Imports

In [1]:
```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
```

In [2]:
```python
import os

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

from sklearn import datasets
from sklearn.compose import ColumnTransformer, make_column_transformer
from sklearn.dummy import DummyRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.impute import SimpleImputer
from sklearn.linear_model import Ridge

from sklearn.model_selection import (
    cross_val_score,
    cross_validate,
    train_test_split,
)

from sklearn.pipeline import Pipeline, make_pipeline
from sklearn.preprocessing import OneHotEncoder, OrdinalEncoder, StandardScaler
from sklearn.tree import DecisionTreeRegressor, export_graphviz

# import seaborn as sns

%matplotlib inline
sns.set_style("whitegrid")
plt.style.use("fivethirtyeight")
```

Reading data into a DataFrame

In [3]:
```python
data = pd.read_csv("./InternAssignmentData4.csv")
```

```
/opt/miniconda3/envs/571/lib/python3.9/site-packages/IPython/core/interactiveshell.py:345
7: DtypeWarning: Columns (107) have mixed types.Specify dtype option on import or set low_
memory=False.
  exec(code_obj, self.user_global_ns, self.user_ns)
```

Data Cleaning

In [4]:
```python
data.head()
```

Out[4]:

	respnum	intdate	gendr	q1	q2a	q2b	q3a	q3b	q3c	q3d	...	q28m	q30a	q31	q32	q33	q34
0	21000001	20021001	1	14	10		4.0	6.0	0.0	0.0	...		5	5	2	4	4
1	21000014	20021001	2	2	4		0.0	4.0	0.0	0.0	...	5	5	5	1	3	4
2	21000016	20021001	1	9	0	2	0.0	0.0	0.0	0.0	...	1	4	5	1	5	6
3	21000041	20021001	2	15	8		8.0	0.0	0.0	0.0	...		95	4	4	3	2

	respnum	intdate	gendr	q1	q2a	q2b	q3a	q3b	q3c	q3d	...	q28m	q30a	q31	q32	q33	q34
4	21000046	20021001	1	9	5		5.0	0.0	0.0	0.0	...	6	5	6	5	3	1

5 rows × 124 columns

Dropping columns that appear to be unconnected and columns with no questions in the dictionary.

In [5]:

```
data = data.drop(['respnum','intdate','q2a',
 'q2b',
 'q3a',
 'q3b',
 'q3c',
 'q3d',
 'q3e',
 'q3f',
 'q3g',
 'q4a',
 'q4b',
 'q4c',
 'q4d',
 'q4e',
 'q5a',
 'q5b',
 'q5c',
 'q5d',
 'q5e',
 'q5f','q28','wt',
 'filter_$'], axis = 1)
```

In [6]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10113 entries, 0 to 10112
Data columns (total 99 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   gendr   10113 non-null  int64
 1   q1      10113 non-null  int64
 2   q6      10113 non-null  int64
 3   q6a     10113 non-null  int64
 4   q8a     10113 non-null  object
 5   q8b     10113 non-null  object
 6   q91     10113 non-null  object
 7   q92     10113 non-null  object
 8   q93     10113 non-null  object
 9   q94     10113 non-null  object
 10  q98     10113 non-null  object
 11  q99     10113 non-null  object
 12  q910    10113 non-null  object
 13  q911    10113 non-null  object
 14  q911a   10113 non-null  object
 15  q912    10113 non-null  object
 16  q10     10113 non-null  object
 17  q11a    10113 non-null  object
 18  q11b    10113 non-null  object
 19  q12     10113 non-null  object
 20  q131    10113 non-null  object
 21  q132    10113 non-null  object
 22  q133    10113 non-null  object
 23  q134    10113 non-null  object
 24  q138    10113 non-null  object
```

```
 25  q139    10113 non-null  object
 26  q1310   10113 non-null  object
 27  q13a0   10113 non-null  object
 28  q1311   10113 non-null  object
 29  q1312   10113 non-null  object
 30  q13a2   10113 non-null  object
 31  q14     10113 non-null  object
 32  q15     10113 non-null  object
 33  q16a    10113 non-null  object
 34  q16b    10113 non-null  object
 35  q16c    10113 non-null  object
 36  q17     10113 non-null  object
 37  q181    10113 non-null  object
 38  q182    10113 non-null  object
 39  q183    10113 non-null  object
 40  q184    10113 non-null  object
 41  q189    10113 non-null  object
 42  q1810   10113 non-null  object
 43  q1811   10113 non-null  object
 44  q1814   10113 non-null  object
 45  q1815   10113 non-null  object
 46  q19     10113 non-null  object
 47  q201    10113 non-null  object
 48  q202    10113 non-null  object
 49  q203    10113 non-null  object
 50  q204    10113 non-null  object
 51  q209    10113 non-null  object
 52  q2010   10113 non-null  object
 53  q2011   10113 non-null  object
 54  q2014   10113 non-null  object
 55  q2015   10113 non-null  object
 56  q2016   10113 non-null  object
 57  q21     10113 non-null  object
 58  q221    10113 non-null  object
 59  q222    10113 non-null  object
 60  q223    10113 non-null  object
 61  q224    10113 non-null  object
 62  q229    10113 non-null  object
 63  q2210   10113 non-null  object
 64  q2211   10113 non-null  object
 65  q2214   10113 non-null  object
 66  q2215   10113 non-null  object
 67  q2216   10113 non-null  object
 68  q23     10113 non-null  object
 69  q23aa   10113 non-null  int64
 70  q23ab   10113 non-null  object
 71  q23a    10113 non-null  int64
 72  q23b    10113 non-null  object
 73  q23c    10113 non-null  int64
 74  q23d    10113 non-null  int64
 75  q23ea   10113 non-null  object
 76  q23eb   10113 non-null  object
 77  q23ec   10113 non-null  object
 78  q23ed   10113 non-null  object
 79  q23ee   10113 non-null  object
 80  q23ef   10113 non-null  object
 81  q23e    10113 non-null  int64
 82  q23e1   10113 non-null  object
 83  q23f    10113 non-null  int64
 84  q23f1   10113 non-null  object
 85  q23fg   10113 non-null  object
 86  q23h    10113 non-null  int64
 87  q24     10113 non-null  int64
 88  q25b    10113 non-null  int64
 89  q26     10113 non-null  int64
 90  q28y    10113 non-null  object
```

```
 91  q28m    10113 non-null  object
 92  q30a    10113 non-null  int64
 93  q31     10113 non-null  int64
 94  q32     10113 non-null  object
 95  q33     10113 non-null  int64
 96  q34     10113 non-null  int64
 97  q35     10113 non-null  int64
 98  q37     10113 non-null  int64
dtypes: int64(20), object(79)
memory usage: 7.6+ MB
```

To deal with NAN values, transforming object types to float types.

In [7]:

```
for column in data.select_dtypes(include=['object']):
    data[column] = pd.to_numeric(data[column], errors='coerce')
```

In [8]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10113 entries, 0 to 10112
Data columns (total 99 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   gendr   10113 non-null  int64
 1   q1      10113 non-null  int64
 2   q6      10113 non-null  int64
 3   q6a     10113 non-null  int64
 4   q8a     922 non-null    float64
 5   q8b     922 non-null    float64
 6   q91     618 non-null    float64
 7   q92     922 non-null    float64
 8   q93     922 non-null    float64
 9   q94     922 non-null    float64
 10  q98     922 non-null    float64
 11  q99     922 non-null    float64
 12  q910    922 non-null    float64
 13  q911    922 non-null    float64
 14  q911a   78 non-null     float64
 15  q912    548 non-null    float64
 16  q10     4457 non-null   float64
 17  q11a    4457 non-null   float64
 18  q11b    4457 non-null   float64
 19  q12     4457 non-null   float64
 20  q131    2462 non-null   float64
 21  q132    4457 non-null   float64
 22  q133    4457 non-null   float64
 23  q134    4457 non-null   float64
 24  q138    4457 non-null   float64
 25  q139    4457 non-null   float64
 26  q1310   4457 non-null   float64
 27  q13a0   1293 non-null   float64
 28  q1311   4457 non-null   float64
 29  q1312   4457 non-null   float64
 30  q13a2   234 non-null    float64
 31  q14     8615 non-null   float64
 32  q15     8615 non-null   float64
 33  q16a    8613 non-null   float64
 34  q16b    2699 non-null   float64
 35  q16c    367 non-null    float64
 36  q17     8517 non-null   float64
 37  q181    8517 non-null   float64
 38  q182    8517 non-null   float64
 39  q183    8517 non-null   float64
 40  q184    8517 non-null   float64
```

```
 41  q189    8517 non-null   float64
 42  q1810   8517 non-null   float64
 43  q1811   8517 non-null   float64
 44  q1814   8517 non-null   float64
 45  q1815   8517 non-null   float64
 46  q19     2575 non-null   float64
 47  q201    2575 non-null   float64
 48  q202    2575 non-null   float64
 49  q203    2575 non-null   float64
 50  q204    2575 non-null   float64
 51  q209    2575 non-null   float64
 52  q2010   2575 non-null   float64
 53  q2011   2575 non-null   float64
 54  q2014   2575 non-null   float64
 55  q2015   2575 non-null   float64
 56  q2016   2250 non-null   float64
 57  q21     315 non-null    float64
 58  q221    315 non-null    float64
 59  q222    315 non-null    float64
 60  q223    315 non-null    float64
 61  q224    315 non-null    float64
 62  q229    315 non-null    float64
 63  q2210   315 non-null    float64
 64  q2211   315 non-null    float64
 65  q2214   315 non-null    float64
 66  q2215   315 non-null    float64
 67  q2216   271 non-null    float64
 68  q23     1383 non-null   float64
 69  q23aa   10113 non-null  int64
 70  q23ab   4891 non-null   float64
 71  q23a    10113 non-null  int64
 72  q23b    3107 non-null   float64
 73  q23c    10113 non-null  int64
 74  q23d    10113 non-null  int64
 75  q23ea   196 non-null    float64
 76  q23eb   196 non-null    float64
 77  q23ec   196 non-null    float64
 78  q23ed   196 non-null    float64
 79  q23ee   196 non-null    float64
 80  q23ef   97 non-null     float64
 81  q23e    10113 non-null  int64
 82  q23e1   2893 non-null   float64
 83  q23f    10113 non-null  int64
 84  q23f1   3969 non-null   float64
 85  q23fg   10037 non-null  float64
 86  q23h    10113 non-null  int64
 87  q24     10113 non-null  int64
 88  q25b    10113 non-null  int64
 89  q26     10113 non-null  int64
 90  q28y    6981 non-null   float64
 91  q28m    1541 non-null   float64
 92  q30a    10113 non-null  int64
 93  q31     10113 non-null  int64
 94  q32     5263 non-null   float64
 95  q33     10113 non-null  int64
 96  q34     10113 non-null  int64
 97  q35     10113 non-null  int64
 98  q37     10113 non-null  int64
dtypes: float64(79), int64(20)
memory usage: 7.6 MB
```

In [9]:

```
data.describe(include ='all')
```

Out[9]:

	gendr	q1	q6	q6a	q8a	q8b	q91

	gendr	q1	q6	q6a	q8a	q8b	q91	
count	10113.000000	10113.000000	10113.000000	10113.000000	922.000000	922.000000	618.000000	922.00
mean	1.609216	11.031346	7.911302	8.223079	2.906725	8.791757	21.448220	9.43
std	0.487950	5.507359	6.941205	10.711020	1.382369	4.378411	31.283066	8.83
min	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.00
25%	1.000000	8.000000	7.000000	6.000000	2.000000	8.000000	8.000000	8.00
50%	2.000000	13.000000	8.000000	7.000000	3.000000	9.000000	9.000000	9.00
75%	2.000000	15.000000	9.000000	9.000000	4.000000	10.000000	10.000000	10.00
max	2.000000	95.000000	98.000000	98.000000	5.000000	98.000000	98.000000	98.00

8 rows × 99 columns

Number of Nan values

In [10]:
```
data.isna().sum().sum()
```

Out[10]:
```
545270
```

Filling the nan values with value that is bigger than the dataset's maximum value, i.e. 995

In [11]:
```
data = data.fillna(1001)
```

In [12]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10113 entries, 0 to 10112
Data columns (total 99 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   gendr   10113 non-null  int64  
 1   q1      10113 non-null  int64  
 2   q6      10113 non-null  int64  
 3   q6a     10113 non-null  int64  
 4   q8a     10113 non-null  float64
 5   q8b     10113 non-null  float64
 6   q91     10113 non-null  float64
 7   q92     10113 non-null  float64
 8   q93     10113 non-null  float64
 9   q94     10113 non-null  float64
 10  q98     10113 non-null  float64
 11  q99     10113 non-null  float64
 12  q910    10113 non-null  float64
 13  q911    10113 non-null  float64
 14  q911a   10113 non-null  float64
 15  q912    10113 non-null  float64
 16  q10     10113 non-null  float64
 17  q11a    10113 non-null  float64
 18  q11b    10113 non-null  float64
 19  q12     10113 non-null  float64
 20  q131    10113 non-null  float64
 21  q132    10113 non-null  float64
 22  q133    10113 non-null  float64
 23  q134    10113 non-null  float64
 24  q138    10113 non-null  float64
 25  q139    10113 non-null  float64
```

```
 26  q1310   10113 non-null  float64
 27  q13a0   10113 non-null  float64
 28  q1311   10113 non-null  float64
 29  q1312   10113 non-null  float64
 30  q13a2   10113 non-null  float64
 31  q14     10113 non-null  float64
 32  q15     10113 non-null  float64
 33  q16a    10113 non-null  float64
 34  q16b    10113 non-null  float64
 35  q16c    10113 non-null  float64
 36  q17     10113 non-null  float64
 37  q181    10113 non-null  float64
 38  q182    10113 non-null  float64
 39  q183    10113 non-null  float64
 40  q184    10113 non-null  float64
 41  q189    10113 non-null  float64
 42  q1810   10113 non-null  float64
 43  q1811   10113 non-null  float64
 44  q1814   10113 non-null  float64
 45  q1815   10113 non-null  float64
 46  q19     10113 non-null  float64
 47  q201    10113 non-null  float64
 48  q202    10113 non-null  float64
 49  q203    10113 non-null  float64
 50  q204    10113 non-null  float64
 51  q209    10113 non-null  float64
 52  q2010   10113 non-null  float64
 53  q2011   10113 non-null  float64
 54  q2014   10113 non-null  float64
 55  q2015   10113 non-null  float64
 56  q2016   10113 non-null  float64
 57  q21     10113 non-null  float64
 58  q221    10113 non-null  float64
 59  q222    10113 non-null  float64
 60  q223    10113 non-null  float64
 61  q224    10113 non-null  float64
 62  q229    10113 non-null  float64
 63  q2210   10113 non-null  float64
 64  q2211   10113 non-null  float64
 65  q2214   10113 non-null  float64
 66  q2215   10113 non-null  float64
 67  q2216   10113 non-null  float64
 68  q23     10113 non-null  float64
 69  q23aa   10113 non-null  int64
 70  q23ab   10113 non-null  float64
 71  q23a    10113 non-null  int64
 72  q23b    10113 non-null  float64
 73  q23c    10113 non-null  int64
 74  q23d    10113 non-null  int64
 75  q23ea   10113 non-null  float64
 76  q23eb   10113 non-null  float64
 77  q23ec   10113 non-null  float64
 78  q23ed   10113 non-null  float64
 79  q23ee   10113 non-null  float64
 80  q23ef   10113 non-null  float64
 81  q23e    10113 non-null  int64
 82  q23e1   10113 non-null  float64
 83  q23f    10113 non-null  int64
 84  q23f1   10113 non-null  float64
 85  q23fg   10113 non-null  float64
 86  q23h    10113 non-null  int64
 87  q24     10113 non-null  int64
 88  q25b    10113 non-null  int64
 89  q26     10113 non-null  int64
 90  q28y    10113 non-null  float64
 91  q28m    10113 non-null  float64
```

