```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.graph_objs as go
from plotly.subplots import make_subplots
import os
from urllib.request import urlretrieve
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import SMOTE

```

Il dataset preso in considerazione contiene informazioni utili per la predizione di infarti. Il dataset contiene le informazioni di 5000 pazienti, per ognuno di essi è specificato se hanno avuto un'infarto (stroke = 1) o no (stroke = 0), l'obbiettivo è predire questa variabile discreta

```
def download(file, url):
    if not os.path.isfile(file):
        urlretrieve(url, file)
```

```
download("strokes.csv", "https://raw.githubusercontent.com/giacomoaccursi/proget
```

```
data = pd.read_csv("strokes.csv")
```

1. id: identificatore unico
2. gender: il genere della persone. "Male", "Female" or "Other"
3. age: l'età del paziente
4. hypertension: 0 se il paziente non soffre di ipertensione, 1 se ne soffre
5. heart_disease: 0 se il paziente non ha malattie cardiache, 1 se ne ha
6. ever_married: "No" se non si è mai sposato o "Yes" altrimenti
7. work_type: "children", "Govt_jov", "Never_worked", "Private" or "Self-employed"
8. Residence_type: "Rural" se vive in campagna o "Urban" se vive in città
9. avg_glucose_level: livello medio di glucosio nel sangue
10. bmi: indice di massa corporea, rapporto fra peso e quadrato dell'altezza
11. smoking_status: "formerly smoked" se ha fumato in precedenza, "never smoked" se non ha mai fumato, "smokes" se fuma attualmente o "Unknown" se il dato è sconosciuto
12. stroke: 1 se il paziente ha avuto un infarto, 0 altrimenti.

Essendo la variabile stroke discreta, siamo di fronte ad un problema di classificazione con due classi.

```
data.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
```

La variabile id identifica univocamente il paziente. Non è quindi utile nella predizione. Può essere usata come indice della riga.

```
1 data.set_index('id', inplace=True)
```

```
1 data.head()
```

	gender	age	hypertension	heart_disease	ever_married	work_type	Resic
id							
9046	Male	67.0	0	1	Yes	Private	
51676	Female	61.0	0	0	Yes	Self-employed	
31112	Male	80.0	0	1	Yes	Private	
60182	Female	49.0	0	0	Yes	Private	
1665	Female	79.0	1	0	Yes	Self-employed	

Rinominiamo la colonna Residence_type cosicchè tutte le feature abbiano la prima lettera minuscola

```
1 data.rename(columns={'Residence_type': 'residence_type'}, inplace=True)
```

```
1 data['ever_married'] = data["ever_married"].replace({'No' : 0, 'Yes' : 1})
```

```
1 data.describe()
```

	age	hypertension	heart_disease	ever_married	avg_glucose_level
count	5110.000000	5110.000000	5110.000000	5110.000000	5110.00000C
mean	43.226614	0.097456	0.054012	0.656164	106.147677
std	22.612647	0.296607	0.226063	0.475034	45.28356C
min	0.080000	0.000000	0.000000	0.000000	55.12000C
25%	25.000000	0.000000	0.000000	0.000000	77.24500C
50%	45.000000	0.000000	0.000000	1.000000	91.88500C
75%	61.000000	0.000000	0.000000	1.000000	114.09000C
max	82.000000	1.000000	1.000000	1.000000	271.74000C

- L'età media dei pazienti è circa 43 anni, il più giovane ha meno di un anno e il più anziano ne ha 42. Il 50% degli esaminati ha più di 45 anni.

```
1 (data.describe(exclude = ['float', 'int64']))
```

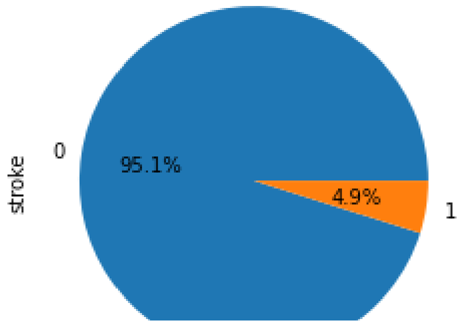
	gender	work_type	residence_type	smoking_status
count	5110	5110	5110	5110
unique	3	5	2	4
top	Female	Private	Urban	never smoked
freq	2994	2925	2596	1892

In un secondo momento occorrerà trattare i valori bmi nulli

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

```
gender                0
age                   0
hypertension          0
heart_disease         0
ever_married          0
work_type             0
residence_type        0
avg_glucose_level     0
bmi                 201
smoking_status        0
stroke                0
dtype: int64
```

```
1 data['stroke'].value_counts().plot.pie(autopct='%1.1f%%');
```



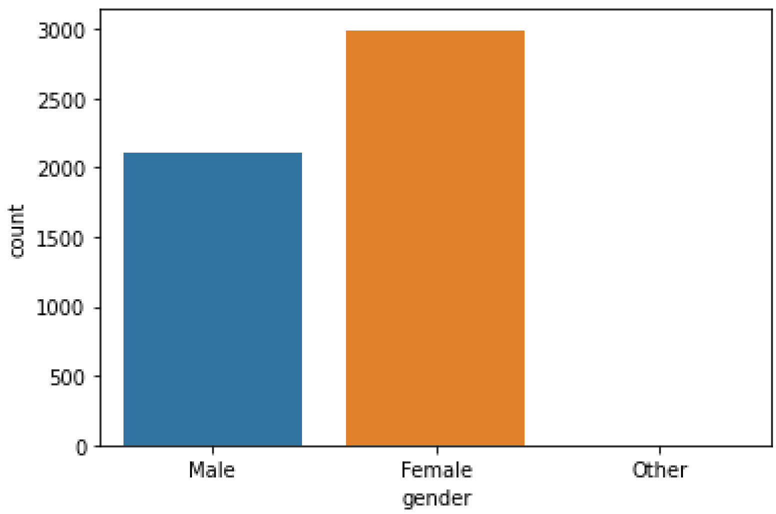
Si noti come il dataset risulti fortemente sbilanciato: il numero di persone che hanno avuto un infarto è nettamente inferiore a quelle che non l'hanno avuto. Nelle fasi successive si cercherà di risolvere questo problema

Data Exploration

Circa il 60% delle persone in esame sono donne.

```
sns.countplot(data['gender']);
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarni
Pass the following variable as a keyword arg: x. From version 0.12, the only
```

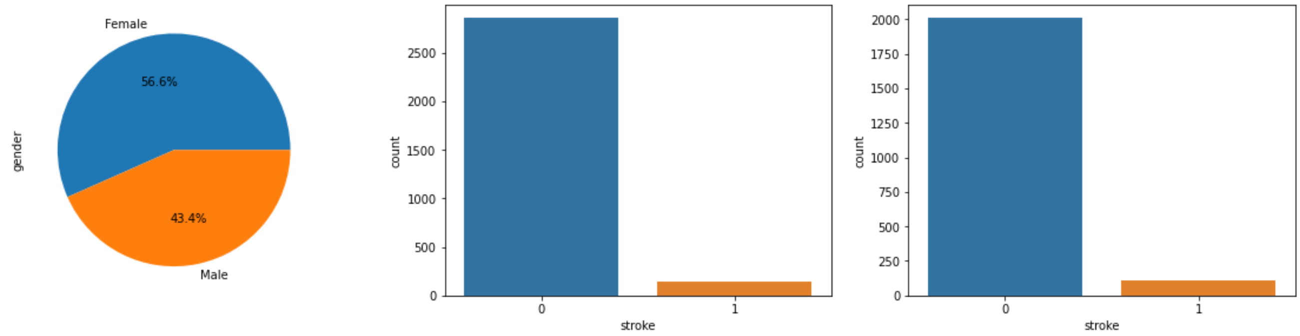


Sembra che il sesso non influisca sulla probabilità di avere un infarto.

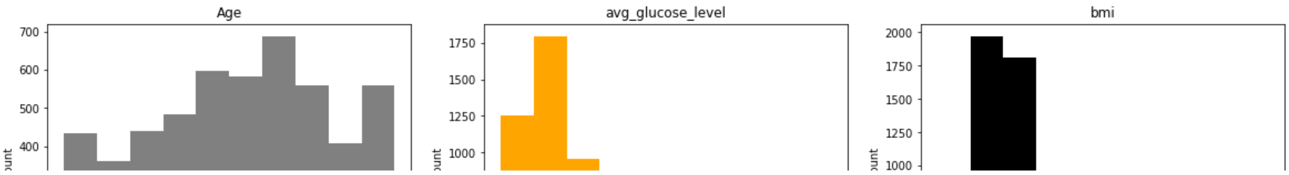
```
fig = plt.figure(figsize=(20, 10))
plt.subplot(2, 3, 1)
(data[data["stroke"] == 1]["gender"]).value_counts().plot.pie(autopct='%1.1f%%')
plt.subplot(2, 3, 2)
sns.countplot((data[data["gender"] == "Female"]["stroke"]))
plt.subplot(2, 3, 3)
sns.countplot((data[data["gender"] == "Male"]["stroke"]))
```

```
sns.countplot((data[data['gender'] == 'Male']['stroke']))
fig.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarni

Pass the following variable as a keyword arg: x. From version 0.12, the only

/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarni

Pass the following variable as a keyword arg: x. From version 0.12, the only
```




```
plt.figure(figsize=(20, 10))

plt.subplot(2, 3, 1)
plt.title('Age')
plt.hist(data['age'], label="weight", color='gray')
plt.ylabel('count')
plt.xlabel('Year')


plt.subplot(2, 3, 2)
plt.title('avg_glucose_level')
plt.hist(data['avg_glucose_level'], label="weight", color="orange")
plt.ylabel('count')
plt.xlabel('mg/dl')

plt.subplot(2, 3, 3)
plt.title('bmi')
plt.hist(data['bmi'], label="weight", color="black")
plt.ylabel('count')
plt.xlabel('kg/m2')

plt.show()
```




```
((data["bmi"] > 25) & (data["bmi"] < 30)).mean()
```

    0.27045009784735813


```
(data["bmi"] > 30).mean()
```

    0.37045009784735813

Non è specificato se i valori di glucosio nel sangue siano stati rilevati a digiuno o dopo 120' dal carico orale di glucosio. Secondo l'indicatore bmi il 27% delle persone in esame risulti sovrappesa e il 37% obesa, si noti però che il bmi non è un buon indicatore per il fatto che tiene in considerazione solo l'altezza in relazione al peso senza considerare la percentuale di grasso corporeo.

Valori glicemici a digiuno:

- Normale : 80-99 mg/dl
- Alterata : 100-125 mg/dl
- DIabete : >126

Valori glicemici dopo 120' dal carico orale di glucosio:

- Normale : <140 mg/dl
- Alterata : 140-200 mg/dl
- DIabete : >200

valori bmi:

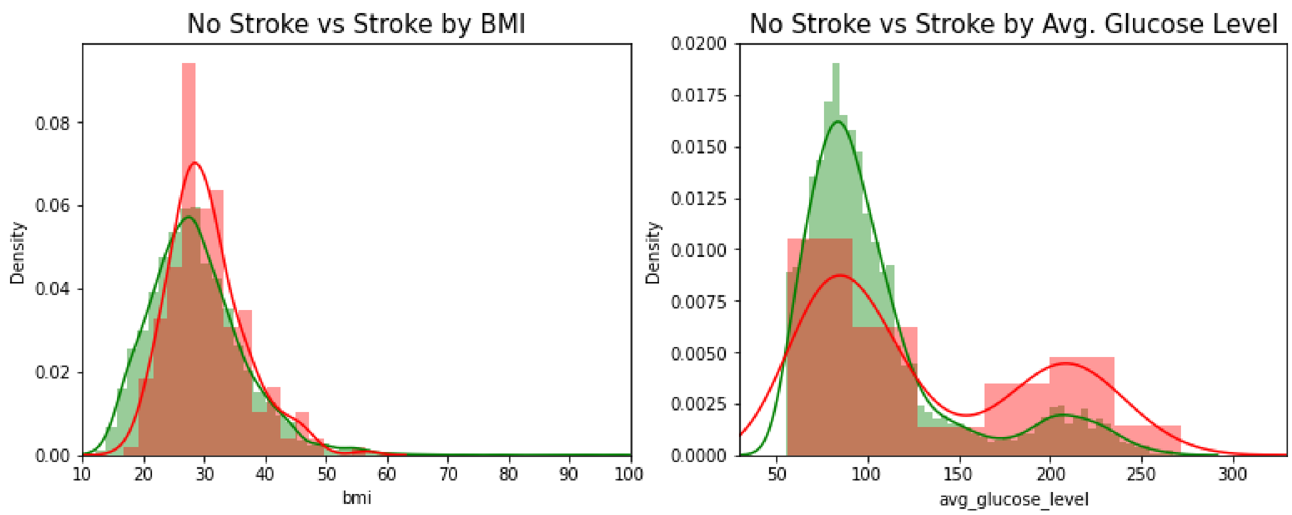
- Sottopeso : <18.5
- Normale : 18.5 - 24.9
- Sovrappeso : 25- 29.9
- Obeso : >30

SI noti come per valori bmi superiori a 30 la probabilità di avere infarti aumenti leggermente e come livelli di glucosio superiori a 150 corrispondano ad un numero maggiore di infarti.

```
plt.figure(figsize=(20, 10))

plt.subplot(2, 3, 1)
sns.distplot(data[data['stroke'] == 0]["bmi"], color='green') # No Stroke - gree
sns.distplot(data[data['stroke'] == 1]["bmi"], color='red') # Stroke - Red

plt.title('No Stroke vs Stroke by BMI', fontsize=15)
```

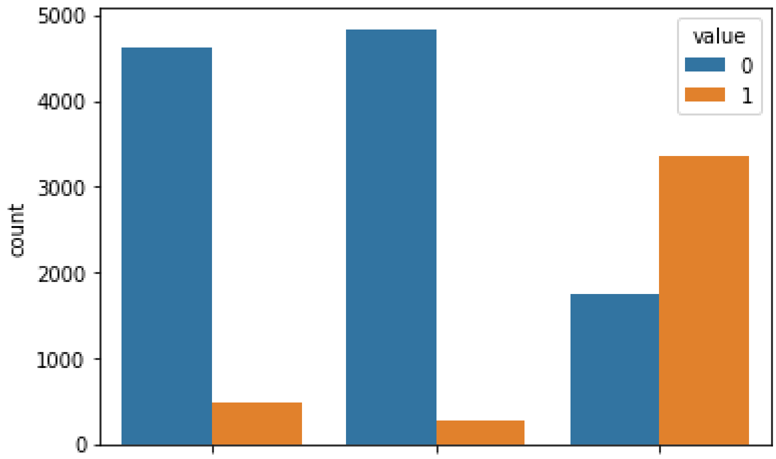
```
plt.xlim([10,100])

plt.subplot(2, 3, 2)
sns.distplot(data[data['stroke'] == 0]["avg_glucose_level"], color='green') # No
sns.distplot(data[data['stroke'] == 1]["avg_glucose_level"], color='red') # Stro

plt.title('No Stroke vs Stroke by Avg. Glucose Level', fontsize=15)
plt.xlim([30,330])
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWa

`distplot` is a deprecated function and will be removed in a future version. I

/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWa

`distplot` is a deprecated function and will be removed in a future version. I

/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWa

`distplot` is a deprecated function and will be removed in a future version. I

/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWa

`distplot` is a deprecated function and will be removed in a future version. I
```



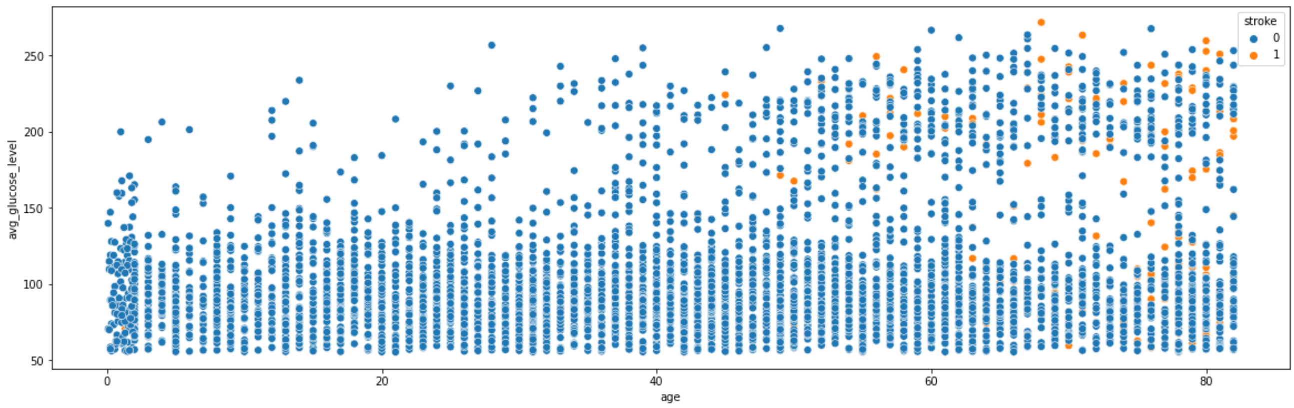
Dal seguente istogramma emerge come le persone che sono state o sono sposate abbiamo una probabilità maggiore di avere un infarto, tuttavia questo è molto probabilmente causato dal fatto che le persone sposate o che sono state sposate hanno un'età maggiore delle persone che non si sono sposate.

```
sns.countplot(x="variable", hue="value", data= pd.melt(data.loc[:, ['hypertensio
```



Dal seguente scatterplot si nota come gli infarti sono più diffusi nelle persone in età avanzata e con livelli di glucosio alti.

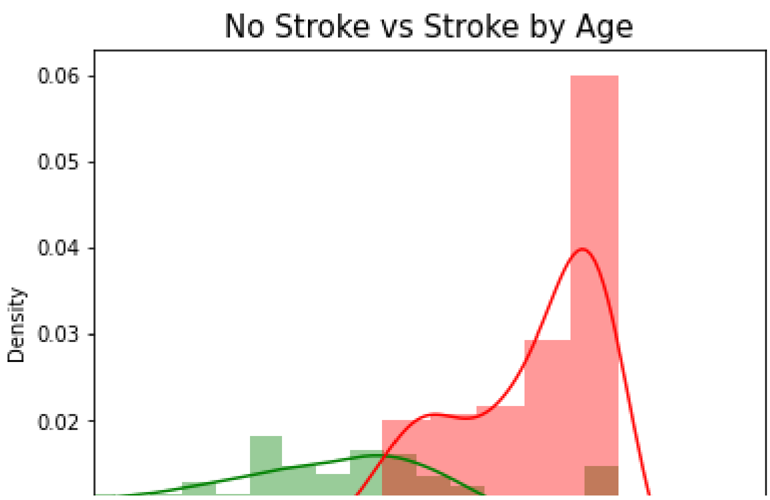
```
fig = plt.gcf()
fig.set_size_inches(20, 6)
sns.scatterplot(x=data['age'],y=data['avg_glucose_level'],hue=data['stroke'], s=
```



Come previsto il numero di infarti è maggiore nelle persone più anziane.

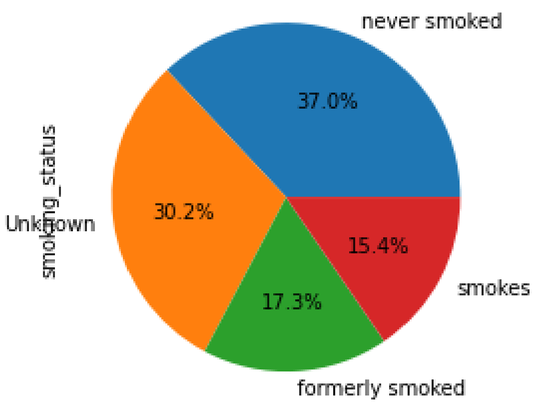
```
plt.figure(figsize=(6,5))

sns.distplot(data[data['stroke'] == 0]["age"], color='green') # No Stroke - gree
sns.distplot(data[data['stroke'] == 1]["age"], color='red') # Stroke - Red

plt.title('No Stroke vs Stroke by Age', fontsize=15)
plt.xlim([18,100])
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWa
`distplot` is a deprecated function and will be removed in a future version. I
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWa
`distplot` is a deprecated function and will be removed in a future version. I
```



Il numero di infarti è maggiore nelle persone che non hanno mai fumato rispetto a quelle che hanno fumato o fumano tuttora. Ricordiamoci comunque che del 30% del dataset in questione non abbiamo informazioni.

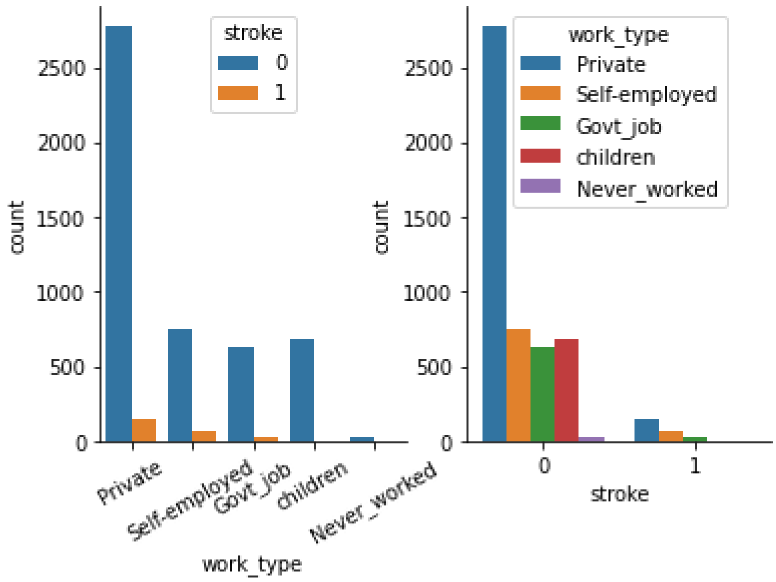
```
data['smoking_status'].value_counts().plot.pie(autopct='%1.1f%%');
```



Non sembra che ci siano lavori che influenzano la probabilità di avere un infarto

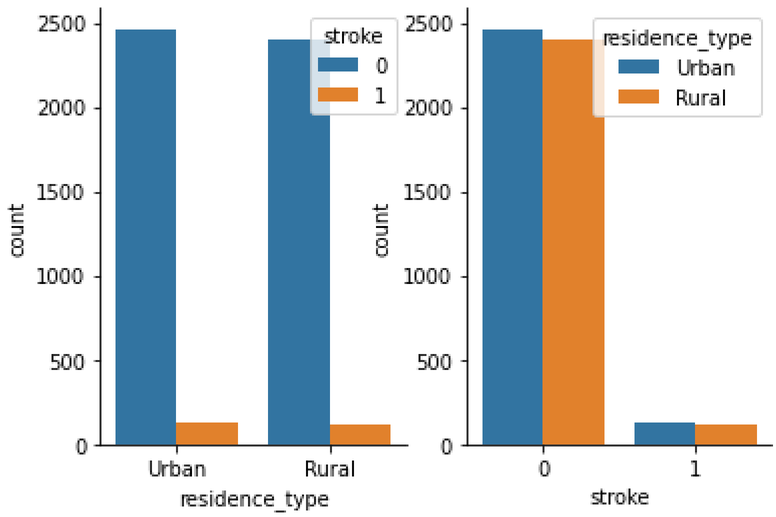
```
plt.subplot(1, 2, 1)

sns.countplot(x='work_type', hue='stroke', data=data)
plt.xticks(rotation=30)
sns.despine()

plt.subplot(1, 2, 2)
sns.countplot(x='stroke', hue='work_type', data=data)
sns.despine()
```

```

plt.show()
```



Lo stesso discorso vale per la residenza delle persone: vivere in città o in campagna non sembra rilevante

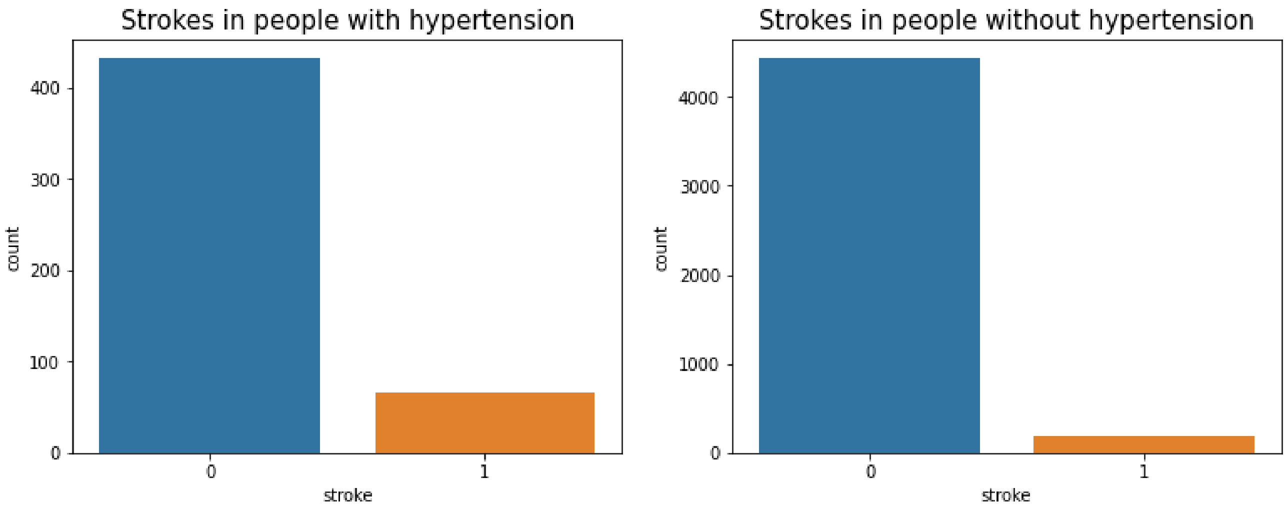
```
plt.subplot(1, 2, 1)

sns.countplot(x='residence_type', hue='stroke', data=data)
sns.despine()

plt.subplot(1, 2, 2)
sns.countplot(x='stroke', hue='residence_type', data=data)
sns.despine()

plt.show()
```



I seguenti istogrammi evidenziano come problemi al cuore e ipertensione aumentino la probabilità di avere un infarto

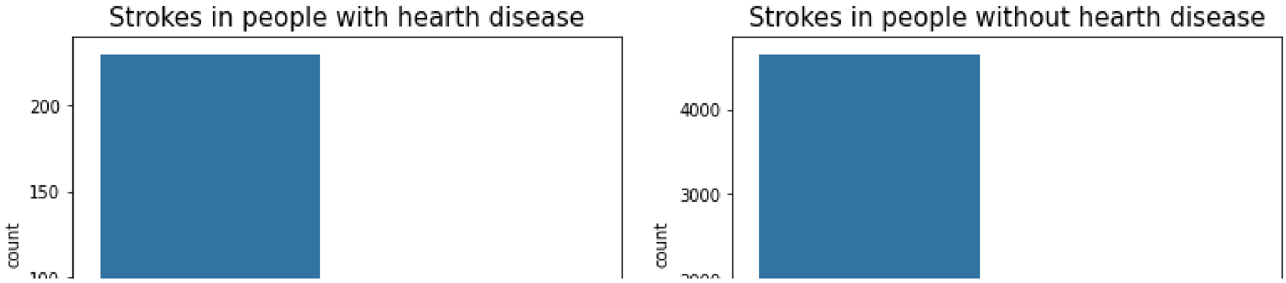
```
plt.figure(figsize=(20, 10))
plt.subplot(2, 3, 1)
plt.title('Strokes in people with hypertension', fontsize=15)
sns.countplot((data[data["hypertension"] == 1]["stroke"]))
plt.subplot(2, 3, 2)
plt.title('Strokes in people without hypertension', fontsize=15)
sns.countplot((data[data["hypertension"] == 0]["stroke"]))
fig.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarni

Pass the following variable as a keyword arg: x. From version 0.12, the only 

/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarni

Pass the following variable as a keyword arg: x. From version 0.12, the only 
```




```
plt.figure(figsize=(20, 10))
plt.subplot(2, 3, 1)
plt.title('Strokes in people with hearth disease', fontsize=15)
sns.countplot((data[data["heart_disease"] == 1]["stroke"]))
plt.subplot(2, 3, 2)
plt.title('Strokes in people without hearth disease', fontsize=15)
sns.countplot((data[data["heart_disease"] == 0]["stroke"]))
fig.show()
```

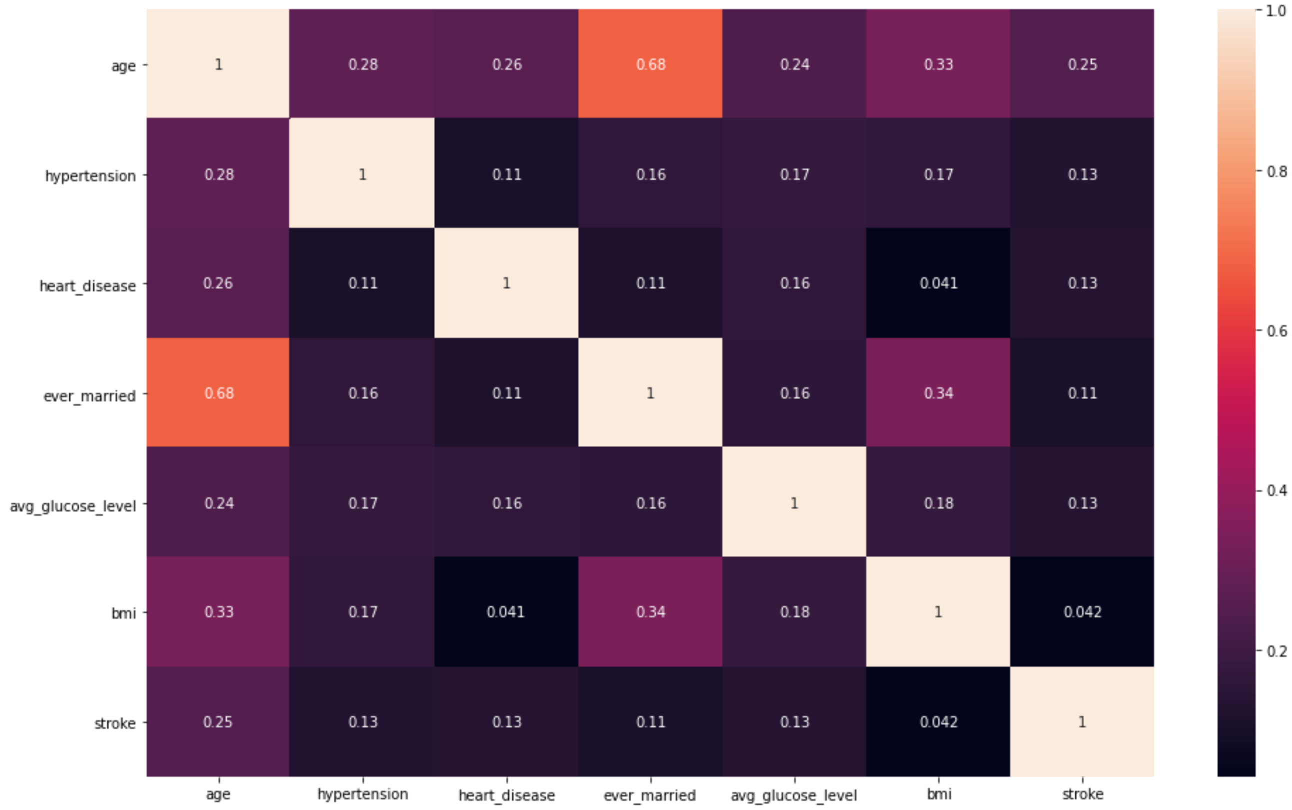
```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarni

Pass the following variable as a keyword arg: x. From version 0.12, the only 

/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarni

Pass the following variable as a keyword arg: x. From version 0.12, the only 
```




```
plt.figure(figsize=(15, 15))
plt.subplot(4,2,1)
sns.countplot(data['work_type'])
plt.subplot(4,2,2)
sns.countplot(data['residence_type'])
plt.subplot(4,2,3)
sns.countplot(data['smoking_status'])
plt.subplot(4,2,4)
sns.countplot(data['ever_married'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarni
Pass the following variable as a keyword arg: x. From version 0.12, the only
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarni
Pass the following variable as a keyword arg: x. From version 0.12, the only
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarni
Pass the following variable as a keyword arg: x. From version 0.12, the only
```

```
plt.figure(figsize=(16,10))
sns.heatmap(data.corr(method='pearson'), annot=True);
```



Come ipotizzato in precedenza esiste una correlazione abbastanza forte fra l'età e il numero di persone sposate.

Feature engineering

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

```
gender                0
```

```
age                   0
hypertension          0
heart_disease         0
ever_married          0
work_type             0
residence_type        0
avg_glucose_level     0
bmi                 201
smoking_status        0
stroke                0
dtype: int64
```

Elimiamo i record con ibm nullo

```
data.dropna(inplace=True)
```

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

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

```
data["age"] = data["age"].astype(int)
data["avg_glucose_level"] = data["avg_glucose_level"].astype(int)
data["bmi"] = data["bmi"].astype(int)
```

Il dataset risulta fortemente sbilanciato, creiamo quindi nuovi record. E' stato utilizzato SMOTENC al posto di SMOTE poichè è più indicato nei casi in cui si hanno sia variaibili categoriche che numeriche

```
categorical_features = ["gender", "work_type", "residence_type", "smoking_status
data = pd.get_dummies(data, columns=categorical_features, prefix=categorical_fea
```

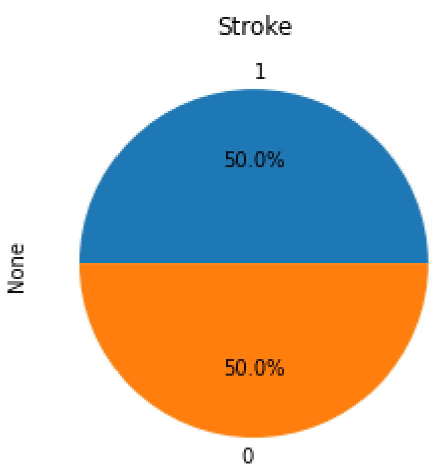
```
data
```

	age	hypertension	heart_disease	ever_married	avg_glucose_level	bmi
id						
9046	67	0	1	1	228	36
31112	80	0	1	1	105	32
60182	49	0	0	1	171	34
1665	79	1	0	1	174	24
56669	81	0	0	1	186	29
...	...	...	...	...	...	...
14180	13	0	0	0	103	18
44873	81	0	0	1	125	40

```
sm = SMOTE(random_state=42)
y = data["stroke"]
X = data.drop("stroke", axis=1)
X, y = sm.fit_resample(X, y)

```

```
/usr/local/lib/python3.7/dist-packages/sklearn/externals/six.py:31: FutureWar
The module is deprecated in version 0.21 and will be removed in version 0.23 
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:144: Futu
The sklearn.neighbors.base module is  deprecated in version 0.22 and will be 
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87: Futur
Function safe_indexing is deprecated; safe_indexing is deprecated in version 
```

```
pd.value_counts(y).plot.pie(autopct="%.1f%%", title="Stroke");
```




```
from sklearn.compose import make_column_transformer
```

```
from sklearn.compose import make_column_transformer
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
from sklearn.pipeline import Pipeline
from sklearn.metrics import classification_report
from sklearn.metrics import mean_squared_error
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import PolynomialFeatures
from sklearn.metrics import precision_score, recall_score, f1_score

```

```
scaler = StandardScaler()
X = scaler.fit_transform(X)
```

```
X_train, X_val, y_train, y_val = train_test_split(
    X,y,
    test_size = 1/3,
    random_state = 42
)
```

```
models = {}
kf = KFold(n_splits=5, shuffle=True, random_state=42)
```

```
def accuracy_interval(f):
  N = len(y_val)
  n_min = f + ( 1.96**2/(2*N) - 1.96 * np.sqrt( (f/N) - (f**2/N) + (1.96**2/(4*N
  n_max = f + ( 1.96**2/(2*N) + 1.96 * np.sqrt( (f/N) - (f**2/N) + (1.96**2/(4*N
  d = 1 + (1.96**2 / N)
  e_min = n_min / d
  e_max = n_max / d
  return np.round(e_min,4), np.round(e_max,4)
```

```
from sklearn.linear_model import Perceptron

std_perceptron = Perceptron(n_jobs=-1, early_stopping=True, n_iter_no_change=5)

parameters = {
    'penalty': [None, 'l1', 'l2', 'elasticnet'],
    'alpha': [0.0001, 0.001, 0.01, 1],
    'tol': [1e-9, 1e-6, 1e-3, 1, 1e3, 1e6],
}

perceptron_cv = GridSearchCV(std_perceptron, parameters, cv=kf, n_jobs=-1)
perceptron_cv.fit(X_train, y_train)

print('Best parameters:', perceptron_cv.best_params_)

models["Perceptron"] = {"Model": perceptron_cv.best_estimator_ , "Score" : perce
```

```
Best parameters: {'alpha': 0.0001, 'penalty': 'l1', 'tol': 1e-09}
```

```
poly_perceptron = Pipeline([
    ('poly', PolynomialFeatures(degree=3)),
    ('perceptron', Perceptron(n_jobs=-1, early_stopping=True, n_iter_no_change=5
])

parameters = {
    'perceptron__penalty': ['l1', 'l2'],
    'perceptron__alpha': [0.0001, 0.001, 0.01],
    'perceptron__tol': [1e-9, 1e-6, 1e-3, 1],
}

poly_perceptron_cv = GridSearchCV(poly_perceptron, parameters, cv=kf, n_jobs=-1,
poly_perceptron_cv.fit(X_train, y_train)

print('Best parameters:', poly_perceptron_cv.best_params_)

models["Perceptron"] = {"Model": perceptron_cv.best_estimator_ , "Score" : poly_
```

```
Best parameters: {'perceptron__alpha': 0.0001, 'perceptron__penalty': 'l1', '
```

```
from sklearn.linear_model import LogisticRegression

std_lr = LogisticRegression(solver="saga", random_state=42)
grid = [
    {
        "penalty": ["l2", "l1"],
        "C": [0.1, 1, 10],
        "tol" : [1e-9, 1e-6, 1e-3, 1e-2, 1e-1, 1]
    },
    {
        "penalty": ["elasticnet"],
        "C": [0.1, 1, 10],
        "l1_ratio": [0.2, 0.5],
        "tol" : [1e-9, 1e-6, 1e-3, 1e-2, 1e-1, 1]
    }
]

lr_gs = GridSearchCV(std_lr, grid, cv=kf, n_jobs=-1, return_train_score=True)
lr_gs.fit(X_train, y_train)

print('Best parameters:', lr_gs.best_params_)

models["Logistic Regression"] = {"Model": lr_gs.best_estimator_ , "Score" : lr_g
```

```
Best parameters: {'C': 0.1, 'l1_ratio': 0.5, 'penalty': 'elasticnet', 'tol': (
```

```
from sklearn.neighbors import KNeighborsClassifier
knc = KNeighborsClassifier(n_jobs=-1)
grid = {
        'n_neighbors': range(1, 10, 1),
        'weights': ['uniform', 'distance']
```

```
}

knc_gs = GridSearchCV(knc, grid, cv=kf, n_jobs=-1, return_train_score=True)
knc_gs.fit(X_train, y_train)

print('Best parameters:', knc_gs.best_params_)

models["KNeighborsClassifier"] = {"Model": knc_gs.best_estimator_ , "Score" : kn
```

```
Best parameters: {'n_neighbors': 2, 'weights': 'uniform'}
```

```
from sklearn.svm import SVC
std_svm = SVC()

grid = {
    'kernel': ['rbf'],
    'C': [0.01, 0.1, 1],
}

svm_gs = GridSearchCV(std_svm, grid, cv=kf, n_jobs=-1, return_train_score=True)
svm_gs.fit(X_train, y_train)

print('Best parameters:', lr_gs.best_params_)

models["Support Vector Machine"] = {"Model": svm_gs.best_estimator_ , "Score" :
```

```
Best parameters: {'C': 0.1, 'l1_ratio': 0.5, 'penalty': 'elasticnet', 'tol': (
```

```
from sklearn.tree import DecisionTreeClassifier

d_tree = DecisionTreeClassifier(random_state=42)

grid = {
            'min_samples_split': range(2, 4, 1),
            'min_samples_leaf': range(1, 4, 1),
            'max_depth': [None] + [i for i in range(2, 7)],
            'max_features': range(2, data.columns.size, 1)}


d_tree = GridSearchCV(d_tree, grid, cv=kf, n_jobs=-1, return_train_score=True)
d_tree.fit(X_train, y_train)

print('Best parameters:', d_tree.best_params_)

models["Decision Tree"] = {"Model": d_tree.best_estimator_ , "Score" : d_tree.sc
```

```
Best parameters: {'max_depth': None, 'max_features': 10, 'min_samples_leaf': 1
```

```
from sklearn.ensemble import RandomForestClassifier

rfc = RandomForestClassifier(n_jobs=-1, random_state=3)

```

```
grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [2, 4, 6, 8, 10],
    'min_samples_leaf': [1, 2, 4],
    'min_samples_split': [2, 5, 10],
}


rfc_gs = GridSearchCV(rfc, grid, cv=kf, n_jobs=-1, return_train_score=True)
rfc_gs.fit(X_train, y_train)

print('Best parameters:', rfc_gs.best_params_)

models["Random Forest"] = {"Model": rfc_gs.best_estimator_ , "Score" : rfc_gs.sc
```

```
Best parameters: {'max_depth': 10, 'min_samples_leaf': 1, 'min_samples_split'
```

```
from xgboost import XGBClassifier

std_xgb = XGBClassifier(nthread=8, objective='binary:logistic')

parameters = {
    'xgb__eta': [0.002, 0.1, 0.5],
    'xgb__min_child_weight': [4, 10],
    'xgb__max_depth': [6],
    'xgb__n_estimators': [150, 300],
    'xgb__alpha': [0.0001, 0.001]
}

xgb_gs = GridSearchCV(std_xgb, parameters, cv=kf, n_jobs=-1, return_train_score=
xgb_gs.fit(X_train, y_train)

print('Best parameters:', xgb_gs.best_params_)

models["XGBoost"] = {"Model": xgb_gs.best_estimator_ , "Score" : xgb_gs.score}
```

```
Best parameters: {'xgb__alpha': 0.0001, 'xgb__eta': 0.002, 'xgb__max_depth':
```

```
from sklearn.dummy import DummyClassifier
random = DummyClassifier(strategy="uniform", random_state=42)
random.fit(X_train, y_train)

models["Random"] = {"Model": random , "Score" : random.score}
```

Model Comparison

```
for name, model in models.items():
  model = models[name]
  y_pred = model["Model"].predict(X_val)
```

```
print(name)
model["Precision"] = precision_score(y_val, y_pred, pos_label=0)
model["Recall"] = recall_score(y_val, y_pred, pos_label=0)
model["F1_Score"] = f1_score(y_val, y_pred, average="macro")
model["mse"] = mean_squared_error(y_val, y_pred)
print("Precision = ", model["Precision"])
print("Recall = ", model["Recall"])
print("F1 score = ", model["F1_Score"])
print( pd.DataFrame(confusion_matrix(y_val, y_pred), index=["No Stroke", "Stro
print("Accuracy interval = ", accuracy_interval(model["F1_Score"]))
print("MSE = ", model["mse"])
print("\n\n")
```

```
Precision =  0.9262295081967213
Recall =  0.9968494013862634
F1 score =  0.9580897781602455
           No Stroke  Stroke
No Stroke       1582       5
Stroke           126    1421
Accuracy interval =  (0.9505, 0.9646)
MSE =  0.041799617102744095



Decision Tree
Precision =  0.9458128078817734
Recall =  0.9678638941398866
F1 score =  0.9556209452154114
           No Stroke  Stroke
No Stroke       1536      51
Stroke            88    1459
Accuracy interval =  (0.9478, 0.9623)
MSE =  0.04435226547543076



Random Forest
Precision =  0.9451476793248945
Recall =  0.9880277252678009
F1 score =  0.9648562013706836
           No Stroke  Stroke
No Stroke       1568      19
Stroke            91    1456
Accuracy interval =  (0.9578, 0.9708)
MSE =  0.03509891512444161



XGBoost
Precision =  0.9303423848878394
Recall =  0.9930686830497795
F1 score =  0.9587477871956984
           No Stroke  Stroke
No Stroke       1576      11
Stroke           118    1429
Accuracy interval =  (0.9512, 0.9652)
MSE =  0.04116145500957243
```

```
Random
Precision =  0.5091714104996837
Recall =  0.5072463768115942
F1 score =  0.5028132127728902
            No Stroke  Stroke
No Stroke        805     782
Stroke           776     771
Accuracy interval =  (0.4853, 0.5203)
MSE =  0.4971282705807275
```

Confrontiamo con una confidenza del 95% i modelli, dati i rispettivi errori.

```
from itertools import combinations

def intervall95(mse1, mse2, confidence):
    z = 1.96
    d = np.abs(mse1 - mse2)
    variance = (mse1 * (1 - mse1)) / len(X_val) + (mse2 * (1 - mse2)) / len(X_va
    d_min = d - z * np.sqrt(variance)
    d_max = d + z * np.sqrt(variance)
    return d_min, d_max

svm_error = models["Support Vector Machine"]["mse"]
lre_error = models["Logistic Regression"]["mse"]
knc_error = models["KNeighborsClassifier"]["mse"]
tree_error = models["Decision Tree"]["mse"]
forest_error = models["Random Forest"]["mse"]
xgb_error = models["XGBoost"]["mse"]

mse = [(svm_error, "svm"), (lre_error,"Logistic Regression"),
       (knc_error, "knc"), (tree_error, "Decision Tree"), (xgb_error, "XGBoost")

print (f"{'Models':<40} {'Interval':<15}")
for m1, m2 in list(combinations(mse, 2)):
  mse1, mse2 = m1[0], m2[0]
  name1, name2 = m1[1], m2[1]
  comparison = name1 + " vs " + name2
  print (f"{comparison:<40} {np.round(intervall95(mse1 , mse2, 0.95), 4)} ")
```

```
Models                                   Interval
svm vs Logistic Regression               [-0.0075  0.0126]
svm vs knc                               [0.0006 0.0192]
svm vs Decision Tree                     [-0.0075  0.0126]
svm vs XGBoost                           [-0.0092  0.0105]
svm vs random forest                     [-0.0028  0.0162]
Logistic Regression vs knc               [0.003  0.0219]
Logistic Regression vs Decision Tree     [-0.0102  0.0102]
Logistic Regression vs XGBoost           [-0.0068  0.0132]
Logistic Regression vs random forest     [-0.0004  0.0189]
knc vs Decision Tree                     [0.003  0.0219]
knc vs XGBoost                           [-0.      0.0185]
knc vs random forest                     [-0.0057  0.0121]
Decision Tree vs XGBoost                 [-0.0068  0.0132]
```

```
Decision Tree vs random forest           [-0.0004  0.0189]
XGBoost vs random forest                 [-0.0034  0.0155]
```

```
for name, model in models.items():
  print(f"{name:<30}{model['F1_Score']}")
```

```
Perceptron                    0.9459809205597873
Logistic Regression           0.9555274334745528
KNeighborsClassifier          0.9680567191987883
Support Vector Machine        0.9580897781602455
Decision Tree                 0.9556209452154114
Random Forest                 0.9648562013706836
XGBoost                       0.9587477871956984
Random                        0.5028132127728902
```

Guardando l'F1 Score dei modelli si può notare come i punteggi più alti siano ottenuti da:

1. KNeighborsClassifier
2. Random Forest
3. XGBoost

tuttavia, dal confronto fra i modelli possiamo notare che non esistono differenze significative fra i modelli.

Si verifica che la differenza fra i modelli e uno casuale sia statisticamente significativa

```
def intervall99(mse1, mse2, confidence):
    z = 2.58
    d = np.abs(mse1 - mse2)
    variance = (mse1 * (1 - mse1)) / len(X_val) + (mse2 * (1 - mse2)) / len(X_va
    d_min = d - z * np.sqrt(variance)
    d_max = d + z * np.sqrt(variance)
    return d_min, d_max

mse_random = models["Random"]["mse"]
print (f"{'Models':<40} Interval")
for m in mse:
  mse_i = m[0]
  name_i = m[1]
  comparison = name_i + " vs Random"
  print (f"{comparison:<40} {np.round(intervall99(mse_i , mse_random, 0.99), 4)}
```

```
Models                                   Interval
svm vs Random                            [0.4305 0.4801]
Logistic Regression vs Random            [0.4279 0.4777]
knc vs Random                            [0.4408 0.4896]
Decision Tree vs Random                  [0.4279 0.4777]
XGBoost vs Random                        [0.4312 0.4808]
random forest vs Random                  [0.4375 0.4866]
```

✓ 0s completed at 3:02 PM