Fáza 2 - Predspracovanie údajov

Práca bola rozdelená férovo pre oboch zúčastnených Adam Kubaliak 50% Norbert Matuška 50%

```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
import scipy.stats as stats

import category_encoders as ce
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler, RobustScaler,
PowerTransformer, QuantileTransformer
from sklearn.feature_selection import SelectKBest, f_classif
from sklearn.ensemble import RandomForestClassifier
from sklearn.pipeline import Pipeline

connections = pd.read_csv("dataset-55/connections.csv", sep="\t")
devices = pd.read_csv("dataset-55/devices.csv", sep="\t")
processes = pd.read_csv("dataset-55/processes.csv", sep="\t")
profiles = pd.read_csv("dataset-55/profiles.csv", sep='\t')
```

2.1 Realizácia predspracovania dát

2.1 A

Dáta si rozdeľte na trénovaciu a testovaciu množinu podľa vami preddefinovaného pomeru. Ďalej pracujte len s trénovacím datasetom.

Pomocou premennej imei sme spojili dáta. Dáta sme si rozdelili na trénovaciu a testovaciu množinu v pomere 80:20, kde 80% dát bude trénovacia množina a 20% testovacia množina. Tento pomer sme zvolili, pretože sa bežne používa a je vhodný pre naše dáta.

```
data = pd.merge(connections, processes, on=['imei', 'ts', 'mwra'],
how='inner')
data.drop_duplicates(inplace=True)

devices = devices.drop_duplicates(subset=['imei'])
profiles = profiles.drop_duplicates(subset=['imei'])
data = pd.merge(data, devices, on='imei', how='inner')
data = pd.merge(data, profiles, on='imei', how='inner')

data_train, data_test = train_test_split(data, test_size=0.2,
random_state=42)
```

```
data_train.to_csv('data_train.csv', index=False)
data_test.to_csv('data_test.csv', index=False)
```

2.1 B

Transformujte dáta na vhodny formát pre ML t.j. jedno pozorovanie musí byt opísané jednym riadkom a kazdý atribút musí byt v numerickom formáte (encoding). Iteratívne integrujte aj kroky v predspracovani dát z prvej fázy (missing values, outlier detection) ako celok.

```
data_train.isnull().sum()
```

```
ts                                0
imei                              0
mwra                              0
c.katana                          0
c.dogalize                        0
c.android.gm                      0
c.android.chrome                  0
c.android.youtube                 0
c.updateassist                    0
c.android.vending                 0
c.UCMobile.intl                   0
c.UCMobile.x86                    0
c.raider                          0
p.android.documentsui             0
p.android.packageinstaller        0
p.android.chrome                  0
p.android.gm                      0
p.android.settings                0
p.system                          0
p.android.externalstorage         0
p.browser.provider                0
p.katana                          0
p.android.gms                     0
p.dogalize                        0
p.notifier                        0
p.android.vending                 0
p.olauncher                       0
p.inputmethod.latin               0
p.gms.persistent                  0
p.google                          0
p.android.defcontainer            0
p.simulator                       0
p.process.gapps                   0
latitude                          0
longitude                         0
store_name                        0
code                             25
location                          0
```

```
residence                    7223
birthdate                    5349
job                          8260
mail                            0
user_id                         0
registration                    0
name                            0
username                        0
ssn                             0
company                         0
address                      1878
dtype: int64
```

Zistili sme, že v dátach chýbajú hodnoty v atribútoch code, residence, birthdate, job a address. Keďže nejde o číselné dátata, sme sa rozhodli dpolniť ich najbežnejšou hodnotou.

```
missing_values = ['code', 'residence', 'birthdate', 'job', 'address']
for column in missing_values:
    data_train[column] =
data_train[column].fillna(data_train[column].mode()[0])

data_train.isnull().sum()
```

```
ts                           0
imei                         0
mwra                         0
c.katana                     0
c.dogalize                   0
c.android.gm                 0
c.android.chrome             0
c.android.youtube            0
c.updateassist               0
c.android.vending            0
c.UCMobile.intl              0
c.UCMobile.x86               0
c.raider                     0
p.android.documentsui        0
p.android.packageinstaller   0
p.android.chrome             0
p.android.gm                 0
p.android.settings           0
p.system                     0
p.android.externalstorage    0
p.browser.provider           0
p.katana                     0
p.android.gms                0
p.dogalize                   0
p.notifier                   0
p.android.vending            0
```

```
p.olauncher                    0
p.inputmethod.latin            0
p.gms.persistent               0
p.google                       0
p.android.defcontainer         0
p.simulator                    0
p.process.gapps                0
latitude                       0
longitude                      0
store_name                     0
code                           0
location                       0
residence                      0
birthdate                      0
job                            0
mail                           0
user_id                        0
registration                   0
name                           0
username                       0
ssn                            0
company                        0
address                        0
dtype: int64
```

Ďalej sme transformovali kategorické atribúty na číselné pomocou OrdinalEncoder. Použili sme ho kvôli tomu, že OrdinalEncoder je vhodný pre kategorické atribúty s vyšším počtom hodnôt.

```
for column in data_train.columns:
    if data_train[column].dtype == 'object':
        print(f'{column} = {data_train[column].nunique()}')

ts = 11908
store_name = 397
code = 91
location = 122
residence = 192
birthdate = 272
job = 136
mail = 496
registration = 485
name = 496
username = 496
ssn = 497
company = 483
address = 421

tmp = []
for column in data_train.columns:
```

```
    if data_train[column].dtype == 'object' and column != 'ts':
        tmp.append(column)

ce_ordinal = ce.OrdinalEncoder(cols=tmp)
data_train = ce_ordinal.fit_transform(data_train)
```

