Task 1:Working with unclean data

We are working with dataset.tsv The data is in a raw, unprocessed format and may therefore contain missing or logically incorrect values. The first warm-up task is to describe the data - try to answer what is the data about, what are the different features and their types and how many rows are there. Next take a look at the missing values ("?", "", NA) - are they missing systematically or randomly? What should you do with the missing values? (e.g. impute them? remove them? do nothing?) Justify your decision. Other than that, check for possible outliers outside 1.5IQR and decide what to do with them (e.g. remove them or not).
Report if you noticed any logically incorrect values.

The data seems to be records of money transfer transactions in the time period from **2016-01-01** to **2017-03-12**.

Most frequent user of the service has the id '**ddbac55d04'** and has done **152** transfers in total.
The user with highest total transfer amount is '**d71d16e6b5'** and has a total transfer sum of 18849552.0 GBP.

Top 10 Users By Total Transfer Sum:

Out[24]:

	user_id_hashed	sum_of_this_user
22371	d71d16e6b5	18849552.0
20501	3ca94ac42b	13432664.0
4500	c98ade9edb	10340256.0
19227	4b2f28326e	9896016.0
38317	3d7cc6fe80	6529974.0
23137	610b87481a	4366814.0
38363	e065dca6e7	4313022.0
11490	3ee46219a3	3994339.0
67202	9701e297dc	3583548.0
50963	37900a9e60	3568898.0

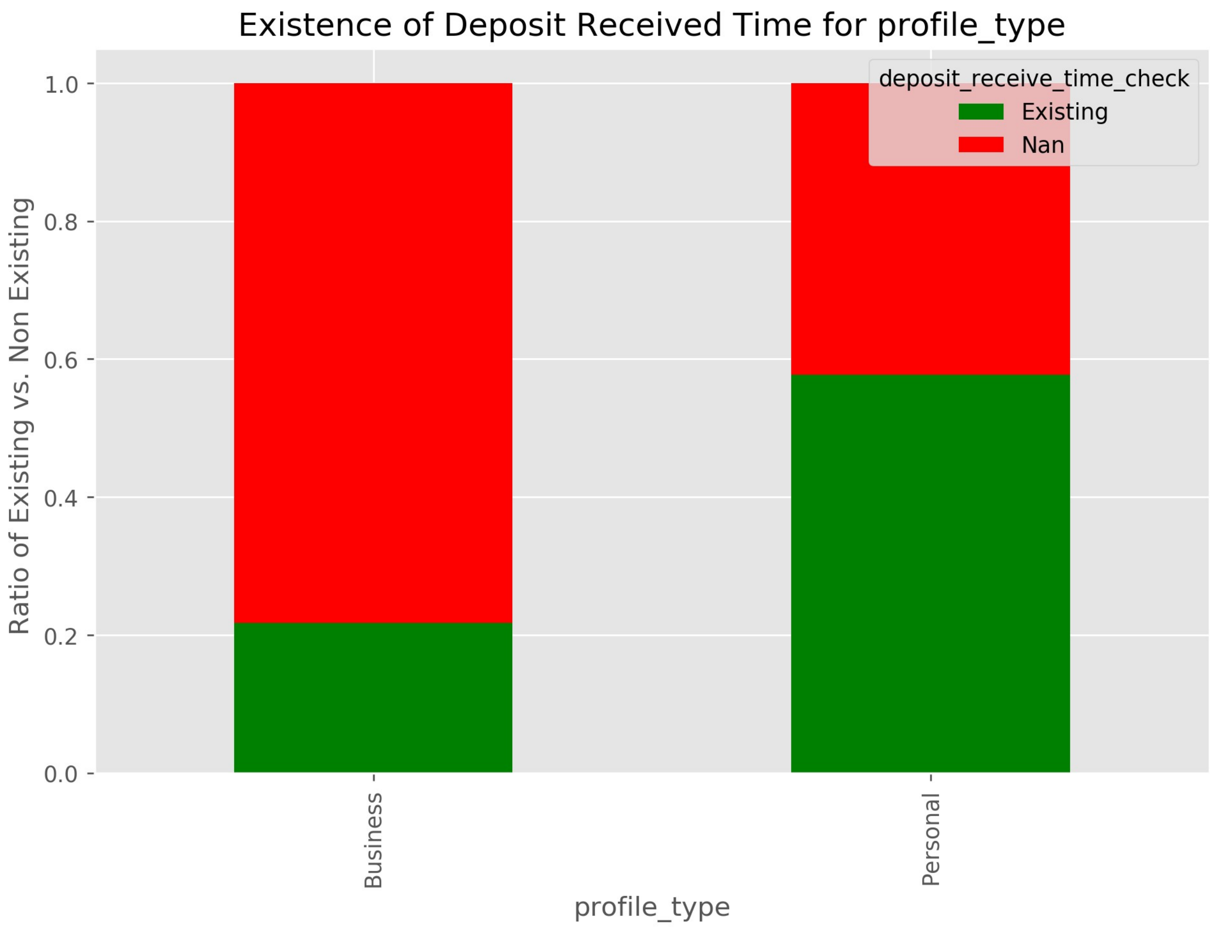
Most of the data was is in string format and hence needed to be converted to an appropriate format for further exploration.

```
In [7]: dataset.isnull().sum()

Out[7]: user_id_hashed                          0
        profile_type                            0
        user_create_date                        0
        user_language                           0
        age_years_bucket                        0
        user_country_code                       0
        transfer_submit_time                    0
        deposit_receive_time                30979
        transfer_amount_gbp                  4239
        payment_status                          0
        payment_reference_classification        0
        source_currency_code                    0
        target_currency_code                    0
        dtype: int64
```

