M5 Forecasting accuracy

The objective of this notebook consists in forecasting unit sales for given products and stores.

The notebook is divided into the following parts:

- **Preprocessing**: data preprocessing to make them more suitable to the final goal;
- **Exploratory Data Analysis (EDA)**: data exploration, looking for possible patterns or correlations;
- **Feature Engineering (FE)**: computation of new features starting from available ones;
- **Model implementation**: implementation of a model for each store;
- **Predictions**: predictions making for public and private data;
- **Submissions**: computation of partial and final submissions;
- **Evaluation**: error computation and its decomposition for each aggregation level.

In [ ]:
```
# Run the following three cells only if using colab
```

In [ ]:
```
!pip install lightgbm==3.3.2
```

In [1]:
```
!git clone https://github.com/michelevece/vece-m5-forecasting-accuracy
```

In [2]:
```
%cd vece-m5-forecasting-accuracy/data/code
```

0) Libraries

In [1]:
```
# libraries
import os
import zipfile
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import tqdm
import lightgbm as lgbm
from sklearn.metrics import mean_squared_error as mse

# my modules
import m5_utils as utils
import m5_preprocessing as preprocessing
import m5_fe as fe
import m5_wrmsse_evaluator as wrmsse_evaluator

# target column
TARGET = 'sales'

# first day of the private leaderboard
D_PUBLIC = 1914
# first day of the public leaderboard
D_PRIVATE = 1942
```

1) Preprocessing

Data concerns three main aspects:

- Prices

- Calendar
- Sales

In the following:

- data is extracted;
- data undergo downcasting (in order to reduce the memory storage);
- some columns are added or removed;
- data is stored in parquet format.

In [3]:
```
utils.extract_data()
```

```
data extracted
```

In [4]:
```
calendar, prices, sales = utils.read_data_csv()
```

Prices

The prices dataframe contains the price (`sell_price`) at which a product (`item_id`) is sold in a store (`store_id`) in a given week of a given year (`wm_yr_wk`).

In this dataframe, weeks start on Saturday and end on Friday.

In [5]:
```
prices.head()
```

Out[5]:

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

In [6]:
```
prices.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6841121 entries, 0 to 6841120
Data columns (total 4 columns):
 #   Column      Dtype  
---  ------      -----  
 0   store_id    object 
 1   item_id     object 
 2   wm_yr_wk    int64  
 3   sell_price  float64
dtypes: float64(1), int64(1), object(2)
memory usage: 208.8+ MB
```

In [7]:
```
# casting
prices['store_id'] = prices['store_id'].astype('category')
prices['item_id'] = prices['item_id'].astype('category')

prices['wm_yr_wk'] = prices['wm_yr_wk'].astype('int16')
prices['sell_price'] = prices['sell_price'].astype('float32')
```

In [8]:
```
# missing values check
print('Missing values:', prices.isna().any().any())
```

```
print('min week:', prices['wm_yr_wk'].min())
print('max week:', prices['wm_yr_wk'].max())
```

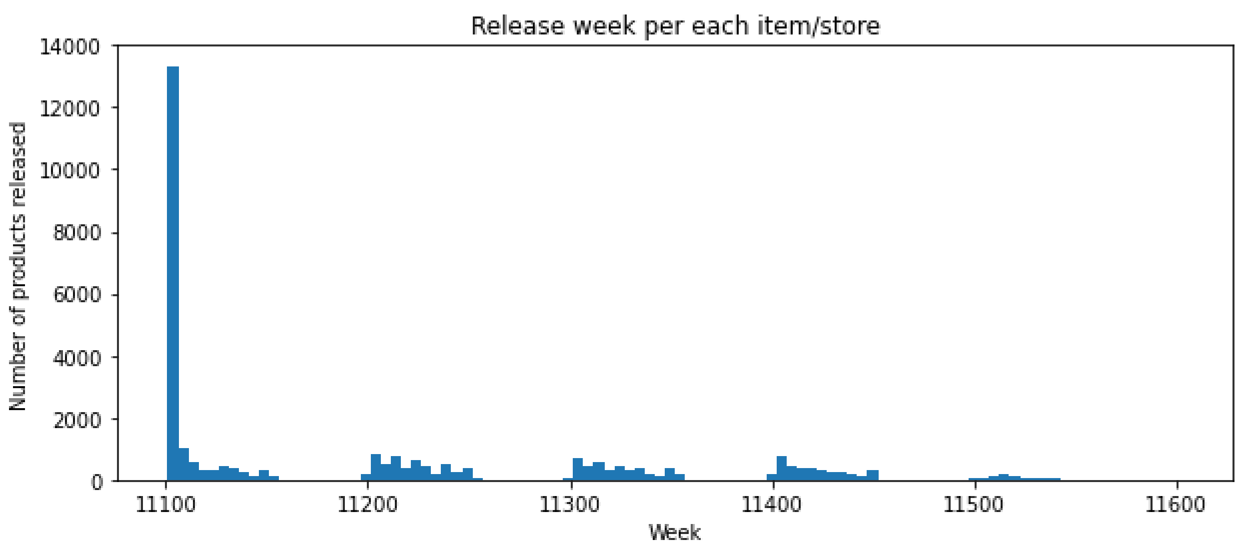
```
Missing values: False
min week: 11101
max week: 11621
```

Release

Not all products are released in the same period. However, most of them are available since the first year

In [9]:
```
plt.figure(figsize=(10,4))
releases = prices.groupby(['store_id','item_id'])['wm_yr_wk'].min()
plt.hist(releases, bins=100)
plt.xlabel('Week')
plt.ylabel('Number of products released')
plt.title('Release week per each item/store')
```

Out[9]:
```
Text(0.5, 1.0, 'Release week per each item/store')
```



Calendar

Calendar contains information about 1969 days from `29-01-2011` to `19-06-2016`.

In details, there are:

- `wm_yr_wk` : a code that identifies a week of a given year;
- `weekday`, `wday` : day of the week;
- `month`, `year` : month and year;
- `d` : day (1-1969);
- `event_name_N`, `event_type_N` : name and category of an event;
- `snap_XX` : presence of SNAP promotion in the state `XX`;

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

Out[10]:

	date	wm_yr_wk	weekday	wday	month	year	d	event_name_1	event_type_1	event_name_2	event_ty
0	2011-01-29	11101	Saturday	1	1	2011	d_1	NaN	NaN	NaN	
1	2011-01-30	11101	Sunday	2	1	2011	d_2	NaN	NaN	NaN	
2	2011-01-31	11101	Monday	3	1	2011	d_3	NaN	NaN	NaN	
3	2011-02-01	11101	Tuesday	4	2	2011	d_4	NaN	NaN	NaN	
4	2011-02-02	11101	Wednesday	5	2	2011	d_5	NaN	NaN	NaN	

In [11]:

```
calendar.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1969 entries, 0 to 1968
Data columns (total 14 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   date          1969 non-null   object
 1   wm_yr_wk      1969 non-null   int64 
 2   weekday       1969 non-null   object
 3   wday          1969 non-null   int64 
 4   month         1969 non-null   int64 
 5   year          1969 non-null   int64 
 6   d             1969 non-null   object
 7   event_name_1  162 non-null    object
 8   event_type_1  162 non-null    object
 9   event_name_2  5 non-null      object
 10  event_type_2  5 non-null      object
 11  snap_CA       1969 non-null   int64 
 12  snap_TX       1969 non-null   int64 
 13  snap_WI       1969 non-null   int64 
dtypes: int64(7), object(7)
memory usage: 215.5+ KB
```

In [12]:

```
# casting
calendar['date'] = calendar['date'].astype('datetime64')

calendar['wm_yr_wk'] = calendar['wm_yr_wk'].astype('int16')
calendar['month'] = calendar['month'].astype('int8')
calendar['year'] = calendar['year'].astype('int16')

# delete 'd_' prefix
calendar['d'] = calendar['d'].apply(lambda x: x[2:]).astype('int16')

calendar['snap_CA'] = calendar['snap_CA'].astype('int8')
calendar['snap_TX'] = calendar['snap_TX'].astype('int8')
calendar['snap_WI'] = calendar['snap_WI'].astype('int8')
```

In [13]:

```
calendar.describe(datetime_is_numeric=True)
```

Out[13]:

	date	wm_yr_wk	wday	month	year	d	snap_CA	snap_TX	
count	1969	1969.000000	1969.000000	1969.000000	1969.000000	1969.000000	1969.000000	1969.000000	196
mean	2013-10-09 00:00:00	11347.086338	3.997461	6.325546	2013.288471	985.000000	0.330117	0.330117	
min	2011-01-29 00:00:00	11101.000000	1.000000	1.000000	2011.000000	1.000000	0.000000	0.000000	
25%	2012-06-04 00:00:00	11219.000000	2.000000	3.000000	2012.000000	493.000000	0.000000	0.000000	
50%	2013-10-09 00:00:00	11337.000000	4.000000	6.000000	2013.000000	985.000000	0.000000	0.000000	
75%	2015-02-13 00:00:00	11502.000000	6.000000	9.000000	2015.000000	1477.000000	1.000000	1.000000	
max	2016-06-19 00:00:00	11621.000000	7.000000	12.000000	2016.000000	1969.000000	1.000000	1.000000	
std	NaN	155.277043	2.001141	3.416864	1.580198	568.545659	0.470374	0.470374	

Events

Some day have more than one event. Since these days are only 5, `event_name_2` and `event_type_2` are removed

In [14]:
```
calendar[calendar.columns[7:11]].describe()
```

Out[14]:

	event_name_1	event_type_1	event_name_2	event_type_2
count	162	162	5	5
unique	30	4	4	2
top	SuperBowl	Religious	Father's day	Cultural
freq	6	55	2	4

In [15]:
```
calendar.drop(columns=['event_name_2', 'event_type_2'], inplace=True)
```

In [16]:
```
# fill empty event records
calendar['event_name_1'].fillna('no_event', inplace=True)
calendar['event_type_1'].fillna('no_event', inplace=True)

calendar['event_name_1'] = calendar['event_name_1'].astype('category')#.astype('int8')
calendar['event_type_1'] = calendar['event_type_1'].astype('category')#.astype('int8')
```

new columns

In [17]:
```
# day of the week, from 0 (monday) to 6 (sunday)
calendar.insert(3, 'dayofweek', calendar['date'].dt.dayofweek.astype('int8'))
# day of the month, 1-31
calendar.insert(4, 'dayofmonth', calendar['date'].dt.day.astype('int8'))
# day of the year, 1-366
```

```python
calendar.insert(5, 'dayofyear', calendar['date'].dt.dayofyear.astype('int16'))
# week in the month, 1-5
calendar.insert(2, 'weekofmonth',calendar['dayofmonth'].apply(lambda x: (x - 1) // 7 + 1
# week in the year, 1-53
calendar.insert(3, 'weekofyear', (calendar['wm_yr_wk'] % 100).astype('int8'))
```

In [18]:
```python
# align non-bisestile year to bisestile year
idx = calendar[(calendar['year'].isin([2011,2013,2014,2015])) & (calendar['dayofyear']>3
calendar.loc[idx, 'dayofyear'] +=1
```

In [19]:
```python
# check no missing values in the 'date' column
(calendar['date'][1:].reset_index(drop=True) - calendar['date'][:-1]).value_counts()
```

Out[19]:
```
1 days    1968
Name: date, dtype: int64
```

In [20]:
```python
print('date min:', calendar['date'].min().date())
print('date max:', calendar['date'].max().date())
```

```
date min: 2011-01-29
date max: 2016-06-19
```

In [21]:
```python
calendar.drop(columns=['weekday', 'wday', 'date'], inplace=True)
calendar.set_index('d', inplace=True)
```

In [22]:
```python
calendar
```

Out[22]:

d	wm_yr_wk	weekofmonth	weekofyear	dayofweek	dayofmonth	dayofyear	month	year	event_name_1
1	11101	5	1	5	29	29	1	2011	no_event
2	11101	5	1	6	30	30	1	2011	no_event
3	11101	5	1	0	31	31	1	2011	no_event
4	11101	1	1	1	1	32	2	2011	no_event
5	11101	1	1	2	2	33	2	2011	no_event
...	...	...	...	...	...	...	...	...	...
1965	11620	3	20	2	15	167	6	2016	no_event
1966	11620	3	20	3	16	168	6	2016	no_event
1967	11620	3	20	4	17	169	6	2016	no_event
1968	11621	3	21	5	18	170	6	2016	no_event
1969	11621	3	21	6	19	171	6	2016	NBAFinalsEnd

1969 rows × 13 columns

Sales

In the directory there are two datasets:

- `sales_train_validation` : historical daily unit sales per product and store in $[d_1; d_{1913}]$, in which the last 28 days represent the **input** for the **public** leaderboard;
- `sales_train_evaluation` : historical daily unit sales per product and store in $[d_1; d_{1941}]$, in which the last 28 days represent both:

- the **label** for the **public** leaderboard and
- the **input** for the **private** leaderboard.

