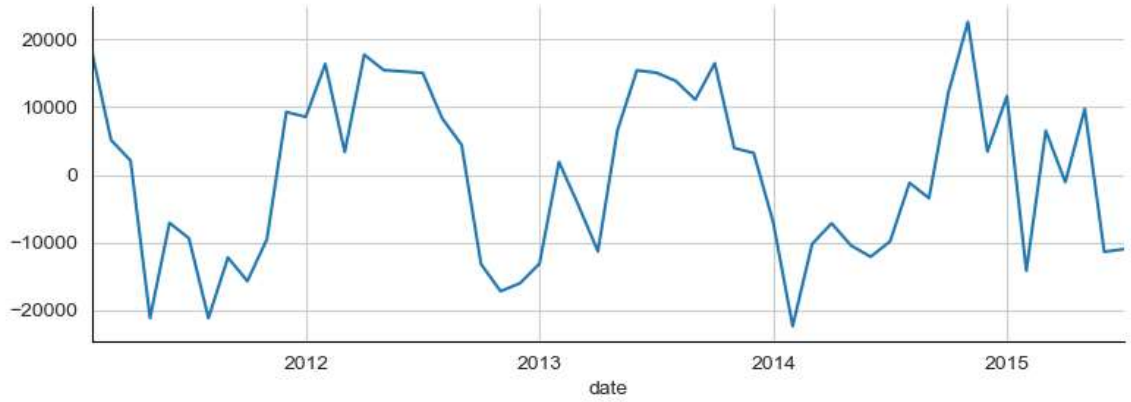
For CA1 and CA3, the model is in the middle when we rank according to RMSE.

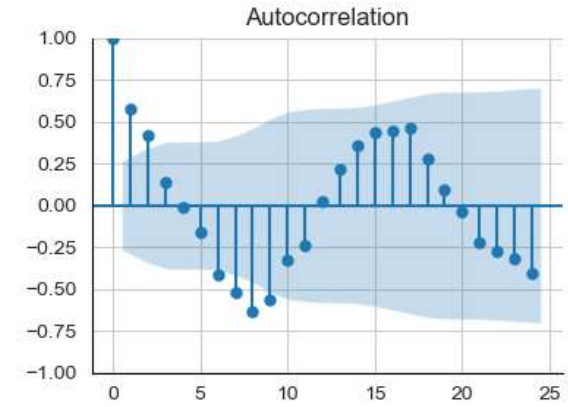
There is not much difference in accuracy for different seasonality modes.

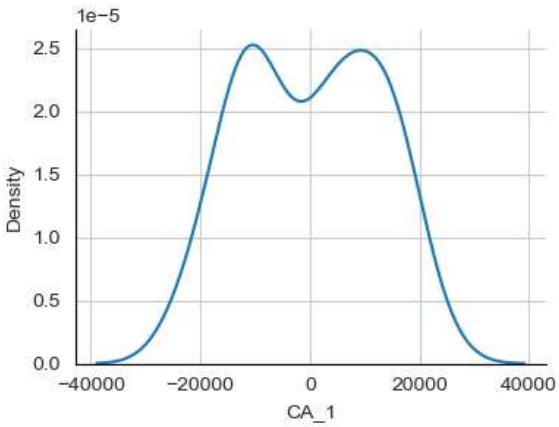
In [101…

```
for i in range(len(store_list)):
    print("\n Store Name CA_"+str(i+1))
    residualcheck(resid_prophet_add["CA_"+str(i+1)],24);
    plt.show()
```

```
 Store Name CA_1
** Mean of the residuals:  0.85

** Ljung Box Test, p-value: 1.1144491339586644e-06 (<0.05, Correlated)

** Jarque Bera Normality Test, p_value: 0.179 (>0.05, Normal)

** AD Fuller, p_value: 0.0005385403219901652 (<0.05, Stationary)
```





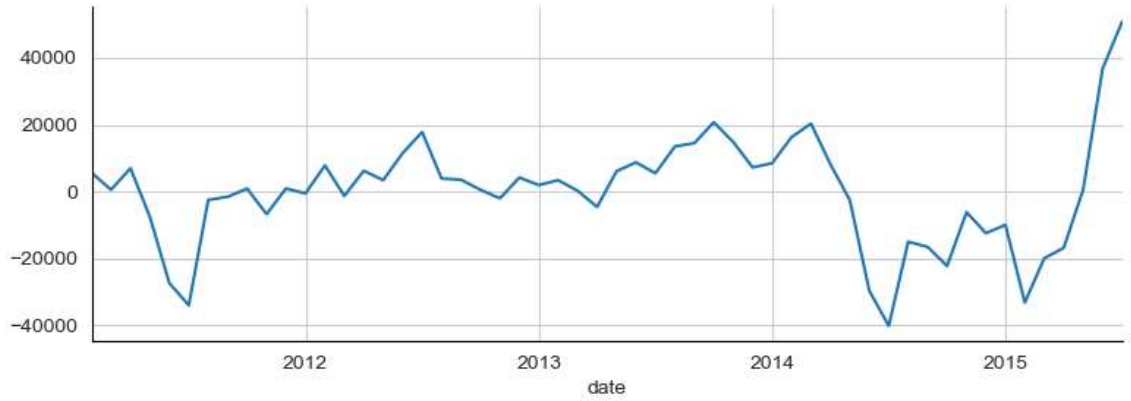


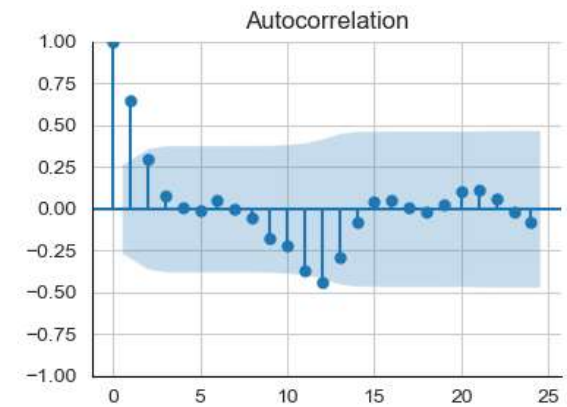
Store Name CA_2
** Mean of the residuals: 0.05

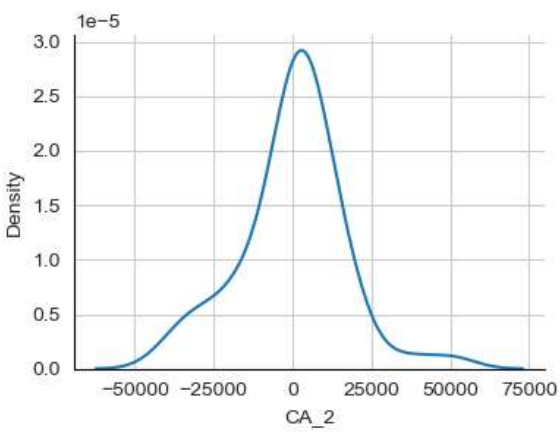
** Ljung Box Test, p-value: 3.320221438279108e-05 (<0.05, Correlated)