As can be seen from above table, columns of ‘**deposit_receive_time**’ and ‘**transfer_amount_gbp**’ contain missing values. All other columns do not contain missing values.

Missing Deposit Received Time values



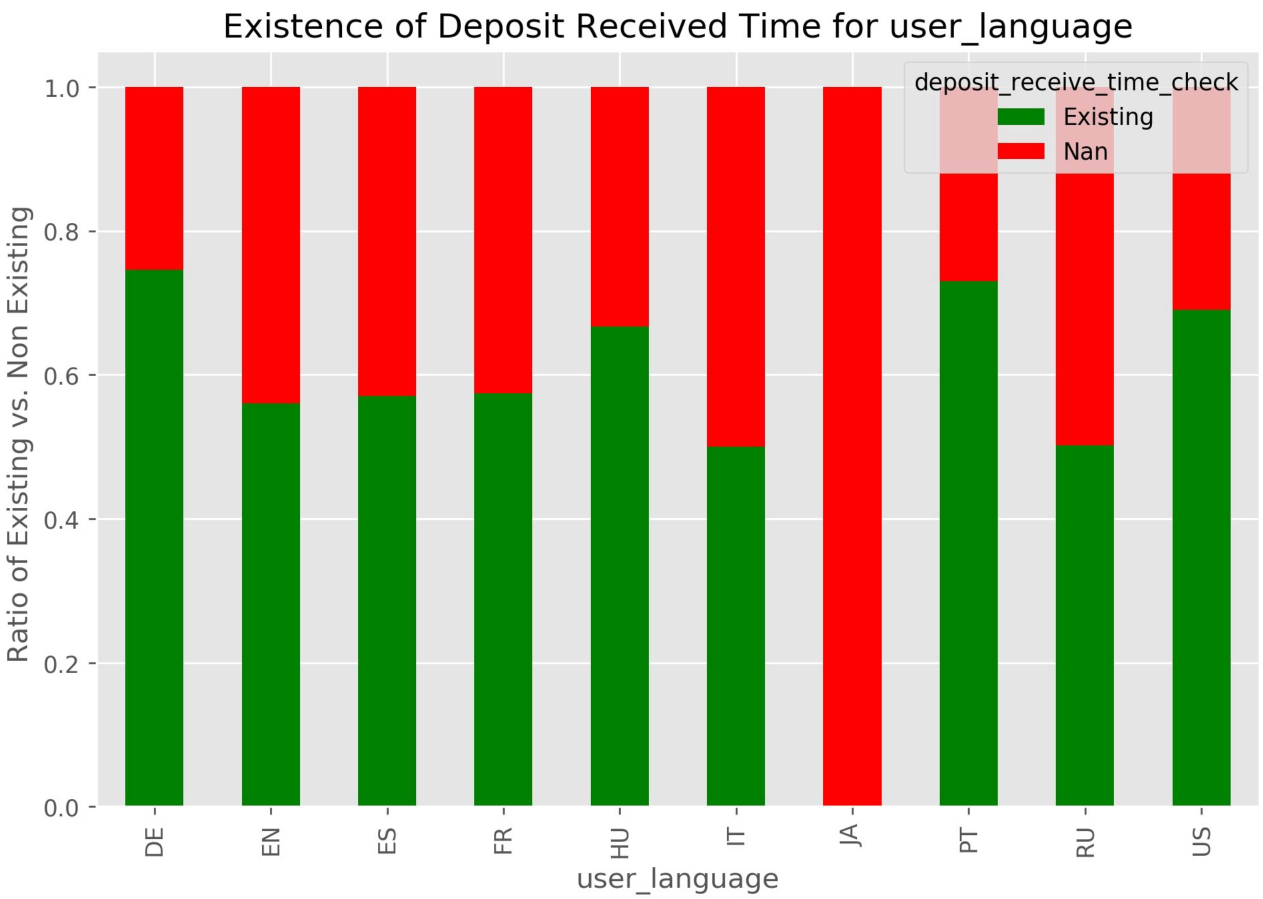
Records with the Profile Type category of ‘Business’ contain a high ratio of missing deposit received time values. Around 80% of 'Business' profile type records are missing deposit received time values.

However, most of these have Payment Status as 'Cancelled' as is shown below:

```
dataset[(dataset.profile_type == 'Business') &\
        (dataset.deposit_receive_time_check=="Nan")].describe(include=['category'])
```

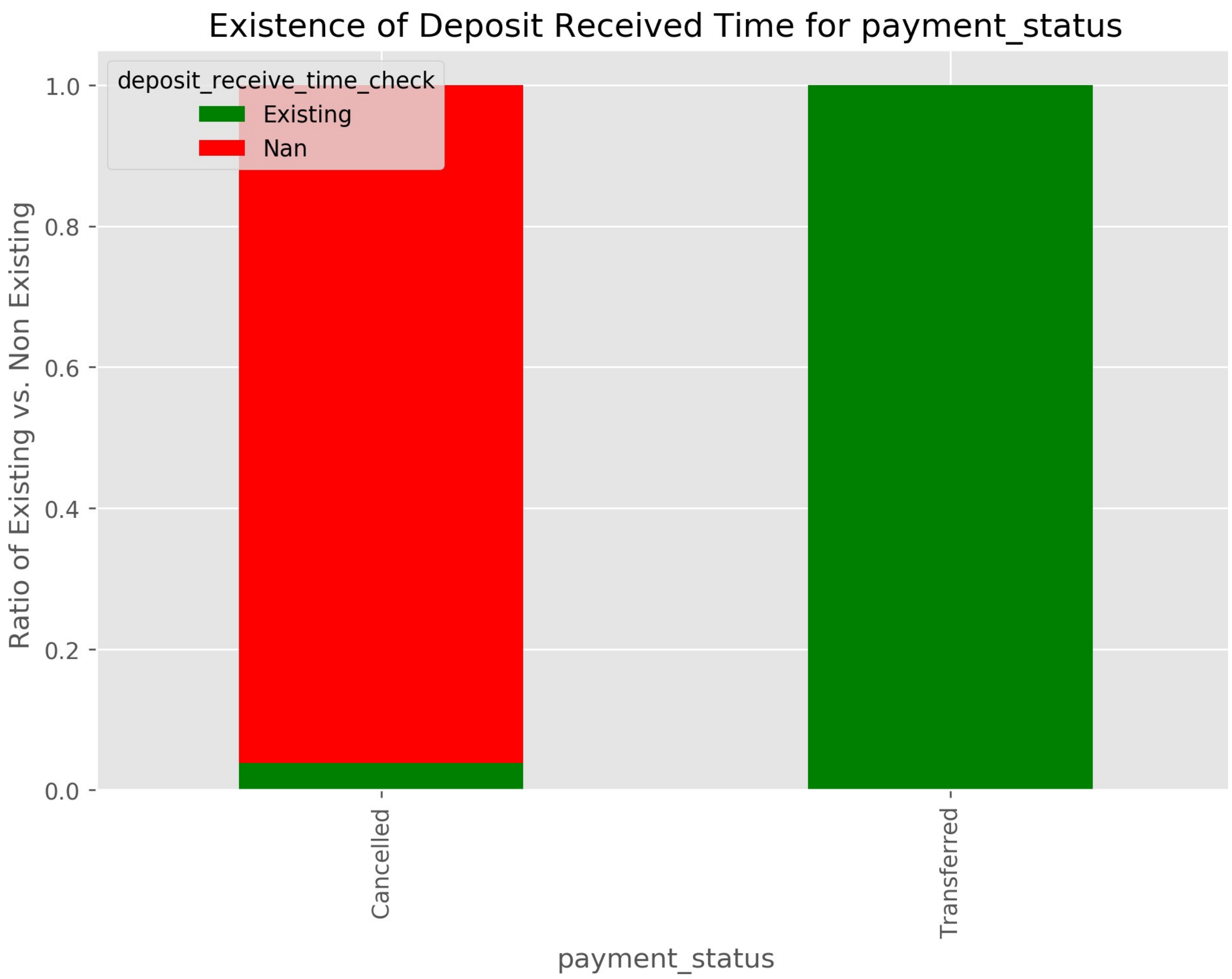
	profile_type	user_language	age_years_bucket	user_country_code	payment_status	payment_reference_classification	source_currency_code
count	852	852	852	852	852	852	852
unique	1	7	5	31	1	16	14
top	Business	EN	3. 26-34	134	Cancelled	blank	3
freq	852	794	371	494	852	534	314

