topos (1)

April 3, 2019

1 Exploratory Analysis

First of all, let's import some useful libraries that will be used in the analysis.

```
In [0]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
```

Now, the dataset stored in drive needs to be retieved. I am using google colab for this exploration with TPU hardware accelerator for faster computation. To get the data from drive the drive needs to be mounted first.

```
In [3]: from google.colab import drive
        drive.mount('/content/drive/')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6

Enter your authorization code:
ůůůůůůůůůů
Mounted at /content/drive/
```

Once the drive is successfully mounted, I fetched the data and stored it in a pandas dataframe.

```
In [4]: dataset = pd.read_csv("/content/drive/My Drive/Colab Notebooks/DOB_Permit_Issuance.csv"
```

```
/usr/local/lib/python3.6/dist-packages/IPython/core/interactiveshell.py:2718: DtypeWarning: Col
  interactivity=interactivity, compiler=compiler, result=result)
```

To get the gist of the dataset, I used pandas describe function that gives a very broad understanding of the data.

```
In [5]: pd.set_option('display.max_colwidth', 1000)
        pd.set_option('display.max_rows', 1000)
        pd.set_option('display.max_columns', 500)
        pd.set_option('display.width', 1000)
        dataset.describe()
```

```
Out[5]:                Job #     Job doc. #       Zip Code      Bldg Type  Permit Sequence #  PERMI
        count  3.508249e+06  3.508249e+06  3.506028e+06  3.453772e+06       3.508249e+06  3.508
        mean   2.521092e+08  1.115809e+00  1.063692e+04  1.758554e+00       1.487494e+00  1.830
        std    1.351914e+08  4.097722e-01  6.001003e+02  4.279601e-01       1.149177e+00  1.028
        min    1.000300e+08  1.000000e+00  0.000000e+00  1.000000e+00       1.000000e+00  1.000
        25%    1.204096e+08  1.000000e+00  1.002200e+04  2.000000e+00       1.000000e+00  9.508
        50%    2.401865e+08  1.000000e+00  1.045700e+04  2.000000e+00       1.000000e+00  1.835
        75%    4.005124e+08  1.000000e+00  1.122600e+04  2.000000e+00       2.000000e+00  2.718
        max    5.401627e+08  1.200000e+01  1.169700e+04  2.000000e+00       2.900000e+01  3.609
```

From the describe function, we now know that the dataset has almost 3.5 M data. Let's take a look at the dataset now.

```
In [6]: dataset.head()
```

```
Out[6]:      BOROUGH    Bin # House #        Street Name       Job #  Job doc. #  Job Type Self_Ce
        0      BRONX  2102476     200     E 135TH STREET  240249842           1        A2
        1  MANHATTAN  1090833     249     WEST 14 STREET  140818435           1        A3
        2  MANHATTAN  1015903      20  WEST 36TH STREET  123372466           2        A2
        3     QUEENS  4467709   14-30           BROADWAY  421105618           1        A2
        4     QUEENS  4048873   42-06         108 STREET  421024689           1        A1

           PERMIT_SI_NO   LATITUDE  LONGITUDE  COUNCIL_DISTRICT  CENSUS_TRACT
        0       3608996  40.810699 -73.931313               8.0          51.0
        1       3609359  40.739151 -74.001075               3.0          81.0  Hudson Yards-Che
        2       3609159  40.750090 -73.984513               4.0          84.0
        3       3609358  40.765826 -73.932800              22.0          45.0
        4       3606599  40.749221 -73.858003              21.0         403.0
```

I can see there are lot's of NaNs in many columns. To better analyse the data, the NaNs needs to be removed or dealt with. But first, let's see hoe many NaNs are there is each column.

```
In [0]: dataset.isna().sum()
```

```
Out[0]: BOROUGH                               0
        Bin #                                 0
        House #                               4
        Street Name                           4
        Job #                                 0
        Job doc. #                            0
        Job Type                              0
        Self_Cert                       1274022
        Block                               499
        Lot                                 508
        Community Board                    4757
        Zip Code                           2221
        Bldg Type                         54477
        Residential                     2139591
        Special District 1              3121182
```

```
Special District 2                 3439516
Work Type                           609717
Permit Status                        10813
Filing Status                            0
Permit Type                              1
Permit Sequence #                        0
Permit Subtype                     1393411
Oil Gas                            3470104
Site Fill                           417333
Filing Date                              1
Issuance Date                        19972
Expiration Date                      11143
Job Start Date                          30
Permittee's First Name               15732
Permittee's Last Name                15748
Permittee's Business Name            48868
Permittee's Phone #                  15963
Permittee's License Type            269081
Permittee's License #               238702
Act as Superintendent              1912116
Permittee's Other Title            3236862
HIC License                        3477843
Site Safety Mgr's First Name       3481885
Site Safety Mgr's Last Name        3481861
Site Safety Mgr Business Name      3490529
Superintendent First & Last Name   1814931
Superintendent Business Name       1847714
Owner's Business Type               164588
Non-Profit                          160499
Owner's Business Name               715709
Owner's First Name                    1858
Owner's Last Name                     1553
Owner's House #                       1125
Owner's House Street Name             1369
Owners House City                     706
Owners House State                    679
Owners House Zip Code                6175
Owner's Phone #                      49040
DOBRunDate                               0
PERMIT_SI_NO                             0
LATITUDE                             12258
LONGITUDE                            12258
COUNCIL_DISTRICT                     12258
CENSUS_TRACT                         12258
NTA_NAME                             12258
dtype: int64
```

The information above is very useful in feature selection. Observing the columns with very high number of NaNs, such as :

Column	NaNs
Special District 1	3121182
Special District 2	3439516
Permittee's Other Title	3236862
HIC License	3477843
Site Safety Mgr's Last Name	3481861
Site Safety Mgr's First Name	3481885
Site Safety Mgr Business Name	3490529
Residential	2139591
Superintendent First & Last Name	1814931
Superintendent Business Name	1847714
Self_Cert	1274022
Permit Subtype	1393411
Oil Gas	3470104

From the column_info sheet of file 'DD_DOB_Permit_Issuance_2018_11_02', I know that some of the column has a meaning related to blanks. For example, for the Residential column, there are either 'Yes' or 'Blanks'. So it's safe to assume that the blanks are associated with 'No'.

Similarly, to fill the blanks based on relevant information from column_info, I am using below mappings for some columns:

- Residential : No
- Site Fill : None
- Oil Gas : None
- Self_Cert : N
- Act as Superintendent : N
- Non-Profit : N

```
In [0]: values = {'Residential': 'No','Site Fill':'NONE', 'Oil Gas':'None', 'Self_Cert':'N', '
                  'Non-Profit':'N' }
        dataset = dataset.fillna(value= values)
```

Since there are many columns with blank spaces and we cannot fill the blanks with appropriate information, it's better to drop these column as they do not add value to the analysis.

