In [2]:

```
#imports
import pandas as pd
import numpy as np
import scipy.stats as st
import plotly.figure_factory as ff
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

In [3]:

```
#import election dataset
election_data = pd.read_csv("election_train.csv")
election_data.head()
```

Out[3]:

	Year	State	County	Office	Party	Votes
0	2018	AZ	Apache County	US Senator	Democratic	16298
1	2018	AZ	Apache County	US Senator	Republican	7810
2	2018	AZ	Cochise County	US Senator	Democratic	17383
3	2018	AZ	Cochise County	US Senator	Republican	26929
4	2018	AZ	Coconino County	US Senator	Democratic	34240

In [4]:

```
#import demographics dataset
demographic_data = pd.read_csv("demographics_train.csv")
demographic_data.head()
```

Out[4]:

	State	County	FIPS	Total Population	Citizen Voting-Age Population	Percent White, not Hispanic or Latino	Percent Black, not Hispanic or Latino	Percent Hispanic or Latino	Perc Fore B
0	Wisconsin	La Crosse	55063	117538	0	90.537528	1.214075	1.724549	2.976(
1	Virginia	Alleghany	51005	15919	12705	91.940449	5.207614	1.432251	1.300:
2	Indiana	Fountain	18045	16741	12750	95.705155	0.400215	2.359477	1.547:
3	Ohio	Geauga	39055	94020	0	95.837056	1.256116	1.294405	2.578:
4	Wisconsin	Jackson	55053	20566	15835	86.662453	1.983857	3.082758	1.376(

Task 1 - Reshape dataset election_train from long format to wide format.

In [5]:

```
wide_format_election_data = pd.pivot_table(election_data, index=['Year','State',
'County', 'Office'], columns=['Party'], values=['Votes'], aggfunc=np.sum).reset_
index()
wide_format_election_data.columns = ["Year", "State", "County", "Office", "Democ
ratic Votes", "Republican Votes"]
print(f'Shape of wide Format dataset - f{wide_format_election_data.shape}')
wide_format_election_data.head(10)
```

```
Shape of wide Format dataset - f(1205, 6)
```

Out[5]:

	Year	State	County	Office	Democratic Votes	Republican Votes
0	2018	AZ	Apache County	US Senator	16298.0	7810.0
1	2018	AZ	Cochise County	US Senator	17383.0	26929.0
2	2018	AZ	Coconino County	US Senator	34240.0	19249.0
3	2018	AZ	Gila County	US Senator	7643.0	12180.0
4	2018	AZ	Graham County	US Senator	3368.0	6870.0
5	2018	AZ	La Paz County	US Senator	1609.0	3265.0
6	2018	AZ	Maricopa County	US Senator	732671.0	672505.0
7	2018	AZ	Mohave County	US Senator	19214.0	50209.0
8	2018	AZ	Navajo County	US Senator	16624.0	18767.0
9	2018	AZ	Pima County	US Senator	221242.0	160550.0

Task 2 Merge Datasets

In [6]:

```
# replacing Country with empty/blank string in County name
wide_format_election_data['County'] = wide_format_election_data['County'].str.re
place('County', '')
# removing widespaces and converting to uppercase -  County and State
wide_format_election_data[['County', 'State']] = wide_format_election_data[['Cou
nty', 'State']].apply(lambda x: x.str.strip().str.upper())
wide_format_election_data.head()
```

Out[6]:

	Year	State	County	Office	Democratic Votes	Republican Votes
0	2018	AZ	APACHE	US Senator	16298.0	7810.0
1	2018	AZ	COCHISE	US Senator	17383.0	26929.0
2	2018	AZ	COCONINO	US Senator	34240.0	19249.0
3	2018	AZ	GILA	US Senator	7643.0	12180.0
4	2018	AZ	GRAHAM	US Senator	3368.0	6870.0

In [7]:

```
# states mapping dictionary
states = {'AK': 'ALASKA', 'AL': 'ALABAMA', 'AR': 'ARKANSAS', 'AS': 'AMERICAN SAMOA', 'AZ': 'ARIZONA',
          'CA': 'CALIFORNIA', 'CO': 'COLORADO', 'CT': 'CONNECTICUT', 'DC': 'DISTRICT OF COLUMBIA',
          'DE': 'DELAWARE', 'FL': 'FLORIDA', 'GA': 'GEORGIA', 'GU': 'GUAM', 'HI': 'HAWAII', 'IA': 'IOWA',
          'ID': 'IDAHO', 'IL': 'ILLINOIS', 'IN': 'INDIANA', 'KS': 'KANSAS', 'KY': 'KENTUCKY',
          'LA': 'LOUISIANA', 'MA': 'MASSACHUSETTS', 'MD': 'MARYLAND', 'ME': 'MAINE', 'MI': 'MICHIGAN',
          'MN': 'MINNESOTA', 'MO': 'MISSOURI', 'MP': 'NORTHERN MARIANA ISLANDS', 'MS': 'MISSISSIPPI',
          'MT': 'MONTANA', 'NA': 'NATIONAL', 'NC': 'NORTH CAROLINA', 'ND': 'NORTH DAKOTA', 'NE': 'NEBRASKA',
          'NH': 'NEW HAMPSHIRE', 'NJ': 'NEW JERSEY', 'NM': 'NEW MEXICO', 'NV': 'NEVADA', 'NY': 'NEW YORK',
          'OH': 'OHIO', 'OK': 'OKLAHOMA', 'OR': 'OREGON', 'PA': 'PENNSYLVANIA', 'PR': 'PUERTO RICO',
          'RI': 'RHODE ISLAND', 'SC': 'SOUTH CAROLINA', 'SD': 'SOUTH DAKOTA', 'TN': 'TENNESSEE',
          'TX': 'TEXAS', 'UT': 'UTAH', 'VA': 'VIRGINIA', 'VI': 'VIRGIN ISLANDS', 'VT': 'VERMONT',
          'WA': 'WASHINGTON', 'WI': 'WISCONSIN', 'WV': 'WEST VIRGINIA', 'WY': 'WYOMING'}
#replacing state codes with state names in State Column
wide_format_election_data = wide_format_election_data.replace({"State":states})
wide_format_election_data.head()
```

Out[7]:

	Year	State	County	Office	Democratic Votes	Republican Votes
0	2018	ARIZONA	APACHE	US Senator	16298.0	7810.0
1	2018	ARIZONA	COCHISE	US Senator	17383.0	26929.0
2	2018	ARIZONA	COCONINO	US Senator	34240.0	19249.0
3	2018	ARIZONA	GILA	US Senator	7643.0	12180.0
4	2018	ARIZONA	GRAHAM	US Senator	3368.0	6870.0

In [8]:

```
# removing widespaces and converting to uppercase -  County and State
demographic_data[['County', 'State']] = demographic_data[['County', 'State']].ap
ply(lambda x: x.str.strip().str.upper())
demographic_data.head()
```

Out[8]:

	State	County	FIPS	Total Population	Citizen Voting-Age Population	Percent White, not Hispanic or Latino	Percent Black, not Hispanic or Latino	Percent Hispanic or Latino
0	WISCONSIN	LA CROSSE	55063	117538	0	90.537528	1.214075	1.724549
1	VIRGINIA	ALLEGHANY	51005	15919	12705	91.940449	5.207614	1.432251
2	INDIANA	FOUNTAIN	18045	16741	12750	95.705155	0.400215	2.359477
3	OHIO	GEAUGA	39055	94020	0	95.837056	1.256116	1.294405
4	WISCONSIN	JACKSON	55053	20566	15835	86.662453	1.983857	3.082758

In [9]:

```
# Merging datasets using inner join on columns - State and County
merged_data = pd.merge(wide_format_election_data, demographic_data, how='inner',
on=['State','County'])
merged_data.head()
```

Out[9]:

	Year	State	County	Office	Democratic Votes	Republican Votes	FIPS	Total Population	Citiz Votin A Populati
0	2018	ARIZONA	APACHE	US Senator	16298.0	7810.0	4001	72346	
1	2018	ARIZONA	COCHISE	US Senator	17383.0	26929.0	4003	128177	929
2	2018	ARIZONA	COCONINO	US Senator	34240.0	19249.0	4005	138064	1042
3	2018	ARIZONA	GILA	US Senator	7643.0	12180.0	4007	53179	
4	2018	ARIZONA	GRAHAM	US Senator	3368.0	6870.0	4009	37529	

5 rows × 21 columns

Task 3 Explore Merged Dataset

In [10]:

```
print(f'Number of variables - {merged_data.shape[1]}\n')
print(f'Data Types for each variable - \n{merged_data.dtypes}\n')
print(f'Number of variables for each data type - \n{merged_data.dtypes.value_cou
nts()}')
```

```
Number of variables - 21

Data Types for each variable -
Year                                       int64
State                                     object
County                                    object
Office                                    object
Democratic Votes                         float64
Republican Votes                         float64
FIPS                                       int64
Total Population                           int64
Citizen Voting-Age Population              int64
Percent White, not Hispanic or Latino    float64
Percent Black, not Hispanic or Latino    float64
Percent Hispanic or Latino               float64
Percent Foreign Born                     float64
Percent Female                           float64
Percent Age 29 and Under                 float64
Percent Age 65 and Older                 float64
Median Household Income                    int64
Percent Unemployed                       float64
Percent Less than High School Degree     float64
Percent Less than Bachelor's Degree      float64
Percent Rural                            float64
dtype: object

Number of variables for each data type -
float64    13
int64       5
object      3
dtype: int64
```

In [11]:

```
#Looking for columns that have a constant value for all observations
columns_with_single_unique_value  = merged_data.columns[merged_data.nunique() <=
1]
for column in columns_with_single_unique_value:
    print(f'Column {column} unique values - {merged_data[column].unique()}')
```

```
Column Year unique values - [2018]
Column Office unique values - ['US Senator']
```

In [12]:

```
#Removing the columns 'Year' and 'Office' from the dataset
merged_data = merged_data.drop(columns_with_single_unique_value,axis=1)
merged_data.head()
```

Out[12]:

	State	County	Democratic Votes	Republican Votes	FIPS	Total Population	Citizen Voting-Age Population	Percent White, not Hispanic or Latino
0	ARIZONA	APACHE	16298.0	7810.0	4001	72346	0	18.571863
1	ARIZONA	COCHISE	17383.0	26929.0	4003	128177	92915	56.299492
2	ARIZONA	COCONINO	34240.0	19249.0	4005	138064	104265	54.619597
3	ARIZONA	GILA	7643.0	12180.0	4007	53179	0	63.222325
4	ARIZONA	GRAHAM	3368.0	6870.0	4009	37529	0	51.461536

Task 4 Search Missing Values

In [13]:

```
#Counting Null values for each column
null_count = merged_data.isnull().sum()
null_count = null_count[null_count>0]

#Printing null counts for columns that have null count >0
print(f'Null count for Columns - \n{null_count}\n\n')

#Printing % of null counts for columns that have null count>0
for column, null_co in null_count.iteritems():
    print(f'Percentage of missing values for Column {column} - {null_co*100/merg
ed_data.shape[0]:.2f} %')
```

```
Null count for Columns -
Democratic Votes    3
Republican Votes    2
dtype: int64


Percentage of missing values for Column Democratic Votes - 0.25 %
Percentage of missing values for Column Republican Votes - 0.17 %
```

In [14]:

```
merged_data[merged_data.isnull().any(axis=1)][['Democratic Votes', 'Republican V
otes', 'Total Population' ]]
```

Out[14]:

	Democratic Votes	Republican Votes	Total Population
425	NaN	49449.0	301707
714	NaN	2694.0	11804
750	2811.0	NaN	32706
865	NaN	632.0	2163
1114	3592.0	NaN	16793

In [15]:

```
merged_data = merged_data.dropna()
```

In [16]:

```
#Counting Null values for each column
null_count = merged_data.isnull().sum()
null_count = null_count[null_count>0]
print(null_count)
```

```
Series([], dtype: int64)
```

In [17]:

```
#Checking boolean False counts for each column, an empty/blank string or integer 
0 will result in a False value
#for boolean type
bool_counts = merged_data.astype(bool).sum(axis=0)
for col, val in bool_counts.iteritems():
    print(f'{col} Percentage Boolean False Counts {(merged_data.shape[0]-val)*10
0/merged_data.shape[0]:.2f}')
```

```
State Percentage Boolean False Counts 0.00
County Percentage Boolean False Counts 0.00
Democratic Votes Percentage Boolean False Counts 0.00
Republican Votes Percentage Boolean False Counts 0.00
FIPS Percentage Boolean False Counts 0.00
Total Population Percentage Boolean False Counts 0.00
Citizen Voting-Age Population Percentage Boolean False Counts 56.49
Percent White, not Hispanic or Latino Percentage Boolean False Count
s 0.00
Percent Black, not Hispanic or Latino Percentage Boolean False Count
s 3.77
Percent Hispanic or Latino Percentage Boolean False Counts 0.42
Percent Foreign Born Percentage Boolean False Counts 0.25
Percent Female Percentage Boolean False Counts 0.00
Percent Age 29 and Under Percentage Boolean False Counts 0.00
Percent Age 65 and Older Percentage Boolean False Counts 0.00
Median Household Income Percentage Boolean False Counts 0.00
Percent Unemployed Percentage Boolean False Counts 0.25
Percent Less than High School Degree Percentage Boolean False Counts
0.00
Percent Less than Bachelor's Degree Percentage Boolean False Counts
0.00
Percent Rural Percentage Boolean False Counts 1.59
```

In [18]:

```
#Removing the column 'Citizen Voting-Age Population' from the dataset
merged_data = merged_data.drop(['Citizen Voting-Age Population'],axis=1)
merged_data.head()
```

Out[18]:

	State	County	Democratic Votes	Republican Votes	FIPS	Total Population	Percent White, not Hispanic or Latino	Percent Black, not Hispanic or Latino	I c
0	ARIZONA	APACHE	16298.0	7810.0	4001	72346	18.571863	0.486551	5
1	ARIZONA	COCHISE	17383.0	26929.0	4003	128177	56.299492	3.714395	34
2	ARIZONA	COCONINO	34240.0	19249.0	4005	138064	54.619597	1.342855	1:
3	ARIZONA	GILA	7643.0	12180.0	4007	53179	63.222325	0.552850	18
4	ARIZONA	GRAHAM	3368.0	6870.0	4009	37529	51.461536	1.811932	32

Task 5 : Create a new variable named “Party” that labels each county as Democratic or Republican. This new variable should be equal to 1 if there were more votes cast for the Democratic party than the Republican party in that county and it should be equal to 0 otherwise.

In [19]:

```
#Confirming that there is no case where # of democratic votes is same as republi
can votes
count = merged_data[merged_data['Democratic Votes'] == merged_data['Republican V
otes']].count()
print ("Count: ", count)
```

```
Count:  State                                        0
County                                       0
Democratic Votes                             0
Republican Votes                             0
FIPS                                         0
Total Population                             0
Percent White, not Hispanic or Latino        0
Percent Black, not Hispanic or Latino        0
Percent Hispanic or Latino                   0
Percent Foreign Born                         0
Percent Female                               0
Percent Age 29 and Under                     0
Percent Age 65 and Older                     0
Median Household Income                      0
Percent Unemployed                           0
Percent Less than High School Degree         0
Percent Less than Bachelor's Degree          0
Percent Rural                                0
dtype: int64
```

In [20]:

```
merged_data['Party'] = merged_data.apply(lambda row: 1 if row['Democratic Votes'
]>row['Republican Votes'] else 0, axis =1)
merged_data[['Democratic Votes', 'Republican Votes', 'Party']].head()
```

Out[20]:

	Democratic Votes	Republican Votes	Party
0	16298.0	7810.0	1
1	17383.0	26929.0	0
2	34240.0	19249.0	1
3	7643.0	12180.0	0
4	3368.0	6870.0	0

Task 6 : Compute the mean median household income for Democratic counties and Republican counties. Which one is higher? Perform a hypothesis test to determine whether this difference is statistically significant at the $\alpha = 0.05$ significance level. What is the result of the test? What conclusion do you make from this result?

In [21]:

```
#Mean of household income
democratic_income_mean = merged_data[merged_data['Party'] == 1]['Median Househol
d Income'].mean()
republic_income_mean = merged_data[merged_data['Party'] == 0]['Median Household
 Income'].mean()
print("Mean Median Household Income for Democratic counties: ", democratic_incom
e_mean)
print("Mean Median Household Income for Republican counties: ", republic_income_
mean)
```

```
Mean Median Household Income for Democratic counties:  53798.7323076
92306
Mean Median Household Income for Republican counties:  48746.8195402
2989
```

In [22]:

```
print("Difference: ", (democratic_income_mean-republic_income_mean))
```

```
Difference:  5051.912767462418
```

Mean Median Household Income for Democratic counties is greater than Republic counties

In [23]:

```
#Hypothesis Test

democratic_income_count = merged_data[merged_data['Party'] == 1]['Median Household Income'].count()
republic_income_count = merged_data[merged_data['Party'] == 0]['Median Household Income'].count()

democratic_income_std = merged_data[merged_data['Party'] == 1]['Median Household Income'].std()
republic_income_std = merged_data[merged_data['Party'] == 0]['Median Household Income'].std()
alpha = 0.05

# #null hypothesis : d = r
# #alternative hypothesis : d>r or d<r

t_stats = (democratic_income_mean-republic_income_mean) / ((((democratic_income_std**2)/democratic_income_count) + ((republic_income_std**2)/republic_income_count))**0.5)
print ("T Stats: ", t_stats)

pvalue = st.t.cdf(t_stats, (democratic_income_count + republic_income_count - 2))
#For two tailed test
pvalue_tail = 2*(1-pvalue)
print("P value: (For Two Tailed Test) ", pvalue_tail)

if pvalue_tail < alpha:
    print ("Statistically significant")
else:
    print ("Not sufficient evidence to say not statistically significant")
```

```
T Stats:  5.479141589767387
P value: (For Two Tailed Test)  5.209857278920538e-08
Statistically significant
```

Task 7 : Compute the mean population for Democratic counties and Republican counties. Which one is higher? Perform a hypothesis test to determine whether this difference is statistically significant at the $\alpha = 0.05$ significance level. What is the result of the test? What conclusion do you make from this result?

In [24]:

```
democratic_population_mean = merged_data[merged_data['Party'] == 1]['Total Population'].mean()
republic_population_mean = merged_data[merged_data['Party'] == 0]['Total Population'].mean()
print("Mean Total Population for Democratic counties: ", democratic_population_mean)
print("Mean Total Population for Republican counties: ", republic_population_mean)
```

```
Mean Total Population for Democratic counties:  300998.3169230769
Mean Total Population for Republican counties:  53864.6724137931
```

In [25]:

```
print("Difference: ", (democratic_population_mean-republic_population_mean))
```

```
Difference:  247133.64450928383
```

Mean Total Population for Democratic counties is greater than Republic counties

In [26]:

```
#Hypothesis Test

democratic_population_count = merged_data[merged_data['Party'] == 1]['Total Popu
lation'].count()
republic_population_count = merged_data[merged_data['Party'] == 0]['Total Popula
tion'].count()

democratic_population_std = merged_data[merged_data['Party'] == 1]['Total Popula
tion'].std()
republic_population_std = merged_data[merged_data['Party'] == 0]['Total Populati
on'].std()
alpha = 0.05

# #null hypothesis : d = r
# #alternative hypothesis : d>r or d<r

t_stats = (democratic_population_mean-republic_population_mean) / ((((democratic
_population_std**2)/democratic_population_count) + ((republic_population_std**2)
/republic_population_count))**0.5)
print ("T Stats: ", t_stats)

pvalue = st.t.cdf(t_stats, (democratic_population_count + republic_population_co
unt - 2))
#For two tailed test
pvalue_tail = 2*(1-pvalue)
print("P value: (For Two Tailed Test) ", pvalue_tail)

if pvalue_tail < alpha:
    print ("Statistically significant")
else:
    print ("Not sufficient evidence to say not statistically significant")
```

```
T Stats:  8.004638577960957
P value: (For Two Tailed Test)  2.886579864025407e-15
Statistically significant
```

Task 8: Compare Democratic counties and Republican counties in terms of age, gender, race and ethnicity, and education by computing descriptive statistics and creating plots to visualize the results. What conclusions do you make for each variable from the descriptive statistics and the plots?

AGE

In [27]:

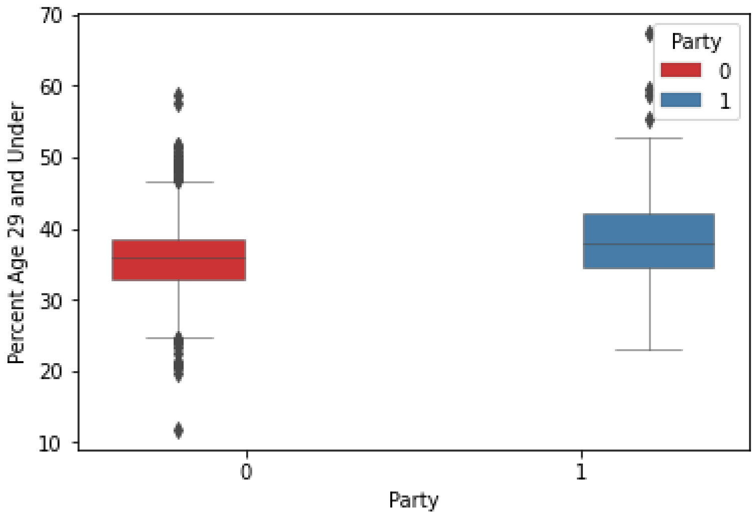
```
#AGE
age = merged_data[['Percent Age 29 and Under','Percent Age 65 and Older','Party'
]]
#found the ages ranges
age['Percent Age between 29 and 65'] = 100 - (age['Percent Age 29 and Under'] +
age['Percent Age 65 and Older'])
#(age.style.set_table_styles([{'selector' : '', 'props' : [('border', '2px solid
green')]}]) )
abc = (age.groupby('Party').describe())
abc.style
```

Out[27]:

	Percent Age 29 and Und							
	count	mean	std	min	25%	50%	75%	ma
Party								
0	870.000000	36.005719	5.181522	11.842105	32.983652	35.846532	38.539787	58.7491
1	325.000000	38.726959	6.252786	23.156452	34.488444	38.074151	42.161162	67.3678

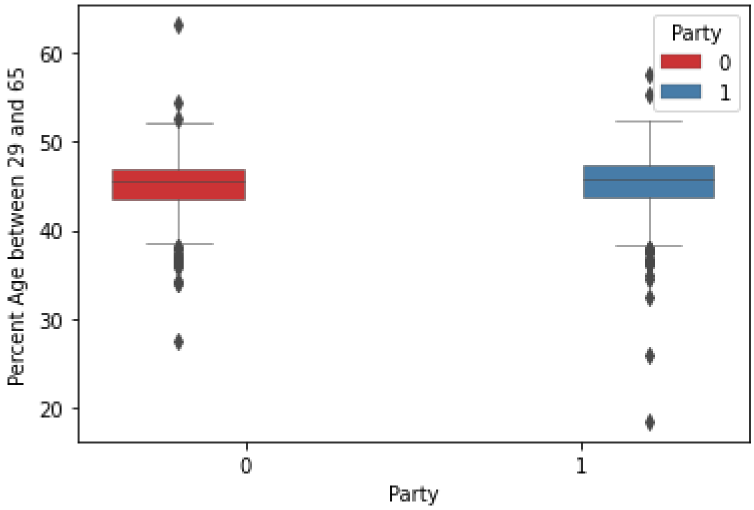
In [28]:

```
ax = sns.boxplot(x="Party", y="Percent Age 29 and Under", data=age,hue="Party",p
alette="Set1",linewidth=0.5)
```



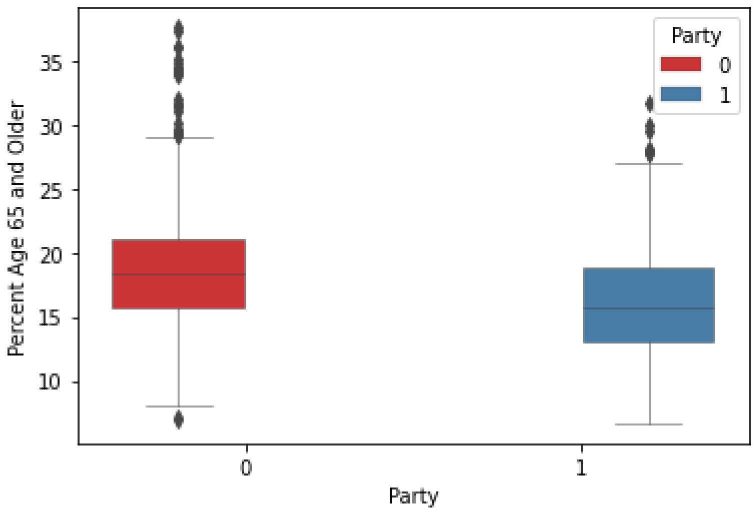
In [29]:

```
ay = sns.boxplot(x="Party", y="Percent Age between 29 and 65",data=age,hue="Party",palette="Set1",linewidth=0.5)
```



In [30]:

```
az = sns.boxplot(x="Party", y="Percent Age 65 and Older",data=age,hue="Party",palette="Set1",linewidth=0.5)
```



GENDER

In [31]:

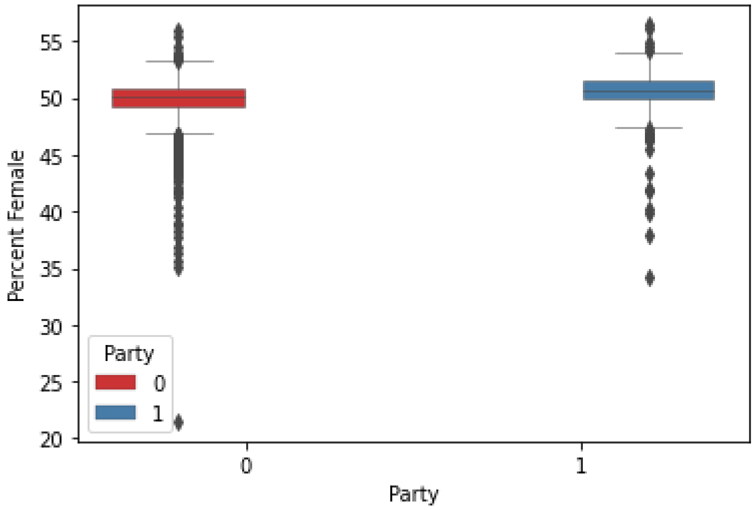
```
#GENDER
gender = merged_data[['Percent Female','Party']]
#found the male gender percent
gender['Percent Male'] = 100 - gender['Percent Female']
(gender.groupby('Party').describe())
```

Out[31]:

	Percent Female								P
	count	mean	std	min	25%	50%	75%	max	c
Party									
0	870.0	49.630898	2.429013	21.513413	49.222905	50.176792	50.829770	55.885023	8
1	325.0	50.385433	2.149359	34.245291	49.854280	50.653830	51.492075	56.418468	3

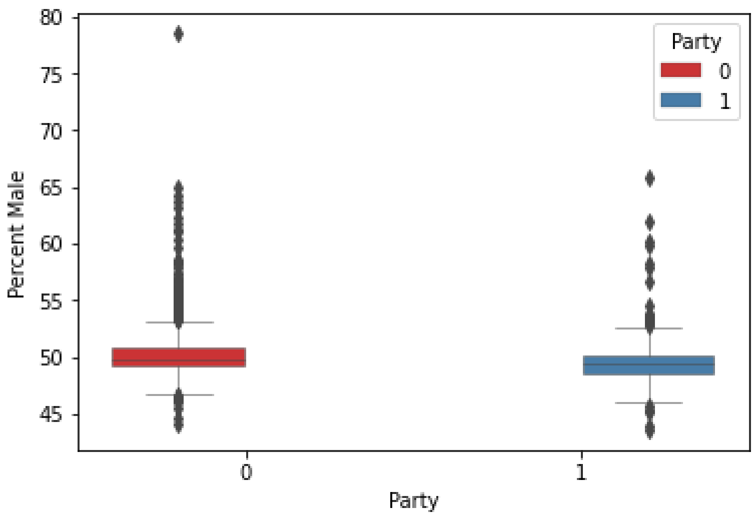
In [32]:

```
ax = sns.boxplot(x="Party", y="Percent Female", data=gender,hue="Party",palette=
"Set1",linewidth=0.5)
```



In [33]:

```
ay = sns.boxplot(x="Party", y="Percent Male",data=gender,hue="Party",palette="Se
t1",linewidth=0.5)
```



RACE

In [34]:

```
#RACE
race = merged_data[['Percent White, not Hispanic or Latino','Percent Black, not
 Hispanic or Latino','Percent Hispanic or Latino','Party']]
(race.groupby('Party').describe())
```

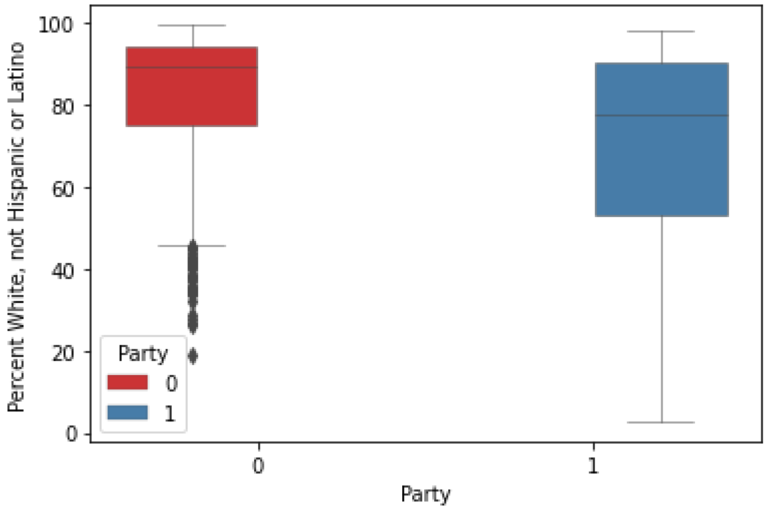
Out[34]:

	Percent White, not Hispanic or Latino								I
	count	mean	std	min	25%	50%	75%	max	c
Party									
0	870.0	82.656646	16.056122	18.758977	75.016397	89.434849	94.466596	99.627329	
1	325.0	69.683766	24.981502	2.776702	53.271579	77.786090	90.300749	98.063495	

2 rows × 24 columns

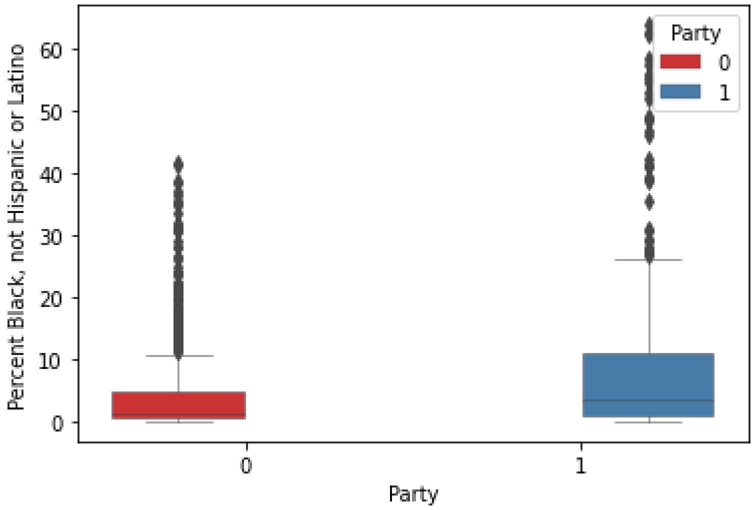
In [35]:

```
ax = sns.boxplot(x="Party", y="Percent White, not Hispanic or Latino",data=race,
hue="Party",palette="Set1",linewidth=0.5)
```



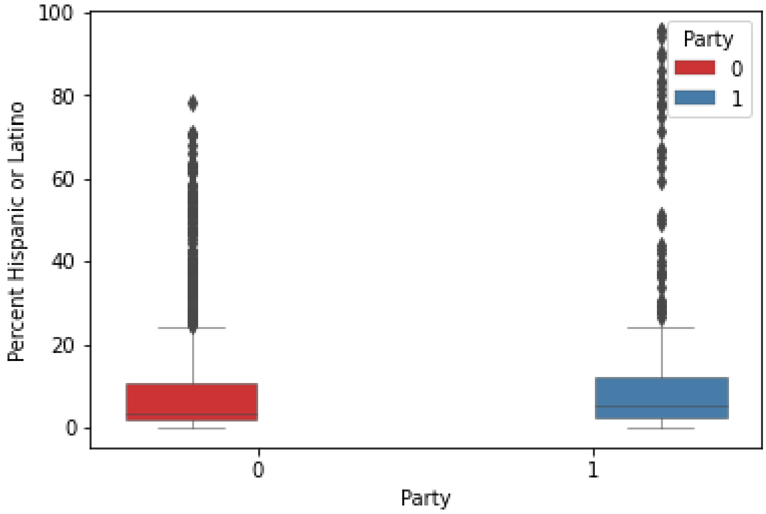
In [36]:

```
ay = sns.boxplot(x="Party", y="Percent Black, not Hispanic or Latino",data=race,
hue="Party",palette="Set1",linewidth=0.5)
```



In [37]:

```
az = sns.boxplot(x="Party", y="Percent Hispanic or Latino",data=race,hue="Party"
,palette="Set1",linewidth=0.5)
```



ETHNICITY

In [38]:

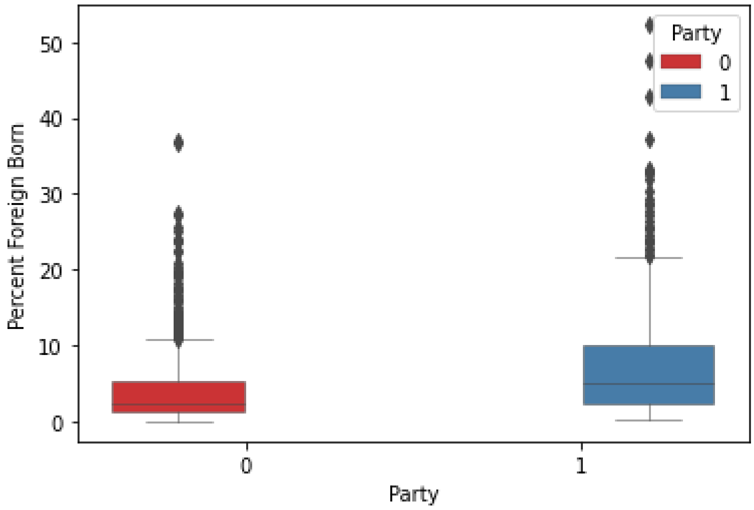
```
#ethnicity
ethnicity = merged_data[['Percent Foreign Born','Party']]
#compute non foreign born
ethnicity['Percent Not Foreign Born'] = 100 - ethnicity['Percent Foreign Born']
ethnicity = ethnicity[['Percent Foreign Born','Percent Not Foreign Born','Party'
]]
ethnicity.groupby('Party').describe()
```

Out[38]:

	Percent Foreign Born								Perce
	count	mean	std	min	25%	50%	75%	max	count
Party									
0	870.0	3.990096	4.507786	0.000000	1.320101	2.326317	5.149429	37.058317	870.0
1	325.0	7.986330	8.330740	0.179769	2.470508	5.105490	10.144555	52.229868	325.0

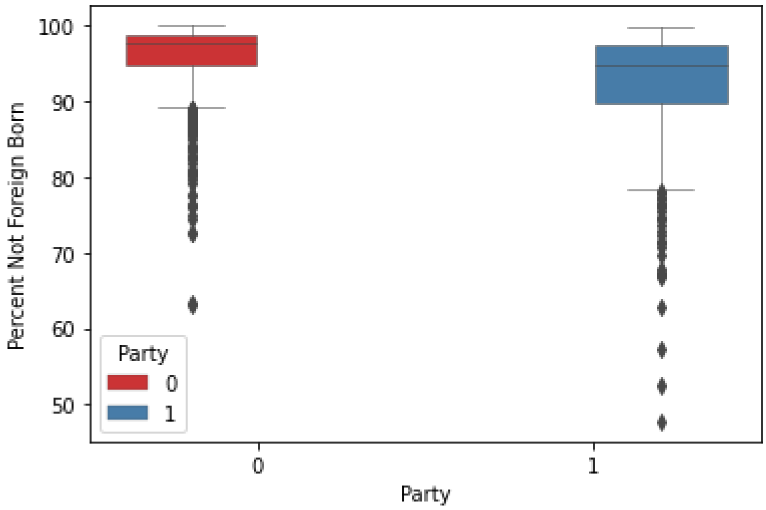
In [39]:

```
ax = sns.boxplot(x="Party", y="Percent Foreign Born",data=ethnicity,hue="Party",
palette="Set1",linewidth=0.5)
```



In [40]:

```
ay = sns.boxplot(x="Party", y="Percent Not Foreign Born",data=ethnicity,hue="Par
ty",palette="Set1",linewidth=0.5)
```



EDUCATION

In [41]:

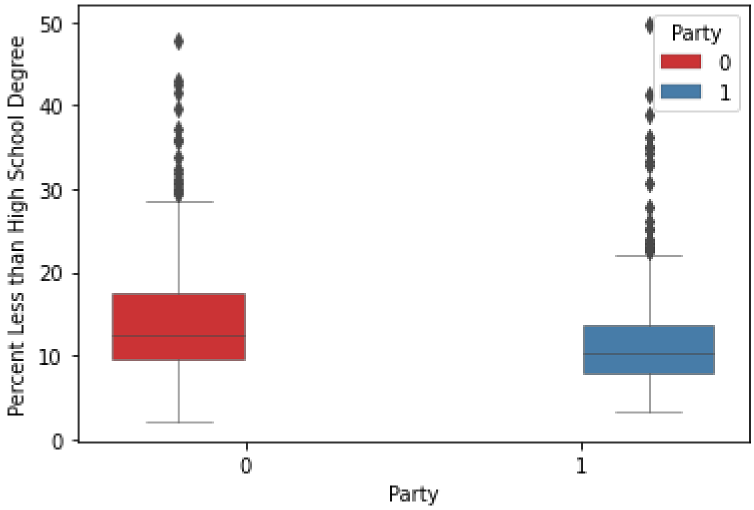
```
#EDUCATION
education = merged_data[['Percent Less than High School Degree',"Percent Less th
an Bachelor's Degree",'Party']]
education.groupby('Party').describe()
```

Out[41]:

	Percent Less than High School Degree								Perc
	count	mean	std	min	25%	50%	75%	max	cou
Party									
0	870.0	14.009112	6.303126	2.134454	9.662491	12.572435	17.447168	47.812773	870
1	325.0	11.883760	6.505613	3.215803	7.893714	10.370080	13.637059	49.673777	325

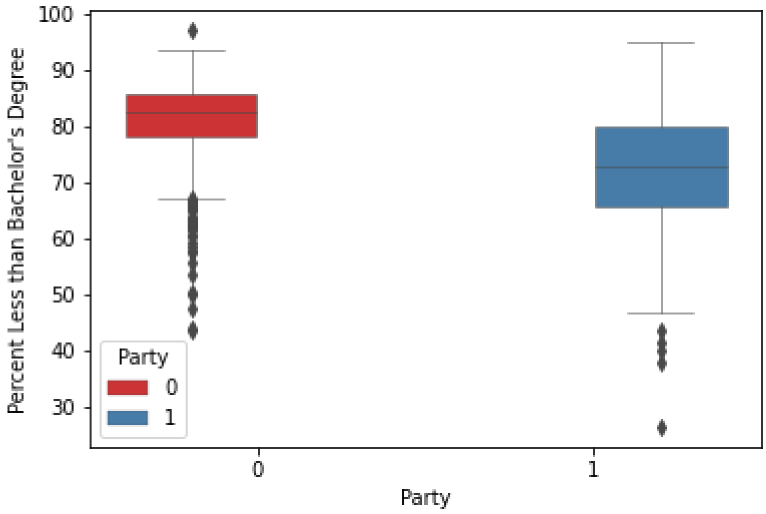
In [42]:

```
ax = sns.boxplot(x="Party", y="Percent Less than High School Degree",data=educat
ion,hue="Party",palette="Set1",linewidth=0.5)
```



In [43]:

```
ay = sns.boxplot(x="Party", y="Percent Less than Bachelor's Degree",data=educati
on,hue="Party",palette="Set1",linewidth=0.5)
```



Task 9:Based on your results for tasks 6-8, which variables in the dataset do you think are more important to determine whether a county is labeled as Democratic or Republican? Justify your answer.

Task 10: Create a map of Democratic counties and Republican counties using the counties' FIPS codes and Python's Plotly library (plot.ly/python/county-choropleth/). Note that this dataset does not include all United States counties

In [44]:

```
fips = merged_data['FIPS']
values = merged_data['Party']
fig = ff.create_choropleth(fips=fips, values=values,title='Democratic counties a
nd Republican counties',legend_title='Democratic or Republican', colorscale=['re
d','blue'])
fig.layout.template = None
fig.show()
```