In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
data = pd.read_csv('brain_stroke.csv')
```

In [3]:

```
data.head()
```

Out[3]:

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_gl
0	Male	67.0	0	1	Yes	Private	Urban	
1	Male	80.0	0	1	Yes	Private	Rural	
2	Female	49.0	0	0	Yes	Private	Urban	
3	Female	79.0	1	0	Yes	Self-employed	Rural	
4	Male	81.0	0	0	Yes	Private	Urban	

In [4]:

```
data.tail()
```

Out[4]:

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg
4976	Male	41.0	0	0	No	Private	Rural	
4977	Male	40.0	0	0	Yes	Private	Urban	
4978	Female	45.0	1	0	Yes	Govt_job	Rural	
4979	Male	40.0	0	0	Yes	Private	Rural	
4980	Female	80.0	1	0	Yes	Private	Urban	

In [5]:

```
data.shape
```

Out[5]:

```
(4981, 11)
```

In [6]:

```
data.columns
```

Out[6]:

```
Index(['gender', 'age', 'hypertension', 'heart_disease', 'ever_married',
       'work_type', 'Residence_type', 'avg_glucose_level', 'bmi',
       'smoking_status', 'stroke'],
      dtype='object')
```

In [7]:

```
data.duplicated().sum()
```

Out[7]:

```
0
```

In [8]:

```
data.isnull().sum()
```

Out[8]:

```
gender               0
age                  0
hypertension         0
heart_disease        0
ever_married         0
work_type            0
Residence_type       0
avg_glucose_level    0
bmi                  0
smoking_status       0
stroke               0
dtype: int64
```

In [9]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4981 entries, 0 to 4980
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   gender             4981 non-null   object 
 1   age                4981 non-null   float64
 2   hypertension       4981 non-null   int64  
 3   heart_disease      4981 non-null   int64  
 4   ever_married       4981 non-null   object 
 5   work_type          4981 non-null   object 
 6   Residence_type     4981 non-null   object 
 7   avg_glucose_level  4981 non-null   float64
 8   bmi                4981 non-null   float64
 9   smoking_status     4981 non-null   object 
 10  stroke             4981 non-null   int64  
dtypes: float64(3), int64(3), object(5)
memory usage: 428.2+ KB
```

In [10]:

```
data.describe()
```

Out[10]:

	age	hypertension	heart_disease	avg_glucose_level	bmi	stroke
count	4981.000000	4981.000000	4981.000000	4981.000000	4981.000000	4981.000000
mean	43.419859	0.096165	0.055210	105.943562	28.498173	0.049789
std	22.662755	0.294848	0.228412	45.075373	6.790464	0.217531
min	0.080000	0.000000	0.000000	55.120000	14.000000	0.000000
25%	25.000000	0.000000	0.000000	77.230000	23.700000	0.000000
50%	45.000000	0.000000	0.000000	91.850000	28.100000	0.000000
75%	61.000000	0.000000	0.000000	113.860000	32.600000	0.000000
max	82.000000	1.000000	1.000000	271.740000	48.900000	1.000000

In [11]:

```
data.nunique()
```

Out[11]:

```
gender                  2
age                   104
hypertension            2
heart_disease           2
ever_married            2
work_type               4
Residence_type          2
avg_glucose_level    3895
bmi                   342
smoking_status          4
stroke                  2
dtype: int64
```

In [12]:

```
data_cat = data[['gender', 'hypertension', 'heart_disease', 'ever_married','work_type', 'Re
                 'smoking_status', 'stroke']]
```

In [13]:

```
for i in data_cat.columns:
    print(data_cat[i].unique())
```

```
['Male' 'Female']
[0 1]
[1 0]
['Yes' 'No']
['Private' 'Self-employed' 'Govt_job' 'children']
['Urban' 'Rural']
['formerly smoked' 'never smoked' 'smokes' 'Unknown']
[1 0]
```