** Jarque Bera Normality Test, p_value: 0.147 (>0.05, Normal)

** AD Fuller, p_value: 0.001266471438619074 (<0.05, Stationary)





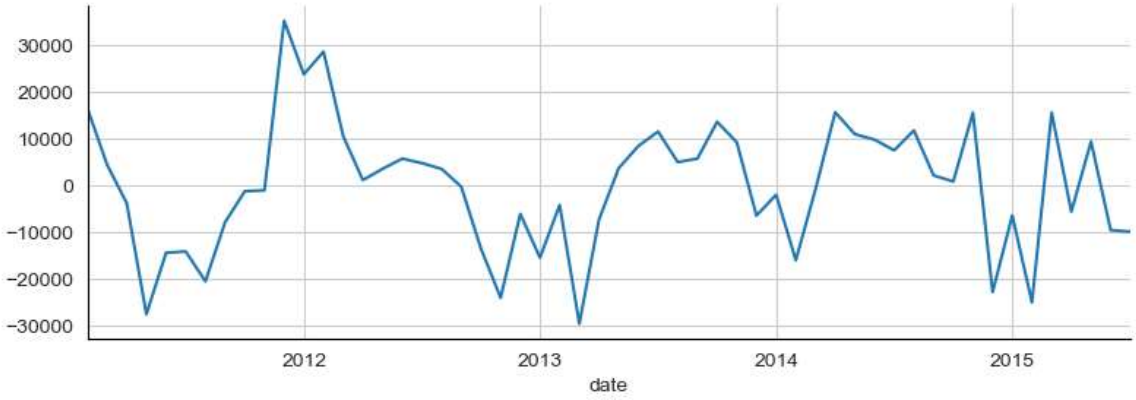


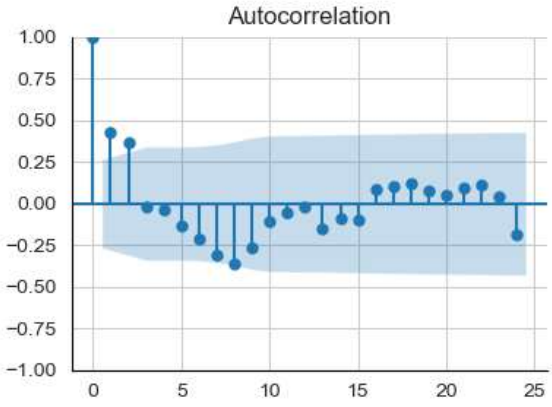
Store Name CA_3
** Mean of the residuals: 0.46

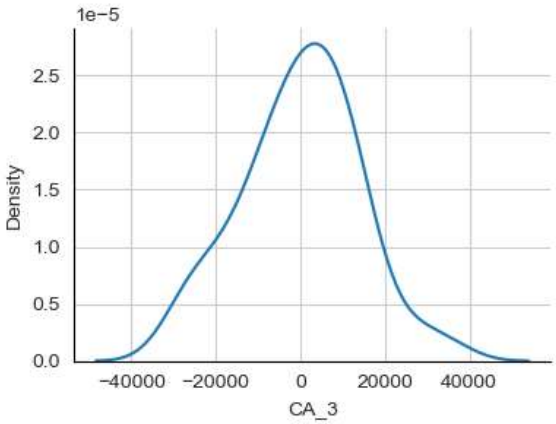
** Ljung Box Test, p-value: 0.0003728787975470495 (<0.05, Correlated)

** Jarque Bera Normality Test, p_value: 0.984 (>0.05, Normal)

** AD Fuller, p_value: 0.005004284944208195 (<0.05, Stationary)





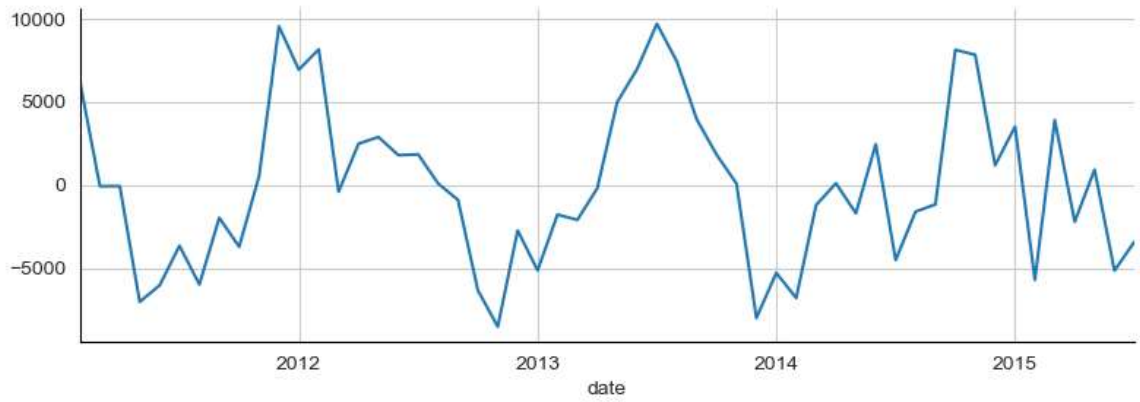


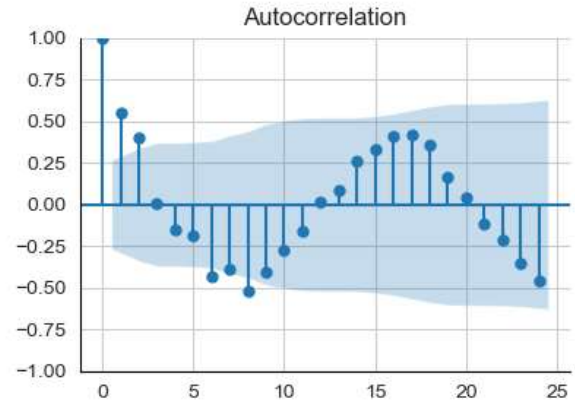
Store Name CA_4
** Mean of the residuals: -1.5

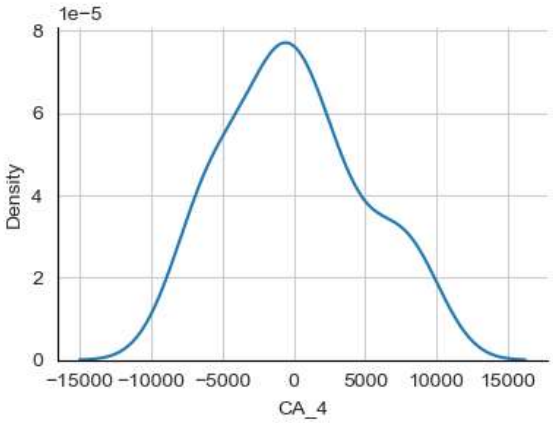
** Ljung Box Test, p-value: 2.9562063262290644e-06 (<0.05, Correlated)

