US Veteran Suicides

By

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Introduction

I decided to do my project on veteran suicides in the Unites States from 2001-2021. I downloaded the data set from:
*U.S. Department of Veterans Affairs
https://www.mentalhealth.va.gov/docs/data-sheets/2021/VA_State_Sheets_2001-2021_Appendix_508.xlsx

A few notes about the dataset:

- For the purpose of this study District of Columbia is listed as a state. U.S. Territories Puerto Rico, U.S. Virgin Islands, American Samoa, Guam, and Northern Marianas are not included as I did not load that worksheet.
- Age-specific counts may not sum to the total counts because the small number of deaths for which age information is unavailable are included in the total counts and rates but are not included in age-specific counts or age-specific rates.
- Counts and rates are suppressed when based on fewer than 10 deaths, and when the count for only one category is lower than 10, a range is presented and the rate suppressed for the next smallest to maintain confidentiality. Rates are marked with an asterisk (*) when the rate is calculated based on fewer than 20 deaths. Rates based on small numbers of deaths are considered unreliable, and a small change in the number of deaths might result in a large change in the rate. Because suicide rates based on fewer than 20 suicide deaths are considered statistically unreliable, any comparisons of age-adjusted rates with underlying age-specific rates with less than 20 suicide deaths should be interpreted with caution.

After reviewing the datasets, I will be able to answer the following questions:

```
1. Which years have the highest and lowest number of veteran
suicides?
2. Which states have the highest and lowest number of veteran
suicides in 2021?
3. Which region has the highest mean of veteran suicides?
4. Are veteran suicides increasing over the years?
5. Are men or women more at risk for veteran suicide?
6. Which age groups have the highest and lowest number of veteran
suicides?
7. Are the age groups and their suicide rates consistent over the
years?
```

8. What are the highest Veteran Suicide Rates per 100k of population for the states in 2021?
9. Did the order of the highest and lowest states change based on the population?
10. What is the mean of Veteran Suicide Rates per 100k of population for each region?
11. Did the order of the regions change based on the population?
12. Are the Veteran Suicide Rates per 100k of population for the Regions changing?
13. Are veterans more vulnerable to suicide than the general population?

In [2]:
```
#Import Required Libraries

import pandas as pd
import numpy as np

#Visualization libraries

import matplotlib.pyplot as plt
import seaborn as sns

#set default seaborn style

sns.set()

#choropleth maps

import plotly.graph_objs as go
from plotly.offline import init_notebook_mode,plot,iplot

#Setup cholorepLth to show in the jupyter notebook

init_notebook_mode(connected=True)

#import cufflinks

import cufflinks as cf

# This will allow you to use cufflinks offline
cf.go_offline()

from plotly import __version__

print(__version__) # requires version >= 1.9.0

#Filter warnings

import warnings
warnings.filterwarnings('ignore')

#Line Magic to display plots in jupyter notebook

%matplotlib inline
```

```
5.9.0
```

Importing Data

Load the VA_State_Sheets_2001-2021_Appendix_508 Excel worksheet into dataframes by worksheet.

In [3]:
```
#Read the VA_State_Sheets_2001-2021_Appendix_508.xlsx into separate dataframes based c

df_state=pd.read_excel('data/VA_State_Sheets_2001-2021_Appendix_508.xlsx',sheet_name='

df_sex=pd.read_excel('data/VA_State_Sheets_2001-2021_Appendix_508.xlsx',sheet_name='Ve

df_age=pd.read_excel('data/VA_State_Sheets_2001-2021_Appendix_508.xlsx',sheet_name='Su
```

In [4]:
```
#Use head to show the first 5 rows of the dataframe that contains'Veteran Suicides by

df_state.head()
```

Out[4]:

	Year\nof\nDeath	Geographic\nRegion	State of Death	Veteran\nSuicides
0	2001	Northeastern	Connecticut	45
1	2001	Northeastern	Maine	38
2	2001	Northeastern	Massachusetts	82
3	2001	Northeastern	New Hampshire	27
4	2001	Northeastern	New Jersey	93

In [5]:
```
#Use head to show the first 5 rows of the dataframe that contains 'Veteran Suicides by

df_sex.head()
```

Out[5]:

	Year\nof\nDeath	Geographic\nRegion	State of Death	Sex	Veteran\nSuicides
0	2001	Northeastern	Connecticut	Male	40-50
1	2001	Northeastern	Connecticut	Female	<10
2	2001	Northeastern	Connecticut	All	45
3	2001	Northeastern	Maine	Male	30-40
4	2001	Northeastern	Maine	Female	<10

In [6]:
```
#Use head to show the first 5 rows of the dataframe that contains 'Suicides by Age'

df_age.head()
```

Out[6]:

	Year	Geographic\nRegion	State of Death	Age\nGroup	Veteran\nSuicides	Veteran\nSuicide\nRate\nper\n1
0	2001	Northeastern	All	18-34	91	
1	2001	Northeastern	All	35-54	293	
2	2001	Northeastern	All	55-74	217	
3	2001	Northeastern	All	75+	159	
4	2001	Northeastern	All	All	762	

Print information about the Dataframe including the number of columns, column labels, column data types, and the non-null values.

In [7]:

```
#use df.info to print information about a DataFrame including the index dtype and colu

df_state.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1092 entries, 0 to 1091
Data columns (total 4 columns):
 #   Column            Non-Null Count  Dtype 
---  ------            --------------  ----- 
 0   Year
of
Death      1092 non-null   int64 
 1   Geographic
Region  1092 non-null   object
 2   State of Death     1092 non-null   object
 3   Veteran
Suicides   1092 non-null   object
dtypes: int64(1), object(3)
memory usage: 34.3+ KB
```

In [8]:

```
#use df.info to print information about a DataFrame including the index dtype and colu

df_sex.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3276 entries, 0 to 3275
Data columns (total 5 columns):
 #   Column            Non-Null Count  Dtype 
---  ------            --------------  ----- 
 0   Year
of
Death      3276 non-null   int64 
 1   Geographic
Region  3276 non-null   object
 2   State of Death     3276 non-null   object
 3   Sex                3276 non-null   object
 4   Veteran
Suicides   3276 non-null   object
dtypes: int64(1), object(4)
memory usage: 128.1+ KB
```

In [9]:
```
#use df.info to print information about a DataFrame including the index dtype and colu

df_age.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5880 entries, 0 to 5879
Data columns (total 8 columns):
 #   Column                               Non-Null Count  Dtype 
---  ------                               --------------  ----- 
 0   Year                                 5880 non-null   int64 
 1   Geographic
Region                0880 non-null   object
 2   State of Death                       5880 non-null   object
 3   Age
Group                          5880 non-null   object
 4   Veteran
Suicides                     5880 non-null   object
 5   Veteran
Suicide
Rate
per
100,000     5880 non-null   object
 6   General
Population
Suicides          5880 non-null   object
 7   General
Population
Rate per
100,000  5880 non-null   object
dtypes: int64(1), object(7)
memory usage: 367.6+ KB
```

Data Cleaning and Organization

Updating Column Names

As you can see above in both the df.head() and df.info() functions the column names while the formatting helped the presentation within the Excel file it does not work well within the dataframe. First, we will update those.

In [10]:
```
#Rename column names in df_state dataframe to remove formatting

rename_Columns= {'Year\nof\nDeath':'Year of Death',
                'Geographic\nRegion':'Geographic Region',
                'Veteran\nSuicides':'Veteran Suicides'}

#changing column names

df_state.rename(columns=rename_Columns,inplace=True)

#display the dataframe using head

df_state.head()
```

Out[10]:

	Year of Death	Geographic Region	State of Death	Veteran Suicides
0	2001	Northeastern	Connecticut	45
1	2001	Northeastern	Maine	38
2	2001	Northeastern	Massachusetts	82
3	2001	Northeastern	New Hampshire	27
4	2001	Northeastern	New Jersey	93

In [11]:
```
#Rename column names in df_sex dataframe to remove formatting

rename_Columns= {'Year\nof\nDeath':'Year of Death',
                'Geographic\nRegion':'Geographic Region',
                'Veteran\nSuicides':'Veteran Suicides'}

#changing column names

df_sex.rename(columns=rename_Columns,inplace=True)

#display the dataframe using head

df_sex.head()
```

Out[11]:

	Year of Death	Geographic Region	State of Death	Sex	Veteran Suicides
0	2001	Northeastern	Connecticut	Male	40-50
1	2001	Northeastern	Connecticut	Female	<10
2	2001	Northeastern	Connecticut	All	45
3	2001	Northeastern	Maine	Male	30-40
4	2001	Northeastern	Maine	Female	<10

In [12]:
```
#Rename column names in df_age dataframe to remove formatting

rename_Columns= {'Geographic\nRegion':'Geographic Region',
                 'Age\nGroup':'Age Group',
                 'Veteran\nSuicides':'Veteran Suicides',
                 'Veteran\nSuicide\nRate\nper\n100,000':'Veteran Suicide Rate Per 100,
                 'General\nPopulation\nSuicides':'General Population Suicides',
                 'General\nPopulation\nRate per\n100,000':'General Population Rate Per
                }

#changing column names

df_age.rename(columns=rename_Columns,inplace=True)

#display the dataframe using head

df_age.head()
```

Out[12]:

	Year	Geographic Region	State of Death	Age Group	Veteran Suicides	Veteran Suicide Rate Per 100,000	General Population Suicides	General Population Rate Per 100,000
0	2001	Northeastern	All	18-34	91	27.9	1171	9.7
1	2001	Northeastern	All	35-54	293	21.8	1814	11
2	2001	Northeastern	All	55-74	217	12	796	9.2
3	2001	Northeastern	All	75+	159	17.2	387	10.6
4	2001	Northeastern	All	All	762	17.3	4168	10.2

Now that we have updated the column names let's run the df.info() function for each dataframe again and see if it easier to read.

In [13]:
```
#use the df.info() for df_state

df_state.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1092 entries, 0 to 1091
Data columns (total 4 columns):
 #   Column              Non-Null Count  Dtype 
---  ------              --------------  ----- 
 0   Year of Death       1092 non-null   int64 
 1   Geographic Region   1092 non-null   object
 2   State of Death      1092 non-null   object
 3   Veteran Suicides    1092 non-null   object
dtypes: int64(1), object(3)
memory usage: 34.3+ KB
```

In [14]:
```
#use the df.info() for df_sex

df_sex.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3276 entries, 0 to 3275
Data columns (total 5 columns):
 #   Column              Non-Null Count  Dtype 
---  ------              --------------  ----- 
 0   Year of Death       3276 non-null   int64 
 1   Geographic Region   3276 non-null   object
 2   State of Death      3276 non-null   object
 3   Sex                 3276 non-null   object
 4   Veteran Suicides    3276 non-null   object
dtypes: int64(1), object(4)
memory usage: 128.1+ KB
```

In [15]:
```
#use the df.info() for df_age

df_age.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5880 entries, 0 to 5879
Data columns (total 8 columns):
 #   Column                              Non-Null Count  Dtype 
---  ------                              --------------  ----- 
 0   Year                                5880 non-null   int64 
 1   Geographic Region                   5880 non-null   object
 2   State of Death                      5880 non-null   object
 3   Age Group                           5880 non-null   object
 4   Veteran Suicides                    5880 non-null   object
 5   Veteran Suicide Rate Per 100,000    5880 non-null   object
 6   General Population Suicides         5880 non-null   object
 7   General Population Rate Per 100,000 5880 non-null   object
dtypes: int64(1), object(7)
memory usage: 367.6+ KB
```

Display descriptive statistics that summarize the central tendency, dispersion, and shape of a dataset's distribution, excluding NaN values. This will display basic statistical details such as percentile, mean, and std, of the numeric values of the 3 dataframes

In [16]:
```
'''This will display basic statistical details such as percentile, mean, and std, of t
dataframe using the df.decribe function'''
df_state.describe()
```

Out[16]:

	Year of Death
count	1092.000000
mean	2011.000000
std	6.058075
min	2001.000000
25%	2006.000000
50%	2011.000000
75%	2016.000000
max	2021.000000

In [17]:
```
'''This will display basic statistical details such as percentile, mean, and std, of t
dataframe using the df.decribe function'''
df_sex.describe()
```

Out[17]:

	Year of Death
count	3276.000000
mean	2011.000000
std	6.056225
min	2001.000000
25%	2006.000000
50%	2011.000000
75%	2016.000000
max	2021.000000

In [18]:
```
'''This will display basic statistical details such as percentile, mean, and std, of t
dataframe using the df.decribe function'''
df_age.describe()
```

Out[18]:

	Year
count	5880.000000
mean	2011.000000
std	6.055816
min	2001.000000
25%	2006.000000
50%	2011.000000
75%	2016.000000
max	2021.000000

Cleaning Data

Though the df_info() function shows there are no non-null rows there was still quite a bit of clean up required before we begin analyzing the data. The first problem was that counts and rates were suppressed when based on fewer than 10 deaths and are represented as <10 in the columns. I will be dropping the '<' symbol to be able to update the datatype. Also there are values that were supplied as a range, eg. 40-50. In those cases I will remove the '-' and second number and only retain the lower number in the range. Also there are columns with either '--' which I will replace with '0' or 'asterisk' which will need to be removed as well.

In [19]:
```
#First we must remove the '<' symbol from the 'Veteran Suicides' column in df_state

df_state['Veteran Suicides']=df_state['Veteran Suicides'].replace({'<':''},regex=True)

'''Next we must remove the '<' and '-' symbols from the 'Veteran Suicides' column in d
we will remove the numbers to the right and leave the lowest number in the range only'
```

```
df_sex['Veteran Suicides']=df_sex['Veteran Suicides'].replace({'<':''},regex=True)
df_sex['Veteran Suicides']=df_sex['Veteran Suicides'].replace({'-[0-9]':''},regex=True

'''Next we must remove the '<' and '-' symbols from the 'Veteran Suicides' and 'Genera
in df_age.  Also for '-' we will remove the numbers to the right and leave the lowest 
Also we will have to remove '--' and '*' from 'Veteran Suicide Rate per 100,000' and '
'''

df_age['Veteran Suicides']=df_age['Veteran Suicides'].replace({'<':''},regex=True)
df_age['Veteran Suicides']=df_age['Veteran Suicides'].replace({'-[0-9]':''},regex=True
df_age['General Population Suicides']=df_age['General Population Suicides'].replace({'
df_age['General Population Suicides']=df_age['General Population Suicides'].replace({'
df_age['Veteran Suicide Rate Per 100,000']=df_age['Veteran Suicide Rate Per 100,000'].
df_age['Veteran Suicide Rate Per 100,000']=df_age['Veteran Suicide Rate Per 100,000'].
df_age['General Population Rate Per 100,000']=df_age['General Population Rate Per 100,
df_age['General Population Rate Per 100,000']=df_age['General Population Rate Per 100,
```

Updating datatype

Now that the df.info() function legible let's update the datatypes so that we will be able do statistical analyis, grouping, and retain decimal points.

In [20]:
```
#Change the necessary columns with object datatypes in df_state

df_state['Geographic Region']=df_state['Geographic Region'].astype('category')
df_state['Veteran Suicides']=df_state['Veteran Suicides'].astype('int64')

#Check data type changes

df_state.dtypes
```

Out[20]:
```
Year of Death            int64
Geographic Region     category
State of Death          object
Veteran Suicides         int64
dtype: object
```

In [21]:
```
#Change the necessary columns with object datatypes in df_sex

df_sex['Geographic Region']=df_sex['Geographic Region'].astype('category')
df_sex['Sex']=df_sex['Sex'].astype('category')
df_sex['Veteran Suicides']=df_sex['Veteran Suicides'].astype('int64')

#Check data type changes
df_sex.dtypes
```

Out[21]:
```
Year of Death            int64
Geographic Region     category
State of Death          object
Sex                   category
Veteran Suicides         int64
dtype: object
```

In [22]:
```
#Change the necessary columns with object datatypes in df_age

df_age['Geographic Region']=df_age['Geographic Region'].astype('category')
df_age['Age Group']=df_age['Age Group'].astype('category')
df_age['Veteran Suicides']=df_age['Veteran Suicides'].astype('int64')
```

```
df_age['General Population Suicides']=df_age['General Population Suicides'].astype('ir
df_age['Veteran Suicide Rate Per 100,000']=df_age['Veteran Suicide Rate Per 100,000'].
df_age['General Population Rate Per 100,000']=df_age['General Population Rate Per 100,

#Check data type changes

df_age.dtypes
```

Out[22]:

```
Year                                    int64
Geographic Region                    category
State of Death                         object
Age Group                            category
Veteran Suicides                        int64
Veteran Suicide Rate Per 100,000      float64
General Population Suicides             int64
General Population Rate Per 100,000   float64
dtype: object
```

Dropping Columns

As I loaded only specific worksheets from the Excel file and there is pertinent data I will not have any columns to drop from the dataframes.

Data Visualization

Which years have the highest and lowest number of veteran suicides?

In [23]:

```
#Create a dataframe named df_years with selected columns

df_years=df_state[['Year of Death','State of Death','Veteran Suicides']]

#print 5 Highest Years of Veteran Suicides Using the ANSI Escape Sequence for Bold

print('\033[1m'+'5 Highest Years of Veteran Suicides: '+'\033[0m')

#Selecting Rows based on 'State of Death' == 'U.S. Total'

df_years_totals=df_years[df_state['State of Death'] == 'U.S. Total']

#Display the head of the df_years_totals sorting from highest to lowest

df_years_totals.sort_values(['Veteran Suicides'],ascending=False).head()
```

5 Highest Years of Veteran Suicides:

Out[23]:

	Year of Death	State of Death	Veteran Suicides
935	2018	U.S. Total	6718
883	2017	U.S. Total	6686
727	2014	U.S. Total	6645
779	2015	U.S. Total	6616
415	2008	U.S. Total	6567

Displaying the first 5 rows of the df_years_totals dataframe sorted by descending order, listing the highest totals first. The 5 years with the highest veteran suicide numbers in order are 2018, 2017, 2014, 2015, and 2008.

In [24]:

```
#print 5 Lowest Years of Veteran Suicides Using the ANSI Escape Sequence for Bold

print('\033[1m'+'5 Lowest Years of Veteran Suicides: '+'\033[0m')

#Selecting Rows based on 'State of Death' == 'U.S. Total'

df_years_totals=df_years[df_state['State of Death'] == 'U.S. Total']

#Display the head of the df_years_totals sorting from lowest to highest

df_years_totals.sort_values(['Veteran Suicides'],ascending=True).head()
```

5 Lowest Years of Veteran Suicides:

Out[24]:

	Year of Death	State of Death	Veteran Suicides
51	2001	U.S. Total	6000
207	2004	U.S. Total	6004
155	2003	U.S. Total	6008
311	2006	U.S. Total	6035
259	2005	U.S. Total	6126

Displaying the first 5 rows of the df_years_totals dataframe sorted by ascending order, listing the lowest totals first. The 5 years with the lowest veteran suicide numbers in order are 2001, 2004, 2003, 2006, and 2005.

Which states have the highest and lowest number of veteran suicides in 2021?

In [25]:

```
#Create a dataframe named df_state_total with selected columns

df_state_total=df_state[['Year of Death','State of Death','Veteran Suicides']]

#Selecting rows based on 'Year of Death' == '2021' and 'State of Death' != 'U.S. Total

df_state_total_2021=df_state_total.loc[(df_state['Year of Death'] == 2021) & (df_state
```

```python
#print 5 Highest States of Veteran Suicides in 2021 Using the ANSI Escape Sequence for
print('\033[1m'+'5 Highest States of Veteran Suicides in 2021: '+'\033[0m')
#Display the head of the df_state_total_2021 sorting from highest to lowest
df_state_total_2021.sort_values(['Veteran Suicides'],ascending=False).head()
```

5 Highest States of Veteran Suicides in 2021:

Out[25]:

	Year of Death	State of Death	Veteran Suicides
1075	2021	Texas	583
1065	2021	Florida	546
1080	2021	California	461
1046	2021	Pennsylvania	246
1058	2021	Ohio	242

Displaying the first 5 rows df_state_total_2021 dataframe sorted by descending order, listing the highest totals first. The 5 states with the highest veteran suicides in order are Texas, Florida, California, Pennsylvania, and Ohio.

In [26]:

```python
#Selecting rows based on 'Year of Death' == '2021' and 'State of Death' != 'U.S. Total
df_state_total_2021=df_state_total.loc[(df_state['Year of Death'] == 2021) & (df_state
#print 5 Lowest States of Veteran Suicides in 2021 Using the ANSI Escape Sequence for
print('\033[1m'+'5 Lowest States of Veteran Suicides in 2021: '+'\033[0m')
#Display the head of the df_state_total_2021 sorting from lowest to highest
df_state_total_2021.sort_values(['Veteran Suicides'],ascending=True).head()
```

5 Lowest States of Veteran Suicides in 2021:

Out[26]:

	Year of Death	State of Death	Veteran Suicides
1064	2021	District of Columbia	10
1047	2021	Rhode Island	11
1057	2021	North Dakota	14
1048	2021	Vermont	18
1082	2021	Hawaii	20

Displaying the first 5 rows df_state_total_2021 dataframe sorted by ascending order, listing the lowest totals first. The 5 states with the lowest veteran suicides in order are District of Columbia, Rhode Island, North Dakota, Vermont, and Hawaii.

Choropleth USA-states map of 2021 Veteran Suicides

As USA-states map needs state abbreviation will create a function state_abbrev_mapping that can convert state names to abbreviations or abbreviations to state names in a new column if specified.

In [27]:
```
#Define function to convert states to abbreviations or abbreviations to states

def state_abbrev_mapping(df, col, output_abbr = False, add_new_col = False, new_col =
    #df =  the Pandas dataframe.
    #col = String. The column with the state name or abbreviation you wish to use
    #output_abbr = True/False. Do you want to the output the state abbreviation? The c
    #add_new_col = True/False. Do you want to add a new column? The new column will ov
    #new_col = String. Name of new column you wish to add.
    #case = 'upper', 'lower', or None. Do you want to specify a letter-case for the da


    #List of states
    state2abbrev = {
        'Alaska': 'AK',
        'Alabama': 'AL',
        'Arkansas': 'AR',
        'Arizona': 'AZ',
        'California': 'CA',
        'Colorado': 'CO',
        'Connecticut': 'CT',
        'District of Columbia': 'DC',
        'Delaware': 'DE',
        'Florida': 'FL',
        'Georgia': 'GA',
        'Hawaii': 'HI',
        'Iowa': 'IA',
        'Idaho': 'ID',
        'Illinois': 'IL',
        'Indiana': 'IN',
        'Kansas': 'KS',
        'Kentucky': 'KY',
        'Louisiana': 'LA',
        'Massachusetts': 'MA',
        'Maryland': 'MD',
        'Maine': 'ME',
        'Michigan': 'MI',
        'Minnesota': 'MN',
        'Missouri': 'MO',
        'Mississippi': 'MS',
        'Montana': 'MT',
        'North Carolina': 'NC',
        'North Dakota': 'ND',
        'Nebraska': 'NE',
        'New Hampshire': 'NH',
        'New Jersey': 'NJ',
        'New Mexico': 'NM',
        'Nevada': 'NV',
        'New York': 'NY',
        'Ohio': 'OH',
        'Oklahoma': 'OK',
        'Oregon': 'OR',
        'Pennsylvania': 'PA',
        'Rhode Island': 'RI',
        'South Carolina': 'SC',
```

```
    'South Dakota': 'SD',
    'Tennessee': 'TN',
    'Texas': 'TX',
    'Utah': 'UT',
    'Virginia': 'VA',
    'Vermont': 'VT',
    'Washington': 'WA',
    'Wisconsin': 'WI',
    'West Virginia': 'WV',
    'Wyoming': 'WY',
}
#List of states
abbrev2state = {
    'AK': 'Alaska',
    'AL': 'Alabama',
    'AR': 'Arkansas',
    'AZ': 'Arizona',
    'CA': 'California',
    'CO': 'Colorado',
    'CT': 'Connecticut',
    'DC': 'District of Columbia',
    'DE': 'Delaware',
    'FL': 'Florida',
    'GA': 'Georgia',
    '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',
    'MS': 'Mississippi',
    'MT': 'Montana',
    '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',
    'RI': 'Rhode Island',
    'SC': 'South Carolina',
    'SD': 'South Dakota',
    'TN': 'Tennessee',
    'TX': 'Texas',
    'UT': 'Utah',
    'VA': 'Virginia',
    'VT': 'Vermont',
```

```
        'WA': 'Washington',
        'WI': 'Wisconsin',
        'WV': 'West Virginia',
        'WY': 'Wyoming',
    }
    #If user wants to add a new column
    if add_new_col == False:

        #Is the output an abbreviation?
        if output_abbr == True:
            df[col] = df[col].str.strip().replace(state2abbrev)
        else:
            df[col] = df[col].str.strip().replace(abbrev2state)

        #Does the user want a specific case sensitivity?
        if case == 'upper':
            df[col] = df[col].str.upper()
        elif case == 'lower':
            df[col] = df[col].str.lower()

    #If user not want to add a new column
    if add_new_col == True:

        #If new column name is missing
        if new_col == None:
            #Prompt user to enter a new column name
            print("Error: You requested to add a new column but did not specify a new
            return()

        #Is the output an abbreviation?
        if output_abbr == True:
            df[new_col] = df[col].str.strip().replace(state2abbrev)
        else:
            df[new_col] = df[col].str.strip().replace(abbrev2state)

        #Does the user want a specific case sensitivity?
        if case == 'upper':
            df[new_col] = df[new_col].str.upper()
        elif case == 'lower':
            df[new_col] = df[new_col].str.lower()

    return(df.head())
```

In [28]:

```
#Call function to create 'State' column in dataframe df_state_total_2021 with state ab

state_abbrev_mapping(df = df_state_total_2021,
                     col= 'State of Death',
                     output_abbr = True,
                     add_new_col = True,
                     new_col = 'State',
                     case = 'upper')

#Display dataframe using head()

df_state_total_2021.head()
```

Out[28]:

	Year of Death	State of Death	Veteran Suicides	State
1040	2021	Connecticut	34	CT
1041	2021	Maine	38	ME
1042	2021	Massachusetts	57	MA
1043	2021	New Hampshire	29	NH
1044	2021	New Jersey	53	NJ

Now that we have the state abbreviation we will create the chloropleth map.

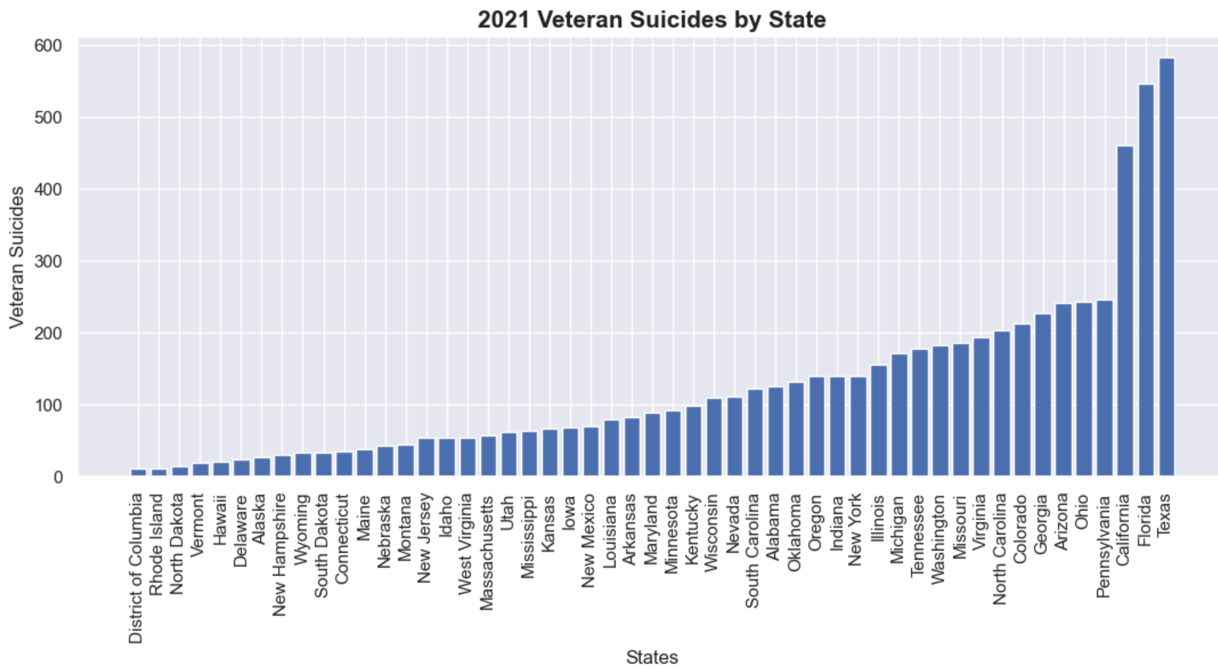
In [29]:
```
#Creating a chloropleth map

fig = go.Figure(data=go.Choropleth(
    locations=df_state_total_2021['State'],
    z = df_state_total_2021['Veteran Suicides'],
    locationmode = 'USA-states',
    colorscale = 'Greens',
    colorbar_title = "2021 Veteran Suicides",
    text = df_state_total_2021['State of Death']
))

#layout for chloropleth

fig.update_layout(
    title_text = '2021 Veteran Suicides by State',
    geo_scope='usa',
)

#shows the chloropleth

fig.show()
```

Displayed as a Cholorpleth map of the Unites States that is interactive and displays veteran suicides by state differentiated by color. The colorscale on the right from top to bottom show the high to low number of verteran suicides in 2021. This allows us to see the difference between the 50 states and determine the states with the highest number of veteran suicides as well as the low ones.

In [30]:
```
#Sort the dataframe df_state_total_2021 by the column 'Veteran Suicides' from lowest t

df_state_total_2021.sort_values(by='Veteran Suicides',inplace=True)

#Set the size of the figure

plt.rcParams['figure.figsize']=[13,5]

#Use tight_layout to ensure the labels are displayed correctly

plt.tight_layout()

#Create the layout

plt.xlabel('States')
plt.ylabel('Veteran Suicides')
plt.title('2021 Veteran Suicides by State',fontsize=15,fontweight='bold')
```

```
#Rotate the state names using xticks(rotation)

plt.xticks(rotation=90)

#plot the barplot

plt.bar(df_state_total_2021['State of Death'],df_state_total_2021['Veteran Suicides'])
```

Out[30]: <BarContainer object of 51 artists>



Display a bar-chart of Veterance Suicides in 2021 of the 50 states and District of Columbia with the highest rates on the right and the lowest rates on the left side of the chart.

Which region has the highest mean of veteran suicides?

In [31]:
```
#Create a dataframe that includes the region named df_region

df_region=df_state[['Geographic Region','Veteran Suicides']]

#print title in bold

print('\033[1m'+'Mean of Veteran Suicides by Region: '+'\033[0m')

#Create a dataframe with .groupby('Geographic Region') and calculate mean with .mean()

df_region_mean=df_region.groupby('Geographic Region').mean()

#Display Dataframe in descending order

print(df_region_mean.sort_values(['Veteran Suicides'],ascending=False))
```

```
Mean of Veteran Suicides by Region:
                       Veteran Suicides
Geographic Region
All                         6374.619048
Southern                     155.176471
Western                      125.190476
Midwestern                   113.690476
Northeastern                  83.296296
```

Displaying a table of all years of veteran suicides shows that the geographic region with the highest mean was the Southern region.

In [32]:

```
#Create a dataframe df_region with the necessary columns

df_region=df_state[['Geographic Region','Veteran Suicides']]

'''Group table by region and use the describe() function to view statistical details e
std,etc'''

df_region.groupby('Geographic Region').describe()
```

Out[32]:

	Veteran Suicides							
	count	mean	std	min	25%	50%	75%	max
Geographic Region								
All	21.0	6374.619048	239.518575	6000.0	6142.00	6447.0	6545.0	6718.0
Midwestern	252.0	113.690476	72.011505	10.0	53.75	105.0	170.0	295.0
Northeastern	189.0	83.296296	82.636715	10.0	29.00	47.0	87.0	299.0
Southern	357.0	155.176471	141.595621	10.0	77.00	113.0	182.0	600.0
Western	273.0	125.190476	133.551049	12.0	38.00	71.0	162.0	621.0

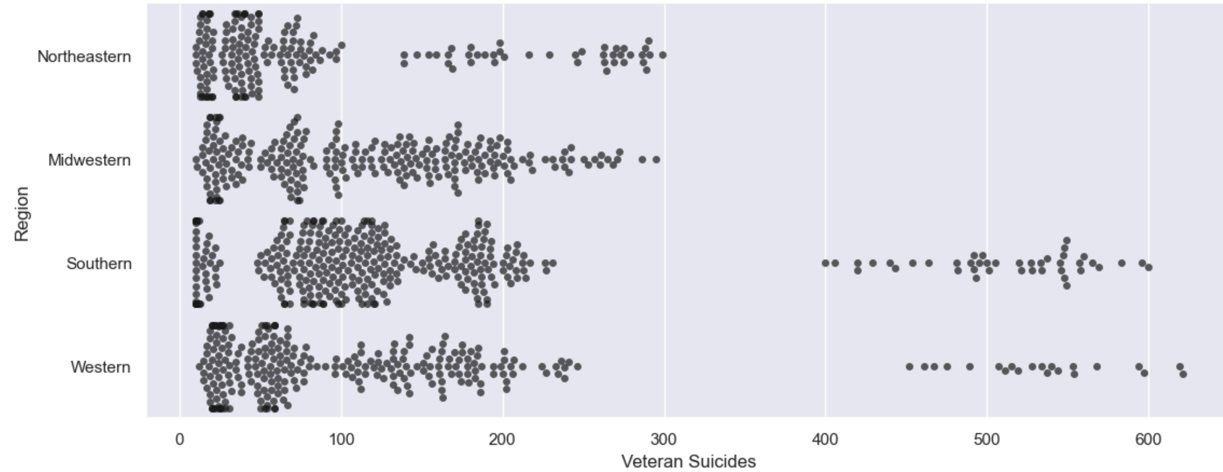
The table shows basic statistical details for veteran suicides from 2001-2021. From the table we can see the count of years and the number of states in each region, their mean, standard deviation, min, percentiles, and max.

In [168…

```
#Create a new column 'Region' to remove All from 'Geographic Region' and then dropna()

data=df_region.assign(Region=df_region['Geographic Region'].map({'Midwestern':'Midwest

#Set the figure size

plt.figure(figsize=(13,5))

#Create a swarmplot with black points and slightly transparent

sns.swarmplot(x='Veteran Suicides',y='Region',data=data,color='k',alpha=0.7)
```

Out[168]:

```
<Axes: xlabel='Veteran Suicides', ylabel='Region'>
```

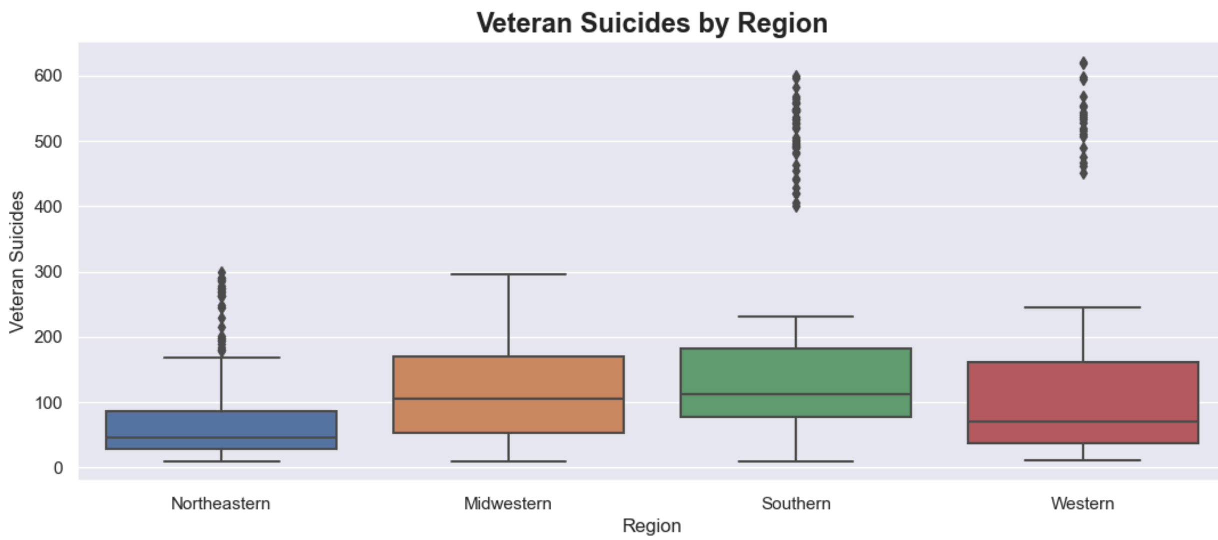


In [161…

```
#Create a bolded title of the boxplot graph with matplotlib

plt.title('Veteran Suicides by Region',fontsize=17,fontweight='bold')

#Create a seaborn boxplot

sns.boxplot(x='Region',y='Veteran Suicides',data=data)
```

Out[161]:

```
<Axes: title={'center': 'Veteran Suicides by Region'}, xlabel='Region', ylabel='Veter
an Suicides'>
```



As we can see in the swarmplot and then reinforced by the boxplot both the Southern and Western have quite a few extreme outliers that are raising their mean. Also the Northeastern has quite a few outliers but they are still closer to the whisker so not as impactful to the overall numbers. The Midwestern region appears to be the most normally distributed of the regions.

Are veteran suicides increasing over the years?

In [35]:

```
#Create a Dataframe from df_sex with only necessary columns

df_state_col=df_state[['Year of Death','State of Death','Veteran Suicides']]

#Create a dataframe from df_sex_col with 'State of Death' == 'U.S. Total'
```

```
df_state_total=df_state_col.loc[(df_state['State of Death'] == 'U.S. Total')]

#Create a pivot_table of df_state_total to view all the years in a table format

df_state_total.pivot_table(index='State of Death',columns='Year of Death')
```

Out[35]:

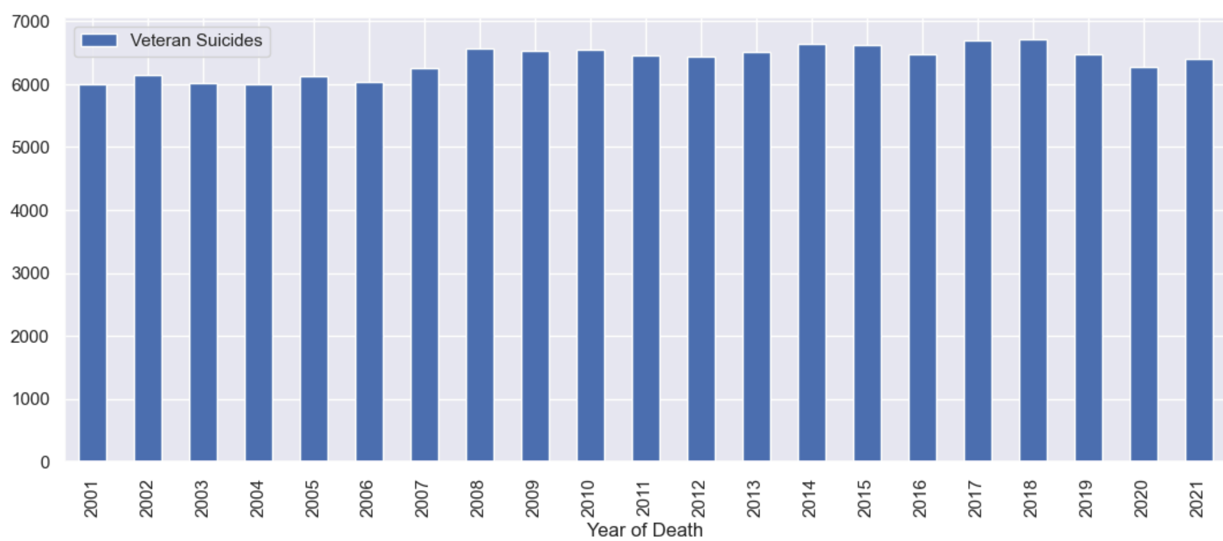
Year of Death	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	...	2012	2013	2014	2015
State of Death															
U.S. Total	6000	6142	6008	6004	6126	6035	6249	6567	6519	6545	...	6441	6501	6645	6616

1 rows × 21 columns

In [36]:

```
#Create a bar plot of the datafrade df_state_total

df_state_total.plot.bar(x='Year of Death')
```

Out[36]: <Axes: xlabel='Year of Death'>



In [37]:

```
'''This will display basic statistical details such as percentile, mean, and std, of t
dataframe using the df.decribe function'''

df_state_total['Veteran Suicides'].describe()
```

Out[37]:

```
count      21.000000
mean     6374.619048
std       239.518575
min      6000.000000
25%      6142.000000
50%      6447.000000
75%      6545.000000
max      6718.000000
Name: Veteran Suicides, dtype: float64
```

Reviewing the pivot table, bar chart, and describe all confirm that while the numbers do vary from year to year there is no evidence to show it is increasing at a high rate. In the 21 years with a min of 6000, max of 6718, and mean of 6374.619048 there is evidence that indicate relatively steady numbers. Also the low standard deviation (std) of 239.518575 also reinforces that.

Are men or women more at risk for veteran suicide?

In [38]:

```
#Create a Dataframe from df_sex with only necessary columns

df_sex_col=df_sex[['Year of Death','Sex','Veteran Suicides']]

#Create a dataframe from df_sex_col with 'State of Death' == 'U.S. Total' & (df_sex['S

df_sex_total=df_sex_col.loc[(df_sex['State of Death'] == 'U.S. Total') & (df_sex['Sex'

#create a countplot with hue Sex
#sns.countplot(x='Year of Death',data=df_sex_total,hue='Sex')
df_sex_total.pivot_table(index='Sex',columns='Year of Death')
```

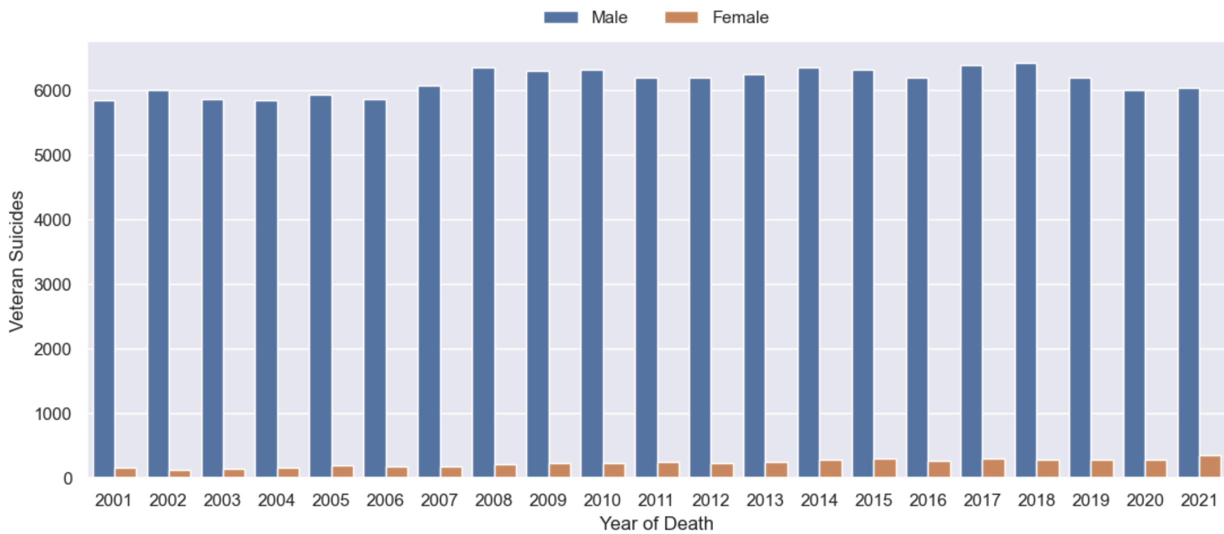
Out[38]:

Year of Death	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	...	2012	2013	2014	2015
Sex															
Female	154	134	151	167	189	173	186	208	226	232	...	240	251	293	305
Male	5846	6008	5857	5837	5937	5862	6063	6359	6293	6313	...	6201	6250	6352	631

2 rows × 21 columns

In [151…

```
#Create a new column 'Gender' with sex of Female and Male to remove All from Legend

data=df_sex_total.assign(Gender=df_sex_total['Sex'].map({'Female':'Female','Male':'Mal

#Create a Seaborn bar plot of df_sex_total using x='Year of Death',y='Veteran Suicides

ax=sns.barplot(data,x='Year of Death',y='Veteran Suicides',hue='Gender')

#Move the legend to ensure it is not on the bar plot

sns.move_legend(ax, "lower center",bbox_to_anchor=(.5, 1), ncol=3, title=None, frameor
```



After reviewing the pivot table and the bar chart there is strong evidence to suggest statistically men are at a higher risk. The only issue is the population does not provide total numbers of the men and women so this data is a bit inconclusive.

Which age groups have the highest and lowest number of veteran suicides?

In [40]:
```
#Create a dataframe from df_age with only the necessaru columns 'Year','Geographic Reg

df_ages=df_age[['Year','Geographic Region','State of Death','Age Group']]

#Create a dataframe using .loc() with 'Geographic Region' == 'All') & 'Age Group' != '

df_ages_total=df_age.loc[(df_age['Geographic Region'] == 'All') & (df_age['Age Group']

#display the dataframe

df_ages_total
```

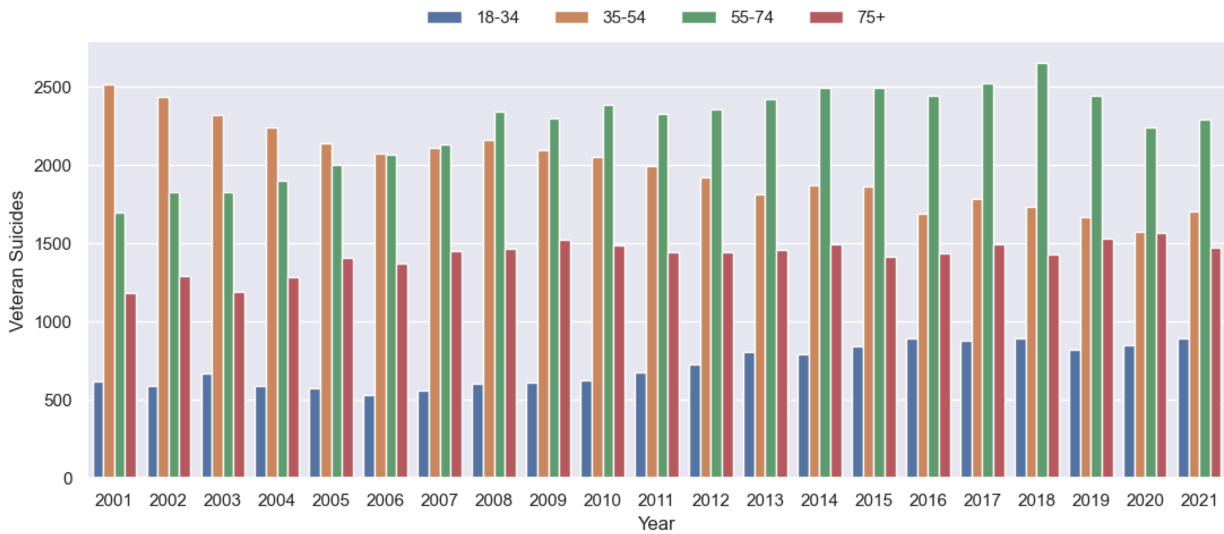
Out[40]:

	Year	Geographic Region	State of Death	Age Group	Veteran Suicides	Veteran Suicide Rate Per 100,000	General Population Suicides	General Population Rate Per 100,000
275	2001	All	U.S. Total	18-34	616	23.5	8293	12.3
276	2001	All	U.S. Total	35-54	2510	28.0	12577	14.9
277	2001	All	U.S. Total	55-74	1693	17.3	5749	13.2
278	2001	All	U.S. Total	75+	1178	26.4	2961	17.5
555	2002	All	U.S. Total	18-34	590	23.5	8346	12.3
...	...	...	...	...	...	...	...	...
5598	2020	All	U.S. Total	75+	1566	34.9	4421	20.2
5875	2021	All	U.S. Total	18-34	894	49.6	14230	18.8
5876	2021	All	U.S. Total	35-54	1704	35.5	15263	18.2
5877	2021	All	U.S. Total	55-74	2286	29.9	12411	16.2
5878	2021	All	U.S. Total	75+	1467	32.1	4508	20.3

84 rows × 8 columns

In [153…

```
#Create a new column 'Age' to remove All from legend in dataframe df_ages_total

data=df_ages_total.assign(Age=df_ages_total['Age Group'].map({'18-34':'18-34','35-54':

#Create a Seaborn bar plot of data using x='Year',y='Veteran Suicides',hue='Age'

ax=sns.barplot(data,x='Year',y='Veteran Suicides',hue='Age')

#Move the legend to ensure it is not on the bar plot

sns.move_legend(ax, "lower center",bbox_to_anchor=(.5, 1), ncol=4, title=None, frameor
```



Reviewing the bar chart it appears that from 2001-2005 the age group 35-54 had the highest number of veteran suicides followed by 55-74, 75+, and 18-34. In 2006 35-54 and 55-74 were similar with 75+ and 18-34 unchanged in their order. Starting in 2007 we see 55-74 with the highest number of veteran suicides with the remaining age groups still in their same order.

Are the age groups and their suicide rates consistent over the years?

In [42]:

```
#import scipy for statistics

from scipy import stats

#Create a dataframe for each 'Age Group'

df_18=df_age.loc[(df_age['Geographic Region'] == 'All') & (df_age['Age Group'] == '18-
df_35=df_age.loc[(df_age['Geographic Region'] == 'All') & (df_age['Age Group'] == '35-
df_55=df_age.loc[(df_age['Geographic Region'] == 'All') & (df_age['Age Group'] == '55-
df_75=df_age.loc[(df_age['Geographic Region'] == 'All') & (df_age['Age Group'] == '75+

#Print each dataframe using the describe() function

print('18-34: ',stats.describe(df_18['Veteran Suicides']),'\n')
print('35-54: ',stats.describe(df_35['Veteran Suicides']),'\n')
print('55-74: ',stats.describe(df_55['Veteran Suicides']),'\n')
print('75+: ',stats.describe(df_75['Veteran Suicides']),'\n')
```

```
18-34:  DescribeResult(nobs=21, minmax=(531, 894), mean=714.8095238095239, variance=1
6605.261904761905, skewness=0.14360825029707977, kurtosis=-1.5961117871540393)

35-54:  DescribeResult(nobs=21, minmax=(1575, 2510), mean=1986.3809523809523, varianc
e=67388.84761904762, skewness=0.325687886391608, kurtosis=-0.7654332338743175)

55-74:  DescribeResult(nobs=21, minmax=(1693, 2653), mean=2243.190476190476, variance
=70556.7619047619, skewness=-0.6263396022502037, kurtosis=-0.6869527000457509)

75+:  DescribeResult(nobs=21, minmax=(1178, 1566), mean=1419.047619047619, variance=1
0781.14761904762, skewness=-1.095186886739689, kurtosis=0.3888985873010835)
```

As we can see there are 21 observations for each dataframe nobs (number of 'observations') for each dataframe which is the 21 years.

With a variance of 10781.14761904762 the evidence indicates that the 75+ age group changes the least. This is further backed up by the minmax of (1178,1566) and mean of 1419.047619047619. We can also see that it is has a negative or left-skewed dsitribution as well. Meaning it is has a long tail on its left side. Also with a value of greater than -1 it indicates it is a highly skewed distribution. Also the kurtosis of 0.3888985873010835 being close to 0 indicates they are normally distributed.

With a variance of 16605.261904761905 shows evidence that the 18-34 varies only slightly as well. Again the minmax (531,894) and mean of 714.8095238095239 further reinforces this Also with a skewness less than 0.5 this distribution is approximately symmetric. The negative skewness of -1.095186886 also indicates that the distribution has lighter tails.

Though the 35-54 and 55-74 have higher variance, 67388.84761904762 and 70556.7619047619 respectively, we can tell from the minmax of (1575,2510) and (1693,2653 there is evidence that they do not vary greatly in the population.

Veteran Suicide Rates per 100k of population for each state

In [43]:
```
#Create a dataframe to rename the columns 'Veteran Suicide Rate Per 100,000' & 'Genera

df_age_rename=df_age.rename(columns={'Veteran Suicide Rate Per 100,000':'Veteran Suici

#Create a dataframe to select only the necessary columns'Year','State of Death','Age G

df_rate=df_age_rename[['Year','State of Death','Age Group','Veteran Suicide Rate']]

#Create a dataframe using .loc() ['Age Group'] == 'All' & ['State of Death'] != 'U.S.

df_rate_state=df_rate.loc[(df_rate['Age Group'] == 'All') & (df_rate['State of Death']

#Display dataframe using head()

df_rate_state.head()
```

Out[43]:

	Year	State of Death	Age Group	Veteran Suicide Rate
4	2001	All	All	17.3
9	2001	Connecticut	All	15.1
14	2001	Maine	All	25.0
19	2001	Massachusetts	All	15.6
24	2001	New Hampshire	All	19.9

In [44]:
```
#Create dataframe to use with cholorpleth

df_rate_state_2021=df_rate.loc[(df_rate['Year'] == 2021) & (df_rate['State of Death']
```

```
#Call function to create 'State' column in dataframe df_state_total_2021 with state ab

state_abbrev_mapping(df = df_rate_state_2021,
                     col= 'State of Death',
                     output_abbr = True,
                     add_new_col = True,
                     new_col = 'State',
                     case = 'upper')

#Display dataframe using head()

df_rate_state_2021.head()
```

Out[44]:

	Year	State of Death	Age Group	Veteran Suicide Rate	State
5609	2021	Connecticut	All	20.6	CT
5614	2021	Maine	All	34.5	ME
5619	2021	Massachusetts	All	19.1	MA
5624	2021	New Hampshire	All	29.3	NH
5629	2021	New Jersey	All	16.3	NJ

In [45]:

```
fig = go.Figure(data=go.Choropleth(
    locations=df_rate_state_2021['State'],
    z = df_rate_state_2021['Veteran Suicide Rate'],
    locationmode = 'USA-states',
    colorscale = 'Oranges',
    colorbar_title = "2021 Veteran Suicide Rate",
    text = df_rate_state_2021['State of Death']
))

#layout for chloropleth

fig.update_layout(
    title_text = '2021 Veteran Suicide Rate by State',
    geo_scope='usa',
)

#shows the chloropleth

fig.show()
```

2021 Veteran Suicide Rate by State

What are the 5 highest states by Veteran Suicide Rates per 100k of population in 2021?

Did the order of the highest and lowest states change based on the population?

In [46]:
```
#print 5 Highest States of Veteran Suicides in 2021 Using the ANSI Escape Sequence for

print('\033[1m'+'5 Highest States of Veteran Suicides in 2021: '+'\033[0m')

#Print head of the df_state_total_2021 sorting from highest to lowest

print(df_state_total_2021[['Year of Death','State of Death','Veteran Suicides']].sort_

#print 5 Highest States of Veteran Suicides in 2021 Using the ANSI Escape Sequence for

print('\033[1m'+'5 Highest States of Veteran Suicide Rate in 2021: '+'\033[0m')

#Print head of the df_rate_state_2021 sorting from highest to lowest

print(df_rate_state_2021[['Year','State of Death','Veteran Suicide Rate']].sort_values
```

```
5 Highest States of Veteran Suicides in 2021:
      Year of Death State of Death  Veteran Suicides
1075           2021          Texas               583
1065           2021        Florida               546
1080           2021     California               461
1046           2021   Pennsylvania               246
1058           2021           Ohio               242
5 Highest States of Veteran Suicide Rate in 2021:
      Year State of Death  Veteran Suicide Rate
5874  2021        Wyoming                  80.0
5829  2021       Colorado                  56.1
5844  2021        Montana                  51.2
5849  2021         Nevada                  50.7
5859  2021         Oregon                  49.6
```

In [47]:
```
#print 5 Lowest States of Veteran Suicides in 2021 Using the ANSI Escape Sequence for

print('\033[1m'+'5 Lowest States of Veteran Suicides in 2021: '+'\033[0m')

#Print head of the df_state_total_2021 sorting from lowest to highest

print(df_state_total_2021[['Year of Death','State of Death','Veteran Suicides']].sort_

#print 5 Highest States of Veteran Suicides in 2021 Using the ANSI Escape Sequence for

print('\033[1m'+'5 Lowest States of Veteran Suicide Rate in 2021: '+'\033[0m')

#Print head of the df_rate_state_2021 sorting from lowest to highest

print(df_rate_state_2021[['Year','State of Death','Veteran Suicide Rate']].sort_values
```

```
5 Lowest States of Veteran Suicides in 2021:
      Year of Death        State of Death  Veteran Suicides
1064           2021  District of Columbia                10
1047           2021          Rhode Island                11
1057           2021          North Dakota                14
1048           2021               Vermont                18
1082           2021                Hawaii                20
5 Lowest States of Veteran Suicide Rate in 2021:
      Year        State of Death  Veteran Suicide Rate
5739  2021  District of Columbia                   0.0
5629  2021            New Jersey                  16.3
5834  2021                Hawaii                  18.5
5644  2021          Rhode Island                  19.0
5619  2021         Massachusetts                  19.1
```

What is the mean of Veteran Suicide Rates per 100k of population for each region?

In [48]:
```
#Create dataframe with only selected columns 'Year','Geographic Region','State of Deat

df_rates=df_age_rename[['Year','Geographic Region','State of Death','Age Group','Veter

#Create dataframe with .loc ['Geographic Region'] != 'All' & ['Age Group'] == 'All' &

df_rate_region=df_rates.loc[(df_rates['Geographic Region'] != 'All') & (df_rates['Age

#display dataframe
```

```
df_rate_region
```

Out[48]:

	Year	Geographic Region	State of Death	Age Group	Veteran Suicide Rate
4	2001	Northeastern	All	All	17.3
54	2001	Midwestern	All	All	23.6
124	2001	Southern	All	All	24.1
214	2001	Western	All	All	26.1
284	2002	Northeastern	All	All	16.6
...	...	...	...	...	...
5534	2020	Western	All	All	36.2
5604	2021	Northeastern	All	All	24.4
5654	2021	Midwestern	All	All	33.5
5724	2021	Southern	All	All	34.4
5814	2021	Western	All	All	39.2

84 rows × 5 columns

In [49]:

```
#Create pivot_table (values='Veteran Suicide Rate',index='Geographic Region',columns='
df_rate_region.pivot_table(values='Veteran Suicide Rate',index='Geographic Region',col
```

Out[49]:

Year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	...	2012	2013	2014
Geographic Region														
Midwestern	23.6	24.9	22.9	22.7	25.9	25.5	25.2	26.4	26.4	27.6	...	28.0	28.5	29.6
Northeastern	17.3	16.6	18.5	18.0	18.4	18.3	19.8	22.6	21.8	23.0	...	22.4	24.1	25.1
Southern	24.1	24.9	25.0	25.9	25.4	25.3	26.9	28.2	28.5	28.8	...	29.2	29.7	29.6
Western	26.1	28.0	27.6	27.4	27.7	28.8	31.6	33.8	34.6	33.8	...	34.2	34.0	37.4

4 rows × 21 columns

Did the order of the regions change based on the population?

In [50]:

```
#Reload dataframe with .groupby('Geographic Region') and calculate mean with .mean()
df_region_mean=df_region.groupby('Geographic Region').mean()
#Display Dataframe in descending order .groupby('Geographic Region') and calculate mea
print(df_region_mean.sort_values(['Veteran Suicides'],ascending=False))
#Create a dataframe with selected columns
```

```
df_rate_region_col=df_rate_region[['Geographic Region','Veteran Suicide Rate']]

#Create dataframe with .groupby('Geographic Region') and calculate mean with .mean()

df_rate_region_mean=df_rate_region_col.groupby('Geographic Region').mean()

#Display Dataframe in descending order .groupby('Geographic Region') and calculate mea

print(df_rate_region_mean.sort_values(['Veteran Suicide Rate'],ascending=False))
```

```
                   Veteran Suicides
Geographic Region
All                     6374.619048
Southern                 155.176471
Western                  125.190476
Midwestern               113.690476
Northeastern              83.296296
                   Veteran Suicide Rate
Geographic Region
Western                       33.238095
Southern                      29.019048
Midwestern                    27.919048
Northeastern                  22.285714
All                                 NaN
```

Reviewing the tables above we see that though the Southern region has the highest number of veteran suicides by population it is replaced as the leader by the Western region. The Midwestern and Northeastern regions did not change in rank.