In the following, only the last dataframe is used.

In [23]:
```
sales.head()
```

Out[23]:

	id	item_id	dept_id	cat_id	store_id	state_id	d_1	d_2	d_3	d_4	...
0	HOBBIES_1_001_CA_1_evaluation	HOBBIES_1_001	HOBBIES_1	HOBBIES	CA_1	CA	0	0	0	0	...
1	HOBBIES_1_002_CA_1_evaluation	HOBBIES_1_002	HOBBIES_1	HOBBIES	CA_1	CA	0	0	0	0	...
2	HOBBIES_1_003_CA_1_evaluation	HOBBIES_1_003	HOBBIES_1	HOBBIES	CA_1	CA	0	0	0	0	...
3	HOBBIES_1_004_CA_1_evaluation	HOBBIES_1_004	HOBBIES_1	HOBBIES	CA_1	CA	0	0	0	0	...
4	HOBBIES_1_005_CA_1_evaluation	HOBBIES_1_005	HOBBIES_1	HOBBIES	CA_1	CA	0	0	0	0	...

5 rows × 1947 columns

In [24]:
```
sales.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30490 entries, 0 to 30489
Columns: 1947 entries, id to d_1941
dtypes: int64(1941), object(6)
memory usage: 452.9+ MB
```

In [25]:
```
# rename day columns by deleting 'd_'
sales.rename(columns={x: x[2:] for x in sales.columns[6:]}, inplace=True)

# casting
cols = sales.columns.tolist()
sales_1 = sales[cols[:6]].astype('category')
sales_2 = sales[cols[6:]].astype('int16')
sales = pd.concat([sales_1, sales_2], axis=1)

# delete 'evaluation' suffix
sales['id'] = sales['id'].apply(lambda x: x[:-11])

del sales_1, sales_2, cols
```

In [26]:
```
sales.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30490 entries, 0 to 30489
Columns: 1947 entries, id to 1941
dtypes: category(6), int16(1941)
memory usage: 114.4 MB
```

Write on disk

In [27]:
```
dst = '../processed/'

if not os.path.exists(dst):
        os.makedirs(dst)

# save data
prices.to_parquet(dst + '/m5_prices.pqt')
calendar.to_parquet(dst + '/m5_calendar.pqt')
sales.to_parquet(dst + '/m5_sales.pqt')
```

2) Data exploration

In [28]:
```
calendar, prices, sales = utils.read_data_pqt()
```

In [29]:
```
%%time
# remove zeros sales before release date
df = preprocessing.remove_leading_zeros(sales, calendar)
```

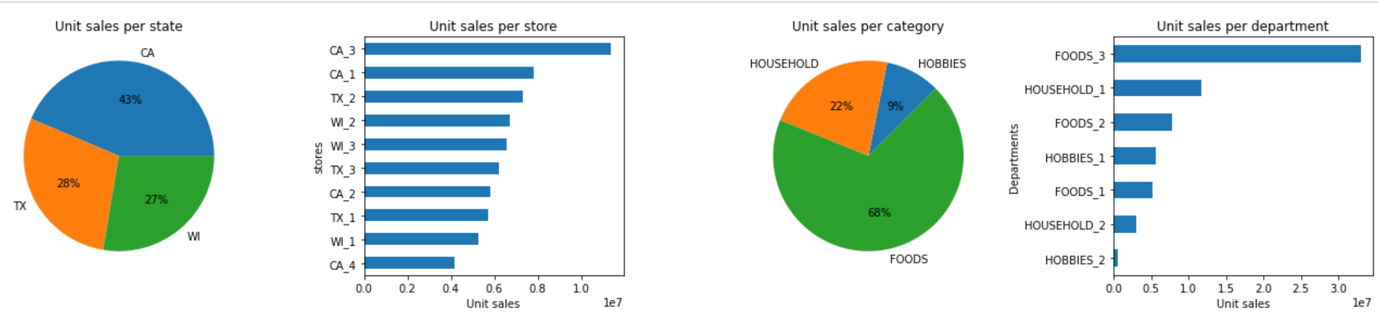
```
CPU times: total: 37.2 s
Wall time: 37.4 s
```

Unit sales per state, store, category and departments

It is possible to notice that the unit sales are **not** uniformly distributed among states, store, category and departments.

- Sales in `CA` represent more than 40% of the total.
- In California there is both the store with the highest amount of sales (`CA_3`) and the store with the lowest amount (`CA_1`).
- About 70% of the total sales comes from `FOODS` products, of which `FOODS_3` represents the major part.

In [30]:
```
fig, ax = plt.subplots(1, 4, figsize=(18, 4))

# flatten
#ax = [cell for row in ax for cell in row]

df.groupby('state_id')['sales'].sum().plot.pie(ax=ax[0], autopct='%d%%')
ax[0].set_title('Unit sales per state')
ax[0].set_ylabel('')

df.groupby('store_id')['sales'].sum().sort_values().plot.barh(ax=ax[1]) #barh(figsize=(6
ax[1].set_title('Unit sales per store')
ax[1].set_ylabel('stores')
ax[1].set_xlabel('Unit sales')

df.groupby('cat_id')['sales'].sum().sort_values().plot.pie(ax=ax[2], startangle=45, auto
ax[2].set_title('Unit sales per category')
ax[2].set_ylabel('')

df.groupby('dept_id')['sales'].sum().sort_values().plot.barh(ax=ax[3])
ax[3].set_xlabel('Unit sales')
ax[3].set_ylabel('Departments')
ax[3].set_title('Unit sales per department')

fig.tight_layout()
```



In [31]:
```
df.groupby(['d', 'cat_id'])['sales'].sum().unstack().plot(figsize=(15,5))
plt.title('Total unit sales per category since 2011')
```

```
plt.xlabel('Days')
plt.ylabel('Unit sales')
```

Out[31]: Text(0, 0.5, 'Unit sales')

In [32]:
```
categories = df['cat_id'].unique()
fig, ax = plt.subplots(len(categories), 1, sharex=True, figsize=(15,8))

for i, c in enumerate(categories):
    df[df['cat_id']==c].groupby(['d', 'dept_id'], observed=True)['sales'].mean().unstack

    ax[i].set_title(f'{c} unit sales per department')
    ax[i].set_xlabel('Days')
    ax[i].set_ylabel('Average unit sales')


plt.suptitle('Average unit sales per category and department', y=0.95, fontsize='x-large
```

Out[32]: Text(0.5, 0.95, 'Average unit sales per category and department')

Similarities across stores, departments

There are similarities both:

- in each **department**, across different states/stores, meaning that similar products behave in a similar manner,
- and in each **store**, across products belonging to different departments, meaning that there are local pattern.

In [33]:

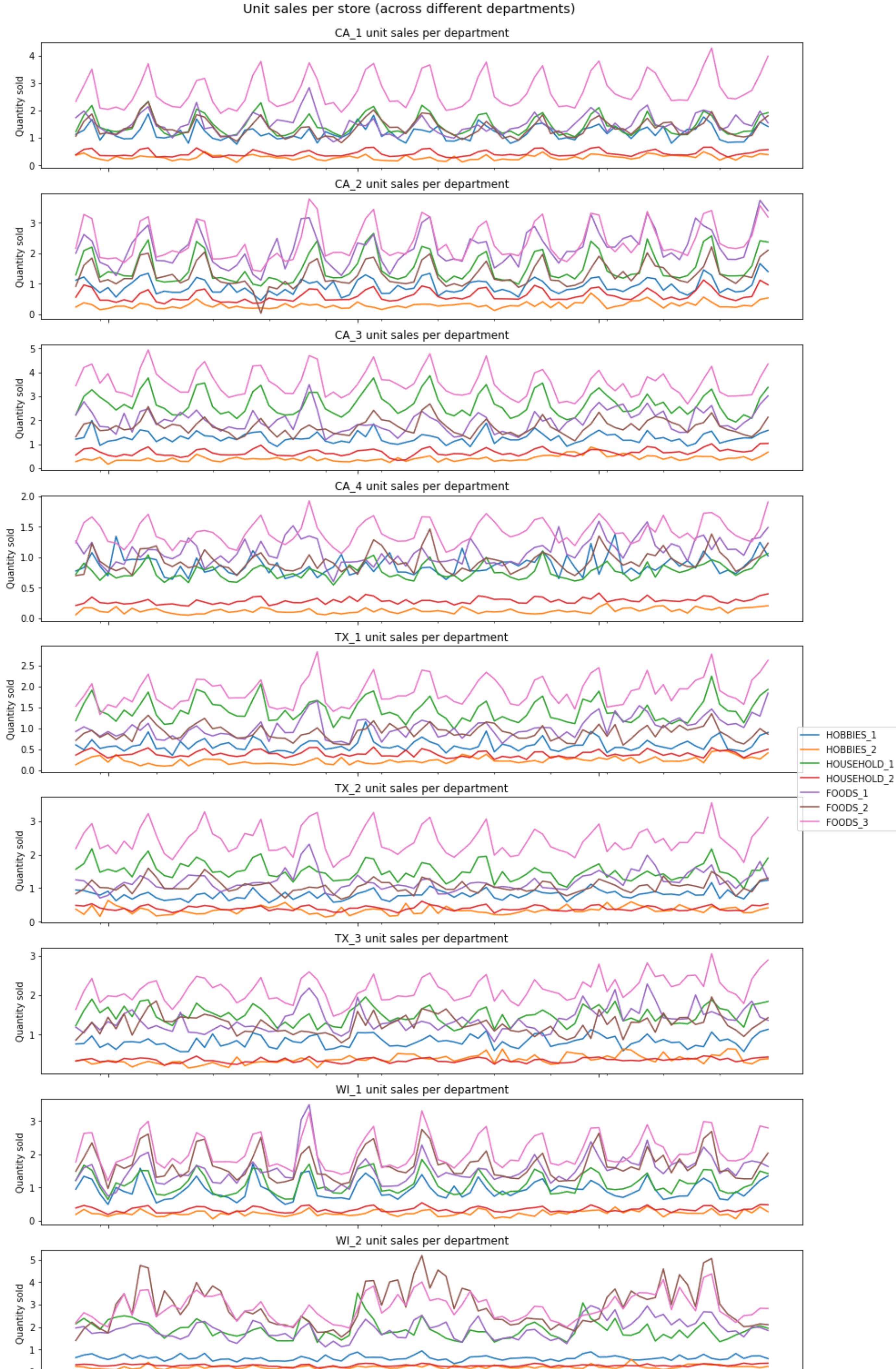
```
%%capture

idx = np.arange(D_PUBLIC - 60, D_PRIVATE).tolist()

# minor ticks every monday
minor_ticks = calendar.loc[idx][calendar['dayofweek'] == 0].index.tolist()
# major ticks every first day of month
major_ticks = calendar.loc[idx][calendar['dayofmonth'] == 1].index.tolist()
```

