0.1 Libraries and Utilities

```
[]: | !pip install matplotlib==3.3.4 pywaffle==0.6.0 umap-learn
    Requirement already satisfied: matplotlib==3.3.4 in
    /usr/local/lib/python3.10/dist-packages (3.3.4)
    Requirement already satisfied: pywaffle==0.6.0 in
    /usr/local/lib/python3.10/dist-packages (0.6.0)
    Requirement already satisfied: umap-learn in /usr/local/lib/python3.10/dist-
    packages (0.5.6)
    Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-
    packages (from matplotlib==3.3.4) (0.12.1)
    Requirement already satisfied: kiwisolver>=1.0.1 in
    /usr/local/lib/python3.10/dist-packages (from matplotlib==3.3.4) (1.4.5)
    Requirement already satisfied: numpy>=1.15 in /usr/local/lib/python3.10/dist-
    packages (from matplotlib==3.3.4) (1.25.2)
    Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-
    packages (from matplotlib==3.3.4) (9.4.0)
    Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.3 in
    /usr/local/lib/python3.10/dist-packages (from matplotlib==3.3.4) (3.1.2)
    Requirement already satisfied: python-dateutil>=2.1 in
    /usr/local/lib/python3.10/dist-packages (from matplotlib==3.3.4) (2.8.2)
    Requirement already satisfied: scipy>=1.3.1 in /usr/local/lib/python3.10/dist-
    packages (from umap-learn) (1.11.4)
    Requirement already satisfied: scikit-learn>=0.22 in
    /usr/local/lib/python3.10/dist-packages (from umap-learn) (1.2.2)
    Requirement already satisfied: numba>=0.51.2 in /usr/local/lib/python3.10/dist-
    packages (from umap-learn) (0.58.1)
    Requirement already satisfied: pynndescent>=0.5 in
    /usr/local/lib/python3.10/dist-packages (from umap-learn) (0.5.12)
    Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages
    (from umap-learn) (4.66.4)
    Requirement already satisfied: llvmlite<0.42,>=0.41.0dev0 in
    /usr/local/lib/python3.10/dist-packages (from numba>=0.51.2->umap-learn)
    (0.41.1)
    Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.10/dist-
    packages (from pynndescent>=0.5->umap-learn) (1.4.2)
    Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-
    packages (from python-dateutil>=2.1->matplotlib==3.3.4) (1.16.0)
    Requirement already satisfied: threadpoolctl>=2.0.0 in
    /usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.22->umap-learn)
    (3.5.0)
[]: import warnings
     warnings.filterwarnings('ignore')
     # basic libraries
     import os
```

```
import numpy as np
import pandas as pd
import re
import string
from collections import Counter
import time
#visulaization modules
import missingno as msno
import matplotlib
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import plotly.graph_objs as go
from plotly.offline import iplot, init_notebook_mode
from pywaffle import Waffle
%matplotlib inline
init_notebook_mode(connected= True)
#Common model helpers
from sklearn.preprocessing import (StandardScaler,
                                   LabelEncoder,
                                   OneHotEncoder)
from sklearn import metrics
from sklearn.model_selection import train_test_split
from sklearn.metrics import (accuracy_score,
                             auc,
                             precision_score,
                             recall_score,
                             f1_score,
                             roc_auc_score,
                             confusion_matrix)
from sklearn.model_selection import (GridSearchCV,
                                     StratifiedKFold,
                                     cross_val_score)
# dimensionality reduction
from sklearn.decomposition import PCA
import pylab as pl
# imbalance dataset handling
```

```
from imblearn.datasets import make_imbalance
from imblearn.under_sampling import (RandomUnderSampler,
                                     ClusterCentroids,
                                     TomekLinks,
                                     NeighbourhoodCleaningRule,
                                     EditedNearestNeighbours,
                                     NearMiss)
from imblearn.over_sampling import (SMOTE,
                                    ADASYN)
# model algorithms
from sklearn.ensemble import (RandomForestClassifier,
                              AdaBoostClassifier,
                              GradientBoostingClassifier)
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from xgboost import XGBClassifier
from lightgbm import LGBMClassifier
```

0.2 Data Preprocessing

[]:		0	1	2
	id	9046	51676	31112
	gender	Male	Female	Male
	age	67.0	61.0	80.0
	hypertension	0	0	0
	heart_disease	1	0	1
	ever_married	Yes	Yes	Yes
	work_type	Private	Self-employed	Private
	Residence_type	Urban	Rural	Rural
	avg_glucose_level	228.69	202.21	105.92
	bmi	36.6	NaN	32.5
	smoking_status	formerly smoked	never smoked	never smoked

stroke 1 1 1

[]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5110 entries, 0 to 5109
Data columns (total 12 columns):

#	Column	Non-Null Count	Dtype
0	id	5110 non-null	int64
1	gender	5110 non-null	object
2	age	5110 non-null	float64
3	hypertension	5110 non-null	int64
4	heart_disease	5110 non-null	int64
5	ever_married	5110 non-null	object
6	work_type	5110 non-null	object
7	Residence_type	5110 non-null	object
8	avg_glucose_level	5110 non-null	float64
9	bmi	4909 non-null	float64
10	smoking_status	5110 non-null	object
11	stroke	5110 non-null	int64

dtypes: float64(3), int64(4), object(5)

memory usage: 479.2+ KB

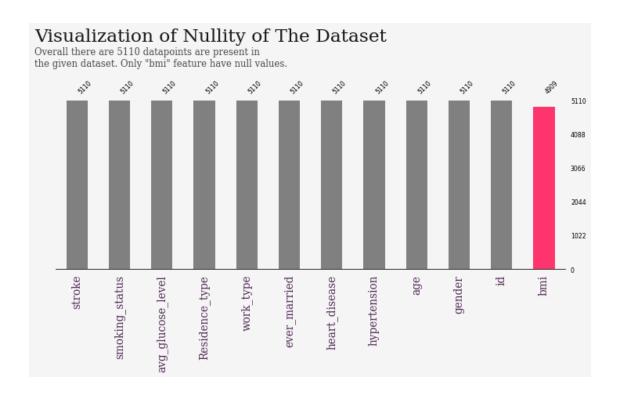
```
[]: # stats of numerical data round (df.describe(exclude = 'object'), 2)
```

[]:		id	age	hypertension	heart_disease	avg_glucose_level	\
	count	5110.00	5110.00	5110.0	5110.00	5110.00	
	mean	36517.83	43.23	0.1	0.05	106.15	
	std	21161.72	22.61	0.3	0.23	45.28	
	min	67.00	0.08	0.0	0.00	55.12	
	25%	17741.25	25.00	0.0	0.00	77.24	
	50%	36932.00	45.00	0.0	0.00	91.88	
	75%	54682.00	61.00	0.0	0.00	114.09	
	max	72940.00	82.00	1.0	1.00	271.74	

	bmi	stroke
count	4909.00	5110.00
mean	28.89	0.05
std	7.85	0.22
min	10.30	0.00
25%	23.50	0.00
50%	28.10	0.00
75%	33.10	0.00
max	97.60	1.00

```
[]: # stats of categorical data
     round (df.describe(exclude = ['float', 'int64']),2)
[]:
             gender ever_married work_type Residence_type smoking_status
                                      5110
               5110
                            5110
                                                      5110
                                                                     5110
     count
    unique
                                         5
     top
             Female
                             Yes
                                   Private
                                                     Urban
                                                             never smoked
     freq
               2994
                            3353
                                      2925
                                                      2596
                                                                     1892
[]: color =_

→ ['grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','#fe346e']
     fig, ax = plt.subplots(figsize = (12,4), dpi = 70)
     fig.patch.set facecolor('#f6f5f5')
     ax.set_facecolor('#f6f5f5')
     msno.bar(df, sort = 'descending',
              color = color,
              ax = ax, fontsize =8,
              labels = 'off',filter = 'top')
     ax.text(-1,1.35,'Visualization of Nullity of The Dataset',{'font': 'Serif', |
     →'fontsize': 24, 'color':'black'},alpha = 0.9)
     ax.text(-1,1.2,'Overall there are 5110 datapoints are present in \nthe given ∪
     \hookrightarrowdataset. Only "bmi" feature have null values.',{'font': 'Serif', 'fontsize':\sqcup
     \hookrightarrow12, 'color':'black'}, alpha = 0.7)
     ax.set_xticklabels(ax.get_xticklabels(),rotation = 90,
                        ha = 'center', **{'font': 'Serif', 'fontsize': 14, 'weight':
     ax.set yticklabels('')
     ax.spines['bottom'].set_visible(True)
     fig.show()
```



```
[]: # handling missing values
df['bmi'] = df['bmi'].fillna(round (df['bmi'].median(), 2))
df.isnull().sum()
```

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

Only bmi feature have some missing data, which was be filled with the median of the same column. For feature extraction, binning was applied for all the continous values, binning values are taken from follow articles.

