traffic_violations

November 13, 2022

[40]:
```python
import pandas as pd
import numpy as np
import plotly.express as px
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import precision_score,recall_score, confusion_matrix,␣
 ↪classification_report,accuracy_score, f1_score
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.compose import ColumnTransformer

from sklearn.utils.validation import check_is_fitted
import plotly.express as px

# Custom written utilities for analysis/modelling/feature engineering
from utils import FeatureImportance, pre_process, get_scores
import pickle
import plotly.io as pio
pio.renderers.default = "svg"
```

0.1 Load data downloaded from S3

[4]:
```python
# Run this incase data is not loaded via bash script
# !wget https://s3-us-west-2.amazonaws.com/pcadsassessment/parking_citations.
 ↪corrupted.csv
```

[5]:
```python
df = pd.read_csv("parking_citations.corrupted.csv")
```

```
/tmp/ipykernel_643/2998227632.py:1: DtypeWarning:

Columns (0,7) have mixed types. Specify dtype option on import or set
low_memory=False.
```

[6]:
```
df.head()
```

[6]:
```
   Ticket number           Issue Date  Issue time Meter Id  Marked Time  \
0     1103341116  2015-12-21T00:00:00      1251.0      NaN          NaN
1     1103700150  2015-12-21T00:00:00      1435.0      NaN          NaN
2     1104803000  2015-12-21T00:00:00      2055.0      NaN          NaN
3     1104820732  2015-12-26T00:00:00      1515.0      NaN          NaN
4     1105461453  2015-09-15T00:00:00       115.0      NaN          NaN

  RP State Plate  Plate Expiry Date  VIN  Make Body Style Color  \
0             CA           200304.0  NaN   NaN         PA    GY
1             CA           201512.0  NaN   NaN         VN    WH
2             CA           201503.0  NaN   NaN         PA    BK
3             CA                NaN  NaN   NaN         PA    WH
4             CA           200316.0  NaN  CHEV         PA    BK

              Location  Route  Agency Violation code Violation Description  \
0      13147 WELBY WAY  01521     1.0         4000A1    NO EVIDENCE OF REG
1        525 S MAIN ST   1C51     1.0         4000A1    NO EVIDENCE OF REG
2        200 WORLD WAY    2R2     2.0           8939            WHITE CURB
3        100 WORLD WAY   2F11     2.0            000                17104h
4   GEORGIA ST/OLYMPIC  1FB70     1.0          8069A  NO STOPPING/STANDING

   Fine amount   Latitude  Longitude
0         50.0    99999.0    99999.0
1         50.0    99999.0    99999.0
2         58.0  6439997.9  1802686.4
3          NaN  6440041.1  1802686.2
4         93.0    99999.0    99999.0
```

[7]:
```
df.describe()
```

[7]:
```
         Issue time    Marked Time  Plate Expiry Date        Agency  \
count  8.723431e+06  290599.000000       7.931187e+06  8.725469e+06
mean   1.203930e+03    1055.399286       1.867823e+05  5.200932e+01
std    4.722413e+02     227.596205       5.276278e+04  9.301675e+00
min    0.000000e+00       1.000000       1.000000e+00  1.000000e+00
25%    9.120000e+02     910.000000       2.016010e+05  5.100000e+01
50%    1.156000e+03    1035.000000       2.017020e+05  5.400000e+01
75%    1.511000e+03    1200.000000       2.018030e+05  5.500000e+01
max    2.359000e+03    2400.000000       8.201080e+05  9.700000e+01

        Fine amount      Latitude     Longitude
count  8.719507e+06  8.726011e+06  8.726011e+06
mean   7.011293e+01  5.501648e+06  1.586792e+06
std    3.211512e+01  3.004177e+06  2.065458e+06
min    1.000000e+01  9.999900e+04  9.999900e+04
```

```
25%     6.300000e+01  6.421512e+06  1.821558e+06
50%     6.800000e+01  6.451540e+06  1.841987e+06
75%     7.300000e+01  6.475013e+06  1.858207e+06
max     5.050000e+02  4.042322e+09  4.042322e+09
```

[8]:
```python
# Finding Top 25 Make based on number of rows
pd_df = df.groupby("Make")['Ticket number'].count().reset_index(name="count").
 ↪sort_values("count",ascending=False)[:25]
pd_df.head()
```

[8]:
```
      Make   count
1331  TOYT  721411
506   HOND  491961
384   FORD  382695
942   NISS  311324
180   CHEV  297076
```

[9]:
```python
# Creating the binary variable indicating whether popular Make or not
popularMakes = pd_df["Make"].values.tolist()
df['popularMakeorNot'] = df['Make'].apply(lambda x: 1 if x in popularMakes else␣
 ↪0,1)
df
```

[9]:
```
        Ticket number           Issue Date  Issue time Meter Id  Marked Time  \
0          1103341116  2015-12-21T00:00:00      1251.0      NaN          NaN
1          1103700150  2015-12-21T00:00:00      1435.0      NaN          NaN
2          1104803000  2015-12-21T00:00:00      2055.0      NaN          NaN
3          1104820732  2015-12-26T00:00:00      1515.0      NaN          NaN
4          1105461453  2015-09-15T00:00:00       115.0      NaN          NaN
…                   …                    …         …        …          …
8726009    4347602394  2019-01-10T00:00:00      1245.0   VN686B          NaN
8726010    4347602405  2019-01-10T00:00:00      1350.0    VN316          NaN
8726011    4347602416  2019-01-10T00:00:00      1354.0    VN914          NaN
8726012    4347602420  2019-01-10T00:00:00      1411.0    VN725          NaN
8726013    4347602431  2019-01-10T00:00:00      1414.0    VN749          NaN

        RP State Plate  Plate Expiry Date  VIN  Make Body Style Color  \
0                   CA           200304.0  NaN   NaN         PA    GY
1                   CA           201512.0  NaN   NaN         VN    WH
2                   CA           201503.0  NaN   NaN         PA    BK
3                   CA                NaN  NaN   NaN         PA    WH
4                   CA           200316.0  NaN  CHEV         PA    BK
…                    …                  …    …     …          …     …
8726009             CA           201905.0  NaN   NaN         PA    WT
8726010             CA           201905.0  NaN  HYUN         PA    SL
8726011             CA           201912.0  NaN  NISS         PA    GY
8726012             CA           201903.0  NaN   NaN         PA    GY
```

```
8726013            CA          201905.0   NaN    BMW         PA     BK

                   Location  Route  Agency Violation code  \
0          13147 WELBY WAY  01521     1.0         4000A1
1            525 S MAIN ST   1C51     1.0         4000A1
2           200 WORLD WAY    2R2     2.0           8939
3           100 WORLD WAY   2F11     2.0            000
4       GEORGIA ST/OLYMPIC  1FB70     1.0          8069A
…                      …      …       …              …
8726009     14301 DELANO ST  00300    53.0        88.13B+
8726010      14500 FRIAR ST  00300    53.0        88.13B+
8726011      14400 FRIAR ST  00300    53.0        88.13B+
8726012      6300 SYLMAR AV  00300    53.0        88.13B+
8726013      6301 SYLMAR AV  00300    53.0        88.13B+

        Violation Description  Fine amount      Latitude     Longitude  \
0          NO EVIDENCE OF REG         50.0  9.999900e+04  9.999900e+04
1          NO EVIDENCE OF REG         50.0  9.999900e+04  9.999900e+04
2                  WHITE CURB         58.0  6.439998e+06  1.802686e+06
3                      17104h          NaN  6.440041e+06  1.802686e+06
4        NO STOPPING/STANDING         93.0  9.999900e+04  9.999900e+04
…                         …          …           …            …
8726009            METER EXP.         63.0  6.427279e+06  1.889149e+06
8726010            METER EXP.         63.0  6.425963e+06  1.890254e+06
8726011            METER EXP.         63.0  6.426623e+06  1.890252e+06
8726012            METER EXP.         63.0  6.426622e+06  1.889882e+06
8726013            METER EXP.         63.0  6.426622e+06  1.889882e+06

         popularMakeorNot
0                       0
1                       0
2                       0
3                       0
4                       1
…                     …
8726009                 0
8726010                 1
8726011                 1
8726012                 0
8726013                 1

[8726014 rows x 20 columns]
```

