In [5]:

```python
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import sklearn.datasets
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import Perceptron
from sklearn.neural_network import MLPClassifier
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import f1_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
```

MP 1

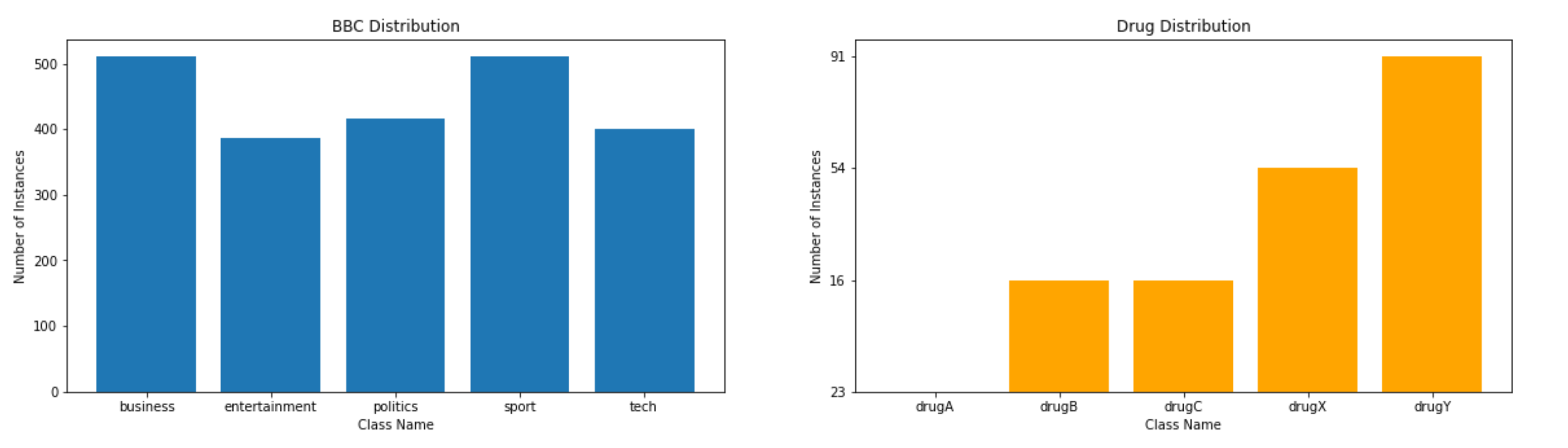
Inital dataset analysis

Plots of the **distributions** of the instances in each class for Task1 and Task2.

In [2]:

```python
fig, (plt1, plt2) = plt.subplots(1 ,2, figsize=(20,5))

'''
TASK1
'''
classes = np.array(["business", "entertainment", "politics", "sport", "tech"])
class_article_count = np.zeros(classes.shape[0])

for i in range(len(classes)):
    direc = "BBC/" + classes[i]
    class_article_count[i] = len(os.listdir(direc))

plt1.bar(classes,class_article_count)
plt1.set_title('BBC Distribution')
plt1.set_xlabel('Class Name')
plt1.set_ylabel('Number of Instances')

'''
TASK2
'''
df = pd.read_csv('drug200.csv')

classes = np.array(['drugA', 'drugB', 'drugC', 'drugX', 'drugY'])
class_instance_count = np.zeros_like(classes)

for i in range(classes.shape[0]):
        class_instance_count[i] = (df.Drug.values == classes[i]).sum()

plt2.bar(classes,class_instance_count, color='orange')
plt2.set_title('Drug Distribution')
plt2.set_xlabel('Class Name')
plt2.set_ylabel('Number of Instances')
```

Out[2]: `Text(0, 0.5, 'Number of Instances')`



The distributions in Task 1 (BBC Distribution) and Task 2 (Drug Distribution) are very different.

The classes in BBC Distribution are evenly distributed.
All five classes (business, entertainment, politics, sport, and tech) have a similar number of sample articles (number of instances).

While on the other hand, the classes in the Drug Distribution are unbalanced, creating a skewed distribution.

Accuracy is well suited for **Task 1** since we have a **well-balanced** dataset.
It is easy to see in the BBC Distribution that all article categories have between 400-500 article instances each.
Also, it is appropriate to use the accuracy metric for Task 1 as all classes are equally important and equally represented in this case. We are not interested in one type of news category more than another.

As for **Task 2**, *precision* and *recall* are better-suited metrics to use to evaluate the model.
Accuracy is not appropriate in this case since we clearly have a very **unbalanced** distribution of instances.

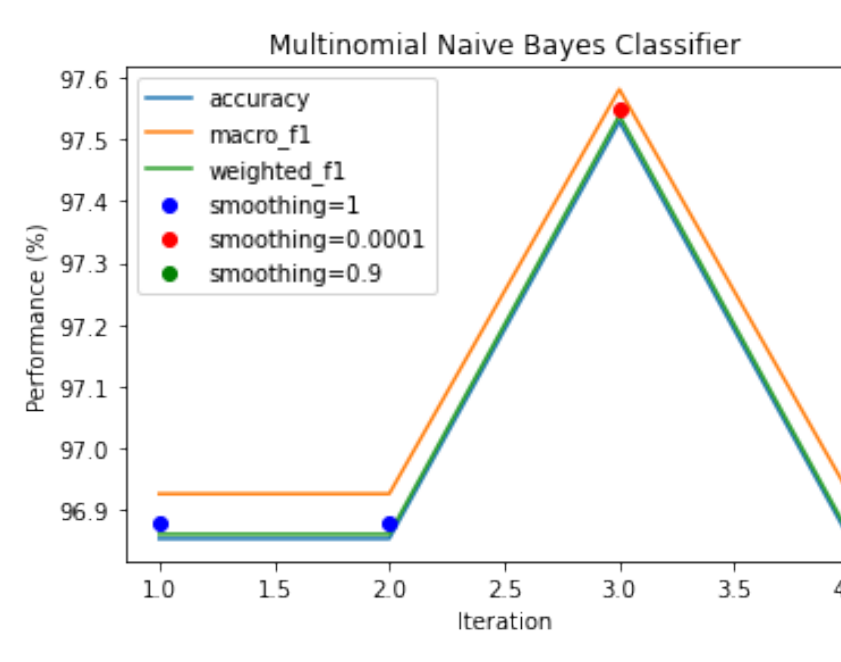
In addition to that, although precision could be used in this task, in a **medical application**, it is preferable to pick a model with the **highest recall**.
Since we are dealing with medical data, one type of drug class could be more important than another.

Analysis of the results of all the models

In [39]:

```python
accuracy, f1_macro, f1_weighted = np.zeros(4), np.zeros(4), np.zeros(4)
# Q3 - Load the corpus using load files, this assigns a class to each article
files_info = sklearn.datasets.load_files(container_path='BBC/', encoding='latin1')

corpus = files_info.data # articles from all classes
vectorizer = CountVectorizer()
X = vectorizer.fit_transform(corpus) # Learns the vocabulary dictionary and return document-term matrix. [article#, word#, word_count]
y = files_info.target

X_train, X_test, y_train, y_test = train_test_split(X.toarray(), y, test_size=.2, random_state=None)

clf = MultinomialNB().fit(X_train, y_train) # Create a model using training data
y_test_pred = clf.predict(X_test) # Use the model created to make predictions on the test data

accuracy[0] = accuracy_score(y_test, y_test_pred)
f1_macro[0] = f1_score(y_test, y_test_pred, average='macro')
f1_weighted[0] = f1_score(y_test, y_test_pred, average='weighted')

clf = MultinomialNB().fit(X_train, y_train) # Create a model using training data
y_test_pred = clf.predict(X_test) # Use the model created to make predictions on the test data

accuracy[1] = accuracy_score(y_test, y_test_pred)
f1_macro[1] = f1_score(y_test, y_test_pred, average='macro')
f1_weighted[1] = f1_score(y_test, y_test_pred, average='weighted')

clf = MultinomialNB(alpha=.0001).fit(X_train, y_train) # Create a model using training data
y_test_pred = clf.predict(X_test) # Use the model created to make predictions on the test data

accuracy[2] = accuracy_score(y_test, y_test_pred)
f1_macro[2] = f1_score(y_test, y_test_pred, average='macro')
f1_weighted[2] = f1_score(y_test, y_test_pred, average='weighted')

clf = MultinomialNB(alpha=.9).fit(X_train, y_train) # Create a model using training data
y_test_pred = clf.predict(X_test) # Use the model created to make predictions on the test data

accuracy[3] = accuracy_score(y_test, y_test_pred)
f1_macro[3] = f1_score(y_test, y_test_pred, average='macro')
f1_weighted[3] = f1_score(y_test, y_test_pred, average='weighted')

plt.plot(np.arange(4,dtype=np.int32)+1, accuracy*100, label='accuracy')
plt.plot(np.arange(4,dtype=np.int32)+1, f1_macro*100, label='macro_f1')
plt.plot(np.arange(4,dtype=np.int32)+1, f1_weighted*100, label='weighted_f1')

plt.plot(1, ((accuracy[0]+f1_macro[0]+f1_weighted[0])/3)*100,'bo', label='smoothing=1')
plt.plot(2, ((accuracy[1]+f1_macro[1]+f1_weighted[1])/3)*100,'bo')
plt.plot(3, ((accuracy[2]+f1_macro[2]+f1_weighted[2])/3)*100,'ro', label='smoothing=0.0001')
plt.plot(4, ((accuracy[3]+f1_macro[3]+f1_weighted[3])/3)*100,'go', label='smoothing=0.9')
plt.legend()
plt.xlabel('Iteration')
plt.ylabel('Performance (%)')
plt.title('Multinomial Naive Bayes Classifier')
```

Out[39]: `Text(0.5, 1.0, 'Multinomial Naive Bayes Classifier')`



Iteration 1 and 2 are the **same** since at both times we used the **default values**.
The default values in *sklearn.naibe_bayes.MultinomialNB* are alpha=1.0 (smoothing), fit-prior=True, and class_prior=None.

However, in **iteration 3 and 4**, we did **change the smoothing values** (alpha=0.0001 and alpha=0.9), so this time we do see slightly different performance results.

In our case, the model with the smallest smoothing value (0.0001) has better accuracy (98%) than models with larger smoothing values (0.9 and the default model with 1.0 smoothing value).

Larger smoothing values typically create a uniform distribution, which often does not represent datasets accurately.

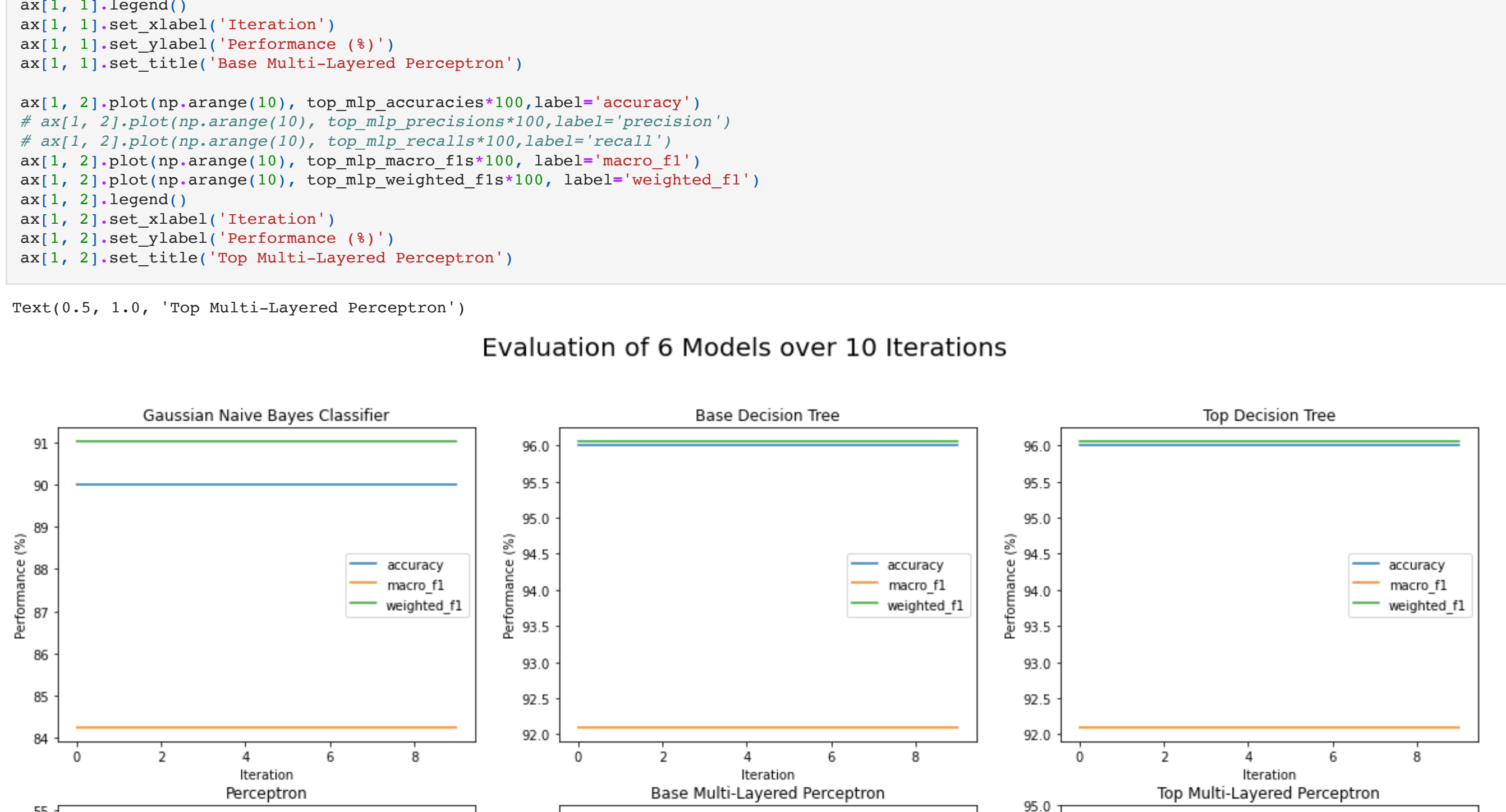
In [3]:

```python
'''
Q4 - Convert all ordinal and nominal features in numerical format
'''
age = df['Age']
sex = np.array(pd.get_dummies(df['Sex'], drop_first=True)).reshape(-1,) # 1=M, 0=F
bp = pd.Categorical(df['BP'], ordered=True, categories=['LOW', 'NORMAL', 'HIGH']).codes
cholesterol = pd.Categorical(df['Cholesterol'], ordered=True, categories=['LOW', 'NORMAL', 'HIGH']).codes
na_to_k = df['Na_to_K']


X = np.column_stack((age, sex, bp, cholesterol, na_to_k))
y = df['Drug']

'''
Q5 - Split the dataset using the default parameter values
'''
X_train, X_test, y_train, y_test = train_test_split(X, y)
```

In [49]:

```python
fig, ax = plt.subplots(2 ,3, figsize=(20,10))
plt.suptitle("Evaluation of 6 Models over 10 Iterations", fontsize=20)

avg_accuracy, avg_macro_f1, avg_weighted_f1, accuracy_sd, macro_f1_sd, weighted_f1_sd   = np.zeros(6), np.zeros(6), np.zeros(6), np.zeros(6), np.zeros(6), np.zeros(6)
nb_accuracies, nb_macro_f1s, nb_weighted_f1s, nb_precisions, nb_recalls = np.zeros(10), np.zeros(10), np.zeros(10), np.zeros(10), np.zeros(10)
base_dt_accuracies, base_dt_macro_f1s, base_dt_weighted_f1s, base_dt_precisions, base_dt_recalls = np.zeros(10), np.zeros(10), np.zeros(10), np.zeros(10), np.zeros(10)
top_dt_accuracies, top_dt_macro_f1s, top_dt_weighted_f1s, top_dt_precisions, top_dt_recalls = np.zeros(10), np.zeros(10), np.zeros(10), np.zeros(10), np.zeros(10)
perceptron_accuracies, perceptron_macro_f1s, perceptron_weighted_f1s, perceptron_precisions, perceptron_recalls = np.zeros(10), np.zeros(10), np.zeros(10), np.zeros(10), np.ze
base_mlp_accuracies, base_mlp_macro_f1s, base_mlp_weighted_f1s, base_mlp_precisions, base_mlp_recalls = np.zeros(10), np.zeros(10), np.zeros(10), np.zeros(10), np.zeros(10)
top_mlp_accuracies, top_mlp_macro_f1s, top_mlp_weighted_f1s, top_mlp_precisions, top_mlp_recalls = np.zeros(10), np.zeros(10), np.zeros(10), np.zeros(10), np.zeros(10)
for i in range(10):
    # (a) NB: a Gaussian Naive Bayes Classifier with the default parameters
    nb = GaussianNB().fit(X_train, y_train) # Create a model using training data
    nb_y_test_pred = nb.predict(X_test) # Use the model created to make predictions on the test data

    accuracy = accuracy_score(y_test, nb_y_test_pred)
    precision = precision_score(y_test, nb_y_test_pred, average='micro')
    recall = recall_score(y_test, nb_y_test_pred, average='micro')
    f1_macro = f1_score(y_test, nb_y_test_pred, average='macro')
    f1_weighted = f1_score(y_test, nb_y_test_pred, average='weighted')

    nb_accuracies[i] = accuracy
    nb_precisions[i] = precision
    nb_recalls[i] = recall
    nb_macro_f1s[i] = f1_macro
    nb_weighted_f1s[i] = f1_weighted

    # (b) Base-DT: a Decision Tree with the default parameters
    base_dt = DecisionTreeClassifier().fit(X_train, y_train)
    base_dt_y_test_pred = base_dt.predict(X_test) # Use the model created to make predictions on the test data

    accuracy = accuracy_score(y_test, base_dt_y_test_pred)
    precision = precision_score(y_test, base_dt_y_test_pred, average='micro')
    recall = recall_score(y_test, base_dt_y_test_pred, average='micro')
    f1_macro = f1_score(y_test, base_dt_y_test_pred, average='macro')
    f1_weighted = f1_score(y_test, base_dt_y_test_pred, average='weighted')

    base_dt_accuracies[i] = accuracy
    base_dt_precisions[i] = precision
    base_dt_recalls[i] = recall
    base_dt_macro_f1s[i] = f1_macro
    base_dt_weighted_f1s[i] = f1_weighted

    # (c) Top-DT: a better performing Decision Tree
    parameters = {'criterion':('gini', 'entropy'), 'max_depth':[3, 10], 'min_samples_split':[3, 5, 6]}
    top_dt = GridSearchCV(base_dt, parameters).fit(X_train, y_train)
    top_dt_y_test_pred = top_dt.predict(X_test) # Use the model created to make predictions on the test data

    accuracy = accuracy_score(y_test, top_dt_y_test_pred)
    precision = precision_score(y_test, top_dt_y_test_pred, average='micro')
    recall = recall_score(y_test, top_dt_y_test_pred, average='micro')
    f1_macro = f1_score(y_test, top_dt_y_test_pred, average='macro')
    f1_weighted = f1_score(y_test, top_dt_y_test_pred, average='weighted')

    top_dt_accuracies[i] = accuracy
    top_dt_precisions[i] = precision
    top_dt_recalls[i] = recall
    top_dt_macro_f1s[i] = f1_macro
    top_dt_weighted_f1s[i] = f1_weighted

    # (d) PER: a Perceptron, with default parameter values
    perceptron = Perceptron().fit(X_train, y_train)
    perceptron_y_test_pred = perceptron.predict(X_test) # Use the model created to make predictions on the test data

    accuracy = accuracy_score(y_test, perceptron_y_test_pred)
    precision = precision_score(y_test, perceptron_y_test_pred, average='micro')
    recall = recall_score(y_test, perceptron_y_test_pred, average='micro')
    f1_macro = f1_score(y_test, perceptron_y_test_pred, average='macro')
    f1_weighted = f1_score(y_test, perceptron_y_test_pred, average='weighted')

    perceptron_accuracies[i] = accuracy
    perceptron_precisions[i] = precision
    perceptron_recalls[i] = recall
    perceptron_macro_f1s[i] = f1_macro
    perceptron_weighted_f1s[i] = f1_weighted

    # (e) Base-MLP: a Multi-Layered Perceptron with 1 hidden layer of 100 neurons, sigmoid/logistic as activation function, stochastic gradient descent, and default values fo
    base_mlp = MLPClassifier(hidden_layer_sizes=(100), activation='logistic', solver='sgd', max_iter=5000).fit(X_train, y_train)
    base_mlp_y_test_pred = base_mlp.predict(X_test) # Use the model created to make predictions on the test data

    accuracy = accuracy_score(y_test, base_mlp_y_test_pred)
    precision = precision_score(y_test, base_mlp_y_test_pred, average='micro')
    recall = recall_score(y_test, base_mlp_y_test_pred, average='micro')
    f1_macro = f1_score(y_test, base_mlp_y_test_pred, average='macro')
    f1_weighted = f1_score(y_test, base_mlp_y_test_pred, average='weighted')

    base_mlp_accuracies[i] = accuracy
    base_mlp_precisions[i] = precision
    base_mlp_recalls[i] = recall
    base_mlp_macro_f1s[i] = f1_macro
    base_mlp_weighted_f1s[i] = f1_weighted

    # (f) Top-MLP: a better performing Multi-Layered Perceptron found using grid search
    parameters = {'activation':('logistic', 'tanh', 'relu', 'identity'), 'hidden_layer_sizes':[(30, 50), (10, 10, 10)], 'solver':('adam', 'sgd')}
    top_mlp = GridSearchCV(base_mlp, parameters).fit(X_train, y_train)
    top_mlp_y_test_pred = top_mlp.predict(X_test) # Use the model created to make predictions on the test data

    accuracy = accuracy_score(y_test, top_mlp_y_test_pred)
    precision = precision_score(y_test, top_mlp_y_test_pred, average='micro')
    recall = recall_score(y_test, top_mlp_y_test_pred, average='micro')
    f1_macro = f1_score(y_test, top_mlp_y_test_pred, average='macro')
    f1_weighted = f1_score(y_test, top_mlp_y_test_pred, average='weighted')

    top_mlp_accuracies[i] = accuracy
    top_mlp_precisions[i] = precision
    top_mlp_recalls[i] = recall
    top_mlp_macro_f1s[i] = f1_macro
    top_mlp_weighted_f1s[i] = f1_weighted

ax[0, 0].plot(np.arange(10), nb_accuracies*100, label='accuracy')
# ax[0, 0].plot(np.arange(10), nb_precisions*100, label='precision')
# ax[0, 0].plot(np.arange(10), nb_recalls*100, label='recall')
ax[0, 0].plot(np.arange(10), nb_macro_f1s*100, label='macro_f1')
ax[0, 0].plot(np.arange(10), nb_weighted_f1s*100, label='weighted_f1')
ax[0, 0].legend()
ax[0, 0].set_xlabel('Iteration')
ax[0, 0].set_ylabel('Performance (%)')
ax[0, 0].set_title('Gaussian Naive Bayes Classifier')

ax[0, 1].plot(np.arange(10), base_dt_accuracies*100,label='accuracy')
# ax[0, 1].plot(np.arange(10), base_dt_precisions*100,label='precision')
# ax[0, 1].plot(np.arange(10), base_dt_recalls*100,label='recall')
ax[0, 1].plot(np.arange(10), base_dt_macro_f1s*100, label='macro_f1')
ax[0, 1].plot(np.arange(10), base_dt_weighted_f1s*100, label='weighted_f1')
ax[0, 1].legend()
ax[0, 1].set_xlabel('Iteration')
ax[0, 1].set_ylabel('Performance (%)')
ax[0, 1].set_title('Base Decision Tree')

ax[0, 2].plot(np.arange(10), top_dt_accuracies*100,label='accuracy')
# ax[0, 2].plot(np.arange(10), top_dt_precisions*100,label='precision')
# ax[0, 2].plot(np.arange(10), top_dt_recalls*100,label='recall')
ax[0, 2].plot(np.arange(10), top_dt_macro_f1s*100, label='macro_f1')
ax[0, 2].plot(np.arange(10), top_dt_weighted_f1s*100, label='weighted_f1')
ax[0, 2].legend()
ax[0, 2].set_xlabel('Iteration')
ax[0, 2].set_ylabel('Performance (%)')
ax[0, 2].set_title('Top Decision Tree')

ax[1, 0].plot(np.arange(10), perceptron_accuracies*100,label='accuracy')
# ax[1, 0].plot(np.arange(10), perceptron_precisions*100,label='precision')
# ax[1, 0].plot(np.arange(10), perceptron_recalls*100,label='recall')
ax[1, 0].plot(np.arange(10), perceptron_macro_f1s*100, label='macro_f1')
ax[1, 0].plot(np.arange(10), perceptron_weighted_f1s*100, label='weighted_f1')
ax[1, 0].legend()
ax[1, 0].set_xlabel('Iteration')
ax[1, 0].set_ylabel('Performance (%)')
ax[1, 0].set_title('Perceptron')

ax[1, 1].plot(np.arange(10), base_mlp_accuracies*100,label='accuracy')
# ax[1, 1].plot(np.arange(10), base_mlp_precisions*100,label='precision')
# ax[1, 1].plot(np.arange(10), base_mlp_recalls*100,label='recall')
ax[1, 1].plot(np.arange(10), base_mlp_macro_f1s*100, label='macro_f1')
ax[1, 1].plot(np.arange(10), base_mlp_weighted_f1s*100, label='weighted_f1')
ax[1, 1].legend()
ax[1, 1].set_xlabel('Iteration')
ax[1, 1].set_ylabel('Performance (%)')
ax[1, 1].set_title('Base Multi-Layered Perceptron')

ax[1, 2].plot(np.arange(10), top_mlp_accuracies*100,label='accuracy')
# ax[1, 2].plot(np.arange(10), top_mlp_precisions*100,label='precision')
# ax[1, 2].plot(np.arange(10), top_mlp_recalls*100,label='recall')
ax[1, 2].plot(np.arange(10), top_mlp_macro_f1s*100, label='macro_f1')
ax[1, 2].plot(np.arange(10), top_mlp_weighted_f1s*100, label='weighted_f1')
ax[1, 2].legend()
ax[1, 2].set_xlabel('Iteration')
ax[1, 2].set_ylabel('Performance (%)')
ax[1, 2].set_title('Top Multi-Layered Perceptron')
```

Out[49]: `Text(0.5, 1.0, 'Top Multi-Layered Perceptron')`



Analyzing the plots above, we see that the **NB, Base DT, Top DT**, and **Perceptron** have **constant performance** over all iterations.

This is because **no element of randomness** goes into the creation of these models.
If the **same training and testing data** is used every time, the same priors and conditionals will be generated/calculated during the model creation, and in turn used to calculate the score of classes or the entropy in DTs.

As for the Perceptron, the initial weights are always set to 1 according to the documentation, so the final weights will be also the same.
This is the reason why we do not see any changes in perfromance.

For the **Base MLP** and **Top MLP**, we see **changes in performance** over the iterations.
This is happening since these models use **random weights** and **bias initialization**. So, each iteration will have different final weights.
The change in performance is less drastic in the Base MLP because we are not changing the hyper-parameters. While in Top MLP, we are not only using random parameters initialization, we are also experimenting with hyper-parameters.