Data Glacier

Your Deep Learning Partner

Bank Marketing

virtual internship

Dec-15-2022

Agenda

Background

EDA

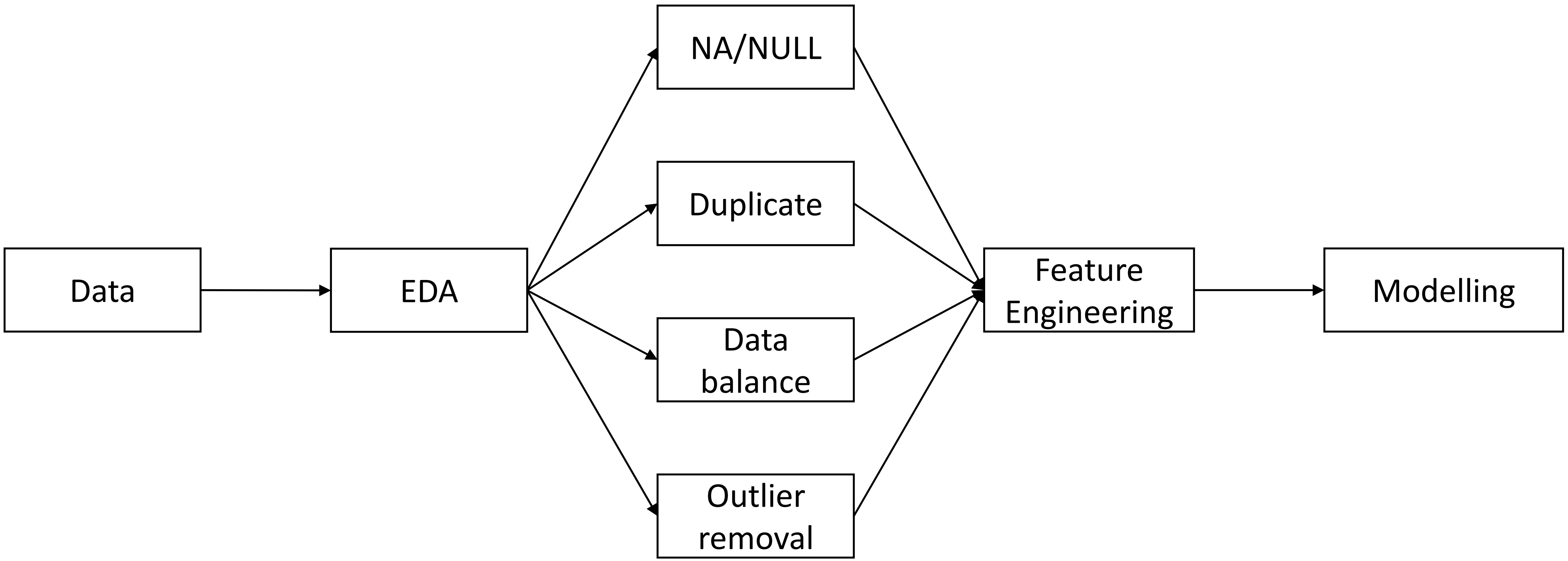
Modelling Recommendations

Background

- ABC Bank wants to sell its term deposit product to customers and before launching the product they want to develop a model which can help them in understanding whether a particular customer will buy their product or not (based on customer's past interaction with the bank or other Financial Institutions).

- Goals : ABC Bank wants to use ML models to shortlist customers whose chances of buying the product is more so that their marketing channel (tele marketing, SMS/email marketing etc) can focus only on those customers.

Roadmap


Data
EDA
NA/NULL
Duplicate
Data balance
Outlier removal
Feature Engineering
Modelling

Data info

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   age             41188 non-null  int64  
 1   job             41188 non-null  object 
 2   marital         41188 non-null  object 
 3   education       41188 non-null  object 
 4   default         41188 non-null  object 
 5   housing         41188 non-null  object 
 6   loan            41188 non-null  object 
 7   contact         41188 non-null  object 
 8   month           41188 non-null  object 
 9   day_of_week     41188 non-null  object 
 10  duration        41188 non-null  int64  
 11  campaign        41188 non-null  int64  
 12  pdays           41188 non-null  int64  
 13  previous        41188 non-null  int64  
 14  poutcome        41188 non-null  object 
 15  emp.var.rate    41188 non-null  float64
 16  cons.price.idx  41188 non-null  float64
 17  cons.conf.idx   41188 non-null  float64
 18  euribor3m       41188 non-null  float64
 19  nr.employed     41188 non-null  float64
 20  y               41188 non-null  object 
dtypes: float64(5), int64(5), object(11)
memory usage: 6.6+ MB
```

```
categorical
```

```
['job',
 'marital',
 'education',
 'default',
 'housing',
 'loan',
 'contact',
 'month',
 'day_of_week',
 'poutcome',
 'y']
```

21 features in total

11 categorical features

Missing values

```
data.isnull().sum()
```

```
age               0
job               0
marital           0
education         0
default           0
housing           0
loan              0
contact           0
month             0
day_of_week       0
duration          0
campaign          0
pdays             0
previous          0
poutcome          0
emp.var.rate      0
cons.price.idx    0
cons.conf.idx     0
euribor3m         0
nr.employed       0
y                 0
dtype: int64
```

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

```
age               0
job               0
marital           0
education         0
default           0
housing           0
loan              0
contact           0
month             0
day_of_week       0
duration          0
campaign          0
pdays             0
previous          0
poutcome          0
emp.var.rate      0
cons.price.idx    0
cons.conf.idx     0
euribor3m         0
nr.employed       0
y                 0
dtype: int64
```

0 Null or NA values

Duplicate rows

```
data.duplicated().value_counts()
```

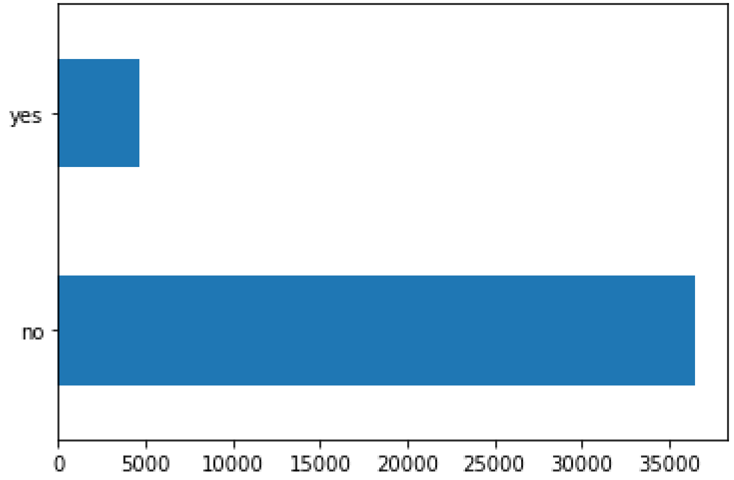
```
False    41176
True        12
dtype: int64
```

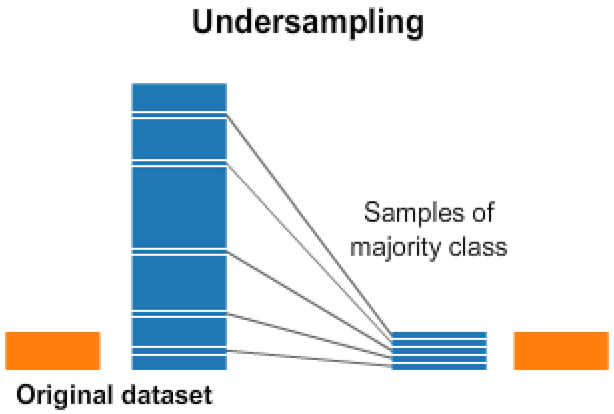
12 duplicate rows

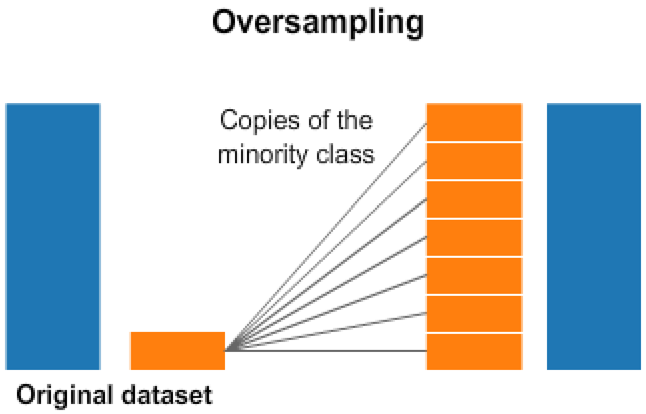
Data balance

```
data['y'].value_counts()
```

```
no     36537
yes     4639
Name: y, dtype: int64
```



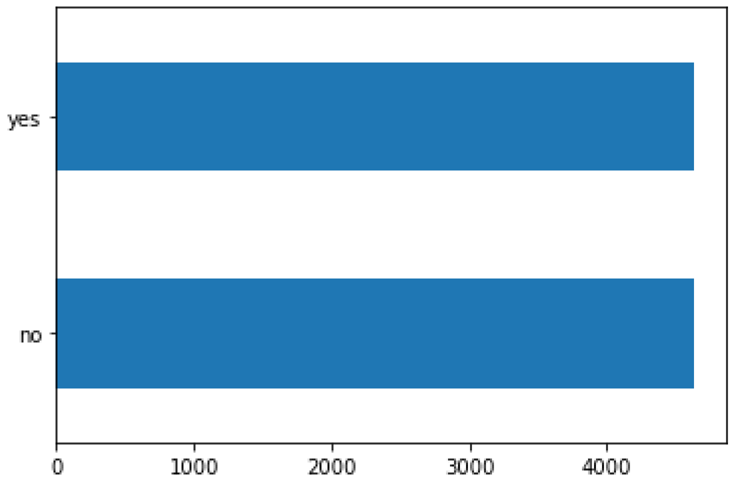




Data balance – undersampling and oversampling