Ďalej sme transformovali atribút ts na numerický formát. Z atribútu sme odstránili znaky, ktoré nám bránili v transformácii na numerický formát, preože táto zmena nám umožní ďalej pracovať s týmto atribútom.

```
data_train['ts_numeric'] = data_train['ts'].str.replace('[-: ]', '',
regex=True).astype(int)
data_train.drop(columns=['ts'], inplace=True)

data_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 11908 entries, 4417 to 7270
Data columns (total 49 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   imei                         11908 non-null  int64
 1   mwra                         11908 non-null  float64
 2   c.katana                     11908 non-null  float64
 3   c.dogalize                   11908 non-null  float64
 4   c.android.gm                 11908 non-null  float64
 5   c.android.chrome             11908 non-null  float64
 6   c.android.youtube            11908 non-null  float64
 7   c.updateassist               11908 non-null  float64
 8   c.android.vending            11908 non-null  float64
 9   c.UCMobile.intl              11908 non-null  float64
 10  c.UCMobile.x86               11908 non-null  float64
 11  c.raider                     11908 non-null  float64
 12  p.android.documentsui        11908 non-null  float64
 13  p.android.packageinstaller   11908 non-null  float64
 14  p.android.chrome             11908 non-null  float64
 15  p.android.gm                 11908 non-null  float64
 16  p.android.settings           11908 non-null  float64
 17  p.system                     11908 non-null  float64
 18  p.android.externalstorage    11908 non-null  float64
 19  p.browser.provider           11908 non-null  float64
 20  p.katana                     11908 non-null  float64
 21  p.android.gms                11908 non-null  float64
 22  p.dogalize                   11908 non-null  float64
 23  p.notifier                   11908 non-null  float64
 24  p.android.vending            11908 non-null  float64
 25  p.olauncher                  11908 non-null  float64
 26  p.inputmethod.latin          11908 non-null  float64
 27  p.gms.persistent             11908 non-null  float64
```

```
 28  p.google                    11908 non-null  float64
 29  p.android.defcontainer      11908 non-null  float64
 30  p.simulator                 11908 non-null  float64
 31  p.process.gapps             11908 non-null  float64
 32  latitude                    11908 non-null  float64
 33  longitude                   11908 non-null  float64
 34  store_name                  11908 non-null  int64
 35  code                        11908 non-null  int64
 36  location                    11908 non-null  int64
 37  residence                   11908 non-null  int64
 38  birthdate                   11908 non-null  int64
 39  job                         11908 non-null  int64
 40  mail                        11908 non-null  int64
 41  user_id                     11908 non-null  int64
 42  registration                11908 non-null  int64
 43  name                        11908 non-null  int64
 44  username                    11908 non-null  int64
 45  ssn                         11908 non-null  int64
 46  company                     11908 non-null  int64
 47  address                     11908 non-null  int64
 48  ts_numeric                  11908 non-null  int64
dtypes: float64(33), int64(16)
memory usage: 4.5 MB
```

Odstránili sme outliery pomocou IQR metódy. Outliery sme sa rozhodli odstrániť, pretože by mohli ovplyvniť výsledky modelu. Po odstránení outlierov nám ostalo dostatočné množstvo dát na trénovanie modelu.

```
for column in data_train.columns:
    Q1 = data_train[column].quantile(0.25)
    Q3 = data_train[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    data_train = data_train[(data_train[column] >= lower_bound) &
(data_train[column] <= upper_bound)]

data_train.shape
```