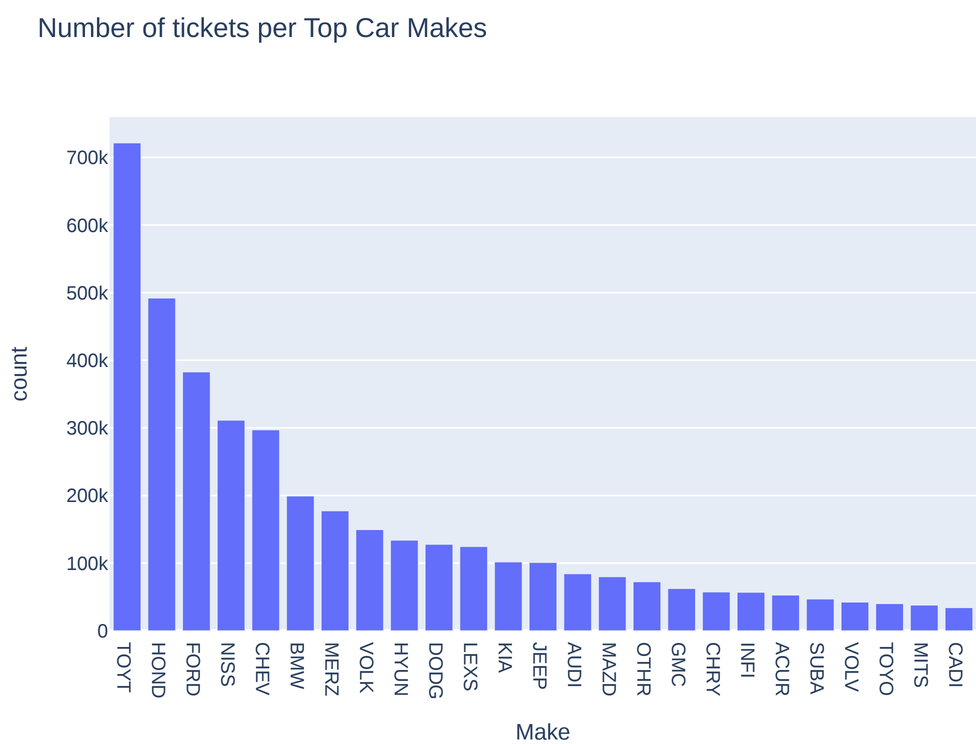
[10]:
```
# Based on task description, separating corrupted rows (having NA values for Make column) as test and rest as training set
df_train = df[~df.Make.isna()]
df_test = df[df.Make.isna()]
```

```
[11]: del df
```

0.2 EDA

```
[12]: # Uncorrupted dataframe with valid make values
df = df_train
```

```
[13]: pd_df = df.groupby("Make")['Ticket number'].count().reset_index(name="count").
    ↪sort_values("count",ascending=False)[:25]
px.bar(pd_df,x="Make",y="count",title="Number of tickets per Top Car Makes")
```




```
[14]: # % of null values per column
100*df.isna().sum()/len(df)

# Marked time + Marked Id + VIN are mostly empty so they can be dropped.
```

```
[14]: Ticket number            0.000000
Issue Date               0.000000
Issue time               0.022834
Meter Id                73.979632
Marked Time             96.674228
```

```
RP State Plate            0.008973
Plate Expiry Date         9.100241
VIN                      99.813152
Make                      0.000000
Body Style                0.091565
Color                     0.034744
Location                  0.003419
Route                     0.726946
Agency                    0.000138
Violation code            0.000000
Violation Description     0.009891
Fine amount               0.073321
Latitude                  0.000023
Longitude                 0.000023
popularMakeorNot          0.000000
dtype: float64
```

[15]:
```
df.describe()
```

[15]:
```
         Issue time    Marked Time  Plate Expiry Date        Agency  \
count  4.356549e+06  144922.000000       3.960997e+06  4.357538e+06
mean   1.203880e+03    1055.147196       1.867826e+05  5.203218e+01
std    4.722652e+02     227.166905       5.276190e+04  9.238550e+00
min    0.000000e+00       1.000000       1.000000e+00  1.000000e+00
25%    9.120000e+02     910.000000       2.016010e+05  5.100000e+01
50%    1.155000e+03    1036.000000       2.017020e+05  5.400000e+01
75%    1.511000e+03    1200.000000       2.018030e+05  5.500000e+01
max    2.359000e+03    2400.000000       5.015120e+05  9.700000e+01

        Fine amount      Latitude     Longitude  popularMakeorNot
count  4.354349e+06  4.357543e+06  4.357543e+06      4.357544e+06
mean   7.010876e+01  5.503485e+06  1.587400e+06      9.147846e-01
std    3.205594e+01  3.025596e+06  2.098413e+06      2.792020e-01
min    1.000000e+01  9.999900e+04  9.999900e+04      0.000000e+00
25%    6.300000e+01  6.421524e+06  1.821596e+06      1.000000e+00
50%    6.800000e+01  6.451586e+06  1.841993e+06      1.000000e+00
75%    7.300000e+01  6.475013e+06  1.858208e+06      1.000000e+00
max    5.050000e+02  4.042322e+09  4.042322e+09      1.000000e+00
```

[16]:
```
# Checking if some variables are correlated with each other for continous␣
↪variables
df.corr()
```

[16]:
```
                   Issue time  Marked Time  Plate Expiry Date    Agency  \
Issue time           1.000000     0.796187           0.015258 -0.044840
Marked Time          0.796187     1.000000           0.104674 -0.049865
Plate Expiry Date    0.015258     0.104674           1.000000 -0.069531
```

```
Agency              -0.044840    -0.049865          -0.069531  1.000000
Fine amount         -0.007937     0.013390          -0.027864 -0.035432
Latitude             0.037449    -0.033271          -0.010927  0.148542
Longitude            0.015635    -0.035778          -0.003974  0.058981
popularMakeorNot    -0.006936    -0.012132           0.056664  0.037669

                   Fine amount  Latitude  Longitude  popularMakeorNot
Issue time           -0.007937  0.037449   0.015635         -0.006936
Marked Time           0.013390 -0.033271  -0.035778         -0.012132
Plate Expiry Date    -0.027864 -0.010927  -0.003974          0.056664
Agency               -0.035432  0.148542   0.058981          0.037669
Fine amount           1.000000 -0.002571  -0.001090         -0.006868
Latitude             -0.002571  1.000000   0.854439          0.009859
Longitude            -0.001090  0.854439   1.000000          0.004334
popularMakeorNot     -0.006868  0.009859   0.004334          1.000000
```

[17]:
```python
# Number of unique values per column
df.nunique()
```

[17]:
```
Ticket number            4357544
Issue Date                  1724
Issue time                  1440
Meter Id                   36456
Marked Time                 1111
RP State Plate                77
Plate Expiry Date            709
VIN                         4948
Make                        1477
Body Style                   145
Color                         80
Location                 1047757
Route                       6795
Agency                        38
Violation code               282
Violation Description        600
Fine amount                   36
Latitude                  704931
Longitude                 697788
popularMakeorNot               2
dtype: int64
```

[18]:
```python
# Given how number of unique values are pretty high, we might
# have to select categoricals to consider which might be useful.

# Preprocessing time related issue date which can be used to find day, week,␣
↪month
# that can be helpful features
```

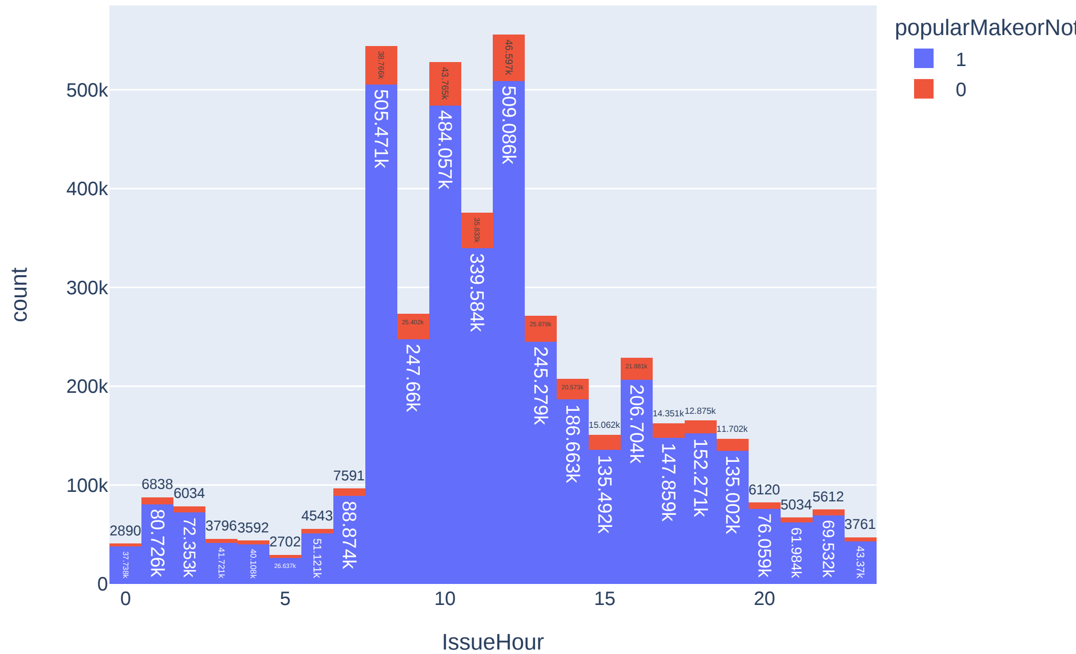
```python
# Parsing Hour from Issue which is a integer
df["IssueHour"] = (
        df["Issue time"]
        .apply(lambda x: int(x) // 100 if pd.notnull(x) else x, 1)
        .astype("category")
    )

# Parse into datetime object
df["IssueDateObj"] = pd.to_datetime(df["Issue Date"])
df["IssueWeek"] = df["IssueDateObj"].dt.isocalendar().week
df["IssueMonth"] = df["IssueDateObj"].dt.month
df["IssueYear"] = df["IssueDateObj"].dt.year
df["IssueWeekDay"] = df["IssueDateObj"].dt.weekday
df["IssueDay"] = df["IssueDateObj"].dt.day
```

```
/tmp/ipykernel_643/3669827805.py:8: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

/tmp/ipykernel_643/3669827805.py:15: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

/tmp/ipykernel_643/3669827805.py:16: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

/tmp/ipykernel_643/3669827805.py:17: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
```

```
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

/tmp/ipykernel_643/3669827805.py:18: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

/tmp/ipykernel_643/3669827805.py:19: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

/tmp/ipykernel_643/3669827805.py:20: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

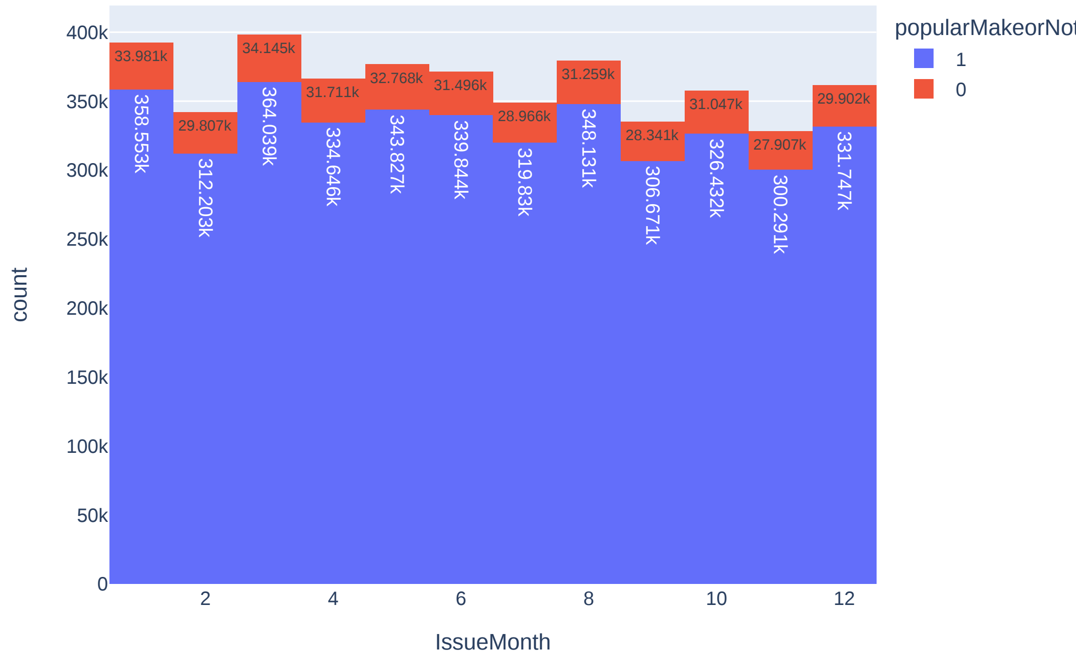
[19]:

```python
# Which hour do most tickets get filed?
# pd_df = df.groupby("IssueHour")["Ticket number"].count().
 ↪reset_index(name="count").sort_values("count",ascending=False)
px.
 ↪histogram(df,x="IssueHour",text_auto=True,color="popularMakeorNot",barmode="stack")
```

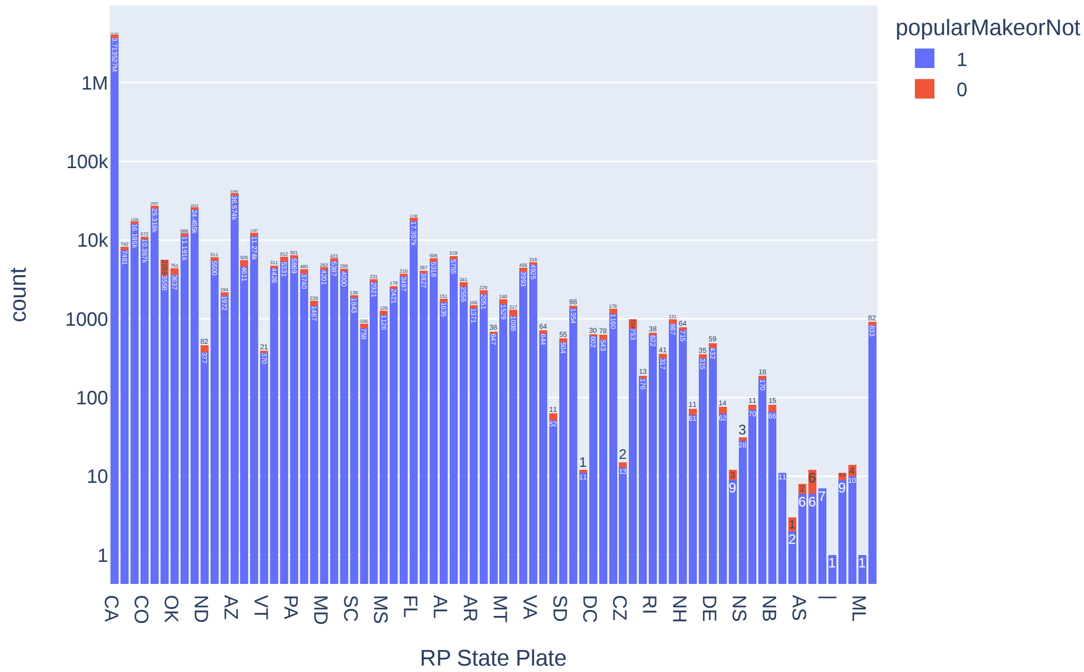


[20]:

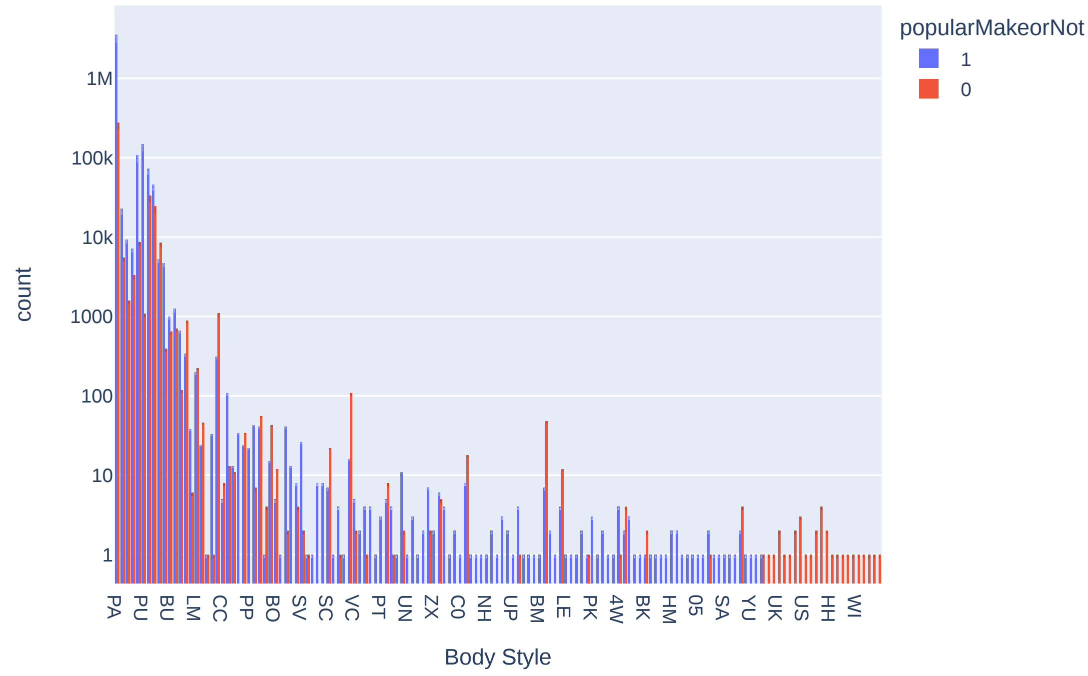
```
# Which month do most tickets get filed?
px.
 ↪histogram(df,x="IssueMonth",text_auto=True,color="popularMakeorNot",barmode="stack")
# More or less it's uniform across months
```



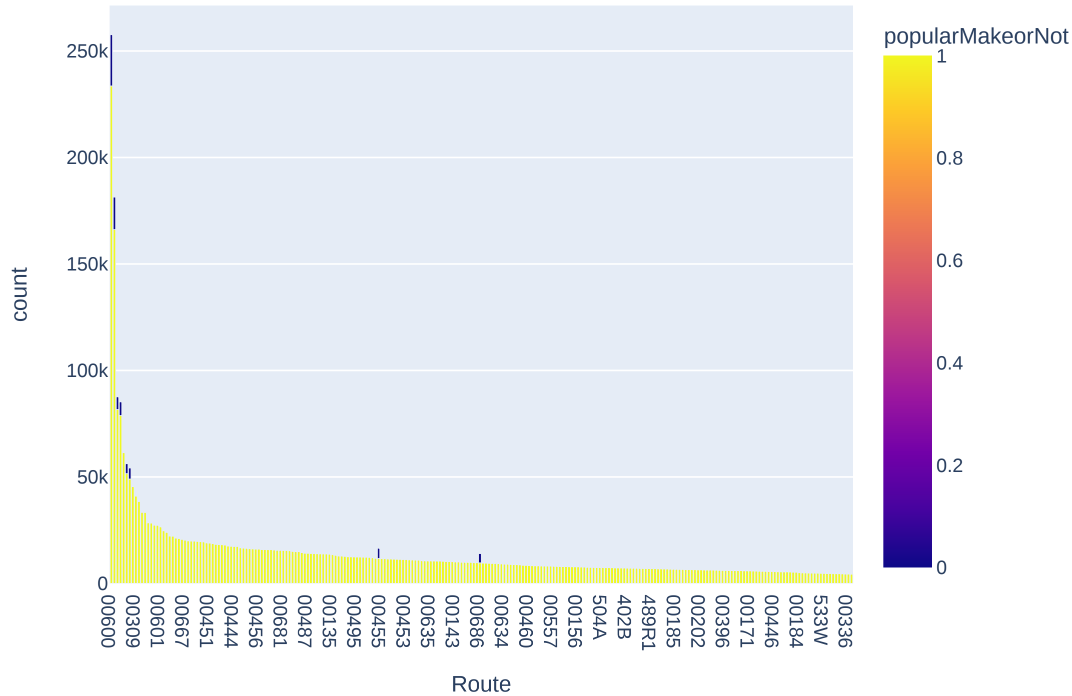
[21]:
```
px.histogram(df,x="RP State␣
↪Plate",text_auto=True,color="popularMakeorNot",barmode="stack",log_y=True)
# This is quite shocking that quite a lot pf data is from California State␣
↪plates by a logarithmic margin
# It makes sense to use this variable in model
```



[22]:
```
px.histogram(df,x="Body␣
 ↪Style",text_auto=True,color="popularMakeorNot",barmode="group",log_y=True)
# This is quite shocking that quite a lot data is for "PA" body style. It makes␣
 ↪sense to use a binary variable for that particular body style/
# Also see there is a separation between
```

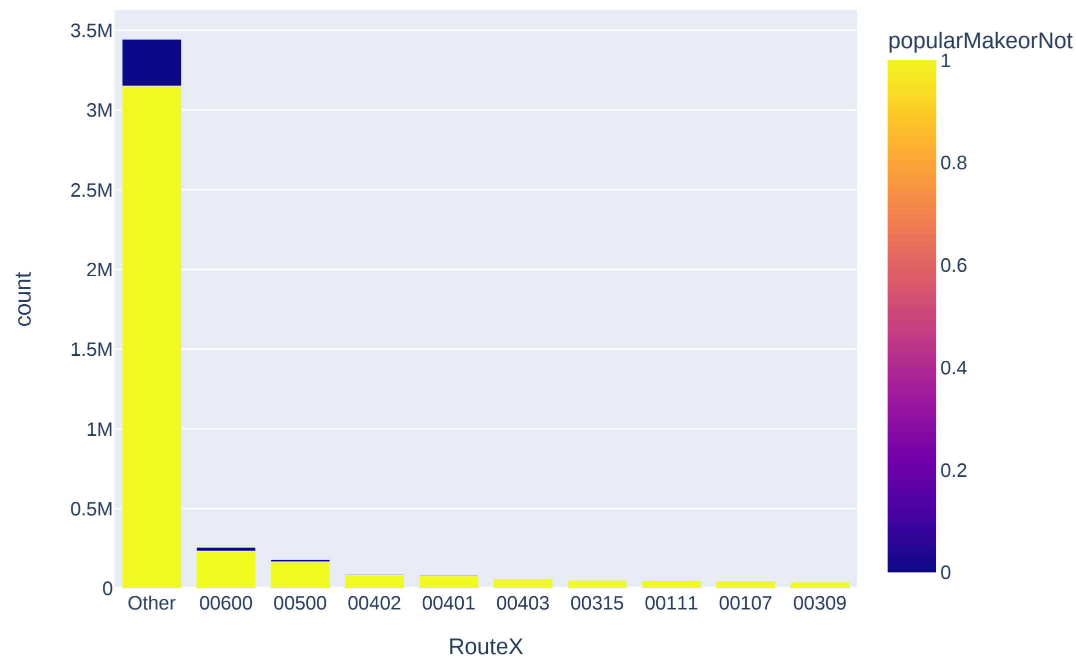


[23]:
```
pd_df = df.groupby(["Route","popularMakeorNot"])["Ticket number"].count().
    ↪reset_index(name="count").sort_values("count",ascending=False)[:250]
px.bar(pd_df,x="Route",y="count",color="popularMakeorNot")

# We can see how one of the routes dominate all others so maybe that can help␣
    ↪as a individual feature
# Therefore we can combine other categories with less frequency into "Other" i.
    ↪e. bottom 1% percent for instance with others
```

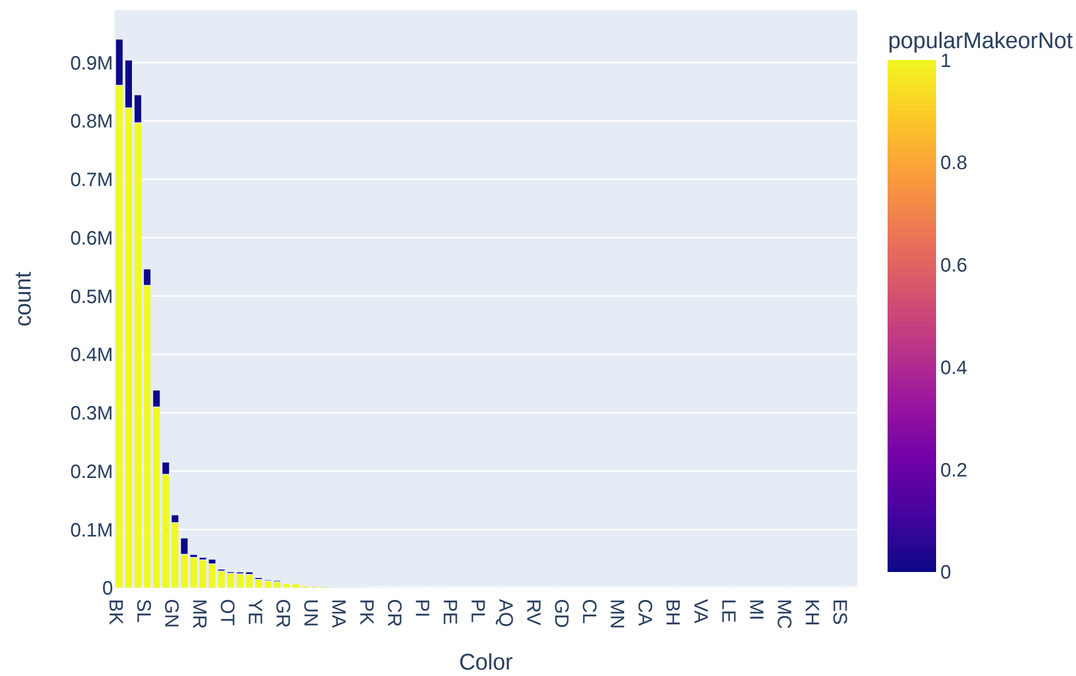


[24]:
```
feature = "Route"
df["RouteX"] = df[feature].mask(df[feature].map(df[feature].
 ↪value_counts(normalize=True)) < 0.01, 'Other')
pd_df = df.groupby(["RouteX","popularMakeorNot"])["Ticket number"].count().
 ↪reset_index(name="count").sort_values("count",ascending=False)

px.bar(pd_df,x="RouteX",y="count",color="popularMakeorNot")

# As it can be seen, it reduces down the categoricals into just 20 after␣
 ↪combining below 1% as Others
```

```
/tmp/ipykernel_643/3799580334.py:2: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

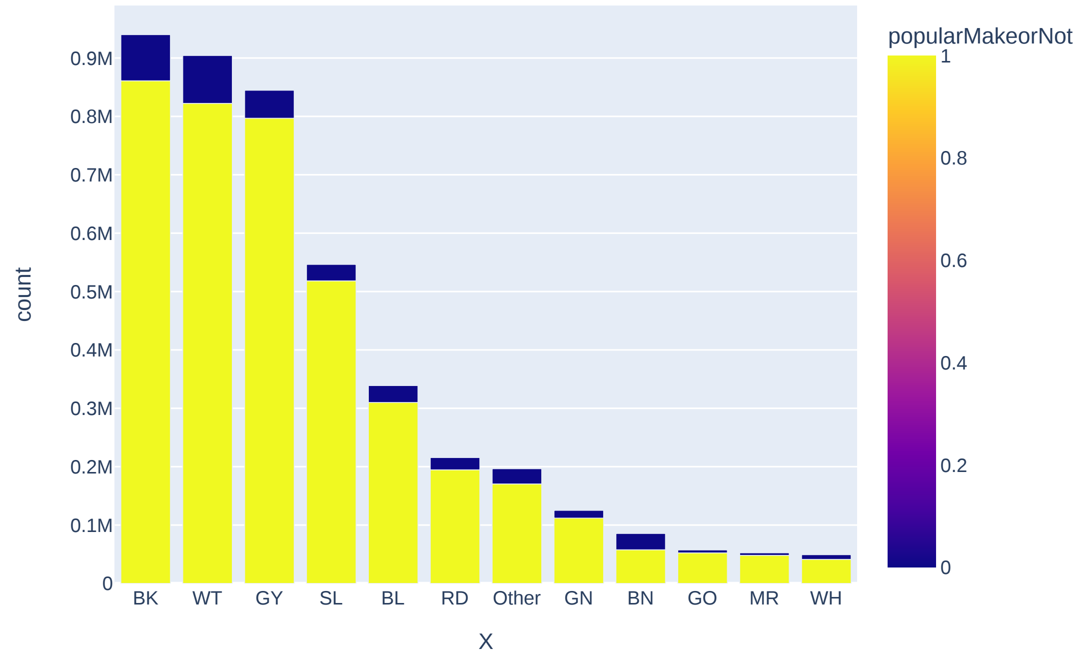


[25]:
```
pd_df = df.groupby(["Color","popularMakeorNot"])["Ticket number"].count().
    ↪reset_index(name="count").sort_values("count",ascending=False)[:500]
px.bar(pd_df,x="Color",y="count",color="popularMakeorNot")

# We can see top ones are more and it's long tailed distribution, so combining␣
    ↪lower ferquency ones into Other
```

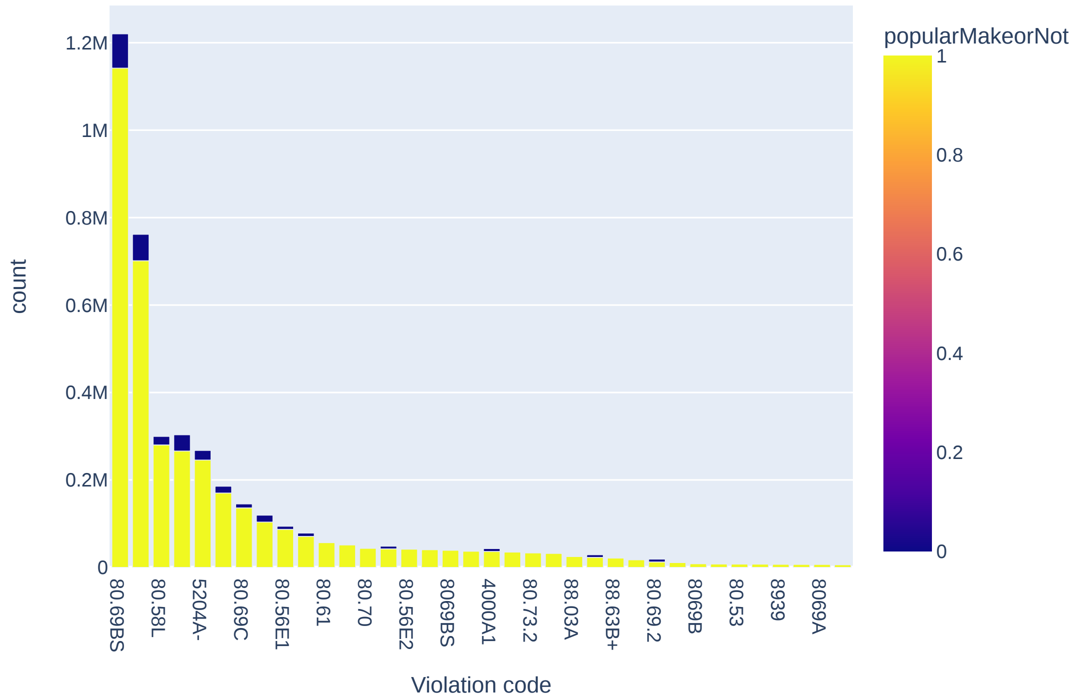


[26]:
```
feature = "Color"
df["X"] = df[feature].mask(df[feature].map(df[feature].
↪value_counts(normalize=True)) < 0.01, 'Other')
pd_df = df.groupby(["X","popularMakeorNot"])["Ticket number"].count().
↪reset_index(name="count").sort_values("count",ascending=False)

px.bar(pd_df,x="X",y="count",color="popularMakeorNot")

# As it can be seen, it reduces down the categoricals into just 20 after␣
↪combining below 1% as Others
```

```
/tmp/ipykernel_643/2466721373.py:2: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

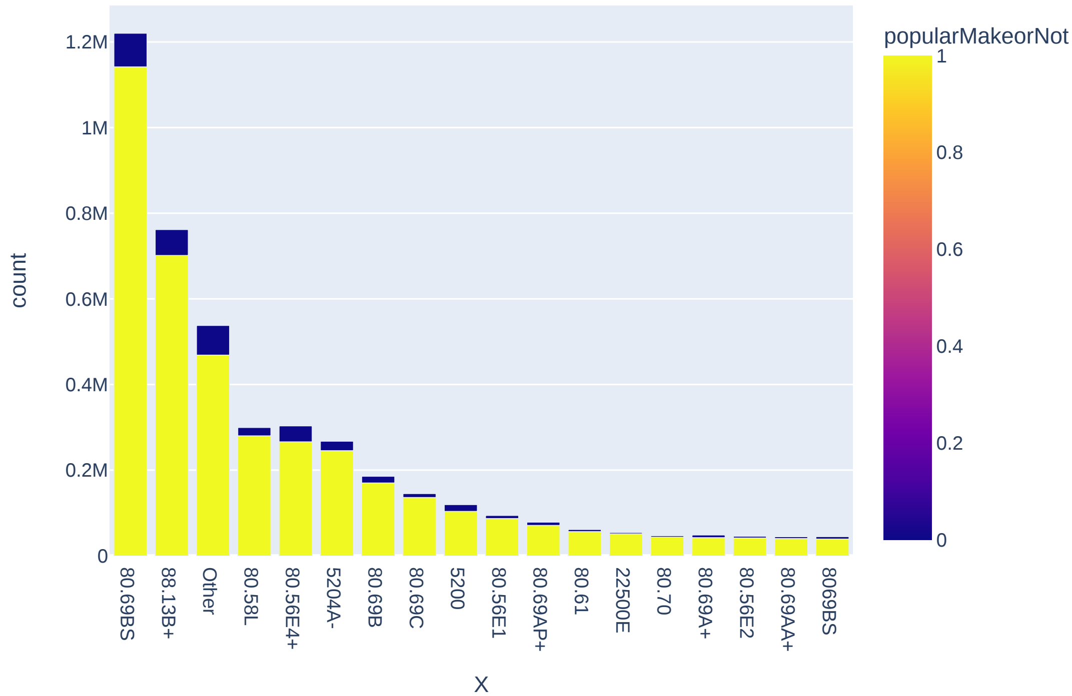


[27]:
```python
pd_df = df.groupby(["Violation code","popularMakeorNot"])["Ticket number"].
    ↪count().reset_index(name="count").sort_values("count",ascending=False)[:50]
px.bar(pd_df,x="Violation code",y="count",color="popularMakeorNot")

# We can see top ones are more and it's long tailed distribution, so combining␣
    ↪lower ferquency ones into Other
```



[28]:
```
feature = "Violation code"
df["X"] = df[feature].mask(df[feature].map(df[feature].
  ↪value_counts(normalize=True)) < 0.01, 'Other')
pd_df = df.groupby(["X","popularMakeorNot"])["Ticket number"].count().
  ↪reset_index(name="count").sort_values("count",ascending=False)

px.bar(pd_df,x="X",y="count",color="popularMakeorNot")

# As it can be seen, it reduces down the categoricals into just 20 after␣
  ↪combining below 1% as Others
```

```
/tmp/ipykernel_643/3940758133.py:2: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```



0.3 Feature Engineering + Modelling

[29]:
```
# Primary Features cps
feats = ['Issue Date', 'Issue time',
       'RP State Plate', 'Body Style',
       'Color', 'Agency', 'Violation code',
         "Route",'Fine amount', 'Latitude', 'Longitude']
out = ["popularMakeorNot"]
```

[30]:
```
X_train, X_test, y_train, y_test = train_test_split(df_train[feats],␣
 ↪df_train[out], test_size=0.33, random_state=42,stratify=df_train[out])
```

[31]:
```
# Categorical features
cat_cols = ['RP State Plate', 'Body Style', 'Color', 'Agency', 'Violation␣
 ↪code',"Route",
        'IssueHour', 'IssueWeek', 'IssueYear', 'IssueWeekDay', 'IssueDay']
```

[33]:
```
X_trainN = pre_process(X_train,cat_cols)
X_testN = pre_process(X_test,cat_cols)
```

[34]:
```
missing_num_vars = ["Latitude","Longitude","Fine amount"]
numeric_transformer = Pipeline(
    steps=[("imputer", SimpleImputer(strategy="median")), ("scaler",␣
 ↪StandardScaler())]
)

categorical_transformer =Pipeline(
    steps=[("imputer", SimpleImputer(strategy="most_frequent")), ("one-hot␣
 ↪encoder",
 OneHotEncoder(handle_unknown="ignore"))]
)


preprocessor = ColumnTransformer(
    transformers=[
        ("num", numeric_transformer, missing_num_vars),
        ("cat", categorical_transformer, cat_cols),
    ],remainder='passthrough'
)
```

[35]:
```
clf = Pipeline(
    steps=[("preprocessor", preprocessor), ("classifier",␣
 ↪RandomForestClassifier(random_state=42,max_depth=2,max_features=8,n_jobs=4,verbose=1))]
)
```

[36]:
```
%%time
clf.fit(X_trainN,y_train.values)
```

```
/opt/conda/lib/python3.9/site-packages/sklearn/pipeline.py:346:
DataConversionWarning:

A column-vector y was passed when a 1d array was expected. Please change the
shape of y to (n_samples,), for example using ravel().

[Parallel(n_jobs=4)]: Using backend ThreadingBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done  42 tasks      | elapsed:    9.3s

CPU times: user 1min 21s, sys: 8.42 s, total: 1min 29s
Wall time: 34.7 s

[Parallel(n_jobs=4)]: Done 100 out of 100 | elapsed:   19.9s finished
```

[36]:
```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('num',
                                                  Pipeline(steps=[('imputer',
SimpleImputer(strategy='median')),
                                                                  ('scaler',
```

```
StandardScaler())]),
                                                  ['Latitude', 'Longitude',
                                                   'Fine amount']),
                                                 ('cat',
                                                  Pipeline(steps=[('imputer',
SimpleImputer(strategy='most_frequent')),
                                                                  ('one-hot '
                                                                   'encoder',
OneHotEncoder(handle_unknown='ignore'))]),
                                                  ['RP State Plate',
                                                   'Body Style', 'Color',
                                                   'Agency', 'Violation code',
                                                   'Route', 'IssueHour',
                                                   'IssueWeek', 'IssueYear',
                                                   'IssueWeekDay',
                                                   'IssueDay'])])),
                ('classifier',
                 RandomForestClassifier(max_depth=2, max_features=8, n_jobs=4,
                                        random_state=42, verbose=1))])
```

[37]:

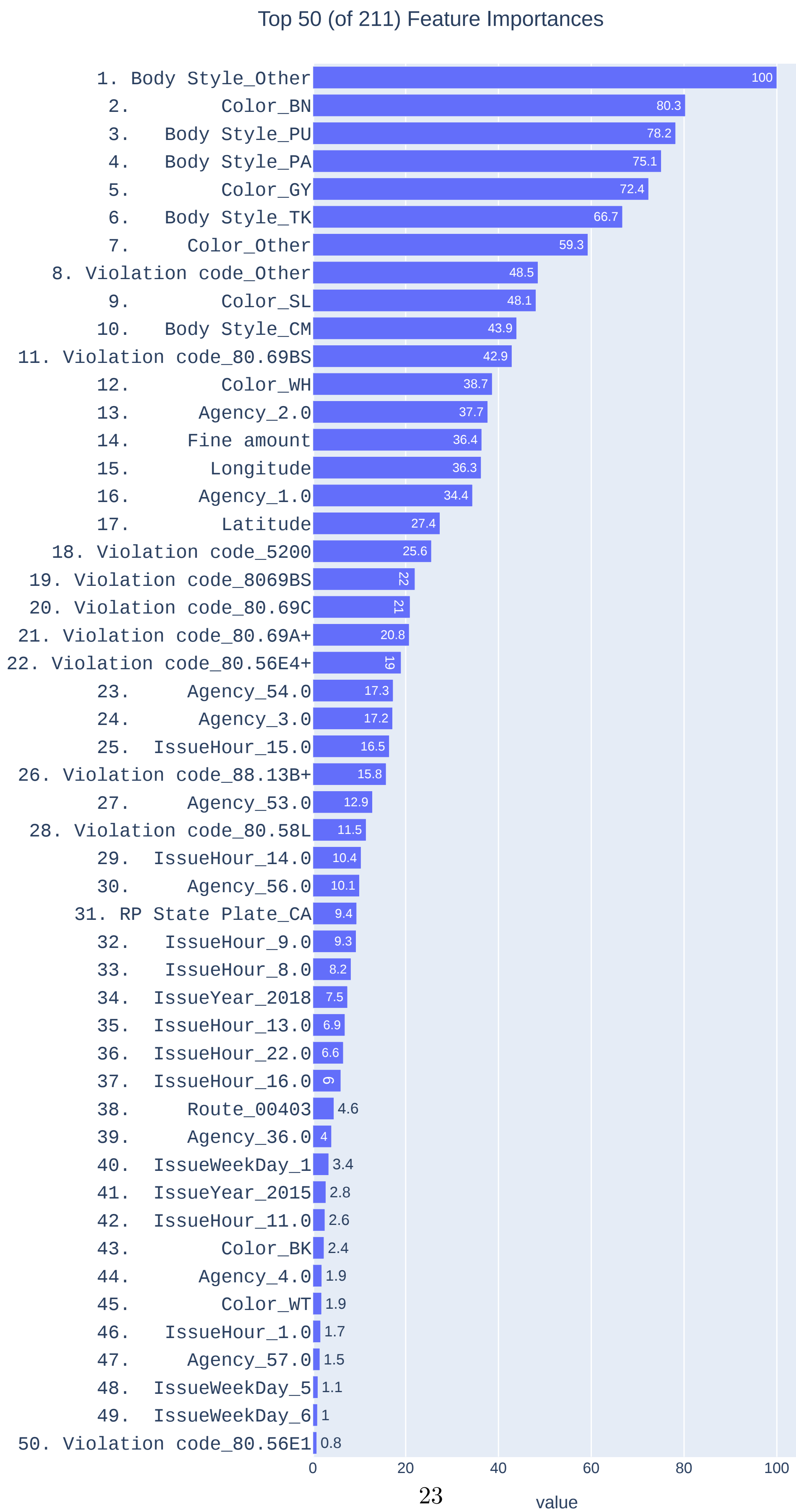
```
%%time

y_pred = clf.predict(X_trainN)
print(f"\n ######## Train set metrics ###### \n")
get_scores(y_train.values,y_pred)


y_pred = clf.predict(X_testN)
print(f"\n ######## Test set metrics ###### \n")
get_scores(y_test.values,y_pred)
```

```
[Parallel(n_jobs=4)]: Using backend ThreadingBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done  42 tasks      | elapsed:    1.9s
[Parallel(n_jobs=4)]: Done 100 out of 100 | elapsed:    4.2s finished


 ######## Train set metrics ######

Accuracy: 0.9147845869608852
F1 score: 0.9554960836746824
Recall: 1.0
Precision: 0.9147845869608852

[Parallel(n_jobs=4)]: Using backend ThreadingBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done  42 tasks      | elapsed:    0.8s
[Parallel(n_jobs=4)]: Done 100 out of 100 | elapsed:    1.8s finished


 ######## Test set metrics ######
```

```
Accuracy: 0.9147845256225704
F1 score: 0.9554960502149855
Recall: 1.0
Precision: 0.9147845256225704
CPU times: user 37.4 s, sys: 4.99 s, total: 42.4 s
Wall time: 24.8 s
```

0.4 Model Explanations + Strength/Weakness + Feasability

[38]:
```
feature_importance = FeatureImportance(clf)
feature_importance.plot(top_n_features=50)
```



Top 50 (of 211) Feature Importances
1. Body Style_Other
2. Color_BN
3. Body Style_PU
4. Body Style_PA
5. Color_GY
6. Body Style_TK
7. Color_Other
8. Violation code_Other
9. Color_SL
10. Body Style_CM
11. Violation code_80.69BS
12. Color_WH
13. Agency_2.0
14. Fine amount
15. Longitude
16. Agency_1.0
17. Latitude
18. Violation code_5200
19. Violation code_8069BS
20. Violation code_80.69C
21. Violation code_80.69A+
22. Violation code_80.56E4+
23. Agency_54.0
24. Agency_3.0
25. IssueHour_15.0
26. Violation code_88.13B+
27. Agency_53.0
28. Violation code_80.58L
29. IssueHour_14.0
30. Agency_56.0
31. RP State Plate_CA
32. IssueHour_9.0
33. IssueHour_8.0
34. IssueYear_2018
35. IssueHour_13.0
36. IssueHour_22.0
37. IssueHour_16.0
38. Route_00403
39. Agency_36.0
40. IssueWeekDay_1
41. IssueYear_2015
42. IssueHour_11.0
43. Color_BK
44. Agency_4.0
45. Color_WT
46. IssueHour_1.0
47. Agency_57.0
48. IssueWeekDay_5
49. IssueWeekDay_6
50. Violation code_80.56E1
100
80.3
78.2
75.1
72.4
66.7
59.3
48.5
48.1
43.9
42.9
38.7
37.7
36.4
36.3
34.4
27.4
25.6
22
21
20.8
19
17.3
17.2
16.5
15.8
12.9
11.5
10.4
10.1
9.4
9.3
8.2
7.5
6.9
6.6
6
4.6
4
3.4
2.8
2.6
2.4
1.9
1.9
1.7
1.5
1.1
1
0.8
0
20
40
60
80
100
value

It can be seen from feature importance how certain violation codes, body style and routes play a major role in determining whether a Make is popular or not whic makes sense inituitevly as well.

Also model accuracy+precision,recall metrics for training and test are almost same which indicates that there's not much overfitting in the model. Since we are using basic Random Forest model it can be deployed easily using the pickle file and nothing complicated.

We can say that for the task of predicitng popular make for corrupted data it should work pretty great since it works well for unseen test split we created. Furthermore, it has high precision as well as recall given we have high F-score. Although we would also say since data is imbalanced (1->90% and 0->10%) it is relatively easy to predict that make is popular so error should be low by default.

[39]:
```python
# Save model for making prediciton using server.py
pickle.dump(clf, open('model.pkl', 'wb'))
```