Time Series Analysis

Reference: [https://www.kaggle.com/competitions/store-sales-time-series-forecasting/data (https://www.kaggle.com/competitions/store-sales-time-series-forecasting/data)](https://www.kaggle.com/competitions/store-sales-time-series-forecasting/data)
This is a kaggle competition and in this competition we will use time-series forecasting to forecast store sales on data from Corporación Favorita, a large Ecuadorian-based grocery retailer.

Specifically, we'll build a model that more accurately predicts the unit sales for thousands of items sold at different Favorita stores.

Import Libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

In [2]:
```
import os
os.listdir('./sample_data/')
```

Out[2]:
```
['holidays_events.csv',
 'oil.csv',
 'sample_submission.csv',
 'stores.csv',
 'test.csv',
 'train.csv',
 'transactions.csv']
```

In [3]:
```
holidays_df = pd.read_csv('./sample_data/holidays_events.csv')
oils_df = pd.read_csv('./sample_data/oil.csv')
stores_df = pd.read_csv('./sample_data/stores.csv')
tran_df = pd.read_csv('./sample_data/transactions.csv')
```

Exploring Datasets

holidays_events.csv

Holidays and Events, with metadata
NOTE: Pay special attention to the transferred column.

- A holiday that is transferred officially falls on that calendar day, but was moved to another date by the government.
- A transferred day is more like a normal day than a holiday.

- To find the day that it was actually celebrated, look for the corresponding row where type is Transfer.
- For example, the holiday Independencia de Guayaquil was transferred from 2012-10-09 to 2012-10-12, which means it was celebrated on 2012-10-12.
- Days that are type Bridge are extra days that are added to a holiday (e.g., to extend the break across a long weekend). These are frequently made up by the type Work Day which is a day not normally scheduled for work (e.g., Saturday) that is meant to payback the Bridge.
- Additional holidays are days added a regular calendar holiday, for example, as typically happens around Christmas (making Christmas Eve a holiday).

In [10]:
```
holidays_df.head()
```

Out[10]:

	date	type	locale	locale_name	description	transferred
0	2012-03-02	Holiday	Local	Manta	Fundacion de Manta	False
1	2012-04-01	Holiday	Regional	Cotopaxi	Provincializacion de Cotopaxi	False
2	2012-04-12	Holiday	Local	Cuenca	Fundacion de Cuenca	False
3	2012-04-14	Holiday	Local	Libertad	Cantonizacion de Libertad	False
4	2012-04-21	Holiday	Local	Riobamba	Cantonizacion de Riobamba	False

In [11]:
```
holidays_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 350 entries, 0 to 349
Data columns (total 6 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   date         350 non-null    object
 1   type         350 non-null    object
 2   locale       350 non-null    object
 3   locale_name  350 non-null    object
 4   description  350 non-null    object
 5   transferred  350 non-null    bool  
dtypes: bool(1), object(5)
memory usage: 14.1+ KB
```

In [12]:
```
holidays_df.shape
```

Out[12]:
```
(350, 6)
```

In [13]:
```
holidays_df.describe().transpose()
```

Out[13]:

	count	unique	top	freq
date	350	312	2014-06-25	4
type	350	6	Holiday	221
locale	350	3	National	174
locale_name	350	24	Ecuador	174
description	350	103	Carnaval	10
transferred	350	2	False	338

In [14]:
```
holidays_df.isna().sum()
```

Out[14]:
```
date           0
type           0
locale         0
locale_name    0
description    0
transferred    0
dtype: int64
```

In [15]:
```
holidays_df['date'] = pd.to_datetime(holidays_df.date)
holidays_df['month']=holidays_df.date.dt.month
holidays_df['year']=holidays_df.date.dt.year
holidays_df['day']=holidays_df.date.dt.day_name()
holidays_df['day_date']=holidays_df.date.dt.day
holidays_df.head(5)
```

Out[15]:

	date	type	locale	locale_name	description	transferred	month	year	day
0	2012-03-02	Holiday	Local	Manta	Fundacion de Manta	False	3	2012	Friday
1	2012-04-01	Holiday	Regional	Cotopaxi	Provincializacion de Cotopaxi	False	4	2012	Sunday
2	2012-04-12	Holiday	Local	Cuenca	Fundacion de Cuenca	False	4	2012	Thursday
3	2012-04-14	Holiday	Local	Libertad	Cantonizacion de Libertad	False	4	2012	Saturday
4	2012-04-21	Holiday	Local	Riobamba	Cantonizacion de Riobamba	False	4	2012	Saturday

oil.csv

- Daily oil price. Includes values during both the train and test data timeframes.
- (Ecuador is an oil-dependent country and it's economical health is highly vulnerable to shocks in oil prices.)

In [16]:
```
oils_df.head(5)
```

Out[16]:

	date	dcoilwtico
0	2013-01-01	NaN
1	2013-01-02	93.14
2	2013-01-03	92.97
3	2013-01-04	93.12
4	2013-01-07	93.20

In [17]:
```
oils_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1218 entries, 0 to 1217
Data columns (total 2 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   date        1218 non-null   object 
 1   dcoilwtico  1175 non-null   float64
dtypes: float64(1), object(1)
memory usage: 19.2+ KB
```

In [18]:
```
oils_df.describe().transpose()
```

Out[18]:

	count	mean	std	min	25%	50%	75%	max
dcoilwtico	1175.0	67.714366	25.630476	26.19	46.405	53.19	95.66	110.62

In [19]:
```
oils_df.isna().sum()
```

Out[19]:
```
date           0
dcoilwtico    43
dtype: int64
```

In [20]:
```
oils_df.shape
```

Out[20]:
```
(1218, 2)
```

In [21]:
```
oils_df['date'] = pd.to_datetime(oils_df.date)
oils_df['month']=oils_df.date.dt.month
oils_df['year']=oils_df.date.dt.year
oils_df['day']=oils_df.date.dt.day_name()
oils_df['day_date']=oils_df.date.dt.day
oils_df.head(5)
```

Out[21]:

	date	dcoilwtico	month	year	day	day_date
0	2013-01-01	NaN	1	2013	Tuesday	1
1	2013-01-02	93.14	1	2013	Wednesday	2
2	2013-01-03	92.97	1	2013	Thursday	3
3	2013-01-04	93.12	1	2013	Friday	4
4	2013-01-07	93.20	1	2013	Monday	7

stores.csv

- Store metadata, including city, state, type, and cluster.
- cluster is a grouping of similar stores.

In [22]:
```
stores_df.head()
```

Out[22]:

	store_nbr	city	state	type	cluster
0	1	Quito	Pichincha	D	13
1	2	Quito	Pichincha	D	13
2	3	Quito	Pichincha	D	8
3	4	Quito	Pichincha	D	9
4	5	Santo Domingo	Santo Domingo de los Tsachilas	D	4

In [23]:
```
stores_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 54 entries, 0 to 53
Data columns (total 5 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   store_nbr  54 non-null     int64 
 1   city       54 non-null     object
 2   state      54 non-null     object
 3   type       54 non-null     object
 4   cluster    54 non-null     int64 
dtypes: int64(2), object(3)
memory usage: 2.2+ KB
```

In [24]:

```
stores_df.describe().transpose()
```

Out[24]:

	count	mean	std	min	25%	50%	75%	max
store_nbr	54.0	27.500000	15.732133	1.0	14.25	27.5	40.75	54.0
cluster	54.0	8.481481	4.693395	1.0	4.00	8.5	13.00	17.0

In [25]:

```
stores_df.shape
```

Out[25]:

```
(54, 5)
```

In [26]:

```
stores_df.isna().sum()
```

Out[26]:

```
store_nbr    0
city         0
state        0
type         0
cluster      0
dtype: int64
```

transactions.csv

- Gives the information on number of transactions on particular date by store number

In [27]:

```
tran_df.head()
```

Out[27]:

	date	store_nbr	transactions
0	2013-01-01	25	770
1	2013-01-02	1	2111
2	2013-01-02	2	2358
3	2013-01-02	3	3487
4	2013-01-02	4	1922

In [28]:

```
tran_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 83488 entries, 0 to 83487
Data columns (total 3 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   date          83488 non-null  object
 1   store_nbr     83488 non-null  int64 
 2   transactions  83488 non-null  int64 
dtypes: int64(2), object(1)
memory usage: 1.9+ MB
```

In [29]:
```
tran_df.describe().transpose()
```

Out[29]:

	count	mean	std	min	25%	50%	75%	max
store_nbr	83488.0	26.939237	15.608204	1.0	13.0	27.0	40.0	54.0
transactions	83488.0	1694.602158	963.286644	5.0	1046.0	1393.0	2079.0	8359.0

In [30]:
```
tran_df.isna().sum()
```

Out[30]:
```
date            0
store_nbr       0
transactions    0
dtype: int64
```

In [31]:
```
tran_df['date'] = pd.to_datetime(tran_df['date'])
tran_df['month']=tran_df.date.dt.month
tran_df['year']=tran_df.date.dt.year
tran_df['day']=tran_df.date.dt.day_name()
tran_df['day_date']=tran_df.date.dt.day
tran_df.head(5)
```

Out[31]:

	date	store_nbr	transactions	month	year	day	day_date
0	2013-01-01	25	770	1	2013	Tuesday	1
1	2013-01-02	1	2111	1	2013	Wednesday	2
2	2013-01-02	2	2358	1	2013	Wednesday	2
3	2013-01-02	3	3487	1	2013	Wednesday	2
4	2013-01-02	4	1922	1	2013	Wednesday	2

train.csv

- The training data, comprising time series of features store_nbr, family, and onpromotion as well as the target sales.
- store_nbr identifies the store at which the products are sold.
- family identifies the type of product sold.
- 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 gives the total number of items in a product family that were being promoted at a store at a given date.

In [32]:
```python
train_df = pd.read_csv('./sample_data/train.csv')
train_df.head(5)
```

Out[32]:

	id	date	store_nbr	family	sales	onpromotion
0	0	2013-01-01	1.0	AUTOMOTIVE	0.0	0.0
1	1	2013-01-01	1.0	BABY CARE	0.0	0.0
2	2	2013-01-01	1.0	BEAUTY	0.0	0.0
3	3	2013-01-01	1.0	BEVERAGES	0.0	0.0
4	4	2013-01-01	1.0	BOOKS	0.0	0.0

In [33]:
```python
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 320768 entries, 0 to 320767
Data columns (total 6 columns):
 #   Column       Non-Null Count   Dtype  
---  ------       --------------   -----  
 0   id           320768 non-null  int64  
 1   date         320768 non-null  object 
 2   store_nbr    320767 non-null  float64
 3   family       320767 non-null  object 
 4   sales        320767 non-null  float64
 5   onpromotion  320767 non-null  float64
dtypes: float64(3), int64(1), object(2)
memory usage: 14.7+ MB
```

In [34]:
```python
train_df.shape
```

Out[34]:
```
(320768, 6)
```

In [35]:
```python
train_df.describe().transpose()
```

Out[35]:

	count	mean	std	min	25%	50%	75%	
id	320768.0	160383.500000	92597.889911	0.0	80191.75	160383.5	240575.25	32
store_nbr	320767.0	27.499422	15.586130	1.0	14.00	27.0	41.00	
sales	320767.0	203.146179	685.402091	0.0	0.00	0.0	93.00	2
onpromotion	320767.0	0.000000	0.000000	0.0	0.00	0.0	0.00	

In [36]:
```python
train_df.isna().sum()
```

Out[36]:
```
id             0
date           0
store_nbr      1
family         1
sales          1
onpromotion    1
dtype: int64
```

In [37]:

```
train_df['date'] = pd.to_datetime(train_df['date'])
train_df['month']=train_df.date.dt.month
train_df['year']=train_df.date.dt.year
train_df['day']=train_df.date.dt.day_name()
train_df['day_date']=train_df.date.dt.day
train_df.head(5)
```

Out[37]:

	id	date	store_nbr	family	sales	onpromotion	month	year	day	day_date
0	0	2013-01-01	1.0	AUTOMOTIVE	0.0	0.0	1	2013	Tuesday	1
1	1	2013-01-01	1.0	BABY CARE	0.0	0.0	1	2013	Tuesday	1
2	2	2013-01-01	1.0	BEAUTY	0.0	0.0	1	2013	Tuesday	1
3	3	2013-01-01	1.0	BEVERAGES	0.0	0.0	1	2013	Tuesday	1
4	4	2013-01-01	1.0	BOOKS	0.0	0.0	1	2013	Tuesday	1

test.csv

- The test data, having the same features as the training data. You will predict the target sales for the dates in this file.
- The dates in the test data are for the 15 days after the last date in the training data.

