-- Workshop #3 ---------------------------------------

- This workshop includes marked tasks that comprise 25% of your final mark in this module.
- You need to read the examples in the 'Lecture #3 - examples' notebook to complete the tasks.

Task

TASK 3.1: Apply four classifiers discussed in Lecture #3, i.e. Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), and K-nearest neighbours (KNN) classifiers to the adult_WS#3 dataset available on Canvas to predict the income column. Calculate the confusion matrix and evaluation metrics for all classifiers. Plot the features' importance values,

determine the three most important features (i.e.

In [69]:
```
############# WRITE YOUR CODE IN THIS CELL (IF APPLICABLE)###################
#importing relevant libraries
import pandas as pd
import numpy as np

#Reading my Csv file into a DataFrame
data = pd.read_csv('C:/Users/HP/Downloads/adult_WS#3.csv')

#Printing data
data
```

Out[69]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	
0	29	Private	216481	Masters	14	Married-civ-spouse	Exec-managerial	Wife	White	F
1	36	Private	280570	Some-college	10	Married-civ-spouse	Craft-repair	Husband	White	
2	25	?	100903	Bachelors	13	Married-civ-spouse	?	Wife	White	F
3	47	Private	145636	Assoc-voc	11	Married-civ-spouse	Handlers-cleaners	Husband	White	
4	33	Private	119422	HS-grad	9	Married-civ-spouse	Exec-managerial	Husband	White	
...	...	...	...	...	...	...	...	...	...	
9995	19	Private	63363	Some-college	10	Never-married	Sales	Own-child	White	F
9996	53	Private	58535	HS-grad	9	Divorced	Sales	Not-in-family	White	F
9997	30	Private	342709	HS-grad	9	Married-civ-spouse	Handlers-cleaners	Husband	White	
9998	41	Self-emp-not-inc	134724	Assoc-voc	11	Married-civ-spouse	Other-service	Wife	White	F
9999	21	Private	252253	Some-college	10	Never-married	Adm-clerical	Unmarried	Black	F

10000 rows × 15 columns

In [70]:
```
#checking sum of null values in columns
data.isna().sum()
```

Out[70]:
```
age                 0
workclass         175
fnlwgt              0
education           0
education-num       0
marital-status      0
occupation        175
relationship        0
race                0
sex                 0
capital-gain        0
capital-loss        0
hours-per-week      0
native-country     61
income              0
dtype: int64
```

In [71]:
```
#dropping null values
data.dropna(inplace=True)

#rechecking columns for null values
data.isna().sum()
```

Out[71]:
```
age               0
workclass         0
fnlwgt            0
education         0
education-num     0
marital-status    0
occupation        0
relationship      0
race              0
sex               0
capital-gain      0
capital-loss      0
hours-per-week    0
native-country    0
income            0
dtype: int64
```

In [72]:
```
#Identifying and Replacing wrong values with modes of columns
#creating a list and assigning into a variable
wrong_value_columns = ['workclass', 'occupation', 'native-country']

#Identifying and filling wrong values in the columns
for column in wrong_value_columns:
    #calculating the mode from each column
    mode_value = data[column].mode().iloc[0]
    #filling in the mode values
    data.loc[data[column] == '?', column] = mode_value
    #printing to verify
    print(data[column].unique())
```

```
['Private' 'Local-gov' 'Self-emp-inc' 'Federal-gov' 'Self-emp-not-inc'
 'State-gov' 'Without-pay' 'Never-worked']
['Exec-managerial' 'Craft-repair' 'Prof-specialty' 'Handlers-cleaners'
 'Sales' 'Other-service' 'Farming-fishing' 'Transport-moving'
 'Protective-serv' 'Adm-clerical' 'Tech-support' 'Machine-op-inspct'
 'Priv-house-serv' 'Armed-Forces']
['United-States' 'Scotland' 'Columbia' 'Haiti' 'Canada' 'El-Salvador'
 'China' 'Cuba' 'Philippines' 'Germany' 'Hong' 'Mexico' 'Puerto-Rico'
 'Dominican-Republic' 'South' 'India' 'Jamaica' 'Vietnam' 'England'
 'Cambodia' 'Portugal' 'Japan' 'Iran' 'Italy' 'Greece' 'Taiwan' 'Thailand'
 'Ecuador' 'Poland' 'Outlying-US(Guam-USVI-etc)' 'Hungary' 'Guatemala'
 'France' 'Nicaragua' 'Honduras' 'Laos' 'Ireland' 'Peru' 'Yugoslavia'
 'Trinadad&Tobago']
```

In [73]:
```
#setting rows and column display options
pd.set_option('display.max_rows', 100)
pd.set_option('display.max_columns', 100)
data.head(100)
```

Out[73]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	rac
0	29	Private	216481	Masters	14	Married-civ-spouse	Exec-managerial	Wife	Whi
1	36	Private	280570	Some-college	10	Married-civ-spouse	Craft-repair	Husband	Whi
2	25	Private	100903	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Whi
3	47	Private	145636	Assoc-voc	11	Married-civ-spouse	Handlers-cleaners	Husband	Whi
4	33	Private	119422	HS-grad	9	Married-civ-spouse	Exec-managerial	Husband	Whi

In [74]:
```
#preparing data for classification
#Extracting input and output data
X=data.drop('income',axis=1)
y=data['income']
```

In [75]:
```
from sklearn.preprocessing import OrdinalEncoder
# define ordinal encoding
encoder = OrdinalEncoder()

# perform ordinal encoding
X = encoder.fit_transform(X)

print(X)
```

```
[[1.200e+01 3.000e+00 5.601e+03 ... 0.000e+00 3.900e+01 3.700e+01]
 [1.900e+01 3.000e+00 6.899e+03 ... 0.000e+00 4.400e+01 3.700e+01]
 [8.000e+00 3.000e+00 1.484e+03 ... 0.000e+00 2.400e+01 3.700e+01]
 ...
 [1.300e+01 3.000e+00 7.604e+03 ... 0.000e+00 3.900e+01 3.700e+01]
 [2.400e+01 5.000e+00 2.550e+03 ... 0.000e+00 3.900e+01 3.700e+01]
 [4.000e+00 3.000e+00 6.456e+03 ... 0.000e+00 3.900e+01 3.700e+01]]
```

In [76]:
```
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
pd.set_option('display.max_rows', 100)
pd.set_option('display.max_columns', 100)


scaler = MinMaxScaler()
X_normalised=scaler.fit_transform(X)
df_normalised=pd.DataFrame(X_normalised)
print(X_normalised)
```

```
[[0.17391304 0.42857143 0.67238896 ... 0.         0.45348837 0.94871795]
 [0.27536232 0.42857143 0.82821128 ... 0.         0.51162791 0.94871795]
 [0.11594203 0.42857143 0.17815126 ... 0.         0.27906977 0.94871795]
 ...
 [0.1884058  0.42857143 0.91284514 ... 0.         0.45348837 0.94871795]
 [0.34782609 0.71428571 0.30612245 ... 0.         0.45348837 0.94871795]
 [0.05797101 0.42857143 0.77503001 ... 0.         0.45348837 0.94871795]]
```

In [77]:
```
#printing y
y
```

Out[77]:
```
0        >50K
1       <=50K
2       <=50K
3        >50K
4       <=50K
        ...
9995    <=50K
9996    <=50K
9997    <=50K
9998     >50K
9999    <=50K
Name: income, Length: 9765, dtype: object
```

In [78]:
```
#importing LabelEncoder to encode target y (income)
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()

#encoding y
y = le.fit_transform(y)
```

In [79]:
```
#printing y
y
```

Out[79]:
```
array([1, 0, 0, ..., 0, 1, 0])
```

In [80]:
```
# splittig the dataset into train and test datasets
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_normalised, y, test_size=
```

In [81]:
```
# Step 1: defining the classification models
from sklearn import svm
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier

SVM = svm.SVC()
DT=DecisionTreeClassifier()
RF = RandomForestClassifier()
KNN = KNeighborsClassifier()
```

In [82]:
```
#Step 2: training the models
SVM.fit(X_train, y_train)
DT.fit(X_train, y_train)
RF.fit(X_train, y_train)
KNN.fit(X_train, y_train)
```

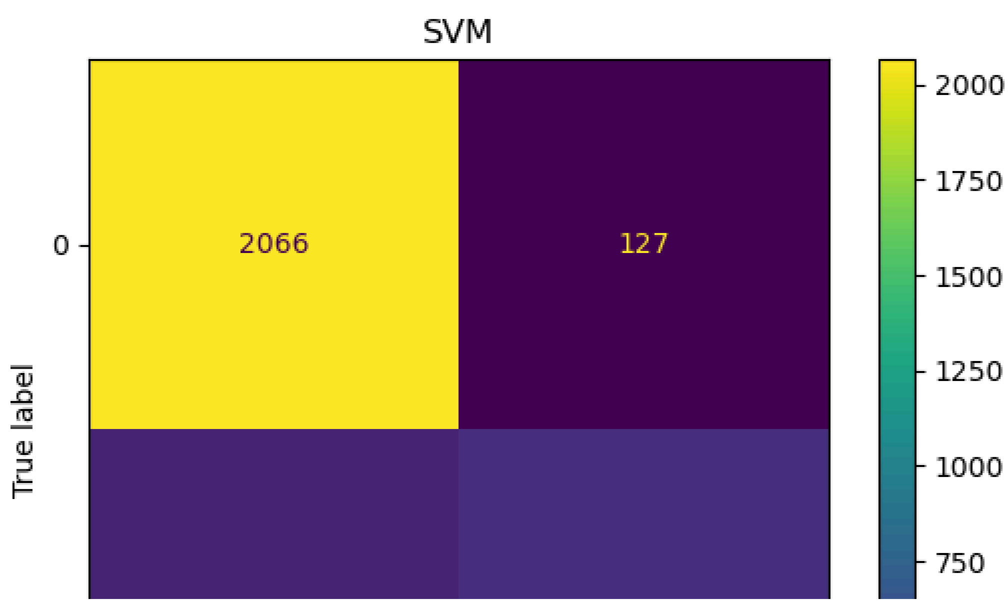
Out[82]:
```
KNeighborsClassifier()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [83]:
```
#Step 3: prediction
y_pred1=SVM.predict(X_test)
y_pred2=DT.predict(X_test)
y_pred3=RF.predict(X_test)
y_pred4=KNN.predict(X_test)
```

In [84]:
```
# Creating the confusion matrics for all classifiers' predictions
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

cm1 = confusion_matrix(y_test, y_pred1, labels=SVM.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm1,display_labels=SVM.classes_)
disp.plot()
plt.title("SVM")

cm2 = confusion_matrix(y_test, y_pred2, labels=RF.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm2,display_labels=RF.classes_)
disp.plot()
plt.title("RF")


cm3 = confusion_matrix(y_test, y_pred3, labels=KNN.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm3,display_labels=KNN.classes_)
disp.plot()
plt.title("KNN")

cm4 = confusion_matrix(y_test, y_pred4, labels=DT.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm4,display_labels=DT.classes_)
disp.plot()
plt.title("DT")
```

Out[84]:
```
Text(0.5, 1.0, 'DT')
```



In [85]:
```python
# This function takes the confusion matrix (cm) from the cell above and produce
def confusion_metrics (conf_matrix):

    TP = conf_matrix[1][1]
    TN = conf_matrix[0][0]
    FP = conf_matrix[0][1]
    FN = conf_matrix[1][0]
    print('True Positives:', TP)
    print('True Negatives:', TN)
    print('False Positives:', FP)
    print('False Negatives:', FN)

    # calculate accuracy
    conf_accuracy = (float (TP+TN) / float(TP + TN + FP + FN))

    # calculate mis-classification
    conf_misclassification = 1- conf_accuracy

    # calculate the sensitivity
    conf_sensitivity = (TP / float(TP + FN))
    # calculate the specificity
    conf_specificity = (TN / float(TN + FP))

    # calculate precision
    conf_precision = (TN / float(TN + FP))
    # calculate f_1 score
    conf_f1 = 2 * ((conf_precision * conf_sensitivity) / (conf_precision + conf
    print('-'*50)
    print(f'Accuracy: {round(conf_accuracy,2)}')
    print(f'Mis-Classification: {round(conf_misclassification,2)}')
    print(f'Sensitivity: {round(conf_sensitivity,2)}')
    print(f'Specificity: {round(conf_specificity,2)}')
    print(f'Precision: {round(conf_precision,2)}')
    print(f'f_1 Score: {round(conf_f1,2)}')
```

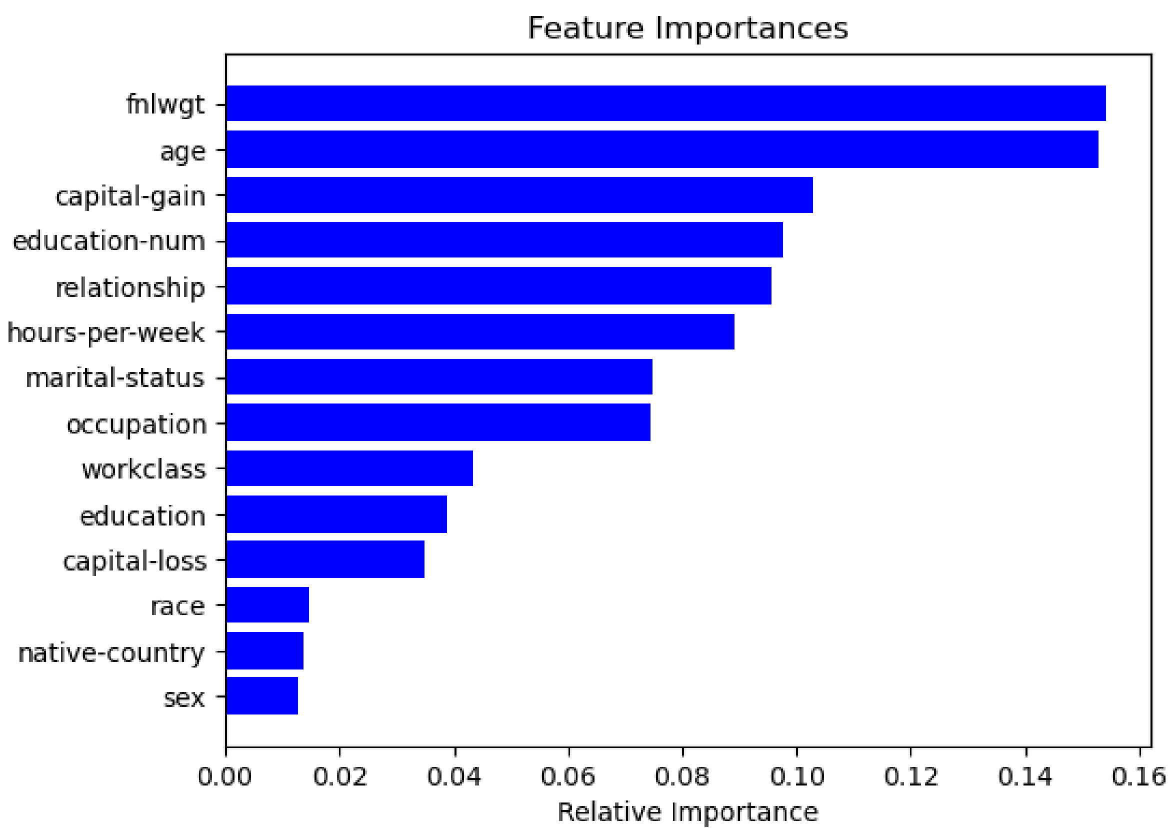
In [86]:
```
#printing the evaluation metrics for all classifiers
print('SVM metrics\n')
confusion_metrics(cm1)
print('\n\n')

print('DT metrics\n')
confusion_metrics(cm2)
print('\n\n')

print('RF metrics\n')
confusion_metrics(cm3)
print('\n\n')

print('KNN metrics\n')
confusion_metrics(cm4)
print('\n\n')
```

```
SVM metrics

True Positives: 403
True Negatives: 2066
False Positives: 127
False Negatives: 334
--------------------------------------------------
Accuracy: 0.84
Mis-Classification: 0.16
Sensitivity: 0.55
Specificity: 0.94
Precision: 0.94
f_1 Score: 0.69



DT metrics

True Positives: 454
True Negatives: 1889
False Positives: 304
False Negatives: 283
--------------------------------------------------
Accuracy: 0.8
Mis-Classification: 0.2
Sensitivity: 0.62
Specificity: 0.86
Precision: 0.86
f_1 Score: 0.72



RF metrics

True Positives: 461
True Negatives: 2009
False Positives: 184
False Negatives: 276
--------------------------------------------------
Accuracy: 0.84
Mis-Classification: 0.16
Sensitivity: 0.63
Specificity: 0.92
Precision: 0.92
f_1 Score: 0.74



KNN metrics

True Positives: 435
True Negatives: 1985
False Positives: 208
False Negatives: 302
--------------------------------------------------
Accuracy: 0.83
Mis-Classification: 0.17
```

```
Sensitivity: 0.59
Specificity: 0.91
Precision: 0.91
f_1 Score: 0.71
```

In [87]:

```
# Getting the most important features
features = data.columns
importances = RF.feature_importances_
indices = np.argsort(importances)

plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='b', align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```



In [88]:

```
importances
```

Out[88]:

```
array([0.15273639, 0.04353164, 0.15434991, 0.03878737, 0.09764714,
       0.07487165, 0.07438061, 0.09560222, 0.01482751, 0.012835  ,
       0.10278341, 0.03478378, 0.08905701, 0.01380636])
```

```
############# WRITE YOUR REPORT IN THIS CELL (IF
APPLICABLE)####################
```

The dataset has 10000 rows and 15 columns. Null values are seen in Workclass, Occupation and Native-country columns. These were replaced with the modes instead of dropping them because there was a considerable amount of null values, they were replaced with the modes. A box plot is plotted to check for outliers and it shows that 'fnlgwt' has a lot of extreme values so this column is dropped. Wrong data (?) were also observed in workclass, occupation and native-country columns. The mode of this columns were also used to replace the wrong data. The categorical columns were then encoded to numeric using both label encoder for nominal columns and ordinal encoder for ordinal column.

The input and output data are extracted removing income which is the output data from the dataset to form the input data (X)
the input data is then normalised using MinMaxScaler to ensure that all features contribute equally to the models decision making.

The data was split into test and train in the ratio 70:30. where the train data is 70% and the test data is 30%.
The classifiers are called and models trained using create regressor. The X test is used for prediction. Confusion matrix is then created for Support Vector Machines (SVM), Random Forest (RF), Decision Tree (DT) and K-Nearest Neighbours (KNN). This is used to check the True positive, true negative, false positive and false negative.

Based on the confusion matrix, all models performed well predicting zero's with SVM and RF as the best but did not perform well predicting 1. Although, RF performed better than SVM in predicting 1.
The higher the true negative and true positive, the better the model. Comparing the true positive and true negative, Random Forest performed better using confusion matrix.

In terms of accuracy, the higher the accuracy the better the model. RF model performed better as it had 84% chance of predicting the target variable.

In terms of specificity the SVM performed best

In terms of the F1 score which takes into consideration the precision and sensitivity, RF performed best. As the higher the F1 score, the better the model.

Comparing the models taking into consideration the important matrics: Accuracy, F1 score and confusion matrix it can be concluded that the Random Forest model performed best.

To improve my model, begining from the preprocessing step, i replaced the missing values with the mode rather than dropped them. there was a slight difference in the performance of the model as the accuracy for SVM model improved slightly from 0.83 to 0.84
Also changed the test train ratio from 70:30 to 80:20 but the accuracy and f1 still remained unchanged. (444 WORDS)