SpaceX Analysis

Insightful and impactful findings from SpaceX data

1: Brief description of data and initial plan

Summary:

- I have chosen a dataset on SpaceX, this was found on Kaggle.com.
- The data contains 41 rows and 16 columns.
- SpaceX have done a total of 100 launches at the time of this writing; As my data only includes 41 examples, this is due to the data ending at Flight FT-11 in February 2017.
- The 16 features are following: Flight number, launch date, launch time, launch site, vehicle type, payload name, payload type, payload mass, payload orbit, customer name, customer type, customer country, mission outcome, failure reasion, landing type and landing outcome.

In [22]:

```
# inspecting data

# imports
import pandas as pd
import numpy as np
import os
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline

#can be changed
sns.set_context("notebook")
sns.set_style("whitegrid")

# reading in csv
data = pd.read_csv('database.csv')
data;


#Printing out info
display(data.head())
print("")
print("Rows:", data.shape[0])
print("Columns:", data.shape[1])
print("")
print("All columns:")
print(data.columns.tolist())
print("")
print("Data types and NaN values:")
print(data.info())
```

	Flight Number	Launch Date	Launch Time	Launch Site	Vehicle Type	Payload Name	Payload Type	Payload Mass (kg)	Payload Orbit
0	F1-1	24 March 2006	22:30	Marshall Islands	Falcon 1	FalconSAT-2	Research Satellite	19.5	NaN
1	F1-2	21 March 2007	01:10	Marshall Islands	Falcon 1	DemoSat	NaN	NaN	NaN
2	F1-3	3 August 2008	03:34	Marshall Islands	Falcon 1	Trailblazer	Communication Satellite	NaN	NaN
3	F1-3	3 August 2008	03:34	Marshall Islands	Falcon 1	PRESat, NanoSail-D	Research Satellites	8.0	NaN
4	F1-3	3 August 2008	03:34	Marshall Islands	Falcon 1	Explorers	Human Remains	NaN	NaN

```
Rows: 41
Columns: 16
```

```
All columns:
['Flight Number', 'Launch Date', 'Launch Time', 'Launch Site', 'Vehicle Ty
pe', 'Payload Name', 'Payload Type', 'Payload Mass (kg)', 'Payload Orbit',
'Customer Name', 'Customer Type', 'Customer Country', 'Mission Outcome',
'Failure Reason', 'Landing Type', 'Landing Outcome']

Data types and NaN values:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41 entries, 0 to 40
Data columns (total 16 columns):
Flight Number        41 non-null object
Launch Date          41 non-null object
Launch Time          41 non-null object
Launch Site          41 non-null object
Vehicle Type         41 non-null object
Payload Name         41 non-null object
Payload Type         38 non-null object
Payload Mass (kg)    33 non-null float64
Payload Orbit        36 non-null object
Customer Name        39 non-null object
Customer Type        39 non-null object
Customer Country     39 non-null object
Mission Outcome      41 non-null object
Failure Reason       8 non-null object
Landing Type         28 non-null object
Landing Outcome      21 non-null object
dtypes: float64(1), object(15)
memory usage: 5.2+ KB
None
```

Initial plan for data cleaning:

- I will need to firstly clean data.
- As some of the variables depend on others, there are a lot of NaN values.
- As example, the first flight failed at launch, and the values for landing type and outcome are NaN.
- I will transform these to "No landing"

Initial plan for data exploration:

- I'm interested in the customers they have had.
- I will seek to find the number of customers, their biggest customer, whether the customer has influence on other features and otherwise be curious as what to find
- I will transform categorical variables into binary so I can make a heat-map of features and find correlations

2: Actions taken for cleaning and feature engineering

Cleaning NaN values:

Many values had NaN as e.g. "Failure Reason" is NaN when the rocket did not fail. This is what I did:

- All Payload Type NaN values has been converted to "Demo launch"
- Payload Mass NaN values changed initially to "No payload/No info", as they may prove usefull later; I considered removing the column completely. I ended up changing to 0 instead, so I could calculate skewness, though I realize, this is not optimal
- Payload Orbit was removed, as I didn't see any interesting objective it could be used for
- Customer name had only 2 NaN values, and as customers was my main interest, I chose to remove the 2 rows.
- Failure Reason column included NaN for succesful flights, so I rewrote them as "No Failure"
- Replaced NaN values for Landing type with "No info" as it was a mix of no landing and not informed
- Landing Outcomes NaN values set to "No landing"

I also tried grouping up values like the origin of customer and the customers' names

In [10]:

```
# Transform Launch Date to Pandas datetime object
data["Launch Date"] = pd.to_datetime(data["Launch Date"])
data.drop("Launch Time", inplace=True, axis=1)

# Summing flight number
# Creating new column
data["Flight Number, sum"] = data["Flight Number"]
# Adding one
i = 0
for i in range(data.shape[0] + 1):
    data["Flight Number, sum"][i] = i
data["Flight Number"] = data["Flight Number, sum"]
data.drop("Flight Number, sum", inplace=True, axis=1)
data["Flight Number"] = pd.to_numeric(data["Flight Number"])

# Changing customers with only one order to "Others" as to better one-hot encode later
customers = data["Customer Name"].value_counts()
other_customer = list(customers[customers <= 1].index)
data["Customer Name"] = data["Customer Name"].replace(other_customer, "Other")

# Changing Asian countries to same group
japan = data["Customer Country"] == "Japan"
china = data["Customer Country"] == "China"
thailand = data["Customer Country"] == "Thailand"
malaysia = data["Customer Country"] == "Malaysia"
asian_countries = japan + china + thailand + malaysia
j = 0
for j in range(data.shape[0]):
    if asian_countries[j] == True:
        data["Customer Country"][j] = "Asia"
    else:
        continue

# Changing non-American and non-Asian to others
customers_country = data["Customer Country"].value_counts()
other_customer_country = list(customers_country[customers_country <= 2].index)
data["Customer Country"] = data["Customer Country"].replace(other_customer_country, "Other"


# Fixing NaN values
data["Payload Type"] = data["Payload Type"].replace(np.nan, "Demo launch", regex=True)
data["Payload Mass (kg)"] = data["Payload Mass (kg)"].replace(np.nan, 0)
data.drop("Payload Orbit", inplace=True, axis=1)
data.drop("Payload Name", inplace=True, axis=1)
data = data.drop([5,7]);
data["Failure Reason"] = data["Failure Reason"].replace(np.nan, "No failure until landing",
data["Landing Type"] = data["Landing Type"].replace(np.nan, "No info", regex=True)
data["Landing Outcome"] = data["Landing Outcome"].replace(np.nan, "No landing", regex=True)

data
```

23	23	2015-03-02	Cape Canaveral AFS LC-40	Falcon 9 (v1.1)	Communication Satellite	4159.0	Asia Broadcast Satellite	Business	Othe
24	24	2015-03-02	Cape Canaveral AFS LC-40	Falcon 9 (v1.1)	Communication Satellite	4159.0	Eutelsat (Satmex)	Business	Othe
25	25	2015-04-14	Cape Canaveral AFS LC-40	Falcon 9 (v1.1)	Space Station Supplies	1898.0	NASA	Government	Unite State

	Flight Number	Launch Date	Launch Site	Vehicle Type	Payload Type	Payload Mass (kg)	Customer Name	Customer Type	Custome Countr
26	26	2015-04-27	Cape Canaveral AFS LC-40	Falcon 9 (v1.1)	Communication Satellite	4707.0	Other	Government	Othe
27	27	2015-06-28	Cape Canaveral AFS LC-40	Falcon 9 (v1.1)	Space Station Supplies	1952.0	NASA	Government	Unite State
28	28	2015-12-22	Cape Canaveral AFS LC-40	Falcon 9 Full Thrust	Communication Satellite	0.0	Orbcomm	Business	Unite State

Feature engineering

As most of variables are string values, I will one-hot encode those, should I use them in regression later on.