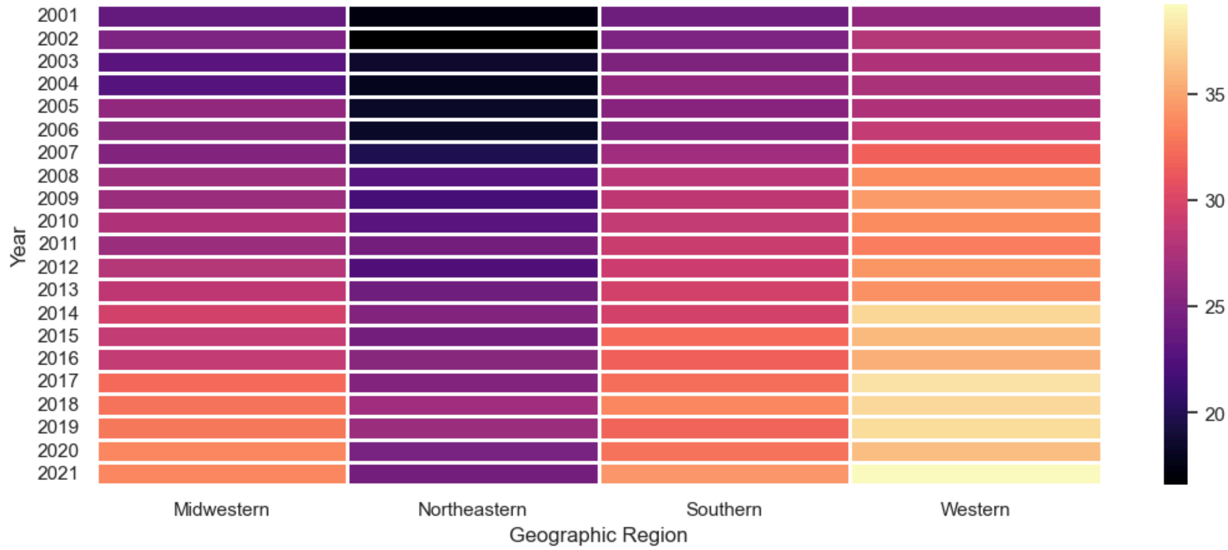
Are the Veteran Suicide Rates per 100k of population for the Regions changing?

In [51]:

```
#Create pivot_table (values='Veteran Suicide Rate',index='Year',columns='Geographic Re

vetrate=df_rate_region.pivot_table(values='Veteran Suicide Rate',index='Year',columns=

#Create sns heatmap with variable vetrate

sns.heatmap(vetrate,cmap='magma',linecolor='white',linewidths=1)
```

Out[51]:

```
<Axes: xlabel='Geographic Region', ylabel='Year'>
```



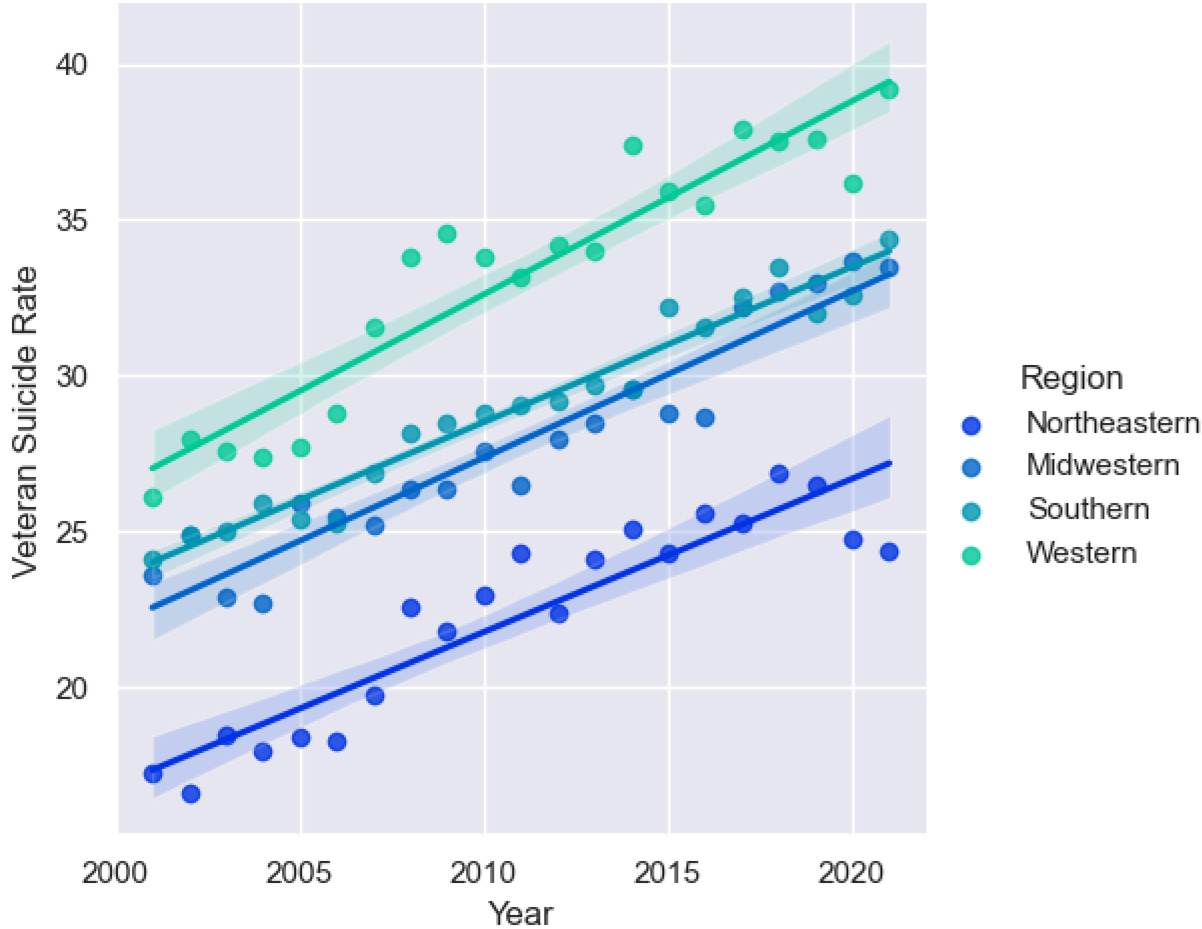
As we can see here though the rates might vary overall there is evidence that indicates an overalll trend of increasing in each of the regions.

In [163…

```
#Create a new column 'Region' to remove All from 'Geographic Region' and then dropna()

data=df_rate_region.assign(Region=df_rate_region['Geographic Region'].map({'Midwestern

#Create lmplot (x='Year',y='Veteran Suicide Rate',hue='Geographic Region',data=df_rate

sns.lmplot(x='Year',y='Veteran Suicide Rate',hue='Region',data=data,palette='winter')
```

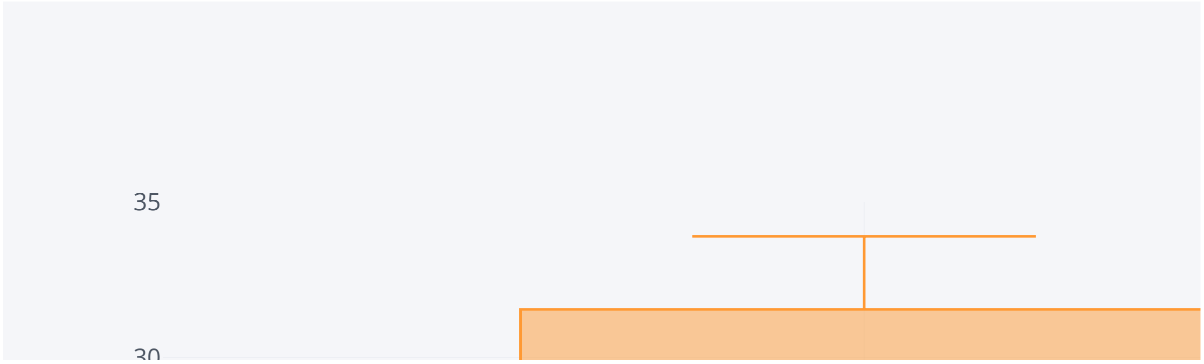
Out[163]:

```
<seaborn.axisgrid.FacetGrid at 0x1e152999850>
```



Are veterans more vulnerable to suicide than the general population?

In [53]:
```
#Load dataframe df_age_rename which was the df_age with renamed columns
df_age_rename

#Create dataframe with .loc() ['State of Death'] == 'U.S. Total' & ['Age Group'] == 'A

df_rate2=df_age_rename.loc[(df_age['State of Death'] == 'U.S. Total') & (df_age['Age G

#Create dataframe with only selected columns to use for iplot

df_rate_only=df_rate2[['Veteran Suicide Rate', 'General Population Suicide Rate']]

#Create plotly interactive image kind='box'

df_rate_only.iplot(kind='box')
```



In [54]:
```
#Print each dataframe using the describe() function

print('Veteran Suicide Rate: ',stats.describe(df_rate_only['Veteran Suicide Rate']),'\
print('General Population Suicide Rate: ',stats.describe(df_rate_only['General Populat
```

```
Veteran Suicide Rate:  DescribeResult(nobs=21, minmax=(23.3, 33.9), mean=28.685714285
714283, variance=11.837285714285715, skewness=-0.11854631683051597, kurtosis=-1.29219
28660521012)

General Population Suicide Rate:  DescribeResult(nobs=21, minmax=(13.9, 18.4), mean=1
6.038095238095234, variance=2.2934761904761896, skewness=0.032962837754799815, kurtos
is=-1.4210950133065836)
```

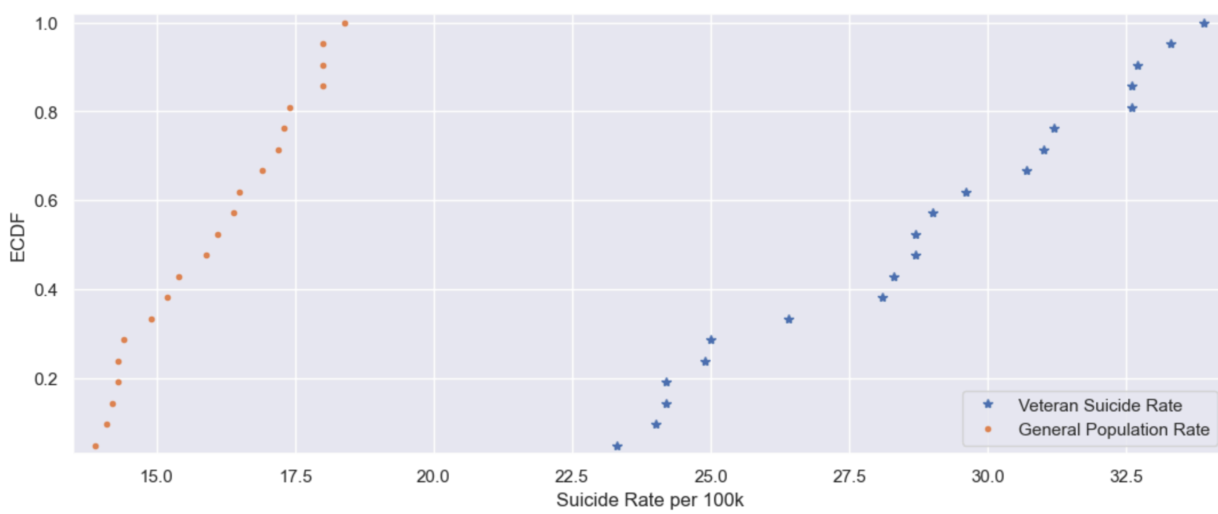
The mean of each of the populations as well as the variance and skewness have strong evidence that each population has a normal distrubtion. Also, the interactive boxplot shows that all measures, including mean, min, max, etc has strong evidence that veterans are a much higher risk for suicide than the general population.

ECDF

In [55]:
```
# Create ECDF function
def ecdf(data):
```

```
    #Number of data points: n
    n=len(data)

    #x-data for the ECDF: x
    x=np.sort(data)

    #y-data for the ECDF: y
    y=np.arange(1,n+1)/n

    return x,y
```

In [56]:
```
#compute ECDFS passing the data for both veteran suicide rate and general population s

#compute x,y for veteran and general population by calling the dataframes

x_vet,y_vet=ecdf(df_rate_only['Veteran Suicide Rate'])
x_genpop,y_genpop=ecdf(df_rate_only['General Population Suicide Rate'])

#Plot both ECDFs on the same plot using variable underscore

_=plt.plot(x_vet,y_vet,marker='*',linestyle='none')
_=plt.plot(x_genpop,y_genpop,marker='.',linestyle='none')

#Make margins

plt.margins(0.02)

#Annotate the plot

plt.legend(('Veteran Suicide Rate','General Population Rate'),loc='lower right')
_=plt.xlabel('Suicide Rate per 100k')
_=plt.ylabel('ECDF')

#Display the plot

plt.show()
```



Correlation

We will see the outpot of the correlation values of the numerical columns. We will also include the pvlaues to see the significance of the correlation:

-The p-value is < 0.001: we say there is strong evidence that the correlation is significant.

-The p-value is < 0.05: there is moderate evidence that the correlation is significant.

-The p-value is < 0.1:there is weak evidence that the correlation is significant.

-The p-value is > 0.1: there is no evidence that the correlation is significant.

In [57]:
```
#Correlation of all numerical columns in df_state

sns.set()
corr_state=df_state.corr(numeric_only=True)
corr_state
```

Out[57]:

	Year of Death	Veteran Suicides
Year of Death	1.000000	0.007332
Veteran Suicides	0.007332	1.000000

In [58]:
```
#Correlation of all numerical columns in df_sex

sns.set()
corr_sex=df_sex.corr(numeric_only=True)
corr_sex
```

Out[58]:

	Year of Death	Veteran Suicides
Year of Death	1.000000	-0.054927
Veteran Suicides	-0.054927	1.000000

In [59]:
```
#Correlation of all numerical columns in df_age

sns.set()
corr_age=df_age.corr(numeric_only=True)
corr_age
```

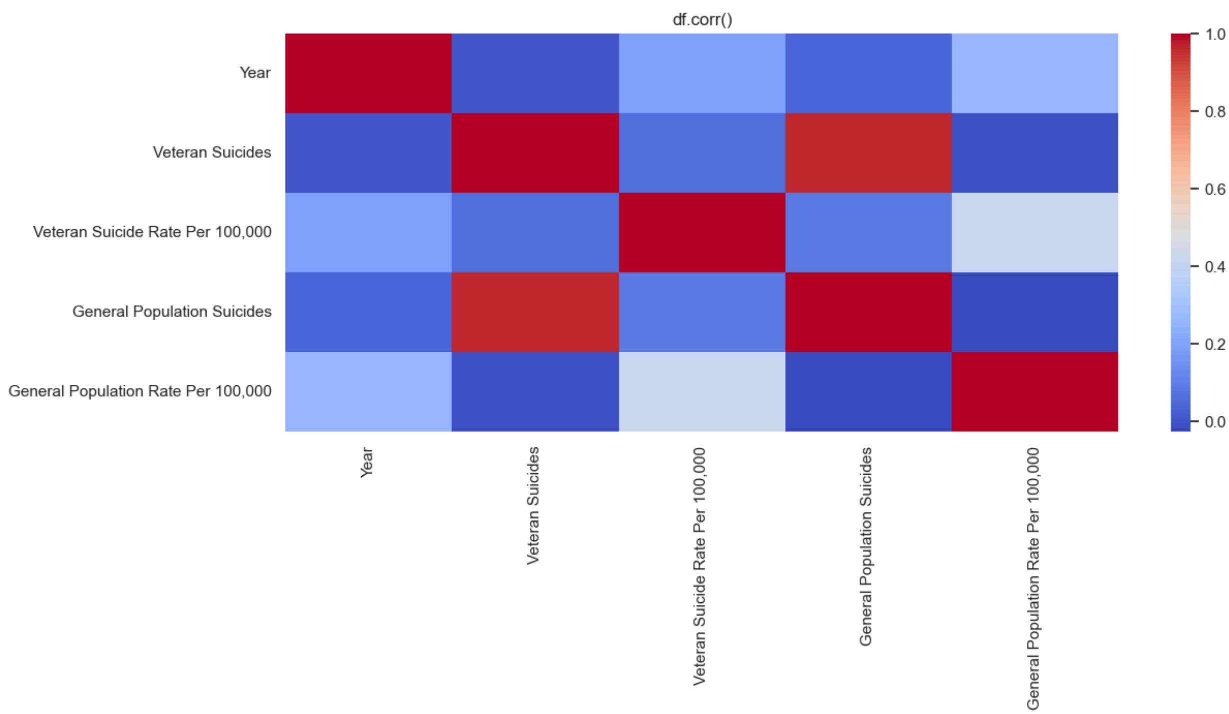
Out[59]:

	Year	Veteran Suicides	Veteran Suicide Rate Per 100,000	General Population Suicides	General Population Rate Per 100,000
Year	1.000000	0.004661	0.196472	0.041934	0.260249
Veteran Suicides	0.004661	1.000000	0.061282	0.964534	-0.017305
Veteran Suicide Rate Per 100,000	0.196472	0.061282	1.000000	0.084813	0.413232
General Population Suicides	0.041934	0.964534	0.084813	1.000000	-0.026004
General Population Rate Per 100,000	0.260249	-0.017305	0.413232	-0.026004	1.000000

In [64]:

```
#Print a heatmap using the correlation function for df_age

sns.heatmap(df_age.corr(numeric_only=True),cmap='coolwarm')
plt.title('df.corr()')
```

Out[64]: Text(0.5, 1.0, 'df.corr()')



Pearson's Correlation Test

In [62]:

```
#Using Pearson's Correlation Test

#Importing scientific library to perform statistical calculations

from scipy.stats import pearsonr

#Define data1 with 'Veteran Suicides'

data1=df_age['Veteran Suicides']
```

```
#Define data2 with 'Veteran Suicides'

data2=df_age['General Population Suicides']

#Declare variable stat and perform pearsonr function

stat,p=pearsonr(data1,data2)

#Print result with 3 decimals

print('stat=%.3f,p=%.3f' % (stat,p))

#Adding a conditional selection

if p > 0.05:
    print('Probably Independent')
else:
    print('Probably Dependent')
```

```
stat=0.965,p=0.000
Probably Dependent
```

According to the Pearson's Correlation test with a p-value of 0.000 there it is likely there is strong evidence that the correlation is significant between the veteran and general population suicides.

Correlation Matrix

In [61]:

```
#define a function name it pearson_r that will take two arguments x and y
def pearson_r(x, y):
    """Compute Pearson correlation coefficient between two arrays."""
    # Compute correlation matrix: corr_mat

    corr_mat=np.corrcoef(x,y)

    # Return entry [0,1]
    return corr_mat[0,1]

# Compute Pearson correlation coefficient of 'Year' and 'Veteran Suicides' from df_age

vet_suicide=df_age['Veteran Suicides']
genpop_suicide=df_age['General Population Suicides']

r=pearson_r(vet_suicide,genpop_suicide)


# Print the result

print(r)
```

```
0.9645344444756127
```

With a value of 0.9645344444756127 this shows strong and positive correlation meaning when one variable increases, the other tends to as well for the Veteran and General Population Suicides.

Normal Distribution test

- The normality tests all report a P value.
- To understand any P value, you need to know the null hypothesis.
  - the null hypothesis is that all the values were sampled from a population that follows a Gaussian distribution. ...If the P value is less than or equal to 0.05 (the significance level), the answer is No.
- P-value ≤ α: The data do not follow a normal distribution (Reject H0).
- If the p-value is less than or equal to the significance level, the decision is to reject the null hypothesis and conclude that your data does not follow a normal distribution.
- P-value > α: Cannot conclude the data do not follow a normal distribution (Fail to reject H0).
- If the p-value is larger than the significance level, the decision is to fail to reject the null hypothesis because you do not have enough evidence to conclude that your data do not follow a normal distribution.

In [170…

```
#Import normaltest from scipy

from scipy.stats import normaltest
```

In [177…

```
#Assign the General Population Suicide Rate to a variable named data

data=df_age['Veteran Suicides']

#Create two variables stat and p then apply the normaltest function

stat,p=normaltest(data)

#Print results with only 3 decimals

print('stat=%.3f,p=%.3f'%(stat,p))

#Add a conditional print

if p <= 0.05:
    print('Data does not follow a normal distribution: Reject H0')
else:
    print('Cannot conclude the data does not follow a normal distribution: Fail to rej
```

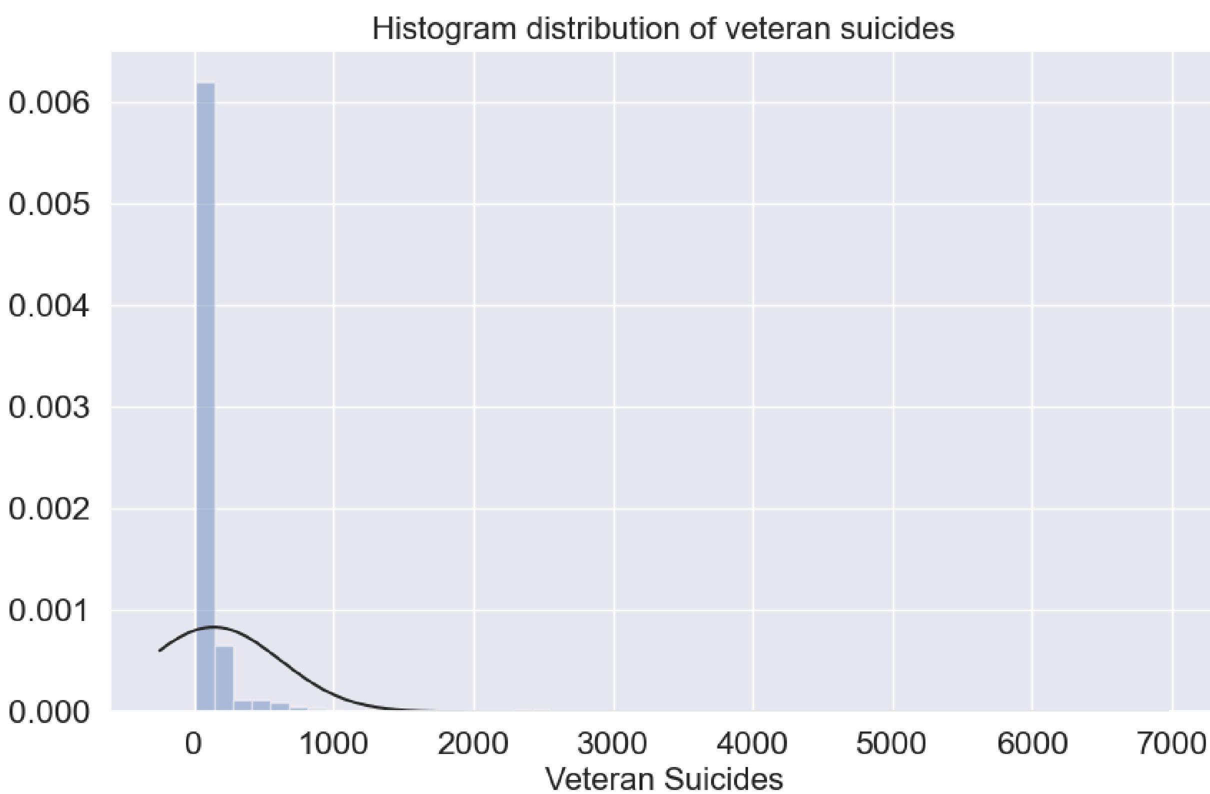
```
stat=8718.814,p=0.000
Data does not follow a normal distribution: Reject H0
```

We will also use a Seaborn distplot to visually convey if the data is normally distributed

In [180…

```
#plt.rcParams to set the figure width width of 10 and height of 6
#sns.set_style('darkgrid')
```

```
plt.rcParams['figure.figsize']=[10,6]
sns.set_style('darkgrid')

#set context,font scale, and font size

sns.set_context('notebook',font_scale=1.5,rc={'font.size':16,'axes.titlesize':16,'axes

#the fit will going to super impose a normal curve to the histogram
# or to the distribution
# we set kde to false because by default it uses the kde

sns.distplot(df_age['Veteran Suicides'],fit=stats.norm,kde=False)

# add title and xlabel to the plot

plt.title('Histogram distribution of eteran suicides')
plt.xlabel('Veteran Suicides')

#Display plot

plt.show()
```



Both the normaltest and the distplot confirm that the data is not normally dsitributed