** Jarque Bera Normality Test, p_value: 0.387 (>0.05, Normal)

** AD Fuller, p_value: 0.0003456110743686855 (<0.05, Stationary)



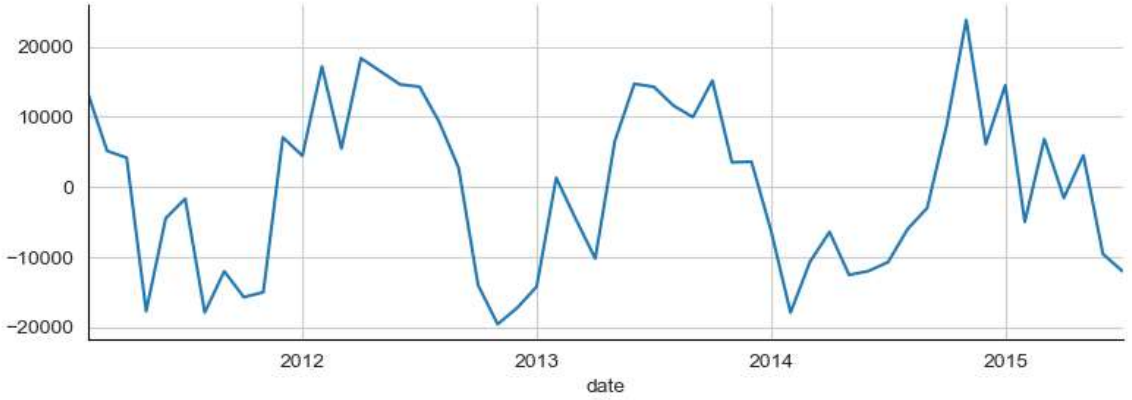


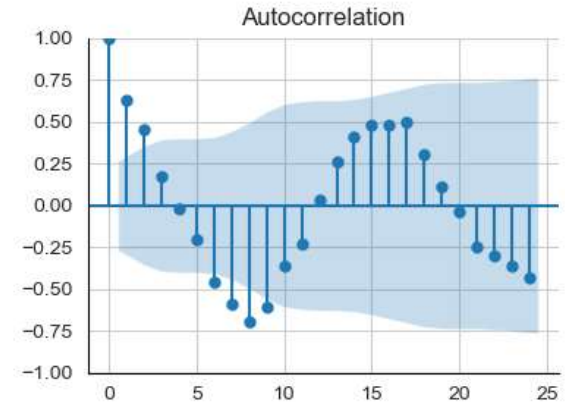


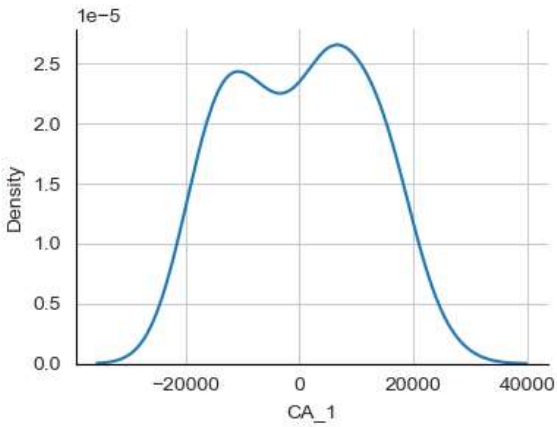
In [102…

```
for i in range(len(store_list)):
    print("\n Store Name CA_"+str(i+1))
    residualcheck(resid_prophet_mul["CA_"+str(i+1)],24);
    plt.show()
```

```
 Store Name CA_1
** Mean of the residuals:  13.75

** Ljung Box Test, p-value: 1.2161022766955153e-07 (<0.05, Correlated)

** Jarque Bera Normality Test, p_value: 0.205 (>0.05, Normal)

** AD Fuller, p_value: 0.0006227423940038788 (<0.05, Stationary)
```





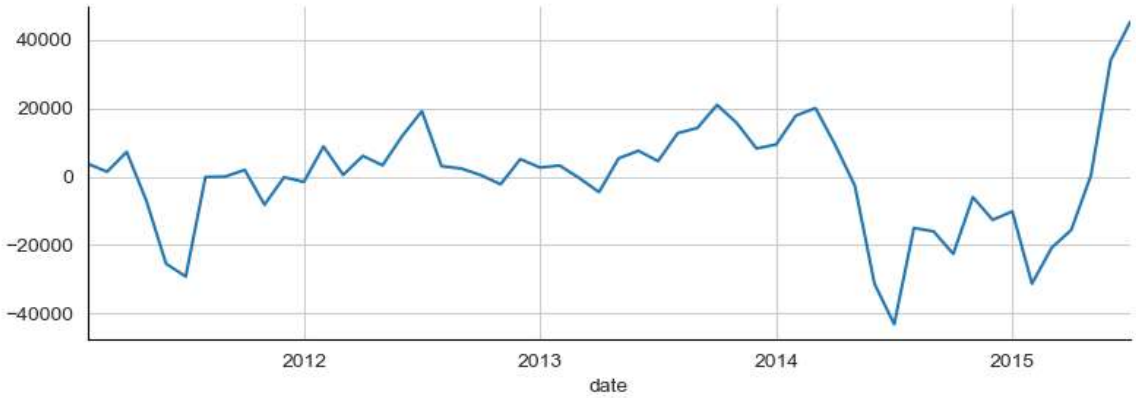


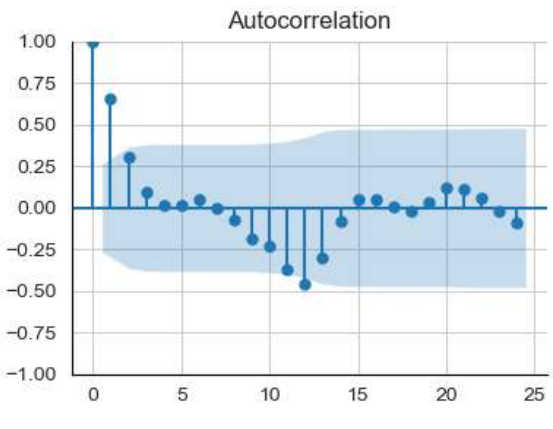
Store Name CA_2
** Mean of the residuals: 21.76

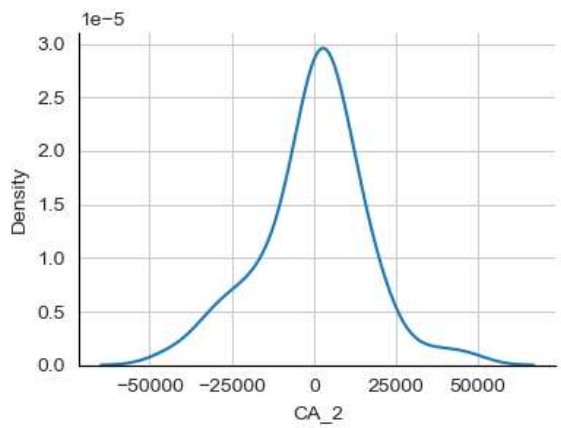
** Ljung Box Test, p-value: 1.8220253623769774e-05 (<0.05, Correlated)

** Jarque Bera Normality Test, p_value: 0.279 (>0.05, Normal)

** AD Fuller, p_value: 0.06133530076955323 (>0.05, Non-stationary)





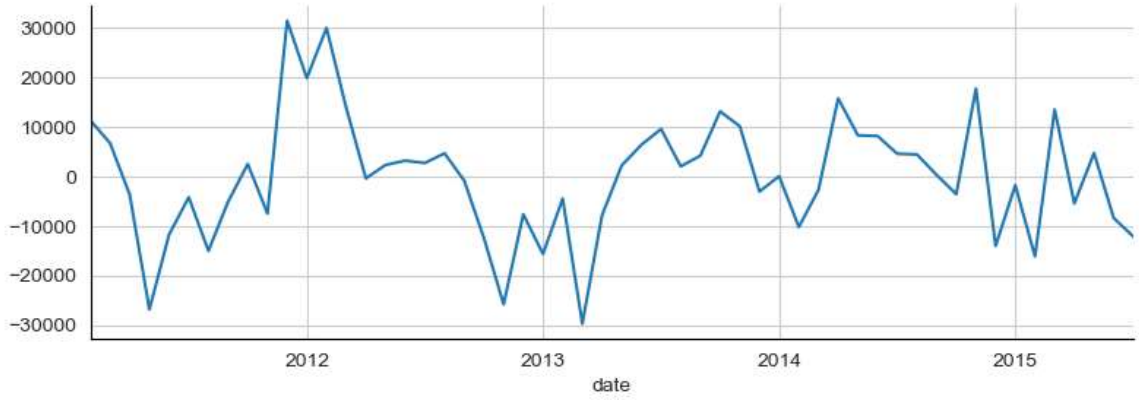


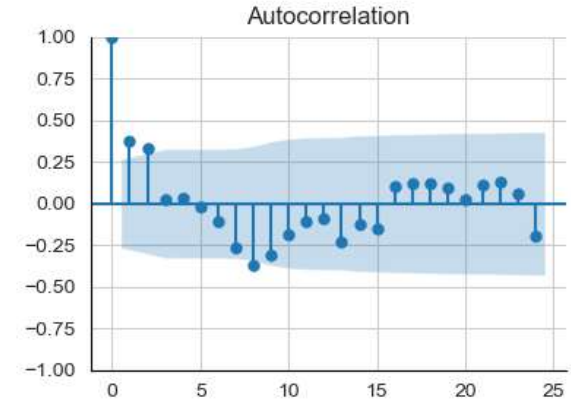
Store Name CA_3
** Mean of the residuals: 18.92

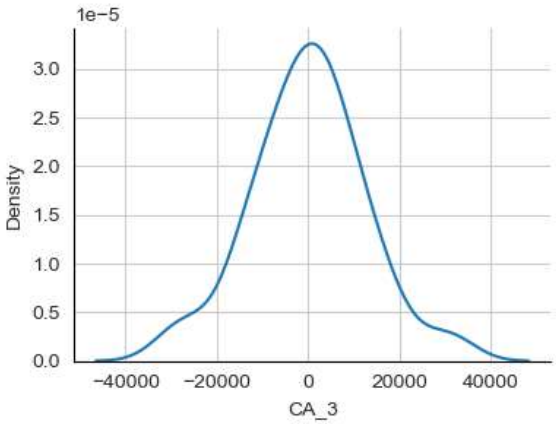
** Ljung Box Test, p-value: 0.0021642538766928937 (<0.05, Correlated)

** Jarque Bera Normality Test, p_value: 0.789 (>0.05, Normal)

** AD Fuller, p_value: 0.01456215383464477 (<0.05, Stationary)





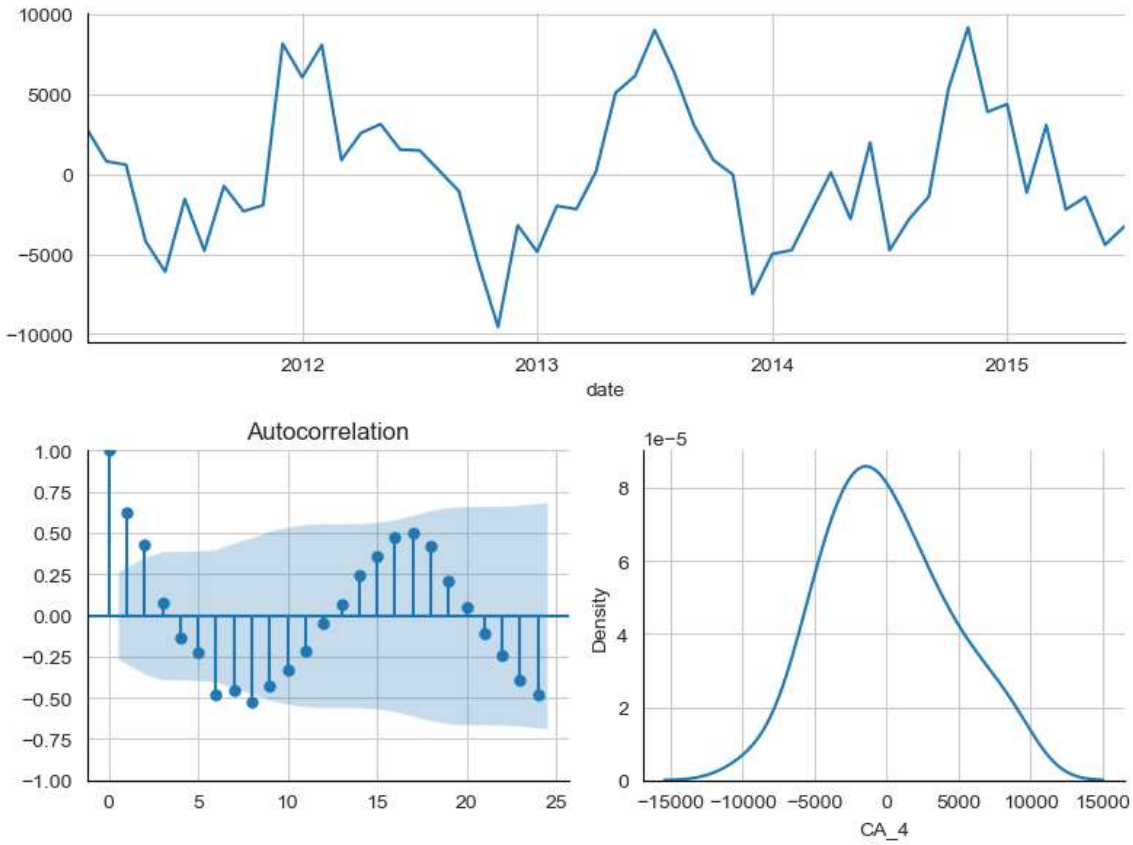


Store Name CA_4
** Mean of the residuals: 5.92

** Ljung Box Test, p-value: 1.6713388498317192e-07 (<0.05, Correlated)

** Jarque Bera Normality Test, p_value: 0.557 (>0.05, Normal)

** AD Fuller, p_value: 0.00019126998614364346 (<0.05, Stationary)



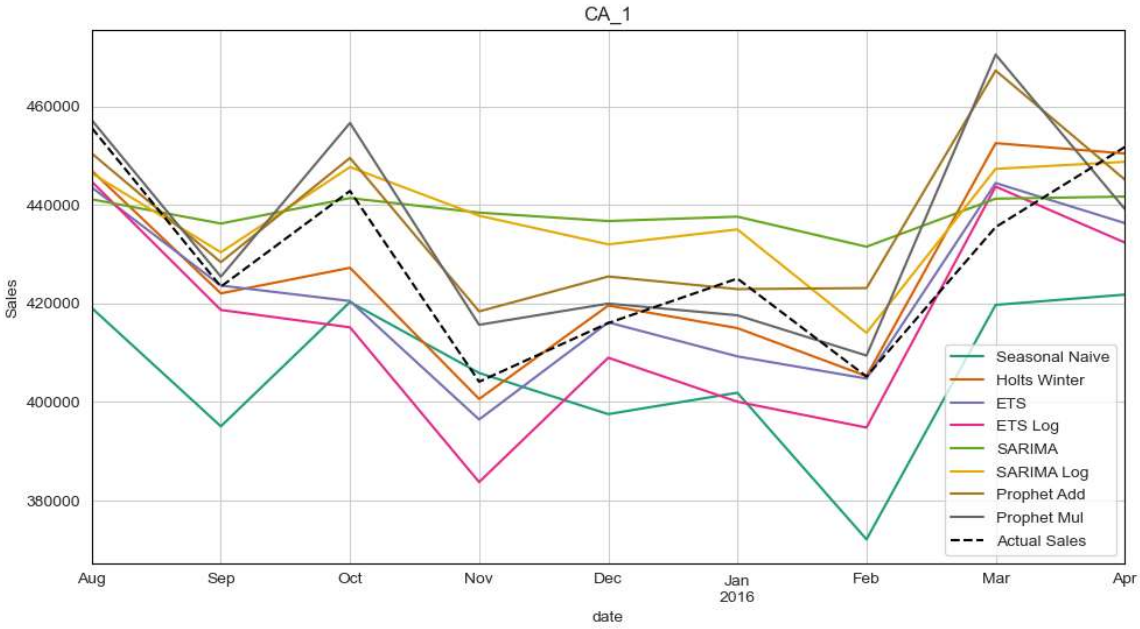
For all the stores and for both seasonality mode, residuals are corelated, normal and stationary.

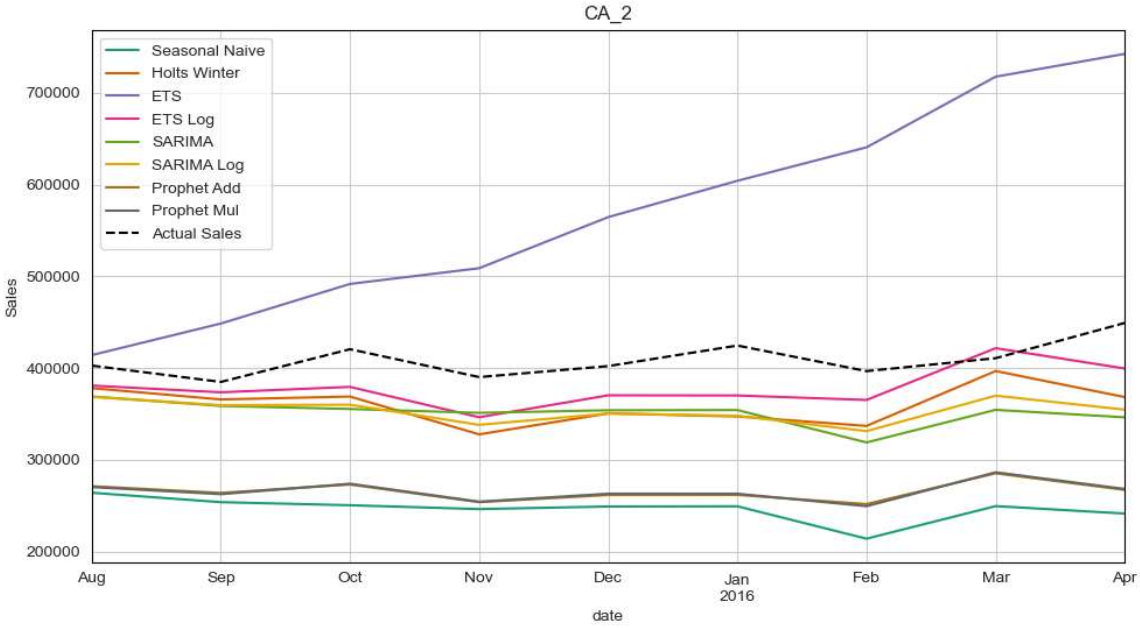
Summary Best Model

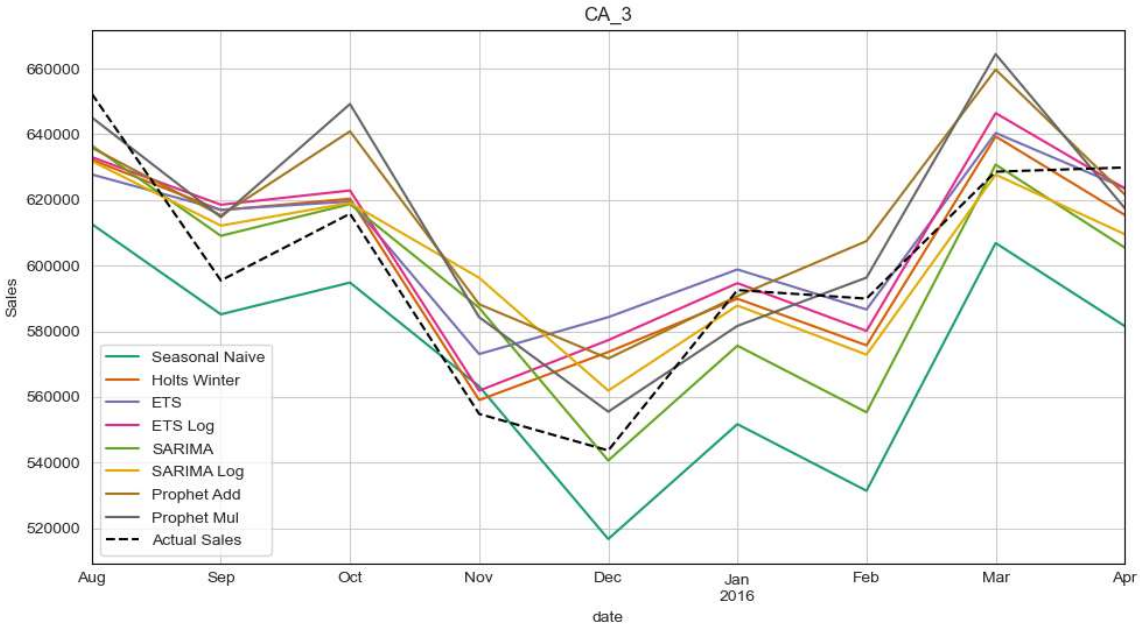
Performance of various models for each stores. We will plot the predicted values of different model and also actual value for different stores.