- body mass index binning
- Age binning
- average glucose binning

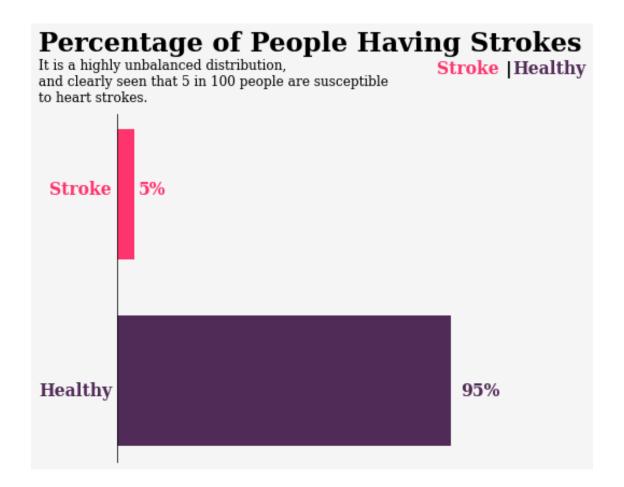
0.3 Data Analysis

```
[]: x = pd.DataFrame(df.groupby(['stroke'])['stroke'].count())
    # plot
    fig, ax = plt.subplots(figsize = (6,6), dpi = 70)
    ax.barh([1], x.stroke[1], height = 0.7, color = '#fe346e')
    plt.text(-1150,-0.08, 'Healthy',{'font': 'Serif','weight':'bold','fontsize':
     plt.text(5000,-0.08, '95%',{'font':'Serif','weight':'bold','fontsize':
     ax.barh([0], x.stroke[0], height = 0.7, color = '#512b58')
    plt.text(-1000,1, 'Stroke', {'font': 'Serif', 'weight': 'bold', 'fontsize':
     →'16','style':'normal', 'color':'#fe346e'})
    plt.text(300,1, '5%',{'font':'Serif', 'weight':'bold','fontsize':'16','color':
     → '#fe346e'})
    fig.patch.set_facecolor('#f6f5f5')
    ax.set_facecolor('#f6f5f5')
    plt.text(-1150,1.77, 'Percentage of People Having Strokes', {'font': 'Serif', __
     →'fontsize': '25', 'weight': 'bold', 'color': 'black'})
    plt.text(4650,1.65, 'Stroke ', {'font': 'Serif', 'weight': 'bold', 'fontsize':
     →'16','weight':'bold','style':'normal', 'color':'#fe346e'})
    plt.text(5650,1.65, '|', {'color':'black', 'fontsize':'16', 'weight': 'bold'})
    plt.text(5750,1.65, 'Healthy', {'font': 'Serif', 'weight': 'bold', 'fontsize':

¬'16','style':'normal', 'weight':'bold','color':'#512b58'})
    plt.text(-1150,1.5, 'It is a highly unbalanced distribution,\nand clearly seen ∪

→that 5 in 100 people are susceptible \nto heart strokes.',

            {'font':'Serif', 'fontsize':'12.5','color': 'black'})
    ax.axes.get_xaxis().set_visible(False)
    ax.axes.get_yaxis().set_visible(False)
    ax.spines['bottom'].set_visible(False)
    ax.spines['left'].set_visible(True)
    ax.spines['right'].set_visible(False)
    ax.spines['top'].set_visible(False)
```



```
fig = plt.figure(figsize = (24,10), dpi = 60)

gs = fig.add_gridspec(10,24)
gs.update(wspace = 1, hspace = 0.05)

ax2 = fig.add_subplot(gs[1:4,0:8]) #distribution plot
ax3 = fig.add_subplot(gs[6:9, 0:8]) #hue distribution plot
ax1 = fig.add_subplot(gs[1:10,13:]) #dumbbell plot

# axes list
axes = [ ax1,ax2, ax3]

# setting of axes; visibility of axes and spines turn off
for ax in axes:
    ax.axes.get_yaxis().set_visible(False)
    ax.set_facecolor('#f6f5f5')

for loc in ['left', 'right', 'top', 'bottom']:
```

```
ax.spines[loc].set_visible(False)
fig.patch.set_facecolor('#f6f5f5')
ax1.axes.get_xaxis().set_visible(False)
ax1.axes.get_yaxis().set_visible(True)
# dumbbell plot of stoke and healthy people
stroke_age = df[df['stroke'] == 1].age_cat.value_counts()
healthy_age = df[df['stroke'] == 0].age_cat.value_counts()
ax1.hlines(y = ['Children', 'Teens', 'Adults', 'Mid Adults', 'Elderly'], xmin =
\hookrightarrow [644,270,1691,1129,1127],
         xmax = [1,1,11,59,177], color = 'grey',**{'linewidth':0.5})
sns.scatterplot(y = stroke_age.index, x = stroke_age.values, s = stroke_age.
→values*2, color = '#fe346e', ax= ax1, alpha = 1)
sns.scatterplot(y = healthy_age.index, x = healthy_age.values, s = healthy_age.
\rightarrowvalues*2, color = '#512b58', ax= ax1, alpha = 1)
ax1.axes.get xaxis().set visible(False)
ax1.set_xlim(xmin = -500, xmax = 2250)
ax1.set_ylim(ymin = -1, ymax = 5)
ax1.set_yticklabels( labels = ['Children', 'Teens', 'Adults', 'Mid Adults', u
→'Elderly'],fontdict = {'font':'Serif', 'fontsize':16,'fontweight':'bold',□
ax1.text(-950,5.8, 'How Age Impact on Having Strokes?', {'font': 'Serif', __
ax1.text(1000,4.8, 'Stroke', {'font': 'Serif', 'weight': 'bold', 'fontsize':
→'16','weight':'bold','style':'normal', 'color':'#fe346e'})
ax1.text(1300,4.8, '|', {'color':'black', 'fontsize':'16', 'weight': 'bold'})
ax1.text(1350,4.8, 'Healthy', {'font': 'Serif', 'weight': 'bold', 'fontsize':
ax1.text(-950,5., 'Age have significant impact on strokes, and clearly seen ⊔

→that strokes are \nhighest for elderly people and mid age adults, \nwhere as

□

{'font':'Serif', 'fontsize':'16','color': 'black'})
ax1.text(stroke_age.values[0] + 30,4.05, stroke_age.values[0], {'font':'Serif', _
ax1.text(healthy_age.values[2] - 300,4.05, healthy_age.values[2], {'font':

¬'Serif', 'fontsize':14, 'weight':'bold', 'color':'#512b58'})
```

```
ax1.text(stroke_age.values[1] + 30,3.05, stroke_age.values[1], {'font':'Serif',
ax1.text(healthy age.values[1] - 300,3.05, healthy age.values[1], {'font':

¬'Serif', 'fontsize':14, 'weight':'bold', 'color':'#512b58'})
# distribution plots ---- only single variable
sns.kdeplot(data = df, x = 'age', ax = ax2, shade = True, color = '#2c003e', __
\rightarrowalpha = 1, )
ax2.set_xlabel('Age of a person', fontdict = {'font':'Serif', 'color': 'black', |
ax2.text(-17,0.025,'Overall Age Distribution - How skewed is it?', {'font':
→ 'Serif', 'color': 'black', 'weight': 'bold', 'fontsize': 24}, alpha = 0.9)
ax2.text(-17,0.021, 'Based on Age we have data from infants to elderly people.
{'font':'Serif', 'fontsize':'16','color': 'black'})
ax2.text(80,0.019, 'Total',{'font':'Serif', 'fontsize':'14','color':
ax2.text(92,0.019, '=',{'font':'Serif', 'fontsize':'14','color':
ax2.text(97,0.019, 'Stroke', {'font': 'Serif', 'fontsize': '14', 'color':
→'#fe346e','weight':'bold'})
ax2.text(113,0.019, '+',{'font':'Serif', 'fontsize':'14','color':
ax2.text(117,0.019, 'Healthy', {'font': 'Serif', 'fontsize': '14', 'color': u
# distribution plots with hue of strokes
sns.kdeplot(data = df[df['stroke'] == 0], x = 'age', ax = ax3, shade = True, u
\rightarrowalpha = 1, color = '#512b58')
sns.kdeplot(data = df[df['stroke'] == 1], x = 'age',ax = ax3, shade = True, __
\rightarrowalpha = 0.8, color = '#fe346e')
ax3.set_xlabel('Age of a person', fontdict = {'font':'Serif', 'color': 'black', |
ax3.text(-17,0.0525,'Age-Stroke Distribution - How serious is it?', {'font':
→'Serif', 'weight':'bold','color': 'black', 'fontsize':24}, alpha= 0.9)
```

```
ax3.text(-17,0.043,'From stoke Distribution it is clear that aged people are

→\nhaving significant number of strokes.', {'font':'Serif', 'color': 'black',

→'fontsize':14})

ax3.text(100,0.043, 'Stroke ', {'font': 'Serif', 'weight':'bold', 'fontsize':

→'16','weight':'bold','style':'normal', 'color':'#fe346e'})

ax3.text(117,0.043, '|', {'color':'black', 'fontsize':'16', 'weight': 'bold'})

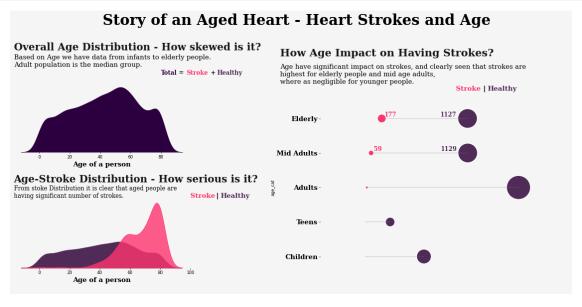
ax3.text(120,0.043, 'Healthy', {'font': 'Serif', 'weight':'bold', 'fontsize':

→'16','style':'normal', 'weight':'bold','color':'#512b58'})

fig.text(0.25,1,'Story of an Aged Heart - Heart Strokes and Age', {'font':

→'Serif', 'weight':'bold','color': 'black', 'fontsize':35})

fig.show()
```



```
fig = plt.figure(figsize = (24,10), dpi = 60)

gs = fig.add_gridspec(10,24)
gs.update(wspace = 1, hspace = 0.05)

ax2 = fig.add_subplot(gs[0:3,0:10]) #distribution plot
ax3 = fig.add_subplot(gs[5:10, 0:10]) #hue distribution plot
ax1 = fig.add_subplot(gs[0:,13:]) #dumbbell plot

# axes list
axes = [ ax1,ax2, ax3]
```

```
# setting of axes; visibility of axes and spines turn off
for ax in axes:
   ax.axes.get_yaxis().set_visible(False)
   ax.set_facecolor('#f6f5f5')
   for loc in ['left', 'right', 'top', 'bottom']:
        ax.spines[loc].set_visible(False)
fig.patch.set_facecolor('#f6f5f5')
ax1.axes.get_xaxis().set_visible(False)
ax1.axes.get_yaxis().set_visible(True)
# dumbbell plot of stoke and healthy people
stroke_glu = df[df['stroke'] == 1].glucose_cat.value_counts()
healthy_glu = df[df['stroke'] == 0].glucose_cat.value_counts()
ax1.hlines(y = ['Low', 'Normal', 'High', 'Very High'], xmin =_
\rightarrow [2316,1966,478,101],
         xmax = [89,71,71,18], color = 'grey',**{'linewidth':0.5})
sns.scatterplot(y = stroke_glu.index, x = stroke_glu.values, s = stroke_glu.
⇒values, color = '#fe346e', ax= ax1, alpha = 1)
sns.scatterplot(y = healthy glu.index, x = healthy glu.values, s = healthy glu.
\rightarrowvalues, color = '#512b58', ax= ax1, alpha = 1)
ax1.axes.get_xaxis().set_visible(False)
ax1.set_xlim(xmin = -500, xmax = 3000)
ax1.set_ylim(ymin = -1.5, ymax = 4.5)
ax1.set_yticklabels( labels = ['Low', 'Normal', 'High', 'Very High'], fontdict = __
→{'font':'Serif', 'fontsize':16,'fontweight':'bold', 'color':'black'})
ax1.text(-1000,4.3, 'How Glucose level Impact on Having Strokes?', {'font': u
ax1.text(1700,3.5, 'Stroke', {'font': 'Serif', 'weight': 'bold', 'fontsize':
→'16','weight':'bold','style':'normal', 'color':'#fe346e'})
ax1.text(2050,3.5, '|', {'color':'black', 'fontsize':'16', 'weight': 'bold'})
ax1.text(2075,3.5, 'Healthy', {'font': 'Serif', 'weight': 'bold', 'fontsize':
→'16','style':'normal', 'weight':'bold','color':'#512b58'})
ax1.text(-1000,3.8, 'Glucose does not have significant impact on strokes,\n and_
→its unclear strokes are which group effected by strokes.',
       {'font':'Serif', 'fontsize':'16','color': 'black'})
```

```
ax1.text(stroke_glu.values[0] + 30,0.05, stroke_glu.values[0], {'font': 'Serif', ___
ax1.text(healthy glu.values[0] + -355,0.05, healthy glu.values[0], {'font':

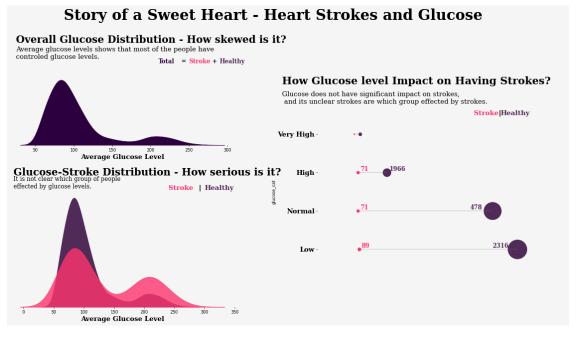
→'Serif', 'fontsize':14, 'weight':'bold', 'color':'#512b58'})
ax1.text(stroke_glu.values[2] + 30,1.05, stroke_glu.values[2], {'font':'Serif', __
ax1.text(healthy glu.values[2] + 1170,1.05, healthy glu.values[2], {'font':

→'Serif', 'fontsize':14, 'weight':'bold', 'color':'#512b58'})
ax1.text(stroke_glu.values[1] + 30,2.05, stroke_glu.values[1], {'font':'Serif',__
ax1.text(healthy_glu.values[1] - 1450,2.05, healthy_glu.values[1], {'font':

→'Serif', 'fontsize':14, 'weight':'bold', 'color':'#512b58'})
# distribution plots ---- only single variable
sns.kdeplot(data = df, x = 'avg_glucose_level', ax = ax2, shade = True, color = u
\rightarrow'#2c003e', alpha = 1, )
ax2.set_xlabel('Average Glucose Level', fontdict = {'font':'Serif', 'color':
ax2.text(25,0.025,'Overall Glucose Distribution - How skewed is it?', {'font':
ax2.text(25,0.021, 'Average glucose levels shows that most of the people have_
{'font':'Serif', 'fontsize':'16','color': 'black'})
ax2.text(210,0.020, 'Total', {'font': 'Serif', 'fontsize': '14', 'color': u
ax2.text(240,0.02, '=',{'font':'Serif', 'fontsize':'14','color':
ax2.text(250,0.02, 'Stroke', {'font': 'Serif', 'fontsize': '14', 'color':
→'#fe346e','weight':'bold'})
ax2.text(280,0.02, '+',{'font':'Serif', 'fontsize':'14','color':
ax2.text(290,0.02, 'Healthy',{'font':'Serif', 'fontsize':'14','color':
# distribution plots with hue of strokes
```

```
sns.kdeplot(data = df[df['stroke'] == 0], x = 'avg_glucose_level',ax = ax3,__
\hookrightarrowshade = True, alpha = 1, color = '#512b58')
sns.kdeplot(data = df[df['stroke'] == 1], x = 'avg_glucose_level',ax = ax3,__
\rightarrowshade = True, alpha = 0.8, color = '#fe346e')
ax3.set_xlabel('Average Glucose Level', fontdict = {'font':'Serif', 'color':
ax3.text(-17,0.0195,'Glucose-Stroke Distribution - How serious is it?', {'font':

→'Serif', 'weight':'bold','color': 'black', 'fontsize':24})
ax3.text(-17,0.0176,'It is not clear which group of people \neffected by_
⇒glucose levels.', {'font':'Serif', 'color': 'black', 'fontsize':14})
ax3.text(240,0.0174, 'Stroke ', {'font': 'Serif', 'weight': 'bold', 'fontsize':
→'16','weight':'bold','style':'normal', 'color':'#fe346e'})
ax3.text(290,0.0174, '|', {'color':'black', 'fontsize':'16', 'weight': 'bold'})
ax3.text(300,0.0174, 'Healthy', {'font': 'Serif', 'weight': 'bold', 'fontsize':
→'16','style':'normal', 'weight':'bold','color':'#512b58'})
fig.text(0.2,1.07,'Story of a Sweet Heart - Heart Strokes and Glucose',{'font':
fig.show()
```



```
[]: fig = plt.figure(figsize = (24,10), dpi = 60)
     gs = fig.add_gridspec(10,24)
     gs.update(wspace = 1, hspace = 0.05)
     ax2 = fig.add_subplot(gs[1:4,0:8]) #distribution plot
     ax3 = fig.add_subplot(gs[6:9, 0:8]) #hue distribution plot
     ax1 = fig.add_subplot(gs[2:9,13:]) #dumbbell plot
     # axes list
     axes = [ax1,ax2,ax3]
     # setting of axes; visibility of axes and spines turn off
     for ax in axes:
         ax.axes.get_yaxis().set_visible(False)
         ax.set_facecolor('#f6f5f5')
         for loc in ['left', 'right', 'top', 'bottom']:
             ax.spines[loc].set_visible(False)
     fig.patch.set_facecolor('#f6f5f5')
     ax1.axes.get xaxis().set visible(False)
     ax1.axes.get_yaxis().set_visible(True)
     ax1.set xlim(xmin = -250, xmax = 2000)
     ax1.set_ylim(ymin = -1, ymax = 3.5)
     # dumbbell plot of stoke and healthy people
     stroke_bmi = df[df['stroke'] == 1].bmi_cat.value_counts()
     healthy_bmi = df[df['stroke'] == 0].bmi_cat.value_counts()
     ax1.hlines(y = ['Obesity', 'Overweight', 'Ideal', 'Underweight'], xmin =
     \rightarrow [96,115,37,1],
               xmax = [1797,1495,1159,410], color = 'grey',**{'linewidth':0.5})
     sns.scatterplot(y = stroke_bmi.index, x = stroke_bmi.values, s = stroke_bmi.
     \rightarrowvalues*2, color = '#fe346e', ax= ax1, alpha = 1)
     sns.scatterplot(y = healthy_bmi.index, x = healthy_bmi.values, s = healthy_bmi.
     \Rightarrowvalues*2, color = '#512b58', ax= ax1, alpha = 1)
     ax1.set_yticklabels( labels = ['Obesity', 'Overweight', 'Ideal', _
     →'Underweight'],fontdict = {'font':'Serif', 'fontsize':16,'fontweight':
```

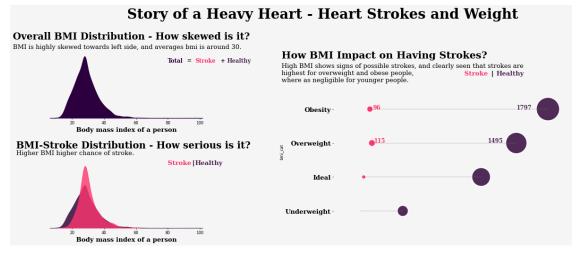
```
ax1.text(-750,-1.5, 'How BMI Impact on Having Strokes?', {'font': 'Serif', __
ax1.text(1000,-1., 'Stroke', {'font': 'Serif', 'weight': 'bold', 'size':
ax1.text(1250,-1, '|', {'color':'black', 'size':'16', 'weight': 'bold'})
ax1.text(1300,-1, 'Healthy', {'font': 'Serif', 'weight': 'bold', 'size':
ax1.text(-750,-0.8, 'High BMI shows signs of possible strokes, and clearly seen,

→that strokes are \nhighest for overweight and obese people, \nwhere as

□

→negligible for younger people.',
      {'font':'Serif', 'size':'16','color': 'black'})
ax1.text(stroke_bmi.values[0] + 20 , 0.98, stroke_bmi.values[0], {'font':
ax1.text(healthy_bmi.values[1] - 275 ,0.98, healthy_bmi.values[1], {'font':
ax1.text(stroke_bmi.values[1] + 30,0, stroke_bmi.values[1], {'font': 'Serif', __
ax1.text(healthy_bmi.values[0] - 300,0, healthy_bmi.values[0], {'font':'Serif',_
# distribution plots ---- only single variable
sns.kdeplot(data = df, x = 'bmi', ax = ax2, shade = True, color = '#2c003e', u
\rightarrowalpha = 1, )
ax2.set_xlabel('Body mass index of a person', fontdict = {'font': 'Serif', u
ax2.text(-17,0.085,'Overall BMI Distribution - How skewed is it?', {'font':
ax2.text(-17,0.075, 'BMI is highly skewed towards left side, and averages bmi_
⇒is around 30.',
      {'font':'Serif', 'size':'16','color': 'black'})
ax2.text(80,0.06, 'Total', {'font': 'Serif', 'size': '14', 'color': ___
ax2.text(92,0.06, '=',{'font':'Serif', 'size':'14','color': 'black','weight':
→'bold'})
ax2.text(97,0.06, 'Stroke', {'font': 'Serif', 'size': '14', 'color':
ax2.text(113,0.06, '+',{'font':'Serif', 'size':'14','color': 'black','weight':
```

```
ax2.text(117,0.06, 'Healthy', {'font': 'Serif', 'size': '14', 'color':
# distribution plots with hue of strokes
sns.kdeplot(data = df[df['stroke'] == 0], x = 'bmi', ax = ax3, shade = True, _
\rightarrowalpha = 1, color = '#512b58')
sns.kdeplot(data = df[df['stroke'] == 1], x = 'bmi',ax = ax3, shade = True, __
\rightarrowalpha = 0.8, color = '#fe346e')
ax3.set_xlabel('Body mass index of a person', fontdict = {'font':'Serif', __
ax3.text(-15,0.12,'BMI-Stroke Distribution - How serious is it?', {'font':
ax3.text(-15,0.11, 'Higher BMI higher chance of stroke.', {'font':'Serif', |
ax3.text(80,0.095, 'Stroke', {'font': 'Serif', 'weight': 'bold', 'size':
→'16','weight':'bold','style':'normal', 'color':'#fe346e'})
ax3.text(95,0.095, '|', {'color':'black', 'size':'16', 'weight': 'bold'})
ax3.text(97,0.095, 'Healthy', {'font': 'Serif', 'weight': 'bold', 'size':
→'16', 'style': 'normal', 'weight': 'bold', 'color': '#512b58'})
fig.text(0.25,0.925, 'Story of a Heavy Heart - Heart Strokes and Weight', { 'font':
⇔'Serif', 'weight':'bold','color': 'black', 'size':35})
fig.show()
```