- Initially I planned to log transform Payload Mass, but the result was actually worse, so I chose not to do it

In [11]:

```
# Making new dataframe
df = data.copy()

one_hot_encode_cols = df.dtypes[df.dtypes == np.object]  # filtering by string categoricals
one_hot_encode_cols = one_hot_encode_cols.index.tolist()  # list of categorical fields

#Doing the encoding
df = pd.get_dummies(df, columns=one_hot_encode_cols, drop_first=True)
df.describe()
```

Out[11]:

	Flight Number	Payload Mass (kg)	Launch Site_Kennedy Space Center LC-39A	Launch Site_Marshall Islands	Launch Site_Vandenberg AFB SLC-4E	Vehicle Type_Falcon 9 (v1.0)	Typ
count	39.000000	39.000000	39.000000	39.000000	39.000000	39.000000	3
mean	20.717949	2314.038462	0.025641	0.153846	0.076923	0.128205	
std	11.838716	2201.865526	0.160128	0.365518	0.269953	0.338688	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	11.500000	165.000000	0.000000	0.000000	0.000000	0.000000	
50%	21.000000	2257.000000	0.000000	0.000000	0.000000	0.000000	
75%	30.500000	3879.500000	0.000000	0.000000	0.000000	0.000000	
max	40.000000	9600.000000	1.000000	1.000000	1.000000	1.000000	

8 rows × 41 columns

In [12]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 39 entries, 0 to 40
Data columns (total 42 columns):
Flight Number                                  39 non-null int64
Launch Date                                    39 non-null datetime64[ns]
Payload Mass (kg)                              39 non-null float64
Launch Site_Kennedy Space Center LC-39A        39 non-null uint8
Launch Site_Marshall Islands                   39 non-null uint8
Launch Site_Vandenberg AFB SLC-4E              39 non-null uint8
Vehicle Type_Falcon 9 (v1.0)                   39 non-null uint8
Vehicle Type_Falcon 9 (v1.1)                   39 non-null uint8
Vehicle Type_Falcon 9 Full Thrust (v1.2)       39 non-null uint8
Payload Type_Communication/Research Satellite  39 non-null uint8
Payload Type_Demo launch                       39 non-null uint8
Payload Type_Human Remains                     39 non-null uint8
Payload Type_Research Satellite                39 non-null uint8
Payload Type_Research Satellites               39 non-null uint8
Payload Type_Space Station Supplies            39 non-null uint8
Payload Type_Weather Satellite                 39 non-null uint8
Customer Name_AsiaSat                          39 non-null uint8
Customer Name_DARPA                            39 non-null uint8
Customer Name_Eutelsat (Satmex)                39 non-null uint8
Customer Name_NASA                             39 non-null uint8
Customer Name_Orbcomm                          39 non-null uint8
Customer Name_Other                            39 non-null uint8
Customer Name_SES                              39 non-null uint8
Customer Name_SKY Perfect JSAT Group           39 non-null uint8
Customer Name_Thaicom                          39 non-null uint8
Customer Type_Government                       39 non-null uint8
Customer Country_Other                         39 non-null uint8
Customer Country_United States                 39 non-null uint8
Mission Outcome_Success                        39 non-null uint8
Failure Reason_Engine Failure During Flight    39 non-null uint8
Failure Reason_Engine Fire During Launch       39 non-null uint8
Failure Reason_Engine Shutdown During Launch   39 non-null uint8
Failure Reason_No failure until landing        39 non-null uint8
Failure Reason_Vehicle Explosion Before Launch 39 non-null uint8
Failure Reason_Vehicle Explosion During Flight 39 non-null uint8
Landing Type_No info                           39 non-null uint8
Landing Type_None                              39 non-null uint8
Landing Type_Ocean                             39 non-null uint8
Landing Type_Parachute                         39 non-null uint8
Landing Type_Ship                              39 non-null uint8
Landing Outcome_No landing                     39 non-null uint8
Landing Outcome_Success                        39 non-null uint8
dtypes: datetime64[ns](1), float64(1), int64(1), uint8(39)
memory usage: 2.7 KB
```

I used the code from the tutorial to look at my float variable, Payload Mass, but I chose not to use this, as the result was rather poor

In [13]:

```
# I chose to add one to all fields to prevent skewness

# df["Payload Mass (kg) + 1"] = df["Payload Mass (kg)"] + 1

# Let's look at what happens to one of these features, when we apply np.log visually.
'''
# Choose a field
field = "Payload Mass (kg) + 1"

# Create two "subplots" and a "figure" using matplotlib
fig, (ax_before, ax_after) = plt.subplots(1, 2, figsize=(20, 5))

# Create a histogram on the "ax_before" subplot
df[field].hist(ax=ax_before)

# Apply a log transformation (numpy syntax) to this column
df[field].apply(np.log).hist(ax=ax_after)

# Formatting of titles etc. for each subplot
ax_before.set(title='before np.log1p', ylabel='frequency', xlabel='value')
ax_after.set(title='after np.log1p', ylabel='frequency', xlabel='value')
fig.suptitle('Field "{}"'.format(field));
'''
```

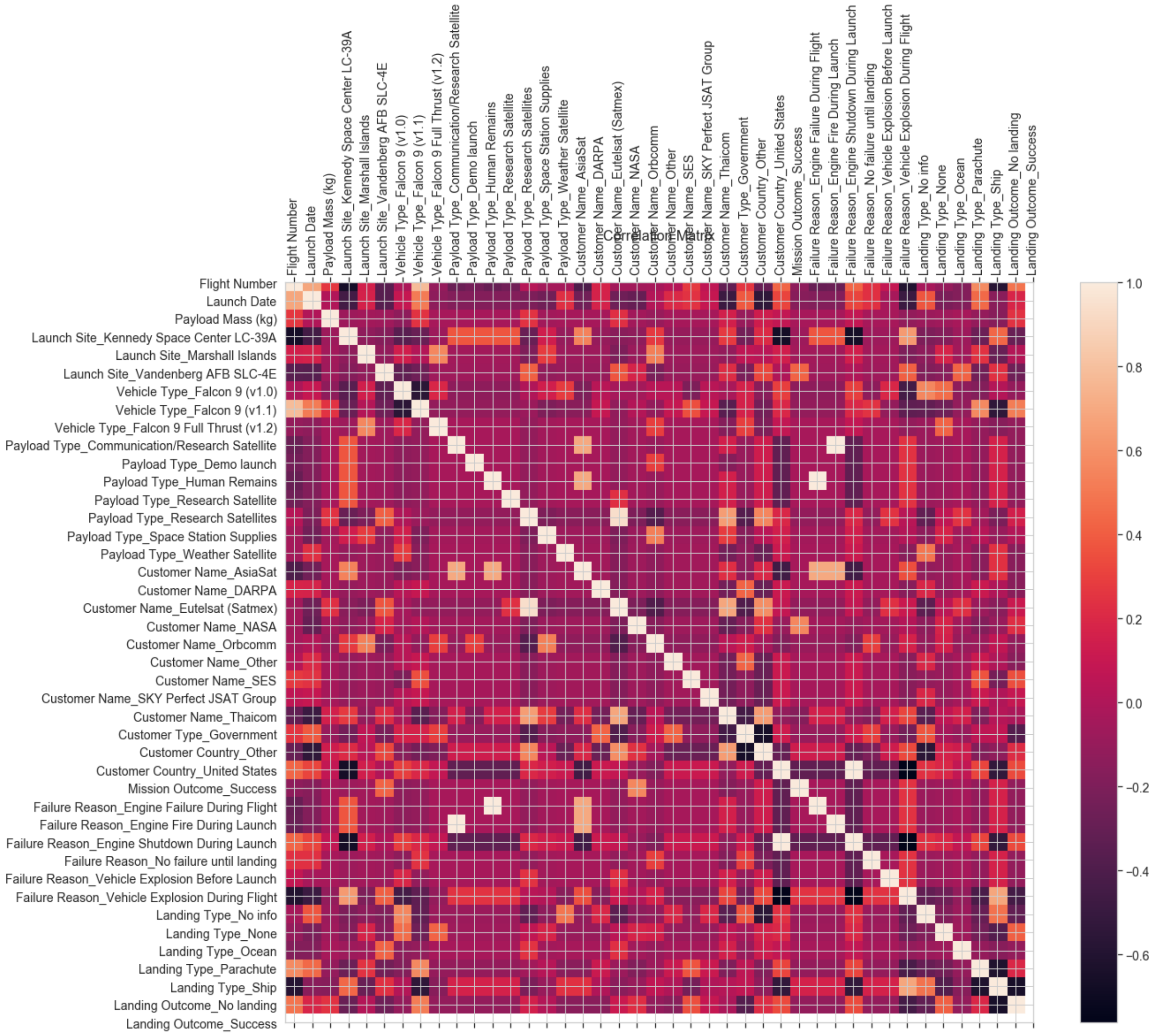
Out[13]:

```
'\n# Choose a field\nfield = "Payload Mass (kg) + 1"\n\n# Create two "subplo
ts" and a "figure" using matplotlib\nfig, (ax_before, ax_after) = plt.subplo
ts(1, 2, figsize=(20, 5))\n\n# Create a histogram on the "ax_before" subplot
\ndf[field].hist(ax=ax_before)\n\n# Apply a log transformation (numpy synta
x) to this column\ndf[field].apply(np.log).hist(ax=ax_after)\n\n# Formatting
of titles etc. for each subplot\nax_before.set(title=\'before np.log1p\', yl
abel=\'frequency\', xlabel=\'value\')\nax_after.set(title=\'after np.log1p
\', ylabel=\'frequency\', xlabel=\'value\')\nfig.suptitle(\'Field "{}"\'.for
mat(field));\n'
```

I could now plot my data into a Correlation Matrix

In [14]:

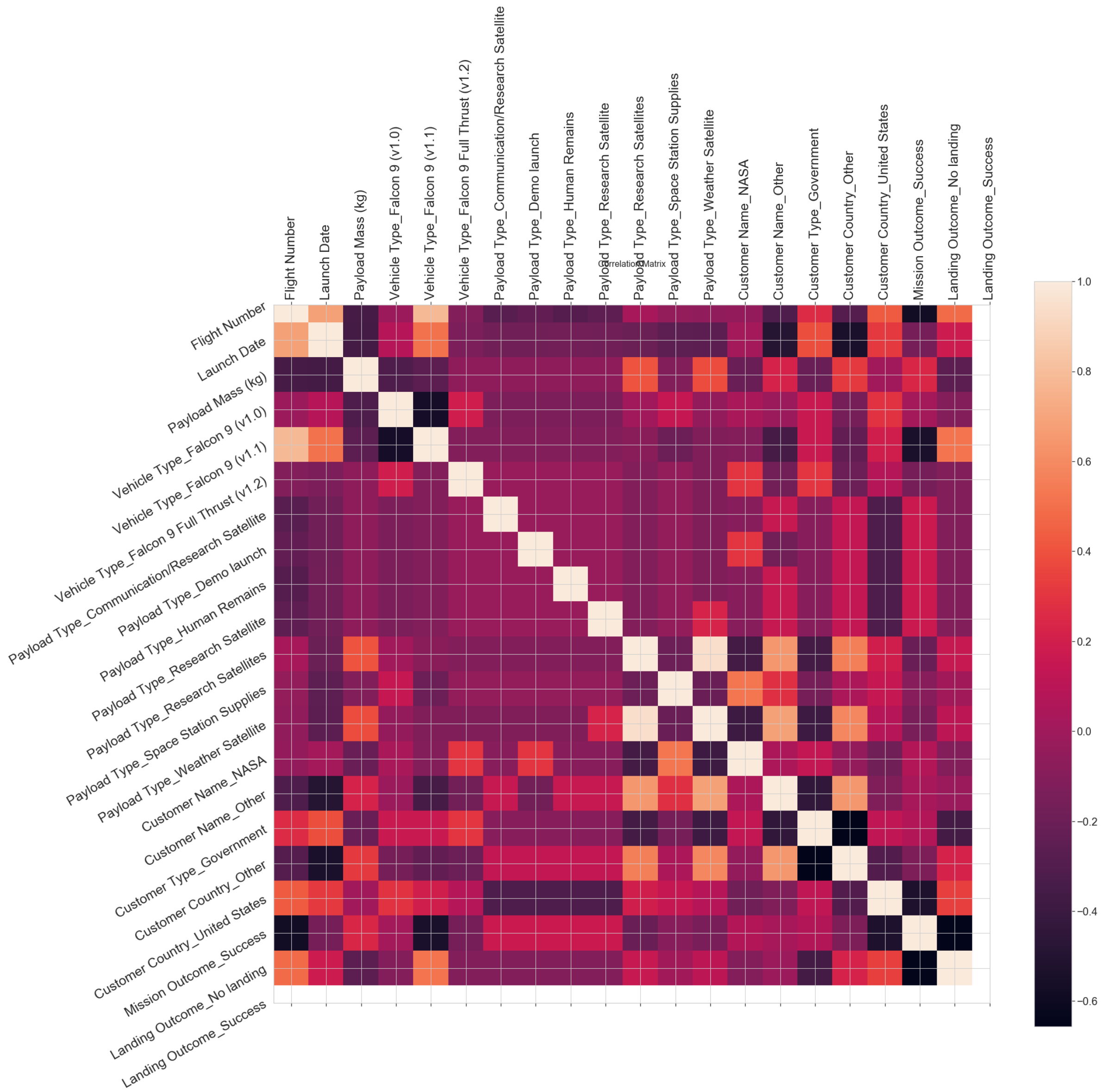
```
import pandas as pd
import seaborn as sn
import matplotlib.pyplot as plt

