TimeSeries_SalesForecast_Grocery

May 19, 2025

1 TASK

#Project 1-Sales Forecasting

1.1 Overview

The main objective of this project (e.g., predicting sales based on historical data). A brief explanation of the approaches used (VARMAX for multi-variable relationships, LSTM for complex time-series patterns).

1.2 Dataset

Data source. Description of key features (date, sales, promotion, external variables). Handling missing value and date.

1.3 Tools & Technologies Used

Environment: Google Colab / Jupyter Notebook / Local Python Environment. Modeling Tools: VARMAX using statsmodels.tsa.statespace.varmax.VARMAX LSTM using tensorflow.keras

1.4 Data Preprocessing

Feature normalization / standardization. Time transformations (lag features, differencing for VARMAX). Splitting data into train and test sets.

1.5 Model Development

VARMAX : Selecting optimal parameters (p, q), performance evaluation using MSE or AIC/BIC. LSTM : Model architecture (number of layers, dropout, activation functions), hyperparameter selection (optimizer, batch size, epochs), callback functions such as EarlyStopping

1.6 Model Evaluation & Comparison

Evaluation metrics: RMSE, MAE, MAPE. Performance comparison of VARMAX vs. LSTM. Visualization of predictions vs. actual values.

2 IMPORTS

[121]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

3 LOAD DATA + EDA

store_nbr store_nbr identifies the store at which the products are sold. **family** family identifies the type of product sold. **sales** sales gives the total sales for a product family at a particular store at a given date. Fractional values are possible since products can be sold in fractional units (1.5 kg of cheese, for instance, as opposed to 1 bag of chips). **onpromotion** onpromotion gives the total number of items in a product family that were being promoted at a store at a given date. **dcoilwtico** dcoilwtico defines daily oil price. It contains the date and the dcoilwtico. The "dcoilwtico" data represents the daily values of the West Texas Intermediate(WTI)crude oil price index, which is important for tracking and analyzing trends in the oil market. Ecuador is an oil-dependent country and its economic health is highly vulnerable to shocks in oil prices.

[122]:
```
original_df = pd.read_csv('store5.csv')
```

[123]:
```
original_df.head()
```

[123]:

	id	date	store_nbr	family	sales	onpromotion	dcoilwtico
0	1452	2013-01-01	5	AUTOMOTIVE	0.0	0	NaN
1	1453	2013-01-01	5	BABY CARE	0.0	0	NaN
2	1454	2013-01-01	5	BEAUTY	0.0	0	NaN
3	1455	2013-01-01	5	BEVERAGES	0.0	0	NaN
4	1456	2013-01-01	5	BOOKS	0.0	0	NaN

[124]:
```
original_df.describe().T
```

[124]:

	count	mean	std	min	25%	\
id	55572.0	1.501021e+06	866289.388951	1452.00	751236.50	
store_nbr	55572.0	5.000000e+00	0.000000	5.00	5.00	
sales	55572.0	2.805802e+02	652.588149	0.00	1.00	
onpromotion	55572.0	2.687864e+00	11.748996	0.00	0.00	
dcoilwtico	38379.0	6.792559e+01	25.666659	26.19	46.38	

	50%	75%	max
id	1501021.00	2250805.5	3000590.00
store_nbr	5.00	5.0	5.00
sales	19.00	237.0	8216.62
onpromotion	0.00	0.0	182.00
dcoilwtico	53.33	95.8	110.62

[125]:
```
original_df[original_df.duplicated()]
```

[125]:
```
Empty DataFrame
Columns: [id, date, store_nbr, family, sales, onpromotion, dcoilwtico]
Index: []
```

[126]:
```
original_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 55572 entries, 0 to 55571
Data columns (total 7 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   id           55572 non-null  int64
 1   date         55572 non-null  object
 2   store_nbr    55572 non-null  int64
 3   family       55572 non-null  object
 4   sales        55572 non-null  float64
 5   onpromotion  55572 non-null  int64
 6   dcoilwtico   38379 non-null  float64
dtypes: float64(2), int64(3), object(2)
memory usage: 3.0+ MB
```

[127]:
```
original_df[original_df.duplicated()]
```

[127]:
```
Empty DataFrame
Columns: [id, date, store_nbr, family, sales, onpromotion, dcoilwtico]
Index: []
```

[128]:
```
sales_df=original_df.copy(deep=True)
print(sales_df[sales_df.duplicated()])
sales_df['date']=pd.to_datetime(sales_df['date'])

sales_df['weekdays'] = sales_df['date'].dt.day_name()  # Weekday name (e.g.,␣
 ↪'Monday')
sales_df['week_of_the_year'] = sales_df['date'].dt.isocalendar().week  # Week␣
 ↪of the year
sales_df['year'] = sales_df['date'].dt.year  # Year
sales_df['month'] = sales_df['date'].dt.month  # Month
sales_df['day'] = sales_df['date'].dt.day  # Day of the month

print(sales_df.info())
print(sales_df[sales_df.duplicated()])
```

```
Empty DataFrame
Columns: [id, date, store_nbr, family, sales, onpromotion, dcoilwtico]
Index: []
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 55572 entries, 0 to 55571
Data columns (total 12 columns):
```

```
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   id                55572 non-null  int64
 1   date              55572 non-null  datetime64[ns]
 2   store_nbr         55572 non-null  int64
 3   family            55572 non-null  object
 4   sales             55572 non-null  float64
 5   onpromotion       55572 non-null  int64
 6   dcoilwtico        38379 non-null  float64
 7   weekdays          55572 non-null  object
 8   week_of_the_year  55572 non-null  UInt32
 9   year              55572 non-null  int64
 10  month             55572 non-null  int64
 11  day               55572 non-null  int64
dtypes: UInt32(1), datetime64[ns](1), float64(2), int64(6), object(2)
memory usage: 4.9+ MB
None
Empty DataFrame
Columns: [id, date, store_nbr, family, sales, onpromotion, dcoilwtico, weekdays,
week_of_the_year, year, month, day]
Index: []
```

[ ]:

[129]:
```
print(sales_df.describe().T)
```

```
                   count         mean            std     min       25%  \
id                55572.0    1501021.0  866289.388951  1452.0  751236.5
store_nbr         55572.0          5.0            0.0     5.0       5.0
sales             55572.0   280.580231     652.588149     0.0       1.0
onpromotion       55572.0     2.687864      11.748996     0.0       0.0
dcoilwtico        38379.0    67.925589      25.666659   26.19     46.38
week_of_the_year  55572.0    25.242874      14.794802     1.0      13.0
year              55572.0  2014.837886        1.34553  2013.0    2014.0
month             55572.0     6.207838       3.385698     1.0       3.0
day               55572.0    15.630048       8.794867     1.0       8.0

                       50%        75%        max
id                1501021.0  2250805.5  3000590.0
store_nbr               5.0        5.0        5.0
sales                  19.0      237.0    8216.62
onpromotion             0.0        0.0      182.0
dcoilwtico            53.33       95.8     110.62
week_of_the_year       25.0       38.0       53.0
year                 2015.0     2016.0     2017.0
month                   6.0        9.0       12.0
day                    16.0       23.0       31.0
```

[130]:
```
print(sales_df.head())
```

```
     id       date  store_nbr      family  sales  onpromotion  dcoilwtico  \
0  1452 2013-01-01          5  AUTOMOTIVE    0.0            0         NaN
1  1453 2013-01-01          5   BABY CARE    0.0            0         NaN
2  1454 2013-01-01          5      BEAUTY    0.0            0         NaN
3  1455 2013-01-01          5   BEVERAGES    0.0            0         NaN
4  1456 2013-01-01          5       BOOKS    0.0            0         NaN

  weekdays  week_of_the_year  year  month  day
0  Tuesday                 1  2013      1    1
1  Tuesday                 1  2013      1    1
2  Tuesday                 1  2013      1    1
3  Tuesday                 1  2013      1    1
4  Tuesday                 1  2013      1    1
```

[131]:
```
print(sales_df.columns)
```

```
Index(['id', 'date', 'store_nbr', 'family', 'sales', 'onpromotion',
       'dcoilwtico', 'weekdays', 'week_of_the_year', 'year', 'month', 'day'],
      dtype='object')
```

[132]:
```
print(sales_df['store_nbr'].unique())
# semua berisi 5 (nomor toko), jadi dibuang saja

sales_df=sales_df[['id', 'date', 'family', 'sales', 'onpromotion',␣
 ↪'dcoilwtico','weekdays', 'week_of_the_year', 'year', 'month', 'day']]
```

```
[5]
```

[133]:
```
print(sales_df.columns)
```

```
Index(['id', 'date', 'family', 'sales', 'onpromotion', 'dcoilwtico',
       'weekdays', 'week_of_the_year', 'year', 'month', 'day'],
      dtype='object')
```

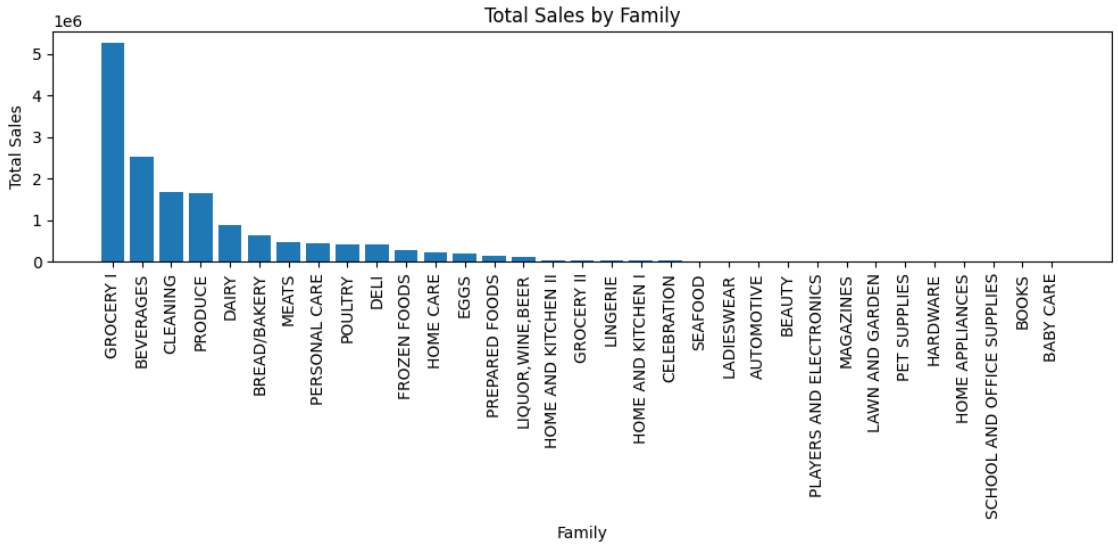
[134]:
```
jml_unique_family = sales_df['family'].nunique()
print(f'jml_unique_family = {jml_unique_family}')
#tiap tanggal seharusnya ada 33 row data
print('')
print(sales_df['family'].unique())
```

```
jml_unique_family = 33

['AUTOMOTIVE' 'BABY CARE' 'BEAUTY' 'BEVERAGES' 'BOOKS' 'BREAD/BAKERY'
 'CELEBRATION' 'CLEANING' 'DAIRY' 'DELI' 'EGGS' 'FROZEN FOODS' 'GROCERY I'
 'GROCERY II' 'HARDWARE' 'HOME AND KITCHEN I' 'HOME AND KITCHEN II'
 'HOME APPLIANCES' 'HOME CARE' 'LADIESWEAR' 'LAWN AND GARDEN' 'LINGERIE'
 'LIQUOR,WINE,BEER' 'MAGAZINES' 'MEATS' 'PERSONAL CARE' 'PET SUPPLIES'
```

```
 'PLAYERS AND ELECTRONICS' 'POULTRY' 'PREPARED FOODS' 'PRODUCE'
 'SCHOOL AND OFFICE SUPPLIES' 'SEAFOOD']
```

[135]:
```
df = sales_df.groupby('family')[['sales']].sum()
df = df.sort_values(by='sales', ascending=False)

plt.figure(figsize=(10,5))
bars=plt.bar(df.index, df['sales'])

plt.xlabel('Family')
plt.ylabel('Total Sales')
plt.title('Total Sales by Family')
plt.xticks(rotation=90)
plt.tight_layout()
plt.show

print(df.head())
```

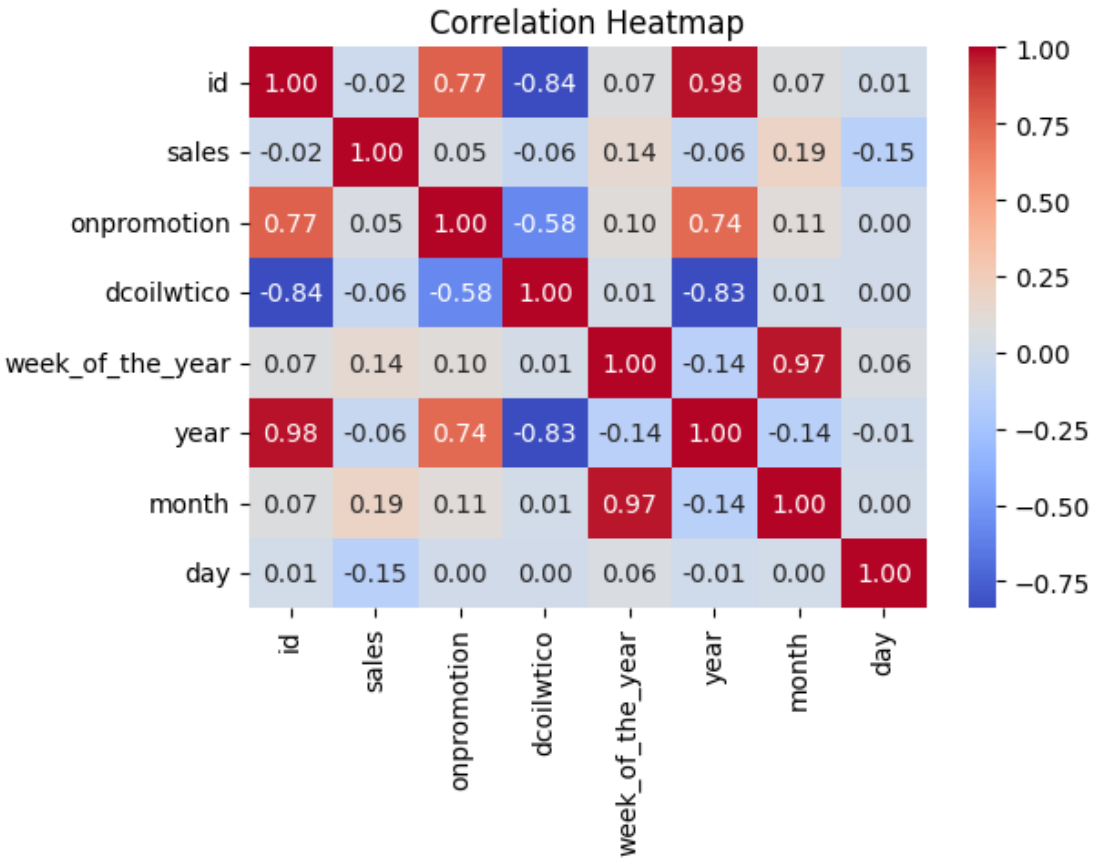
```
                 sales
family
GROCERY I   5.262682e+06
BEVERAGES   2.533831e+06
CLEANING    1.667748e+06
PRODUCE     1.653582e+06
DAIRY       8.712830e+05
```



[136]:
```
sales_df = sales_df[sales_df['family']=='GROCERY I']
```

[137]:
```
# Heatmap of correlation
df = sales_df
pearson_corr = df.corr()
plt.figure(figsize=(6, 4))
sns.heatmap(pearson_corr, annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation Heatmap")
plt.show()
```

```
C:\Users\andyp\AppData\Local\Temp\ipykernel_26060\3286099896.py:3:
FutureWarning: The default value of numeric_only in DataFrame.corr is
deprecated. In a future version, it will default to False. Select only valid
columns or specify the value of numeric_only to silence this warning.
  pearson_corr = df.corr()
```



[138]:
```
weekday_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday',␣
 ↪'Saturday', 'Sunday']
df = sales_df
temp=df.
 ↪groupby('weekdays')[['date','family','sales','onpromotion','dcoilwtico']].
 ↪count().reindex(weekday_order)
```

```
# temp = temp.div(33).astype(int)
temp

#melihat dari data ini , family, sales, onpromotion ada datanya , sedangkan␣
 ↪dcoilwtico banyak missing data, dan selalu kosong pada saturday dan sunday
```

[138]:

weekdays	date	family	sales	onpromotion	dcoilwtico
Monday	241	241	241	241	218
Tuesday	242	242	242	242	240
Wednesday	240	240	240	240	239
Thursday	240	240	240	240	234
Friday	240	240	240	240	232
Saturday	241	241	241	241	0
Sunday	240	240	240	240	0

3.1 Insert Missing Date

[139]:
```
min_date = sales_df['date'].min()
max_date = sales_df['date'].max()
print(f'min_date={min_date}')
print(f'max_date={max_date}')


tanggalan = pd.date_range(start=min_date, end=max_date, freq='D')
print(tanggalan)

# Find the missing dates by comparing the full range with the existing dates
missing_dates = tanggalan.difference(sales_df['date'])

print()
print(f'missing_dates = {missing_dates}')
```

```
min_date=2013-01-01 00:00:00
max_date=2017-08-15 00:00:00
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
               '2013-01-05', '2013-01-06', '2013-01-07', '2013-01-08',
               '2013-01-09', '2013-01-10',
               …
               '2017-08-06', '2017-08-07', '2017-08-08', '2017-08-09',
               '2017-08-10', '2017-08-11', '2017-08-12', '2017-08-13',
               '2017-08-14', '2017-08-15'],
              dtype='datetime64[ns]', length=1688, freq='D')

missing_dates = DatetimeIndex(['2013-12-25', '2014-12-25', '2015-12-25',
'2016-12-25'], dtype='datetime64[ns]', freq=None)
```

[140]:
```
temp = sales_df[sales_df['date'] == pd.to_datetime('2013-01-01')]
# temp['date']=pd.to_datetime('2013-12-25')
temp.loc[:, 'date'] = pd.to_datetime('2013-12-25')

temp2 = sales_df[sales_df['date'] == pd.to_datetime('2013-01-01')]
# temp2['date']=pd.to_datetime('2014-12-25')
temp2.loc[:, 'date'] = pd.to_datetime('2014-12-25')

temp = pd.concat([temp, temp2])

temp2 = sales_df[sales_df['date'] == pd.to_datetime('2013-01-01')]
# temp2['date']=pd.to_datetime('2015-12-25')
temp2.loc[:, 'date'] = pd.to_datetime('2015-12-25')
temp = pd.concat([temp, temp2])

temp2 = sales_df[sales_df['date'] == pd.to_datetime('2013-01-01')]
# temp2['date']=pd.to_datetime('2016-12-25')
temp2.loc[:, 'date'] = pd.to_datetime('2016-12-25')
temp = pd.concat([temp, temp2], ignore_index=True)


sales_df = pd.concat([sales_df, temp], ignore_index=True)
```

```
C:\Users\andyp\AppData\Local\Temp\ipykernel_26060\4006493657.py:3:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  temp.loc[:, 'date'] = pd.to_datetime('2013-12-25')
C:\Users\andyp\AppData\Local\Temp\ipykernel_26060\4006493657.py:3:
DeprecationWarning: In a future version, `df.iloc[:, i] = newvals` will attempt
to set the values inplace instead of always setting a new array. To retain the
old behavior, use either `df[df.columns[i]] = newvals` or, if columns are non-
unique, `df.isetitem(i, newvals)`
  temp.loc[:, 'date'] = pd.to_datetime('2013-12-25')
C:\Users\andyp\AppData\Local\Temp\ipykernel_26060\4006493657.py:7:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  temp2.loc[:, 'date'] = pd.to_datetime('2014-12-25')
C:\Users\andyp\AppData\Local\Temp\ipykernel_26060\4006493657.py:7:
DeprecationWarning: In a future version, `df.iloc[:, i] = newvals` will attempt
to set the values inplace instead of always setting a new array. To retain the
```

```
old behavior, use either `df[df.columns[i]] = newvals` or, if columns are non-
unique, `df.isetitem(i, newvals)`
  temp2.loc[:, 'date'] = pd.to_datetime('2014-12-25')
C:\Users\andyp\AppData\Local\Temp\ipykernel_26060\4006493657.py:13:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  temp2.loc[:, 'date'] = pd.to_datetime('2015-12-25')
C:\Users\andyp\AppData\Local\Temp\ipykernel_26060\4006493657.py:13:
DeprecationWarning: In a future version, `df.iloc[:, i] = newvals` will attempt
to set the values inplace instead of always setting a new array. To retain the
old behavior, use either `df[df.columns[i]] = newvals` or, if columns are non-
unique, `df.isetitem(i, newvals)`
  temp2.loc[:, 'date'] = pd.to_datetime('2015-12-25')
C:\Users\andyp\AppData\Local\Temp\ipykernel_26060\4006493657.py:18:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  temp2.loc[:, 'date'] = pd.to_datetime('2016-12-25')
C:\Users\andyp\AppData\Local\Temp\ipykernel_26060\4006493657.py:18:
DeprecationWarning: In a future version, `df.iloc[:, i] = newvals` will attempt
to set the values inplace instead of always setting a new array. To retain the
old behavior, use either `df[df.columns[i]] = newvals` or, if columns are non-
unique, `df.isetitem(i, newvals)`
  temp2.loc[:, 'date'] = pd.to_datetime('2016-12-25')
```

[141]:
```
#sorting the dataframe
sales_df = sales_df.sort_values(by=['date', 'family']).reset_index(drop=True)
sales_df=sales_df.sort_values(by='date')
```

3.2 Creating Dummy Variable (separating date components)

[142]:
```
sales_df['weekdays'] = sales_df['date'].dt.day_name()  # Weekday name (e.g.,␣
 ↪'Monday')
sales_df['week_of_the_year'] = sales_df['date'].dt.isocalendar().week  # Week␣
 ↪of the year
sales_df['year'] = sales_df['date'].dt.year  # Year
sales_df['month'] = sales_df['date'].dt.month  # Month
sales_df['day'] = sales_df['date'].dt.day  # Day of the month
```

[143]:
```
df=sales_df[(sales_df['month']==1) & (sales_df['day']==1)]
print(df)
#tahun baru
#toko libur, promo libur, harga minyak kosong
```

```
          id       date     family  sales  onpromotion  dcoilwtico  \
0       1464 2013-01-01  GROCERY I    0.0            0         NaN
365   650112 2014-01-01  GROCERY I    0.0            0         NaN
730  1298760 2015-01-01  GROCERY I    0.0            0         NaN
1095 1947408 2016-01-01  GROCERY I    0.0            0         NaN
1461 2597838 2017-01-01  GROCERY I    0.0            0         NaN

       weekdays  week_of_the_year  year  month  day
0       Tuesday                 1  2013      1    1
365   Wednesday                 1  2014      1    1
730    Thursday                 1  2015      1    1
1095     Friday                53  2016      1    1
1461     Sunday                52  2017      1    1
```

[144]:
```
df=sales_df[(sales_df['month']==12) & (sales_df['day']==31)]
print(df)
#akhir tahun tetap buka
```

```
          id       date     family    sales  onpromotion  dcoilwtico  \
364   648330 2013-12-31  GROCERY I  4271.00            0       98.17
729  1296978 2014-12-31  GROCERY I  4459.00           11       53.45
1094 1945626 2015-12-31  GROCERY I  4327.23            1       37.13
1460 2596056 2016-12-31  GROCERY I  4615.00          112         NaN

       weekdays  week_of_the_year  year  month  day
364     Tuesday                 1  2013     12   31
729   Wednesday                 1  2014     12   31
1094   Thursday                53  2015     12   31
1460   Saturday                52  2016     12   31
```

[145]:
```
df=sales_df[(sales_df['month']==12) & (sales_df['day']==25)]
print(df)
#natal libur
#toko libur, promo libur, harga minyak kosong
```

```
        id       date     family  sales  onpromotion  dcoilwtico   weekdays  \
358   1464 2013-12-25  GROCERY I    0.0            0         NaN  Wednesday
723   1464 2014-12-25  GROCERY I    0.0            0         NaN   Thursday
1088  1464 2015-12-25  GROCERY I    0.0            0         NaN     Friday
1454  1464 2016-12-25  GROCERY I    0.0            0         NaN     Sunday

      week_of_the_year  year  month  day
358                 52  2013     12   25
723                 52  2014     12   25
```

```
1088                52  2015      12   25
1454                51  2016      12   25
```

3.3 Creating Dummy Variable (Weekend and Holiday)

[146]:
```
sales_df['isWeekend'] = sales_df['weekdays'].isin(['Saturday', 'Sunday']).
 ↪astype(int)
sales_df['isHoliday'] = ((sales_df['month'] == 12) & (sales_df['day']== 25)).
 ↪astype(int)
sales_df['isHoliday'] = sales_df['isHoliday'] | ((sales_df['date'].dt.month ==␣
 ↪1) & (sales_df['date'].dt.day == 1)).astype(int)
```

[147]:
```
df=sales_df[(sales_df['isWeekend']==1) ]
print(df)
#weekend tetap jualan
# info harga oil kosong
```

```
           id       date     family   sales  onpromotion  dcoilwtico  \
4        8592 2013-01-05  GROCERY I  3398.0            0         NaN
5       10374 2013-01-06  GROCERY I  4643.0            0         NaN
11      21066 2013-01-12  GROCERY I  2938.0            0         NaN
12      22848 2013-01-13  GROCERY I  4064.0            0         NaN
18      33540 2013-01-19  GROCERY I  2941.0            0         NaN
…         …        …         …     …              …          …
1671  2972058 2017-07-30  GROCERY I  3780.0           62         NaN
1677  2982750 2017-08-05  GROCERY I  3396.0           41         NaN
1678  2984532 2017-08-06  GROCERY I  3460.0           37         NaN
1684  2995224 2017-08-12  GROCERY I  2476.0           31         NaN
1685  2997006 2017-08-13  GROCERY I  3141.0           31         NaN

      weekdays  week_of_the_year  year  month  day  isWeekend  isHoliday
4     Saturday                 1  2013      1    5          1          0
5       Sunday                 1  2013      1    6          1          0
11    Saturday                 2  2013      1   12          1          0
12      Sunday                 2  2013      1   13          1          0
18    Saturday                 3  2013      1   19          1          0
…        …                 …    …     …  …         …          …
1671    Sunday                30  2017      7   30          1          0
1677  Saturday                31  2017      8    5          1          0
1678    Sunday                31  2017      8    6          1          0
1684  Saturday                32  2017      8   12          1          0
1685    Sunday                32  2017      8   13          1          0

[482 rows x 13 columns]
```

[148]:
```
sales_df
```

[148]:

	id	date	family	sales	onpromotion	dcoilwtico	\
0	1464	2013-01-01	GROCERY I	0.0	0	NaN	
1	3246	2013-01-02	GROCERY I	4558.0	0	93.14	
2	5028	2013-01-03	GROCERY I	3260.0	0	92.97	
3	6810	2013-01-04	GROCERY I	3085.0	0	93.12	
4	8592	2013-01-05	GROCERY I	3398.0	0	NaN	
…	…	…	…	…	…	…	
1683	2993442	2017-08-11	GROCERY I	2864.0	35	48.81	
1684	2995224	2017-08-12	GROCERY I	2476.0	31	NaN	
1685	2997006	2017-08-13	GROCERY I	3141.0	31	NaN	
1686	2998788	2017-08-14	GROCERY I	2717.0	32	47.59	
1687	3000570	2017-08-15	GROCERY I	2696.0	26	47.57	

	weekdays	week_of_the_year	year	month	day	isWeekend	isHoliday
0	Tuesday	1	2013	1	1	0	1
1	Wednesday	1	2013	1	2	0	0
2	Thursday	1	2013	1	3	0	0
3	Friday	1	2013	1	4	0	0
4	Saturday	1	2013	1	5	1	0
…	…	…	…	…	…	…	
1683	Friday	32	2017	8	11	0	0
1684	Saturday	32	2017	8	12	1	0
1685	Sunday	32	2017	8	13	1	0
1686	Monday	33	2017	8	14	0	0
1687	Tuesday	33	2017	8	15	0	0

[1688 rows x 13 columns]

3.4 Handle Missing Value for dcoilwtico

[149]:
```
sales_df['oil_fill']=sales_df['dcoilwtico']
sales_df['oil_fill']=sales_df['oil_fill'].interpolate(method='linear')
sales_df['oil_fill'] = sales_df['oil_fill'].fillna(method='bfill')

sales_df
```

[149]:

	id	date	family	sales	onpromotion	dcoilwtico	\
0	1464	2013-01-01	GROCERY I	0.0	0	NaN	
1	3246	2013-01-02	GROCERY I	4558.0	0	93.14	
2	5028	2013-01-03	GROCERY I	3260.0	0	92.97	
3	6810	2013-01-04	GROCERY I	3085.0	0	93.12	
4	8592	2013-01-05	GROCERY I	3398.0	0	NaN	
…	…	…	…	…	…	…	
1683	2993442	2017-08-11	GROCERY I	2864.0	35	48.81	
1684	2995224	2017-08-12	GROCERY I	2476.0	31	NaN	
1685	2997006	2017-08-13	GROCERY I	3141.0	31	NaN	
1686	2998788	2017-08-14	GROCERY I	2717.0	32	47.59	

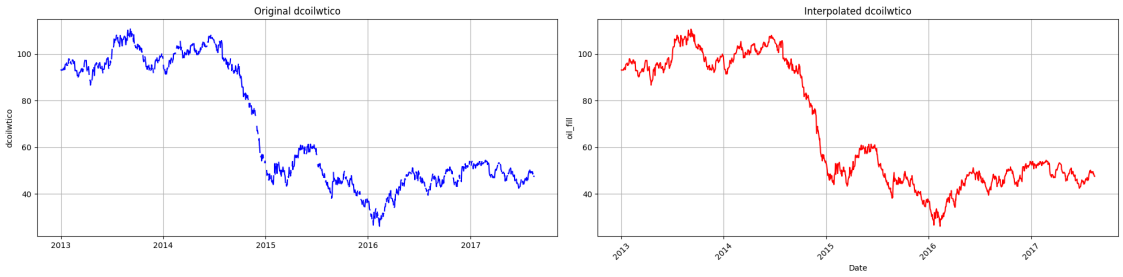
```
1687  3000570 2017-08-15  GROCERY I  2696.0           26       47.57

       weekdays  week_of_the_year  year  month  day  isWeekend  isHoliday  \
0       Tuesday                 1  2013      1    1          0          1
1     Wednesday                 1  2013      1    2          0          0
2      Thursday                 1  2013      1    3          0          0
3        Friday                 1  2013      1    4          0          0
4      Saturday                 1  2013      1    5          1          0
…         …               …    …    …  …         …          …
1683     Friday                32  2017      8   11          0          0
1684   Saturday                32  2017      8   12          1          0
1685     Sunday                32  2017      8   13          1          0
1686     Monday                33  2017      8   14          0          0
1687    Tuesday                33  2017      8   15          0          0

       oil_fill
0     93.140000
1     93.140000
2     92.970000
3     93.120000
4     93.146667
…         …
1683  48.810000
1684  48.403333
1685  47.996667
1686  47.590000
1687  47.570000

[1688 rows x 14 columns]
```