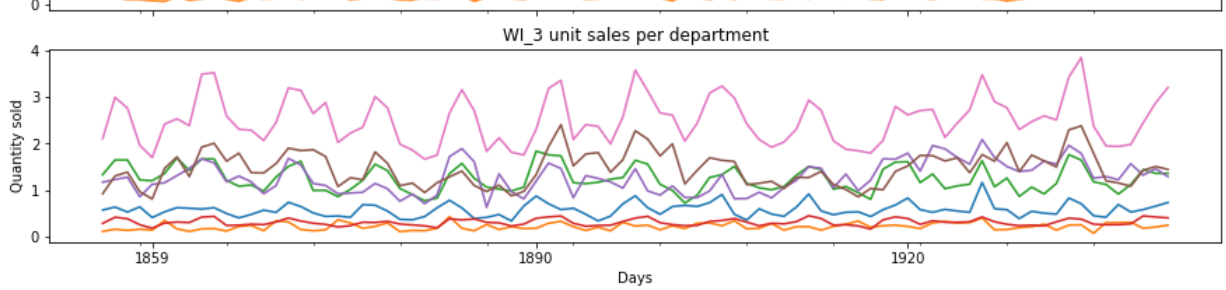
In [34]:

```
stores = df['store_id'].unique()
fig, ax = plt.subplots(10, 1, sharex=True, sharey=False, figsize=(15, 30))

for i, s in enumerate(stores):
    df[(df['store_id'] == s) & (df['d'] > D_PUBLIC-60)].groupby(['d', 'dept_id'], observ

    ax[i].get_legend().remove()
    ax[i].set_title(f'{s} unit sales per department')
    ax[i].set_xlabel('Days')
    ax[i].set_ylabel('Quantity sold')
    ax[i].set_xticks(minor_ticks, minor=True)
    ax[i].set_xticks(major_ticks, minor=False)

handles, labels = ax[-1].get_legend_handles_labels()
fig.legend(handles, labels, loc='right')
plt.suptitle('Unit sales per store (across different departments)', y=0.9, fontsize='x-l
```

Out[34]:

```
Text(0.5, 0.9, 'Unit sales per store (across different departments)')
```


Unit sales per store (across different departments)
CA_1 unit sales per department
CA_2 unit sales per department
CA_3 unit sales per department
CA_4 unit sales per department
TX_1 unit sales per department
TX_2 unit sales per department
TX_3 unit sales per department
WI_1 unit sales per department
WI_2 unit sales per department
Quantity sold
HOBBIES_1
HOBBIES_2
HOUSEHOLD_1
HOUSEHOLD_2
FOODS_1
FOODS_2
FOODS_3

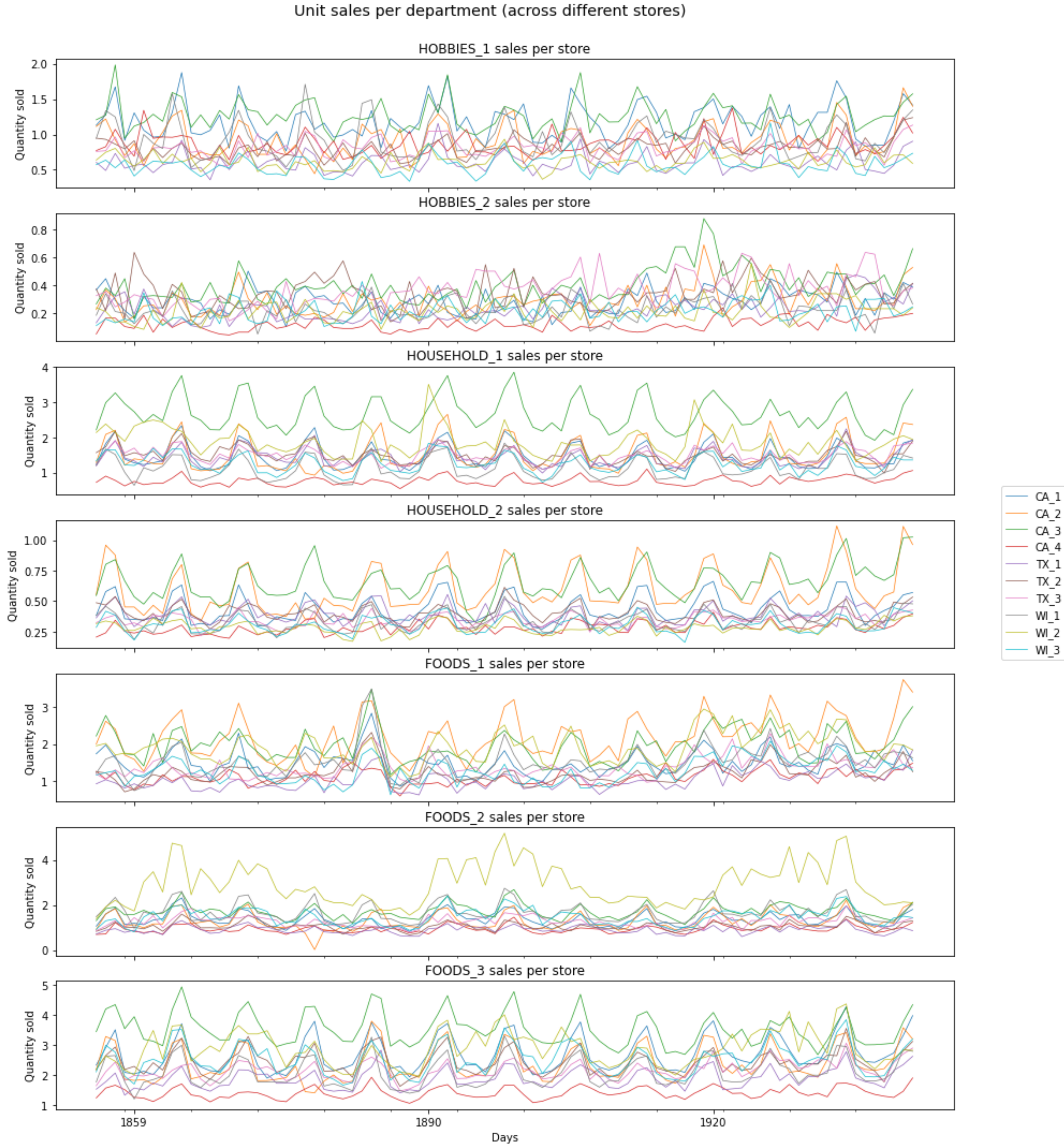


In [35]:

```
departments = df['dept_id'].unique()

fig, ax = plt.subplots(len(departments), sharex=True, sharey=False, figsize=(15, 18))

for i, d in enumerate(departments):
    df[(df['dept_id'] == d) & (df['d'] > D_PUBLIC-60)].groupby(['d', 'store_id'])['sales
        .plot(linewidth=0.7, ax=ax[i])

    ax[i].get_legend().remove()
    ax[i].set_title(f'{d} sales per store')
    ax[i].set_xlabel('Days')
    ax[i].set_ylabel('Quantity sold')
    ax[i].set_xticks(minor_ticks, minor=True)
    ax[i].set_xticks(major_ticks, minor=False)

handles, labels = ax[-1].get_legend_handles_labels()
fig.legend(handles, labels, loc='right')

plt.suptitle('Unit sales per department (across different stores)', y=0.92, fontsize='x-
```

Out[35]:

```
Text(0.5, 0.92, 'Unit sales per department (across different stores)')
```



Categories across stores

By looking at whole timeseries (since 2011) per each store, it is possible to notice:

- some seasonal patterns (that will be covered in the next sessions)
- some periods which differ a lot from the general behaviour of the timeseries. These periods will be removed.

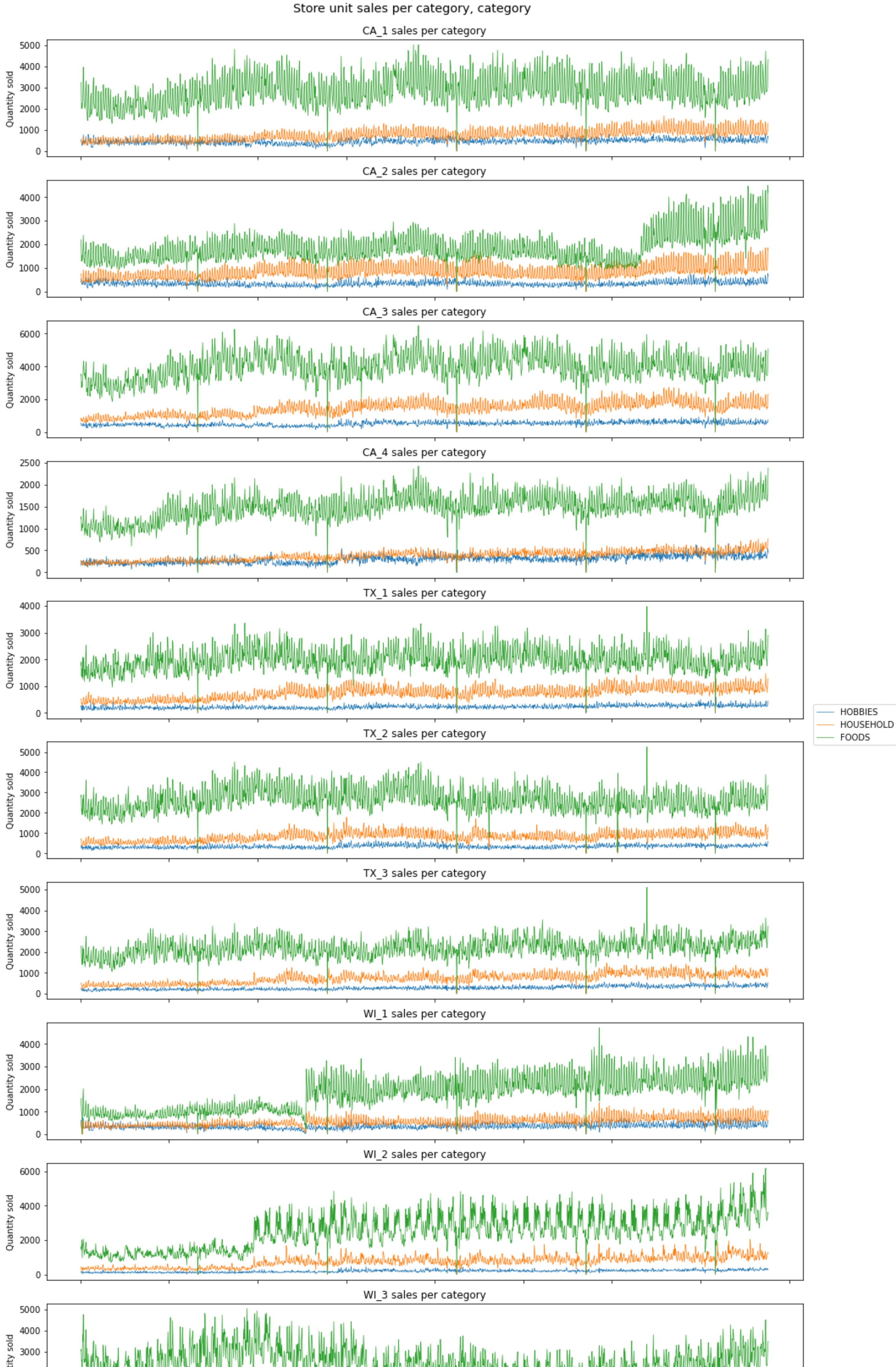
In [36]:

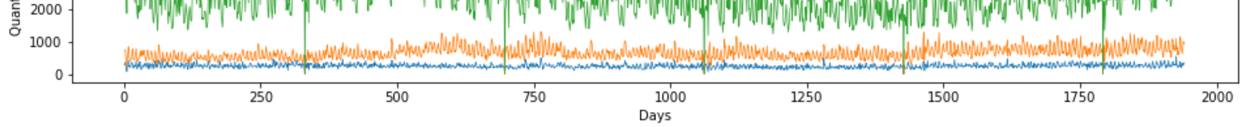
```
fig, ax = plt.subplots(10, 1, sharex=True, figsize=(16,30))


for i, s in enumerate(df['store_id'].unique()):
    df[df['store_id']==s].groupby(['d', 'cat_id'], observed=True)['sales'].sum().unstack

    ax[i].get_legend().remove()
```

```python
    ax[i].set_title(f'{s} sales per category')
    ax[i].set_xlabel('Days')
    ax[i].set_ylabel('Quantity sold')

handles, labels = ax[-1].get_legend_handles_labels()
fig.legend(handles, labels, loc='right')

plt.suptitle('Store unit sales per category, category', y=0.9, fontsize='x-large')
```

Out[36]:

```
Text(0.5, 0.9, 'Store unit sales per category, category')
```


Store unit sales per category, category
CA_1 sales per category
CA_2 sales per category
CA_3 sales per category
CA_4 sales per category
TX_1 sales per category
TX_2 sales per category
TX_3 sales per category
WI_1 sales per category
WI_2 sales per category
WI_3 sales per category
Quantity sold
HOBBIES
HOUSEHOLD
FOODS