f = plt.figure(figsize=(19, 15))
plt.matshow(df.corr(), fignum=f.number)
plt.xticks(range(df.shape[1]), df.columns, fontsize=14, rotation=90)
plt.yticks(range(df.shape[1]), df.columns, fontsize=14)
cb = plt.colorbar()
cb.ax.tick_params(labelsize=14)
plt.title('Correlation Matrix', fontsize=16);
```



As this was hard to grasp, I tried with a smaller

In [16]:

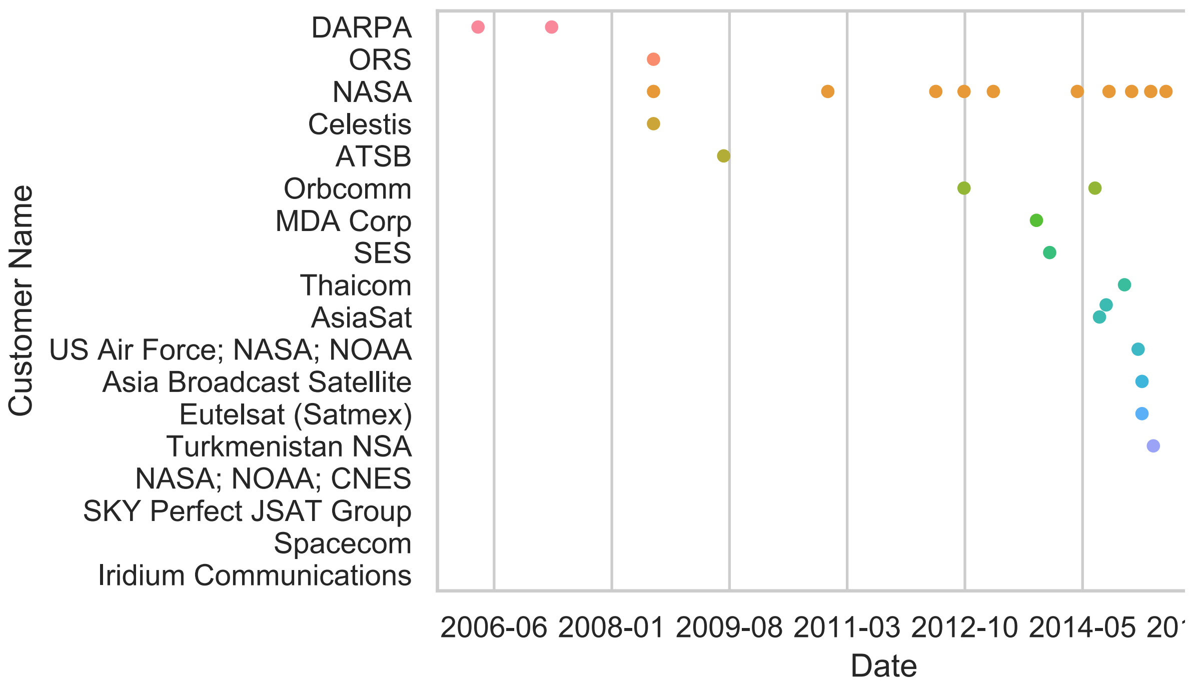
```
df_small = df.copy()
df_small.drop(["Launch Site_Kennedy Space Center LC-39A", "Launch Site_Marshall Islands", "
df_small.drop(["Customer Name_AsiaSat","Customer Name_DARPA", "Customer Name_Eutelsat (Satm
df_small.drop(["Failure Reason_Engine Failure During Flight", "Failure Reason_Engine Fire D
df_small.drop(["Landing Type_No info", "Landing Type_None", "Landing Type_Ocean", "Landing 

f = plt.figure(figsize=(30, 25))
plt.matshow(df_small.corr(), fignum=f.number)
plt.xticks(range(df_small.shape[1]), df_small.columns, fontsize=25, rotation=90)
plt.yticks(range(df_small.shape[1]), df_small.columns, fontsize=25, rotation=30)
cb = plt.colorbar()
cb.ax.tick_params(labelsize=20)
plt.title('Correlation Matrix', fontsize=16);
```



```
Findings:
* Landing Outcome being a success is correlated with Flight Number and newer Falcon
model. This makes sense, as SpaceX had most failures in the beginning
* Customer Type: Government is correlated with Launch Date. This is due to SpaceX having
NASA as biggest customer in the beginning, but slowly developed to serve more business
clients (Look at graphs under)
```

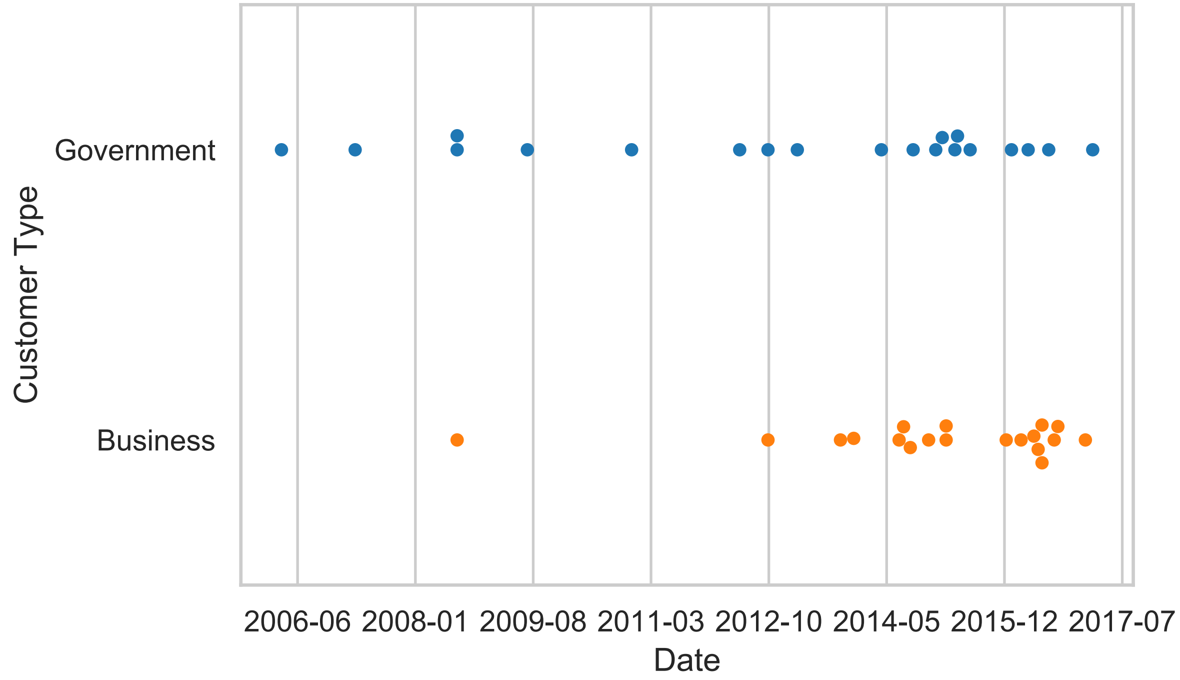
In [26]:

```
# Following code is courtesy of Kaggle user: danaugrs. Code found https://www.kaggle.com/da
# Thank you for the great graphs :)

import calendar
import time
import datetime

month = {v: k for k,v in enumerate(calendar.month_name)}

def dateToTimestamp(d):
    t = d.split()
    d = '{0}/{1}/{2}'.format(month[t[1]], t[0], t[2])
    return time.mktime(datetime.datetime.strptime(d, "%m/%d/%Y").timetuple())

data['timestamp'] = data['Launch Date'].apply(dateToTimestamp)

# This code is courtesy of Kaggle user: danaugrs. Code found https://www.kaggle.com/danaugr
# Thank you for the great graphs :)

import seaborn as sns
import matplotlib
%matplotlib inline

sns.set_context("notebook")
sns.set_style("whitegrid")

def myFormatter(x, pos):
    return datetime.datetime.fromtimestamp(x).strftime('%Y-%m')

def plotOverTime(col):
    ax = sns.swarmplot(x="timestamp", y=col, data=data)
    ax.xaxis.set_major_formatter(matplotlib.ticker.FuncFormatter(myFormatter))
    ax.set(xlabel='Date')

plotOverTime('Customer Name')
# This code is courtesy of Kaggle user: danaugrs. Code found https://www.kaggle.com/danaugr
# Thank you for the great graphs :)
```



In [25]:

```
# Following code is courtesy of Kaggle user: danaugrs. Code found https://www.kaggle.com/da
plotOverTime('Customer Type')
```



3: Hypothesis

First hypothesis:

NASA is SpaceX's biggest customer.

- Null: The number of NASA contracts is equal to other firms. P(Nasa) = P(Others)
- Alternative: The number of NASA contracts is bigger than other firms. P(Nasa) > P(Others)

In [20]:

```
from scipy.stats import binom
evenly_distributed = 18/39
prob = 1 - binom.cdf(13, evenly_distributed, 0.5)

print("P-value: ")
print(str(round(prob*100, 1))+"%")
```

```
P-value: 
0.0%
```

- I then tested this with p-value (As this is requested in the assignment description)
- Null: The number of NASA contracts is equal to other firms
- Alternative: The number of NASA contracts is bigger than other firms
- As the p-value < 0, the null-hypothesis is rejected, the alternative hypothesis is accepted, and the number of NASA contracts are more than other firms. This is also seen as NASA has 4 times more contracts than the second-largest, Orbcomm.

Second hypothesis:

Since 2014, SpaceX has been getting a lot more different customers

Third hypothesis:

There is one failure reason more frequent than others

4: Key insights

Customer information:

- SpaceX' supremely biggest customer is NASA (Hypothesis tested)
- Landing Outcome being a success is correlated with Flight Number and newer Falcon model. This makes sense, as SpaceX had most failures in the beginning
- Customer Type: Government is correlated with Launch Date. This is due to SpaceX having NASA as biggest customer in the beginning, but slowly developed to serve more business clients

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5: Next step and looking-back

- Suggestions for next step would be to look at the trend of SpaceX' customer. Look into the companies and the division between business contracts and governmental
- Though there were few examples, it was possible to derive insight. To continue investigating SpaceX, it would be preferable to find newer data

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