In [38]:

```
test_df = pd.read_csv('./sample_data/test.csv')
test_df.head(5)
```

Out[38]:

	id	date	store_nbr	family	onpromotion
0	3000888	2017-08-16	1	AUTOMOTIVE	0
1	3000889	2017-08-16	1	BABY CARE	0
2	3000890	2017-08-16	1	BEAUTY	2
3	3000891	2017-08-16	1	BEVERAGES	20
4	3000892	2017-08-16	1	BOOKS	0

In [39]:
```
test_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 28512 entries, 0 to 28511
Data columns (total 5 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   id           28512 non-null  int64 
 1   date         28512 non-null  object
 2   store_nbr    28512 non-null  int64 
 3   family       28512 non-null  object
 4   onpromotion  28512 non-null  int64 
dtypes: int64(3), object(2)
memory usage: 1.1+ MB
```

In [40]:
```
test_df.shape
```

Out[40]:
```
(28512, 5)
```

In [41]:
```
test_df.describe().transpose()
```

Out[41]:

	count	mean	std	min	25%	50%	7
id	28512.0	3.015144e+06	8230.849774	3000888.0	3008015.75	3015143.5	3022271
store_nbr	28512.0	2.750000e+01	15.586057	1.0	14.00	27.5	41
onpromotion	28512.0	6.965383e+00	20.683952	0.0	0.00	0.0	6

In [42]:
```
test_df.isna().sum()
```

Out[42]:
```
id             0
date           0
store_nbr      0
family         0
onpromotion    0
dtype: int64
```

In [43]:

```
test_df['date'] = pd.to_datetime(test_df['date'])
test_df['month']=test_df.date.dt.month
test_df['year']=test_df.date.dt.year
test_df['day']=test_df.date.dt.day_name()
test_df['day_date']=test_df.date.dt.day
test_df.head(5)
```

Out[43]:

	id	date	store_nbr	family	onpromotion	month	year	day	day_dat
0	3000888	2017-08-16	1	AUTOMOTIVE	0	8	2017	Wednesday	1
1	3000889	2017-08-16	1	BABY CARE	0	8	2017	Wednesday	1
2	3000890	2017-08-16	1	BEAUTY	2	8	2017	Wednesday	1
3	3000891	2017-08-16	1	BEVERAGES	20	8	2017	Wednesday	1
4	3000892	2017-08-16	1	BOOKS	0	8	2017	Wednesday	1

Exploratory Data Analysis

- Holidays

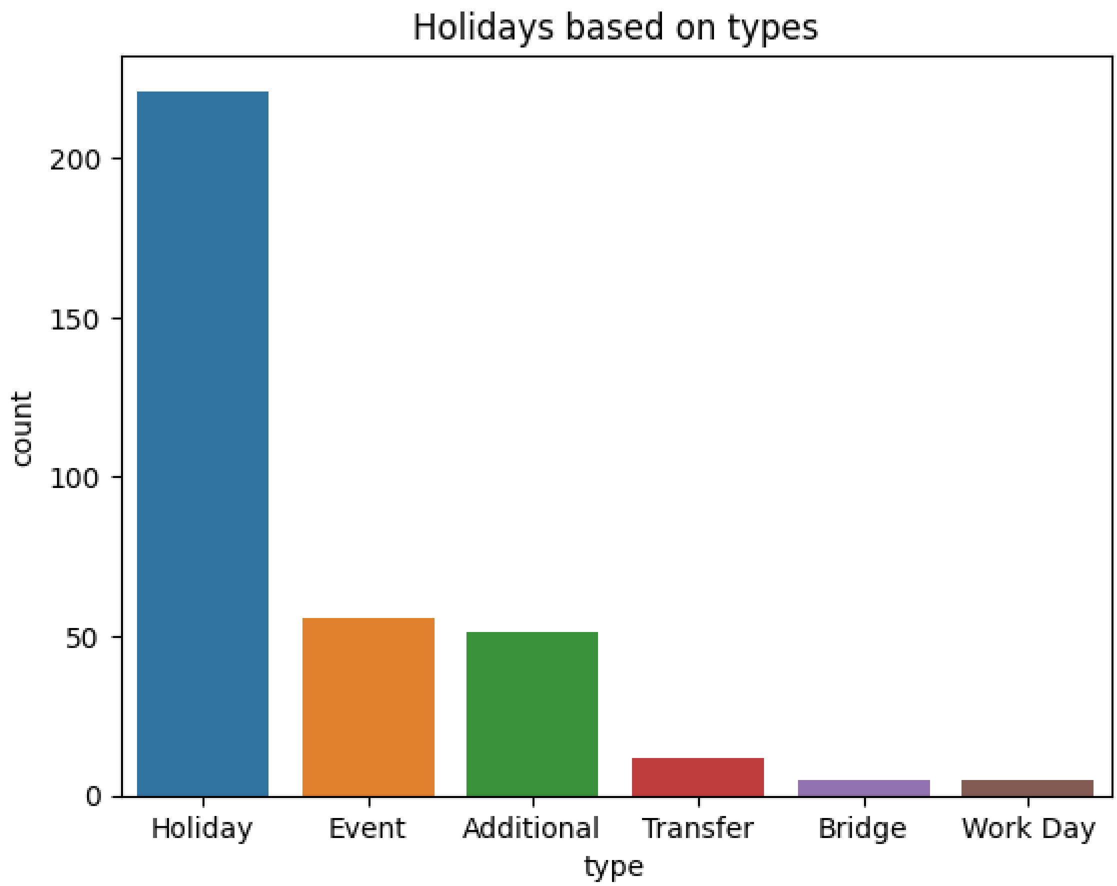
In [44]:
```
holidays_df.head(10)
```

Out[44]:

	date	type	locale	locale_name	description	transferred	month	year	day
0	2012-03-02	Holiday	Local	Manta	Fundacion de Manta	False	3	2012	Friday
1	2012-04-01	Holiday	Regional	Cotopaxi	Provincializacion de Cotopaxi	False	4	2012	Sunday
2	2012-04-12	Holiday	Local	Cuenca	Fundacion de Cuenca	False	4	2012	Thursday
3	2012-04-14	Holiday	Local	Libertad	Cantonizacion de Libertad	False	4	2012	Saturday
4	2012-04-21	Holiday	Local	Riobamba	Cantonizacion de Riobamba	False	4	2012	Saturday
5	2012-05-12	Holiday	Local	Puyo	Cantonizacion del Puyo	False	5	2012	Saturday
6	2012-06-23	Holiday	Local	Guaranda	Cantonizacion de Guaranda	False	6	2012	Saturday
7	2012-06-25	Holiday	Regional	Imbabura	Provincializacion de Imbabura	False	6	2012	Monday
8	2012-06-25	Holiday	Local	Latacunga	Cantonizacion de Latacunga	False	6	2012	Monday
9	2012-06-25	Holiday	Local	Machala	Fundacion de Machala	False	6	2012	Monday

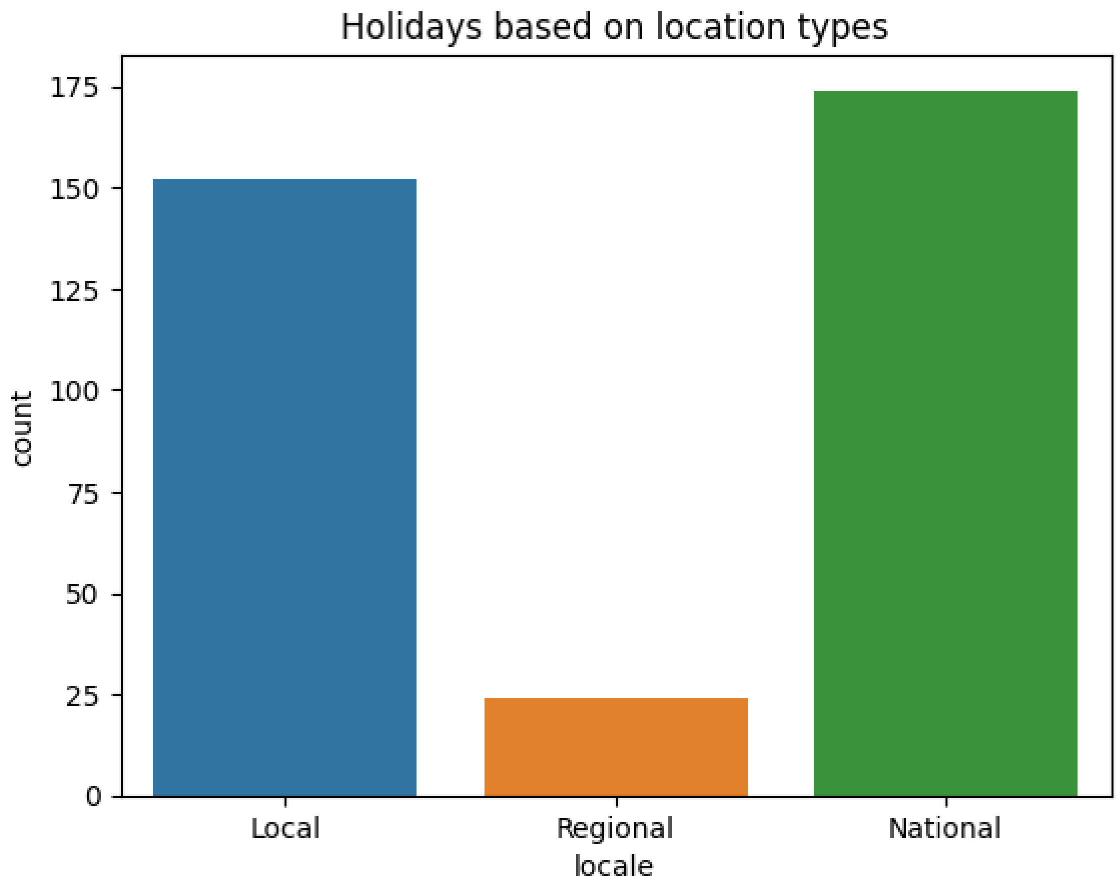
In [45]:

```
type_order = holidays_df['type'].value_counts().index
sns.countplot(data=holidays_df, x='type', order=type_order)
plt.title('Holidays based on types')
plt.show()
```