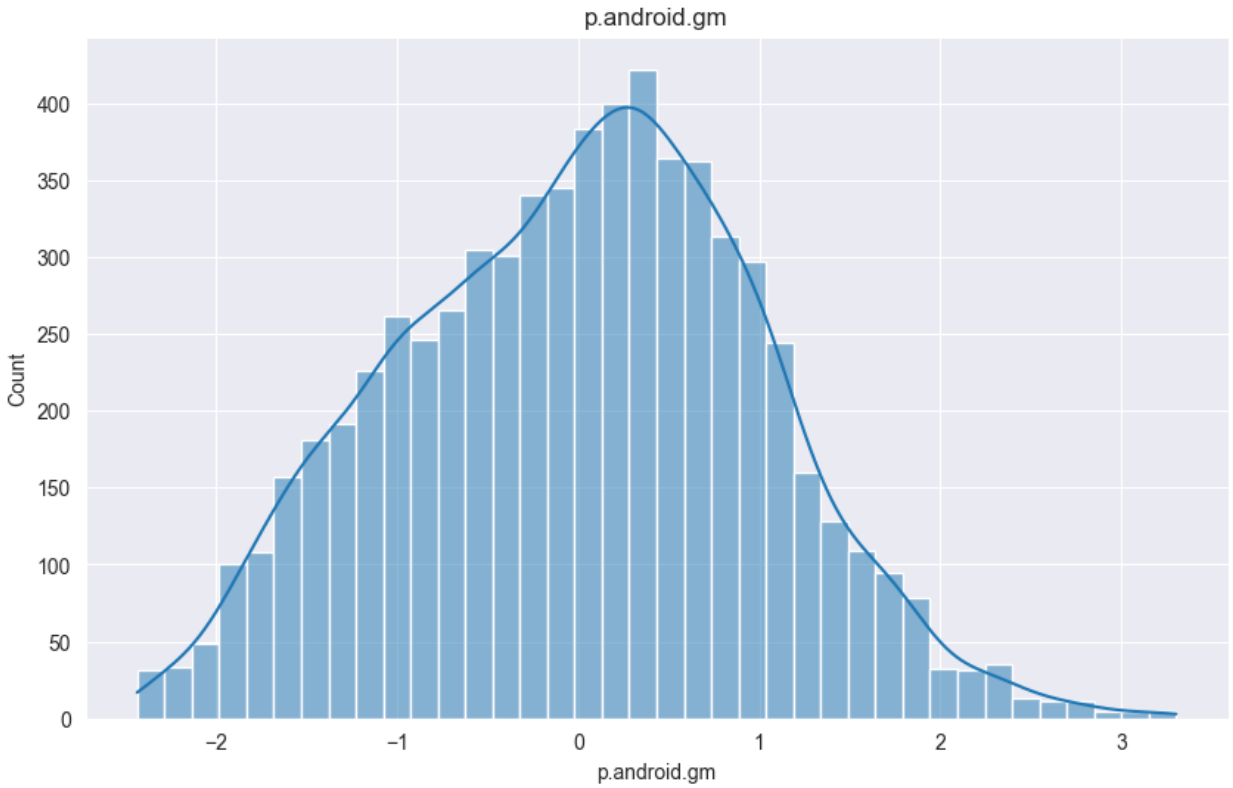
```
(6644, 49)
```

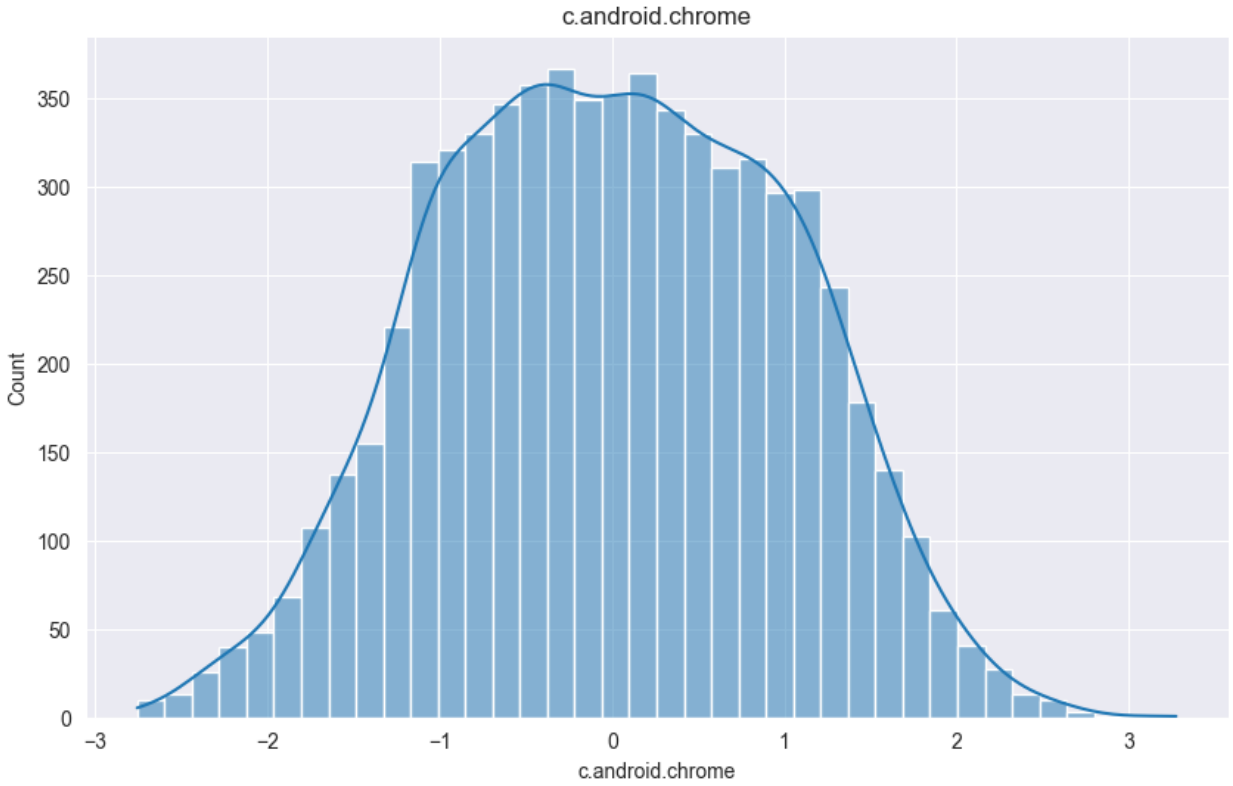
2.1 C

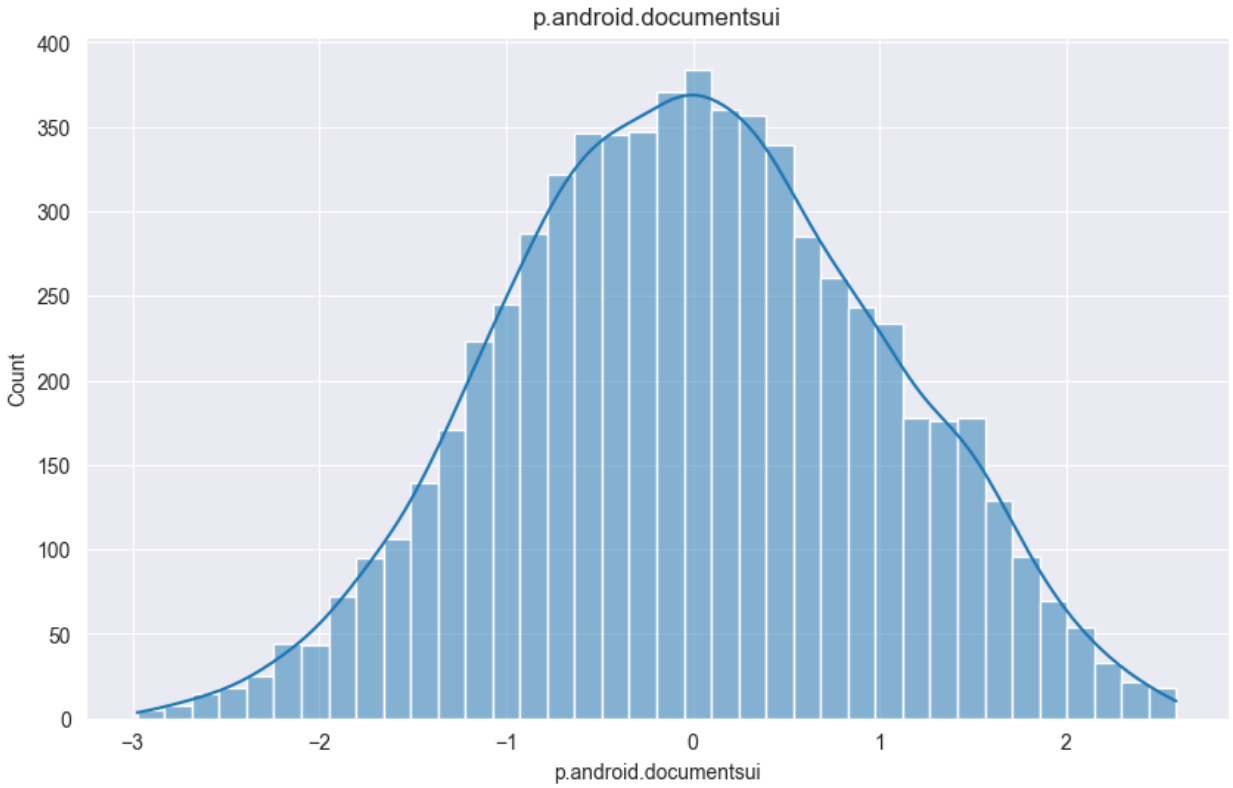
Transformujte atribúty dát pre strojové ucenie podia dostupných technik minimálne: scaling (2 techniky), transformers (2 techniky) a d'alsie. Cielom je aby ste testovali efekty a vhodne kombinovali v dátovom pipeline (od easti 2.3 a v 3. fáze).

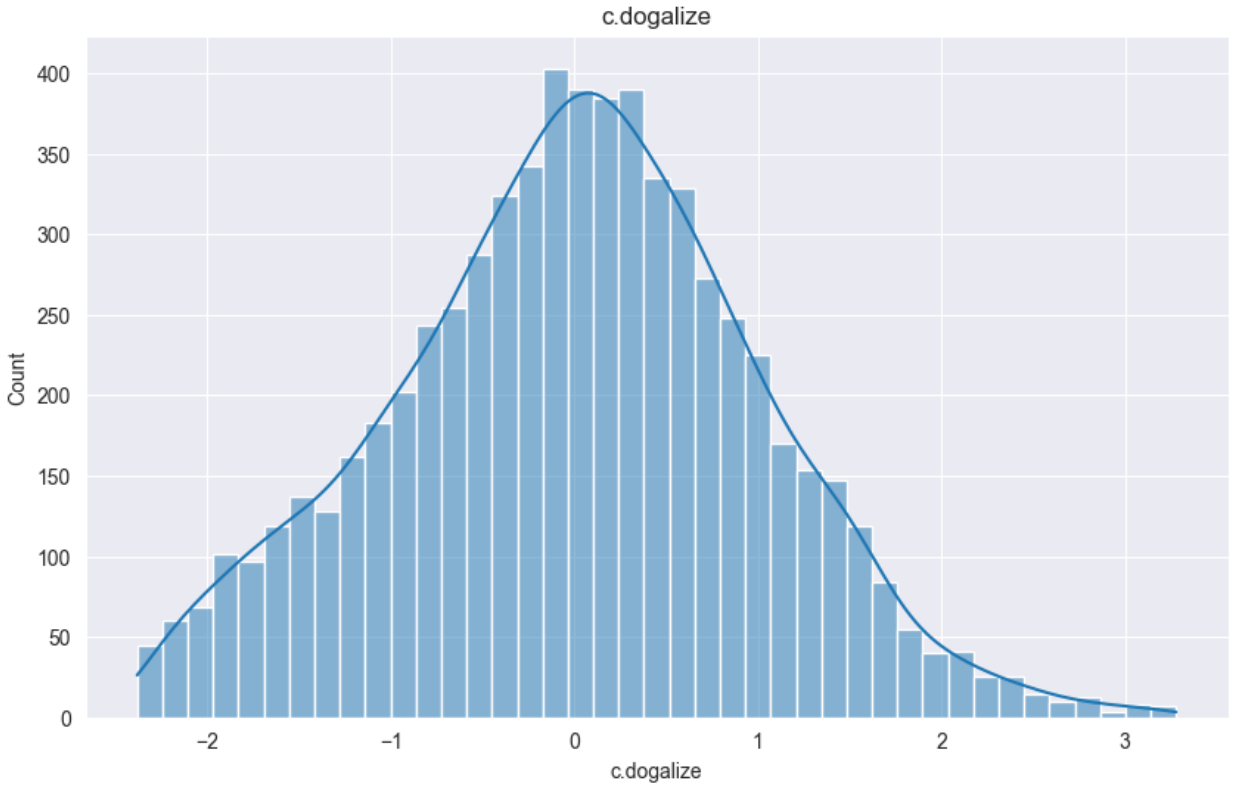
Atribúty sme transformovali pomocou MinMaxScaler a RobustScaler. Ďalej sme transformovali dáta pomocou PowerTransformer a QuantileTransformer. Po transformácii sme vizualizovali dáta pomocou histogramov, aby sme porovnali výsledky transformácie. Pre machine learning pipeline sme zvolili kombináciu RobustScaler a PowerTransformer, pretože tieto techniky nám dali najlepšie výsledky.

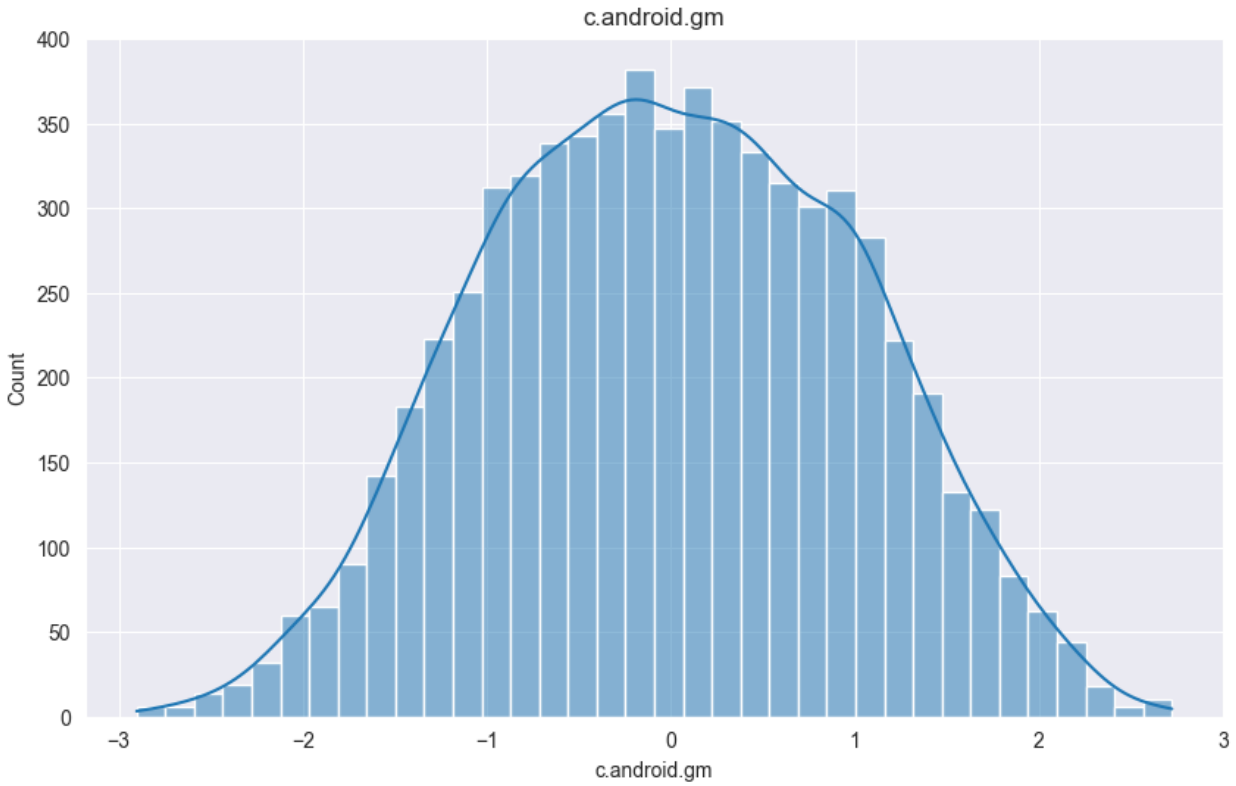
```
data_features = data_train.drop(columns=['mwra'])
mwra_column = data_train['mwra']

scalers = {
    'minmax': MinMaxScaler(),
    'robust': RobustScaler()
}

transformers = {
    'yeo_johnson': PowerTransformer(method='yeo-johnson'),
    'quantile': QuantileTransformer(n_quantiles=100,
output_distribution='normal')
}
results = {}

for scaler_name, scaler in scalers.items():
    scaled_data = scaler.fit_transform(data_features)

    for transformer_name, transformer in transformers.items():
        transformed_data = transformer.fit_transform(scaled_data)
        transformed_df = pd.DataFrame(transformed_data,
columns=data_features.columns)
        transformed_df['mwra'] = mwra_column.values
        results[f"{scaler_name}_{transformer_name}"] = transformed_df

data_train = results['robust_yeo_johnson']

for column in ['p.android.gm', 'c.android.chrome',
'p.android.documentsui',
       'c.dogalize', 'c.android.gm', 'p.android.chrome', 'p.system',
       'p.android.settings', 'p.android.externalstorage',
       'c.android.youtube']:
    plt.figure(figsize=(10, 6))
    sns.histplot(data_train[column], kde=True)
    plt.title(column)
    plt.show()
```

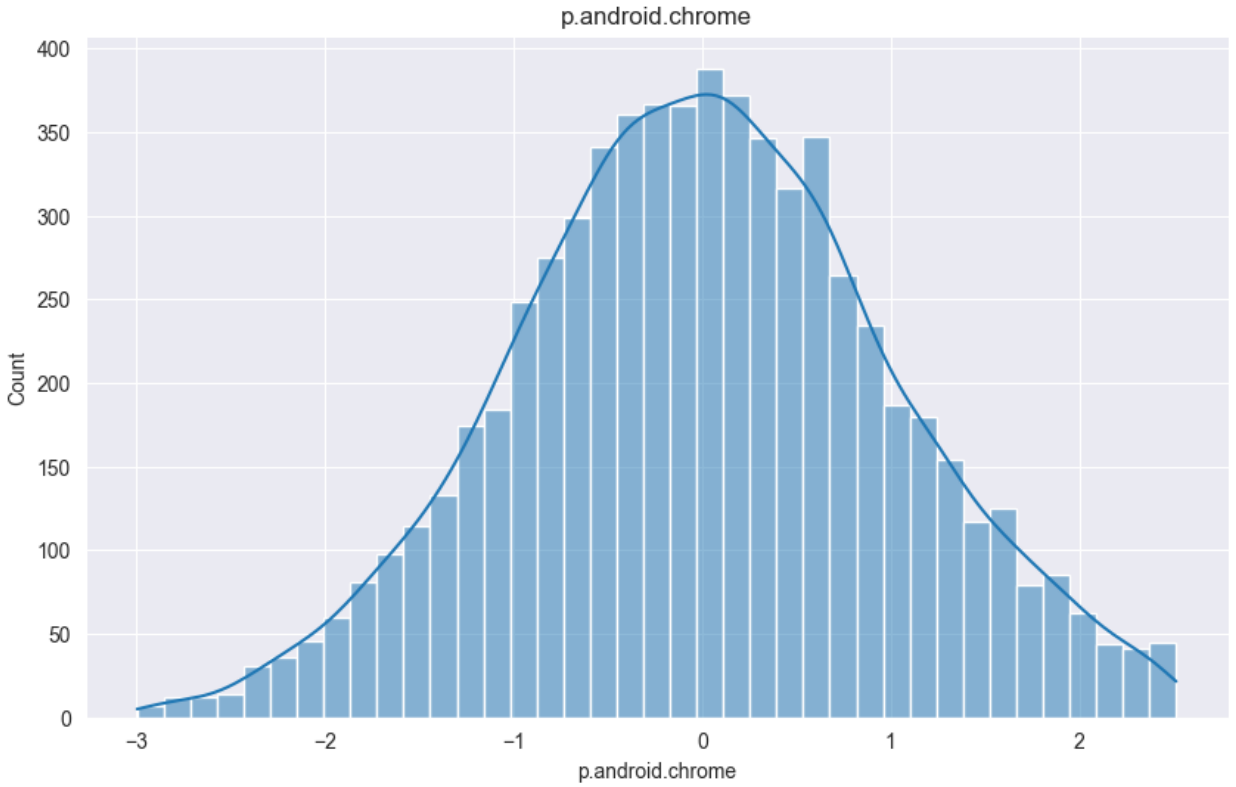

p.android.gm
Count
p.android.gm
0
50
100
150
200
250
300
350
400
−2
−1
0
1
2
3

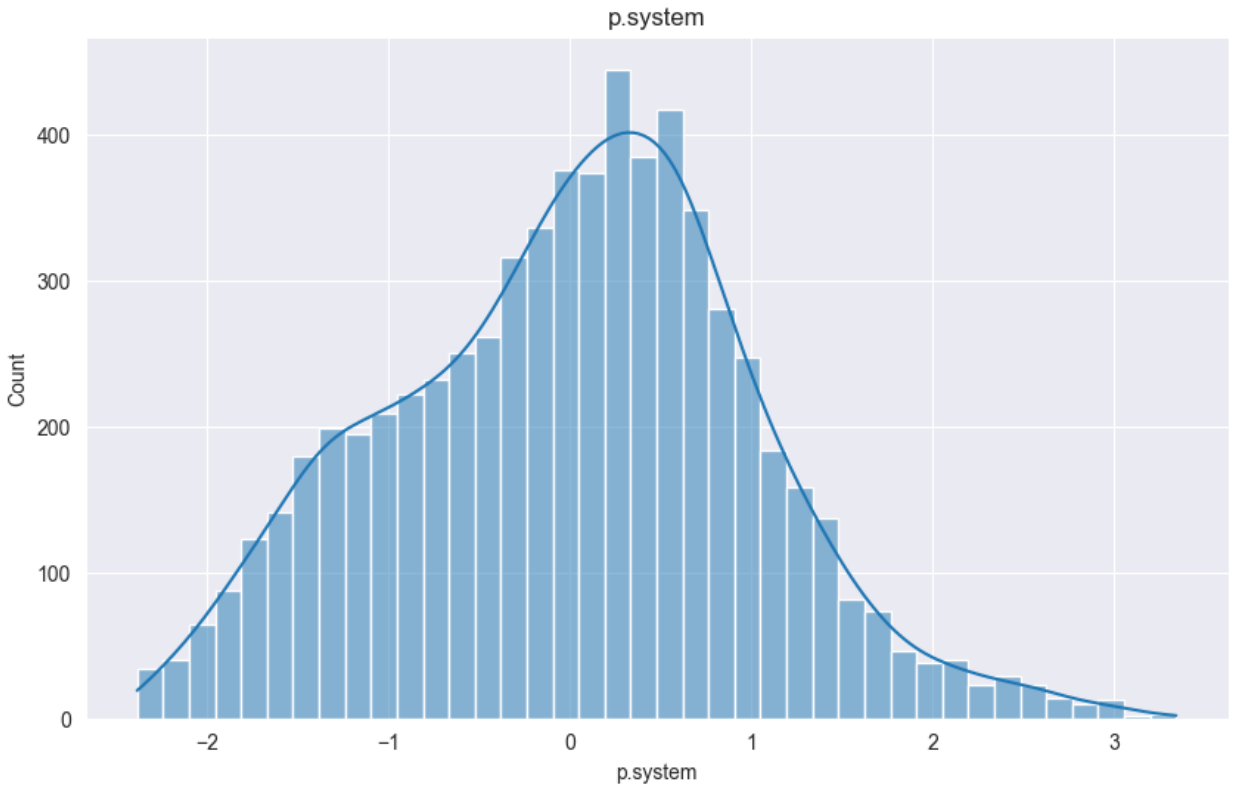

c.android.chrome
Count
c.android.chrome
0
50
100
150
200
250
300
350
−3
−2
−1
0
1
2
3

