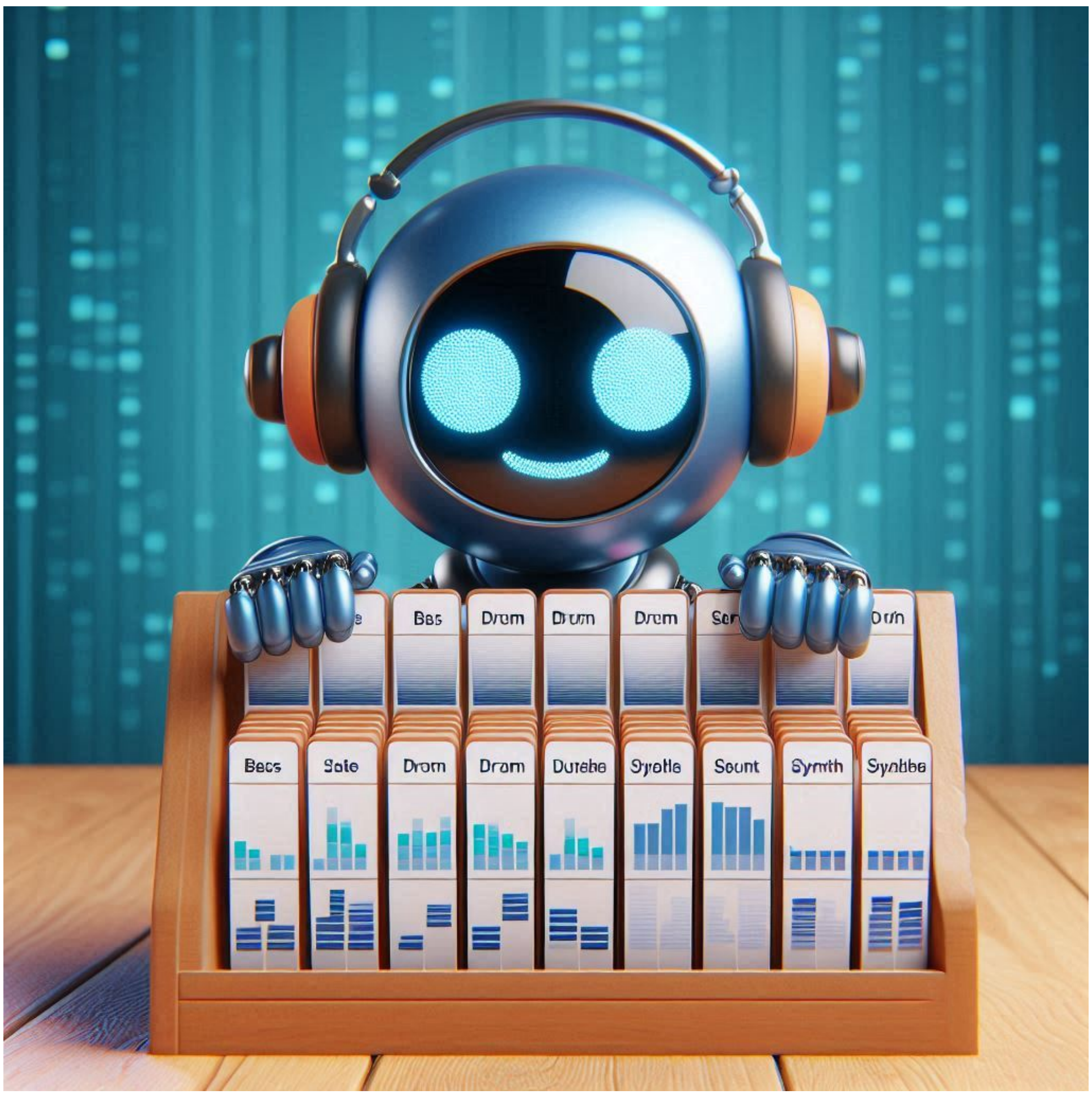
audio-file-classification

December 3, 2024

1 Audio sample file name classification

1.0.1 Contents



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1.0.2 1. Data analysis

Data columns

- category: sample category (bass, drum, synth, vocal etc.)
- file_path (eg: BGE_13_Mid_Reece_Bass_1.wav)
- file_size (in bytes)
- duration (in miliseconds)
- sample_rate: number of sample-frames per second (in Hz)
- channels: number of audio channels (2 for stereo, 1 for mono)
- frame_count: duration * sample_rate
- sample_type: information size of a single sample-frame

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import swifter
import nltk
nltk.download('punkt_tab')

from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.naive_bayes import MultinomialNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler

import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.preprocessing.text import Tokenizer as KerasTokenizer
from tensorflow.keras.metrics import Precision, Recall
from tensorflow.keras.models import load_model

from joblib import dump, load

%matplotlib inline
```

```
[nltk_data] Downloading package punkt_tab to
[nltk_data]     /Users/tashvit/nltk_data…
```

```
[nltk_data]   Package punkt_tab is already up-to-date!
```

Check first 5 rows

[2]:
```python
audio_data_df = pd.read_csv('audio-file-category-data.csv')

audio_data_df.head()
```

[2]:
```
  category                     file_path  file_size  duration  sample_rate  \
0     bass  BGE_13_Mid_Reece_Bass_1.wav    1240832  4.673016        44100
1     bass  BGE_14_Mid_Reece_Bass_2.wav    1207952  4.548753        44100
2     bass    BGE_15_808_Sat_Bass_1.wav    1123810  4.233061        44100
3     bass    BGE_16_808_Sat_Bass_2.wav     656276  2.468413        44100
4     bass            FJ_09_Bass_01.wav     701182  2.644036        44100

   channels  frame_count sample_type
0         2       206080      PCM_24
1         2       200600      PCM_24
2         2       186678      PCM_24
3         2       108857      PCM_24
4         2       116602      PCM_24
```

Check number of rows, columns

[3]:
```python
audio_data_df.shape
```

[3]:
```
(34110, 8)
```

Check for duplicate data rows

[4]:
```python
audio_data_df[audio_data_df.duplicated()]
```

[4]:
```
         category                                  file_path  file_size  \
311          bass                         DH4_10_Bass 02 C#.wav      74468
333          bass                         SMH_G_Syn_Bass 13.wav     239660
6159         drum                              CLE_Snare_8.wav      94508
6176         drum                            09_HConga_808.wav      25010
6231         drum                             SDAM_Kick_01.wav     139382
…             …                                           …          …
27878  synth-loop  PLPTB_Voices_Lead_Synth_(Wet)_140_C.wav    3636206
27879  synth-loop        PLPTB_Wheel_Whine_Lead_132_F#.wav    3853064
27880  synth-loop          PLPTB_Window_Da_Glide_133_E.wav    3823396
27881  synth-loop       PLPTB_Window_Sea_of_Blue_133_E.wav    3824964
27882  synth-loop     PLPTB_Window_Sync_Blaster_133_A.wav    3822884

       duration  sample_rate  channels  frame_count sample_type
311    0.281270        44100         2        12404      PCM_24
333    0.905578        44100         2        39936      PCM_24
6159   0.357007        44100         2        15744      PCM_24
```

```
6176    0.267007        44100          1          11775       PCM_16
6231    0.495238        44100          2          21840       PCM_24
…           …        …        …          …          …
27878  13.714263        44100          2         604799       PCM_24
27879  14.545442        44100          2         641454       PCM_24
27880  14.436100        44100          2         636632       PCM_24
27881  14.436100        44100          2         636632       PCM_24
27882  14.436100        44100          2         636632       PCM_24

[510 rows x 8 columns]
```

Remove duplicates

[5]:
```python
# Make copy of dataframe
audio_files_df = audio_data_df.copy()

audio_files_df = audio_files_df.drop_duplicates(subset=['file_path'])

audio_files_df[audio_files_df.duplicated()]
```

[5]:
```
Empty DataFrame
Columns: [category, file_path, file_size, duration, sample_rate, channels,
frame_count, sample_type]
Index: []
```

Check new shape

[6]:
```python
audio_files_df.shape
```

[6]:
```
(32929, 8)
```

[7]:
```python
audio_files_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 32929 entries, 0 to 34109
Data columns (total 8 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   category     32929 non-null  object
 1   file_path    32929 non-null  object
 2   file_size    32929 non-null  int64
 3   duration     32929 non-null  float64
 4   sample_rate  32929 non-null  int64
 5   channels     32929 non-null  int64
 6   frame_count  32929 non-null  int64
 7   sample_type  32929 non-null  object
dtypes: float64(1), int64(4), object(3)
memory usage: 2.3+ MB
```

[8]:
```
audio_files_df.describe()
```

[8]:
```
          file_size      duration    sample_rate      channels   frame_count
count  3.292900e+04  32929.000000   32929.000000  32929.000000  3.292900e+04
mean   2.617031e+06     10.414803   44547.808922      1.973762  4.637037e+05
std    6.131048e+06     24.170615    2815.429229      0.159846  1.072703e+06
min    3.640000e+03      0.000250   22050.000000      1.000000  1.200000e+01
25%    1.243640e+05      0.457256   44100.000000      2.000000  2.024000e+04
50%    3.840440e+05      1.714286   44100.000000      2.000000  7.717500e+04
75%    2.230166e+06      9.155283   44100.000000      2.000000  4.115040e+05
max    1.336231e+08    378.750000  192000.000000      2.000000  1.670288e+07
```

See the unique categories,

[9]:
```
audio_files_df['category'].unique()
```

[9]:
```
array(['bass', 'bass-loop', 'drum', 'drum-loop', 'effects',
       'instrumental-loops', 'instruments', 'kits-n-templates',
       'stems-n-midi', 'synth', 'synth-loop', 'vocal'], dtype=object)
```

[10]:
```
audio_files_df['category'].nunique()
```

[10]:
```
12
```

Checking the diversity of the 12 category groups,

[11]:
```
audio_files_df.groupby('category').count()
```

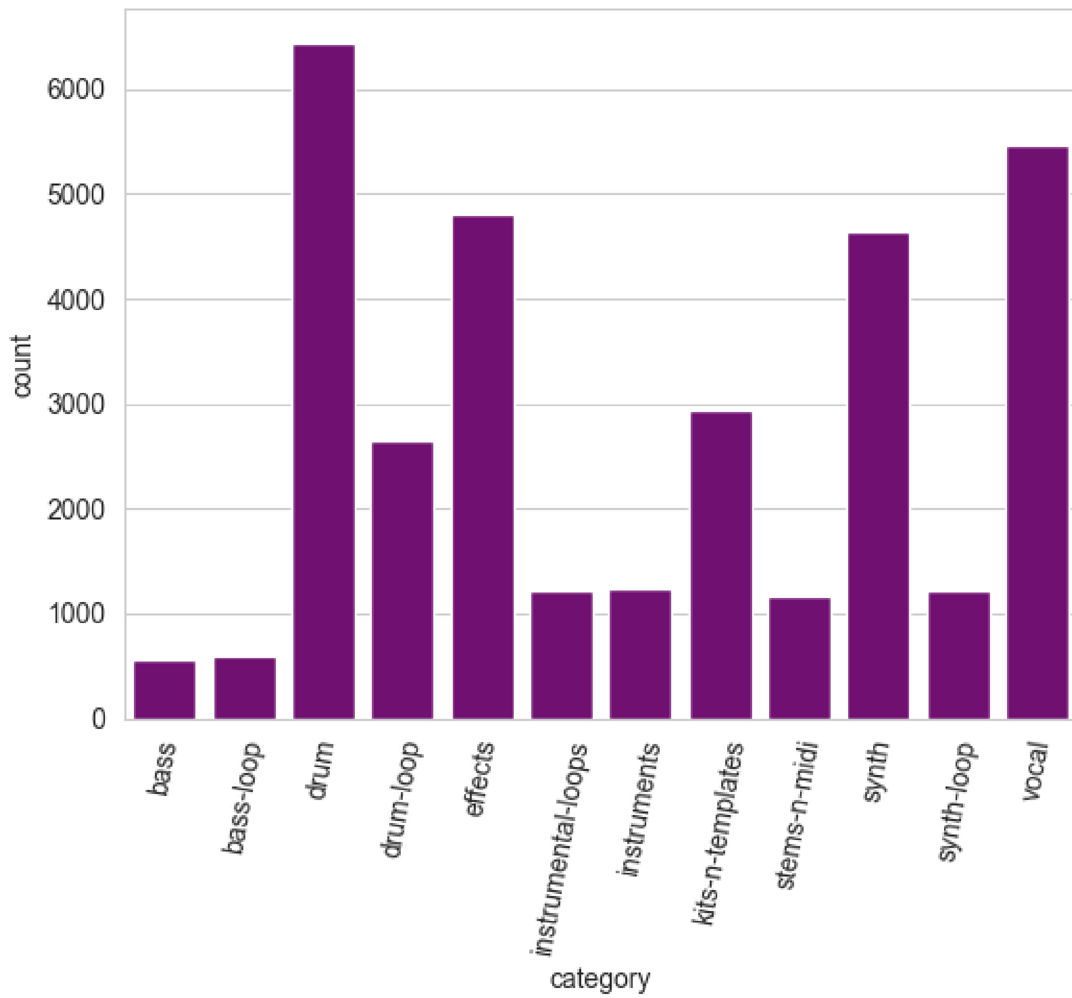
[11]:
```
                    file_path  file_size  duration  sample_rate  channels  \
category
bass                      560        560       560          560       560
bass-loop                 598        598       598          598       598
drum                     6445       6445      6445         6445      6445
drum-loop                2652       2652      2652         2652      2652
effects                  4801       4801      4801         4801      4801
instrumental-loops       1211       1211      1211         1211      1211
instruments              1237       1237      1237         1237      1237
kits-n-templates         2932       2932      2932         2932      2932
stems-n-midi             1168       1168      1168         1168      1168
synth                    4640       4640      4640         4640      4640
synth-loop               1226       1226      1226         1226      1226
vocal                    5459       5459      5459         5459      5459