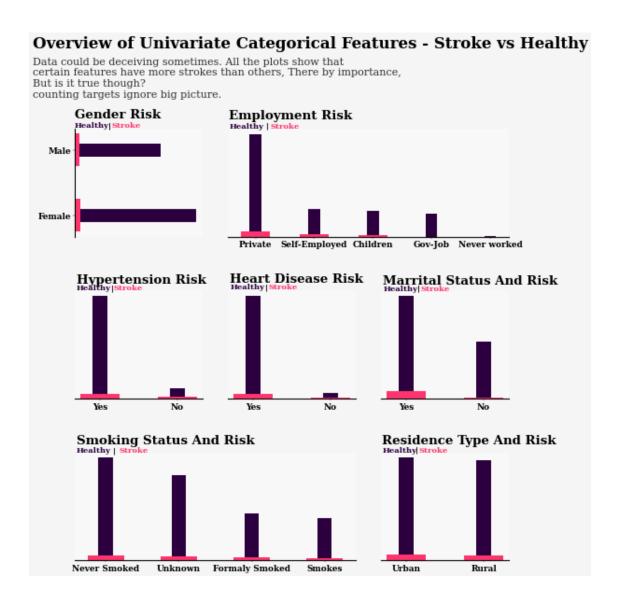


```
[]: fig = plt.figure(figsize = (15, 15), dpi = 40)
    gs = fig.add_gridspec(3,3)
    gs.update(wspace = 0.2, hspace = 0.5)
    ax1 = fig.add_subplot(gs[0,0])
    ax2 = fig.add_subplot(gs[0,1:])
    ax3 = fig.add_subplot(gs[1,0])
    ax4 = fig.add_subplot(gs[1,1])
    ax5 = fig.add subplot(gs[1,2])
    ax6 = fig.add_subplot(gs[2,0:2])
    ax7 = fig.add_subplot(gs[2,2])
    axes = [ax1, ax2, ax3, ax4, ax5, ax6, ax7]
    fig.patch.set_facecolor('#f5f5f5')
    # setting of axes; visibility of axes and spines turn off
    for ax in axes:
        ax.axes.get_yaxis().set_visible(False)
        ax.set facecolor('#f8f8f8')
        ax.spines['bottom'].set_linewidth(2)
        for loc in ['left', 'right', 'top']:
            ax.spines[loc].set_visible(False)
            ax.spines[loc].set linewidth(2)
    title_args = {'font':'Serif', 'weight':'bold','color': 'black', 'size':24}
    font_dict = {'size':16, 'family':'Serif', 'color':'black', 'weight':'bold'}
    health_dict = {'font':'Serif', 'color': '#2c003e', 'size':15, 'weight':'bold'}
    dash_dict = {'font':'Serif', 'color': 'black', 'size':15,'weight':'bold'}
    stroke_dict = {'font':'Serif', 'color': '#fe346e', 'size':15,'weight':'bold'}
    stroke col = '#fe346e'
    healthy_col = '#2c003e'
    # Ax1: Gender- stroke distributions
    healthy_gen = df[df['stroke'] == 0].gender.value_counts()
    stroke_gen = df[df['stroke'] == 1].gender.value_counts()
    ax1.barh( stroke_gen.index , width = healthy_gen.values[0:2], height = 0.2,
     ax1.barh( np.arange(len(stroke_gen.index)) , width = stroke_gen.values, height_
     →= 0.5, color = stroke_col)
    ax1.set_yticklabels(stroke_gen.index, **font_dict)
```

```
ax1.axes.get_yaxis().set_visible(True)
ax1.axes.get_xaxis().set_visible(False)
ax1.spines['bottom'].set_visible(False)
ax1.spines['left'].set_visible(True)
ax1.text(0,1.5, 'Gender Risk',**title_args)
ax1.text(0,1.35, 'Healthy',**health_dict)
ax1.text(790,1.35, '|',**dash_dict)
ax1.text(870,1.35, 'Stroke',**stroke_dict)
# Ax2: work type - stroke distributions
healthy_gen = df[df['stroke'] == 0].work_type.value_counts()
stroke_gen = df[df['stroke'] == 1].work_type.value_counts()
ax2.bar(healthy_gen.index, height = healthy_gen.values, width = 0.2, color = u
→healthy_col)
ax2.bar(np.arange(len(stroke_gen.index))), height = stroke_gen.values, width =
→0.5, color= stroke_col)
ax2.set_xticklabels(['Private','Self-Employed','Children', 'Gov-Job','Neveru
→worked'], **font_dict)
ax2.text(-0.45,3200, 'Employment Risk',**title_args)
ax2.text(-0.45,2950, 'Healthy',**health_dict)
ax2.text(0.18,2950, '|',**dash_dict)
ax2.text(0.25,2950, 'Stroke',**stroke_dict)
# Ax3: hypertension - stroke distributions
healthy_gen = df[df['stroke'] == 0].hypertension.value_counts()
stroke_gen = df[df['stroke'] == 1].hypertension.value_counts()
ax3.bar(['Yes','No'] , height = healthy_gen.values, width = 0.2,color = u
→healthy_col)
ax3.bar( stroke_gen.index, height = stroke_gen.values, width = 0.5,color=_
→stroke col)
ax3.set_xticklabels(['Yes','No'], **font_dict)
ax3.text(-0.3,5000, 'Hypertension Risk',**title_args)
ax3.text(-0.3,4700, 'Healthy',**health_dict)
ax3.text(0.14,4700, '|',**dash_dict)
ax3.text(0.18,4700, 'Stroke',**stroke_dict)
# Ax4: Heart Disease - stroke distributions
healthy_gen = df[df['stroke'] == 0].heart_disease.value_counts()
stroke_gen = df[df['stroke'] == 1].heart_disease.value_counts()
```

```
ax4.bar(['Yes','No'] , height = healthy_gen.values, width = 0.2,color = ___
→healthy_col)
ax4.bar( stroke_gen.index, height = stroke_gen.values, width = 0.5,color=_
→stroke_col)
ax4.set_xticklabels(['Yes', 'No'],**font_dict)
ax4.text(-0.3,5250, 'Heart Disease Risk',**title_args)
ax4.text(-0.3,4950, 'Healthy',**health_dict)
ax4.text(0.15,4950, '|',**dash_dict)
ax4.text(0.20,4950, 'Stroke',**stroke_dict)
# Ax5: Married - stroke distributions
healthy_gen = df[df['stroke'] == 0].ever_married.value_counts()
stroke_gen = df[df['stroke'] == 1].ever_married.value_counts()
ax5.bar(healthy_gen.index, height = healthy_gen.values, width = 0.2,color = 0.2
→healthy_col)
ax5.bar(np.arange(len(stroke_gen.index)), height = stroke_gen.values, width = ___
→0.5,color= stroke_col )
ax5.set xticklabels(healthy gen.index, **font dict)
ax5.text(-0.3,3500, 'Marrital Status And Risk',**title_args)
ax5.text(-0.3,3300, 'Healthy',**health_dict)
ax5.text(0.14,3300, '|',**dash_dict)
ax5.text(0.18,3300, 'Stroke',**stroke_dict)
# Ax6: Smoking status - stroke distributions
healthy_gen = df[df['stroke'] == 0].smoking_status.value_counts()
stroke_gen = df[df['stroke'] == 1].smoking_status.value_counts()
ax6.bar(healthy_gen.index, height = healthy_gen.values, width = 0.2,color = 0.2
→healthy col)
ax6.bar(np.arange(len(stroke_gen.index)), height = stroke_gen.values, width = __
→0.5,color= stroke_col)
ax6.set_xticklabels(['Never Smoked', 'Unknown', 'Formaly Smoked', 'Smokes'], __
→**font_dict)
ax6.text(-0.4,2050, 'Smoking Status And Risk',**title_args)
ax6.text(-0.4,1900, 'Healthy',**health_dict)
ax6.text(0.095,1900, '|',**dash_dict)
```

```
ax6.text(0.18,1900, 'Stroke', **stroke_dict)
# Ax7: Residence type - stroke distributions
healthy_gen = df[df['stroke'] == 0].Residence_type.value_counts()
stroke_gen = df[df['stroke'] == 1].Residence_type.value_counts()
ax7.bar( healthy_gen.index , height = healthy_gen.values, width = 0.2,color = 0.2
→healthy_col)
ax7.bar( np.arange(len(stroke_gen.index)) , height = stroke_gen.values, width = __
→0.5,color= stroke_col)
ax7.set_xticklabels(healthy_gen.index, **font_dict)
ax7.text(-0.31,2800, 'Residence Type And Risk',**title_args)
ax7.text(-0.31,2600, 'Healthy',**health_dict)
ax7.text(0.12,2600, '|', **dash_dict)
ax7.text(0.165,2600, 'Stroke', **stroke_dict)
fig.text(0.05,1.025, 'Overview of Univariate Categorical Features - Stroke vs⊔
→Healthy', {'font':'Serif', 'color':'black','size':30, 'weight':'bold'})
fig.text(0.05,0.9375, 'Data could be deceiving sometimes. All the plots show_
⇒that\ncertain features have more strokes than others, There by importance,
→\nBut is it true though? \ncounting targets ignore big picture.',{'font':
→'Serif', 'color': 'black', 'size': 20, 'weight': 'normal'}, alpha = 0.8)
fig.show()
```



```
[]: stroke_gen = df[df['stroke'] == 1]['gender'].value_counts()
   healthy_gen = df[df['stroke'] == 0]['gender'].value_counts()

female = df['gender'].value_counts().values[0]
   male = df['gender'].value_counts().values[1]

stroke_female = int(round (stroke_gen.values[0] / female * 100, 0))
   stroke_male = int(round( stroke_gen.values[1] / male *100, 0))
   healthy_female = int(round(healthy_gen.values[0] / female * 100, 0))
   healthy_male = int(round(healthy_gen.values[1] / male *100, 0))

female_per = int(round(female/(female+male) * 100, 0))

male_per = int(round(male/(female+male) * 100, 0))
```

```
fig = plt.figure(FigureClass = Waffle,
                 constrained_layout = True,
                 figsize = (7,10),
                 facecolor = '#f6f5f5',dpi = 100,
                 plots = {'121':
                          {
                           'rows':7,
                           'columns': 7,
                           'values' : [healthy_male,stroke_male],
                             'colors' : ['#512b58','#fe346e'],
                               'vertical' : True,
                              'interval_ratio_y': 0.1,
                               'interval_ratio_x': 0.1,
                              'icons' : 'male',
                               'icon_legend': False,
                               'icon_size':20,
                               'plot_anchor':'C',
                               'alpha':0.1
                          },
                          '122' :
                             'rows': 7,
                             'columns':7,
                             'values': [healthy_female, stroke_female],
                              'colors' : ['#512b58','#fe346e'],
                              'vertical': True,
                              'interval_ratio_y': 0.1,
                               'interval_ratio_x': 0.1,
                               'icons' : 'female',
                               'icon_legend' :False,
                               'icon_size':20,
                              'plot_anchor':'C',
                              'alpha':0.1
                           }
                         },
#fig.text ('asdfasdfasd0', {'font':'Serif', 'size':35, 'color':'black'} )
fig.text(0., 0.8, 'Gender Risk for Stroke - effect of gender on strokes?', u
→{'font':'Serif', 'size':20, 'color':'black', 'weight':'bold'})
```

```
fig.text(0., 0.73, 'Risk of stroke in both male and female are same,\nprove our_
→initial assumption is wrong. ', {'font':'Serif', 'size':13, 'color':'black',
fig.text(0.24, 0.22, 'ooo', {'font':'Serif', 'size':16,'weight':'bold','color':
→ '#f6f5f5'})
fig.text(0.65, 0.22, 'ooo', {'font':'Serif', 'size':16,'weight':'bold', 'color':
→ '#f6f5f5'})
fig.text(0.23, 0.28, '{}%'.format(healthy_male), {'font':'Serif', 'size':
→20, 'weight': 'bold', 'color': '#512b58'},alpha = 1,)
fig.text(0.65, 0.28, '{}%'.format(healthy_female), {'font':'Serif', 'size':
→20, 'weight': 'bold', 'color': '#512b58'}, alpha = 1)
fig.text(0.21, 0.67, 'Male ({}%)'.format(male_per), {'font':'Serif', 'size':
fig.text(0.61, 0.67, 'Female({}",)'.format(female_per), {'font':'Serif', 'size':
#fig.text(0., 0.8, 'Assumption was proven wrong', {'font':'Serif', 'size':24, _
fig.text(0.9,0.73, 'Stroke ', {'font': 'Serif', 'weight': 'bold', 'Size':
fig.text(1.02,0.73, '|', {'color':'black', 'size':'16', 'weight': 'bold'})
fig.text(1.035,0.73, 'No Stroke', {'font': 'Serif', 'weight': 'bold', 'Size':
fig.show()
```

Gender Risk for Stroke - effect of gender on strokes?

Risk of stroke in both male and female are same, prove our initial assumption is wrong.

Stroke | No Stroke



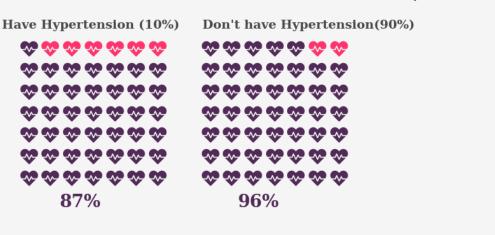
```
[]: stroke hyper = df[df['stroke'] == 1]['hypertension'].value_counts()
     healthy_hyper = df[df['stroke'] == 0]['hypertension'].value_counts()
     no = df['hypertension'].value_counts().values[0]
     yes = df['hypertension'].value counts().values[1]
     stroke no = int(round(stroke hyper.values[0] / no * 100, 0))
     stroke_yes = int(round(stroke_hyper.values[1] / yes * 100, 0))
     healthy_no = int(round(healthy_hyper.values[0] / no * 100, 0))
     healthy_yes = int(round(healthy_hyper.values[1] / yes * 100, 0))
     no_per = int(round(no / (no + yes) * 100, 0))
     yes_per = int(round(yes / (no + yes) * 100, 0))
     fig = plt.figure(
         FigureClass=Waffle,
         constrained_layout=True,
         figsize=(7, 7),
         facecolor='#f6f5f5', dpi=100,
         plots={
             '121': {
```

```
'rows': 7,
           'columns': 7,
           'values': [stroke_yes, healthy_yes],
           'colors': ['#fe346e', '#512b58'],
           'vertical': True,
           'interval_ratio_x': 0.005,
           'interval_ratio_y': 0.005,
           'icons': 'heartbeat',
           'icon legend': False,
           'icon_size': 20,
           'plot_anchor': 'C',
           'alpha': 1,
          'starting location': 'NE'
       },
       '122': {
           'rows': 7,
           'columns': 7,
           'values': [stroke_no, healthy_no],
           'colors': ['#fe346e', '#512b58'],
           'vertical': True,
           'interval_ratio_x': 0.005,
           'interval_ratio_y': 0.005,
           'icons': 'heartbeat',
          'icon legend': False,
           'icon_size': 20,
           'plot_anchor': 'C',
           'alpha': 1,
          'starting location': 'NE'
       }
   }
)
fig.text(0.0, 0.85, 'Hypertension Risk for Stroke- effect of blood pressure?', __
→{'font': 'Serif', 'size': 20, 'color': 'black', 'weight': 'bold'})
fig.text(0.0, 0.75, 'Risk of stroke for people with hypertension is_
→comparatively high,\nnearly 9% more people are having strokes \nwhen they⊔
→have hypertension.', {'font': 'Serif', 'size': 13, 'color': 'black', □
fig.text(0.24, 0.22, 'ooo', {'font': 'Serif', 'size': 16, 'weight': 'bold', __
fig.text(0.65, 0.22, 'ooo', {'font': 'Serif', 'size': 16, 'weight': 'bold', __
fig.text(0.23, 0.28, '{}%'.format(healthy_yes), {'font': 'Serif', 'size': 20,__
fig.text(0.63, 0.28, '{}%'.format(healthy_no), {'font': 'Serif', 'size': 20, __
```

Hypertension Risk for Stroke- effect of blood pressure?