I will drop the following columns :

- Special District 1
- Special District 2
- Work Type
- Permit Subtype
- Permittee's First Name
- Permittee's Last Name
- Permittee's Business Name

- Permittee's Phone #
- Permittee's Other Title
- HIC License
- Site Safety Mgr's First Name
- Site Safety Mgr's Last Name
- Site Safety Mgr Business Name
- Superintendent First & Last Name
- Superintendent Business Name
- Owner's Business Name
- Owner's First Name
- Owner's Last Name
- Owner's House #
- Owner's House Street Name
- Owner's Phone #
- DOBRunDate

In [0]:
```
dataset.drop("Special District 1", axis=1, inplace=True)
dataset.drop("Special District 2", axis=1, inplace=True)
dataset.drop("Work Type", axis=1, inplace=True) #since work type and permit type give
dataset.drop("Permit Subtype", axis=1, inplace=True)
dataset.drop("Permittee's First Name", axis=1, inplace=True)
dataset.drop("Permittee's Last Name", axis=1, inplace=True)
dataset.drop("Permittee's Business Name", axis=1, inplace=True)
dataset.drop("Permittee's Phone #", axis=1, inplace=True)
dataset.drop("Permittee's Other Title", axis=1, inplace=True) #Permit Subtype
dataset.drop("HIC License", axis=1, inplace=True)
dataset.drop("Site Safety Mgr's First Name", axis=1, inplace=True)
dataset.drop("Site Safety Mgr's Last Name", axis=1, inplace=True)
dataset.drop("Site Safety Mgr Business Name", axis=1, inplace=True)
dataset.drop("Superintendent First & Last Name", axis=1, inplace=True)
dataset.drop("Superintendent Business Name", axis=1, inplace=True)
dataset.drop("Owner's Business Name", axis=1, inplace=True)
dataset.drop("Owner's First Name", axis=1, inplace=True)
dataset.drop("Owner's Last Name", axis=1, inplace=True)
dataset.drop("Owner's House #", axis=1, inplace=True)
dataset.drop("Owner's House Street Name", axis=1, inplace=True)
dataset.drop("Owner's Phone #", axis=1, inplace=True)
dataset.drop("DOBRunDate", axis=1, inplace=True)
```

Let's take a look at the remaining columns and their number of blanks again.

In [9]:
```
dataset.isna().sum()
```

Out[9]:
```
BOROUGH                          0
Bin #                            0
House #                          4
Street Name                      4
Job #                            0
Job doc. #                       0
```

```
Job Type                       0
Self_Cert                      0
Block                        499
Lot                          508
Community Board             4757
Zip Code                    2221
Bldg Type                  54477
Residential                    0
Permit Status              10813
Filing Status                  0
Permit Type                    1
Permit Sequence #              0
Oil Gas                        0
Site Fill                      0
Filing Date                    1
Issuance Date              19972
Expiration Date            11143
Job Start Date                30
Permittee's License Type  269081
Permittee's License #     238702
Act as Superintendent          0
Owner's Business Type     164588
Non-Profit                     0
Owners House City            706
Owners House State           679
Owners House Zip Code       6175
PERMIT_SI_NO                   0
LATITUDE                   12258
LONGITUDE                  12258
COUNCIL_DISTRICT           12258
CENSUS_TRACT               12258
NTA_NAME                   12258
dtype: int64
```

We still have blanks in few columns left. One way to deal with them is to replace them with mean of that column or the most frequent entry of that column. Mean can onlly be applied to numerical columns and even for numerical columns such as Longitude and Lattitude, this mean might not be right to replace all the missing value with single longitude or lattitude. This will skew the column and would not result in fair analysis of data.

Similarly, if we use the most frequently used entry to replace all the blanks in that column, it will either skew the matrix or the data itself would not make sense. For example, the for a particular location, there is a state, city, zip code and street name associated with it. If we replace the missing entries in zip code with most frequent entry, then it might result in a data that is having a different state, city and a zip code of another location.

Therefore, to clean the data I will drop the rows with NaNs. We will still have enough data for exploration.

```
In [7]: dataset.dropna(inplace=True)
        dataset.isna().sum()
```

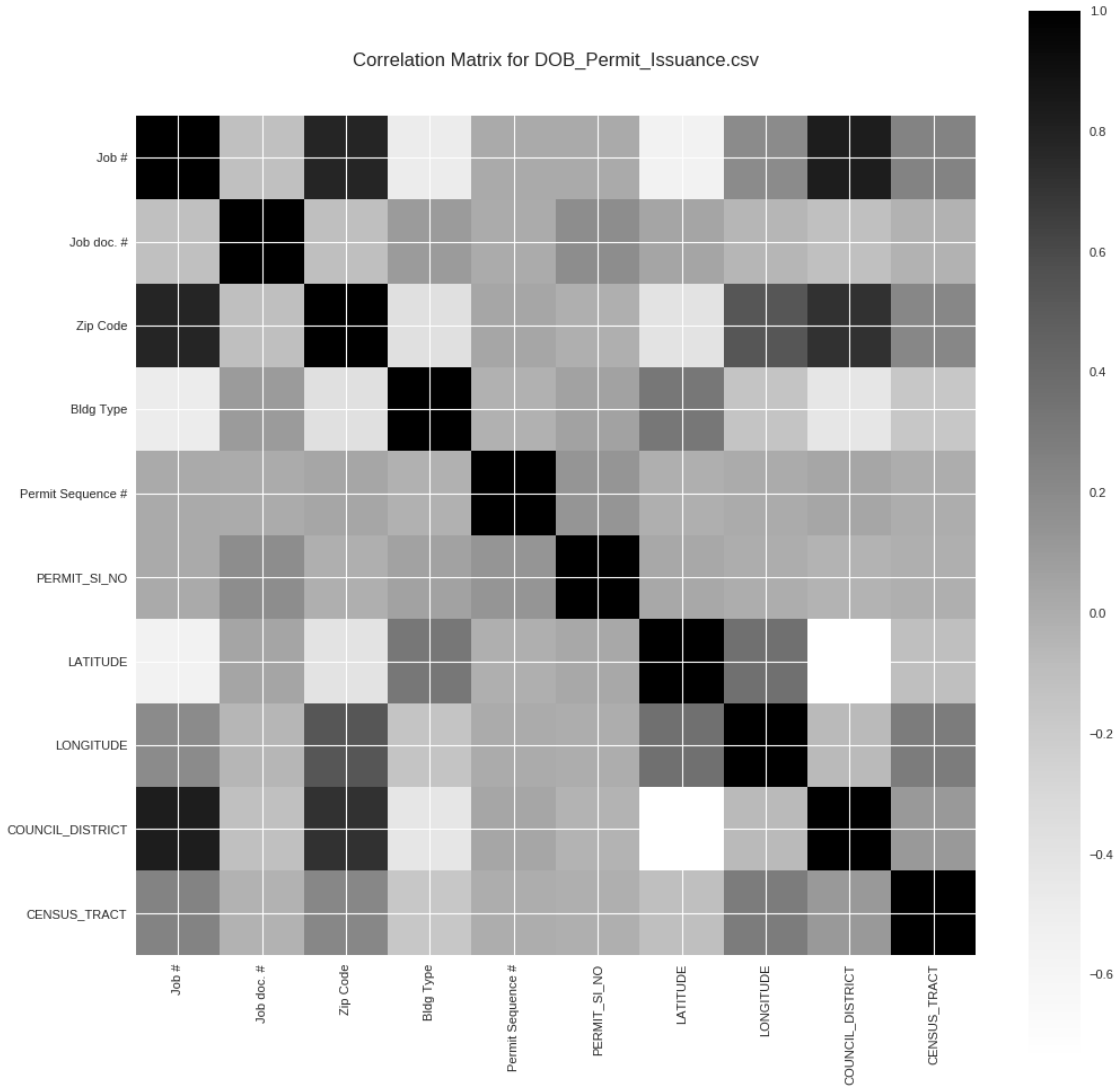
Out[7]:
```
BOROUGH                     0
Bin #                       0
House #                     0
Street Name                 0
Job #                       0
Job doc. #                  0
Job Type                    0
Self_Cert                   0
Block                       0
Lot                         0
Community Board             0
Zip Code                    0
Bldg Type                   0
Residential                 0
Permit Status               0
Filing Status               0
Permit Type                 0
Permit Sequence #           0
Oil Gas                     0
Site Fill                   0
Filing Date                 0
Issuance Date               0
Expiration Date             0
Job Start Date              0
Permittee's License Type    0
Permittee's License #       0
Act as Superintendent       0
Owner's Business Type       0
Non-Profit                  0
Owners House City         0
Owners House State        0
Owners House Zip Code     0
PERMIT_SI_NO                0
LATITUDE                    0
LONGITUDE                   0
COUNCIL_DISTRICT            0
CENSUS_TRACT                0
NTA_NAME                    0
dtype: int64
```

Now the dataset looks clean and we can proceed with analysis. I will try find the correlation between columns using the correlation matrix.