In [176…

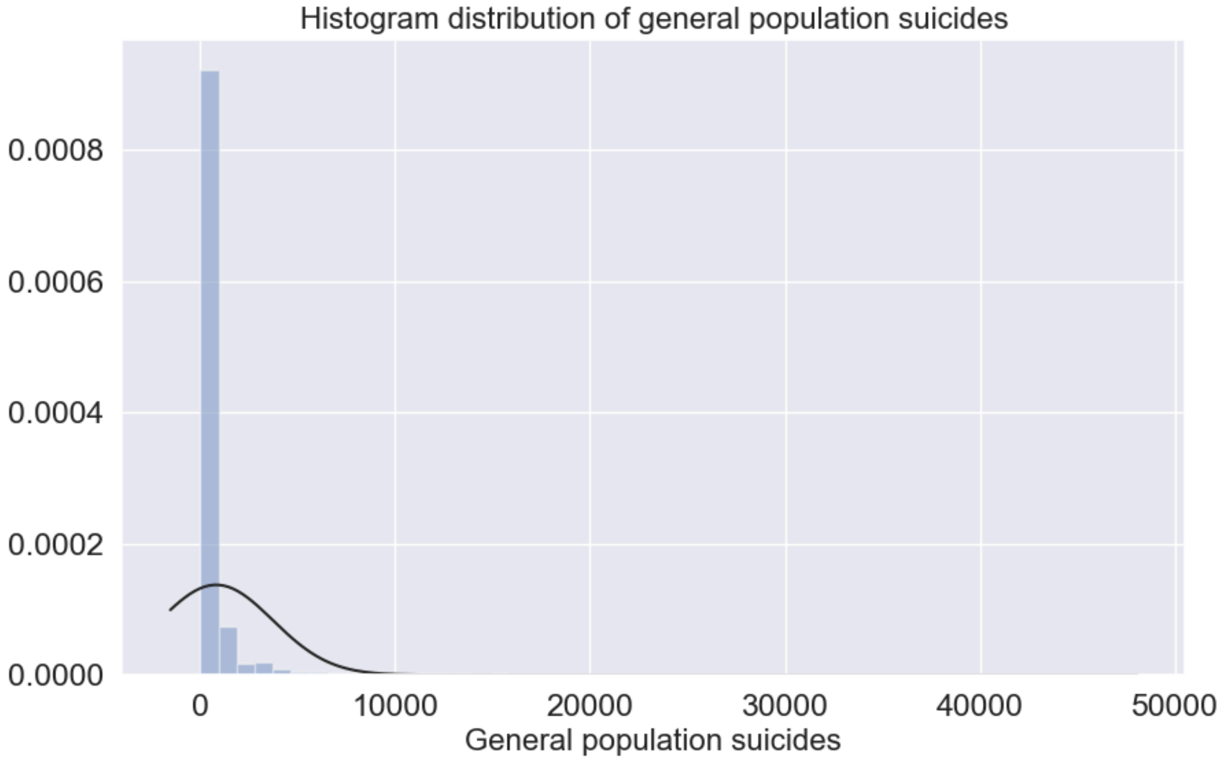
```
#Assign the Veteran Suicide Rate to a variable named data

data=df_age['General Population Suicides']

#Create two variables stat and p then apply the normaltest function

stat,p=normaltest(data)

#Print results with only 3 decimals
```

```
print('stat=%.3f,p=%.3f'%(stat,p))

#Add a conditional print

if p <= 0.05:
    print('Data does not follow a normal distribution: Reject H0')
else:
    print('Cannot conclude the data does not follow a normal distribution: Fail to rej
```

```
stat=8872.723,p=0.000
Data does not follow a normal distribution: Reject H0
```

In [181…

```
#plt.rcParams to set the figure width width of 10 and height of 6
#sns.set_style('darkgrid')

plt.rcParams['figure.figsize']=[10,6]
sns.set_style('darkgrid')

#set context,font scale, and font size

sns.set_context('notebook',font_scale=1.5,rc={'font.size':16,'axes.titlesize':16,'axes

#the fit will going to super impose a normal curve to the histogram
# or to the distribution
# we set kde to false because by default it uses the kde

sns.distplot(df_age['General Population Suicides'],fit=stats.norm,kde=False)

# add title and xlabel to the plot

plt.title('Histogram distribution of general population suicides')
plt.xlabel('General population suicides')

#Display plot

plt.show()
```



Again both the normaltest and the distplot confirm that the data is not normally distributed

Chi-Squared Test

- Tests whether two categorical variables are related or independent.
- H0: the two samples are independent.
- H1: there is a dependency between the samples.

In [184…

```
#Import Chi-squared test from scipy

from scipy.stats import chi2_contingency
```

In [186…

```
#Assign Veteran Suicides and General Population Suicides to a variable named data

data=df_age[['Veteran Suicides','General Population Suicides']]

#Create variables stat,p,dof (degrees of freedom),expected (expectedvalues) and apply

stat,p,dof,expected=chi2_contingency(data)

#Print stat and p with only 3 decimals

print('stat=%.3f,p=%.3f'%(stat,p))

#Add a conditional print

if p > 0.05:
    print('H0: Probably independent')
else:
    print('H1: Probably dependent')
```

```
stat=246462.750,p=0.000
H1: Probably dependent
```

One sample z test

In [188…

```
#Import ztest from statsmodels.stats.weightstats

from statsmodels.stats.weightstats import ztest

#import scipy.stats

import scipy.stats as stats
```

In [196…

```
df_age.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5880 entries, 0 to 5879
Data columns (total 8 columns):
 #   Column                              Non-Null Count  Dtype
---  ------                              --------------  -----
 0   Year                                5880 non-null   int64
 1   Geographic Region                   5880 non-null   category
 2   State of Death                      5880 non-null   object
 3   Age Group                           5880 non-null   category
 4   Veteran Suicides                    5880 non-null   int64
 5   Veteran Suicide Rate Per 100,000    5880 non-null   float64
 6   General Population Suicides         5880 non-null   int64
 7   General Population Rate Per 100,000 5880 non-null   float64
dtypes: category(2), float64(2), int64(3), object(1)
memory usage: 287.7+ KB
```

In [200…

```
#Create dataframe df_age_rename with renamed columns to Veteran Suicides and General P

df_age_rename=df_age.rename(columns={'Veteran Suicide Rate Per 100,000':'Veteran Suici

#Assign Veteran Suicides and General Population Suicides to a variable named data

data=df_age_rename[['Veteran Suicide Rate','General Population Rate']]

#Display data with .head() function

data.head()
```

Out[200]:

	Veteran Suicide Rate	General Population Rate
0	27.9	9.7
1	21.8	11.0
2	12.0	9.2
3	17.2	10.6
4	17.3	10.2

Before completing the one z test we need to calculate some descriptive summaries of the data.

- We are going to create a data frame one column is the suicide rate type and other one is the suicide rate.
- The suicide type will be Veteran Suicide Type and General Population Rate and then the suicide rate.
- This will allow to do a groupby.
- I will then call the melt function of pandas
- I will then create a new dataframe melted_df that will contain the two new columns.
- The new variable name will be Suicide_Type. So Suicide_Type will be Veteran Suicides Rate or General Population Rate. The values will be the suicides rate so the argument value_name will have the value "Suicide_Rate"

In [202…

```
#Created melted_df with Pandas melt with var_name='Suicide_type' and value_name='Suici

melted_df=pd.melt(data,var_name='Suicide_type',value_name='Suicide_rate')

#Display melted_df using print with .head()  and .tail()function

print(melted_df.head())

print(melted_df.tail())
```

```
            Suicide_type  Suicide_rate
0  Veteran Suicide Rate          27.9
1  Veteran Suicide Rate          21.8
2  Veteran Suicide Rate          12.0
3  Veteran Suicide Rate          17.2
4  Veteran Suicide Rate          17.3
                   Suicide_type  Suicide_rate
11755  General Population Rate          18.8
11756  General Population Rate          18.2
11757  General Population Rate          16.2
11758  General Population Rate          20.3
11759  General Population Rate          18.0
```

In [203…

```
#Create new dataframe bygroup with groupy of the melted_df by Suicide_Type and numeric

bygroup=melted_df.groupby(['Suicide_type'])['Suicide_rate']

#Aggregate the dataframe bygroup

bygroup.aggregate(['count',np.mean,np.std]).round(2)
```

Out[203]:

Suicide_type	count	mean	std
General Population Rate	5880	17.39	7.17
Veteran Suicide Rate	5880	24.59	17.84

Testing the hypothesis that the mean is 16 against the alternative it is GREATER

$H0{:}\mu=\mu0\ H1{:}\mu\mu0$

- Call ztest that takes the following arguments:
  - General Population Rate of data
  - value=16
  - alternative='larger'
  - ddof=1.0 (Degrees of freedom use in the calculation of the variance of the mean estimate. In the case of comparing means this is one.)
- Returns stat,p

In [221…

```
#Create variables stat and p and apply the ztest larger test

(stat,p)=ztest(data['General Population Rate'],value=16,alternative='larger',ddof=1.0)

#Print ztest results round to 5 decimal places

print('The test statistic is: ',round(stat,5))
print('The p-value is: ',round(p,7))

#Add a conditional print

if p < 0.05:
    print('The result is not significant')
else:
    print('The result is significant')
```

```
The test statistic is:  14.89528
The p-value is:  0.0
The result is not significant
```

Based on the p-value we say it is unlikely there is enough evidence to reject the null hypothesis in favor of the the alternative hypothesis.

Conclusion

After cleaning, organizing, plotting, and using data visualization we were able to answer the following questions:

```
1. Which years have the highest and lowest number of veteran
suicides?

   2018 has the highest number of veteran suicides with 6718.
Followed by 2017, 2014, 2015, and 2008.
   2001 has the lowest number of veteran suicides with 6000.
Followed by 2004, 2003, 2006, and 2005.

2. Which states have the highest and lowest number of veteran
suicides in 2021?

   The state with the highest number of veteran suicides in 2021 is
Texas with 583.
   Followed by Florida, California, Pennsylvania, and Ohio.
```

The state with the lowest number of veteran suicides in 2021 is District of Columbia with 10.
Followed by Rhode Island, North Dakota, Vermont, and Hawaii.
We will determine later if population factors into this.

3. Which region has the highest mean of veteran suicides?

The region with the highest mean of veteran suicides is the Southern region with a mean of 155.176471.
We will determine later if population factors into this.

4. Are veteran suicides increasing over the years?

Though the numbers do vary, including a general increase, there is no evidence that there is a dramatic
change in the suicide rate.

5. Are men or women more at risk for veteran suicide?

There appears to be evidence that men are at a higher risk than women but without the population providing
numbers of each gender the findings are a bit incomplete.

6. Which age groups have the highest and lowest number of veteran suicides?

From 2001-2005 the age group 35-54 had the highest number of veteran suicides followed by 55-74, 75+,
and 18-34. In 2006 35-54 and 55-74 were similar with 75+ and 18-34 unchanged in their order. Starting
in 2007 we see 55-74 with the highest number of veteran suicides with the remaining age groups still in
their same order.

7. Are the age groups and their suicide rates consistent over the years?

Though there is slight variance in each of the 4 age groups there is strong (18-34,75+) to moderate
(35-54,55-74) evidence that suicides are fairly consistent and normally distributed.

8. What are the highest Veteran Suicide Rates per 100k of population for the states in 2021?

The 5 higest states by suicide rate are Wyoming(80.0), Colorado(56.1),Montana(51.2), Nevada (50.7),
and Oregon(49.6).

9. Did the order of the highest and lowest states change based on the population?

The highest ranked states changed drastically. By number they

```
were Texas, Florida, California,
   Pennsylvania, and Ohio.  By rate they were Wyoming, Colorado,
Montana, Nevada, and Oregon.  The
   lowest ranked states also had minor changes but had some
consistency as well.  By just numbers they
   were District of Columbia, Rhode Island, North Dakota, Vermont,
and Hawaii.  By rate they were
   District of Columbia (based on the 0 this data was a bit
inconclusive), New Jersey, Hawaii, Rhode
   Island, and Massachusetts.

10. What is the mean of Veteran Suicide Rates per 100k of population
for each region?

    The mean of the regions are as follows:
    Western       33.238095
    Southern      29.019048
    Midwestern    27.919048
    Northeastern  22.285714

11. Did the order of the regions change based on the population?

    Southern was the highest by number and Western by ratem but each
was no lower than second.  Midwestern
    and Northeastern were unchanged.

12. Are the Veteran Suicide Rates per 100k of population for the
Regions changing?

    There is moderate evidence it is generally increasing over the
years but not at a static rate and can vary.

13. Are veterans more vulnerable to suicide than the general
population?

    There is strong evidence that suggest veterans are at a much
higher risk than the general population.
```

Hypothesis Testing Conclusion

We completed the following hypothesis testing along with their conclusions:

- Pearson's Correlation Test
    - According to the Pearson's Correlation test with a p-value of 0.000 there it is likely there is strong evidence that the correlation is significant between the veteran and general population suicides.
- Correlation Matrix

- With a value of 0.9645344444756127 this shows strong and positive correlation meaning when one variable increases, the other tends to as well for the Veteran and General Population Suicides.
- Normal distribution Test
  - Based on the p-value of 0.00 for both the Veteran and General Population Suicides we say data does not follow a normal distribution: Reject H0. We also visually confirmed this with a Seaborn histogram.
- Chi-Squared Test
  - Based on the p-value of 0.000 we say that it the Veteran and General Population suicides are probably dependent.
- One sample z test
  - Based on the p-value of 0.0 we say the result is not significant or it is unlikely there is enough evidence to reject the null hypothesis in favor of the the alternative hypothesis.

In [ ]:

```

```