```
data_under['y'].value_counts().plot(kind='barh')
```

<AxesSubplot:>



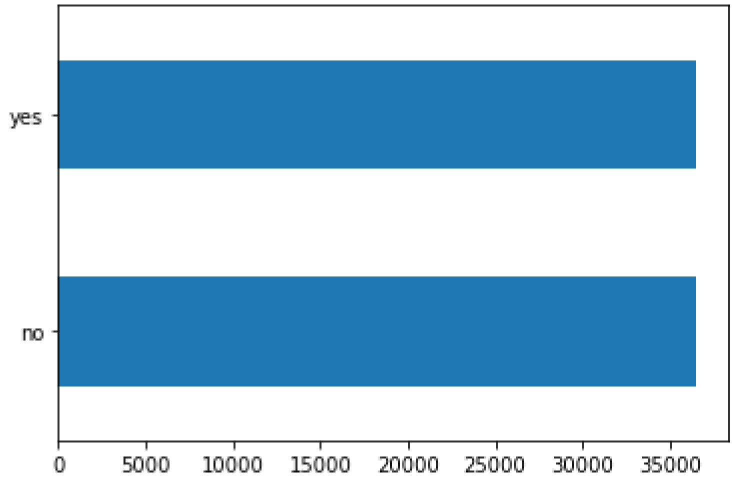

```
data_under.duplicated().value_counts()
```

```
False    9278
dtype: int64
```

0 duplicate row for undersampling

```
data_over['y'].value_counts().plot(kind='barh')
```

<AxesSubplot:>




```
data_over.duplicated().value_counts()
```

```
False    41175
True     31899
dtype: int64
```

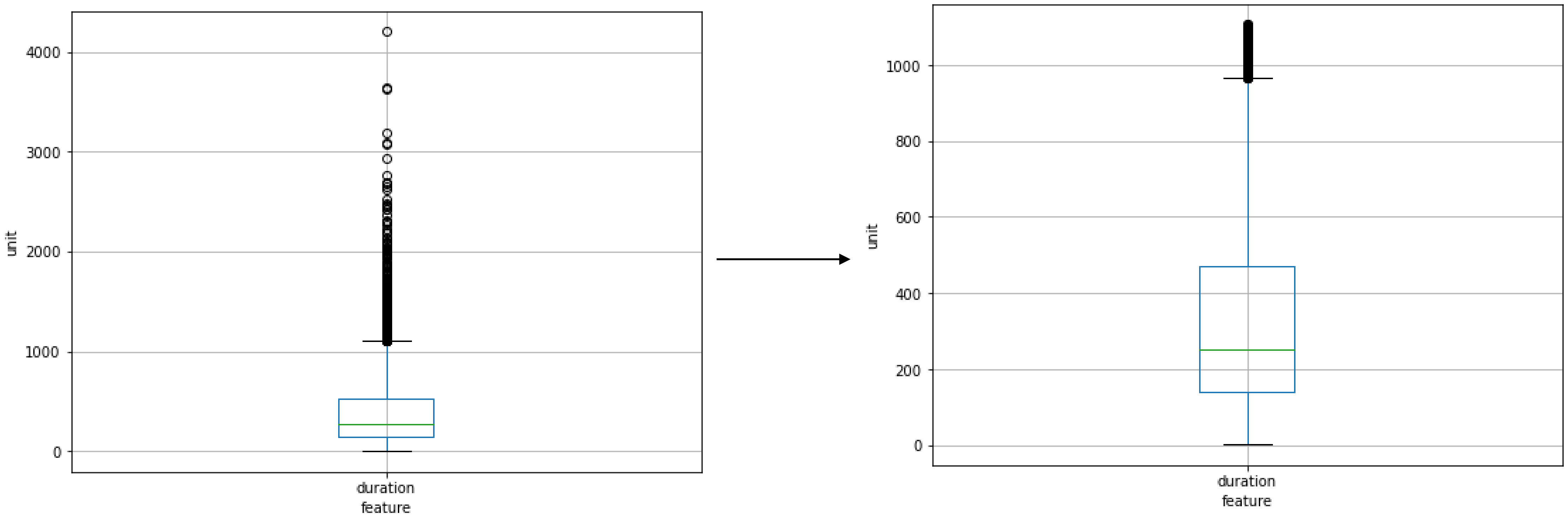
Many duplicate rows for oversampling

Outlier removal