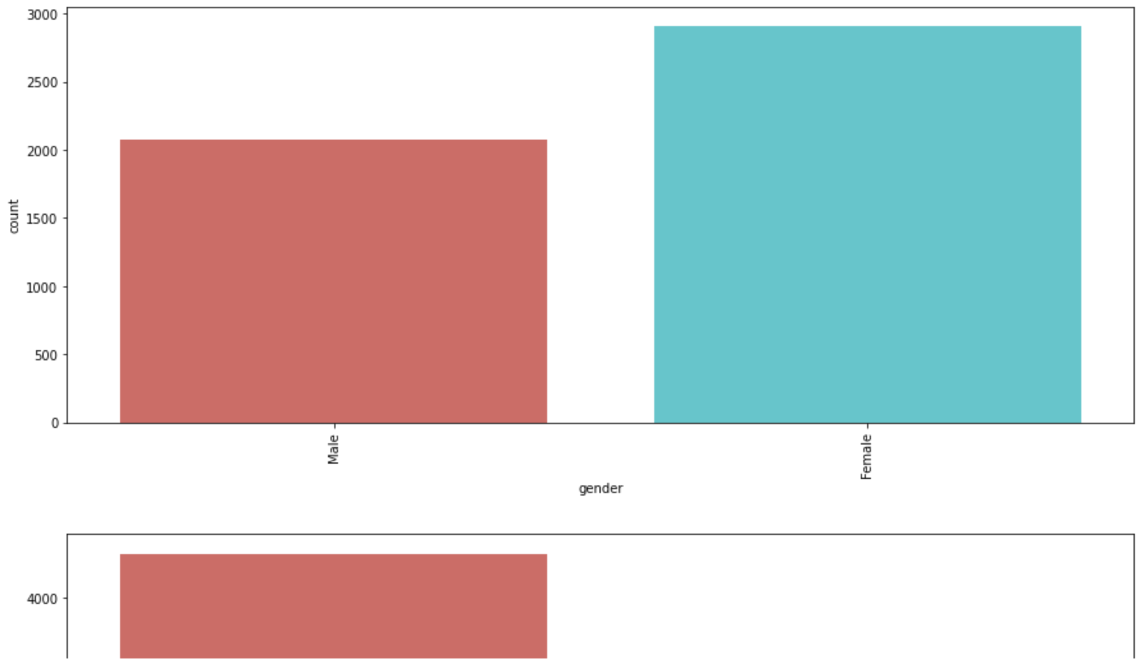
In [14]:

```
for i in data_cat.columns:
    print(data_cat[i].value_counts())
```

```
Female    2907
Male      2074
Name: gender, dtype: int64
0    4502
1     479
Name: hypertension, dtype: int64
0    4706
1     275
Name: heart_disease, dtype: int64
Yes    3280
No     1701
Name: ever_married, dtype: int64
Private          2860
Self-employed     804
children          673
Govt_job          644
Name: work_type, dtype: int64
Urban    2532
Rural    2449
Name: Residence_type, dtype: int64
never smoked       1838
Unknown            1500
formerly smoked     867
smokes              776
Name: smoking_status, dtype: int64
0    4733
1     248
Name: stroke, dtype: int64
```

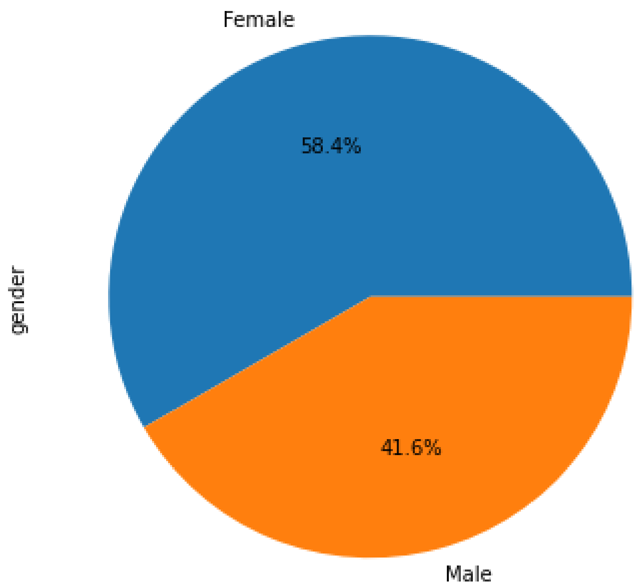
In [15]:

```
for i in data_cat.columns:
    plt.figure(figsize = (15,6))
    sns.countplot(data_cat[i], data = data_cat, palette = 'hls')
    plt.xticks(rotation = 90)
    plt.show()
```