[150]:
```
print(sales_df['oil_fill'].isna().sum())

sales_df.info()
```

```
0
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1688 entries, 0 to 1687
Data columns (total 14 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   id                1688 non-null   int64
 1   date              1688 non-null   datetime64[ns]
 2   family            1688 non-null   object
 3   sales             1688 non-null   float64
 4   onpromotion       1688 non-null   int64
 5   dcoilwtico        1163 non-null   float64
 6   weekdays          1688 non-null   object
 7   week_of_the_year  1688 non-null   UInt32
```

```
 8   year              1688 non-null   int64
 9   month             1688 non-null   int64
 10  day               1688 non-null   int64
 11  isWeekend         1688 non-null   int32
 12  isHoliday         1688 non-null   int32
 13  oil_fill          1688 non-null   float64
dtypes: UInt32(1), datetime64[ns](1), float64(3), int32(2), int64(5), object(2)
memory usage: 179.7+ KB
```

[151]:
```
fig, axes = plt.subplots(1, 2, figsize=(20, 5), sharex=True)

axes[0].plot(sales_df['date'], sales_df['dcoilwtico'], color='b')
axes[0].set_title('Original dcoilwtico')
axes[0].set_ylabel('dcoilwtico')
axes[0].grid(True)

axes[1].plot(sales_df['date'], sales_df['oil_fill'],  color='r')
axes[1].set_title('Interpolated dcoilwtico')
axes[1].set_xlabel('Date')
axes[1].set_ylabel('oil_fill')
axes[1].grid(True)

plt.xticks(rotation=45)

plt.tight_layout()

plt.show()
```



[152]:
```
sales_df.sample(n=21 , random_state=42)
```

[152]:

	id	date	family	sales	onpromotion	dcoilwtico	\
1251	2225400	2016-06-05	GROCERY I	4383.000	69	NaN	
494	879990	2014-05-10	GROCERY I	4144.000	0	NaN	
203	363210	2013-07-23	GROCERY I	2703.000	0	107.13	
479	853260	2014-04-25	GROCERY I	2286.000	0	100.85	
886	1576752	2015-06-06	GROCERY I	3725.000	18	NaN	

1134	2016906	2016-02-09	GROCERY I	2167.000	64	27.96	
1211	2154120	2016-04-26	GROCERY I	2210.000	32	42.52	
427	760596	2014-03-04	GROCERY I	2539.000	0	103.64	
1277	2271732	2016-07-01	GROCERY I	3502.000	56	49.02	
1633	2904342	2017-06-22	GROCERY I	2652.000	54	42.53	
173	309750	2013-06-23	GROCERY I	3848.000	0	NaN	
745	1325490	2015-01-16	GROCERY I	2744.000	12	48.49	
986	1754952	2015-09-14	GROCERY I	2820.000	9	44.07	
1398	2487354	2016-10-30	GROCERY I	3577.000	82	NaN	
1667	2964930	2017-07-26	GROCERY I	2757.000	73	48.58	
1230	2187978	2016-05-15	GROCERY I	3602.000	26	NaN	
1100	1956318	2016-01-06	GROCERY I	3071.451	24	33.97	
785	1396770	2015-02-25	GROCERY I	2679.000	8	50.25	
857	1525074	2015-05-08	GROCERY I	3370.000	10	59.41	
1507	2679810	2017-02-16	GROCERY I	2199.000	50	53.41	
135	242034	2013-05-16	GROCERY I	2636.000	0	94.85	

	weekdays	week_of_the_year	year	month	day	isWeekend	isHoliday	\
1251	Sunday	22	2016	6	5	1	0	
494	Saturday	19	2014	5	10	1	0	
203	Tuesday	30	2013	7	23	0	0	
479	Friday	17	2014	4	25	0	0	
886	Saturday	23	2015	6	6	1	0	
1134	Tuesday	6	2016	2	9	0	0	
1211	Tuesday	17	2016	4	26	0	0	
427	Tuesday	10	2014	3	4	0	0	
1277	Friday	26	2016	7	1	0	0	
1633	Thursday	25	2017	6	22	0	0	
173	Sunday	25	2013	6	23	1	0	
745	Friday	3	2015	1	16	0	0	
986	Monday	38	2015	9	14	0	0	
1398	Sunday	43	2016	10	30	1	0	
1667	Wednesday	30	2017	7	26	0	0	
1230	Sunday	19	2016	5	15	1	0	
1100	Wednesday	1	2016	1	6	0	0	
785	Wednesday	9	2015	2	25	0	0	
857	Friday	19	2015	5	8	0	0	
1507	Thursday	7	2017	2	16	0	0	
135	Thursday	20	2013	5	16	0	0	

	oil_fill
1251	49.37
494	100.51
203	107.13
479	100.85
886	58.79
1134	27.96

```
1211     42.52
427     103.64
1277     49.02
1633     42.53
173      94.65
745      48.49
986      44.07
1398     47.46
1667     48.58
1230     47.22
1100     33.97
785      50.25
857      59.41
1507     53.41
135      94.85
```

[153]:
```
sales_df=sales_df.sort_values(by='date')
df = sales_df
# df=df[df['date']>=pd.to_datetime('2015-12-01')]
# df=df[df['date']<pd.to_datetime('2016-02-01')]


plt.figure(figsize=(16, 12))


plt.subplot(5, 1, 1)
plt.plot(df['date'], df['sales'], color='blue', label='Sales')
plt.xlabel('Date')
plt.ylabel('Sales')
plt.title('Sales Over Time')
plt.legend()

plt.subplot(5, 1, 2)
plt.plot(df['date'], df['isHoliday'], color='red', label='On Holiday')
plt.xlabel('Date')
plt.ylabel('On Holiday')
plt.title('On Holiday Over Time')
plt.legend()

plt.subplot(5, 1, 3)
plt.plot(df['date'], df['isWeekend'], color='red', label='On Weekend')
plt.xlabel('Date')
plt.ylabel('On Weekend')
plt.title('On Weekend Over Time')
plt.legend()

plt.subplot(5, 1, 4)
```

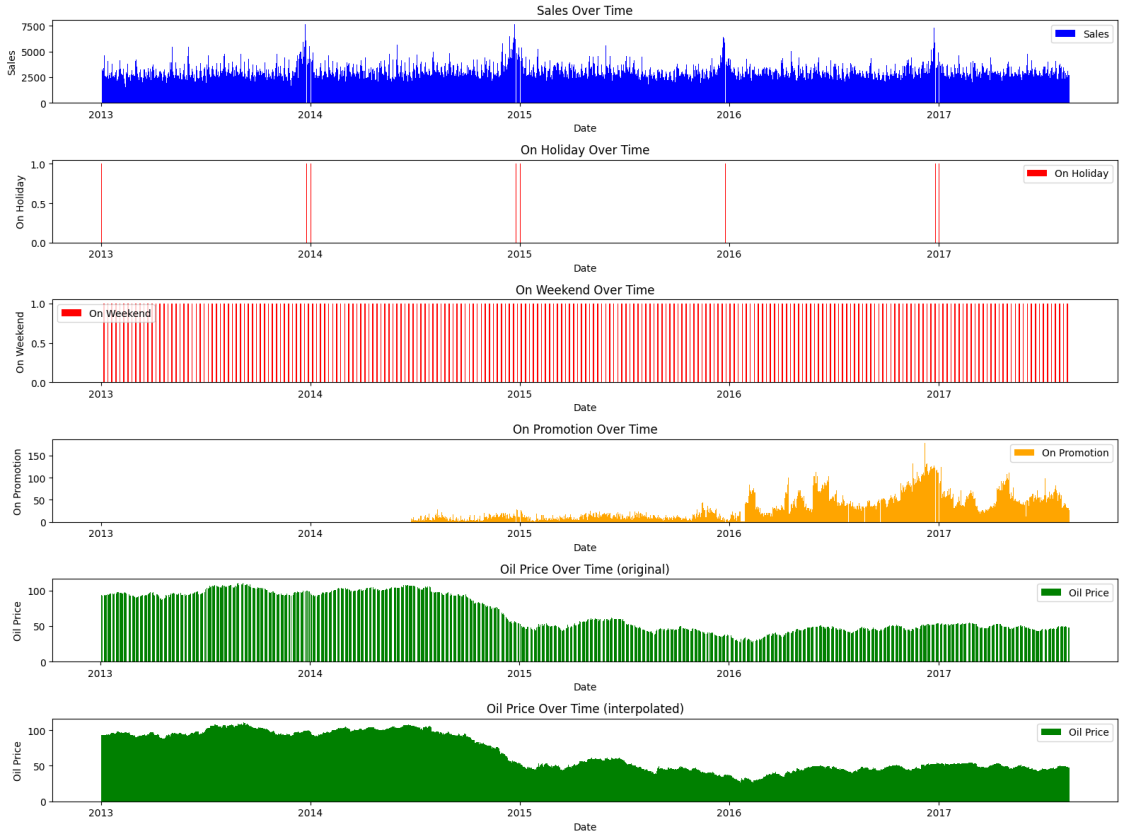
```
plt.plot(df['date'], df['onpromotion'], color='orange', label='On Promotion')
plt.xlabel('Date')
plt.ylabel('On Promotion')
plt.title('On Promotion Over Time')
plt.legend()

plt.subplot(5, 1, 5)
plt.plot(df['date'], df['oil_fill'], color='green', label='Oil Price')
plt.xlabel('Date')
plt.ylabel('Oil Price')
plt.title('Oil Price Over Time')
plt.legend()

plt.tight_layout()
plt.show()
```

[154]:
```
df = sales_df
# df=df[df['date']>=pd.to_datetime('2015-12-01')]
# df=df[df['date']<pd.to_datetime('2016-02-01')]
```

```
plt.figure(figsize=(16, 12))


plt.subplot(6, 1, 1)
plt.bar(df['date'], df['sales'], color='blue', label='Sales', align='edge',␣
 ↪width=1)
plt.xlabel('Date')
plt.ylabel('Sales')
plt.title('Sales Over Time')
plt.legend()

plt.subplot(6, 1, 2)
plt.bar(df['date'], df['isHoliday'], color='red', label='On Holiday',␣
 ↪align='edge', width=1)
plt.xlabel('Date')
plt.ylabel('On Holiday')
plt.title('On Holiday Over Time')
plt.legend()

plt.subplot(6, 1, 3)
plt.bar(df['date'], df['isWeekend'], color='red', label='On Weekend',␣
 ↪align='edge', width=1)
plt.xlabel('Date')
plt.ylabel('On Weekend')
plt.title('On Weekend Over Time')
plt.legend()

plt.subplot(6, 1, 4)
plt.bar(df['date'], df['onpromotion'], color='orange', label='On Promotion',␣
 ↪align='edge', width=1)
plt.xlabel('Date')
plt.ylabel('On Promotion')
plt.title('On Promotion Over Time')
plt.legend()

plt.subplot(6, 1, 5)
plt.bar(df['date'], df['dcoilwtico'], color='green', label='Oil Price',␣
 ↪align='edge', width=1)
plt.xlabel('Date')
plt.ylabel('Oil Price')
plt.title('Oil Price Over Time (original)')
plt.legend()

plt.subplot(6, 1, 6)
plt.bar(df['date'], df['oil_fill'], color='green', label='Oil Price',␣
 ↪align='edge', width=1)
```

```
plt.xlabel('Date')
plt.ylabel('Oil Price')
plt.title('Oil Price Over Time (interpolated)')
plt.legend()

plt.tight_layout()
plt.show()
```

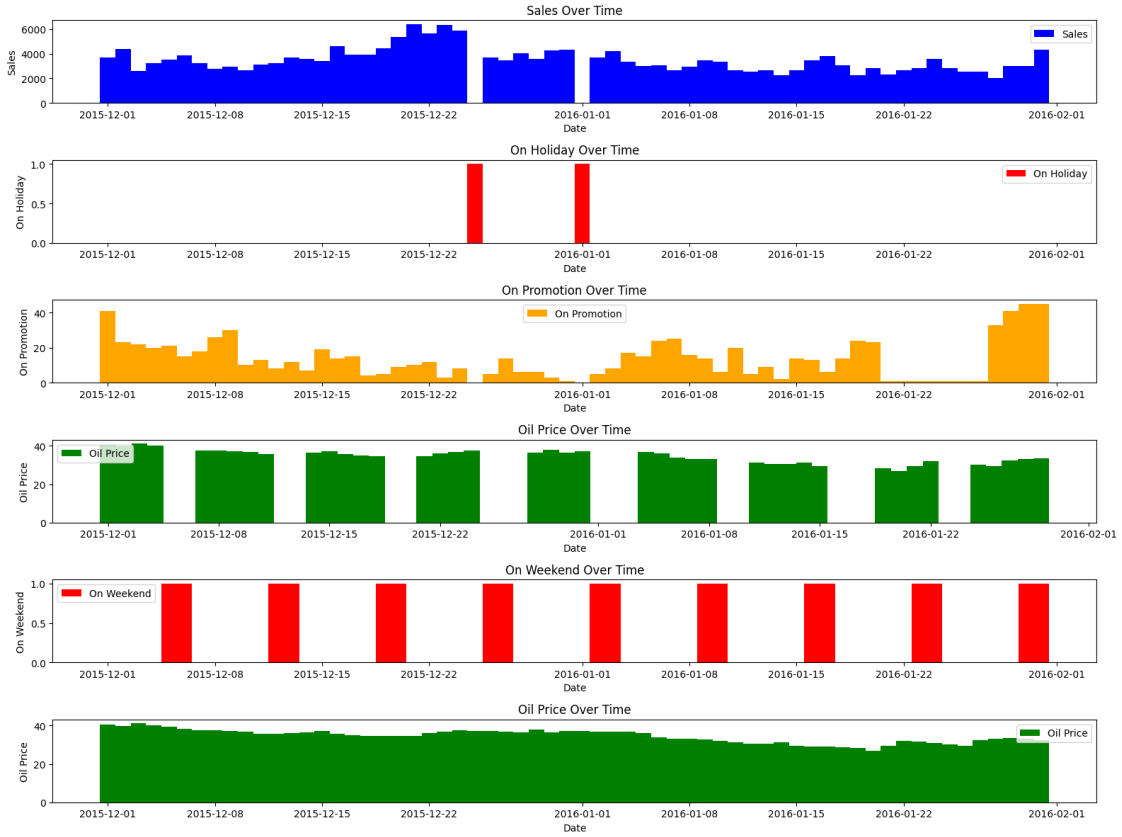
```
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\IPython\core\pylabtools.py:152: UserWarning: Creating legend with
loc="best" can be slow with large amounts of data.
  fig.canvas.print_figure(bytes_io, **kw)
```



[155]:
```
#ingin zooom in sedikit dari grafik di atas

sales_df=sales_df.sort_values(by='date')
df = sales_df
df=df[df['date']>=pd.to_datetime('2015-12-01')]
df=df[df['date']<pd.to_datetime('2016-02-01')]
```

```
plt.figure(figsize=(16, 12))


plt.subplot(6, 1, 1)
plt.bar(df['date'], df['sales'], color='blue', label='Sales', align='center',␣
 ↪width=1)
plt.xlabel('Date')
plt.ylabel('Sales')
plt.title('Sales Over Time')
plt.legend()

plt.subplot(6, 1, 2)
plt.bar(df['date'], df['isHoliday'], color='red', label='On Holiday',␣
 ↪align='center', width=1)
plt.xlabel('Date')
plt.ylabel('On Holiday')
plt.title('On Holiday Over Time')
plt.legend()

plt.subplot(6, 1, 3)
plt.bar(df['date'], df['onpromotion'], color='orange', label='On Promotion',␣
 ↪align='center', width=1)
plt.xlabel('Date')
plt.ylabel('On Promotion')
plt.title('On Promotion Over Time')
plt.legend()

plt.subplot(6, 1, 4)
plt.bar(df['date'], df['dcoilwtico'], color='green', label='Oil Price',␣
 ↪align='center', width=1)
plt.xlabel('Date')
plt.ylabel('Oil Price')
plt.title('Oil Price Over Time')
plt.legend()

plt.subplot(6, 1, 5)
plt.bar(df['date'], df['isWeekend'], color='red', label='On Weekend',␣
 ↪align='center', width=1)
plt.xlabel('Date')
plt.ylabel('On Weekend')
plt.title('On Weekend Over Time')
plt.legend()

plt.subplot(6, 1, 6)
plt.bar(df['date'], df['oil_fill'], color='green', label='Oil Price',␣
 ↪align='center', width=1)
```

```
plt.xlabel('Date')
plt.ylabel('Oil Price')
plt.title('Oil Price Over Time')
plt.legend()

plt.tight_layout()
plt.show()
```



3.5 Correlation Check

[156]:
```
correlation_sales = sales_df[['sales', 'onpromotion']].corr()
print(f'correlation_sales:\n{correlation_sales}')

correlation_sales = sales_df[['sales', 'oil_fill']].corr()
print(f'correlation_oil:\n{correlation_sales}')
```

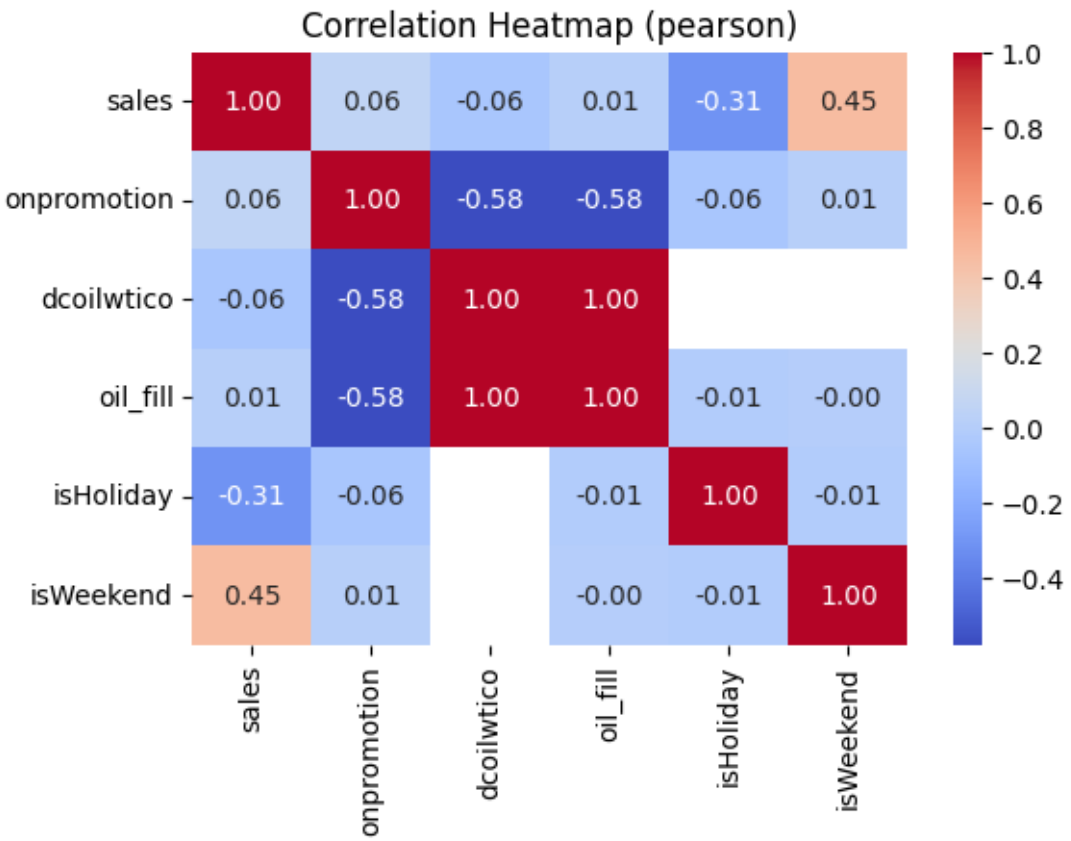
```
correlation_sales:
                sales  onpromotion
sales        1.000000     0.056009
onpromotion  0.056009     1.000000
correlation_oil:
```

```
              sales  oil_fill
sales     1.000000  0.013262
oil_fill  0.013262  1.000000
```

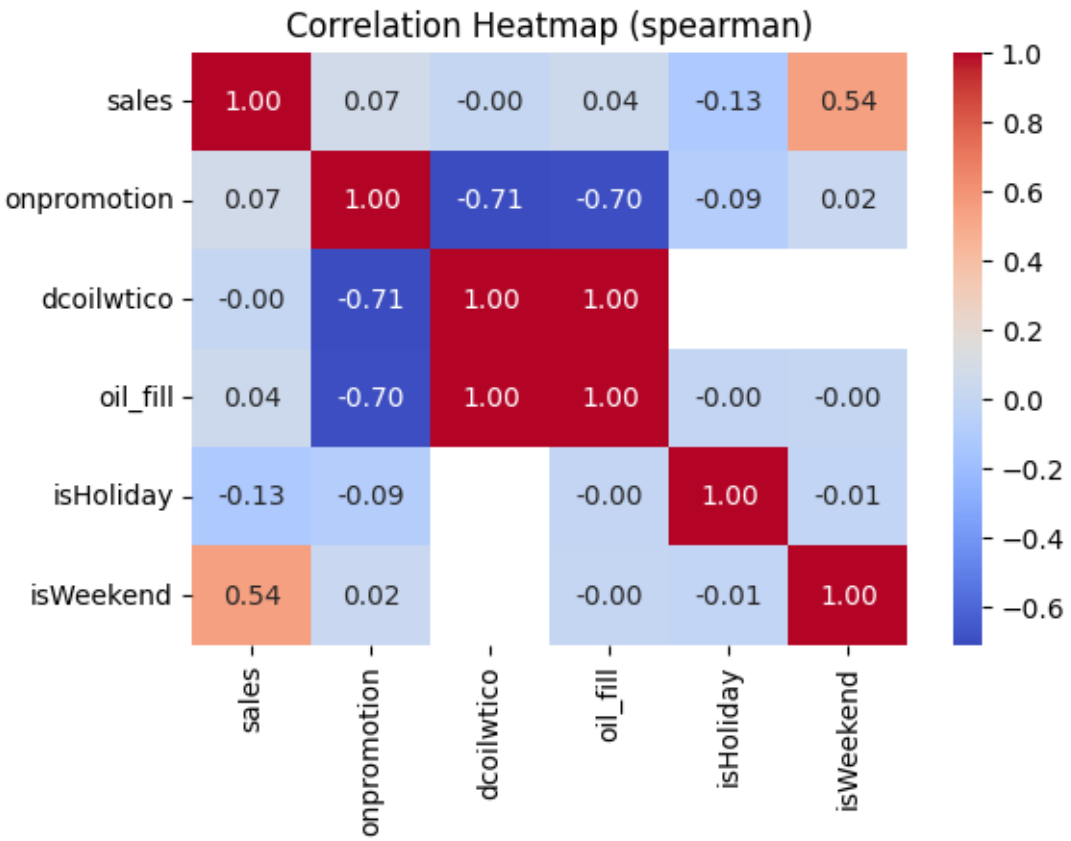
[157]:
```
pearson_corr = sales_df[['sales', 'onpromotion',␣
 ↪'dcoilwtico','oil_fill','isHoliday', 'isWeekend']].corr(method='pearson')
spearman_corr = sales_df[['sales', 'onpromotion',␣
 ↪'dcoilwtico','oil_fill','isHoliday', 'isWeekend']].corr(method='spearman')

# Print correlation values
print("Pearson Correlation:\n", pearson_corr)
print("\nSpearman Correlation:\n", spearman_corr)
```

```
Pearson Correlation:
                 sales  onpromotion  dcoilwtico  oil_fill  isHoliday  isWeekend
sales         1.000000     0.056009   -0.058505  0.013262  -0.305741   0.454681
onpromotion   0.056009     1.000000   -0.575283 -0.576094  -0.056980   0.013231
dcoilwtico   -0.058505    -0.575283    1.000000  1.000000        NaN        NaN
oil_fill      0.013262    -0.576094    1.000000  1.000000  -0.010776  -0.000536
isHoliday    -0.305741    -0.056980         NaN -0.010776   1.000000  -0.010264
isWeekend     0.454681     0.013231         NaN -0.000536  -0.010264   1.000000

Spearman Correlation:
                 sales  onpromotion  dcoilwtico  oil_fill  isHoliday  isWeekend
sales         1.000000     0.065550   -0.000117  0.041012  -0.126135   0.544110
onpromotion   0.065550     1.000000   -0.708980 -0.700737  -0.087016   0.022155
dcoilwtico   -0.000117    -0.708980    1.000000  1.000000        NaN        NaN
oil_fill      0.041012    -0.700737    1.000000  1.000000  -0.003890  -0.000751
isHoliday    -0.126135    -0.087016         NaN -0.003890   1.000000  -0.010264
isWeekend     0.544110     0.022155         NaN -0.000751  -0.010264   1.000000
```

[158]:
```
# Heatmap of correlation
plt.figure(figsize=(6, 4))
sns.heatmap(pearson_corr, annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation Heatmap (pearson)")
plt.show()
```



[159]:
```
# Heatmap of correlation
plt.figure(figsize=(6, 4))
sns.heatmap(spearman_corr, annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation Heatmap (spearman)")
plt.show()
```

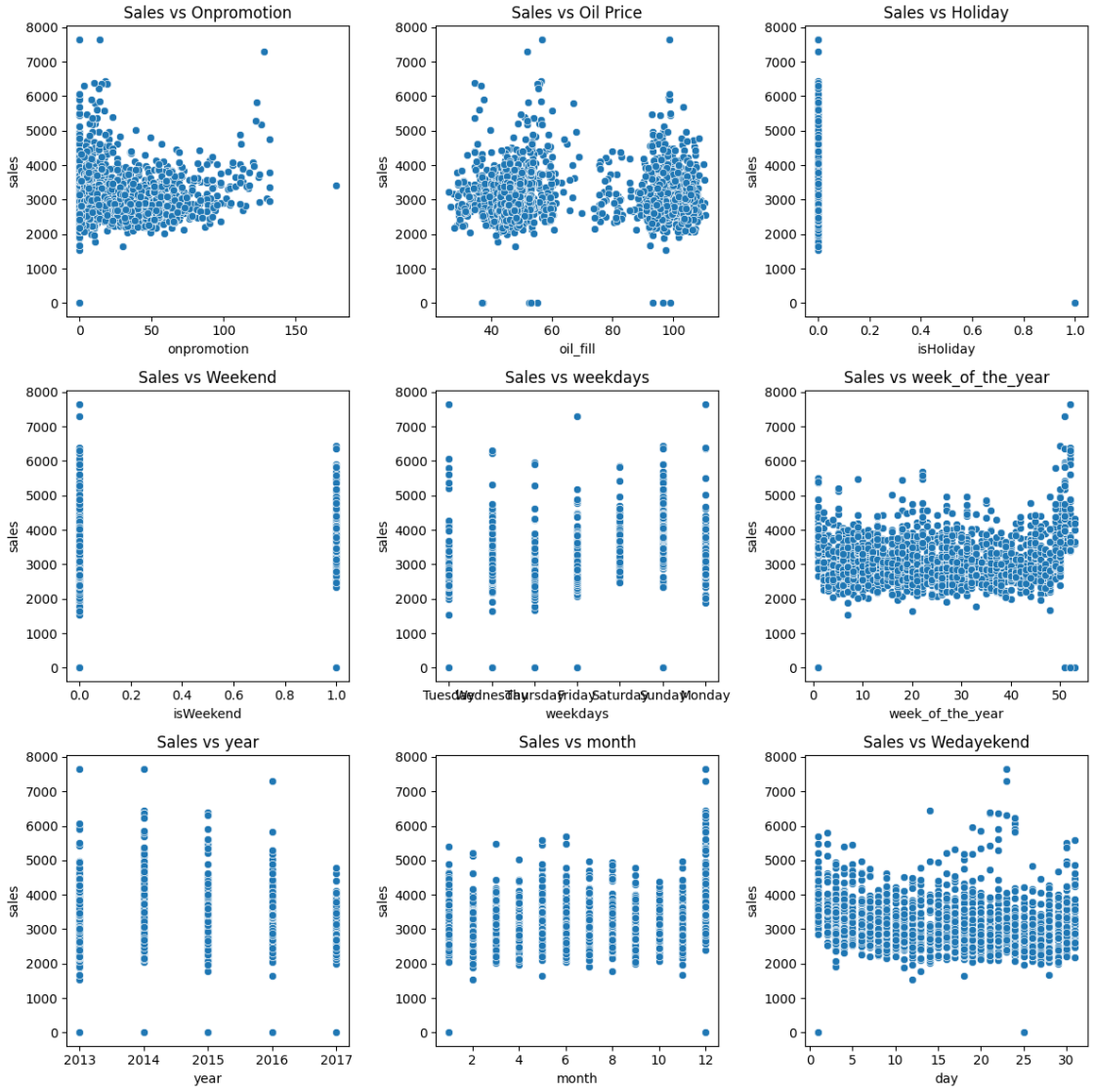


[160]:
```
df.columns
```

[160]:
```
Index(['id', 'date', 'family', 'sales', 'onpromotion', 'dcoilwtico',
       'weekdays', 'week_of_the_year', 'year', 'month', 'day', 'isWeekend',
       'isHoliday', 'oil_fill'],
      dtype='object')
```

[161]:
```
# Scatter plots
plt.figure(figsize=(12, 12))

plt.subplot(3, 3, 1)
sns.scatterplot(data=sales_df, x='onpromotion', y='sales')
plt.title("Sales vs Onpromotion")

plt.subplot(3, 3, 2)
sns.scatterplot(data=sales_df, x='oil_fill', y='sales')
plt.title("Sales vs Oil Price")

plt.subplot(3, 3, 3)
sns.scatterplot(data=sales_df, x='isHoliday', y='sales')
```

```
plt.title("Sales vs Holiday")

plt.subplot(3, 3, 4)
sns.scatterplot(data=sales_df, x='isWeekend', y='sales')
plt.title("Sales vs Weekend")

plt.subplot(3, 3, 5)
sns.scatterplot(data=sales_df, x='weekdays', y='sales')
plt.title("Sales vs weekdays")

plt.subplot(3, 3, 6)
sns.scatterplot(data=sales_df, x='week_of_the_year', y='sales')
plt.title("Sales vs week_of_the_year")

plt.subplot(3, 3, 7)
sns.scatterplot(data=sales_df, x='year', y='sales')
plt.title("Sales vs year")

plt.subplot(3, 3, 8)
sns.scatterplot(data=sales_df, x='month', y='sales')
plt.title("Sales vs month")

plt.subplot(3, 3, 9)
sns.scatterplot(data=sales_df, x='day', y='sales')
plt.title("Sales vs Wedayekend")


plt.tight_layout()
plt.show()
```



terdapat multi collinearity antara ‘onpromotion’ dan ‘oil_fill’ bahasa umumnya “saat harga minyak naik , promosi juga –> akan dibuang kolom oil_fill dan dcoilwtico