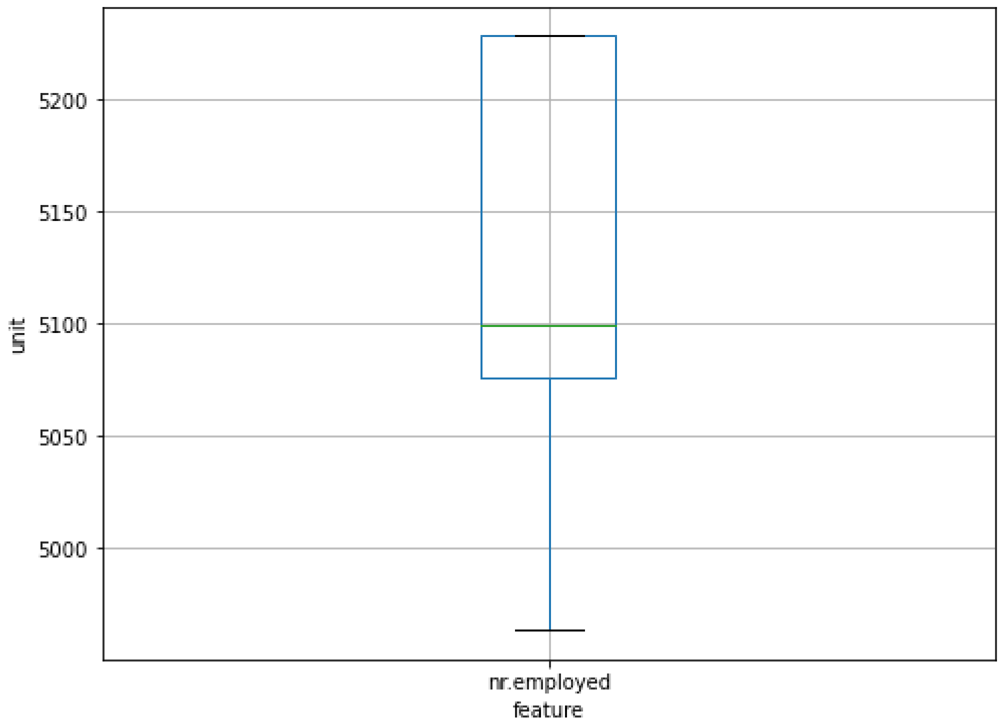
```
data_under.describe()
```

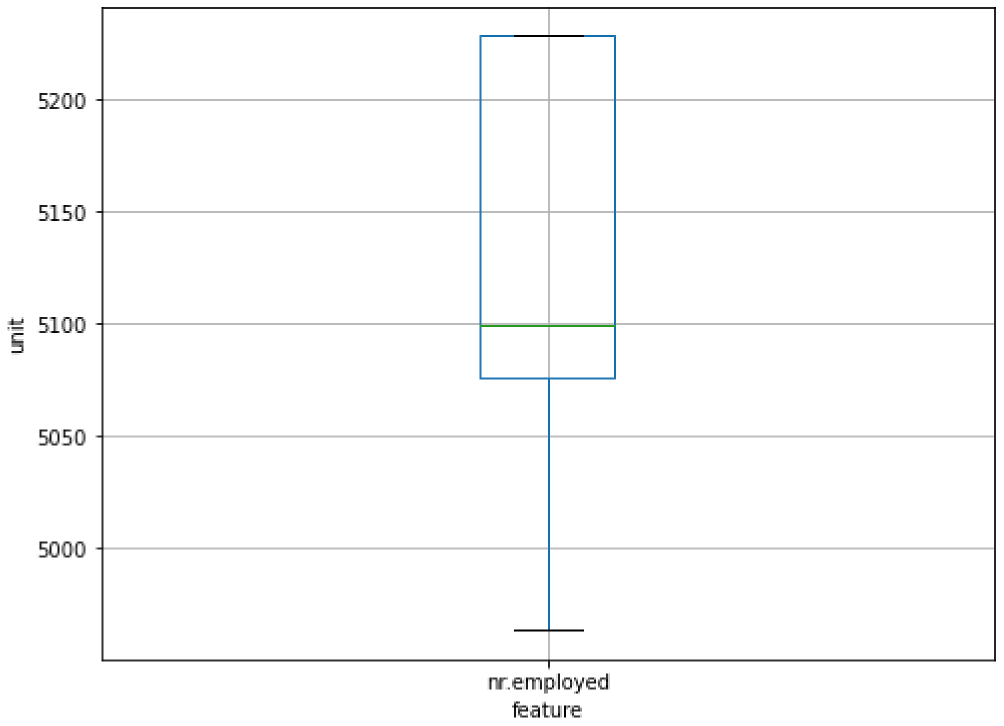
	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed
count	9278.000000	9278.000000	9278.000000	9278.000000	9278.000000	9278.000000	9278.000000	9278.000000	9278.000000	9278.000000
mean	40.432960	389.552598	2.326471	887.687217	0.312891	-0.489211	93.479128	-40.206585	2.971193	5135.853471
std	12.025501	360.742255	2.335458	313.304195	0.697914	1.722400	0.631613	5.344737	1.889231	87.171539
min	17.000000	3.000000	1.000000	0.000000	0.000000	-3.400000	92.201000	-50.800000	0.634000	4963.600000
25%	31.000000	145.000000	1.000000	999.000000	0.000000	-1.800000	92.893000	-42.700000	1.244000	5076.200000
50%	38.000000	266.000000	2.000000	999.000000	0.000000	-0.100000	93.444000	-41.800000	4.021000	5191.000000
75%	48.000000	530.000000	3.000000	999.000000	0.000000	1.400000	93.994000	-36.400000	4.959000	5228.100000
max	98.000000	4199.000000	43.000000	999.000000	6.000000	1.400000	94.767000	-26.900000	5.045000	5228.100000

Outlier removal

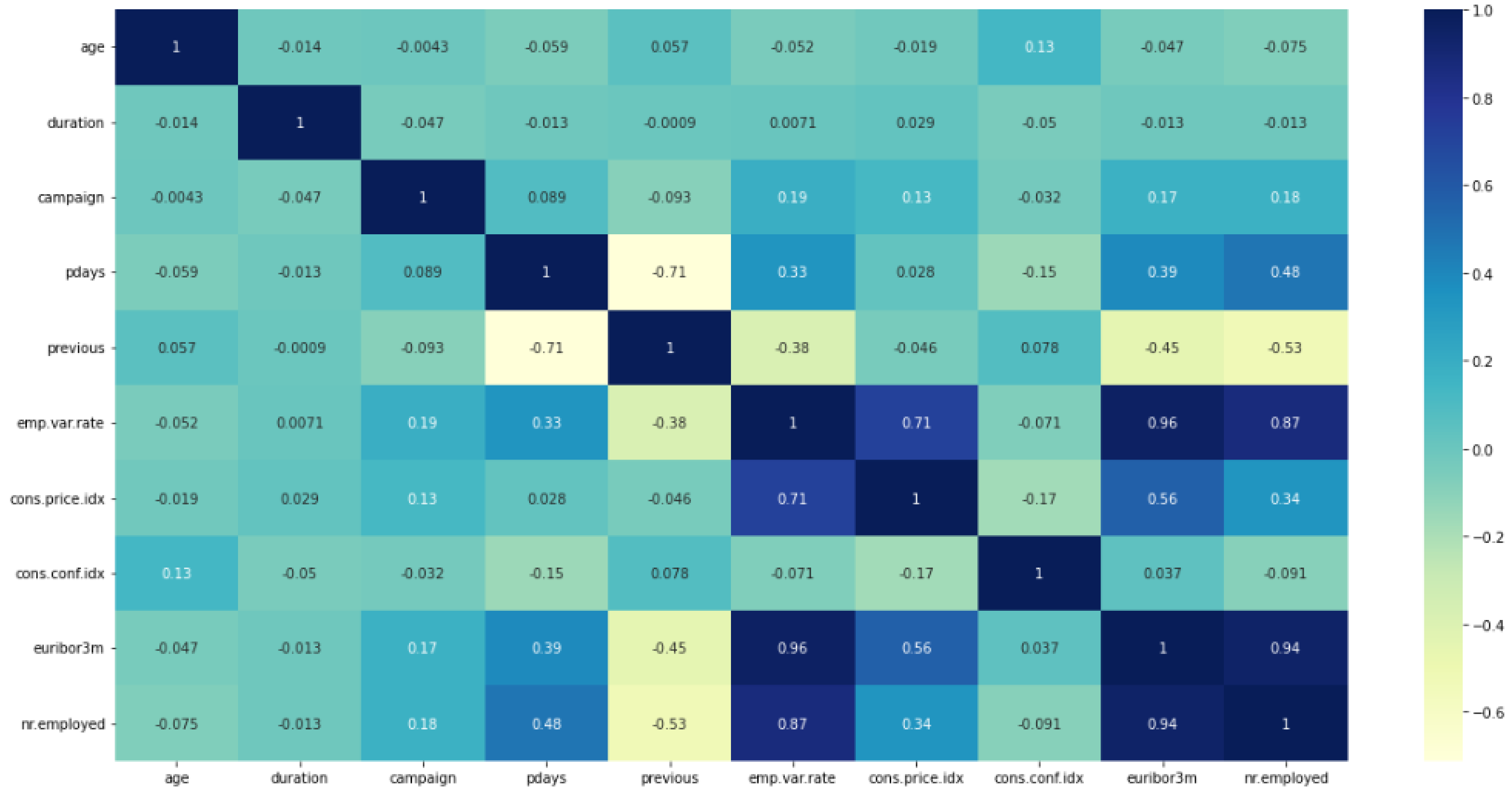


Outlier removal



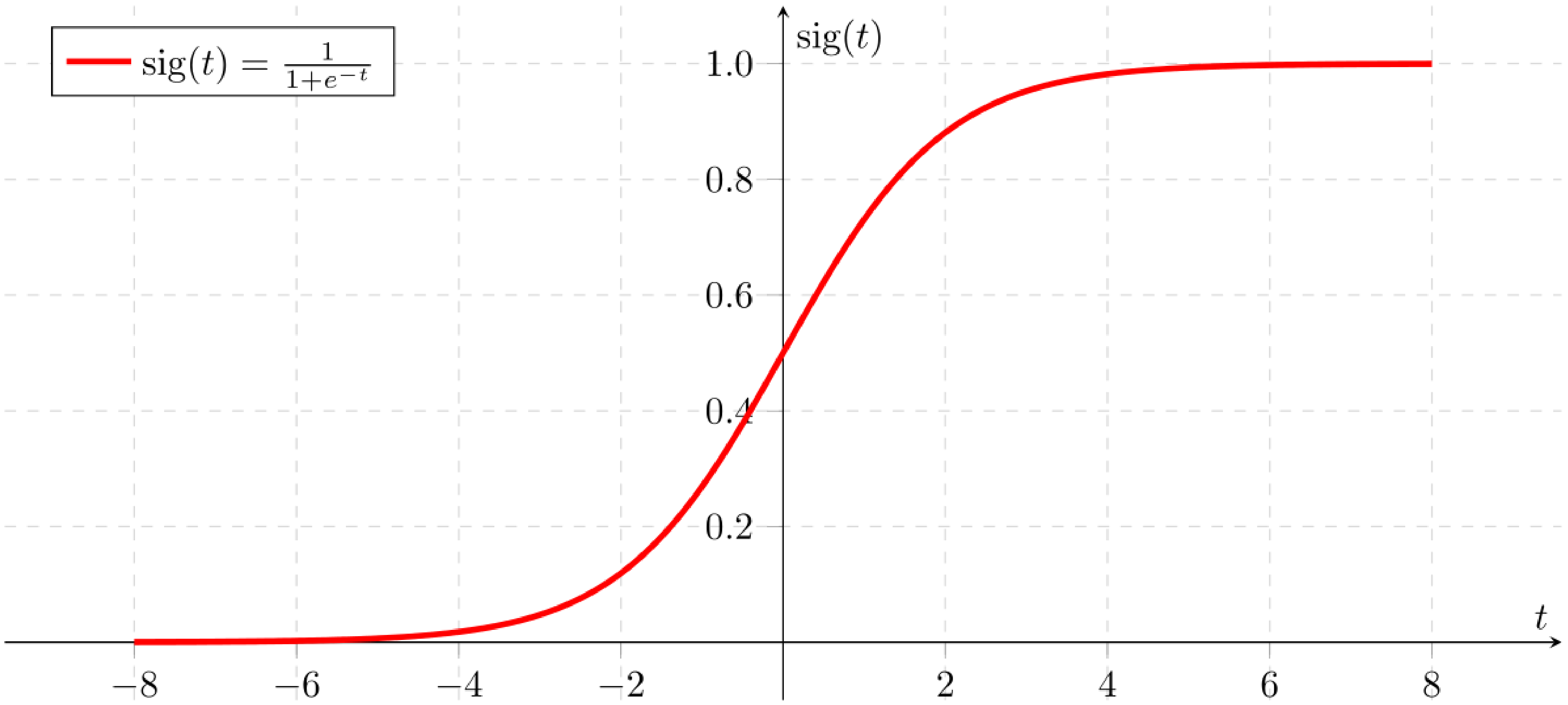


Feature Engineering



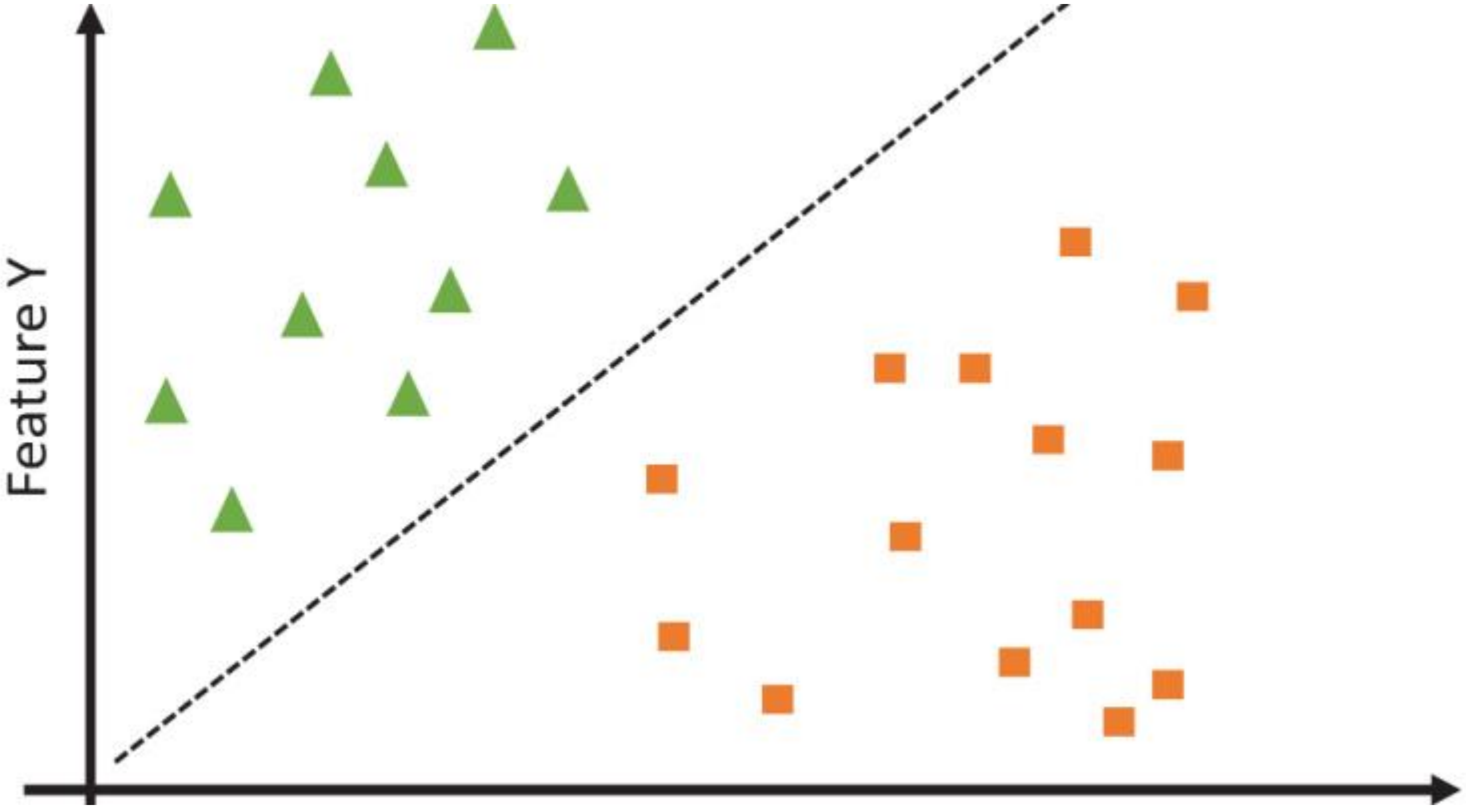
Modelling Recommendations

Logistic Regression



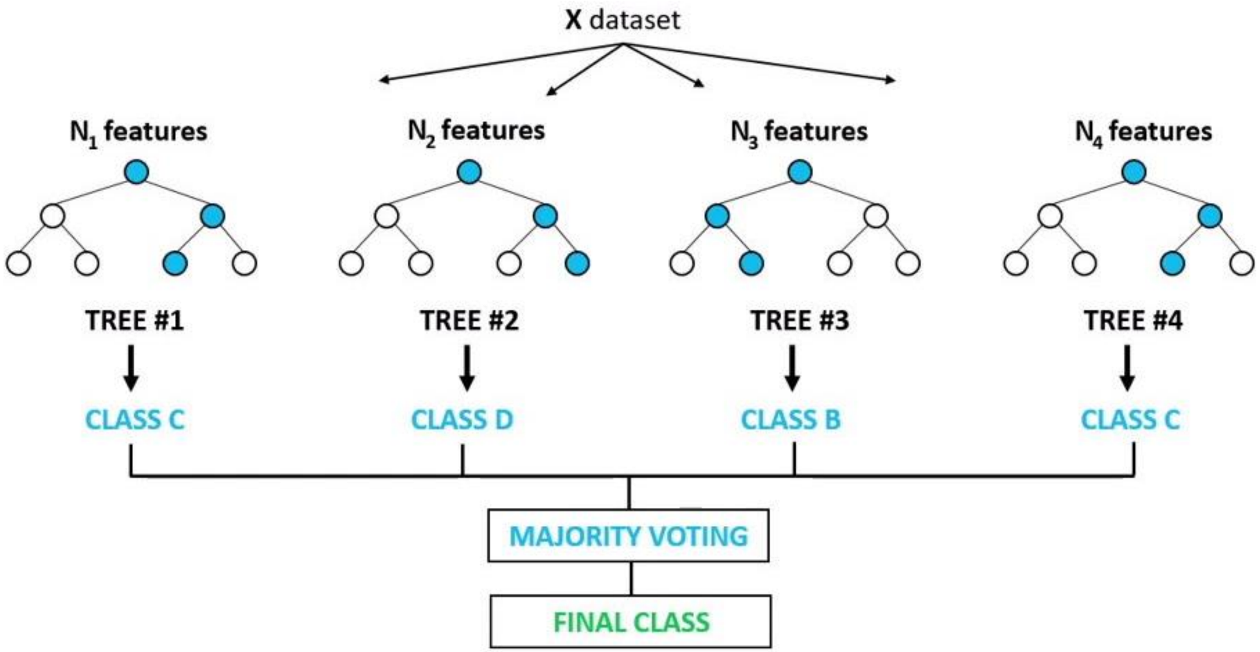
Modelling Recommendations

SVM



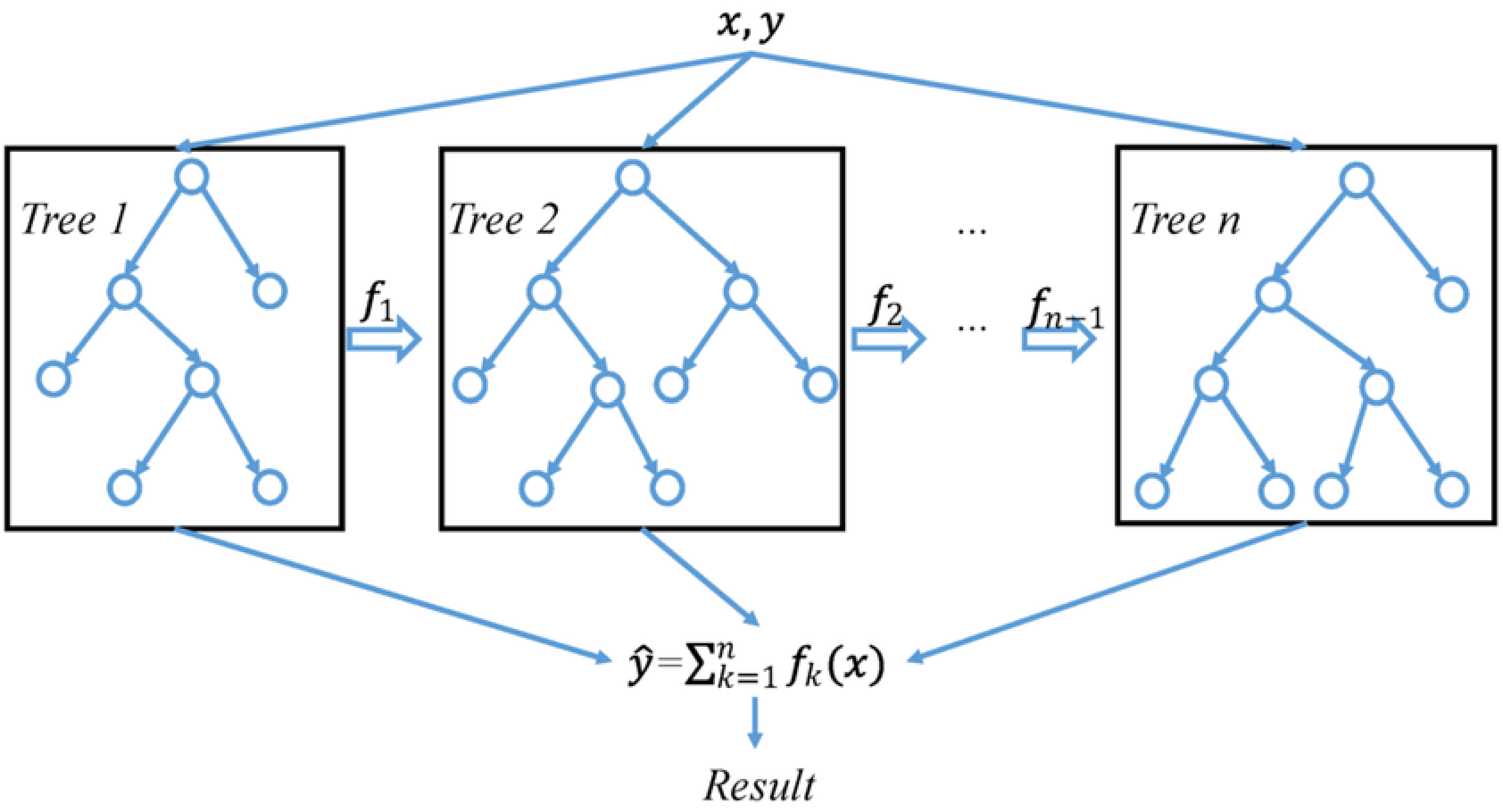
Modelling Recommendations

Random Forest



Modelling Recommendations

Xgboost



Thank You

Data Glacier
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