```
 92  q30a    10113 non-null  int64
 93  q31     10113 non-null  int64
 94  q32     10113 non-null  float64
 95  q33     10113 non-null  int64
 96  q34     10113 non-null  int64
 97  q35     10113 non-null  int64
 98  q37     10113 non-null  int64
dtypes: float64(79), int64(20)
memory usage: 7.6 MB
```

In [13]:

```python
data.describe(include ='all')
```

Out[13]:

	gendr	q1	q6	q6a	q8a	q8b	q91	
count	10113.000000	10113.000000	10113.000000	10113.000000	10113.000000	10113.000000	10113.000000	10
mean	1.609216	11.031346	7.911302	8.223079	910.004054	910.540591	941.140117	[illegible]
std	0.487950	5.507359	6.941205	10.711020	287.316056	285.624717	234.771818	[illegible]
min	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	
25%	1.000000	8.000000	7.000000	6.000000	1001.000000	1001.000000	1001.000000	1[illegible]
50%	2.000000	13.000000	8.000000	7.000000	1001.000000	1001.000000	1001.000000	1[illegible]
75%	2.000000	15.000000	9.000000	9.000000	1001.000000	1001.000000	1001.000000	1[illegible]
max	2.000000	95.000000	98.000000	98.000000	1001.000000	1001.000000	1001.000000	1[illegible]

8 rows × 99 columns

Number of NaN values after transforming

In [14]:

```python
data.isna().sum().sum()
```

Out[14]:

```
0
```

Substituting 1000 for the Don't Know, Refused, and Other values, i.e. larger than 995.

Then, for any numbers bigger than 995, set them to zero.

In [15]:

```python
data.where(data != 95  , 1000, inplace=True)
data.where(data != 98  , 1000, inplace=True)
data.where(data != 97  , 1000, inplace=True)
data.where(data <= 995  , 0, inplace=True)
```

In [16]:

```python
data.head()
```

Out[16]:

	gendr	q1	q6	q6a	q8a	q8b	q91	q92	q93	q94	...	q26	q28y	q28m	q30a	q31	q32	q33	q34
0	1	14	10	10	0.0	0.0	0.0	0.0	0.0	0.0	...	3	10.0	0.0	5	5	2.0	4	4
1	2	2	10	10	0.0	0.0	0.0	0.0	0.0	0.0	...	3	0.0	5.0	5	5	1.0	3	4
2	1	9	9	5	2.0	10.0	10.0	10.0	10.0	10.0	...	1	0.0	1.0	4	5	1.0	5	6
3	2	15	8	8	0.0	0.0	0.0	0.0	0.0	0.0	...	3	10.0	0.0	0	4	4.0	3	2
4	1	9	8	9	0.0	0.0	0.0	0.0	0.0	0.0	...	1	0.0	6.0	5	6	5.0	3	1

5 rows × 99 columns

Investigated the dataset and identified the ordinal (or columns with an ordered scale), category, binary,numerical and target columns.

In [17]:
```
binary_columns= ['gendr']
categorical_columns = ['q1', 'q8a', 'q911a', 'q10', 'q11a', 'q11b', 'q13a0', 'q13a2', 'q14
                       'q23e', 'q23f', 'q23h', 'q25b', 'q26', 'q33', 'q34', 'q35', 'q37' ]
numerical_columns= ['q15','q24','q32']
target_columns = ['q28y', 'q28m', 'q30a', 'q31']
ordinal_columns= list(set(data.columns)- set(binary_columns)-set(categorical_columns)-set
```

In ordinal columns, replaced any values equal to zero with a neutral value.

In [18]:
```
for i in ordinal_columns:
    data[i] = data[i].map( lambda x : round((data[i].max()-data[i].min())/2) if x == 0 els
```

In [19]:
```
data
```

Out[19]:

	gendr	q1	q6	q6a	q8a	q8b	q91	q92	q93	q94	...	q26	q28y	q28m	q30a	q31	q32	q33
0	1	14	10	10	0.0	5.0	5.0	5.0	5.0	5.0	...	3	10.0	0.0	5	5	2.0	4
1	2	2	10	10	0.0	5.0	5.0	5.0	5.0	5.0	...	3	0.0	5.0	5	5	1.0	3
2	1	9	9	5	2.0	10.0	10.0	10.0	10.0	10.0	...	1	0.0	1.0	4	5	1.0	5
3	2	15	8	8	0.0	5.0	5.0	5.0	5.0	5.0	...	3	10.0	0.0	0	4	4.0	3
4	1	9	8	9	0.0	5.0	5.0	5.0	5.0	5.0	...	1	0.0	6.0	5	6	5.0	3
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
10108	2	14	7	4	0.0	5.0	5.0	5.0	5.0	5.0	...	2	2.0	0.0	4	5	0.0	2
10109	1	1	8	7	0.0	5.0	5.0	5.0	5.0	5.0	...	3	10.0	0.0	4	4	0.0	3
10110	2	12	9	9	0.0	5.0	5.0	5.0	5.0	5.0	...	3	15.0	0.0	5	5	0.0	6
10111	2	12	8	5	0.0	5.0	5.0	5.0	5.0	5.0	...	3	9.0	0.0	5	3	0.0	1
10112	2	9	8	7	4.0	9.0	5.0	7.0	8.0	9.0	...	3	12.0	0.0	4	4	0.0	3

10113 rows × 99 columns

Creating the target feature

- The number of years were converted to months and added to the number of months to create a loyalty statistic based on how long the consumer has been taking transportation on a regular basis.
- As a weight, added the value for the question: "How likely are you to continue to take transport as frequently as you do today in the near future?" to the value above.
- As a weight, added the value for the question "How likely would you be to suggest Greater Vancouver's transit service to a friend?" to the value above.
- To get a normal distribution, converted the value to log scale.

In [20]:
```
data['Target']= np.log((data['q28y']*12)+data['q28m']+data['q30a']+data['q31'])
```

```
/opt/miniconda3/envs/571/lib/python3.9/site-packages/pandas/core/arraylike.py:364: Runtime
Warning: divide by zero encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
```

Getting rid of the unrealistic target values, such as those below zero.

In [21]:

```
data = data[data['Target'] > 0]
```

In [22]:

```
data['Target'].max()
```

Out[22]:

```
7.057897937411856
```

In [23]:

```
data['Target'].min()
```

Out[23]:

```
0.6931471805599453
```

In [24]:

```
data = data.drop(['q28y','q28m','q30a','q31' ],axis = 1)
```

In [25]:

```
data
```

Out[25]:

	gendr	q1	q6	q6a	q8a	q8b	q91	q92	q93	q94	...	q23h	q24	q25b	q26	q32	q33	q34	c
0	1	14	10	10	0.0	5.0	5.0	5.0	5.0	5.0	...	0	3	1	3	2.0	4	4	
1	2	2	10	10	0.0	5.0	5.0	5.0	5.0	5.0	...	1	2	1	3	1.0	3	4	
2	1	9	9	5	2.0	10.0	10.0	10.0	10.0	10.0	...	1	1	2	1	1.0	5	6	
3	2	15	8	8	0.0	5.0	5.0	5.0	5.0	5.0	...	0	1	1	3	4.0	3	2	
4	1	9	8	9	0.0	5.0	5.0	5.0	5.0	5.0	...	2	2	1	1	5.0	3	1	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
10108	2	14	7	4	0.0	5.0	5.0	5.0	5.0	5.0	...	1	1	1	2	0.0	2	1	
10109	1	1	8	7	0.0	5.0	5.0	5.0	5.0	5.0	...	8	1	1	3	0.0	3	2	
10110	2	12	9	9	0.0	5.0	5.0	5.0	5.0	5.0	...	2	2	1	3	0.0	6	1	
10111	2	12	8	5	0.0	5.0	5.0	5.0	5.0	5.0	...	1	1	2	3	0.0	1	3	
10112	2	9	8	7	4.0	9.0	5.0	7.0	8.0	9.0	...	2	2	1	3	0.0	3	1	

10103 rows × 96 columns

In [26]:

```
# Code to drop columns which were not adding any revelance
# data=data.drop(['q8b', 'q91', 'q92', 'q93', 'q94',
#          'q98', 'q99', 'q910', 'q911','q19', 'q201', 'q202', 'q203', 'q204', 'q209', 'q20
#          'q2011', 'q2014', 'q2015', 'q21', 'q221', 'q222', 'q223',
#          'q224', 'q229', 'q2210', 'q2211', 'q2214', 'q2215', 'q23'],axis= 1)
```

Splitting and seperating the targets

In [27]:

```
data.shape
```

Out[27]:

```
(10103, 96)
```

In [28]:

```
train_df, test_df = train_test_split(data, test_size=0.2, random_state=123)
```

In [29]:

```
train_df.shape
```

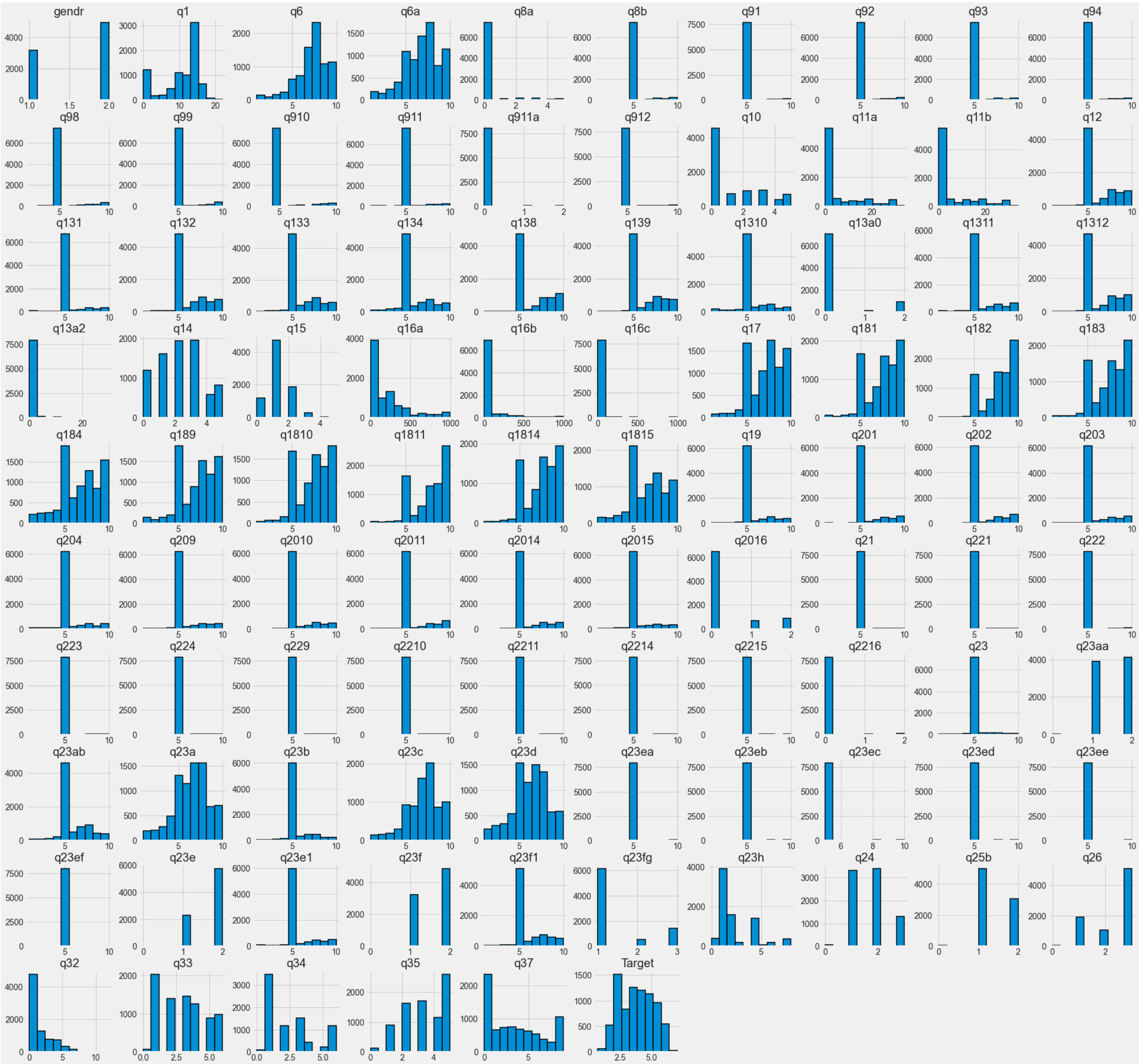
Out[29]:
```
(8082, 96)
```

In [30]:
```
test_df.shape
```

Out[30]:
```
(2021, 96)
```

EDA

In [31]:
```
train_df.iloc[:,:].hist(edgecolor="black", linewidth=1.5, figsize=(30, 30));
```



As you can see, most of the features had nan values that were changed with a neutral value for analytical purposes.

In [32]:
```
# Code to plot co-relation plots
# import seaborn as sns
# plt.figure(figsize=(100, 100))
# sns.heatmap(train_df.corr(), annot=True, cmap=plt.cm.Blues)
# plt.show()
```

Preprocessing and transformations

I looked at the q23fg feature and discovered that the ordinal value for 3 should be smaller than 1. So I set it to zero.

In [33]:
```
data.loc[data['q23fg'] == 3., 'q23fg'] = 0
```

In [34]:
```
data['q23fg'].unique()
```

Out[34]:
```
array([2., 1., 0.])
```

In [35]:
```
binary_features= ['gendr']
categorical_features = ['q1', 'q8a', 'q911a', 'q10', 'q11a', 'q11b', 'q13a0', 'q13a2', 'q1
                        'q23e', 'q23f', 'q23h', 'q25b', 'q26', 'q33', 'q34', 'q35', 'q37' ]
numerical_features= ['q15','q24','q32']
target = 'Target'
passthrough_feats = list(set(train_df.columns)- set(binary_features)-set(categorical_featu
```

In [36]:
```
preprocessor_all = make_column_transformer(
    (OneHotEncoder(drop="if_binary", dtype="int"),binary_features),
    (StandardScaler(), numerical_features),
    (OneHotEncoder(handle_unknown="ignore", dtype="int"), categorical_features),
    ("passthrough", passthrough_feats)
)
```

- StandardScalar is used to all numeric features to convert them to standardised scales because they are in different units.
- After running an EDA, used OneHotEncoding to the category and binary characteristics we chose.
- Ordinal features are passed as is, as they are already encoded in an ordinal manner.

In [37]:
```
X_train, y_train = train_df.drop(columns=[target]), train_df[target]
X_test, y_test = test_df.drop(columns=[target]), test_df[target]
```

In [38]:
```
preprocessor_all.fit(X_train)
```

Out[38]:
```
ColumnTransformer(transformers=[('onehotencoder-1',
                                 OneHotEncoder(drop='if_binary', dtype='int'),
                                 ['gendr']),
                                ('standardscaler', StandardScaler(),
                                 ['q15', 'q24', 'q32']),
                                ('onehotencoder-2',
                                 OneHotEncoder(dtype='int',
                                               handle_unknown='ignore'),
                                 ['q1', 'q8a', 'q911a', 'q10', 'q11a', 'q11b',
                                  'q13a0', 'q13a2', 'q14', 'q16a', 'q16b',
                                  'q16c', 'q2016', 'q2216', 'q23aa', 'q23e',
                                  'q23f', 'q23h', 'q25b', 'q26', 'q33', 'q34',
                                  'q35', 'q37']),
                                ('passthrough', 'passthrough',
                                 ['q91', 'q2011', 'q23b', 'q2010', 'q221',
                                  'q224', 'q19', 'q222', 'q139', 'q209',
                                  'q2215', 'q181', 'q94', 'q183', 'q1311',
                                  'q99', 'q23a', 'q203', 'q23fg', 'q17',
                                  'q23ed', 'q12', 'q23ec', 'q23d', 'q2014',
                                  'q229', 'q2210', 'q8b', 'q2211', 'q2214', ...])])
```

Baseline Model

In [39]:
```
from sklearn.metrics import make_scorer


def mape(true, pred):
    return 100.0 * np.mean(np.abs((pred - true) / true))