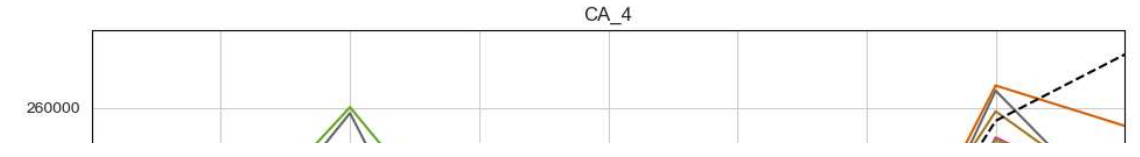
In [103…

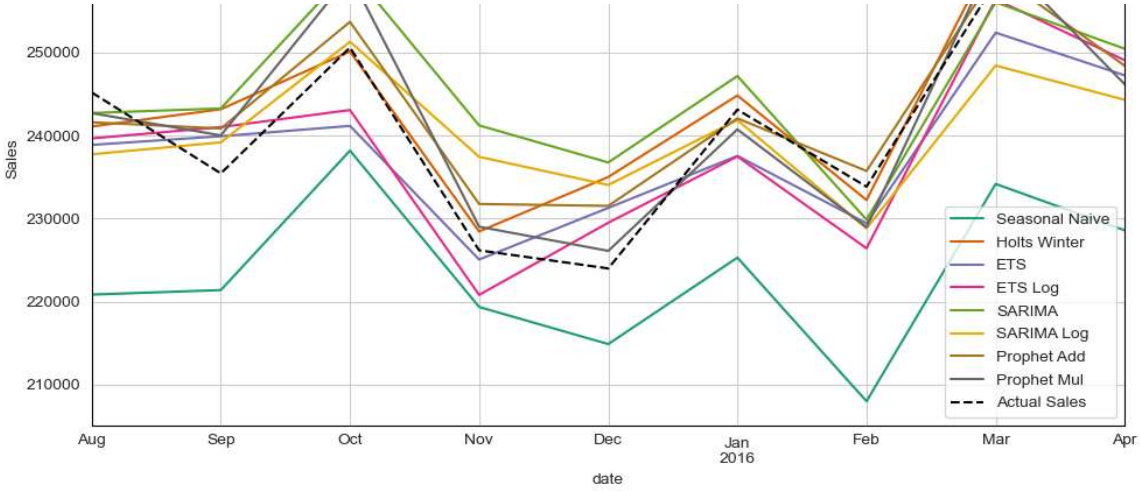
```
fig,axs=plt.subplots(figsize=(10,22),nrows=4,ncols=1)
for j,i in enumerate(store_list):
    axs[j].set_prop_cycle(cycler('color', plt.cm.Dark2.colors))
    predicted_naive[i].plot(legend=True, label="Seasonal Naive",ax=axs[j]).set_t
    predicted_HW[i].plot(legend=True, label="Holts Winter",ax=axs[j])
    predicted_ETS[i].plot(legend=True, label="ETS",ax=axs[j])
    predicted_ETSL[i].plot(legend=True, label="ETS Log",ax=axs[j])
    predicted_SARIMA[i].plot(legend=True, label="SARIMA",ax=axs[j])
    predicted_SARIMAL[i].plot(legend=True, label="SARIMA Log",ax=axs[j])
    predicted_prophet_add[i].plot(legend=True, label="Prophet Add",ax=axs[j])
    predicted_prophet_mul[i].plot(legend=True, label="Prophet Mul",ax=axs[j])
    Test[i].plot(color="black",label="Actual Sales",style="--",legend=True,ax=ax
    #axs[j].xaxis.set_major_locator(mdates.MonthLocator(interval=1))
    axs[j].set_ylabel("Sales")
    axs[j].grid(which='minor')
fig.tight_layout()
```


CA_1
Sales
460000
440000
420000
400000
380000
Aug
Sep
Oct
Nov
Dec
Jan
2016
Feb
Mar
Apr
date
Seasonal Naive
Holts Winter
ETS
ETS Log
SARIMA
SARIMA Log
Prophet Add
Prophet Mul
Actual Sales


CA_2
Sales
700000
600000
500000
400000
300000
200000
Aug
Sep
Oct
Nov
Dec
Jan
2016
Feb
Mar
Apr
date
Seasonal Naive
Holts Winter
ETS
ETS Log
SARIMA
SARIMA Log
Prophet Add
Prophet Mul
Actual Sales


CA_3
Sales
660000
640000
620000
600000
580000
560000
540000
520000
Aug
Sep
Oct
Nov
Dec
Jan
2016
Feb
Mar
Apr
date
Seasonal Naive
Holts Winter
ETS
ETS Log
SARIMA
SARIMA Log
Prophet Add
Prophet Mul
Actual Sales


CA_4
260000



Now we will select the best model for projecting sales at each of our stores in California. We will train the dataset using all the data, and then forecast for 6 months ahead. We will also use simulate the forecast 5000 times and calculate 95% Prediction Interval for our model.

95% Prediction Interval is the range within which Total Monthly sale would occur. There is 95% probability that sale will occur within this range and there is 5% probability that sale will occur outside this range.

In [104…
```
Model_Performance.sort_values(by=["store_id","RMSE","MAPE"],inplace=True)
Model_Performance.set_index("store_id",inplace=True)
```

1. **CA_1**

In [105…
```
Model_Performance.loc["CA_1"]
```

Out[105]:

store_id	Forecast Method	MAPE	RMSE
CA_1	Holts-Winter Log	1.6	9057.5
CA_1	ETS	2.1	11887.0
CA_1	Prophet Additive	2.6	14021.4
CA_1	Prophet Multiplicative	2.4	14154.9
CA_1	SARIMA Log	2.8	14430.3
CA_1	ETS Log	3.5	16821.5
CA_1	SARIMA	3.7	18163.2
CA_1	Seasonal Naive	5.4	25314.8

Here Holts-Winter log is the best model by a substantial margin. We will select

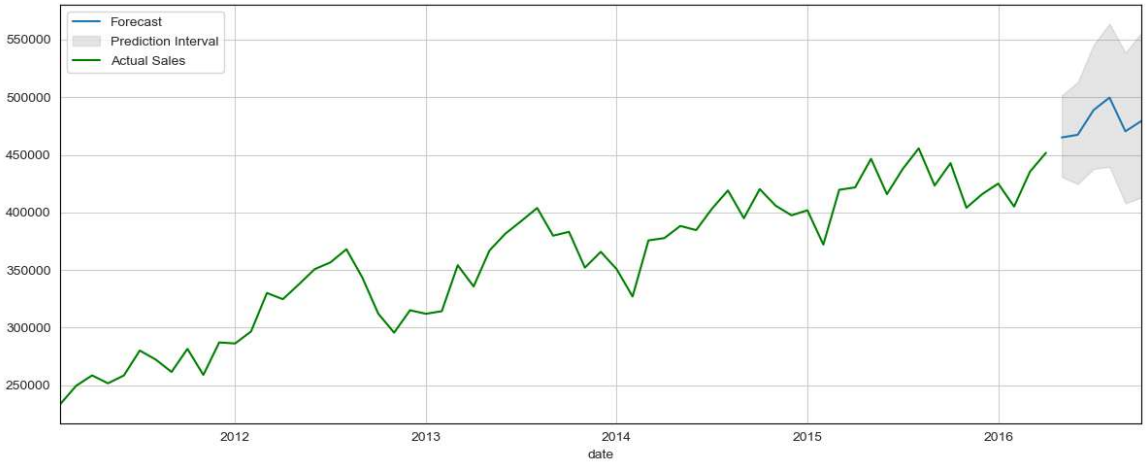
In [106…
```
HW_model_best.loc["CA_1"]
```

Out[106]:
```
Trend                        mul
Seasonal                     add
Damped                     False
Box_Cox                      log
AICc_Train                -312.1
MAPE_Train                   2.6
RMSE_Train               11757.9
MAPE_Test                    1.6
RMSE_Test                 9057.5
lj_residual         Uncorrelated
jb_norm_residual      Not Normal
resid_mean                -160.9
Name: CA_1, dtype: object
```

In [107…
```
CA1_model=ExponentialSmoothing(np.log(CA_monthly["CA_1"]),
                      trend=HW_model_best.loc["CA_1"].Trend,
                      seasonal=HW_model_best.loc["CA_1"].Seasonal,
                      damped_trend=HW_model_best.loc["CA_1"].Damped,
                      seasonal_periods=12,
                      use_boxcox=False,
                      initialization_method="heuristic",
                      freq='MS').fit()
fit_CA1=np.exp(CA1_model.fittedvalues)
predicted_CA1=np.exp(CA1_model.forecast(6))
sim_frame_CA1=CA1_model.simulate(6, anchor='end',repetitions=5000 ).T.apply(np.e
```

In [108…
```
percentile_CA1=pd.DataFrame(columns=["2.5th_percentile","97.5th_percentile"],inc
for i in sim_frame_CA1.columns:
    percentile_CA1.loc[i,"2.5th_percentile"]=np.quantile(sim_frame_CA1[i],0.025)
    percentile_CA1.loc[i,"97.5th_percentile"]=np.quantile(sim_frame_CA1[i],0.975
```