In [0]:
```python
# Correlation matrix
def plotCorrelationMatrix(df, graphWidth):
    filename = 'DOB_Permit_Issuance.csv'
```

```
    df = df[[col for col in df if df[col].nunique() > 1]] # keep columns where there a
    corr = df.corr()
    plt.figure(num=None, figsize=(graphWidth, graphWidth), dpi=80, facecolor='w', edge
    corrMat = plt.matshow(corr, fignum = 1)
    plt.xticks(range(len(corr.columns)), corr.columns, rotation=90)
    plt.yticks(range(len(corr.columns)), corr.columns)
    plt.gca().xaxis.tick_bottom()
    plt.colorbar(corrMat)
    plt.title(f'Correlation Matrix for {filename}', fontsize=15)
    plt.show()
```

```
In [12]: plotCorrelationMatrix(dataset, 15)
```



We can see that there is strong positive relationship between :

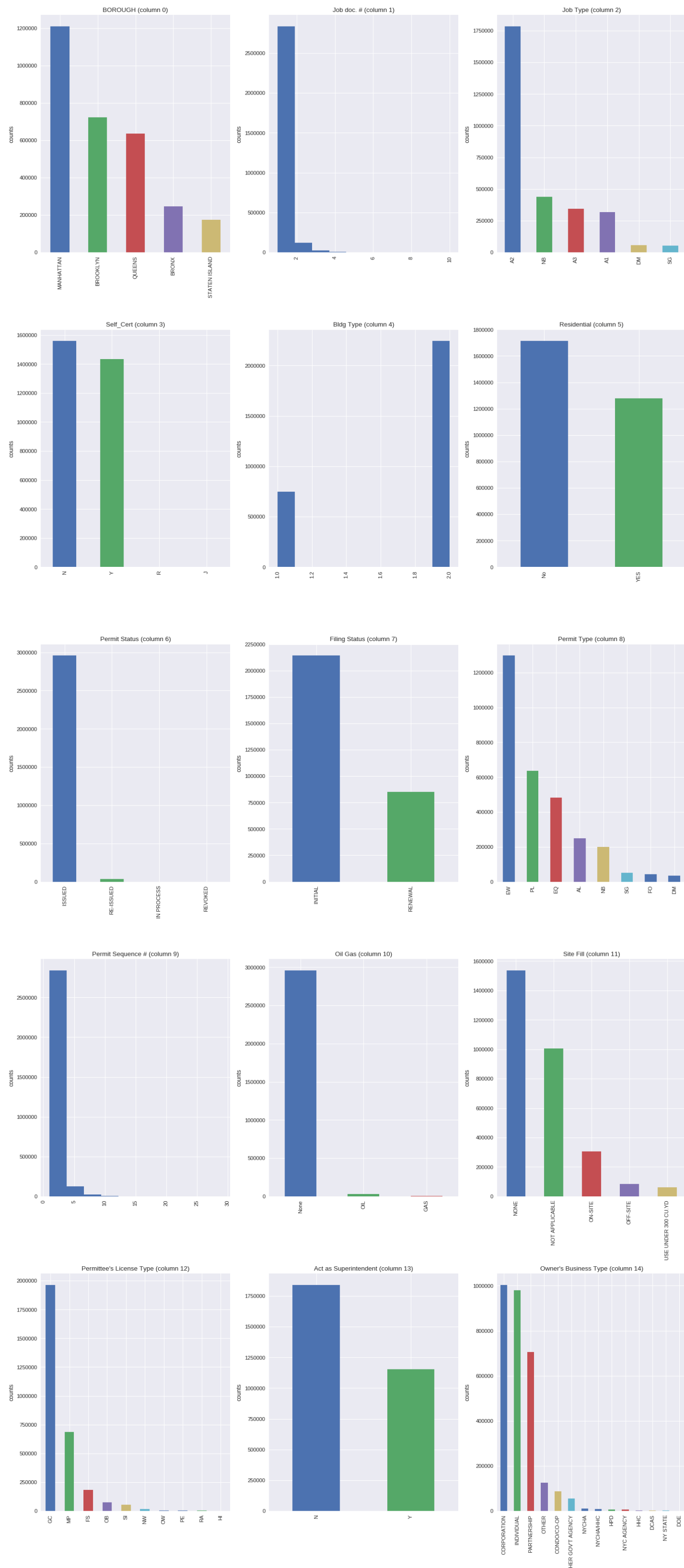
- Zip Code and Job #

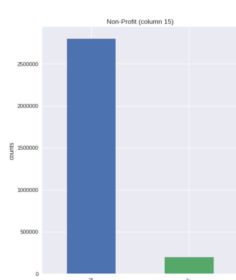
- Job # and Council_District
- Zip Code and Council_District

To get more insight of the data and its column-wise data distribution, I will plot the columns using bar graphs. For displaying purposes, I will pick columns that have between 1 and 50 unique values.

```
In [0]: def plotColumns(dataframe, nGraphShown, nGraphPerRow):
            nunique = dataframe.nunique()
            dataframe = dataframe[[col for col in dataframe if nunique[col] > 1 and nunique[co
            nRow, nCol = dataframe.shape
            columnNames = list(dataframe)
            nGraphRow = (nCol + nGraphPerRow - 1) / nGraphPerRow
            plt.figure(num = None, figsize = (6 * nGraphPerRow, 8 * nGraphRow), dpi = 80, face
            for i in range(min(nCol, nGraphShown)):
                plt.subplot(nGraphRow, nGraphPerRow, i + 1)
                columndataframe = dataframe.iloc[:, i]
                if (not np.issubdtype(type(columndataframe.iloc[0]), np.number)):
                    valueCounts = columndataframe.value_counts()
                    valueCounts.plot.bar()
                else:
                    columndataframe.hist()
                plt.ylabel('counts')
                plt.xticks(rotation = 90)
                plt.title(f'{columnNames[i]} (column {i})')
            plt.tight_layout(pad = 1.0, w_pad = 1.0, h_pad = 1.0)
            plt.show()
```

```
In [9]: plotColumns(dataset, 38, 3)
```


BOROUGH (column 0)
MANHATTAN
BROOKLYN
QUEENS
BRONX
STATEN ISLAND
Job doc. # (column 1)
Job Type (column 2)
A2
NB
A3
A1
DM
SG
Self_Cert (column 3)
Bldg Type (column 4)
Residential (column 5)
YES
Permit Status (column 6)
ISSUED
RE-ISSUED
IN PROCESS
REVOKED
Filing Status (column 7)
INITIAL
RENEWAL
Permit Type (column 8)
Permit Sequence # (column 9)
Oil Gas (column 10)
None
OIL
GAS
Site Fill (column 11)
NONE
NOT APPLICABLE
ON-SITE
OFF-SITE
USE UNDER 300 CU.YD
Permittee's License Type (column 12)
Act as Superintendent (column 13)
Owner's Business Type (column 14)
CORPORATION
INDIVIDUAL
PARTNERSHIP
OTHER
CONDO/CO-OP
OTHER GOV'T AGENCY
NYCHA
NYCHA/HHC
HPD
NYC AGENCY
HHC
DCAS
NY STATE
DOE
counts


Non-Profit (column 15)
counts

From the Borough graph, it's evident that the Manhattan has highest number of filing for the permit. Then the second popuar borough after manhattan is Brooklyn with huge margin. Then comes the Queens with almost same number of permits as Brooklyn. We see another plunge in permit numbers with Bronx and Staten Island.

Job Document number is the number of documents that were added with the file during the application. Mostly all the filings required a single document. There are some permits that had two documents and then higher number of documents are negligible.

There is a pattern in Job Type as well. We can see that the most populat Job Type or Work Type is A2 with more than 1.75 M permits. The second most popular work type is NB (new building) with around 400,000 permits. The number of permits decreases with A3, A1, DM and SG where DM and SG are significantly less than other types.

Self_Cert indicates whether or not the application was submitted as Professionally Certified. A Professional Engineer (PE) or Registered Architect (RA) can certify compliance with applicable laws and codes on applications filed by him/her as applicant. Plot shows mostly were not filed by Professional Engineer or Registered Architect.

Bldg Type indicates legal occupancy classification. The most popular type of building type is '2' with more than 2M permits.

Most of the buildings are non Residential and only about 1.3M buildinngs were residential.

Permit Status indicates the current status of the permit application. Corresponding plot for the column suggests that most of the permits are 'Issued' and very small number were 'Reissued'. The 'In-Progress' and 'Revoked' are negligible.

Permit Type The specific type of work covered by the permit. This is a two character code to indicate the type of work. There are 7 types of permits where EW has the highest number. The number indicates decreasing trend with PL, EQ, AL, NB, SG, and FO.

A sequential number assigned to each issuance of the particular permit from initial issuance to each subsequent renewal. Every initial permit should have a 01 sequence number. Every additional renewal receives a number that increases by 1 (ex: 02, 03, 04). Most of the permits have less than 5 sequence number.

If the permit is for work on fuel burning equipment, this indicates whether it burns oil or gas. Most of the permits are for neither Oil nor Gas. A very small fraction of permits is for Oil and there is negligible number of permits for Gas.

Site Fill indicates the source of any fill dirt that will be used on the construction site. When over 300 cubic yards of fill is being used, the Department is required to inform Sanitation of where the fill is coming from and the amount. About 1.1M entries didn't mention any Site Fill type indicating that the less than 300 cubic yards of fill is being used. Almost permits are not applicable. About 300,000 permits were for on-site fill and less than 100,000 were for off-site.

Act as Superintendent indicates if the permittee acts as the Construction Superintendent for the work site. Only about 1.1M people responded 'Yes' to this and majority respondded with 'No'

Owner's Business Type indicates the type of entity that owns the building where the work will be performed. Mostly the entities owning the builing were 'Corporations'. With slightly less than 'Corporation', 'Individual' type stands at the second position and 'Partnership' holds the third position. Other business types like are less significant in number.

Non-Profit indicates if the building is owned by a non-profit. Less than 250,000 buildings were owned by 'Non-Profit' and more than 2.75M were not 'Non-Profit'.

2 Borough-wise analysis

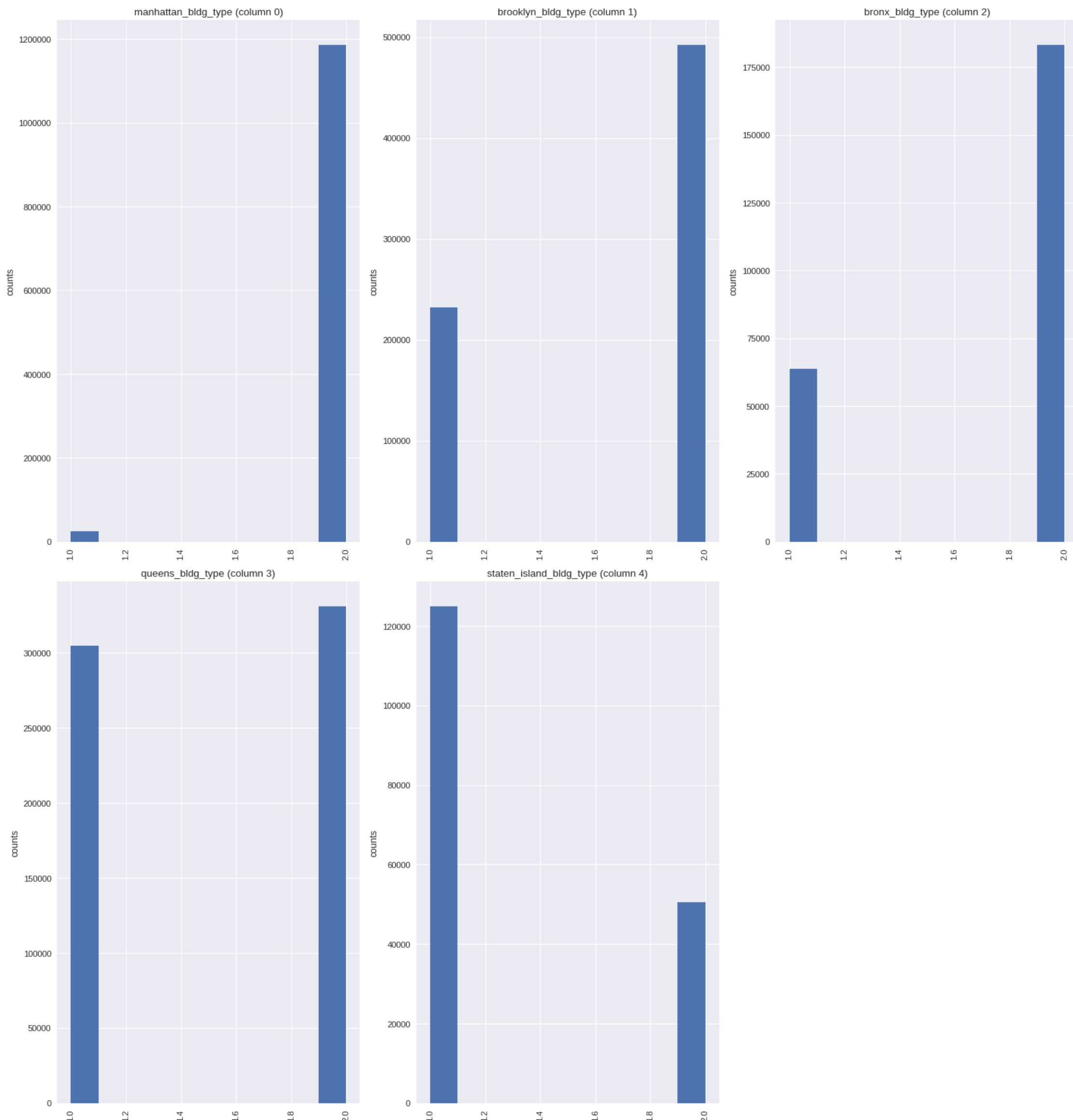
Let's now dive deeper in the data and take a closer look. Is the trend we see above is same across all Boroughs ?. Does every borough have same type of building? Is 'EW' the most popular permit type across all cities? What about the 'owner's business type' and 'Job Type' ? I will try to find the answers to all these by exploring the pattern in each bouough.

2.0.1 Bldg Type in each borough

In [0]:
```
manhattan_bldg_type = dataset[dataset.BOROUGH == 'MANHATTAN'][['Bldg Type']]
manhattan_bldg_type.reset_index(drop=True, inplace=True)

brooklyn_bldg_type = dataset[dataset.BOROUGH == 'BROOKLYN'][['Bldg Type']]
brooklyn_bldg_type.reset_index(drop=True, inplace=True)

bronx_bldg_type = dataset[dataset.BOROUGH == 'BRONX'][['Bldg Type']]
bronx_bldg_type.reset_index(drop=True, inplace=True)

queens_bldg_type = dataset[dataset.BOROUGH == 'QUEENS'][['Bldg Type']]
queens_bldg_type.reset_index(drop=True, inplace=True)
```

```
staten_island_bldg_type = dataset[dataset.BOROUGH == 'STATEN ISLAND'][['Bldg Type']]
staten_island_bldg_type.reset_index(drop=True, inplace=True)

building_type = pd.DataFrame()
building_type['manhattan_bldg_type'] = manhattan_bldg_type #brooklyn_bldg_type
building_type['brooklyn_bldg_type'] = brooklyn_bldg_type
building_type['bronx_bldg_type'] = bronx_bldg_type
building_type['queens_bldg_type'] = queens_bldg_type
building_type['staten_island_bldg_type'] = staten_island_bldg_type
```

```
In [18]: plotColumns(building_type, 5, 3)
```