GAK JADI DING … ternyata disuruh predict juga nilai ‘onpromtion’ nya

[162]:
```
print(f'sales_df.columns:\n{sales_df.columns}')
sales_df_selected=sales_df[['id', 'date', 'sales', 'onpromotion',␣
 ↪'isWeekend','isHoliday']]
print('')
print(f'sales_df_selected.columns:\n{sales_df_selected.columns}')
```

```
sales_df.columns:
Index(['id', 'date', 'family', 'sales', 'onpromotion', 'dcoilwtico',
       'weekdays', 'week_of_the_year', 'year', 'month', 'day', 'isWeekend',
```

```
       'isHoliday', 'oil_fill'],
      dtype='object')

sales_df_selected.columns:
Index(['id', 'date', 'sales', 'onpromotion', 'isWeekend', 'isHoliday'],
dtype='object')
```

3.6 ADF Test

[163]:
```
from statsmodels.tsa.stattools import adfuller

def adf_test(series, name):
    result = adfuller(series.dropna())
    print(f'ADF Test for {name}')
    print(f'ADF Statistic: {result[0]:.4f}')
    print(f'p-value: {result[1]:.4f}')
    print('Critical Values:', result[4])

    gc='\u2713'
    rc='\u2716'
    if result[1] <= 0.05:
        print(f"{gc} {name} is STATIONARY (Reject null hypothesis)")
    else:
        print(f"{rc} {name} is NOT STATIONARY (Fail to reject null hypothesis)")
    print("-" * 50)

# Run ADF Test on Sales
adf_test(sales_df['sales'], "Sales [sales]")
adf_test(sales_df['onpromotion'], 'On Promotion [onpromotion]')

#yg di bawah ini tidak perlu , karena yg di cek stationernya cukup yang mau di
adf_test(sales_df['oil_fill'], 'oil_fill')
adf_test(sales_df['isWeekend'], 'isWeekend')
adf_test(sales_df['isHoliday'], 'isHoliday')
```

```
ADF Test for Sales [sales]
ADF Statistic: -7.1433
p-value: 0.0000
Critical Values: {'1%': -3.434283579780684, '5%': -2.863277451883613, '10%':
-2.5676949772294817}
 Sales [sales] is STATIONARY (Reject null hypothesis)
--------------------------------------------------
ADF Test for On Promotion [onpromotion]
ADF Statistic: -2.6803
p-value: 0.0775
Critical Values: {'1%': -3.434283579780684, '5%': -2.863277451883613, '10%':
-2.5676949772294817}
 On Promotion [onpromotion] is NOT STATIONARY (Fail to reject null hypothesis)
```

```
------------------------------------------------
ADF Test for oil_fill
ADF Statistic: -0.8659
p-value: 0.7990
Critical Values: {'1%': -3.4342322039823197, '5%': -2.863254774066211, '10%':
-2.5676829016514233}
 oil_fill is NOT STATIONARY (Fail to reject null hypothesis)
------------------------------------------------
ADF Test for isWeekend
ADF Statistic: -1032450383434032.6250
p-value: 0.0000
Critical Values: {'1%': -3.434243762106336, '5%': -2.863259875977509, '10%':
-2.567685618332742}
 isWeekend is STATIONARY (Reject null hypothesis)
------------------------------------------------
ADF Test for isHoliday
ADF Statistic: -7.4417
p-value: 0.0000
Critical Values: {'1%': -3.43427885313169, '5%': -2.863275365507293, '10%':
-2.5676938662645394}
 isHoliday is STATIONARY (Reject null hypothesis)
------------------------------------------------
```

[164]:
```
print(f'onpromotion = {sales_df.shape}')
```

```
onpromotion = (1688, 14)
```

[165]:
```
from scipy.stats import boxcox

# sales_df['oil_fill_donpromotionifferencing'] = sales_df['onpromotion'].diff()
sales_df['onpromotion_differencing'] = sales_df['onpromotion'].diff(periods=7).
 ↪fillna(0)
adf_test(sales_df['onpromotion_differencing'], 'On Promotion Differencing')

# sales_df['onpromotion_boxcox'], lam = boxcox(sales_df['onpromotion'] + 1)
# adf_test(sales_df['onpromotion_boxcox'], 'On Promotion BoxCox')

sales_df['oil_fill_differencing'] = sales_df['oil_fill'].diff(periods=7).
 ↪fillna(0)
adf_test(sales_df['oil_fill_differencing'], 'On Oil Price Differencing')

# sales_df['oil_fill_boxcox'], lam = boxcox(sales_df['oil_fill'] + 1)
# adf_test(sales_df['oil_fill_boxcox'], 'On Oil Price BoxCox')
```

```
ADF Test for On Promotion Differencing
ADF Statistic: -8.8653
p-value: 0.0000
Critical Values: {'1%': -3.4342812150354276, '5%': -2.8632764080687307, '10%':
```

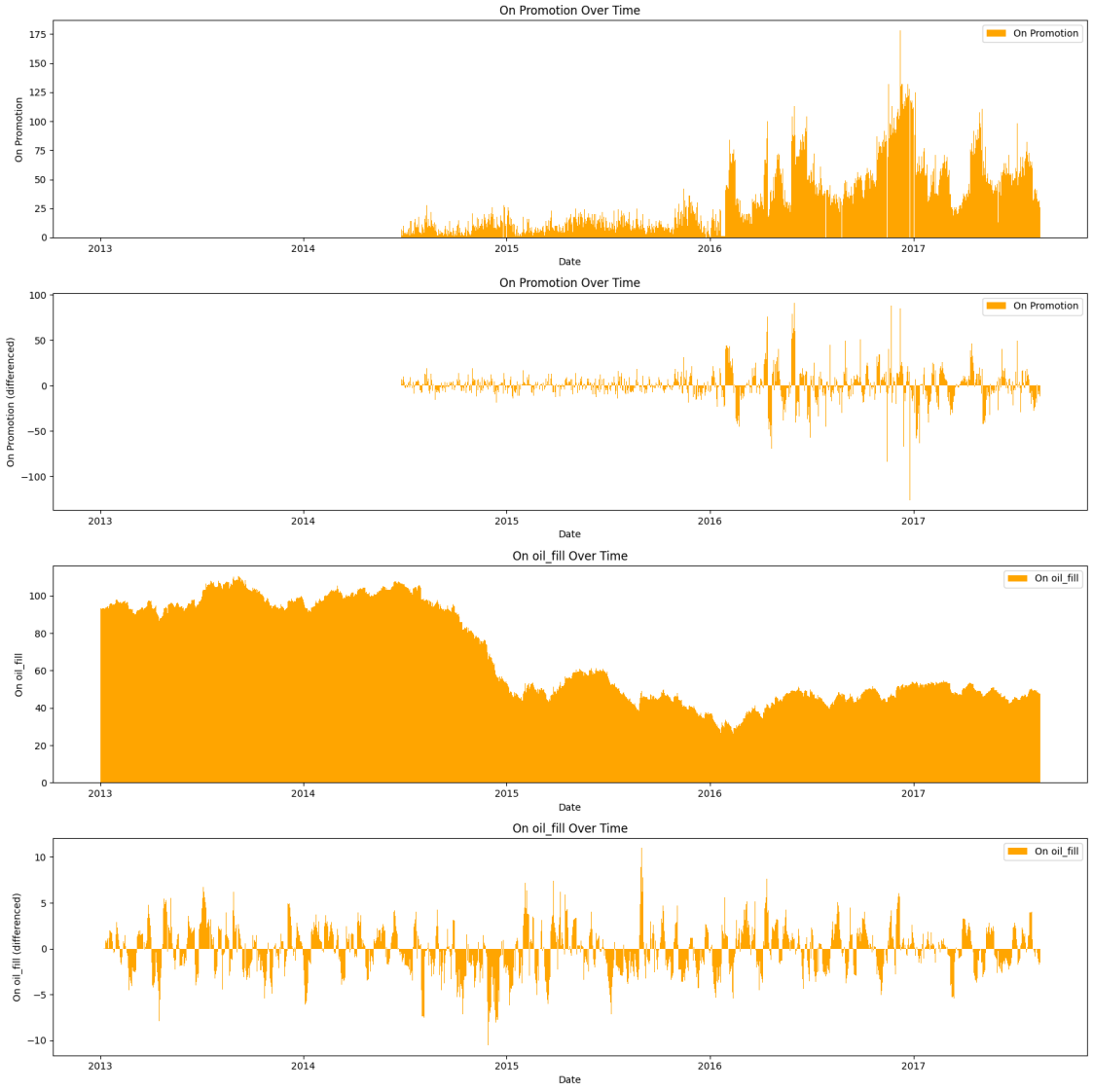
```
-2.5676944214132233}
 On Promotion Differencing is STATIONARY (Reject null hypothesis)
--------------------------------------------------
ADF Test for On Oil Price Differencing
ADF Statistic: -6.6143
p-value: 0.0000
Critical Values: {'1%': -3.4342812150354276, '5%': -2.8632764080687307, '10%':
-2.5676944214132233}
 On Oil Price Differencing is STATIONARY (Reject null hypothesis)
--------------------------------------------------
```

[166]:
```
print(f'onpromotion = {sales_df.shape}')
sales_df.to_csv('store_grocery.csv') #bikin backup saja kalau2 nanti ada perlu
```

```
onpromotion = (1688, 16)
```

[167]:
```
sales_df=sales_df.sort_values(by='date')
df = sales_df
# df=df[df['date']>=pd.to_datetime('2015-12-01')]
# df=df[df['date']<pd.to_datetime('2016-02-01')]


plt.figure(figsize=(16, 16))


plt.subplot(4, 1, 1)
plt.bar(df['date'], df['onpromotion'], color='orange', label='On Promotion',␣
 ↪align='edge', width=1)
plt.xlabel('Date')
plt.ylabel('On Promotion')
plt.title('On Promotion Over Time')
plt.legend()

plt.subplot(4, 1, 2)
plt.bar(df['date'], df['onpromotion_differencing'], color='orange', label='On␣
 ↪Promotion', align='edge', width=1)
plt.xlabel('Date')
plt.ylabel('On Promotion (differenced)')
plt.title('On Promotion Over Time')
plt.legend()


plt.subplot(4, 1, 3)
plt.bar(df['date'], df['oil_fill'], color='orange', label='On oil_fill',␣
 ↪align='edge', width=1)
plt.xlabel('Date')
plt.ylabel('On oil_fill')
plt.title('On oil_fill Over Time')
```

```
plt.legend()

plt.subplot(4, 1, 4)
plt.bar(df['date'], df['oil_fill_differencing'], color='orange', label='On␣
 ↪oil_fill', align='edge', width=1)
plt.xlabel('Date')
plt.ylabel('On oil_fill (differenced)')
plt.title('On oil_fill Over Time')
plt.legend()



plt.tight_layout()
plt.show()
```



[168]:
```
sales_df
```

[168]:

	id	date	family	sales	onpromotion	dcoilwtico	\
0	1464	2013-01-01	GROCERY I	0.0	0	NaN	
1	3246	2013-01-02	GROCERY I	4558.0	0	93.14	
2	5028	2013-01-03	GROCERY I	3260.0	0	92.97	
3	6810	2013-01-04	GROCERY I	3085.0	0	93.12	
4	8592	2013-01-05	GROCERY I	3398.0	0	NaN	
…	…	…	…	…	…	…	
1683	2993442	2017-08-11	GROCERY I	2864.0	35	48.81	
1684	2995224	2017-08-12	GROCERY I	2476.0	31	NaN	
1685	2997006	2017-08-13	GROCERY I	3141.0	31	NaN	
1686	2998788	2017-08-14	GROCERY I	2717.0	32	47.59	
1687	3000570	2017-08-15	GROCERY I	2696.0	26	47.57	

	weekdays	week_of_the_year	year	month	day	isWeekend	isHoliday	\
0	Tuesday	1	2013	1	1	0	1	
1	Wednesday	1	2013	1	2	0	0	
2	Thursday	1	2013	1	3	0	0	
3	Friday	1	2013	1	4	0	0	
4	Saturday	1	2013	1	5	1	0	
…	…	…	…	…	…	…	…	
1683	Friday	32	2017	8	11	0	0	
1684	Saturday	32	2017	8	12	1	0	
1685	Sunday	32	2017	8	13	1	0	
1686	Monday	33	2017	8	14	0	0	
1687	Tuesday	33	2017	8	15	0	0	

	oil_fill	onpromotion_differencing	oil_fill_differencing
0	93.140000	0.0	0.00
1	93.140000	0.0	0.00
2	92.970000	0.0	0.00
3	93.120000	0.0	0.00
4	93.146667	0.0	0.00
…	…	…	…
1683	48.810000	2.0	-0.76
1684	48.403333	-10.0	-1.10
1685	47.996667	-6.0	-1.44
1686	47.590000	-10.0	-1.78
1687	47.570000	-12.0	-1.50

[1688 rows x 16 columns]

[169]:
```
sales_df.info()
```

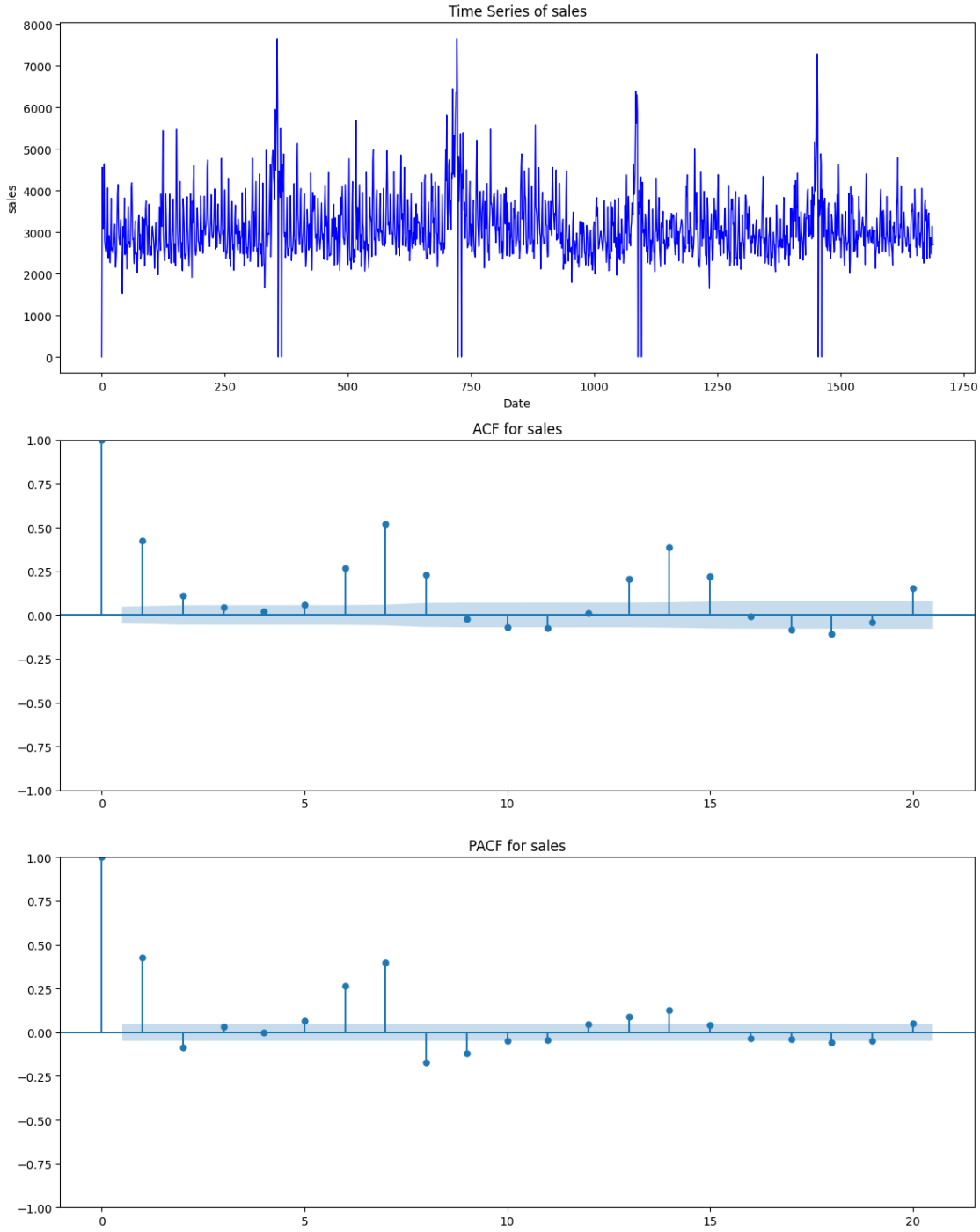
```
<class 'pandas.core.frame.DataFrame'>
```

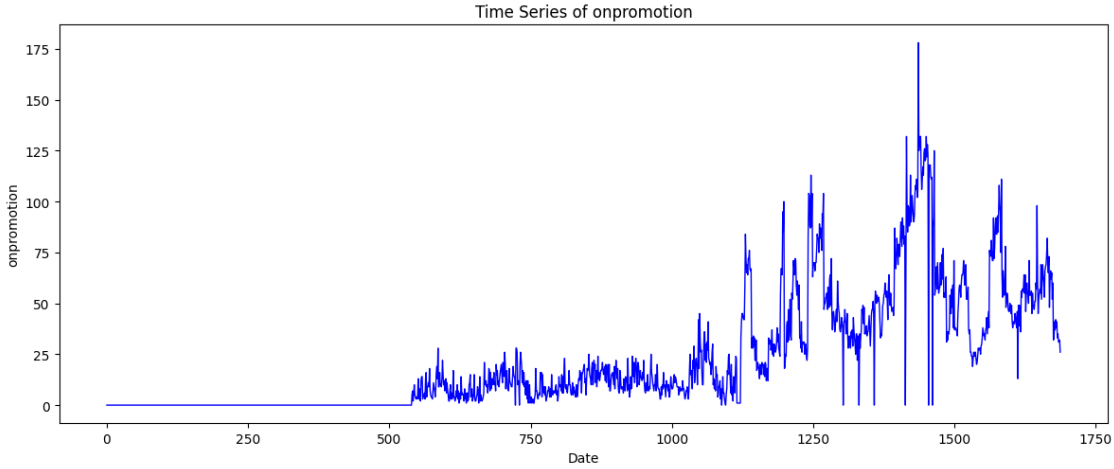
```
Int64Index: 1688 entries, 0 to 1687
Data columns (total 16 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   id                         1688 non-null   int64
 1   date                       1688 non-null   datetime64[ns]
 2   family                     1688 non-null   object
 3   sales                      1688 non-null   float64
 4   onpromotion                1688 non-null   int64
 5   dcoilwtico                 1163 non-null   float64
 6   weekdays                   1688 non-null   object
 7   week_of_the_year           1688 non-null   UInt32
 8   year                       1688 non-null   int64
 9   month                      1688 non-null   int64
 10  day                        1688 non-null   int64
 11  isWeekend                  1688 non-null   int32
 12  isHoliday                  1688 non-null   int32
 13  oil_fill                   1688 non-null   float64
 14  onpromotion_differencing   1688 non-null   float64
 15  oil_fill_differencing      1688 non-null   float64
dtypes: UInt32(1), datetime64[ns](1), float64(5), int32(2), int64(5), object(2)
memory usage: 206.1+ KB
```

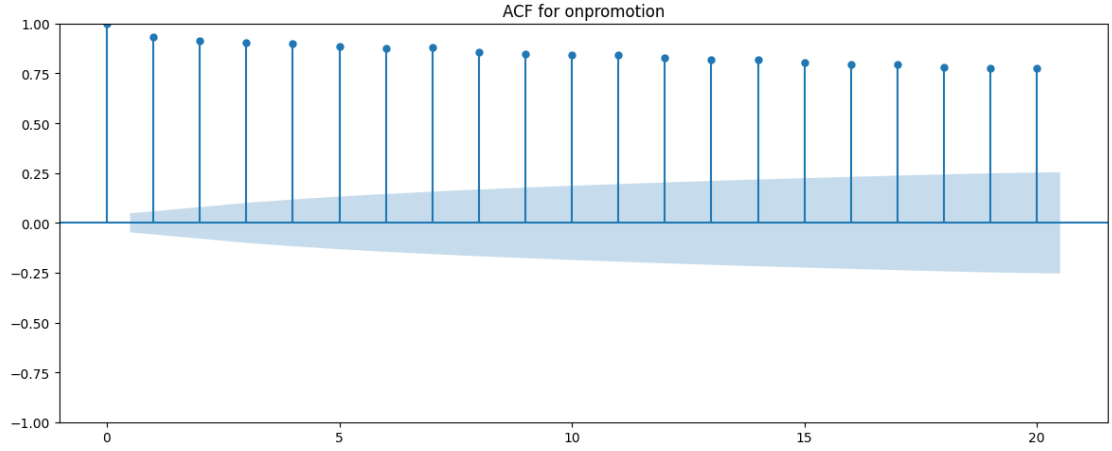
3.7 Check Seasonality

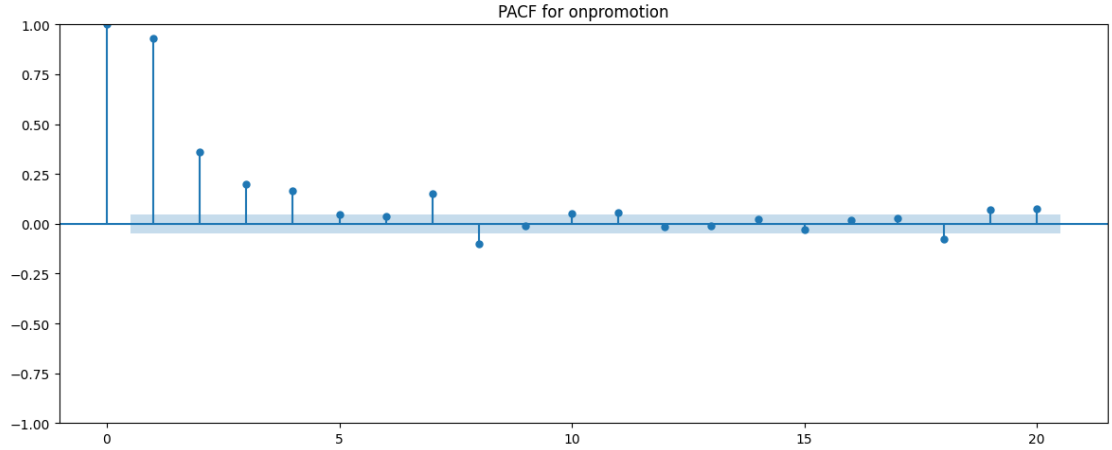
[170]:
```python
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

daftarFeature=['sales','onpromotion','onpromotion_differencing','oil_fill','oil_fill_differenc
df = sales_df
lagsnya = 20

# df=df[df['date']>=pd.to_datetime('2015-12-01')]
# df=df[df['date']<pd.to_datetime('2016-02-01')]


for feature in daftarFeature :

    fig, axes = plt.subplots(3, 1, figsize=(12, 15))


    axes[0].plot(df.index, df[feature], color='blue', linewidth=1)
    axes[0].set_title(f'Time Series of {feature}')
    axes[0].set_xlabel("Date")
    axes[0].set_ylabel(feature)

    plot_acf(df[feature], lags=lagsnya, ax=axes[1])
    axes[1].set_title(f'ACF for {feature}')
```

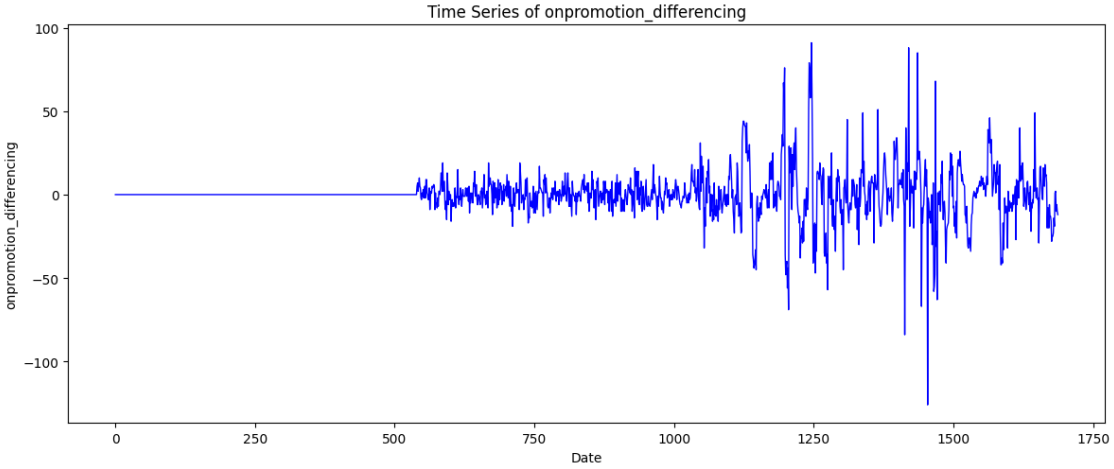
```
plot_pacf(df[feature], lags=lagsnya, ax=axes[2])
axes[2].set_title(f'PACF for {feature}')

plt.tight_layout()
plt.show()
```

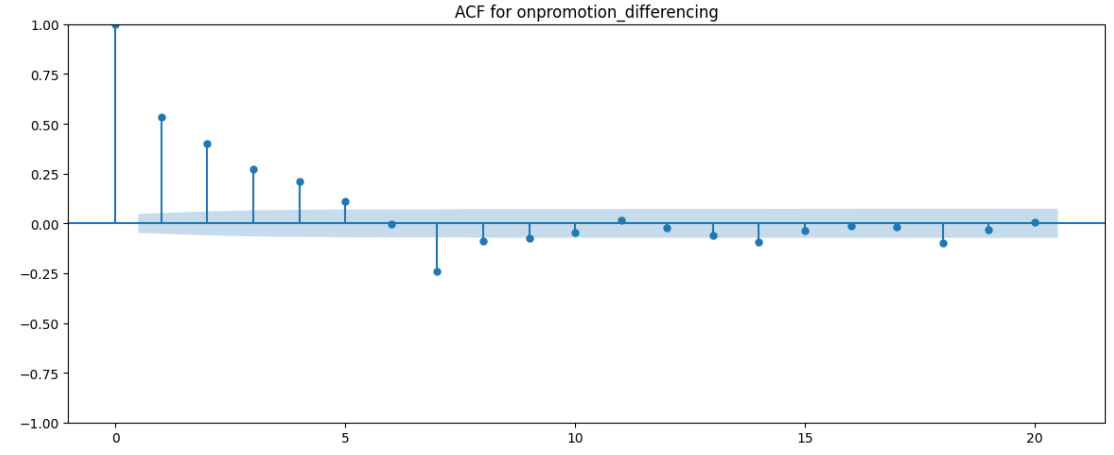


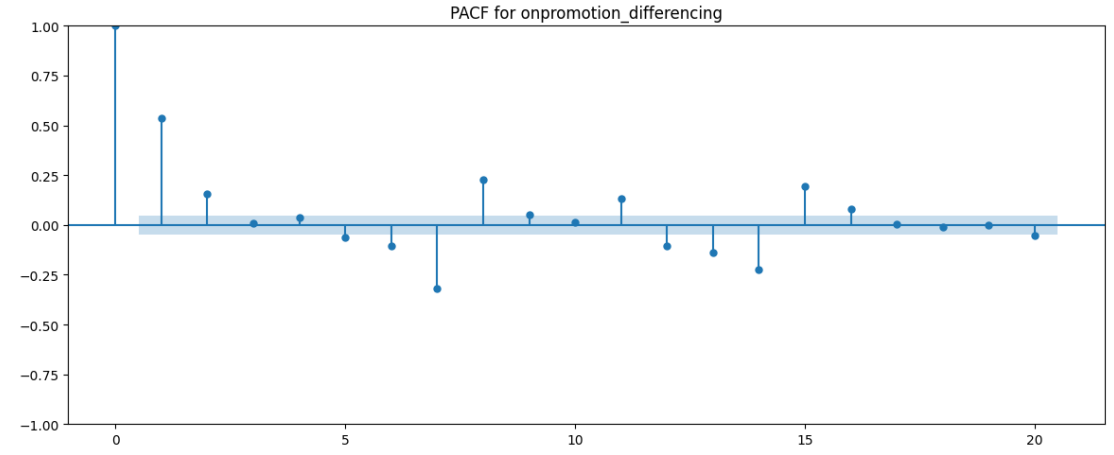

Time Series of onpromotion
onpromotion
Date
0
25
50
75
100
125
150
175
0
250
500
750
1000
1250
1500
1750