In [109…
```
percentile_CA1["97.5th_percentile"]=percentile_CA1["97.5th_percentile"].astype(i
percentile_CA1["2.5th_percentile"]=percentile_CA1["2.5th_percentile"].astype(int
fig, ax = plt.subplots(figsize=(12,5),nrows=1,ncols=1)
predicted_CA1.plot(ax=ax, legend=True, label="Forecast" )
ax.fill_between(percentile_CA1.index,y1=percentile_CA1["2.5th_percentile"],y2=pe
CA_monthly["CA_1"].plot(legend=True, label="Actual Sales",color="green", ax=ax);
ax.legend(loc="upper left")
fig.tight_layout()
```



1. **CA_2**

In [110…
```
Model_Performance.loc["CA_2"]
```

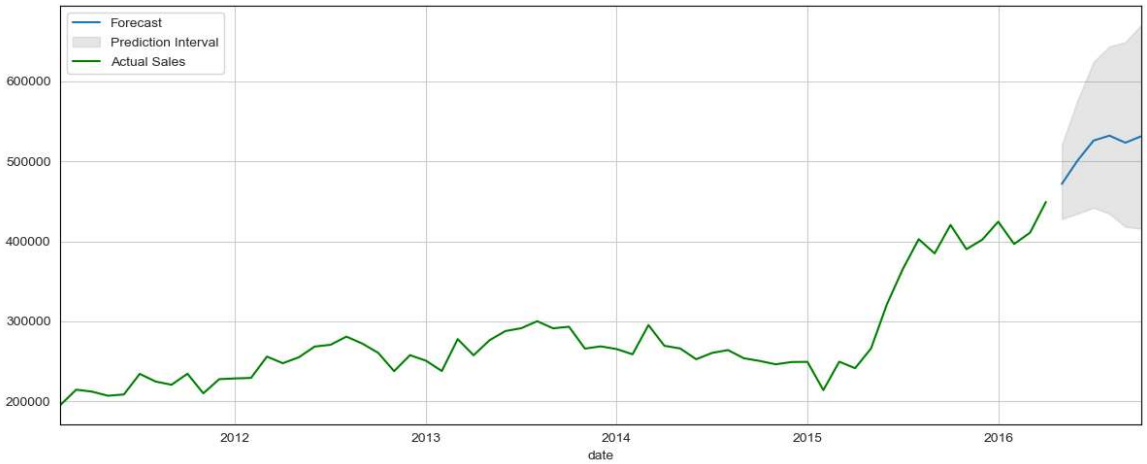
Out[110]:

store_id	Forecast Method	MAPE	RMSE
CA_2	ETS Log	8.0	36155.5
CA_2	Holts-Winter Box-Cox	11.9	54227.2
CA_2	SARIMA Log	13.5	59256.9
CA_2	SARIMA	13.9	62055.6
CA_2	Prophet Multiplicative	35.0	144465.9
CA_2	Prophet Additive	35.0	144694.5
CA_2	Seasonal Naive	39.6	164229.7
CA_2	ETS	39.0	189053.3

In [111…
```
CA2_model=sm.tsa.statespace.ExponentialSmoothing(np.log(CA_monthly["CA_2"]),
                                                 trend=True,
                                                 initialization_method= 'heuristic
                                                 seasonal=12,
                                                 damped_trend=False).fit()
fit_CA2=np.exp(CA2_model.fittedvalues)
predicted_CA2=np.exp(CA2_model.forecast(6))
sim_frame_CA2=CA2_model.simulate(6, anchor='end',repetitions=5000 ).T.apply(np.e
```

In [112…
```
percentile_CA2=pd.DataFrame(columns=["2.5th_percentile","97.5th_percentile"],inc
for i in sim_frame_CA2.columns:
    percentile_CA2.loc[i,"2.5th_percentile"]=np.quantile(sim_frame_CA2[i],0.025)
    percentile_CA2.loc[i,"97.5th_percentile"]=np.quantile(sim_frame_CA2[i],0.975
```

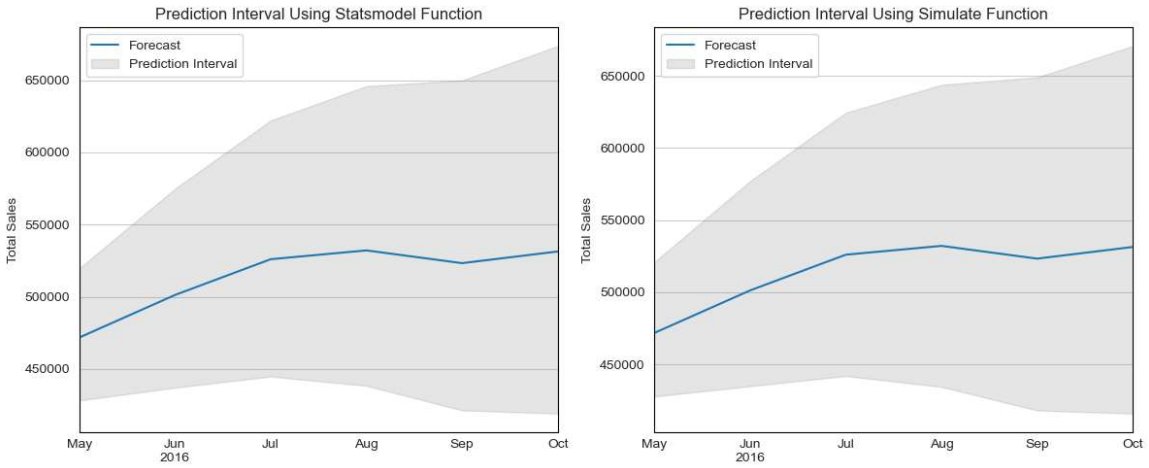
In [113…
```
percentile_CA2["97.5th_percentile"]=percentile_CA2["97.5th_percentile"].astype(i
percentile_CA2["2.5th_percentile"]=percentile_CA2["2.5th_percentile"].astype(int
fig, ax = plt.subplots(figsize=(12,5),nrows=1,ncols=1)
predicted_CA2.plot(ax=ax, legend=True, label="Forecast" )
ax.fill_between(percentile_CA2.index,y1=percentile_CA2["2.5th_percentile"],y2=pe
CA_monthly["CA_2"].plot(legend=True, label="Actual Sales",color="green", ax=ax);
ax.legend(loc="upper left")
fig.tight_layout()
```



In [114…
```
t1=CA2_model.get_forecast(6)
t2=t1.summary_frame(alpha=0.05).apply(np.exp)[["mean","mean_ci_lower","mean_ci_u
```

statsmodel.tsa.statespace.ExponentialSmoothing model also provides prediction interval when making forecast using get_forecast method. This is approximately the same as prediction interval calculated after simulating the forecast mutliple times.