Records with the User Language category of 'JA' are entirely missing deposit received time values. This is not the case with any other user language category.However number of records with missing values with missing deposit received time values for 'JA' language category are only 2 out of 71k. Hence, missing values cannot be attributed to the user language being 'JA'.



Records with the source curreny code of 11 and 35 and records with target currency code of 65 and 73 are entirely missing deposit received time values. This is not the case with any source/target curreny code .Records with user country code of 7,43,47,54,75,93,117,119,121,179,198,217,225 are entirely missing deposit received time values.

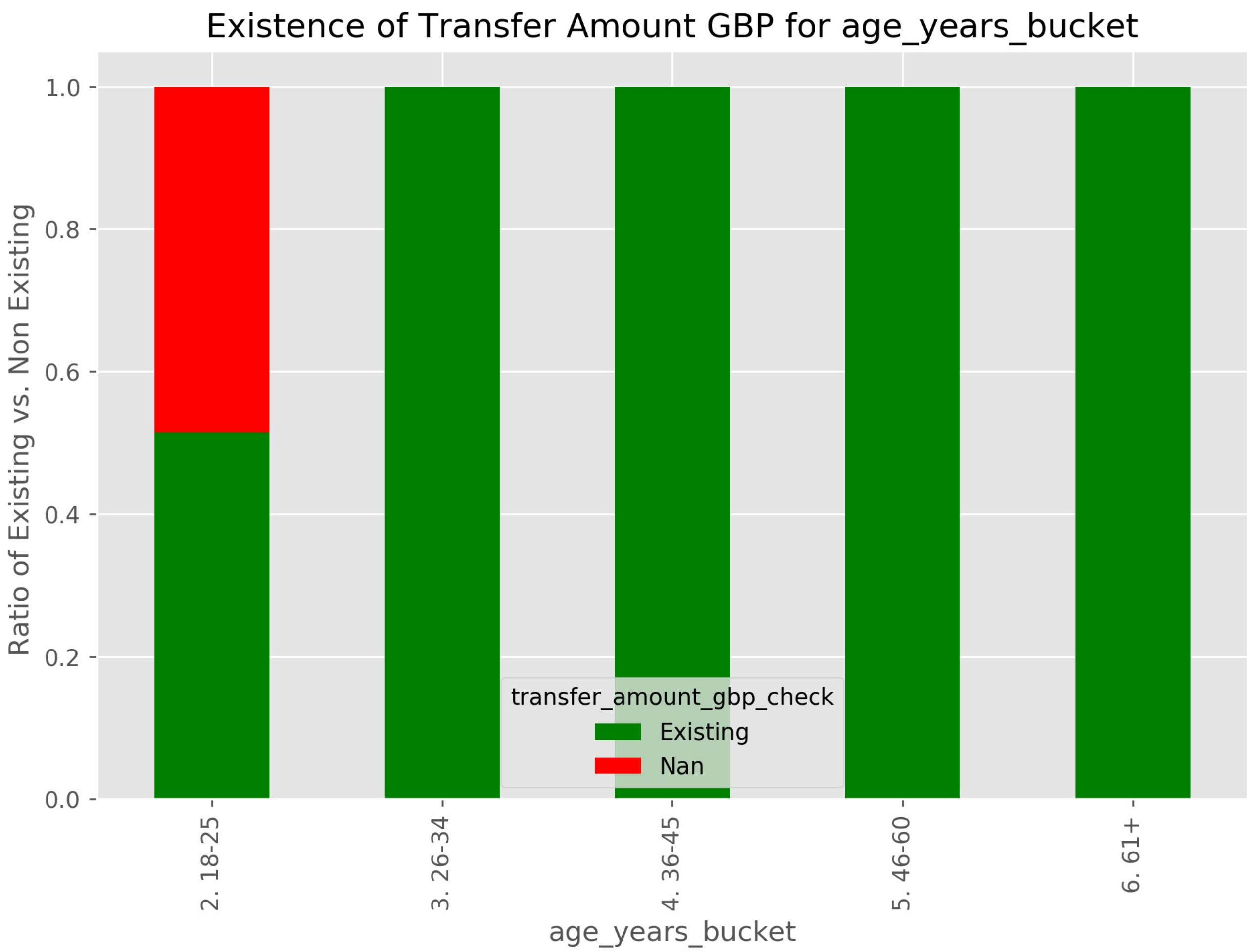
Despite the above facts almost all the records(>96%) with 'Cancelled' payment status are missing deposit received time values while none of the records with 'Transferred' payment status are missing deposit recived time values. Hence the mising of Deposit Received time values can be logically attributed to the 'Cancelled' payment status.