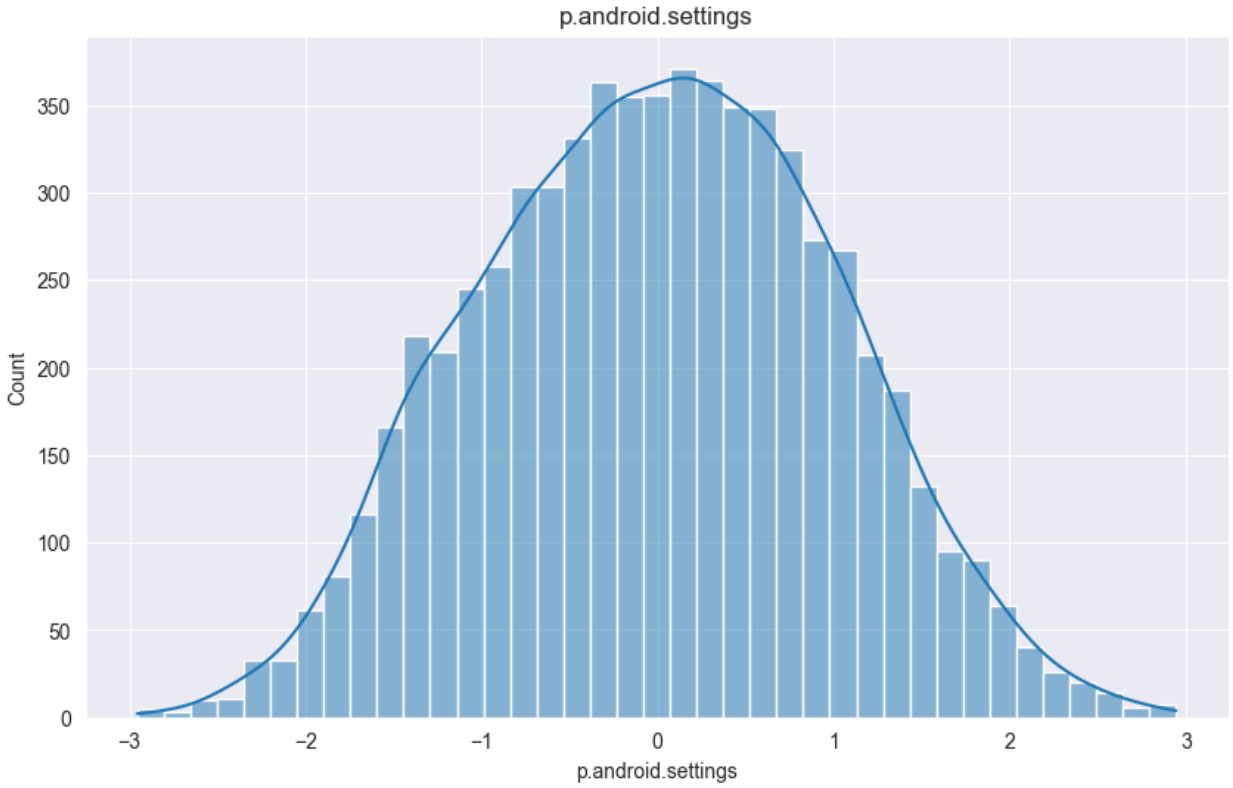

p.android.documentsui
Count
p.android.documentsui
0
50
100
150
200
250
300
350
400
−3
−2
−1
0
1
2