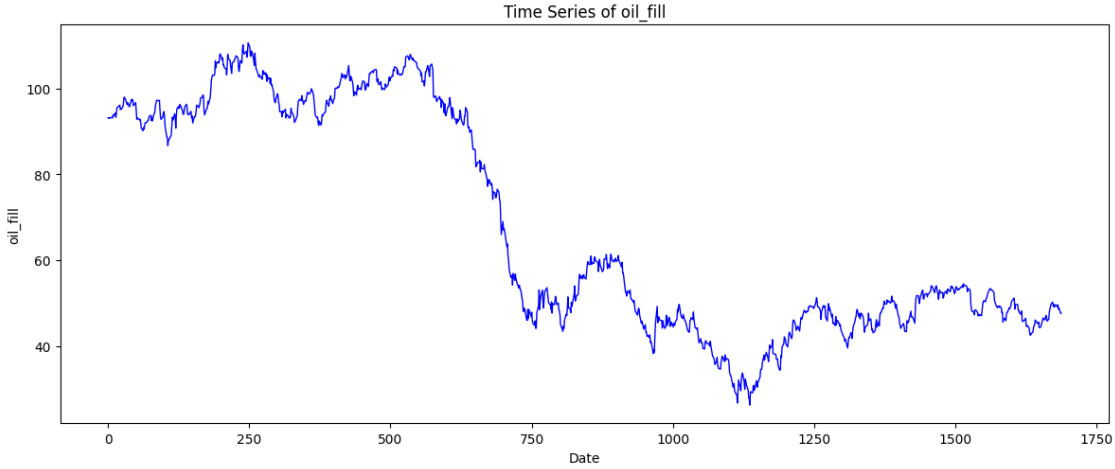

ACF for onpromotion
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20

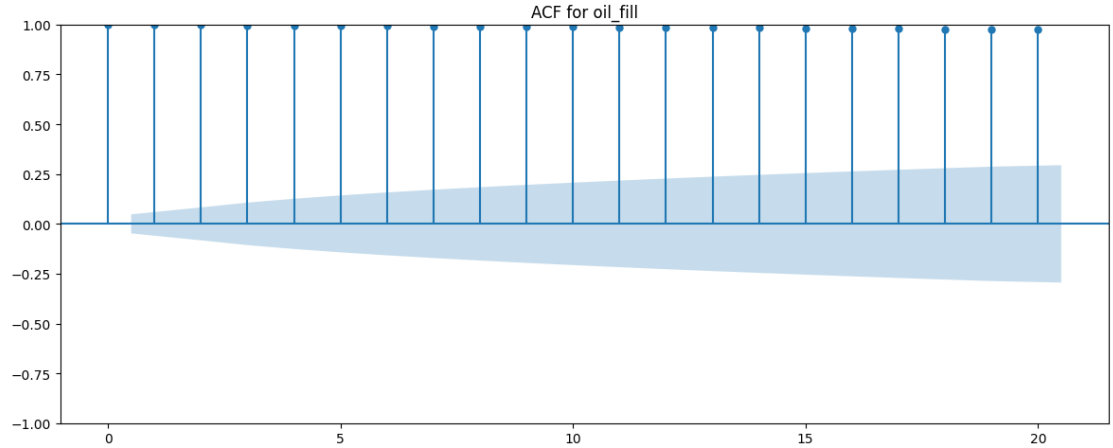

PACF for onpromotion
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20

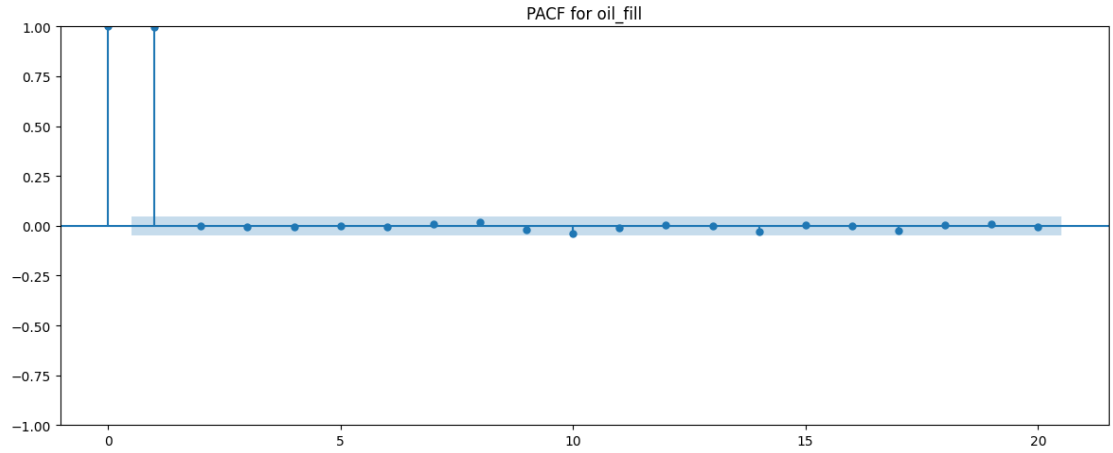

Time Series of onpromotion_differencing
onpromotion_differencing
Date

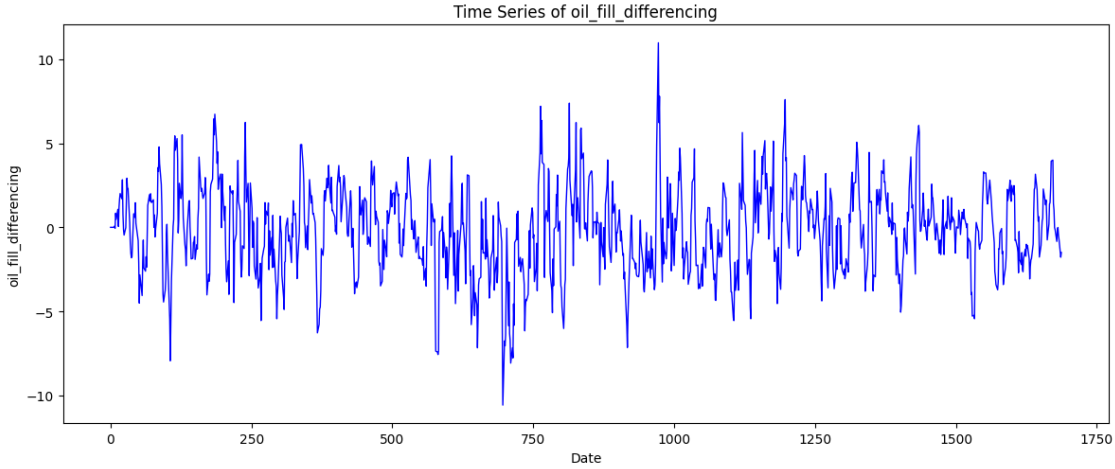

ACF for onpromotion_differencing

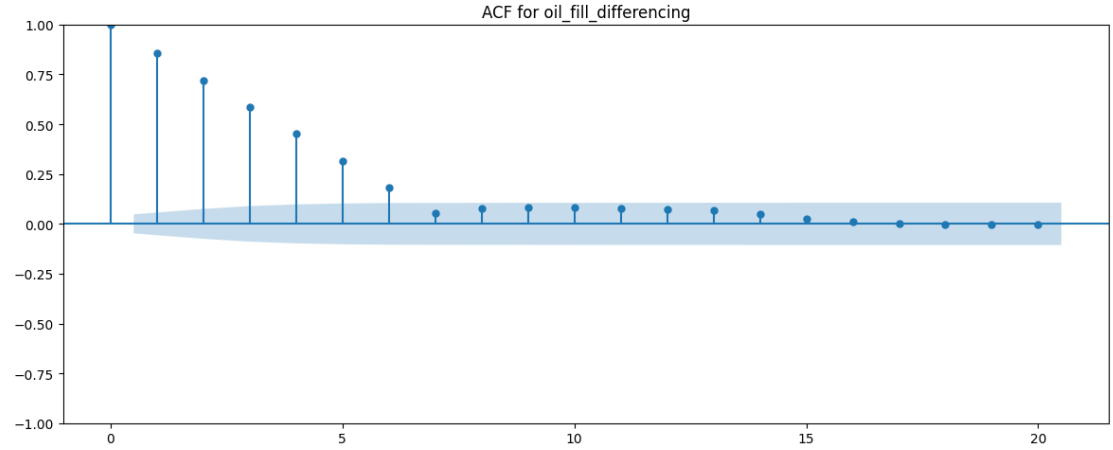

PACF for onpromotion_differencing

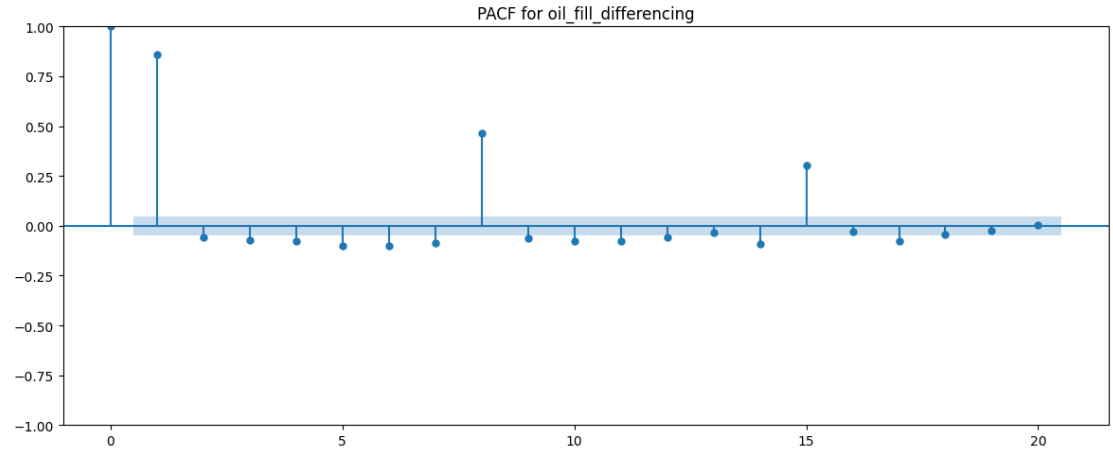

Time Series of oil_fill
oil_fill
Date
100
80
60
40
0
250
500
750
1000
1250
1500
1750

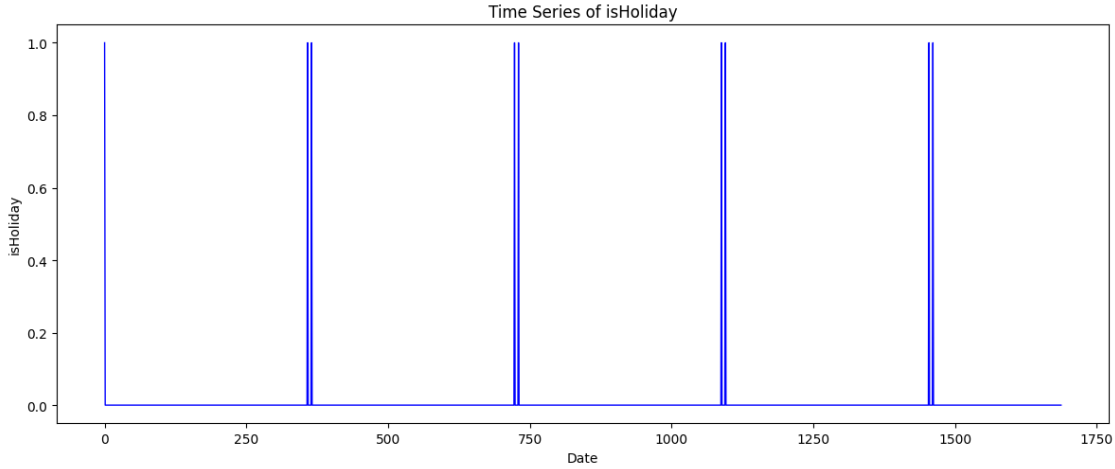

ACF for oil_fill
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20

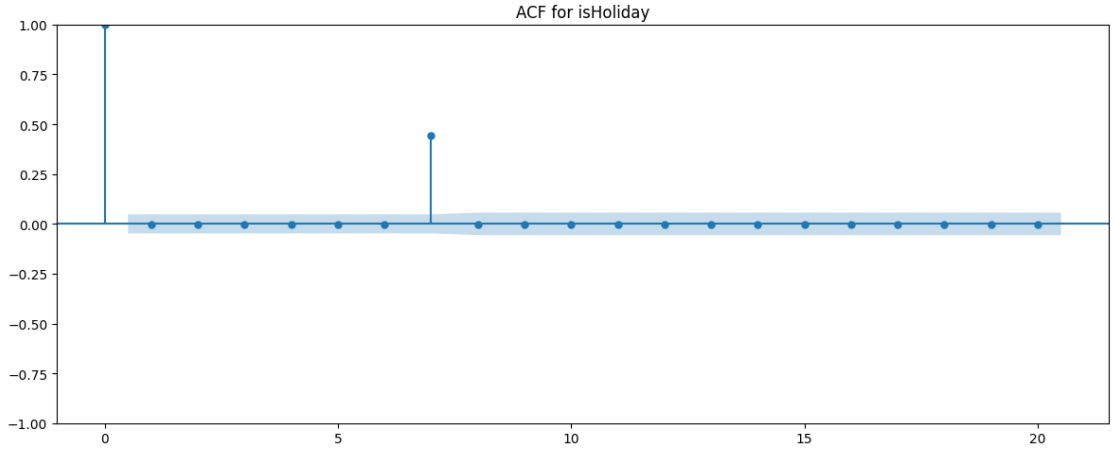

PACF for oil_fill
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20

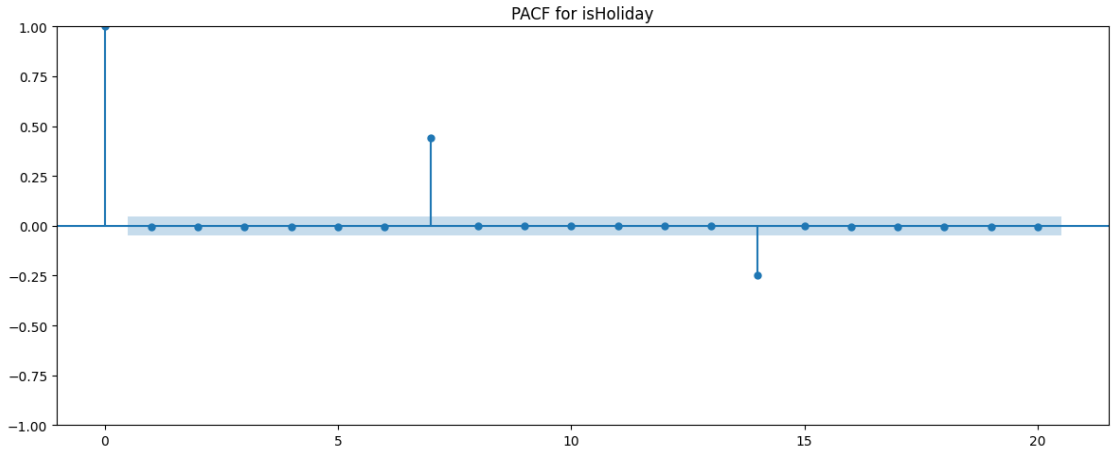

Time Series of oil_fill_differencing
oil_fill_differencing
Date
10
5
0
−5
−10
0
250
500
750
1000
1250
1500
1750

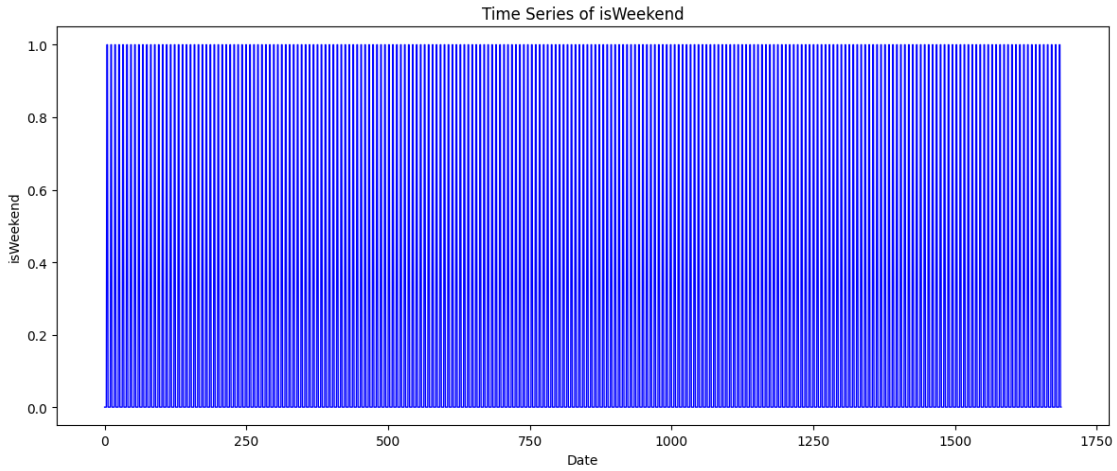

ACF for oil_fill_differencing
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20

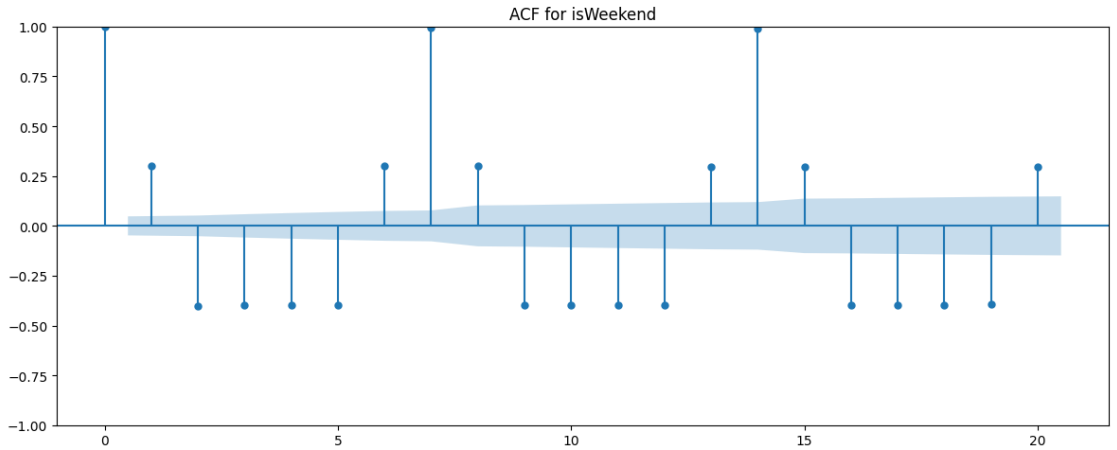

PACF for oil_fill_differencing
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20

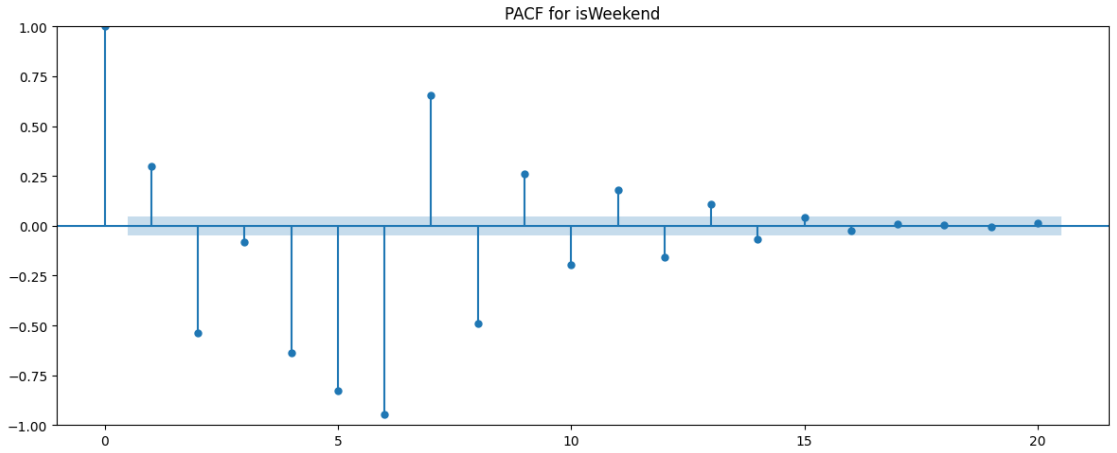

Time Series of isHoliday
isHoliday
Date
1.0
0.8
0.6
0.4
0.2
0.0
0
250
500
750
1000
1250
1500
1750


ACF for isHoliday
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20


PACF for isHoliday
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20







[171]:
```
sales_df
```

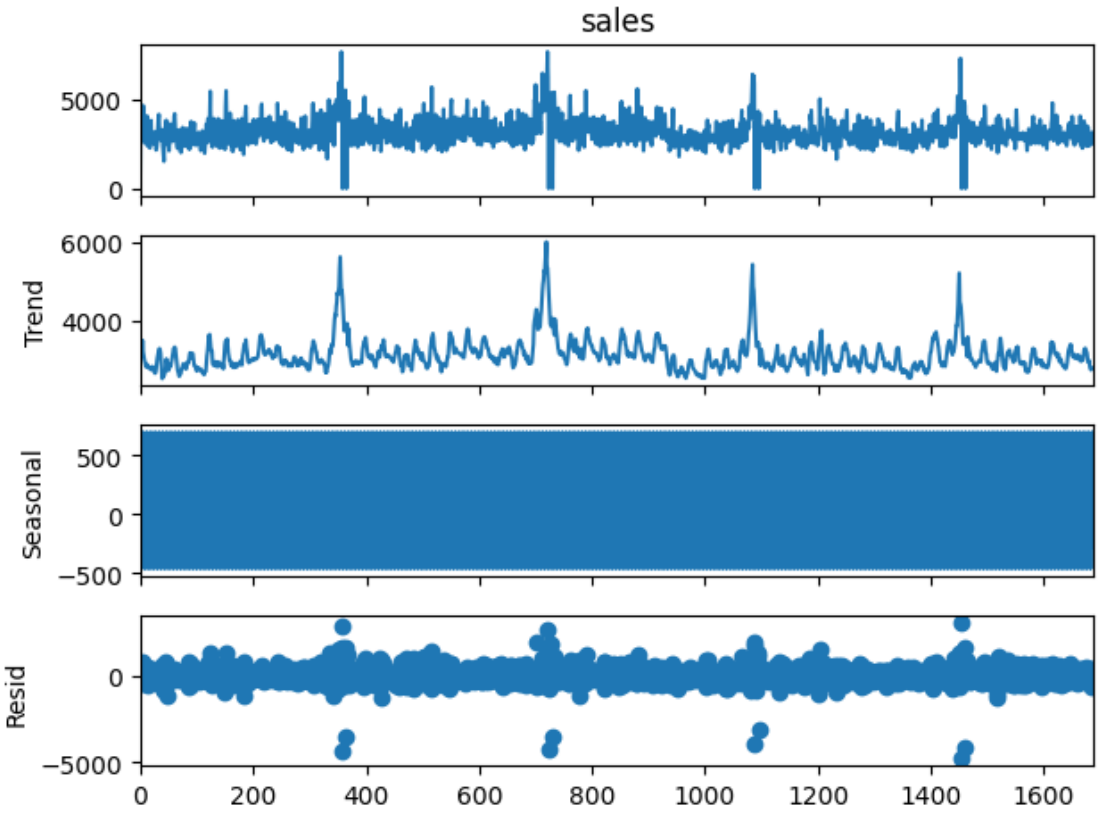
[171]:

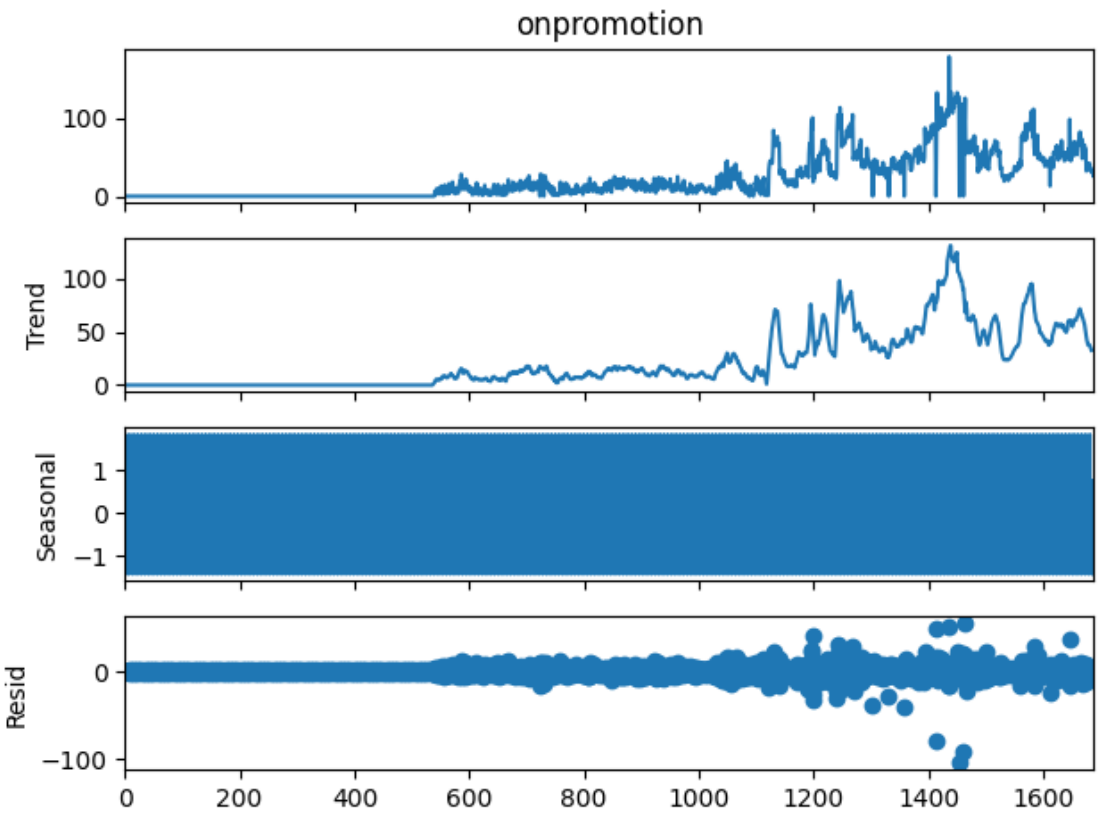
	id	date	family	sales	onpromotion	dcoilwtico
0	1464	2013-01-01	GROCERY I	0.0	0	NaN
1	3246	2013-01-02	GROCERY I	4558.0	0	93.14

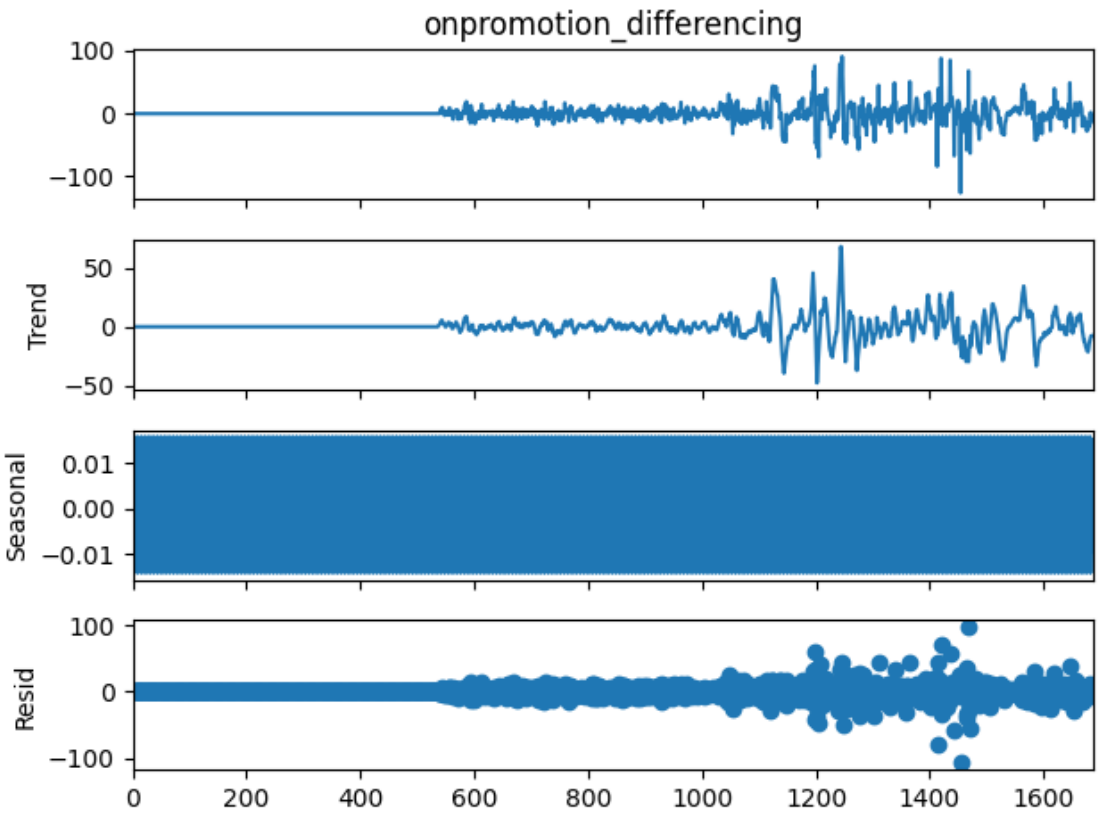
```
2        5028 2013-01-03  GROCERY I  3260.0            0       92.97
3        6810 2013-01-04  GROCERY I  3085.0            0       93.12
4        8592 2013-01-05  GROCERY I  3398.0            0         NaN
…         …         …         …     …              …          …
1683  2993442 2017-08-11  GROCERY I  2864.0           35       48.81
1684  2995224 2017-08-12  GROCERY I  2476.0           31         NaN
1685  2997006 2017-08-13  GROCERY I  3141.0           31         NaN
1686  2998788 2017-08-14  GROCERY I  2717.0           32       47.59
1687  3000570 2017-08-15  GROCERY I  2696.0           26       47.57

       weekdays  week_of_the_year  year  month  day  isWeekend  isHoliday  \
0       Tuesday                 1  2013      1    1          0          1
1     Wednesday                 1  2013      1    2          0          0
2      Thursday                 1  2013      1    3          0          0
3        Friday                 1  2013      1    4          0          0
4      Saturday                 1  2013      1    5          1          0
…         …                 …    …     …  …        …          …
1683     Friday                32  2017      8   11          0          0
1684   Saturday                32  2017      8   12          1          0
1685     Sunday                32  2017      8   13          1          0
1686     Monday                33  2017      8   14          0          0
1687    Tuesday                33  2017      8   15          0          0

       oil_fill  onpromotion_differencing  oil_fill_differencing
0     93.140000                       0.0                   0.00
1     93.140000                       0.0                   0.00
2     92.970000                       0.0                   0.00
3     93.120000                       0.0                   0.00
4     93.146667                       0.0                   0.00
…         …                         …                     …
1683  48.810000                       2.0                 -0.76
1684  48.403333                     -10.0                 -1.10
1685  47.996667                      -6.0                 -1.44
1686  47.590000                     -10.0                 -1.78
1687  47.570000                     -12.0                 -1.50

[1688 rows x 16 columns]
```

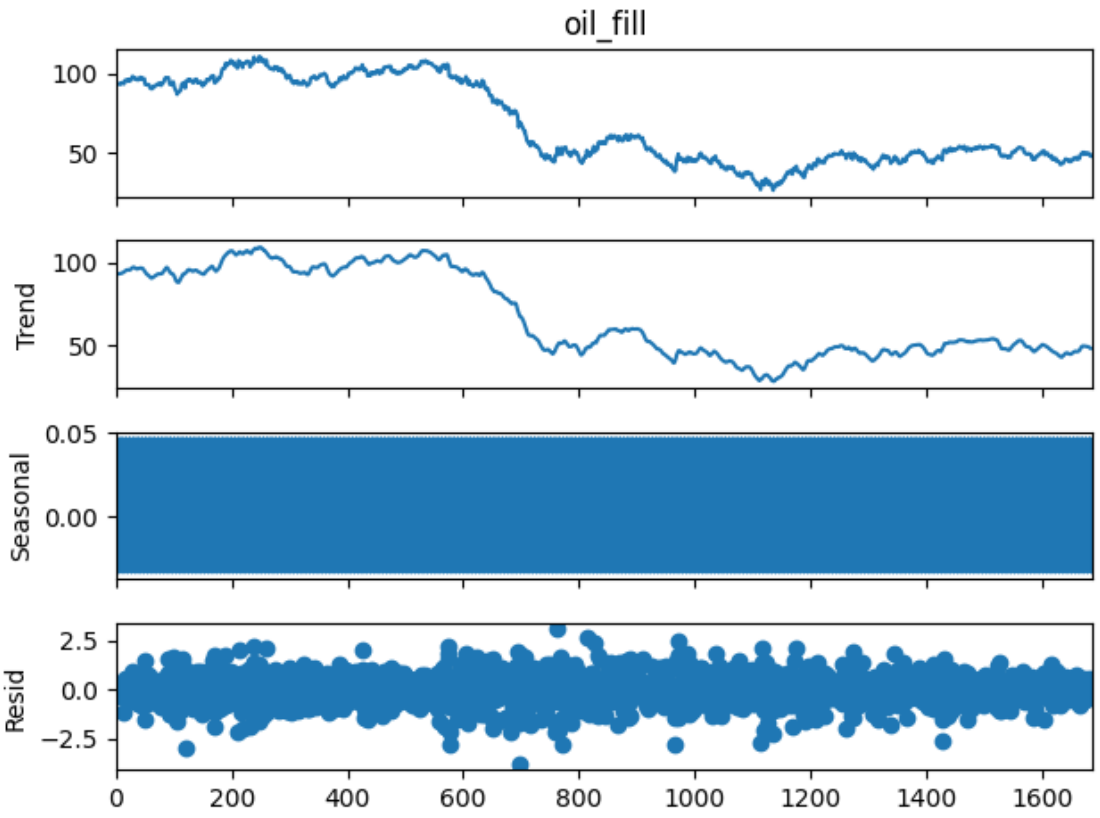
[172]:
```
from statsmodels.tsa.seasonal import seasonal_decompose
import matplotlib.pyplot as plt

df = sales_df
# df=df[df['date']>=pd.to_datetime('2016-01-01')]
# df=df[df['date']<pd.to_datetime('2017-01-01')]

vPariodenya = 7
```

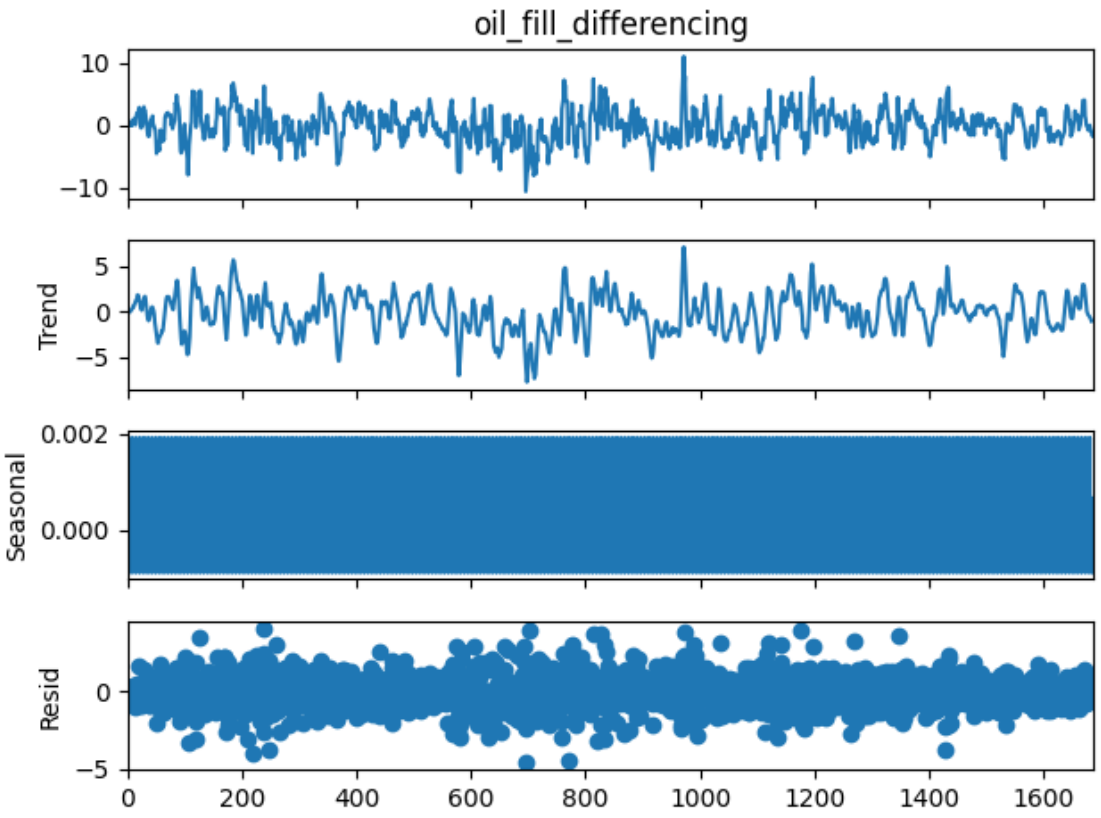
```
#karena seasonal_decompose tidak bisa handle missing value
#maka baris pertama untuk kolom on``
df['onpromotion_differencing'] = df['onpromotion_differencing'].
 ↪fillna(method='bfill')
df['oil_fill_differencing'] = df['oil_fill_differencing'].fillna(method='bfill')

daftarFeature=['sales','onpromotion','onpromotion_differencing','oil_fill','oil_fill_differenc

for feature in daftarFeature:

    # Decompose sales data (Assuming daily data, adjust period if needed)
    result = seasonal_decompose(df[feature], model='additive',␣
 ↪period=vPariodenya  )

    # Plot decomposition
    result.plot()
    plt.show()
```

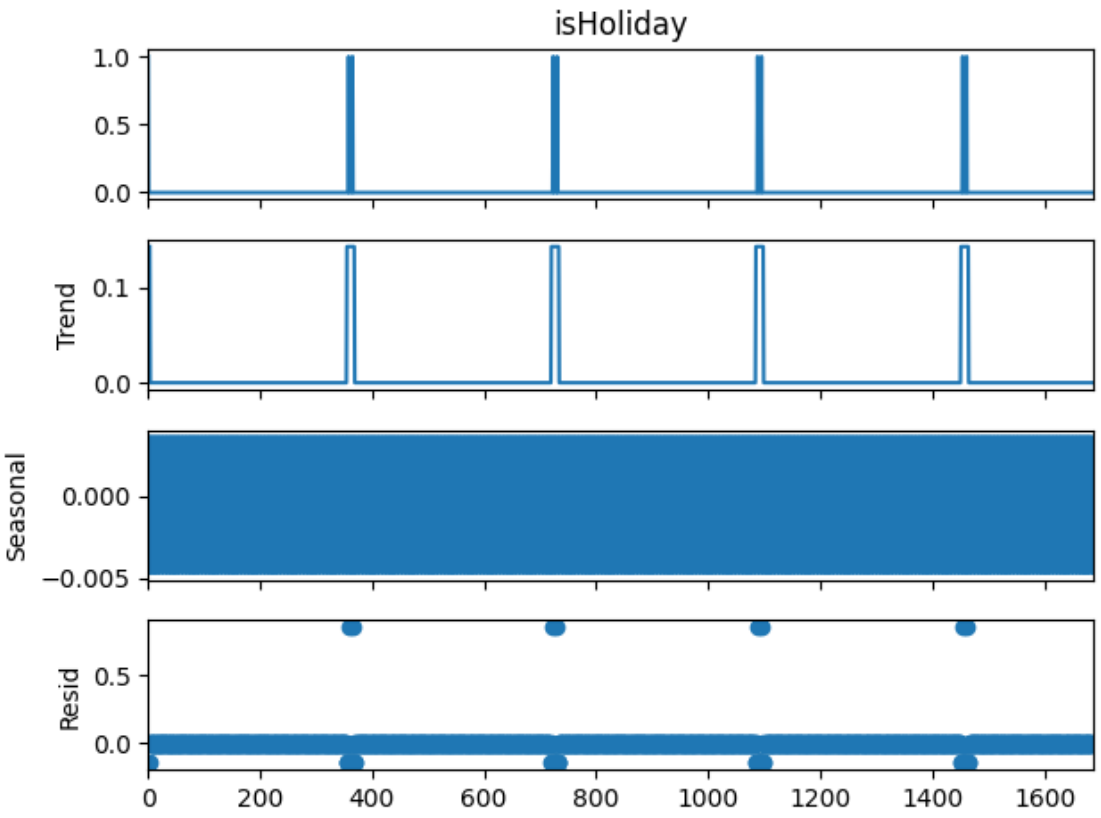


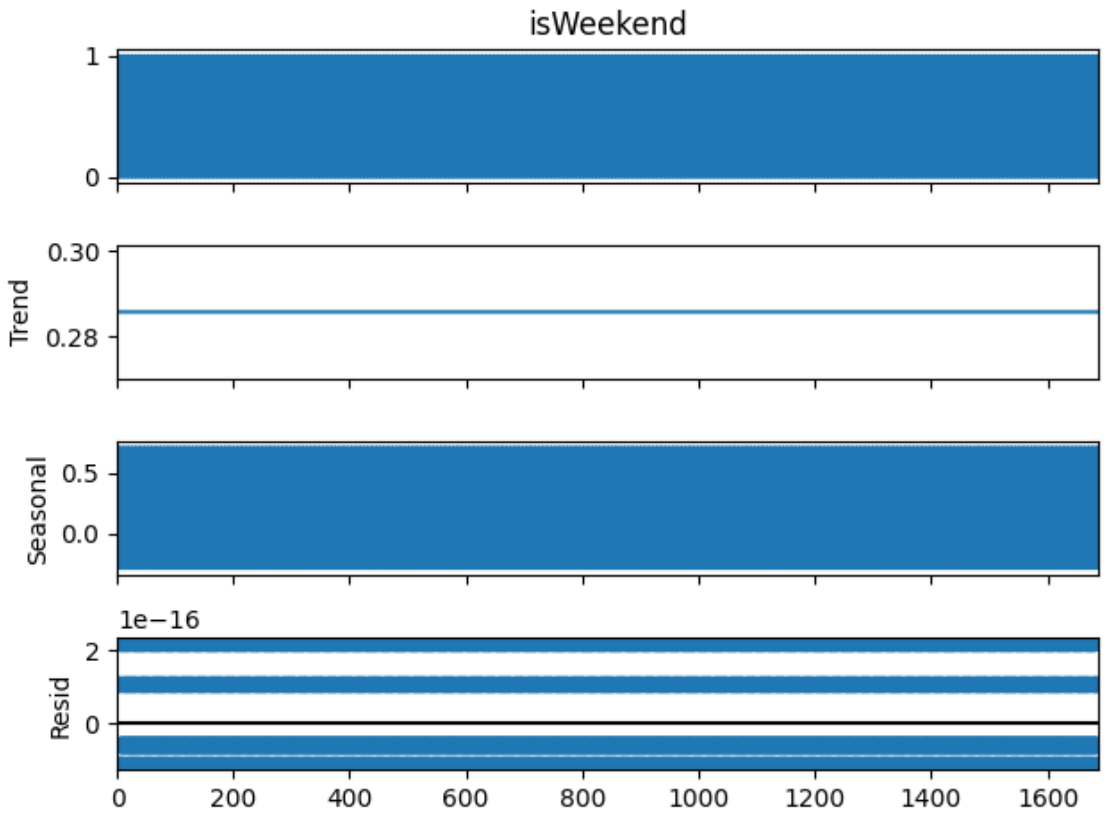

onpromotion
100
0
Trend
100
50
0
Seasonal
1
0
−1
Resid
0
−100
0
200
400
600
800
1000
1200
1400
1600


onpromotion_differencing
100
0
−100
Trend
50
0
−50
Seasonal
0.01
0.00
−0.01
Resid
100
0
−100
0
200
400
600
800
1000
1200
1400
1600


oil_fill
100
50
Trend
100
50
Seasonal
0.05
0.00
Resid
2.5
0.0
−2.5
0
200
400
600
800
1000
1200
1400
1600

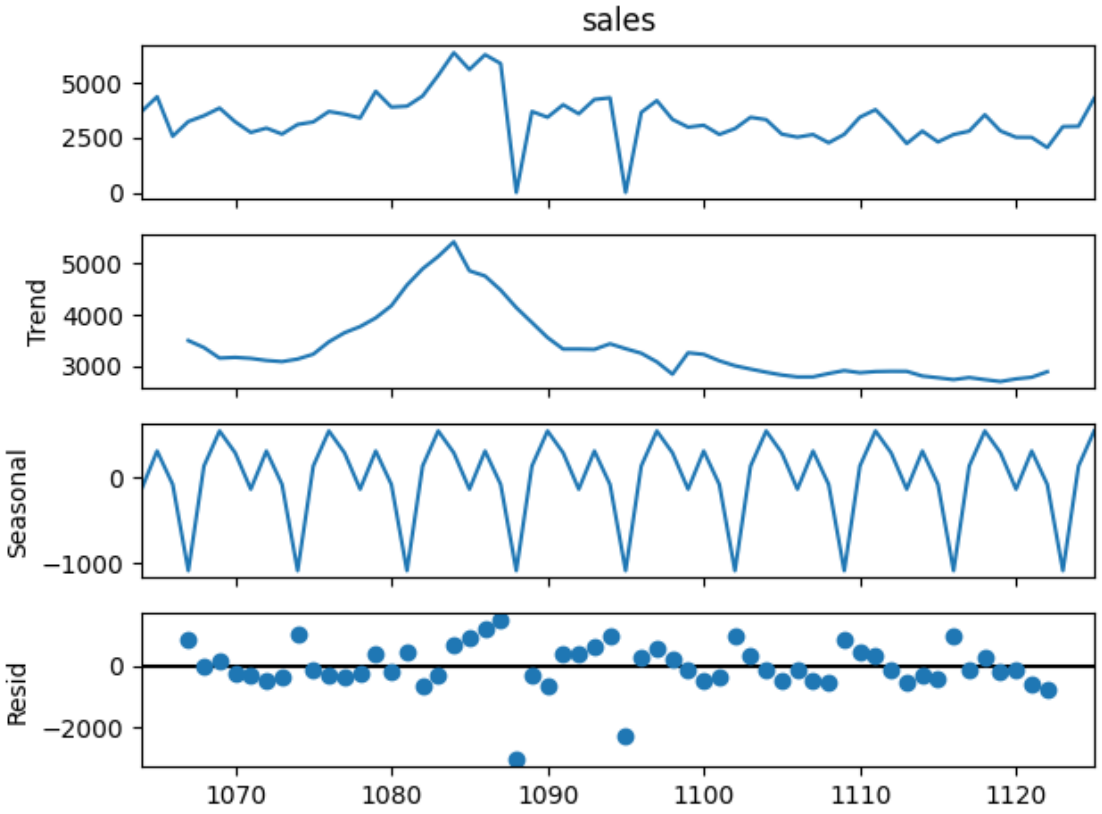

oil_fill_differencing
10
0
−10
Trend
5
0
−5
Seasonal
0.002
0.000
Resid
0
−5
0
200
400
600
800
1000
1200
1400
1600

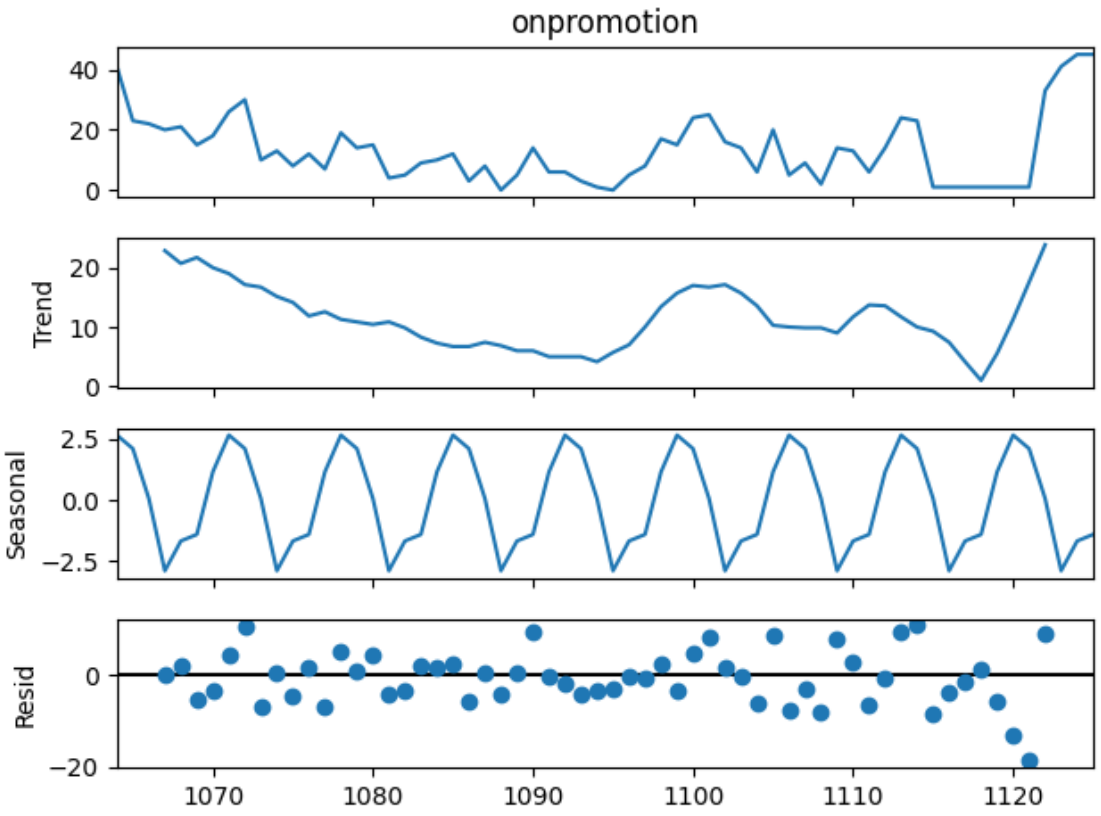

isHoliday
1.0
0.5
0.0
Trend
0.1
0.0
Seasonal
0.000
−0.005
Resid
0.5
0.0
0
200
400
600
800
1000
1200
1400
1600

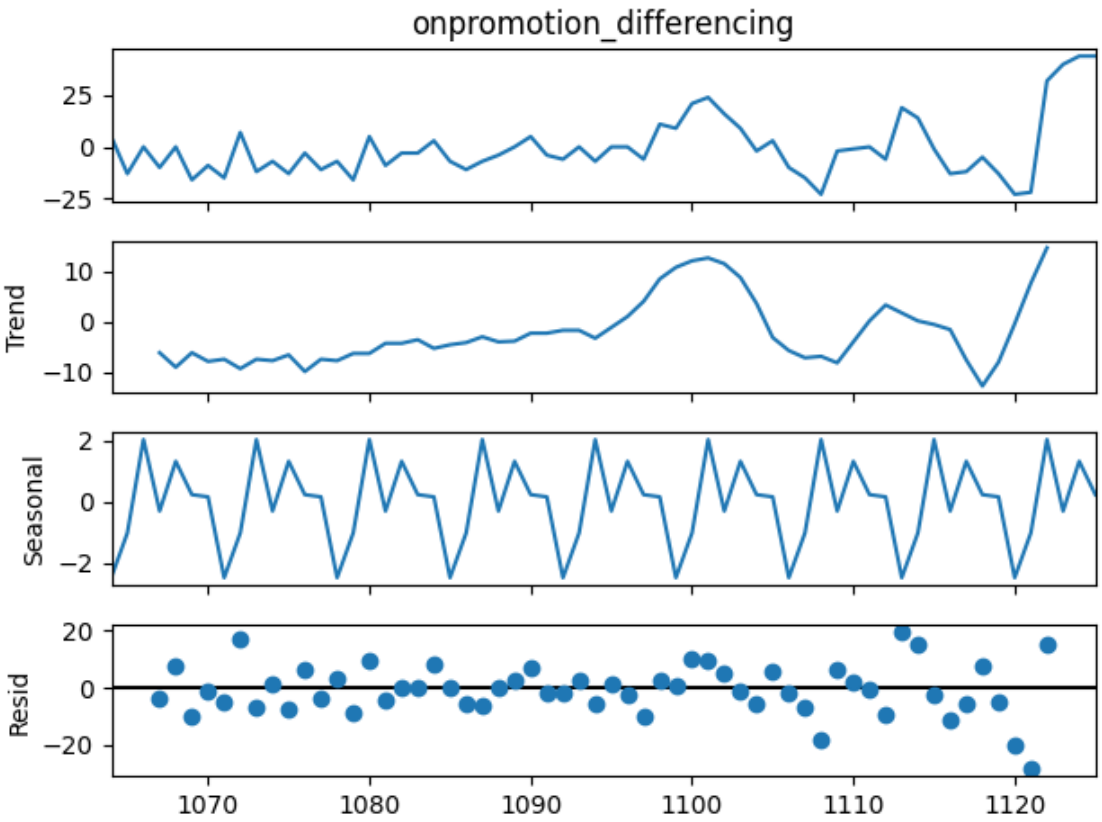


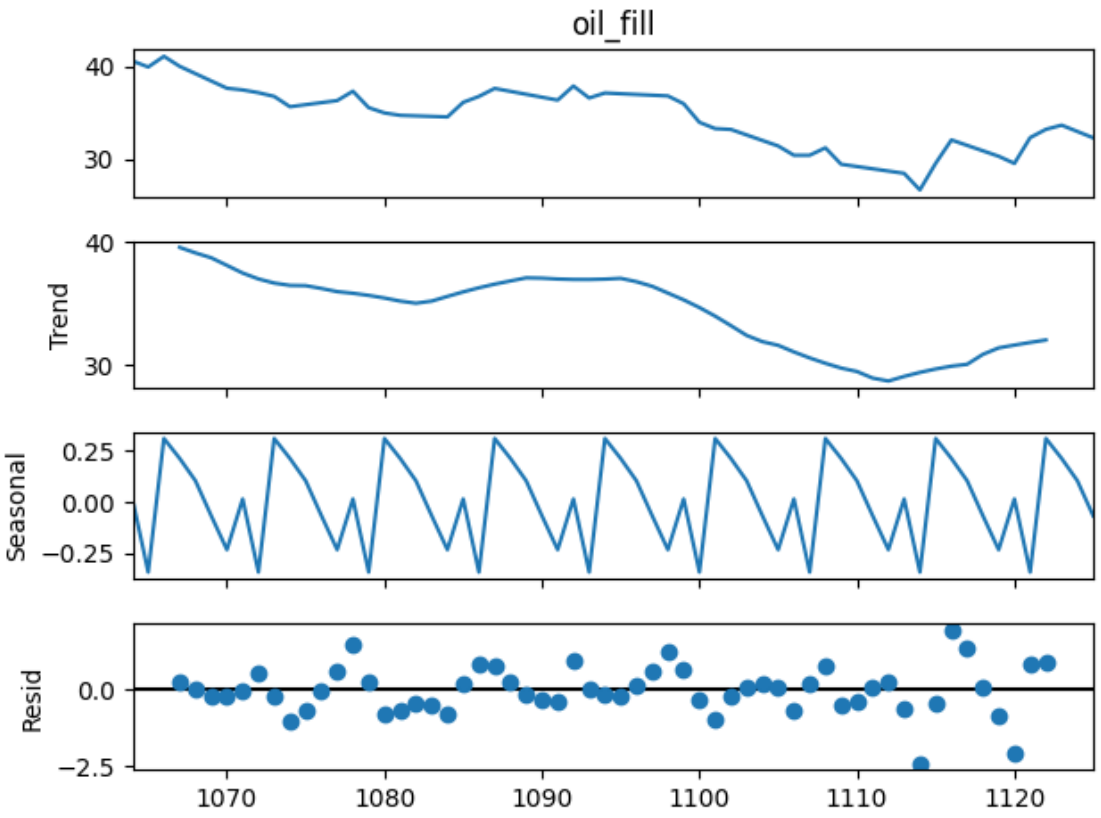
[173]:
```
from statsmodels.tsa.seasonal import seasonal_decompose
import matplotlib.pyplot as plt

df = sales_df
df=df[df['date']>=pd.to_datetime('2015-12-01')]
df=df[df['date']<pd.to_datetime('2016-02-01')]

vPariodenya = 7

#karena seasonal_decompose tidak bisa handle missing value
#maka baris pertama untuk kolom on``
df['onpromotion_differencing'] = df['onpromotion_differencing'].
 ↪fillna(method='bfill')
df['oil_fill_differencing'] = df['oil_fill_differencing'].fillna(method='bfill')

daftarFeature=['sales','onpromotion','onpromotion_differencing','oil_fill','oil_fill_differenc

for feature in daftarFeature:

    # Decompose sales data (Assuming daily data, adjust period if needed)
```

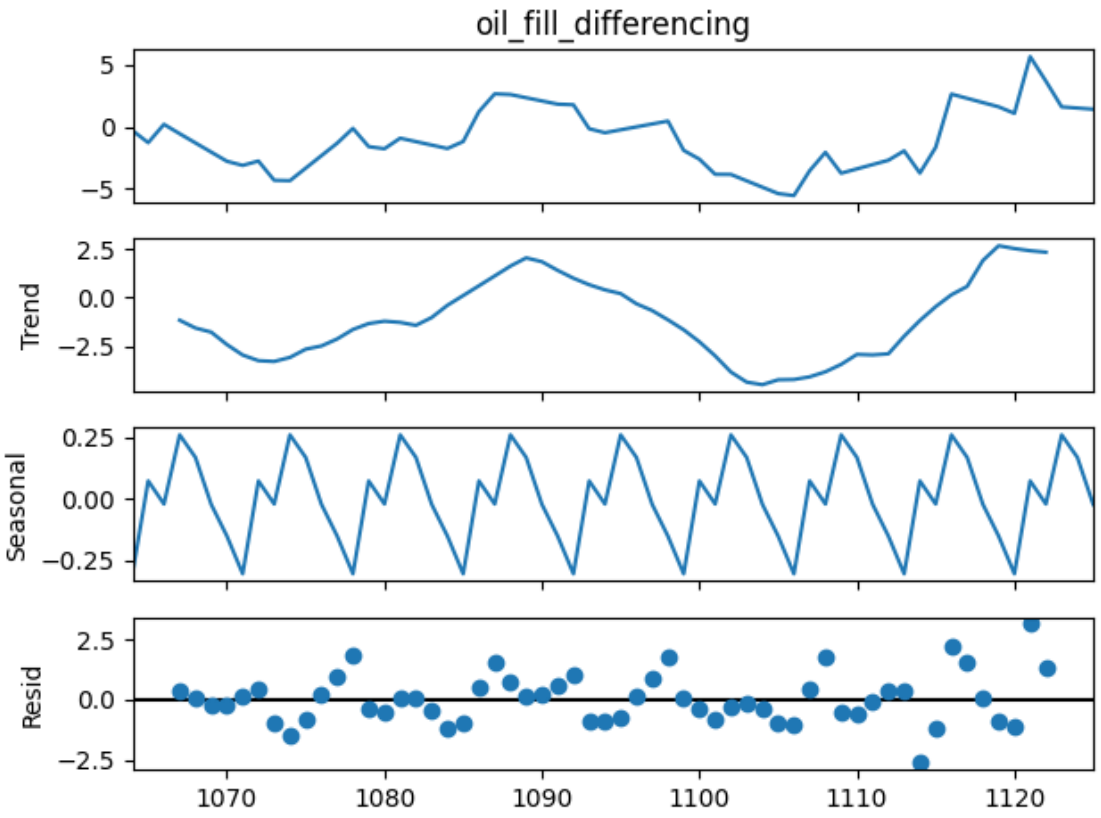
```
   result = seasonal_decompose(df[feature], model='additive',␣
↪period=vPariodenya  )

   # Plot decomposition
   result.plot()
   plt.show()
```

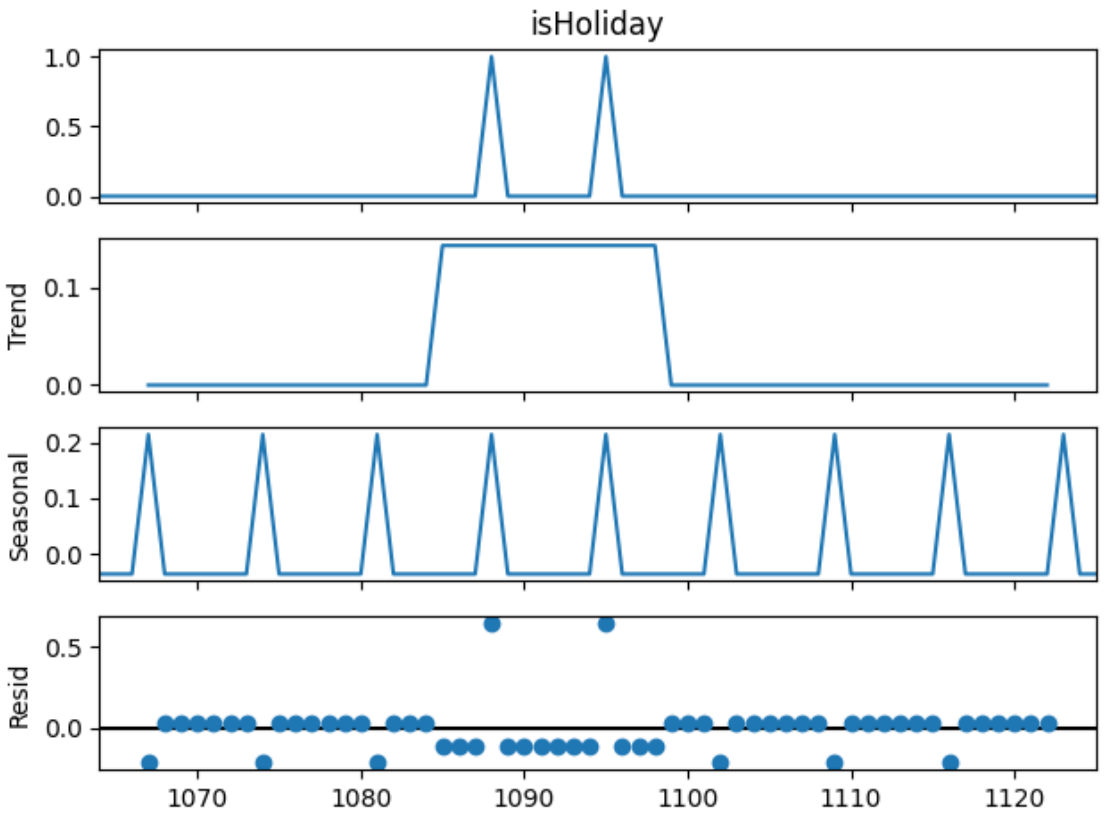


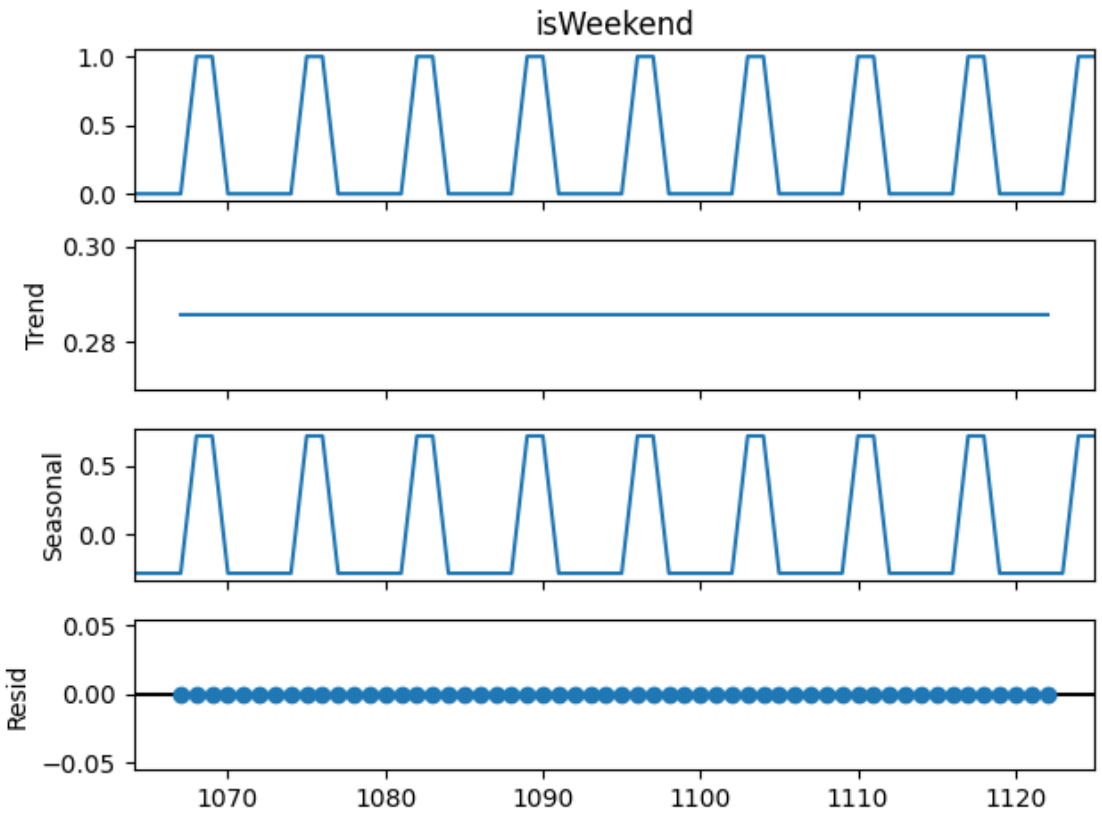

onpromotion
40
20
0
Trend
20
10
0
Seasonal
2.5
0.0
−2.5
Resid
0
−20
1070
1080
1090
1100
1110
1120


onpromotion_differencing
25
0
−25
Trend
10
0
−10
Seasonal
2
0
−2
Resid
20
0
−20
1070
1080
1090
1100
1110
1120


oil_fill
40
30
Trend
40
30
Seasonal
0.25
0.00
−0.25
Resid
0.0
−2.5
1070
1080
1090
1100
1110
1120

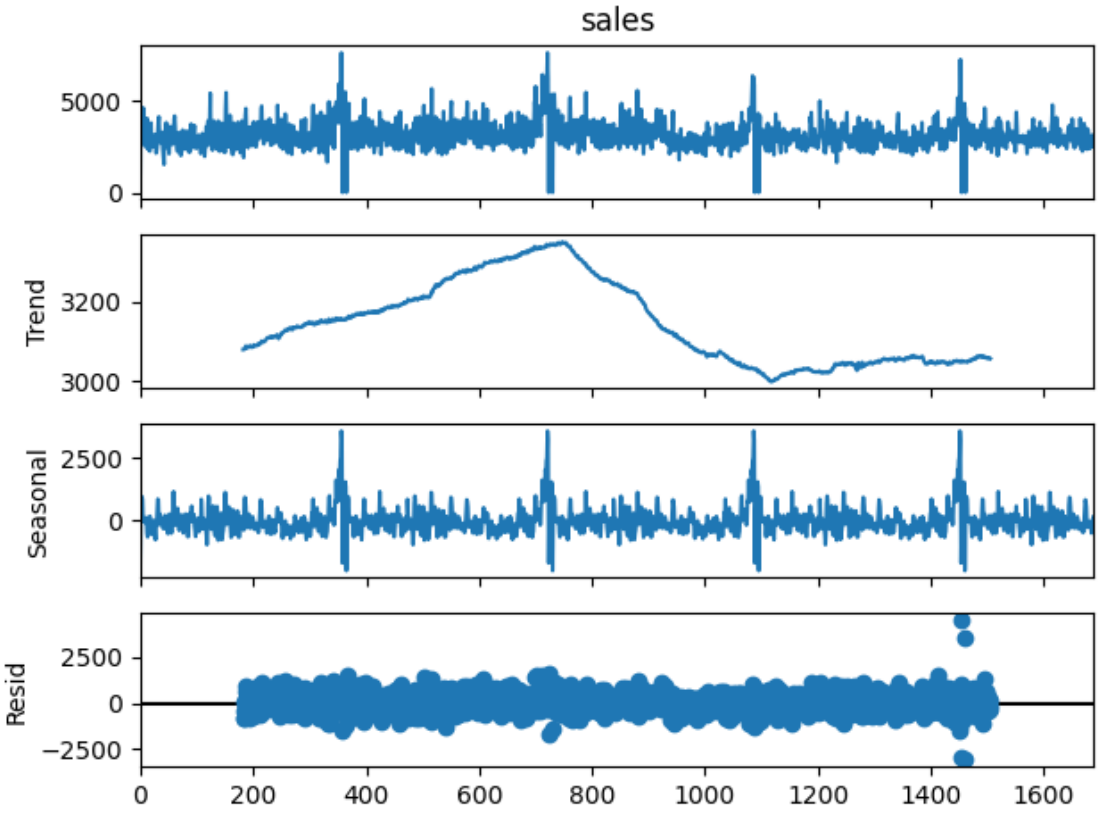

oil_fill_differencing
5
0
−5
Trend
2.5
0.0
−2.5
Seasonal
0.25
0.00
−0.25
Resid
2.5
0.0
−2.5
1070
1080
1090
1100
1110
1120

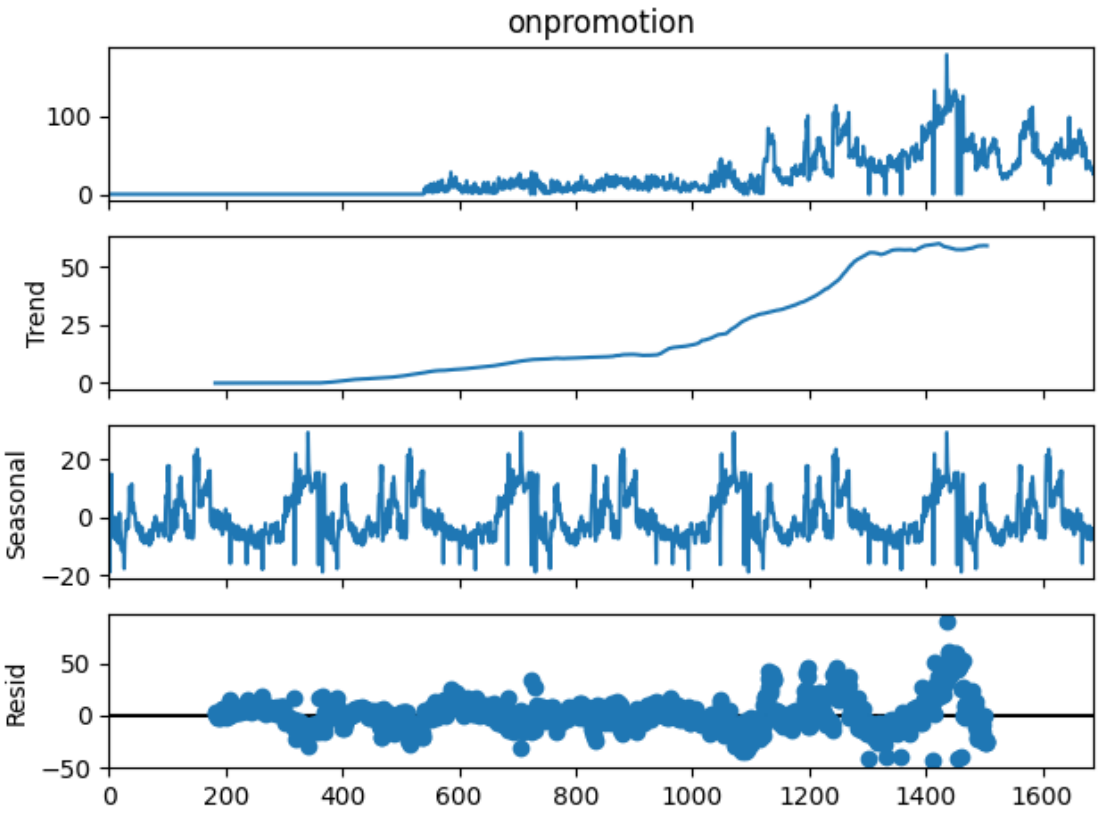

isHoliday
1.0
0.5
0.0
Trend
0.1
0.0
Seasonal
0.2
0.1
0.0
Resid
0.5
0.0
1070
1080
1090
1100
1110
1120

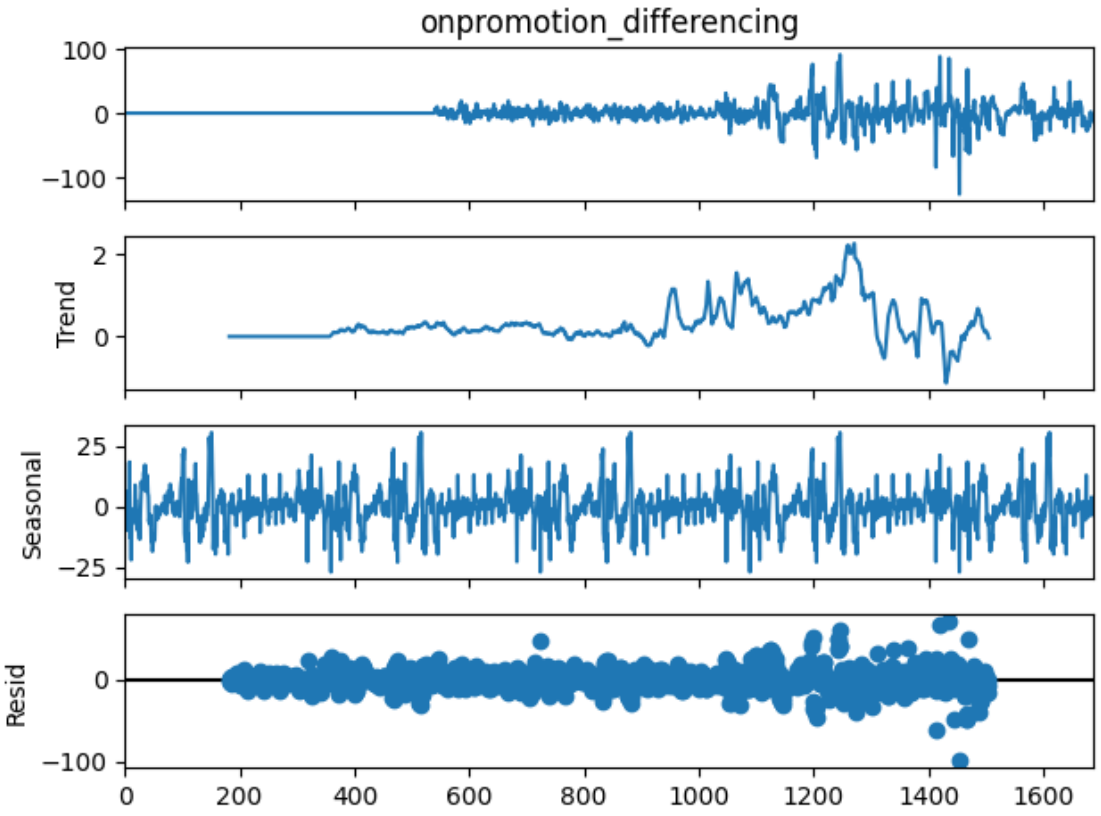


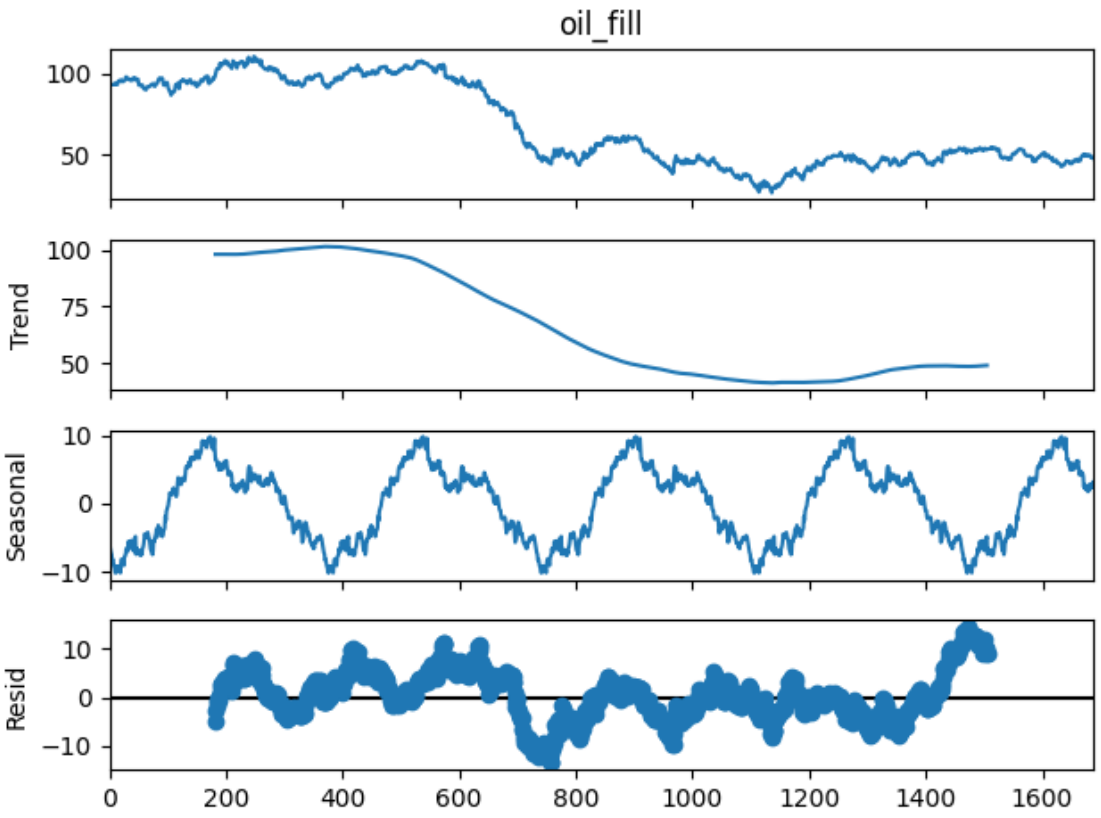
[174]:
```
from statsmodels.tsa.seasonal import seasonal_decompose
import matplotlib.pyplot as plt

df = sales_df
# df=df[df['date']>=pd.to_datetime('2016-01-01')]
# df=df[df['date']<pd.to_datetime('2017-01-01')]

vPariodenya = 365

#karena seasonal_decompose tidak bisa handle missing value
#maka baris pertama untuk kolom on``
df['onpromotion_differencing'] = df['onpromotion_differencing'].
 ↪fillna(method='bfill')
df['oil_fill_differencing'] = df['oil_fill_differencing'].fillna(method='bfill')

daftarFeature=['sales','onpromotion','onpromotion_differencing','oil_fill','oil_fill_differenc

for feature in daftarFeature:

    # Decompose sales data (Assuming daily data, adjust period if needed)
```

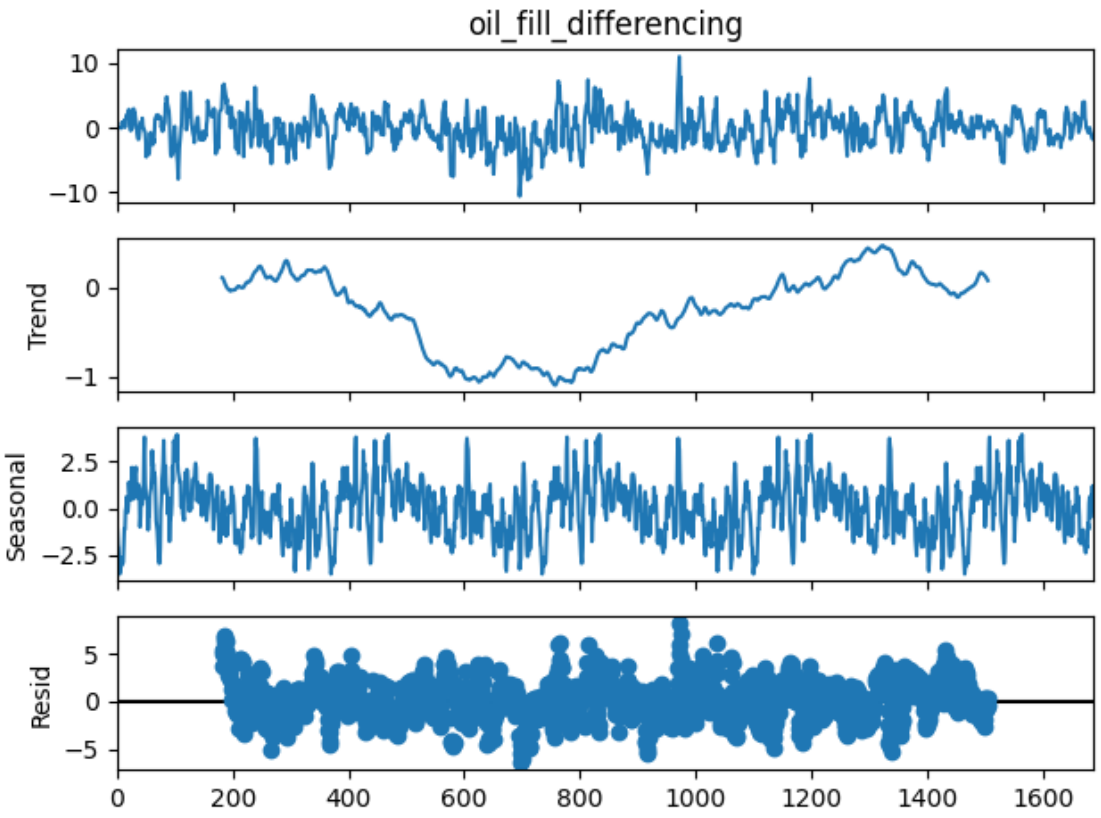
```
   result = seasonal_decompose(df[feature], model='additive',␣
↪period=vPariodenya  )

   # Plot decomposition
   result.plot()
   plt.show()
```

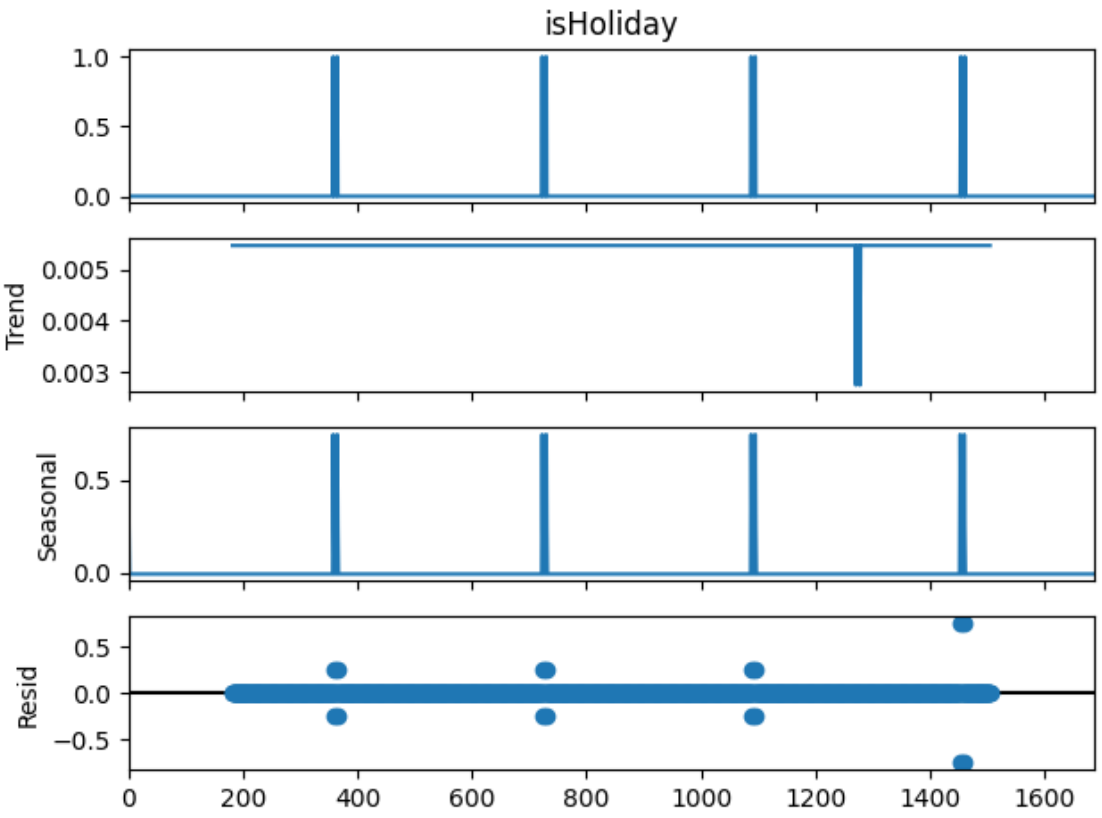


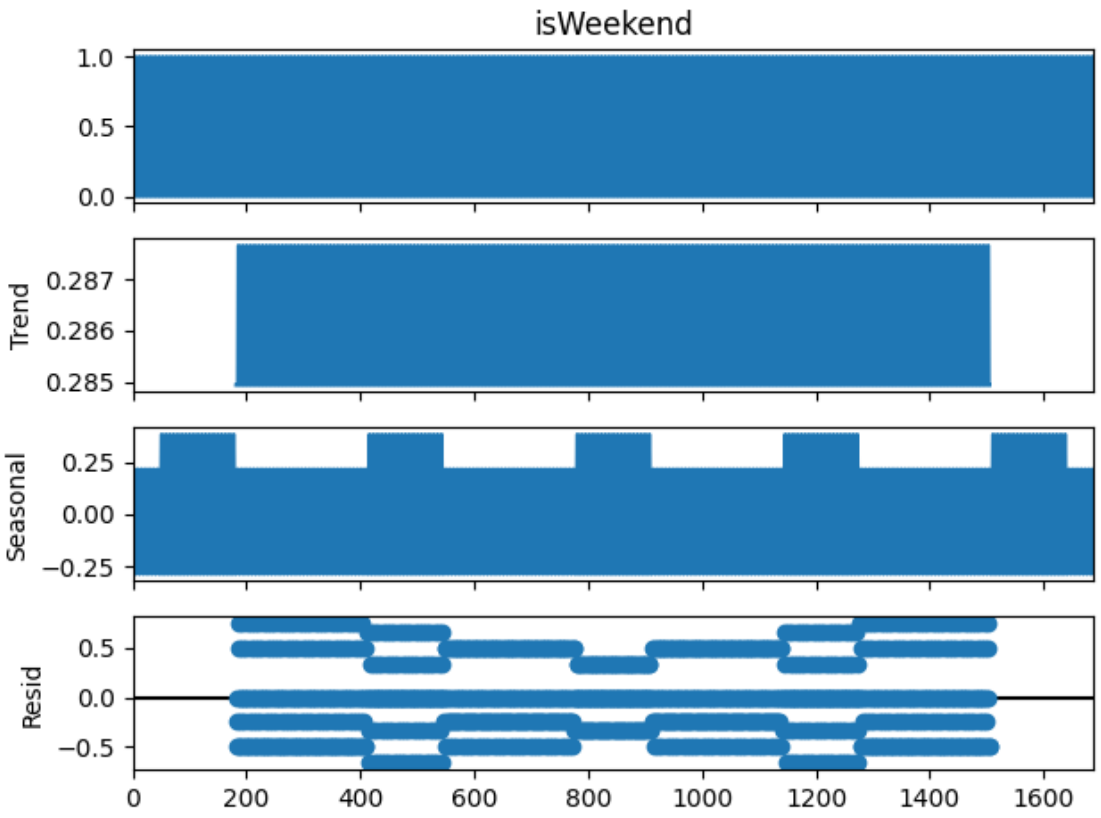

onpromotion
100
0
Trend
50
25
0
Seasonal
20
0
−20
Resid
50
0
−50
0
200
400
600
800
1000
1200
1400
1600


onpromotion_differencing
100
0
−100
Trend
2
0
Seasonal
25
0
−25
Resid
0
−100
0
200
400
600
800
1000
1200
1400
1600


oil_fill
100
50
Trend
100
75
50
Seasonal
10
0
−10
Resid
10
0
−10
0
200
400
600
800
1000
1200
1400
1600


oil_fill_differencing
10
0
−10
Trend
0
−1
Seasonal
2.5
0.0
−2.5
Resid
5
0
−5
0
200
400
600
800
1000
1200
1400
1600


isHoliday
1.0
0.5
0.0
Trend
0.005
0.004
0.003
Seasonal
0.5
0.0
Resid
0.5
0.0
−0.5
0
200
400
600
800
1000
1200
1400
1600



4 Preparation for Modelling

[175]:
```
print(sales_df.columns)
print(sales_df.head())
```

```
Index(['id', 'date', 'family', 'sales', 'onpromotion', 'dcoilwtico',
       'weekdays', 'week_of_the_year', 'year', 'month', 'day', 'isWeekend',
       'isHoliday', 'oil_fill', 'onpromotion_differencing',
       'oil_fill_differencing'],
      dtype='object')
     id       date     family   sales  onpromotion  dcoilwtico   weekdays  \
0  1464 2013-01-01  GROCERY I     0.0            0         NaN    Tuesday
1  3246 2013-01-02  GROCERY I  4558.0            0       93.14  Wednesday
2  5028 2013-01-03  GROCERY I  3260.0            0       92.97   Thursday
3  6810 2013-01-04  GROCERY I  3085.0            0       93.12     Friday
4  8592 2013-01-05  GROCERY I  3398.0            0         NaN   Saturday

   week_of_the_year  year  month  day  isWeekend  isHoliday   oil_fill  \
0                 1  2013      1    1          0          1  93.140000
1                 1  2013      1    2          0          0  93.140000
```

```
2                 1  2013      1    3          0          0  92.970000
3                 1  2013      1    4          0          0  93.120000
4                 1  2013      1    5          1          0  93.146667

   onpromotion_differencing  oil_fill_differencing
0                       0.0                    0.0
1                       0.0                    0.0
2                       0.0                    0.0
3                       0.0                    0.0
4                       0.0                    0.0
```

[ ]:

4.1 copy sales_df -> data_df

[176]:
```
data_df = sales_df[['date','sales',␣
 ↪'onpromotion_differencing','oil_fill_differencing', 'isWeekend','isHoliday']]
data_df
```

[176]:
```
           date   sales  onpromotion_differencing  oil_fill_differencing  \
0    2013-01-01     0.0                       0.0                   0.00
1    2013-01-02  4558.0                       0.0                   0.00
2    2013-01-03  3260.0                       0.0                   0.00
3    2013-01-04  3085.0                       0.0                   0.00
4    2013-01-05  3398.0                       0.0                   0.00
…           …     …                         …                      …
1683 2017-08-11  2864.0                       2.0                  -0.76
1684 2017-08-12  2476.0                     -10.0                  -1.10
1685 2017-08-13  3141.0                      -6.0                  -1.44
1686 2017-08-14  2717.0                     -10.0                  -1.78
1687 2017-08-15  2696.0                     -12.0                  -1.50

      isWeekend  isHoliday
0             0          1
1             0          0
2             0          0
3             0          0
4             1          0
…           …        …
1683          0          0
1684          1          0
1685          1          0
1686          0          0
1687          0          0

[1688 rows x 6 columns]
```

[177]:
```
duplicate_rows = data_df[data_df.duplicated()]
print(duplicate_rows)

data_df = data_df.drop_duplicates().reset_index(drop=True)
data_df
```

```
Empty DataFrame
Columns: [date, sales, onpromotion_differencing, oil_fill_differencing,
isWeekend, isHoliday]
Index: []
```

[177]:

	date	sales	onpromotion_differencing	oil_fill_differencing	\
0	2013-01-01	0.0	0.0	0.00	
1	2013-01-02	4558.0	0.0	0.00	
2	2013-01-03	3260.0	0.0	0.00	
3	2013-01-04	3085.0	0.0	0.00	
4	2013-01-05	3398.0	0.0	0.00	
…	…	…	…	…	
1683	2017-08-11	2864.0	2.0	-0.76	
1684	2017-08-12	2476.0	-10.0	-1.10	
1685	2017-08-13	3141.0	-6.0	-1.44	
1686	2017-08-14	2717.0	-10.0	-1.78	
1687	2017-08-15	2696.0	-12.0	-1.50	

	isWeekend	isHoliday
0	0	1
1	0	0
2	0	0
3	0	0
4	1	0
…	…	…
1683	0	0
1684	1	0
1685	1	0
1686	0	0
1687	0	0

[1688 rows x 6 columns]

4.2 Splitting Data

[178]:
```
# splitting the data
percentage = 80
x = round((len(data_df)-1)*percentage/100)
data_df.loc[1350]
```

[178]:
```
date                          2016-09-12 00:00:00
sales                                      2815.0
onpromotion_differencing                      1.0
oil_fill_differencing                       1.545
isWeekend                                       0
isHoliday                                       0
Name: 1350, dtype: object
```

[179]:
```
original_train_data_df = sales_df[sales_df['date'] <= '2016-09-12']
original_val_data_df = sales_df[sales_df['date'] > '2016-09-12']

varmax_train_data_df = data_df[data_df['date'] <= '2016-09-12']
varmax_val_data_df = data_df[data_df['date'] > '2016-09-12']

print(f'tail varmax_train_data_df :\n {varmax_train_data_df.tail()}')
print(f'head varmax_val_data_df :\n {varmax_val_data_df.head()}')
```

```
tail varmax_train_data_df :
            date   sales  onpromotion_differencing  oil_fill_differencing  \
1346 2016-09-08  2253.0                      -4.0               4.460000
1347 2016-09-09  2307.0                     -12.0               1.490000
1348 2016-09-10  3048.0                       5.0               1.508333
1349 2016-09-11  3341.0                       8.0               1.526667
1350 2016-09-12  2815.0                       1.0               1.545000

      isWeekend  isHoliday
1346          0          0
1347          0          0
1348          1          0
1349          1          0
1350          0          0
head varmax_val_data_df :
            date   sales  onpromotion_differencing  oil_fill_differencing  \
1351 2016-09-13  2396.0                     -10.0               0.060000
1352 2016-09-14  2463.0                       3.0              -1.850000
1353 2016-09-15  2231.0                       9.0              -3.780000
1354 2016-09-16  2909.0                      11.0              -2.840000
1355 2016-09-17  3018.0                       7.0              -2.873333

      isWeekend  isHoliday
1351          0          0
1352          0          0
1353          0          0
1354          0          0
1355          1          0
```

[180]:
```
print(varmax_train_data_df.dtypes)
```

```
date                          datetime64[ns]
sales                                float64
onpromotion_differencing             float64
oil_fill_differencing                float64
isWeekend                              int32
isHoliday                              int32
dtype: object
```

[181]:
```
print(varmax_train_data_df.isna().sum())
```

```
date                          0
sales                         0
onpromotion_differencing      0
oil_fill_differencing         0
isWeekend                     0
isHoliday                     0
dtype: int64
```

4.2.1 cell dibawah ini saya jadikan COMMENT

agar tidak makan waktu banyak, hasil **model.fit()** sudah saya jadikan pickle file ; jadi tinggal di load di cell berikutnya

[182]:
```
from statsmodels.tsa.statespace.varmax import VARMAX


# Define Endogenous (Variables to Predict)
endog_vars = ['sales', 'onpromotion_differencing']  # Targets
endog = varmax_train_data_df[endog_vars]

# Define Exogenous (Other Features)
exog_vars = ['oil_fill_differencing', 'isWeekend', 'isHoliday']  # Predictors
exog = varmax_train_data_df[exog_vars]

# Fit VARMAX Model
model = VARMAX(endog=endog, exog=exog, order=(7, 2))
model_fit = model.fit()


# Print summary
print(model_fit.summary())


import pickle

# Save the trained model
with open('varmax_grocery_model_awal_sebelum_tuning.pkl', 'wb') as f:
    pickle.dump(model_fit, f)
```

```
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\base\model.py:607: ConvergenceWarning: Maximum Likelihood
optimization failed to converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
                                    Statespace Model Results
==============================================================================
=================
Dep. Variable:     ['sales', 'onpromotion_differencing']   No. Observations:
1351
Model:                                       VARMAX(7,2)   Log Likelihood
-15193.323
                                             + intercept   AIC
30480.647
Date:                                  Wed, 12 Feb 2025   BIC
30725.451
Time:                                         20:46:10   HQIC
30572.322
Sample:                                               0
                                                  - 1351
Covariance Type:                                    opg
==============================================================================
===
Ljung-Box (L1) (Q):             0.98, 6.22   Jarque-Bera (JB):    4343.17,
13797.86
Prob(Q):                        0.32, 0.01   Prob(JB):                 0.00,
0.00
Heteroskedasticity (H):       0.79, 180.92   Skew:                    -0.06,
0.14
Prob(H) (two-sided):            0.01, 0.00   Kurtosis:                11.78,
18.65
                                   Results for equation sales
==============================================================================
==================
                                    coef    std err          z      P>|z|
[0.025      0.975]
------------------------------------------------------------------------------
------------------
intercept                         572.8200     70.587      8.115      0.000
434.472     711.168
L1.sales                            0.2790      0.025     11.196      0.000
0.230       0.328
L1.onpromotion_differencing         6.2534      3.375      1.853      0.064
```

```
-0.361      12.868
L2.sales                          -0.0694      0.036     -1.937      0.053
-0.140       0.001
L2.onpromotion_differencing       -1.7042      3.760     -0.453      0.650
-9.074       5.666
L3.sales                           0.0500      0.021      2.348      0.019
0.008       0.092
L3.onpromotion_differencing       -1.8236      2.525     -0.722      0.470
-6.772       3.125
L4.sales                          -0.0074      0.015     -0.480      0.631
-0.038       0.023
L4.onpromotion_differencing       -0.8291      1.670     -0.496      0.620
-4.103       2.445
L5.sales                          -0.0069      0.016     -0.439      0.661
-0.038       0.024
L5.onpromotion_differencing        0.3216      1.722      0.187      0.852
-3.054       3.697
L6.sales                           0.0863      0.019      4.595      0.000
0.049       0.123
L6.onpromotion_differencing       -2.1242      1.885     -1.127      0.260
-5.819       1.571
L7.sales                           0.4640      0.015     30.216      0.000
0.434       0.494
L7.onpromotion_differencing        2.8465      1.572      1.811      0.070
-0.235       5.928
L1.e(sales)                        0.1168      0.033      3.594      0.000
0.053       0.181
L1.e(onpromotion_differencing)    -0.5530      3.981     -0.139      0.890
-8.355       7.249
L2.e(sales)                        0.1276      0.036      3.581      0.000
0.058       0.197
L2.e(onpromotion_differencing)     0.0325      3.687      0.009      0.993
-7.194       7.259
beta.oil_fill_differencing        -4.8578      5.591     -0.869      0.385
-15.815       6.100
beta.isWeekend                   157.6145     31.845      4.949      0.000
95.200     220.029
beta.isHoliday                  -571.1137     92.875     -6.149      0.000
-753.145    -389.083
                          Results for equation onpromotion_differencing
==============================================================================
==================
                                    coef    std err          z      P>|z|
[0.025      0.975]
------------------------------------------------------------------------------
------------------
intercept                          1.0629      3.357      0.317      0.752
-5.516       7.642
```

```
L1.sales                            0.0008      0.001      0.898      0.369
-0.001       0.003
L1.onpromotion_differencing         0.3360      0.037      9.154      0.000
0.264       0.408
L2.sales                         -5.808e-05      0.001     -0.057      0.955
-0.002       0.002
L2.onpromotion_differencing         0.1672      0.048      3.512      0.000
0.074       0.260
L3.sales                           -0.0004      0.001     -0.785      0.433
-0.002       0.001
L3.onpromotion_differencing         0.0779      0.029      2.643      0.008
0.020       0.136
L4.sales                            0.0004      0.000      0.771      0.441
-0.001       0.001
L4.onpromotion_differencing         0.0276      0.020      1.349      0.177
-0.013       0.068
L5.sales                           -0.0007      0.001     -1.191      0.234
-0.002       0.000
L5.onpromotion_differencing         0.0581      0.019      3.112      0.002
0.022       0.095
L6.sales                            0.0002      0.001      0.370      0.711
-0.001       0.001
L6.onpromotion_differencing         0.0398      0.020      2.006      0.045
0.001       0.079
L7.sales                           -0.0006      0.001     -0.956      0.339
-0.002       0.001
L7.onpromotion_differencing        -0.4799      0.018    -26.624      0.000
-0.515      -0.445
L1.e(sales)                        -0.0015      0.001     -1.524      0.128
-0.003       0.000
L1.e(onpromotion_differencing)      0.2086      0.042      4.972      0.000
0.126       0.291
L2.e(sales)                        -0.0008      0.001     -0.801      0.423
-0.003       0.001
L2.e(onpromotion_differencing)      0.1591      0.045      3.569      0.000
0.072       0.246
beta.oil_fill_differencing          0.0847      0.131      0.645      0.519
-0.173       0.342
beta.isWeekend                      0.2599      0.977      0.266      0.790
-1.656       2.175
beta.isHoliday                     -2.1909      8.064     -0.272      0.786
-17.995      13.614
                                          Error covariance matrix
==============================================================================
============================
                                             coef    std err          z
P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
```

```
---------------------------
sqrt.var.sales                                494.0182      6.007     82.244
0.000     482.245     505.791
sqrt.cov.sales.onpromotion_differencing     0.3977      0.375      1.061
0.289      -0.337       1.132
sqrt.var.onpromotion_differencing           8.1801      0.084     97.666
0.000       8.016       8.344
==============================================================================
==========================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
```

[183]:
```
import pickle
```

4.3 Iterasi hyper parameter

4.3.1 cell dibawah ini saya jadikan COMMENT kara hasilnya sudah di save jadi file pickle ; silahkan di uncomment jika ingin coba di run

[ ]:
```
import itertools
import numpy as np
from statsmodels.tsa.statespace.varmax import VARMAX
from sklearn.metrics import mean_squared_error


p_values = [1,2,5,7]  # Endogenous lags
q_values = [1,2,5,7,30]  # Exogenous lags


endog_vars = ['sales', 'onpromotion_differencing']  # Targets
endog = varmax_train_data_df[endog_vars]


exog_vars = ['oil_fill_differencing', 'isWeekend', 'isHoliday']
exog = varmax_train_data_df[exog_vars]

# Loop through all combinations of p and q
for p, q in itertools.product(p_values, q_values):
    print(f"Trying VARMAX({p}, {q})")

    # Create and fit the VARMAX model
    model = VARMAX(endog=endog, exog=exog, order=(p, q))
    model_fit = model.fit(disp=False)

    # Forecast for validation data
    forecast_steps = len(varmax_val_data_df)
```

```
    forecast = model_fit.forecast(steps=forecast_steps,␣
↪exog=varmax_val_data_df[exog_vars])

    # Save the trained model
    filename = (f'varmax_grocery_model_p{p}_q{q}_.pkl')
    with open(filename, 'wb') as f:
        pickle.dump(model_fit, f)
```

[ ]:
```
'\n\nimport itertools\nimport numpy as np\nfrom
statsmodels.tsa.statespace.varmax import VARMAX\nfrom sklearn.metrics import
mean_squared_error\n\n\np_values = [1,2,5,7]  # Endogenous lags\nq_values =
[1,2,5,7,30]  # Exogenous lags\n\n\nendog_vars = [\'sales\',
\'onpromotion_differencing\']  # Targets\nendog =
varmax_train_data_df[endog_vars]\n\n\nexog_vars = [\'oil_fill_differencing\',
\'isWeekend\', \'isHoliday\']  \nexog = varmax_train_data_df[exog_vars]\n\n#
Loop through all combinations of p and q\nfor p, q in
itertools.product(p_values, q_values):\n    print(f"Trying VARMAX({p}, {q})")\n
\n    # Create and fit the VARMAX model\n    model = VARMAX(endog=endog,
exog=exog, order=(p, q))\n    model_fit = model.fit(disp=False)\n    \n    #
Forecast for validation data\n    forecast_steps = len(varmax_val_data_df)\n
forecast = model_fit.forecast(steps=forecast_steps,
exog=varmax_val_data_df[exog_vars])\n    \n    # Save the trained model\n
filename = (f\'varmax_grocery_model_p{p}_q{q}_.pkl\')\n    with open(filename,
\'wb\') as f:\n        pickle.dump(model_fit, f)\n\n\n'
```

[185]:
```
import os
import glob
```

4.4 trying All created models to find best model

[191]:
```
from sklearn.metrics import mean_squared_error
import numpy as np

# daftarModel = ['varmax_grocery_model_awal_sebelum_tuning.
↪pkl','varmax_grocery_model_p1_q1_.pkl',
#                'varmax_grocery_model_p1_q2_.pkl','varmax_grocery_model_p1_q5_.
↪pkl','varmax_grocery_model_p1_q7_.pkl','varmax_grocery_model_p1_q30_.pkl',
#                'varmax_grocery_model_p2_q2_.pkl','varmax_grocery_model_p2_q5_.
↪pkl','varmax_grocery_model_p2_q7_.pkl','varmax_grocery_model_p2_q30_.pkl',
#                'varmax_grocery_model_p5_q2_.pkl','varmax_grocery_model_p5_q5_.
↪pkl','varmax_grocery_model_p5_q7_.pkl','varmax_grocery_model_p5_q30_.pkl',
#                'varmax_grocery_model_p7_q2_.pkl','varmax_grocery_model_p7_q5_.
↪pkl','varmax_grocery_model_p7_q7_.pkl','varmax_grocery_model_p7_q30_.pkl',
#                'varmax_grocery_model_p30_q2_.
↪pkl','varmax_grocery_model_p30_q5_.pkl','varmax_grocery_model_p30_q7_.
↪pkl','varmax_grocery_model_p30_q30_.pkl'
#                ]
```

```
directory = r'D:
 ↪\__DOWNLOADS\_AIForINDONESIA\Codes\git\learnWithAIforIndonesia\Sesi15_Project01'
pattern = os.path.join(directory, 'varmax_grocery_model*.pkl')
full_file_list = glob.glob(pattern)
daftarModel = [os.path.basename(file) for file in full_file_list]

endog_vars = ['sales', 'onpromotion_differencing']
endog = varmax_train_data_df[endog_vars]


exog_vars = ['oil_fill_differencing', 'isWeekend', 'isHoliday']
exog = varmax_train_data_df[exog_vars]

lastValueOf_originalOnPromotion = original_train_data_df['onpromotion'].tail(1).
 ↪values[0]


results_coba_model = []


for namaFile in daftarModel :
    print(f"Loading Model {namaFile}")
    try:
        with open(namaFile, 'rb') as f:
            loaded_model = pickle.load(f)

        # lakukan forcasting
        forecast_steps = len(varmax_val_data_df)
        forecast = loaded_model.forecast(steps=forecast_steps,␣
 ↪exog=varmax_val_data_df[exog_vars])

        # membalikkan nilai differncing ke nilai semul
        forecast['onpromotion'] = lastValueOf_originalOnPromotion +␣
 ↪forecast['onpromotion_differencing'].cumsum()

        # ambil nilai actual dan rata2 actual untuk nanti menghitung RMSE
        actual_sales = varmax_val_data_df['sales']
        actual_onpromotion_differencing =␣
 ↪varmax_val_data_df['onpromotion_differencing']
        actual_onpromotion = original_val_data_df['onpromotion']

        mean_actual_sales = varmax_val_data_df['sales'].mean()
        mean_actual_onpromotion_differencing =␣
 ↪varmax_val_data_df['onpromotion_differencing'].mean()
        mean_actual_onpromotion = original_val_data_df['onpromotion'].mean()
```

```
        # ambil nilai hasil forcast
        forecast_sales = forecast['sales']
        forecast_onpromotion_differencing = forecast['onpromotion_differencing']
        forecast_onpromotion = forecast['onpromotion']

        # Hitung RMSE
        rmse_sales = np.sqrt(mean_squared_error(actual_sales, forecast_sales))
        rmse_onpromotion_differencing = np.
↪sqrt(mean_squared_error(actual_onpromotion_differencing,␣
↪forecast_onpromotion_differencing))
        rmse_onpromotion = np.sqrt(mean_squared_error(actual_onpromotion,␣
↪forecast_onpromotion))

        # nilai rata2 dan pembobotan untuk RMSE
        avg_rmse = (rmse_sales + rmse_onpromotion) / 2
        weighted_rmse = (rmse_sales/mean_actual_sales) + (rmse_onpromotion/
↪mean_actual_onpromotion)

        # simpan hasilnya di variable results_coba_model
        results_coba_model.append((namaFile,weighted_rmse, avg_rmse,␣
↪rmse_sales, rmse_onpromotion_differencing,rmse_onpromotion))

    except FileNotFoundError:
        print(f"Error: {namaFile} not found. Skipping this file.")
    except Exception as e:
        print(f"An unexpected error occurred while loading {namaFile}: {e}")
```

```
Loading Model varmax_grocery_model.pkl
```

```
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'
```

```
Loading Model varmax_grocery_model_awal_sebelum_tuning.pkl
```

```
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
```

```
of VARMA(p,q) models is not generically robust, due especially to identification
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  warn('Estimation of VARMA(p,q) models is not generically robust,'
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
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issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'

Loading Model varmax_grocery_model_p1_q1_.pkl

c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
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  warn('Estimation of VARMA(p,q) models is not generically robust,'
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'

Loading Model varmax_grocery_model_p1_q2_.pkl

c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
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  warn('Estimation of VARMA(p,q) models is not generically robust,'
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'

Loading Model varmax_grocery_model_p1_q30_.pkl

c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
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  warn('Estimation of VARMA(p,q) models is not generically robust,'
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'

Loading Model varmax_grocery_model_p1_q5_.pkl

c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
```

```
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
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issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'

Loading Model varmax_grocery_model_p1_q7_.pkl

c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
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  warn('Estimation of VARMA(p,q) models is not generically robust,'
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
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c:\Users\andyp\.conda\envs\datly\lib\site-
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issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'

Loading Model varmax_grocery_model_p2_q1_.pkl
Loading Model varmax_grocery_model_p2_q2_.pkl

c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'

Loading Model varmax_grocery_model_p2_q30_.pkl

c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
```

```
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'

Loading Model varmax_grocery_model_p2_q5_.pkl

c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'

Loading Model varmax_grocery_model_p2_q7_.pkl

c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'

Loading Model varmax_grocery_model_p5_q1_.pkl

c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'

Loading Model varmax_grocery_model_p5_q2_.pkl

c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
```

```
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'

Loading Model varmax_grocery_model_p5_q30_.pkl

c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'

Loading Model varmax_grocery_model_p5_q5_.pkl

c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'

Loading Model varmax_grocery_model_p5_q7_.pkl

c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'

Loading Model varmax_grocery_model_p7_q1_.pkl

c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
```

```
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'

Loading Model varmax_grocery_model_p7_q2_.pkl

c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'

Loading Model varmax_grocery_model_p7_q30_.pkl

c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'

Loading Model varmax_grocery_model_p7_q5_.pkl

c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'

Loading Model varmax_grocery_model_p7_q7_.pkl

c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
```

```
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'
```

[192]:
```
# print(type(results_coba_model))

print('Nama model ,RMSE weighted,  RMSE rata-rata , RMSE Sales , RMSE␣
 ↪onpromotion_differencing, RMSE onpromotion')
for baris in results_coba_model:
    print(baris)
```

```
Nama model ,RMSE weighted,  RMSE rata-rata , RMSE Sales , RMSE
onpromotion_differencing, RMSE onpromotion
('varmax_grocery_model.pkl', 0.8314371197287034, 319.4991767412912,
600.0473859318834, 20.483792472275002, 38.95096755069904)
('varmax_grocery_model_awal_sebelum_tuning.pkl', 0.6586614191927805,
316.12341140096277, 603.9573189363848, 20.617951747817003, 28.289503865540777)
('varmax_grocery_model_p1_q1_.pkl', 1.1296958316773162, 334.5820542113466,
612.1855629533862, 20.529798807095666, 56.97854546930693)
('varmax_grocery_model_p1_q2_.pkl', 1.1031450129377232, 333.8247889781873,
612.2996862782454, 20.547878191627518, 55.34989167812925)
('varmax_grocery_model_p1_q30_.pkl', 1.9081424763860382, 357.5715663063566,
610.4459597066824, 20.61410646624705, 104.6971729060308)
('varmax_grocery_model_p1_q5_.pkl', 0.9464833321891403, 328.5601313559645,
611.3477079590442, 20.54452790238563, 45.77255475288479)
('varmax_grocery_model_p1_q7_.pkl', 7.393416862607144, 540.1290098034156,
640.1523409897778, 20.686913646083777, 440.10567861705334)
('varmax_grocery_model_p2_q1_.pkl', 1.4297278225239647, 348.0424239591322,
620.9017888513577, 20.522137193318475, 75.18305906690674)
('varmax_grocery_model_p2_q2_.pkl', 1.1022110353249746, 336.96558120440164,
618.7676020884131, 20.563818752656687, 55.16356032039018)
('varmax_grocery_model_p2_q30_.pkl', 0.8168986742455875, 327.4883166082964,
617.2598367648663, 20.527864716402185, 37.71679645172638)
('varmax_grocery_model_p2_q5_.pkl', 6.262843664519583, 494.471293367517,
617.6409885126592, 20.63082495663726, 371.30159822237476)
('varmax_grocery_model_p2_q7_.pkl', 0.9167642088144072, 340.6343915130174,
637.8456632242353, 20.562538514660332, 43.423119801799594)
('varmax_grocery_model_p5_q1_.pkl', 0.9845435612450973, 333.8362251486941,
619.7359654408252, 20.54289940483053, 47.936484856563006)
('varmax_grocery_model_p5_q2_.pkl', 0.7036942477784442, 325.10672180775805,
619.4752325591314, 20.54966633874438, 30.738211056384664)
('varmax_grocery_model_p5_q30_.pkl', 1.008647374377122, 332.97256989334835,
616.4669103658989, 20.513851494270032, 49.47822942079775)
('varmax_grocery_model_p5_q5_.pkl', 2.4064514438568745, 376.6819464982709,
```

```
618.2994898679922, 20.551616818166284, 135.06440312854963)
('varmax_grocery_model_p5_q7_.pkl', 3.2416392921772728, 401.81608537982436,
617.3900189308425, 20.57660475454757, 186.24215182880616)
('varmax_grocery_model_p7_q1_.pkl', 1.6430665966228664, 345.5879422489347,
602.5585272423281, 20.601083889078435, 88.61735725554142)
('varmax_grocery_model_p7_q2_.pkl', 0.6586614191927805, 316.12341140096277,
603.9573189363848, 20.617951747817003, 28.289503865540777)
('varmax_grocery_model_p7_q30_.pkl', 1.0843010617240905, 329.9327021471359,
605.5347526740042, 20.56255914148429, 54.330651620267645)
('varmax_grocery_model_p7_q5_.pkl', 2.2540698302619857, 363.9603703624211,
601.8623649066806, 20.613302475689665, 126.05837581816164)
('varmax_grocery_model_p7_q7_.pkl', 3.4616241412279662, 406.4641960386357,
613.125900384104, 20.557102930091663, 199.8024916931673)
```

[193]:
```
# best model yg nilainya terendah
fileName, best_weighted_rmse, best_avg_rmse, best_rmse_sales,␣
 ↪best_rmse_onpromotion_differencing, best_rmse_onpromotion =␣
 ↪min(results_coba_model, key=lambda x: x[1])

print(f"Best Model: {fileName} with Weighted RMSE: {best_weighted_rmse}")
print(f"  RMSE for Sales: {best_rmse_sales}")
print(f"  RMSE for onpromotion: {best_rmse_sales}")
print(f"  RMSE for onpromotion_differencing:␣
 ↪{best_rmse_onpromotion_differencing}")
```

```
Best Model: varmax_grocery_model_awal_sebelum_tuning.pkl with Weighted RMSE:
0.6586614191927805
  RMSE for Sales: 603.9573189363848
  RMSE for onpromotion: 603.9573189363848
  RMSE for onpromotion_differencing: 20.617951747817003
```

dari Grid Search , ternyata yg terbaik adalah model yang pertama (varmax_model_awal_sebelum_tuning.pkl)

[ ]:
```
```

[194]:
```
#varmax_model_p7_q2_.pkl
with open('varmax_grocery_model_p7_q2_.pkl', 'rb') as f:
    loaded_model = pickle.load(f)

print(loaded_model.summary())
```

```
                                Statespace Model Results
==========================================================================
=================
Dep. Variable:     ['sales', 'onpromotion_differencing']   No. Observations:
1351
Model:                                        VARMAX(7,2)   Log Likelihood
-15193.323
```

```
                                          + intercept   AIC
30480.647
Date:                                Wed, 12 Feb 2025   BIC
30725.451
Time:                                       20:49:48   HQIC
30572.322
Sample:                                            0
                                                - 1351
Covariance Type:                                  opg
==============================================================================
===
Ljung-Box (L1) (Q):             0.98, 6.22   Jarque-Bera (JB):    4343.17,
13797.86
Prob(Q):                        0.32, 0.01   Prob(JB):                 0.00,
0.00
Heteroskedasticity (H):       0.79, 180.92   Skew:                    -0.06,
0.14
Prob(H) (two-sided):            0.01, 0.00   Kurtosis:                11.78,
18.65
                                Results for equation sales
==============================================================================
==================
                                   coef    std err          z      P>|z|
[0.025      0.975]
------------------------------------------------------------------------------
------------------
intercept                        572.8200     70.587      8.115      0.000
434.472     711.168
L1.sales                           0.2790      0.025     11.196      0.000
0.230       0.328
L1.onpromotion_differencing        6.2534      3.375      1.853      0.064
-0.361      12.868
L2.sales                          -0.0694      0.036     -1.937      0.053
-0.140       0.001
L2.onpromotion_differencing       -1.7042      3.760     -0.453      0.650
-9.074       5.666
L3.sales                           0.0500      0.021      2.348      0.019
0.008       0.092
L3.onpromotion_differencing       -1.8236      2.525     -0.722      0.470
-6.772       3.125
L4.sales                          -0.0074      0.015     -0.480      0.631
-0.038       0.023
L4.onpromotion_differencing       -0.8291      1.670     -0.496      0.620
-4.103       2.445
L5.sales                          -0.0069      0.016     -0.439      0.661
-0.038       0.024
L5.onpromotion_differencing        0.3216      1.722      0.187      0.852
-3.054       3.697
```

```
L6.sales                            0.0863      0.019      4.595      0.000
0.049       0.123
L6.onpromotion_differencing        -2.1242      1.885     -1.127      0.260
-5.819       1.571
L7.sales                            0.4640      0.015     30.216      0.000
0.434       0.494
L7.onpromotion_differencing         2.8465      1.572      1.811      0.070
-0.235       5.928
L1.e(sales)                         0.1168      0.033      3.594      0.000
0.053       0.181
L1.e(onpromotion_differencing)     -0.5530      3.981     -0.139      0.890
-8.355       7.249
L2.e(sales)                         0.1276      0.036      3.581      0.000
0.058       0.197
L2.e(onpromotion_differencing)      0.0325      3.687      0.009      0.993
-7.194       7.259
beta.oil_fill_differencing         -4.8578      5.591     -0.869      0.385
-15.815       6.100
beta.isWeekend                    157.6145     31.845      4.949      0.000
95.200     220.029
beta.isHoliday                   -571.1137     92.875     -6.149      0.000
-753.145    -389.083
                          Results for equation onpromotion_differencing
==============================================================================
==================
                                    coef    std err          z      P>|z|
[0.025      0.975]
------------------------------------------------------------------------------
------------------
intercept                           1.0629      3.357      0.317      0.752
-5.516       7.642
L1.sales                            0.0008      0.001      0.898      0.369
-0.001       0.003
L1.onpromotion_differencing         0.3360      0.037      9.154      0.000
0.264       0.408
L2.sales                       -5.808e-05      0.001     -0.057      0.955
-0.002       0.002
L2.onpromotion_differencing         0.1672      0.048      3.512      0.000
0.074       0.260
L3.sales                           -0.0004      0.001     -0.785      0.433
-0.002       0.001
L3.onpromotion_differencing         0.0779      0.029      2.643      0.008
0.020       0.136
L4.sales                            0.0004      0.000      0.771      0.441
-0.001       0.001
L4.onpromotion_differencing         0.0276      0.020      1.349      0.177
-0.013       0.068
L5.sales                           -0.0007      0.001     -1.191      0.234
```

```
-0.002       0.000
L5.onpromotion_differencing        0.0581      0.019      3.112      0.002
0.022       0.095
L6.sales                           0.0002      0.001      0.370      0.711
-0.001       0.001
L6.onpromotion_differencing        0.0398      0.020      2.006      0.045
0.001       0.079
L7.sales                          -0.0006      0.001     -0.956      0.339
-0.002       0.001
L7.onpromotion_differencing       -0.4799      0.018    -26.624      0.000
-0.515      -0.445
L1.e(sales)                       -0.0015      0.001     -1.524      0.128
-0.003       0.000
L1.e(onpromotion_differencing)     0.2086      0.042      4.972      0.000
0.126       0.291
L2.e(sales)                       -0.0008      0.001     -0.801      0.423
-0.003       0.001
L2.e(onpromotion_differencing)     0.1591      0.045      3.569      0.000
0.072       0.246
beta.oil_fill_differencing         0.0847      0.131      0.645      0.519
-0.173       0.342
beta.isWeekend                     0.2599      0.977      0.266      0.790
-1.656       2.175
beta.isHoliday                    -2.1909      8.064     -0.272      0.786
-17.995      13.614
                                        Error covariance matrix
==============================================================================
============================
                                              coef    std err          z
P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
---------------------------
sqrt.var.sales                             494.0182      6.007     82.244
0.000     482.245     505.791
sqrt.cov.sales.onpromotion_differencing     0.3977      0.375      1.061
0.289      -0.337       1.132
sqrt.var.onpromotion_differencing           8.1801      0.084     97.666
0.000       8.016       8.344
==============================================================================
============================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
```

[195]:
```
forecast_steps = len(varmax_val_data_df)  # Example: Forecasting 7 steps ahead
```

```
forecast = loaded_model.forecast(steps=forecast_steps,␣
  ↪exog=varmax_val_data_df[exog_vars])
print(forecast)
```

```
            sales  onpromotion_differencing
1351  2723.138113                  3.067428
1352  2748.870693                  6.558862
1353  2551.770698                  4.666397
1354  2503.021813                  8.967771
1355  3097.385049                  2.160507
…             …                         …
1683  2876.849528                 -0.482883
1684  3215.658979                 -0.321660
1685  3346.090558                 -0.111740
1686  3061.135312                 -0.031979
1687  2918.677872                 -0.153034

[337 rows x 2 columns]
```

```
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'
c:\Users\andyp\.conda\envs\datly\lib\site-
packages\statsmodels\tsa\statespace\varmax.py:161: EstimationWarning: Estimation
of VARMA(p,q) models is not generically robust, due especially to identification
issues.
  warn('Estimation of VARMA(p,q) models is not generically robust,'
```

[196]:
```
varmax_train_data_df
```

[196]:
```
            date   sales  onpromotion_differencing  oil_fill_differencing  \
0     2013-01-01     0.0                       0.0               0.000000
1     2013-01-02  4558.0                       0.0               0.000000
2     2013-01-03  3260.0                       0.0               0.000000
3     2013-01-04  3085.0                       0.0               0.000000
4     2013-01-05  3398.0                       0.0               0.000000
…          …     …                         …                      …
1346  2016-09-08  2253.0                      -4.0               4.460000
1347  2016-09-09  2307.0                     -12.0               1.490000
1348  2016-09-10  3048.0                       5.0               1.508333
1349  2016-09-11  3341.0                       8.0               1.526667
1350  2016-09-12  2815.0                       1.0               1.545000

      isWeekend  isHoliday
0             0          1
1             0          0
```

```
2             0          0
3             0          0
4             1          0
…           …          …
1346          0          0
1347          0          0
1348          1          0
1349          1          0
1350          0          0

[1351 rows x 6 columns]
```

[197]:
```
varmax_train_data_df
```

[197]:
```
           date   sales  onpromotion_differencing  oil_fill_differencing  \
0    2013-01-01     0.0                       0.0               0.000000
1    2013-01-02  4558.0                       0.0               0.000000
2    2013-01-03  3260.0                       0.0               0.000000
3    2013-01-04  3085.0                       0.0               0.000000
4    2013-01-05  3398.0                       0.0               0.000000
…           …     …                         …                 …
1346 2016-09-08  2253.0                      -4.0               4.460000
1347 2016-09-09  2307.0                     -12.0               1.490000
1348 2016-09-10  3048.0                       5.0               1.508333
1349 2016-09-11  3341.0                       8.0               1.526667
1350 2016-09-12  2815.0                       1.0               1.545000

      isWeekend  isHoliday
0             0          1
1             0          0
2             0          0
3             0          0
4             1          0
…           …          …
1346          0          0
1347          0          0
1348          1          0
1349          1          0
1350          0          0

[1351 rows x 6 columns]
```