                    frame_count  sample_type
category
bass                        560          560
bass-loop                   598          598
drum                       6445         6445
drum-loop                  2652         2652
```

```
effects                    4801        4801
instrumental-loops         1211        1211
instruments                1237        1237
kits-n-templates           2932        2932
stems-n-midi               1168        1168
synth                      4640        4640
synth-loop                 1226        1226
vocal                      5459        5459
```

Create a countplot of files by category

[12]:
```python
sns.set_style("whitegrid")
sns.countplot(data=audio_files_df, x='category', color='purple')
plt.xticks(rotation=80)
plt.show()
```



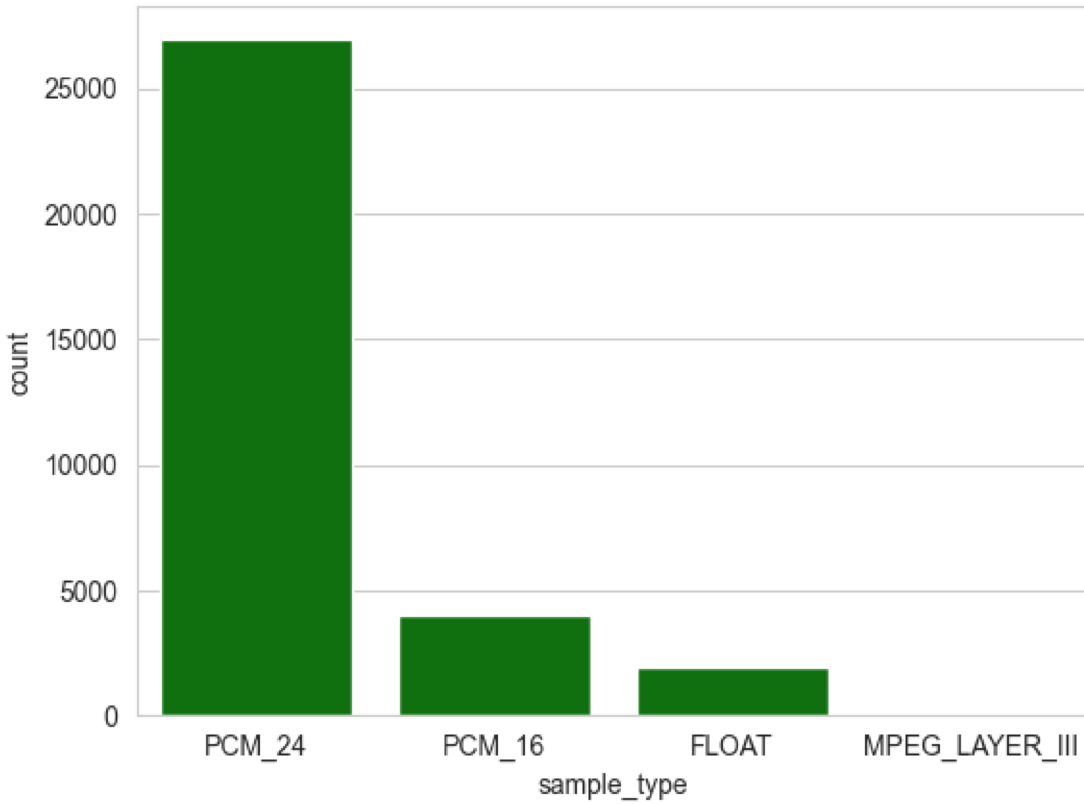
Due to the class imbalance, we may need to oversample minority classes or use class weights.

Checking sample types

[13]:
```
audio_files_df['sample_type'].unique()
```

[13]:
```
array(['PCM_24', 'PCM_16', 'FLOAT', 'MPEG_LAYER_III'], dtype=object)
```

[14]:
```
sns.set_style("whitegrid")
sns.countplot(data=audio_files_df, x='sample_type', color='green')
plt.show()
```



1.0.3 2. Preprocessing data

Convert the category and sample_type columns to numbers

[15]:
```
category_mapping = {'bass': 0, 'bass-loop': 1, 'drum': 2, 'drum-loop': 3,␣
↪'effects': 4,
            'instrumental-loops': 5, 'instruments': 6, 'kits-n-templates': 7,
            'stems-n-midi': 8, 'synth': 9, 'synth-loop': 10, 'vocal': 11}

sample_type_mapping = {'PCM_24': 0, 'PCM_16': 1, 'FLOAT': 2, 'MPEG_LAYER_III':␣
↪3}
```

```
audio_files_df['category_num'] = audio_files_df['category'].
↪map(category_mapping)

audio_files_df['sample_type_num'] = audio_files_df['sample_type'].
↪map(sample_type_mapping)

audio_files_df.head()
```

[15]:

```
  category                    file_path  file_size  duration  sample_rate  \
0     bass  BGE_13_Mid_Reece_Bass_1.wav    1240832  4.673016        44100
1     bass  BGE_14_Mid_Reece_Bass_2.wav    1207952  4.548753        44100
2     bass    BGE_15_808_Sat_Bass_1.wav    1123810  4.233061        44100
3     bass    BGE_16_808_Sat_Bass_2.wav     656276  2.468413        44100
4     bass             FJ_09_Bass_01.wav     701182  2.644036        44100

   channels  frame_count sample_type  category_num  sample_type_num
0         2       206080      PCM_24             0                0
1         2       200600      PCM_24             0                0
2         2       186678      PCM_24             0                0
3         2       108857      PCM_24             0                0
4         2       116602      PCM_24             0                0
```

Create a dataframe of file names and categories

[16]:

```
audio_text_df = audio_files_df[['file_path', 'category_num']]

audio_text_df.head()
```

[16]:

```
                     file_path  category_num
0  BGE_13_Mid_Reece_Bass_1.wav             0
1  BGE_14_Mid_Reece_Bass_2.wav             0
2    BGE_15_808_Sat_Bass_1.wav             0
3    BGE_16_808_Sat_Bass_2.wav             0
4             FJ_09_Bass_01.wav             0
```

Clean the file names

[17]:

```
# Make copy of data
audio_filenames_df = audio_files_df.copy()

# Remove the file extension and underscores from file names
def clean_filename(file_name):
    split_filename = file_name.split('.')[0].split('_')
    # if file name end with a number, remove it
    return ' '.join(split_filename[:-1]) if split_filename[-1].isdigit() else '␣
↪'.join(split_filename)
```

```
# Using swifter to improve performance
audio_filenames_df['clean_filenames'] = audio_filenames_df['file_path'].swifter.
↪allow_dask_on_strings(enable=True).apply(clean_filename)

audio_filenames_df.head(3)
```

```
Pandas Apply:   0%|          | 0/32929 [00:00<?, ?it/s]
```

[17]:
```
  category                     file_path  file_size  duration  sample_rate  \
0     bass  BGE_13_Mid_Reece_Bass_1.wav    1240832  4.673016        44100
1     bass  BGE_14_Mid_Reece_Bass_2.wav    1207952  4.548753        44100
2     bass    BGE_15_808_Sat_Bass_1.wav    1123810  4.233061        44100

   channels  frame_count sample_type  category_num  sample_type_num  \
0         2       206080      PCM_24             0                0
1         2       200600      PCM_24             0                0
2         2       186678      PCM_24             0                0

         clean_filenames
0  BGE 13 Mid Reece Bass
1  BGE 14 Mid Reece Bass
2    BGE 15 808 Sat Bass
```

Tokenise the file names

[18]:
```
audio_filenames_df['tokens'] = audio_filenames_df['clean_filenames'].swifter.
↪allow_dask_on_strings(enable=True).apply(nltk.word_tokenize)

audio_filenames_df.head(3)
```

```
Pandas Apply:   0%|          | 0/32929 [00:00<?, ?it/s]
```

[18]:
```
  category                     file_path  file_size  duration  sample_rate  \
0     bass  BGE_13_Mid_Reece_Bass_1.wav    1240832  4.673016        44100
1     bass  BGE_14_Mid_Reece_Bass_2.wav    1207952  4.548753        44100
2     bass    BGE_15_808_Sat_Bass_1.wav    1123810  4.233061        44100

   channels  frame_count sample_type  category_num  sample_type_num  \
0         2       206080      PCM_24             0                0
1         2       200600      PCM_24             0                0
2         2       186678      PCM_24             0                0

         clean_filenames                       tokens
0  BGE 13 Mid Reece Bass  [BGE, 13, Mid, Reece, Bass]
1  BGE 14 Mid Reece Bass  [BGE, 14, Mid, Reece, Bass]
2    BGE 15 808 Sat Bass    [BGE, 15, 808, Sat, Bass]
```

Extract columns useful for machine learning

[19]:
```python
# Create dataframe with useful columns for machine learning
audio_data_ml = audio_filenames_df.drop(['category', 'file_path',␣
↪'sample_type', 'clean_filenames'], axis=1)

audio_data_ml.head()
```

[19]:
```
   file_size  duration  sample_rate  channels  frame_count  category_num  \
0    1240832  4.673016        44100         2       206080             0
1    1207952  4.548753        44100         2       200600             0
2    1123810  4.233061        44100         2       186678             0
3     656276  2.468413        44100         2       108857             0
4     701182  2.644036        44100         2       116602             0

   sample_type_num                         tokens
0                0  [BGE, 13, Mid, Reece, Bass]
1                0  [BGE, 14, Mid, Reece, Bass]
2                0    [BGE, 15, 808, Sat, Bass]
3                0    [BGE, 16, 808, Sat, Bass]
4                0               [FJ, 09, Bass]
```

Remove holdout set to be used for model evaluation

[20]:
```python
X_all_data = audio_data_ml.drop('category_num', axis=1)
y_all_data = audio_data_ml['category_num']

# Split between seen and unseen data
# (seen data will be used for training and validation, while unseen data can be␣
↪used to test the final models)
# Data shuffled automatically
X_seen_data, X_holdout_data, y_seen_data, y_holdout_data =␣
↪train_test_split(X_all_data, y_all_data, test_size=0.33, random_state=4567)

X_seen_data.shape, y_seen_data.shape, X_holdout_data.shape, y_holdout_data.shape
```

[20]:
```
((22062, 7), (22062,), (10867, 7), (10867,))
```

Use TfidfVectorizer vectorization to create vocabularies

[21]:
```python
# Limiting vocabulary size to reduce computational time
MAX_VOCABULARY = 5000
CLASSES = ['bass', 'bass-loop', 'drum', 'drum-loop', 'effects',
           'instrumental-loops', 'instruments', 'kits-n-templates',
           'stems-n-midi', 'synth', 'synth-loop', 'vocal']

def do_nothing(x):
    return x

def baseline_vectorize(documents):
```

```
    """
    Create a vectorizer based on given training documents
    this is used for the baseline model
    :param dataframe: array of word-tokens
    :return: vectorizer
    """
    # Disable the tokenizer and preprocessor, as it was done in previous␣
↪pre-processing steps
    vectorizer = TfidfVectorizer(tokenizer=do_nothing, preprocessor=do_nothing,␣
↪lowercase=False, max_features=MAX_VOCABULARY)
    # Tokenize and build vocabulary
    vectorizer.fit(documents.copy())
    # Summarize
    print(sorted(vectorizer.vocabulary_)[:50]) # Only show 50 words
    print("vocabulary size =", len(vectorizer.vocabulary_))
    return vectorizer
```

Building vocabulary from 'X_seen_data'

[22]:
```
vectorizer = baseline_vectorize(X_seen_data['tokens'])
X = vectorizer.transform(X_seen_data['tokens'])
y = y_seen_data
```

```
['!', '#', '&', "'ll", "'m", "'re", "'s", '(', ')', '-', '-1', '-2', '-24b',
'-3', '-5', '-6', '0', '00', '000', '0001', '0002', '0004', '0005', '0007',
'0008', '0009', '001', '0010', '0011', '0012', '0014', '0015', '0016', '0017',
'0019', '002', '0020', '0021', '0022', '0023', '0024', '0025', '0026', '0027',
'0028', '0029', '003', '0030', '0031', '0032']
vocabulary size = 5000
```