In addition, from the figure below we can see that records with payment status of ‘Cancelled’ make up for the (30977/30979 x 100) = 99.99% of the missing ‘Deposit Received time’ values. Hence, we can effectively conclude this as the cause of missing Deposit Missing time values. In this case, the missing values shall be given a new category. Imputation with some other values will necessarily mean introduction of false information into our data.

Missing Transfer Amount GBP values

Records with the Age Year bucket value of '2. 18-25' is the only age-years bucket value that is missing Transfer Amount values. All other age buckets are not missing Transger Amount GBP Values.



Records with the User country code of '134' is the only country code value that is missing Transfer Amount values. All other country code values are not missing Transger Amount GBP Values.

```
In [100]: dataset[(dataset.age_years_bucket == "2. 18-25") & \
                (dataset.transfer_amount_gbp_check=="Nan")].describe(include='all')
```

Out[100]:

	user_id_hashed	profile_type	user_create_date	user_language	age_years_bucket	user_country_code	transfer_submit_time	deposit_receive_time	tra
count	4239	4239	4239	4239	4239	4239.0	4239	1918	
unique	1570	2	302	7	1	1.0	4239	1908	
top	5bc078ba04	Personal	2016-02-26 00:00:00	EN	2. 18-25	134.0	2016-10-09 15:53:02	2016-05-13 11:37:05	
freq	68	4065	73	3790	4239	4239.0	1	2	
first	NaN	NaN	2016-01-01 00:00:00	NaN	NaN	NaN	2016-01-01 17:11:05	2016-01-02 14:11:43	
last	NaN	NaN	2016-12-31 00:00:00	NaN	NaN	NaN	2017-03-11 20:54:10	2017-03-11 20:55:20	
mean	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
std	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
min	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
25%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
50%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
75%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
max	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

All the transfer amount values are attributed to the age bucket of "2. 18-25". Further more as can be seen from the above results there is only 1 unique value of country code in this subset of age bucket and missing transfer amount values. This country code value is 134. Hence we can conclude users with country code of "134" and age bucket of "2. 18-25" are the source of these missing values.

Check for possible outliers outside 1.5 IQR

It seems like only features that can suitably be assessed for being outside the IQR are 'transfer_amount_gbp'.

```
In [32]: numeric_dataset = dataset.select_dtypes(include=['int','float'])
         numeric_dataset
```

Out[32]:

	transfer_amount_gbp
0	6056.0
1	1359.0
2	1571.0
3	8323.0
4	1571.0
...	...
72357	NaN
72358	NaN
72359	NaN
72360	NaN
72361	NaN

72362 rows × 1 columns

It seems like only features that can suitably be assessed for being outside the IQR are 'transfer_amount_gbp'.

```
In [33]: datacolumn=numeric_dataset.transfer_amount_gbp
         sorted(datacolumn)
         Q1,Q3 = np.nanpercentile(datacolumn , [25,75])
         IQR = Q3 - Q1
         lower_range = Q1 - (1.5 * IQR)
         upper_range = Q3 + (1.5 * IQR)
         print(lower_range,upper_range)

         -2184.0 4376.0
```

```
In [36]: data_outside_IQR=numeric_dataset[(numeric_dataset.transfer_amount_gbp < lower_range) \
                                          | (numeric_dataset.transfer_amount_gbp > upper_range)]
```

```
In [116]: print("\n\nPercentage of Non-Missing values outside 1.5 IQR : ",\
                round(len(data_outside_IQR)/dataset['transfer_amount_gbp'].notnull().sum(),4)*100)


          Percentage of Non-Missing values outside 1.5 IQR :  9.0
```

Percentage of Non-Missing values outside 1.5 IQR is 9%.

The data with values outside IQR covers most categories of other features. Hence, it is not advisable to remove the values that are outside IQR as by removeing them we may lose valuable information.

Task2