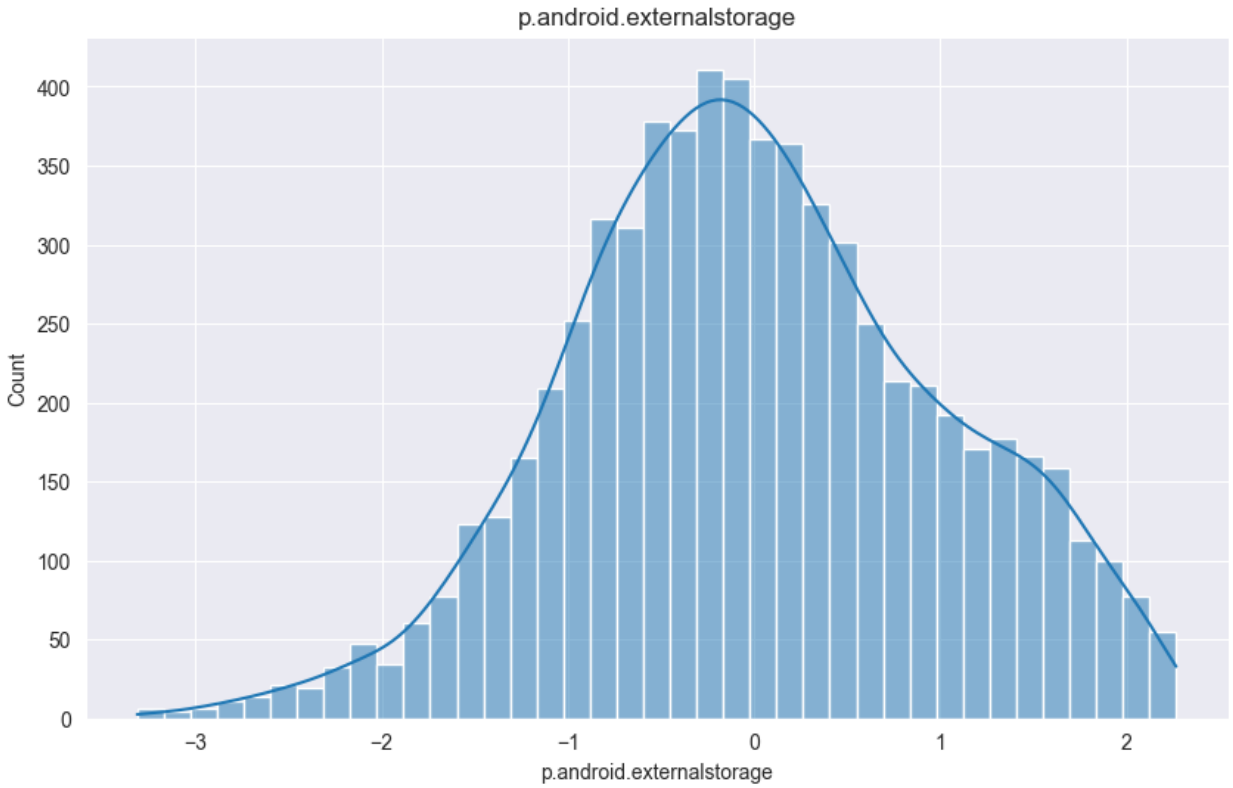

c.dogalize
Count
c.dogalize
0
50
100
150
200
250
300
350
400
−2
−1
0
1
2
3

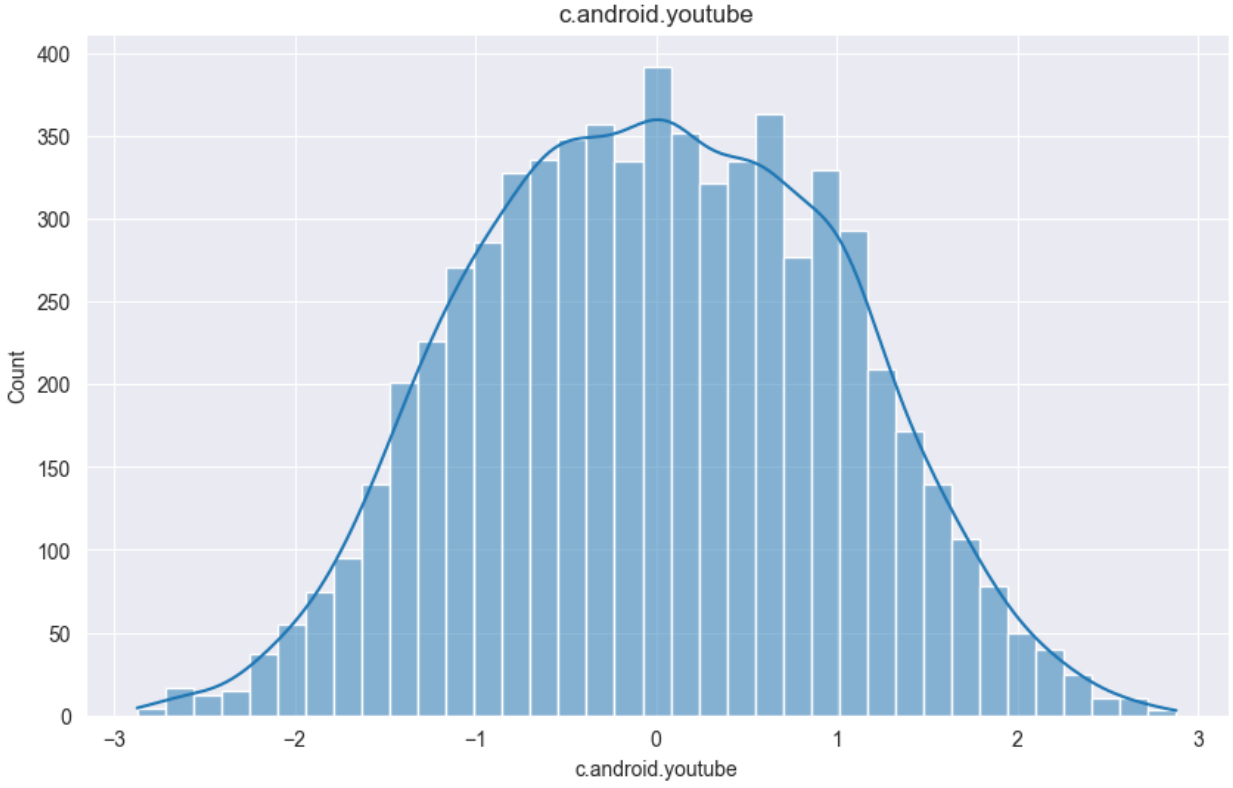

c.android.gm
Count
400
350
300
250
200
150
100
50
0
−3
−2
−1
0
1
2
3
c.android.gm


p.android.chrome
Count
400
350
300
250
200
150
100
50
0
−3
−2
−1
0
1
2
p.android.chrome


p.system
Count
400
300
200
100
0
−2
−1
0
1
2
3
p.system


p.android.settings
Count
350
300
250
200
150
100
50
0
−3
−2
−1
0
1
2
3
p.android.settings


p.android.externalstorage
Count
0
50
100
150
200
250
300
350
400
−3
−2
−1
0
1
2
p.android.externalstorage


c.android.youtube
Count
0
50
100
150
200
250
300
350
400
−3
−2
−1
0
1
2
3
c.android.youtube

2.1 D

Zdôvodnite Vase volby/rozhodnutie pre realizáciu (t.j. zdokumentovanie)

Našim cieľom bolo transformovať dáta do vhodného formátu pre strojové učenie. Aby sme dosiahli tento cieľ, museli sme vykonať niekoľko krokov:

- Ako prvé sme odhalili chýbajúce hodnoty v atribútoch code, residence, birthdate, job a address. Keďže nejde o číselné dátata, sme sa rozhodli doplniť ich najbežnejšou hodnotou.
- Ďalej sme transformovali kategorické atribúty na číselné pomocou ordinal encoderu. Použili sme ho kvôli tomu, že je vhodný pre atribúty s vyšším počtom hodnôt.
- Potom sme transformovali atribút ts na numerický formát. Z atribútu sme odstránili znaky a táto zmena nám umožní ďalej pracovať s týmto atribútom.
- Odstránili sme outliery pomocou IQR metódy. Outliery sme sa rozhodli odstrániť, pretože by mohli ovplyvniť výsledky modelu. Po odstránení outlierov nám ostalo dostatočné množstvo dát na trénovanie modelu.
- Atribúty sme transformovali pomocou MinMaxScaler a RobustScaler. Ďalej sme transformovali dáta pomocou PowerTransformer a QuantileTransformer.
- Po transformácii sme vizualizovali dáta pomocou histogramov, aby sme porovnali výsledky transformácie.

Pre machine learning sme sa rozhodli použiť kombináciu RobustScaler a PowerTransformer, pretože tieto techniky nám dali najlepšie výsledky.

2.2 A

Zistite, ktore atributy (features) vo vasich datach pre ML su informativne k predikovane premenne (minimalne 3 techniky s porovnanim meazi sebou).

2.2 Vyber atribútov pre strojové ucenie

```
X_train = data_train.drop(columns=['mwra'])
y_train = data_train['mwra'].astype(int)

# 1. Correlation Analysis
correlations = X_train.corrwith(y_train).abs()

# 2. ANOVA F-test
anova_selector = SelectKBest(f_classif, k='all')
anova_selector.fit(X_train, y_train)
anova_scores = anova_selector.scores_

# 3. Random Forest Feature Importance
rf_model = RandomForestClassifier(random_state=42)
rf_model.fit(X_train, y_train)
rf_importances = rf_model.feature_importances_

# Combine results into a DataFrame for comparison
feature_names = X_train.columns
```

```
selection_results = pd.DataFrame({
    'Feature': feature_names,
    'Correlation': correlations.values,
    'ANOVA F-score': anova_scores,
    'RFI': rf_importances
})

print(selection_results)
```

	Feature	Correlation	ANOVA F-score	RFI
0	imei	0.010425	0.721956	0.002390
1	c.katana	0.007229	0.347142	0.025839
2	c.dogalize	0.326154	790.659715	0.063815
3	c.android.gm	0.289642	608.242099	0.044083
4	c.android.chrome	0.540403	2739.822110	0.133442
5	c.android.youtube	0.020504	2.793606	0.029961
6	c.updateassist	0.013871	1.278173	0.010527
7	c.android.vending	0.018472	2.267013	0.009457
8	c.UCMobile.intl	0.014824	1.459971	0.008969
9	c.UCMobile.x86	0.018451	2.261913	0.008809
10	c.raider	0.004152	0.114521	0.008456
11	p.android.documentsui	0.527141	2555.883253	0.118060
12	p.android.packageinstaller	0.014942	1.483222	0.010280
13	p.android.chrome	0.210066	306.626782	0.042113
14	p.android.gm	0.571154	3215.767775	0.142176
15	p.android.settings	0.283064	578.548861	0.040079
16	p.system	0.277362	553.553616	0.041114
17	p.android.externalstorage	0.295922	637.458926	0.038079
18	p.browser.provider	0.008294	0.456971	0.008124
19	p.katana	0.002869	0.054662	0.009849
20	p.android.gms	0.001581	0.016594	0.008536
21	p.dogalize	0.006357	0.268462	0.009629
22	p.notifier	0.006029	0.241440	0.009002
23	p.android.vending	0.023044	3.528800	0.008191
24	p.olauncher	0.000839	0.004673	0.009450
25	p.inputmethod.latin	0.003732	0.092492	0.009828
26	p.gms.persistent	0.010472	0.728461	0.009089
27	p.google	0.007164	0.340950	0.009492
28	p.android.defcontainer	0.004274	0.121336	0.010848
29	p.simulator	0.004881	0.158246	0.010135
30	p.process.gapps	0.002811	0.052468	0.009230
31	latitude	0.019382	2.495956	0.008131
32	longitude	0.008950	0.532059	0.007805
33	store_name	0.008560	0.486744	0.006402
34	code	0.006934	0.319370	0.005267
35	location	0.004466	0.132469	0.006059
36	residence	0.003367	0.075309	0.003822
37	birthdate	0.003328	0.073582	0.004814
38	job	0.004719	0.147937	0.002049
39	mail	0.011284	0.845784	0.005252

40	user_id	0.014286	1.355879	0.008464
41	registration	0.013019	1.126028	0.005761
42	name	0.011336	0.853642	0.005541
43	username	0.011320	0.851300	0.005388
44	ssn	0.011305	0.848908	0.005628
45	company	0.011173	0.829321	0.005718
46	address	0.018572	2.291781	0.005409
47	ts_numeric	0.015652	1.627578	0.009437

2.2 B

Zoradte zistené atribúty v poradí podia dôlezitosti.

```
selection_results_sorted = selection_results.sort_values(
    by=['RFI', 'ANOVA F-score', 'Correlation'],
    ascending=False
)

print(selection_results_sorted[['Feature', 'RFI', 'ANOVA F-score',
'Correlation']])
important_features = selection_results_sorted['Feature'].values[:10]
```

	Feature	RFI	ANOVA F-score	Correlation
14	p.android.gm	0.142176	3215.767775	0.571154
4	c.android.chrome	0.133442	2739.822110	0.540403
11	p.android.documentsui	0.118060	2555.883253	0.527141
2	c.dogalize	0.063815	790.659715	0.326154
3	c.android.gm	0.044083	608.242099	0.289642
13	p.android.chrome	0.042113	306.626782	0.210066
16	p.system	0.041114	553.553616	0.277362
15	p.android.settings	0.040079	578.548861	0.283064
17	p.android.externalstorage	0.038079	637.458926	0.295922
5	c.android.youtube	0.029961	2.793606	0.020504
1	c.katana	0.025839	0.347142	0.007229
28	p.android.defcontainer	0.010848	0.121336	0.004274
6	c.updateassist	0.010527	1.278173	0.013871
12	p.android.packageinstaller	0.010280	1.483222	0.014942
29	p.simulator	0.010135	0.158246	0.004881
19	p.katana	0.009849	0.054662	0.002869
25	p.inputmethod.latin	0.009828	0.092492	0.003732
21	p.dogalize	0.009629	0.268462	0.006357
27	p.google	0.009492	0.340950	0.007164
7	c.android.vending	0.009457	2.267013	0.018472
24	p.olauncher	0.009450	0.004673	0.000839
47	ts_numeric	0.009437	1.627578	0.015652
30	p.process.gapps	0.009230	0.052468	0.002811
26	p.gms.persistent	0.009089	0.728461	0.010472
22	p.notifier	0.009002	0.241440	0.006029
8	c.UCMobile.intl	0.008969	1.459971	0.014824

9	c.UCMobile.x86	0.008809	2.261913	0.018451
20	p.android.gms	0.008536	0.016594	0.001581
40	user_id	0.008464	1.355879	0.014286
10	c.raider	0.008456	0.114521	0.004152
23	p.android.vending	0.008191	3.528800	0.023044
31	latitude	0.008131	2.495956	0.019382
18	p.browser.provider	0.008124	0.456971	0.008294
32	longitude	0.007805	0.532059	0.008950
33	store_name	0.006402	0.486744	0.008560
35	location	0.006059	0.132469	0.004466
41	registration	0.005761	1.126028	0.013019
45	company	0.005718	0.829321	0.011173
44	ssn	0.005628	0.848908	0.011305
42	name	0.005541	0.853642	0.011336
46	address	0.005409	2.291781	0.018572
43	username	0.005388	0.851300	0.011320
34	code	0.005267	0.319370	0.006934
39	mail	0.005252	0.845784	0.011284
37	birthdate	0.004814	0.073582	0.003328
36	residence	0.003822	0.075309	0.003367
0	imei	0.002390	0.721956	0.010425
38	job	0.002049	0.147937	0.004719

```
for column in data_train.columns:
    if column not in important_features and column != 'mwra':
        data_train.drop(columns=[column], inplace=True)

data_train.to_csv('data_train_best_features.csv', index=False)
```

2.2 C

Pre proces výberu atribútov boli použité tri rôzne metódy – korelačná analýza, ANOVA F-test a dôležitosť atribútov pomocou Random Forest modelu.

1. Korelačná analýza: Táto metóda meria silu lineárneho vzťahu medzi jednotlivými atribútmi a mwra. Atribúty s najvyššou koreláciou ukazujú na silnú asociáciu s cieľovou premennou.

2. ANOVA F-test: ANOVA vyhodnocuje rozdiely medzi skupinami, čo umožňuje získať lepší pohľad na rozptyl medzi atribútmi a cieľovou premennou. Atribúty s vysokým F-score boli identifikované ako významné faktory ovplyvňujúce mwra.

3. Random Forest dôležitosť atribútov: Random Forest model poskytol zoznam najdôležitejších atribútov pre predikciu na základe ich využitia v modeloch.

2.3 Replikovatelnost predspracovania

2.3 A

Upravte váš kód realizujúci predspracovanie trénovacej množiny tak, aby ho bolo možné bez dalsich úprav znovu použiť na predspracovanie testovacej mnoziny v kontexte strojového učenia.

```
data_test = pd.read_csv('data_test.csv')
important_features_data = None

for column in data_test.columns:
    if column in important_features or column == 'mwra':
        important_features_data = pd.concat([important_features_data,
data_test[[column]]], axis=1)

for column in important_features_data.columns:
    Q1 = important_features_data[column].quantile(0.25)
    Q3 = important_features_data[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    important_features_data =
important_features_data[(important_features_data[column] >=
lower_bound) & (important_features_data[column] <= upper_bound)]
```

Z testovacích dát sme odstránili atribúty, ktoré nie sú v trénovacej množine. Následne sme odstránili outliery pomocou IQR metódy.

2.3 B

Vyuzite moznosti sklearn.pipeline

```
pipeline = Pipeline([
    ('scaling', RobustScaler()),
    ('transformation', PowerTransformer(method='yeo-johnson'))
])

features_to_transform = important_features_data.drop(columns=['mwra'])
transformed_features = pipeline.fit_transform(features_to_transform)

data_test_best_features = pd.DataFrame(transformed_features,
columns=features_to_transform.columns)
data_test_best_features['mwra'] =
important_features_data['mwra'].values

data_test_best_features.to_csv('data_test_best_features.csv',
index=False)
```

Pomocou pipeline sme transformovali dáta z testovacej množiny. Použili sme rovnaké techniky ako pri trénovacej množine.