# make a scorer function that we can pass into cross-validation
mape_scorer = make_scorer(mape, greater_is_better=False)

scoring_metrics = {
    "neg RMSE": "neg_root_mean_squared_error",
    "r2": "r2",
    "mape": mape_scorer,
}
```

- Root Mean Squared Error is the square root of Mean Squared error. It measures the standard deviation of residuals.
- The coefficient of determination or R-squared represents the proportion of the variance in the dependent variable which is explained by the model. It is a scale-free score i.e. irrespective of the values being small or large, the value of R square will be less than one.
- The mean absolute percentage error (MAPE) is a measure of how accurate a forecast system is. It measures this accuracy as a percentage, and can be calculated as the average absolute percent error for each time period minus actual values divided by actual values.

In [40]:
```
results = {}
```

In [41]:
```
def mean_std_cross_val_scores(model, X_train, y_train, **kwargs):
    """
    Returns mean and std of cross validation

    Parameters
    ----------
    model :
        scikit-learn model
    X_train : numpy array or pandas DataFrame
        X in the training data
    y_train :
        y in the training data

    Returns
    ----------
        pandas Series with mean scores from cross_validation
    """

    scores = cross_validate(model, X_train, y_train, **kwargs)

    mean_scores = pd.DataFrame(scores).mean()
    std_scores = pd.DataFrame(scores).std()
    out_col = []

    for i in range(len(mean_scores)):
        out_col.append((f"%0.3f (+/- %0.3f)" % (mean_scores[i], std_scores[i])))

    return pd.Series(data=out_col, index=mean_scores.index)
```

In [42]:

```
results["Dummy"] = mean_std_cross_val_scores(
    DummyRegressor(), X_train, y_train, return_train_score=True, scoring=scoring_metrics
)
pd.DataFrame(results).T
```

Out[42]:

	fit_time	score_time	test_neg RMSE	train_neg RMSE	test_r2	train_r2	test_mape	train_mape
Dummy	0.003 (+/- 0.001)	0.001 (+/- 0.000)	-1.325 (+/- 0.018)	-1.325 (+/- 0.004)	-0.001 (+/- 0.001)	0.000 (+/- 0.000)	-37.553 (+/- 0.652)	-37.548 (+/- 0.142)

Linear Model

In [43]:

```
pipe_ridge = make_pipeline(
    preprocessor_all, Ridge(max_iter =2000,random_state=123)
)
results["Ridge"] = mean_std_cross_val_scores(
    pipe_ridge,X_train, y_train, return_train_score=True, scoring=scoring_metrics,n_jobs=-
)
pd.DataFrame(results).T
```

Out[43]:

	fit_time	score_time	test_neg RMSE	train_neg RMSE	test_r2	train_r2	test_mape	train_mape
Dummy	0.003 (+/- 0.001)	0.001 (+/- 0.000)	-1.325 (+/- 0.018)	-1.325 (+/- 0.004)	-0.001 (+/- 0.001)	0.000 (+/- 0.000)	-37.553 (+/- 0.652)	-37.548 (+/- 0.142)
Ridge	3.072 (+/- 0.005)	0.070 (+/- 0.007)	-1.234 (+/- 0.015)	-1.130 (+/- 0.004)	0.131 (+/- 0.033)	0.273 (+/- 0.007)	-33.406 (+/- 0.869)	-30.511 (+/- 0.215)

In [44]:

```
from sklearn.model_selection import RandomizedSearchCV

param_random = {"ridge__alpha": [0.01,0.1,0.5,0.75,0.8,0.9,1]}

random_search = RandomizedSearchCV(
    pipe_ridge, param_distributions=param_random, n_jobs=-1,random_state =123,scoring = "r
)
random_search.fit(X_train, y_train)

print("Best Hyper-Parameters are:", random_search.best_params_)
```

```
/opt/miniconda3/envs/571/lib/python3.9/site-packages/sklearn/model_selection/_search.py:29
2: UserWarning: The total space of parameters 7 is smaller than n_iter=20. Running 7 itera
tions. For exhaustive searches, use GridSearchCV.
  warnings.warn(
Best Hyper-Parameters are: {'ridge__alpha': 1}
```

In [45]:

```
print("Best Score is:", random_search.best_score_)
```

```
Best Score is: 0.130807063839026
```

- Ridge is a simple linear model that fits quickly and produces accurate results.
- As can be observed from the scores, ridge does not do well on our data because it does not appear to follow a linear trend.
- Ridge is performing better than the dummy.
- The best reported alpha after hyper parameter optimization is 1 and the best r2 score is 0.1307, which is the same as the default model.

Tree Based and Boosting based models

In [46]:

```
from xgboost import XGBRegressor
from catboost import CatBoostRegressor
from lightgbm.sklearn import LGBMRegressor


pipe_rf = make_pipeline(preprocessor_all, RandomForestRegressor(random_state=123))

pipe_xgb = make_pipeline(
    preprocessor_all, XGBRegressor(random_state=123, eval_metric = "logloss",verbosity=0)
)
pipe_lgbm = make_pipeline(preprocessor_all, LGBMRegressor(random_state=123))
pipe_catboost = make_pipeline(
    preprocessor_all, CatBoostRegressor(random_state=123, verbose = 0)
)
models = {
    "random forest": pipe_rf,
    "XGBoost": pipe_xgb,
    "LightGBM": pipe_lgbm,
    "CatBoost": pipe_catboost,
}
```

In [47]:

```
for (name, model) in models.items():
    results[name] = mean_std_cross_val_scores(
        model, X_train, y_train, return_train_score=True, n_jobs= -1, scoring = scoring_me
    )
pd.DataFrame(results).T
```

Out[47]:

	fit_time	score_time	test_neg RMSE	train_neg RMSE	test_r2	train_r2	test_mape	train_mape
Dummy	0.003 (+/- 0.001)	0.001 (+/- 0.000)	-1.325 (+/- 0.018)	-1.325 (+/- 0.004)	-0.001 (+/- 0.001)	0.000 (+/- 0.000)	-37.553 (+/- 0.652)	-37.548 (+/- 0.142)
Ridge	3.072 (+/- 0.005)	0.070 (+/- 0.007)	-1.234 (+/- 0.015)	-1.130 (+/- 0.004)	0.131 (+/- 0.033)	0.273 (+/- 0.007)	-33.406 (+/- 0.869)	-30.511 (+/- 0.215)
random forest	163.049 (+/- 1.809)	0.842 (+/- 0.154)	-1.209 (+/- 0.013)	-0.451 (+/- 0.002)	0.166 (+/- 0.025)	0.884 (+/- 0.002)	-32.736 (+/- 0.689)	-12.078 (+/- 0.059)
XGBoost	8.465 (+/- 0.156)	0.052 (+/- 0.009)	-1.236 (+/- 0.009)	-0.755 (+/- 0.015)	0.129 (+/- 0.015)	0.675 (+/- 0.012)	-32.814 (+/- 0.591)	-19.069 (+/- 0.400)
LightGBM	2.158 (+/- 1.525)	0.044 (+/- 0.012)	-1.198 (+/- 0.013)	-0.903 (+/- 0.003)	0.182 (+/- 0.015)	0.536 (+/- 0.005)	-32.310 (+/- 0.739)	-24.186 (+/- 0.142)
CatBoost	12.529 (+/- 0.154)	0.161 (+/- 0.049)	-1.195 (+/- 0.014)	-0.868 (+/- 0.004)	0.186 (+/- 0.018)	0.570 (+/- 0.003)	-32.298 (+/- 0.832)	-23.207 (+/- 0.122)

- Tree-based and boosting-based models outperform the dummy and the ridge(linear) model
- The CatBoost model has the best test r2 of 0.189.

Overfitting/Underfitting:

- Because the difference between the train and test scores is so large, the Random forests model overfits.
- All other models seem to be performing fine on the data.

Fit time:

- The Random forest takes the longest to fit because the maximum depth isn't specified and the model overfits the data.
- LGBM has the lowest fit time compared to all other models.

Score time:

- Random forests has the highest score time.
- LGBM has the lowest score time compared to all other models.

Feature Selection- Lasso- L1 Regularization

In [48]:

```
from sklearn.linear_model import Lasso, LassoCV
from sklearn.feature_selection import SelectFromModel

pipe_cat_las = make_pipeline(preprocessor_all, SelectFromModel(Lasso(alpha=0.01, max_iter=

res = mean_std_cross_val_scores(pipe_cat_las,X_train, y_train,scoring=scoring_metrics,retu
res
```

Out[48]:

```
fit_time              3.934 (+/- 1.308)
score_time            0.060 (+/- 0.037)
test_neg RMSE        -1.205 (+/- 0.019)
train_neg RMSE       -0.813 (+/- 0.016)
test_r2               0.173 (+/- 0.019)
train_r2              0.624 (+/- 0.014)
test_mape           -32.385 (+/- 0.769)
train_mape          -21.037 (+/- 0.440)
dtype: object
```

- Since the test R2 score has reduced using the feature selection. Its not a good idea to include the given feature selection.

Hyper-parameter optimization

In [49]:

```
params = {
    "random forest": {'randomforestregressor__max_depth': [10,20]},
    "XGBoost": {'xgbregressor__max_depth' : [10, 20]},
    "CatBoost": {'catboostregressor__max_depth' : [10, 20]} }
models = {
    "random forest": pipe_rf,
    "XGBoost": pipe_xgb,
    "CatBoost": pipe_catboost,
}

for (name, model) in models.items():
    print("Running hyperparameter optimization for",name)
    random_search = RandomizedSearchCV(model, param_distributions=params[name], n_jobs=-1,
    random_search.fit(X_train,y_train)
    print("Best Hyper-Parameters are", random_search.best_params_)
    print("Best Score", random_search.best_score_)
```

```
Running hyperparameter optimization for random forest
/opt/miniconda3/envs/571/lib/python3.9/site-packages/sklearn/model_selection/_search.py:29
2: UserWarning: The total space of parameters 2 is smaller than n_iter=3. Running 2 iterat
ions. For exhaustive searches, use GridSearchCV.
  warnings.warn(
Best Hyper-Parameters are {'randomforestregressor__max_depth': 10}
Best Score 0.1764583133075977
Running hyperparameter optimization for XGBoost
/opt/miniconda3/envs/571/lib/python3.9/site-packages/sklearn/model_selection/_search.py:29
```

```
2: UserWarning: The total space of parameters 2 is smaller than n_iter=3. Running 2 iterat
ions. For exhaustive searches, use GridSearchCV.
  warnings.warn(
Best Hyper-Parameters are {'xgbregressor__max_depth': 10}
Best Score 0.06960731571283127
Running hyperparameter optimization for CatBoost
/opt/miniconda3/envs/571/lib/python3.9/site-packages/sklearn/model_selection/_search.py:29
2: UserWarning: The total space of parameters 2 is smaller than n_iter=3. Running 2 iterat
ions. For exhaustive searches, use GridSearchCV.
  warnings.warn(
/opt/miniconda3/envs/571/lib/python3.9/site-packages/sklearn/model_selection/_validation.p
y:372: FitFailedWarning:
5 fits failed out of a total of 10.
The score on these train-test partitions for these parameters will be set to nan.
If these failures are not expected, you can try to debug them by setting error_score='rais
e'.

Below are more details about the failures:
--------------------------------------------------------------------------------
5 fits failed with the following error:
Traceback (most recent call last):
  File "/opt/miniconda3/envs/571/lib/python3.9/site-packages/sklearn/model_selection/_vali
dation.py", line 680, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/opt/miniconda3/envs/571/lib/python3.9/site-packages/sklearn/pipeline.py", line 39
4, in fit
    self._final_estimator.fit(Xt, y, **fit_params_last_step)
  File "/opt/miniconda3/envs/571/lib/python3.9/site-packages/catboost/core.py", line 5504,
in fit
    return self._fit(X, y, cat_features, None, None, None, sample_weight, None, None, Non
e, None, baseline,
  File "/opt/miniconda3/envs/571/lib/python3.9/site-packages/catboost/core.py", line 2176,
in _fit
    train_params = self._prepare_train_params(
  File "/opt/miniconda3/envs/571/lib/python3.9/site-packages/catboost/core.py", line 2108,
in _prepare_train_params
    _check_train_params(params)
  File "_catboost.pyx", line 5855, in _catboost._check_train_params
  File "_catboost.pyx", line 5874, in _catboost._check_train_params
_catboost.CatBoostError: catboost/private/libs/options/oblivious_tree_options.cpp:122: Max
imum tree depth is 16

  warnings.warn(some_fits_failed_message, FitFailedWarning)
/opt/miniconda3/envs/571/lib/python3.9/site-packages/sklearn/model_selection/_search.py:96
9: UserWarning: One or more of the test scores are non-finite: [0.18736082        nan]
  warnings.warn(
Best Hyper-Parameters are {'catboostregressor__max_depth': 10}
Best Score 0.1873608209370368
```

- The r2 scores have decreased as a result of the above hyper parameter optimization tests, yielding no noteworthy results.

Interpretation and feature importances

In [50]:

```python
import shap
```

In [51]:

```python
pipe_catboost_opti = make_pipeline(
    preprocessor_all, CatBoostRegressor(random_state=123, verbose = 0))
```

In [52]:

```python
pipe_catboost_opti.fit(X_train, y_train)
```

Out[52]:
```
Pipeline(steps=[('columntransformer',
                 ColumnTransformer(transformers=[('onehotencoder-1',
                                                  OneHotEncoder(drop='if_binary',
                                                                dtype='int'),
                                                  ['gendr']),
                                                 ('standardscaler',
                                                  StandardScaler(),
                                                  ['q15', 'q24', 'q32']),
                                                 ('onehotencoder-2',
                                                  OneHotEncoder(dtype='int',
                                                                handle_unknown='ignore'),
                                                  ['q1', 'q8a', 'q911a', 'q10',
                                                   'q11a', 'q11b', 'q13a0',
                                                   'q13a2', 'q14', 'q16a',
                                                   'q16b', 'q16c...
                                                   'q26', 'q33', 'q34', 'q35',
                                                   'q37']),
                                                 ('passthrough', 'passthrough',
                                                  ['q91', 'q2011', 'q23b',
                                                   'q2010', 'q221', 'q224',
                                                   'q19', 'q222', 'q139',
                                                   'q209', 'q2215', 'q181',
                                                   'q94', 'q183', 'q1311',
                                                   'q99', 'q23a', 'q203',
                                                   'q23fg', 'q17', 'q23ed',
                                                   'q12', 'q23ec', 'q23d',
                                                   'q2014', 'q229', 'q2210',
                                                   'q8b', 'q2211', 'q2214', ...])])),
                ('catboostregressor',
                 <catboost.core.CatBoostRegressor object at 0x13915e880>)])
```

In [53]:
```
standard_scalar_names= pipe_catboost_opti.named_steps['columntransformer'].named_transforr
onehot_names= pipe_catboost_opti.named_steps['columntransformer'].named_transformers_['one

feature_names = binary_features+standard_scalar_names + onehot_names+ passthrough_feats
```

In [54]:
```
X_train_enc = pd.DataFrame(
    data=preprocessor_all.transform(X_train).toarray(),
    columns=feature_names,
    index=X_train.index,
)
X_train_enc.head()
```

Out[54]:

	gendr	q15	q24	q32	q1_0	q1_1	q1_2	q1_3	q1_4	q1_5	...	q23e1	q21	q182
5440	1.0	1.172089	1.730809	-0.816227	0.0	0.0	0.0	0.0	0.0	0.0	...	5.0	5.0	10.0
8832	1.0	-0.220973	-1.006379	-0.816227	0.0	0.0	0.0	0.0	0.0	0.0	...	10.0	5.0	10.0
6929	1.0	1.172089	0.362215	-0.816227	0.0	0.0	0.0	0.0	0.0	0.0	...	8.0	5.0	9.0
8199	0.0	-1.614035	1.730809	-0.816227	0.0	0.0	0.0	0.0	0.0	0.0	...	5.0	5.0	5.0
5442	1.0	-0.220973	0.362215	-0.816227	0.0	0.0	1.0	0.0	0.0	0.0	...	5.0	5.0	8.0

5 rows × 717 columns

In [55]:
```
X_test_enc = pd.DataFrame(
    data=preprocessor_all.transform(X_test).toarray(),
    columns=feature_names,
    index=X_test.index,
```