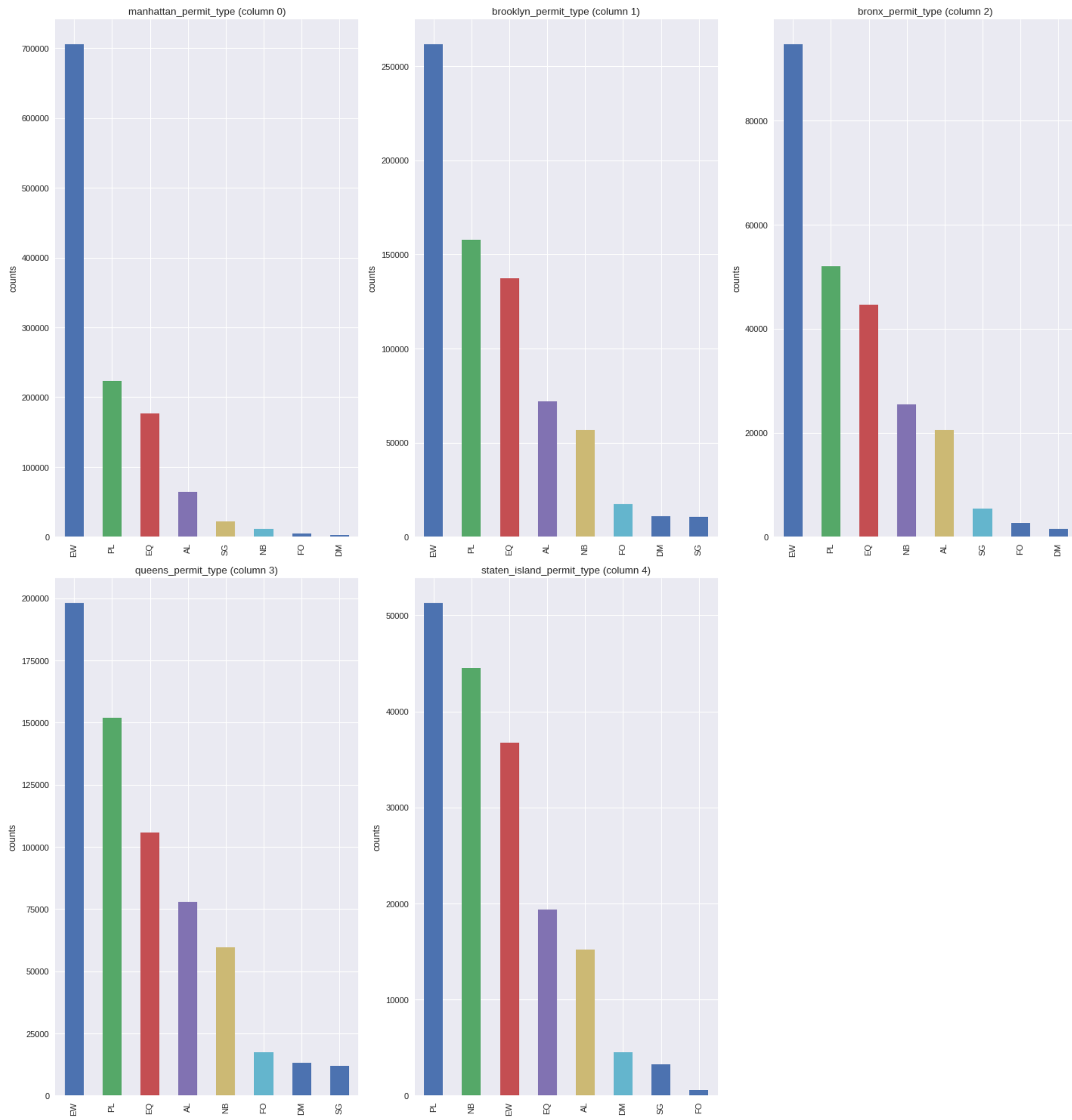
Analysis

The builing type is either '1' or '2' and we earlier discovered that type '2' were significantly popular as compared to type '1'. However, this is not true for all the Boroughs. For manhattan, this trend still holds true. But for other locations, the type '1' buildings are comparable in number with that of type '2'. More interestingly, in case of Staten Island, the type '1' is significantly popular beating type '2' with a good margin.

2.0.2 Permit Type in Each Borough

In [0]:
```
manhattan_permit_type = dataset[dataset.BOROUGH == 'MANHATTAN'][['Permit Type']]
manhattan_permit_type.reset_index(drop=True, inplace=True)

brooklyn_permit_type = dataset[dataset.BOROUGH == 'BROOKLYN'][['Permit Type']]
brooklyn_permit_type.reset_index(drop=True, inplace=True)

bronx_permit_type = dataset[dataset.BOROUGH == 'BRONX'][['Permit Type']]
bronx_permit_type.reset_index(drop=True, inplace=True)

queens_permit_type = dataset[dataset.BOROUGH == 'QUEENS'][['Permit Type']]
queens_permit_type.reset_index(drop=True, inplace=True)

staten_island_permit_type = dataset[dataset.BOROUGH == 'STATEN ISLAND'][['Permit Type'
staten_island_permit_type.reset_index(drop=True, inplace=True)

permit_type = pd.DataFrame()
permit_type['manhattan_permit_type'] = manhattan_permit_type #brooklyn_permit_type
permit_type['brooklyn_permit_type'] = brooklyn_permit_type
permit_type['bronx_permit_type'] = bronx_permit_type
permit_type['queens_permit_type'] = queens_permit_type
permit_type['staten_island_permit_type'] = staten_island_permit_type
```

In [19]:
```
plotColumns(permit_type, 5, 3)
```



Analysis

In Permit Type we earlier discovered that type 'EW' was the most popular and significantly higher in number as compared to other types. However, this is true for most of the Boroughs except Staten Island. However, other types of Permit are shuffled in each Borough. Below is the type of permits in decreasing order for each borough.