[198]:
```
original_train_data_df = sales_df[sales_df['date'] <= '2016-09-12']
original_val_data_df = sales_df[sales_df['date'] > '2016-09-12']

lastValueOf_originalOnPromotion = original_train_data_df['onpromotion'].tail(1).
 ↪values[0]
```

```
forecast['onpromotion'] = lastValueOf_originalOnPromotion +␣
 ↪forecast['onpromotion_differencing'].cumsum()
forecast
```

[198]:

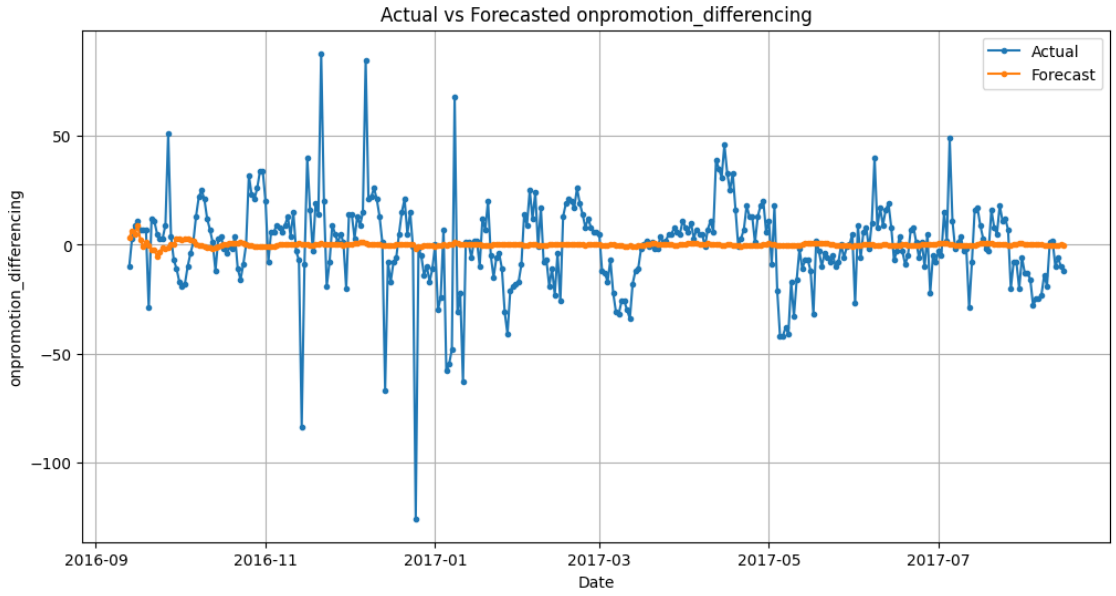
	sales	onpromotion_differencing	onpromotion
1351	2723.138113	3.067428	39.067428
1352	2748.870693	6.558862	45.626290
1353	2551.770698	4.666397	50.292688
1354	2503.021813	8.967771	59.260459
1355	3097.385049	2.160507	61.420965
…	…	…	…
1683	2876.849528	-0.482883	68.939005
1684	3215.658979	-0.321660	68.617345
1685	3346.090558	-0.111740	68.505605
1686	3061.135312	-0.031979	68.473625
1687	2918.677872	-0.153034	68.320592

[337 rows x 3 columns]

[ ]:

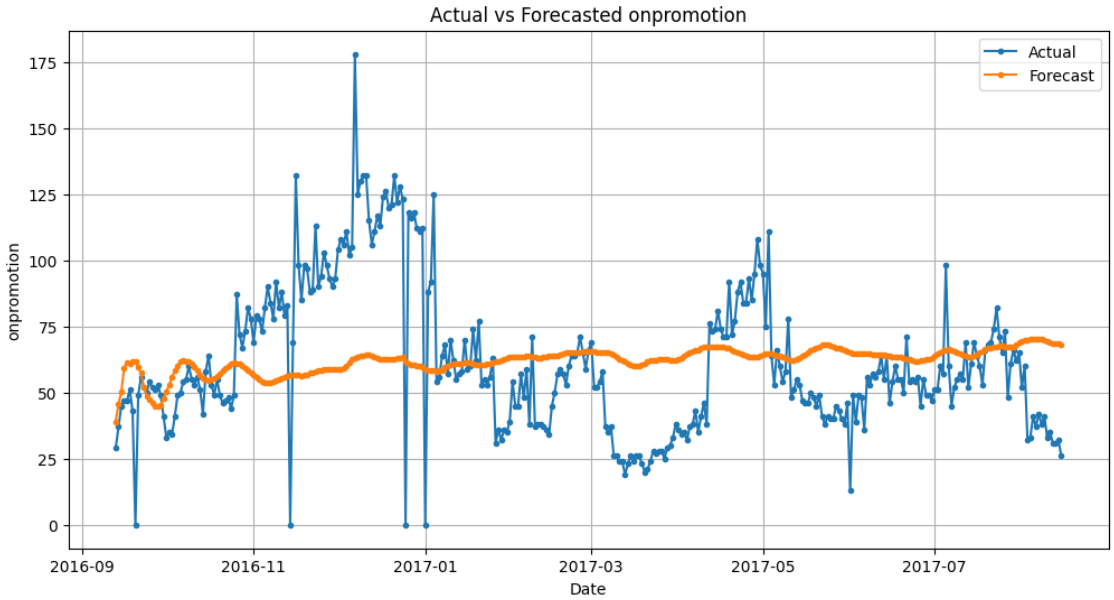
[199]:
```
from sklearn.metrics import mean_squared_error


#actual value
actual_values = varmax_val_data_df['onpromotion_differencing']

#forecast value
forecast_values = forecast['onpromotion_differencing']

# Calculate RMSE
rmse = np.sqrt(mean_squared_error(actual_values, forecast_values))
print(f"RMSE: {rmse}")


# Plot actual vs forecast
plt.figure(figsize=(12, 6))
plt.plot(varmax_val_data_df['date'], actual_values, label='Actual', marker='.')
plt.plot(varmax_val_data_df['date'], forecast_values, label='Forecast',␣
 ↪marker='.')
plt.xlabel('Date')
plt.ylabel('onpromotion_differencing')
plt.title('Actual vs Forecasted onpromotion_differencing')
plt.legend()
plt.grid(True)
plt.show()
```

```
RMSE: 20.617951747817003
```



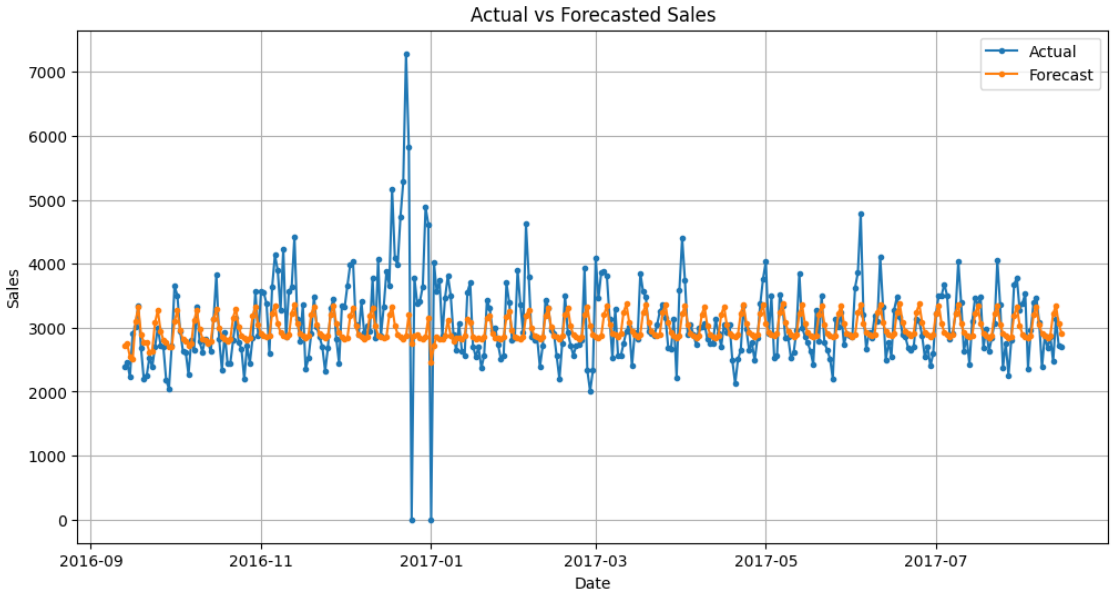
[200]:
```
from sklearn.metrics import mean_squared_error


#Actual Value
actual_values = original_val_data_df['onpromotion']  # Adjust as per your data

#Forecast Value
forecast_values = forecast['onpromotion']

# Calculate RMSE
varmax_rmse_onpromotion = np.sqrt(mean_squared_error(actual_values,␣
 ↪forecast_values))
print(f"RMSE: {varmax_rmse_onpromotion}")


# Plot actual vs forecast
plt.figure(figsize=(12, 6))
plt.plot(original_val_data_df['date'], actual_values, label='Actual', marker='.
 ↪')
plt.plot(varmax_val_data_df['date'], forecast_values, label='Forecast',␣
 ↪marker='.')
plt.xlabel('Date')
plt.ylabel('onpromotion')
plt.title('Actual vs Forecasted onpromotion')
plt.legend()
plt.grid(True)
plt.show()
```

```
RMSE: 28.289503865540777
```



[201]:
```
from sklearn.metrics import mean_squared_error


#Actual Value
actual_values = varmax_val_data_df['sales']  # Adjust as per your data

#Forecast Value
forecast_values = forecast['sales']

# Calculate RMSE
varmax_rmse_sales = np.sqrt(mean_squared_error(actual_values, forecast_values))
print(f"RMSE: {varmax_rmse_sales}")


# Plot actual vs forecast
plt.figure(figsize=(12, 6))
plt.plot(varmax_val_data_df['date'], actual_values, label='Actual', marker='.')
plt.plot(varmax_val_data_df['date'], forecast_values, label='Forecast',␣
 ↪marker='.')
plt.xlabel('Date')
plt.ylabel('Sales')
plt.title('Actual vs Forecasted Sales')
plt.legend()
plt.grid(True)
plt.show()
```

```
RMSE: 603.9573189363848
```



5 Modelling menggunakan LSTM

[202]:
```
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
import time
from sklearn.metrics import mean_squared_error


from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping
```

5.1 splitting data train dan test

[203]:
```
original_train_data_df = sales_df[sales_df['date'] <= '2016-09-12']
print(f'original_train_data_df shape = {original_train_data_df.shape}')
original_test_data_df = sales_df[sales_df['date'] > '2016-09-12']
print(f'original_test_data_df shape = {original_test_data_df.shape}')

#ambil kolom yang diperlukan saja
lstm_train_data_df=original_train_data_df.
 ↪copy(deep=True)[['id','date','sales','onpromotion','oil_fill','isWeekend','isHoliday']]
lstm_test_data_df= original_test_data_df.
 ↪copy(deep=True)[['id','date','sales','onpromotion','oil_fill','isWeekend','isHoliday']]
```

```
lstm_train_data_date_only_df=original_train_data_df.copy(deep=True)[['date']]
lstm_test_data_date_only_df= original_test_data_df.copy(deep=True)[['date']]


lstm_train_endog_df =lstm_train_data_df[['sales','onpromotion']]
lstm_train_exog_df = lstm_train_data_df[['oil_fill']]
#untuk data yg category tidak perlu di scaling nantinya
lstm_train_exog_cat_df =lstm_train_data_df[['isWeekend','isHoliday']]

lstm_test_endog_df = lstm_test_data_df[['sales','onpromotion']]
lstm_test_exog_df = lstm_test_data_df[['oil_fill']]
#untuk data yg category tidak perlu di scaling nantinya
lstm_test_exog_cat_df =lstm_test_data_df[['isWeekend','isHoliday']]
```

```
original_train_data_df shape = (1351, 16)
original_test_data_df shape = (337, 16)
```

5.2 scaling data train dan test

[204]:
```
endog_scaler = MinMaxScaler(feature_range=(0, 1))
exog_scaler = MinMaxScaler(feature_range=(0, 1))

lstm_train_endog_df_scaled = lstm_train_endog_df.copy(deep=True)
lstm_train_exog_df_scaled =lstm_train_exog_df.copy(deep=True)
lstm_test_endog_df_scaled =lstm_test_endog_df.copy(deep=True)
lstm_test_exog_df_scaled =lstm_test_exog_df.copy(deep=True)

#fitting scaler hanya pada data training (menghindari data leakage)
endog_scaler = endog_scaler.
 ↪fit(lstm_train_endog_df_scaled[['sales','onpromotion']])
exog_scaler = exog_scaler.fit(lstm_train_exog_df_scaled[['oil_fill']])

#scaling kemudian dijakdikan dataframe lagi
lstm_train_endog_df_scaled=endog_scaler.transform(lstm_train_endog_df_scaled)
lstm_train_endog_df_scaled=pd.
 ↪DataFrame(lstm_train_endog_df_scaled,columns=lstm_train_endog_df.columns)
lstm_train_exog_df_scaled=exog_scaler.transform(lstm_train_exog_df_scaled)
lstm_train_exog_df_scaled=pd.
 ↪DataFrame(lstm_train_exog_df_scaled,columns=lstm_train_exog_df.columns)

lstm_test_endog_df_scaled=endog_scaler.transform(lstm_test_endog_df_scaled)
lstm_test_endog_df_scaled=pd.
 ↪DataFrame(lstm_test_endog_df_scaled,columns=lstm_test_endog_df.columns)
lstm_test_exog_df_scaled=exog_scaler.transform(lstm_test_exog_df_scaled)
lstm_test_exog_df_scaled=pd.
 ↪DataFrame(lstm_test_exog_df_scaled,columns=lstm_test_exog_df.columns)
```

[205]:
```
#membentuk kembali data train dan test untuk versi yang sudah di scaling kolom2␣
 ↪yang perlu di scaling

lstm_train_data_date_only_df.reset_index(drop=True, inplace=True)
lstm_train_endog_df_scaled.reset_index(drop=True, inplace=True)
lstm_train_exog_df_scaled.reset_index(drop=True, inplace=True)
lstm_train_exog_cat_df.reset_index(drop=True, inplace=True)
lstm_train_data_scaled_df = pd.
 ↪concat([lstm_train_data_date_only_df,lstm_train_endog_df_scaled,lstm_train_exog_df_scaled,l
 ↪axis=1)

lstm_test_data_date_only_df.reset_index(drop=True, inplace=True)
lstm_test_endog_df_scaled.reset_index(drop=True, inplace=True)
lstm_test_exog_df_scaled.reset_index(drop=True, inplace=True)
lstm_test_exog_cat_df.reset_index(drop=True, inplace=True)
lstm_test_data_scaled_df  = pd.
 ↪concat([lstm_test_data_date_only_df,lstm_test_endog_df_scaled␣
 ↪,lstm_test_exog_df_scaled ,lstm_test_exog_cat_df], axis=1 )
```

[206]:
```
print(f'lstm_train_data_scaled_df :\n{lstm_train_data_scaled_df}')
print('------------------------------')
print(f'lstm_test_data_scaled_df :\n{lstm_test_data_scaled_df}')
print('------------------------------')
```

```
lstm_train_data_scaled_df :
           date     sales  onpromotion  oil_fill  isWeekend  isHoliday
0    2013-01-01  0.000000     0.000000  0.792965          0          1
1    2013-01-02  0.595350     0.000000  0.792965          0          0
2    2013-01-03  0.425810     0.000000  0.790951          0          0
3    2013-01-04  0.402952     0.000000  0.792728          0          0
4    2013-01-05  0.443835     0.000000  0.793044          1          0
…          …       …           …         …         …
1346 2016-09-08  0.294279     0.318584  0.253938          0          0
1347 2016-09-09  0.301332     0.318584  0.233211          0          0
1348 2016-09-10  0.398119     0.353982  0.234790          1          0
1349 2016-09-11  0.436390     0.389381  0.236369          1          0
1350 2016-09-12  0.367685     0.318584  0.237949          0          0

[1351 rows x 6 columns]
------------------------------
lstm_test_data_scaled_df :
          date     sales  onpromotion  oil_fill  isWeekend  isHoliday
0   2016-09-13  0.312957     0.256637  0.221722          0          0
1   2016-09-14  0.321708     0.327434  0.206443          0          0
2   2016-09-15  0.291405     0.398230  0.209167          0          0
3   2016-09-16  0.379963     0.415929  0.199574          0          0
4   2016-09-17  0.394201     0.415929  0.200758          1          0
..         …       …           …         …         …         …
```

```
332 2017-08-11  0.374086     0.309735  0.267914          0          0
333 2017-08-12  0.323406     0.274336  0.263098          1          0
334 2017-08-13  0.410266     0.274336  0.258281          1          0
335 2017-08-14  0.354885     0.283186  0.253464          0          0
336 2017-08-15  0.352142     0.230088  0.253228          0          0

[337 rows x 6 columns]
------------------------------
```

[207]:
```python
print(f'original_train_data_df :\n{original_train_data_df.columns}')
print('------------------------------')
print(f'original_val_data_df :\n{original_val_data_df.columns}')
print('------------------------------')
print(f'lstm_train_data_scaled_df :\n{lstm_train_data_scaled_df.columns}')
print('------------------------------')
print(f'lstm_test_data_scaled_df :\n{lstm_test_data_scaled_df.columns}')
```

```
original_train_data_df :
Index(['id', 'date', 'family', 'sales', 'onpromotion', 'dcoilwtico',
       'weekdays', 'week_of_the_year', 'year', 'month', 'day', 'isWeekend',
       'isHoliday', 'oil_fill', 'onpromotion_differencing',
       'oil_fill_differencing'],
      dtype='object')
------------------------------
original_val_data_df :
Index(['id', 'date', 'family', 'sales', 'onpromotion', 'dcoilwtico',
       'weekdays', 'week_of_the_year', 'year', 'month', 'day', 'isWeekend',
       'isHoliday', 'oil_fill', 'onpromotion_differencing',
       'oil_fill_differencing'],
      dtype='object')
------------------------------
lstm_train_data_scaled_df :
Index(['date', 'sales', 'onpromotion', 'oil_fill', 'isWeekend', 'isHoliday'],
dtype='object')
------------------------------
lstm_test_data_scaled_df :
Index(['date', 'sales', 'onpromotion', 'oil_fill', 'isWeekend', 'isHoliday'],
dtype='object')
```

[208]:
```python
# function untuk membuat sequence untuk LSTM
def create_sequences(data, seq_len):
    sequences = [data[i: i + seq_len + 1] for i in range(len(data) - seq_len)]
    sequences = np.array(sequences)
    X = sequences[:, :-1]
    y = sequences[:, -1, :2]
    return X, y

# Setting sequence length
```

```
SEQ_LENGTH = 7
X_train, y_train = create_sequences(lstm_train_data_scaled_df.
 ↪drop(columns=['date']).values, SEQ_LENGTH)
X_test, y_test   = create_sequences(lstm_test_data_scaled_df.
 ↪drop(columns=['date']).values , SEQ_LENGTH)
print(f'X_train shape  BEFORE reshape= {X_train.shape}')
print('----------------------------------------')

# reshape value untuk LSTM
amount_of_features = X_train.shape[2]
X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1],␣
 ↪amount_of_features))
X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1],␣
 ↪amount_of_features))
print(f'X_train shape  AFTER reshape= {X_train.shape}')
print('----------------------------------------')
```

```
X_train shape  BEFORE reshape= (1344, 7, 5)
----------------------------------------
X_train shape  AFTER reshape= (1344, 7, 5)
----------------------------------------
```

[209]:
```
# Build LSTM model
model = Sequential([
    LSTM(64, return_sequences=True, input_shape=(SEQ_LENGTH,␣
 ↪amount_of_features)),
    Dropout(0.2),
    LSTM(32, return_sequences=False),
    Dropout(0.2),
    Dense(2)  # Predict only sales and onpromotion
])

model.compile(optimizer=Adam(learning_rate=0.001), loss='mse')

# Early Stop agar menghindari overfit
early_stop = EarlyStopping(monitor='val_loss', patience=5,␣
 ↪restore_best_weights=True)

# Train model
model.fit(X_train, y_train, epochs=50, batch_size=16, validation_data=(X_test,␣
 ↪y_test), callbacks=[early_stop])

# Predict
y_pred = model.predict(X_test)

# Reverse scaling
y_pred_unscaled = endog_scaler.inverse_transform(y_pred)
```

```
y_test_unscaled = endog_scaler.inverse_transform(y_test)
```

```
Epoch 1/50
84/84 [==============================] - 33s 140ms/step - loss: 0.0188 -
val_loss: 0.0191
Epoch 2/50
84/84 [==============================] - 5s 58ms/step - loss: 0.0095 - val_loss:
0.0150
Epoch 3/50
84/84 [==============================] - 3s 40ms/step - loss: 0.0083 - val_loss:
0.0160
Epoch 4/50
84/84 [==============================] - 4s 47ms/step - loss: 0.0079 - val_loss:
0.0141
Epoch 5/50
84/84 [==============================] - 2s 22ms/step - loss: 0.0077 - val_loss:
0.0186
Epoch 6/50
84/84 [==============================] - 2s 22ms/step - loss: 0.0076 - val_loss:
0.0214
Epoch 7/50
84/84 [==============================] - 2s 23ms/step - loss: 0.0071 - val_loss:
0.0169
Epoch 8/50
84/84 [==============================] - 3s 35ms/step - loss: 0.0068 - val_loss:
0.0169
Epoch 9/50
84/84 [==============================] - 2s 28ms/step - loss: 0.0069 - val_loss:
0.0164
11/11 [==============================] - 6s 11ms/step
```

[210]:
```
kolomTanggal=pd.DataFrame(original_test_data_df.iloc[SEQ_LENGTH:].
  ↪reset_index(drop=True)['date'])

y_test_unscaled_withDate = pd.concat([kolomTanggal, pd.
  ↪DataFrame(y_test_unscaled, columns=['sales', 'onpromotion'])], axis=1)
y_pred_unscaled_withDate = pd.concat([kolomTanggal, pd.
  ↪DataFrame(y_pred_unscaled, columns=['sales', 'onpromotion'])], axis=1)

print(y_test_unscaled_withDate)
print(y_pred_unscaled_withDate)
```

```
         date   sales  onpromotion
0  2016-09-20  2191.0          0.0
1  2016-09-21  2248.0         49.0
2  2016-09-22  2536.0         56.0
3  2016-09-23  2386.0         52.0
4  2016-09-24  2701.0         50.0
```

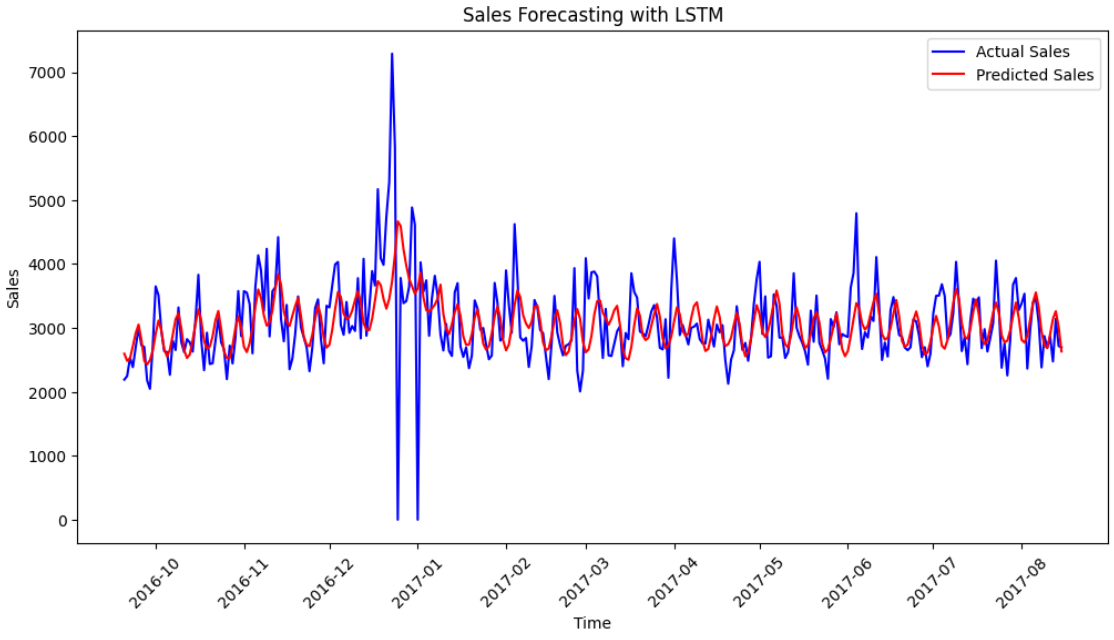
```
..          …     …           …
325 2017-08-11  2864.0          35.0
326 2017-08-12  2476.0          31.0
327 2017-08-13  3141.0          31.0
328 2017-08-14  2717.0          32.0
329 2017-08-15  2696.0          26.0

[330 rows x 3 columns]
          date        sales  onpromotion
0   2016-09-20  2596.351562    40.927391
1   2016-09-21  2484.008057    39.754307
2   2016-09-22  2524.034180    39.266003
3   2016-09-23  2715.598145    39.291729
4   2016-09-24  2920.092285    39.971535
..         …           …           …
325 2017-08-11  2897.693604    36.277489
326 2017-08-12  3141.437500    37.022491
327 2017-08-13  3261.481445    36.198540
328 2017-08-14  3015.623779    34.967552
329 2017-08-15  2632.076904    33.102531

[330 rows x 3 columns]
```

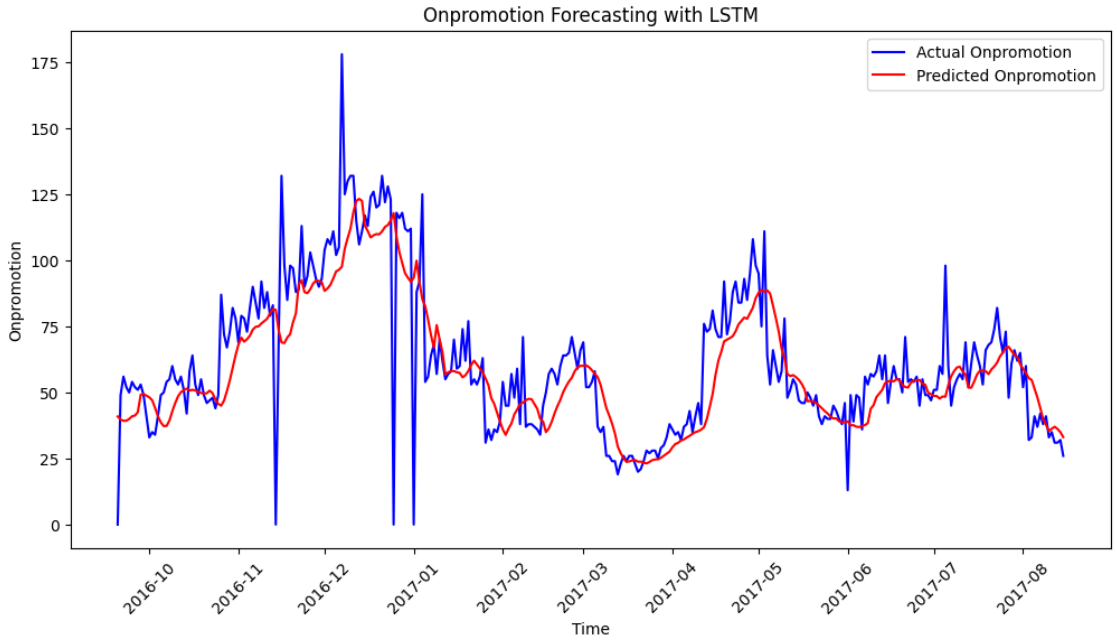
[211]:
```
lstm_rmse_sales = np.sqrt(mean_squared_error(y_test_unscaled_withDate['sales'],␣
 ↪y_pred_unscaled_withDate['sales']))

lstm_rmse_onpromotion = np.
 ↪sqrt(mean_squared_error(y_test_unscaled_withDate['onpromotion'],␣
 ↪y_pred_unscaled_withDate['onpromotion']))

lstm_weighted_rmse = (lstm_rmse_sales/y_test_unscaled_withDate['sales'].mean())␣
 ↪+(lstm_rmse_onpromotion/y_test_unscaled_withDate['onpromotion'].mean())

# Print the RMSE values
print(f'RMSE for Sales: {rmse_sales}')
print(f'RMSE for Onpromotion: {rmse_onpromotion}')
```

```
RMSE for Sales: 613.125900384104
RMSE for Onpromotion: 199.8024916931673
```

[212]:
```
# Plot results for sales
plt.figure(figsize=(12, 6))
plt.plot(kolomTanggal['date'], y_test_unscaled_withDate['sales'], label='Actual␣
 ↪Sales', color='blue')
plt.plot(kolomTanggal['date'], y_pred_unscaled_withDate['sales'],␣
 ↪label='Predicted Sales', color='red')
plt.xlabel('Time')
plt.ylabel('Sales')
```

```
plt.legend()
plt.title('Sales Forecasting with LSTM')
plt.xticks(rotation=45)
plt.show()

# Plot results for onpromotion
plt.figure(figsize=(12, 6))
plt.plot(kolomTanggal['date'], y_test_unscaled_withDate['onpromotion'],␣
 ↪label='Actual Onpromotion', color='blue')
plt.plot(kolomTanggal['date'], y_pred_unscaled_withDate['onpromotion'],␣
 ↪label='Predicted Onpromotion', color='red')
plt.xlabel('Time')
plt.ylabel('Onpromotion')
plt.legend()
plt.title('Onpromotion Forecasting with LSTM')
plt.xticks(rotation=45)
plt.show()
```





6 membandingkan kembali hasil Varmax dan LSTM

[213]:
```
RMSE_Comparison ={
    "Topic" :['RMSE Sales','RMSE Onpromotion', 'Normalize RMSE'],
    "Varmax" : [varmax_rmse_sales,varmax_rmse_onpromotion,best_weighted_rmse],
    "LSTM" : [lstm_rmse_sales,lstm_rmse_onpromotion,lstm_weighted_rmse]
}

RMSE_Comparison_df = pd.DataFrame(RMSE_Comparison)
RMSE_Comparison_df
```

[213]:

	Topic	Varmax	LSTM
0	RMSE Sales	603.957319	597.977274
1	RMSE Onpromotion	28.289504	16.760521
2	Normalize RMSE	0.658661	0.466287