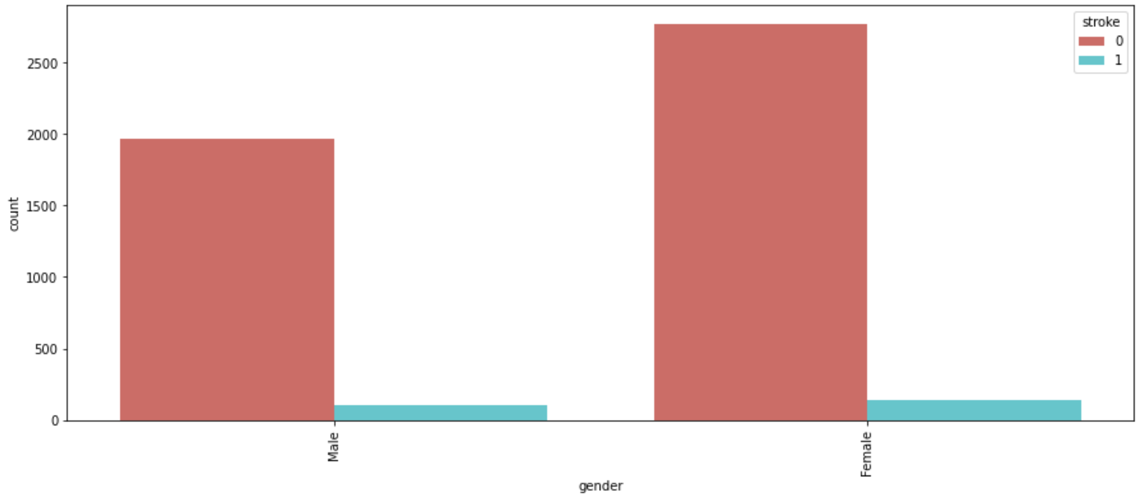
In [16]:

```
for i in data_cat.columns:
    plt.figure(figsize = (15,6))
    data_cat[i].value_counts().plot(kind = 'pie', autopct = '%1.1f%%')
    plt.xticks(rotation = 90)
    plt.show()
```



In [17]:

```
for i in data_cat.columns:
    plt.figure(figsize = (15,6))
    sns.countplot(data_cat[i], data = data_cat, hue = 'stroke' , palette = 'hls')
    plt.xticks(rotation = 90)
    plt.show()
```

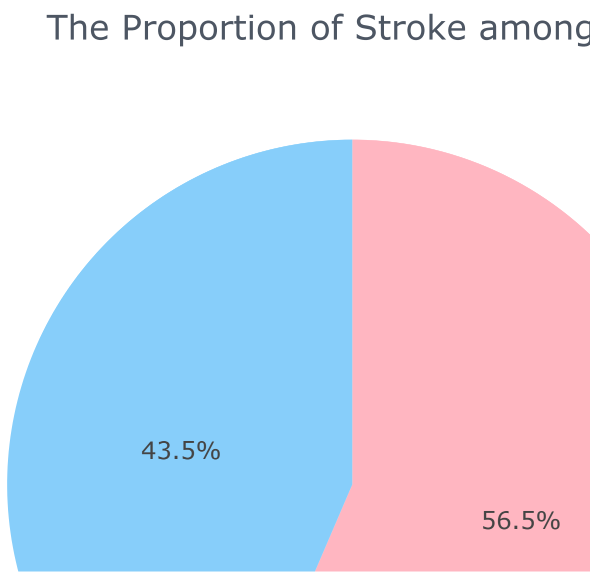


In [18]:

```
import cufflinks as cf
cf.go_offline()
cf.set_config_file(offline=False, world_readable=True)
```

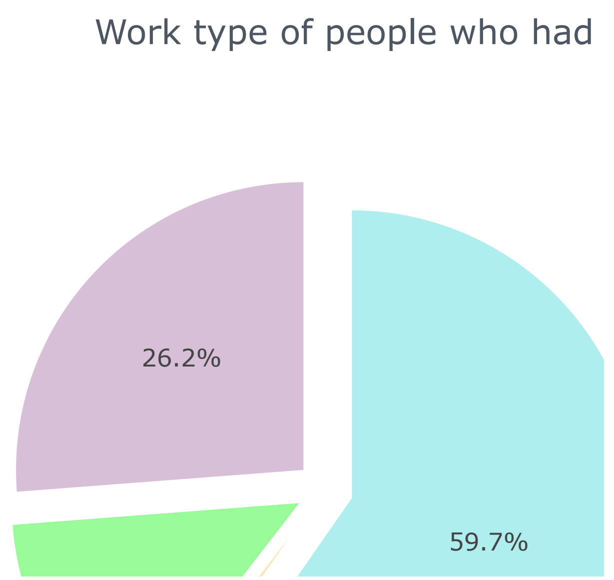
In [19]:

```
gender = data.groupby(data['gender'])['stroke'].sum()
data_gender = pd.DataFrame({'labels': gender.index,
                   'values': gender.values
                  })
colors = ['lightpink', 'lightskyblue']
data_gender.iplot(kind='pie',labels='labels',values='values', title='The Proportion of Stro
```



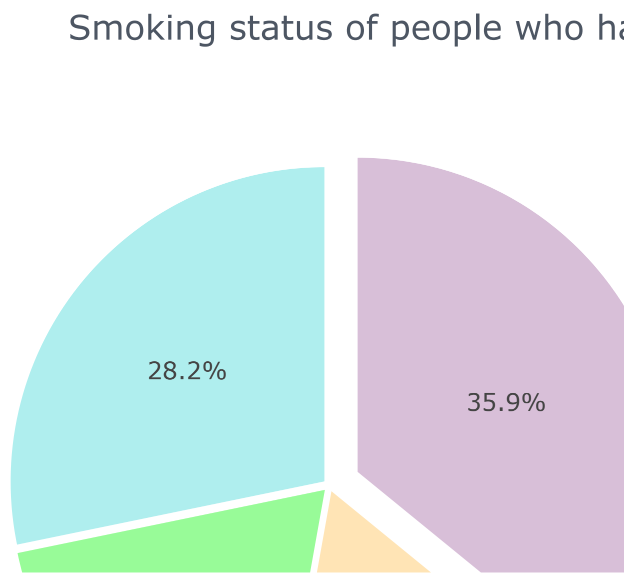
In [20]:

```
job = data.groupby(data['work_type'])['stroke'].sum()
data_job = pd.DataFrame({'labels': job.index,
                   'values': job.values
                  })
colors2= ['palegreen','paleturquoise','thistle','moccasin']
data_job.iplot(kind='pie',labels='labels',values='values', title='Work type of people who h
            pull=[0.1, 0.1, 0.1, 0.2])
```



In [21]:

```
smoke = data.groupby(data['smoking_status'])['stroke'].sum()
data_smoke = pd.DataFrame({'labels': smoke.index,
                   'values': smoke.values
                  })
data_smoke.iplot(kind='pie',labels='labels',values='values', title='Smoking status of peopl
            pull=[0.02, 0.02, 0.1, 0.02])
```

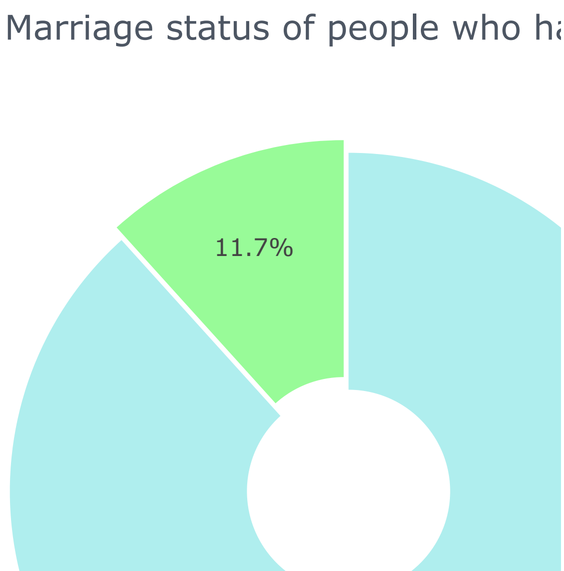


In [22]:

```
Residence = data.groupby(data['Residence_type'])['stroke'].sum()
data_Residence = pd.DataFrame({'labels': Residence.index,
                   'values': Residence.values
                  })
data_Residence.iplot(kind='pie',labels='labels',values='values', title='Residence area of p
            pull=[0.02, 0.02],hole = 0.3)
```

In [23]:

```
Married = data.groupby(data['ever_married'])['stroke'].sum()
data_Married = pd.DataFrame({'labels': Married.index,
                   'values': Married.values
                  })
data_Married.iplot(kind='pie',labels='labels',values='values', title='Marriage status of pe
            pull=[0.02, 0.02],hole = 0.3)
```

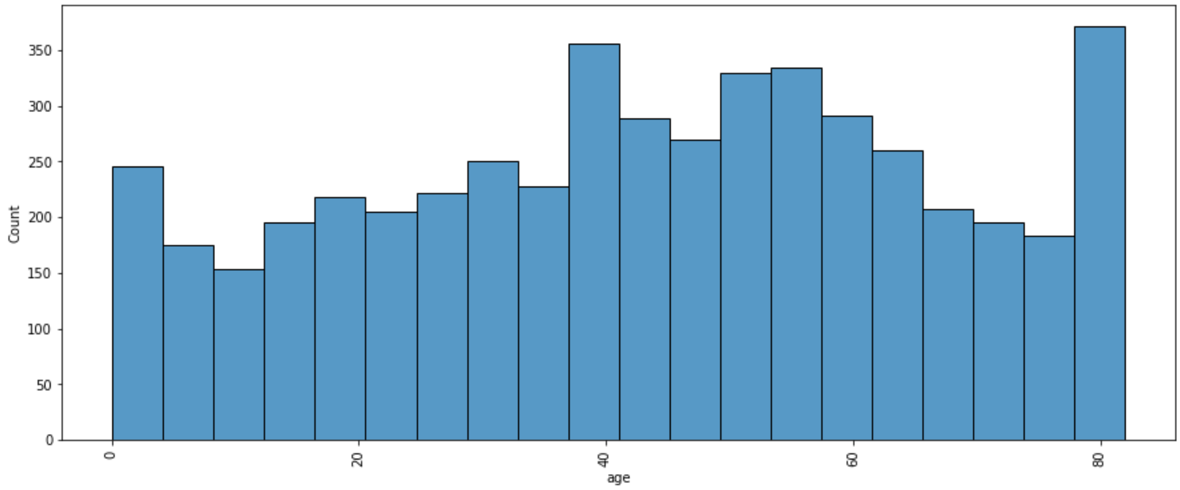


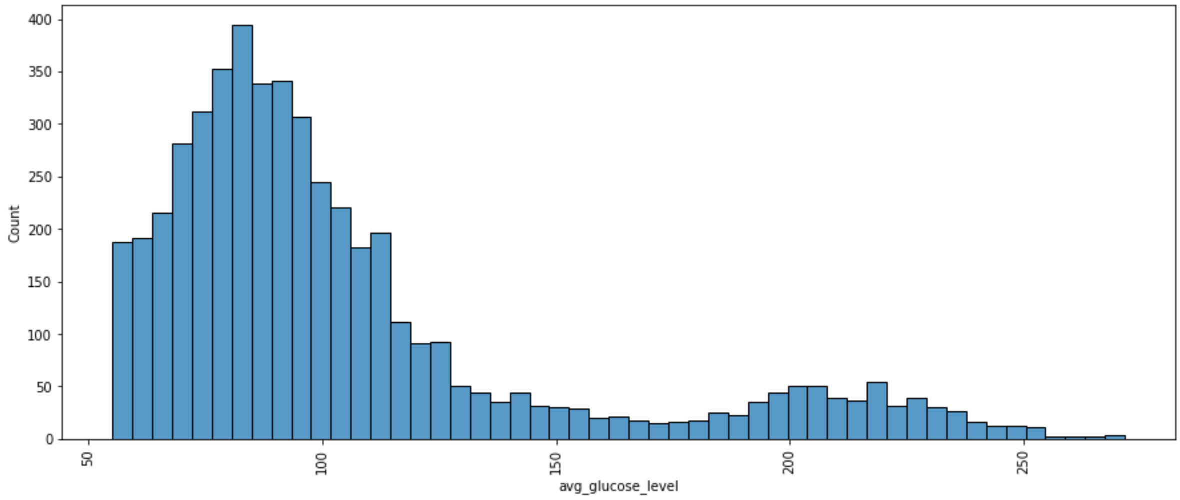
In [24]:

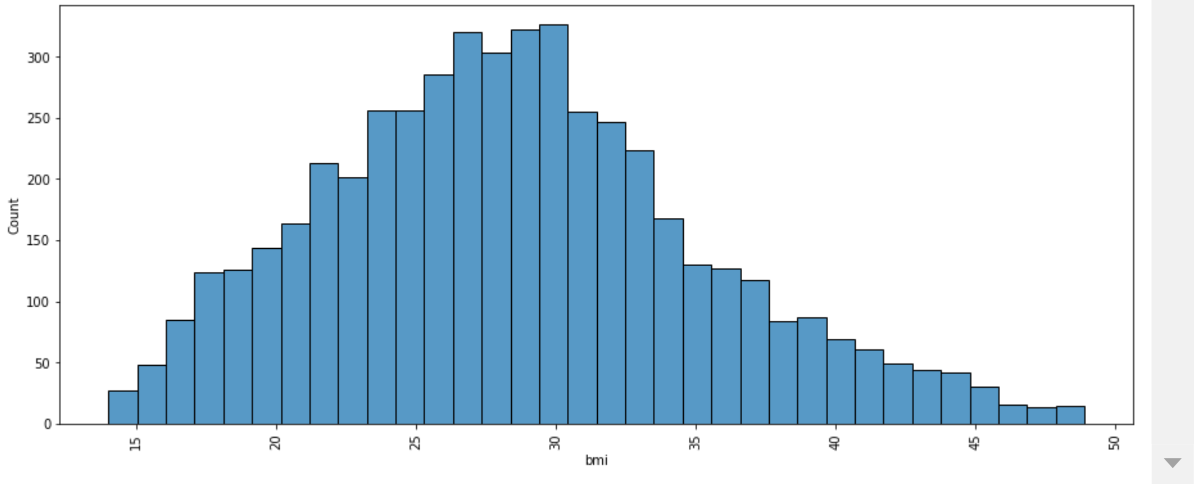
```
data_num = data[['age', 'avg_glucose_level', 'bmi']]
```

In [25]:

```
for i in data_num.columns:
    plt.figure(figsize = (15,6))
    sns.histplot(data_num[i], palette = 'hls')
    plt.xticks(rotation = 90)
    plt.show()
```

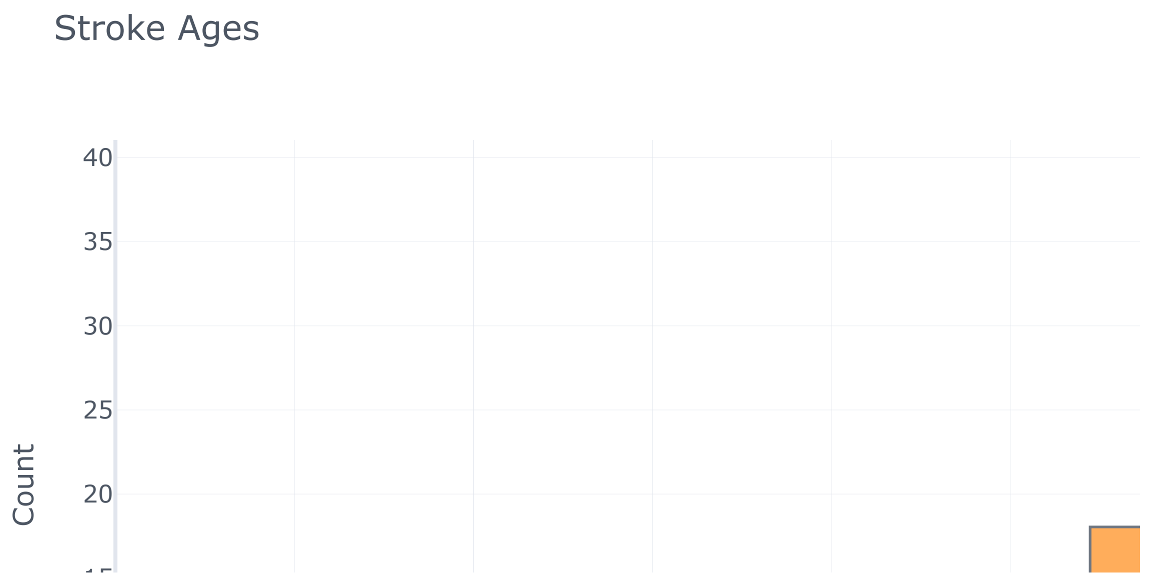






In [26]:

```
stroke = data.loc[data['stroke']== 1].reset_index()
stroke["male_age"]=stroke[stroke["gender"]=="Male"]["age"]
stroke["female_age"]=stroke[stroke["gender"]=="Female"]["age"]
stroke[["male_age","female_age"]].iplot(kind="histogram", bins=20, theme="white", title="St
         xTitle='Ages', yTitle='Count')
```



In [27]:

```
data['ever_married'] = [ 0 if i !='Yes' else 1 for i in data['ever_married'] ]
data['gender'] = [0 if i != 'Female' else 1 for i in data['gender']]
```

In [28]:

```
data.head()
```

Out[28]:

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_gl
0	0	67.0	0	1	1	Private	Urban	
1	0	80.0	0	1	1	Private	Rural	
2	1	49.0	0	0	1	Private	Urban	
3	1	79.0	1	0	1	Self-employed	Rural	
4	0	81.0	0	0	1	Private	Urban	

In [29]:

```
data = pd.get_dummies(data, columns = ['work_type', 'Residence_type','smoking_status'])
```

In [30]:

```
data.sample(10)
```

Out[30]:

	gender	age	hypertension	heart_disease	ever_married	avg_glucose_level	bmi	stroke
3768	1	64.0	0	1	1	114.71	30.6	0
1263	0	41.0	0	0	1	101.79	26.7	0
1124	1	20.0	0	0	0	112.08	23.0	0
3349	1	49.0	0	0	0	104.08	26.6	0
3041	1	27.0	0	0	1	127.28	23.4	0
4837	0	40.0	0	0	0	88.27	30.1	0
131	1	57.0	0	0	1	221.89	37.3	1
3536	1	19.0	0	0	0	76.57	26.6	0
2671	1	62.0	0	0	1	91.82	19.6	0
1965	0	53.0	0	0	1	76.03	27.3	0

In [31]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
```

In [32]:

```
X = data.drop(['stroke'], axis = 1)
y = data['stroke']
```

In [33]:

```
X_train, X_test, y_train , y_test = train_test_split(X,y, test_size = 0.33, random_state =
X_train.shape, X_test.shape
```

Out[33]:

```
((3337, 17), (1644, 17))
```

In [34]:

```
classifier_log= LogisticRegression(random_state=0)
classifier_log.fit(X_train, y_train)
```

Out[34]:

```
▾ LogisticRegression
LogisticRegression(random_state=0)
```

In [35]:

```
y_pred= classifier_log.predict(X_test)
```

In [36]:

```
from sklearn.metrics import confusion_matrix
cm= confusion_matrix(y_test,y_pred)
```

In [37]:

```
print(cm)
```

```
[[1559    0]
 [  85    0]]
```

In [38]:

```
print('Training-set accuracy score:', classifier_log.score(X_train, y_train))
```

```
Training-set accuracy score: 0.9511537308960144
```

In [39]:

```
print('Test-set accuracy score:', classifier_log.score(X_test, y_test))
```

```
Test-set accuracy score: 0.9482968369829684
```

In [40]:

```
classifier_dt = DecisionTreeClassifier(criterion='gini', random_state=0,max_depth= 5)
classifier_dt.fit(X_train, y_train)
```

Out[40]:

```
DecisionTreeClassifier
DecisionTreeClassifier(max_depth=5, random_state=0)
```

In [41]:

```
y_pred= classifier_dt.predict(X_test)
```

In [42]:

```
cm= confusion_matrix(y_test,y_pred)
```

In [43]:

```
print(cm)
```

```
[[1559    0]
 [  81    4]]
```

In [44]:

```
print('Training-set accuracy score:', classifier_dt.score(X_train, y_train))
```

```
Training-set accuracy score: 0.9526520827090201
```

In [45]:

```
print('Training-set accuracy score:', classifier_dt.score(X_test, y_test))
```

```
Training-set accuracy score: 0.9507299270072993
```

In [46]:

```
classifier_rf= RandomForestClassifier(n_estimators= 10, criterion="entropy")
classifier_rf.fit(X_train, y_train)
```

Out[46]:

```
RandomForestClassifier
RandomForestClassifier(criterion='entropy', n_estimators=10)
```

In [47]:

```
y_pred= classifier_rf.predict(X_test)
```

In [48]:

```
cm= confusion_matrix(y_test,y_pred)
```

In [49]:

```
print(cm)
```

```
[[1555    4]
 [  85    0]]
```

In [50]:

```
print('Training-set accuracy score:', classifier_rf.score(X_train, y_train))
```

```
Training-set accuracy score: 0.9883128558585556
```

In [51]:

```
print('Training-set accuracy score:', classifier_rf.score(X_test, y_test))
```

```
Training-set accuracy score: 0.9458637469586375
```