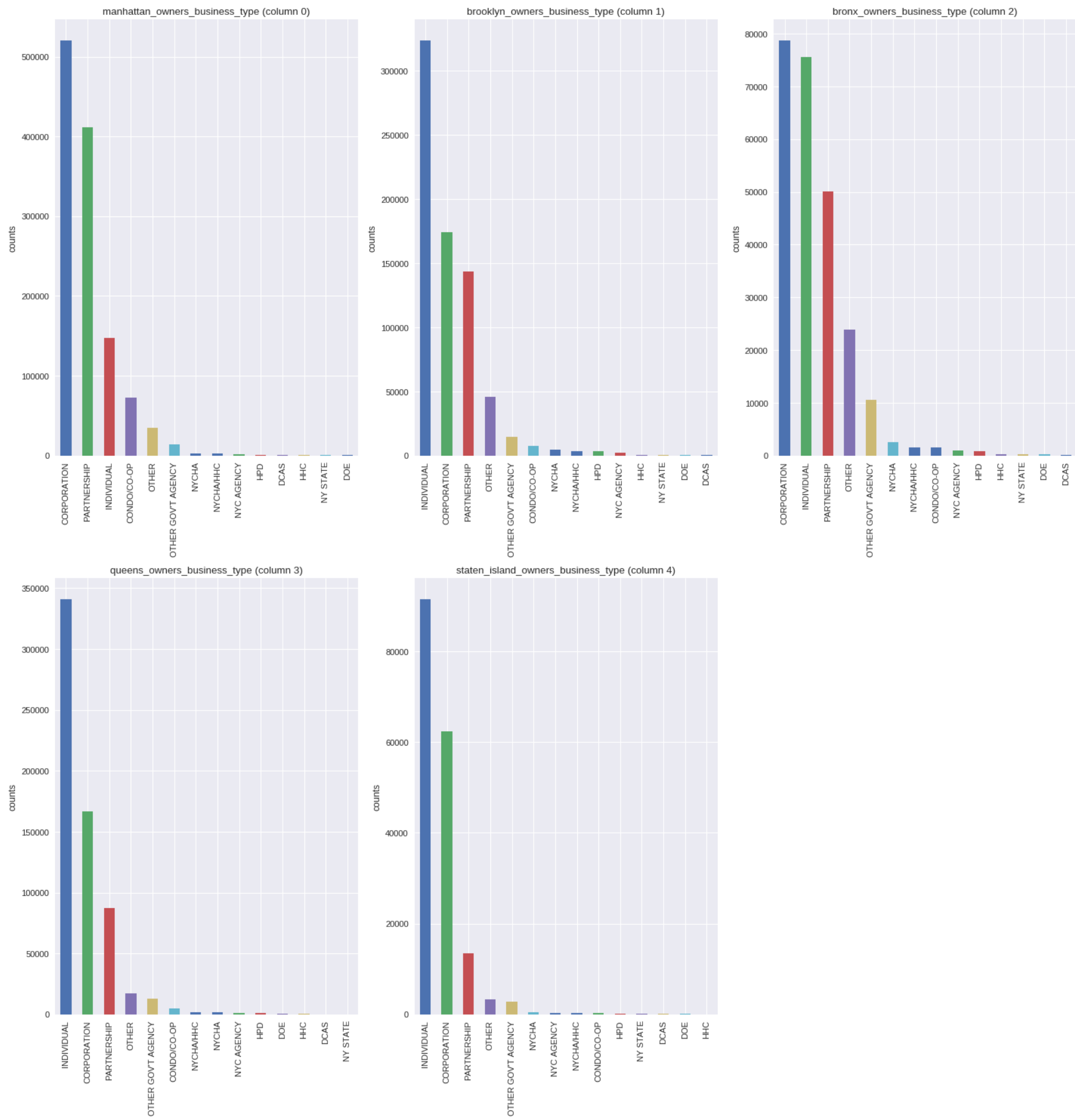
Manhattan	Brooklyn	Queens	Bronx
EW	EW	EW	EW
PL	PL	PL	PL
EQ	EQ	EQ	EQ
AL	AL	NB	AL
SQ	NB	AL	SQ

Manhattan	Brooklyn	Queens	Bronx
NB	FO	SG	FO
FO	DM	FO	DM
DM	SG	DM	SG

2.0.3 Owner's Business Type in Each Borough

In [0]:
```
manhattan_owners_business_type = dataset[dataset.BOROUGH == 'MANHATTAN'][['Owner\'s Bus
manhattan_owners_business_type.reset_index(drop=True, inplace=True)

brooklyn_owners_business_type = dataset[dataset.BOROUGH == 'BROOKLYN'][['Owner\'s Busi
brooklyn_owners_business_type.reset_index(drop=True, inplace=True)

bronx_owners_business_type = dataset[dataset.BOROUGH == 'BRONX'][['Owner\'s Business Ty
bronx_owners_business_type.reset_index(drop=True, inplace=True)

queens_owners_business_type = dataset[dataset.BOROUGH == 'QUEENS'][['Owner\'s Business
queens_owners_business_type.reset_index(drop=True, inplace=True)

staten_island_owners_business_type = dataset[dataset.BOROUGH == 'STATEN ISLAND'][['Owne
staten_island_owners_business_type.reset_index(drop=True, inplace=True)

owners_business_type = pd.DataFrame()
owners_business_type['manhattan_owners_business_type'] = manhattan_owners_business_type
owners_business_type['brooklyn_owners_business_type'] = brooklyn_owners_business_type
owners_business_type['bronx_owners_business_type'] = bronx_owners_business_type
owners_business_type['queens_owners_business_type'] = queens_owners_business_type
owners_business_type['staten_island_owners_business_type'] = staten_island_owners_busin
```

In [21]:
```
plotColumns(owners_business_type, 5, 3)
```



Analysis

We earlier discovered that the 'Corporation' was the most popular 'Owner's Business type' and 'Individual' type was closely competing with it. Taking a closer look at each borough reveals that the trend highly varies in all the Boroughs. In Manhattan, the 'Corporation' is still the highest but the 'Individual' is substituted by 'Partnership'. In Brooklyn, 'Individual' holds the top place and 'Corporation' and 'Partnership' are on second and third place respectively.

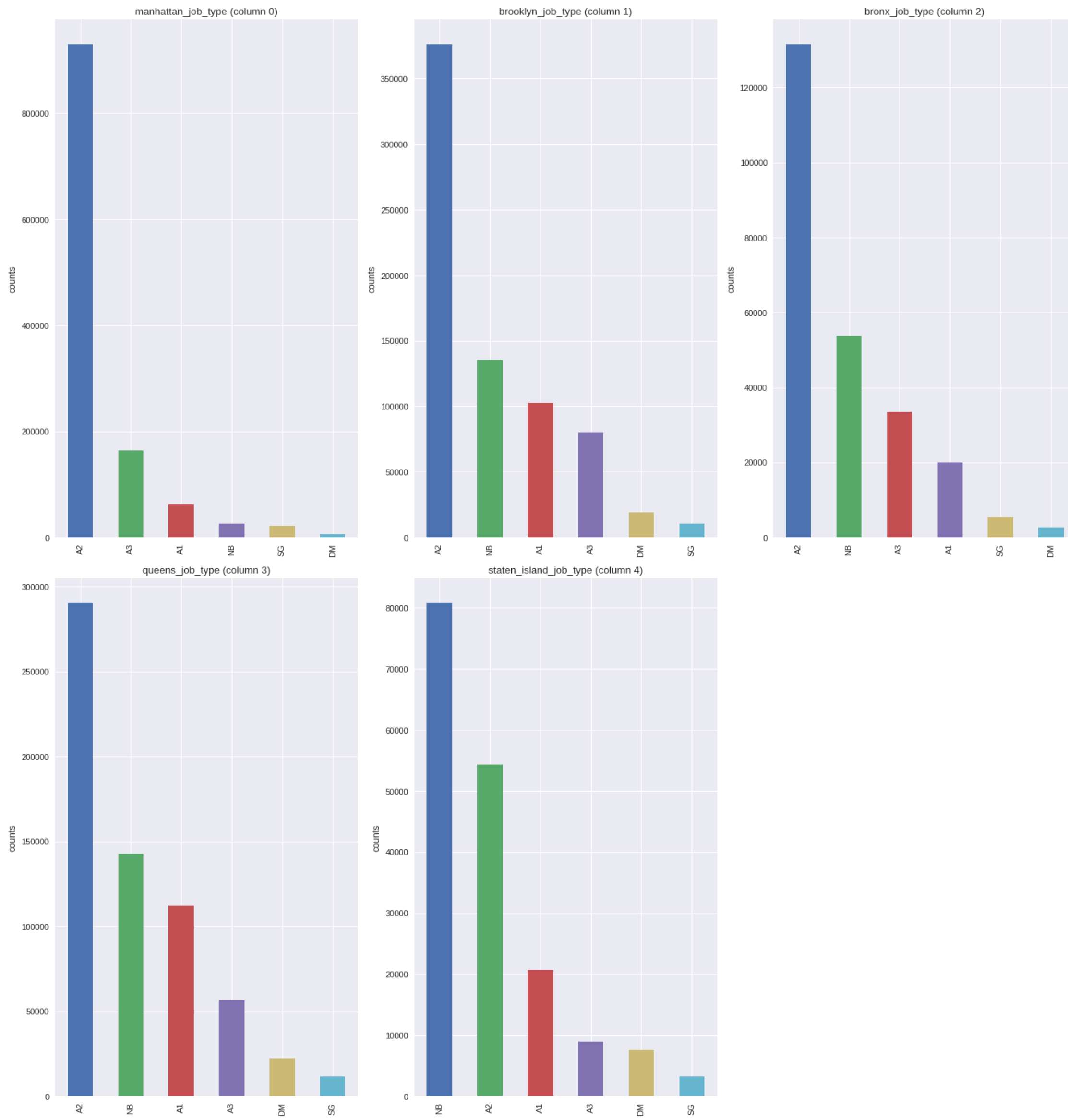
In Bronx, the 'Corporation' and 'Individual' are closely competing while 'Corporation' holds the highest number and 'Partnership' is on third place.

For Queens and Staten Island, the 'Individual' holds the top place and 'Corporation' and 'Partnership' are on second and third place respectively. This is consistent with the trend observed in 'Brooklyn'.

2.0.4 Job Type in Each Borough

In [0]:
```
manhattan_job_type = dataset[dataset.BOROUGH == 'MANHATTAN'][['Job Type']]
manhattan_job_type.reset_index(drop=True, inplace=True)

brooklyn_job_type = dataset[dataset.BOROUGH == 'BROOKLYN'][['Job Type']]
brooklyn_job_type.reset_index(drop=True, inplace=True)

bronx_job_type = dataset[dataset.BOROUGH == 'BRONX'][['Job Type']]
bronx_job_type.reset_index(drop=True, inplace=True)

queens_job_type = dataset[dataset.BOROUGH == 'QUEENS'][['Job Type']]
queens_job_type.reset_index(drop=True, inplace=True)

staten_island_job_type = dataset[dataset.BOROUGH == 'STATEN ISLAND'][['Job Type']]
staten_island_job_type.reset_index(drop=True, inplace=True)

job_type = pd.DataFrame()
job_type['manhattan_job_type'] = manhattan_job_type #brooklyn_job_type
job_type['brooklyn_job_type'] = brooklyn_job_type
job_type['bronx_job_type'] = bronx_job_type
job_type['queens_job_type'] = queens_job_type
job_type['staten_island_job_type'] = staten_island_job_type
```

In [23]:
```
plotColumns(job_type, 5, 3)
```



Analysis

We earlier discovered that the 'A2' was the most popular 'Job type' and numbers showed a decreasing trend with 'NB', 'A3', 'A1', 'DM', and 'SG'. Taking a closer look at each borough revealsa slightly different trend. For example, in Manhattan, the 'A2' is still the highest but the 'NB' is pushed beyond 'A1' to the fourth place while in Staten Island 'NB' holds the first place. Below is the type of Jobs in decreasing order for each borough.

Overall	Manhattan	Brooklyn	Queens
A2	A2	A2	A2
NB	A3	NB	NB
A3	A1	A1	A3
A1	NB	A3	A1

Overall	Manhattan	Brooklyn	Queens
DM	SG	DM	SG
SG	DM	SG	DM

3 Permits Per Years

3.0.1 Is there is trend in the number of permits issued each year? Let's find out!

First, the date format of 'Issuance Date' needs to be converted to python Datetime format and then only the year needs to be extracted from the date.

```
In [0]: dataset['Issuance Date'] = pd.to_datetime(dataset['Issuance Date'])
        dataset['Issuance Date'] =dataset['Issuance Date'].dt.year
```

Once the dates are replaced by the corresponding years, we can plot the graph.

```
In [0]: timeline = dataset['Issuance Date'].value_counts(ascending=True)
        timeline = timeline.sort_index()
```

```
In [19]: timeline.to_frame()
```

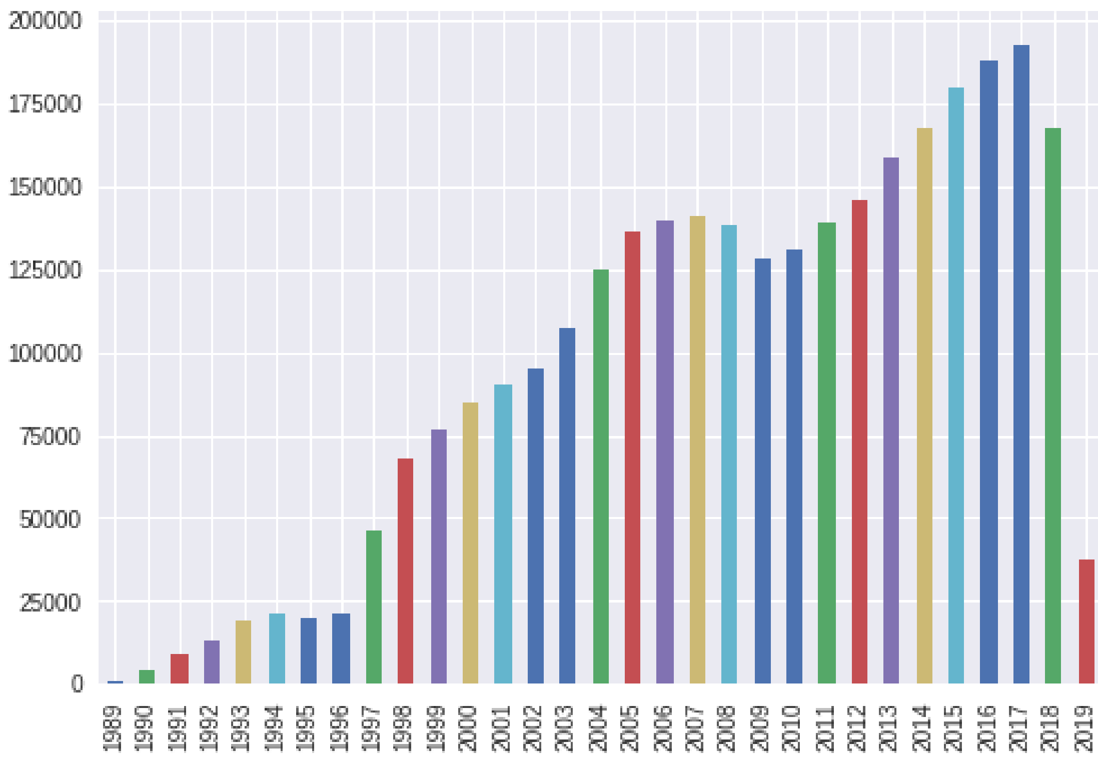
Out[19]:

	Issuance Date
1989	596
1990	4552
1991	9001
1992	12818
1993	19253
1994	21048
1995	19993
1996	21193
1997	46568
1998	68201
1999	76535
2000	84548
2001	90106
2002	95364
2003	107118
2004	124610
2005	136101
2006	139974
2007	141213
2008	138700
2009	128274
2010	130638
2011	139107
2012	145521
2013	158933
2014	167735

```
2015           179854
2016           188064
2017           192859
2018           167233
2019            37654
```