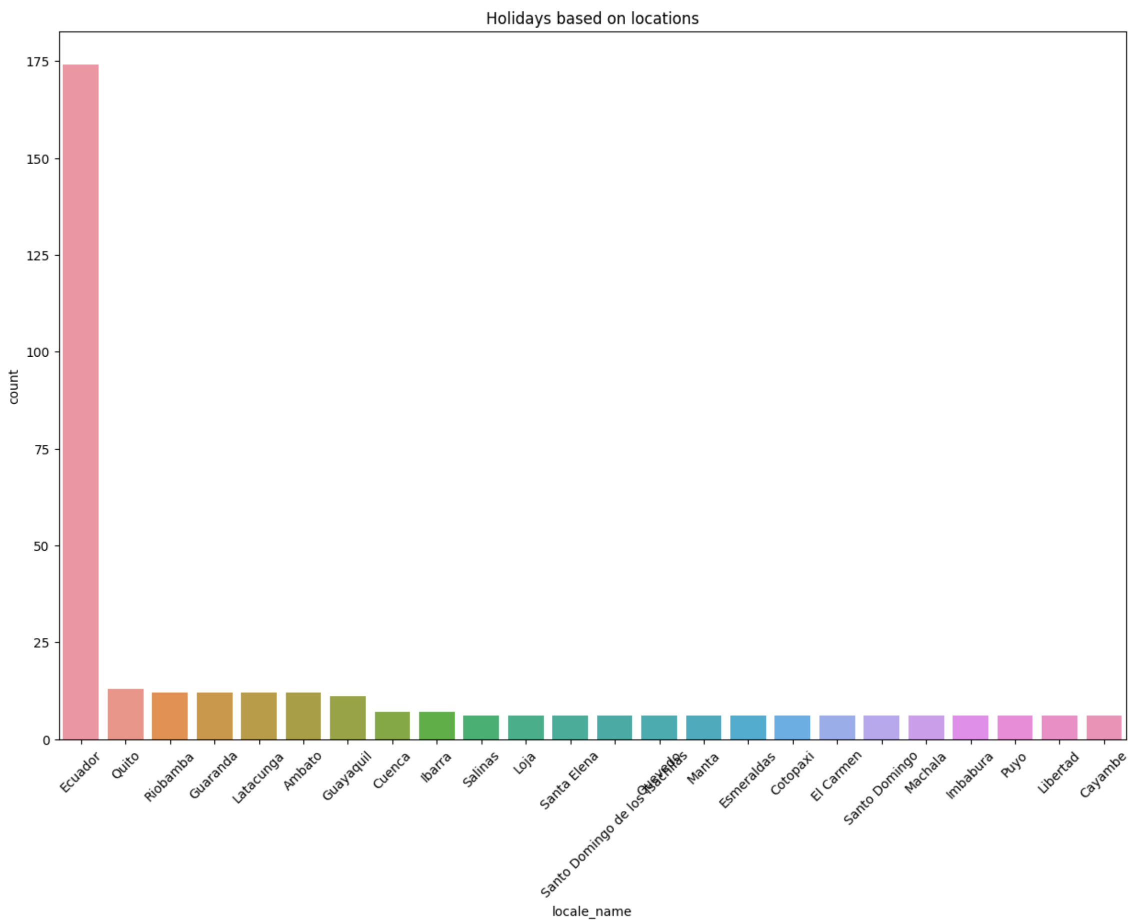
In [46]:

```
sns.countplot(data=holidays_df, x='locale')
plt.title('Holidays based on location types')
plt.show()
```



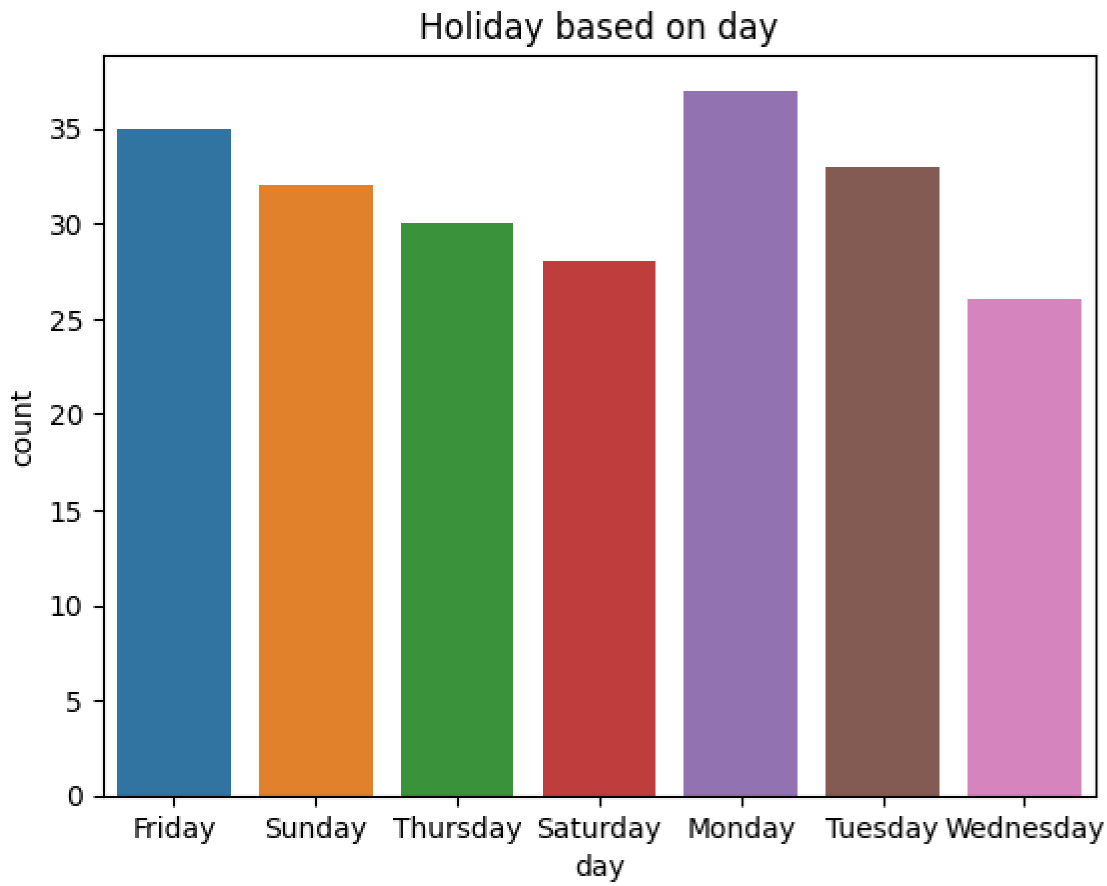
In [47]:

```
l_order = holidays_df['locale_name'].value_counts().index
plt.figure(figsize=(15,10))
sns.countplot(data=holidays_df, x='locale_name',order=l_order)
plt.title('Holidays based on locations')
plt.xticks(rotation=45)
plt.show()
```

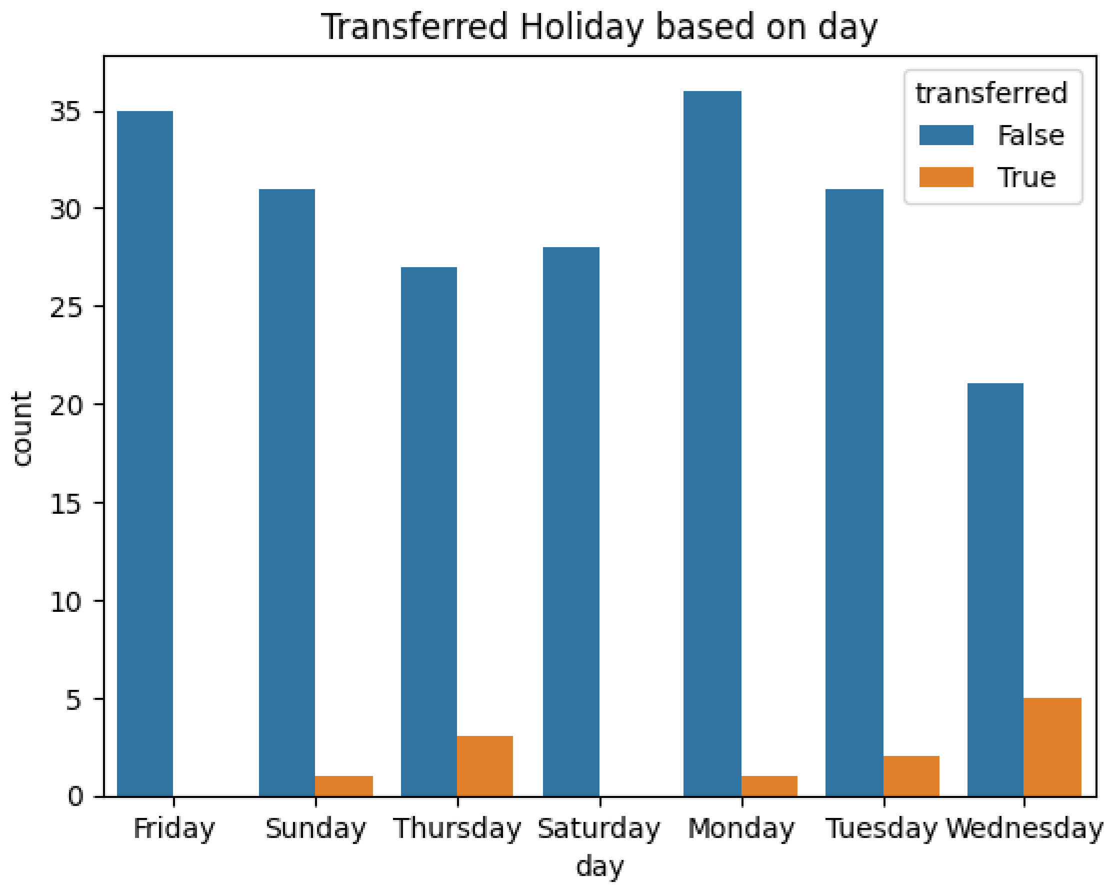


In [48]:

```
sns.countplot(data=holidays_df[holidays_df.type=='Holiday'],x='day')
plt.title("Holiday based on day")
plt.show()
```



In [49]:
```
sns.countplot(data=holidays_df[holidays_df.type=='Holiday'],x='day', hue='t
plt.title("Transferred Holiday based on day")
plt.show()
```



- Oils

In [50]:
```
oils_df.head(10)
```

Out[50]:

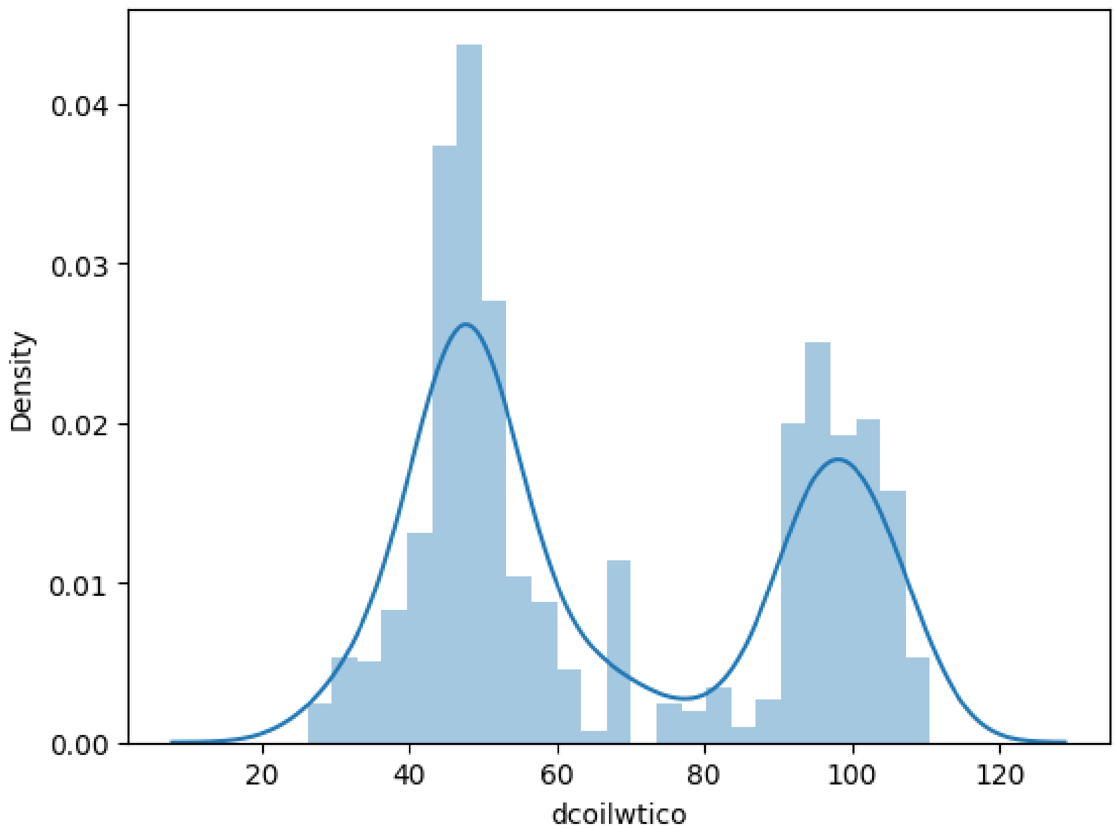
	date	dcoilwtico	month	year	day	day_date
0	2013-01-01	NaN	1	2013	Tuesday	1
1	2013-01-02	93.14	1	2013	Wednesday	2
2	2013-01-03	92.97	1	2013	Thursday	3
3	2013-01-04	93.12	1	2013	Friday	4
4	2013-01-07	93.20	1	2013	Monday	7
5	2013-01-08	93.21	1	2013	Tuesday	8
6	2013-01-09	93.08	1	2013	Wednesday	9
7	2013-01-10	93.81	1	2013	Thursday	10
8	2013-01-11	93.60	1	2013	Friday	11
9	2013-01-14	94.27	1	2013	Monday	14

In [51]:
```
oils_mean = oils_df.dcoilwtico.mean()
oils_df.dcoilwtico.fillna(oils_mean,inplace=True)
oils_df.isna().sum()
```

Out[51]:
```
date          0
dcoilwtico    0
month         0
year          0
day           0
day_date      0
dtype: int64
```

In [52]:
```
sns.distplot(oils_df['dcoilwtico'], kde=True, bins=25)
```

Out[52]:
```
<Axes: xlabel='dcoilwtico', ylabel='Density'>
```

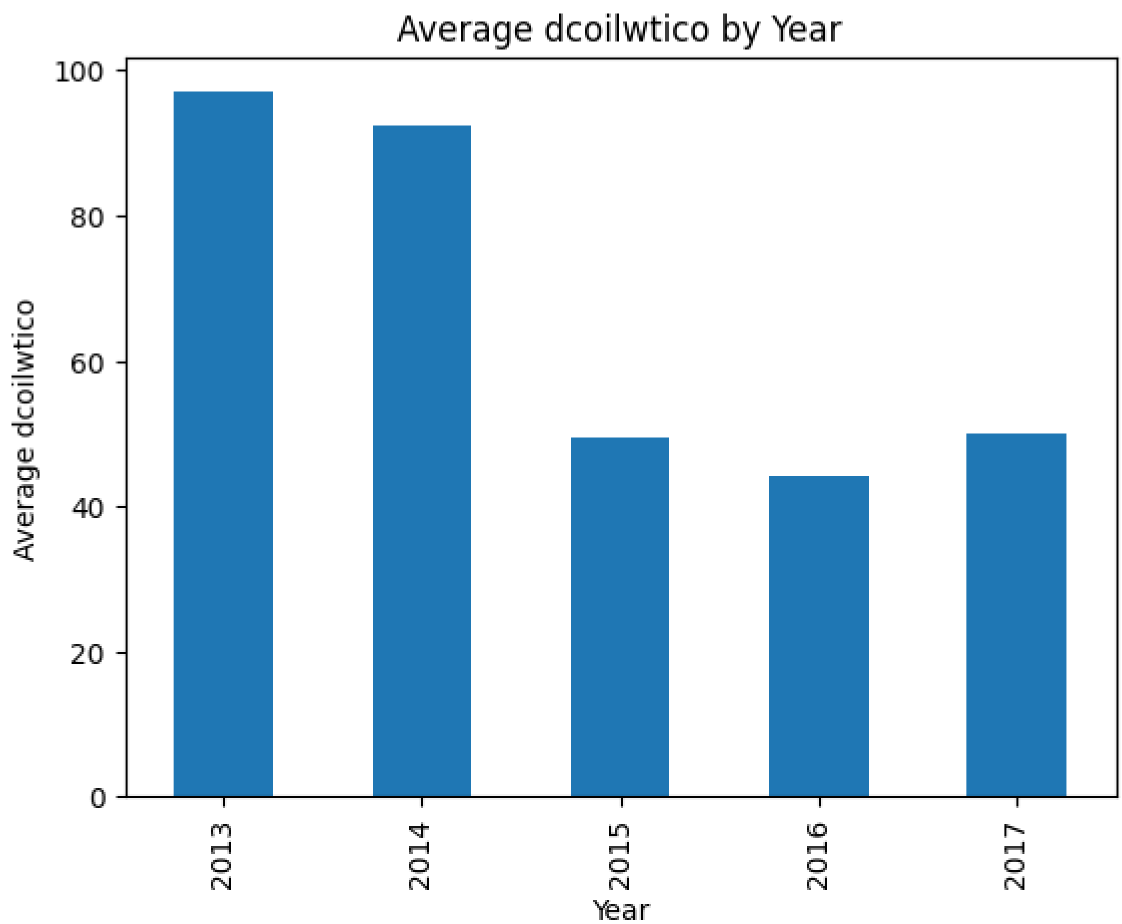


In [53]:
```
oils_df.groupby('year')['dcoilwtico'].mean()
```

Out[53]:
```
year
2013    96.938810
2014    92.294365
2015    49.313867
2016    44.135744
2017    49.976383
Name: dcoilwtico, dtype: float64
```

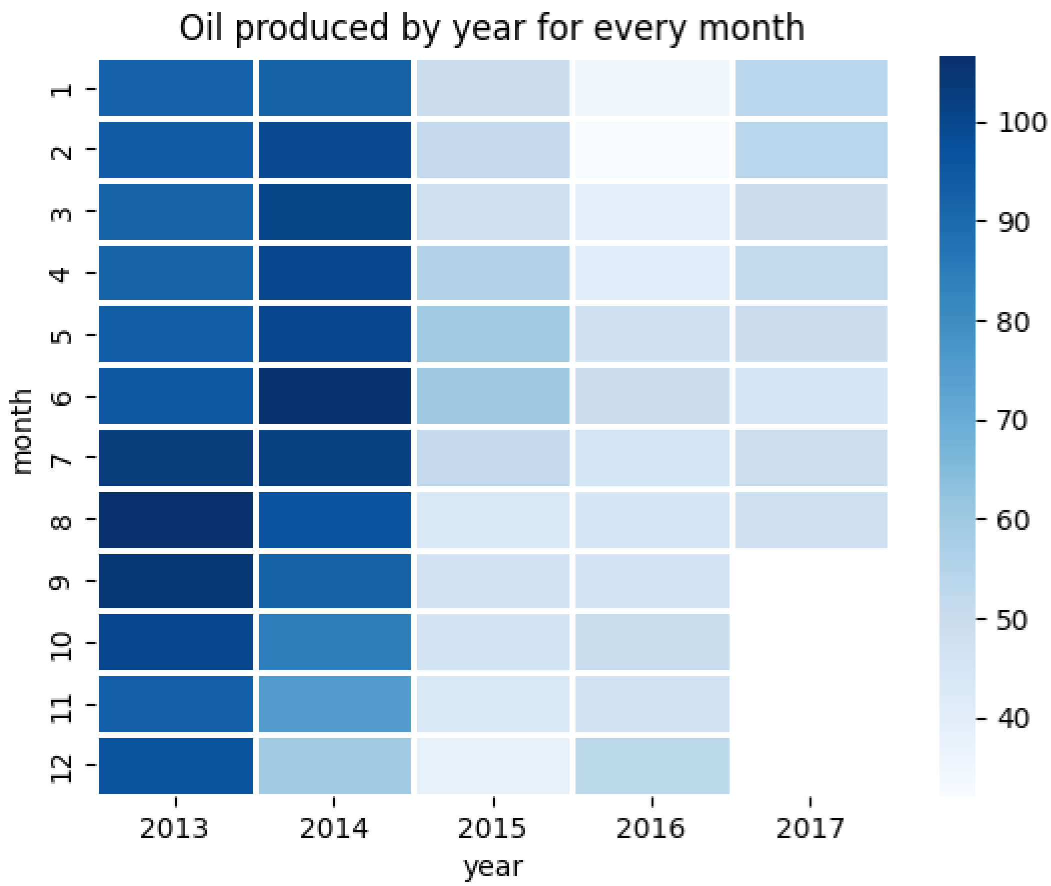
In [54]:

```
pivot_table = oils_df.pivot_table(index='year', values='dcoilwtico', aggfun

# Plotting the graph
pivot_table.plot(kind='bar', legend=False)
plt.xlabel('Year')
plt.ylabel('Average dcoilwtico')
plt.title('Average dcoilwtico by Year')
plt.show()
```



In [55]:

```
oils_year_month = oils_df.pivot_table(index='month', columns='year', values
# You can separate data with lines
sns.heatmap(oils_year_month, cmap='Blues', linecolor='white', linewidth=1)
plt.title('Oil produced by year for every month')
plt.show()
```



In [56]:

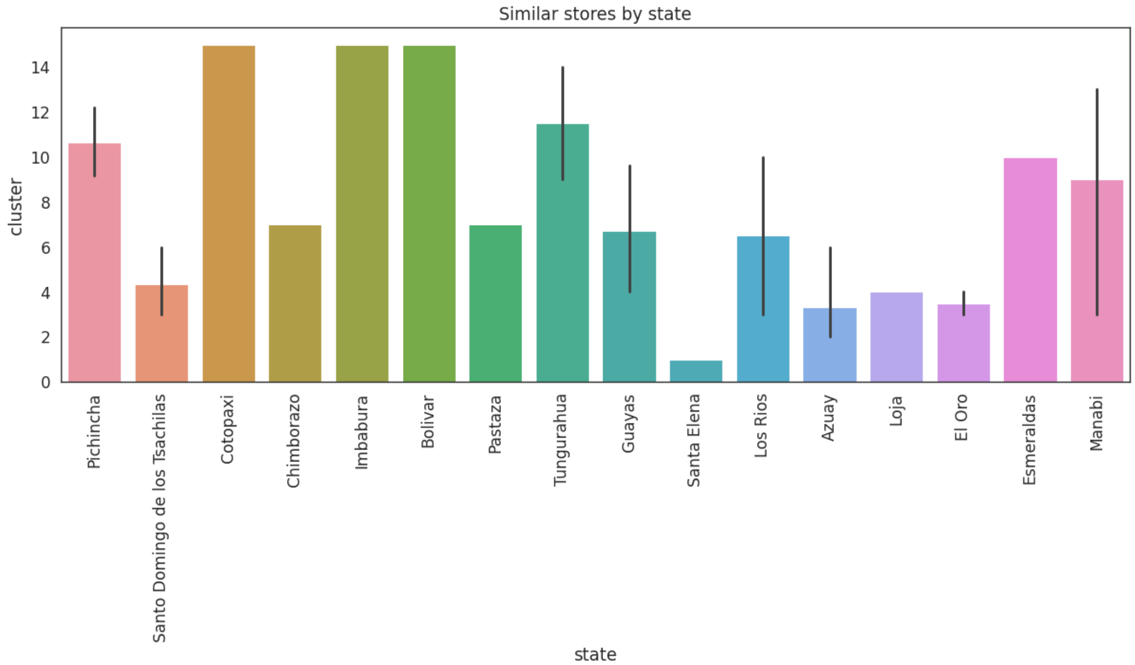
```
stores_df.head(10)
```

Out[56]:

	store_nbr	city	state	type	cluster
0	1	Quito	Pichincha	D	13
1	2	Quito	Pichincha	D	13
2	3	Quito	Pichincha	D	8
3	4	Quito	Pichincha	D	9
4	5	Santo Domingo	Santo Domingo de los Tsachilas	D	4
5	6	Quito	Pichincha	D	13
6	7	Quito	Pichincha	D	8
7	8	Quito	Pichincha	D	8
8	9	Quito	Pichincha	B	6
9	10	Quito	Pichincha	C	15

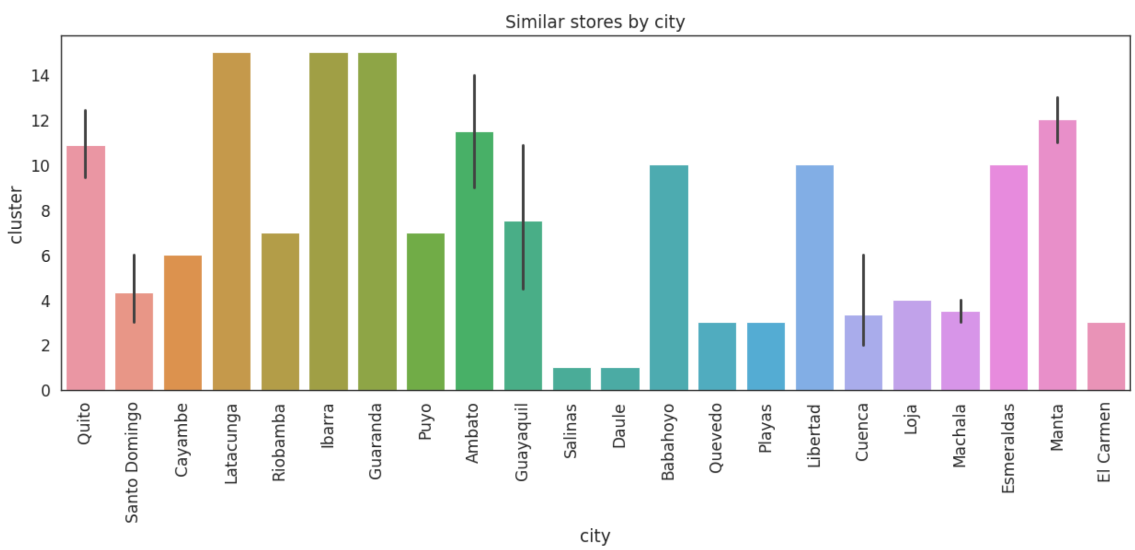
In [96]:

```
plt.figure(figsize=(15,5))
sns.barplot(x='state',y='cluster',data=stores_df)
plt.xticks(rotation=90)
plt.title("Similar stores by state")
plt.show()
```



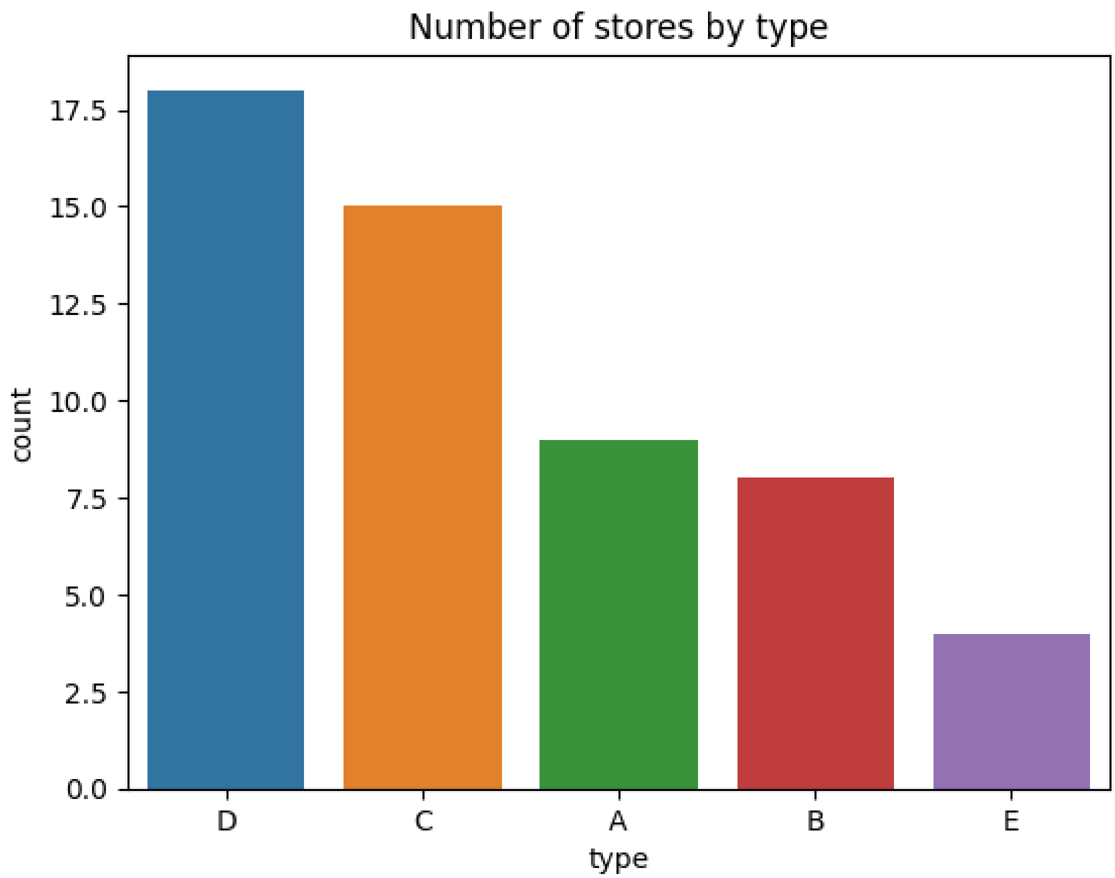
In [95]:

```
plt.figure(figsize=(15,5))
sns.barplot(x='city',y='cluster',data=stores_df)
plt.xticks(rotation=90)
plt.title("Similar stores by city")
plt.show()
```



In [59]:

```
s_order = stores_df['type'].value_counts().index
sns.countplot(x='type',data=stores_df,order=s_order)
plt.title('Number of stores by type')
plt.show()
```



In [60]:

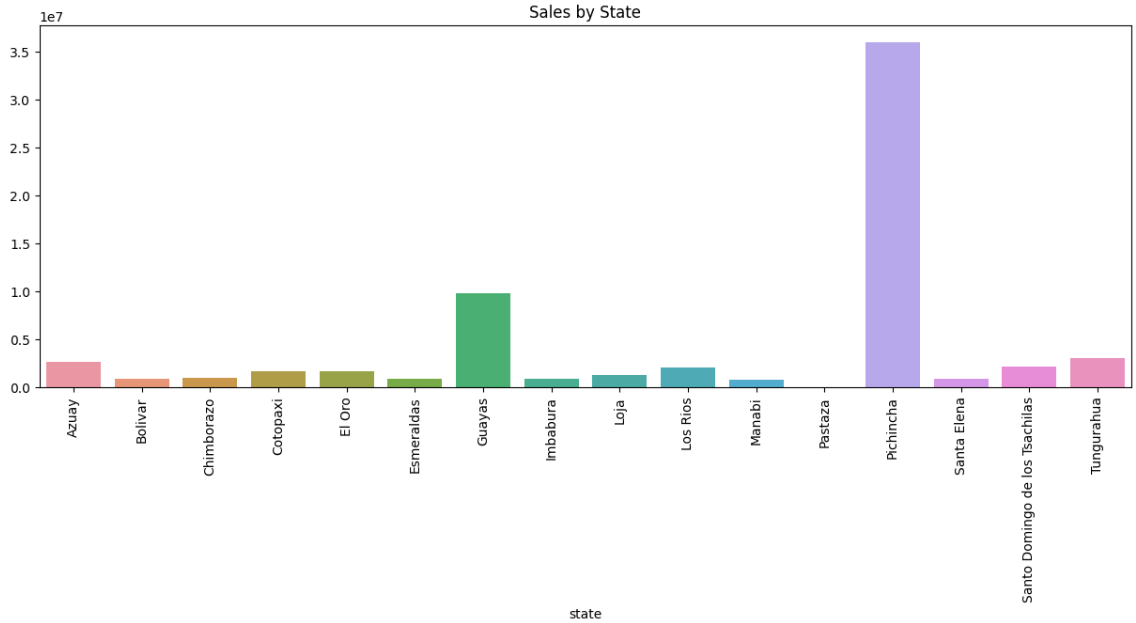
```
stores_sales_df=pd.merge(train_df,stores_df,on='store_nbr',how='inner')
stores_sales_df.head(5)
```

Out[60]:

	id	date	store_nbr	family	sales	onpromotion	month	year	day	day_date
0	0	2013-01-01	1.0	AUTOMOTIVE	0.0	0.0	1	2013	Tuesday	1
1	1	2013-01-01	1.0	BABY CARE	0.0	0.0	1	2013	Tuesday	1
2	2	2013-01-01	1.0	BEAUTY	0.0	0.0	1	2013	Tuesday	1
3	3	2013-01-01	1.0	BEVERAGES	0.0	0.0	1	2013	Tuesday	1
4	4	2013-01-01	1.0	BOOKS	0.0	0.0	1	2013	Tuesday	1

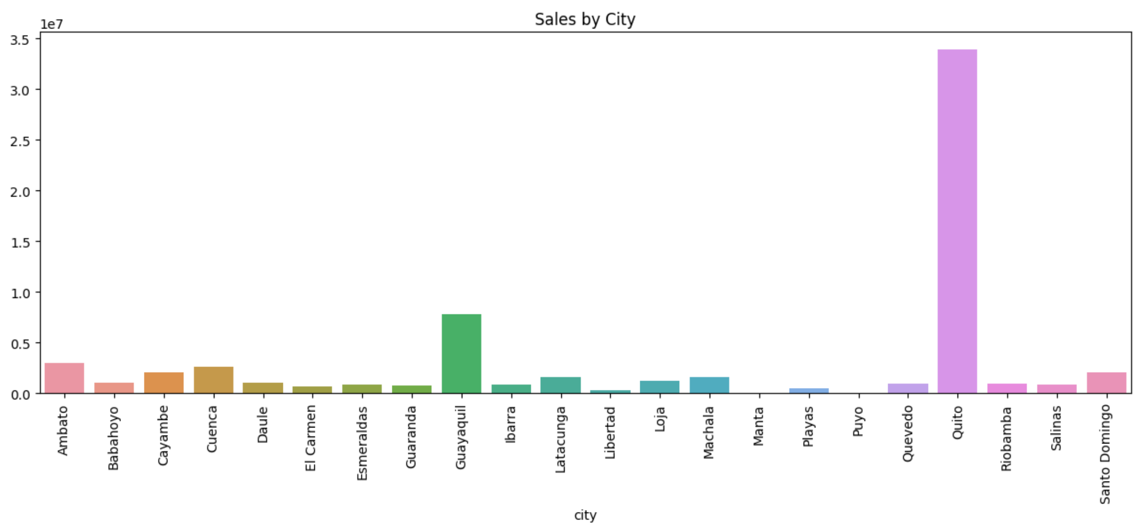
In [61]:

```
sales_by_sate=stores_sales_df.groupby('state').sales.sum().to_frame()
plt.figure(figsize=(15,5))
sns.barplot(data=sales_by_sate,x=sales_by_sate.sales.index,y=sales_by_sate.
plt.title('Sales by State')
plt.xticks(rotation=90)
plt.show()
```



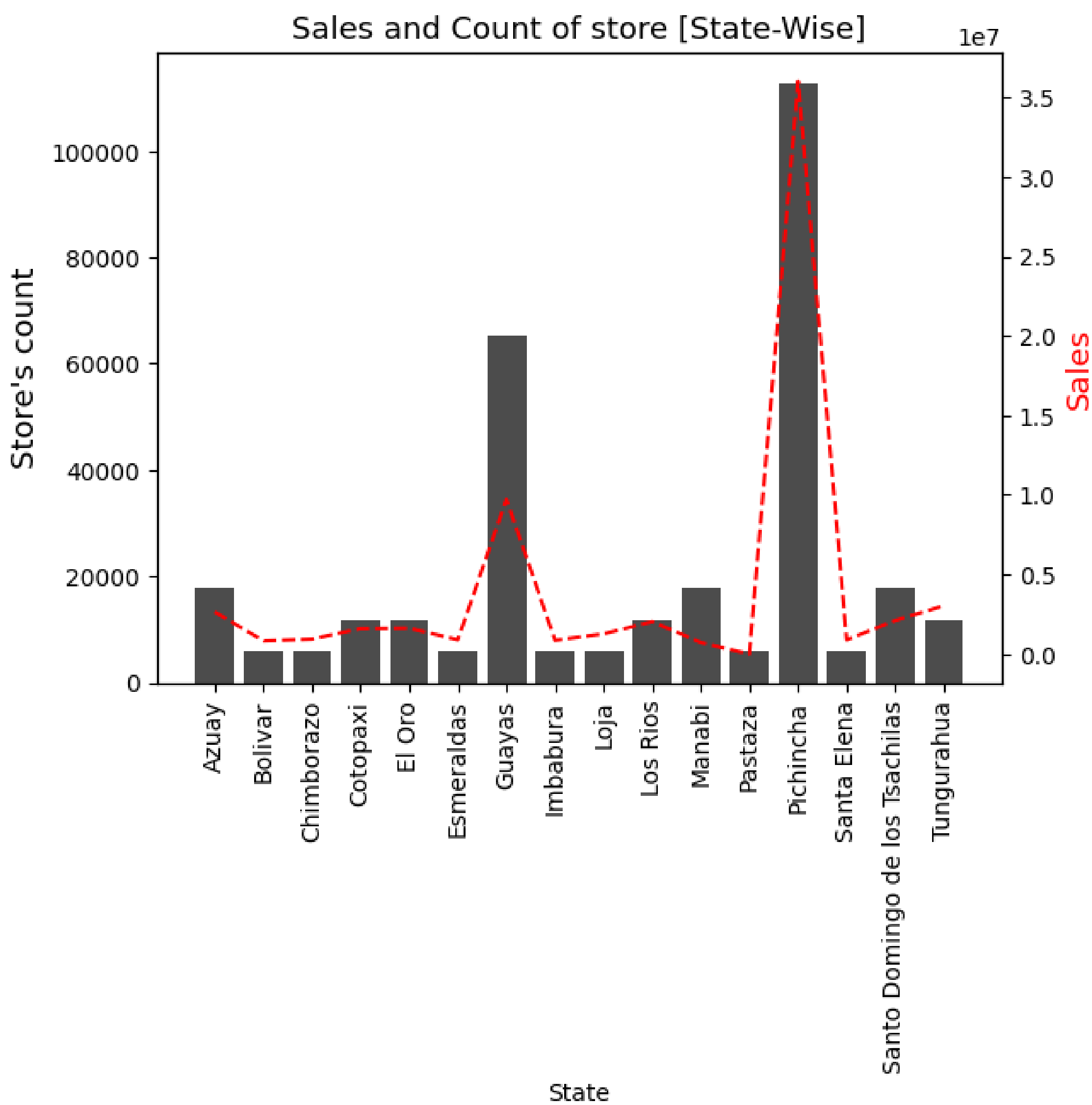
In [62]:

```
sales_by_city=stores_sales_df.groupby('city').sales.sum().to_frame()
plt.figure(figsize=(15,5))
sns.barplot(data=sales_by_city,x=sales_by_city.sales.index,y=sales_by_city.
plt.title('Sales by City')
plt.xticks(rotation=90)
plt.show()
```



In [63]:

```
# Creating list based of requirements i.e (name and value should be on same
state=stores_sales_df.groupby('state')
count_store=state.store_nbr.count()
states=[s for s,df in state]
sales_state=state.sales.sum()


# Ploting
fig,ax1=plt.subplots()
ax2=ax1.twinx()
ax1.bar(states,count_store,color='black',alpha=0.7)
ax2.plot(states,sales_state,'r--')

ax1.set_xlabel("State")
ax1.set_ylabel("Store's count",color='black',size=13)
ax2.set_ylabel("Sales",color='red',size=13)
ax1.set_xticklabels(states,rotation='vertical',size=10)
plt.title("Sales and Count of store [State-Wise]",size=13)
plt.show()
```



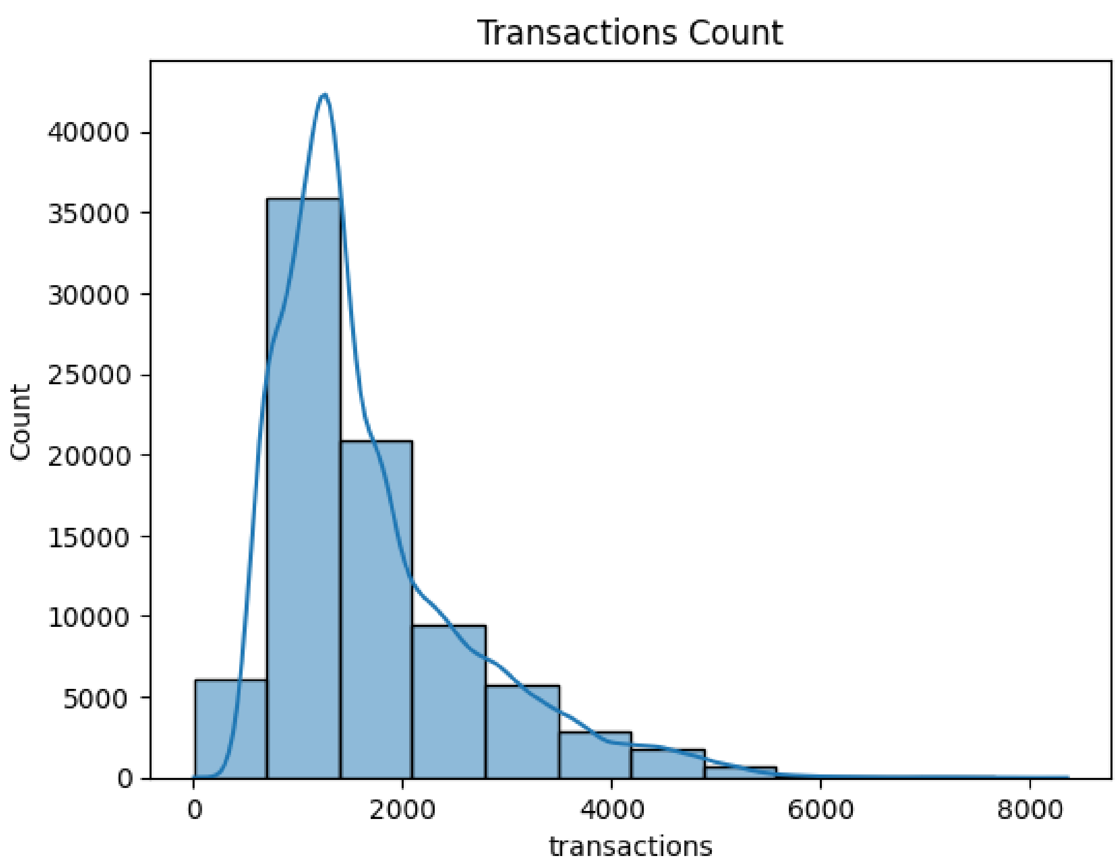
- Transactions

In [64]:
```
tran_df.head()
```

Out[64]:

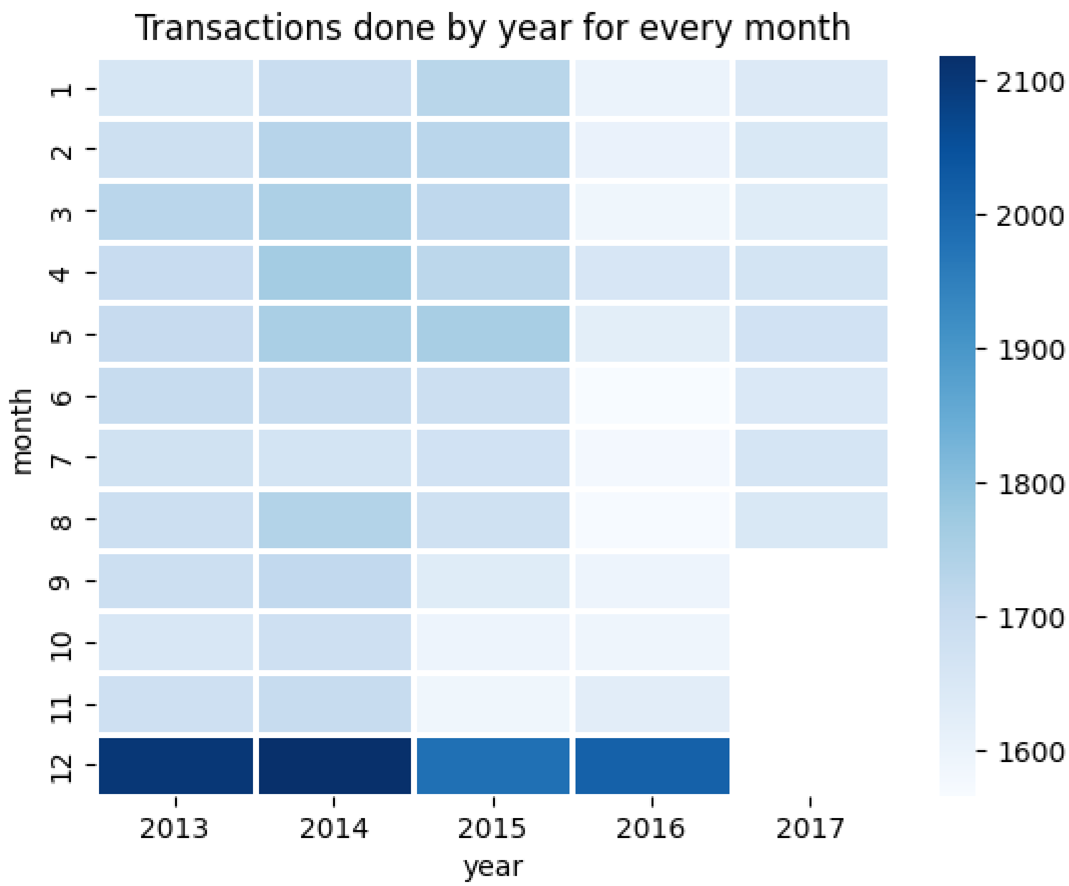
	date	store_nbr	transactions	month	year	day	day_date
0	2013-01-01	25	770	1	2013	Tuesday	1
1	2013-01-02	1	2111	1	2013	Wednesday	2
2	2013-01-02	2	2358	1	2013	Wednesday	2
3	2013-01-02	3	3487	1	2013	Wednesday	2
4	2013-01-02	4	1922	1	2013	Wednesday	2

In [65]:
```
sns.histplot(data=tran_df,x='transactions',kde=True,bins=12)
plt.title("Transactions Count")
plt.show()
```



In [66]:

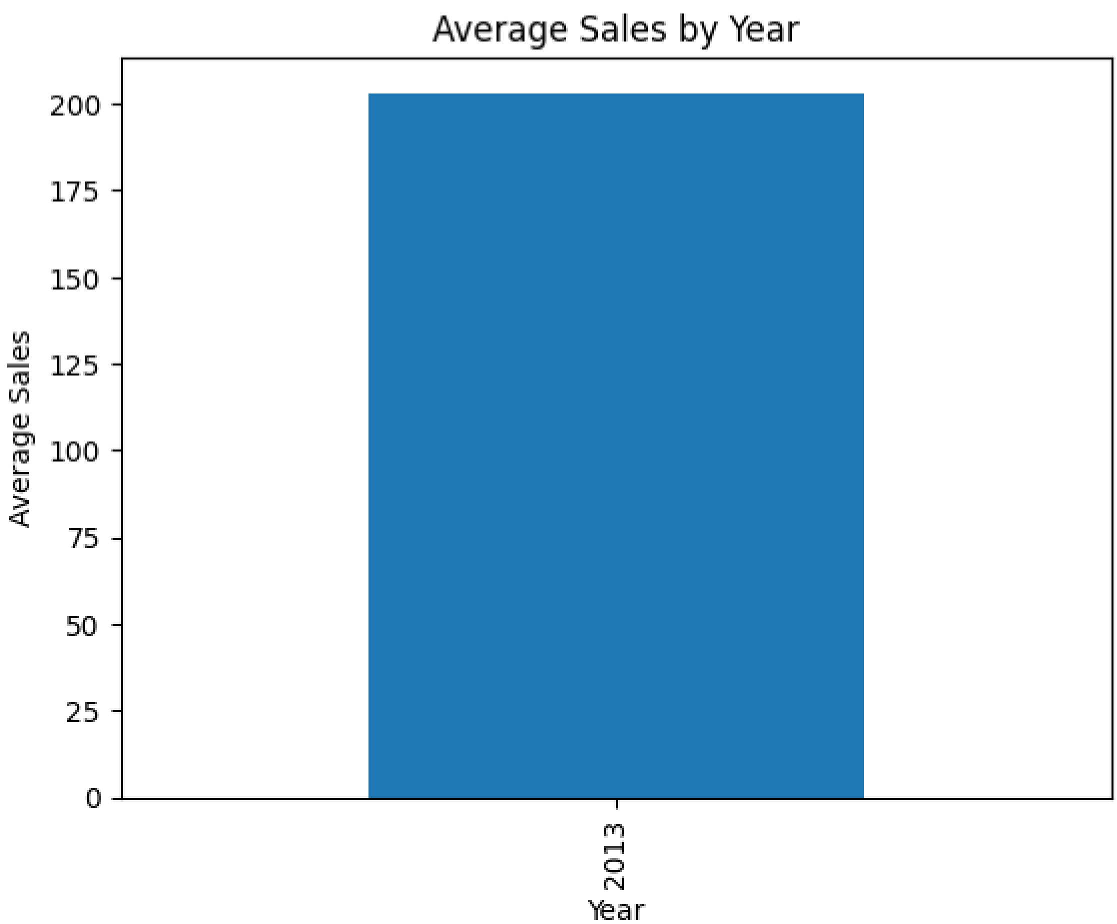
```
transactions_year_month = tran_df.pivot_table(index='month', columns='year'
# You can separate data with lines
sns.heatmap(transactions_year_month, cmap='Blues', linecolor='white', linew
plt.title('Transactions done by year for every month')
plt.show()
```



- Train DataFrame

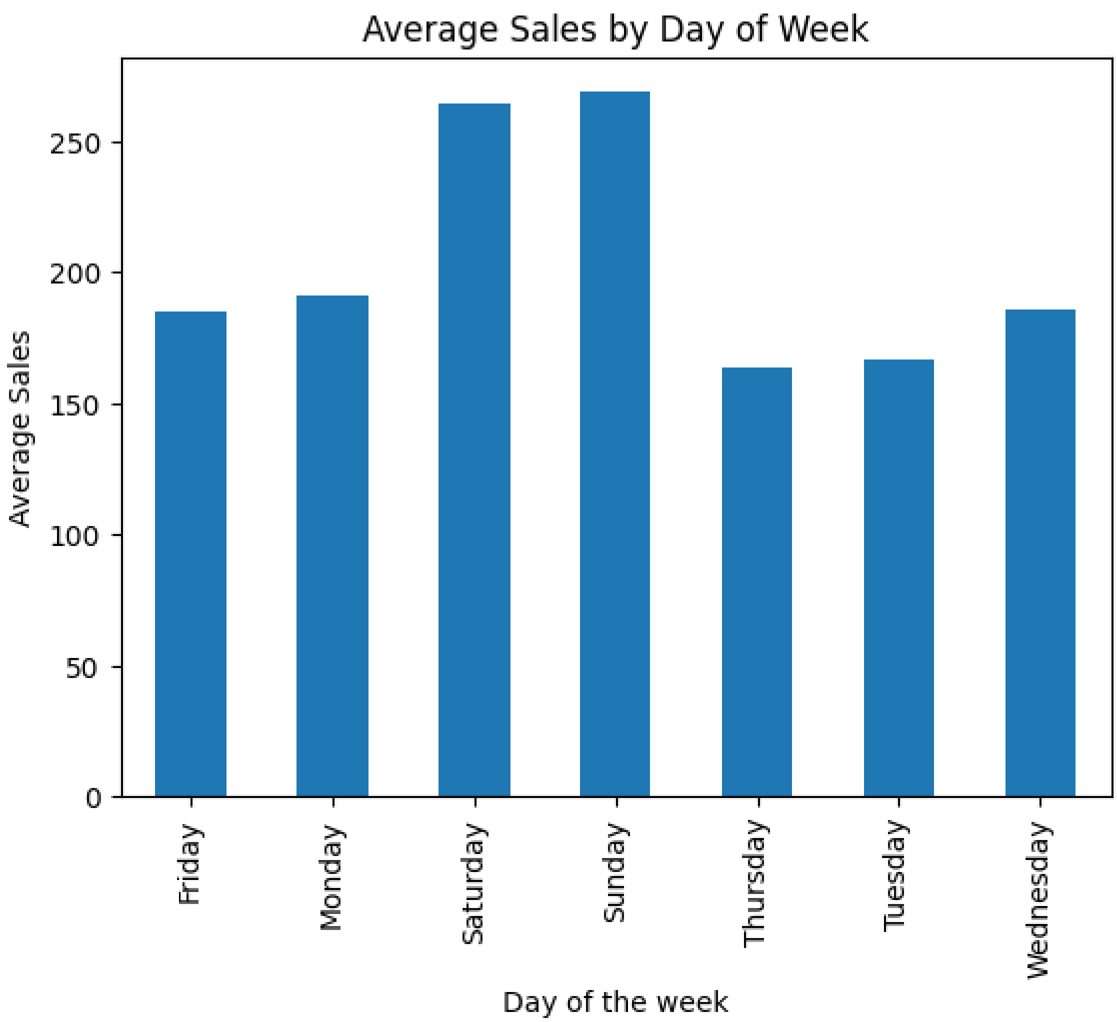
In [67]:

```
spivot_table = train_df.pivot_table(index='year', values='sales', aggfunc='

# Plotting the graph
spivot_table.plot(kind='bar', legend=False)
plt.xlabel('Year')
plt.ylabel('Average Sales')
plt.title('Average Sales by Year')
plt.show()
```



In [68]:

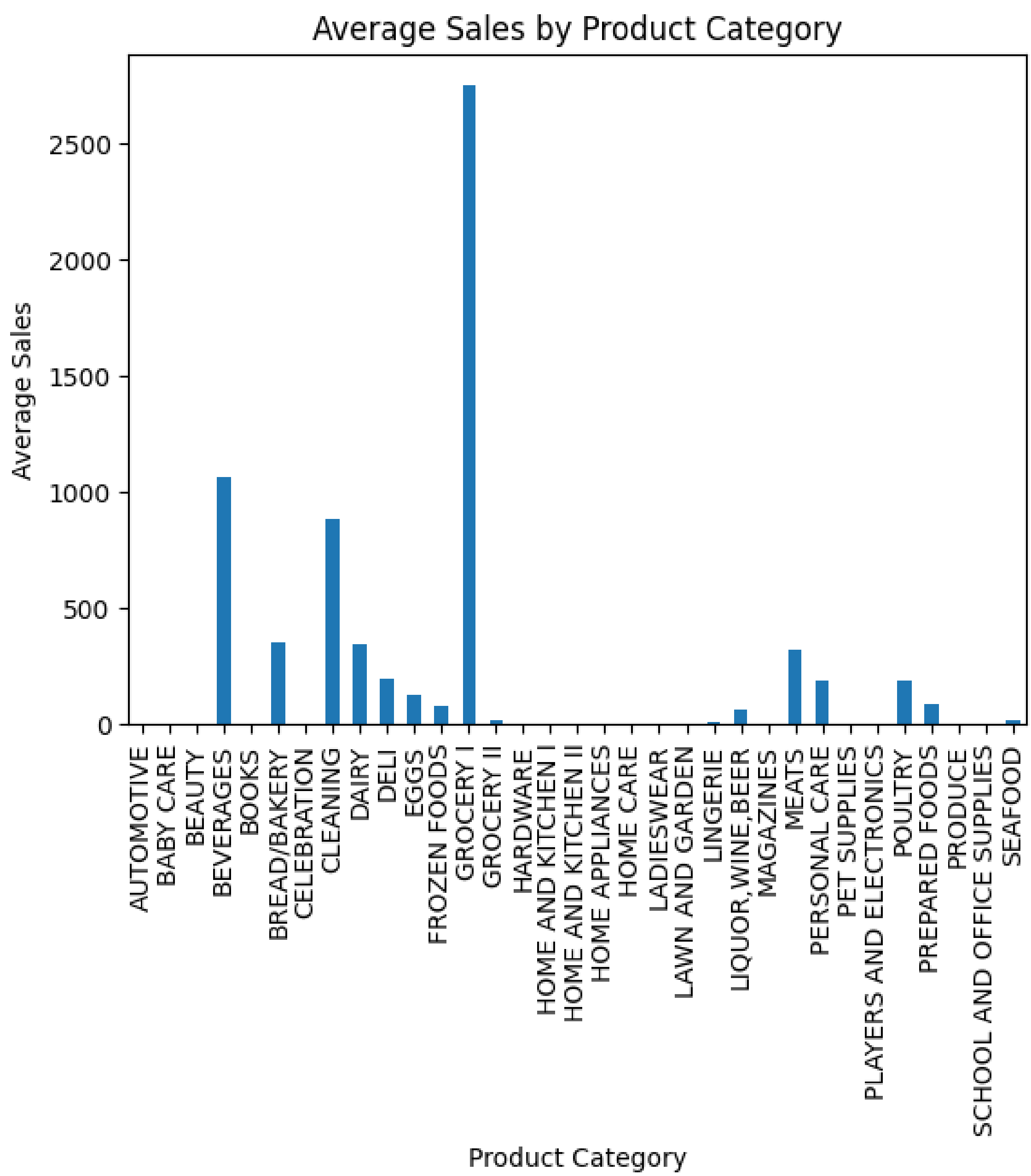
```
dowpivot_table = train_df.pivot_table(index='day', values='sales', aggfunc=

# Plotting the graph
dowpivot_table.plot(kind='bar', legend=False)
plt.xlabel('Day of the week')
plt.ylabel('Average Sales')
plt.title('Average Sales by Day of Week')
plt.show()
```



In [69]:

```
pf_pivot_table = train_df.pivot_table(index='family', values='sales', aggfu

# Plotting the graph
plt.figure(figsize=(15,5))
pf_pivot_table.plot(kind='bar', legend=False)
plt.xlabel('Product Category')
plt.ylabel('Average Sales')
plt.title('Average Sales by Product Category')
plt.show()
```

```
<Figure size 1500x500 with 0 Axes>
```



Feature Engineering

In [72]:
```python
print("Train Data set columns : ",list(train_df.columns))
print("Test Data set columns : ",list(test_df.columns))
print("Store Data set columns : ",list(stores_df.columns))
```

```
Train Data set columns :  ['id', 'date', 'store_nbr', 'family', 'sales',
'onpromotion', 'month', 'year', 'day', 'day_date']
Test Data set columns :  ['id', 'date', 'store_nbr', 'family', 'onpromotio
n', 'month', 'year', 'day', 'day_date']
Store Data set columns :  ['store_nbr', 'city', 'state', 'type', 'cluste
r']
```

In [73]:
```python
trainDf = pd.merge(train_df,stores_df,how='inner',on='store_nbr')
testDf = pd.merge(test_df,stores_df,how='inner',on='store_nbr')
print("Train Data set columns : ",list(trainDf.columns))
print("Test Data set columns : ",list(testDf.columns))
```

```
Train Data set columns :  ['id', 'date', 'store_nbr', 'family', 'sales',
'onpromotion', 'month', 'year', 'day', 'day_date', 'city', 'state', 'typ
e', 'cluster']
Test Data set columns :  ['id', 'date', 'store_nbr', 'family', 'onpromotio
n', 'month', 'year', 'day', 'day_date', 'city', 'state', 'type', 'cluste
r']
```

Defining the input and target columns

In [74]:
```python
input_cols = ['store_nbr', 'family', 'onpromotion', 'month', 'year', 'day',
target_cols = ['sales']
```

In [75]:
```python
#obtaining the non object dtypes
numerical_features = [feature for feature in trainDf[input_cols] if trainDf
print(numerical_features)
categorical_features = [feature for feature in trainDf[input_cols] if train
print(categorical_features)
```

```
['store_nbr', 'onpromotion', 'month', 'year', 'day_date', 'cluster']
['family', 'day', 'city', 'state', 'type']
```

In [76]:
```python
print(trainDf[numerical_features].isna().sum())
print(trainDf[categorical_features].isna().sum())
```

```
store_nbr      0
onpromotion    0
month          0
year           0
day_date       0
cluster        0
dtype: int64
family    0
day       0
city      0
state     0
type      0
dtype: int64
```

Data Preprocessing

In [77]:
```python
trainDf[numerical_features]
```

Out[77]:

	store_nbr	onpromotion	month	year	day_date	cluster
0	1.0	0.0	1	2013	1	13
1	1.0	0.0	1	2013	1	13
2	1.0	0.0	1	2013	1	13
3	1.0	0.0	1	2013	1	13
4	1.0	0.0	1	2013	1	13
...	...	...	...	...	...	...
320762	9.0	0.0	6	2013	29	6
320763	9.0	0.0	6	2013	29	6
320764	9.0	0.0	6	2013	29	6
320765	9.0	0.0	6	2013	29	6
320766	9.0	0.0	6	2013	29	6

320767 rows × 6 columns

In [78]:
```python
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(trainDf[numerical_features])
```

Out[78]:
```
StandardScaler()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [79]:
```
trainDf[numerical_features]=scaler.transform(trainDf[numerical_features])
testDf[numerical_features]=scaler.transform(testDf[numerical_features])
```

Encoding for categorical features

In [80]:
```
from sklearn.preprocessing import OneHotEncoder
```

In [81]:
```
encoder=OneHotEncoder(sparse_output=False,handle_unknown='ignore')
encoder.fit(trainDf[categorical_features])
```

Out[81]:
```
OneHotEncoder(handle_unknown='ignore', sparse_output=False)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [82]:
```
encoded_cols=list(encoder.get_feature_names_out(categorical_features))
```

In [83]:
```
trainDf[encoded_cols]=encoder.transform(trainDf[categorical_features])
testDf[encoded_cols]=encoder.transform(testDf[categorical_features])
```

In [84]:
```
trainData=trainDf[numerical_features+encoded_cols]
testData=testDf[numerical_features+encoded_cols]
trainData.shape,testData.shape
```

Out[84]:
```
((320767, 89), (28512, 89))
```

Model Building

In [85]:
```
from sklearn.model_selection import train_test_split
```

In [86]:
```
X = trainData.copy()
y = trainDf[target_cols]
```

In [87]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y ,
                                   random_state=104,
                                   test_size=0.25,
                                   shuffle=True)
```

In [94]:

```python
from sklearn.model_selection import train_test_split, GridSearchCV, cross_v
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error

# Models to evaluate
models = [
    ('Linear Regression', LinearRegression()),
    ('Decision Tree Regressor', DecisionTreeRegressor(random_state=42)),
    # ('Random Forest Regressor', RandomForestRegressor(random_state=42))
]

# Evaluate models using k-fold cross-validation
for model_name, model in models:
    # For RandomForestRegressor, add hyperparameters to the parameter grid
    if model_name == 'Random Forest Regressor':
        param_grid = {
            'n_estimators': [10, 15, 30],
            'max_depth': [5, 10, 20],
            'min_samples_split': [2, 5, 8],
            'min_samples_leaf': [1, 2, 4]
        }
    else:
        # For other models, use a basic parameter grid
        param_grid = {}

    # Create the GridSearchCV object
    grid_search = GridSearchCV(model, param_grid, cv=5, scoring='neg_mean_s

    # Fit the model to the training data
    grid_search.fit(X_train, y_train)

    # Get the best parameters and the best model
    best_params = grid_search.best_params_
    best_model = grid_search.best_estimator_

    # Print the best parameters
    print(f"\nBest Parameters for {model_name}:", best_params)

    # Evaluate the best model using k-fold cross-validation
    mse_scores = cross_val_score(best_model, X_train, y_train, cv=5, scorin
    rmse_scores = np.sqrt(-mse_scores)

    # Print cross-validation results
    print(f"Cross-validation RMSE scores for {model_name}: {rmse_scores}")
    print(f"Mean RMSE: {np.mean(rmse_scores)}")

    # Make predictions on the test set
    y_pred = best_model.predict(X_test)

    # Evaluate the model on the test set
    mse = mean_squared_error(y_test, y_pred)
    rmse = np.sqrt(mse)
    print(f"\nTest set RMSE for {model_name}: {rmse}")

    # Optionally, you can print other metrics as well, like R2 score
```

```python
    from sklearn.metrics import r2_score
    r2 = r2_score(y_test, y_pred)
    print(f"R2 score for {model_name}: {r2}")
```

```
Best Parameters for Linear Regression: {}
Cross-validation RMSE scores for Linear Regression: [448.43794289 434.2791
5129 431.68155695 427.60886844 446.64514099]
Mean RMSE: 437.73053211292955

Test set RMSE for Linear Regression: 437.92352023957966
R2 score for Linear Regression: 0.5888385989674367

Best Parameters for Decision Tree Regressor: {}
Cross-validation RMSE scores for Decision Tree Regressor: [179.7441305  18
1.23371422 214.30101129 173.26191091 221.32767169]
Mean RMSE: 193.9736877194814

Test set RMSE for Decision Tree Regressor: 182.30486476295638
R2 score for Decision Tree Regressor: 0.9287454977477645
```

In [88]:

```python

```