In [115…
```
fig, (ax,ax2) = plt.subplots(figsize=(12,5),nrows=1,ncols=2)
predicted_CA2.plot(ax=ax, legend=True, label="Forecast" )
ax.fill_between(percentile_CA2.index,y1=t2.mean_ci_lower,y2=t2.mean_ci_upper,lab
ax.legend(loc="upper left")
ax.set_title("Prediction Interval Using Statsmodel Function")
ax.set_ylabel("Total Sales")
predicted_CA2.plot(ax=ax2, legend=True, label="Forecast" )
ax2.fill_between(percentile_CA2.index,y1=percentile_CA2["2.5th_percentile"],y2=p
ax2.legend(loc="upper left")
ax2.set_title("Prediction Interval Using Simulate Function")
ax2.set_ylabel("Total Sales")
fig.tight_layout()
```



1. **CA_3**

In [116…
```
Model_Performance.loc["CA_3"]
```

Out[116]:

store_id	Forecast Method	MAPE	RMSE
CA_3	Holts-Winter	2.3	16106.3
CA_3	ETS Log	2.4	16981.6
CA_3	ETS	2.6	19131.5
CA_3	SARIMA Log	2.7	19690.8
CA_3	SARIMA	2.7	19955.4
CA_3	Prophet Multiplicative	3.1	21454.0
CA_3	Prophet Additive	3.4	22460.5
CA_3	Seasonal Naive	5.1	34676.5

In [117…
```
ets_LAdA=sm.tsa.statespace.ExponentialSmoothing(np.log(Train["CA_3"]),
                                                trend=True,
                                                initialization_method= 'heuristic
                                                seasonal=12,
```

```
                                                damped_trend=False).fit()
print("Holts Winter AICc:",HW_model_best.loc["CA_3"].AICc_Train,"\nETS Log AICc:
```

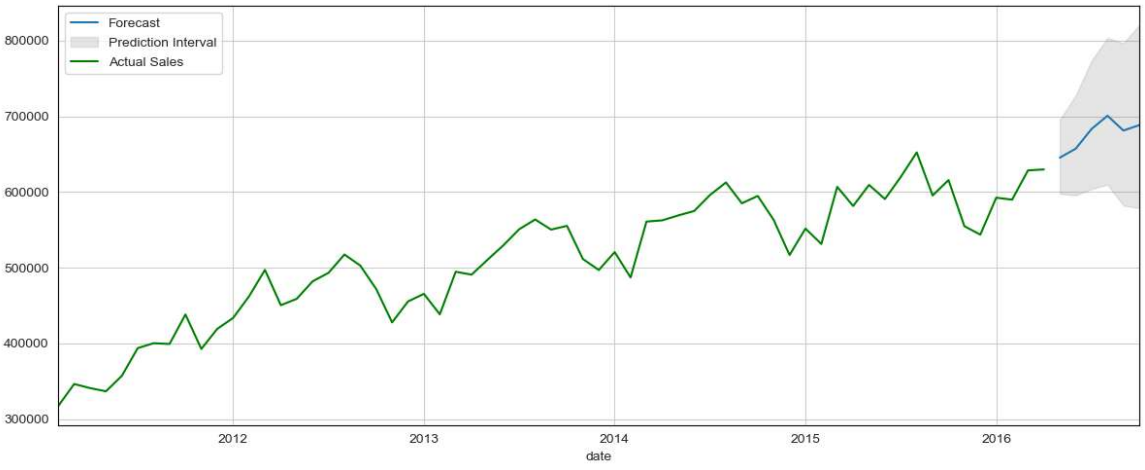
```
Holts Winter AICc: 1115.4
ETS Log AICc: -183.71370448178146
```

We will be selecting ETS Log method here as the AICc fot ETS log is considerably smaller, while accuracy is almost the same as Holts Winter Method.

In [118…
```
CA3_model=sm.tsa.statespace.ExponentialSmoothing(np.log(CA_monthly["CA_3"]),
                                                 trend=True,
                                                 initialization_method= 'heuristic
                                                 seasonal=12,
                                                 damped_trend=False).fit()
fit_CA3=np.exp(CA3_model.fittedvalues)
predicted_CA3=np.exp(CA3_model.forecast(6))
sim_frame_CA3=CA3_model.simulate(6, anchor='end',repetitions=5000 ).T.apply(np.e
```

In [119…
```
percentile_CA3=pd.DataFrame(columns=["2.5th_percentile","97.5th_percentile"],inc
for i in sim_frame_CA3.columns:
    percentile_CA3.loc[i,"2.5th_percentile"]=np.quantile(sim_frame_CA3[i],0.025)
    percentile_CA3.loc[i,"97.5th_percentile"]=np.quantile(sim_frame_CA3[i],0.975
```

In [120…
```
percentile_CA3["97.5th_percentile"]=percentile_CA3["97.5th_percentile"].astype(i
percentile_CA3["2.5th_percentile"]=percentile_CA3["2.5th_percentile"].astype(int
fig, ax = plt.subplots(figsize=(12,5),nrows=1,ncols=1)
predicted_CA3.plot(ax=ax, legend=True, label="Forecast" )
ax.fill_between(percentile_CA3.index,y1=percentile_CA3["2.5th_percentile"],y2=pe
CA_monthly["CA_3"].plot(legend=True, label="Actual Sales",color="green", ax=ax);
ax.legend(loc="upper left")
fig.tight_layout()
```



1. **CA_4**

In [121…
```
Model_Performance.loc["CA_4"]
```

Out[121]:

store_id	Forecast Method	MAPE	RMSE
CA_4	Holts-Winter Log	1.9	5780.3
CA_4	Prophet Additive	2.1	7227.0
CA_4	Prophet Multiplicative	2.3	7947.3
CA_4	ETS Log	2.8	7953.6
CA_4	ETS	2.9	8546.3
CA_4	SARIMA	3.4	9649.6
CA_4	SARIMA Log	3.2	10071.2
CA_4	Seasonal Naive	7.8	21282.6

In [122…
```
CA4_model=ExponentialSmoothing(np.log(CA_monthly["CA_4"]),
                      trend=HW_model_best.loc["CA_4"].Trend,
                      seasonal=HW_model_best.loc["CA_4"].Seasonal,
                      damped_trend=HW_model_best.loc["CA_4"].Damped,
                      seasonal_periods=12,
                      use_boxcox=False,
                      initialization_method="heuristic",
                      freq='MS').fit()
fit_CA4=np.exp(CA4_model.fittedvalues)
predicted_CA4=np.exp(CA4_model.forecast(6))
sim_frame_CA4=CA4_model.simulate(6, anchor='end',repetitions=5000 ).T.apply(np.e
```

In [123…
```
percentile_CA4=pd.DataFrame(columns=["2.5th_percentile","97.5th_percentile"],inc
for i in sim_frame_CA4.columns:
    percentile_CA4.loc[i,"2.5th_percentile"]=np.quantile(sim_frame_CA4[i],0.025)
    percentile_CA4.loc[i,"97.5th_percentile"]=np.quantile(sim_frame_CA4[i],0.975
```

In [124…
```
percentile_CA4["97.5th_percentile"]=percentile_CA4["97.5th_percentile"].astype(i
percentile_CA4["2.5th_percentile"]=percentile_CA4["2.5th_percentile"].astype(int
fig, ax = plt.subplots(figsize=(12,5),nrows=1,ncols=1)
predicted_CA4.plot(ax=ax, legend=True, label="Forecast" )
ax.fill_between(percentile_CA4.index,y1=percentile_CA4["2.5th_percentile"],y2=pe
CA_monthly["CA_4"].plot(legend=True, label="Actual Sales",color="green", ax=ax);
ax.legend(loc="upper left")
fig.tight_layout()
```

Power Bi Deployment

We are going to use the selected model in Power Bi. Screen shorts and .pbix files is on the git hub link. Please visit the link also.

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