```
/Users/tashvit/Documents/GitHub/python_fun/.venv/lib/python3.12/site-
packages/sklearn/feature_extraction/text.py:521: UserWarning: The parameter
'token_pattern' will not be used since 'tokenizer' is not None'
  warnings.warn(
```

[23]:
```
X.shape, y.shape
```

[23]:
```
((22062, 5000), (22062,))
```

Split the seen data into training and testing sets

[24]:
```
X_train, X_validation, y_train, y_validation = train_test_split(X, y,␣
↪test_size=0.2, random_state=6789)

# Check sizes
X_train.shape, X_validation.shape, y_train.shape, y_validation.shape
```

[24]:
```
((17649, 5000), (4413, 5000), (17649,), (4413,))
```

1.0.4 3. Choosing performance metrics

Precision is the most important metric for this multi-class classification problem, as this will minimize false positives.

However a healthy F1-score is also desirable (a high Recall will minimize false negatives).

- True Positives : Instances correctly classified as class .
- False Positives : Instances incorrectly classified as class , but belong to another class.
- False Negatives : Instances that belong to class but were incorrectly classified as another class.

1.1 Analyse performance without oversampling

The author will first analyse performance without oversampling.

If the results are poor, the author will consider oversampling minority classes or use class weights.

1.1.1 4. Multinomial Naive Bayes

[25]:
```
mnb = MultinomialNB()
mnb.fit(X_train.copy(), y_train.copy())
```

[25]:
```
MultinomialNB()
```

[26]:
```
mnb_predictions = mnb.predict(X_validation)

def print_results(y_true, y_pred):
    print('Classification report')
    print(classification_report(y_true, y_pred))
    print('\n')

    print('Confusion matrix')
    print(confusion_matrix(y_true, y_pred))

print_results(y_validation, mnb_predictions)
```

```
Classification report
              precision    recall  f1-score   support

           0       0.94      0.27      0.42        60
           1       1.00      0.14      0.24        72
           2       0.88      0.99      0.93       894
           3       0.77      0.87      0.82       354
           4       0.88      0.94      0.91       649
           5       0.77      0.59      0.67       145
           6       0.96      0.50      0.66       161
           7       0.83      0.83      0.83       386
           8       0.80      0.67      0.73       149
```

```
           9       0.88      0.99      0.93       637
          10       0.84      0.62      0.71       149
          11       0.97      0.96      0.97       757

    accuracy                           0.88      4413
   macro avg       0.88      0.70      0.74      4413
weighted avg       0.88      0.88      0.87      4413



Confusion matrix
[[ 16   0  19   1   1   1   3   0   0  19   0   0]
 [  0  10   5  23   1   4   0  11   0   7  11   0]
 [  0   0 887   4   3   0   0   0   0   0   0   0]
 [  0   0  29 309   5   0   0   4   5   1   1   0]
 [  0   0  14   8 612   3   0   3   3   1   3   2]
 [  0   0   1   8  15  86   0  16  14   2   2   1]
 [  0   0   8   1   2   1  80   9   0  40   0  20]
 [  0   0  44   8  13   0   0 319   0   2   0   0]
 [  1   0   0  25  11   9   0   0 100   1   1   1]
 [  0   0   0   1   1   0   0   1   0 633   0   1]
 [  0   0   0   8  12   5   0  19   0  13  92   0]
 [  0   0   0   4  16   2   0   1   3   1   0 730]]
```

1.1.2 5. Random Forest Classifier

[27]:
```python
rfc = RandomForestClassifier(n_estimators=200, n_jobs=-1, random_state=14785,␣
 ↪verbose=1)
rfc.fit(X_train.copy(), y_train.copy())
```

```
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:    0.5s
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed:    2.3s
[Parallel(n_jobs=-1)]: Done 200 out of 200 | elapsed:    2.5s finished
```

[27]:
```
RandomForestClassifier(n_estimators=200, n_jobs=-1, random_state=14785,
                       verbose=1)
```

[28]:
```python
rfc_predictions = rfc.predict(X_validation)

print_results(y_validation, rfc_predictions)
```

```
Classification report
              precision    recall  f1-score   support

           0       0.95      0.90      0.92        60
           1       0.94      0.89      0.91        72
           2       0.97      0.97      0.97       894
           3       0.95      0.94      0.94       354
```

```
           4       0.97      0.97      0.97       649
           5       0.82      0.77      0.79       145
           6       0.94      0.72      0.81       161
           7       0.80      0.93      0.86       386
           8       0.87      0.87      0.87       149
           9       0.98      1.00      0.99       637
          10       0.91      0.85      0.88       149
          11       0.99      0.98      0.99       757

    accuracy                           0.94      4413
   macro avg       0.92      0.90      0.91      4413
weighted avg       0.95      0.94      0.94      4413
```

```
Confusion matrix
[[ 54   0   0   0   0   0   1   2   0   3   0   0]
 [  3  64   0   2   0   0   0   2   0   0   1   0]
 [  0   0 865   2   1   0   0  26   0   0   0   0]
 [  0   0   7 331   3   1   0   2   5   2   2   1]
 [  0   0   5   1 628   1   0   6   2   1   1   4]
 [  0   2   0   1   6 111   3   4  10   0   7   1]
 [  0   0   1   1   1   0 116  40   0   2   0   0]
 [  0   0  11   6   6   0   0 360   0   3   0   0]
 [  0   0   0   3   0  13   0   3 129   0   0   1]
 [  0   1   0   0   0   0   2   0   0 634   0   0]
 [  0   1   0   2   2   6   1   5   0   5 127   0]
 [  0   0   0   1   3   3   1   0   3   0   1 745]]
[Parallel(n_jobs=8)]: Using backend ThreadingBackend with 8 concurrent workers.
[Parallel(n_jobs=8)]: Done  34 tasks      | elapsed:    0.0s
[Parallel(n_jobs=8)]: Done 184 tasks      | elapsed:    0.0s
[Parallel(n_jobs=8)]: Done 200 out of 200 | elapsed:    0.0s finished
```

1.1.3 6. LSTM (with Tensorflow and Keras)

Split seen data into training and testing sets using original seen data

[29]:
```
X_train, X_validation, y_train, y_validation = train_test_split(X_seen_data,
    y_seen_data, test_size=0.2, random_state=6789)
```

Function for sequence feature transformation

[30]:
```
vocab_size = 500
max_length = 6
embedding_dim = 25

def create_feature_transform(texts):
    """
```

```python
    Convert text to a sequence that can be used for LSTM training
    :param texts: tokens list
    :returns: input sequence padded to max_length
    """
    tokenizer = KerasTokenizer(num_words=vocab_size, oov_token='<oov>')
    tokenizer.fit_on_texts(texts)

    def transform(to_transform_text):
        sequences = tokenizer.texts_to_sequences(to_transform_text)
        # Using lstm pad_sequences function to pad the end of the sequence with␣
↪shorter sequences
        # Longer sequences will be truncated
        return pad_sequences(sequences, maxlen=max_length, padding='post')
    return transform
```

Function to train LSTM model

[31]:
```python
def train_lstm_model(x_features, y_target):
    num_classes = 12  # 0-11, inclusive
    labels = np.array(y_target)
    model = Sequential()
    model.add(Embedding(input_dim=vocab_size, output_dim=embedding_dim))
    model.add(LSTM(units=100))
    model.add(Dense(units=num_classes, activation='softmax'))  # Softmax for␣
↪mutually exclusive classes