```
)
X_test_enc.head()
```

Out[55]:

	gendr	q15	q24	q32	q1_0	q1_1	q1_2	q1_3	q1_4	q1_5	...	q23e1	q21	q182
221	0.0	-1.614035	1.730809	0.882215	0.0	0.0	0.0	0.0	0.0	0.0	...	5.0	5.0	5.0
7279	1.0	-0.220973	-1.006379	-0.816227	0.0	0.0	0.0	0.0	0.0	0.0	...	10.0	5.0	8.0
8415	0.0	-0.220973	-1.006379	-0.816227	0.0	0.0	0.0	0.0	0.0	0.0	...	5.0	5.0	4.0
7202	0.0	-0.220973	0.362215	-0.816227	0.0	0.0	0.0	0.0	0.0	0.0	...	5.0	5.0	5.0
759	1.0	-0.220973	0.362215	1.448362	0.0	0.0	0.0	0.0	0.0	0.0	...	10.0	5.0	8.0

5 rows × 717 columns

In [56]:

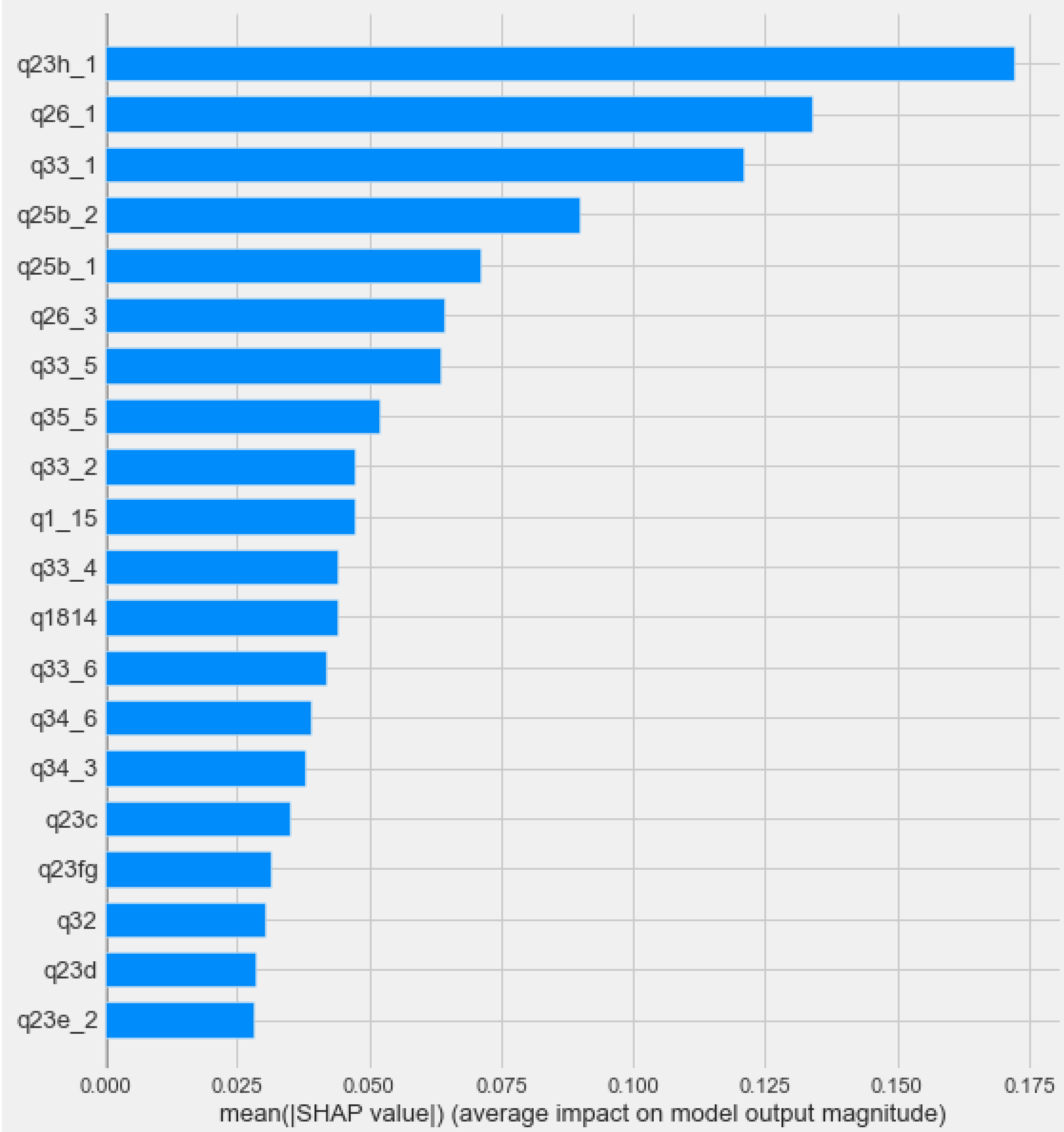
```
cat_explainer = shap.TreeExplainer(pipe_catboost_opti.named_steps["catboostregressor"])
train_cat_shap_values = cat_explainer.shap_values(X_train_enc)
```

In [57]:

```
shap.initjs()
```

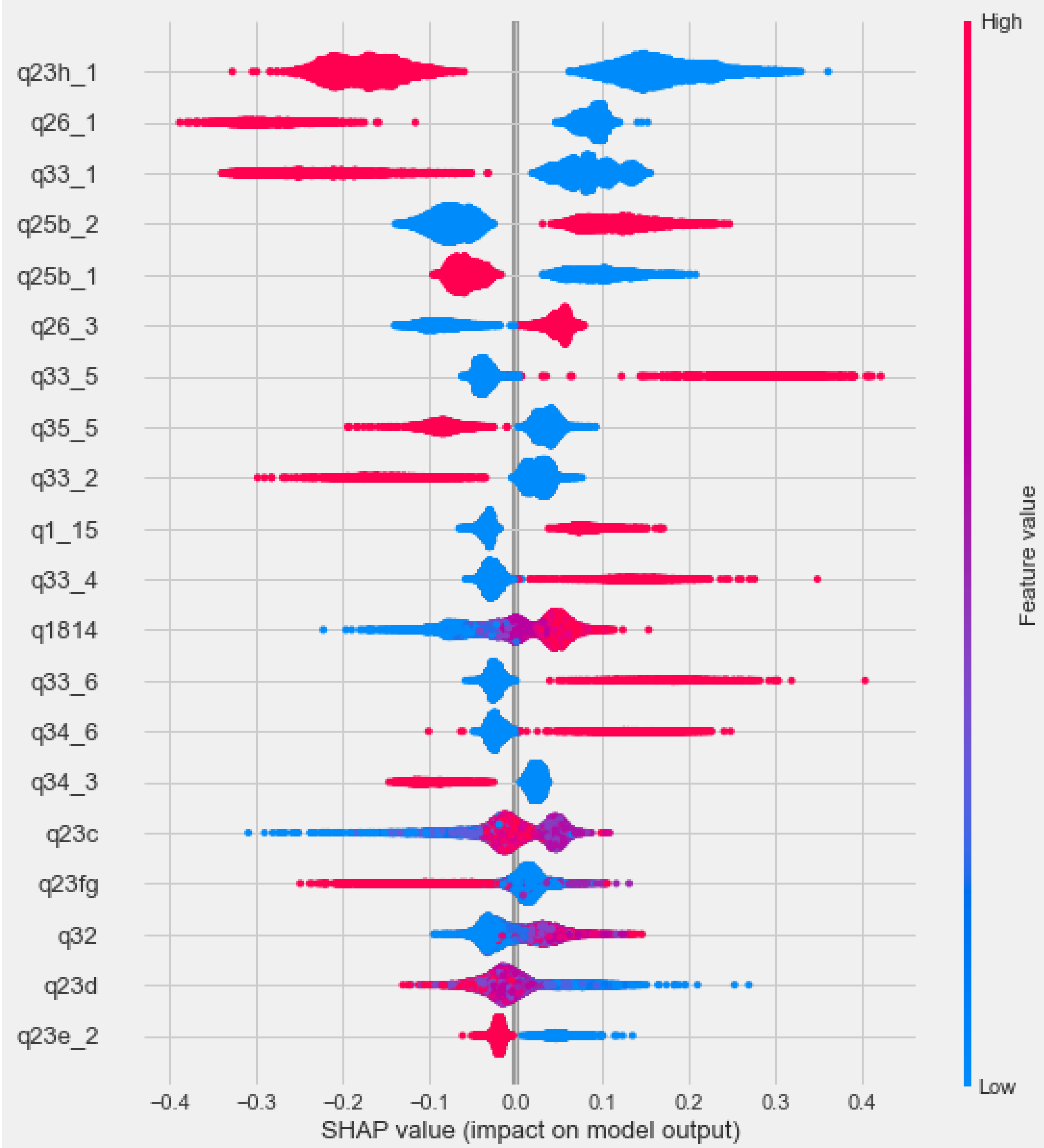
In [58]:

```
shap.summary_plot(train_cat_shap_values, X_train_enc, plot_type="bar")
```



In [59]:

```
shap.summary_plot(train_cat_shap_values, X_train_enc)
```



Plot1:

The average SHAP value for each feature is shown in plot 1, or the first plot. The feature 'q23h' with value 1, i.e. the use of cash as a payment method, has the biggest impact on the predictions, according to the plot, while the feature 'q26' with value 1, i.e. the feature representing new consumers, has the second highest impact.

Plot2:

Plot 2 depicts the importance of each feature as well as the direction in which that feature influences the prediction.

Top 5 interpretations from both the plots: 1) Customers are more loyal since they use less cash as a mode of payment. 2) The loyalty score of new customers is lower. 3) Customers who are older are more loyal. 4) People without access to personal transportation or who do not possess a car are more loyal. 5) Compared to six months ago, customers who are riding transit about the same are more loyal.

Result on the test set

In [60]:

```
print ("R2 Score:",pipe_catboost_opti.score(X_test, y_test))
```

```
R2 Score: 0.21026136515872562
```

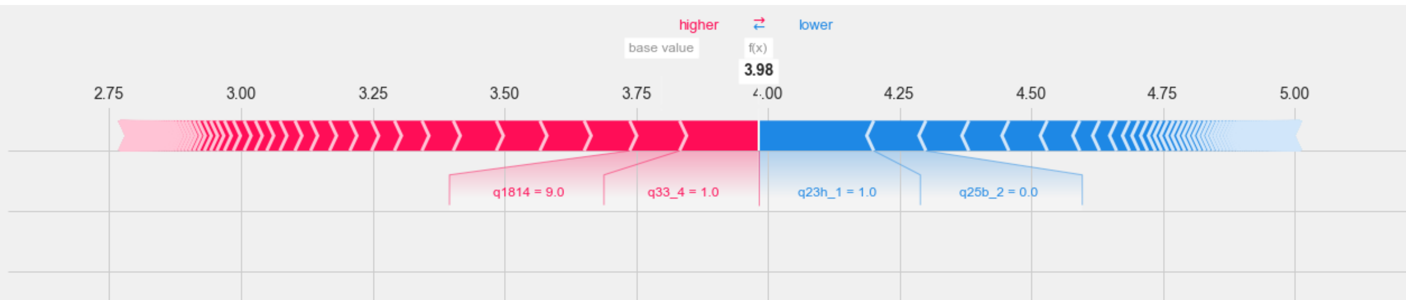
In [61]:
```
from sklearn.metrics import mean_squared_error
preds = pipe_catboost_opti.predict(X_test)
print ("RMSE Score:",mean_squared_error(y_test, preds))
print ("Mape Score:",mape(y_test, preds))
```

```
RMSE Score: 1.3593312064812169
Mape Score: 31.042889962173316
```

In [62]:
```
X_train_enc = X_train_enc.round(3)
X_test_enc = X_test_enc.round(3)

test_cat_shap_values = cat_explainer.shap_values(X_test_enc[:100])

shap.force_plot(
    cat_explainer.expected_value,
    test_cat_shap_values[2],
    X_test_enc.iloc[2, :],
    matplotlib=True,
)
```



- As can be observed, the higher value/presence of cash payment drives the prediction in negative direction.
- The lack of access to a car or other personal transportation modes drives the prediction in negative direction.
- Being in the 45-54 age group drives the forecast in a favourable direction, implying that older customers are more loyal.

Summary of results

In [63]:
```
from tabulate import tabulate
head= ['Model','Type','Dataset','Test R2 score','Test mape','Remarks']

data= [('Dummy Regressor','Non-linear','Train','0.001','37.55','Baseline'),
       ('Ridge','Linear','Train','0.131','33.40','Liner/simple model, less fit time ,low r2
       ('Random Forest Regressor','Non-linear','Train','0.165','32.75','Low mape score, Ove
       ('XGBoost Regressor','Non-linear','Train','0.129', '32.81', 'High mape score, low r2
       ('LGBM Regressor','Non-linear','Train','0.182','32.31','Less fit time, low r2 '),
       ('CatBoost Regressor','Non-linear','Train','0.189','32.23','Best individual model,si

print(tabulate(data,headers= head,tablefmt= "grid"))
```

```
+-------------------------+------------+-----------+-----------------+-------------+------
--------------------------------------+
| Model                   | Type       | Dataset   |   Test R2 score |   Test mape | Remar
ks                                    |
+=========================+============+===========+=================+=============+======
======================================+
| Dummy Regressor         | Non-linear | Train     |           0.001 |       37.55 | Basel
ine                                   |
+-------------------------+------------+-----------+-----------------+-------------+------
```

Ridge	Linear	Train	0.131	33.4	Linear/simple model, less fit time ,low r2
Random Forest Regressor	Non-linear	Train	0.165	32.75	Low mape score, Overfitting, high fit time
XGBoost Regressor	Non-linear	Train	0.129	32.81	High mape score, low r2
LGBM Regressor	Non-linear	Train	0.182	32.31	Less fit time, low r2
CatBoost Regressor	Non-linear	Train	0.189	32.23	Best individual model,significant fit time

Using the survey data from Translink , started with the problem statement of predicting a loyalty score for the data points.

Performed the given steps.

1) Data cleaning: According to my understanding, the data was changed or enhanced. Features with no questions and those that were unrelated were removed. Unrealistic target data was removed.

2) EDA: Obtaining the connection between features and determining which features should be engineered and preprocessed in which manner.

3) Loyalty Metric : Created a new loyalty metric based on 4 other features from the dataset.

4) Preprocessing: Preprocessed our features according to their kind and what was learned from the EDA.

5) Different Models: Tried out different regression models on the train data i.e. The Baseline, Linear and Non Linear Models.Compared them based on scores, fit and score time and Underfit or Overfit. Got the Best model as CatBoost based on the scores.

6) Feature Selection: Using lasso and select from Model, tried feature selection and looked for improvements in cross val scores. There was no use in considering feature selection because there was no improvement.

7) Hyper parameter optimization: On the non-linear models ,performed Hyper parameter optimization and checked for improvements in scores.

8) Interpretation and feature importances: Implemented shap on our best model i.e. CatBoost to gain insights as to which features have major impact on our prediction and which direction they drive the predictions to. From the given step we are able to infer the feature 'q23h' with value 1, i.e. the use of cash as a payment method, has the biggest impact on the predictions, while the feature 'q26' with value 1, i.e. the feature representing new consumers, has the second highest impact.

9) Test data Evaluation: We used test data to evaluate our trained best model and presented the results as well as our knowledge of the predictions.

Executive Summary:

- The features 'q23h' with value 1, i.e. the usage of cash as a payment method, and 'q26' with value 1, i.e. the feature indicating new customers, are important in predicting a customer's loyalty.
- Translink can use these characteristics to anticipate a customer's loyalty in advance.
- Also, use these features to provide a better user experience and focus on a certain user group.
- Alternatively, improve the experience for the users who were left out.

Future enhancements:

- May have attempted stacking or averaging the regressors to improve the scores.

- The data may have been changed to incorporate polynomial features in order to create a linear model.

- A better feature selection method can also be utilised.

Thank you

In [ ]:
```

```