In [21]:
```python
timeline.plot.bar()
```

Out[21]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f592b74d5f8>
```



Analysis
We can observe that the number of permits has been consistently increasing each year. The number got stagnant from 1993 to 1996 and then it increased exponentially from 1997 until 2007. The applications decreasedfor a couple of years and then rose exponentially from 2010 to 2017.

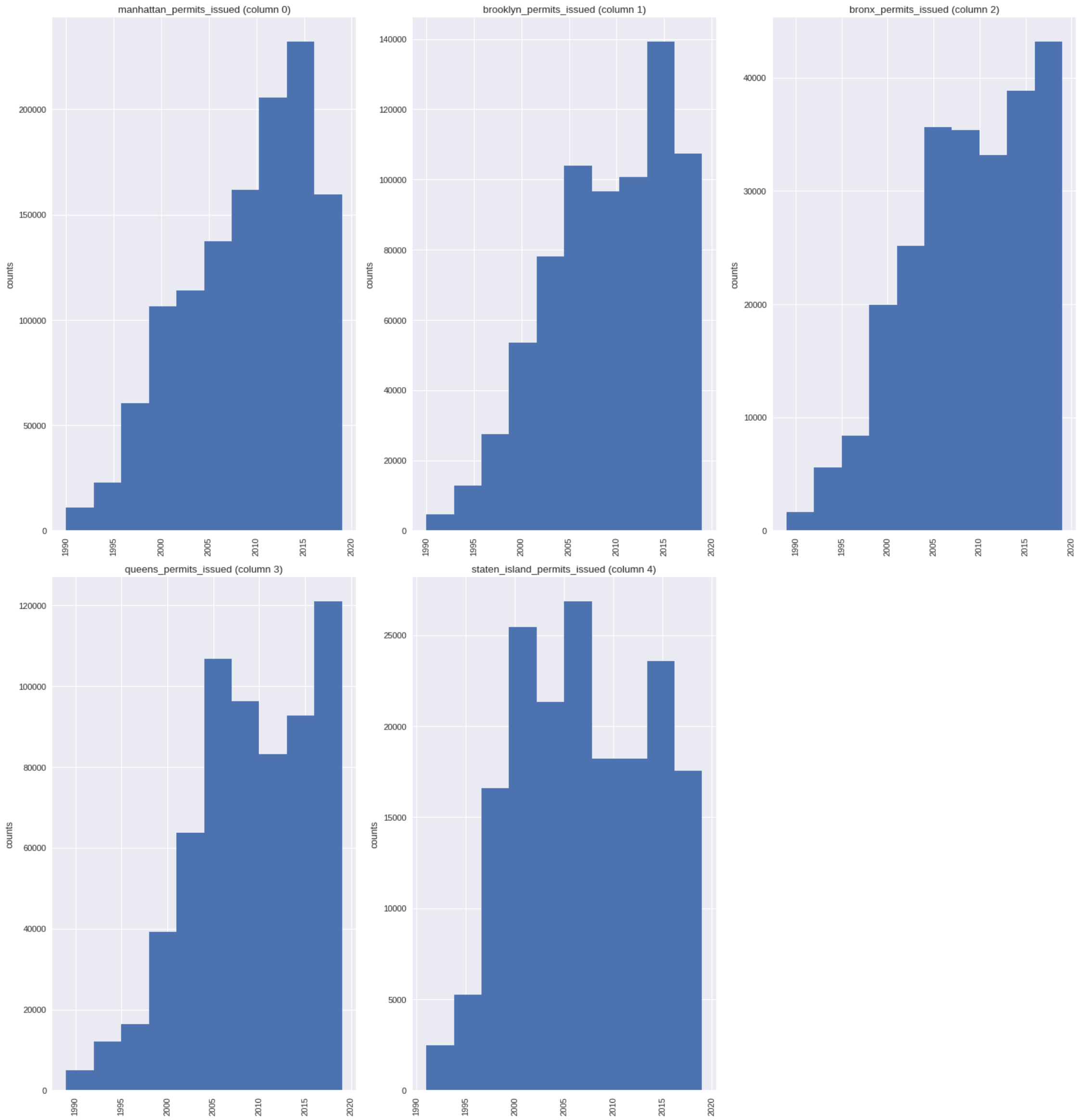
3.0.2 Borough-Wise Analysis of Timeline

Whether the trend is consistent across all borough? Is there a time when construction slowed down in a city and surged in other ?

In [0]:
```python
manhattan_permits_issued = dataset[dataset.BOROUGH == 'MANHATTAN'][['Issuance Date']]
manhattan_permits_issued.reset_index(drop=True, inplace=True)

brooklyn_permits_issued = dataset[dataset.BOROUGH == 'BROOKLYN'][['Issuance Date']]
```

```
brooklyn_permits_issued.reset_index(drop=True, inplace=True)

bronx_permits_issued = dataset[dataset.BOROUGH == 'BRONX'][['Issuance Date']]
bronx_permits_issued.reset_index(drop=True, inplace=True)

queens_permits_issued = dataset[dataset.BOROUGH == 'QUEENS'][['Issuance Date']]
queens_permits_issued.reset_index(drop=True, inplace=True)

staten_island_permits_issued = dataset[dataset.BOROUGH == 'STATEN ISLAND'][['Issuance D
staten_island_permits_issued.reset_index(drop=True, inplace=True)

permits_issued = pd.DataFrame()
permits_issued['manhattan_permits_issued'] = manhattan_permits_issued #brooklyn_permit
permits_issued['brooklyn_permits_issued'] = brooklyn_permits_issued
permits_issued['bronx_permits_issued'] = bronx_permits_issued
permits_issued['queens_permits_issued'] = queens_permits_issued
permits_issued['staten_island_permits_issued'] = staten_island_permits_issued
```

In [23]:
```
plotColumns(permits_issued, 5, 3)
```



In Manhattan and Brooklyn, most number of applications were filed during 2010 and 2015 period.

Bronx and Queens observed the highest number of filings in recent years from 2015 to 2019.

Staten Island had most applications during 2000 to 2015 and then there is again a surge in applications around 2015 but the number of applications is very less compared to its counterparts.

4 Permits per month

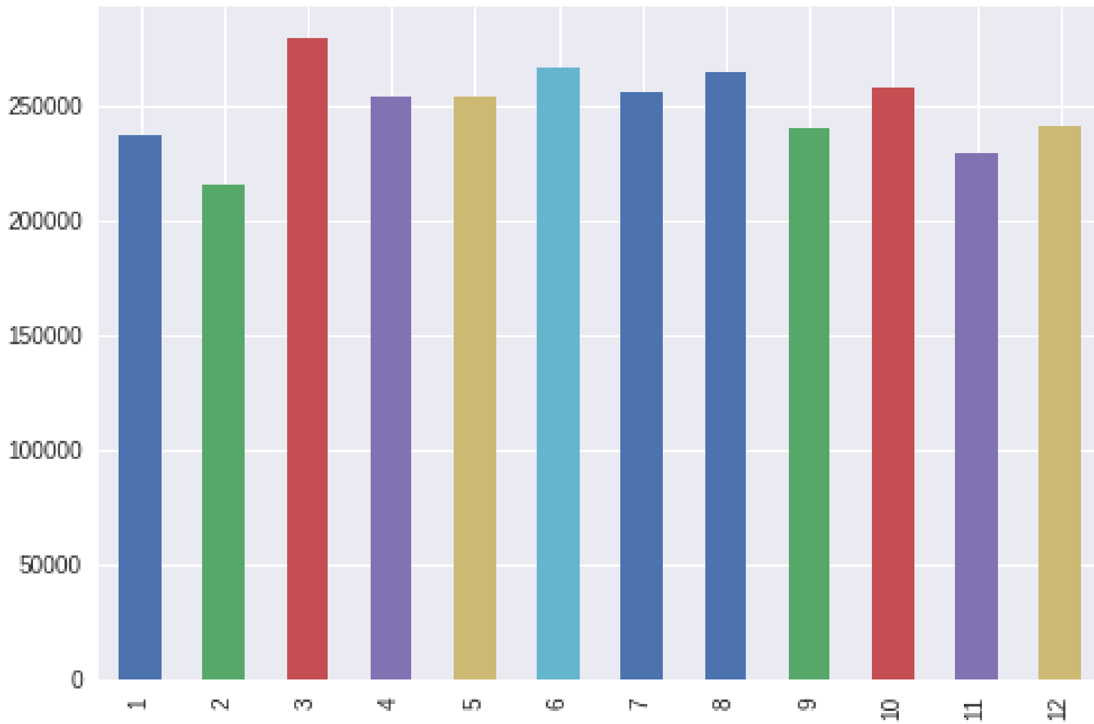
4.0.1 Is there is trend in the number of permits filed every month? Let's explore!

First, the date format of 'Filing Date' needs to be converted to python Datetime format and then only the month needs to be extracted from the date.

In [0]:
```
dataset['Filing Date'] = pd.to_datetime(dataset['Filing Date'])
dataset['Filing Date'] =dataset['Filing Date'].dt.month
```

In [29]:
```
months = dataset['Filing Date'].value_counts()
months.to_frame()
months = months.sort_index()
plotColumns(months, 1, 1)
```

Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc6e6de16d8>



Mostly all the months gets equal number of permit applications. February has less days, so that justifies the less number.

Overall, Month of 'March' has highest permit filings.