    # Compile the model
    model.compile(optimizer='adam',
                  loss='sparse_categorical_crossentropy',  # Suitable for␣
↪integer labels
                  metrics=[Precision(), Recall()])

    # Example training
    model.fit(x_features, labels, epochs=20, batch_size=1)
    return model

# Create a feature transforming function
to_features = create_feature_transform(X_train['tokens'])

# Convert text to features for training and validation
train_features = to_features(X_train['tokens'])
validation_features = to_features(X_validation['tokens'])
```

[32]:
```python
train_features.shape
```

[32]:
```
(17649, 6)
```

Train model using the created function and save it

[33]:

```python
lstm_model = train_lstm_model(train_features, y_train)
lstm_model.save('lstm_model.h5')  # Save the entire model to a file
```

```
Epoch 1/20
17649/17649                 27s 1ms/step
- loss: 0.8420 - precision: 0.9892 - recall: 0.0583
Epoch 2/20
17649/17649                 26s 1ms/step
- loss: 0.2731 - precision: 0.9846 - recall: 0.0799
Epoch 3/20
17649/17649                 25s 1ms/step
- loss: 0.2020 - precision: 0.9813 - recall: 0.0806
Epoch 4/20
17649/17649                 25s 1ms/step
- loss: 0.1512 - precision: 0.9836 - recall: 0.0816
Epoch 5/20
17649/17649                 25s 1ms/step
- loss: 0.1340 - precision: 0.9817 - recall: 0.0818
Epoch 6/20
17649/17649                 25s 1ms/step
- loss: 0.1256 - precision: 0.9837 - recall: 0.0816
Epoch 7/20
17649/17649                 25s 1ms/step
- loss: 0.1062 - precision: 0.9808 - recall: 0.0823
Epoch 8/20
17649/17649                 25s 1ms/step
- loss: 0.0866 - precision: 0.9822 - recall: 0.0824
Epoch 9/20
17649/17649                 26s 1ms/step
- loss: 0.0797 - precision: 0.9833 - recall: 0.0827
Epoch 10/20
17649/17649                 25s 1ms/step
- loss: 0.0711 - precision: 0.9832 - recall: 0.0827
Epoch 11/20
17649/17649                 25s 1ms/step
- loss: 0.0729 - precision: 0.9826 - recall: 0.0825
Epoch 12/20
17649/17649                 25s 1ms/step
- loss: 0.0699 - precision: 0.9819 - recall: 0.0825
Epoch 13/20
17649/17649                 25s 1ms/step
- loss: 0.0650 - precision: 0.9840 - recall: 0.0826
Epoch 14/20
17649/17649                 25s 1ms/step
- loss: 0.0625 - precision: 0.9822 - recall: 0.0829
Epoch 15/20
17649/17649                 25s 1ms/step
- loss: 0.0643 - precision: 0.9826 - recall: 0.0826
```

```
Epoch 16/20
17649/17649              25s 1ms/step
- loss: 0.0595 - precision: 0.9831 - recall: 0.0828
Epoch 17/20
17649/17649              25s 1ms/step
- loss: 0.0611 - precision: 0.9814 - recall: 0.0827
Epoch 18/20
17649/17649              25s 1ms/step
- loss: 0.0585 - precision: 0.9832 - recall: 0.0829
Epoch 19/20
17649/17649              25s 1ms/step
- loss: 0.0549 - precision: 0.9813 - recall: 0.0828
Epoch 20/20
17649/17649              25s 1ms/step
- loss: 0.0547 - precision: 0.9820 - recall: 0.0829
```

```
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or
`keras.saving.save_model(model)`. This file format is considered legacy. We
recommend using instead the native Keras format, e.g.
`model.save('my_model.keras')` or `keras.saving.save_model(model,
'my_model.keras')`.
```

[34]:
```
# Load the saved model
lstm_model = load_model('lstm_model.h5')
```

```
WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be
built. `model.compile_metrics` will be empty until you train or evaluate the
model.
```

Obtain the predicted classes and print results

[35]:
```
# Get predicted probabilities
predicted_probabilities = lstm_model.predict(validation_features)

# Convert predicted probabilities to class labels
predicted_classes = predicted_probabilities.argmax(axis=1)

# Print classification report and confusion matrix
print_results(y_validation, predicted_classes)
```

```
138/138            0s 1ms/step
Classification report
              precision    recall  f1-score   support

           0       0.95      0.92      0.93        60
           1       0.86      0.86      0.86        72
           2       0.98      0.96      0.97       894
           3       0.94      0.91      0.92       354
           4       0.96      0.96      0.96       649
           5       0.85      0.87      0.86       145
```

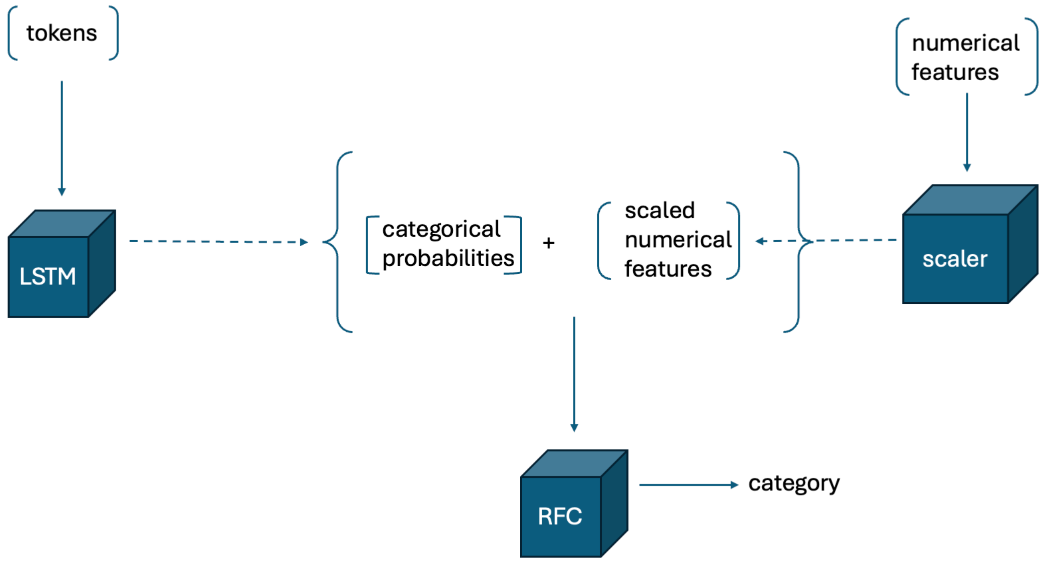
```
           6       0.91      0.89      0.90       161
           7       0.85      0.93      0.89       386
           8       0.91      0.93      0.92       149
           9       0.98      0.98      0.98       637
          10       0.86      0.83      0.84       149
          11       0.99      0.99      0.99       757

    accuracy                           0.95      4413
   macro avg       0.92      0.92      0.92      4413
weighted avg       0.95      0.95      0.95      4413
```

