Walmart - Trip Type Classification

January 24, 2017

1 Walmart - Trip type classification

This use-case deals with the preparation of the data for Kaggle's Walmart Trip Type Classification competition. It is advised to have a look at the data before starting to work with it.

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        from time import time
        from os import getcwd

        pd.set_option('notebook_repr_html', True, 'max_columns', 0)
        %matplotlib inline
```

1.1 Getting the data

Each record in the data refers to a single **item**, but since we use the data to predict something about a **trip**, we will construct a data frame with a record per trip. We note that *VisitNumber* is inuitively the index of the data frame, although it is not unique. So, for the rest of this analysis, unless specified otherwise, the index of the data-frames will be the *VisitNumber*.

```
In [2]: train = pd.read_csv(getcwd() + "\\train.csv",
                            index_col='VisitNumber')
        train.columns = ['TripType', 'Weekday', 'UPC', 'ScanCount', 'DepDesc', 'Fi
        train.index.rename('Visit', inplace=True)
        train.head()
```

```
Out[2]:        TripType Weekday           UPC  ScanCount                DepDesc  Fi
        Visit
        5           999  Friday  6.811315e+10         -1     FINANCIAL SERVICES
        7            30  Friday  6.053882e+10          1                  SHOES
        7            30  Friday  7.410811e+09          1          PERSONAL CARE
        8            26  Friday  2.238404e+09          2  PAINT AND ACCESSORIES
        8            26  Friday  2.006614e+09          2  PAINT AND ACCESSORIES
```

NOTE: I changed the names of the index andd some of the columns for better printout.

Since we are going to aggregate many things by *VisitNumber* it will be useful to evaluate the corresponding GroupBy objects once.

```
In [3]: train_grp = train.groupby(level='Visit')
```

The features *Weekday* and *DepartmentDescription* are obviously categorical, so we cast them accordingly.

```
In [4]: days = ['Monday', 'Tuesday', 'Wednesday', 'Thursday',
                'Friday', 'Saturday', 'Sunday']
        train['Weekday'] = train['Weekday']\
            .astype('category', categories=days, ordered=True)
        train['DepDesc'] = train['DepDesc']\
            .astype('category')
```

1.2 Data Exploration

1.2.1 Getting to know the details

General information First we have an overview using the *info()* method.

```
In [5]: train.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 647054 entries, 5 to 191347
Data columns (total 6 columns):
TripType     647054 non-null int64
Weekday      647054 non-null category
UPC          642925 non-null float64
ScanCount    647054 non-null int64
DepDesc      645693 non-null category
Fineline     642925 non-null float64
dtypes: category(2), float64(2), int64(2)
memory usage: 25.9 MB
```

> **Conclusion:** We immediately see there are null entries in the data, but before we deal with that, we would like to further explore the data itself.

Unique values

```
In [6]: train.apply(pd.Series.nunique)

Out[6]: TripType        38
        Weekday          7
        UPC          97714
        ScanCount       39
        DepDesc         68
        Fineline      5195
        dtype: int64
```

```
In [7]: n_visits = train.index.nunique()
        print train.index.nunique(), len(train)
```

```
95674 647054
```

Examplary visits One of the simplest features of any visit (cart) is the amount of items it contains, so we evaluate the proper aggregation and use it for exploring the data.

```
In [8]: df_n_items = train_grp['ScanCount'].sum()
        df_n_items.head()
```

```
Out[8]: Visit
        5     -1
        7      2
        8     28
        9      3
        10     3
        Name: ScanCount, dtype: int64
```

For inspection purposes we can now find trips with a specific number of items.

```
In [9]: for n_items in [50, 20, 1, 0, -1]:
            i_visit = df_n_items.ix[df_n_items == n_items].index[0]
            print "Visit {:4} has {:2} items.".format(i_visit, n_items)
```

```
Visit   98 has 50 items.
Visit  274 has 20 items.
Visit   29 has  1 items.
Visit  133 has  0 items.
Visit    5 has -1 items.
```

Now we can see exemplary visits with different number of items.

```
In [10]: train.ix[98].head()
```

```
Out[10]:        TripType Weekday           UPC  ScanCount                   DepDesc
         Visit
         98           40  Friday  7.874202e+09          1               DSD GROCERY
         98           40  Friday  3.400001e+09          1  CANDY, TOBACCO, COOKIES
         98           40  Friday  7.874201e+09          1               DSD GROCERY
         98           40  Friday  6.053882e+10          2                     SHOES
         98           40  Friday  7.431255e+09          1              PHARMACY OTC
```

```
In [11]: train.ix[274].head()
```

```
Out[11]:        TripType Weekday          UPC  ScanCount                 DepDesc  F
         Visit
         274          40  Friday  4.460031e+09          1          LAWN AND GARDEN
         274          40  Friday  6.811311e+10          1  HOUSEHOLD PAPER GOODS
         274          40  Friday  7.874207e+09          1  HOUSEHOLD PAPER GOODS
         274          40  Friday  7.874204e+09          2              DSD GROCERY
         274          40  Friday  5.450019e+09          2          PRE PACKED DELI
```

```
In [12]: train.ix[29].head()
```

```
Out[12]: TripType               8
         Weekday           Friday
         UPC              1.2e+09
         ScanCount              1
         DepDesc      DSD GROCERY
         Name: 29, dtype: object
```

```
In [13]: train.ix[133].head()
```

```
Out[13]:        TripType Weekday          UPC  ScanCount      DepDesc  Fineline
         Visit
         133         999  Friday  9.933894e+09         -1  LADIESWEAR    1180.0
         133         999  Friday  9.933894e+09          1  LADIESWEAR    1180.0
```

```
In [14]: train.ix[5].head()
```

```
Out[14]: TripType                     999
         Weekday                   Friday
         UPC                  6.81132e+10
         ScanCount                     -1
         DepDesc      FINANCIAL SERVICES
         Name: 5, dtype: object
```

1.2.2 Data visualization

***TripType* frequency** We want to see how the *TripType* is distributed in the data. Since the *TripType* is repeated for all the items in a group of *train_grp*, we can take only the *TripType* of the first record. We can do it either by the method *nth()* or by the method *min()* (this is not very natural, but it works), so this is a good opportunity to make a short benchmark.

```
In [15]: %%timeit
         train_grp.nth(0)['TripType'].value_counts()\
             .sort_values(ascending=False)
```

```
10 loops, best of 3: 77.8 ms per loop
```

```
In [16]: %%timeit
         train_grp['TripType'].min().value_counts()\
             .sort_values(ascending=False)
```

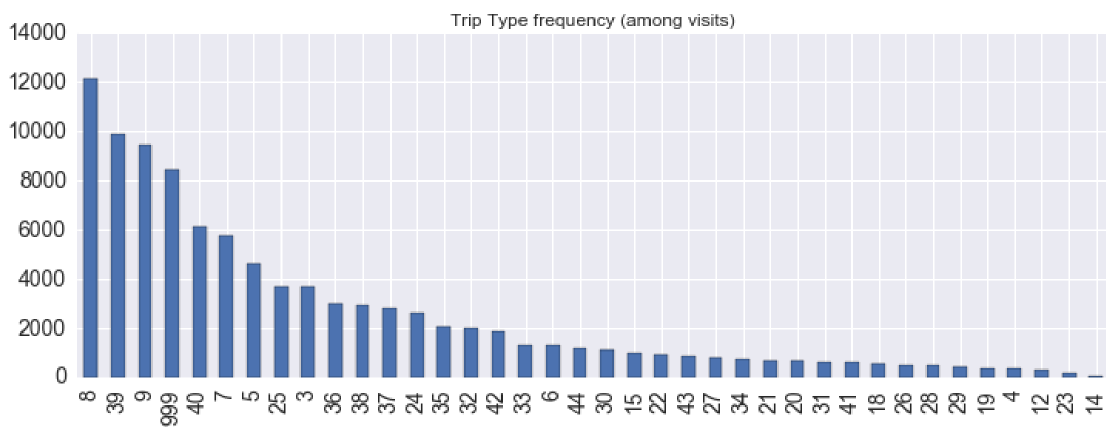
```
100 loops, best of 3: 5.38 ms per loop
```