Risk of stroke for people with hypertension is comparatively high, nearly 9% more people are having strokes when they have hypertension.

Stroke | No Stroke



```
[]: stroke_hyper = df[df['stroke'] == 1]['heart_disease'].value_counts()
healthy_hyper = df[df['stroke'] == 0]['heart_disease'].value_counts()

no = df['heart_disease'].value_counts().values[0]
yes = df['heart_disease'].value_counts().values[1]

stroke_no = int(round (stroke_hyper.values[0] / no * 100, 0))
stroke_yes = int(round( stroke_hyper.values[1] / yes *100, 0))
healthy_no = int(round(healthy_hyper.values[0] / no * 100, 0))
healthy_yes = int(round(healthy_hyper.values[1] / yes *100, 0))

no_per = int(round(no/(no+yes) * 100, 0))
yes_per = int(round(yes/(no+yes)* 100, 0))
```

```
fig = plt.figure(FigureClass = Waffle,
                 constrained_layout = True,
                 figsize = (7,10),
                 facecolor = '#f6f5f5',dpi = 100,
                 plots = {'121':
                            'rows':7,
                            'columns': 7,
                            'values' : [stroke_yes,healthy_yes],
                             'colors' : ['#fe346e','#512b58'],
                               'vertical' : True,
                               'interval_ratio_x': 0.005,
                               'interval_ratio_y': 0.005,
                               'icons' : 'heart',
                               'icon_legend': False,
                               'icon_size':20,
                               'plot_anchor':'C',
                               'alpha':0.8,
                               'starting_location': 'NE'
                          },
                           '122' :
                             'rows': 7,
                             'columns':7,
                             'values': [stroke_no,healthy_no],
                               'colors' : ['#fe346e','#512b58'],
                               'vertical': True,
                               'interval_ratio_x': 0.005,
                               'interval_ratio_y':0.005,
                               'icons' : 'heart',
                               'icon_legend' :False,
                               'icon_size':20,
                               'plot_anchor':'C',
                               'alpha':0.8,
                               'starting_location': 'NE'
                           }
                         },
)
```

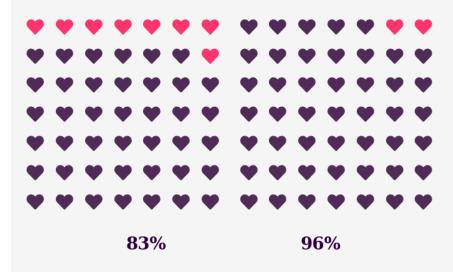
```
fig.text(0., 0.85, 'Heart disease Risk for Stroke- effect of Heart condition?', __
→{'font':'Serif', 'size':20, 'color':'black', 'weight':'bold'})
fig.text(0., 0.75, 'Risk of stroke for people with heart condition is,
⇒significant,\nnearly 12% of people are having strokes \nwhen they have heart ⊔
→condition previously. ', {'font':'Serif', 'size':13, 'color':'black',⊔
fig.text(0.24, 0.22, 'ooo', {'font':'Serif', 'size':16,'weight':'bold','color':
→ '#f6f5f5'})
fig.text(0.65, 0.22, 'ooo', {'font':'Serif', 'size':16,'weight':'bold', 'color':
→ '#f6f5f5'})
fig.text(0.25, 0.27, '{}%'.format(healthy_yes), {'font':'Serif', 'size':
→20, 'weight': 'bold', 'color': '#2c003e'},alpha = 1,)
fig.text(0.65, 0.27, '{}%'.format(healthy_no), {'font':'Serif', 'size':
→20, 'weight': 'bold', 'color': '#2c003e'}, alpha = 1)
fig.text(0.12, 0.68, 'UnHealthy Heart ({}%)'.format(yes per), {'font': 'Serif', |
fig.text(0.55, 0.68, "Healthy Heart({}%)".format(no per), {'font':'Serif', |
#fig.text(0., 0.8, 'Assumption was proven wrong', {'font':'Serif', 'size':24, u
→ 'color': 'black', 'weight': 'bold'})
fig.text(0.9,0.75, 'Stroke', {'font': 'Serif', 'weight': 'bold', 'Size':
fig.text(1.02,0.75, '|', {'color':'black', 'size':'16', 'weight': 'bold'})
fig.text(1.04,0.75, 'No Stroke', {'font': 'Serif', 'weight': 'bold', 'Size':
fig.show()
```

Heart disease Risk for Stroke- effect of Heart condition?

Risk of stroke for people with heart condition is significant, nearly 12% of people are having strokes when they have heart condition previously.

Stroke | No Stroke

UnHealthy Heart (5%) Healthy Heart (95%)



```
plots = {'121':
                        {
                         'rows':7,
                         'columns': 7,
                         'values' : [stroke_yes,healthy_yes],
                          'colors' : ['#fe346e','#512b58'],
                            'vertical' : True,
                            'interval ratio x': 0.005,
                            'interval_ratio_y': 0.005,
                            'icons' : 'ring',
                            'icon_legend': False,
                            'icon_size':20,
                            'plot_anchor':'C',
                            'alpha':0.8,
                            'starting_location': 'NE'
                        },
                        '122' :
                          'rows': 7,
                          'columns':7,
                          'values': [stroke_no,healthy_no],
                           'colors' : ['#fe346e','#512b58'],
                            'vertical': True,
                            'interval ratio x': 0.005,
                            'interval_ratio_y':0.005,
                            'icons' : 'universal-access',
                            'icon_legend' :False,
                            'icon_size':20,
                            'plot_anchor':'C',
                            'alpha':0.8,
                            'starting_location': 'NE'
                        }
                       },
)
fig.text(0., 0.8, 'Marriage and stroke- effects of marriage on heart?', {'font':
fig.text(0., 0.74, 'Risk of stroke in married people is relatively,\nhigh and_
→its only in margin of 5%.', {'font':'Serif', 'size':13, 'color':'black',
fig.text(0.24, 0.22, 'ooo', {'font':'Serif', 'size':16,'weight':'bold','color':
→ '#f6f5f5'})
```

```
fig.text(0.65, 0.22, 'ooo', {'font':'Serif', 'size':16, 'weight':'bold', 'color':
→ '#f6f5f5'})
fig.text(0.25, 0.28, '{}%'.format(healthy_yes), {'font':'Serif', 'size':
\Rightarrow20, 'weight': 'bold', 'color': '#2c003e'}, alpha = 1,)
fig.text(0.65, 0.28, '{}%'.format(healthy_no), {'font':'Serif', 'size':
\hookrightarrow20, 'weight': 'bold', 'color': '#2c003e'}, alpha = 1)
fig.text(0.20, 0.68, 'Married({}%)'.format(yes_per), {'font':'Serif', 'size':
→16,'weight':'bold' ,'color':'black'},alpha = 0.5,)
fig.text(0.58, 0.68, "Unmarried({}%)".format(no_per), {'font':'Serif', 'size':
→16, 'weight': 'bold', 'color': 'black'}, alpha = 0.5)
#fiq.text(0., 0.8, 'Assumption was proven wrong', {'font':'Serif', 'size':24, __
→ 'color': 'black', 'weight': 'bold'})
fig.text(0.9,0.72, 'Stroke', {'font': 'Serif', 'weight': 'bold', 'Size':
fig.text(1.02,0.72, '|', {'color':'black', 'size':'16', 'weight': 'bold'})
fig.text(1.04,0.72, 'No Stroke', {'font': 'Serif', 'weight': 'bold', 'Size':
fig.show()
```

Marriage and stroke- effects of marriage on heart?

Risk of stroke in married people is relatively, high and its only in margin of 5%.

Stroke | No Stroke

```
[]: stroke home = df[df['stroke'] == 1]['Residence_type'].value_counts()
     healthy_home= df[df['stroke'] == 0]['Residence_type'].value_counts()
     urban = df['Residence_type'].value_counts().values[0]
     rural = df['Residence_type'].value_counts().values[1]
     stroke_urban = int(round (stroke_home.values[0] / urban * 100, 0))
     stroke_rural= int(round( stroke_home.values[1] / rural *100, 0))
     healthy urban = int(round(healthy home.values[0] / urban * 100, 0))
     healthy_rural = int(round(healthy_home.values[1] / rural *100, 0))
     urban_per = int(round(urban/(urban+rural) * 100, 0))
     rural_per = int(round(rural/(urban+rural)* 100, 0))
     fig = plt.figure(FigureClass = Waffle,
                      constrained_layout = True,
                      figsize = (7,10),
                      facecolor = '#f6f5f5',dpi = 100,
                      plots = {'121':
                                'rows':7,
                                'columns': 7,
                                 'values' : [stroke_urban,healthy_urban],
                                 'colors' : ['#fe346e','#512b58'],
                                    'vertical' : True,
                                   'interval_ratio_x': 0.005,
                                   'interval_ratio_y': 0.005,
                                    'icons' : 'city',
                                   'icon_legend': False,
                                   'icon_size':15,
                                   'plot_anchor':'C',
                                    'alpha':0.8,
                                   'starting location': 'NE'
                               },
                               '122' :
                               {
                                 'rows': 7,
                                  'columns':7,
                                  'values': [stroke_rural, healthy_rural],
                                   'colors' : ['#fe346e','#512b58'],
                                    'vertical': True,
                                    'interval_ratio_x': 0.005,
```

```
'interval_ratio_y':0.005,
                           'icons' : 'home',
                           'icon_legend' :False,
                           'icon_size':20,
                           'plot_anchor':'C',
                           'alpha':0.8,
                           'starting_location': 'NE'
                       }
                      },
)
fig.text(0., 0.85, 'Lifestyle and Strokes- effect of residence location on L

→strokes?', {'font':'Serif', 'size':20, 'color':'black', 'weight':'bold'})
fig.text(0., 0.79, 'Location of home does not have much of the effect on heart,
⇒strokes of individuals.\nBoth rural and urban people have similar ⊔
→possibilities of Strokes.', {'font':'Serif', 'size':13, 'color':'black',
fig.text(0.23, 0.28, '{}%'.format(healthy_urban), {'font':'Serif', 'size':
→20, 'weight': 'bold', 'color': '#2c003e'},alpha = 1,)
fig.text(0.68, 0.28, '{}%'.format(healthy_rural), {'font':'Serif', 'size':
\rightarrow 20, 'weight': 'bold', 'color': '#2c003e'}, alpha = 1)
fig.text(0.13, 0.68, 'Urban Home({}%)'.format(urban_per), {'font':'Serif', ___
fig.text(0.57, 0.68, "Rural Home({}%)".format(rural per), {'font':'Serif', |
#fiq.text(0., 0.8, 'Assumption was proven wrong', {'font':'Serif', 'size':24, __
→ 'color': 'black', 'weight': 'bold'})
fig.text(0.88,0.75, 'Stroke ', {'font': 'Serif', 'weight': 'bold', 'Size':
fig.text(1,0.75, '|', {'color':'black', 'size':'16', 'weight': 'bold'})
fig.text(1.025,0.75, 'No Stroke', {'font': 'Serif', 'weight': 'bold', 'Size':
→'16','style':'normal', 'weight':'bold','color':'#512b58'},alpha = 1)
fig.show()
```

Lifestyle and Strokes- effect of residence location on strokes?

Location of home does not have much of the effect on heart strokes of individuals. Both rural and urban people have similar possibilities of Strokes.

Stroke | No Stroke

```
Urban Home(51%)
               Rural Home(49%)
              #
              ***
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         曲
           曲
              ***
 #Ba
   #Ba
     曲
         畾
           曲
              ~ ~ ~ ~ ~ ~ ~
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       曲
         Ш
               ~ ~ ~ ~ ~ ~
曲
 H
   iii
     曲
       曲
         曲
           曲
               ~ ~ ~ ~ ~ ~
           曲
   iii ii
     曲
       曲
         曲
               曲
     曲
       曲
         曲
                   95%
     95%
```

```
[]: smoke = df['smoking_status'].value_counts()
     stroke_smoke = df[df['stroke'] == 1]['smoking_status'].value_counts()
     healthy_smoke = df[df['stroke'] == 0]['smoking status'].value_counts()
     never = smoke.values[0]
     unknown = smoke.values[1]
     former = smoke.values[2]
     smokes = smoke.values[3]
     stroke never = int(round (stroke smoke.values[0] / never * 100, 0))
     stroke_unknown = int(round( stroke_smoke.values[2] / unknown *100, 0))
     stroke former = int(round (stroke smoke.values[1] / former * 100, 0))
     stroke smokes = int(round( stroke smoke.values[3] / smokes *100, 0))
     healthy_never = int(round(healthy_smoke.values[0] / never * 100, 0))
     healthy_unknown = int(round(healthy_smoke.values[1] / unknown *100, 0))
     healthy_former = int(round(healthy_smoke.values[2] / former * 100, 0))
     healthy_smokes = int(round(healthy_smoke.values[3] / smokes *100, 0))
     never_per = int(round(never/(never+unknown+former+smokes) * 100, 0))
     unknown_per = int(round(unknown/(never+unknown+former+smokes)* 100, 0))
     former per = int(round(former/(never+unknown+former+smokes) * 100, 0))
     smokes_per = int(round(smokes/(never+unknown+former+smokes)* 100, 0))
```

```
fig = plt.figure(FigureClass = Waffle,
                 constrained_layout = True,
                 figsize = (15,20),
                 facecolor = '#f6f5f5',dpi = 100,
                 plots = {'141':
                            'rows':7,
                            'columns': 7,
                            'values' : [stroke_never,healthy_never],
                             'colors' : ['#fe346e','#512b58'],
                               'vertical' : True,
                               'interval_ratio_x': 0.005,
                               'interval_ratio_y': 0.005,
                               'icons' : 'ban',
                               'icon_legend': False,
                               'icon_size':20,
                               'plot_anchor':'C',
                               'alpha':0.8,
                               'starting_location': 'NE'
                          },
                           '142' :
                             'rows': 7,
                             'columns':7,
                             'values': [stroke_former, healthy_former],
                               'colors' : ['#fe346e','#512b58'],
                               'vertical': True,
                               'interval_ratio_x': 0.005,
                               'interval_ratio_y':0.005,
                               'icons' : 'smoking-ban',
                               'icon_legend' :False,
                               'icon_size':20,
                               'plot_anchor':'C',
                               'alpha':0.8,
                               'starting_location': 'NE'
                           },
                           '143':
                            'rows':7,
                            'columns': 7,
```

```
'values' : [stroke_unknown,healthy_unknown],
                              'colors' : ['#fe346e','#512b58'],
                                'vertical' : True,
                                'interval_ratio_x': 0.005,
                                'interval_ratio_y': 0.005,
                                'icons' : 'question-circle',
                                'icon_legend': False,
                                'icon_size':20,
                                'plot_anchor':'C',
                                'alpha':0.8,
                                'starting location': 'NE'
                           },
                           '144' :
                           {
                              'rows': 7,
                              'columns':7,
                              'values': [stroke_smokes, healthy_smokes],
                                'colors' : ['#fe346e','#512b58'],
                                'vertical': True,
                                'interval_ratio_x': 0.006,
                                'interval ratio y':0.006,
                                'icons' : 'smoking',
                                'icon legend' :False,
                                'icon_size':15,
                                'plot_anchor':'C',
                                'alpha':0.8,
                                'starting location': 'NE'
                            }
                          },
)
fig.text(0.1, 0.65, 'Smoking and Stroke- Does smoking habit could cause Stroke?
-', {'font':'Serif', 'size':20, 'color':'black', 'weight':'bold'})
fig.text(0.1, 0.62, 'Risk of stroke with smoking is interesting one, it seems,
\rightarrowsmoking does have effect on strokes, and \nformer smokers are most likely to_{\sqcup}

→get strokes. ', {'font':'Serif', 'size':13, 'color':'black', 'weight':
\rightarrow 'normal'}, alpha = 0.7)
fig.text(0.18, 0.38, '{}%'.format(healthy_never), {'font':'Serif', 'size':
\rightarrow24, 'weight': 'bold', 'color': '#2c003e'}, alpha = 1,)
fig.text(0.38, 0.38, '{}%'.format(healthy_former), {'font':'Serif', 'size':
\Rightarrow24, 'weight': 'bold', 'color': '#2c003e'}, alpha = 1)
```

```
fig.text(0.58, 0.38, '{}%'.format(healthy_unknown), {'font':'Serif', 'size':
\hookrightarrow24, 'weight': 'bold', 'color': '#2c003e'}, alpha = 1,)
fig.text(0.78, 0.38, '{}%'.format(healthy_smokes), {'font':'Serif', 'size':
→24, 'weight': 'bold', 'color': '#2c003e'}, alpha = 1)
fig.text(0.05, 0.58, 'Never Smoked({}%)'.format(never_per), {'font':'Serif', __
fig.text(0.30, 0.58, "Formerly Smoked({}",)".format(former_per), {'font':
fig.text(0.55, 0.58, 'Unknown({}%)'.format(unknown_per), {'font':'Serif', __
fig.text(0.75, 0.58, "Smokes({}%)".format(smokes per), {'font':'Serif', 'size':
→14, 'weight': 'bold', 'color': 'black'}, alpha = 0.5)
#fig.text(0., 0.8, 'Assumption was proven wong', {'font':'Serif', 'size':24, __
→ 'color': 'black', 'weight': 'bold'})
fig.text(0.7,0.62, 'Stroke ', {'font': 'Serif', 'weight': 'bold', 'Size':
→'16','weight':'bold','style':'normal', 'color':'#fe346e'})
fig.text(0.76,0.62, '|', {'color':'black', 'size':'16', 'weight': 'bold'})
fig.text(0.77,0.62, 'No Stroke', {'font': 'Serif', 'weight': 'bold', 'Size':
→'16','style':'normal', 'weight':'bold','color':'#512b58'},alpha = 1)
fig.show()
```

```
Smoking and Stroke- Does smoking habit could cause Stroke?
   Risk of stroke with smoking is interesting one, it seems smoking does have effect on strokes, and former smokers are most likely to get strokes.

Stroke | No Stroke
 Never Smoked(37%)
          Formerly Smoked(17%)
                   Unknown(30%)
                          Smokes(15%)
0000000
                         95%
             92%
                    97%
                           95%
```

```
[]: work = df['work_type'].value_counts()
    stroke_work = df[df['stroke'] == 1]['work_type'].value_counts()
    healthy_work = df[df['stroke'] == 0]['work_type'].value_counts()

    private = work.values[0]
    self = work.values[1]
    child = work.values[2]
```

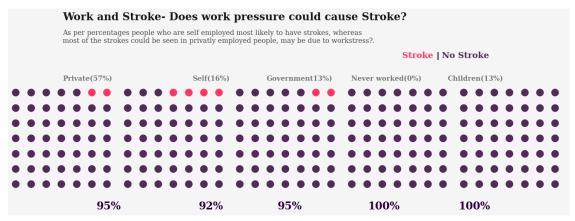
```
gov = work.values[3]
never = work.values[4]
stroke_private = int(round (stroke_work.values[0] / private * 100, 0))
stroke_self = int(round( stroke_work.values[1] / self *100, 0))
stroke_child = int(round (stroke_work.values[3] / child * 100, 0))
stroke_gov = int(round( stroke_work.values[2] / gov *100, 0))
stroke_never = int(round( 0, 0))
healthy_private = int(round(healthy_work.values[0] / private * 100, 0))
healthy self = int(round(healthy work.values[1] / self *100, 0))
healthy_child = int(round(healthy_work.values[2] / child * 100, 0))
healthy_gov = int(round(healthy_work.values[3]/ gov *100, 0))
healthy_never = int(round(healthy_work.values[4]/ never *100, 0))
private_per = int(round(private/(private+self+child+gov+never) * 100, 0))
self_per = int(round(self/(private+self+child+gov+never)* 100, 0))
child_per = int(round(child/(private+self+child+gov+never) * 100, 0))
gov_per = int(round(gov/(private+self+child+gov+never)* 100, 0))
never_per = int(round(never/(private+self+child+gov+never)* 100, 0))
fig = plt.figure(FigureClass = Waffle,
                 constrained layout = True,
                 figsize = (15,20),
                 facecolor = '#f6f5f5',dpi = 100,
                 plots = {'151':
                          {
                           'rows':7,
                           'columns': 7,
                           'values' : [stroke_private, healthy_private],
                            'colors' : ['#fe346e','#512b58'],
                              'vertical' : True,
                              'interval_ratio_x': 0.005,
                              'interval_ratio_y': 0.005,
                              'icons' : 'circle',
                              'icon_legend': False,
                              'icon size':15,
                              'plot_anchor':'C',
                              'alpha':0.2,
                              'starting_location': 'NE'
                          },
                          '152':
                            'rows': 7,
```

```
'columns':7,
  'values': [stroke_self, healthy_self],
    'colors' : ['#fe346e','#512b58'],
    'vertical': True,
    'interval_ratio_x': 0.005,
    'interval_ratio_y':0.005,
    'icons' : 'circle',
    'icon_legend' :False,
    'icon_size':15,
    'plot_anchor':'C',
    'alpha':0.2,
    'starting_location': 'NE'
},
'153':
{
 'rows':7,
 'columns': 7,
 'values' : [stroke_gov,healthy_gov],
  'colors' : ['#fe346e','#512b58'],
    'vertical' : True,
    'interval_ratio_x': 0.005,
    'interval ratio y': 0.005,
    'icons' : 'circle',
    'icon_legend': False,
    'icon_size':15,
    'plot_anchor':'C',
    'alpha':0.2,
    'starting_location': 'NE'
},
'154' :
{
  'rows': 7,
  'columns':7,
  'values': [stroke_never, healthy_never],
    'colors' : ['#fe346e','#512b58'],
    'vertical': True,
    'interval_ratio_x': 0.006,
    'interval_ratio_y':0.006,
    'icons' : 'circle',
    'icon_legend' :False,
    'icon_size':15,
    'plot_anchor':'C',
    'alpha':0.2,
    'starting_location': 'NE'
```

```
},
                          '155':
                          ₹
                            'rows': 7,
                            'columns':7,
                            'values': [stroke_child, healthy_child],
                              'colors' : ['#fe346e','#512b58'],
                              'vertical': True,
                              'interval ratio x': 0.006,
                              'interval_ratio_y':0.006,
                              'icons' : 'circle',
                              'icon_legend' :False,
                              'icon_size':15,
                              'plot_anchor':'C',
                              'alpha':0.2,
                              'starting_location': 'NE'
                           }
                         },
)
fig.text(0.1, 0.65, 'Work and Stroke- Does work pressure could cause Stroke?', u
→{'font':'Serif', 'size':20, 'color':'black', 'weight':'bold'},alpha = 0.9)
fig.text(0.1, 0.62, 'As per percentages people who are self employed most ...
\hookrightarrowlikely to have strokes, whereas \mbox{nmost} of the strokes could be seen in.
⇒privatly employed people, may be due to workstress?.', {'font':'Serif', __
fig.text(0.16, 0.40, '{}%'.format(healthy_private), {'font':'Serif', 'size':
\rightarrow20, 'weight': 'bold', 'color': '#2c003e'}, alpha = 1,)
fig.text(0.34, 0.40, '{}%'.format(healthy_self), {'font':'Serif', 'size':
\hookrightarrow20,'weight':'bold', 'color':'#2c003e'}, alpha = 1)
fig.text(0.48, 0.40, '{}%'.format(healthy_gov), {'font':'Serif', 'size':
→20,'weight':'bold','color':'#2c003e'},alpha = 1,)
fig.text(0.64, 0.40, '{}%'.format(healthy_never), {'font':'Serif', 'size':
→20, 'weight': 'bold', 'color': '#2c003e'}, alpha = 1)
fig.text(0.8, 0.40, '{}%'.format(healthy_child), {'font':'Serif', 'size':
\rightarrow20, 'weight': 'bold', 'color': '#2c003e'}, alpha = 1)
fig.text(0.10, 0.57, 'Private({}%)'.format(private_per), {'font':'Serif', ___

¬'size':13,'weight':'bold' ,'color':'black'},alpha = 0.5,)
```

```
fig.text(0.33, 0.57, "Self({}%)".format(self_per), {'font':'Serif', 'size':
→13,'weight':'bold', 'color':'black'}, alpha = 0.5)
fig.text(0.46, 0.57, 'Government{}%)'.format(gov_per), {'font':'Serif', 'size':
→13, 'weight': 'bold', 'color': 'black'}, alpha = 0.5,)
fig.text(0.61, 0.57, "Never worked({}%)".format(never_per), {'font':'Serif', __
fig.text(0.78, 0.57, "Children({}%)".format(child_per), {'font':'Serif', 'size':
→13,'weight':'bold', 'color':'black'}, alpha = 0.5)
#fiq.text(0., 0.8, 'Assumption was proven wong', {'font':'Serif', 'size':24, __
→ 'color': 'black', 'weight': 'bold'})
fig.text(0.7,0.6, 'Stroke', {'font': 'Serif', 'weight': 'bold', 'Size':
fig.text(0.76,0.6, '|', {'color': 'black', 'size': '16', 'weight': 'bold'})
fig.text(0.77,0.6, 'No Stroke', {'font': 'Serif', 'weight': 'bold', 'Size':
fig.show()
```



```
[]: fig = plt.figure(figsize=(12,6),dpi = 100)
gs = fig.add_gridspec(1,2)
gs.update(wspace=0.25, hspace=0.5)

ax0 = fig.add_subplot(gs[0,0])
ax1 = fig.add_subplot(gs[0,1])

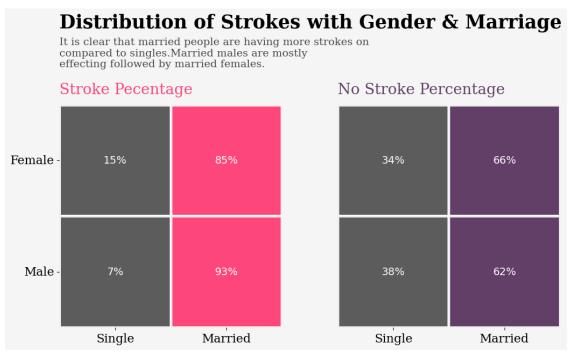
fig.patch.set_facecolor('#f6f5f5')
ax0.set_facecolor('#f6f5f5')
ax1.set_facecolor('#f6f5f5')
```

```
# ever married, gender, residence, heart disease and work type
healthy = df[df['stroke']==0]
stroke = df[df['stroke']==1]
col1 = ["#4b4b4c", "#fe346e"]
colormap1 = matplotlib.colors.LinearSegmentedColormap.from_list("", col1, N = __
→256)
col2 = ["#4b4b4c", "#512b58"]
colormap2 = matplotlib.colors.LinearSegmentedColormap.from_list("", col2)
stroke = pd.

¬crosstab(stroke['gender'],[stroke['ever_married']],normalize='index')

no_stroke = pd.crosstab(healthy['gender'],[healthy['ever_married']],_u
→normalize='index')
sns.heatmap(ax=ax0, data=stroke, linewidths= 0,
            square=True, cbar_kws={"orientation": "horizontal"},__
⇒cbar=False,linewidth=3, cmap = col1,annot=True, fmt='1.
\rightarrow0%',annot_kws={"fontsize":14}, alpha = 0.9)
sns.heatmap(ax=ax1, data=no stroke[0:-1], linewidths=0,
            square=True, cbar_kws={"orientation": "horizontal"},__
⇒cbar=False,linewidth=3, cmap = col2,annot=True, fmt='1.
\hookrightarrow 0\%', annot_kws={"fontsize":14}, alpha = 0.9)
ax0.text(0, -0.69, 'Distribution of Strokes with Gender & Marriage', {'font':
ax0.text(0, -0.34, 'It is clear that married people are having more strokes on ⊔
→\ncompared to singles.Married males are mostly \neffecting followed by \_
→married females.', {'font':'Serif', 'color':'black', 'size':14}, alpha = 0.7)
ax0.text(0,-0.1,'Stroke Pecentage ', {'font':'serif', 'color':"#fe346e", 'size':
\rightarrow20},alpha = 0.9)
ax1.text(0,-0.1,'No Stroke Percentage', {'font':'serif', 'color':"#512b58", |
\rightarrow 'size':20}, alpha =0.9)
ax0.axes.set_xticklabels(['Single', 'Married'], {'font':'serif', 'color':
ax1.axes.set_xticklabels(['Single', 'Married'], {'font':'serif', 'color':
ax0.axes.set_yticklabels(['Female', 'Male'], {'font':'serif', 'color':'black', __
\rightarrow 'size':16}, rotation = 0)
```

```
ax0.set_xlabel('')
ax0.set_ylabel('')
ax1.set_xlabel('')
ax1.set_ylabel('')
ax1.axes.get_yaxis().set_visible(False)
fig.show()
```



```
fig = plt.figure(figsize=(12,6), dpi = 100)
gs = fig.add_gridspec(1,2)
gs.update(wspace=0.25, hspace=0.5)

ax0 = fig.add_subplot(gs[0,0])
ax1 = fig.add_subplot(gs[0,1])

fig.patch.set_facecolor('#f6f5f5')
ax0.set_facecolor('#f6f5f5')

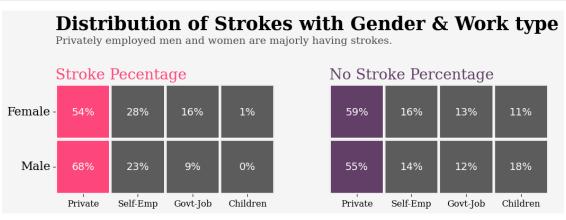
ax1.set_facecolor('#f6f5f5')

# ever_married, gender, residence, heart_disease and work_type

healthy = df[df['stroke']==0]
stroke = df[df['stroke']==1]
```

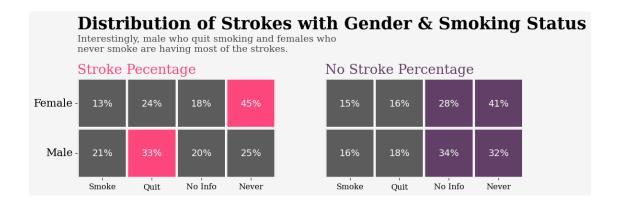
```
gender_order = ['Female','Male']
work_order = ['Private', 'Self-employed','Govt_job', 'children']
col1 = ["#4b4b4c", "#fe346e"]
colormap1 = matplotlib.colors.LinearSegmentedColormap.from_list("", col1, N =__
<sup>→</sup>256)
col2 = ["#4b4b4c", "#512b58"]
colormap2 = matplotlib.colors.LinearSegmentedColormap.from_list("", col2)
stroke = pd.crosstab(stroke['gender'],[stroke['work_type']],normalize='index').
→loc[gender_order,work_order]
no_stroke = pd.crosstab(healthy['gender'], [healthy['work_type']], u
→normalize='index').loc[gender_order,work_order]
sns.heatmap(ax=ax0, data=stroke, linewidths= 0,
           square=True, cbar_kws={"orientation": "horizontal"},__
\rightarrow 0\%', annot_kws={"fontsize":14}, alpha = 0.9)
sns.heatmap(ax=ax1, data=no_stroke, linewidths=0,
           square=True, cbar kws={"orientation": "horizontal"},
⇒cbar=False,linewidth=3, cmap = col2,annot=True, fmt='1.
\rightarrow 0\%', annot_kws={"fontsize":14}, alpha = 0.9)
ax0.text(0, -1., 'Distribution of Strokes with Gender & Work type', {'font':
ax0.text(0, -0.75, 'Privately employed men and women are majorly having strokes.
ax0.text(0,-0.1,'Stroke Pecentage ', {'font':'serif', 'color':"#fe346e", 'size':
\rightarrow20},alpha = 0.9)
ax1.text(0,-0.1,'No Stroke Percentage', {'font':'serif', 'color':"#512b58", |
\hookrightarrow 'size':20}, alpha =0.9)
ax0.axes.set_xticklabels(['Private', 'Self-Emp','Govt-Job', 'Children'],
→{'font':'serif', 'color':'black', 'size':12})
ax1.axes.set_xticklabels(['Private', 'Self-Emp','Govt-Job', 'Children'],
ax0.axes.set_yticklabels(gender_order, {'font':'serif', 'color':'black', 'size':
\rightarrow16}, rotation = 0)
ax0.set xlabel('')
ax0.set_ylabel('')
```

```
ax1.set_xlabel('')
ax1.set_ylabel('')
ax1.axes.get_yaxis().set_visible(False)
fig.show()
```



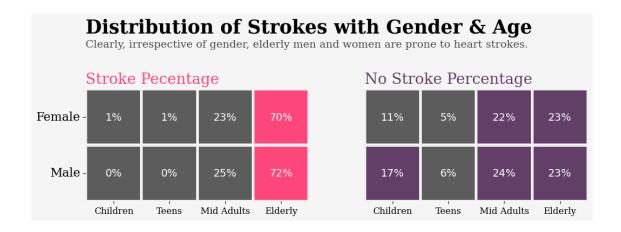
```
[]: fig = plt.figure(figsize=(12,6), dpi = 100)
     gs = fig.add_gridspec(1,2)
     gs.update(wspace=0.25, hspace=0.5)
     ax0 = fig.add_subplot(gs[0,0])
     ax1 = fig.add_subplot(gs[0,1])
     fig.patch.set_facecolor('#f6f5f5')
     ax0.set_facecolor('#f6f5f5')
     ax1.set_facecolor('#f6f5f5')
     # ever_married, gender, residence, heart_disease and work_type
     healthy = df[df['stroke']==0]
     stroke = df[df['stroke']==1]
     gender_order = ['Female','Male']
     smoking_order = ['smokes', 'formerly smoked', 'Unknown', 'never smoked']
     col1 = ["#4b4b4c", "#fe346e"]
     colormap1 = matplotlib.colors.LinearSegmentedColormap.from_list("", col1, N = __
     →256)
     col2 = ["#4b4b4c", "#512b58"]
     colormap2 = matplotlib.colors.LinearSegmentedColormap.from list("", col2)
```

```
stroke = pd.
Grosstab(stroke['gender'],[stroke['smoking status']],normalize='index').
→loc[gender_order,smoking_order]
no stroke = pd.crosstab(healthy['gender'],[healthy['smoking status']],
→normalize='index').loc[gender_order,smoking_order]
sns.heatmap(ax=ax0, data=stroke, linewidths= 0,
            square=True, cbar_kws={"orientation": "horizontal"},__
⇒cbar=False,linewidth=3, cmap = col1,annot=True, fmt='1.
\rightarrow 0\%', annot_kws={"fontsize":14}, alpha = 0.9)
sns.heatmap(ax=ax1, data=no stroke, linewidths=0,
            square=True, cbar_kws={"orientation": "horizontal"},__
⇒cbar=False,linewidth=3, cmap = col2,annot=True, fmt='1.
\rightarrow 0\%', annot_kws={"fontsize":14}, alpha = 0.9)
ax0.text(0, -1., 'Distribution of Strokes with Gender & Smoking Status', __
→{'font':'Serif', 'color':'black', 'weight':'bold','size':25})
ax0.text(0, -0.55, 'Interestingly, male who quit smoking and females who⊔
→\nnever smoke are having most of the strokes.', {'font':'Serif', 'color':
\rightarrow 'black', 'size':14}, alpha = 0.7)
ax0.text(0,-0.1,'Stroke Pecentage ', {'font':'serif', 'color':"#fe346e", 'size':
\rightarrow20},alpha = 0.9)
ax1.text(0,-0.1,'No Stroke Percentage', {'font':'serif', 'color':"#512b58", |
ax0.axes.set_xticklabels(['Smoke', 'Quit','No Info', 'Never'], {'font':'serif', ___
ax1.axes.set_xticklabels(['Smoke', 'Quit', 'No Info', 'Never'], {'font':'serif', __
ax0.axes.set_yticklabels(gender_order, {'font':'serif', 'color':'black', 'size':
\rightarrow16}, rotation = 0)
ax0.set_xlabel('')
ax0.set_ylabel('')
ax1.set xlabel('')
ax1.set_ylabel('')
ax1.axes.get_yaxis().set_visible(False)
fig.show()
```



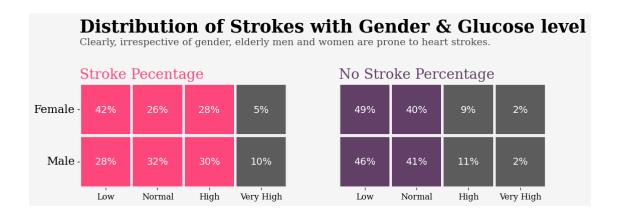
```
[]: fig = plt.figure(figsize=(12,6), dpi = 100)
     gs = fig.add_gridspec(1,2)
     gs.update(wspace=0.25, hspace=0.5)
     ax0 = fig.add_subplot(gs[0,0])
     ax1 = fig.add_subplot(gs[0,1])
     fig.patch.set_facecolor('#f6f5f5')
     ax0.set_facecolor('#f6f5f5')
     ax1.set facecolor('#f6f5f5')
     # ever married, gender, residence, heart disease and work type
     healthy = df[df['stroke']==0]
     stroke = df[df['stroke']==1]
     gender_order = ['Female','Male']
     age_order = ['Children', 'Teens', 'Mid Adults', 'Elderly']
     col1 = ["#4b4b4c", "#fe346e"]
     colormap1 = matplotlib.colors.LinearSegmentedColormap.from list("", col1, N = 1
     →256)
     col2 = ["#4b4b4c", "#512b58"]
     colormap2 = matplotlib.colors.LinearSegmentedColormap.from_list("", col2)
     stroke = pd.crosstab(stroke['gender'],[stroke['age_cat']],normalize='index').
     →loc[gender_order,age_order]
     no_stroke = pd.crosstab(healthy['gender'],[healthy['age_cat']],__
     →normalize='index').loc[gender order,age order]
     sns.heatmap(ax=ax0, data=stroke, linewidths= 0,
```

```
square=True, cbar_kws={"orientation": "horizontal"},__
⇒cbar=False,linewidth=3, cmap = col1,annot=True, fmt='1.
 \rightarrow 0\%', annot_kws={"fontsize":14}, alpha = 0.9)
sns.heatmap(ax=ax1, data=no_stroke, linewidths=0,
            square=True, cbar kws={"orientation": "horizontal"},
⇒cbar=False,linewidth=3, cmap = col2,annot=True, fmt='1.
\rightarrow 0\%', annot_kws={"fontsize":14}, alpha = 0.9)
ax0.text(0, -1., 'Distribution of Strokes with Gender & Age', {'font':'Serif', __
ax0.text(0, -0.75, 'Clearly, irrespective of gender, elderly men and women are⊔
⇒prone to heart strokes.', {'font':'Serif', 'color':'black','size':14}, alpha⊔
\rightarrow = 0.7
ax0.text(0,-0.1,'Stroke Pecentage ', {'font':'serif', 'color':"#fe346e", 'size':
\rightarrow20},alpha = 0.9)
ax1.text(0,-0.1,'No Stroke Percentage', {'font':'serif', 'color':"#512b58", __
\rightarrow 'size':20}, alpha =0.9)
ax0.axes.set_xticklabels(age_order, {'font':'serif', 'color':'black', 'size':
→12})
ax1.axes.set_xticklabels(age_order, {'font':'serif', 'color':'black', 'size':
→12})
ax0.axes.set_yticklabels(gender_order, {'font':'serif', 'color':'black', 'size':
\rightarrow16}, rotation = 0)
ax0.set_xlabel('')
ax0.set_ylabel('')
ax1.set_xlabel('')
ax1.set_ylabel('')
ax1.axes.get_yaxis().set_visible(False)
fig.show()
```



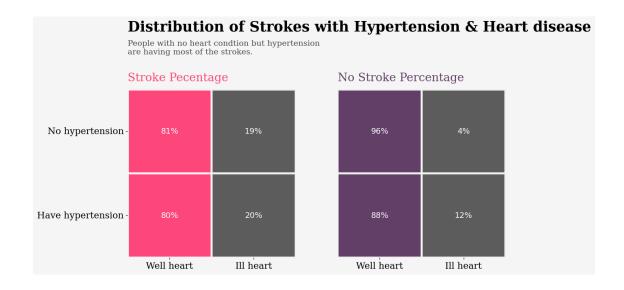
```
[]: fig = plt.figure(figsize=(12,6), dpi = 100)
     gs = fig.add_gridspec(1,2)
     gs.update(wspace=0.25, hspace=0.5)
     ax0 = fig.add subplot(gs[0,0])
     ax1 = fig.add_subplot(gs[0,1])
     fig.patch.set facecolor('#f6f5f5')
     ax0.set_facecolor('#f6f5f5')
     ax1.set_facecolor('#f6f5f5')
     # ever_married, gender, residence, heart_disease and work_type
     healthy = df[df['stroke']==0]
     stroke = df[df['stroke']==1]
     gender_order = ['Female','Male']
     glucose_order = ['Low', 'Normal', 'High', 'Very High']
     col1 = ["#4b4b4c","#fe346e"]
     colormap1 = matplotlib.colors.LinearSegmentedColormap.from list("", col1, N = 1
     <sup>→</sup>256)
     col2 = ["#4b4b4c", "#512b58"]
     colormap2 = matplotlib.colors.LinearSegmentedColormap.from list("", col2)
     stroke = pd.
     crosstab(stroke['gender'],[stroke['glucose_cat']],normalize='index').
     →loc[gender_order,glucose_order]
     no_stroke = pd.crosstab(healthy['gender'], [healthy['glucose_cat']],__
      →normalize='index').loc[gender_order,glucose_order]
```

```
sns.heatmap(ax=ax0, data=stroke, linewidths= 0,
            square=True, cbar_kws={"orientation": "horizontal"},__
⇒cbar=False,linewidth=3, cmap = col1,annot=True, fmt='1.
\rightarrow 0\%', annot_kws={"fontsize":14}, alpha = 0.9)
sns.heatmap(ax=ax1, data=no_stroke, linewidths=0,
            square=True, cbar_kws={"orientation": "horizontal"},__
⇒cbar=False,linewidth=3, cmap = col2,annot=True, fmt='1.
\rightarrow 0\%', annot_kws={"fontsize":14}, alpha = 0.9)
ax0.text(0, -1., 'Distribution of Strokes with Gender & Glucose level', {'font':
ax0.text(0, -0.75, 'Clearly, irrespective of gender, elderly men and women are⊔
⇒prone to heart strokes.', {'font':'Serif', 'color':'black','size':14}, alpha⊔
\rightarrow = 0.7
ax0.text(0,-0.1,'Stroke Pecentage ', {'font':'serif', 'color':"#fe346e", 'size':
\rightarrow20},alpha = 0.9)
ax1.text(0,-0.1,'No Stroke Percentage', {'font':'serif', 'color':"#512b58", |
\rightarrow 'size':20}, alpha =0.9)
ax0.axes.set_xticklabels(glucose_order, {'font':'serif', 'color':'black',u
ax1.axes.set_xticklabels(glucose_order, {'font':'serif', 'color':'black', __
ax0.axes.set_yticklabels(gender_order, {'font':'serif', 'color':'black', 'size':
\rightarrow16}, rotation = 0)
ax0.set_xlabel('')
ax0.set_ylabel('')
ax1.set_xlabel('')
ax1.set_ylabel('')
ax1.axes.get_yaxis().set_visible(False)
fig.show()
```



```
[]: fig = plt.figure(figsize=(12,6))
    gs = fig.add_gridspec(1,2)
    gs.update(wspace=0.25, hspace=0.5)
    ax0 = fig.add subplot(gs[0,0])
    ax1 = fig.add_subplot(gs[0,1])
    fig.patch.set_facecolor('#f6f5f5')
    ax0.set_facecolor('#f6f5f5')
    ax1.set_facecolor('#f6f5f5')
    # ever_married, gender, residence, heart_disease and work_type
    healthy = df[df['stroke']==0]
    stroke = df[df['stroke']==1]
    col1 = ["#4b4b4c", "#fe346e"]
    colormap1 = matplotlib.colors.LinearSegmentedColormap.from_list("", col1, N =__
     <sup>→</sup>256)
    col2 = ["#4b4b4c", "#512b58"]
    colormap2 = matplotlib.colors.LinearSegmentedColormap.from_list("", col2)
    stroke = pd.
     no_stroke = pd.crosstab(healthy['hypertension'], [healthy['heart_disease']],_u
     →normalize='index')
    sns.heatmap(ax=ax0, data=stroke, linewidths= 0,
                square=True, cbar_kws={"orientation": "horizontal"},__
     ⇒cbar=False,linewidth=3, cmap = col1,annot=True, fmt='1.
     \hookrightarrow 0\%', annot_kws={"fontsize":14}, alpha = 0.9)
```

```
sns.heatmap(ax=ax1, data=no_stroke, linewidths=0,
           square=True, cbar_kws={"orientation": "horizontal"},__
⇒cbar=False,linewidth=3, cmap = col2,annot=True, fmt='1.
\rightarrow 0\%', annot_kws={"fontsize":14}, alpha = 0.9)
ax0.text(0, -0.69, 'Distribution of Strokes with Hypertension & Heart disease', __
→{'font':'Serif', 'color':'black', 'weight':'bold','size':25})
ax0.text(0, -0.42, 'People with no heart condtion but hypertension \nare having_
→most of the strokes.', {'font':'Serif', 'color':'black', 'size':14}, alpha =
\rightarrow 0.7)
ax0.text(0,-0.1,'Stroke Pecentage ', {'font':'serif', 'color':"#fe346e", 'size':
\rightarrow20},alpha = 0.9)
ax1.text(0,-0.1,'No Stroke Percentage', {'font':'serif', 'color':"#512b58", |
ax0.axes.set_xticklabels(['Well heart', 'Ill heart'], {'font':'serif', 'color':
ax1.axes.set_xticklabels(['Well heart', 'Ill heart'], {'font':'serif', 'color':
→'black', 'size':16})
ax0.axes.set_yticklabels(['No hypertension', 'Have hypertension'], {'font':
ax0.set xlabel('')
ax0.set_ylabel('')
ax1.set xlabel('')
ax1.set_ylabel('')
ax1.axes.get_yaxis().set_visible(False)
fig.show()
```

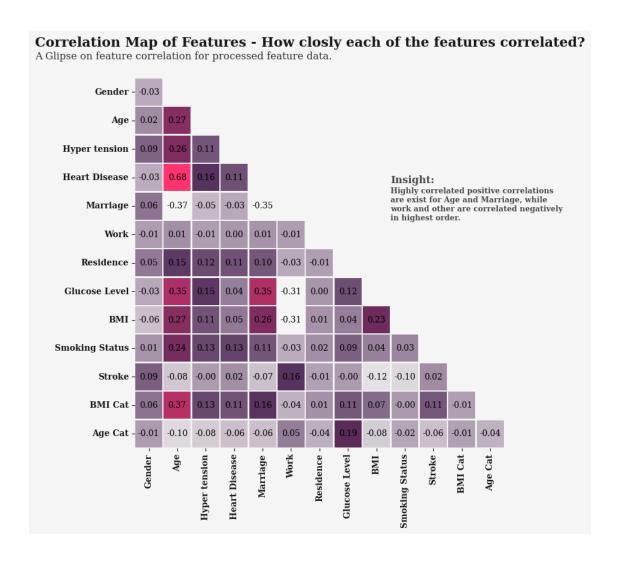


```
[]: df_copy = df.copy()
     # feature log transformations
     df_copy['age'] = df_copy['age'].apply(lambda x: np.log(x+10)*3)
     df_copy['avg_glucose_level'] = df_copy['avg_glucose_level'].apply(lambda x: np.
      \rightarrowlog(x+10)*2)
     df_copy['bmi'] = df_copy['bmi'].apply(lambda x: np.log(x+10)*2)
     # preprocessing - label enconding and numerical value scaling
     ohe = OneHotEncoder()
     ss = StandardScaler()
     le = LabelEncoder()
     ## label encoding of ordinal categorical features
     for col in df_copy.columns:
         df_copy[col] = le.fit_transform(df_copy[col])
     cols = df_copy.columns
     ## normalizing with standard scaler of numerical features
     df_copy[cols] = ss.fit_transform(df_copy[cols])
     # correlation map for all the features
     df_corr = df_copy.drop(columns = ['id']).corr()
     mask = np.triu(np.ones_like(df_corr, dtype=bool))
     fig, ax = plt.subplots(figsize = (8,8))
     fig.patch.set_facecolor('#f6f5f5')
```

```
ax.set_facecolor('#f6f5f5')
mask = mask[1:, :-1]
corr = df_corr.iloc[1:,:-1].copy()
colors = ['#f6f5f5','#512b58','#fe346e']
colormap = matplotlib.colors.LinearSegmentedColormap.from_list("", colors)
# plot heatmap
sns.heatmap(corr, mask=mask, annot=True, fmt=".2f",cmap = colormap,
          vmin=-0.15, vmax=0.5, cbar_kws={"shrink": .5, }, ax = ax, cbar =__
→False,
           linewidth = 1,linecolor = '#f6f5f5', square = True,annot_kws =
# yticks
ax.tick_params(axis = 'y', rotation=0)
xticks = ['Gender', 'Age', 'Hyper tension', 'Heart Disease', 'Marriage', 'Work',
→'Residence', 'Glucose Level', 'BMI', 'Smoking Status', 'Stroke', 'BMI⊔
yticks = ['Gender', 'Age', 'Hyper tension', 'Heart Disease', 'Marriage', 'Work', u
→'Residence', 'Glucose Level', 'BMI', 'Smoking Status', 'Stroke', 'BMI_

→Cat','Age Cat']
ax.set_xticklabels(xticks, {'font':'serif', 'size':10, 'weight':
\rightarrow 'bold'},rotation = 90, alpha = 0.9)
ax.set yticklabels(yticks, {'font':'serif', 'size':10, 'weight':'bold'},
\rightarrowrotation = 0, alpha = 0.9)
ax.text(-3.5,-1.1, 'Correlation Map of Features - How closly each of the
⇒features correlated?',{'font':'serif', 'size': 16, 'weight':'bold'}, alpha = ∪
\rightarrow 0.9)
ax.text(-3.5,-0.65, 'A Glipse on feature correlation for processed feature data.

→',{'font':'serif', 'size': 12, 'weight':'normal'}, alpha = 0.8)
ax.text(9,5, 'Highly correlated positive correlations \nare exist for Age and ∪
→Marriage, while \nwork and other are correlated negatively \nin highest
→order.',{'font':'serif', 'size': 9, 'weight':'bold'},alpha = 0.7)
ax.text(9,3.7, 'Insight:',{'font':'serif', 'size': 12, 'weight':'bold'},alpha =
\rightarrow 0.7
fig.show()
```



```
[]: labels = ['Smoking', 'BMI','Age', 'Marriage', 'Heart Disease',

→'Stroke','Hypertension', 'Age Cat', 'Gender', 'Work', 'BMI Cat',

→'Residence','Glucose Level', 'Glucose Cat']

g = sns.clustermap(df_corr, annot = True, fmt = '0.2f',

cbar= False, cbar_pos=(0,0,0,0),linewidth = 0.5,

cmap = colormap,dendrogram_ratio=0.1,

facecolor = '#f6f5f5', figsize = (8,8),square = True,

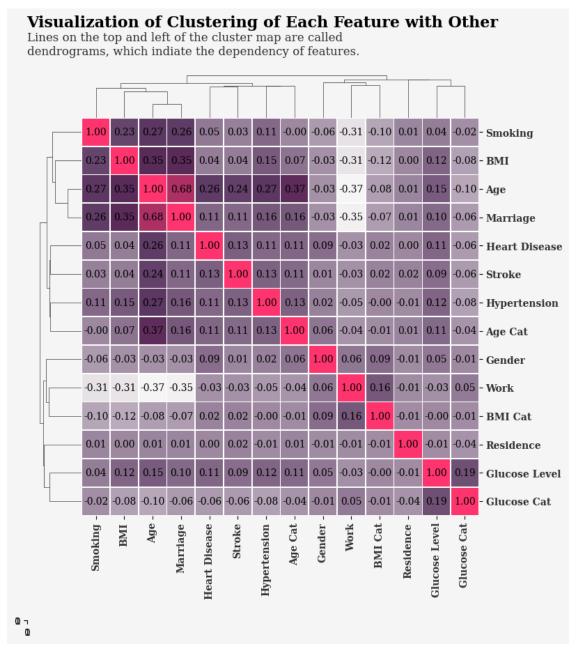
annot_kws = {'font':'serif', 'size':10, 'color':'black'})

plt.gcf().set_facecolor('#f6f5f5')

label_args = {'font':'serif', 'font':18, 'weight':'bold'}

plt.setp(g.ax_heatmap.set_yticklabels(labels), rotation=0, fontsize = 10,

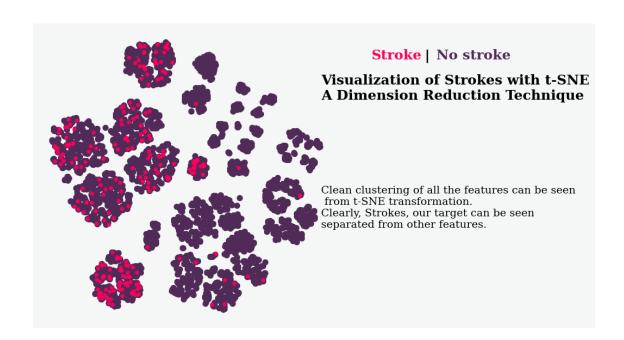
→fontfamily = 'Serif', fontweight = 'bold', alpha = 0.8) # For y axis
```



```
[]: # final data preprocessing and preperation
    df_copy = df.copy()
     # feature log transformations
    df['age'] = df['age'].apply(lambda x: np.log(x+10)*3)
    df['avg_glucose_level'] = df['avg_glucose_level'].apply(lambda x: np.
     \rightarrowlog(x+10)*2)
    df['bmi'] = df['bmi'].apply(lambda x: np.log(x+10)*2)
    # preprocessing - label enconding and numerical value scaling
    ohe = OneHotEncoder()
    ss = StandardScaler()
    le = LabelEncoder()
    X = df.drop(['stroke','id'], axis = 1)
    y = df['stroke']
    ordinal = ['age_cat', 'glucose_cat', 'bmi_cat', 'hypertension', _
     →'heart_disease'] # label enconding
    nominal = ['gender', 'ever_married', 'work_type', 'Residence_type', |
     numerical = ['age','bmi', 'avg glucose level']
    ## label encoding of ordinal categorical features
    for col in ordinal:
        X[col] = le.fit_transform(X[col])
    ## normalizing with standard scaler of numerical features
    X[numerical] = ss.fit_transform(X[numerical])
     ## norminal data one hot encoding for categorical features
    temp = X.drop(columns = nominal)
    dummies = pd.get_dummies(X[nominal])
    X = pd.concat([temp,dummies], axis = 1)
[]: from sklearn.manifold import TSNE
[]: # t-SNE transformation
    tsne = TSNE(random_state=2021)
    stroke_tsne = tsne.fit_transform(X)
[]: # Create figure
    fig = plt.figure(figsize=(7, 7))
    gs = fig.add_gridspec(1, 1)
```

```
gs.update(wspace=0.4, hspace=0.5)
ax0 = fig.add_subplot(gs[0, 0])
# Change background color
background_color = "#f5f6f6"
fig.patch.set_facecolor(background_color) # figure background color
ax0.set_facecolor(background_color)
# Scatter plot for the two classes
ax0.scatter(stroke_tsne[df['stroke'] == 0][:, 0], stroke_tsne[df['stroke'] == 0]
\rightarrow 0][:, 1], c='#512b58', alpha=1, s=50)
ax0.scatter(stroke_tsne[df['stroke'] == 1][:, 0], stroke_tsne[df['stroke'] ==__
\hookrightarrow1][:, 1], c='#ff005c', alpha=0.9, s=20)
# Add text annotations
ax0.text(80, -25, 'Clean clustering of all the features can be seen\n from_
→t-SNE transformation. \nClearly, Strokes, our target can be seen \nseparated_
→from other features.', fontsize=14, fontfamily='serif')
ax0.text(80, 45, 'Visualization of Strokes with t-SNE\nA Dimension Reduction_
→Technique', fontsize=18, fontweight='bold', fontfamily='serif')
# Remove axis spines
for s in ["top", "right", "left", "bottom"]:
   ax0.spines[s].set_visible(False)
# Remove axis ticks
ax0.set_xticks([])
ax0.set_yticks([])
# Add legend
fig.text(1, 0.8, "Stroke", fontweight="bold", fontfamily='serif', fontsize=18, __

color='#ff005c')
fig.text(1.14, 0.8, "|", fontweight="bold", fontfamily='serif', fontsize=18,__
fig.text(1.17, 0.8, "No stroke", fontweight="bold", fontfamily='serif', u
# Show plot
plt.show()
```



0.4 Visualization of Data Balancing with Data Sampling techniques

```
[]: ##### visualization class for dimension reduction and plotting result
     class sampling():
         def __init__(self,feat,tar,method,ax):
             self.feat = feat
             self.tar = tar
             self.method = method
             self.ax = ax
         # under sampling visualization
         def visualize_data(self):
             temp_y = pd.DataFrame({'y':self.tar})
             # dimension reduction
             pca = PCA(n_components= 2).fit_transform(self.feat)
             self.ax.set_facecolor('#f5f6f6')
             # plotting4
             self.ax.scatter(pca[temp_y['y'] == 0][:,0], pca[temp_y['y'] == 0][:,1],_{\sqcup}
      \hookrightarrowc = '#512b58', s = 10)
```

```
self.ax.scatter(pca[temp_y['y'] == 1][:,0], pca[temp_y['y'] == 1][:,1],
      \rightarrowc = '#ff005c', s =10)
             for loc in ['left','right','top', 'bottom']:
                 self.ax.spines[loc].set_visible(False)
             self.ax.axes.get xaxis().set visible(False)
             self.ax.axes.get_yaxis().set_visible(False)
             self.ax.set_xticklabels('')
             self.ax.set_yticklabels('')
             self.ax.set_xlim(xmin = -6, xmax = 6)
             self.ax.set_ylim(ymin = -5, ymax = 6)
             self.ax.text(1.6,3.8,"Stroke", fontweight="bold", fontfamily='serif',
      →fontsize=13, color='#ff005c')
             self.ax.text(3.2,3.8,"|", fontweight="bold", fontfamily='serif',

→fontsize=13, color='black')
             self.ax.text(3.4,3.8,"No stroke", fontweight="bold",

→fontfamily='serif', fontsize=13, color='#512b58')
             self.ax.text(-6,5.5,self.method, {'font': 'serif', 'weight': 'bold', __
      \rightarrow 'size': 20}, alpha = 0.8)
             self.ax.text(-6,4.5,'{} contain {} number of datapoint, \nand targets_\(\)
      →distribution as {}.'.format(self.method,len(self.feat), {0:Counter(self.
      →tar)[0],1:Counter(self.tar)[1]}), {'font': 'serif', 'weight': 'normal', |
      \rightarrow 'size': 12}, alpha = 0.7)
[]: fig = plt.figure(figsize =(14,7))
     gs = fig.add_gridspec(1,2)
     gs.update(wspace = 0.1, hspace = 0.1)
     ax1 = fig.add_subplot(gs[0,0])
     ax2 = fig.add_subplot(gs[0,1])
     axes = [ax1, ax2]
     fig.patch.set_facecolor('#f5f5f5')
     # setting of axes; visibility of axes and spines turn off
     for ax in axes:
         ax.axes.get_yaxis().set_visible(False)
         ax.set_facecolor('#f8f8f8')
     random_state = 2021
     # Original Data
```

```
sampling(X,y.ravel(),'Original Data',ax=ax1).visualize_data()

#randomundersampling
X_rs, y_rs = make_imbalance(X, y.ravel(),random_state= 2021, sampling_strategy_\( \text{\circ} = \) 0: 2500, 1:249},)

sampling(X_rs,y_rs,'Random Sampling',ax=ax2).visualize_data()
fig.text(0.15,1,'Visualization of Original Data and Random Sampling', {'font':_\( \text{\circ} \tex
```

Original Data Original Data Original Data Original Data Original Data Original Data Stroke | No stroke Stroke | No stroke

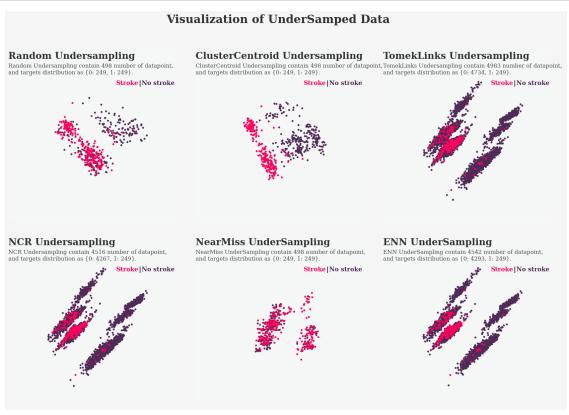
```
fig = plt.figure(figsize =(21,21))

gs = fig.add_gridspec(3,3)
gs.update(wspace = 0.1, hspace = 0.1)

ax1 = fig.add_subplot(gs[0,0])
ax2 = fig.add_subplot(gs[0,1])
ax3 = fig.add_subplot(gs[0,2])

ax4 = fig.add_subplot(gs[1,0])
ax5 = fig.add_subplot(gs[1,1])
ax6 = fig.add_subplot(gs[1,2])
```

```
axes = [ax1, ax2, ax3, ax4, ax5, ax6]
fig.patch.set_facecolor('#f5f5f5')
# setting of axes; visibility of axes and spines turn off
for ax in axes:
   ax.axes.get_yaxis().set_visible(False)
   ax.set facecolor('#f8f8f8')
random_state = 2021
# RandomUnderSampler
sampler = RandomUnderSampler(random_state = random_state)
X_rs, y_rs = sampler.fit_resample(X, y.ravel())
sampling(X rs,y_rs,'Random Undersampling',ax=ax1).visualize_data()
# ClusterCentroids
sampler = ClusterCentroids(random_state = random_state)
X_rs, y_rs = sampler.fit_resample(X, y.ravel())
sampling(X_rs,y_rs,'ClusterCentroid Undersampling',ax=ax2).visualize_data()
# TomekLinks
sampler = TomekLinks()
X_rs, y_rs = sampler.fit_resample(X, y.ravel())
sampling(X_rs,y_rs,'TomekLinks Undersampling',ax=ax3).visualize_data()
# NeighbourhoodCleaningRule
sampler = NeighbourhoodCleaningRule()
X_rs, y_rs = sampler.fit_resample(X, y.ravel())
sampling(X_rs,y_rs,'NCR Undersampling',ax=ax4).visualize_data()
# NearMiss
sampler = NearMiss()
X_rs, y_rs = sampler.fit_resample(X,y.ravel())
sampling(X_rs,y_rs,'NearMiss UnderSampling',ax=ax5).visualize_data()
# EditedNearestNeighbours
sampler = EditedNearestNeighbours()
X_rs, y_rs = sampler.fit_resample(X, y)
sampling(X_rs,y_rs,'ENN UnderSampling',ax=ax6).visualize_data()
```



```
[]: fig = plt.figure(figsize =(14,7))

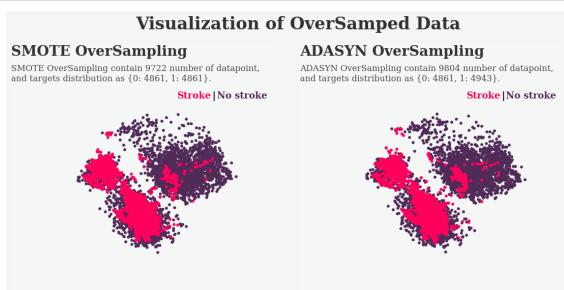
gs = fig.add_gridspec(1,2)
gs.update(wspace = 0.1, hspace = 0.1)

ax1 = fig.add_subplot(gs[0,0])
ax2 = fig.add_subplot(gs[0,1])

axes = [ax1, ax2]

fig.patch.set_facecolor('#f5f5f5')

# setting of axes; visibility of axes and spines turn off
for ax in axes:
    ax.axes.get_yaxis().set_visible(False)
    ax.set_facecolor('#f8f8f8')
```



0.5 Modelling and Results

```
[]: # training and testing data split

X_train, X_test, y_train, y_test = train_test_split(X,y, test_size = 0.25, □

⇒shuffle = True, random_state = 2021)
```

```
#smoteresampling
smote = SMOTE()
X_resample, y_resample = smote.fit_resample(X_train, y_train.ravel())

print('Shape of Training features: {}'.format(X_resample.shape))
print('Shape of Training targets: {}'.format(y_resample.shape))
print('Shape of Testing features: {}'.format(X_test.shape))
print('Shape of Testing targets: {}'.format(y_test.shape))

Shape of Training features: (7284, 24)
Shape of Training targets: (7284,)
Shape of Testing features: (1278, 24)
Shape of Testing targets: (1278,)

[]: # Null accuracy Score for current data
NUll_acc = round (max(y_test.mean(), 1 - y_test.mean()), 2)
print('Null Accuracy Score for Current Data is {}'.format(NUll_acc))
```

Null Accuracy Score for Current Data is 0.95

```
[]: #### predictions with resampled data
     def predictions(x_set,y_set):
         t1 = time.time()
         print('Classification Process Starts....')
         accuracy, precision, recall, f1, auc, conf_mat= [], [], [], [], [], []
         random state = 2021
         ##classifiers list
         classifiers = []
         classifiers.append(SVC(random_state=random_state, probability = True))
         classifiers.append(DecisionTreeClassifier(random_state=random_state))
         classifiers.
      →append(AdaBoostClassifier(DecisionTreeClassifier(random_state=random_state)))
         classifiers.append(RandomForestClassifier(random state=random state))
         classifiers.append(GradientBoostingClassifier(random_state=random_state))
         classifiers.append(KNeighborsClassifier())
         classifiers.append(LogisticRegression(random_state = random_state))
         classifiers.append(XGBClassifier(random_state = random_state,eval_metric =_u
      →'logloss',learning_rate = 0.054))
         classifiers.append(LGBMClassifier(random_state = random_state,learning_rate_
      \rightarrow= 0.067))
```

```
for classifier in classifiers:
            t =time.time()
            print('fitting on classifier with parameters: {}'.format(classifier))
            #classifier and fitting
            clf = classifier
            clf.fit(x set,y set)
            #predictions
            y_preds = clf.predict(X_test)
            y_probs = clf.predict_proba(X_test)
            # metrics
            accuracy.append((round(accuracy_score(y_test,y_preds),2))*100)
            precision.append((round(precision_score(y_test,y_preds),2))*100)
            recall.append((round(recall_score(y_test,y_preds),2))*100)
            f1.append((round(f1_score(y_test,y_preds),2))*100)
            auc.append((round (roc_auc_score(y_test,y_probs[:,1]), 2))*100)
            conf_mat.append(confusion_matrix(y_test,y_preds))
            elapsed = time.time() - t
            print('Done and elapsed time is {}seconds'.format(round(elapsed,3)))
            print('\n')
        results_df = pd.DataFrame({"Accuracy Score":accuracy, "Precision Score":
     →precision,
                           "Recall Score":recall, "f1 Score":f1, "AUC Score":auc,
                           "Confusion Matrix":conf_mat,
                            "Algorithm":["SVC","DecisionTree","AdaBoost",
                                        "RandomForest", "GradientBoosting",
                                        "KNeighboors", "LogisticRegression",
                                        "XGBoost", "LightGBM"]})
        results_df = (results_df.sort_values(by = 'Algorithm', ascending = False)
                      .reset_index(drop = True))
        t2 = time.time() - t1
        print('\nClassification is Completed and results are strored in dataframe.
     →\ntotal time elapsed is {}seconds'.format(t2))
        return results_df
[]: orig_results = predictions(X_train,y_train)
```

```
Classification Process Starts...
```

resamp_results = predictions(X_resample,y_resample)

```
fitting on classifier with parameters: SVC(probability=True, random state=2021)
Done and elapsed time is 3.053seconds
fitting on classifier with parameters: DecisionTreeClassifier(random_state=2021)
Done and elapsed time is 0.11seconds
fitting on classifier with parameters:
AdaBoostClassifier(estimator=DecisionTreeClassifier(random_state=2021))
Done and elapsed time is 0.108seconds
fitting on classifier with parameters: RandomForestClassifier(random_state=2021)
Done and elapsed time is 1.186seconds
fitting on classifier with parameters:
GradientBoostingClassifier(random_state=2021)
Done and elapsed time is 1.335seconds
fitting on classifier with parameters: KNeighborsClassifier()
Done and elapsed time is 0.4seconds
fitting on classifier with parameters: LogisticRegression(random_state=2021)
Done and elapsed time is 0.203seconds
fitting on classifier with parameters: XGBClassifier(base_score=None,
booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable categorical=False, eval metric='logloss',
              feature_types=None, gamma=None, grow_policy=None,
              importance_type=None, interaction_constraints=None,
              learning_rate=0.054, max_bin=None, max_cat_threshold=None,
              max_cat_to_onehot=None, max_delta_step=None, max_depth=None,
              max_leaves=None, min_child_weight=None, missing=nan,
              monotone_constraints=None, multi_strategy=None, n_estimators=None,
              n_jobs=None, num_parallel_tree=None, random_state=2021, ...)
Done and elapsed time is 1.541seconds
fitting on classifier with parameters: LGBMClassifier(learning_rate=0.067,
random_state=2021)
[LightGBM] [Warning] Found whitespace in feature names, replace with underlines
```

[LightGBM] [Info] Number of positive: 190, number of negative: 3642 [LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing was 0.000765 seconds. You can set `force_row_wise=true` to remove the overhead. And if memory is not enough, you can set `force col wise=true`. [LightGBM] [Info] Total Bins 654 [LightGBM] [Info] Number of data points in the train set: 3832, number of used features: 22 [LightGBM] [Info] [binary:BoostFromScore]: pavg=0.049582 -> initscore=-2.953264 [LightGBM] [Info] Start training from score -2.953264 Done and elapsed time is 0.385seconds Classification is Completed and results are strored in dataframe. total time elapsed is 8.357976913452148seconds ************************ Classification Process Starts... fitting on classifier with parameters: SVC(probability=True, random_state=2021) Done and elapsed time is 11.161seconds fitting on classifier with parameters: DecisionTreeClassifier(random_state=2021)

Done and elapsed time is 0.056seconds

fitting on classifier with parameters: AdaBoostClassifier(estimator=DecisionTreeClassifier(random_state=2021)) Done and elapsed time is 0.063seconds

fitting on classifier with parameters: RandomForestClassifier(random_state=2021) Done and elapsed time is 0.813seconds

fitting on classifier with parameters: GradientBoostingClassifier(random_state=2021) Done and elapsed time is 1.309seconds

fitting on classifier with parameters: KNeighborsClassifier() Done and elapsed time is 0.179seconds

fitting on classifier with parameters: LogisticRegression(random_state=2021) Done and elapsed time is 0.119seconds

```
fitting on classifier with parameters: XGBClassifier(base score=None,
    booster=None, callbacks=None,
                  colsample bylevel=None, colsample bynode=None,
                  colsample_bytree=None, device=None, early_stopping_rounds=None,
                  enable categorical=False, eval metric='logloss',
                 feature_types=None, gamma=None, grow_policy=None,
                  importance_type=None, interaction_constraints=None,
                 learning_rate=0.054, max_bin=None, max_cat_threshold=None,
                 max_cat_to_onehot=None, max_delta_step=None, max_depth=None,
                 max_leaves=None, min_child_weight=None, missing=nan,
                 monotone constraints=None, multi_strategy=None, n_estimators=None,
                 n_jobs=None, num_parallel_tree=None, random_state=2021, ...)
    Done and elapsed time is 0.287seconds
    fitting on classifier with parameters: LGBMClassifier(learning_rate=0.067,
    random state=2021)
    [LightGBM] [Warning] Found whitespace in feature names, replace with underlines
    [LightGBM] [Info] Number of positive: 3642, number of negative: 3642
    [LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
    testing was 0.001480 seconds.
    You can set `force_row_wise=true` to remove the overhead.
    And if memory is not enough, you can set `force_col_wise=true`.
    [LightGBM] [Info] Total Bins 810
    [LightGBM] [Info] Number of data points in the train set: 7284, number of used
    features: 22
    [LightGBM] [Info] [binary:BoostFromScore]: payg=0.500000 -> initscore=0.000000
    Done and elapsed time is 0.218seconds
    Classification is Completed and results are strored in dataframe.
    total time elapsed is 14.21110987663269seconds
    *******************
[]: def multi_visualize(data, vmin = -0.5, vmax = 1):
        fig = plt.figure(figsize =(24,24))
        gs = fig.add_gridspec(8,6)
        gs.update(wspace = 0.2, hspace = 0.1)
```

```
fig = plt.figure(figsize = (24,24))
gs = fig.add_gridspec(8,6)
gs.update(wspace = 0.2, hspace = 0.1)

ax1 = fig.add_subplot(gs[0,0])
ax2 = fig.add_subplot(gs[0,1])
ax3 = fig.add_subplot(gs[0,2])
```

```
ax4 = fig.add_subplot(gs[1,0])
ax5 = fig.add_subplot(gs[1,1])
ax6 = fig.add_subplot(gs[1,2])
ax7 = fig.add_subplot(gs[2,0])
ax8 = fig.add_subplot(gs[2,1])
ax9 = fig.add_subplot(gs[2,2])
ax10 = fig.add_subplot(gs[0,3])
ax11 = fig.add_subplot(gs[0,4])
ax12 = fig.add_subplot(gs[0,5])
ax13 = fig.add_subplot(gs[1,3])
ax14 = fig.add_subplot(gs[1,4])
ax15 = fig.add_subplot(gs[1,5])
ax16 = fig.add_subplot(gs[2,3])
ax17 = fig.add_subplot(gs[2,4])
ax18 = fig.add_subplot(gs[2,5])
axes1 = [ax1, ax2, ax3, ax4, ax5, ax6, ax7, ax8, ax9]
axes2 = [ax10, ax11, ax12, ax13, ax14, ax15, ax16, ax17, ax18]
axes = [axes1, axes2]
fig.patch.set_facecolor('#f6f5f5')
# setting of axes; visibility of axes and spines turn off
for ax_list in axes:
    for ax in ax_list:
        ax.axes.get_yaxis().set_visible(False)
        ax.axes.get_xaxis().set_visible(False)
        ax.set_facecolor('#f6f5f5')
colors = ['#512b58','#fe346e']
colormap = matplotlib.colors.LinearSegmentedColormap.from_list("", colors)
for ax_list in axes:
    if ax_list == axes1:
        res_df = data[0]
    else:
        res_df = data[1]
```

```
alg = res_df['Algorithm']
      cf = res_df['Confusion Matrix']
      auc = res_df['AUC Score']
      f1 = res_df['f1 Score']
      forig = data[0]['f1 Score']
      fresam = data[1]['f1 Score']
      n = 0
      for ax in ax_list:
          cf_mat = cf[n]
          #### annotations
          labels = ['True Neg', 'False Pos', 'False Neg', 'True Pos']
          counts = ["{0:0.0f}".format(value) for value in cf_mat.flatten()]
          percentages = ["{0:.2%}".format(value) for value in cf_mat.
→flatten()/np.sum(cf_mat)]
          #### final annotations
          label = (np.array([f'{v1}\n{v2}\n{v3}' for v1,v2,v3 in_{})
→zip(labels,counts,percentages)])).reshape(2,2)
          #### heatmap
          sns.heatmap(data = cf_mat, vmin = vmin, vmax = vmax, cmap = u
→['grey'],linewidth=2,linecolor = '#f6f5f5',
             ax = ax, annot = label, fmt ='', cbar = False, annot_kws =_u
→{'font':'serif','size':10, 'color':'white','weight':'bold'}, alpha =0.8)
          #### subtitle
          if ax_list == axes1:
              ax.text(0,-0,'{}'.format(alg[n]),{'font':'serif','size':12,__
else:
              ax.text(0,-0,'SMOTE {}'.format(alg[n]),{'font':'serif','size':
→12, 'color':'black', 'weight':'bold'})
          #### Auc and F1 score plotting
          if ax_list == axes2:
              if (fresam[n] > forig[n]) & (auc[n] > 75):
                  ax.scatter( 1 , 1 , s = 3500, c = '#fe346e')
                  ax.text(0.75,1.1, 'F1: {}\nAUC: {}'.
→format(int(round(f1[n],1)), int(round(auc[n],1))), {'font': 'serif', 'size':12, □
else:
```

```
ax.scatter(1, 1, s = 3500, c = 'white')
                 ax.text(0.75,1.1, 'F1: {}\nAUC: {}'.
→format(int(round(f1[n],1)), int(round(auc[n],1))), {'font': 'serif', 'size':12, ___
else:
              if (forig[n] > 5) & (auc[n] > 75):
                  ax.scatter(1, 1, s = 3500, c = \frac{$12b58}{}, alpha = 0.9)
                  ax.text(0.75,1.1, 'F1: {}\nAUC: {}'.

¬format(int(round(f1[n],1)), int(round(auc[n],1))), {'font': 'serif', 'size':12, □
→'color':'white', 'weight':'bold'})
              else:
                  ax.scatter(1, 1, s = 3500, c = 'white')
                  ax.text(0.75,1.1, 'F1: {}\nAUC: {}'.
→format(int(round(f1[n],1)), int(round(auc[n],1))), {'font': 'serif', 'size':12, □
n +=1
      if ax_list == axes1:
          ax1.text(0,-0.55,'Visualization of Results with - Original
→Data',{'font':'serif','size':24, 'color':'black', 'weight':'bold'},)
      else:
          ax10.text(0,-0.55,'Visualization of Results with - Oversampled_
→Data',{'font':'serif','size':24, 'color':'black', 'weight':'bold'}, alpha = (
→0.9)
  fig.show()
```

[]: multi_visualize(data = [orig_results, resamp_results], vmin=30,vmax = 100)