```
Confusion matrix
[[ 55   1   1   0   0   0   0   1   0   2   0   0]
 [  0  62   0   3   1   1   0   0   1   0   4   0]
 [  0   0 859   1   4   0   0  29   0   1   0   0]
 [  0   1   9 322   3   2   0   6   7   2   2   0]
 [  0   0   2   3 622   4   0  11   0   1   2   4]
 [  0   3   0   0   5 126   2   0   4   0   4   1]
 [  0   0   0   0   1   2 144   7   0   7   0   0]
 [  0   0   4   3   5   0   9 359   0   1   5   0]
 [  0   0   0   3   0   4   0   4 138   0   0   0]
 [  3   1   0   1   1   0   4   1   0 625   1   0]
 [  0   4   0   8   4   6   0   1   1   1 123   1]
 [  0   0   0   0   3   4   0   2   0   0   2 746]]
```

1.1.4 7. Random Forest Classifier - using LSTM model output + numerical features

This model uses the category probability output from the previous LSTM model with the other numerical features from the dataset.



Getting category probability outputs for 'train_features' derived using file name tokens.

[36]:
```
training_probabilities = lstm_model.predict(train_features)

# Print first probability array - 12 probability values for the 12 categories
training_probabilities[0]
```

```
552/552              0s 658us/step
```

[36]:
```
array([2.1760758e-11, 4.3379949e-09, 9.8595965e-10, 1.9547879e-09,
       3.0972520e-09, 1.9669439e-08, 1.3731193e-08, 8.1804269e-10,
       3.3757136e-10, 1.0000000e+00, 1.6661808e-08, 2.8434726e-09],
      dtype=float32)
```

Pre-process numerical data columns - normalization and standardization

[37]:
```
# Check head - 6 numerical features
X_train.head()
```

[37]:
```
       file_size   duration  sample_rate  channels  frame_count  \
25864     124194   0.422925        44100         2        18651
23929      99330   0.328957        44100         2        14507
21201    4417718  16.695669        44100         2       736279
19428   16128448  60.952381        44100         2      2688000
19954   11907338  45.000000        44100         2      1984500

       sample_type_num                                tokens
25864                0             [MPS1, Synth, Shot, 323, B]
23929                0           [MPESS4, Synth, Shot, 088, F]
```

```
21201                0  [Cymatics, -, Hairspray, -, 115, BPM, G, Maj, …
19428                0                      [WAES, Kit5, Kick, 126, Fm]
19954                0               [WALE2, Kit3, FX, Line02, 128, Gm]
```

[38]:
```
numerical_data_X_train = X_train.drop('tokens', axis=1).values
numerical_data_X_val = X_validation.drop('tokens', axis=1).values

# Scale the data
scaler = StandardScaler()

# Fit the scaler to the training data and transform
scaled_numerical_data_X_train = scaler.fit_transform(numerical_data_X_train)

# Save the scaler to a file with joblib
dump(scaler, 'numerical_scaler.joblib')
```

[38]:
```
['numerical_scaler.joblib']
```

Use the same scaler on the validation data

[39]:
```
# Load the saved scaler from the file
scaler = load('numerical_scaler.joblib')

# Scale the validation data without fitting
scaled_numerical_data_X_val = scaler.transform(numerical_data_X_val)

# Check first entry in scaled training data - 6 values for the 6 numerical␣
↪features
scaled_numerical_data_X_train[0]
```

[39]:
```
array([-0.40473935, -0.41566295, -0.15263433,  0.16540552, -0.4169775 ,
       -0.43768843])
```

Combine the scaled numerical features with the category probability outputs derived from text features

[40]:
```
# Combined features - X train
X_train_combined_features = np.concatenate([training_probabilities,␣
↪scaled_numerical_data_X_train], axis=1)

# Combined features - X validation - use predicted probabilities for X␣
↪validation
X_val_combined_features = np.concatenate([predicted_probabilities,␣
↪scaled_numerical_data_X_val], axis=1)

# Check first array in combined training feature
# -> 6 numerical columns + 12 category probabilities = 18 total values
X_train_combined_features[0]
```

[40]:
```
array([ 2.17607581e-11,  4.33799485e-09,  9.85959647e-10,  1.95478789e-09,
        3.09725201e-09,  1.96694394e-08,  1.37311931e-08,  8.18042689e-10,
        3.37571360e-10,  1.00000000e+00,  1.66618079e-08,  2.84347257e-09,
       -4.04739352e-01, -4.15662947e-01, -1.52634330e-01,  1.65405516e-01,
       -4.16977505e-01, -4.37688430e-01])
```

Create a second random forest classifier model object, fit the model and save it.

This random forest classifier model uses the previous LSTM model output and numerical features from the dataset.

[41]:
```
# Random forest classifier model that uses previous LSTM model output and␣
 ↪numerical features from the dataset
rfc_secondary = RandomForestClassifier(n_estimators=200, n_jobs=-1,␣
 ↪random_state=14785, verbose=1)

rfc_secondary.fit(X_train_combined_features.copy(), y_train.copy())

# Save the model to a file with joblib
dump(rfc_secondary, 'rfc_with_lstm_output_num_features.joblib')
```

```
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:    0.1s
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed:    0.6s
[Parallel(n_jobs=-1)]: Done 200 out of 200 | elapsed:    0.7s finished
```

[41]:
```
['rfc_with_lstm_output_num_features.joblib']
```

Load the saved model

[42]:
```
# Load the model from the file
rfc_secondary = load('rfc_with_lstm_output_num_features.joblib')
```

Print classification report and confusion matrix results

[43]:
```
rfc_secondary_predictions = rfc_secondary.predict(X_val_combined_features)

print_results(y_validation, rfc_secondary_predictions)
```

```
Classification report
              precision    recall  f1-score   support

           0       0.92      0.93      0.93        60
           1       0.89      0.88      0.88        72
           2       0.99      0.98      0.98       894
           3       0.95      0.93      0.94       354
           4       0.96      0.96      0.96       649
           5       0.86      0.86      0.86       145
           6       0.94      0.92      0.93       161
           7       0.92      0.95      0.94       386
```

```
           8       0.92      0.93      0.93       149
           9       0.98      0.98      0.98       637
          10       0.84      0.87      0.86       149
          11       0.99      0.99      0.99       757

    accuracy                           0.96      4413
   macro avg       0.93      0.93      0.93      4413
weighted avg       0.96      0.96      0.96      4413
```

```
Confusion matrix
[[ 56   1   1   0   0   0   0   1   0   1   0   0]
 [  0  63   0   2   0   1   0   0   1   0   5   0]
 [  0   0 877   1   5   0   0  10   0   1   0   0]
 [  0   3   3 328   3   0   0   4   7   2   4   0]
 [  0   0   2   3 624   4   0   6   0   1   3   6]
 [  0   0   0   3   5 125   2   0   4   0   5   1]
 [  0   0   0   0   1   1 148   4   0   7   0   0]
 [  0   0   5   3   4   0   1 367   0   1   4   1]
 [  0   0   0   3   0   4   0   3 139   0   0   0]
 [  5   0   0   0   2   0   5   1   0 623   1   0]
 [  0   4   0   3   3   6   0   1   0   1 130   1]
 [  0   0   0   0   3   4   1   1   0   0   2 746]]
[Parallel(n_jobs=8)]: Using backend ThreadingBackend with 8 concurrent workers.
[Parallel(n_jobs=8)]: Done  34 tasks      | elapsed:    0.0s
[Parallel(n_jobs=8)]: Done 184 tasks      | elapsed:    0.0s
[Parallel(n_jobs=8)]: Done 200 out of 200 | elapsed:    0.0s finished
```

This final attempt has produced the overall best results so far, with a F1 score of 96 and high precision. No data oversampling was necessary.

1.1.5 8. Model validation on unseen data

Validate the final model by testing against the holdout data

[44]:
```
# Check head of X holdout data
X_holdout_data.head(3)
```

[44]:
```
       file_size  duration  sample_rate  channels  frame_count  \
26026      74770  0.235828        44100         2        10400
30730     105884  0.400000        44100         2        17640
31499     137460  0.473061        44100         2        20862

       sample_type_num                                  tokens
26026                0                [MPS2, Synth, 117, F, #]
30730                0           [mp1vs2, vocal, shot, 0612, d, #]
31499                0  [MPVGW3, Vocal, Glitch, One, Shot, 081]
```

Process the unseen data so it can be used by the LSTM model

[45]:
```
# Holdout data tokens - convert text to features
holdout_features = to_features(X_holdout_data['tokens'])

holdout_features.shape
```

[45]:
```
(10867, 6)
```

Get predicted probabilities from the trained LSTM model, and combine with the scaled numerical features of the unseen data

[46]:
```
# Arrays that each contain 12 probability values for the 12 categories
holdout_probabilities = lstm_model.predict(holdout_features)

# Scale the holdout data using the existing Scaler without fitting
numerical_data_X_holdout = X_holdout_data.drop('tokens', axis=1).values
scaled_numerical_data_X_holdout = scaler.transform(numerical_data_X_holdout)

# Combine the scaled numerical features with the category probability outputs
X_holdout_combined_features = np.concatenate([holdout_probabilities,␣
↪scaled_numerical_data_X_holdout], axis=1)

# Check first array in combined holdout feature
# -> 6 numerical columns + 12 category probabilities = 18 total values
X_holdout_combined_features[0]
```

```
340/340              0s 780us/step
```

[46]:
```
array([ 1.41787788e-11,  1.74825016e-10,  5.77761927e-12,  4.99887562e-11,
        1.35361067e-09,  1.15742314e-08,  1.85001459e-09,  7.77609435e-11,
        4.40123042e-11,  1.00000000e+00,  7.29537430e-10,  3.35666583e-09,
       -4.12780575e-01, -4.23497271e-01, -1.52634330e-01,  1.65405516e-01,
       -4.24747638e-01, -4.37688430e-01])
```

Get predictions from model and print classification report and confusion matrix results

[47]:
```
predictions_unseen_data = rfc_secondary.predict(X_holdout_combined_features)

print_results(y_holdout_data, predictions_unseen_data)
```

```
Classification report
              precision    recall  f1-score   support

           0       0.89      0.94      0.91       186
           1       0.83      0.86      0.84       203
           2       0.99      0.98      0.98      2118
           3       0.96      0.94      0.95       861
           4       0.97      0.97      0.97      1570
           5       0.85      0.84      0.84       417
```

```
           6       0.95      0.94      0.94       431
           7       0.93      0.94      0.94       982
           8       0.91      0.91      0.91       382
           9       0.98      0.98      0.98      1514
          10       0.83      0.85      0.84       399
          11       0.98      0.99      0.98      1804

    accuracy                           0.95     10867
   macro avg       0.92      0.93      0.92     10867
weighted avg       0.95      0.95      0.95     10867
```

```
Confusion matrix
[[ 174    1    2    0    0    0    0    1    0    5    1    2]
 [   3  175    0    3    1    4    0    0    0    1   16    0]
 [   3    0 2078    1    6    0    1   21    0    2    0    6]
 [   0    6    5  807    5    3    1    4   12    3   12    3]
 [   0    1    7    7 1519    9    3    8    0    0    9    7]
 [   0    8    0    4    5  349    4    1   21    2   16    7]
 [   3    0    0    0    8    0  403    9    0    6    2    0]
 [   1    6   17    4    8    1    3  924    2    2    8    6]
 [   0    0    0   11    1   17    0    5  348    0    0    0]
 [  11    3    0    3    3    1    5    5    0 1477    5    1]
 [   0   11    0    5    8   19    1    9    0    4  341    1]
 [   0    1    0    0    7   10    1    3    0    2    2 1778]]
```

```
[Parallel(n_jobs=8)]: Using backend ThreadingBackend with 8 concurrent workers.
[Parallel(n_jobs=8)]: Done  34 tasks      | elapsed:    0.0s
[Parallel(n_jobs=8)]: Done 184 tasks      | elapsed:    0.0s
[Parallel(n_jobs=8)]: Done 200 out of 200 | elapsed:    0.0s finished
```

It can be seen that the model performs just about the same on unseen data, which indicates that the model is generalizing well and is not overfitting to the training data.

```
[ ]:
```