```
In [17]: ttf = train_grp['TripType'].min().value_counts()\
             .sort_values(ascending=False)
         ttf.head(5)
```

```
Out[17]: 8      12161
         39      9896
         9       9464
         999     8444
         40      6130
         Name: TripType, dtype: int64
```

```
In [18]: ttf.plot(kind='bar', figsize=(12, 4), fontsize=14,
                  title='Trip Type frequency (among visits)')
```

```
Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x104f8320>
```



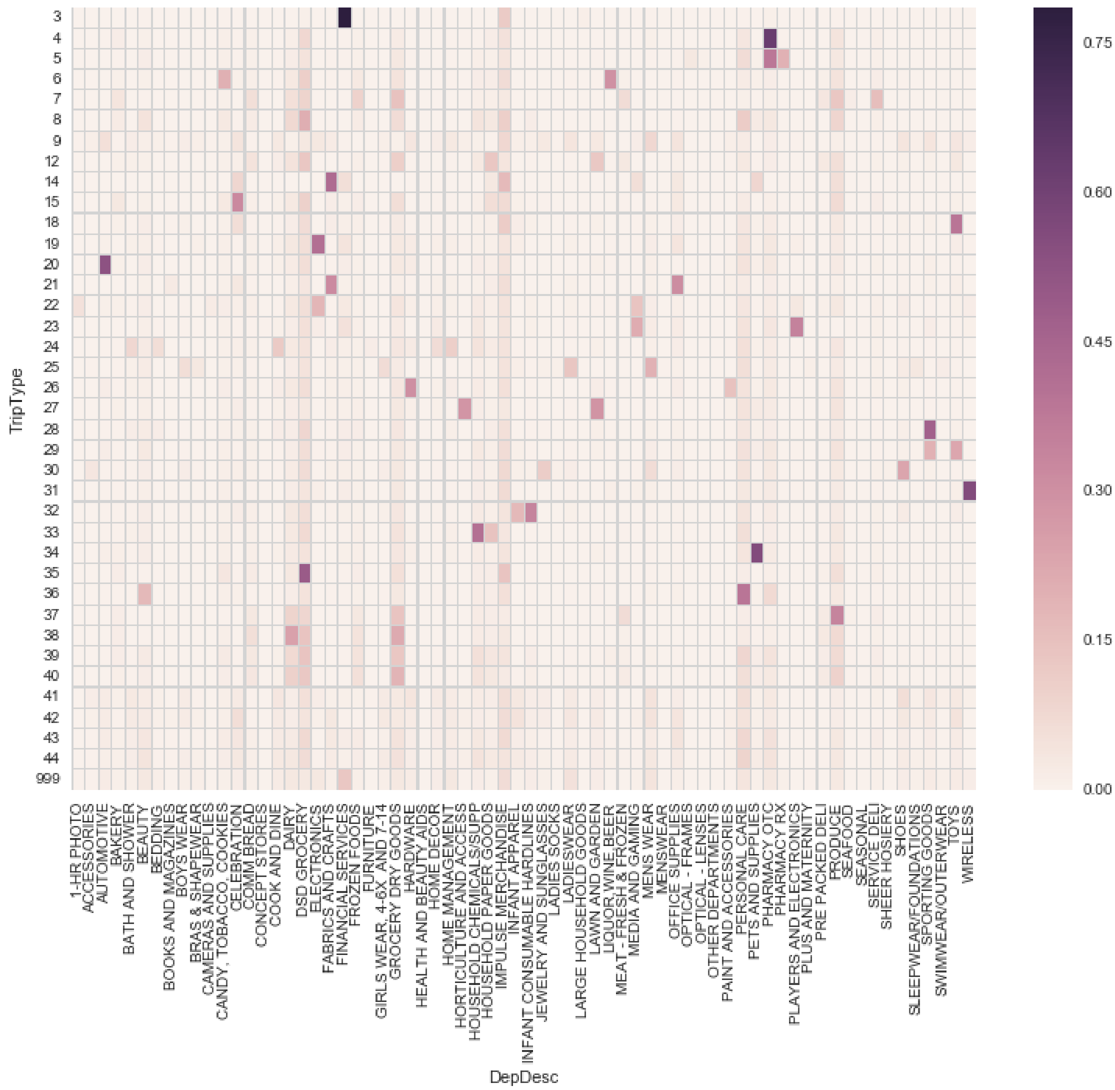
TripType vs. Departments We want to see whather there is a relation between the departments of a trip and it type. Note the different conclusions that can be extracted by the different normalizations.

> **NOTE:** We can use the *hist2d()* method of matplotlib, but this is a good opportunity to explore the seaborn package, which is widely used lately by data scientist. More specifically we are going to use the *heatmap()* method.

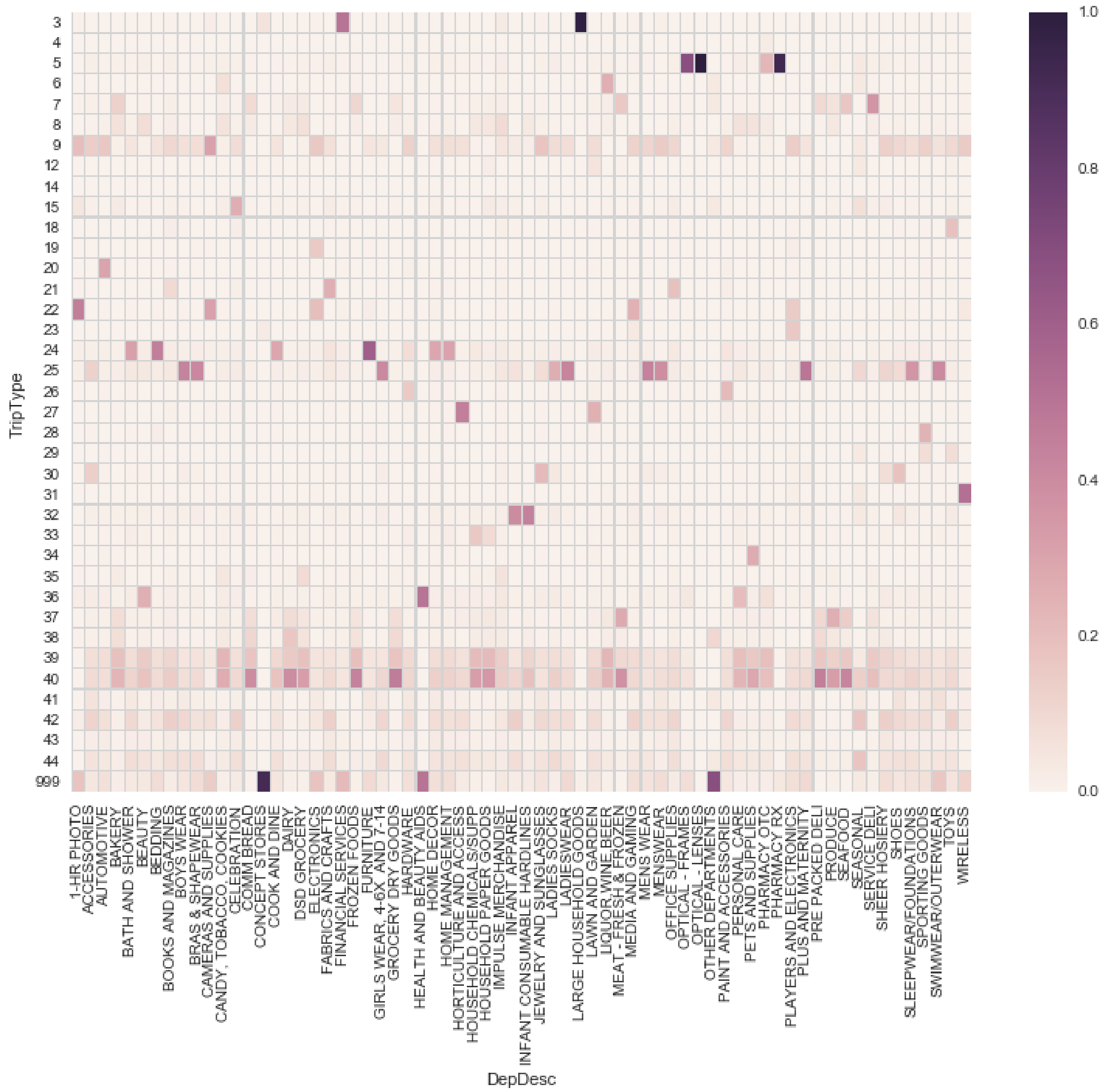
```
In [19]: tt_vs_dd = pd.crosstab(index=train.TripType,
                                columns=train.DepDesc,
                                normalize='index')
```

```
In [20]: fig, ax = plt.subplots(figsize=(13, 9))
         sns.heatmap(ax=ax, data=tt_vs_dd,
                     linecolor='lightgrey', linewidths=.1)
```

```
Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x14f02c18>
```

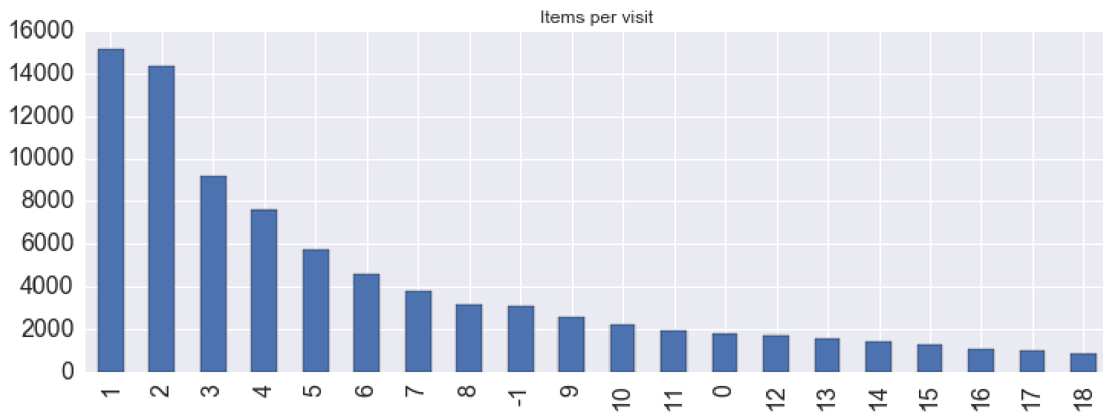



```
In [21]: tt_vs_dd = pd.crosstab(index=train.TripType,
                                columns=train.DepDesc,
                                normalize='columns')

In [22]: fig, ax = plt.subplots(figsize=(13, 9))
         sns.heatmap(ax=ax, data=tt_vs_dd,
                     linecolor='lightgrey', linewidths=.1)

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x1716f240>
```



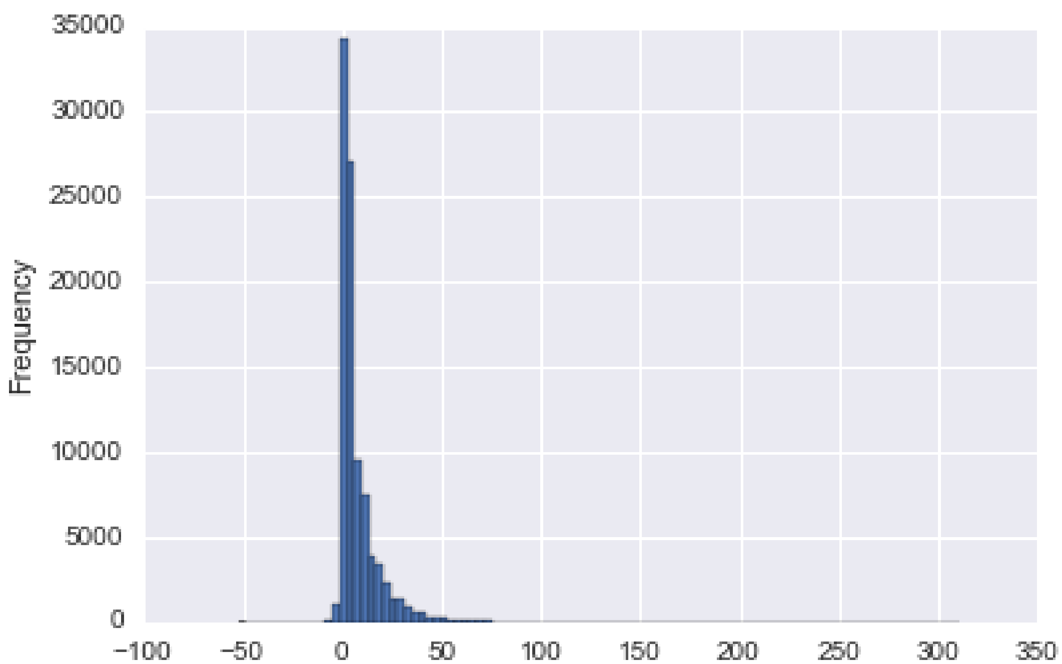
#items frequency We already saw that the number of items in the cart can vary a lot. In this section we see what are the most common cart sizes and what is their general distribution.

```
In [23]: n_items_freq = train_grp['ScanCount'].sum().value_counts()[:20]
         n_items_freq.plot(kind='bar', figsize=(12, 4),
                           fontsize=16, title='Items per visit')

Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x177b53c8>
```




```
In [24]: cart_sizes = train_grp['ScanCount'].sum()
         cart_sizes.plot(kind='hist', bins=100)
         # Try zoom-in with xlim=(-50, 150), ylim=(0, 1000)
```

```
Out[24]: <matplotlib.axes._subplots.AxesSubplot at 0xb542f98>
```




```
In [25]: print cart_sizes.min(), cart_sizes.max()
```

```
-52 311
```

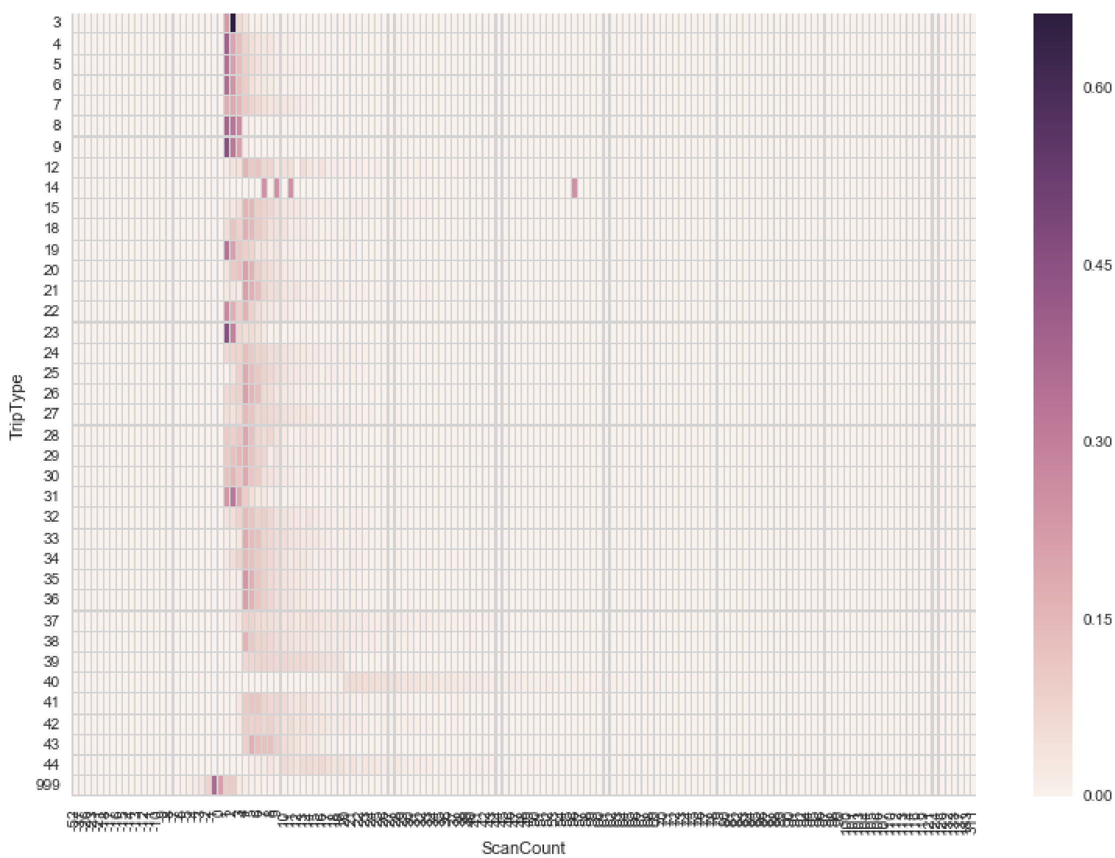
TripType vs. #items We want to see whether there is any relation between the *TripType* and the number of items purchased. Since this is a relation between to aggregative features of a visit we start the inspection by applying the proper aggregations per visit.

```
In [26]: tt_vs_n_items = train_grp.agg({'TripType': min,
                                        'ScanCount': sum})
         tt_vs_n_items.head()
```

```
Out[26]:        TripType  ScanCount
         Visit
         5           999         -1
         7            30          2
         8            26         28
         9             8          3
         10            8          3
```

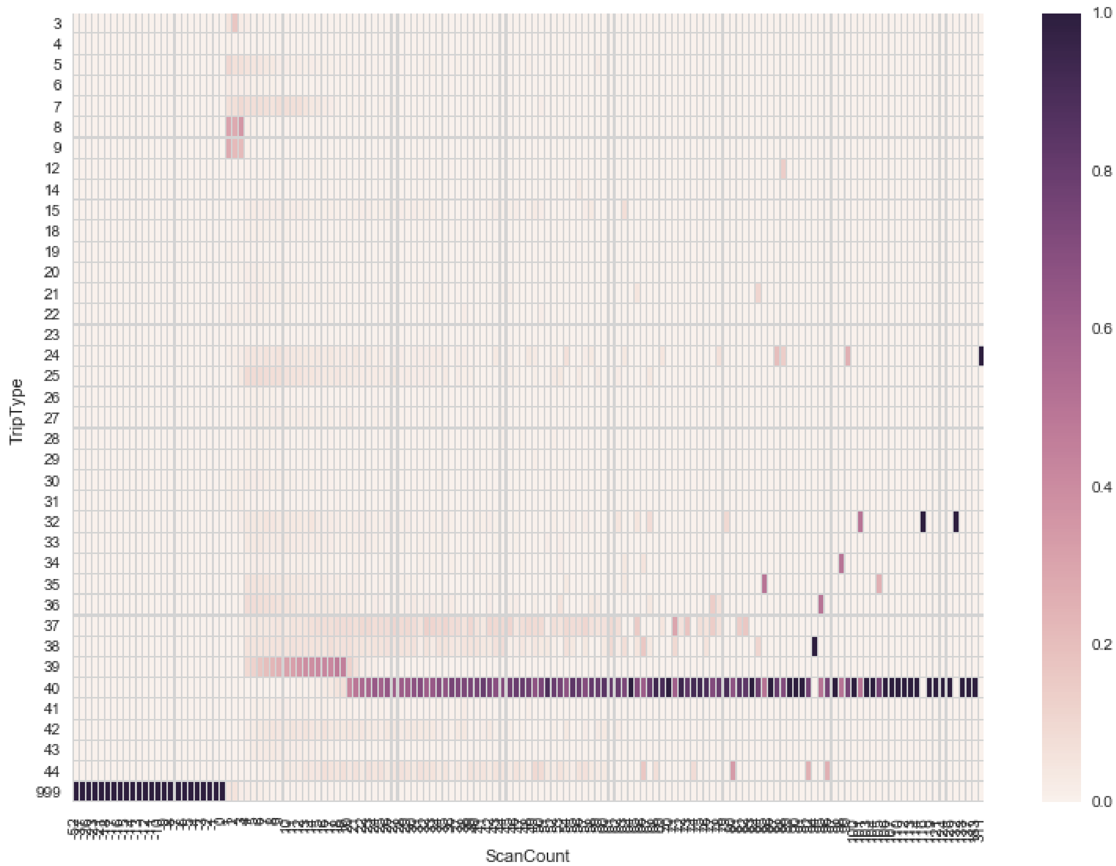
```
In [27]: ct_tt_vs_n_items = pd.crosstab(index=tt_vs_n_items.TripType,
                                        columns=tt_vs_n_items.ScanCount,
                                        normalize='index')
         fig, ax = plt.subplots(figsize=(13, 9))
         sns.heatmap(ax=ax, data=ct_tt_vs_n_items,
                     linecolor='lightgrey',
                     linewidths=.1)
```

```
Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0xb6bf7b8>
```



```
In [28]: ct_tt_vs_n_items = pd.crosstab(index=tt_vs_n_items.TripType,
                                        columns=tt_vs_n_items.ScanCount,
                                        normalize='columns')
         fig, ax = plt.subplots(figsize=(13, 9))
         sns.heatmap(ax=ax, data=ct_tt_vs_n_items,
                     linecolor='lightgrey',
                     linewidths=.1)
```

```
Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0x17a99a20>
```



STATUS: Until now we made no changes in the data, but only examined it.

1.3 Cleaning the data

1.3.1 Missing values

The *info()* method showed that some data is missing. Let's see where is the missing data and how does it look.

```
In [29]: train.isnull().sum()

Out[29]: TripType        0
         Weekday         0
         UPC          4129
         ScanCount       0
         DepDesc      1361
         Fineline     4129
         dtype: int64

In [30]: train.ix[train.UPC.isnull()].head()

Out[30]:        TripType Weekday  UPC  ScanCount DepDesc  Fineline
         Visit
         8            26  Friday  NaN          1     NaN       NaN
         259          27  Friday  NaN          3     NaN       NaN
         259          27  Friday  NaN          1     NaN       NaN
         409         999  Friday  NaN         -1     NaN       NaN
         479          39  Friday  NaN          1     NaN       NaN
```

We see that the NAs are not very common, and also that there is a significant overlap between the missing data entries in the different columns. Therefore we decide to drop the records that contain missing data, and we do it with the *dropna()* method.

```
In [31]: train.dropna(axis=0, how='any', inplace=True)

In [32]: print train.index.nunique(), len(train)

94247 642925
```

After the removal of the missing data, we recreate the GroupBy object.

```
In [33]: train_grp = train.groupby(level='Visit')
```

STATUS: There are no NaNs in the data.

1.3.2 Duplicated UPCs and returned items

Duplicated UPCs and returned items may correspond to several scenarios:

- **Regular duplications** indicate normal cashier work, in which items with the same UPC are not necessarily processed together.
- **Unique returns** (returns with a unique UPC within a visit) may indicate **planned** trip with an item to be returned.
- **Non-unique returns** may indicate a human "error" (or price check) at the POS (Point of sale).

We now see if there are any *regular* duplications.

```
In [34]: def is_upc_duplicate(visit):
             if -1 in visit.ScanCount.values:
                 return False  # returns --> irrelevant duplicate
             else:
                 return (visit.UPC.value_counts() > 1).any()
```

```
In [35]: mini_train = train.ix[train.index.unique()[:100], :]
         grouped = mini_train\
             .groupby(level='Visit')\
             .apply(is_upc_duplicate)
         print grouped.any()
```

```
True
```

The *True* above proves that our concerns were correct. We can find an example.

```
In [36]: grouped[grouped]
```

```
Out[36]: Visit
         19      True
         61      True
         86      True
         140     True
         dtype: bool
```

```
In [37]: train.ix[19]
```

```
Out[37]:        TripType Weekday           UPC  ScanCount                DepDesc
         Visit
         19           42  Friday  7.675336e+09          1    IMPULSE MERCHANDISE
         19           42  Friday  6.115665e+10          1  JEWELRY AND SUNGLASSES
         19           42  Friday  8.874396e+10          1              MENS WEAR
         19           42  Friday  6.926568e+11          1      FABRICS AND CRAFTS
         19           42  Friday  7.675336e+09          1    IMPULSE MERCHANDISE
         19           42  Friday  6.953344e+11          1            ACCESSORIES
         19           42  Friday  8.853064e+10          1              MENS WEAR
         19           42  Friday  8.830961e+10          1              MENS WEAR
         19           42  Friday  3.181070e+09          1        HOME MANAGEMENT
```

For illustration purposes we can see that 132 is an example of a visit with non-unique returns, but not only, while 333 and 1579 are examples of visits made of non-unique returns only.

```
In [38]: train.ix[132]
```

```
Out[38]:        TripType Weekday           UPC  ScanCount      DepDesc  Fineline
         Visit
         132           9  Friday  6.700886e+09          1  CELEBRATION       6.0
         132           9  Friday  6.454161e+10         -1  CELEBRATION       6.0
         132           9  Friday  6.454161e+10          2  CELEBRATION       6.0
         132           9  Friday  6.700886e+09         -1  CELEBRATION       6.0
```

```
In [39]: train.ix[333]   # See also 1579

Out[39]:        TripType Weekday           UPC  ScanCount                  DepDesc
         Visit
         333         999  Friday  6.565145e+10          1  JEWELRY AND SUNGLASSES
         333         999  Friday  6.565145e+10         -1  JEWELRY AND SUNGLASSES
```

To eliminate regular duplications we aggregate by the *ScanCount* of such items. This aggregation is applied to the *ScanCount* column only, while leaving the other columns unchaged. This can be done by indexing manipulation.

```
In [40]: temp = train.groupby([train.index, 'UPC', 'Weekday', 'DepDesc',
                               'Fineline', 'TripType'])['ScanCount'].sum()
         temp.head()

Out[40]: Visit  UPC           Weekday  DepDesc                Fineline  TripType
         5      6.811315e+10  Friday   FINANCIAL SERVICES     1000.0    999
         7      7.410811e+09  Friday   PERSONAL CARE          4504.0    30
                6.053882e+10  Friday   SHOES                  8931.0    30
         8      2.006614e+09  Friday   PAINT AND ACCESSORIES  1017.0    26
                                                                        26
         Name: ScanCount, dtype: int64

In [41]: train = temp.reset_index(['UPC', 'Weekday', 'DepDesc',
                                   'Fineline', 'TripType'])
         train.head()

Out[41]:                 UPC Weekday                DepDesc  Fineline  TripType  Sc
         Visit
         5      6.811315e+10  Friday     FINANCIAL SERVICES    1000.0       999
         7      7.410811e+09  Friday          PERSONAL CARE    4504.0        30
         7      6.053882e+10  Friday                  SHOES    8931.0        30
         8      2.006614e+09  Friday  PAINT AND ACCESSORIES    1017.0        26
         8      2.006614e+09  Friday  PAINT AND ACCESSORIES    1017.0        26
```

We note that this aggregation also created records with *ScanCount = 0*, which reflect items that were scanned and cancelled by the cashier (e.g. check the price, regret, mistake, etc.). For illustration purposes we can look again at visits 132, 333 and 1579 to see how the aggregation influenced them.

```
In [42]: train.ix[132]

Out[42]:                 UPC Weekday      DepDesc  Fineline  TripType  ScanCount
         Visit
         132    6.700886e+09  Friday  CELEBRATION       6.0         9          0
         132    6.454161e+10  Friday  CELEBRATION       6.0         9          1

In [43]: train.ix[333]
```

```
Out[43]: UPC                      6.56514e+10
         Weekday                       Friday
         DepDesc      JEWELRY AND SUNGLASSES
         Fineline                        6812
         TripType                         999
         ScanCount                          0
         Name: 333, dtype: object
```

```
In [44]: train.ix[1579]
```

```
Out[44]:                UPC Weekday        DepDesc  Fineline  TripType  ScanCount
         Visit
         1579   5.027695e+09  Friday     HOME DECOR     856.0       999          0
         1579   8.280307e+09  Friday     HOME DECOR     856.0       999          0
         1579   6.442257e+10  Friday  PHARMACY OTC     509.0       999          0
```

After combining duplicated items, we have fewer records, but the same number of visits. Anyway we recreate the GroupBy object.

```
In [45]: print train.index.nunique(), len(train)
```

```
94247 628483
```

```
In [46]: train_grp = train.groupby(level='Visit')
```

We assume that visits which contain only *ScanCount* of 0 carry no information and we omit them. For illustration purposes we first have a look on some of the visits we are filtering out.

```
In [47]: mini_train = train.ix[train.index.unique()[:1000], :]
         grouped = mini_train.groupby(level='Visit')
         sc_0_only = grouped.filter(lambda grp: (grp.ScanCount == 0).all())
         sc_0_only
```

```
Out[47]:                UPC Weekday                  DepDesc  Fineline  TripType
         Visit
         333    6.565145e+10  Friday   JEWELRY AND SUNGLASSES    6812.0       999
         685    7.013201e+09  Friday        GROCERY DRY GOODS    2996.0       999
         781    2.471911e+09  Friday  HORTICULTURE AND ACCESS    8294.0       999
         1120   7.149518e+10  Friday                 WIRELESS    1590.0       999
         1460   2.471922e+09  Friday  HORTICULTURE AND ACCESS    8615.0       999
         1579   5.027695e+09  Friday               HOME DECOR     856.0       999
         1579   8.280307e+09  Friday               HOME DECOR     856.0       999
         1579   6.442257e+10  Friday             PHARMACY OTC     509.0       999
         1783   6.030842e+10  Friday            PERSONAL CARE    5300.0       999
         1943   9.800008e+08  Friday      IMPULSE MERCHANDISE     145.0       999
```

NOTE: The *TripType* of such trips is 999. We can call this kind of visits **cashier_check**, since we assume this is the origin of such visits. This will be important when we will build the classification model in the future. We can run the line *sc_0_only.TripType.value_counts()* for illustration of this fact.

And now the actual filtration...

```
In [48]: train = train_grp.filter(lambda grp: (grp.ScanCount != 0).any())
```

NOTE: For some reason, *filter()* is very slow...

```
In [49]: print train.index.nunique(), len(train)
```

```
93154 626968
```

STATUS: At this stage there are no NaNs, no duplicted UPCs and all returns are unique returns.

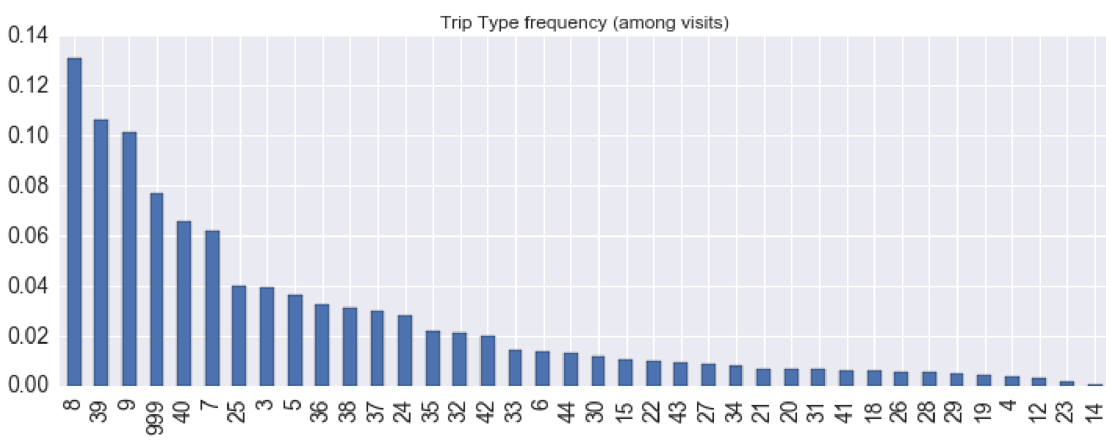
After the removal of the missing data, we recreate the GroupBy object.

```
In [50]: train_grp = train.groupby(level='Visit')
```

TripType = 999 We naturally believe that *TripType* 999 has irregular structure, and therefore it is advised to understand its content. Moreover, even after filtering many of the visits with *TripType 999*, it is still representing, as illustrated below, nearly 8% of the visits. For this analysis we introduce the *train999* data frame.

```
In [51]: ttf = train_grp['TripType'].min().value_counts(normalize=True)\
              .sort_values(ascending=False)
         ttf.plot(kind='bar', figsize=(12, 4), fontsize=14,
                  title='Trip Type frequency (among visits)')
```

```
Out[51]: <matplotlib.axes._subplots.AxesSubplot at 0x16a75cf8>
```




```
In [52]: train999 = train.ix[train.TripType == 999]
         train999.head()   # Look at 20
```

Out[52]:

```
                    UPC Weekday            DepDesc  Fineline  TripType  ScanC
Visit
5      6.811315e+10  Friday  FINANCIAL SERVICES    1000.0       999
133    9.933894e+09  Friday          LADIESWEAR    1180.0       999
133    9.933894e+09  Friday          LADIESWEAR    1180.0       999
182    5.473282e+09  Friday            HARDWARE    8410.0       999
190    4.316875e+09  Friday            HARDWARE    4513.0       999
```

We see several types of 999 visits:

- Unique returns
  - No replacement, e.g. 182, 190, 261, 400
  - Item replacement, e.g. 133
- Financial services
  - Negative, e.g. 5, 253, 281, 317
  - Positive, e.g. 351, 357
- Regular (or not?) visits, e.g. 207, 295

We test their "confidence" one by one, to see whether the other direction works (e.g. whether the mere presence of unique returns indicate *TripType* 999)

Unique returns At this stage all returns are unique returns ,so we can exanime the *TripType* associated with them.

In [53]:

```
unique_returns_cnt = train.ix[train.ScanCount < 0]\
    .TripType.value_counts()
print unique_returns_cnt
```

```
999    7632
7         2
39        1
35        1
38        1
22        1
29        1
44        1
40        1
8         1
Name: TripType, dtype: int64
```

Conclusion #1: If a visit has a unique return, then we can predict that its *TripType* is 999.

This means that we can ignore visits which include unique returns and deal with them (namely, classify such visits) separately.

In [54]:

```
# train = train_grp.filter(lambda grp: (grp.ScanCount>0).all())
```

```
In [55]: visits_with_returns = train.ix[train.ScanCount<0]
         print visits_with_returns.index.nunique(), len(visits_with_returns)
         train.drop(visits_with_returns.index.unique(), inplace=True)
```

```
5157 7642
```

NOTE: The (commented) filtration implementation is more natural, but it looks like *filter()* is not very fast...

```
In [56]: print train.index.nunique(), len(train)
```

```
87997 617547
```

NOTE: 626968 != 617547 + 7642 because some visits include unique returns AND other items.

Again, after the filtration we recreate the GroupBy object.

```
In [57]: train_grp = train.groupby(level='Visit')
```

STATUS: At this stage there are no NaNs, no duplicted UPCs and no returns ($\rightarrow$ all *ScanCount* values are greater than 0).

Financial services (regardless of *TripType = 999*) We first create a dataframe with only the records of the financial service data.

```
In [58]: df_fs = train.ix[train.DepDesc == 'FINANCIAL SERVICES']
         print df_fs.shape
         df_fs.head()
```

```
(9452, 6)
```

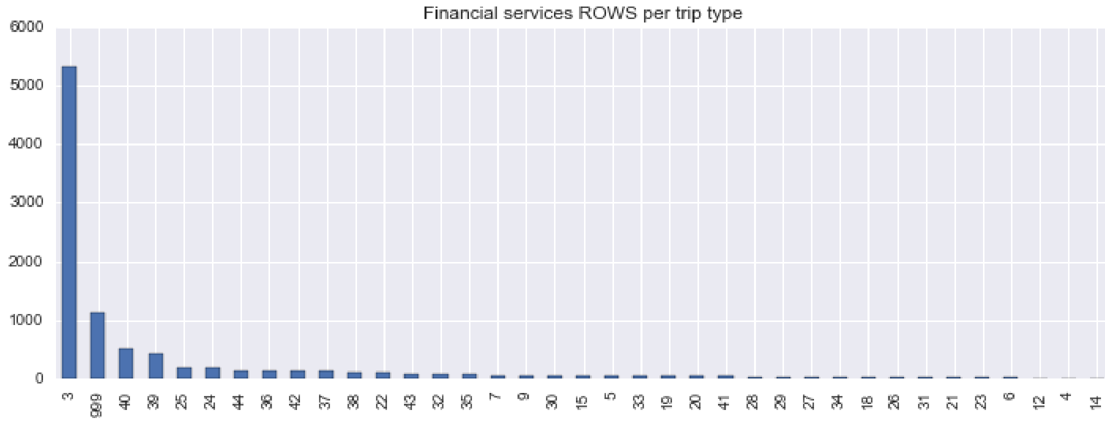
Out[58]:

	UPC	Weekday	DepDesc	Fineline	TripType	Scan(
Visit						
106	6.053890e+10	Friday	FINANCIAL SERVICES	276.0	3	
106	6.811316e+10	Friday	FINANCIAL SERVICES	275.0	3	
121	6.811316e+10	Friday	FINANCIAL SERVICES	278.0	3	
121	6.811316e+10	Friday	FINANCIAL SERVICES	277.0	3	
153	6.053889e+10	Friday	FINANCIAL SERVICES	285.0	3	

We note that the information in the *rows* and the information in the *visits* is not the same.

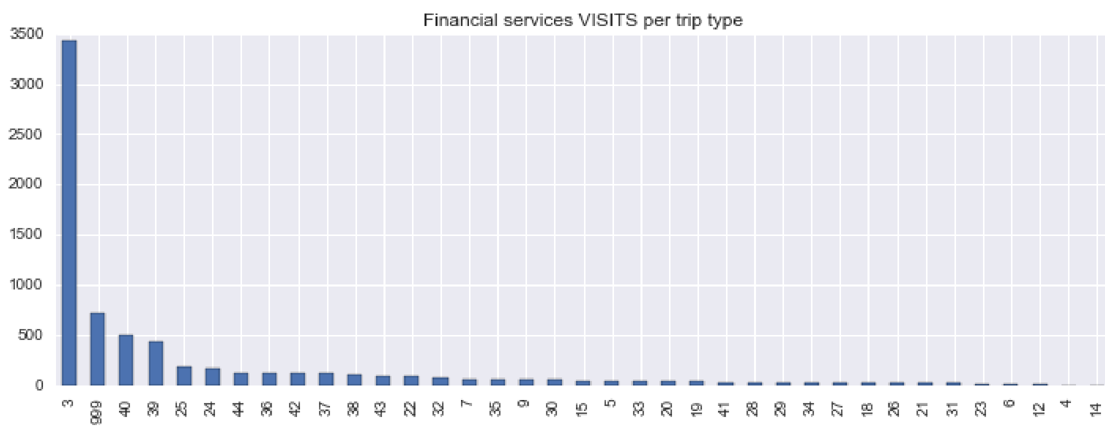
```
In [59]: df_fs['TripType'].value_counts()\
              .plot(kind='bar', figsize=(12, 4),
                    title='Financial services ROWS per trip type')
```

```
Out[59]: <matplotlib.axes._subplots.AxesSubplot at 0x158b9080>
```




```
In [60]: grouped = df_fs.groupby(level='Visit')
         grouped['TripType'].min().value_counts()\
             .plot(kind='bar', figsize=(12, 4),
                   title='Financial services VISITS per trip type')
```

```
Out[60]: <matplotlib.axes._subplots.AxesSubplot at 0x11353ef0>
```



What is the difference between visits that include the *DepartmentDescription* FINANCIAL SERVICES, but have different *TripType* values?

```
In [61]: fs_rows_tt3 = df_fs.ix[df_fs.TripType == 3]
         train.ix[fs_rows_tt3.index.unique()[::1000]] # Look at step=100
```

```
Out[61]:                      UPC    Weekday             DepDesc  Fineline  TripType
         Visit
         106        6.053890e+10     Friday  FINANCIAL SERVICES     276.0         3
         106        6.811316e+10     Friday  FINANCIAL SERVICES     275.0         3
         46274      6.053882e+10     Friday  FINANCIAL SERVICES    1000.0         3
```

```
46274   8.303240e+10     Friday  IMPULSE MERCHANDISE    1001.0         3
101274  6.053889e+10     Sunday   FINANCIAL SERVICES     285.0         3
101274  6.811311e+10     Sunday   FINANCIAL SERVICES     200.0         3
164572  6.053882e+10  Wednesday   FINANCIAL SERVICES    1000.0         3
164572  6.811318e+10  Wednesday   FINANCIAL SERVICES     283.0         3
```

```
In [62]: fs_rows_tt999 = df_fs.ix[df_fs.TripType == 999]
         train.ix[fs_rows_tt999.index.unique()[::200]] # Look at step=100
```

```
Out[62]:                  UPC    Weekday              DepDesc  Fineline  TripType  S
         Visit
         351     6.811318e+10     Friday   FINANCIAL SERVICES     281.0       999
         351     6.811318e+10     Friday   FINANCIAL SERVICES     280.0       999
         40596   6.811318e+10   Thursday   FINANCIAL SERVICES     281.0       999
         40596   6.811318e+10   Thursday   FINANCIAL SERVICES     280.0       999
         92387   2.519222e+09     Friday     MEDIA AND GAMING    9257.0       999
         92387   2.724289e+09     Friday          ELECTRONICS    4294.0       999
         92387   4.141942e+09     Friday  IMPULSE MERCHANDISE     808.0       999
         92387   6.053880e+10     Friday   FINANCIAL SERVICES    3903.0       999
         156965  6.053881e+10    Tuesday  IMPULSE MERCHANDISE    1001.0       999
         156965  6.053882e+10    Tuesday   FINANCIAL SERVICES    1000.0       999
```

We see that *TripType* = *3* and *TripType=999* are very similar when it comes to Financial Services, so how can we distinguish between them? We can use the *FinelineNumber*!

Illustration 1

```
In [63]: d_fs_tt = {}  # {TripType: Fineline value counts (Series)}
         for tt in df_fs.TripType.unique():
             df_fs_tt = df_fs.ix[df_fs.TripType == tt]
             d_fs_tt[tt] = df_fs_tt.Fineline.value_counts()
```

```
In [64]: df_fl = pd.DataFrame(d_fs_tt).transpose()
         df_fl.head().iloc[:, :10]
```

```
Out[64]:   0.0  200.0  275.0  276.0  277.0  278.0  280.0  281.0  282.0  283.0
         3  805.0  282.0  691.0  691.0  829.0  829.0    NaN    NaN   35.0  427.0
         4    5.0    NaN    NaN    NaN    NaN    NaN    NaN    NaN    NaN    NaN
         5   50.0    NaN    NaN    NaN    NaN    NaN    NaN    NaN    NaN    NaN
         6   13.0    NaN    NaN    NaN    NaN    NaN    NaN    NaN    NaN    NaN
         7   65.0    NaN    NaN    NaN    NaN    NaN    NaN    NaN    NaN    NaN
```

```
In [65]: df_fl_sample = df_fl.iloc[:, :10]
         df_fl_sample.plot(kind='bar', figsize=(12, 4), fontsize=16,
                           title='Fineline distribution for financial services')
```

```
Out[65]: <matplotlib.axes._subplots.AxesSubplot at 0x10cff358>
```

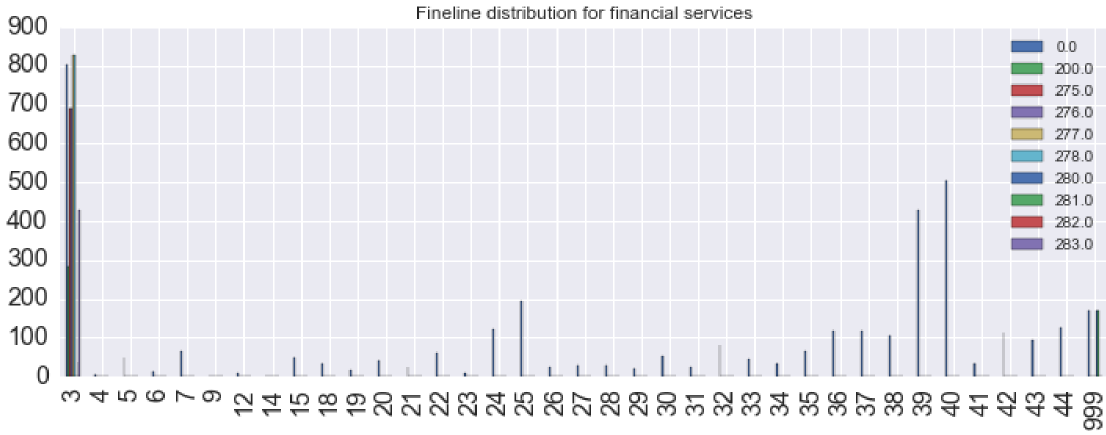
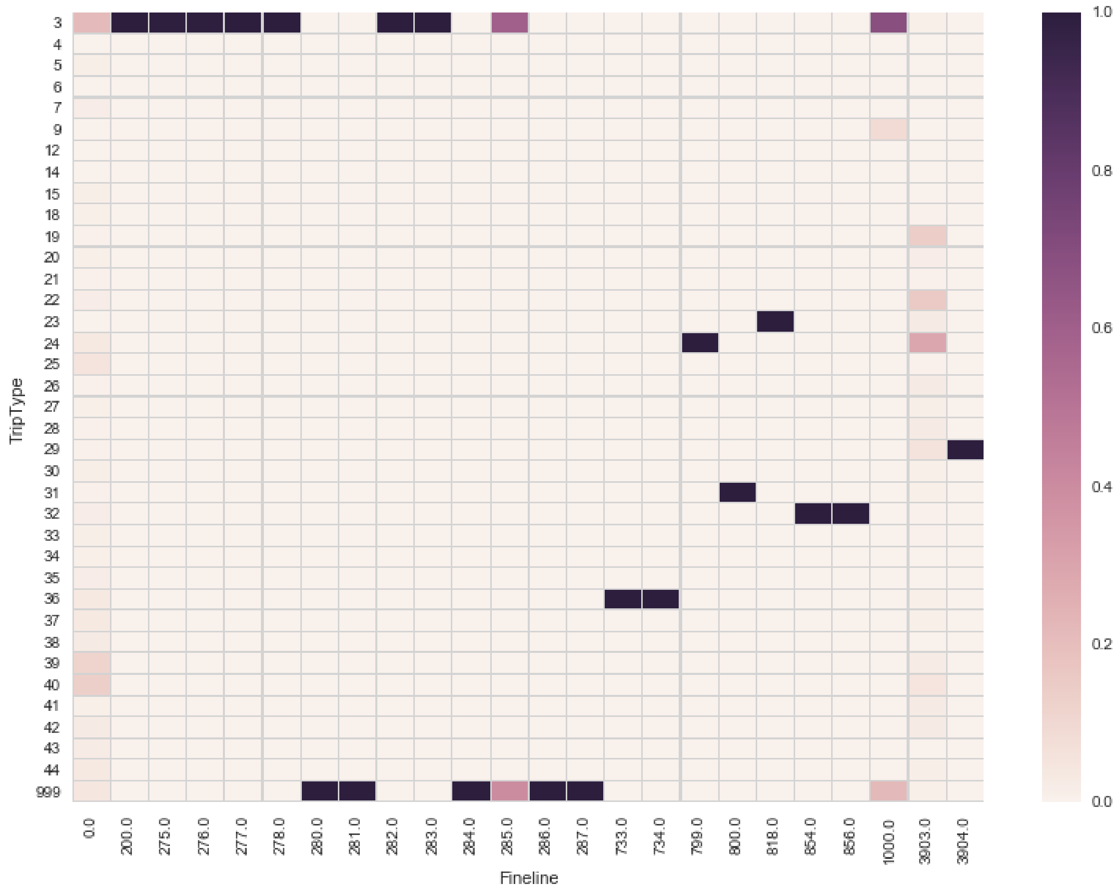


Illustration 2

```
In [66]: df_fs_fl = pd.crosstab(index=df_fs.TripType,
                                 columns=df_fs.Fineline,
                                 normalize='columns')
         df_fs_fl.head().iloc[:, :10]

Out[66]: Fineline      0.0    200.0     275.0     276.0  277.0  278.0  280.0  281.0
         TripType
         3         0.216223     1.0  0.995677  0.995677    1.0    1.0    0.0    0.0
         4         0.001343     0.0  0.000000  0.000000    0.0    0.0    0.0    0.0
         5         0.013430     0.0  0.000000  0.000000    0.0    0.0    0.0    0.0
         6         0.003492     0.0  0.000000  0.000000    0.0    0.0    0.0    0.0
         7         0.017459     0.0  0.000000  0.000000    0.0    0.0    0.0    0.0

In [67]: fig, ax = plt.subplots(figsize=(13, 9))
         sns.heatmap(ax=ax, data=df_fs_fl,
                     linecolor='lightgrey',
                     linewidths=.1)

Out[67]: <matplotlib.axes._subplots.AxesSubplot at 0x15d495f8>
```



Conclusion #2: We note that the data frame *fs_fl* is actually the classification probabilities for visits with financial services.

Decisive Fineline numbers So there are *FinelineNumber* values that give nearly 100% prediction of the *TripType* while others do not.

```
In [68]: print df_fs_fl.columns
```

```
Float64Index([   0.0,  200.0,  275.0,  276.0,  277.0,  278.0,  280.0,  281.0,
               282.0,  283.0,  284.0,  285.0,  286.0,  287.0,  733.0,  734.0,
               799.0,  800.0,  818.0,  854.0,  856.0, 1000.0, 3903.0, 3904.0],
             dtype='float64', name=u'Fineline')
```

```
In [69]: decisive_fl = [fl for fl in df_fs_fl.columns
                        if df_fs_fl[fl].max() > 0.99]
         print decisive_fl
```

```
[200.0, 275.0, 276.0, 277.0, 278.0, 280.0, 281.0, 282.0, 283.0, 284.0, 286.0, 287.(
```

```
In [70]: non_decisive_fl = [fl for fl in df_fs_fl.columns
                            if df_fs_fl[fl].max() <= 0.99]
         print non_decisive_fl
```

```
[0.0, 285.0, 1000.0, 3903.0]
```

For classification purposes we can drop visits with decisive *FinelineNumber*.

```
In [71]: df_decisive = df_fs.ix[df_fs.Fineline.isin(decisive_fl)]
         train.drop(df_decisive.index.unique(), inplace=True)
```

```
In [72]: print train.index.nunique(), len(train)
```

```
85339 612510
```

> **STATUS:** At this stage there are no NANs, no duplicate UPCs, no unique returns (999), and no visits with FINANCIAL SERVICES which have *FinelineNumber* other than 0, 285, 1000 or 3903.

```
In [73]: train_grp = train.groupby(level='Visit')
```

1.4 Final dataset assembly

In this part we create the features that will be used by the model. Each feature(s) will be presented by a dataframe indexed by the *VisitNumber*, and at the end all of these data frames will be merged together. Along the preprocessing we've dropped visits that can be ignored by the (future) classification model, so we can now think of more "business-oriented" features .

The following features will be considered:

- deps - number of items from each department (68 new features)
- n_departments - the number of unique departments represented in the cart
- n_items - the number of items in the cart
- n_upcs - the number of unique UPCs in the cart
- common_dep - the most common department within the visit
- TripType - dahh...

1.4.1 Items per department (*df_deps*)

```
In [74]: df_deps = pd.pivot_table(data=train,
                                  values='ScanCount',
                                  index=train.index,
                                  columns='DepDesc',
                                  aggfunc=np.sum,
                                  fill_value=0)
         df_deps.columns = df_deps.columns.astype(str)  # Otherwise we get Categori
         df_deps.head().iloc[:, ::10]
```

```
Out[74]: DepDesc  1-HR PHOTO  CAMERAS AND SUPPLIES       ...       PERSONAL CARE  SE
         Visit                                          ...
         7                 0                     0      ...                   1
         8                 0                     0      ...                   0
         9                 0                     0      ...                   0
         10                0                     0      ...                   0
         11                0                     0      ...                   0

         [5 rows x 7 columns]
```

1.4.2 Number of departments (*df_n_deps*)

We can use the latest *df_deps* in order to evaluate the number of unique departments within a visit. The aggregation returns a *Series* object, which we will not be able to concat with *df_deps*, so we make it a one-column *DataFrame*.

```
In [75]: df_n_deps = pd.DataFrame(df_deps.astype(bool).sum(axis=1),
                                  columns=['n_deps'],
                                  index=df_deps.index)
         df_n_deps.head()
```

```
Out[75]:        n_deps
         Visit
         7           2
         8           6
         9           2
         10          2
         11          3
```

1.4.3 Number of items (*df_n_items*)

For this task also we can use the latest *df_deps*.

```
In [76]: df_n_items = pd.DataFrame(df_deps.sum(axis=1),
                                   columns=['n_items'],
                                   index=df_deps.index)
         df_n_items.head()
```

```
Out[76]:        n_items
         Visit
         7            2
         8           27
         9            3
         10           3
         11           4
```

1.4.4 Number of UPCs (*df_n_upcs*)

```
In [77]: df_n_upcs = pd.DataFrame(train_grp['UPC'].nunique().values,
                                  columns=['n_upcs'],
```

```
                                    index=df_deps.index)
df_n_upcs.head()
```

Out[77]:

```
       n_upcs
Visit
7           2
8          20
9           3
10          3
11          4
```

NOTE: The need for the *.values* attribute is due to the index that is added to the Series due to the groupby operation.

1.4.5 Weekday

In [78]:

```
df_weekday = pd.DataFrame(train_grp['Weekday'].min(),
                          columns=['Weekday'],
                          index=df_deps.index)
df_weekday.head()
```

Out[78]:

```
      Weekday
Visit
7      Friday
8      Friday
9      Friday
10     Friday
11     Friday
```

In [79]:

```
days = ['Monday', 'Tuesday', 'Wednesday', 'Thursday',
        'Friday', 'Saturday', 'Sunday']
df_weekday['Weekday'] = df_weekday['Weekday']\
    .astype('category', categories=days, ordered=True)
```

1.4.6 *TripType*

In [80]:

```
df_trip_type = pd.DataFrame(train_grp['TripType'].min(),
                            columns=['TripType'],
                            index=df_deps.index)
df_trip_type.head()
```

Out[80]:

```
       TripType
Visit
7            30
8            26
9             8
10            8
11           35
```

1.4.7 Put it all together

```
In [81]: data = pd.concat((df_deps, df_n_deps, df_n_items,
                           df_n_upcs, df_weekday, df_trip_type),
                          axis=1)
         data.head().iloc[:, ::10]

Out[81]:        1-HR PHOTO  CAMERAS AND SUPPLIES  FINANCIAL SERVICES   ...    PERSO
         Visit                                                          ...
         7               0                     0                   0   ...
         8               0                     0                   0   ...
         9               0                     0                   0   ...
         10              0                     0                   0   ...
         11              0                     0                   0   ...

         [5 rows x 8 columns]
```

1.4.8 Export the result

```
In [82]: data.to_csv(getcwd() + "\\triptype final data.csv")
```