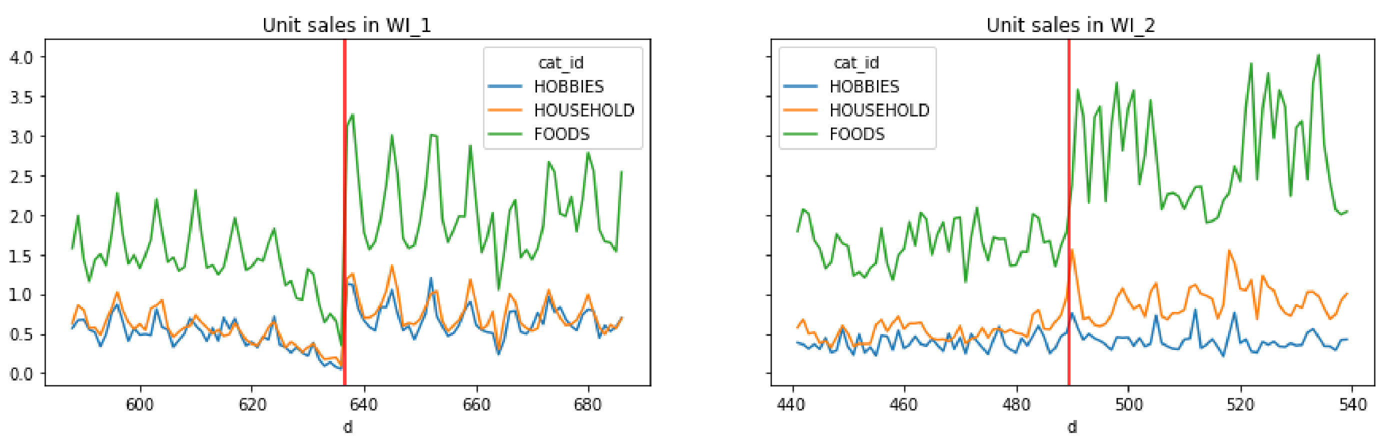


Detail

- Sales in **WI_1** are sensibily lower before day 637, and they drop down near that date
- Sales in **WI_2** are sensibly lower before day 490, and it looks like they do not show the seasonal pattern present in the successive years

In [37]:
```
fig, ax = plt.subplots(1,2, sharey=True, figsize=(15, 4))

d = 637
df[(df['store_id']=='WI_1') & (df['d']>d-50) & (df['d']<d+50)] \
    .groupby(['d', 'cat_id'], observed=True)['sales'].mean().unstack().plot(ax=ax[0])
ax[0].axvline(d-0.5, 0, 1, color='red')
ax[0].set_title('Unit sales in WI_1')

d = 490
df[(df['store_id']=='WI_2') & (df['d']>d-50) & (df['d']<d+50)] \
    .groupby(['d', 'cat_id'], observed=True)['sales'].mean().unstack().plot(ax=ax[1])
ax[1].axvline(d-0.5, 0, 1, color='red')
ax[1].set_title('Unit sales in WI_2')
```

Out[37]:
```
Text(0.5, 1.0, 'Unit sales in WI_2')
```



Seasonality

Year, Month

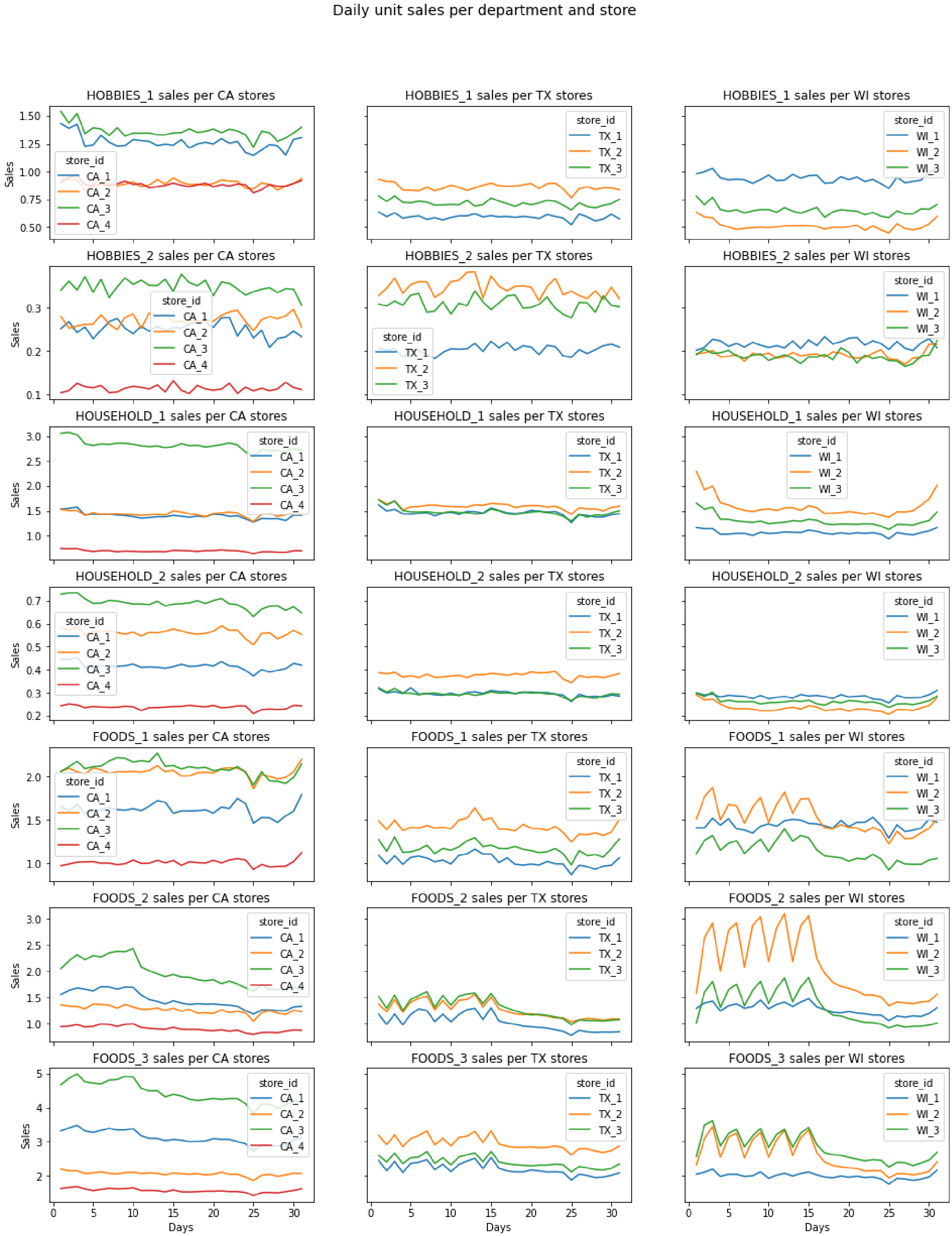
In [38]:
```
categories = df['cat_id'].unique()
states = df['state_id'].unique()

fig, ax = plt.subplots(len(categories), len(states), sharex=True, sharey='row', figsize=
ax = [cell for row in ax for cell in row]

for i, c in enumerate(categories):
    data = df[(df['cat_id']==c) & (df['d']>3)]
    for j, s in enumerate(states):
        k = 3*i+j
        data[data['state_id']==s].groupby(['month', 'year'], observed=True)['sales'].mea
        ax[k].get_legend().remove()
        ax[k].set_title(f'Average {c} unit sales in {s}')
        ax[k].set_xlabel('Months')
        ax[k].set_ylabel('Average unit sales')
```

```
handles, labels = ax[-1].get_legend_handles_labels()
fig.legend(handles, labels, loc='right')

plt.suptitle('Monthly Average sales per category and state', y=0.95, fontsize='x-large')

del data
```

Day of month

- FOODS_2 , FOODS_3 products are generally higher in the first half of the month.
  - This situation is enhanced in WI_2 , WI_3 , where there is an evident pattern.
- The day of month seems almost irrilevant for HOBBIES and HOUSEHOLD products.

In [39]:
```
departments = df['dept_id'].unique()
states = df['state_id'].unique()

fig, ax = plt.subplots(len(departments), len(states), sharex=True, sharey='row', figsize

for i, d in enumerate(departments):
    data = df[df['dept_id']==d]
    for j, s in enumerate(states):
        data[data['state_id']==s].groupby(['dayofmonth', 'store_id'], observed=True)['sa

        ax[i][j].set_title(f'{d} sales per {s} stores')
        ax[i][j].set_xlabel('Days')
        ax[i][j].set_ylabel('Sales')

plt.suptitle('Daily unit sales per department and store', y=0.95, fontsize='x-large')

del data
```

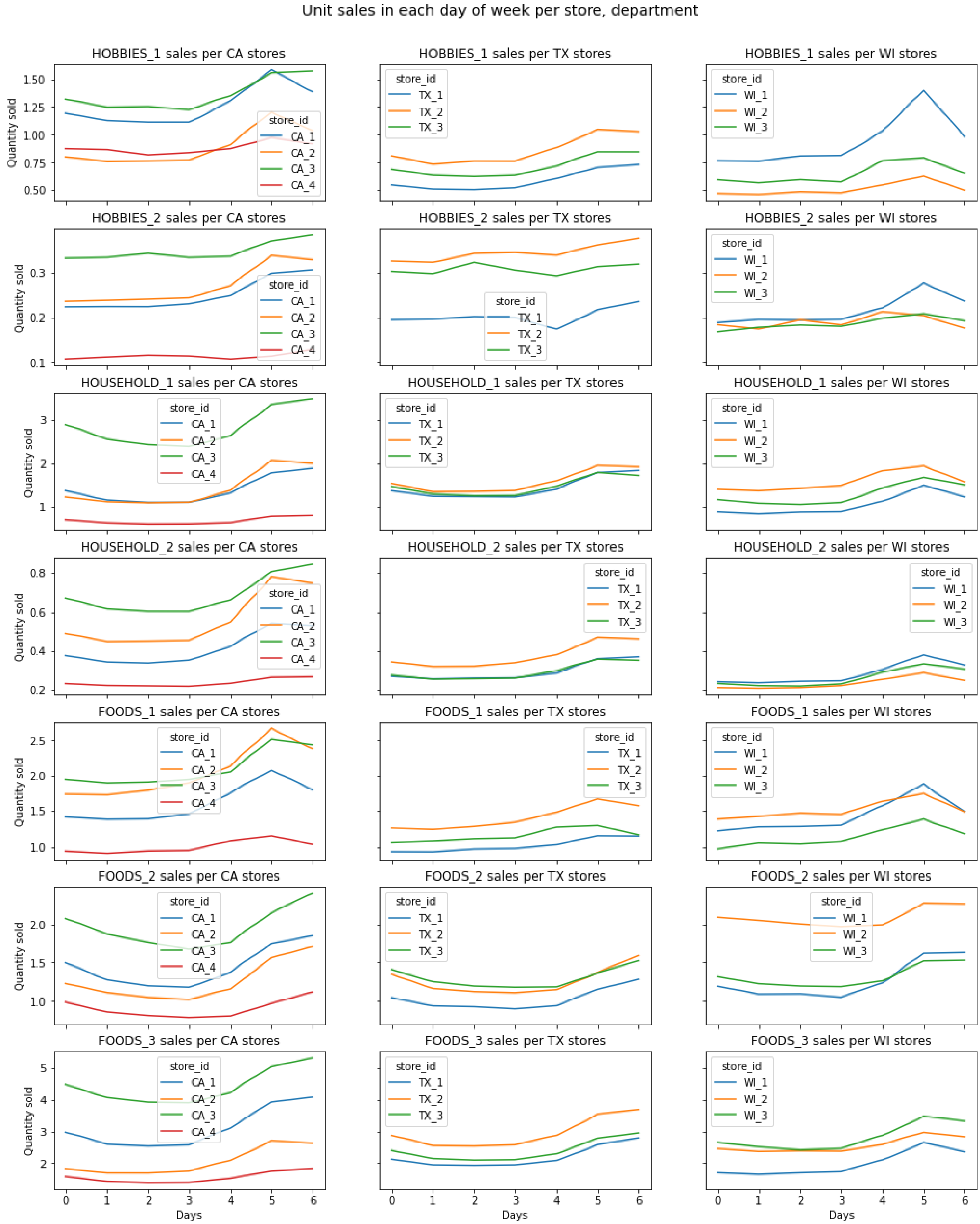


Day of week

All departments and stores have higher sales in the weekends

In [40]:
```
departments = df['dept_id'].unique()
states = df['state_id'].unique()
```

```
fig, ax = plt.subplots(len(departments), len(states), sharex=True, sharey='row', figsize

for i, d in enumerate(departments):
    data = df[df['dept_id']==d]
    for j, s in enumerate(states):
        data[data['state_id']==s].groupby(['dayofweek', 'store_id'], observed=True)['sal

        ax[i][j].set_title(f'{d} sales per {s} stores')
        ax[i][j].set_xlabel('Days')
        ax[i][j].set_ylabel('Quantity sold')

plt.suptitle('Unit sales in each day of week per store, department', y=0.92, fontsize='x

del data
```



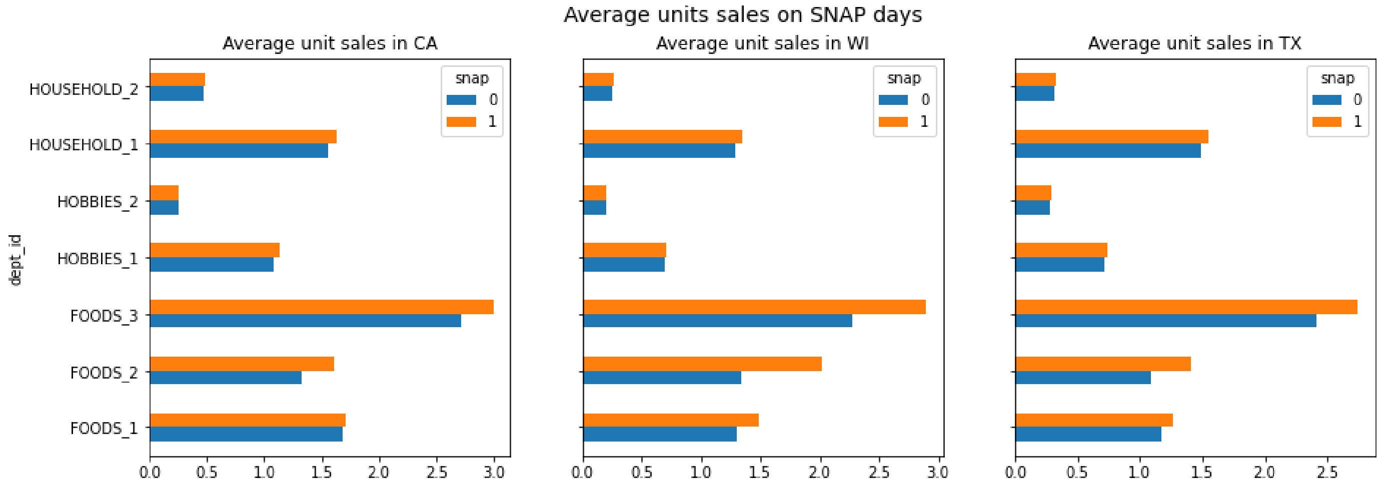
SNAP days

- Average unit sales are usually slightly higher on SNAP days, especially for `FOODS` products.
- `WI` is the state that benefits more from SNAP promotions.

In [41]:
```
states = ['CA', 'WI', 'TX']
fig, ax = plt.subplots(1, len(states), figsize=(15, 5), sharey=True)

for i, s in enumerate(states):
```

```
    df[df['state_id']==s].groupby(['dept_id', 'snap'])['sales'].mean().unstack().plot.ba
    ax[i].set_title(f'Average unit sales in {s}')

plt.suptitle('Average units sales on SNAP days', fontsize='x-large')
```

Out[41]: `Text(0.5, 0.98, 'Average units sales on SNAP days')`



Event days

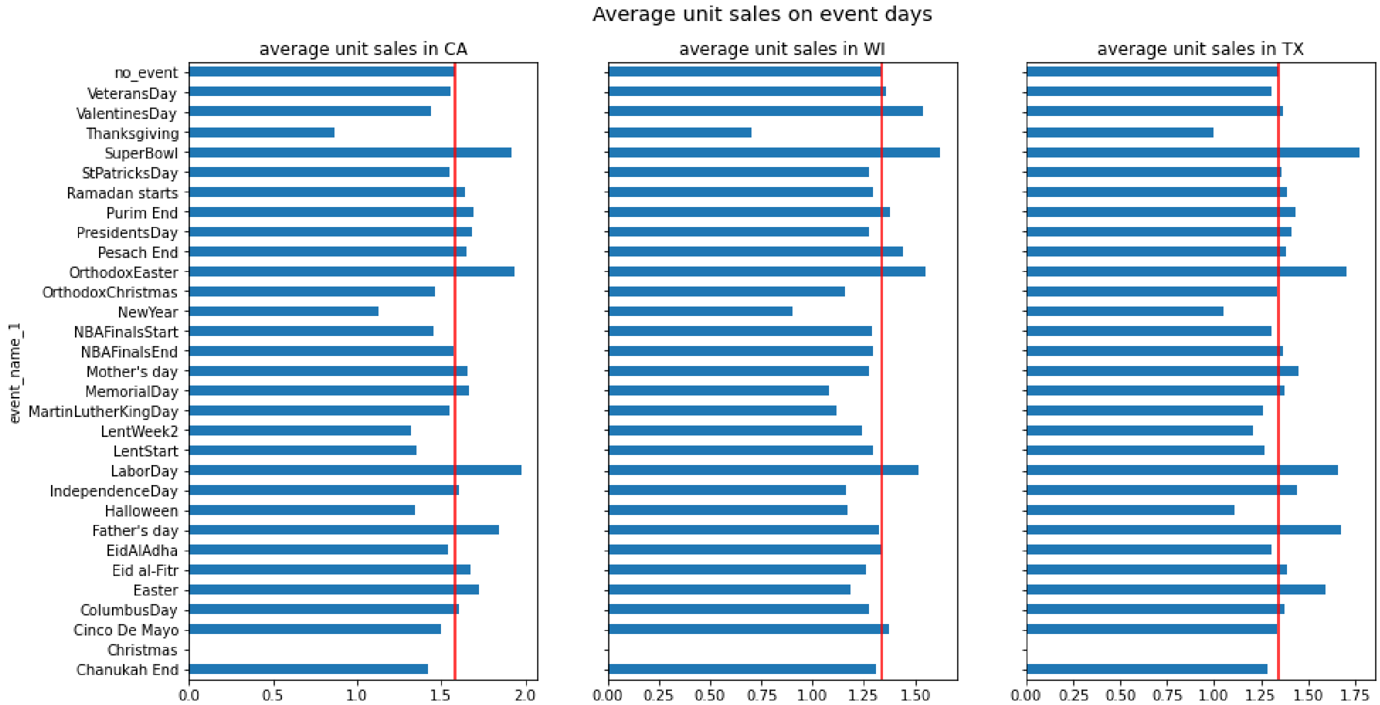
The presence of an event influences the sales. The red line shows the average unit sales on no-event days.

The behaviour is slightly different across the states, but it is possible to outline that:

- in some occasions such as `SuperBowl`, `OrthodoxEaster` and `LaborDay` sales are higher than the average
- On other days, such as `Thanksgiving` or `NewYear`, sales are lower, instead.
- On `Christmas` sales are zero since stores are closed.

In [42]:
```
states = ['CA', 'WI', 'TX']
fig, ax = plt.subplots(1, len(states), figsize=(15, 8), sharey=True)

for i, s in enumerate(states):
    tmp = df[df['state_id']==s].groupby('event_name_1')['sales'].mean()
    tmp.plot.barh(ax=ax[i])
    ax[i].axvline(tmp['no_event'], color='red')
    ax[i].set_title(f'average unit sales in {s}')

plt.suptitle('Average unit sales on event days', y=0.95, fontsize='x-large')
del tmp
```

Out[42]: `Text(0.5, 0.95, 'Average unit sales on event days')`



Autocorrelation

Autocorrelation is computed in order to find possible lag values that may be useful in making predictions.

For most of departments/stores, lag 7 (and its multiples) are the most relevant, but there are few exceptions:

- no/little correlation:
  - `FOODS_1` in `WI_2`, `CA_4`;
  - `HOBBIES_1` in `WI_2`, `CA_4`;
  - `HOBBIES_2` (all stores);
  - `HOUSEHOLD_2` in `WI_2`, `CA_4`,
- lag 28 or 30 more relevant than lag 7:
  - `FOODS_2` in `CA_3`, `TX_1`, `TX_3`, `WI_2`, `WI_3`;
  - `FOODS_3` in `WI_2`.

In [43]:
```python
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
```

In [44]:
```python
# average sales of product in the same department and store in different days
df2 = df.groupby(['dept_id', 'store_id', 'd'], as_index=False)['sales'].mean()
```

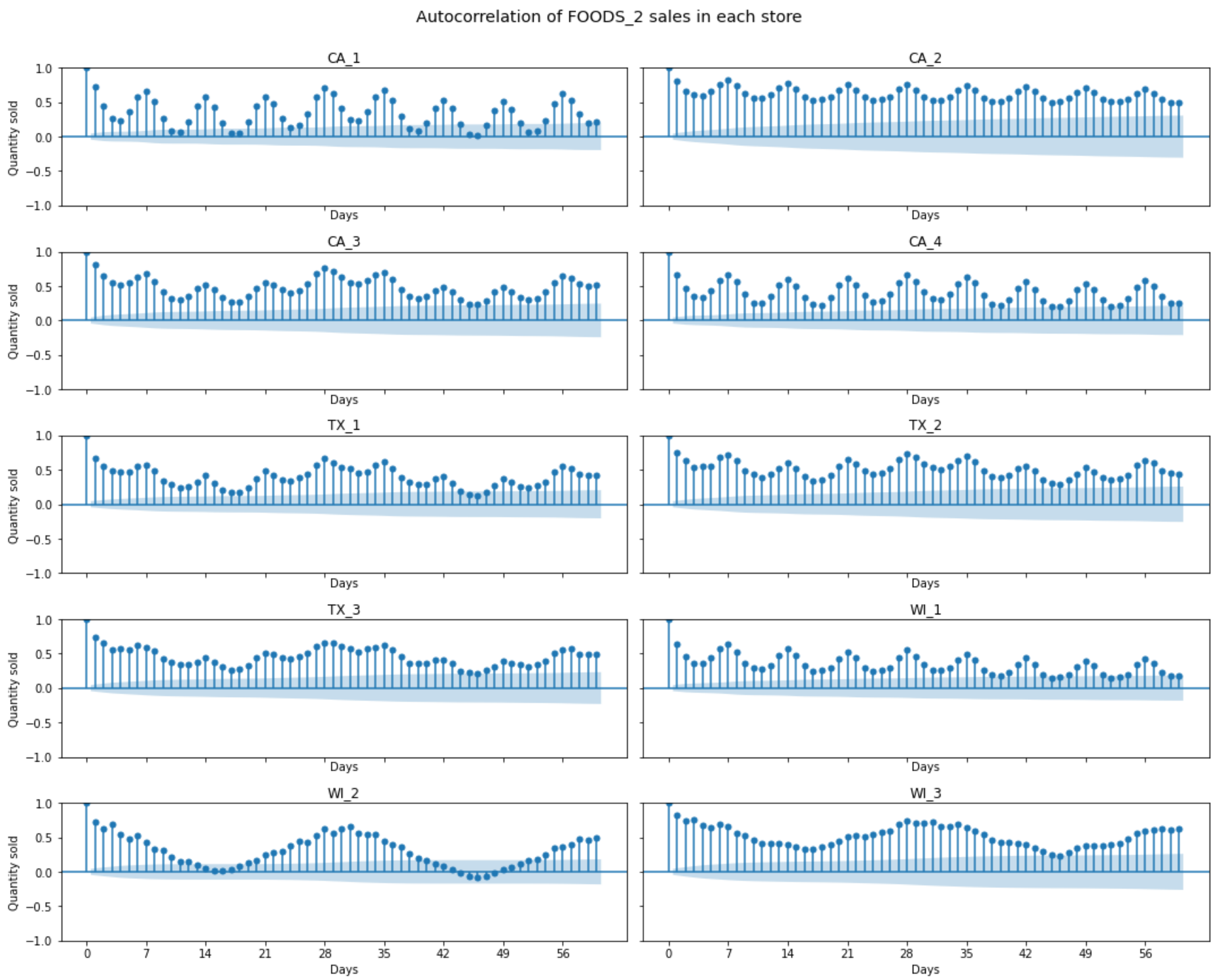
In [45]:
```python
df2.head()
```

Out[45]:

	dept_id	store_id	d	sales
0	FOODS_1	CA_1	1	4.242857
1	FOODS_1	CA_1	2	3.302326
2	FOODS_1	CA_1	3	2.431818
3	FOODS_1	CA_1	4	1.923077
4	FOODS_1	CA_1	5	1.936170

In [46]:
```python
departments = df2['dept_id'].unique()
stores = df2['store_id'].unique()
```

```
lags = 60

fig, ax = plt.subplots(5, 2, sharex=True, sharey=True, figsize=(15, 12))

ax = [cell for row in ax for cell in row]

cur_dept = departments[1] # change to select another department

data = df2[df2['dept_id']==cur_dept]

for i, s in enumerate(stores):
    plot_acf(data[data['store_id']==s]['sales'], ax=ax[i], lags=lags)

    ax[i].set_title(f'{s}')
    ax[i].set_xlabel('Days')
    if not(i % 2):
        ax[i].set_ylabel('Quantity sold')
    ax[i].set_xticks(np.arange(0, lags, 7))

plt.suptitle(f'Autocorrelation of {cur_dept} sales in each store', y=1, fontsize='x-larg
plt.tight_layout()
del data
```



3) Feature engineering

Compute new features starting from available information

In [47]:
```
if 'df' in globals():
    del df

if 'df2' in globals():
    del df2
```

In [49]:
```
calendar, prices, sales = utils.read_data_pqt()

prices['sell_price'] = prices['sell_price'].astype('float16')
```

In [55]:
```
%%time

# change to select another state
cur_state = 'WI' #'CA', 'TX', 'WI'

df = sales[(sales['state_id']==cur_state)]
df.reset_index(drop=True, inplace=True)

df = preprocessing.add_days(df)
df = preprocessing.remove_leading_zeros(df, calendar)

if cur_state == 'WI':
    df = df[(df['store_id']!='WI_1') | (df['d']>636)]
    df = df[(df['store_id']!='WI_2') | (df['d']>489)]
    df.reset_index(inplace=True, drop=True)

fe.compute_and_save_products(df, cur_state)
fe.compute_and_save_prices(df, prices, cur_state)
fe.compute_and_save_sales(df)
```

```
Saving products...
Computing prices...
Computing sales...
CPU times: total: 3min 25s
Wall time: 3min 25s
```

4) Model Implementation

In [ ]:
```
D_MAX = df['d'].max()
D_MIN = df['d'].min()
D_PRIVATE = D_MAX - 28 + 1 # 1942 - 1969
D_PUBLIC = D_PRIVATE - 28 # 1914 - 1941

print(f'Training range:\t {D_MIN} - {D_PRIVATE - 1}')
print(f'Evaluation range: {D_PRIVATE} - {D_MAX}')
```

In [57]:
```
if 'prices' in globals():
    del prices
if 'calendar' in globals():
    del calendar
if 'sales' in globals():
    del sales
if 'df' in globals():
    del df
```

Load dataframe related to a specific store

In [377…
```
cur_store = 'WI_3' # change to select a different store
```

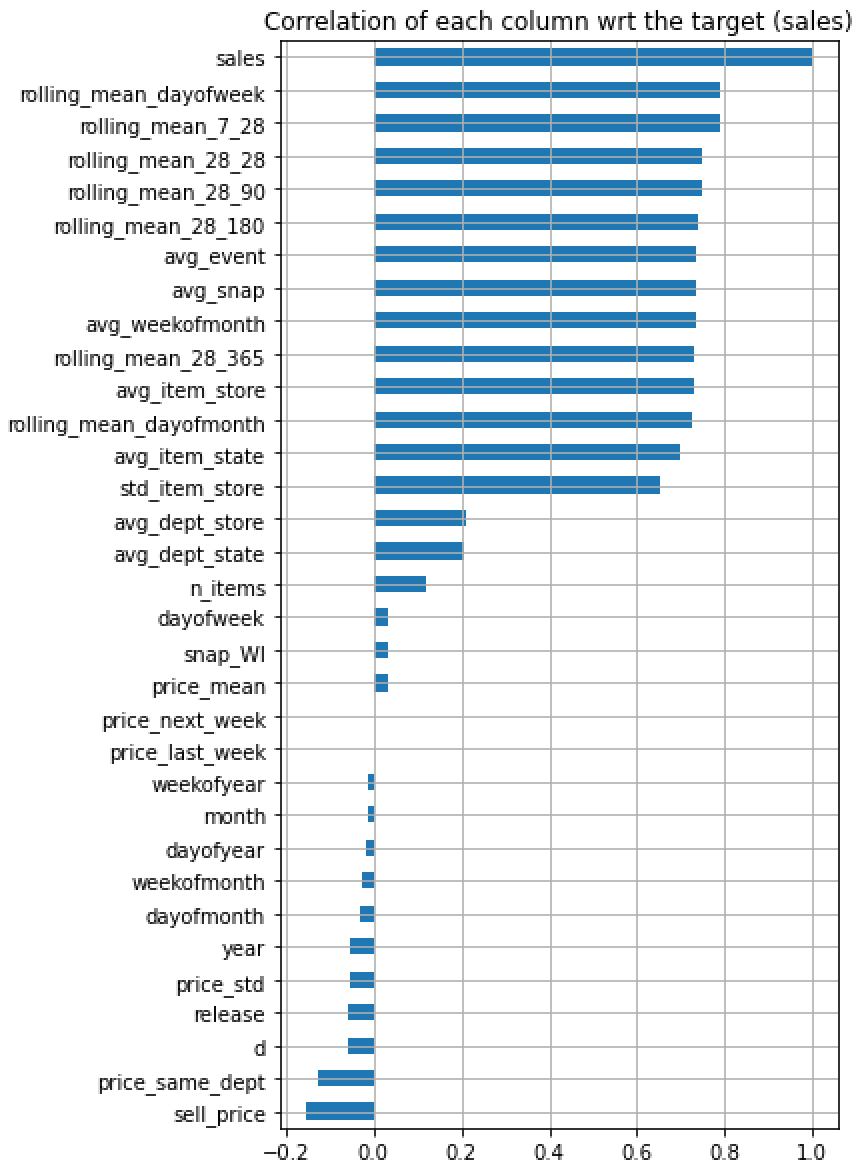
In [378…
```
df = utils.load_df(cur_store)
```

In [379…
```
df.drop(columns=['store_id', 'state_id', 'wm_yr_wk'], inplace=True)
```

Correlation

Correlation of each column wrt the label (`sales`)

In [380…
```
corr = df.corrwith(df['sales']).sort_values()
corr.plot.barh(figsize=(5, 10))
plt.grid(True)
plt.title('Correlation of each column wrt the target (sales)')

del corr
```



In [381…
```
df.head()
```

Out[381]:

	id	d	sales	rolling_mean_dayofweek	rolling_mean_7_28	rolling_mean_28_28	rolling_mean_
0	HOBBIES_1_002_WI_3	338	0.0	1.000000	1.500000	0.678711	0.5
1	HOBBIES_1_004_WI_3	338	0.0	2.333984	2.535156	2.357422	2.0
2	HOBBIES_1_005_WI_3	338	2.0	1.666992	2.892578	2.322266	2.1
3	HOBBIES_1_008_WI_3	338	0.0	3.500000	4.355469	5.035156	3.6
4	HOBBIES_1_009_WI_3	338	2.0	1.666992	1.428711	1.142578	0.9

5 rows × 39 columns

In [382...

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4312966 entries, 0 to 4312965
Data columns (total 39 columns):
 #   Column                  Dtype
---  ------                  -----
 0   id                      category
 1   d                       int16
 2   sales                   float16
 3   rolling_mean_dayofweek  float16
 4   rolling_mean_7_28       float16
 5   rolling_mean_28_28      float16
 6   rolling_mean_28_90      float16
 7   rolling_mean_28_180     float16
 8   rolling_mean_28_365     float16
 9   rolling_mean_dayofmonth float16
 10  avg_item_store          float16
 11  std_item_store          float16
 12  avg_item_state          float16
 13  avg_dept_store          float16
 14  avg_dept_state          float16
 15  avg_snap                float16
 16  avg_event               float16
 17  avg_weekofmonth         float16
 18  n_items                 int16
 19  item_id                 category
 20  dept_id                 category
 21  cat_id                  category
 22  release                 int16
 23  weekofmonth             int8
 24  weekofyear              int8
 25  dayofweek               int8
 26  dayofmonth              int8
 27  dayofyear               int16
 28  month                   int8
 29  year                    int16
 30  event_name_1            category
 31  event_type_1            category
 32  snap_WI                 int8
 33  sell_price              float16
 34  price_last_week         float16
 35  price_next_week         float16
 36  price_same_dept         float16
 37  price_mean              float16
 38  price_std               float16
dtypes: category(6), float16(22), int16(5), int8(6)
memory usage: 281.0 MB
```

In [385...

```
x_cols = df.columns.tolist()
# label is removed
```

```
x_cols.remove('sales')

# remove id/item_id for better generalization
x_cols.remove('id')
x_cols.remove('item_id')
# remove other columns not used by the model
x_cols.remove('avg_dept_state')
x_cols.remove('year')
x_cols.remove('event_type_1')
```

In [386…

```
x_cols
```

Out[386]:

```
['d',
 'rolling_mean_dayofweek',
 'rolling_mean_7_28',
 'rolling_mean_28_28',
 'rolling_mean_28_90',
 'rolling_mean_28_180',
 'rolling_mean_28_365',
 'rolling_mean_dayofmonth',
 'avg_item_store',
 'std_item_store',
 'avg_item_state',
 'avg_dept_store',
 'avg_snap',
 'avg_event',
 'avg_weekofmonth',
 'n_items',
 'dept_id',
 'cat_id',
 'release',
 'weekofmonth',
 'weekofyear',
 'dayofweek',
 'dayofmonth',
 'dayofyear',
 'month',
 'event_name_1',
 'snap_WI',
 'sell_price',
 'price_last_week',
 'price_next_week',
 'price_same_dept',
 'price_mean',
 'price_std']
```

LGBM model

In [387…

```
import lightgbm as lgbm
lgbm.__version__
```

Out[387]:

```
'3.3.2'
```

Public and private data

Public data is used as validation, private data as evaluation (once submitted)

In [390…

```
mask_valid = (df['d']>=D_PUBLIC) & (df['d']<D_PRIVATE)
mask_eval = df['d']>=D_PRIVATE

# public data
x_valid = df[mask_valid][x_cols]
y_valid = df[mask_valid]['sales']
```

```
# private data
x_eval = df[mask_eval][x_cols]
```

In [391…

```
def cv_training(params, df, x_cols, target='sales', cv=3, dim_cv=28, early_stopping=100,
    """
    Train a LGBM model with cross validation
    @param params: LGBM parameters
    @param df: input dataframe
    @param x_cols: input columns
    @oaram target: label column
    @param cv: number of cross validation periods
    @param dim_cv: length of each cv period
    @param early_stopping: number of epochs for early stopping
    @param d_max: last day used in validation
    @param lr: starting learning rate
    @param min_lr: minimum learning rate
    @return LGBM boosters
    """

    # start/end days of the cross validation
    d_val = [d_max - dim_cv*i for i in range(cv+1)]
    d_val.reverse()
    print('CV ranges:')
    for i in range(cv):
        print(f'CV {i+1}: {d_val[i]} - {d_val[i+1]-1}')

    # train indices
    tr_idx = [df[df['d']==d].index[0] for d in d_val[:-1]]
    tr_indices = [pd.RangeIndex(0, i) for i in tr_idx]
    # validation indices
    val_idx = [df[df['d']==d].index[0] for d in d_val[1:]]
    val_indices = [pd.RangeIndex(tr_idx[i], val_idx[i]) for i in range(cv)]

    ds = lgbm.Dataset(df[x_cols], df[target])

    # early stopping, adaptive learning rate, log evaluation every 20 steps
    cb = [lgbm.early_stopping(early_stopping),
          lgbm.reset_parameter(learning_rate=lambda iter: max(min_lr, lr*(0.99**iter))),
          lgbm.log_evaluation(period=20, show_stdv=False)]

    booster = lgbm.cv(params,
                      folds=list(zip(tr_indices, val_indices)),
                      train_set=ds,
                      num_boost_round=2000,
                      shuffle=False,
                      callbacks=cb,
                      return_cvbooster=True,
                      eval_train_metric=True,
                      seed=0)

    return booster
```

In [392…

```
# parameters for training the odel
lr = 0.1
params =  {'boosting': 'gbdt',
           'num_leaves': 2**5-1,
           'objective':'tweedie',
           'tweedie_variance_power': 1.1, #1.1, 1.3., 1.5
           'metric': 'rmse',
           'learning_rate': lr,
           'bagging_freq': 10, 'bagging_fraction': 0.25,
           'force_col_wise': True,
           'deterministic':True
          }
```

In [393…
```
boost = cv_training(params, df, x_cols, d_max=D_PRIVATE, lr=lr)
```

```
CV ranges:
CV 1: 1858 - 1885
CV 2: 1886 - 1913
CV 3: 1914 - 1941
[LightGBM] [Info] Total Bins 6005
[LightGBM] [Info] Number of data points in the train set: 3971478, number of used featur
es: 33
[LightGBM] [Info] Total Bins 6005
[LightGBM] [Info] Number of data points in the train set: 4056850, number of used featur
es: 33
[LightGBM] [Info] Total Bins 6005
[LightGBM] [Info] Number of data points in the train set: 4142222, number of used featur
es: 33
[LightGBM] [Info] Start training from score 0.252069
[LightGBM] [Info] Start training from score 0.252210
[LightGBM] [Info] Start training from score 0.252575
Training until validation scores don't improve for 100 rounds
[20]	cv_agg's train rmse: 2.57496	cv_agg's valid rmse: 2.15739
[40]	cv_agg's train rmse: 2.43478	cv_agg's valid rmse: 2.04282
[60]	cv_agg's train rmse: 2.39848	cv_agg's valid rmse: 2.02069
[80]	cv_agg's train rmse: 2.37389	cv_agg's valid rmse: 2.02407
[100]	cv_agg's train rmse: 2.35354	cv_agg's valid rmse: 2.02136
[120]	cv_agg's train rmse: 2.33343	cv_agg's valid rmse: 2.04788
[140]	cv_agg's train rmse: 2.31513	cv_agg's valid rmse: 2.04443
[160]	cv_agg's train rmse: 2.29742	cv_agg's valid rmse: 2.03964
Early stopping, best iteration is:
[70]	cv_agg's train rmse: 2.3846 + 0.0066803 cv_agg's valid rmse: 2.01546 + 0.0287035
```

Model selection

For each of the 3 models returned, RMSE on validation is computed. The model with the smallest error is mantained.

In [394…
```
models = boost['cvbooster']
```

In [395…
```
y_valid_pred = models.predict(x_valid)

errors = [mse(y_valid, y, squared=False) for y in y_valid_pred]

print('RMSE of each cvbooster on public data:')
for i, err in enumerate(errors):
    print(f'CVBooster {i}:\t{err: .3f}')
```

```
RMSE of each cvbooster on public data:
CVBooster 0:	 2.091
CVBooster 1:	 2.005
CVBooster 2:	 1.994
```

In [396…
```
np.argmin(errors)
```

Out[396]:
```
2
```

In [397…
```
model = models.boosters[np.argmin(errors)]
```

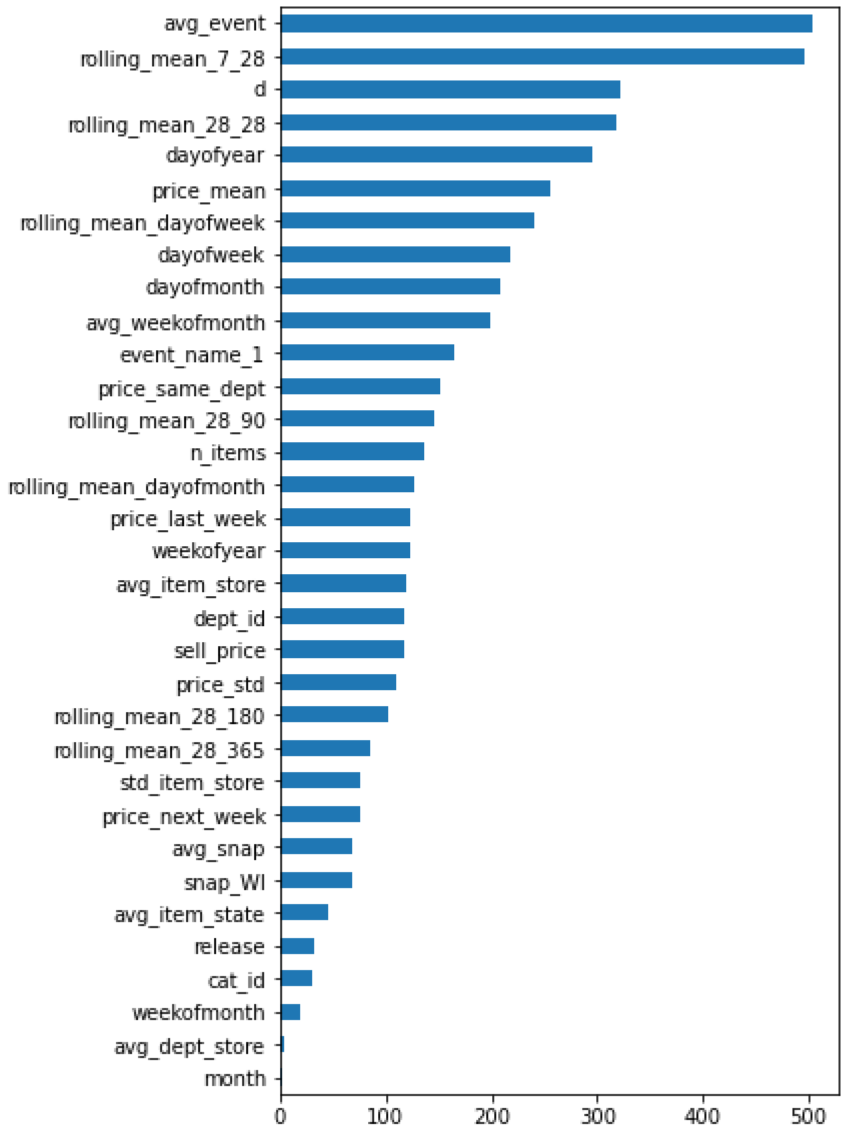
Feature importance

Have a look at the importance of each input feature in the model

In [400…
```
plt.figure(figsize=(5,10))
```

```
pd.Series(model.feature_importance(), model.feature_name()).sort_values().plot.barh()
```

Out[400]: <AxesSubplot:>



In [401…

```
model.feature_importance()
```

Out[401]:

```
array([322, 241, 496, 318, 145, 102,  85, 126, 120,  76,  45,   4,  69,
       503, 198, 137, 118,  31,  33,  19, 123, 218, 208, 296,   2, 164,
        68, 118, 124,  75, 151, 256, 109])
```

In [402…

```
dict(zip(model.feature_name(), model.feature_importance()))
```

Out[402]:
```
{'d': 322,
 'rolling_mean_dayofweek': 241,
 'rolling_mean_7_28': 496,
 'rolling_mean_28_28': 318,
 'rolling_mean_28_90': 145,
 'rolling_mean_28_180': 102,
 'rolling_mean_28_365': 85,
 'rolling_mean_dayofmonth': 126,
 'avg_item_store': 120,
 'std_item_store': 76,
 'avg_item_state': 45,
 'avg_dept_store': 4,
 'avg_snap': 69,
 'avg_event': 503,
 'avg_weekofmonth': 198,
 'n_items': 137,
 'dept_id': 118,
 'cat_id': 31,
 'release': 33,
 'weekofmonth': 19,
 'weekofyear': 123,
 'dayofweek': 218,
 'dayofmonth': 208,
 'dayofyear': 296,
 'month': 2,
 'event_name_1': 164,
 'snap_WI': 68,
 'sell_price': 118,
 'price_last_week': 124,
 'price_next_week': 75,
 'price_same_dept': 151,
 'price_mean': 256,
 'price_std': 109}
```

In [404…
```
# save the model
#utils.save_model(model, f'm5_{cur_store}.txt')
```

In [405…
```
# load the model
#model = utils.load_model(store=cur_store)
```

In [406…
```
cur_store
```

Out[406]:
```
'WI_3'
```

5) Predictions

In [407…
```
y_valid_pred = utils.predict(df, D_PUBLIC, model, x_cols)
print(f'RMSE: {mse(y_valid, y_valid_pred, squared=False):.3f}')
```

```
RMSE: 2.049
```

In [408…
```
y_eval_pred = utils.predict(df, D_PRIVATE, model, x_cols)
```

6) Submission

Partial submission

Compute public and private submission for a **single** store

In [409…
```
valid_submission = utils.partial_submission(df.loc[mask_valid, ['id', 'd']], y_valid_pre
```

```
eval_submission = utils.partial_submission(df.loc[mask_eval, ['id', 'd']], y_eval_pred,

submission = pd.concat([valid_submission, eval_submission])

dst = '../partial_submissions'
if not os.path.exists(dst):
    os.makedirs(dst)

submission.to_csv(f'{dst}/m5_{cur_store}.csv', index=False)
```

Final submission

Compute final submission for **all** stores

In [410…
```
final_submission = utils.final_submission()
```

7) Evaluation

Compute WRMSSE on public data and decompose it for all aggregation levels

In [1]:
```
# extract data if not done already
#utils.extract_data()
```

In [6]:
```
calendar, prices, sales = utils.read_data_csv()

sales = sales.sort_values(by='id').reset_index(drop=True)

train_df = sales.iloc[:, :-28]
valid_df = sales.iloc[:, -28:]
```

In [7]:
```
evaluator = wrmsse_evaluator.WRMSSEEvaluator(train_df, valid_df, calendar, prices)
```

```
100%|██████████| 12/12 [00:21<00:00,  1.75s/it]
```

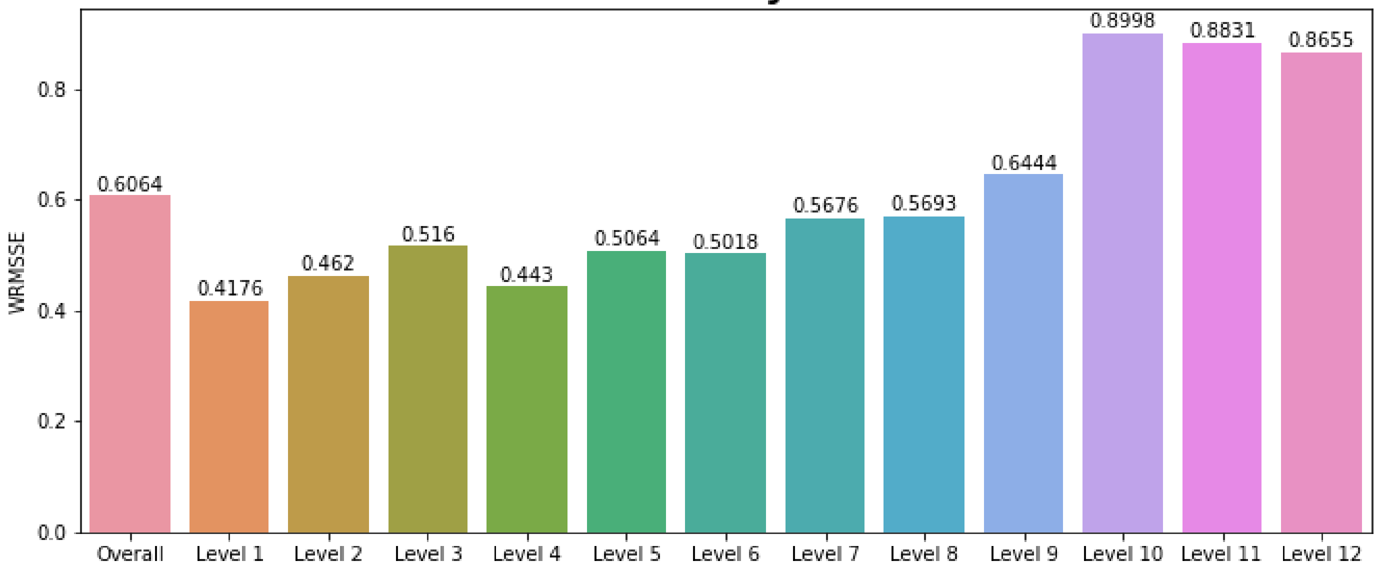
In [9]:
```
final_submission = pd.read_csv('../final_submission/m5_final_submission.csv')
valid_submission = final_submission[final_submission['id'].str[-10:]=='validation']
valid_submission = valid_submission.sort_values(by='id').reset_index(drop=True)
```

In [18]:
```
wrmsse = evaluator.score(valid_submission.iloc[:, -28:].values)
print(f'WRMSSE on public data: {wrmsse: .5f}')
```

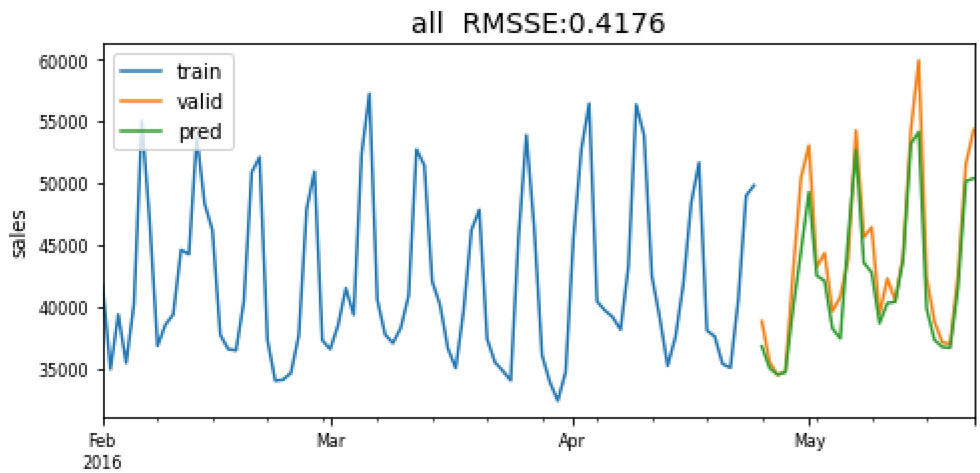
```
WRMSSE on public data:  0.60637
```

In [19]:
```
wrmsse_evaluator.create_dashboard(evaluator)
```

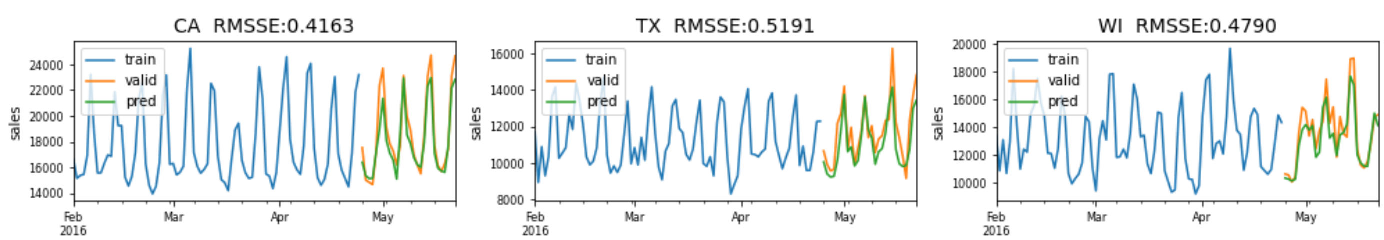
WRMSSE by Level



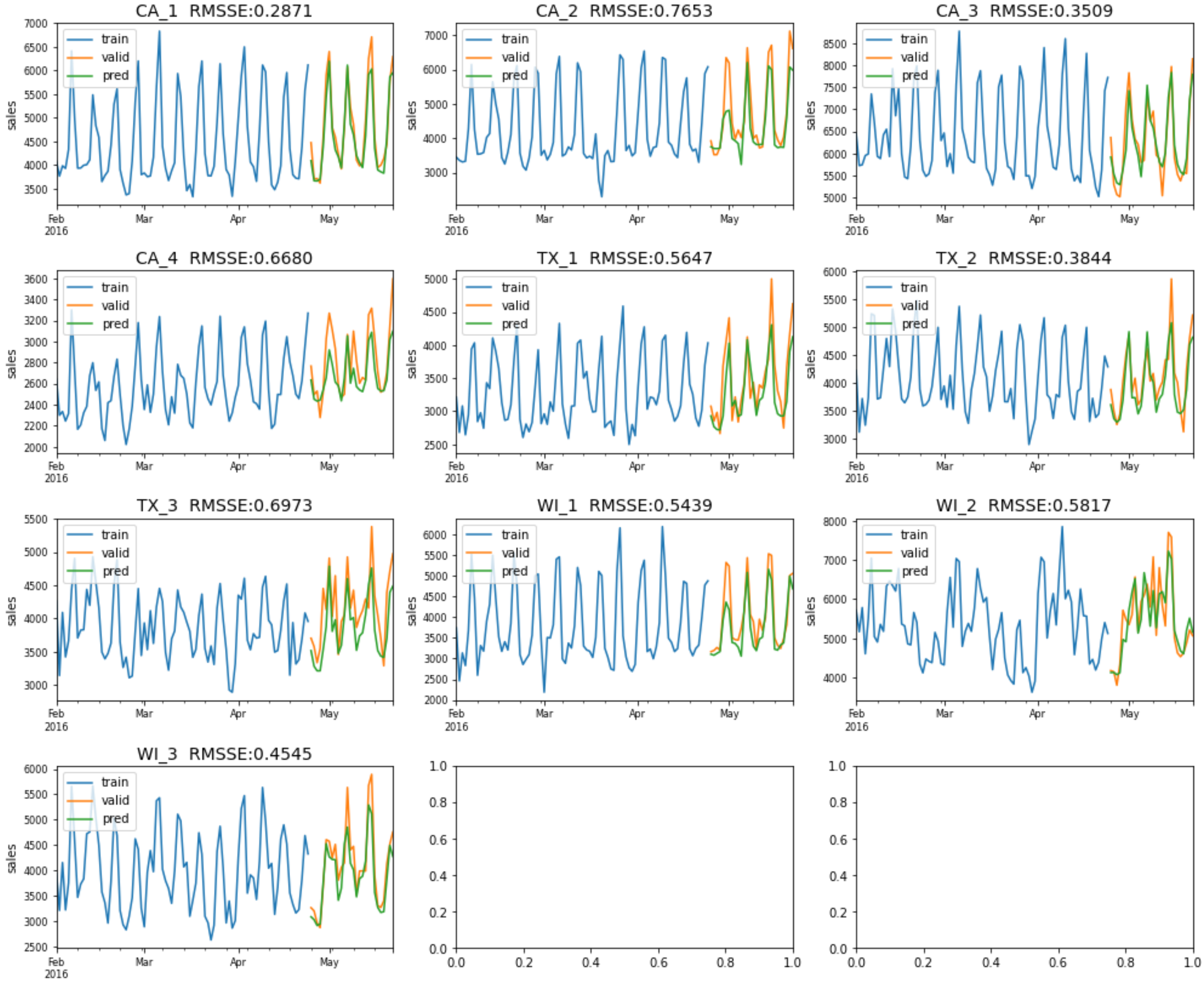
Level 1: all_id



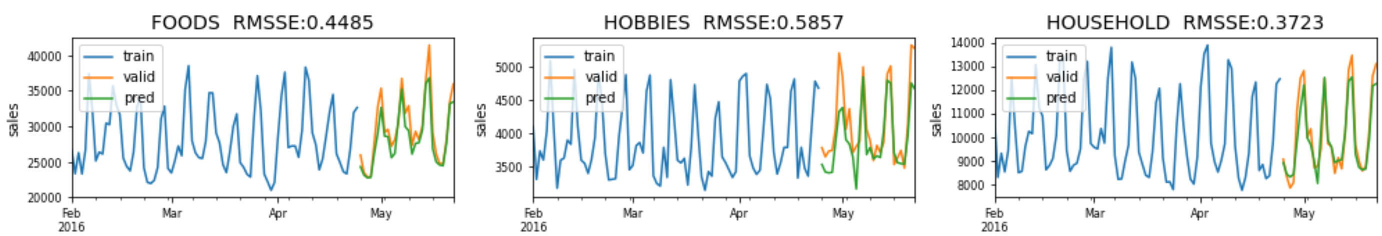
Level 2: state_id

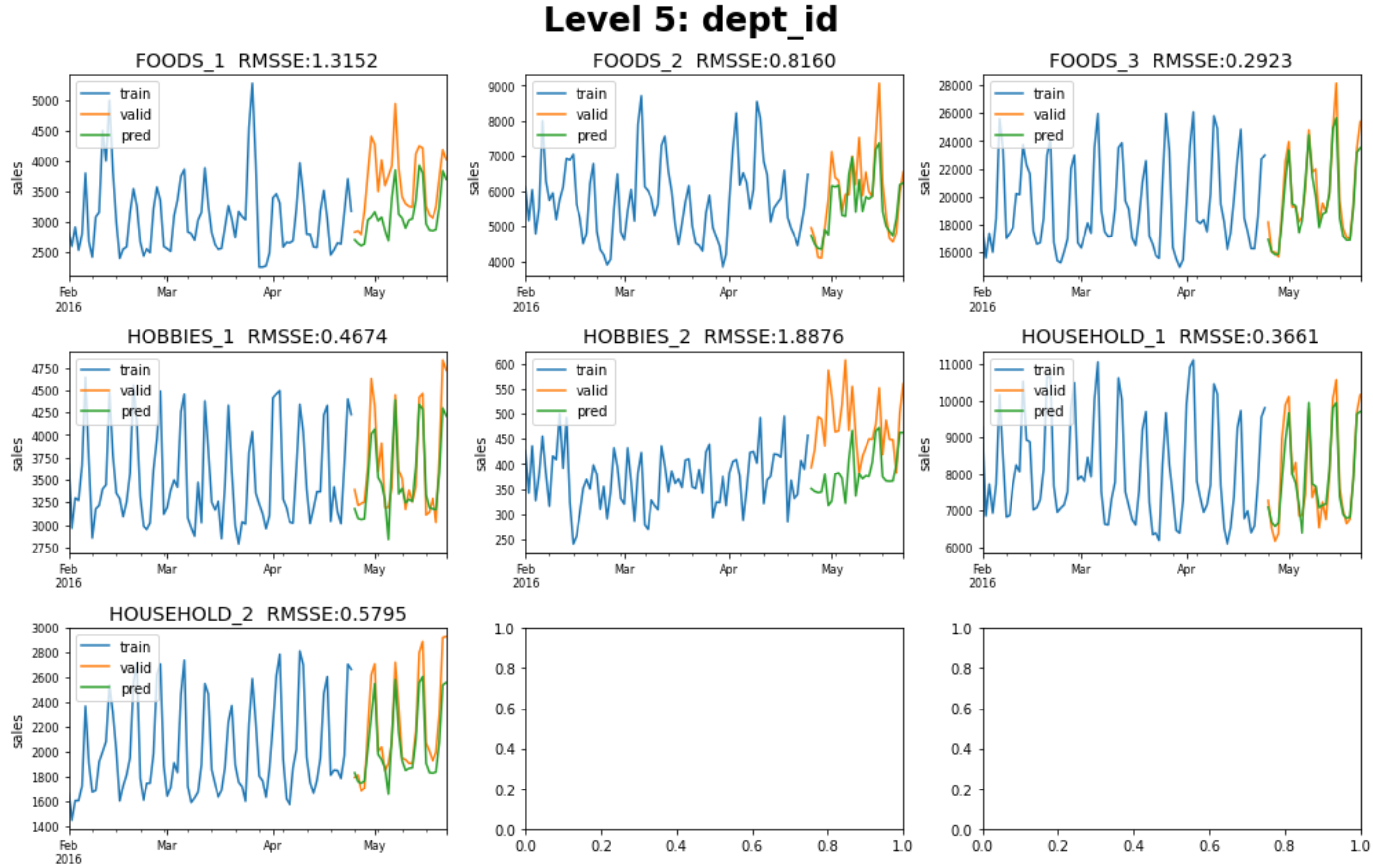


Level 3: store_id



Level 4: cat_id





Level 5: dept_id
FOODS_1 RMSSE:1.3152
FOODS_2 RMSSE:0.8160
FOODS_3 RMSSE:0.2923
HOBBIES_1 RMSSE:0.4674
HOBBIES_2 RMSSE:1.8876
HOUSEHOLD_1 RMSSE:0.3661
HOUSEHOLD_2 RMSSE:0.5795
train
valid
pred
sales
Feb 2016
Mar
Apr
May

In [ ]: