Loading Data

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pylab as plt
```

In [2]:

```
sns.set_style('whitegrid')
sns.set_context(font_scale=1.2)
```

In [3]:

```
pres_cdt = pd.read_csv('2019-GENERAL-ELECTIONS-FINAL-LIST-OF-PRESIDENTIAL-CANDIDATES.csv',i
```

Preliminary Data Exploration

In [4]:

```
pres_cdt.head()
```

Out[4]:

	POSITION	NAME OF CANDIDATE	PARTY	PWD	AGE	GENDER	QUALIFICATION	REMARKS	S O
SN									
1	PRESIDENT	OSITELU ISAAC BABATUNDE	A	None	64.0	M	FSLC, BSc, WASC, MSc	NaN	
2	VICE-	LAWAL NAFIU MUHAMMAD	A	None	33.0	M	FSLC, BSc, NECO	NaN	
3	PRESIDENT	ABDULRASHID HASSAN BABA	AA	None	46.0	M	SSCE	NaN	
4	VICE-	UCHENDU UJU PEACE OZOKA	AA	None	49.0	F	LLB	NaN	
5	PRESIDENT	OMOYELE SOWORE	AAC	None	47.0	M	WAEC	NaN	

In [5]:

```
del pres_cdt['PWD']
pres_cdt.dropna(axis=1,inplace=True,how='all')
pres_cdt.dropna(axis=0,inplace=True,)
pres_cdt.reset_index(inplace=True)
```

In [6]:

```
pres_cdt.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144 entries, 0 to 143
Data columns (total 7 columns):
SN                   144 non-null int64
POSITION             144 non-null object
NAME OF CANDIDATE    144 non-null object
PARTY                144 non-null object
AGE                  144 non-null float64
GENDER               144 non-null object
QUALIFICATION        144 non-null object
dtypes: float64(1), int64(1), object(5)
memory usage: 8.0+ KB
```

Data Cleaning and Feature Engineering

In this section, I tried to group the qualifications into meaningful subgroups. I then used a series of hierarchical for loops to map each candidates to a 'highest level of education' feature.

P.S: I know there may be more Pythonic ways to do this. I would love to see your improvements.

Data Cleaning

In [7]:

```
z=pres_cdt['QUALIFICATION'].str.split(',')
```

In [8]:

```
ls = z[1]
for i in range(2, len(z)):
    for x in z[i]:
            ls.append(x)
```

In [9]:

```
lst=list(set(list((','.join(ls)).lower().split(','))))
```

In [10]:

```
print(lst)
print(len(lst))
```

```
[' ll.m', '', 'wasc', 'pgd', ' bsc', ' wasc o&a', ' it fm (mba)', 'mbbs', '
mph', 'ssce', ' hnd', '  bl', ' ma', 'hnd', 'nce', ' ol', ' mba', ' pgd',
'p.', 'bed', ' nce', 'nd', 'hdpa', ' cdt', ' wasc', 'waec', ' executive cert
ificate', ' bed', 'bl', ' waec', ' ps', ' nda cert', ' llb', ' ond', ' btec
h', ' pharm. d', ' dip', ' b.sc', ' hsc', 'diploma', 'ond', ' nabteb', 'ph
d', ' neco', ' ba', 'fnipr', ' nd', ' od', 'dba', ' ssce', ' mba mphil', ' g
ce', ' al', ' bsc.', ' diploma', ' llm', 'llb', ' msc', 'b.phil', ' juris do
ctor', ' phd', 'msc', 'ba', ' b.eng', 'bsc', ' bl', 'fslc']
67
```

In [11]:

```
lst = [i.strip() for i in lst]
lst=list(set(lst))
print(lst)
print(len(lst))
```

```
['', 'nabteb', 'pgd', 'wasc', 'll.m', 'juris doctor', 'btech', 'mbbs', 'ssc
e', 'mph', 'nce', 'hnd', 'p.', 'nd', 'ma', 'pharm. d', 'bsc.', 'ps', 'bed',
'hdpa', 'waec', 'bl', 'od', 'al', 'executive certificate', 'mba mphil', 'b.e
ng', 'diploma', 'ond', 'phd', 'fnipr', 'dba', 'neco', 'gce', 'llm', 'mba',
'nda cert', 'cdt', 'llb', 'b.sc', 'dip', 'b.phil', 'ba', 'msc', 'hsc', 'bs
c', 'it fm (mba)', 'wasc o&a', 'ol', 'fslc']
50
```

In [12]:

```
lst.remove('')
```

In [13]:

```
uni = ['nda cert']
for i in lst:
#    i = i.strip()
    if i.startswith('b')==True or i=='mbbs' or i=='ll.m' or i=='llb' or i =='llm' or i == '
        uni.append(i)
lst=list(set(lst)-set(uni))
```

In [14]:

```
ps = ['fslc']
ss = ['neco']
for i in lst:
#    i = i.strip()
    if i.startswith('w')==True  or i.startswith('g') or i.startswith('s'):
        ss.append(i)
lst=list(set(lst)-set(ps)-set(ss))
```

In [15]:

```
pg = []
for i in lst:
#    i = i.strip()
    if i.startswith('m')==True or i == 'it fm (mba)' or i == 'pgd':
        pg.append(i)
lst=list(set(lst)-set(pg))
```

In [16]:

```
ond = ['ond','diploma','nd']
hnd = ['hnd']
phd = ['phd']
nce=['nce']
```

In [17]:

```
others=list(set(lst)-set(ond)-set(hnd)-set(phd)-set(nce))
```

In [18]:

```
print(others,'\n',ond,'\n',hnd,'\n',phd,'\n',pg,'\n',ps,'\n',uni,'\n',ss,'\n',nce)
```

```
['nabteb', 'cdt', 'juris doctor', 'fnipr', 'dba', 'dip', 'od', 'p.', 'al',
'hsc', 'executive certificate', 'ps', 'ol', 'hdpa']
 ['ond', 'diploma', 'nd']
 ['hnd']
 ['phd']
 ['pgd', 'mph', 'ma', 'mba mphil', 'mba', 'msc', 'it fm (mba)']
 ['fslc']
 ['nda cert', 'll.m', 'btech', 'mbbs', 'pharm. d', 'bsc.', 'bed', 'bl', 'b.e
ng', 'llm', 'llb', 'b.sc', 'b.phil', 'ba', 'bsc']
 ['neco', 'wasc', 'ssce', 'waec', 'gce', 'wasc o&a']
 ['nce']
```

Feature Engineering

In [19]:

```
cer=dict()
for i in ','.join(others).split(','):
    for j in pres_cdt['QUALIFICATION'].index:
        if i in pres_cdt['QUALIFICATION'][j].lower():
           cer[j]='Others'
        else:
            cer[j]='x'
```

In [20]:

```
for i in ','.join(phd).split(','):
    for key in cer.keys():
        if i in pres_cdt['QUALIFICATION'][key].lower() and cer[key]=='x':
           cer[key]='Doctorate'
```

In [21]:

```
for i in ','.join(pg).split(','):
    for key in cer.keys():
        if i in pres_cdt['QUALIFICATION'][key].lower() and cer[key]=='x':
           cer[key]='Postgraduate'
```

In [22]:

```
for i in ','.join(uni).split(','):
    for key in cer.keys():
        if i in pres_cdt['QUALIFICATION'][key].lower() and cer[key]=='x':
           cer[key]='University'
```

In [23]:

```
for i in ','.join(hnd).split(','):
    for key in cer.keys():
        if i in pres_cdt['QUALIFICATION'][key].lower() and cer[key]=='x':
           cer[key]='HND'
```

In [24]:

```
for i in ','.join(nce).split(','):
    for key in cer.keys():
        if i in pres_cdt['QUALIFICATION'][key].lower() and cer[key]=='x':
           cer[key]='NCE'
```

In [25]:

```
for i in ','.join(ond).split(','):
    for key in cer.keys():
        if i in pres_cdt['QUALIFICATION'][key].lower() and cer[key]=='x':
           cer[key]='OND'
```

In [26]:

```
for i in ','.join(ss).split(','):
    for key in cer.keys():
        if i in pres_cdt['QUALIFICATION'][key].lower() and cer[key]=='x':
           cer[key]='Secondary School'
```

In [27]:

```
for i in ','.join(ps).split(','):
    for key in cer.keys():
        if i in pres_cdt['QUALIFICATION'][key].lower() and cer[key]=='x':
           cer[key]='Primary School'
```

In [28]:

```
 for key in cer.keys():
        if cer[key]=='x':
           cer[key]='Others'
```

In [29]:

```
print(cer)
```

```
{0: 'Postgraduate', 1: 'University', 2: 'Secondary School', 3: 'University',
4: 'Secondary School', 5: 'Postgraduate', 6: 'University', 7: 'University',
8: 'Secondary School', 9: 'University', 10: 'University', 11: 'University',
12: 'Doctorate', 13: 'Others', 14: 'Doctorate', 15: 'Doctorate', 16: 'Univer
sity', 17: 'Secondary School', 18: 'University', 19: 'Postgraduate', 20: 'Se
condary School', 21: 'Secondary School', 22: 'Doctorate', 23: 'University',
24: 'Postgraduate', 25: 'Postgraduate', 26: 'University', 27: 'Secondary Sch
ool', 28: 'Postgraduate', 29: 'University', 30: 'Doctorate', 31: 'Postgradua
te', 32: 'Secondary School', 33: 'University', 34: 'University', 35: 'Doctor
ate', 36: 'Secondary School', 37: 'University', 38: 'University', 39: 'Unive
rsity', 40: 'Primary School', 41: 'Primary School', 42: 'Postgraduate', 43:
'Postgraduate', 44: 'University', 45: 'University', 46: 'University', 47: 'P
ostgraduate', 48: 'Secondary School', 49: 'NCE', 50: 'Secondary School', 51:
'University', 52: 'University', 53: 'NCE', 54: 'Postgraduate', 55: 'HND', 5
6: 'OND', 57: 'University', 58: 'Postgraduate', 59: 'Secondary School', 60:
'Doctorate', 61: 'HND', 62: 'University', 63: 'University', 64: 'Doctorate',
65: 'University', 66: 'Doctorate', 67: 'HND', 68: 'Postgraduate', 69: 'HND',
70: 'Secondary School', 71: 'Secondary School', 72: 'Secondary School', 73:
'OND', 74: 'Doctorate', 75: 'Doctorate', 76: 'Doctorate', 77: 'University',
78: 'Postgraduate', 79: 'Secondary School', 80: 'Doctorate', 81: 'Universit
y', 82: 'Secondary School', 83: 'HND', 84: 'Postgraduate', 85: 'NCE', 86: 'P
ostgraduate', 87: 'University', 88: 'HND', 89: 'Secondary School', 90: 'Post
graduate', 91: 'Secondary School', 92: 'Secondary School', 93: 'Postgraduat
e', 94: 'University', 95: 'Postgraduate', 96: 'OND', 97: 'University', 98:
'University', 99: 'Postgraduate', 100: 'University', 101: 'University', 102:
'University', 103: 'University', 104: 'NCE', 105: 'University', 106: 'Univer
sity', 107: 'Postgraduate', 108: 'Postgraduate', 109: 'University', 110: 'ON
D', 111: 'University', 112: 'Postgraduate', 113: 'University', 114: 'Postgra
duate', 115: 'University', 116: 'University', 117: 'OND', 118: 'Secondary Sc
hool', 119: 'Secondary School', 120: 'Postgraduate', 121: 'Doctorate', 122:
'Doctorate', 123: 'Postgraduate', 124: 'HND', 125: 'University', 126: 'Unive
rsity', 127: 'OND', 128: 'HND', 129: 'HND', 130: 'Secondary School', 131: 'P
ostgraduate', 132: 'Postgraduate', 133: 'University', 134: 'University', 13
5: 'Postgraduate', 136: 'HND', 137: 'HND', 138: 'Doctorate', 139: 'Postgradu
ate', 140: 'OND', 141: 'Postgraduate', 142: 'Doctorate', 143: 'HND'}
```

In [30]:

```
a=pd.DataFrame(pd.Series(cer,index=cer.keys()),columns=['Highest Education'])
```

In [31]:

```
a.head()
```

Out[31]:

	Highest Education
0	Postgraduate
1	University
2	Secondary School
3	University
4	Secondary School

In [32]:

```
del pres_cdt['QUALIFICATION']
pres_cdt=pres_cdt.join(a)
pres_cdt.reset_index(level=0,drop=True, inplace=True)
```

In [33]:

```
del pres_cdt['SN']
```

Explorative Data Analysis

Descriptive Statistics

In [34]:

```
pres_cdt.describe()
```

Out[34]:

	AGE
count	144.000000
mean	49.888889
std	9.844320
min	30.000000
25%	42.000000
50%	48.500000
75%	57.000000
max	76.000000

In [35]:

```
pres_cdt[pres_cdt['AGE']==30]
```

Out[35]:

	POSITION	NAME OF CANDIDATE	PARTY	AGE	GENDER	Highest Education
103	VICE-	JOHNSON OMEDE	NNPP	30.0	M	University

In [36]:

```
pres_cdt[pres_cdt['AGE']==76]
```

Out[36]:

	POSITION	NAME OF CANDIDATE	PARTY	AGE	GENDER	Highest Education
121	VICE-	AGWUNCHA NWANKWO ARTHUR	PT	76.0	M	Doctorate

We can see that the youngest and oldest people participating in the presidential elections are both vice-presidential candidates. Let us try to split the data into just presidential and vice-presidential candidates. The mean age is about 50 years for all the candidates.

In [37]:

```
pres_only=pres_cdt[pres_cdt['POSITION']=='PRESIDENT']
vice_only=pres_cdt[pres_cdt['POSITION']=='VICE-']
```

In [38]:

```
pres_only.describe()
```

Out[38]:

	AGE
count	72.000000
mean	51.902778
std	9.892606
min	33.000000
25%	45.750000
50%	51.500000
75%	59.000000
max	75.000000

The average of presidential candidates is about 52 years. While it might be true that leading candidates are much older, the average age is relatively young.

Let us take a look at the youngest and oldest presidential candidates and their portfolios.

In [39]:

```
print('Oldest presidential candidate is:')
pres_only[pres_only['AGE']==75]
```

```
Oldest presidential candidate is:
```

Out[39]:

	POSITION	NAME OF CANDIDATE	PARTY	AGE	GENDER	Highest Education
32	PRESIDENT	BUHARI MUHAMMADU	APC	75.0	M	Secondary School

In [40]:

```
print('Youngest presidential candidate is:')
pres_only[pres_only['AGE']==33]
```

```
Youngest presidential candidate is:
```

Out[40]:

	POSITION	NAME OF CANDIDATE	PARTY	AGE	GENDER	Highest Education
126	PRESIDENT	NSEHE NSEOBONG	RP	33.0	M	University

In [41]:

```
vice_only.describe()
```

Out[41]:

	AGE
count	72.000000
mean	47.875000
std	9.439112
min	30.000000
25%	42.000000
50%	45.000000
75%	54.000000
max	76.000000

```
The average of vice-presidential candidates is about 48 years. While it might be true that
leading candidates are much older, the average age is relatively young.

Let us take a look at the youngest and oldest presidential candidates and their
portfolios.
```

In [42]:

```
print('Youngest vice-presidential candidate is:')
vice_only[vice_only['AGE']==30]
```

Youngest vice-presidential candidate is:

Out[42]:

	POSITION	NAME OF CANDIDATE	PARTY	AGE	GENDER	Highest Education
103	VICE-	JOHNSON OMEDE	NNPP	30.0	M	University

In [43]:

```
print('Oldest vice-presidential candidate is:')
vice_only[vice_only['AGE']==76]
```

Oldest vice-presidential candidate is:

Out[43]:

	POSITION	NAME OF CANDIDATE	PARTY	AGE	GENDER	Highest Education
121	VICE-	AGWUNCHA NWANKWO ARTHUR	PT	76.0	M	Doctorate

Visualization

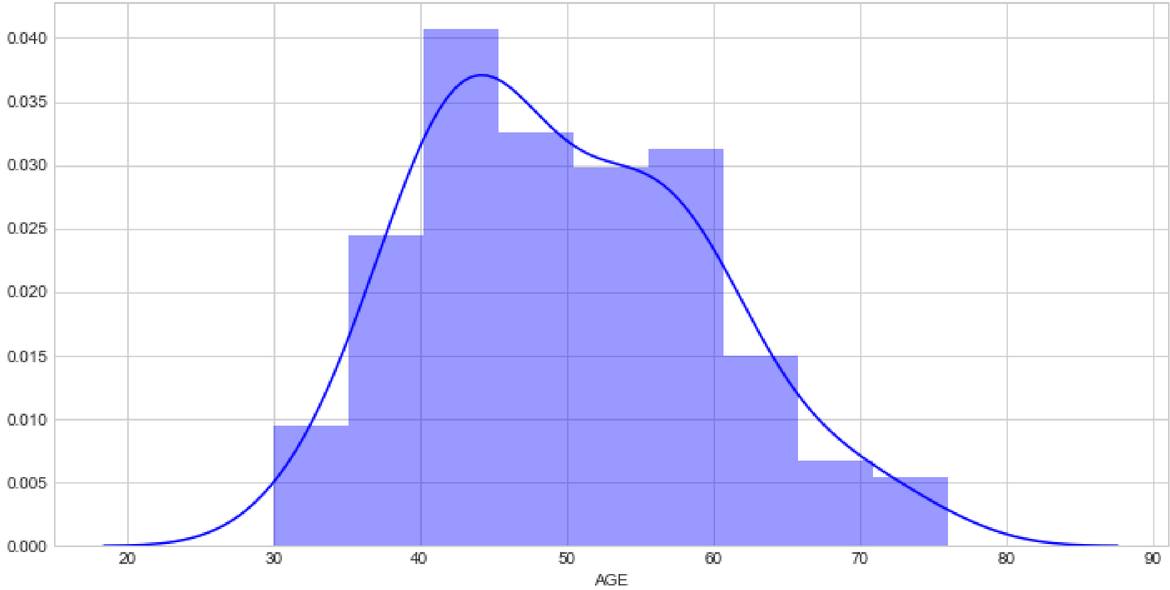
Let us view the distributions of the age for both the general dataset and those of the presidential & vice-presidential candidates only.

In [44]:

```
plt.figure(figsize=(12,6))
sns.distplot(pres_cdt['AGE'],color='blue')
```

Out[44]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x26ccb0df978>
```

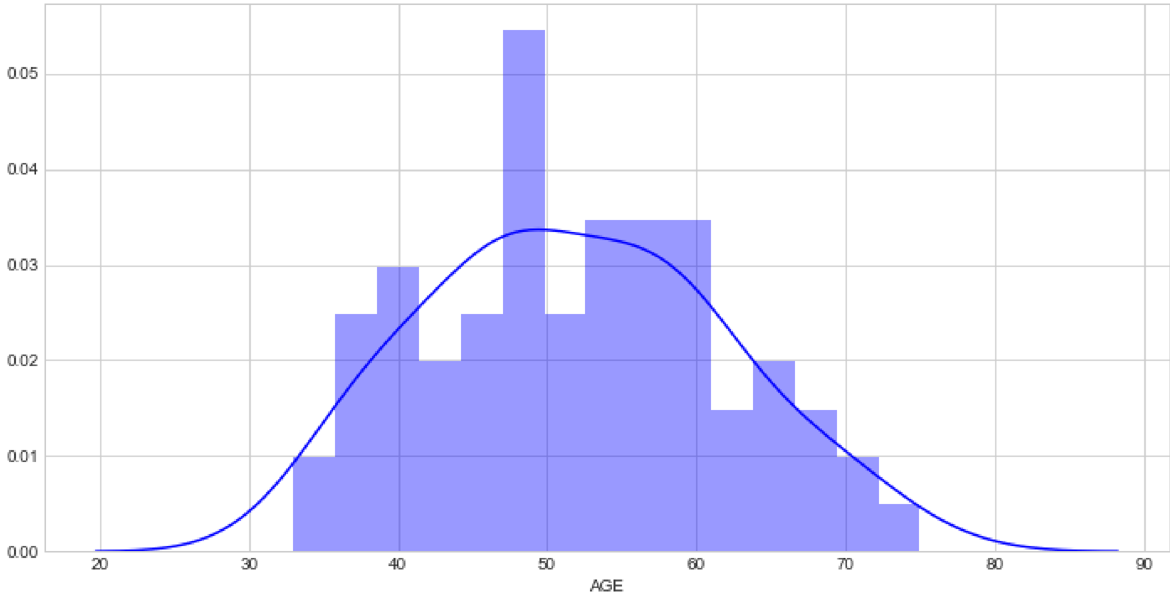


In [45]:

```
plt.figure(figsize=(12,6))
sns.distplot(pres_only['AGE'],bins=15,color='blue')
```

Out[45]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x26ccb1c8c88>
```

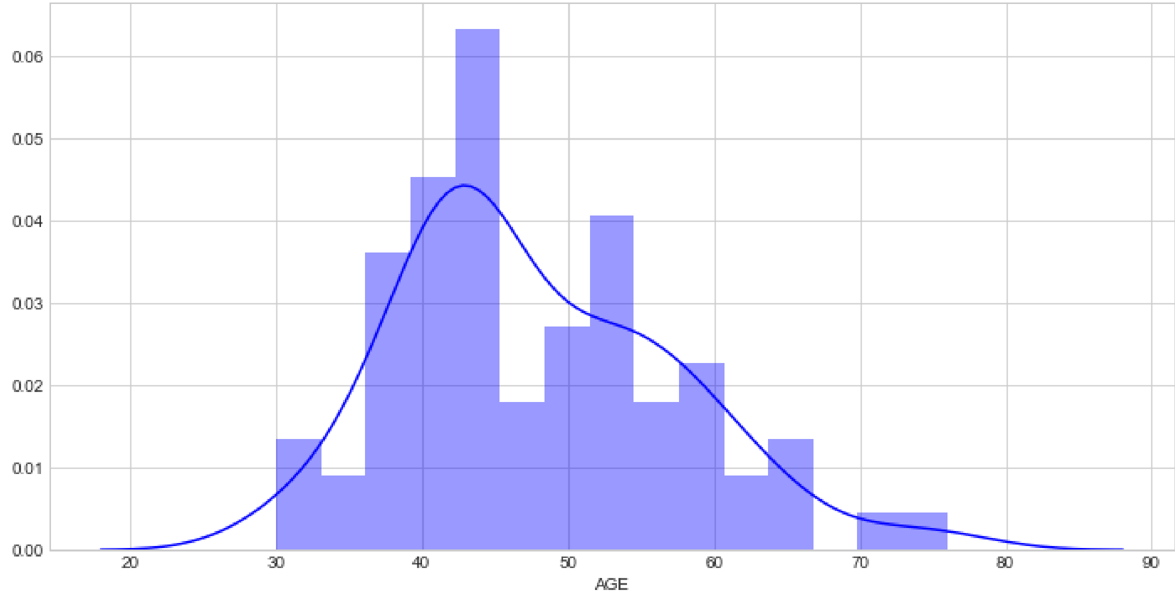


In [46]:

```
plt.figure(figsize=(12,6))
sns.distplot(vice_only['AGE'],bins=15,color='blue')
```

Out[46]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x26ccb1ffb00>
```



The age distributions for all the dataset is rougly normal. Thus candidates are equally as likely to be young as to be old.

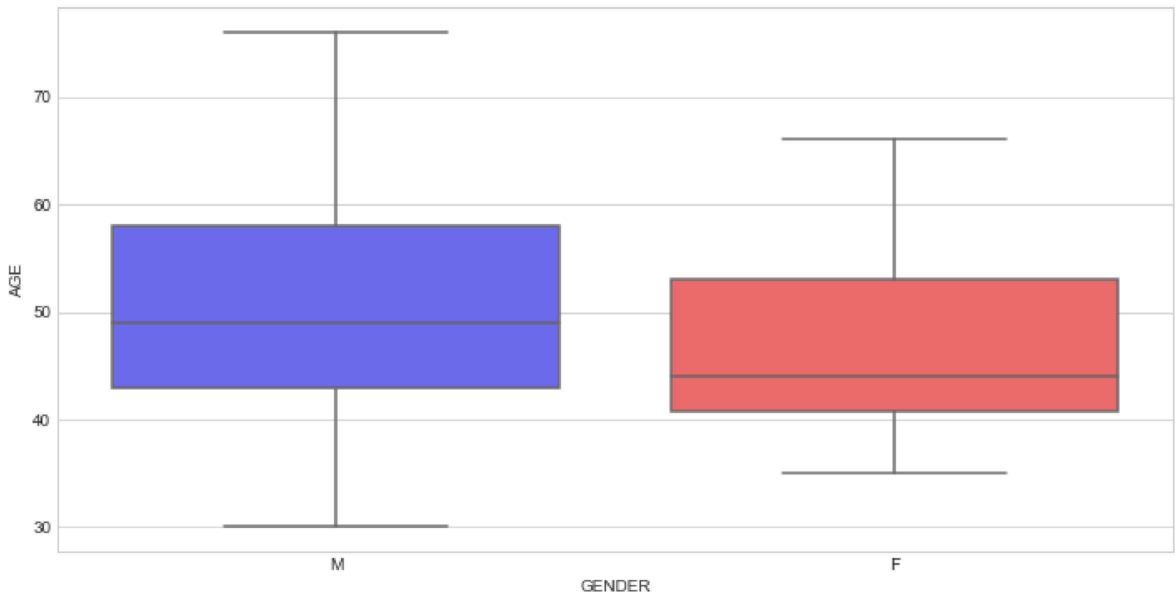
Let us now explore the age feature

In [47]:

```
plt.figure(figsize=(12,6))
sns.boxplot(data=pres_cdt,x='GENDER',y='AGE',palette='seismic')
```

Out[47]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x26ccb2cff60>
```

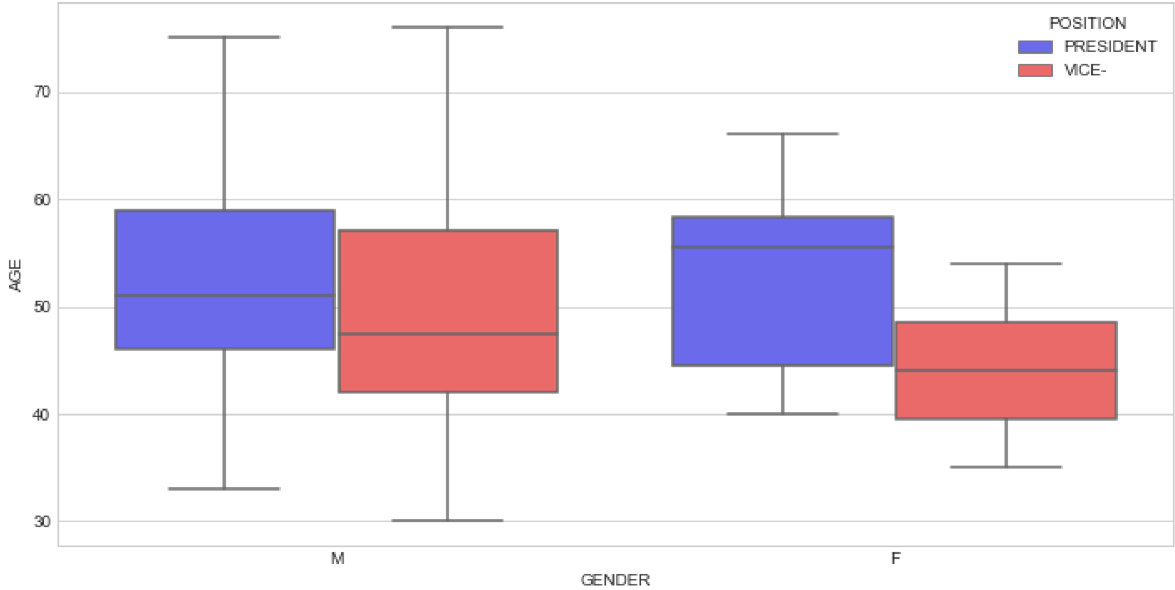


In [48]:

```
plt.figure(figsize=(12,6))
sns.boxplot(data=pres_cdt,x='GENDER',y='AGE',hue='POSITION',palette='seismic')
```

Out[48]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x26ccb281a20>
```



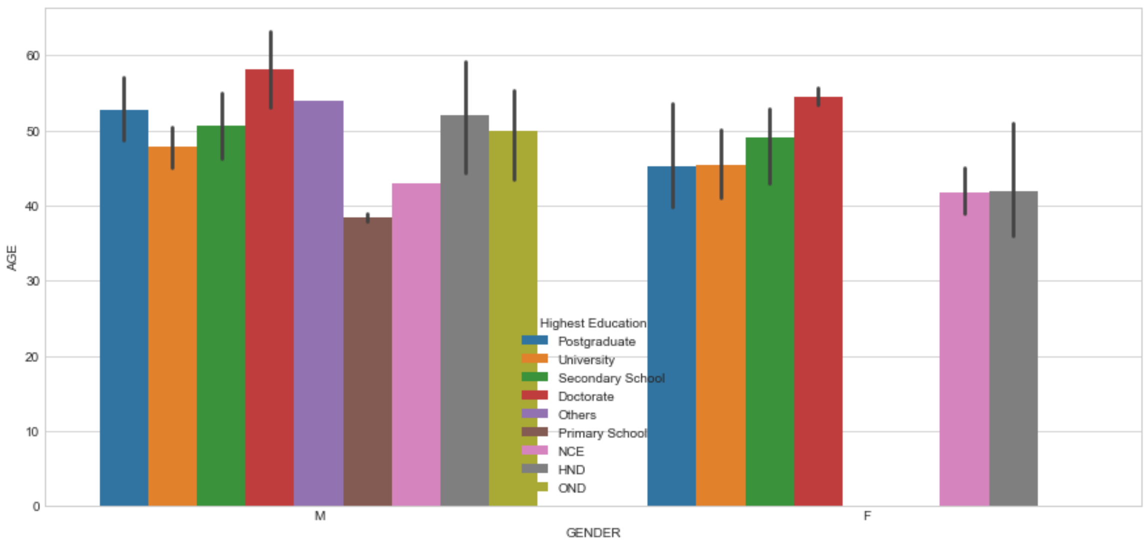
From the first plot, it can be seen that average age for all the female candidates is about five years less than that of their male counterparts. When seperated by position, it can be easily seen that while presidential candidates are generally on an average older than the vice-presidential candidates, the difference is less pronoued in males than females. It is interesting to know that the average age for female presidential candidates is about four years higher than that of male presidential candidates. Generally, the age range is lesser for female candidates than males.

In [49]:

```
plt.figure(figsize=(15,7))
sns.barplot(data=pres_cdt,x='GENDER',y='AGE',hue='Highest Education')
```

Out[49]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x26ccb35ba58>
```



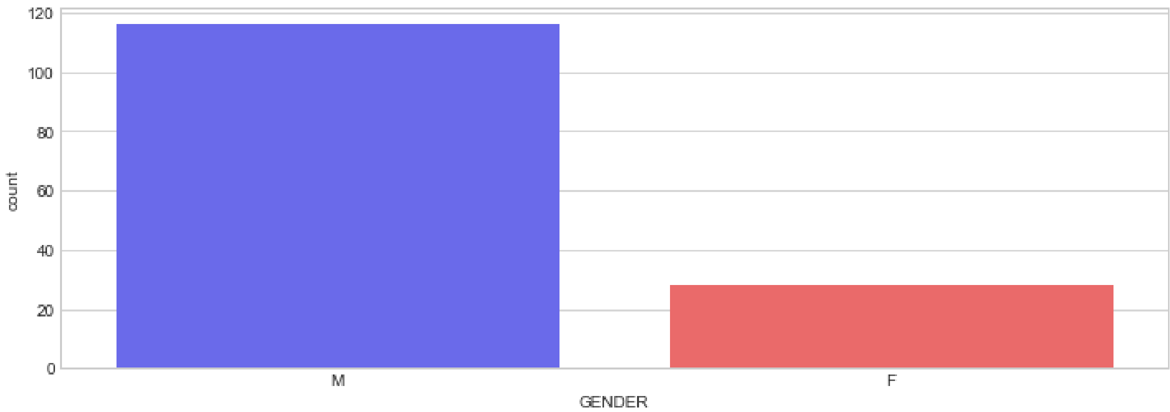
There seem to be no direct relationship between the level of education and the average age of candidates with that level of education for both sexes

In [50]:

```
plt.figure(figsize=(12,4))
sns.countplot(data=pres_cdt,x='GENDER',palette='seismic')
```

Out[50]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x26ccb4f6518>
```

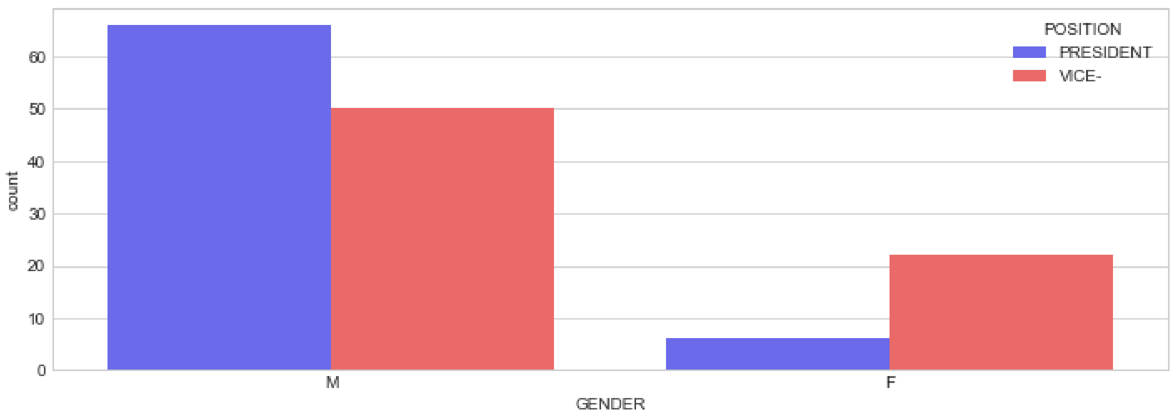


In [51]:

```
plt.figure(figsize=(12,4))
sns.countplot(data=pres_cdt,x='GENDER',hue='POSITION',palette='seismic')
```

Out[51]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x26ccb5340b8>
```



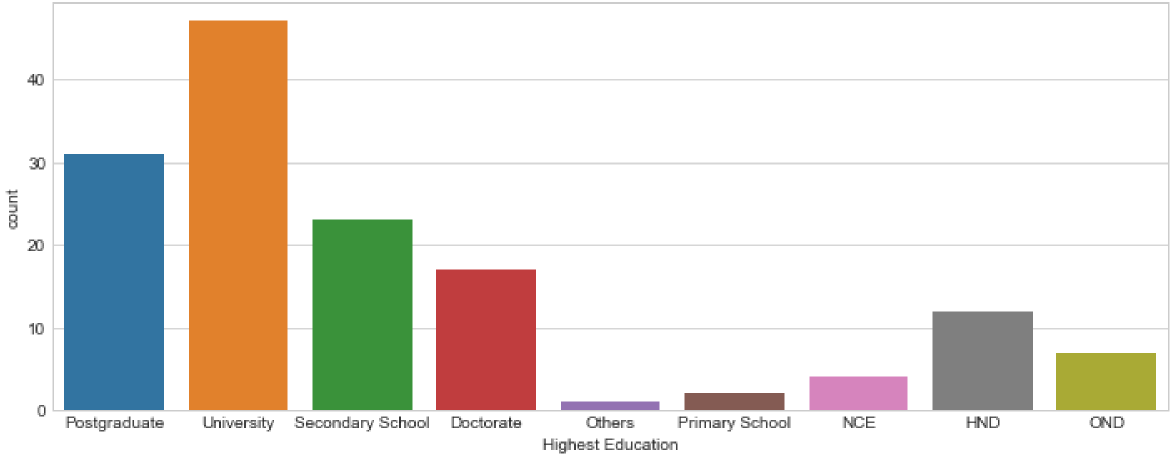
It is evident that there are far more men in the general candidates' list than female (about 3.5x more than females). The ratio of male presidential candidates to female is about 13:1. Most female candidates are vice-presidential candidates (about 4x more than the female presidential candidates.

In [52]:

```
plt.figure(figsize=(12,4.5))
sns.countplot(data=pres_cdt,x='Highest Education')
```

Out[52]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x26ccb55b6d8>
```

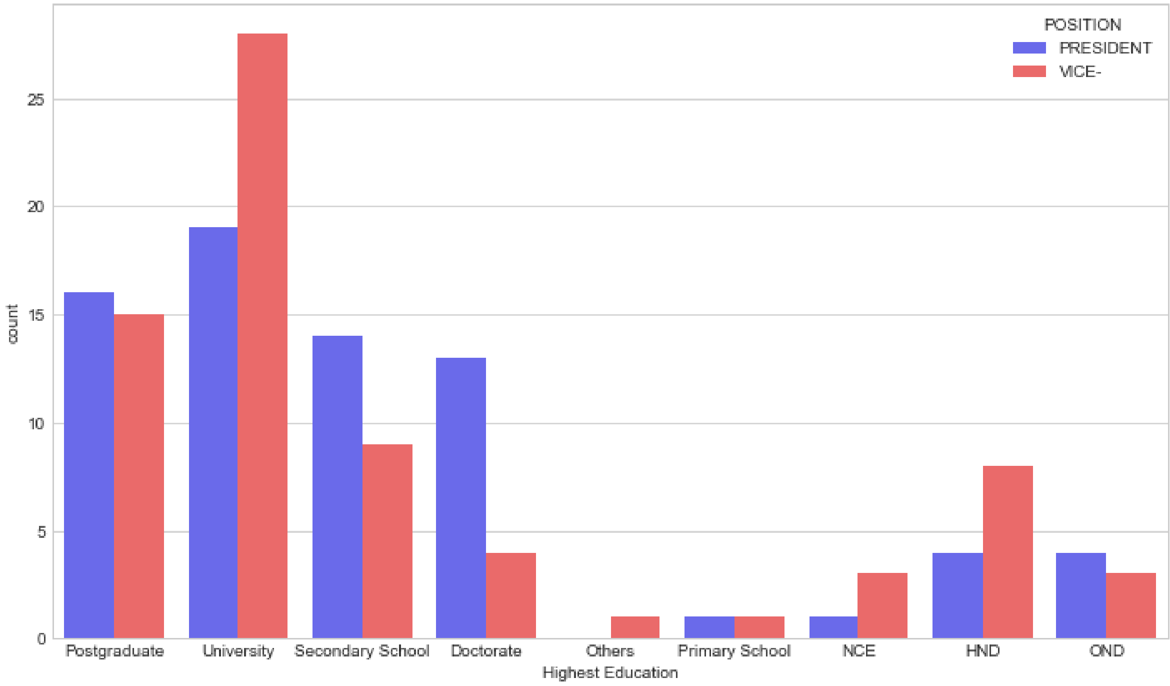


In [53]:

```
plt.figure(figsize=(12,7))
sns.countplot(data=pres_cdt,x='Highest Education',hue='POSITION',palette='seismic')
```

Out[53]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x26ccb5da898>
```

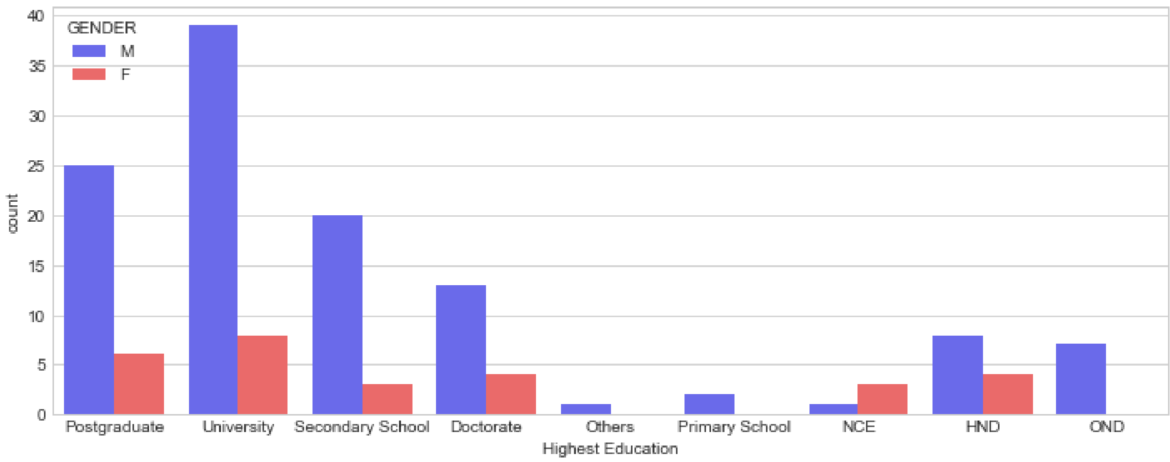


In [54]:

```
plt.figure(figsize=(12,4.5))
sns.countplot(data=pres_cdt,x='Highest Education',hue='GENDER',palette='seismic')
```

Out[54]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x26ccb5c1470>
```



The most popular level of education for all the candidates is the university education. Postgraduate comes in second while secondary school comes in third.

Exploring for the specific position, it is clear the trend still remains. Exploring for gender, it is seen that females are more likely to have a doctorate or an HND than a secondary school certificate

Finally, I pivoted the candidates list and then plotted the age of the Vice-Presidential candidates to the Presidential Candidates for each party. This helps see at a glance the parties whose candidates are generally very old or vice-versa or an interesting mix.

In [55]:

```
df=pres_cdt.pivot_table(index='PARTY',values='AGE',columns='POSITION')
df.reset_index(level=0, inplace=True)
```

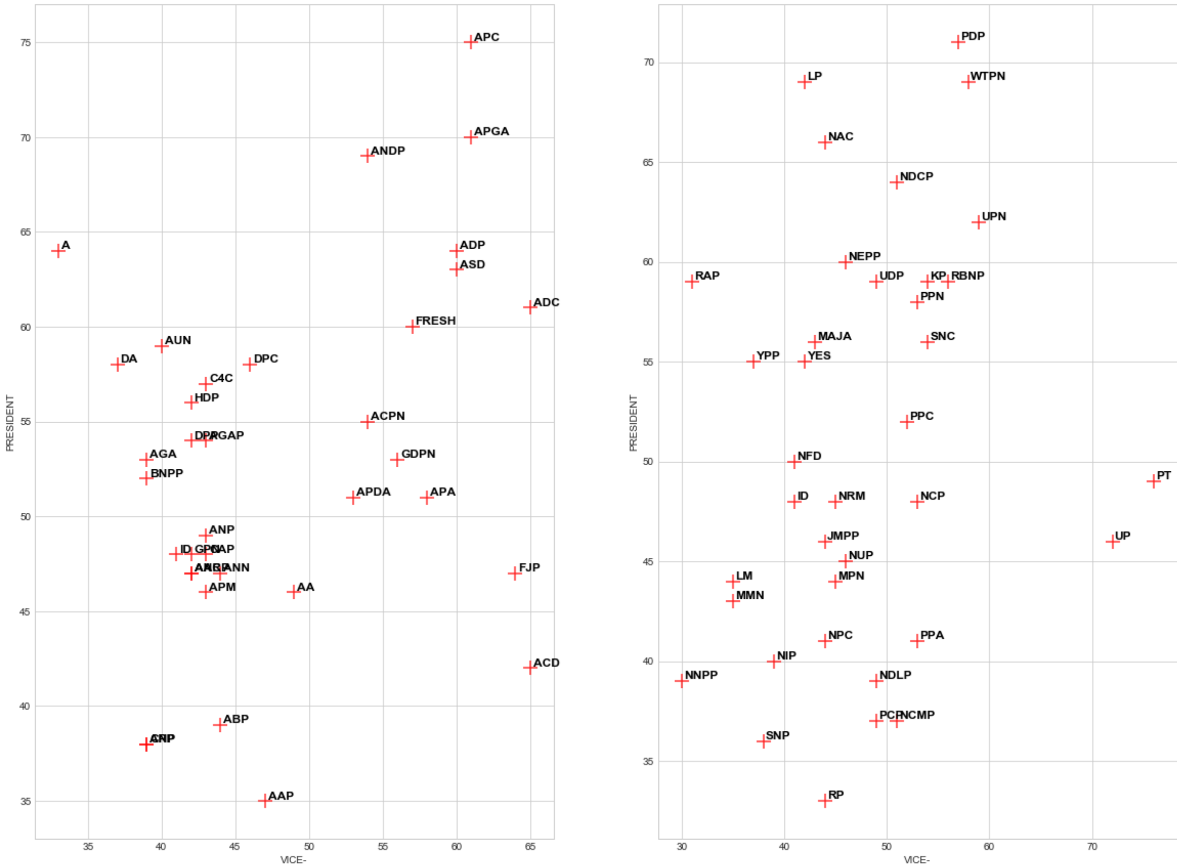
In [56]:

```
f, (axs1,axs2) = plt.subplots(1,2,figsize=(20,15))

p1=sns.regplot(data=df[0:int(df.shape[0]/2)], y="PRESIDENT", x="VICE-", fit_reg=False, mark
p2=sns.regplot(data=df[int(df.shape[0]/2)-1:df.shape[0]], y="PRESIDENT", x="VICE-", fit_reg

# add annotations one by one with a loop
for line in range(0,int(df.shape[0]/2)):
     p1.text(df['VICE-'][line]+0.2, df["PRESIDENT"][line]+0.1, df["PARTY"][line], horizonta

for line in range(int(df.shape[0]/2)-1,df.shape[0]):
     p2.text(df['VICE-'][line]+0.2, df["PRESIDENT"][line]+0.1, df["PARTY"][line], horizonta
```



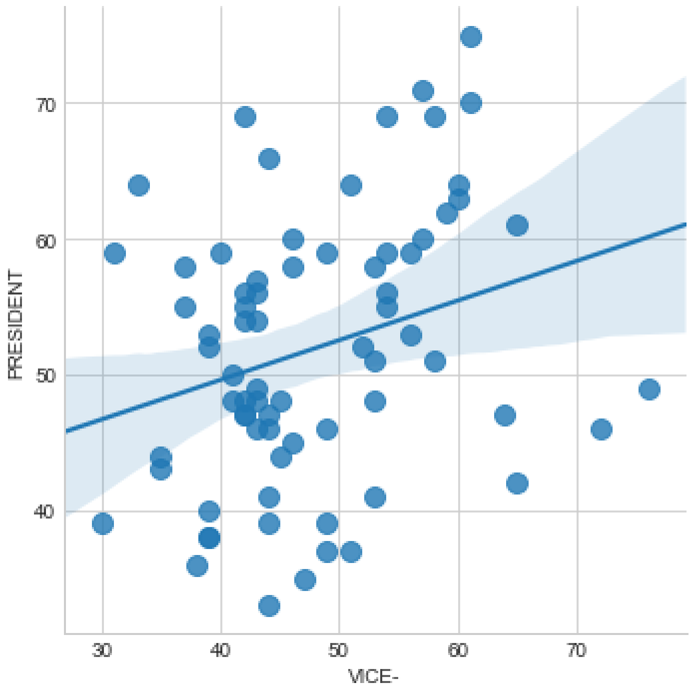
In [57]:

```
plt.figure(figsize=(20,20))
sns.lmplot(data=df, y="PRESIDENT", x="VICE-", fit_reg=True, scatter_kws={'s':100})
```

Out[57]:

```
<seaborn.axisgrid.FacetGrid at 0x26ccb6e93c8>
```

```
<matplotlib.figure.Figure at 0x26ccb7060b8>
```



It can be seen that in general the higher the age of the vice-presidential candidate, the higher the rate of the presidential candidate.

In [ ]: