County level population by race ethicity 2010-2019

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Overview of Problem Statement

The population by race and ethicity census data of 2010-2019 of 'US' is a collection of population of different ethnic groups like the white population, Asian population, Native American population, and so on. By predicting the major ethnic group or race population, we can identify which population of people contributes more to the country in various aspects.

Objective

To figure out major ethnic group predictions using machine learning techniques.

Data Description

Source:

County level population by race ethnicity 2010-2019

Features:

(1).fips:- State and county FIPS code,
(2).stfips:- State FIPS code,
(3).cofips:- County FIPS code,
(4).state_abbrev:- Stae abbrevation,
(5).state:- State name,
(6).county:- County name,
(7).year:- Year,
(8).pop:- Total population(all races),
(9).white_pop:- White population,
(10).black_pop:- Black population,
(11).asian_pop:- Asian population,
(12).indian_pop:- Naive American or Alaska native population,
(13).pacific_pop:- Native Hawaiian or other Pacific islander Population,
(14).two_pop:- Tow or more races population,
(15).not_hisp_pop:- Non-Hispanic population (independent of race),
(16).hisp_pop:- Hispanic population(independent of race)

Data Collection

In [6]:
```
# importing library
import numpy as np
import pandas as pd
```

In [7]:
```
# Reading downloded Dataset from loacl directory
data = pd.read_csv('US_county_census_est_race_eth_2010_2019.csv')
# Converging Data to panda DataFrame
df = pd.DataFrame(data)
```

In [8]:
```
## For result and title printing, create a custom definition.
def print_title(title):
    print(f'\n{'-'*60}\n\033[1m{title}\033[0m')
def print_section(title):
    print(f'{'-'*60}\n{title}\n{'-'*60}')
```

In [9]:
```
df.head(3)
```

Out[9]:

	FIPS	STFIPS	COFIPS	state_abbrev	state	county	year	pop	white_pop	black_pop	asian_pop	indian
0	1001	1	1	AL	Alabama	Autauga	2010	54571	43297	9689	484	
1	1001	1	1	AL	Alabama	Autauga	2011	55227	43699	9883	514	
2	1001	1	1	AL	Alabama	Autauga	2012	54954	43315	9949	552	

In [10]:
```
df.tail(3)
```

Out[10]:

	FIPS	STFIPS	COFIPS	state_abbrev	state	county	year	pop	white_pop	black_pop	asian_pop	ir
31407	56045	56	45	WY	Wyoming	Weston	2017	6968	6558	44	97	
31408	56045	56	45	WY	Wyoming	Weston	2018	6924	6474	47	109	
31409	56045	56	45	WY	Wyoming	Weston	2019	6927	6454	48	117	

Data Preprocessing - Data Cleaing

In [12]:
```
df1 = pd.DataFrame(df)
print_section(f'Since column "state_abbrev" and "state" columns are same, \ndorping "sta
df1 = df1.drop("state_abbrev", axis=1)
print_section("DataFrame after dropping the column")
df1.head(3)
```

```
------------------------------------------------------------
Since column "state_abbrev" and "state" columns are same,
dorping "state_abbrev" columns and creating df1 the from datafrme
------------------------------------------------------------
------------------------------------------------------------
DataFrame after dropping the column
------------------------------------------------------------
```

Out[12]:

	FIPS	STFIPS	COFIPS	state	county	year	pop	white_pop	black_pop	asian_pop	indian_pop	pacific_p
0	1001	1	1	Alabama	Autauga	2010	54571	43297	9689	484	258	
1	1001	1	1	Alabama	Autauga	2011	55227	43699	9883	514	261	
2	1001	1	1	Alabama	Autauga	2012	54954	43315	9949	552	275	

In [13]:
```
# data frme information
```

```python
print_title("DataFrame Information")
print_section(df1.info())
```

```
-------------------------------------------------------------
DataFrame Information
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 31410 entries, 0 to 31409
Data columns (total 15 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   FIPS          31410 non-null  int64
 1   STFIPS        31410 non-null  int64
 2   COFIPS        31410 non-null  int64
 3   state         31410 non-null  object
 4   county        31410 non-null  object
 5   year          31410 non-null  int64
 6   pop           31410 non-null  int64
 7   white_pop     31410 non-null  int64
 8   black_pop     31410 non-null  int64
 9   asian_pop     31410 non-null  int64
 10  indian_pop    31410 non-null  int64
 11  pacific_pop   31410 non-null  int64
 12  two_pop       31410 non-null  int64
 13  not_hisp_pop  31410 non-null  int64
 14  hisp_pop      31410 non-null  int64
dtypes: int64(13), object(2)
memory usage: 3.6+ MB
-------------------------------------------------------------
None
-------------------------------------------------------------
```

In [14]:

```python
# Data frame Description
print_title("DataFrame Description")
print_section(df1.describe())
```

```
-------------------------------------------------------------
DataFrame Description
-------------------------------------------------------------
               FIPS        STFIPS        COFIPS          year           pop  \
count  31410.000000  31410.000000  31410.000000  31410.000000  3.141000e+04
mean   30389.820121     30.286215    103.605540   2014.500000  1.014097e+05
std    15158.803727     15.140671    107.690218      2.872327  3.251245e+05
min     1001.000000      1.000000      1.000000   2010.000000  8.200000e+01
25%    18179.000000     18.000000     35.000000   2012.000000  1.098500e+04
50%    29177.000000     29.000000     79.000000   2014.500000  2.573350e+04
75%    45081.000000     45.000000    133.000000   2017.000000  6.741675e+04
max    56045.000000     56.000000    840.000000   2019.000000  1.010571e+07

          white_pop     black_pop     asian_pop     indian_pop   pacific_pop  \
count  3.141000e+04  3.141000e+04  3.141000e+04   31410.000000  31410.000000
mean   7.844218e+04  1.335439e+04  5.543686e+03    1264.135371    236.176313
std    2.333952e+05  5.778493e+04  4.089464e+04    5203.210936   2150.884073
min    2.400000e+01  0.000000e+00  0.000000e+00       0.000000      0.000000
25%    9.105000e+03  1.170000e+02  4.700000e+01      64.000000      4.000000
50%    2.217200e+04  8.400000e+02  1.560000e+02     179.000000     14.000000
75%    5.846450e+04  5.697750e+03  7.750000e+02     618.750000     60.000000
max    7.181207e+06  1.311698e+06  1.545445e+06  146005.000000  95285.000000

            two_pop  not_hisp_pop      hisp_pop
count  31410.000000  3.141000e+04  3.141000e+04
mean    2569.121999  8.370397e+04  1.770571e+04
std    10265.356718  2.222491e+05  1.228180e+05
min        0.000000  6.400000e+01  0.000000e+00
25%      156.000000  9.944500e+03  3.240000e+02
50%      392.000000  2.386300e+04  1.015500e+03
75%     1348.750000  6.290925e+04  4.764500e+03
```

```
max    315568.000000  5.211947e+06  4.899383e+06
------------------------------------------------------------
```

In [15]:
```python
# Finding null value for each features
print_title("Null values in DataFrame")
print_section(df1.isnull().sum())
```

```
------------------------------------------------------------
Null values in DataFrame
------------------------------------------------------------
FIPS            0
STFIPS          0
COFIPS          0
state           0
county          0
year            0
pop             0
white_pop       0
black_pop       0
asian_pop       0
indian_pop      0
pacific_pop     0
two_pop         0
not_hisp_pop    0
hisp_pop        0
dtype: int64
------------------------------------------------------------
```

In [16]:
```python
# Features data type
print_title("Data Types of Dataframe Varible columns")
print_section(df1.dtypes)
```

```
------------------------------------------------------------
Data Types of Dataframe Varible columns
------------------------------------------------------------
FIPS             int64
STFIPS           int64
COFIPS           int64
state           object
county          object
year             int64
pop              int64
white_pop        int64
black_pop        int64
asian_pop        int64
indian_pop       int64
pacific_pop      int64
two_pop          int64
not_hisp_pop     int64
hisp_pop         int64
dtype: object
------------------------------------------------------------
```

In [17]:
```python
# Finding Duplicated valus
print_section(f"Duplicated values: {df1.duplicated().sum()}")
```

```
------------------------------------------------------------
Duplicated values: 0
------------------------------------------------------------
```

Outlier Removel

In [19]:
```python
# Creating custom definition to remove outliers using IQR method
def outliers(data):
    for col in data.select_dtypes(include=['int64','float64']).columns:
        Q1 = data[col].quantile(0.25)
```

```
        Q3 = data[col].quantile(0.75)
        IQR = Q3 - Q1

        lower = Q1 - (1.5*IQR)
        upper = Q3 + (1.5*IQR)

        # Capping
        data[col] = data[col].apply(lambda x: lower if x < lower else upper if x > upper

    return data
```

In [20]:

```
df2 = pd.DataFrame(df1) # data frame after outlier remove
outliers(df2)
```

Out[20]:

	FIPS	STFIPS	COFIPS	state	county	year	pop	white_pop	black_pop	asian_pop	indian_pop
0	1001	1	1.0	Alabama	Autauga	2010	54571.0	43297.0	9689.0	484.0	258.0
1	1001	1	1.0	Alabama	Autauga	2011	55227.0	43699.0	9883.0	514.0	261.0
2	1001	1	1.0	Alabama	Autauga	2012	54954.0	43315.0	9949.0	552.0	275.0
3	1001	1	1.0	Alabama	Autauga	2013	54727.0	42943.0	9984.0	561.0	279.0
4	1001	1	1.0	Alabama	Autauga	2014	54893.0	42945.0	10103.0	573.0	279.0
...	...	...	...	...	...	...	...	...	...	...	...
31405	56045	56	45.0	Wyoming	Weston	2015	7208.0	6835.0	39.0	81.0	107.0
31406	56045	56	45.0	Wyoming	Weston	2016	7220.0	6826.0	38.0	88.0	108.0
31407	56045	56	45.0	Wyoming	Weston	2017	6968.0	6558.0	44.0	97.0	114.0
31408	56045	56	45.0	Wyoming	Weston	2018	6924.0	6474.0	47.0	109.0	125.0
31409	56045	56	45.0	Wyoming	Weston	2019	6927.0	6454.0	48.0	117.0	131.0

31410 rows × 15 columns

Skewness

In [22]:

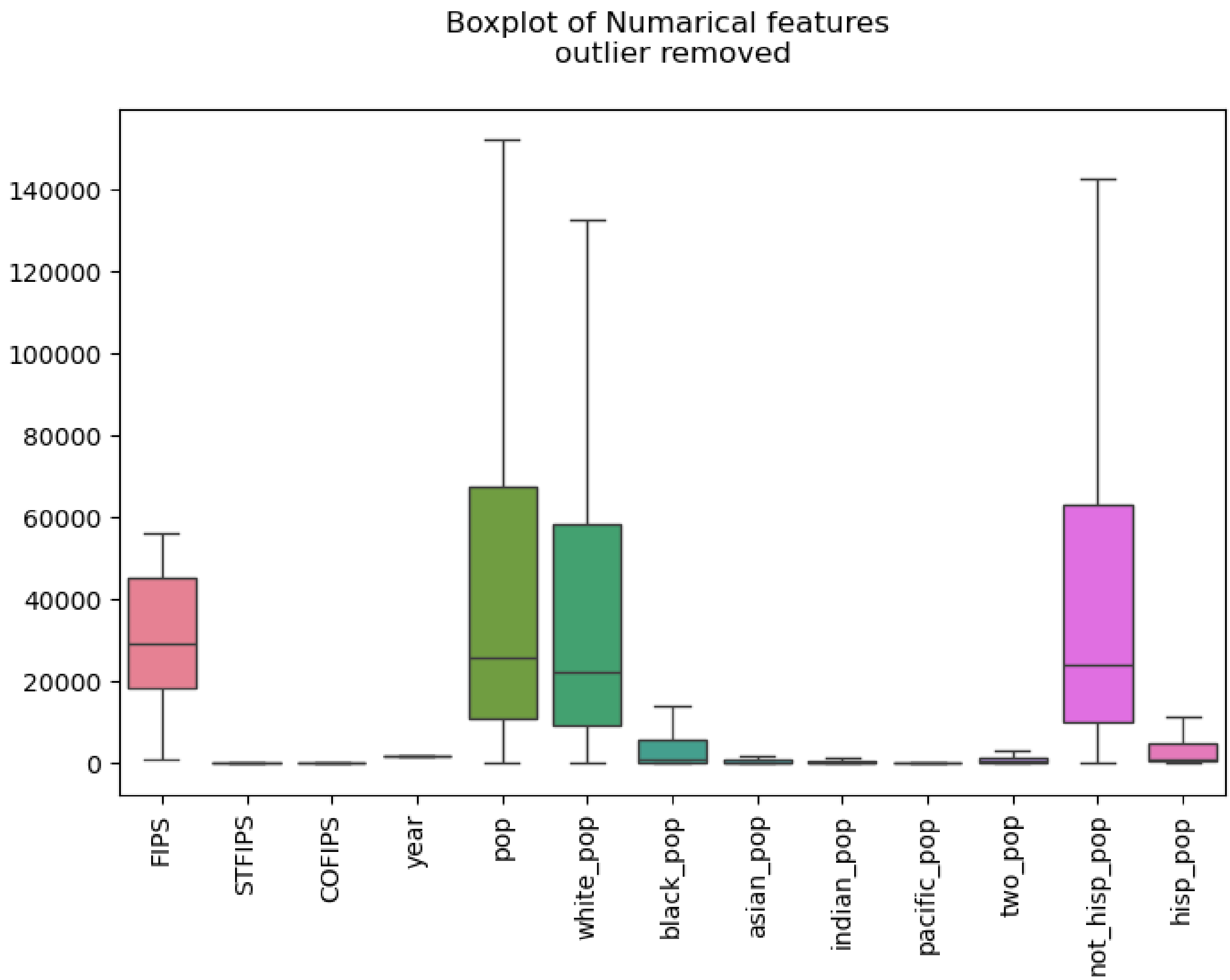
```
skewness = df2.select_dtypes(include = ['int64','float64']).skew()
print_section("\033[1mSkewness of numerical Features \033[0m")
print_section(skewness)
```

```
------------------------------------------------------------
Skewness of numerical Features
------------------------------------------------------------
------------------------------------------------------------
FIPS            -0.080233
STFIPS          -0.082250
COFIPS           0.968919
year             0.000000
pop              1.148729
white_pop        1.164347
black_pop        1.221158
asian_pop        1.203443
indian_pop       1.158144
pacific_pop      1.198770
two_pop          1.190157
not_hisp_pop     1.168889
hisp_pop         1.208730
dtype: float64
------------------------------------------------------------
```

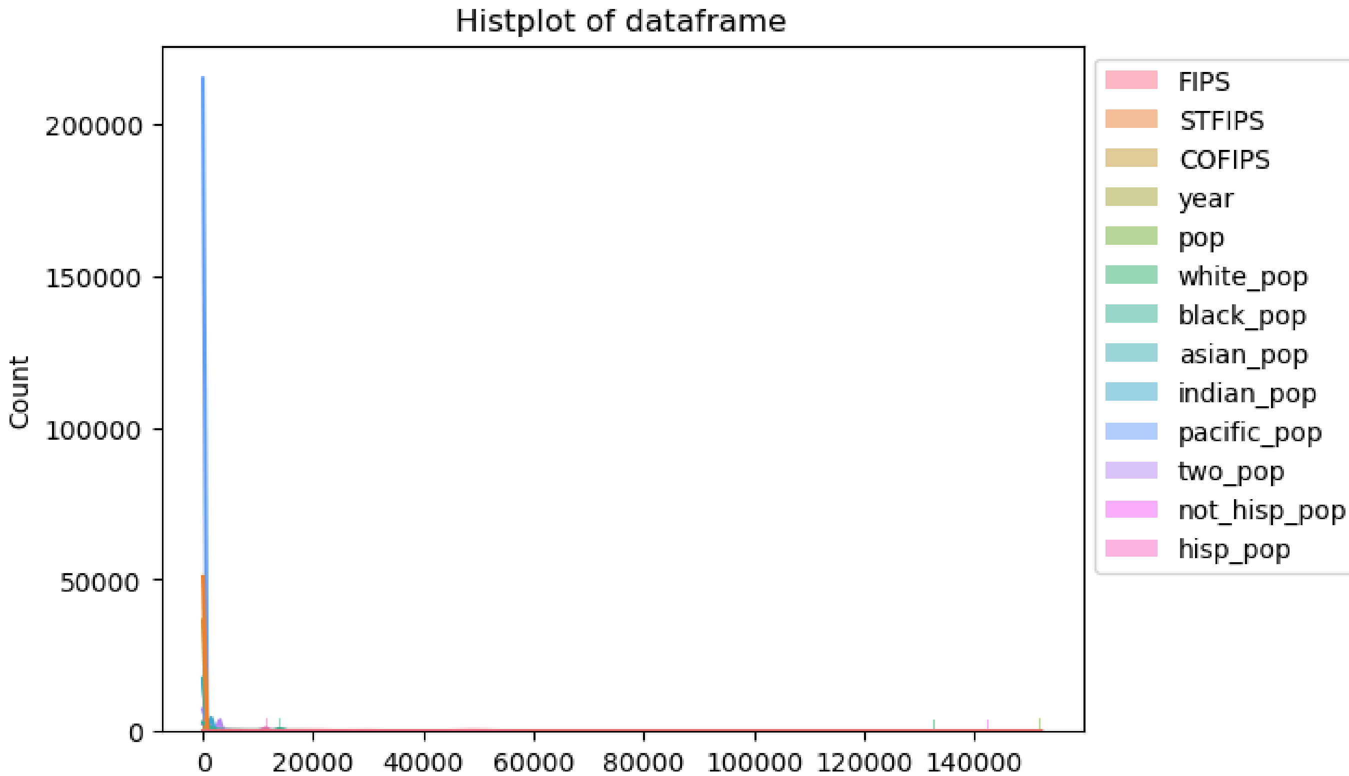
Exploratory Data analysis (EDA)

In [24]:
```
# Importing the plotting library
import matplotlib.pyplot as plt
import seaborn as sns
```

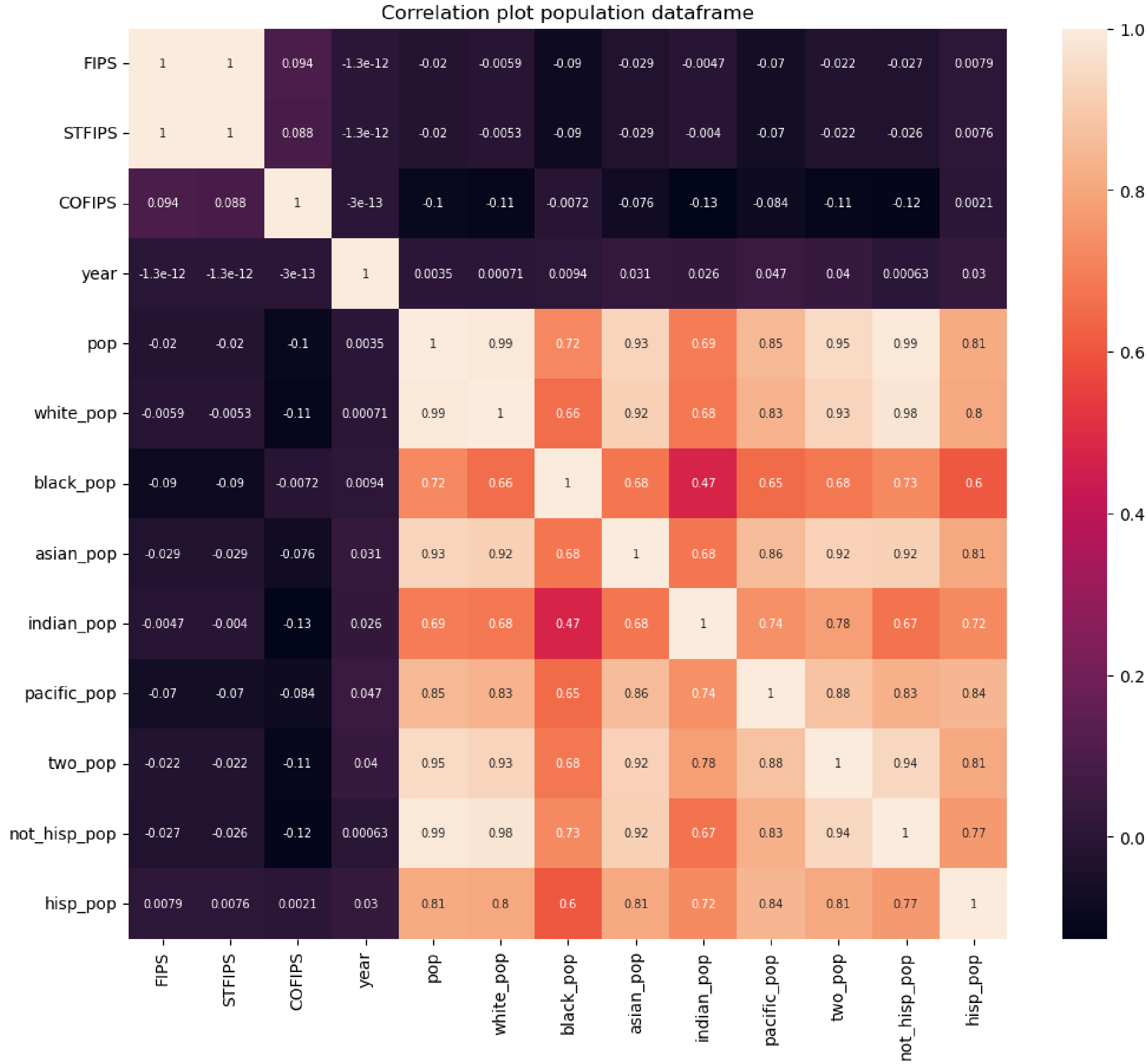
In [25]:
```
plt.figure(figsize=(8,5))
sns.boxplot(data=df2)
plt.title(f'''Boxplot of Numarical features
outlier removed
''')
plt.xticks(rotation = 90)
plt.show()
```



In [26]:
```
ax=sns.histplot(df2,kde=True,linewidth=0,legend=True)
plt.title('Histplot of dataframe')
sns.move_legend(ax, "upper left", bbox_to_anchor=(1, 1))
plt.show()
```

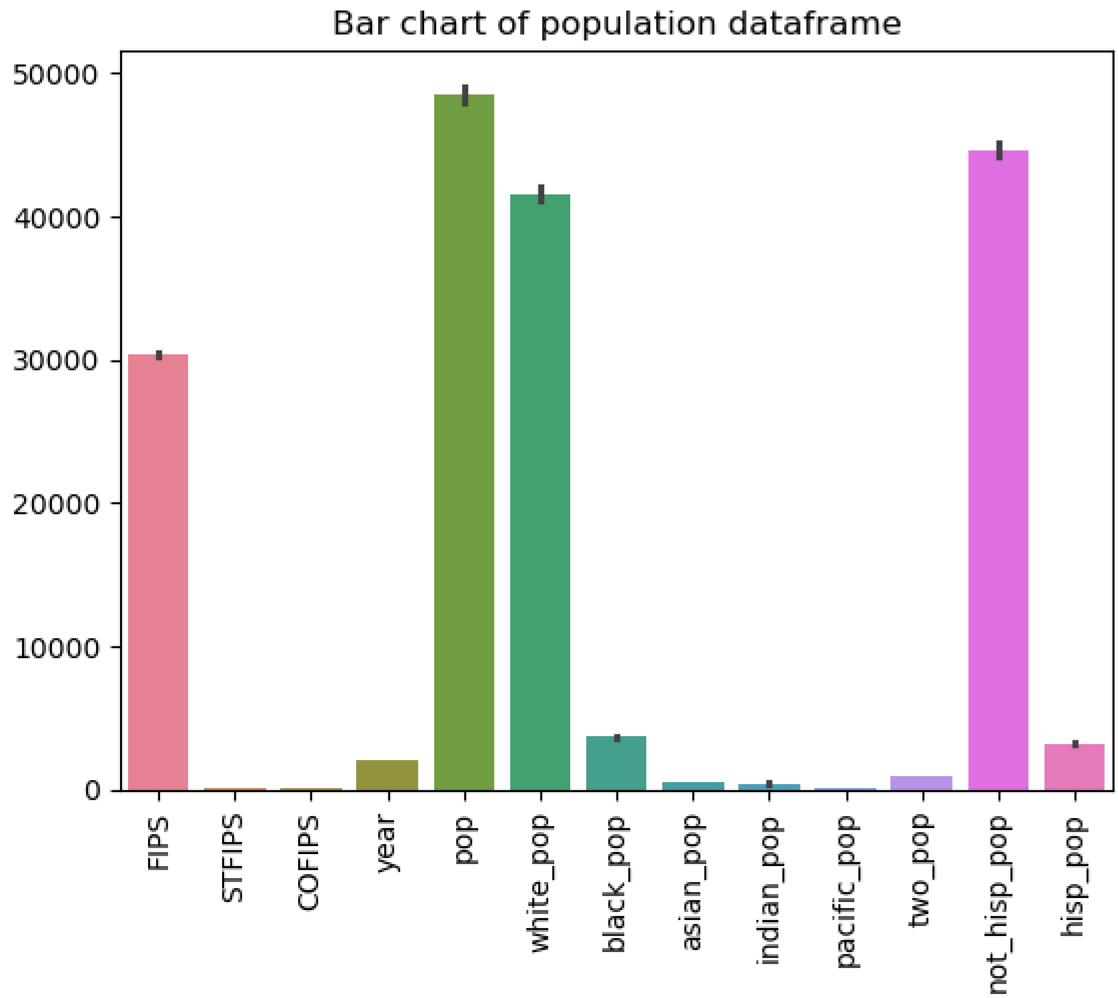


In [27]:
```
#correlation of data frame
cor_df = df2.select_dtypes(include = ['int64','float64']).corr()
#correlation plot
plt.figure(figsize=(12,10))
sns.heatmap(cor_df,annot=True,annot_kws={'size': 7})
plt.title('Correlation plot population dataframe')
plt.show()
```



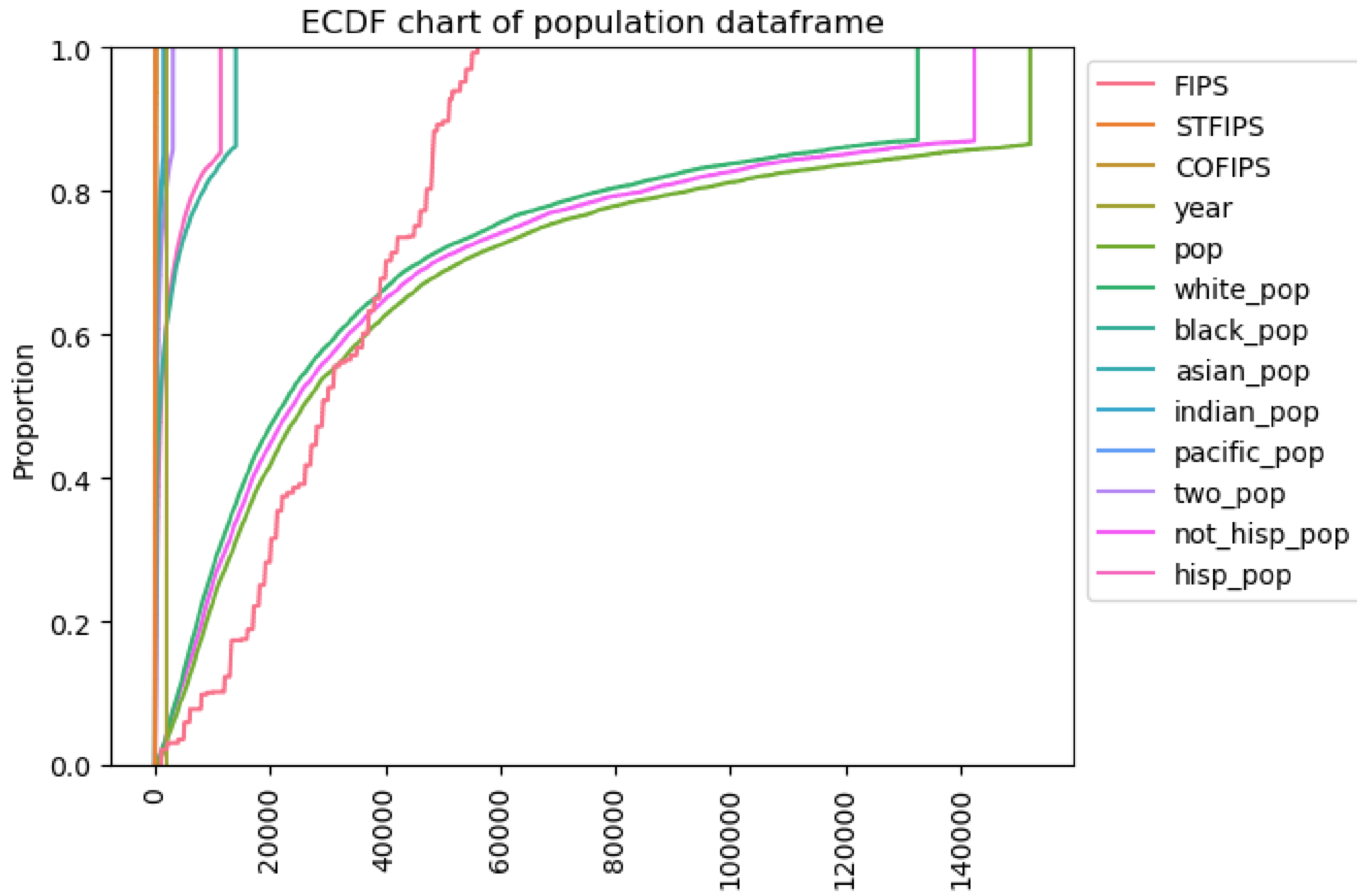
In [28]:

```
# Barchard for data visualization
nu_col=df2.select_dtypes(include=['int64','float64'])
df3 = pd.DataFrame(df2.select_dtypes(include=['int64','float64']))
sns.barplot(data=df3)
plt.xticks(rotation = 90)
plt.title('Bar chart of population dataframe')
plt.show()
```



In [29]:

```
# ECDF cahrt for data visualization
ax=sns.ecdfplot(data=df3,legend=True)
sns.move_legend(ax, "upper left", bbox_to_anchor=(1, 1))
plt.xticks(rotation = 90)
plt.title('ECDF chart of population dataframe')
plt.show()
```



Feature Engineering

Encoding

Encoding of object-type columns

In [31]:
```
# importing category encoder from library
from category_encoders import TargetEncoder
```

In [32]:
```
df4 = pd.DataFrame(df2)
## finding Object type columns and count the number of unique values
col_object_type=df4.select_dtypes(include=['object']).columns.tolist()
print_title('Object type columns in DataFrame')
print_section(pd.DataFrame({'Colums':col_object_type}))
print_title('Counted unique values in object type columns')
for column_name in col_object_type:
  print(f'{column_name} has {df4[column_name].nunique()} unique values')
```

```
-------------------------------------------------------------
Object type columns in DataFrame
-------------------------------------------------------------
   Colums
0   state
1  county
-------------------------------------------------------------

-------------------------------------------------------------
Counted unique values in object type columns
state has 50 unique values
county has 1876 unique values
```

In [33]:
```
print_title('Aggrigation of Cont and Mean of object type column to target column')
```

```
for column_name in col_object_type:
    print_section(df4['pop'].groupby(df4[column_name]).agg(['count','mean']))
```

```
------------------------------------------------------------
Aggrigation of Cont and Mean of object type column to target column
------------------------------------------------------------
                count          mean
state
Alabama           670   54314.985821
Alaska            290   20300.575000
Arizona           150  101803.436667
Arkansas          750   34223.004333
California        580  107221.903879
Colorado          640   39205.986328
Connecticut        80  147631.015625
Delaware           30  152064.375000
Florida           670   94364.632090
Georgia          1590   42915.739072
Hawaii             50  105304.565000
Idaho             440   29997.327273
Illinois         1020   47549.117402
Indiana           920   52840.632065
Iowa              990   27400.281061
Kansas           1050   19803.138095
Kentucky         1200   30299.577708
Louisiana         640   54741.042188
Maine             160   71594.773438
Maryland          240  101035.480729
Massachusetts     140  124844.246429
Michigan          830   61218.862952
Minnesota         870   39366.908764
Mississippi       820   34445.540701
Missouri         1150   34649.018261
Montana           560   18284.945759
Nebraska          930   14168.279839
Nevada            170   37332.132353
New Hampshire     100   92950.175000
New Jersey        210  141338.985119
New Mexico        330   45511.919697
New York          620   95734.444355
North Carolina   1000   69040.397125
North Dakota      530   13482.289387
Ohio              880   75729.046307
Oklahoma          770   34584.166558
Oregon            360   62544.022917
Pennsylvania      670   92346.280224
Rhode Island       50  112496.330000
South Carolina    460   73805.552446
South Dakota      660   12452.670833
Tennessee         950   47494.407105
Texas            2540   40466.837598
Utah              290   45889.747845
Vermont           140   44047.512500
Virginia         1330   43871.389850
Washington        390   72563.562821
West Virginia     550   32728.988636
Wisconsin         720   57258.012153
Wyoming           230   25117.400000
------------------------------------------------------------
------------------------------------------------------------
                           count         mean
county
Abbeville                     10   24834.5000
Acadia Parish                 10   62288.4000
Accomack                      10   32896.4000
Ada                           10  152064.3750
```

```
Adair                          40   18568.0250
...                           ...          ...
Yukon-Koyukuk Census Area      10    5474.7000
Yuma                           20   81062.6875
Zapata                         10   14280.3000
Zavala                         10   12020.1000
Ziebach                        10    2818.4000

[1876 rows x 2 columns]
------------------------------------------------------------
```

In [34]:
```
print_section(f'Since high cardinality in state and county coluns Target\nEncoding is mo
encoder=TargetEncoder()
```

```
------------------------------------------------------------
Since high cardinality in state and county coluns Target
Encoding is moste prefered
------------------------------------------------------------
```

In [35]:
```
df5 = pd.DataFrame(df4)
df4.head(3)
```

Out[35]:

	FIPS	STFIPS	COFIPS	state	county	year	pop	white_pop	black_pop	asian_pop	indian_pop	pacific
0	1001	1	1.0	Alabama	Autauga	2010	54571.0	43297.0	9689.0	484.0	258.0	
1	1001	1	1.0	Alabama	Autauga	2011	55227.0	43699.0	9883.0	514.0	261.0	
2	1001	1	1.0	Alabama	Autauga	2012	54954.0	43315.0	9949.0	552.0	275.0	

In [36]:
```
print_section(f'Since high cardinality in state and county coluns Target\nEncoding is mo
encoder.fit(df4['state'],df4['pop'])
df5['state'] = encoder.transform(df4['state'],df4['pop'])
encoder.fit(df4['county'],df4['pop'])
df5['county'] = encoder.transform(df4['county'],df4['pop'])
df5.head(3)
```

```
------------------------------------------------------------
Since high cardinality in state and county coluns Target
Encoding is moste prefered
------------------------------------------------------------
```

Out[36]:

	FIPS	STFIPS	COFIPS	state	county	year	pop	white_pop	black_pop	asian_pop	indian_po
0	1001	1	1.0	54314.985821	50281.243963	2010	54571.0	43297.0	9689.0	484.0	258.
1	1001	1	1.0	54314.985821	50281.243963	2011	55227.0	43699.0	9883.0	514.0	261.
2	1001	1	1.0	54314.985821	50281.243963	2012	54954.0	43315.0	9949.0	552.0	275.

Feature Scaling

Min Max scaling

In [38]:
```
# importing MinMaxScaler library for feature Scaling
from sklearn.preprocessing import MinMaxScaler
```

In [39]:
```
df6 = pd.DataFrame(df5)
```

In [40]:
```
scaling=MinMaxScaler()
numerical_col = df6.select_dtypes(include=['int64','float64'])
```

```
df6 = scaling.fit_transform(numerical_col)
df6=pd.DataFrame(df6, columns=numerical_col.columns, index=df2.index) #datafrme after mi
```

PowerTransformer

In [42]:
```
# importing powertransformer library
from sklearn.preprocessing import PowerTransformer
```

In [43]:
```
pt = PowerTransformer(method='yeo-johnson',standardize=True)
numeriacal_features = df6.select_dtypes(include=['int64','float64']).columns
df6[numeriacal_features] = pt.fit_transform(df6[numeriacal_features])
```

In [44]:
```
df6.head(5)
```

Out[44]:

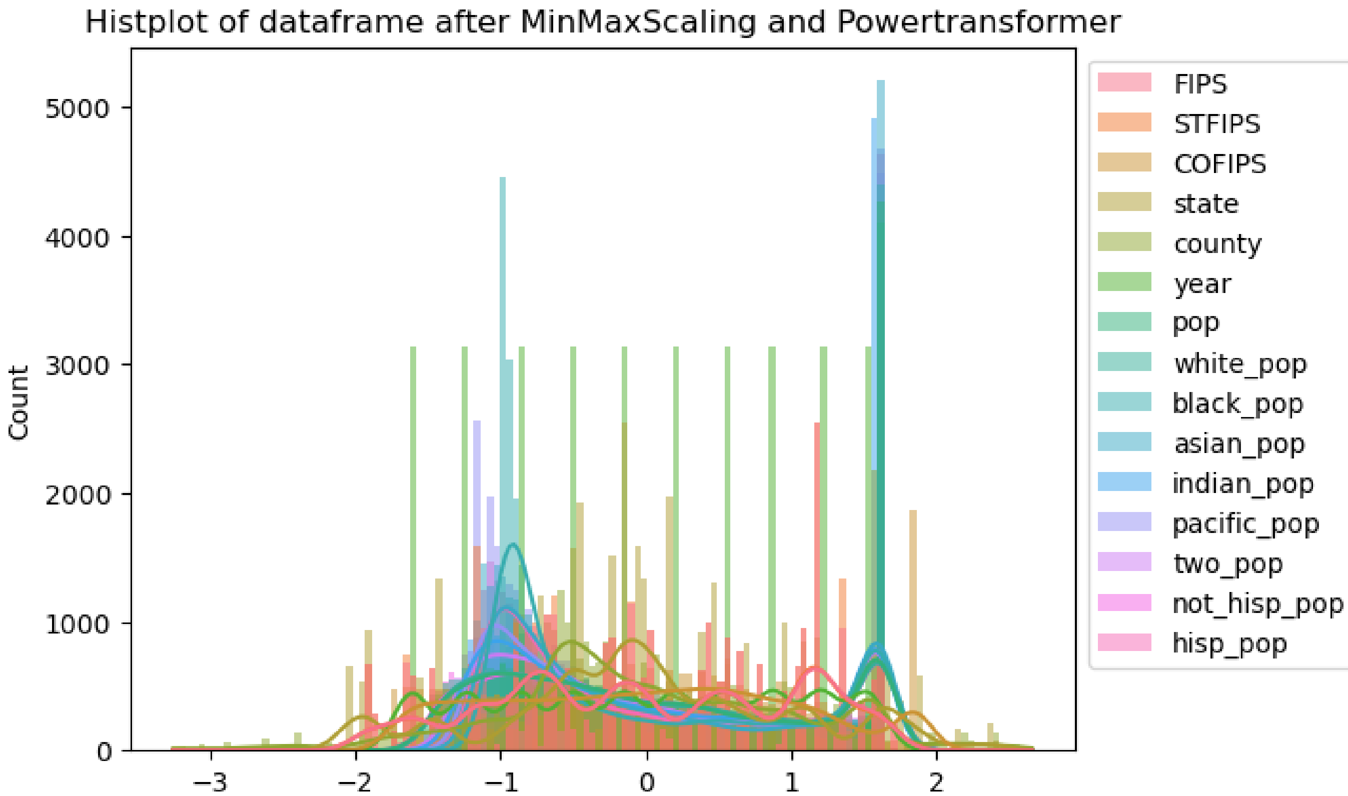
	FIPS	STFIPS	COFIPS	state	county	year	pop	white_pop	black_pop	asian_pop	india
0	-1.928755	-1.92287	-1.726894	0.458593	0.274188	-1.610567	0.616111	0.527443	1.420259	0.566839	0.(
1	-1.928755	-1.92287	-1.726894	0.458593	0.274188	-1.230735	0.629712	0.537918	1.432322	0.625005	0.(
2	-1.928755	-1.92287	-1.726894	0.458593	0.274188	-0.860716	0.624072	0.527914	1.436322	0.693883	0.(
3	-1.928755	-1.92287	-1.726894	0.458593	0.274188	-0.499397	0.619361	0.518138	1.438423	0.709458	0.'
4	-1.928755	-1.92287	-1.726894	0.458593	0.274188	-0.145869	0.622808	0.518191	1.445458	0.729805	0.'

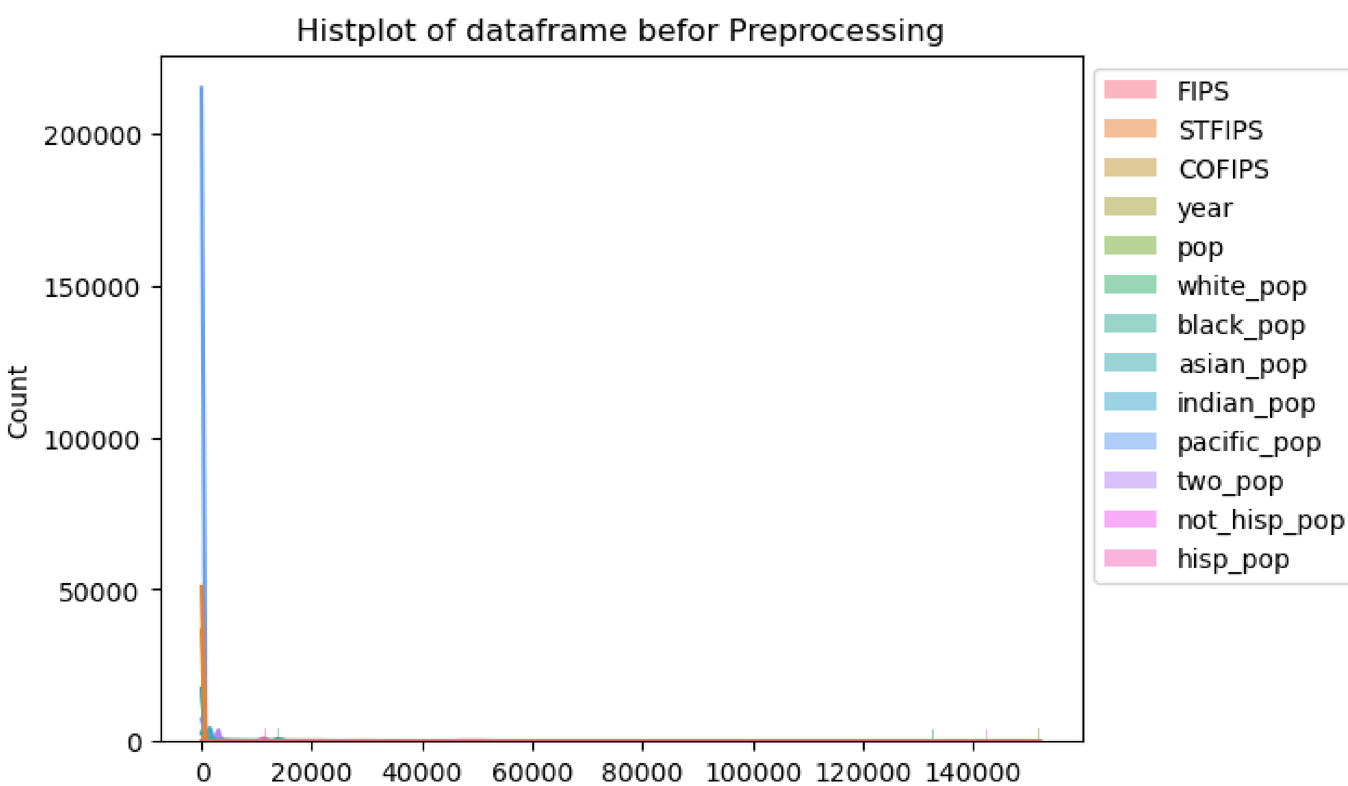
In [45]:
```
skewness = df6.skew()
print_section("\033[1mSkewness of Features in dataframe after Scaling\033[0m")
print_section(skewness)
```

```
------------------------------------------------------------
Skewness of Features in dataframe after Scaling
------------------------------------------------------------
------------------------------------------------------------
FIPS          -0.070539
STFIPS        -0.071084
COFIPS         0.098267
state          0.033800
county        -0.000077
year          -0.066401
pop            0.336701
white_pop      0.336056
black_pop      0.557582
asian_pop      0.554942
indian_pop     0.438283
pacific_pop    0.486517
two_pop        0.444147
not_hisp_pop   0.335262
hisp_pop       0.505745
dtype: float64
------------------------------------------------------------
```

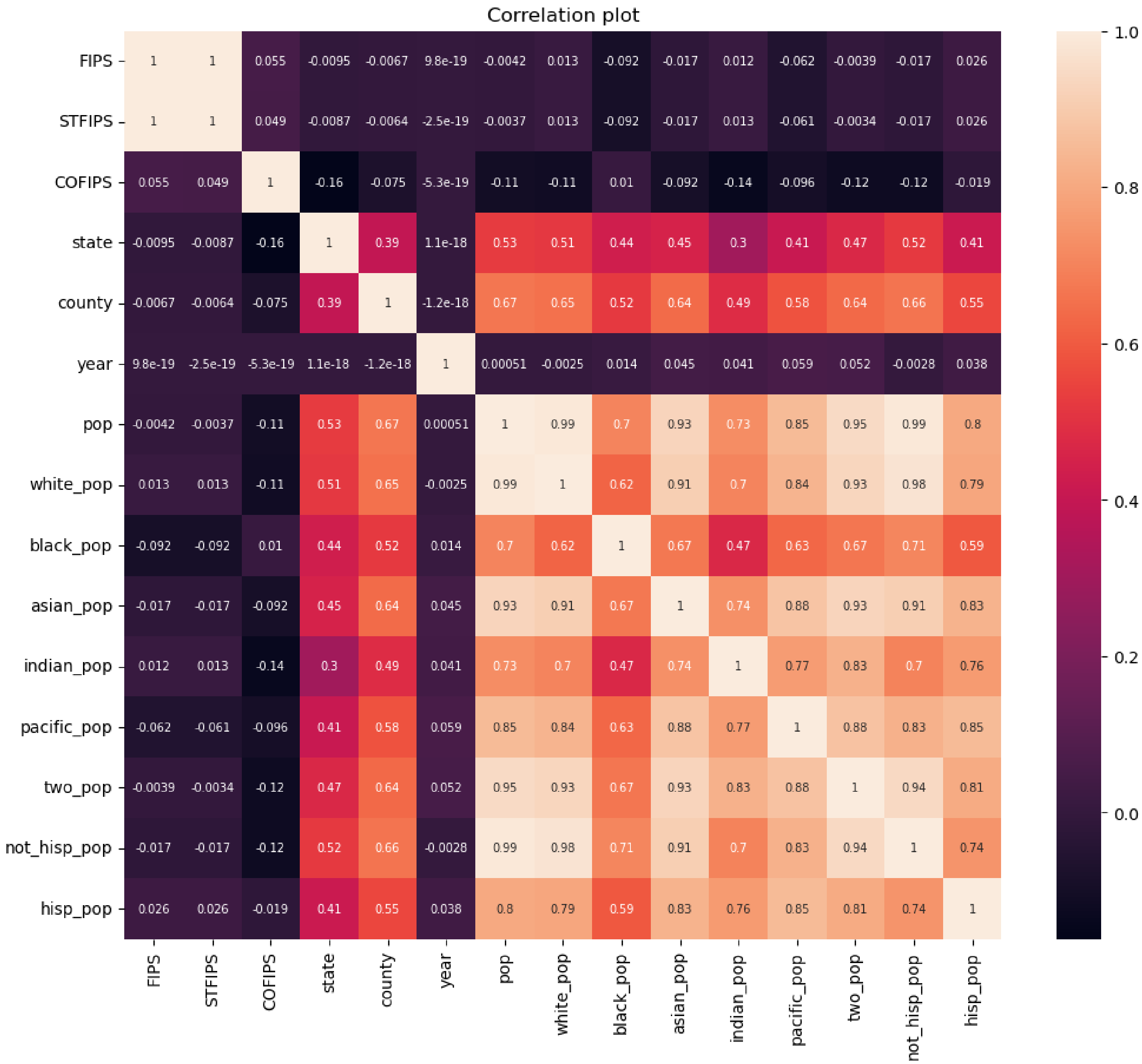
In [46]:
```
ax=sns.histplot(df6,kde=True,linewidth=0,legend=True)
plt.title('Histplot of dataframe after MinMaxScaling and Powertransformer')
sns.move_legend(ax, "upper left", bbox_to_anchor=(1, 1))
plt.show()

ax=sns.histplot(df2,kde=True,linewidth=0,legend=True)
plt.title('Histplot of dataframe befor Preprocessing')
sns.move_legend(ax, "upper left", bbox_to_anchor=(1, 1))
plt.show()
```





In [47]:
```
#correlation of data frame after EDA
cor_df = df6.corr()
#correlation plot
plt.figure(figsize=(12,10))
sns.heatmap(cor_df,annot=True,annot_kws={'size': 7})
plt.title('Correlation plot')
plt.show()
```



Feature Selection

In [49]:
```
# importing SelectKBest library for feature selection
from sklearn.feature_selection import SelectKBest,f_regression
```

In [50]:
```
#converting df6 to new dataset name for futher process
df_pop = pd.DataFrame(df6)
```

In [51]:
```
df_pop.head(5)
```

Out[51]:

	FIPS	STFIPS	COFIPS	state	county	year	pop	white_pop	black_pop	asian_pop	india
0	-1.928755	-1.92287	-1.726894	0.458593	0.274188	-1.610567	0.616111	0.527443	1.420259	0.566839	0.(
1	-1.928755	-1.92287	-1.726894	0.458593	0.274188	-1.230735	0.629712	0.537918	1.432322	0.625005	0.(
2	-1.928755	-1.92287	-1.726894	0.458593	0.274188	-0.860716	0.624072	0.527914	1.436322	0.693883	0.(
3	-1.928755	-1.92287	-1.726894	0.458593	0.274188	-0.499397	0.619361	0.518138	1.438423	0.709458	0.:

4	-1.928755	-1.92287	-1.726894	0.458593	0.274188	-0.145869	0.622808	0.518191	1.445458	0.729805	0.

In [52]:
```
x = df_pop.drop('pop', axis=1)
y = df_pop['pop']
```

In [53]:
```
sk = SelectKBest(score_func=f_regression,k=14)
x_new = sk.fit_transform(x,y)
```

In [54]:
```
#Get selected feture names and scores
selected_features = x.columns[sk.get_support()]
features_scores = pd.DataFrame({'feature':x.columns,'Score':sk.scores_}).sort_values(by=

print_title('Selected Features:')
print_section(pd.DataFrame(list(selected_features)))
print_title("\nFeature Scores:")
print_section(features_scores)
```

```
------------------------------------------------------------
Selected Features:
------------------------------------------------------------
               0
0           FIPS
1         STFIPS
2         COFIPS
3          state
4         county
5           year
6      white_pop
7      black_pop
8      asian_pop
9     indian_pop
10   pacific_pop
11       two_pop
12  not_hisp_pop
13      hisp_pop
------------------------------------------------------------

------------------------------------------------------------

Feature Scores:
------------------------------------------------------------
         feature         Score
12  not_hisp_pop  1.540729e+06
6      white_pop  1.164183e+06
11       two_pop  2.898884e+05
8      asian_pop  1.947178e+05
10   pacific_pop  8.474241e+04
13      hisp_pop  5.658111e+04
9     indian_pop  3.518288e+04
7      black_pop  3.100110e+04
4         county  2.508289e+04
3          state  1.200154e+04
2         COFIPS  3.584230e+02
0           FIPS  5.526506e-01
1         STFIPS  4.202460e-01
5           year  8.231369e-03
------------------------------------------------------------
```

In [55]:
```
x_select=x[selected_features]
```

In [56]:
```
x_select.columns
```

Out[56]:
```
Index(['FIPS', 'STFIPS', 'COFIPS', 'state', 'county', 'year', 'white_pop',
       'black_pop', 'asian_pop', 'indian_pop', 'pacific_pop', 'two_pop',
```

```
        'not_hisp_pop', 'hisp_pop'],
      dtype='object')
```

Feature Scaling

In [58]:
```
# importing standardScaler from library
from sklearn.preprocessing import StandardScaler
```

In [59]:
```
scaler = StandardScaler()
x_scaled = scaler.fit_transform(x_select)
```

Split data into Training and Testing Sets

In [61]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn.svm import SVR
```

In [62]:
```
# Split data into training and testing sets.
x_train, x_test, y_train, y_test = train_test_split(x_scaled, y, test_size=0.2, random_s
```

In [63]:
```
print(f"""
shape x_train: {x_train.shape}
shape x_test: {x_test.shape}
shape y_train: {y_train.shape}
shape y_test: {y_test.shape}""")
```

```
shape x_train: (25128, 14)
shape x_test: (6282, 14)
shape y_train: (25128,)
shape y_test: (6282,)
```

ML Model

In [65]:
```
# Creating a dictinary named models for model selection
models = {
    '1.linear Regression':LinearRegression(),
    '2.Dicision Tree Regression':DecisionTreeRegressor(),
    '3.Random Forest Regressor':RandomForestRegressor(),
    '4.Gradient Boosting Regressor':GradientBoostingRegressor(),
    '5.Support Vector Regressor':SVR()
}
```

In [66]:
```
# This for loop syntax fit the x train and y train for each moledl in modles dictionary
result = {}
for model_name, model in models.items():
    model.fit(x_train,y_train)
    y_pred = model.predict(x_test)
```

```
    mae = mean_absolute_error(y_test,y_pred)
    mse = mean_squared_error(y_test,y_pred)
    rmse = np.sqrt(mse)
    r2 = r2_score(y_test,y_pred)
    result[model_name] = {'mae':mae, 'mse':mse,'rmse':rmse,'r2':r2}
```

Model Evaluation

In [68]:
```
result_df = pd.DataFrame(result).T
print_title('Score details for variuse modles')
print_section(result_df)
```

```
------------------------------------------------------------
Score details for variuse modles
------------------------------------------------------------
                                  mae       mse      rmse        r2
1.linear Regression          0.041690  0.005840  0.076422  0.994167
2.Dicision Tree Regression   0.004505  0.000284  0.016866  0.999716
3.Random Forest Regressor    0.002195  0.000039  0.006210  0.999961
4.Gradient Boosting Regressor  0.017988  0.000743  0.027252  0.999258
5.Support Vector Regressor   0.044232  0.002742  0.052367  0.997261
------------------------------------------------------------
```

Hyperparameter turning

In [70]:
```
rfg = RandomForestRegressor(random_state=42,
                            n_estimators=50,
                            max_depth=10,
                            min_samples_split=5,
                            min_samples_leaf=2,
                            max_features='sqrt',
                            ccp_alpha=0.1,
                            n_jobs=-1)
```

In [71]:
```
param_grid = {
    'n_estimators':[50,100,200],
    'max_depth':[10,20,None],
    'min_samples_split':[2,5,10],
    'min_samples_leaf':[1,2,4]
}
```

In [72]:
```
RandomGrid = RandomizedSearchCV(estimator = rfg,
                                param_distributions=param_grid,
                                cv=10,
                                scoring = 'r2',
                                n_jobs=-1,
                                verbose=2)
```

In [73]:
```
RandomGrid.fit(x_train,y_train)
```

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits
```

Out[73]:

RandomizedSearchCV

best_estimator_:
RandomForestRegressor

RandomForestRegressor

In [74]:
```
print("Best Parameters:",RandomGrid.best_params_)
print("best R2 Score:",RandomGrid.best_score_)
```

```
Best Parameters: {'n_estimators': 100, 'min_samples_split': 10, 'min_samples_leaf': 1,
'max_depth': 10}
best R2 Score: 0.8916889641886694
```

Save the Model

Best Model

In [77]:
```
#creating best model variable using best estimator
best_model = RandomGrid.best_estimator_
best_model
```

Out[77]:

RandomForestRegressor

```
RandomForestRegressor(ccp_alpha=0.1, max_depth=10, max_features='sqrt',
                      min_samples_split=10, n_jobs=-1, random_state=42)
```

In [78]:
```
# applaing paramiter to RandomForestRegrssor genarated from RandomGrid
best_model = RandomForestRegressor(ccp_alpha=0.1,
                                   max_features='sqrt',
                                   min_samples_leaf=2,
                                   min_samples_split=5, n_estimators=50,
                                   n_jobs=-1,
                                   random_state=42)
```

In [79]:
```
#fitting best model to traing data
best_model.fit(x_train,y_train)
```

Out[79]:

RandomForestRegressor

```
RandomForestRegressor(ccp_alpha=0.1, max_features='sqrt', min_samples_leaf=2,
                      min_samples_split=5, n_estimators=50, n_jobs=-1,
                      random_state=42)
```

In [80]:
```
# genarating predictin from traing best model
y_pred = best_model.predict(x_test)
```

In [81]:
```
MAE = mean_absolute_error(y_test,y_pred)
MSE = mean_squared_error(y_test,y_pred)
RMSE = np.sqrt(MSE)
R2 = r2_score(y_test,y_pred)
print(f"MAE:{MAE}\nMSE:{MSE}\nRMSE:{RMSE}\nR2:{R2}")
```

```
MAE:0.2815571913338196
MSE:0.1130972519058628
RMSE:0.3362993486551272
R2:0.8870478371921949
```

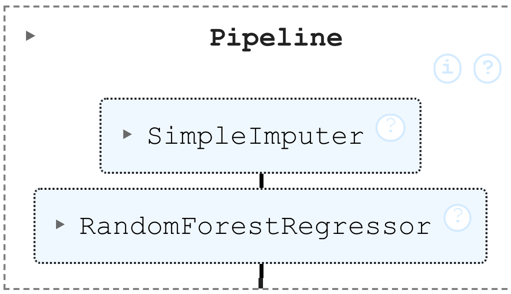
Model saving steps

In [83]:
```python
# inporting library to save the model
import joblib
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
```

In [96]:
```python
pipeline  = Pipeline([
    ('imputer',SimpleImputer(strategy = 'mean')),('model',best_model)
])
```

In [98]:
```python
pipeline.fit(x_train,y_train)
```

Out[98]:



In [100…
```python
y_pred = pipeline.predict(x_test)
```

In [102…
```python
# saving the tested model as pop-data.joblib
joblib.dump(pipeline,'pop_data.joblib')
```

Out[102]:
```
['pop_data.joblib']
```

Test with Unseen Data

In [89]:
```python
# Select 12 random indices
random_indices = np.random.choice(x.shape[0], 12, replace=False)
# Use NumPy indexing directly
x_random = x.iloc[random_indices]
y_random = y[random_indices]
```

In [90]:
```python
# Apply the SelectKBest transformation to the random selection of features
x_random_selected = sk.transform(x_random)
```

In [104…
```python
prdiction = pipeline.predict(x_random_selected)
```

In [106…
```python
prdiction
```

Out[106]:
```
array([-0.58078496,  1.08377055, -0.74831413, -0.76455391, -0.74629612,
        1.19104726,  1.17044925,  1.19104726, -0.49268782, -0.76455391,
       -0.76455391,  0.43492751])
```

In [110…
```python
result = pd.DataFrame(
    {
        "county":df.loc[x_random.index,'county'],
        "pop":y_random.values,
```

```
        "Predicted pop":prdiction
    }
)
```

Final Result

In [112…

```
print(f'''Final Result
{result}
''')
```

```
Final Result
             county       pop  Predicted pop
2559        Conejos -1.024288      -0.580785
16118      Flathead  1.280929       1.083771
13003  Presque Isle -0.763746      -0.748314
9067        Decatur -1.353057      -0.764554
4555        Hancock -1.002940      -0.746296
27810         Davis  1.604283       1.191047
3923         Barrow  0.914631       1.170449
19784         Union  1.604283       1.191047
10179          Clay -0.438988      -0.492688
16382      Richland -0.880852      -0.764554
23818       Douglas -1.348913      -0.764554
18396      Delaware  0.406305       0.434928
```