Detroit Blidht Ticket Compliance

Goal

- Predict whether a blight ticket will be paid on time.

Steps

1. Data loading
2. Exploratory Data Analysis
3. Baseline model
4. Evaluation

1. Import, data loading + Merge

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

from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.metrics import roc_curve, roc_auc_score, classification_report
```

```
addresses = pd.read_csv(
    "/Users/User/Desktop/PYTHONPRO/DATA_SCIENCE_KURZUS_4_blokk/notebooks/project_hazi/addresses.csv")
addresses.head()
```

	ticket_id	address
0	22056	2900 tyler, Detroit MI
1	27586	4311 central, Detroit MI
2	22062	1449 longfellow, Detroit MI
3	22084	1441 longfellow, Detroit MI
4	22093	2449 churchill, Detroit MI

```
latlons = pd.read_csv(
    "/Users/User/Desktop/PYTHONPRO/DATA_SCIENCE_KURZUS_4_blokk/notebooks/project_hazi/latlons.csv")
latlons.head()
```

	address	lat	lon
0	4300 rosa parks blvd, Detroit MI 48208	42.346169	-83.079962
1	14512 sussex, Detroit MI	42.394657	-83.194265
2	3456 garland, Detroit MI	42.373779	-82.986228
3	5787 wayburn, Detroit MI	42.403342	-82.957805
4	5766 haverhill, Detroit MI	42.407255	-82.946295

```
train = pd.read_csv(
    "/Users/User/Desktop/PYTHONPRO/DATA_SCIENCE_KURZUS_4_blokk/notebooks/project_hazi/train.csv")
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_36392\3855574826.py:1: DtypeWarning: Columns (11,12,31) have
mixed types. Specify dtype option on import or set low_memory=False.
  train = pd.read_csv(
```

```
#========================================================================
# train.csv file vilation_street_number transformation original 2900.0 -> new 2900
#========================================================================

train['violation_street_number'] = (
    train['violation_street_number']
    .astype(str)
    .apply(lambda x: str(int(float(x))) if x.replace('.', '').isdigit() else "")
)
train.head()
```

	ticket_id	agency_name	inspector_name	violator_name	violation_street_number	violation_street_name	violation_zip_cod
0	22056	Buildings, Safety Engineering & Env Department	Sims, Martinzie	INVESTMENT INC., MIDWEST MORTGAGE	2900	TYLER	NaN

	ticket_id	agency_name	inspector_name	violator_name	violation_street_number	violation_street_name	violation_zip_cod
1	27586	Buildings, Safety Engineering & Env Department	Williams, Darrin	Michigan, Covenant House	4311	CENTRAL	NaN
2	22062	Buildings, Safety Engineering & Env Department	Sims, Martinzie	SANDERS, DERRON	1449	LONGFELLOW	NaN
3	22084	Buildings, Safety Engineering & Env Department	Sims, Martinzie	MOROSI, MIKE	1441	LONGFELLOW	NaN
4	22093	Buildings, Safety Engineering & Env Department	Sims, Martinzie	NATHANIEL, NEAL	2449	CHURCHILL	NaN

5 rows × 34 columns

```
#=======================================================================
# train.csv file vilation_street_name lowercase and concatenate
#=======================================================================

train['violation_street_name'] = train['violation_street_name'].str.lower().str.strip()
train['address'] = (
    train['violation_street_number'].astype(str) + ' ' +
    train['violation_street_name'].astype(str) + ', Detroit MI'
)

train.head()
```

	ticket_id	agency_name	inspector_name	violator_name	violation_street_number	violation_street_name	violation_zip_cod
0	22056	Buildings, Safety Engineering & Env Department	Sims, Martinzie	INVESTMENT INC., MIDWEST MORTGAGE	2900	tyler	NaN
1	27586	Buildings, Safety Engineering & Env Department	Williams, Darrin	Michigan, Covenant House	4311	central	NaN
2	22062	Buildings, Safety Engineering & Env Department	Sims, Martinzie	SANDERS, DERRON	1449	longfellow	NaN
3	22084	Buildings, Safety Engineering & Env Department	Sims, Martinzie	MOROSI, MIKE	1441	longfellow	NaN
4	22093	Buildings, Safety Engineering & Env Department	Sims, Martinzie	NATHANIEL, NEAL	2449	churchill	NaN

5 rows × 35 columns

```
#=======================================================================
# train.csv és latlons.csv merge
#=======================================================================

df = train.merge(latlons, on='address', how='left')
df.head()
```

	ticket_id	agency_name	inspector_name	violator_name	violation_street_number	violation_street_name	violation_zip_cod
0	22056	Buildings, Safety Engineering & Env Department	Sims, Martinzie	INVESTMENT INC., MIDWEST MORTGAGE	2900	tyler	NaN
1	27586	Buildings, Safety Engineering & Env Department	Williams, Darrin	Michigan, Covenant House	4311	central	NaN
2	22062	Buildings, Safety Engineering & Env Department	Sims, Martinzie	SANDERS, DERRON	1449	longfellow	NaN
3	22084	Buildings, Safety Engineering & Env Department	Sims, Martinzie	MOROSI, MIKE	1441	longfellow	NaN
4	22093	Buildings, Safety Engineering & Env Department	Sims, Martinzie	NATHANIEL, NEAL	2449	churchill	NaN

5 rows × 37 columns

==

2. EDA + missing values analysis

