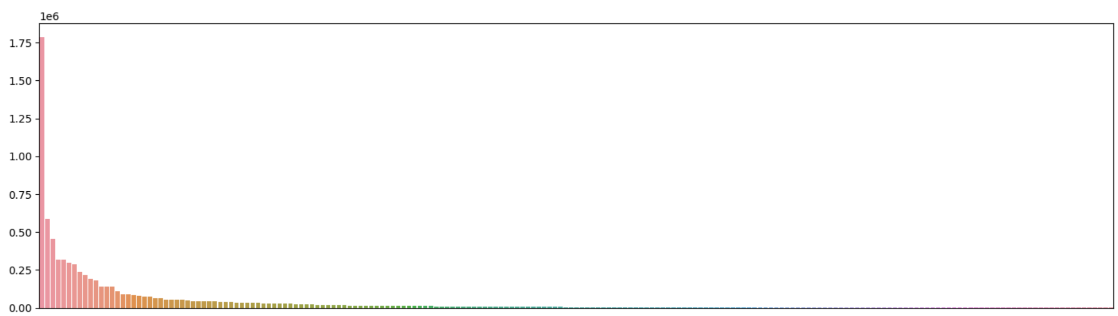
Data Preprocessing

```python
# Import the necessary libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Read the data
bids_df = pd.read_csv('bids.csv')
train_df = pd.read_csv('train.csv')
test_df = pd.read_csv('test.csv')# Count the number of bids from each
country
country_counts = bids_df['country'].value_counts()

# Create a bar plot to visualize the distribution of bids by country
fig, ax = plt.subplots(figsize=(18, 4.8))
countries_plot = sns.barplot(x=country_counts.index,
y=country_counts.values, ax=ax)

# Hide the x-axis labels to improve readability
ax.get_xaxis().set_visible(False)

# Display the plot
plt.show()
```




```python
bids_df.head()
```

```
   bid_id                              bidder_id auction merchandise
device  \
0       0  8dac2b259fd1c6d1120e519fb1ac14fbqvax8   ewmzr     jewelry
phone0
1       1  668d393e858e8126275433046bbd35c6tywop   aeqok   furniture
phone1
2       2  aa5f360084278b35d746fa6af3a7a1a5ra3xe   wa00e  home goods
phone2
3       3  3939ac3ef7d472a59a9c5f893dd3e39fh9ofi   jefix     jewelry
phone4
4       4  8393c48eaf4b8fa96886edc7cf27b372dsibi   jefix     jewelry
phone5
```

```
               time country               ip              url
0  9759243157894736      us    69.166.231.58  vasstdc27m7nks3
1  9759243157894736      in    50.201.125.84  jmqlhflrzwuay9c
2  9759243157894736      py  112.54.208.157  vasstdc27m7nks3
3  9759243157894736      in    18.99.175.133  vasstdc27m7nks3
4  9759243157894736      in     145.138.5.37  vasstdc27m7nks3
```

```
train_df.head()
```

```
                              bidder_id  \
0  91a3c57b13234af24875c56fb7e2b2f4rb56a
1  624f258b49e77713fc34034560f93fb3hu3jo
2  1c5f4fc669099bfbfac515cd26997bd12ruaj
3  4bee9aba2abda51bf43d639013d6efe12iycd
4  4ab12bc61c82ddd9c2d65e60555808acqgos1

                        payment_account  \
0  a3d2de7675556553a5f08e4c88d2c228754av
1  a3d2de7675556553a5f08e4c88d2c228v1sga
2  a3d2de7675556553a5f08e4c88d2c2280cybl
3  51d80e233f7b6a7dfdee484a3c120f3b2ita8
4  a3d2de7675556553a5f08e4c88d2c22857ddh

                                address  outcome
0  a3d2de7675556553a5f08e4c88d2c228vt0u4      0.0
1  ae87054e5a97a8f840a3991d12611fdcrfbq3      0.0
2  92520288b50f03907041887884ba49c0cl0pd      0.0
3  4cb9717c8ad7e88a9a284989dd79b98dbevyi      0.0
4  2a96c3ce94b3be921e0296097b88b56a7x1ji      0.0
```

```
bids_df.shape
```

```
(7656334, 9)
```

```
bids_df.isnull().sum()
```

```
bid_id            0
bidder_id         0
auction           0
merchandise       0
device            0
time              0
country        8859
ip                0
url               0
dtype: int64
```

```
missing_percent = bids_df['country'].isnull().mean()
print(f"Percentage of missing data in country column:
{missing_percent*100: .2f}%")
```

```
Percentage of missing data in country column:  0.12%
```

```
# Import additional libraries
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

# Count the number of bids from each country
country_counts = bids_df['country'].value_counts()

# Create a bar plot to visualize the distribution of bids by country
fig, ax = plt.subplots(figsize=(18, 4.8))

# Create a custom color map with a gradient
color_map = plt.get_cmap("Greens")
norm = plt.Normalize(country_counts.values.min(),
country_counts.values.max())

# Generate the bar plot using the custom gradient color
countries_plot = sns.barplot(x=country_counts.index,
y=country_counts.values, ax=ax,

palette=color_map(norm(country_counts.values)))

# Hide the x-axis labels to improve readability
ax.get_xaxis().set_visible(False)

# Add a title to the plot
plt.title("Distribution of Bids by Country")

# Display the plot
plt.show()
```


```
bids_df['country'] =
bids_df['country'].fillna(bids_df['country'].mode()[0])
```

Feature Engineering

```
# Sorting the bids DataFrame based on bidder_id and time
sorted_bids = bids_df.sort_values(['bidder_id', 'time'])
sorted_bids.head(15)
```

```
          bid_id                              bidder_id auction
merchandise  \
7179832  7179832  001068c415025a009fee375a12cff4fcnht8y   4ifac
jewelry
1281292  1281292  002d229ffb247009810828f648afc2ef593rb   2tdw2
mobile
1281311  1281311  002d229ffb247009810828f648afc2ef593rb   2tdw2
mobile
6805028  6805028  0030a2dd87ad2733e0873062e4f83954mkj86   obbny
mobile
3967330  3967330  003180b29c6a5f8f1d84a6b7b6f7be57tjj1o   obbny
mobile
6166636  6166636  003180b29c6a5f8f1d84a6b7b6f7be57tjj1o   cqsh6
mobile
7140567  7140567  003180b29c6a5f8f1d84a6b7b6f7be57tjj1o   efh5o
mobile
2597846  2597846  00486a11dff552c4bd7696265724ff81yeo9v   no958  home
goods
2599005  2599005  00486a11dff552c4bd7696265724ff81yeo9v   6plix  home
goods
2750709  2750709  00486a11dff552c4bd7696265724ff81yeo9v   gst86  home
goods
3062627  3062627  00486a11dff552c4bd7696265724ff81yeo9v   9ul86  home
goods
3302219  3302219  00486a11dff552c4bd7696265724ff81yeo9v   6plix  home
goods
3682352  3682352  00486a11dff552c4bd7696265724ff81yeo9v   no958  home
goods
3682395  3682395  00486a11dff552c4bd7696265724ff81yeo9v   lx0hm  home
goods
3786154  3786154  00486a11dff552c4bd7696265724ff81yeo9v   gst86  home
goods

           device              time country               ip
url
7179832  phone561  9706345052631578      bn  139.226.147.115
vasstdc27m7nks3
1281292  phone640  9766744105263157      sg    37.40.254.131
vasstdc27m7nks3
1281311  phone219  9766744210526315      sg    37.40.254.131
vasstdc27m7nks3
6805028  phone313  9704553947368421      ir     21.67.17.162
vnw40k8zzokijsv
3967330  phone420  9640018631578947      id     44.241.8.179
sj4jidex850loas
6166636  phone102  9700605052631578      id     190.88.89.83
sj4jidex850loas
7140567  phone257  9705974315789473      id   115.47.140.180
vasstdc27m7nks3
2597846    phone4  9632636526315789      ng   143.118.40.162
```

```
vasstdc27m7nks3
2599005    phone4  9632641157894736      ng   143.118.40.162
vasstdc27m7nks3
2750709   phone45  9633339684210526      ng   54.212.177.220
0wfuwlacucr1cdl
3062627   phone45  9635439947368421      ng    236.63.15.129
n01mdzlusu12kso
3302219  phone788  9636501894736842      ng  127.247.172.237
n01mdzlusu12kso
3682352   phone45  9637993315789473      ng    236.63.15.129
vasstdc27m7nks3
3682395   phone45  9637993684210526      ng    236.63.15.129
vasstdc27m7nks3
3786154    phone4  9638911421052631      ng   220.193.41.160
mm1kg05ew2b5wk6
```

```
# Calculating the time differences between consecutive bids for every
bidder
time_differences = sorted_bids.groupby('bidder_id')[['time']].diff()
time_differences.head(15)
```

```
                 time
7179832           NaN
1281292           NaN
1281311  1.052632e+08
6805028           NaN
3967330           NaN
6166636  6.058642e+13
7140567  5.369263e+12
2597846           NaN
2599005  4.631579e+09
2750709  6.985263e+11
3062627  2.100263e+12
3302219  1.061947e+12
3682352  1.491421e+12
3682395  3.684211e+08
3786154  9.177368e+11
```

```
# Adding the calculated time differences to the sorted_bids DataFrame
sorted_bids['time_difference'] = time_differences
time_diff_features = sorted_bids[['bidder_id',
'time_difference']].dropna()
time_diff_features.head()
```

```
                                     bidder_id  time_difference
1281311  002d229ffb247009810828f648afc2ef593rb     1.052632e+08
6166636  003180b29c6a5f8f1d84a6b7b6f7be57tjj1o     6.058642e+13
7140567  003180b29c6a5f8f1d84a6b7b6f7be57tjj1o     5.369263e+12
2599005  00486a11dff552c4bd7696265724ff81yeo9v     4.631579e+09
2750709  00486a11dff552c4bd7696265724ff81yeo9v     6.985263e+11
```

```python
# Grouping the bid intervals by bidder_id and computing descriptive
statistics
bid_stats = time_diff_features.groupby('bidder_id')
[['time_difference']].describe().reset_index()
bid_stats.columns = bid_stats.columns.droplevel(level=0)
bid_stats = bid_stats.rename(columns={'': 'bidder_id', 'mean':
'mean_time_diff', 'std': 'std_time_diff', '50%': 'median_time_diff',
'min': 'min_time_diff', 'max': 'max_time_diff'}).fillna(0)
bid_stats['iqr_time_diff'] = bid_stats['75%'] - bid_stats['25%']
bid_stats = bid_stats.drop(['25%', '75%', 'count'], axis=1)
bid_stats.head()
```

```
                               bidder_id  mean_time_diff
std_time_diff  \
0  002d229ffb247009810828f648afc2ef593rb    1.052632e+08
0.000000e+00
1  003180b29c6a5f8f1d84a6b7b6f7be57tjj1o    3.297784e+13
3.904443e+13
2  00486a11dff552c4bd7696265724ff81yeo9v    4.018413e+12
1.153730e+13
3  0051aef3fdeacdadba664b9b3b07e04e4coc6    1.635106e+11
5.770740e+11
4  0053b78cde37c4384a20d2da9aa4272aym4pb    7.065316e+09
4.784394e+11

   min_time_diff  median_time_diff  max_time_diff  iqr_time_diff
0   1.052632e+08      1.052632e+08   1.052632e+08   0.000000e+00
1   5.369263e+12      3.297784e+13   6.058642e+13   2.760858e+13
2   3.684211e+08      9.177368e+11   5.094174e+13   1.696763e+12
3   5.263158e+07      2.736842e+09   3.792368e+12   1.228947e+10
4   0.000000e+00      3.684211e+08   5.002753e+13   1.000000e+09
```

```python
import pandas as pd

# Load the bids dataset
bids_df = pd.read_csv('bids.csv')

# Compute bid statistics by bidder
bid_stats = bids_df.groupby('bidder_id')['bid_id'].agg(['count',
'mean', 'median'])

# Rename the 'mean' and 'median' columns in the bid_stats DataFrame to
avoid conflicts with existing column names in train_set
bid_stats = bid_stats.rename(columns={'mean': 'bid_mean', 'median':
'bid_median'})

# Merge the bid_stats DataFrame with train_set and test_set DataFrames
train_set = pd.merge(train_df, bid_stats, on='bidder_id', how='left')
train_set = train_set.fillna(train_df.median())
```

```python
test_set = pd.merge(test_df, bid_stats, on='bidder_id', how='left')
test_set = test_set.fillna(test_df.median())
```

```
C:\Users\egodd\AppData\Local\Temp\ipykernel_30568\2778142480.py:14:
FutureWarning: The default value of numeric_only in DataFrame.median
is deprecated. In a future version, it will default to False. In
addition, specifying 'numeric_only=None' is deprecated. Select only
valid columns or specify the value of numeric_only to silence this
warning.
  train_set = train_set.fillna(train_df.median())
C:\Users\egodd\AppData\Local\Temp\ipykernel_30568\2778142480.py:17:
FutureWarning: The default value of numeric_only in DataFrame.median
is deprecated. In a future version, it will default to False. In
addition, specifying 'numeric_only=None' is deprecated. Select only
valid columns or specify the value of numeric_only to silence this
warning.
  test_set = test_set.fillna(test_df.median())
```

```python
# Calculating the number of simultaneous bids (bids with a time
difference of 0)
simultaneous_bids =
time_diff_features[time_diff_features['time_difference'] ==
0].groupby('bidder_id').count().reset_index()
simultaneous_bids =
simultaneous_bids.rename(columns={'time_difference':
'num_simultaneous_bids'})
simultaneous_bids.head()
```

	bidder_id	num_simultaneous_bids
0	0053b78cde37c4384a20d2da9aa4272aym4pb	728
1	00a79ebd15f0b24a0a3b5794457cd8ed7dng1	29
2	00b519ec8ed5e370328451379bb708a306eoj	1
3	00e0f614d9dd32dd27f6080f472d2934emlos	15
4	019cf2d366df756c092c91e26f406acdozha7	1

```python
# Merging the simultaneous_bids DataFrame with train_set and test_set
DataFrames
train_set = train_set.merge(simultaneous_bids, on='bidder_id',
how='left').fillna(0)

test_set = test_set.merge(simultaneous_bids, on='bidder_id',
how='left').fillna(0)

# Total number of bids made by each
num_bids = bids_df.groupby('bidder_id')
['bid_id'].count().reset_index().rename(columns={'bid_id':
'num_bids'})
num_bids.head()

# Merging with train_set and test_set
train_set = train_set.merge(num_bids, on='bidder_id',
```

```
how='left').fillna(0)
test_set = test_set.merge(num_bids, on='bidder_id',
how='left').fillna(0)

# Count the number of auctions for each bidder
num_auct = bids_df.groupby('bidder_id')
['auction'].nunique().reset_index()
num_auct = num_auct.rename(columns={'auction': 'num_auct'})

# Merge the num_auct DataFrame with train_set and test_set
train_set = train_set.merge(num_auct, on='bidder_id', how='left')
test_set = test_set.merge(num_auct, on='bidder_id',
how='left').fillna(0)

# Count the number of unique device types for each bidder
num_device_type = bids_df.groupby('bidder_id')
['device'].nunique().reset_index()
num_device_type = num_device_type.rename(columns={'device':
'num_device_type'})

# Merge the num_device_type DataFrame with train_set and test_set
train_set = train_set.merge(num_device_type, on='bidder_id',
how='left')
test_set = test_set.merge(num_device_type, on='bidder_id',
how='left').fillna(0)

# Count the number of unique URLs for each bidder
num_url = bids_df.groupby('bidder_id')['url'].nunique().reset_index()
num_url = num_url.rename(columns={'url': 'num_url'})

# Merge the num_url DataFrame with train_set
train_set = train_set.merge(num_url, on='bidder_id', how='left')
test_set = test_set.merge(num_url, on='bidder_id', how='left')

# Total number of unique IPs and countries for each bidder_id
num_ip_ctry = bids_df.groupby('bidder_id')[['ip',
'country']].nunique().reset_index().rename(columns={'ip': 'num_ip',
'country': 'num_ctry'})

# Merging with train_set and test_set
train_set = train_set.merge(num_ip_ctry, on='bidder_id',
how='left').fillna(0)
test_set = test_set.merge(num_ip_ctry, on='bidder_id',
how='left').fillna(0)

# Maximum number of bids per device for each bidder_id
max_bids_per_device = bids_df.groupby(['bidder_id', 'device'])
['bid_id'].count().reset_index().groupby('bidder_id')
['bid_id'].max().reset_index().rename(columns={'bid_id':
'max_bids_per_device'})
```

```python
# Merging with train_set and test_set
train_set = train_set.merge(max_bids_per_device, on='bidder_id',
how='left').fillna(0)
test_set = test_set.merge(max_bids_per_device, on='bidder_id',
how='left').fillna(0)

# Sorting bids by auction and time, then counting the number of first
bids for each bidder
sorted_first_bids = bids_df.sort_values(['auction', 'time'])
first_bids =
sorted_first_bids.groupby('auction').first().reset_index()
first_bids_count = first_bids.groupby('bidder_id').count()
['bid_id'].reset_index()
first_bids_count = first_bids_count.rename(columns={'bid_id':
'num_first_bids'})
first_bids_count.head()
```

```
                               bidder_id  num_first_bids
0  0053b78cde37c4384a20d2da9aa4272aym4pb               4
1  00a79ebd15f0b24a0a3b5794457cd8ed7dng1               7
2  00e0f614d9dd32dd27f6080f472d2934emlos               6
3  019cf2d366df756c092c91e26f406acdozha7               2
4  01cda52665845500091395 0f20cf31a2q6nsf               8
```

```python
# Sorting bids by auction and time in descending order, then counting
the number of last bids for each bidder
sorted_last_bids = bids_df.sort_values(['auction', 'time'],
ascending=[True, False])
last_bids = sorted_last_bids.groupby('auction').first().reset_index()
last_bids_count = last_bids.groupby('bidder_id').count()
['bid_id'].reset_index()
last_bids_count = last_bids_count.rename(columns={'bid_id':
'num_last_bids'})
last_bids_count.head()
```

```
                               bidder_id  num_last_bids
0  0053b78cde37c4384a20d2da9aa4272aym4pb              6
1  00b519ec8ed5e370328451379bb708a306eoj              1
2  00e0f614d9dd32dd27f6080f472d2934emlos              3
3  01067975436d123f717ee5aba0dd4bbfa0937              1
4  0113d101ec6aabd354adac645a1ec3e82ln88              1
```

```python
# Check if 'bidder_id' exists in train_set dataframe
if 'bidder_id' in train_set.columns:
    # Merging the first_bids_count and last_bids_count DataFrames with
the train_set and test_set DataFrames
    train_set = train_set.merge(first_bids_count, on='bidder_id',
how='left').fillna(0)
    train_set = train_set.merge(last_bids_count, on='bidder_id',
how='left').fillna(0)
```

```
# Check if 'bidder_id' exists in test_set dataframe
if 'bidder_id' in test_set.columns:
    test_set = test_set.merge(first_bids_count, on='bidder_id',
how='left').fillna(0)
    test_set = test_set.merge(last_bids_count, on='bidder_id',
how='left').fillna(0)

# Calculate auction duration
auct_duration = bids_df.sort_values(['auction', 'time'])[['bidder_id',
'auction', 'time']]
auct_duration =
auct_duration[['auction','time']].groupby('auction').agg([max,min]).re
set_index().droplevel(axis=1, level=0).rename(columns={'': 'auction'})
auct_duration['auct_duration'] = auct_duration['max'] -
auct_duration['min']
auct_duration.head()
```

```
  auction                max                min    auct_duration
0   00270  9709212894736842  9699049894736842  10163000000000
1   008vv  9760397157894736  9759369421052631   1027736842105
2   00cwr  9698636578947368  9695641631578947   2994947368421
3   00do0  9759865210526315  9759323842105263    541368421052
4   00hjy  9772723842105263  9759410368421052  13313473684211
```

```
# Calculate bid ratios in the first and second half of auctions
time_ratio = bids_df.sort_values(['auction', 'time'])[['bidder_id',
'auction', 'time']]
time_ratio = time_ratio.merge(auct_duration, on='auction', how='left')
time_ratio['temp'] = time_ratio['time'] - time_ratio['auct_duration']
/ 2
time_ratio['firsthalf'] = time_ratio['temp'] < time_ratio['min']

# Aggregate bid ratios
ratio_firsthalf = time_ratio[['bidder_id',
'firsthalf']].groupby('bidder_id').agg(['count',
sum]).reset_index().droplevel(axis=1, level=0).rename(columns={'':
'bidder_id', 'count': 'num_total_bids', 'sum': 'num_firsthalf_bids'})
ratio_firsthalf['num_secondhalf_bids'] =
ratio_firsthalf['num_total_bids'] -
ratio_firsthalf['num_firsthalf_bids']

print(train_set.columns)
```

```
Index(['bidder_id', 'payment_account', 'address', 'outcome', 'count',
       'bid_mean', 'bid_median', 'num_simultaneous_bids', 'num_bids',
       'num_auct', 'num_device_type', 'num_url', 'num_ip', 'num_ctry',
       'max_bids_per_device', 'num_first_bids', 'num_last_bids'],
      dtype='object')
```

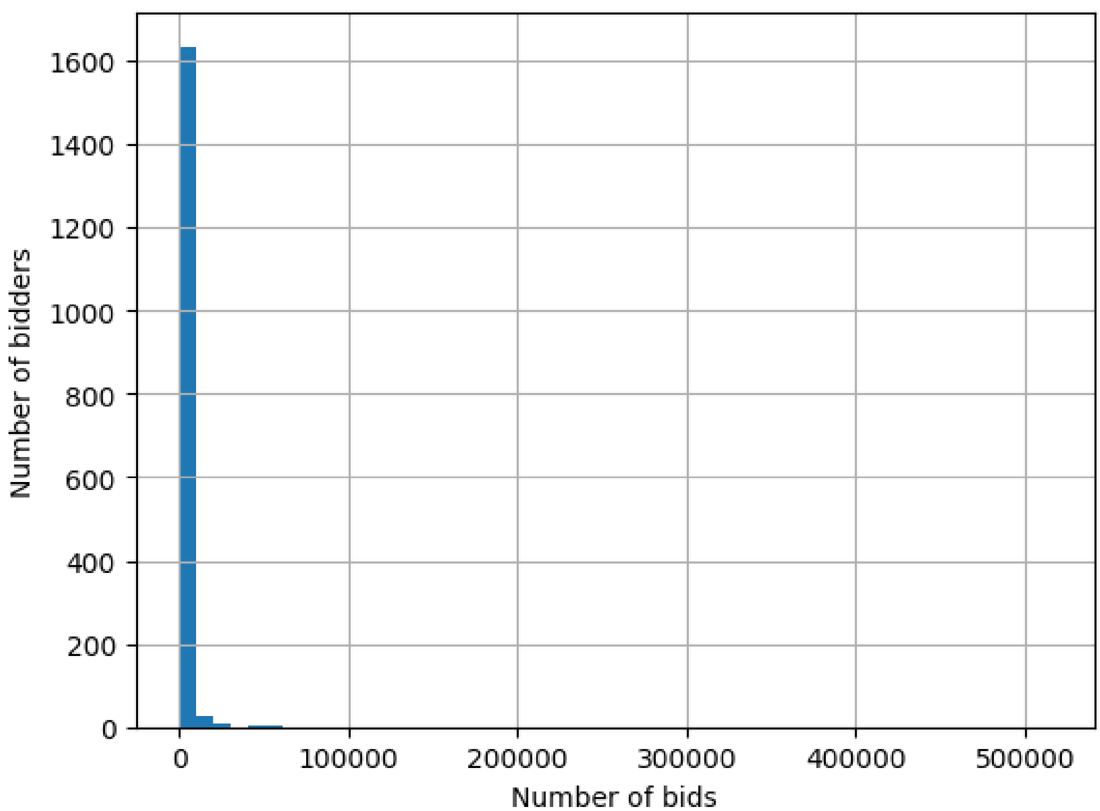
```
# Calculate various ratios and percentages for train_set
if 'num_simultaneous_bids' not in train_set.columns:
    print("Missing 'num_simultaneous_bids' column in train_set.")
```

```
else:
    train_set['percent_simultaneous_bids'] =
train_set['num_simultaneous_bids'] / train_set['num_bids']
if 'num_bids' not in train_set.columns:
    print("Missing 'num_bids' column in train_set.")
else:
    train_set['bids_per_auct'] = train_set['num_bids'] /
train_set['num_auct']
    train_set['bids_per_device'] = train_set['num_bids'] /
train_set['num_device_type']
    train_set['bids_per_url'] = train_set['num_bids'] /
train_set['num_url']
if 'num_auct' not in train_set.columns:
    print("Missing 'num_auct' column in train_set.")
else:
    train_set['device_per_auct'] = train_set['num_device_type'] /
train_set['num_auct']
if 'num_ip' not in train_set.columns or 'num_ctry' not in
train_set.columns:
    print("Missing 'num_ip' or 'num_ctry' columns in train_set.")
else:
    train_set['ip_per_ctry'] = train_set['num_ip'] /
train_set['num_ctry']
if 'max_bids_per_device' not in train_set.columns:
    print("Missing 'max_bids_per_device' column in train_set.")
else:
    train_set['percent_max_bids'] = train_set['max_bids_per_device'] /
train_set['num_bids']

# Fill any NaN values with 0 for train_set
train_set = train_set.fillna(0)

# Calculate various ratios and percentages for test_set
if 'num_simultaneous_bids' not in test_set.columns:
    print("Missing 'num_simultaneous_bids' column in test_set.")
else:
    test_set['percent_simultaneous_bids'] =
test_set['num_simultaneous_bids'] / test_set['num_bids']

if 'num_bids' not in test_set.columns:
    print("Missing 'num_bids' column in test_set.")
else:
    test_set['bids_per_auct'] = test_set['num_bids'] /
test_set['num_auct']
    test_set['bids_per_device'] = test_set['num_bids'] /
test_set['num_device_type']
    test_set['bids_per_url'] = test_set['num_bids'] /
test_set['num_url']

if 'num_auct' not in test_set.columns:
    print("Missing 'num_auct' column in test_set.")
```

```
else:
    test_set['device_per_auct'] = test_set['num_device_type'] /
test_set['num_auct']

if 'num_ip' not in test_set.columns or 'num_ctry' not in
test_set.columns:
    print("Missing 'num_ip' or 'num_ctry' columns in test_set.")
else:
    test_set['ip_per_ctry'] = test_set['num_ip'] /
test_set['num_ctry']

if 'max_bids_per_device' not in test_set.columns:
    print("Missing 'max_bids_per_device' column in test_set.")
else:
    test_set['percent_max_bids'] = test_set['max_bids_per_device'] /
test_set['num_bids']

# Fill any NaN values with 0 for test_set
test_set = test_set.fillna(0)

import pandas as pd
import matplotlib.pyplot as plt

# Load data
bids = pd.read_csv('bids.csv')

# Identify outliers with only one bid
num_bids = bids.groupby('bidder_id')
['bid_id'].count().reset_index(name='num_bids')
outliers = num_bids[num_bids['num_bids'] == 1]

# Print outliers
print('Outliers:')
print(outliers)

# Remove outliers
bids = bids[~bids['bidder_id'].isin(outliers['bidder_id'])]

# Load train data
train = pd.read_csv('train.csv')
train = train.rename(columns={'outcome': 'bot'})

# Merge bids with train to get outcome for each bidder
bids_with_outcome = bids.merge(train[['bidder_id', 'bot']],
on='bidder_id')

# Aggregate number of bids per bidder with outcome
num_bids_with_outcome = bids_with_outcome.groupby('bidder_id')
['bid_id'].count().reset_index(name='num_bids')
```

```python
# Plot histogram
fig, ax = plt.subplots()
num_bids_with_outcome['num_bids'].hist(ax=ax, bins=50)
ax.set_xlabel('Number of bids')
ax.set_ylabel('Number of bidders')
plt.show()
```

```
Outliers:
                                   bidder_id  num_bids
0     001068c415025a009fee375a12cff4fcnht8y         1
2     0030a2dd87ad2733e0873062e4f83954mkj86         1
9     009479273c288b1dd096dc3087653499lrx3c         1
16    00dd948c3a88f7b68f1952dbeeac68ffb6qoc         1
27    0176025cc599cb59f825d592b8ef3ee3p5aqv         1
...                                     ...       ...
6587  fecea7c93f6fc416ab1165267723b0bewb7le         1
6596  ff375d34745157a44e3ba3de0f30dd1bhypuh         1
6600  ff5069626488d0409be146cff3f1f2eak2n7a         1
6611  ffd29eb307a4c54610dd2d3d212bf3bagmmpl         1
6613  fff2c070d8200e0a09150bd81452ce29ngcnv         1

[1057 rows x 2 columns]
```




```python
import pandas as pd
```

```python
# Read in the bids and train data
bids = pd.read_csv('bids.csv')
train = pd.read_csv('train.csv')

# Identify the bots and humans
bots = train[train['outcome'] == 1]['bidder_id']
humans = train[train['outcome'] == 0]['bidder_id']

# Filter the bids for bots and humans
bot_bids = bids[bids['bidder_id'].isin(bots)]
human_bids = bids[bids['bidder_id'].isin(humans)]

# Count the occurrences of each merchandise category for bots and
humans
bot_merchandise_counts = bot_bids['merchandise'].value_counts()
human_merchandise_counts = human_bids['merchandise'].value_counts()

# Print the merchandise counts for bots and humans
print("Merchandise counts for bots:\n", bot_merchandise_counts)
print("Merchandise counts for humans:\n", human_merchandise_counts)

# Investigate the merchandise feature
print(bids['merchandise'].value_counts())
```

```
Merchandise counts for bots:
 sporting goods      230326
mobile              105138
jewelry              37101
home goods           18708
computers            11667
office equipment      7967
books and music       1509
Name: merchandise, dtype: int64
Merchandise counts for humans:
 sporting goods      939398
jewelry             555634
mobile              492350
home goods          389249
office equipment    160671
furniture            87807
books and music      13733
auto parts            9757
computers             9733
clothing               476
Name: merchandise, dtype: int64
mobile              2126587
jewelry             1902058
sporting goods      1855207
home goods          1224234
office equipment     289838
```

```
furniture             99181
computers             81084
books and music       51941
clothing              16447
auto parts             9757
Name: merchandise, dtype: int64
```

```
# Load data
train = pd.read_csv('train.csv')
bids = pd.read_csv('bids.csv')

# Merge bids with train to get outcome for each bidder
bids_with_outcome = bids.merge(train[['bidder_id', 'outcome']],
on='bidder_id')

# Get the top 3 merchandises bidded by humans and bots
top_merchandises = bids_with_outcome.groupby(['merchandise',
'outcome'])['bid_id'].count().reset_index(name='count')
top_merchandises = top_merchandises.pivot(index='merchandise',
columns='outcome', values='count').fillna(0)
top_merchandises['total'] = top_merchandises.sum(axis=1)
top_merchandises = top_merchandises.sort_values('total',
ascending=False).head(3)

print(top_merchandises)
```

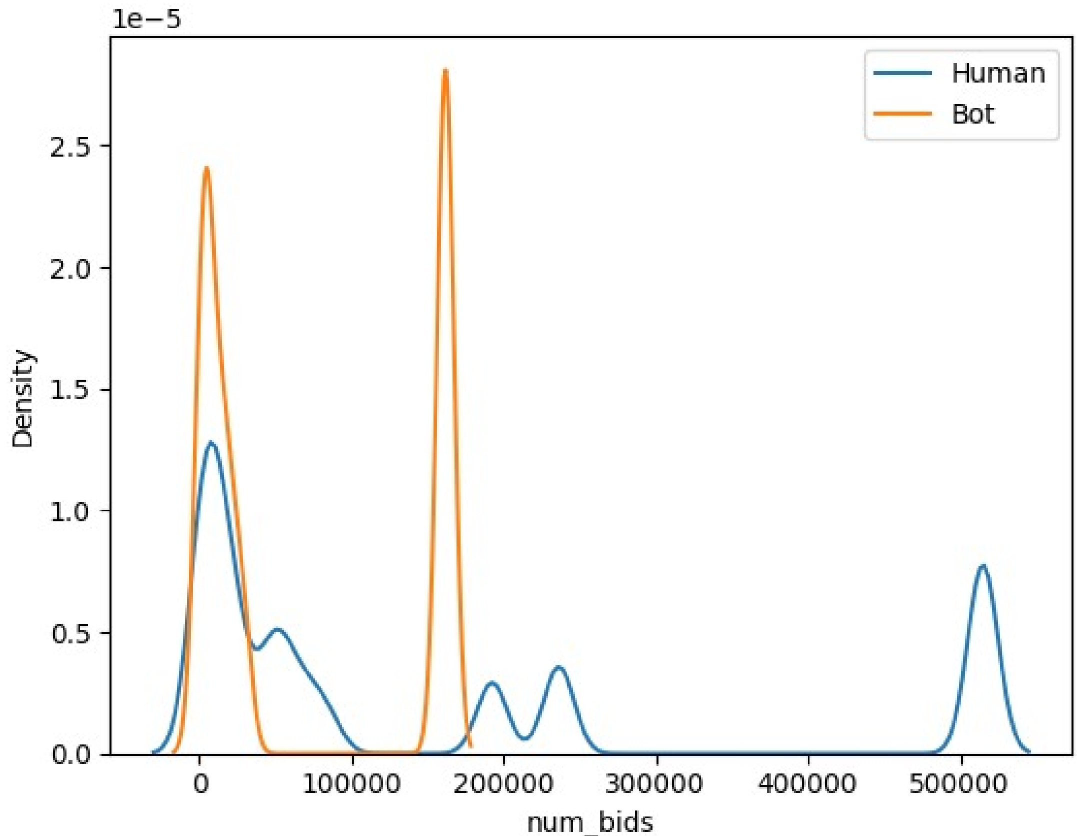
```
outcome              0.0       1.0      total
merchandise
sporting goods  939398.0  230326.0  1169724.0
mobile          492350.0  105138.0   597488.0
jewelry         555634.0   37101.0   592735.0
```

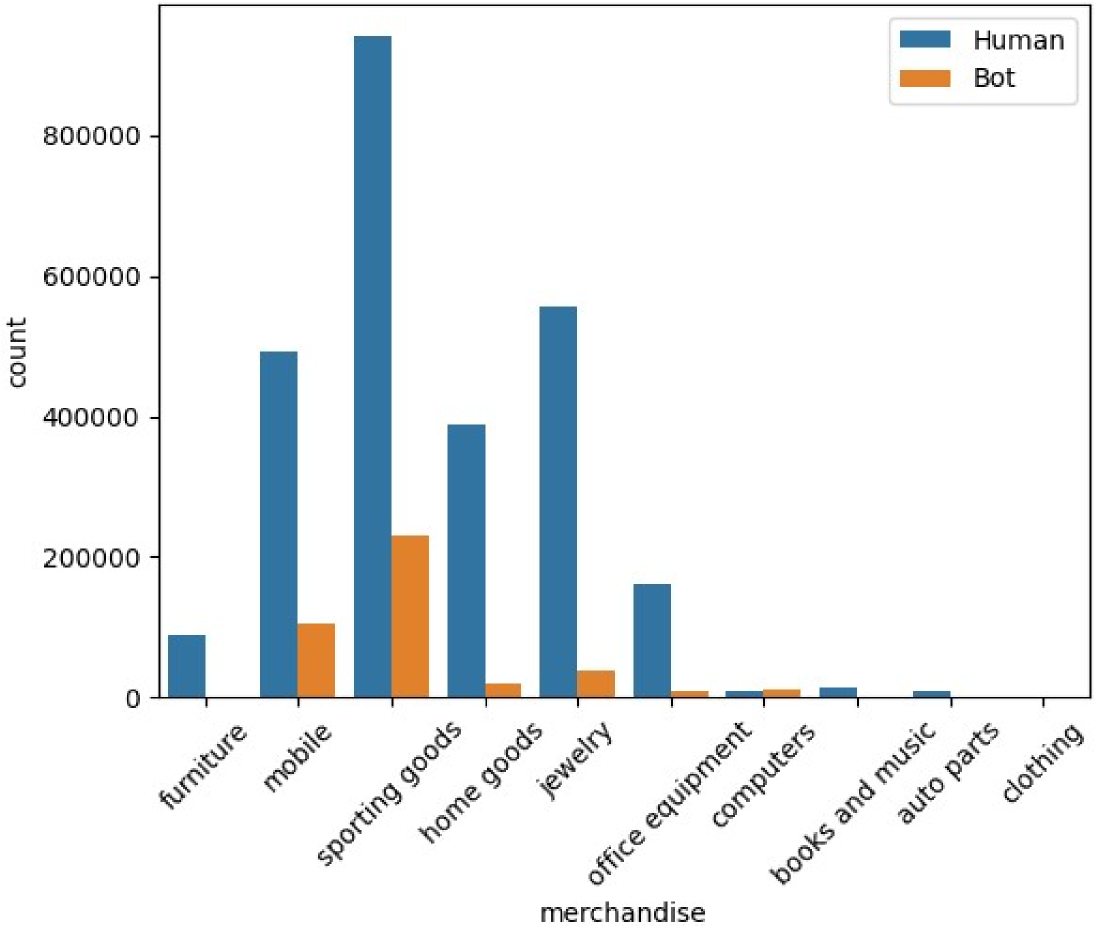
```
# Compute the number of bids for each bidder
num_bids_per_bidder = bids.groupby('bidder_id')
['bid_id'].count().reset_index(name='num_bids')

# Merge with the bids_with_outcome
bids_with_outcome = bids_with_outcome.merge(num_bids_per_bidder,
on='bidder_id', how='left').fillna(0)

print(bids.columns)
```

```
Index(['bid_id', 'bidder_id', 'auction', 'merchandise', 'device',
'time',
       'country', 'ip', 'url'],
      dtype='object')
```

```
# Select features to plot
features = ['num_bids', 'merchandise']

# Generate density plots for each feature
```

```
# Generate density plot for num_bids
plt.figure()
sns.kdeplot(bids_with_outcome.loc[bids_with_outcome['outcome'] == 0,
'num_bids'], label='Human')
sns.kdeplot(bids_with_outcome.loc[bids_with_outcome['outcome'] == 1,
'num_bids'], label='Bot')
plt.xlabel('num_bids')
plt.legend()
plt.show()

# Generate count plot for merchandise
plt.figure()
sns.countplot(data=bids_with_outcome, x='merchandise', hue='outcome')
plt.xlabel('merchandise')
plt.legend(['Human', 'Bot'])
plt.xticks(rotation=45)
plt.show()
```





Model Validation

```
print(train.columns)

Index(['bidder_id', 'payment_account', 'address', 'outcome'],
dtype='object')

import numpy as np
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import RandomOverSampler
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV,
RepeatedStratifiedKFold
from sklearn.metrics import classification_report, accuracy_score
from imblearn.pipeline import make_pipeline

# Create RandomOverSampler object to oversample minority class
oversampler = RandomOverSampler()

# Create a DataFrame containing only the features
features = train_set[['count', 'bid_mean', 'bid_median',
```

```
'num_simultaneous_bids', 'num_bids',
                      'num_auct', 'num_device_type', 'num_url',
'num_ip', 'num_ctry',
                      'max_bids_per_device', 'num_first_bids',
'num_last_bids',
                      'percent_simultaneous_bids', 'bids_per_auct',
'bids_per_device',
                      'bids_per_url', 'device_per_auct',
'ip_per_ctry', 'percent_max_bids']]

# Replace infinite values with NaN
features = features.replace([np.inf, -np.inf], np.nan)

# Fill missing values with median of respective columns
features_filled = features.fillna(features.median())

# Create a Series containing the target variable ('outcome' column)
target = train_set['outcome']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(features_filled,
target, test_size=0.3, random_state=42)

# Oversample the training data
X_train_resampled, y_train_resampled =
oversampler.fit_resample(X_train, y_train)

# Define a function to perform hyperparameter tuning for a single
Random Forest model
def tune_model(X, y):
    # Define parameter grid for GridSearchCV
    param_grid = {'n_estimators': [50, 100, 150], 'max_depth': [5, 10,
15], 'min_samples_split': [2, 5, 10], 'min_samples_leaf': [1, 2, 4]}
    # Create RandomForestClassifier object
    rf = RandomForestClassifier(random_state=42)
    # Create GridSearchCV object
    grid_search = GridSearchCV(rf, param_grid, cv=5,
scoring='accuracy')
    # Fit GridSearchCV object to data
    grid_search.fit(X, y)
    # Print best hyperparameters and corresponding accuracy score
    print('Best hyperparameters:', grid_search.best_params_)
    print('Accuracy:', grid_search.best_score_)

# Perform hyperparameter tuning for each model
for i in range(5):
    # Set different random_state for each model
    random_state = 42 + i
    # Create RandomForestClassifier object with given random_state
```

```
    rf = RandomForestClassifier(random_state=random_state)
    # Train the model on the oversampled training data
    rf.fit(X_train_resampled, y_train_resampled)
    # Make predictions on the testing data
    y_pred = rf.predict(X_test)
    # Print classification report and accuracy score
    print('Model', i+1, 'Classification Report:')
    print(classification_report(y_test, y_pred))
    print('Model', i+1, 'Accuracy Score:', accuracy_score(y_test,
y_pred))
    # Perform hyperparameter tuning for the model
    tune_model(X_train_resampled, y_train_resampled)
```

```
Model 1 Classification Report:
              precision    recall  f1-score   support

         0.0       0.97      0.99      0.98       577
         1.0       0.60      0.33      0.43        27

    accuracy                           0.96       604
   macro avg       0.78      0.66      0.70       604
weighted avg       0.95      0.96      0.95       604

Model 1 Accuracy Score: 0.9602649006622517
Best hyperparameters: {'max_depth': 15, 'min_samples_leaf': 1,
'min_samples_split': 5, 'n_estimators': 100}
Accuracy: 0.9872490531301163
Model 2 Classification Report:
              precision    recall  f1-score   support

         0.0       0.97      0.99      0.98       577
         1.0       0.56      0.33      0.42        27

    accuracy                           0.96       604
   macro avg       0.77      0.66      0.70       604
weighted avg       0.95      0.96      0.95       604

Model 2 Accuracy Score: 0.9586092715231788
Best hyperparameters: {'max_depth': 15, 'min_samples_leaf': 1,
'min_samples_split': 5, 'n_estimators': 100}
Accuracy: 0.9872490531301163
Model 3 Classification Report:
              precision    recall  f1-score   support

         0.0       0.97      0.99      0.98       577
         1.0       0.56      0.33      0.42        27

    accuracy                           0.96       604
   macro avg       0.77      0.66      0.70       604
weighted avg       0.95      0.96      0.95       604
```

```
Model 3 Accuracy Score: 0.9586092715231788
Best hyperparameters: {'max_depth': 15, 'min_samples_leaf': 1,
'min_samples_split': 5, 'n_estimators': 100}
Accuracy: 0.9872490531301163
Model 4 Classification Report:
              precision    recall  f1-score   support

         0.0       0.97      0.99      0.98       577
         1.0       0.54      0.26      0.35        27

    accuracy                           0.96       604
   macro avg       0.75      0.62      0.66       604
weighted avg       0.95      0.96      0.95       604

Model 4 Accuracy Score: 0.956953642384106
Best hyperparameters: {'max_depth': 15, 'min_samples_leaf': 1,
'min_samples_split': 5, 'n_estimators': 100}
Accuracy: 0.9872490531301163
Model 5 Classification Report:
              precision    recall  f1-score   support

         0.0       0.97      0.99      0.98       577
         1.0       0.54      0.26      0.35        27

    accuracy                           0.96       604
   macro avg       0.75      0.62      0.66       604
weighted avg       0.95      0.96      0.95       604

Model 5 Accuracy Score: 0.956953642384106
Best hyperparameters: {'max_depth': 15, 'min_samples_leaf': 1,
'min_samples_split': 5, 'n_estimators': 100}
Accuracy: 0.9872490531301163
```

```python
import numpy as np

# Load data
bids = pd.read_csv('bids.csv')

# Remove outliers
outliers =
bids.groupby('bidder_id').size().reset_index(name='num_bids')
outliers = outliers[outliers['num_bids'] == 1]['bidder_id']
bids = bids[~bids['bidder_id'].isin(outliers)]

# Use train_set DataFrame
train = train_set

# Replace infinite values with NaN
```

```
train = train.replace([np.inf, -np.inf], np.nan)

# Fill missing values with the mean
train = train.fillna(train.mean())

# Define features
features = ['count', 'bid_mean', 'bid_median',
'num_simultaneous_bids', 'num_bids',
            'num_auct', 'num_device_type', 'num_url', 'num_ip',
'num_ctry',
            'max_bids_per_device', 'num_first_bids', 'num_last_bids',
            'percent_simultaneous_bids', 'bids_per_auct',
'bids_per_device',
            'bids_per_url', 'device_per_auct', 'ip_per_ctry',
'percent_max_bids']

# Separate features and target
X = train[features]
y = train['outcome']

# Perform over-sampling
ros = RandomOverSampler(random_state=42)
X_resampled, y_resampled = ros.fit_resample(X, y)

# Initialize base models
rf1 = RandomForestClassifier(random_state=1)
rf2 = RandomForestClassifier(random_state=2)
rf3 = RandomForestClassifier(random_state=3)

# Calculate AUC for each base model
for model in [rf1, rf2, rf3]:
    model.fit(X_resampled, y_resampled)
    y_pred = model.predict_proba(X)[:, 1]
    auc = roc_auc_score(y, y_pred)
    print(f"AUC for model with random state {model.random_state}:
{auc}")
```

```
C:\Users\egodd\AppData\Local\Temp\ipykernel_30568\797303328.py:18:
FutureWarning: The default value of numeric_only in DataFrame.mean is
deprecated. In a future version, it will default to False. In
addition, specifying 'numeric_only=None' is deprecated. Select only
valid columns or specify the value of numeric_only to silence this
warning.
  train = train.fillna(train.mean())

AUC for model with random state 1: 1.0
AUC for model with random state 2: 1.0
AUC for model with random state 3: 1.0
```

```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc_auc_score

# Initialize the model
rfc = RandomForestClassifier(random_state=42)

# Fit the model on the training data
rfc.fit(X_train_resampled, y_train_resampled)

# Predict the probabilities of class 1 (bot)
y_pred_prob = rfc.predict_proba(X_test)[:, 1]

# Compute the AUC score
auc_score = roc_auc_score(y_test, y_pred_prob)
print("AUC score:", auc_score)
```

```
AUC score: 0.8899159124462417
```

```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc_auc_score

# Initialize the models with different random states
rfc1 = RandomForestClassifier(random_state=42)
rfc2 = RandomForestClassifier(random_state=10)
rfc3 = RandomForestClassifier(random_state=123)

# Fit the models on the training data
rfc1.fit(X_train_resampled, y_train_resampled)
rfc2.fit(X_train_resampled, y_train_resampled)
rfc3.fit(X_train_resampled, y_train_resampled)

# Predict the probabilities of class 1 (bot) for each model
y_pred_prob1 = rfc1.predict_proba(X_test)[:, 1]
y_pred_prob2 = rfc2.predict_proba(X_test)[:, 1]
y_pred_prob3 = rfc3.predict_proba(X_test)[:, 1]

# Ensemble averaging by taking the mean of the probabilities
y_pred_prob = (y_pred_prob1 + y_pred_prob2 + y_pred_prob3) / 3

# Compute the AUC score
auc_score = roc_auc_score(y_test, y_pred_prob)
print("AUC score:", auc_score)
```

```
AUC score: 0.8878297708453687
```

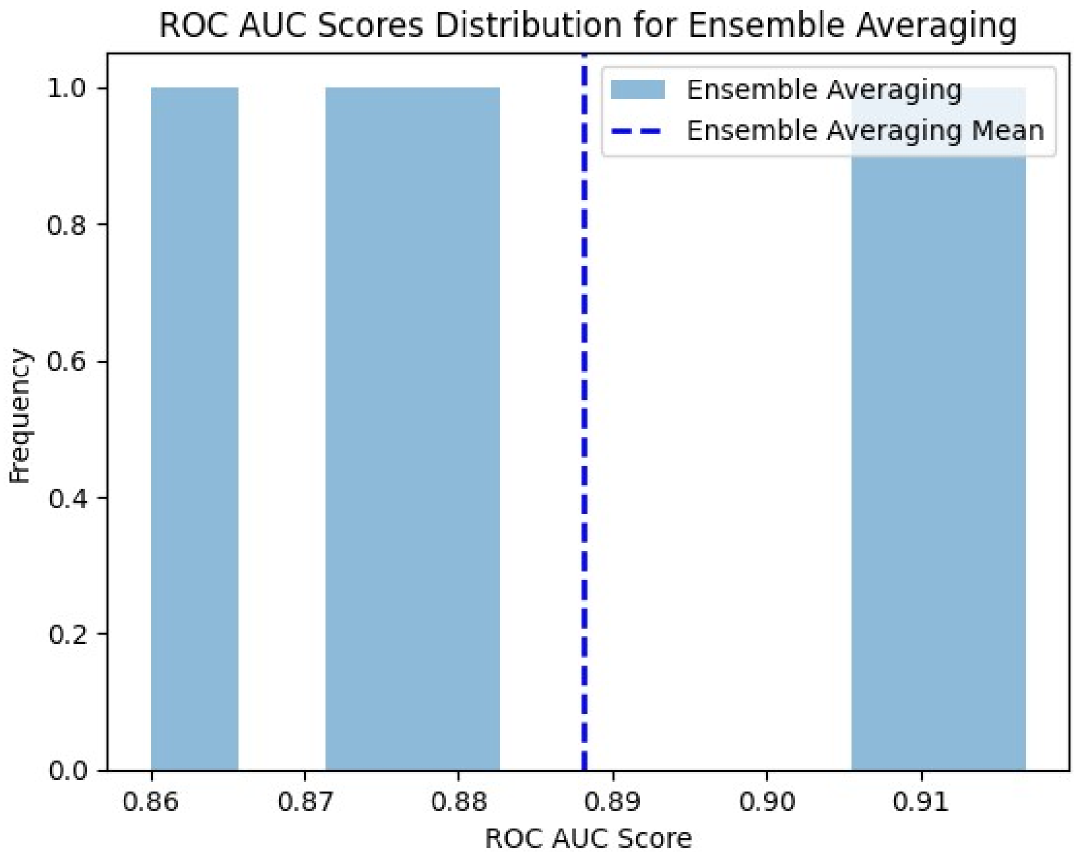
```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import GridSearchCV

# Initialize the model
```

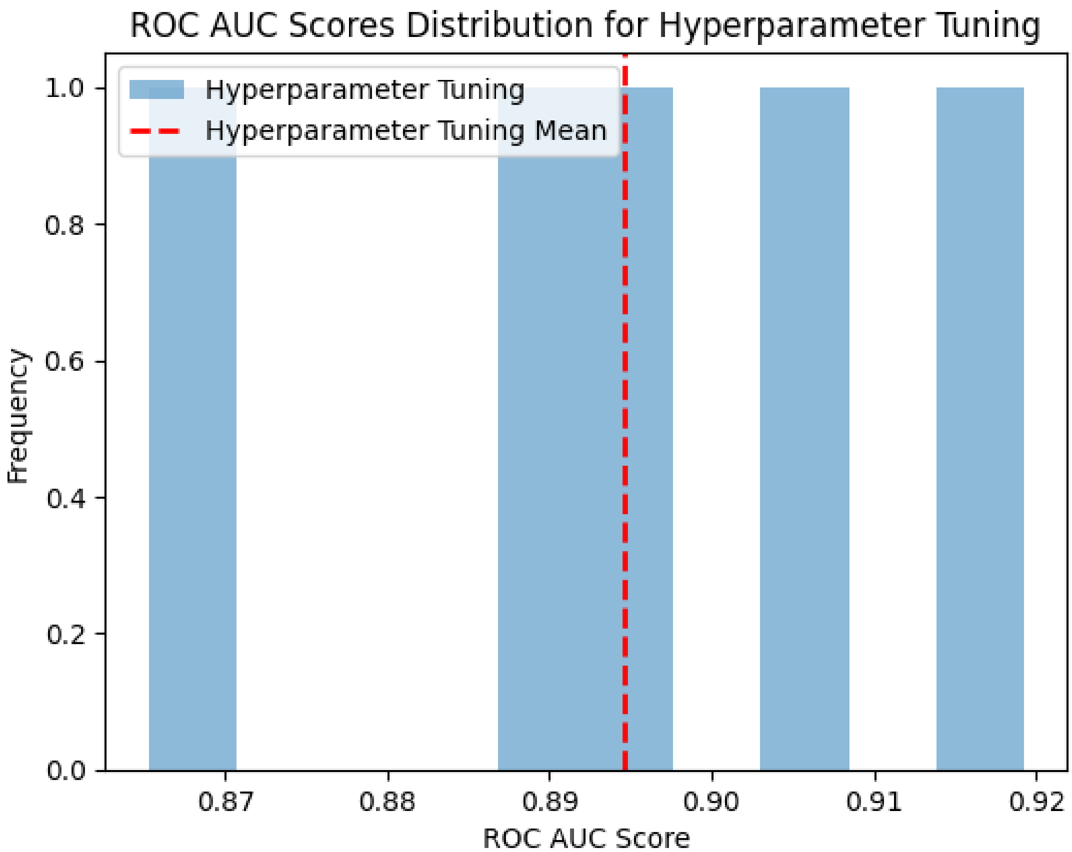
```
rfc = RandomForestClassifier(random_state=42)

# Define the hyperparameter grid
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [5, 10, 15],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 5]
}

# Initialize GridSearchCV with 5-fold cross-validation
grid_search = GridSearchCV(rfc, param_grid, cv=5, scoring='roc_auc')

# Fit GridSearchCV on the training data
grid_search.fit(X_train_resampled, y_train_resampled)

# Print the best hyperparameters and AUC score
print("Best hyperparameters:", grid_search.best_params_)
print("AUC score:", grid_search.best_score_)
```

```
Best hyperparameters: {'max_depth': 15, 'min_samples_leaf': 1,
'min_samples_split': 2, 'n_estimators': 50}
AUC score: 1.0
```

```
import numpy as np
from sklearn.model_selection import StratifiedKFold

# Initialize StratifiedKFold with 5 splits
skf = StratifiedKFold(n_splits=5, random_state=42, shuffle=True)

# Create empty lists to store the ensemble_scores and
grid_search_scores
ensemble_scores = []
grid_search_scores = []

# Loop through the splits created by StratifiedKFold
for train_index, test_index in skf.split(X, y):
    X_train, X_test = X.iloc[train_index], X.iloc[test_index]
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]

    # Perform over-sampling
    X_train_resampled, y_train_resampled = ros.fit_resample(X_train,
y_train)

    # Ensemble averaging
    rfc1.fit(X_train_resampled, y_train_resampled)
    rfc2.fit(X_train_resampled, y_train_resampled)
    rfc3.fit(X_train_resampled, y_train_resampled)

    y_pred_prob1 = rfc1.predict_proba(X_test)[:, 1]
```

```
    y_pred_prob2 = rfc2.predict_proba(X_test)[:, 1]
    y_pred_prob3 = rfc3.predict_proba(X_test)[:, 1]

    y_pred_prob = (y_pred_prob1 + y_pred_prob2 + y_pred_prob3) / 3
    ensemble_auc_score = roc_auc_score(y_test, y_pred_prob)
    ensemble_scores.append(ensemble_auc_score)

    # Hyperparameter tuning
    grid_search.fit(X_train_resampled, y_train_resampled)
    best_model = grid_search.best_estimator_
    y_pred_prob = best_model.predict_proba(X_test)[:, 1]
    grid_search_auc_score = roc_auc_score(y_test, y_pred_prob)
    grid_search_scores.append(grid_search_auc_score)

# Plot ROC AUC score distribution for ensemble averaging
plt.hist(ensemble_scores, alpha=0.5, label='Ensemble Averaging')
plt.axvline(x=np.mean(ensemble_scores), color='b', linestyle='dashed',
linewidth=2, label='Ensemble Averaging Mean')
plt.title('ROC AUC Scores Distribution for Ensemble Averaging')
plt.xlabel('ROC AUC Score')
plt.ylabel('Frequency')
plt.legend()
plt.show()

# Plot ROC AUC score distribution for hyperparameter tuning
plt.hist(grid_search_scores, alpha=0.5, label='Hyperparameter Tuning')
plt.axvline(x=np.mean(grid_search_scores), color='r',
linestyle='dashed', linewidth=2, label='Hyperparameter Tuning Mean')
plt.title('ROC AUC Scores Distribution for Hyperparameter Tuning')
plt.xlabel('ROC AUC Score')
plt.ylabel('Frequency')
plt.legend()
plt.show()
```


ROC AUC Scores Distribution for Ensemble Averaging
Ensemble Averaging
Ensemble Averaging Mean
Frequency
1.0
0.8
0.6
0.4
0.2
0.0
0.86
0.87
0.88
0.89
0.90
0.91
ROC AUC Score



Final Model

```
# Define the final models
final_models = [RandomForestClassifier(n_estimators=100, max_depth=8,
random_state=42),
                RandomForestClassifier(n_estimators=200, max_depth=10,
random_state=123),
                RandomForestClassifier(n_estimators=300, max_depth=12,
random_state=456)]

# Fit the models and store their predictions on the test set
proba = []
for model in final_models:
    model.fit(X_resampled, y_resampled)
    proba_rforest = model.predict_proba(X_test)[:,1]
    proba.append(proba_rforest)

# Average the predictions of the models
result = np.mean(proba, axis = 0)

# Create the output dataframe and save it to a CSV file
output_dataframe = pd.DataFrame({
    'bidder_id': test_set['bidder_id'].iloc[:len(result)],
    'prediction': result
```

```
})
output_dataframe.to_csv('my_predictions.csv', index=False)
```