Project 3

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Project 3: Classification of Gender based on Names

Problem Description

Using any of the three classifiers described in chapter 6 of Natural Language Processing with Python, and any features you can think of, build the best name gender classifier you can. Begin by splitting the Names Corpus into three subsets: 500 words for the test set, 500 words for the dev-test set, and the remaining 6900 words for the training set. Then, starting with the example name gender classifier, make incremental improvements. Use the dev-test set to check your progress. Once you are satisfied with your classifier, check its final performance on the test set. How does the performance on the test set compare to the performance on the dev-test set? Is this what you'd expect?

Importing the Packages

[25]:
```
import nltk
from nltk.corpus import names
import random
import numpy
import pandas

from nltk.metrics import *

import re

import operator
import string
from textstat.textstat import textstat

from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix

import matplotlib.pyplot as plt
import itertools
```

```
# set display digits
display_digits=4


# inline matplotlib
%matplotlib inline
```

[26]:
```
nltk.download('names')
```

```
[nltk_data] Downloading package names to /Users/MECCA/nltk_data…
[nltk_data]   Package names is already up-to-date!
```

[26]: True

[27]:
```
names_lst = ([(name, 'male') for name in names.words('male.txt')] + \
         [(name, 'female') for name in names.words('female.txt')])
```

[30]:
```
random_seed=1234678
random.seed(random_seed)
random.shuffle(names_lst)

# let's see what the randomly shuffles names look like
names_lst[1:15]
```

[30]:
```
[('Blanche', 'female'),
 ('Esme', 'female'),
 ('Chloris', 'female'),
 ('Poul', 'male'),
 ('Arne', 'male'),
 ('Johannah', 'female'),
 ('Beverlie', 'female'),
 ('Sibley', 'female'),
 ('Carmelia', 'female'),
 ('Garrott', 'male'),
 ('Ahmed', 'male'),
 ('Sibbie', 'female'),
 ('Roy', 'male'),
 ('Sid', 'male')]
```

Splitting the Data

To construct our model effectively, it's essential to partition our data into three distinct subsets, each serving a specific purpose. The dataset contains a total of 7944 names. Among these, 7444 entries will be allocated for developmental purposes, with 6900 earmarked for training and 500 for testing. The remaining 500 entries will be reserved exclusively for the final model evaluation.

The breakdown of subsets is as follows:

Development Set: - 6900 names designated for training (train_names) - 500 names allocated for testing during development (devtest_names)

Test Set: - 500 names exclusively reserved for final model testing (test_names)

[23]:
```
test_names, devtest_names, train_names = names_lst[0:500], names_lst[500:1000],␣
    ↪names_lst[1000:]
```

Below, we verify that our data has been partitioned as described.

[31]:
```
# Confirm the size of the three subsets
print("Training Set = {}".format(len(train_names)))
print("Dev-Test Set = {}".format(len(devtest_names)))
print("Test Set = {}".format(len(test_names)))
```

```
Training Set = 6944
Dev-Test Set = 500
Test Set = 500
```

Data Exploration

Initially, we'll examine certain features of the names to identify potential indicators of gender. We'll then visualize the distribution of females and males within our training set as follows:

[33]:
```
train_set_gold = [g  for (n, g) in train_names]
nltk.FreqDist(train_set_gold)
```

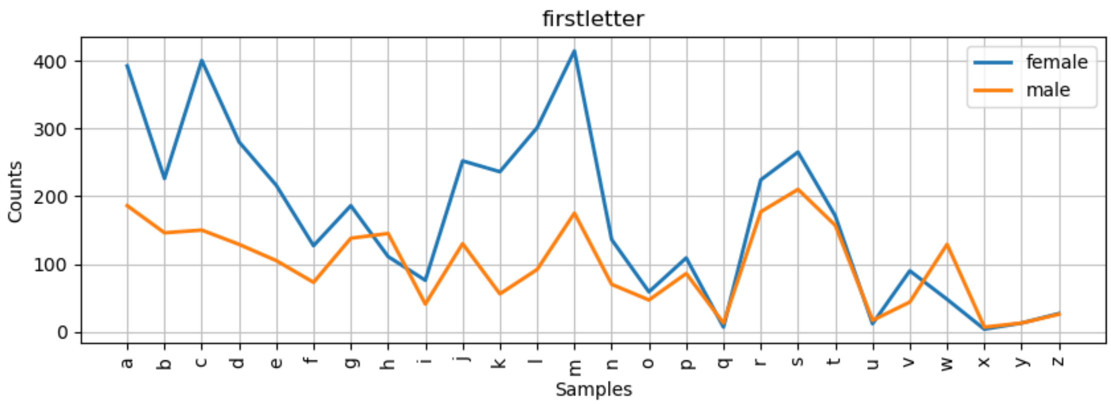
[33]:
```
FreqDist({'female': 4382, 'male': 2562})
```

1. First Letter

A prominent characteristic within a name that could serve as a strong indicator of gender is the initial letter. The subsequent visualization will depict the distribution of initial letters concerning gender.

[96]:
```
# firstletter
cfd_firstletter = nltk.ConditionalFreqDist(
    (gender, name[0].lower()) for name, gender in train_names)

# Normalize for male and female data
fem_count = float(len([gender for name, gender in train_names if gender ==␣
    ↪'female']))
male_count = float(len([gender for name, gender in train_names if gender ==␣
    ↪'male']))

for i in [counts for gender,counts in [i for i in cfd_firstletter.items()] if␣
    ↪gender == 'male']:
    for freq in i.values():
```

```
        freq = freq/male_count

for i in [counts for gender,counts in [i for i in cfd_firstletter.items()] if␣
 ↪gender == 'female']:
    for freq in i.values():
        freq = freq/fem_count

# define title
titleName='firstletter'

# set figure size
plt.figure(figsize=(10,3))
# add title
plt.title(titleName)
# add conditional frequency distribution
cfd_firstletter.plot()
```

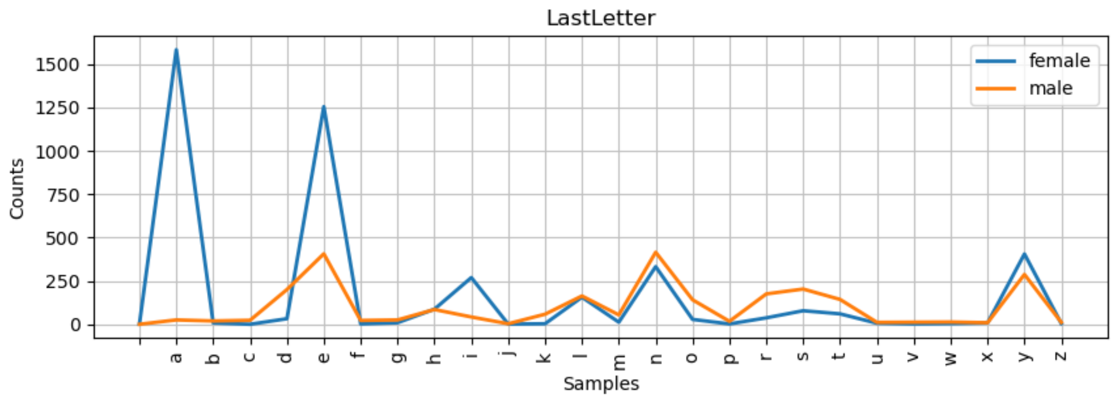


[96]: <Axes: title={'center': 'firstletter'}, xlabel='Samples', ylabel='Counts'>

2. Last Letter

[94]:
```
# lastletter
cfd_lastletter = nltk.ConditionalFreqDist(
    (gender, name[-1].lower()) for name, gender in train_names)

# define title
titleName='LastLetter'

# set figure size
plt.figure(figsize=(10,3))
# add title
plt.title(titleName)
```

```python
# add conditional frequency distribution
cfd_lastletter.plot()
```

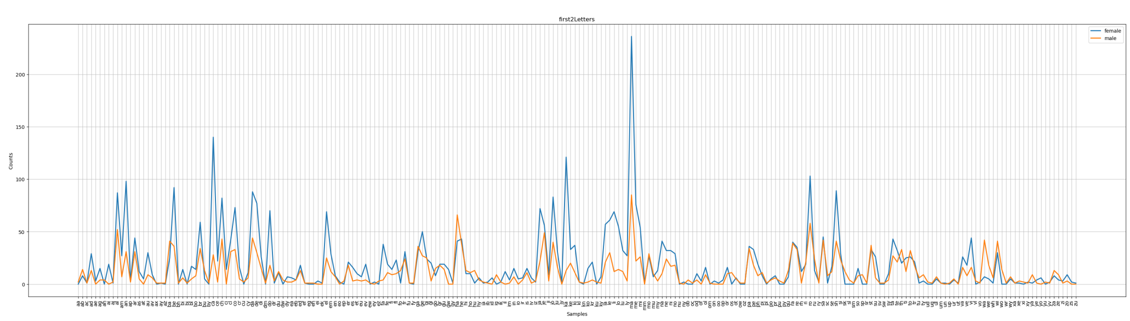


[94]: <Axes: title={'center': 'LastLetter'}, xlabel='Samples', ylabel='Counts'>

Names that conclude with the letters ‘a’ and ‘e’ seem to serve as reliable indicators of female gender.

3. First 2 letters

[39]:
```python
# first2Letters
cfd_first2Letters = nltk.ConditionalFreqDist(
    (gender, name[:2].lower()) for name, gender in train_names)

# define title
titleName='first2Letters'

# set figure size
plt.figure(figsize=(40,10))
# add title
plt.title(titleName)
# add conditional frequency distribution
cfd_first2Letters.plot()
```

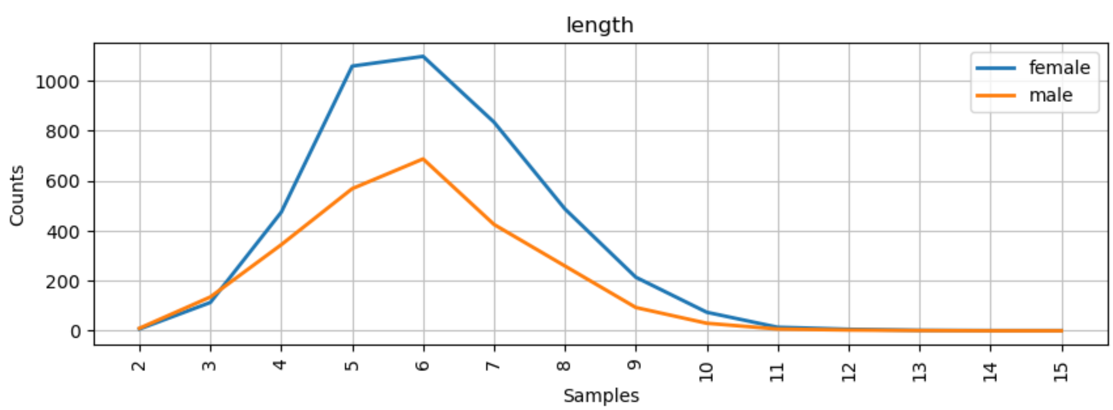


[39]: <Axes: title={'center': 'first2Letters'}, xlabel='Samples', ylabel='Counts'>

There appears to be a noticeable difference in the last two letters between male and female. We'll delve deeper into this characteristic since it's challenging to discern solely from the output.

4. Length

[40]:
```
# length
cfd_length = nltk.ConditionalFreqDist(
    (gender, len(name)) for name, gender in train_names)

# define title
titleName='length'

# set figure size
plt.figure(figsize=(10,3))
# add title
plt.title(titleName)
# add conditional frequency distribution
cfd_length.plot()
```

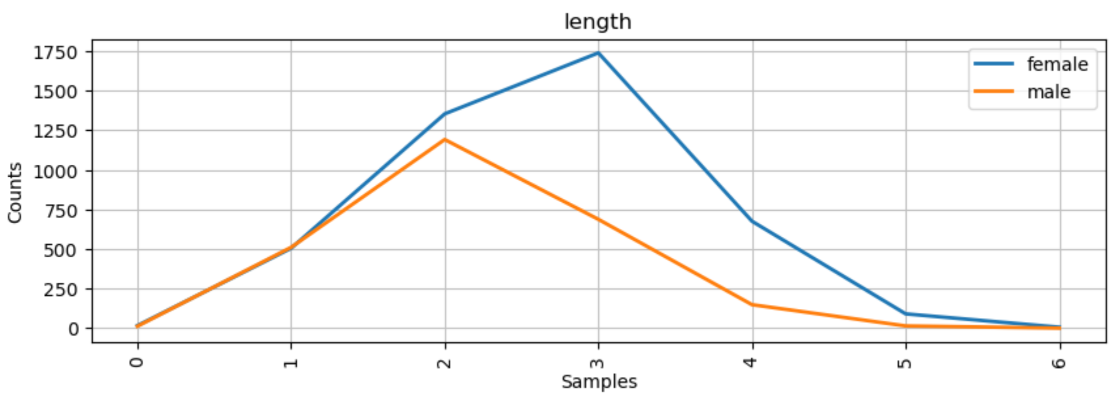


[40]: <Axes: title={'center': 'length'}, xlabel='Samples', ylabel='Counts'>

The length does not appear to be a great indicator of gender on its own.

5. Vowel Counts

[41]:
```
# Vowel Counts
cfd_vowels = nltk.ConditionalFreqDist(
    (gender, len(re.sub(r'[^aeiou]', '', name.lower()))) for name, gender in␣
 ↪train_names)

# define title
titleName='length'

# set figure size
plt.figure(figsize=(10,3))
# add title
plt.title(titleName)
# add conditional frequency distribution
cfd_vowels.plot()
```



[41]: `<Axes: title={'center': 'length'}, xlabel='Samples', ylabel='Counts'>`

Concluding Remarks on Exploration

The initial examination of certain features provided a foundational understanding for feature selection. However, these features alone do not demonstrate strong predictive capabilities for gender classification. To develop a robust model, I must employ more sophisticated tools. My approach will involve constructing a feature extractor capable of generating multiple features, followed by the application of introductory machine learning techniques to optimize model performance.

Feature Extraction Methodology

The following section aims to iteratively enhance the feature extraction functions, which will subsequently be applied to both the development and test datasets.

Drawing from various examples in existing literature and the aforementioned analysis, I will commence our model development with the following features:

- First Letter: Recognizing that many names starting with vowels are often associated with females.
- First 2 letters
- Last letter
- Last 2 letters
- Last 3 letters
- Vowels count
- Hard consonants following general rules of 'c' and 'g'
- Soft consonants following general rules of 'c' and 'g'
- Syllable Count of names via textstat
- Name length
- Character count
- Presence of specific characters
- Count of each letter
- Count of pairs of letters in the alphabet

I have crafted a function capable of returning either a single feature or a combination of features based on input feature numbers.

[42]:
```
def get_features(name,feat_num):
    '''
    Parameters:
        name - string of name to extract feature
        feat_num - itterable collection of integers specifying features.␣
↪*Defaults to 1:9 inclusive
            1: first letter
            2: first 2 letters
            3: last letter
            4: last 2 letters
            5: last 3 letters
            6: Vowel counts
            7: Hard consonant count
            8: Soft consonant count
            9: Syllable Count
            10: Name length
            11: char count --> feature for all alpha chars
            12: char present --> feature for all alpha chars (boolean)
            13: count each letter
            14: Count pairs
    Returns:
        features: a dictionary of extracted features
    '''
    features = {}

    # Converts feat_num to itterable if type is int
    if type(feat_num) is int:
        feat_num = (0, feat_num)
```

```python
    # Gender Feature 1: First letter - book example
    if 1 in feat_num:
        features['firstletter'] = name[0].lower()

    # Gender Feature 2: First 2 letters
    if 2 in feat_num:
        features['first2Letters'] = name[0:2].lower()

    # Gender Feature 3: last letter
    if 3 in feat_num:
        features['last_letter'] = name[-1].lower()

    # Gender Feature 4: last 2 letter
    if 4 in feat_num:
        features["last2letters"] = name[-2:].lower()

    # Gender feature 5: last 3 letter
    if 5 in feat_num:
        features["last3letters"] = name[-3:].lower()

    # Gender feature 6: Vowels count
    if 6 in feat_num:
        features['vowel_count'] = len(re.sub(r'[^aeiou]', '', name.lower()))

    # Gender Feature 7: Hard consonants using general rules of c and g
    if 7 in feat_num:
        features['hard_consts'] = len(re.findall(r'[cg][^eiy]', name.lower()))/2

    # Gender Feature 8: Soft consonants using general rules of c and g
    if 8 in feat_num:
            features['soft_consts'] = len(re.findall(r'[cg][eiy]', name.
↪lower()))/2

    # Gender Feature 9: Syllable Count of names via textstat
    if 9 in feat_num:
        features['syllable_count'] = textstat.syllable_count(name.lower())

    # Gender Feature 10: Name length
    if 10 in feat_num:
        features["length"] = len(name)

    # Gender Feature 11: Char Counts (overfitts)
    if 11 in feat_num:
        for letter in string.ascii_lowercase:
            features["count_{0}".format(letter)] = name.lower().count(letter)

    # Gender Feature 12: Char Booleans (overfitts)
```

```
    if 12 in feat_num:
        for letter in string.ascii_lowercase:
            features["has_{0}".format(letter)] = letter in name.lower()


    if 13 in feat_num:
        features = {}
        letters=list(map(chr, range(ord('a'), ord('z') + 1)))
        for letter in letters:
            features["count(%s)" % letter] = name.lower().count(letter)


    if 14 in feat_num:
        features = {}
        letters=list(map(chr, range(ord('a'), ord('z') + 1)))
        for letter1 in letters:
            for letter2 in letters:
                features["has("+letter1+letter2+")"] = (letter1+letter2 in name.
↪lower())

    #### Complex Features
    # Gender Feature 15: Last Letter/Last 2 Letter
    if 15 in feat_num:
        features = {}
        features["lastletter"] = name[-1].lower()
        features["last2letter"] = name[-2:].lower()

    if 16 in feat_num:
        features = {}
        features["firstletter"] = name[0].lower()
        features["lastletter"] = name[-1].lower()
        features["last2letter"] = name[-2:].lower()
        features["last3letter"] = name[-3:].lower()

        letters=list(map(chr, range(ord('a'), ord('z') + 1)))
        for letter1 in letters:
            features["count("+letter1+")"] = name.lower().count(letter1)
            features["has("+letter1+")"] = (letter1 in name.lower())
            # iterate over 2-grams
            for letter2 in letters:

                features["has("+letter1+letter2+")"] = (letter1+letter2 in name.
↪lower())


    if 17 in feat_num:
        # define features
```

```python
    features = {}
    # has(fo) = True
    features["has(fo)"] = ('fo' in name.lower())
    # has(hu) = True
    features["has(hu)"] = ('hu' in name.lower())
    # has(rv) = True
    features["has(rv)"] = ('rv' in name.lower())
    # has(rw) = True
    features["has(rw)"] = ('rw' in name.lower())
    # has(sp) = True
    features["has(sp)"] = ('sp' in name.lower())

    # lastletter = 'a'
    features["lastletter=a"] = ('a' in name[-1:].lower())
    # lastletter = 'f'
    features["lastletter=f"] = ('f' in name[-1:].lower())
    # lastletter = 'k'
    features["lastletter=k"] = ('k' in name[-1:].lower())

    # last2letter = 'ch'
    features["last2letter=ch"] = ('ch' in name[-2:].lower())
    # last2letter = 'do'
    features["last2letter=do"] = ('do' in name[-2:].lower())
    # last2letter = 'ia'
    features["last2letter=ia"] = ('ia' in name[-2:].lower())
    # last2letter = 'im'
    features["last2letter=im"] = ('im' in name[-2:].lower())
    # last2letter = 'io'
    features["last2letter=io"] = ('io' in name[-2:].lower())
    # last2letter = 'la'
    features["last2letter=la"] = ('la' in name[-2:].lower())
    # last2letter = 'ld'
    features["last2letter=ld"] = ('ld' in name[-2:].lower())
    # last2letter = 'na'
    features["last2letter=na"] = ('na' in name[-2:].lower())
    # last2letter = 'os'
    features["last2letter=os"] = ('os' in name[-2:].lower())
    # last2letter = 'ra'
    features["last2letter=ra"] = ('ra' in name[-2:].lower())
    # last2letter = 'rd'
    features["last2letter=rd"] = ('rd' in name[-2:].lower())
    # last2letter = 'rt'
    features["last2letter=rt"] = ('rt' in name[-2:].lower())
    # last2letter = 'sa'
    features["last2letter=sa"] = ('sa' in name[-2:].lower())
    # last2letter = 'ta'
    features["last2letter=ta"] = ('ta' in name[-2:].lower())
```

```python
        # last2letter = 'us'
        features["last2letter=us"] = ('us' in name[-2:].lower())

        # last3letter = 'ana'
        features["last3letter=ana"] = ('ana' in name[-3:].lower())
        # last3letter = u'ard'
        features["last3letter=ard"] = ('ard' in name[-3:].lower())
        # last3letter = u'ita'
        features["last3letter=ita"] = ('ita' in name[-3:].lower())
        # last3letter = u'nne'
        features["last3letter=nne"] = ('nne' in name[-3:].lower())
        # last3letter = u'tta'
        features["last3letter=tta"] = ('tta' in name[-3:].lower())

    return features
```

Functions for Analysis and Helper Functions

I have developed a few functions to facilitate the analysis and display of results:

- normalize_confusion_matrix: Returns a normalized confusion matrix.
- plot_confusion_matrix: Plots a confusion matrix.
- plot_both_confusion_matrix: Plots two confusion matrices side by side.
- evaluate_naive_bayes_classifier: Trains a model using the naive Bayes classifier.
- evaluate_decision_tree_classifier: Trains a model using the decision tree classifier.
- get_sorted_feature_accuracies: Returns a tuple of sorted features and their corresponding accuracies in the dataset.
- optimized_solution: Returns a tuple containing a list of features that yield the highest accuracy and the achieved accuracy.

Helper Functions:

- generate_errors
- show_errors
- generate_prediction

These functions aim to streamline the analysis process and aid in the interpretation of results.

[43]:
```python
### Functions for analysis
def normalize_confusion_matrix(cm):
    # normalize confusion matrix
    cm = cm.astype('float') / cm.sum(axis=1)[:, numpy.newaxis]
    # return confusion matrix
    return cm

def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion Matrix',
```

```python
                            cmap=plt.cm.Blues):
    """
    Plots the confusion matrix. Set `normalize=True` for normalization.
    """
    if normalize:
        cm = normalize_confusion_matrix(cm)

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = numpy.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=90)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True Label')
    plt.xlabel('Predicted Label')

    return

def plot_both_confusion_matrix(cm,label_names):
    # size figure
    plt.figure(figsize=(10,6))
    # add first subplot
    plt.subplot(2, 2, 1)
    # plot confusion matrix
    plot_confusion_matrix(cm,classes=label_names,normalize=False)
    # add second subplot
    plt.subplot(2, 2, 2)
    # plot confusion matrix (normalized)
    plot_confusion_matrix(cm,classes=label_names,normalize=True)

    return

def␣
 ↪evaluate_naive_bayes_classifier(train_names,devtest_names,test_names,feat_num):
 ↪
    # create feature set (train)
    train_set = [(get_features(n,feat_num), g)  for (n, g) in train_names]
    # create feature set (dev test)
```

```
    devtest_set = [(get_features(n,feat_num), g)  for (n, g) in devtest_names]
    # create test set (dev test)
    test_set = [(get_features(n,feat_num), g)  for (n, g) in test_names]
    # build classifier
    classifier = nltk.NaiveBayesClassifier.train(train_set)
    # compute accuracy (train set)
    train_accuracy=nltk.classify.accuracy(classifier, train_set)
    # compute accuracy (development test set)
    devtest_accuracy=nltk.classify.accuracy(classifier, devtest_set)
    # create predicted classes (train)
    train_set_predictions = [classifier.classify(get_features(n,feat_num))  for␣
 ↪(n, g) in train_names]
    # extract actual classes (gold)
    train_set_gold = [g  for (n, g) in train_names]
    # create confusion matrix
    train_cm=confusion_matrix(train_set_gold, train_set_predictions)
    # get unique classes (train)
    train_label_names =  list(set(train_set_gold) | set(train_set_predictions))
    # create table with precision, recall, f1-score, and support
    train_report=classification_report(train_set_gold, train_set_predictions,
        digits=display_digits)

    # create predicted classes (dev test)
    devtest_set_predictions = [classifier.classify(get_features(n,feat_num)) ␣
 ↪for (n, g) in devtest_names]
    # extract actual classes (gold)
    devtest_set_gold = [g  for (n, g) in devtest_names]
    # create confusion matrix (dev test)
    devtest_cm=confusion_matrix(devtest_set_gold, devtest_set_predictions)
    # get unique classes (dev test)
    devtest_label_names =  list(set(devtest_set_gold) |␣
 ↪set(devtest_set_predictions))
    # create table with precision, recall, f1-score, and support
    devtest_report=classification_report(devtest_set_gold,␣
 ↪devtest_set_predictions,
        digits=display_digits)

    return␣
 ↪train_accuracy,train_cm,train_label_names,train_report,devtest_accuracy,devtest_cm,devtest_

def␣
 ↪evaluate_decision_tree_classifier(train_names,devtest_names,test_names,feat_num):
 ↪
    # create feature set (train)
    train_set = [(get_features(n,feat_num), g)  for (n, g) in train_names]
    # create feature set (dev test)
```

```
    devtest_set = [(get_features(n,feat_num), g)  for (n, g) in devtest_names]
    # create test set (dev test)
    test_set = [(get_features(n,feat_num), g)  for (n, g) in test_names]
    # build classifier
    classifier = nltk.DecisionTreeClassifier.train(train_set)
    # compute accuracy (train set)
    train_accuracy=nltk.classify.accuracy(classifier, train_set)
    # compute accuracy (development test set)
    devtest_accuracy=nltk.classify.accuracy(classifier, devtest_set)
    # create predicted classes (train)
    train_set_predictions = [classifier.classify(get_features(n,feat_num))  for␣
 ↪(n, g) in train_names]
    # extract actual classes (gold)
    train_set_gold = [g  for (n, g) in train_names]
    # create confusion matrix
    train_cm=confusion_matrix(train_set_gold, train_set_predictions)
    # get unique classes (train)
    train_label_names =  list(set(train_set_gold) | set(train_set_predictions))
    # create table with precision, recall, f1-score, and support
    train_report=classification_report(train_set_gold, train_set_predictions,
        digits=display_digits)

    # create predicted classes (dev test)
    devtest_set_predictions = [classifier.classify(get_features(n,feat_num)) ␣
 ↪for (n, g) in devtest_names]
    # extract actual classes (gold)
    devtest_set_gold = [g  for (n, g) in devtest_names]
    # create confusion matrix (dev test)
    devtest_cm=confusion_matrix(devtest_set_gold, devtest_set_predictions)
    # get unique classes (dev test)
    devtest_label_names =  list(set(devtest_set_gold) |␣
 ↪set(devtest_set_predictions))
    # create table with precision, recall, f1-score, and support
    devtest_report=classification_report(devtest_set_gold,␣
 ↪devtest_set_predictions,
        digits=display_digits)

    return␣
 ↪train_accuracy,train_cm,train_label_names,train_report,devtest_accuracy,devtest_cm,devtest_


def get_sorted_feature_accuracies(feat_num_start, feat_num, model_id):
        feature_accuracy = {}
        for i in numpy.arange(feat_num_start, feat_num+1):
            feat_num =int(i)
            errors = []
```

```python
            # devtest-set and training set are constructed
            #random.shuffle(development_set_names)
            #devtest_names, train_names = development_set_names[0:500],␣
↪development_set_names[500:]

            train_set = [(get_features(n,feat_num), g)  for (n, g) in␣
↪train_names]
            devtest_set = [(get_features(n,feat_num), g)  for (n, g) in␣
↪devtest_names]
            test_set = [(get_features(n,feat_num), g)  for (n, g) in test_names]

            if (model_id == 'nbc'):
                classifier = nltk.NaiveBayesClassifier.train(train_set)
            elif (model_id == 'dtc'):
                classifier = nltk.DecisionTreeClassifier.train(train_set)

            # For errors list
            for (name, tag) in devtest_names:
                guess = classifier.classify(get_features(name,feat_num))
                if guess != tag:
                    errors.append((tag, guess, name))


            feature_accuracy[feat_num] = nltk.classify.accuracy(classifier,␣
↪devtest_set)


        #sort for accuracy, and then reverse the array to return the array as␣
↪most accurate to least accurate
        sorted_by_accuracy = sorted(feature_accuracy.items(), key=operator.
↪itemgetter(1))
        return sorted_by_accuracy[::-1]

def optimized_solution(model_id):
    # for each of the features, append to the list of features, and check if␣
↪the accuracy
    #went up or down. If it went down, take it out, if it went up, make that␣
↪the new accuracy to beat.

    optimized_feature_list = []
    last_accuracy = -1
    for feat_num in range(1,15):
        errors = []
        optimized_feature_list.append(feat_num)

        #random.shuffle(development_set_names)
```

```python
        #devtest_names, train_names = development_set_names[0:500],␣
 ↪development_set_names[500:]

        train_set = [(get_features(n,optimized_feature_list), g)  for (n, g) in␣
 ↪train_names]
        devtest_set = [(get_features(n,optimized_feature_list), g)  for (n, g)␣
 ↪in devtest_names]
        test_set = [(get_features(n,optimized_feature_list), g)  for (n, g) in␣
 ↪test_names]

        if (model_id == 'nbc'):
            classifier = nltk.NaiveBayesClassifier.train(train_set)
        elif (model_id == 'dtc'):
            classifier = nltk.DecisionTreeClassifier.train(train_set)

        for (name, tag) in devtest_names:
            guess = classifier.
 ↪classify(get_features(name,optimized_feature_list))
            if guess != tag:
                errors.append((tag, guess, name))


        current_accuracy= nltk.classify.accuracy(classifier, devtest_set)
        if current_accuracy > last_accuracy:
            last_accuracy = current_accuracy
        else:
            del optimized_feature_list[-1]

    return (optimized_feature_list, last_accuracy)

### Helper functions:

# Generic function to generate an error list based the arguments provided
# Accepts the classifer, names dataset, and the extractor function
# Returns the list of errors

def generate_errors(classifier, dataset, feat_num):

    errors = []

    for (name, tag) in dataset:
        guess = classifier.classify(get_features(name,feat_num))
        if guess != tag:
            errors.append((tag, guess, name))

    return errors
```

```
# Generic function to display classification errors
# Accepts the error list and an optional argument to show only n number of␣
↪errors

def show_errors(errors, n=None):

    if n is not None: errors = errors[:n]

    for (tag, guess, name) in sorted(errors):
        print('correct=%-8s guess=%-8s name=%-30s' %(tag, guess, name))


def generate_prediction(classifier, dataset, extractor_function):

    classification = []

    for (name, tag) in dataset:
        guess = classifier.classify(extractor_function(name))
        classification.append((name,guess))

    return classification
```

Models for Gender Identification - Naive Bayes Classifier:

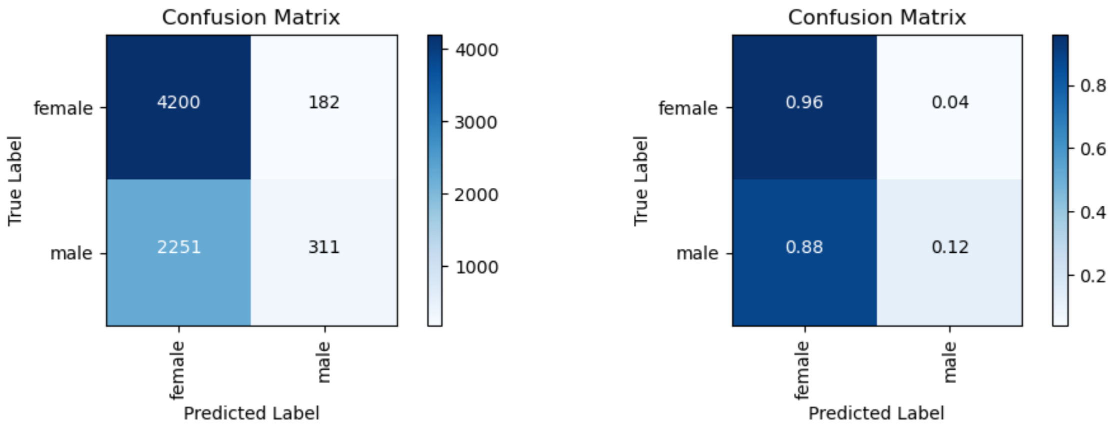
Utilizing the basic features identified earlier, I will assess the performance of the model for each.

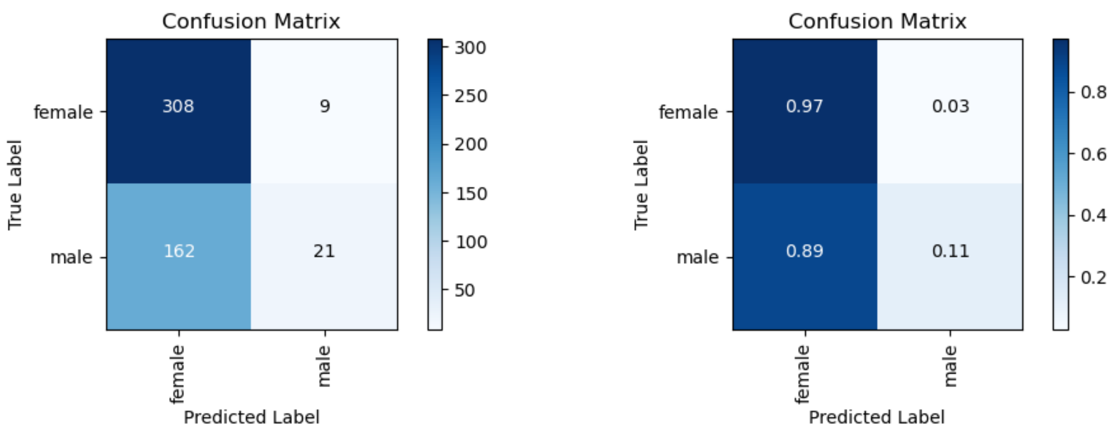
Feature 1 - Initial Letter:

In this model, I will train a Naive Bayes classifier using a straightforward feature set, focusing solely on the first letter of the name.

[44]:
```
feat_num = 1
# evaluate the Naive Bayes classifier using gender_features1
train_accuracy_nb1,train_cm_nb1,train_label_names_nb1,train_report_nb1, \
    devtest_accuracy_nb1, devtest_cm_nb1,devtest_label_names_nb1, \
    devtest_report_nb1, classifier_nb1=evaluate_naive_bayes_classifier( \
    train_names,devtest_names,test_names,feat_num)

# display model accuracy (train and development test)
print('Accuracy (Train): '+str(train_accuracy_nb1))
print('Accuracy (Development Test): '+str(devtest_accuracy_nb1))
# plot confusion matrix (train)
plot_both_confusion_matrix(train_cm_nb1,['female','male'])
# plot confusion matrix (dev test)
plot_both_confusion_matrix(devtest_cm_nb1,['female','male'])
```

```
Accuracy (Train): 0.6496255760368663
Accuracy (Development Test): 0.658
```





[45]:
```python
# display performance report (train)
print('Model Performance Metrics (Train):')
print(train_report_nb1)
# display performance report (dev test)
print('Model Performance Metrics (Development Test):')
print(devtest_report_nb1)
```

```
Model Performance Metrics (Train):
              precision    recall  f1-score   support

      female     0.6511    0.9585    0.7754      4382
        male     0.6308    0.1214    0.2036      2562

    accuracy                         0.6496      6944
```

```
   macro avg     0.6409    0.5399    0.4895      6944
weighted avg     0.6436    0.6496    0.5644      6944

Model Performance Metrics (Development Test):
              precision    recall  f1-score   support

      female     0.6553    0.9716    0.7827       317
        male     0.7000    0.1148    0.1972       183

    accuracy                         0.6580       500
   macro avg     0.6777    0.5432    0.4900       500
weighted avg     0.6717    0.6580    0.5684       500
```

[46]:

```
# set number of informative features to display
n_informative_features=20
# examine likelihood ratios
classifier_nb1.show_most_informative_features(n_informative_features)
```

```
Most Informative Features
             firstletter = 'w'              male : female =      4.6 : 1.0
             firstletter = 'q'              male : female =      3.1 : 1.0
             firstletter = 'x'              male : female =      2.8 : 1.0
             firstletter = 'k'            female : male   =      2.5 : 1.0
             firstletter = 'u'              male : female =      2.4 : 1.0
             firstletter = 'h'              male : female =      2.2 : 1.0
             firstletter = 'l'            female : male   =      1.9 : 1.0
             firstletter = 'y'              male : female =      1.7 : 1.0
             firstletter = 'z'              male : female =      1.6 : 1.0
             firstletter = 't'              male : female =      1.6 : 1.0
             firstletter = 'c'            female : male   =      1.6 : 1.0
             firstletter = 'm'            female : male   =      1.4 : 1.0
             firstletter = 'o'              male : female =      1.4 : 1.0
             firstletter = 's'              male : female =      1.4 : 1.0
             firstletter = 'r'              male : female =      1.3 : 1.0
             firstletter = 'p'              male : female =      1.3 : 1.0
             firstletter = 'd'            female : male   =      1.3 : 1.0
             firstletter = 'g'              male : female =      1.3 : 1.0
             firstletter = 'a'            female : male   =      1.2 : 1.0
             firstletter = 'e'            female : male   =      1.2 : 1.0
```

[47]:

```
# Show error
show_errors(generate_errors(classifier_nb1, devtest_names, feat_num))
```

```
correct=female   guess=male     name=Hadria
correct=female   guess=male     name=Hanni
correct=female   guess=male     name=Hestia
correct=female   guess=male     name=Hollie
```

```
correct=female   guess=male     name=Wenonah
correct=female   guess=male     name=Winnifred
correct=female   guess=male     name=Wren
correct=female   guess=male     name=Wrennie
correct=female   guess=male     name=Xenia
correct=male     guess=female   name=Adam
correct=male     guess=female   name=Adams
correct=male     guess=female   name=Adger
correct=male     guess=female   name=Alastair
correct=male     guess=female   name=Alford
correct=male     guess=female   name=Amadeus
correct=male     guess=female   name=Ambrose
correct=male     guess=female   name=Andrew
correct=male     guess=female   name=Andros
correct=male     guess=female   name=Anthony
correct=male     guess=female   name=Antoine
correct=male     guess=female   name=Antoni
correct=male     guess=female   name=Augusto
correct=male     guess=female   name=Avram
correct=male     guess=female   name=Baillie
correct=male     guess=female   name=Barclay
correct=male     guess=female   name=Barnie
correct=male     guess=female   name=Barret
correct=male     guess=female   name=Bartholomew
correct=male     guess=female   name=Bartolemo
correct=male     guess=female   name=Barton
correct=male     guess=female   name=Benson
correct=male     guess=female   name=Bernardo
correct=male     guess=female   name=Bjorn
correct=male     guess=female   name=Boris
correct=male     guess=female   name=Bryant
correct=male     guess=female   name=Buster
correct=male     guess=female   name=Calhoun
correct=male     guess=female   name=Calvin
correct=male     guess=female   name=Chad
correct=male     guess=female   name=Charley
correct=male     guess=female   name=Charlton
correct=male     guess=female   name=Chev
correct=male     guess=female   name=Clark
correct=male     guess=female   name=Curtis
correct=male     guess=female   name=Darrel
correct=male     guess=female   name=Dionysus
correct=male     guess=female   name=Domenic
correct=male     guess=female   name=Donny
correct=male     guess=female   name=Dorian
correct=male     guess=female   name=Douglas
correct=male     guess=female   name=Drew
correct=male     guess=female   name=Dunstan
```

```
correct=male     guess=female   name=Edwin
correct=male     guess=female   name=Elbert
correct=male     guess=female   name=Ellis
correct=male     guess=female   name=Emilio
correct=male     guess=female   name=Erny
correct=male     guess=female   name=Ezra
correct=male     guess=female   name=Fairfax
correct=male     guess=female   name=Felipe
correct=male     guess=female   name=Ferdinand
correct=male     guess=female   name=Flem
correct=male     guess=female   name=Flinn
correct=male     guess=female   name=Fowler
correct=male     guess=female   name=Franky
correct=male     guess=female   name=Fred
correct=male     guess=female   name=Fremont
correct=male     guess=female   name=Garv
correct=male     guess=female   name=Gayle
correct=male     guess=female   name=Gibb
correct=male     guess=female   name=Godart
correct=male     guess=female   name=Gregg
correct=male     guess=female   name=Guthry
correct=male     guess=female   name=Ichabod
correct=male     guess=female   name=Irving
correct=male     guess=female   name=Jake
correct=male     guess=female   name=Jason
correct=male     guess=female   name=Jervis
correct=male     guess=female   name=John-Patrick
correct=male     guess=female   name=Josephus
correct=male     guess=female   name=Julie
correct=male     guess=female   name=Kalman
correct=male     guess=female   name=Keene
correct=male     guess=female   name=Kenn
correct=male     guess=female   name=Kermit
correct=male     guess=female   name=Kimmo
correct=male     guess=female   name=Konrad
correct=male     guess=female   name=Kory
correct=male     guess=female   name=Kris
correct=male     guess=female   name=Krishna
correct=male     guess=female   name=Lamar
correct=male     guess=female   name=Lawton
correct=male     guess=female   name=Leonidas
correct=male     guess=female   name=Levon
correct=male     guess=female   name=Llewellyn
correct=male     guess=female   name=Loren
correct=male     guess=female   name=Lorenzo
correct=male     guess=female   name=Luce
correct=male     guess=female   name=Ludwig
correct=male     guess=female   name=Marcel
```

```
correct=male     guess=female   name=Marlin
correct=male     guess=female   name=Marwin
correct=male     guess=female   name=Matty
correct=male     guess=female   name=Maurise
correct=male     guess=female   name=Merril
correct=male     guess=female   name=Michal
correct=male     guess=female   name=Millicent
correct=male     guess=female   name=Milt
correct=male     guess=female   name=Moise
correct=male     guess=female   name=Monty
correct=male     guess=female   name=Mordecai
correct=male     guess=female   name=Mose
correct=male     guess=female   name=Mylo
correct=male     guess=female   name=Nichole
correct=male     guess=female   name=Nickie
correct=male     guess=female   name=Orville
correct=male     guess=female   name=Ozzy
correct=male     guess=female   name=Patel
correct=male     guess=female   name=Patricio
correct=male     guess=female   name=Patrick
correct=male     guess=female   name=Pattie
correct=male     guess=female   name=Pierce
correct=male     guess=female   name=Prasun
correct=male     guess=female   name=Prent
correct=male     guess=female   name=Prentice
correct=male     guess=female   name=Prescott
correct=male     guess=female   name=Ramon
correct=male     guess=female   name=Randall
correct=male     guess=female   name=Raul
correct=male     guess=female   name=Rawley
correct=male     guess=female   name=Ray
correct=male     guess=female   name=Renaud
correct=male     guess=female   name=Richmond
correct=male     guess=female   name=Riley
correct=male     guess=female   name=Roberto
correct=male     guess=female   name=Roderick
correct=male     guess=female   name=Rudolf
correct=male     guess=female   name=Rustie
correct=male     guess=female   name=Sandro
correct=male     guess=female   name=Sargent
correct=male     guess=female   name=Sasha
correct=male     guess=female   name=Sayers
correct=male     guess=female   name=Sebastiano
correct=male     guess=female   name=Selby
correct=male     guess=female   name=Serge
correct=male     guess=female   name=Shalom
correct=male     guess=female   name=Sholom
correct=male     guess=female   name=Sidnee
```

```
correct=male     guess=female   name=Silvio
correct=male     guess=female   name=Slade
correct=male     guess=female   name=Smith
correct=male     guess=female   name=Son
correct=male     guess=female   name=Sting
correct=male     guess=female   name=Tabb
correct=male     guess=female   name=Ted
correct=male     guess=female   name=Terrel
correct=male     guess=female   name=Thom
correct=male     guess=female   name=Thorny
correct=male     guess=female   name=Timothee
correct=male     guess=female   name=Tom
correct=male     guess=female   name=Tracy
correct=male     guess=female   name=Trev
correct=male     guess=female   name=Tuckie
correct=male     guess=female   name=Tulley
correct=male     guess=female   name=Turner
correct=male     guess=female   name=Tyrone
correct=male     guess=female   name=Vergil
correct=male     guess=female   name=Vinnie
correct=male     guess=female   name=Virgil
correct=male     guess=female   name=Voltaire
correct=male     guess=female   name=Zachary
```

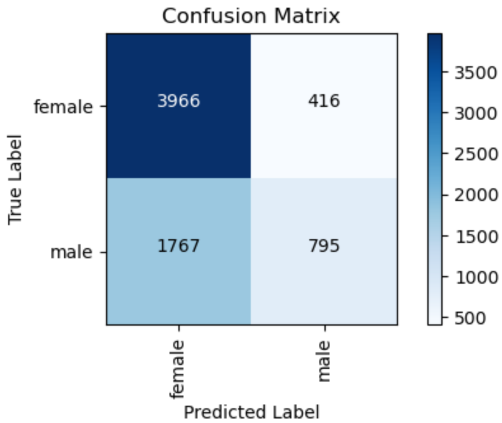
First letter alone does not lead to very good results as is indicated by the analysis above.

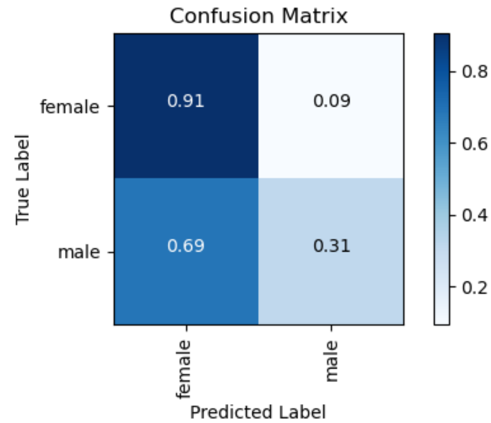
Feature 2 - First 2 letters

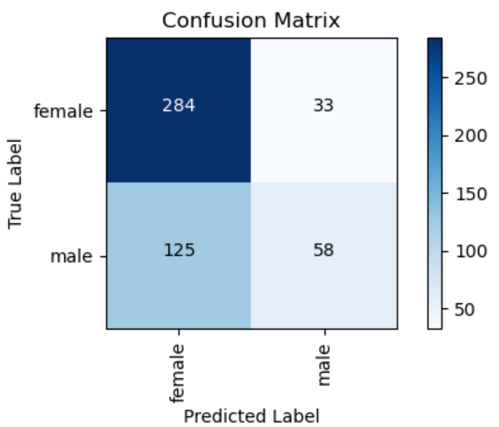
I will now consider the first 2 letters as our feature.

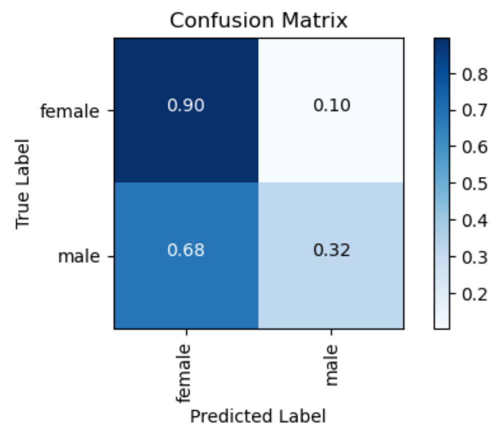
[53]:
```
feat_num = 2
# evaluate the Naive Bayes classifier using gender_features2
train_accuracy_nb2,train_cm_nb2,train_label_names_nb2,train_report_nb2, \
    devtest_accuracy_nb2, devtest_cm_nb2,devtest_label_names_nb2, \
    devtest_report_nb2, classifier_nb2=evaluate_naive_bayes_classifier( \
    train_names,devtest_names,test_names,feat_num)

# display model accuracy (train and development test)
print('Accuracy (Train): '+str(train_accuracy_nb2))
print('Accuracy (Development Test): '+str(devtest_accuracy_nb2))
# plot confusion matrix (train)
plot_both_confusion_matrix(train_cm_nb2,['female','male'])
# plot confusion matrix (dev test)
plot_both_confusion_matrix(devtest_cm_nb2,['female','male'])
```

```
Accuracy (Train): 0.6856278801843319
Accuracy (Development Test): 0.684
```









[54]:
```
# set number of informative features to display
n_informative_features=20
# examine likelihood ratios
classifier_nb2.show_most_informative_features(n_informative_features)
```

```
Most Informative Features
            first2Letters = 'fo'              male : female =     15.1 : 1.0
            first2Letters = 'hu'              male : female =     15.1 : 1.0
            first2Letters = 'ya'              male : female =     10.6 : 1.0
            first2Letters = 'sc'              male : female =      9.5 : 1.0
            first2Letters = 'wa'              male : female =      9.5 : 1.0
            first2Letters = 'tu'              male : female =      7.3 : 1.0
            first2Letters = 'wh'              male : female =      7.3 : 1.0
            first2Letters = 'we'              male : female =      5.7 : 1.0
            first2Letters = 'ce'            female : male   =      5.4 : 1.0
            first2Letters = 'ka'            female : male   =      5.4 : 1.0
            first2Letters = 'fa'            female : male   =      5.1 : 1.0
```

```
            first2Letters = 'rh'           female : male   =      5.0 : 1.0
            first2Letters = 'ly'           female : male   =      4.7 : 1.0
            first2Letters = 'ty'             male : female =      4.6 : 1.0
            first2Letters = 'bu'             male : female =      4.1 : 1.0
            first2Letters = 'dr'             male : female =      3.9 : 1.0
            first2Letters = 'xe'             male : female =      3.9 : 1.0
            first2Letters = 'ko'           female : male   =      3.7 : 1.0
            first2Letters = 'ze'             male : female =      3.5 : 1.0
            first2Letters = 'gl'           female : male   =      3.5 : 1.0
```

[55]:
```
# Show error
show_errors(generate_errors(classifier_nb2, devtest_names, feat_num))
```

```
correct=female   guess=male     name=Abigail
correct=female   guess=male     name=Barbaraanne
correct=female   guess=male     name=Fortune
correct=female   guess=male     name=Gabriella
correct=female   guess=male     name=Gigi
correct=female   guess=male     name=Gilbertine
correct=female   guess=male     name=Ginni
correct=female   guess=male     name=Giorgia
correct=female   guess=male     name=Giovanna
correct=female   guess=male     name=Gisele
correct=female   guess=male     name=Hadria
correct=female   guess=male     name=Hanni
correct=female   guess=male     name=Hollie
correct=female   guess=male     name=Moira
correct=female   guess=male     name=Molly
correct=female   guess=male     name=Morena
correct=female   guess=male     name=Moya
correct=female   guess=male     name=Moyna
correct=female   guess=male     name=Octavia
correct=female   guess=male     name=Riane
correct=female   guess=male     name=Rubia
correct=female   guess=male     name=Ruth
correct=female   guess=male     name=Steffie
correct=female   guess=male     name=Stephanie
correct=female   guess=male     name=Thea
correct=female   guess=male     name=Theresina
correct=female   guess=male     name=Tomi
correct=female   guess=male     name=Wenonah
correct=female   guess=male     name=Winnifred
correct=female   guess=male     name=Wren
correct=female   guess=male     name=Wrennie
correct=female   guess=male     name=Xenia
correct=female   guess=male     name=Zena
correct=male     guess=female   name=Adam
correct=male     guess=female   name=Adams
```

```
correct=male     guess=female   name=Adger
correct=male     guess=female   name=Alastair
correct=male     guess=female   name=Alford
correct=male     guess=female   name=Amadeus
correct=male     guess=female   name=Ambrose
correct=male     guess=female   name=Andrew
correct=male     guess=female   name=Andros
correct=male     guess=female   name=Anthony
correct=male     guess=female   name=Antoine
correct=male     guess=female   name=Antoni
correct=male     guess=female   name=Augusto
correct=male     guess=female   name=Avram
correct=male     guess=female   name=Benson
correct=male     guess=female   name=Bernardo
correct=male     guess=female   name=Boris
correct=male     guess=female   name=Bryant
correct=male     guess=female   name=Calhoun
correct=male     guess=female   name=Calvin
correct=male     guess=female   name=Chad
correct=male     guess=female   name=Charley
correct=male     guess=female   name=Charlton
correct=male     guess=female   name=Chev
correct=male     guess=female   name=Clark
correct=male     guess=female   name=Darrel
correct=male     guess=female   name=Dionysus
correct=male     guess=female   name=Domenic
correct=male     guess=female   name=Donny
correct=male     guess=female   name=Dorian
correct=male     guess=female   name=Douglas
correct=male     guess=female   name=Edwin
correct=male     guess=female   name=Elbert
correct=male     guess=female   name=Ellis
correct=male     guess=female   name=Emilio
correct=male     guess=female   name=Erny
correct=male     guess=female   name=Fairfax
correct=male     guess=female   name=Felipe
correct=male     guess=female   name=Ferdinand
correct=male     guess=female   name=Flem
correct=male     guess=female   name=Flinn
correct=male     guess=female   name=Franky
correct=male     guess=female   name=Fred
correct=male     guess=female   name=Fremont
correct=male     guess=female   name=Gregg
correct=male     guess=female   name=Guthry
correct=male     guess=female   name=Hermon
correct=male     guess=female   name=Herold
correct=male     guess=female   name=Ichabod
correct=male     guess=female   name=Irving
```

```
correct=male     guess=female   name=Jake
correct=male     guess=female   name=Jason
correct=male     guess=female   name=Jervis
correct=male     guess=female   name=John-Patrick
correct=male     guess=female   name=Josephus
correct=male     guess=female   name=Julie
correct=male     guess=female   name=Kalman
correct=male     guess=female   name=Keene
correct=male     guess=female   name=Kenn
correct=male     guess=female   name=Kermit
correct=male     guess=female   name=Kimmo
correct=male     guess=female   name=Konrad
correct=male     guess=female   name=Kory
correct=male     guess=female   name=Kris
correct=male     guess=female   name=Krishna
correct=male     guess=female   name=Lamar
correct=male     guess=female   name=Lawton
correct=male     guess=female   name=Leonidas
correct=male     guess=female   name=Levon
correct=male     guess=female   name=Llewellyn
correct=male     guess=female   name=Loren
correct=male     guess=female   name=Lorenzo
correct=male     guess=female   name=Luce
correct=male     guess=female   name=Ludwig
correct=male     guess=female   name=Marcel
correct=male     guess=female   name=Marlin
correct=male     guess=female   name=Marwin
correct=male     guess=female   name=Matty
correct=male     guess=female   name=Maurise
correct=male     guess=female   name=Merril
correct=male     guess=female   name=Michal
correct=male     guess=female   name=Millicent
correct=male     guess=female   name=Milt
correct=male     guess=female   name=Mylo
correct=male     guess=female   name=Nichole
correct=male     guess=female   name=Nickie
correct=male     guess=female   name=Orville
correct=male     guess=female   name=Patel
correct=male     guess=female   name=Patricio
correct=male     guess=female   name=Patrick
correct=male     guess=female   name=Pattie
correct=male     guess=female   name=Prasun
correct=male     guess=female   name=Prent
correct=male     guess=female   name=Prentice
correct=male     guess=female   name=Prescott
correct=male     guess=female   name=Ramon
correct=male     guess=female   name=Randall
correct=male     guess=female   name=Raul
```

```
correct=male       guess=female    name=Rawley
correct=male       guess=female    name=Ray
correct=male       guess=female    name=Renaud
correct=male       guess=female    name=Roberto
correct=male       guess=female    name=Roderick
correct=male       guess=female    name=Sandro
correct=male       guess=female    name=Sargent
correct=male       guess=female    name=Sasha
correct=male       guess=female    name=Sayers
correct=male       guess=female    name=Sebastiano
correct=male       guess=female    name=Selby
correct=male       guess=female    name=Serge
correct=male       guess=female    name=Shalom
correct=male       guess=female    name=Sholom
correct=male       guess=female    name=Sidnee
correct=male       guess=female    name=Silvio
correct=male       guess=female    name=Son
correct=male       guess=female    name=Tabb
correct=male       guess=female    name=Ted
correct=male       guess=female    name=Terrel
correct=male       guess=female    name=Timothee
correct=male       guess=female    name=Tracy
correct=male       guess=female    name=Trev
correct=male       guess=female    name=Vergil
correct=male       guess=female    name=Vinnie
correct=male       guess=female    name=Virgil
correct=male       guess=female    name=Voltaire
```

Initial observations suggest that first letter features may not be optimal for model development. Consequently, I will shift my focus to consider features related to the last letter(s).

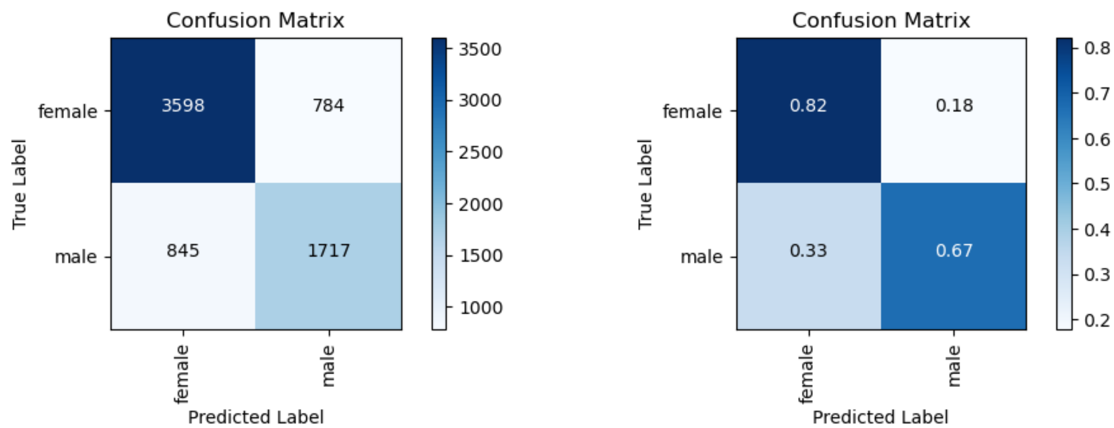
Feature 3 - Last Letter

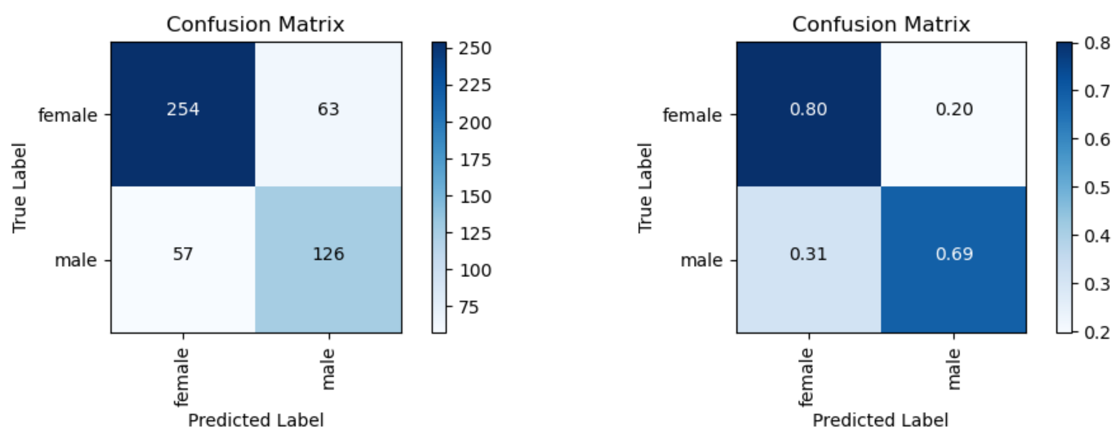
My attention will now be directed towards analyzing the last letter of the name. Through our preliminary feature exploration, discernible patterns have emerged, which are potentially exploitable by our classifier.

[56]:
```
feat_num = 3
# evaluate the Naive Bayes classifier using gender_features1
train_accuracy_nb3,train_cm_nb3,train_label_names_nb3,train_report_nb3, \
    devtest_accuracy_nb3, devtest_cm_nb3,devtest_label_names_nb3, \
    devtest_report_nb3, classifier_nb3=evaluate_naive_bayes_classifier( \
    train_names,devtest_names,test_names,feat_num)

# display model accuracy (train and development test)
print('Accuracy (Train): '+str(train_accuracy_nb3))
print('Accuracy (Development Test): '+str(devtest_accuracy_nb3))
# plot confusion matrix (train)
```

```
plot_both_confusion_matrix(train_cm_nb3,['female','male'])
# plot confusion matrix (dev test)
plot_both_confusion_matrix(devtest_cm_nb3,['female','male'])
```

```
Accuracy (Train): 0.7654089861751152
Accuracy (Development Test): 0.76
```





[57]:
```
# set number of informative features to display
n_informative_features=20
# examine likelihood ratios
classifier_nb3.show_most_informative_features(n_informative_features)
```

```
Most Informative Features
             last_letter = 'a'            female : male   =     36.4 : 1.0
             last_letter = 'k'              male : female =     28.5 : 1.0
             last_letter = 'f'              male : female =     15.4 : 1.0
             last_letter = 'p'              male : female =     11.9 : 1.0
```

```
                last_letter = 'd'              male : female =     10.5 : 1.0
                last_letter = 'v'              male : female =      8.5 : 1.0
                last_letter = 'o'              male : female =      8.5 : 1.0
                last_letter = 'r'              male : female =      8.0 : 1.0
                last_letter = 'm'              male : female =      7.4 : 1.0
                last_letter = 'w'              male : female =      5.1 : 1.0
                last_letter = 'g'              male : female =      4.6 : 1.0
                last_letter = 's'              male : female =      4.4 : 1.0
                last_letter = 'z'              male : female =      4.4 : 1.0
                last_letter = 't'              male : female =      4.0 : 1.0
                last_letter = 'j'              male : female =      4.0 : 1.0
                last_letter = 'b'              male : female =      3.9 : 1.0
                last_letter = 'i'            female : male   =      3.7 : 1.0
                last_letter = 'u'              male : female =      3.0 : 1.0
                last_letter = 'n'              male : female =      2.1 : 1.0
                last_letter = 'x'              male : female =      1.9 : 1.0
```

[58]:
```
show_errors(generate_errors(classifier_nb3, devtest_names, feat_num))
```

```
correct=female   guess=male     name=Abigail
correct=female   guess=male     name=Adel
correct=female   guess=male     name=Agnes
correct=female   guess=male     name=Anne-Mar
correct=female   guess=male     name=Arleen
correct=female   guess=male     name=Bess
correct=female   guess=male     name=Bryn
correct=female   guess=male     name=Caitlin
correct=female   guess=male     name=Caitrin
correct=female   guess=male     name=Cal
correct=female   guess=male     name=Carlyn
correct=female   guess=male     name=Carol-Jean
correct=female   guess=male     name=Caroleen
correct=female   guess=male     name=Carroll
correct=female   guess=male     name=Caryl
correct=female   guess=male     name=Charlot
correct=female   guess=male     name=Darell
correct=female   guess=male     name=Daryl
correct=female   guess=male     name=Del
correct=female   guess=male     name=Diamond
correct=female   guess=male     name=Doreen
correct=female   guess=male     name=Doris
correct=female   guess=male     name=Dorit
correct=female   guess=male     name=Eryn
correct=female   guess=male     name=Gennifer
correct=female   guess=male     name=Greer
correct=female   guess=male     name=Gretel
correct=female   guess=male     name=Ingeberg
correct=female   guess=male     name=Iris
```

```
correct=female   guess=male     name=Janel
correct=female   guess=male     name=Janot
correct=female   guess=male     name=Joan
correct=female   guess=male     name=Karil
correct=female   guess=male     name=Karleen
correct=female   guess=male     name=Karyl
correct=female   guess=male     name=Keren
correct=female   guess=male     name=Kimberlyn
correct=female   guess=male     name=Kirstyn
correct=female   guess=male     name=Leanor
correct=female   guess=male     name=Lian
correct=female   guess=male     name=Lib
correct=female   guess=male     name=Maren
correct=female   guess=male     name=Margo
correct=female   guess=male     name=Marys
correct=female   guess=male     name=Melisent
correct=female   guess=male     name=Meris
correct=female   guess=male     name=Michal
correct=female   guess=male     name=Mikako
correct=female   guess=male     name=Miran
correct=female   guess=male     name=Nil
correct=female   guess=male     name=Raven
correct=female   guess=male     name=Robbyn
correct=female   guess=male     name=Rozamond
correct=female   guess=male     name=Sal
correct=female   guess=male     name=Sharleen
correct=female   guess=male     name=Shaun
correct=female   guess=male     name=Shaylyn
correct=female   guess=male     name=Siobhan
correct=female   guess=male     name=Sioux
correct=female   guess=male     name=Val
correct=female   guess=male     name=Vivian
correct=female   guess=male     name=Winnifred
correct=female   guess=male     name=Wren
correct=male     guess=female   name=Ambrose
correct=male     guess=female   name=Anthony
correct=male     guess=female   name=Antoine
correct=male     guess=female   name=Antoni
correct=male     guess=female   name=Baillie
correct=male     guess=female   name=Barclay
correct=male     guess=female   name=Barnie
correct=male     guess=female   name=Charley
correct=male     guess=female   name=Donny
correct=male     guess=female   name=Erny
correct=male     guess=female   name=Ezra
correct=male     guess=female   name=Felipe
correct=male     guess=female   name=Franky
correct=male     guess=female   name=Gayle
```

```
correct=male     guess=female   name=Guthry
correct=male     guess=female   name=Hari
correct=male     guess=female   name=Jake
correct=male     guess=female   name=Julie
correct=male     guess=female   name=Keene
correct=male     guess=female   name=Kory
correct=male     guess=female   name=Krishna
correct=male     guess=female   name=Luce
correct=male     guess=female   name=Matty
correct=male     guess=female   name=Maurise
correct=male     guess=female   name=Moise
correct=male     guess=female   name=Monty
correct=male     guess=female   name=Mordecai
correct=male     guess=female   name=Mose
correct=male     guess=female   name=Nichole
correct=male     guess=female   name=Nickie
correct=male     guess=female   name=Orville
correct=male     guess=female   name=Ozzy
correct=male     guess=female   name=Pattie
correct=male     guess=female   name=Pierce
correct=male     guess=female   name=Prentice
correct=male     guess=female   name=Rawley
correct=male     guess=female   name=Ray
correct=male     guess=female   name=Riley
correct=male     guess=female   name=Rustie
correct=male     guess=female   name=Sasha
correct=male     guess=female   name=Selby
correct=male     guess=female   name=Serge
correct=male     guess=female   name=Sidnee
correct=male     guess=female   name=Slade
correct=male     guess=female   name=Smith
correct=male     guess=female   name=Thorny
correct=male     guess=female   name=Timothee
correct=male     guess=female   name=Tracy
correct=male     guess=female   name=Tuckie
correct=male     guess=female   name=Tulley
correct=male     guess=female   name=Tyrone
correct=male     guess=female   name=Vinnie
correct=male     guess=female   name=Voltaire
correct=male     guess=female   name=Westbrooke
correct=male     guess=female   name=Wittie
correct=male     guess=female   name=Woody
correct=male     guess=female   name=Zachary
```

Even though names ending with the letter ‘a’ ranked as our second-best feature within this feature set, other rules that seemed promising for gender prediction did not rank highly.

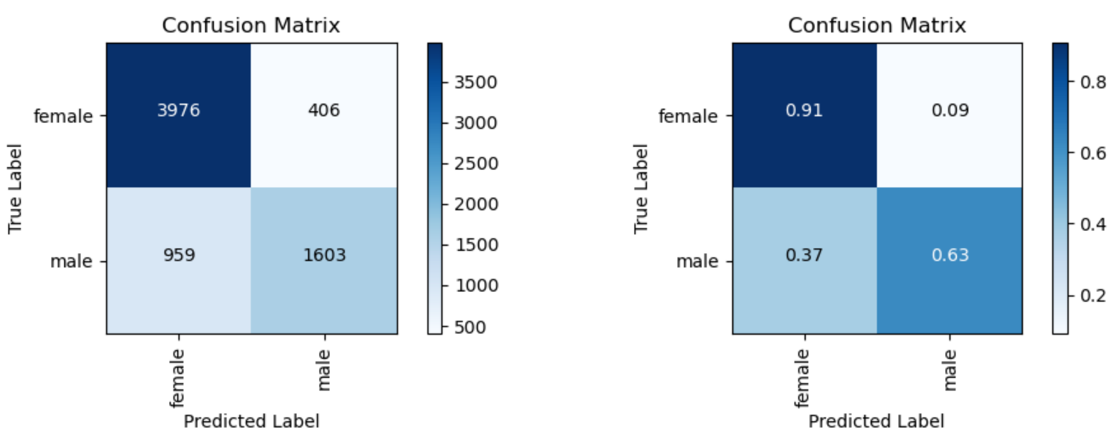
This might be attributed to my exploration of conditional frequency rather than percent conditional frequency.

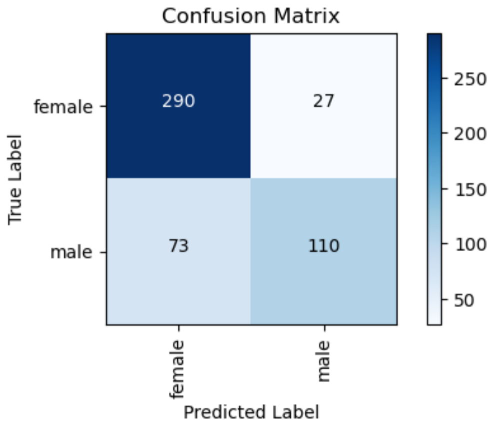
Regarding Feature 4 - Last 2 letters:

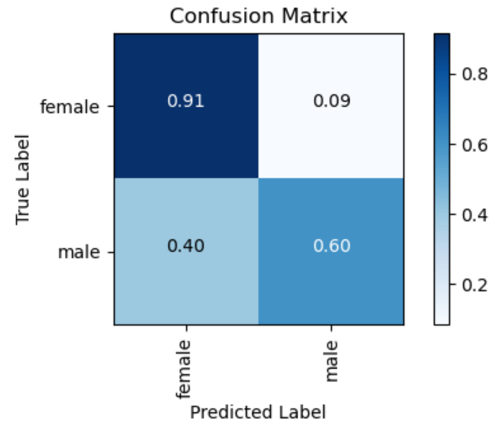
Within this model, I employed a Naive Bayes classifier trained on a feature set consisting of the first two letters of a name.

[59]:
```
feat_num = 4
# evaluate the Naive Bayes classifier using gender_features2
train_accuracy_nb4,train_cm_nb4,train_label_names_nb4,train_report_nb4, \
    devtest_accuracy_nb4, devtest_cm_nb4,devtest_label_names_nb4, \
    devtest_report_nb4, classifier_nb4=evaluate_naive_bayes_classifier( \
    train_names,devtest_names,test_names,feat_num)

# display model accuracy (train and development test)
print('Accuracy (Train): '+str(train_accuracy_nb4))
print('Accuracy (Development Test): '+str(devtest_accuracy_nb4))
# plot confusion matrix (train)
plot_both_confusion_matrix(train_cm_nb4,['female','male'])
# plot confusion matrix (dev test)
plot_both_confusion_matrix(devtest_cm_nb4,['female','male'])
```

```
Accuracy (Train): 0.8034274193548387
Accuracy (Development Test): 0.8
```







[60]:

```
# set number of informative features to display
n_informative_features=20
# examine likelihood ratios
classifier_nb4.show_most_informative_features(n_informative_features)
```

```
Most Informative Features
             last2letters = 'na'           female : male   =    158.2 : 1.0
             last2letters = 'la'           female : male   =     69.1 : 1.0
             last2letters = 'ia'           female : male   =     36.8 : 1.0
             last2letters = 'sa'           female : male   =     34.8 : 1.0
             last2letters = 'ra'           female : male   =     33.6 : 1.0
             last2letters = 'ta'           female : male   =     31.8 : 1.0
             last2letters = 'rd'             male : female =     31.3 : 1.0
             last2letters = 'us'             male : female =     28.0 : 1.0
             last2letters = 'do'             male : female =     25.1 : 1.0
             last2letters = 'io'             male : female =     24.0 : 1.0
             last2letters = 'ld'             male : female =     23.1 : 1.0
             last2letters = 'rt'             male : female =     22.3 : 1.0
             last2letters = 'os'             male : female =     17.3 : 1.0
             last2letters = 'ch'             male : female =     14.4 : 1.0
             last2letters = 'ka'           female : male   =     14.1 : 1.0
             last2letters = 'ya'           female : male   =     10.9 : 1.0
             last2letters = 'em'             male : female =     10.6 : 1.0
             last2letters = 'ff'             male : female =     10.6 : 1.0
             last2letters = 'ip'             male : female =     10.6 : 1.0
             last2letters = 'ns'             male : female =     10.6 : 1.0
```

[61]:

```
# Show error
show_errors(generate_errors(classifier_nb4, devtest_names, feat_num))
```

```
correct=female   guess=male     name=Abigail
correct=female   guess=male     name=Agnes
```

```
correct=female   guess=male     name=Anne-Mar
correct=female   guess=male     name=Caitlin
correct=female   guess=male     name=Caitrin
correct=female   guess=male     name=Carol-Jean
correct=female   guess=male     name=Carroll
correct=female   guess=male     name=Charlot
correct=female   guess=male     name=Cloe
correct=female   guess=male     name=Darell
correct=female   guess=male     name=Diamond
correct=female   guess=male     name=Gennifer
correct=female   guess=male     name=Greer
correct=female   guess=male     name=Janot
correct=female   guess=male     name=Joan
correct=female   guess=male     name=Karil
correct=female   guess=male     name=Leanor
correct=female   guess=male     name=Lian
correct=female   guess=male     name=Margo
correct=female   guess=male     name=Melisent
correct=female   guess=male     name=Miran
correct=female   guess=male     name=Nil
correct=female   guess=male     name=Rozamond
correct=female   guess=male     name=Siobhan
correct=female   guess=male     name=Vivian
correct=female   guess=male     name=Winnifred
correct=female   guess=male     name=Zoe
correct=male     guess=female   name=Adams
correct=male     guess=female   name=Ambrose
correct=male     guess=female   name=Anthony
correct=male     guess=female   name=Antoine
correct=male     guess=female   name=Antoni
correct=male     guess=female   name=Baillie
correct=male     guess=female   name=Barnie
correct=male     guess=female   name=Barret
correct=male     guess=female   name=Boris
correct=male     guess=female   name=Calhoun
correct=male     guess=female   name=Charley
correct=male     guess=female   name=Curtis
correct=male     guess=female   name=Darrel
correct=male     guess=female   name=Donny
correct=male     guess=female   name=Ellis
correct=male     guess=female   name=Erny
correct=male     guess=female   name=Ezra
correct=male     guess=female   name=Flinn
correct=male     guess=female   name=Gayle
correct=male     guess=female   name=Gregg
correct=male     guess=female   name=Guthry
correct=male     guess=female   name=Hari
correct=male     guess=female   name=Hiralal
```

```
correct=male     guess=female   name=Jervis
correct=male     guess=female   name=Julie
correct=male     guess=female   name=Keene
correct=male     guess=female   name=Kenn
correct=male     guess=female   name=Kermit
correct=male     guess=female   name=Kory
correct=male     guess=female   name=Kris
correct=male     guess=female   name=Krishna
correct=male     guess=female   name=Llewellyn
correct=male     guess=female   name=Loren
correct=male     guess=female   name=Luce
correct=male     guess=female   name=Marcel
correct=male     guess=female   name=Matty
correct=male     guess=female   name=Maurise
correct=male     guess=female   name=Michal
correct=male     guess=female   name=Moise
correct=male     guess=female   name=Monty
correct=male     guess=female   name=Mose
correct=male     guess=female   name=Nichole
correct=male     guess=female   name=Nickie
correct=male     guess=female   name=Orville
correct=male     guess=female   name=Ozzy
correct=male     guess=female   name=Patel
correct=male     guess=female   name=Pattie
correct=male     guess=female   name=Pierce
correct=male     guess=female   name=Prasun
correct=male     guess=female   name=Prentice
correct=male     guess=female   name=Rawley
correct=male     guess=female   name=Riley
correct=male     guess=female   name=Rustie
correct=male     guess=female   name=Sasha
correct=male     guess=female   name=Selby
correct=male     guess=female   name=Serge
correct=male     guess=female   name=Sidnee
correct=male     guess=female   name=Slade
correct=male     guess=female   name=Smith
correct=male     guess=female   name=Terrel
correct=male     guess=female   name=Thorny
correct=male     guess=female   name=Timothee
correct=male     guess=female   name=Tracy
correct=male     guess=female   name=Tuckie
correct=male     guess=female   name=Tulley
correct=male     guess=female   name=Tyrone
correct=male     guess=female   name=Vinnie
correct=male     guess=female   name=Voltaire
correct=male     guess=female   name=Wendel
correct=male     guess=female   name=Winn
correct=male     guess=female   name=Wittie
```

```
correct=male      guess=female   name=Woody
correct=male      guess=female   name=Zachary
```

Gender Identification Models - Decision Tree Classifier:

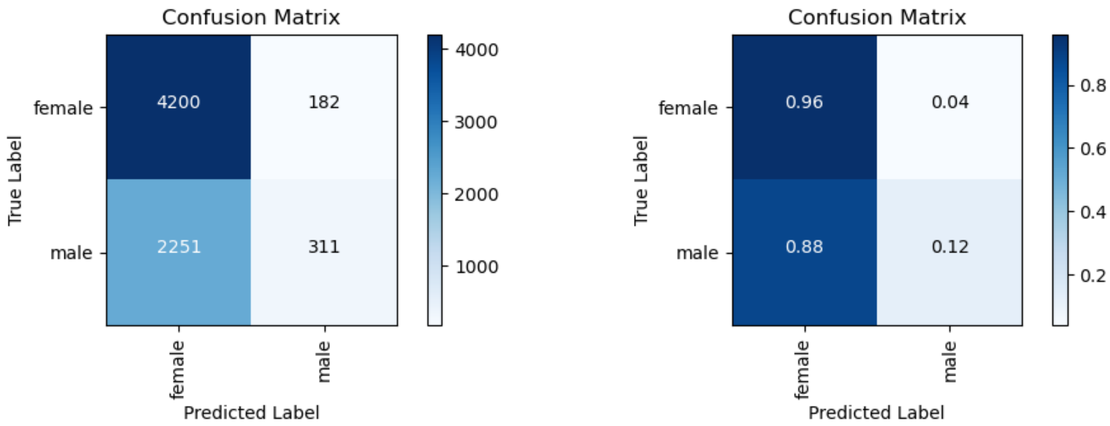
Employing the previously identified simple features, I will evaluate the performance of the model for each.

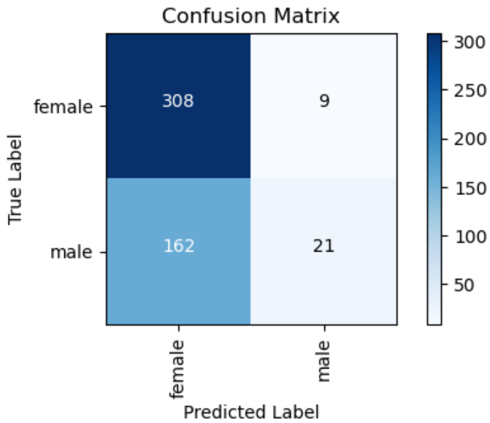
Feature 1 - First Letter:

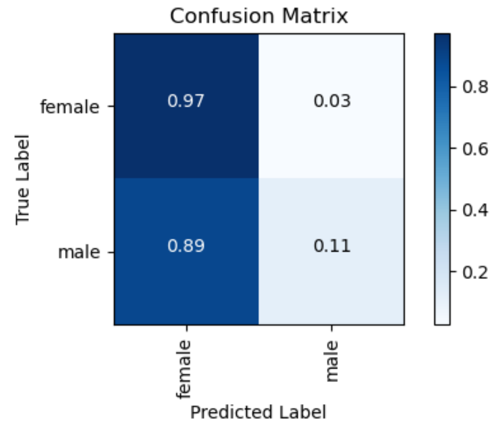
In this model, I will train a Decision Tree classifier using a basic feature set, specifically focusing on the first letter of the name.

[65]:
```
feat_num = 1
# evaluate the Naive Bayes classifier using gender_features10
train_accuracy_dt1,train_cm_dt1,train_label_names_dt1,train_report_dt1,devtest_accuracy_dt1,␣
↪devtest_cm_dt1,devtest_label_names_dt1,devtest_report_dt1,␣
↪classifier_dt1=evaluate_decision_tree_classifier(train_names,devtest_names,test_names,feat_
# display model accuracy (train and development test)
print('Accuracy (Train): '+str(train_accuracy_dt1))
print('Accuracy (Development Test): '+str(devtest_accuracy_dt1))
# plot confusion matrix (train)
plot_both_confusion_matrix(train_cm_dt1,['female','male'])
# plot confusion matrix (dev test)
plot_both_confusion_matrix(devtest_cm_dt1,['female','male'])
```

```
Accuracy (Train): 0.6496255760368663
Accuracy (Development Test): 0.658
```







[66]:

```
# display performance report (train)
print('Model Performance Metrics (Train):')
print(train_report_dt1)
# display performance report (dev test)
print('Model Performance Metrics (Development Test):')
print(devtest_report_dt1)
```

```
Model Performance Metrics (Train):
              precision    recall  f1-score   support

      female     0.6511    0.9585    0.7754      4382
        male     0.6308    0.1214    0.2036      2562

    accuracy                         0.6496      6944
   macro avg     0.6409    0.5399    0.4895      6944
weighted avg     0.6436    0.6496    0.5644      6944

Model Performance Metrics (Development Test):
              precision    recall  f1-score   support

      female     0.6553    0.9716    0.7827       317
        male     0.7000    0.1148    0.1972       183

    accuracy                         0.6580       500
   macro avg     0.6777    0.5432    0.4900       500
weighted avg     0.6717    0.6580    0.5684       500
```

[67]:

```
# Show error
show_errors(generate_errors(classifier_dt1, devtest_names, feat_num))
```

```
correct=female   guess=male      name=Hadria
```

```
correct=female   guess=male     name=Hanni
correct=female   guess=male     name=Hestia
correct=female   guess=male     name=Hollie
correct=female   guess=male     name=Wenonah
correct=female   guess=male     name=Winnifred
correct=female   guess=male     name=Wren
correct=female   guess=male     name=Wrennie
correct=female   guess=male     name=Xenia
correct=male     guess=female   name=Adam
correct=male     guess=female   name=Adams
correct=male     guess=female   name=Adger
correct=male     guess=female   name=Alastair
correct=male     guess=female   name=Alford
correct=male     guess=female   name=Amadeus
correct=male     guess=female   name=Ambrose
correct=male     guess=female   name=Andrew
correct=male     guess=female   name=Andros
correct=male     guess=female   name=Anthony
correct=male     guess=female   name=Antoine
correct=male     guess=female   name=Antoni
correct=male     guess=female   name=Augusto
correct=male     guess=female   name=Avram
correct=male     guess=female   name=Baillie
correct=male     guess=female   name=Barclay
correct=male     guess=female   name=Barnie
correct=male     guess=female   name=Barret
correct=male     guess=female   name=Bartholomew
correct=male     guess=female   name=Bartolemo
correct=male     guess=female   name=Barton
correct=male     guess=female   name=Benson
correct=male     guess=female   name=Bernardo
correct=male     guess=female   name=Bjorn
correct=male     guess=female   name=Boris
correct=male     guess=female   name=Bryant
correct=male     guess=female   name=Buster
correct=male     guess=female   name=Calhoun
correct=male     guess=female   name=Calvin
correct=male     guess=female   name=Chad
correct=male     guess=female   name=Charley
correct=male     guess=female   name=Charlton
correct=male     guess=female   name=Chev
correct=male     guess=female   name=Clark
correct=male     guess=female   name=Curtis
correct=male     guess=female   name=Darrel
correct=male     guess=female   name=Dionysus
correct=male     guess=female   name=Domenic
correct=male     guess=female   name=Donny
correct=male     guess=female   name=Dorian
```

```
correct=male     guess=female   name=Douglas
correct=male     guess=female   name=Drew
correct=male     guess=female   name=Dunstan
correct=male     guess=female   name=Edwin
correct=male     guess=female   name=Elbert
correct=male     guess=female   name=Ellis
correct=male     guess=female   name=Emilio
correct=male     guess=female   name=Erny
correct=male     guess=female   name=Ezra
correct=male     guess=female   name=Fairfax
correct=male     guess=female   name=Felipe
correct=male     guess=female   name=Ferdinand
correct=male     guess=female   name=Flem
correct=male     guess=female   name=Flinn
correct=male     guess=female   name=Fowler
correct=male     guess=female   name=Franky
correct=male     guess=female   name=Fred
correct=male     guess=female   name=Fremont
correct=male     guess=female   name=Garv
correct=male     guess=female   name=Gayle
correct=male     guess=female   name=Gibb
correct=male     guess=female   name=Godart
correct=male     guess=female   name=Gregg
correct=male     guess=female   name=Guthry
correct=male     guess=female   name=Ichabod
correct=male     guess=female   name=Irving
correct=male     guess=female   name=Jake
correct=male     guess=female   name=Jason
correct=male     guess=female   name=Jervis
correct=male     guess=female   name=John-Patrick
correct=male     guess=female   name=Josephus
correct=male     guess=female   name=Julie
correct=male     guess=female   name=Kalman
correct=male     guess=female   name=Keene
correct=male     guess=female   name=Kenn
correct=male     guess=female   name=Kermit
correct=male     guess=female   name=Kimmo
correct=male     guess=female   name=Konrad
correct=male     guess=female   name=Kory
correct=male     guess=female   name=Kris
correct=male     guess=female   name=Krishna
correct=male     guess=female   name=Lamar
correct=male     guess=female   name=Lawton
correct=male     guess=female   name=Leonidas
correct=male     guess=female   name=Levon
correct=male     guess=female   name=Llewellyn
correct=male     guess=female   name=Loren
correct=male     guess=female   name=Lorenzo
```

```
correct=male     guess=female   name=Luce
correct=male     guess=female   name=Ludwig
correct=male     guess=female   name=Marcel
correct=male     guess=female   name=Marlin
correct=male     guess=female   name=Marwin
correct=male     guess=female   name=Matty
correct=male     guess=female   name=Maurise
correct=male     guess=female   name=Merril
correct=male     guess=female   name=Michal
correct=male     guess=female   name=Millicent
correct=male     guess=female   name=Milt
correct=male     guess=female   name=Moise
correct=male     guess=female   name=Monty
correct=male     guess=female   name=Mordecai
correct=male     guess=female   name=Mose
correct=male     guess=female   name=Mylo
correct=male     guess=female   name=Nichole
correct=male     guess=female   name=Nickie
correct=male     guess=female   name=Orville
correct=male     guess=female   name=Ozzy
correct=male     guess=female   name=Patel
correct=male     guess=female   name=Patricio
correct=male     guess=female   name=Patrick
correct=male     guess=female   name=Pattie
correct=male     guess=female   name=Pierce
correct=male     guess=female   name=Prasun
correct=male     guess=female   name=Prent
correct=male     guess=female   name=Prentice
correct=male     guess=female   name=Prescott
correct=male     guess=female   name=Ramon
correct=male     guess=female   name=Randall
correct=male     guess=female   name=Raul
correct=male     guess=female   name=Rawley
correct=male     guess=female   name=Ray
correct=male     guess=female   name=Renaud
correct=male     guess=female   name=Richmond
correct=male     guess=female   name=Riley
correct=male     guess=female   name=Roberto
correct=male     guess=female   name=Roderick
correct=male     guess=female   name=Rudolf
correct=male     guess=female   name=Rustie
correct=male     guess=female   name=Sandro
correct=male     guess=female   name=Sargent
correct=male     guess=female   name=Sasha
correct=male     guess=female   name=Sayers
correct=male     guess=female   name=Sebastiano
correct=male     guess=female   name=Selby
correct=male     guess=female   name=Serge
```

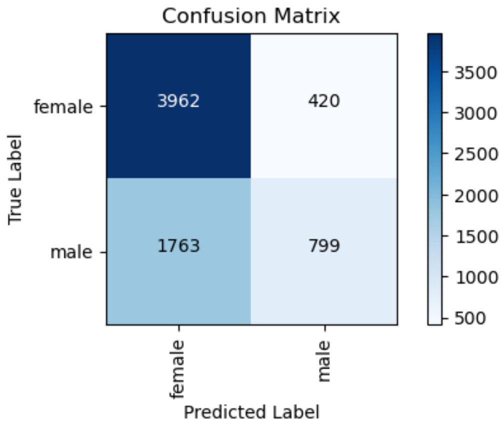
```
correct=male     guess=female   name=Shalom
correct=male     guess=female   name=Sholom
correct=male     guess=female   name=Sidnee
correct=male     guess=female   name=Silvio
correct=male     guess=female   name=Slade
correct=male     guess=female   name=Smith
correct=male     guess=female   name=Son
correct=male     guess=female   name=Sting
correct=male     guess=female   name=Tabb
correct=male     guess=female   name=Ted
correct=male     guess=female   name=Terrel
correct=male     guess=female   name=Thom
correct=male     guess=female   name=Thorny
correct=male     guess=female   name=Timothee
correct=male     guess=female   name=Tom
correct=male     guess=female   name=Tracy
correct=male     guess=female   name=Trev
correct=male     guess=female   name=Tuckie
correct=male     guess=female   name=Tulley
correct=male     guess=female   name=Turner
correct=male     guess=female   name=Tyrone
correct=male     guess=female   name=Vergil
correct=male     guess=female   name=Vinnie
correct=male     guess=female   name=Virgil
correct=male     guess=female   name=Voltaire
correct=male     guess=female   name=Zachary
```

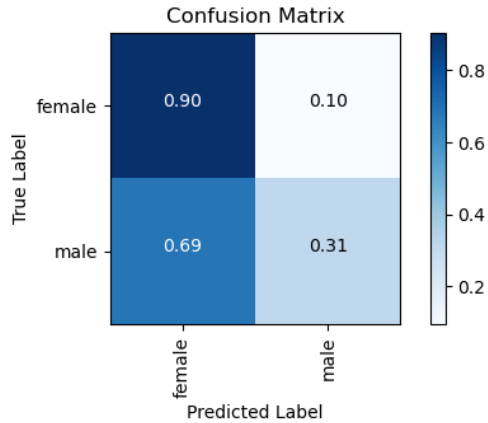
Feature 2 - Initial 2 Letters

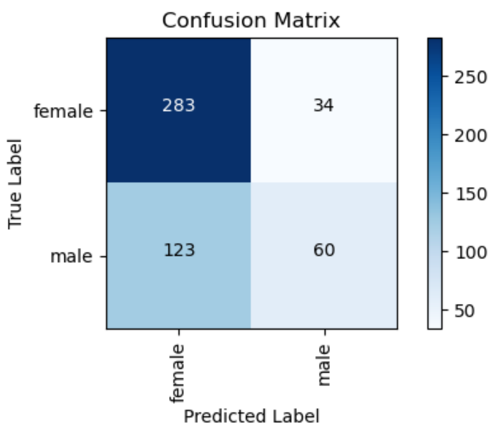
In this model, I trained a Decision Tree classifier utilizing the first 2 letters of each name.

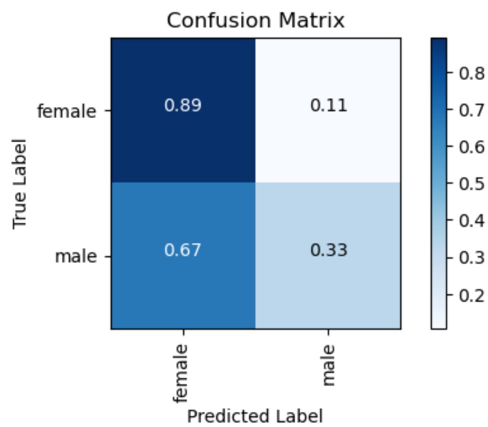
[68]:
```
feat_num = 2
# evaluate the Naive Bayes classifier using gender_features2
train_accuracy_dt2,train_cm_dt2,train_label_names_dt2,train_report_dt2,devtest_accuracy_dt2,␣
 ↪devtest_cm_dt2,devtest_label_names_dt2,devtest_report_dt2,␣
 ↪classifier_dt2=evaluate_decision_tree_classifier(train_names,devtest_names,test_names,feat_
# display model accuracy (train and development test)
print('Accuracy (Train): '+str(train_accuracy_dt2))
print('Accuracy (Development Test): '+str(devtest_accuracy_dt2))
# plot confusion matrix (train)
plot_both_confusion_matrix(train_cm_dt2,['female','male'])
# plot confusion matrix (dev test)
plot_both_confusion_matrix(devtest_cm_dt2,['female','male'])
```

```
Accuracy (Train): 0.6856278801843319
Accuracy (Development Test): 0.686
```



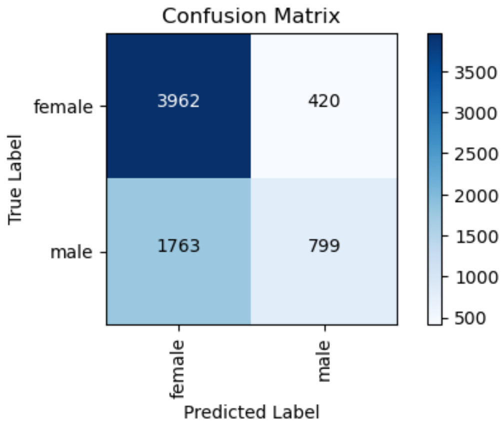


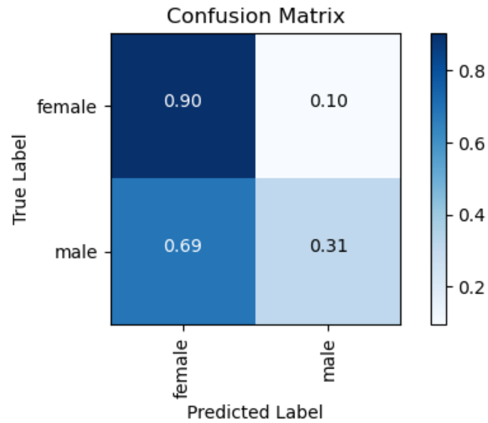


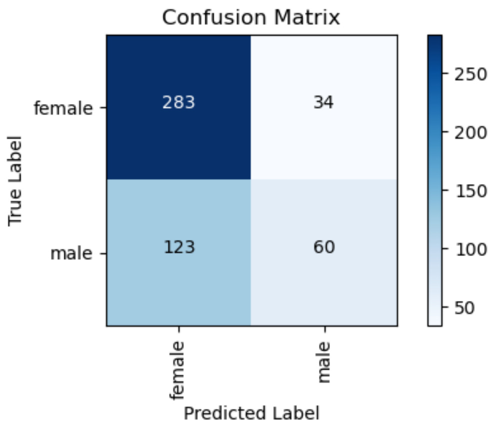


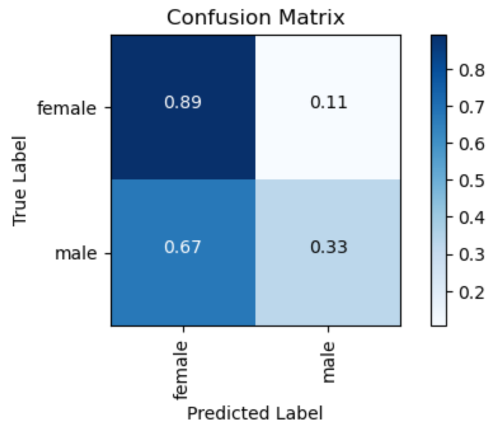
[69]:
```
feat_num = 2
# evaluate the Naive Bayes classifier using gender_features2
train_accuracy_dt2,train_cm_dt2,train_label_names_dt2,train_report_dt2,devtest_accuracy_dt2,␣
↪devtest_cm_dt2,devtest_label_names_dt2,devtest_report_dt2,␣
↪classifier_dt2=evaluate_decision_tree_classifier(train_names,devtest_names,test_names,feat_
# display model accuracy (train and development test)
print('Accuracy (Train): '+str(train_accuracy_dt2))
print('Accuracy (Development Test): '+str(devtest_accuracy_dt2))
# plot confusion matrix (train)
plot_both_confusion_matrix(train_cm_dt2,['female','male'])
# plot confusion matrix (dev test)
plot_both_confusion_matrix(devtest_cm_dt2,['female','male'])
```

```
Accuracy (Train): 0.6856278801843319
Accuracy (Development Test): 0.686
```









[71]:
```python
# display performance report (train)
print('Model Performance Metrics (Train):')
print(train_report_dt2)
# display performance report (dev test)
print('Model Performance Metrics (Development Test):')
print(devtest_report_dt2)
```

```
Model Performance Metrics (Train):
              precision    recall  f1-score   support

      female     0.6921    0.9042    0.7840      4382
        male     0.6555    0.3119    0.4226      2562

    accuracy                         0.6856      6944
   macro avg     0.6738    0.6080    0.6033      6944
weighted avg     0.6785    0.6856    0.6507      6944
```

```
Model Performance Metrics (Development Test):
              precision    recall  f1-score   support

      female     0.6970    0.8927    0.7828       317
        male     0.6383    0.3279    0.4332       183

    accuracy                         0.6860       500
   macro avg     0.6677    0.6103    0.6080       500
weighted avg     0.6755    0.6860    0.6549       500
```

[70]:
```
# Show error
show_errors(generate_errors(classifier_dt2, devtest_names, feat_num))
```

```
correct=female   guess=male     name=Abigail
correct=female   guess=male     name=Barbaraanne
correct=female   guess=male     name=Fortune
correct=female   guess=male     name=Gabriella
correct=female   guess=male     name=Gigi
correct=female   guess=male     name=Gilbertine
correct=female   guess=male     name=Ginni
correct=female   guess=male     name=Giorgia
correct=female   guess=male     name=Giovanna
correct=female   guess=male     name=Gisele
correct=female   guess=male     name=Hadria
correct=female   guess=male     name=Hanni
correct=female   guess=male     name=Hollie
correct=female   guess=male     name=Klara
correct=female   guess=male     name=Moira
correct=female   guess=male     name=Molly
correct=female   guess=male     name=Morena
correct=female   guess=male     name=Moya
correct=female   guess=male     name=Moyna
correct=female   guess=male     name=Octavia
correct=female   guess=male     name=Riane
correct=female   guess=male     name=Rubia
correct=female   guess=male     name=Ruth
correct=female   guess=male     name=Steffie
correct=female   guess=male     name=Stephanie
correct=female   guess=male     name=Thea
correct=female   guess=male     name=Theresina
correct=female   guess=male     name=Tomi
correct=female   guess=male     name=Wenonah
correct=female   guess=male     name=Winnifred
correct=female   guess=male     name=Wren
correct=female   guess=male     name=Wrennie
correct=female   guess=male     name=Xenia
correct=female   guess=male     name=Zena
```

```
correct=male     guess=female   name=Adam
correct=male     guess=female   name=Adams
correct=male     guess=female   name=Adger
correct=male     guess=female   name=Alastair
correct=male     guess=female   name=Alford
correct=male     guess=female   name=Amadeus
correct=male     guess=female   name=Ambrose
correct=male     guess=female   name=Andrew
correct=male     guess=female   name=Andros
correct=male     guess=female   name=Anthony
correct=male     guess=female   name=Antoine
correct=male     guess=female   name=Antoni
correct=male     guess=female   name=Augusto
correct=male     guess=female   name=Avram
correct=male     guess=female   name=Benson
correct=male     guess=female   name=Bernardo
correct=male     guess=female   name=Boris
correct=male     guess=female   name=Bryant
correct=male     guess=female   name=Calhoun
correct=male     guess=female   name=Calvin
correct=male     guess=female   name=Chad
correct=male     guess=female   name=Charley
correct=male     guess=female   name=Charlton
correct=male     guess=female   name=Chev
correct=male     guess=female   name=Clark
correct=male     guess=female   name=Darrel
correct=male     guess=female   name=Dionysus
correct=male     guess=female   name=Domenic
correct=male     guess=female   name=Donny
correct=male     guess=female   name=Dorian
correct=male     guess=female   name=Douglas
correct=male     guess=female   name=Edwin
correct=male     guess=female   name=Elbert
correct=male     guess=female   name=Ellis
correct=male     guess=female   name=Emilio
correct=male     guess=female   name=Erny
correct=male     guess=female   name=Fairfax
correct=male     guess=female   name=Felipe
correct=male     guess=female   name=Ferdinand
correct=male     guess=female   name=Flem
correct=male     guess=female   name=Flinn
correct=male     guess=female   name=Franky
correct=male     guess=female   name=Fred
correct=male     guess=female   name=Fremont
correct=male     guess=female   name=Gregg
correct=male     guess=female   name=Guthry
correct=male     guess=female   name=Hermon
correct=male     guess=female   name=Herold
```

```
correct=male     guess=female   name=Irving
correct=male     guess=female   name=Jake
correct=male     guess=female   name=Jason
correct=male     guess=female   name=Jervis
correct=male     guess=female   name=John-Patrick
correct=male     guess=female   name=Josephus
correct=male     guess=female   name=Julie
correct=male     guess=female   name=Kalman
correct=male     guess=female   name=Keene
correct=male     guess=female   name=Kenn
correct=male     guess=female   name=Kermit
correct=male     guess=female   name=Kimmo
correct=male     guess=female   name=Konrad
correct=male     guess=female   name=Kory
correct=male     guess=female   name=Kris
correct=male     guess=female   name=Krishna
correct=male     guess=female   name=Lamar
correct=male     guess=female   name=Lawton
correct=male     guess=female   name=Leonidas
correct=male     guess=female   name=Levon
correct=male     guess=female   name=Loren
correct=male     guess=female   name=Lorenzo
correct=male     guess=female   name=Luce
correct=male     guess=female   name=Ludwig
correct=male     guess=female   name=Marcel
correct=male     guess=female   name=Marlin
correct=male     guess=female   name=Marwin
correct=male     guess=female   name=Matty
correct=male     guess=female   name=Maurise
correct=male     guess=female   name=Merril
correct=male     guess=female   name=Michal
correct=male     guess=female   name=Millicent
correct=male     guess=female   name=Milt
correct=male     guess=female   name=Mylo
correct=male     guess=female   name=Nichole
correct=male     guess=female   name=Nickie
correct=male     guess=female   name=Orville
correct=male     guess=female   name=Patel
correct=male     guess=female   name=Patricio
correct=male     guess=female   name=Patrick
correct=male     guess=female   name=Pattie
correct=male     guess=female   name=Prasun
correct=male     guess=female   name=Prent
correct=male     guess=female   name=Prentice
correct=male     guess=female   name=Prescott
correct=male     guess=female   name=Ramon
correct=male     guess=female   name=Randall
correct=male     guess=female   name=Raul
```

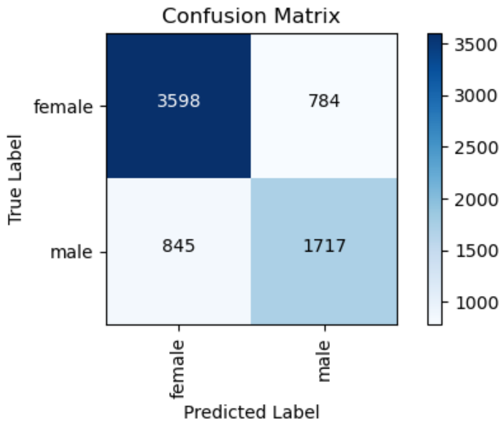
```
correct=male     guess=female   name=Rawley
correct=male     guess=female   name=Ray
correct=male     guess=female   name=Renaud
correct=male     guess=female   name=Roberto
correct=male     guess=female   name=Roderick
correct=male     guess=female   name=Sandro
correct=male     guess=female   name=Sargent
correct=male     guess=female   name=Sasha
correct=male     guess=female   name=Sayers
correct=male     guess=female   name=Sebastiano
correct=male     guess=female   name=Selby
correct=male     guess=female   name=Serge
correct=male     guess=female   name=Shalom
correct=male     guess=female   name=Sholom
correct=male     guess=female   name=Sidnee
correct=male     guess=female   name=Silvio
correct=male     guess=female   name=Son
correct=male     guess=female   name=Tabb
correct=male     guess=female   name=Ted
correct=male     guess=female   name=Terrel
correct=male     guess=female   name=Timothee
correct=male     guess=female   name=Tracy
correct=male     guess=female   name=Trev
correct=male     guess=female   name=Vergil
correct=male     guess=female   name=Vinnie
correct=male     guess=female   name=Virgil
correct=male     guess=female   name=Voltaire
```

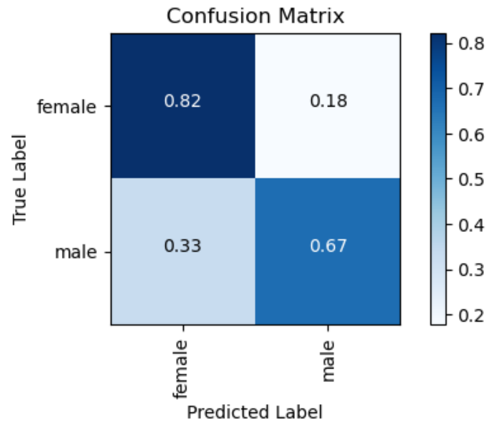
Feature 3 - Last Letter

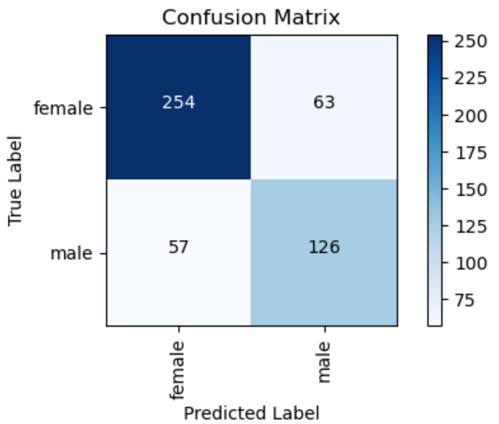
In this approach, I trained a Decision Tree classifier by utilizing the last letter of each name.

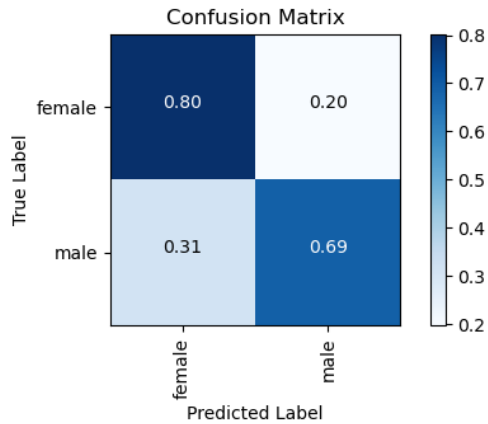
[72]:
```
feat_num = 3
# evaluate the Naive Bayes classifier using gender_features3
train_accuracy_dt3,train_cm_dt3,train_label_names_dt3,train_report_dt3,devtest_accuracy_dt3,
  ↪devtest_cm_dt3,devtest_label_names_dt3,devtest_report_dt3,
  ↪classifier_dt3=evaluate_decision_tree_classifier(train_names,devtest_names,test_names,feat_
# display model accuracy (train and development test)
print('Accuracy (Train): '+str(train_accuracy_dt3))
print('Accuracy (Development Test): '+str(devtest_accuracy_dt3))
# plot confusion matrix (train)
plot_both_confusion_matrix(train_cm_dt3,['female','male'])
# plot confusion matrix (dev test)
plot_both_confusion_matrix(devtest_cm_dt3,['female','male'])
```

```
Accuracy (Train): 0.7654089861751152
Accuracy (Development Test): 0.76
```









[73]:
```python
# display performance report (train)
print('Model Performance Metrics (Train):')
print(train_report_dt3)
# display performance report (dev test)
print('Model Performance Metrics (Development Test):')
print(devtest_report_dt3)
```

```
Model Performance Metrics (Train):
              precision    recall  f1-score   support

      female     0.8098    0.8211    0.8154      4382
        male     0.6865    0.6702    0.6783      2562

    accuracy                         0.7654      6944
   macro avg     0.7482    0.7456    0.7468      6944
weighted avg     0.7643    0.7654    0.7648      6944
```

```
Model Performance Metrics (Development Test):
              precision    recall  f1-score   support

      female     0.8167    0.8013    0.8089       317
        male     0.6667    0.6885    0.6774       183

    accuracy                         0.7600       500
   macro avg     0.7417    0.7449    0.7432       500
weighted avg     0.7618    0.7600    0.7608       500
```

[74]:
```python
# Show error
show_errors(generate_errors(classifier_dt3, devtest_names, feat_num))
```

```
correct=female   guess=male     name=Abigail
correct=female   guess=male     name=Adel
correct=female   guess=male     name=Agnes
correct=female   guess=male     name=Anne-Mar
correct=female   guess=male     name=Arleen
correct=female   guess=male     name=Bess
correct=female   guess=male     name=Bryn
correct=female   guess=male     name=Caitlin
correct=female   guess=male     name=Caitrin
correct=female   guess=male     name=Cal
correct=female   guess=male     name=Carlyn
correct=female   guess=male     name=Carol-Jean
correct=female   guess=male     name=Caroleen
correct=female   guess=male     name=Carroll
correct=female   guess=male     name=Caryl
correct=female   guess=male     name=Charlot
correct=female   guess=male     name=Darell
correct=female   guess=male     name=Daryl
correct=female   guess=male     name=Del
correct=female   guess=male     name=Diamond
correct=female   guess=male     name=Doreen
correct=female   guess=male     name=Doris
correct=female   guess=male     name=Dorit
correct=female   guess=male     name=Eryn
correct=female   guess=male     name=Gennifer
correct=female   guess=male     name=Greer
correct=female   guess=male     name=Gretel
correct=female   guess=male     name=Ingeberg
correct=female   guess=male     name=Iris
correct=female   guess=male     name=Janel
correct=female   guess=male     name=Janot
correct=female   guess=male     name=Joan
correct=female   guess=male     name=Karil
correct=female   guess=male     name=Karleen
```

```
correct=female   guess=male     name=Karyl
correct=female   guess=male     name=Keren
correct=female   guess=male     name=Kimberlyn
correct=female   guess=male     name=Kirstyn
correct=female   guess=male     name=Leanor
correct=female   guess=male     name=Lian
correct=female   guess=male     name=Lib
correct=female   guess=male     name=Maren
correct=female   guess=male     name=Margo
correct=female   guess=male     name=Marys
correct=female   guess=male     name=Melisent
correct=female   guess=male     name=Meris
correct=female   guess=male     name=Michal
correct=female   guess=male     name=Mikako
correct=female   guess=male     name=Miran
correct=female   guess=male     name=Nil
correct=female   guess=male     name=Raven
correct=female   guess=male     name=Robbyn
correct=female   guess=male     name=Rozamond
correct=female   guess=male     name=Sal
correct=female   guess=male     name=Sharleen
correct=female   guess=male     name=Shaun
correct=female   guess=male     name=Shaylyn
correct=female   guess=male     name=Siobhan
correct=female   guess=male     name=Sioux
correct=female   guess=male     name=Val
correct=female   guess=male     name=Vivian
correct=female   guess=male     name=Winnifred
correct=female   guess=male     name=Wren
correct=male     guess=female   name=Ambrose
correct=male     guess=female   name=Anthony
correct=male     guess=female   name=Antoine
correct=male     guess=female   name=Antoni
correct=male     guess=female   name=Baillie
correct=male     guess=female   name=Barclay
correct=male     guess=female   name=Barnie
correct=male     guess=female   name=Charley
correct=male     guess=female   name=Donny
correct=male     guess=female   name=Erny
correct=male     guess=female   name=Ezra
correct=male     guess=female   name=Felipe
correct=male     guess=female   name=Franky
correct=male     guess=female   name=Gayle
correct=male     guess=female   name=Guthry
correct=male     guess=female   name=Hari
correct=male     guess=female   name=Jake
correct=male     guess=female   name=Julie
correct=male     guess=female   name=Keene
```

```
correct=male     guess=female   name=Kory
correct=male     guess=female   name=Krishna
correct=male     guess=female   name=Luce
correct=male     guess=female   name=Matty
correct=male     guess=female   name=Maurise
correct=male     guess=female   name=Moise
correct=male     guess=female   name=Monty
correct=male     guess=female   name=Mordecai
correct=male     guess=female   name=Mose
correct=male     guess=female   name=Nichole
correct=male     guess=female   name=Nickie
correct=male     guess=female   name=Orville
correct=male     guess=female   name=Ozzy
correct=male     guess=female   name=Pattie
correct=male     guess=female   name=Pierce
correct=male     guess=female   name=Prentice
correct=male     guess=female   name=Rawley
correct=male     guess=female   name=Ray
correct=male     guess=female   name=Riley
correct=male     guess=female   name=Rustie
correct=male     guess=female   name=Sasha
correct=male     guess=female   name=Selby
correct=male     guess=female   name=Serge
correct=male     guess=female   name=Sidnee
correct=male     guess=female   name=Slade
correct=male     guess=female   name=Smith
correct=male     guess=female   name=Thorny
correct=male     guess=female   name=Timothee
correct=male     guess=female   name=Tracy
correct=male     guess=female   name=Tuckie
correct=male     guess=female   name=Tulley
correct=male     guess=female   name=Tyrone
correct=male     guess=female   name=Vinnie
correct=male     guess=female   name=Voltaire
correct=male     guess=female   name=Westbrooke
correct=male     guess=female   name=Wittie
correct=male     guess=female   name=Woody
correct=male     guess=female   name=Zachary
```

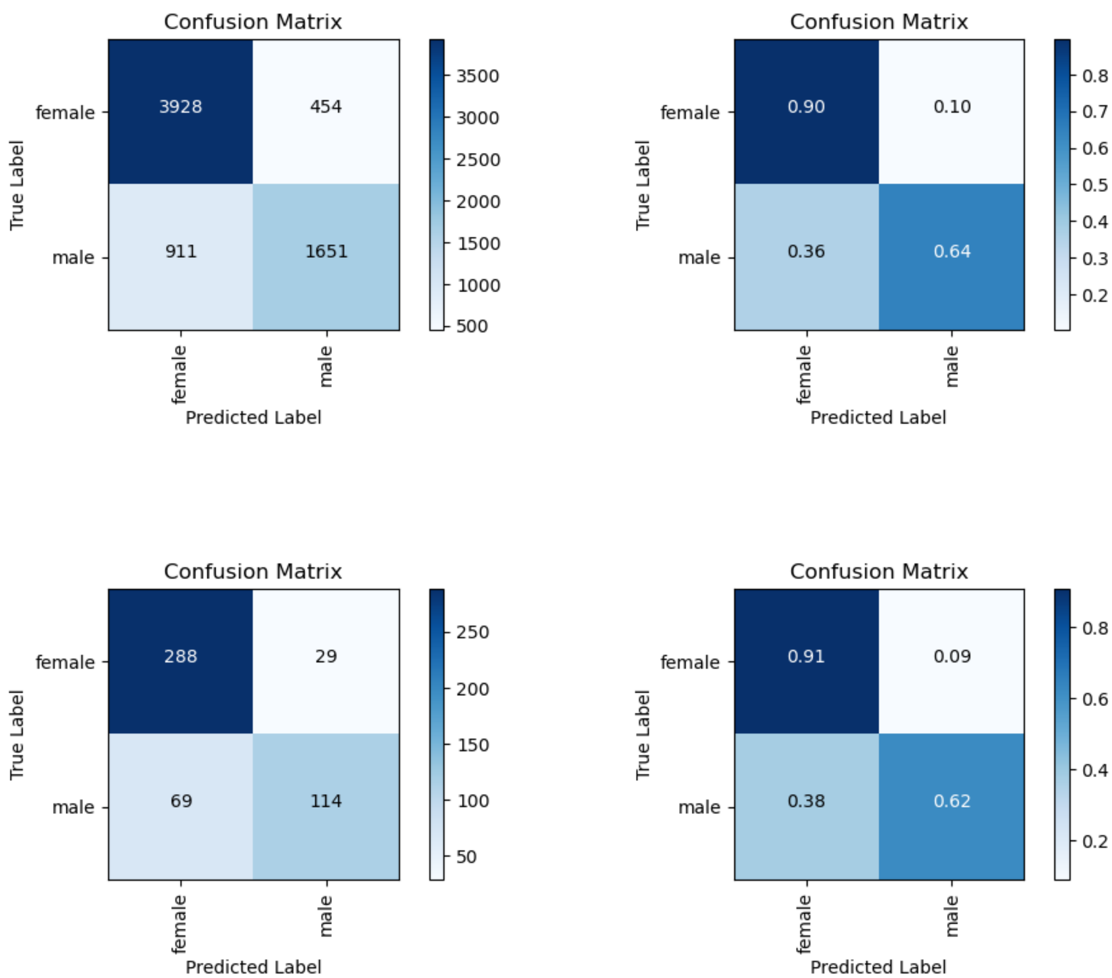
Feature 4 - Last 2 Letters

In this model, I trained a Decision Tree classifier utilizing the final 2 letters of each name.

[75]:
```
feat_num = 4
# evaluate the Naive Bayes classifier using gender_features10
```

```
train_accuracy_dt4,train_cm_dt4,train_label_names_dt4,train_report_dt4,devtest_accuracy_dt4,␣
↪devtest_cm_dt4,devtest_label_names_dt4,devtest_report_dt4,␣
↪classifier_dt4=evaluate_decision_tree_classifier(train_names,devtest_names,test_names,feat_
# display model accuracy (train and development test)
print('Accuracy (Train): '+str(train_accuracy_dt4))
print('Accuracy (Development Test): '+str(devtest_accuracy_dt4))
# plot confusion matrix (train)
plot_both_confusion_matrix(train_cm_dt4,['female','male'])
# plot confusion matrix (dev test)
plot_both_confusion_matrix(devtest_cm_dt4,['female','male'])
```

```
Accuracy (Train): 0.8034274193548387
Accuracy (Development Test): 0.804
```



[76]:
```
# display performance report (train)
print('Model Performance Metrics (Train):')
print(train_report_dt4)
```

```python
# display performance report (dev test)
print('Model Performance Metrics (Development Test):')
print(devtest_report_dt4)
```

```
Model Performance Metrics (Train):
              precision    recall  f1-score   support

      female     0.8117    0.8964    0.8520      4382
        male     0.7843    0.6444    0.7075      2562

    accuracy                         0.8034      6944
   macro avg     0.7980    0.7704    0.7797      6944
weighted avg     0.8016    0.8034    0.7987      6944

Model Performance Metrics (Development Test):
              precision    recall  f1-score   support

      female     0.8067    0.9085    0.8546       317
        male     0.7972    0.6230    0.6994       183

    accuracy                         0.8040       500
   macro avg     0.8020    0.7657    0.7770       500
weighted avg     0.8032    0.8040    0.7978       500
```

[77]:
```python
# Show error
show_errors(generate_errors(classifier_dt4, devtest_names, feat_num))
```

```
correct=female   guess=male     name=Abigail
correct=female   guess=male     name=Agnes
correct=female   guess=male     name=Anne-Mar
correct=female   guess=male     name=Caitlin
correct=female   guess=male     name=Caitrin
correct=female   guess=male     name=Carol-Jean
correct=female   guess=male     name=Carroll
correct=female   guess=male     name=Charlot
correct=female   guess=male     name=Cloe
correct=female   guess=male     name=Darell
correct=female   guess=male     name=Diamond
correct=female   guess=male     name=Gennifer
correct=female   guess=male     name=Greer
correct=female   guess=male     name=Janot
correct=female   guess=male     name=Joan
correct=female   guess=male     name=Karil
correct=female   guess=male     name=Leanor
correct=female   guess=male     name=Lian
correct=female   guess=male     name=Margo
correct=female   guess=male     name=Melisent
```

```
correct=female   guess=male     name=Miran
correct=female   guess=male     name=Nil
correct=female   guess=male     name=Rozamond
correct=female   guess=male     name=Shelby
correct=female   guess=male     name=Siobhan
correct=female   guess=male     name=Tiffy
correct=female   guess=male     name=Vivian
correct=female   guess=male     name=Winnifred
correct=female   guess=male     name=Zoe
correct=male     guess=female   name=Ambrose
correct=male     guess=female   name=Anthony
correct=male     guess=female   name=Antoine
correct=male     guess=female   name=Antoni
correct=male     guess=female   name=Baillie
correct=male     guess=female   name=Barnie
correct=male     guess=female   name=Barret
correct=male     guess=female   name=Boris
correct=male     guess=female   name=Calhoun
correct=male     guess=female   name=Charley
correct=male     guess=female   name=Curtis
correct=male     guess=female   name=Darrel
correct=male     guess=female   name=Donny
correct=male     guess=female   name=Ellis
correct=male     guess=female   name=Erny
correct=male     guess=female   name=Ezra
correct=male     guess=female   name=Flinn
correct=male     guess=female   name=Gayle
correct=male     guess=female   name=Guthry
correct=male     guess=female   name=Hari
correct=male     guess=female   name=Hiralal
correct=male     guess=female   name=Jervis
correct=male     guess=female   name=Julie
correct=male     guess=female   name=Keene
correct=male     guess=female   name=Kenn
correct=male     guess=female   name=Kermit
correct=male     guess=female   name=Kory
correct=male     guess=female   name=Kris
correct=male     guess=female   name=Krishna
correct=male     guess=female   name=Llewellyn
correct=male     guess=female   name=Loren
correct=male     guess=female   name=Luce
correct=male     guess=female   name=Marcel
correct=male     guess=female   name=Matty
correct=male     guess=female   name=Maurise
correct=male     guess=female   name=Michal
correct=male     guess=female   name=Moise
correct=male     guess=female   name=Monty
correct=male     guess=female   name=Mose
```

```
correct=male      guess=female    name=Nichole
correct=male      guess=female    name=Nickie
correct=male      guess=female    name=Orville
correct=male      guess=female    name=Ozzy
correct=male      guess=female    name=Patel
correct=male      guess=female    name=Pattie
correct=male      guess=female    name=Pierce
correct=male      guess=female    name=Prasun
correct=male      guess=female    name=Prentice
correct=male      guess=female    name=Rawley
correct=male      guess=female    name=Riley
correct=male      guess=female    name=Rustie
correct=male      guess=female    name=Sasha
correct=male      guess=female    name=Sidnee
correct=male      guess=female    name=Slade
correct=male      guess=female    name=Smith
correct=male      guess=female    name=Terrel
correct=male      guess=female    name=Thorny
correct=male      guess=female    name=Timothee
correct=male      guess=female    name=Tracy
correct=male      guess=female    name=Tuckie
correct=male      guess=female    name=Tulley
correct=male      guess=female    name=Tyrone
correct=male      guess=female    name=Vinnie
correct=male      guess=female    name=Voltaire
correct=male      guess=female    name=Wendel
correct=male      guess=female    name=Winn
correct=male      guess=female    name=Wittie
correct=male      guess=female    name=Woody
correct=male      guess=female    name=Zachary
```

Feature Optimization

To construct the most effective Naive Bayes model, I will identify the optimal features based on their accuracy ratings.

[79]:
```
ranked_features = get_sorted_feature_accuracies(1, 4, 'dtc')
```

[80]:
```
features = {
    1: "First Letter",
    2: "First 2 Letters",
    3: "Last Letter",
    4: "Last 2 Letters",
}

print("Top Two Single Features with the Highest Accuracy")
print("----------------------------------------------------------------")
```

```
for (feat_num, accuracy) in ranked_features[0:2]:
    print('Feature: %-30s Accuracy: %-8s' %(features[feat_num], accuracy))

print("----------------------------------------------------------------")
```

```
Top Two Single Features with the Highest Accuracy
---------------------------------------------------------------
Feature: Last 2 Letters                 Accuracy: 0.804
Feature: Last Letter                    Accuracy: 0.76
---------------------------------------------------------------
```

[82]:
```
optimized_features = optimized_solution('dtc')
optimized_features
```

```
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
Cell In[82], line 1
----> 1 optimized_features = optimized_solution('dtc')
      2 optimized_features

Cell In[43], line 184, in optimized_solution(model_id)
    182     classifier = nltk.NaiveBayesClassifier.train(train_set)
    183 elif (model_id == 'dtc'):
--> 184     classifier = nltk.DecisionTreeClassifier.train(train_set)
    186 for (name, tag) in devtest_names:
    187     guess = classifier.
 ↪classify(get_features(name,optimized_feature_list))

File ~/anaconda3/lib/python3.11/site-packages/nltk/classify/decisiontree.py:175
 ↪in DecisionTreeClassifier.train(labeled_featuresets, entropy_cutoff,
 ↪depth_cutoff, support_cutoff, binary, feature_values, verbose)
    170     tree = DecisionTreeClassifier.best_binary_stump(
    171         feature_names, labeled_featuresets, feature_values, verbose
    172     )
    174 # Refine the stump.
--> 175 tree.refine(
    176     labeled_featuresets,
    177     entropy_cutoff,
    178     depth_cutoff - 1,
    179     support_cutoff,
    180     binary,
    181     feature_values,
    182     verbose,
    183 )
    185 # Return it
    186 return tree
```

```
File ~/anaconda3/lib/python3.11/site-packages/nltk/classify/decisiontree.py:231 ␣
↪in DecisionTreeClassifier.refine(self, labeled_featuresets, entropy_cutoff,␣
↪depth_cutoff, support_cutoff, binary, feature_values, verbose)
    229     label_freqs = FreqDist(label for (featureset, label) in␣
↪fval_featuresets)
    230     if entropy(MLEProbDist(label_freqs)) > entropy_cutoff:
--> 231         self._decisions[fval] = DecisionTreeClassifier.train(
    232             fval_featuresets,
    233             entropy_cutoff,
    234             depth_cutoff,
    235             support_cutoff,
    236             binary,
    237             feature_values,
    238             verbose,
    239         )
    240 if self._default is not None:
    241     default_featuresets = [
    242         (featureset, label)
    243         for (featureset, label) in labeled_featuresets
    244         if featureset.get(self._fname) not in self._decisions
    245     ]

File ~/anaconda3/lib/python3.11/site-packages/nltk/classify/decisiontree.py:175 ␣
↪in DecisionTreeClassifier.train(labeled_featuresets, entropy_cutoff,␣
↪depth_cutoff, support_cutoff, binary, feature_values, verbose)
    170     tree = DecisionTreeClassifier.best_binary_stump(
    171         feature_names, labeled_featuresets, feature_values, verbose
    172     )
    174 # Refine the stump.
--> 175 tree.refine(
    176     labeled_featuresets,
    177     entropy_cutoff,
    178     depth_cutoff - 1,
    179     support_cutoff,
    180     binary,
    181     feature_values,
    182     verbose,
    183 )
    185 # Return it
    186 return tree

File ~/anaconda3/lib/python3.11/site-packages/nltk/classify/decisiontree.py:231 ␣
↪in DecisionTreeClassifier.refine(self, labeled_featuresets, entropy_cutoff,␣
↪depth_cutoff, support_cutoff, binary, feature_values, verbose)
    229     label_freqs = FreqDist(label for (featureset, label) in␣
↪fval_featuresets)
    230     if entropy(MLEProbDist(label_freqs)) > entropy_cutoff:
--> 231         self._decisions[fval] = DecisionTreeClassifier.train(
```

```
    232             fval_featuresets,
    233             entropy_cutoff,
    234             depth_cutoff,
    235             support_cutoff,
    236             binary,
    237             feature_values,
    238             verbose,
    239         )
    240 if self._default is not None:
    241     default_featuresets = [
    242         (featureset, label)
    243         for (featureset, label) in labeled_featuresets
    244         if featureset.get(self._fname) not in self._decisions
    245     ]

    [... skipping similar frames: DecisionTreeClassifier.refine at line 231 (5 times), DecisionTreeClassifier.train at line 175 (5 times)]

File ~/anaconda3/lib/python3.11/site-packages/nltk/classify/decisiontree.py:175 in DecisionTreeClassifier.train(labeled_featuresets, entropy_cutoff, depth_cutoff, support_cutoff, binary, feature_values, verbose)
    170     tree = DecisionTreeClassifier.best_binary_stump(
    171         feature_names, labeled_featuresets, feature_values, verbose
    172     )
    174 # Refine the stump.
--> 175 tree.refine(
    176     labeled_featuresets,
    177     entropy_cutoff,
    178     depth_cutoff - 1,
    179     support_cutoff,
    180     binary,
    181     feature_values,
    182     verbose,
    183 )
    185 # Return it
    186 return tree

File ~/anaconda3/lib/python3.11/site-packages/nltk/classify/decisiontree.py:231 in DecisionTreeClassifier.refine(self, labeled_featuresets, entropy_cutoff, depth_cutoff, support_cutoff, binary, feature_values, verbose)
    229     label_freqs = FreqDist(label for (featureset, label) in fval_featuresets)
    230     if entropy(MLEProbDist(label_freqs)) > entropy_cutoff:
--> 231         self._decisions[fval] = DecisionTreeClassifier.train(
    232             fval_featuresets,
    233             entropy_cutoff,
    234             depth_cutoff,
    235             support_cutoff,
```

```
    236             binary,
    237             feature_values,
    238             verbose,
    239         )
    240 if self._default is not None:
    241     default_featuresets = [
    242         (featureset, label)
    243         for (featureset, label) in labeled_featuresets
    244         if featureset.get(self._fname) not in self._decisions
    245     ]

File ~/anaconda3/lib/python3.11/site-packages/nltk/classify/decisiontree.py:166 in DecisionTreeClassifier.train(labeled_featuresets, entropy_cutoff, depth_cutoff, support_cutoff, binary, feature_values, verbose)
    164 # Start with a stump.
    165 if not binary:
--> 166     tree = DecisionTreeClassifier.best_stump(
    167         feature_names, labeled_featuresets, verbose
    168     )
    169 else:
    170     tree = DecisionTreeClassifier.best_binary_stump(
    171         feature_names, labeled_featuresets, feature_values, verbose
    172     )

File ~/anaconda3/lib/python3.11/site-packages/nltk/classify/decisiontree.py:263 in DecisionTreeClassifier.best_stump(feature_names, labeled_featuresets, verbose)
    261 best_error = best_stump.error(labeled_featuresets)
    262 for fname in feature_names:
--> 263     stump = DecisionTreeClassifier.stump(fname, labeled_featuresets)
    264     stump_error = stump.error(labeled_featuresets)
    265     if stump_error < best_error:

File ~/anaconda3/lib/python3.11/site-packages/nltk/classify/decisiontree.py:200 in DecisionTreeClassifier.stump(feature_name, labeled_featuresets)
    198 freqs = defaultdict(FreqDist)  # freq(label|value)
    199 for featureset, label in labeled_featuresets:
--> 200     feature_value = featureset.get(feature_name)
    201     freqs[feature_value][label] += 1
    203 decisions = {val: DecisionTreeClassifier(freqs[val].max()) for val in freqs}

KeyboardInterrupt:
```

I observe that the optimized solution resulted in an accuracy of 0.76, whereas the highest accuracy achieved by any single feature was 0.804. It seems that there is a case of overfitting with the optimization approach for the decision tree classifier. Therefore, I have decided not to use this feature set for the best model for the decision tree classifier.

The following features contributed to the optimized solution:

[ ]:
```
print("Following features provide the most optmized solution: ")
for feat_num in optimized_features[0]:
    print('    -> %-30s' %(features[feat_num]))
```