```
df.isnull().sum()
```

```
ticket_id                          0
agency_name                        0
inspector_name                     0
violator_name                     34
violation_street_number            0
violation_street_name              0
violation_zip_code            250306
mailing_address_str_number      3602
mailing_address_str_name           4
city                               0
state                             93
zip_code                           1
non_us_str_code               250303
country                            0
ticket_issued_date                 0
hearing_date                   12491
violation_code                     0
violation_description              0
disposition                        0
fine_amount                        1
admin_fee                          0
state_fee                          0
late_fee                           0
discount_amount                    0
clean_up_cost                      0
judgment_amount                    0
payment_amount                     0
balance_due                        0
payment_date                  209193
payment_status                     0
collection_status             213409
grafitti_status               250305
compliance_detail                  0
compliance                     90426
address                            0
lat                                3
lon                                3
dtype: int64
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 250306 entries, 0 to 250305
Data columns (total 37 columns):
```

```
 #   Column                      Non-Null Count   Dtype  
---  ------                      --------------   -----  
 0   ticket_id                   250306 non-null  int64  
 1   agency_name                 250306 non-null  object 
 2   inspector_name              250306 non-null  object 
 3   violator_name               250272 non-null  object 
 4   violation_street_number     250306 non-null  object 
 5   violation_street_name       250306 non-null  object 
 6   violation_zip_code          0 non-null       float64
 7   mailing_address_str_number  246704 non-null  float64
 8   mailing_address_str_name    250302 non-null  object 
 9   city                        250306 non-null  object 
 10  state                       250213 non-null  object 
 11  zip_code                    250305 non-null  object 
 12  non_us_str_code             3 non-null       object 
 13  country                     250306 non-null  object 
 14  ticket_issued_date          250306 non-null  object 
 15  hearing_date                237815 non-null  object 
 16  violation_code              250306 non-null  object 
 17  violation_description       250306 non-null  object 
 18  disposition                 250306 non-null  object 
 19  fine_amount                 250305 non-null  float64
 20  admin_fee                   250306 non-null  float64
 21  state_fee                   250306 non-null  float64
 22  late_fee                    250306 non-null  float64
 23  discount_amount             250306 non-null  float64
 24  clean_up_cost               250306 non-null  float64
 25  judgment_amount             250306 non-null  float64
 26  payment_amount              250306 non-null  float64
 27  balance_due                 250306 non-null  float64
 28  payment_date                41113 non-null   object 
 29  payment_status              250306 non-null  object 
 30  collection_status           36897 non-null   object 
 31  grafitti_status             1 non-null       object 
 32  compliance_detail           250306 non-null  object 
 33  compliance                  159880 non-null  float64
 34  address                     250306 non-null  object 
 35  lat                         250303 non-null  float64
 36  lon                         250303 non-null  float64
dtypes: float64(14), int64(1), object(22)
memory usage: 70.7+ MB
```

```
#=========================================================================
# Features Nan values summary
#=========================================================================

df.isna().sum().sort_values(ascending=False)
```

```
violation_zip_code            250306
grafitti_status               250305
non_us_str_code               250303
collection_status             213409
payment_date                  209193
compliance                     90426
hearing_date                   12491
mailing_address_str_number      3602
state                             93
violator_name                     34
mailing_address_str_name           4
lon                                3
lat                                3
fine_amount                        1
zip_code                           1
agency_name                        0
ticket_id                          0
violation_street_number            0
inspector_name                     0
city                               0
violation_street_name              0
admin_fee                          0
disposition                        0
violation_description              0
violation_code                     0
country                            0
ticket_issued_date                 0
discount_amount                    0
state_fee                          0
balance_due                        0
payment_amount                     0
judgment_amount                    0
clean_up_cost                      0
late_fee                           0
payment_status                     0
compliance_detail                  0
```

```
address                          0
dtype: int64
```

```
==========================================================================================
```

```
==========================================================================================
```

```python
#========================================================================
# Leakage és irreleváns oszlopok (jellemzők) eldobása
#========================================================================

leak_cols = [
    'payment_date',
    'payment_amount',
    'payment_status',
    'balance_due',
    'compliance_detail'
]

df = df.drop(columns=leak_cols, errors='ignore')

drop_cols = [
    'violation_zip_code',
    'grafitti_status',
    'non_us_str_code',
    'collection_status'
]

df = df.drop(columns=drop_cols)
df.head()
```

	ticket_id	agency_name	inspector_name	violator_name	violation_street_number	violation_street_name	mailing_address_s
0	22056	Buildings, Safety Engineering & Env Department	Sims, Martinzie	INVESTMENT INC., MIDWEST MORTGAGE	2900	tyler	3.0
1	27586	Buildings, Safety Engineering & Env Department	Williams, Darrin	Michigan, Covenant House	4311	central	2959.0
2	22062	Buildings, Safety Engineering & Env Department	Sims, Martinzie	SANDERS, DERRON	1449	longfellow	23658.0
3	22084	Buildings, Safety Engineering & Env Department	Sims, Martinzie	MOROSI, MIKE	1441	longfellow	5.0
4	22093	Buildings, Safety Engineering & Env Department	Sims, Martinzie	NATHANIEL, NEAL	2449	churchill	7449.0

5 rows × 28 columns

```python
df.isnull().sum()
```

```
ticket_id                      0
agency_name                    0
inspector_name                 0
violator_name                 34
violation_street_number        0
violation_street_name          0
mailing_address_str_number  3602
mailing_address_str_name       4
city                           0
state                         93
zip_code                       1
country                        0
ticket_issued_date             0
hearing_date               12491
violation_code                 0
```

```
violation_description            0
disposition                      0
fine_amount                      1
admin_fee                        0
state_fee                        0
late_fee                         0
discount_amount                  0
clean_up_cost                    0
judgment_amount                  0
compliance                   90426
address                          0
lat                              3
lon                              3
dtype: int64
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 250306 entries, 0 to 250305
Data columns (total 28 columns):
 #   Column                      Non-Null Count   Dtype  
---  ------                      --------------   -----  
 0   ticket_id                   250306 non-null  int64  
 1   agency_name                 250306 non-null  object 
 2   inspector_name              250306 non-null  object 
 3   violator_name               250272 non-null  object 
 4   violation_street_number     250306 non-null  object 
 5   violation_street_name       250306 non-null  object 
 6   mailing_address_str_number  246704 non-null  float64
 7   mailing_address_str_name    250302 non-null  object 
 8   city                        250306 non-null  object 
 9   state                       250213 non-null  object 
 10  zip_code                    250305 non-null  object 
 11  country                     250306 non-null  object 
 12  ticket_issued_date          250306 non-null  object 
 13  hearing_date                237815 non-null  object 
 14  violation_code              250306 non-null  object 
 15  violation_description       250306 non-null  object 
 16  disposition                 250306 non-null  object 
 17  fine_amount                 250305 non-null  float64
 18  admin_fee                   250306 non-null  float64
 19  state_fee                   250306 non-null  float64
 20  late_fee                    250306 non-null  float64
 21  discount_amount             250306 non-null  float64
 22  clean_up_cost               250306 non-null  float64
 23  judgment_amount             250306 non-null  float64
 24  compliance                  159880 non-null  float64
 25  address                     250306 non-null  object 
 26  lat                         250303 non-null  float64
 27  lon                         250303 non-null  float64
dtypes: float64(11), int64(1), object(16)
memory usage: 53.5+ MB
```

===

3. Feature enigineering

```
#=======================================================================
# Target creation
#=======================================================================


df = df[df['compliance'].isin([0,1])].copy()
df['target'] = df['compliance']
df.drop(columns=['compliance'], inplace=True)
```

```
#=======================================================================
# Datums transformation
# #=======================================================================


df['ticket_issued_date'] = pd.to_datetime(df['ticket_issued_date'])
df['hearing_date'] = pd.to_datetime(df['hearing_date'], errors='coerce')

df['days_until_hearing'] = (
    df['hearing_date'] - df['ticket_issued_date']
).dt.days.fillna(-1)

df['issue_year'] = df['ticket_issued_date'].dt.year
df['issue_month'] = df['ticket_issued_date'].dt.month
df['issue_dow'] = df['ticket_issued_date'].dt.dayofweek
```

```
#=======================================================================
# Log-transzformation
#=======================================================================

money_cols = ['fine_amount', 'admin_fee', 'state_fee', 'late_fee', 'judgment_amount']
for c in money_cols:
    if c in df.columns:
        df[f"log_{c}"] = np.log1p(df[c].fillna(0))
```

```
#=======================================================================
# Address / geo feature engineering
#=======================================================================

# lat (latitude) column checking, if it there are coordinates  ->1 otherwise ->0
df['has_latlon'] = df['lat'].notna().astype(int)

df['prior_tickets_by_address'] = df.groupby(
    ['violation_street_name', 'violation_street_number']
)['ticket_id'].transform('count')


df['prior_tickets_by_violator'] = df.groupby(
    'violator_name'
)['ticket_id'].transform('count')
```

```
#=======================================================================
# Feature list
#=======================================================================

numeric_feats = [
    'days_until_hearing', 'prior_tickets_by_address',
    'prior_tickets_by_violator', 'has_latlon'
] + [f"log_{c}" for c in money_cols if f"log_{c}" in df.columns]

cat_feats = [
    'violation_code', 'violation_description',
    'disposition', 'agency_name', 'city', 'state'
]
```

==

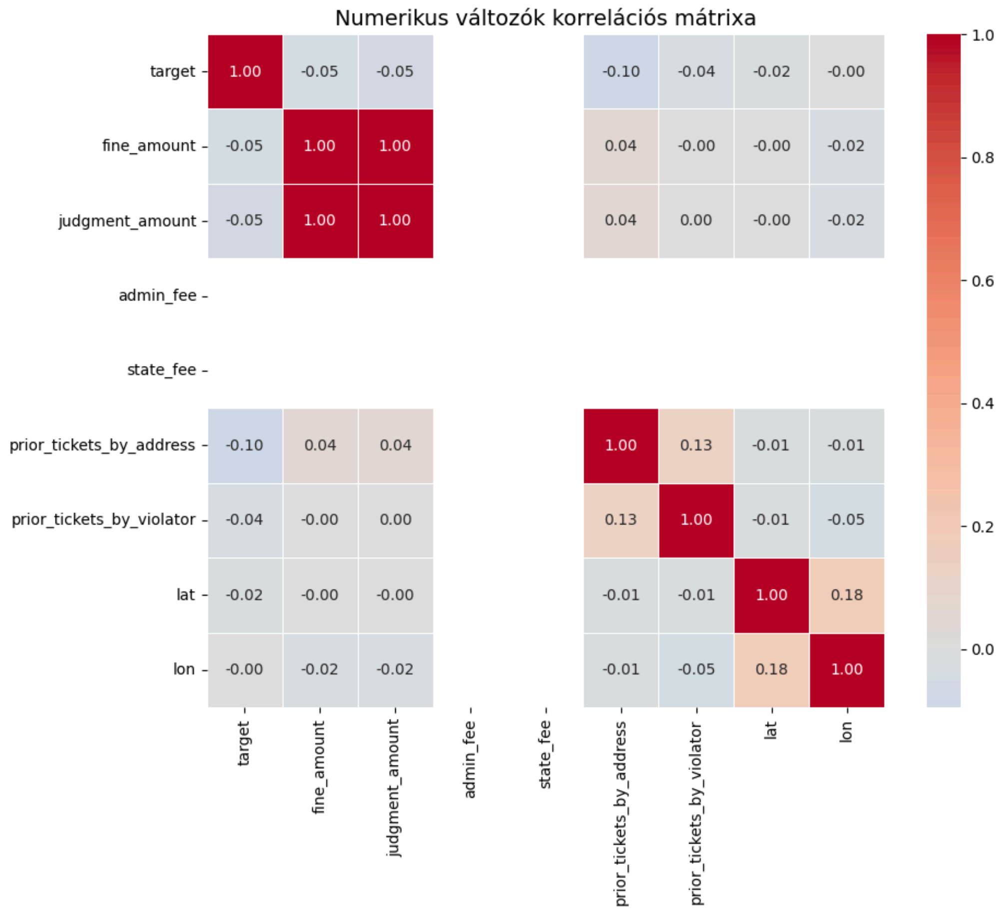
4. Baseline Model - Preprocessing & Logistic Regression

```
numeric_transformer = Pipeline([
    ('impute', SimpleImputer(strategy='median')),
    ('scale', StandardScaler())
])

categorical_transformer = Pipeline([
    ('impute', SimpleImputer(strategy='most_frequent')),
    ('ohe', OneHotEncoder(handle_unknown="ignore"))
])

preprocess = ColumnTransformer([
    ('num', numeric_transformer, numeric_feats),
    ('cat', categorical_transformer, cat_feats)
])
```

```
==========================================================================================================================================
```

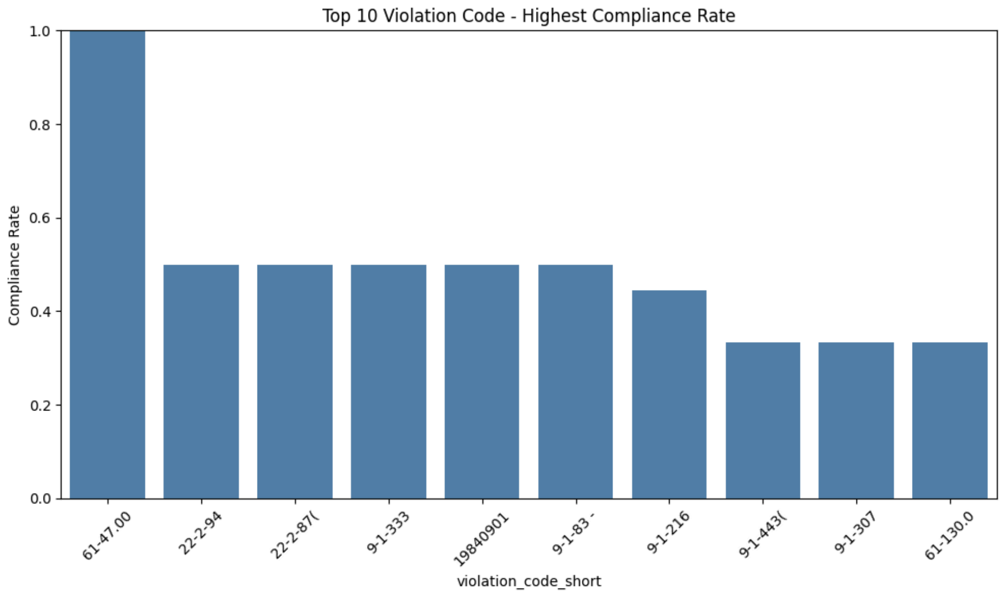
5. Vizualization

```
#========================================================================
# Korrelációs mátrix
#========================================================================

import seaborn as sns

num_for_corr = [
    'target',
    'fine_amount',
    'judgment_amount',
    'admin_fee',
    'state_fee',
    'prior_tickets_by_address',
    'prior_tickets_by_violator',
    'lat',
    'lon'
]

corr = df[num_for_corr].corr()

plt.figure(figsize=(10, 8))
sns.heatmap(corr, annot=True, cmap='coolwarm', center=0, fmt='.2f', linewidths=0.5)
plt.title('Numerikus változók korrelációs mátrixa', fontsize=14)
plt.show()
```




```
#========================================================================
# Pivot tábla
#  - violation_code TOP10
#  - compliance_rate átlaggal
#========================================================================
vc_compliance = (
        df.groupby('violation_code')['target']
        .mean()
        .reset_index(name='compliance_rate')
        .sort_values(by= 'compliance_rate', ascending=False)
)

data = vc_compliance.head(10).copy()

# Rövidített címkék
data['violation_code_short'] = data['violation_code'].str[:8]
```

```python
plt.figure(figsize=(10,6))
sns.barplot(
        data = data,
        x = 'violation_code_short',
        y = 'compliance_rate',
        color ='steelblue'
)

plt.title('Top 10 Violation Code - Highest Compliance Rate')
plt.ylabel('Compliance Rate')
plt.xticks(rotation=45)
plt.ylim(0, 1)
plt.tight_layout()
plt.show()
```



```python
# Több numerikus feature aggregálása violation code szerint
pca_features = df.groupby('violation_code').agg({
    'target': 'mean',
    'fine_amount': 'mean',
    'judgment_amount': 'mean',
    'admin_fee': 'mean',
    'state_fee': 'mean'
})

# Hiányzó értékek kitöltése
pca_features = pca_features.fillna(pca_features.mean())
pca_features.head()
```

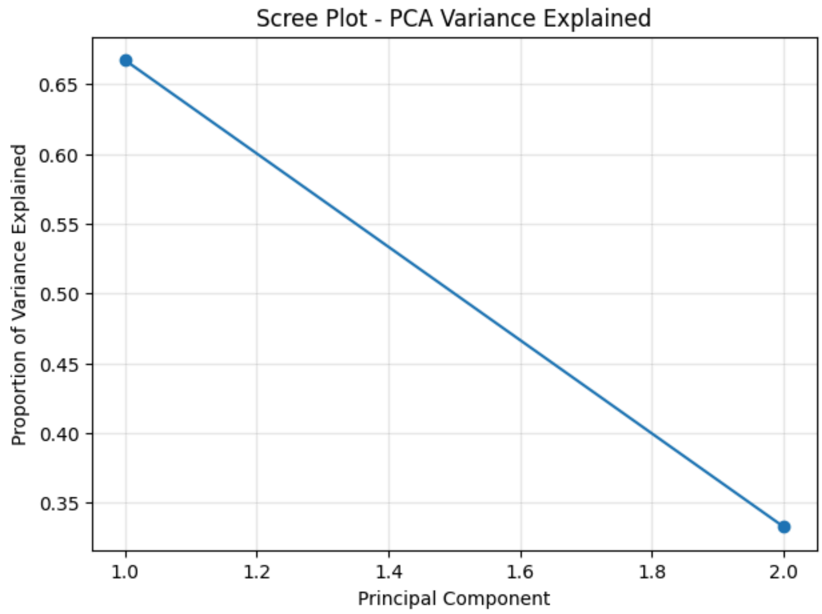
	target	fine_amount	judgment_amount	admin_fee	state_fee
violation_code					
19420901	0.250000	475.000000	549.375000	20.0	10.0
19450901	0.027778	309.753086	369.950617	20.0	10.0
19830901	0.000000	47.500000	82.000000	20.0	10.0
19840901	0.500000	25.000000	57.500000	20.0	10.0
19850901	0.000000	50.000000	85.000000	20.0	10.0

```python
#=========================================================================
#  Scaler before PCA
#=========================================================================

from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
scaled = scaler.fit_transform(pca_features)
```

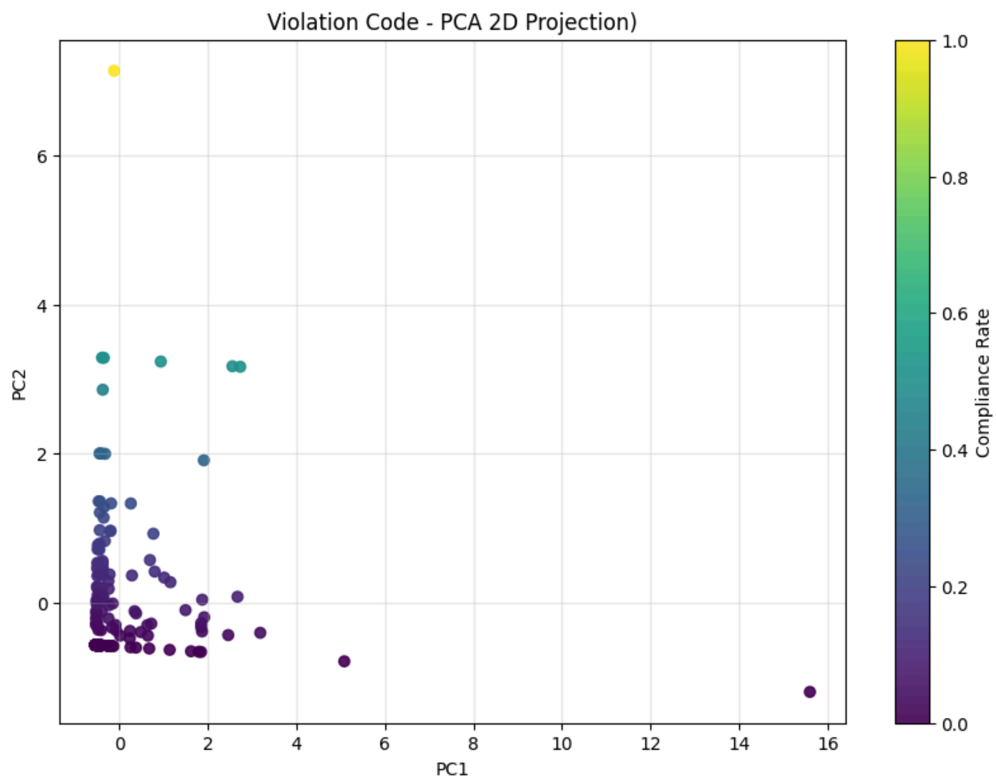
```python
#=========================================================================
# PCA futtatása
#=========================================================================

from sklearn.decomposition import PCA

# Csak 2 komponens kell a vizualizációhoz
pca = PCA(n_components=2)
pca_result = pca.fit_transform(scaled)

# Hozzáadjuk az eredményt a dataframe-hez
pca_features['PC1'] = pca_result[:,0]
pca_features['PC2'] = pca_result[:,1]

pca_features.head()
```

	target	fine_amount	judgment_amount	admin_fee	state_fee	PC1	PC2
violation_code							
19420901	0.250000	475.000000	549.375000	20.0	10.0	0.267544	1.327232
19450901	0.027778	309.753086	369.950617	20.0	10.0	-0.064850	-0.376539
19830901	0.000000	47.500000	82.000000	20.0	10.0	-0.496860	-0.574262
19840901	0.500000	25.000000	57.500000	20.0	10.0	-0.382449	3.283952
19850901	0.000000	50.000000	85.000000	20.0	10.0	-0.492634	-0.574428

```python
import matplotlib.pyplot as plt

plt.figure(figsize=(7, 5))
plt.plot(
    range(1, len(pca.explained_variance_ratio_)+1),
    pca.explained_variance_ratio_,
    marker='o'
)
plt.title('Scree Plot - PCA Variance Explained')
plt.xlabel('Principal Component')
plt.ylabel('Proportion of Variance Explained')
plt.grid(alpha=0.3)
plt.show()
```




```
plt.figure(figsize=(10, 7))

plt.scatter(
    pca_features['PC1'],
    pca_features['PC2'],
    c=pca_features["target"],
    cmap='viridis',
    alpha=0.9
)

plt.title('Violation Code - PCA 2D Projection)')
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.colorbar(label='Compliance Rate')
plt.grid(alpha=0.3)
plt.show()
```



PCA Scree Plot

Shows the proportion of variance explained by each principal component, helping us understand how many components capture most of the information.

2D PCA Projection

```
Visualizes the first two principal components colored by target variable (Compliance).
This highlights clusters and separation patterns in the data.

==========================================================================================
```

6. Modells

```
#=======================================================================
# Függvény a modell betanításhoz
# Train model on train/test split and return:
#  - probabilities indexed by ticket_id
#  - AUC score
#=======================================================================
from sklearn.model_selection import train_test_split


def train_and_predict(df, model):
    X = df.drop(columns=['target'])
    y = df['target']

    # ticket_id külön kezelése visszaadás miatt
    ticket_ids = X['ticket_id'].copy()
    X = X.drop(columns=['ticket_id'])

    X_train, X_test, y_train, y_test, id_train, id_test = train_test_split(
    X, y, ticket_ids,
    test_size=0.2, random_state=42, stratify=y
    )

    model.fit(X_train, y_train)
    y_pred_proba = model.predict_proba(X_test)[:,1]

    pred_series = pd.Series(y_pred_proba, index=id_test, name='probability')

    auc = roc_auc_score(y_test, y_pred_proba)

    print(f"Model AUC: {auc:.4f}")

    return pred_series, auc, y_test
```

```
#=======================================================================
# Modell1: Logistic Regression (baseline)
#=======================================================================


from sklearn.linear_model import LogisticRegression

model_lr = Pipeline([
    ('prep', preprocess),
    ('clf', LogisticRegression(max_iter=200))
])

pred_lr, auc_lr, y_test_lr = train_and_predict(df, model_lr)
pred_lr.head()
```

```
Model AUC: 0.8139

ticket_id
138138    0.035212
149161    0.022452
57262     0.357084
30505     0.061585
192339    0.013783
Name: probability, dtype: float64
```

```
#=======================================================================
# Modell 2: RandomForest
#=======================================================================

from sklearn.ensemble import RandomForestClassifier

model_rf = Pipeline([
    ("prep", preprocess),
    ('clf', RandomForestClassifier(
        n_estimators=100,
        random_state=42,
        max_depth=15))
])

pred_rf, auc_rf, y_test_rf = train_and_predict(df, model_rf)
pred_rf.head()
```

```
Model AUC: 0.8171
```

```
ticket_id
138138    0.046453
149161    0.046118
57262     0.203390
30505     0.066659
192339    0.035467
Name: probability, dtype: float64
```

```python
#======================================================================
# Modell 3: GradientBoostingClassifier
#======================================================================


from sklearn.ensemble import GradientBoostingClassifier

model_gb = Pipeline([
    ("prep", preprocess),
    ('clf', GradientBoostingClassifier())
])

pred_gb, auc_gb, y_test_gb = train_and_predict(df, model_gb)
pred_rf.head()
```

```
Model AUC: 0.8314

ticket_id
138138    0.046453
149161    0.046118
57262     0.203390
30505     0.066659
192339    0.035467
Name: probability, dtype: float64
```

Interpretation

Gradient Boosting achived the highest ROC-AUC score, indicating better ranking performance compared to Logistic Regression and Random Forest.

Given the class imbalence, RO-AUC is a more appropriate metric than accuracy.

==

7. Evaluation

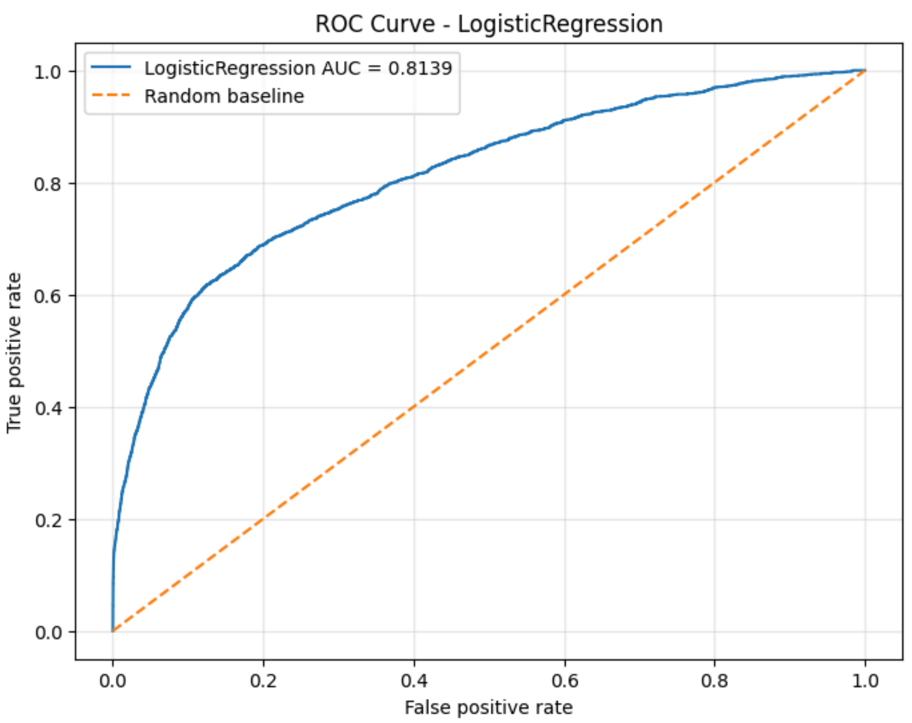
```
results = pd.DataFrame({
    'Model': ['Logistic Regression', 'Random Forest', 'Gradient Boosting'],
    'ROC AUC': [auc_lr, auc_rf, auc_gb]
})

results.style.background_gradient(cmap='Blues').format({'AUC': '{:.4f}'})
```

	Model	ROC AUC
0	Logistic Regression	0.813936
1	Random Forest	0.817129
2	Gradient Boosting	0.831400

```
import matplotlib.pyplot as plt

def plot_roc_curve(y_true, y_pred_proba, model_name='Model'):
    fpr, tpr, tresholds = roc_curve(y_true, y_pred_proba)
    auc = roc_auc_score(y_true, y_pred_proba)

    plt.figure(figsize=(8, 6))
    plt.plot(fpr, tpr, label=f'{model_name} AUC = {auc:.4f}')
    plt.plot([0, 1], [0, 1], linestyle='--', label='Random baseline')
    plt.xlabel('False positive rate')
    plt.ylabel('True positive rate')
    plt.title(f'ROC Curve - {model_name}')
    plt.legend()
    plt.grid(alpha=0.3)
    plt.show()
```

```
pred_lr, auc_lr, y_test_lr =train_and_predict(df, model_lr)

plot_roc_curve(y_test_lr, pred_lr.values, "LogisticRegression")
```

```
Model AUC: 0.8139
```



Classification reports for Logistic Regression:

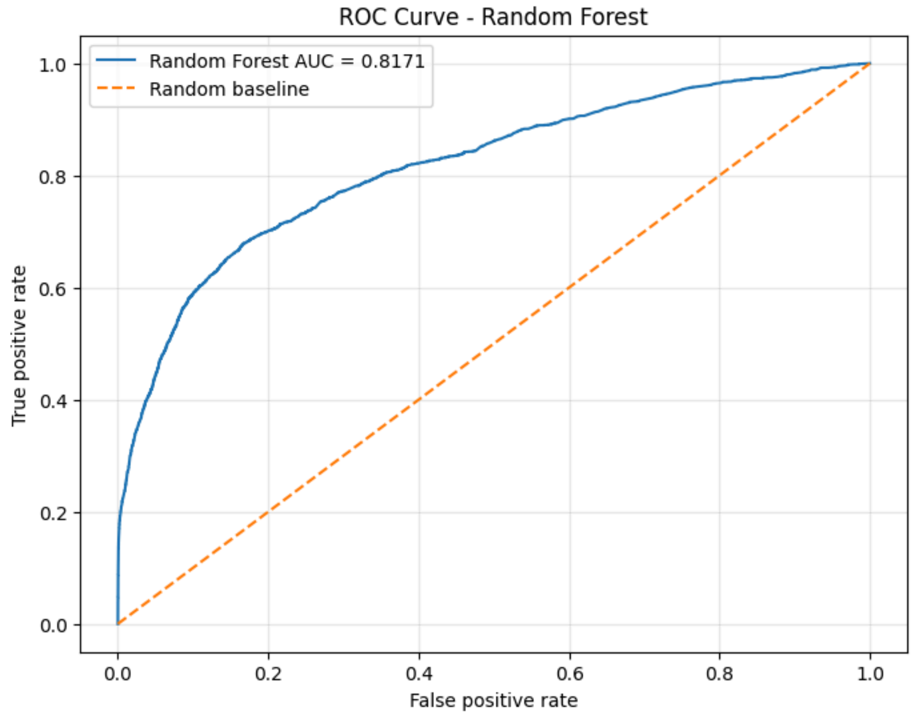
```
def print_classification_report(y_test, probas, threshold=0.5):
    y_pred = (probas >= threshold).astype(int)
    print("Classification report for Logistic Regression:\n")
    print(classification_report(y_test, y_pred))

print_classification_report(y_test_lr, pred_lr.values)
```

```
Classification report for Logistic Regression:

              precision    recall  f1-score   support
```

```
         0.0       0.94      1.00      0.97     29657
         1.0       0.82      0.15      0.26      2319

    accuracy                           0.94     31976
   macro avg       0.88      0.58      0.61     31976
weighted avg       0.93      0.94      0.92     31976
```

```
pred_rf, auc_rf, y_test_rf =train_and_predict(df, model_rf)

plot_roc_curve(y_test_rf, pred_rf.values, "Random Forest")
```

```
Model AUC: 0.8171
```



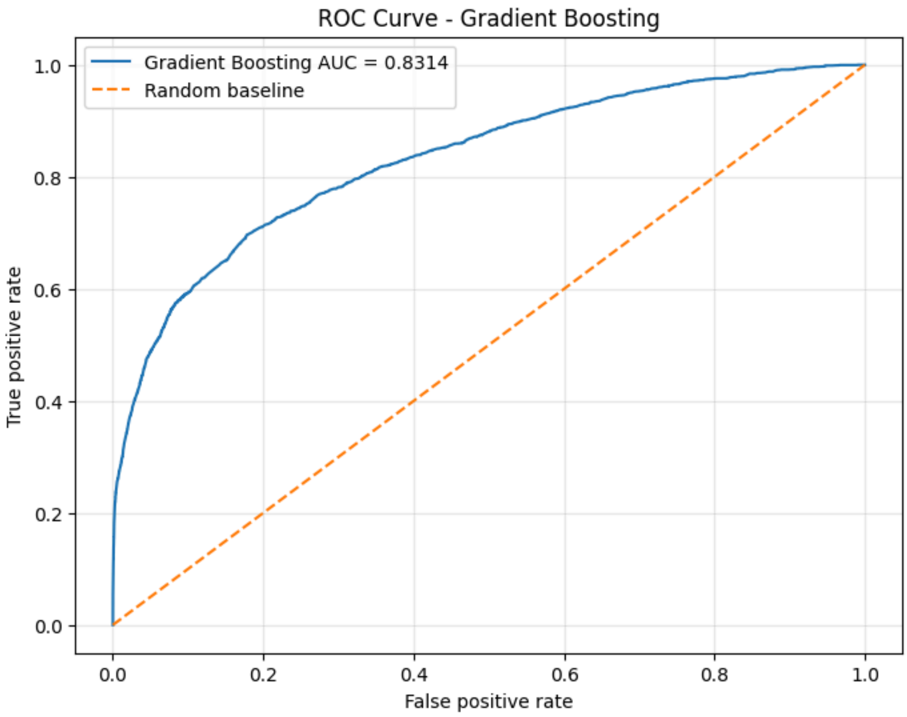
Classification reports for Random Forest:

```
def print_classification_report(y_test, probas, threshold=0.5):
    y_pred = (probas >= threshold).astype(int)
    print("Classification report for Random Forest:\n")
    print(classification_report(y_test, y_pred))

print_classification_report(y_test_rf, pred_rf.values)
```

```
Classification report for Random Forest:

              precision    recall  f1-score   support

         0.0       0.93      1.00      0.96     29657
         1.0       1.00      0.00      0.01      2319

    accuracy                           0.93     31976
   macro avg       0.96      0.50      0.49     31976
weighted avg       0.93      0.93      0.89     31976
```

```
pred_gb, auc_gb, y_test_gb =train_and_predict(df, model_gb)

plot_roc_curve(y_test_gb, pred_gb.values, "Gradient Boosting")
```

```
Model AUC: 0.8314
```



Classification reports for Gradient Boosting:

```
def print_classification_report(y_test, probas, threshold=0.5):
    y_pred = (probas >= threshold).astype(int)
    print("Classification report for Gradient Boosting:\n")
    print(classification_report(y_test, y_pred))

print_classification_report(y_test_gb, pred_gb.values)
```

```
Classification report for Gradient Boosting:

              precision    recall  f1-score   support

         0.0       0.94      1.00      0.97     29657
         1.0       0.84      0.22      0.35      2319

    accuracy                           0.94     31976
   macro avg       0.89      0.61      0.66     31976
weighted avg       0.94      0.94      0.92     31976
```

==