saki_1

May 9, 2021

[1]:
```python
import pandas as pd
from sklearn.naive_bayes import MultinomialNB
from tqdm import tqdm
from sklearn.metrics import accuracy_score,␣
↪classification_report,plot_confusion_matrix
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
from sklearn.feature_extraction.text import CountVectorizer, TfidfTransformer
from sklearn.pipeline import Pipeline
import numpy as np
from sklearn.model_selection import cross_val_score
```

[2]:
```python
# Represents the proportion of the dataset used for training. Remaining will be␣
↪used for validation.
TRAIN_SIZE = 0.7
```

[3]:
```python
# Load dataset

source = pd.read_csv("./SAKI Exercise 1 - Transaction Classification - Data Set.
↪csv", delimiter=";")
source.drop("Unnamed: 0", axis=1, inplace=True)

source.head()
```

[3]:
```
   Auftragskonto Buchungstag Valutadatum              Buchungstext  \
0     89990201.0  28.07.2016  28.07.2016             Lohn / Gehalt
1     89990201.0  27.07.2016  27.07.2016                     Miete
2     89990201.0  21.07.2016  21.07.2016                   Bargeld
3     89990201.0  20.07.2016  20.07.2016  Lebensmittel / Getraenke
4     89990201.0  18.07.2016  18.07.2016            Spontanausgabe

                                    Verwendungszweck  \
0  Gehalt Adorsys GmbH & Co. KG End-To-End-Ref.: …
1  Byladem1Sbt De12773501123456789889 Miete Beuth…
2  21.07/16.34Uhr Nuernberg All Eur 70,00 Geb.Eur…
3  2831 Edeka Neubauer Nuernb.//Nuernb 2016-07-20…
4                                             Amazon
```

```
  Beguenstigter/Zahlungspflichtiger             Kontonummer          BLZ  \
0             Adorsys GmbH & Co. KG              7807800780     25190001
1                      Georg Tasche  DE31251900019123456780  VOHADE2HXXX
2                          Bargeld              9999900780     25190001
3                    Kartenzahlung              9736000780     25190001
4                  neue Playstation              9988776655     25125100

    Betrag Waehrung            label
0  2000.00      EUR           income
1  -670.00      EUR           living
2   -70.00      EUR          private
3   -73.21      EUR  standardOfLiving
4     -363      EUR          leisure
```

[4]:

```python
# Extract relevant features and concatenate them to a single lower case string␣
↪per feature

# Removing some characters could be helpful.
# However these are almost always part of a word and are not surrounded by␣
↪whitespace.
# Hence they are not detected as a single token by the count tokenizer and it
# increases the accuracy by a very tiny amount, though that might change with a
# bigger dataset
def remove_stopwords(feature: str)-> str:
    feature = feature.replace(".", "")
    feature = feature.replace(",", "")
    feature = feature.replace(":", "")
    feature = feature.replace("/", "")
    feature = feature.replace("&", "")
    return feature


# Concatenate all relevant features into one big string
features = []
for i in range(len(source.index)):
    combined = []
    combined.append(source.loc[i, "Buchungstext"])
    combined.append(source.loc[i, "Verwendungszweck"])
    combined.append(source.loc[i, "Beguenstigter/Zahlungspflichtiger"])

    feature = remove_stopwords(" ".join(combined))

    features.append(feature.lower())

# Extract labels as well
labels = list(source["label"])
```

```
print("Example of features as a single string:")
print(features[0])
```

```
Example of features as a single string:
lohn  gehalt gehalt adorsys gmbh  co kg end-to-end-ref notprovided
kundenreferenz nsct1603300013660000000000000000001 gutschrift adorsys gmbh  co
kg
```

[5]:
```
# I would like to know how many tokens each feature has to judge whether or not␣
↪using a tfidf transformer makes sense
def inspect_tokens(features: [str]) -> None:
    tokens_per_feature = []
    unique_tokens_per_feature = []
    for feature in features:
        tokens = feature.split(" ")
        tokens_per_feature.append(len(tokens))
        unique_tokens_per_feature.append(len(set(tokens)))

    print("Maximum tokens:", max(tokens_per_feature))
    print("Average tokens:", np.average(tokens_per_feature))
    print("Average unique tokens", np.average(unique_tokens_per_feature) )

inspect_tokens(features)
```

```
Maximum tokens: 19
Average tokens: 11.311004784688995
Average unique tokens 10.311004784688995
```

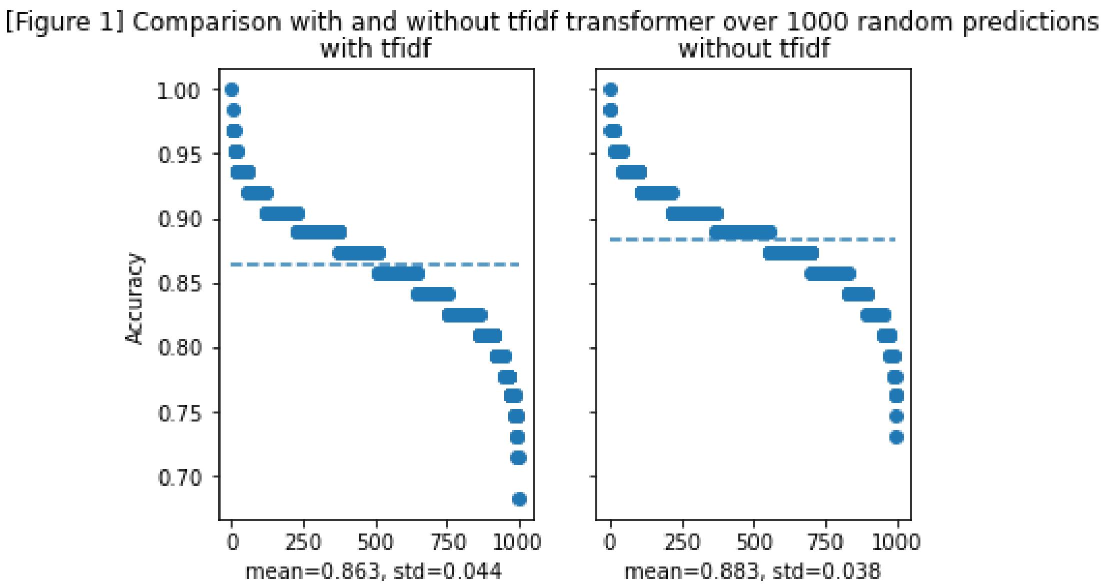
We can see that there really aren't that many duplicate tokens in each feature, so I think a tfidf transformer will not help us a lot. I am testing this directly further down.

[6]:
```
# Helper function to create a new pipeline with or without tfidf transformer
def create_pipeline(with_tfidf: bool) -> Pipeline:
    steps = [ ("vectorizer", CountVectorizer())]
    if (with_tfidf is True):
        steps.append(("tfidf", TfidfTransformer()))
    steps.append(("nb", MultinomialNB()))
    return Pipeline(steps)


# Split our dataset
def split_data(features: [str], labels: [str]):
    return train_test_split(features, labels, train_size=TRAIN_SIZE,␣
↪shuffle=True)
```

[7]:
```
# Runs a bunch of predictions with random train/test splits to get an average␣
↪accuracy.
```

```python
def do_random_runs(with_tfidf: bool) -> [float]:
    accuracies = []
    for i in tqdm(range(1000)):
        x_train, x_test, y_train, y_test = split_data(features, labels)
        classifier = create_pipeline(with_tfidf=with_tfidf)
        classifier.fit(x_train, y_train)

        accuracies.append(accuracy_score(y_test,classifier.predict(x_test)))
    return accuracies


# Plot accuracies inside a subplot
def plot(ax, accuracies: [float]) -> None:
    accuracies.sort(reverse=True)
    mean = np.mean(accuracies)
    std = np.array(accuracies).std()

    ax.set_xlabel("mean={:.3f}, std={:.3f}".format(mean,std))
    x = range(0,len(accuracies))

    y = accuracies

    ax.scatter(x=x,y=y,label="Accuracy")
    ax.plot(x,[mean]*len(x),label="Mean", linestyle="--")

# Calculate and plot the difference when using a tfidf transformer or not
def compare_tfidf(features: [str], labels: [str]) -> None:
    fig, (ax1,ax2) = plt.subplots(1,2,sharex=True,sharey=True)
    fig.suptitle("[Figure 1] Comparison with and without tfidf transformer over␣
 ↪1000 random predictions")

    # 1. with tfidf
    plot(ax1, do_random_runs(True))
    ax1.set_title("with tfidf")
    ax1.set_ylabel("Accuracy")

    # 2. without tfidf
    plot(ax2, do_random_runs(False))
    ax2.set_title("without tfidf")

    plt.show()


compare_tfidf(features,labels)
```

```
100%|          | 1000/1000 [00:05<00:00, 175.64it/s]
100%|          | 1000/1000 [00:04<00:00, 214.77it/s]
```



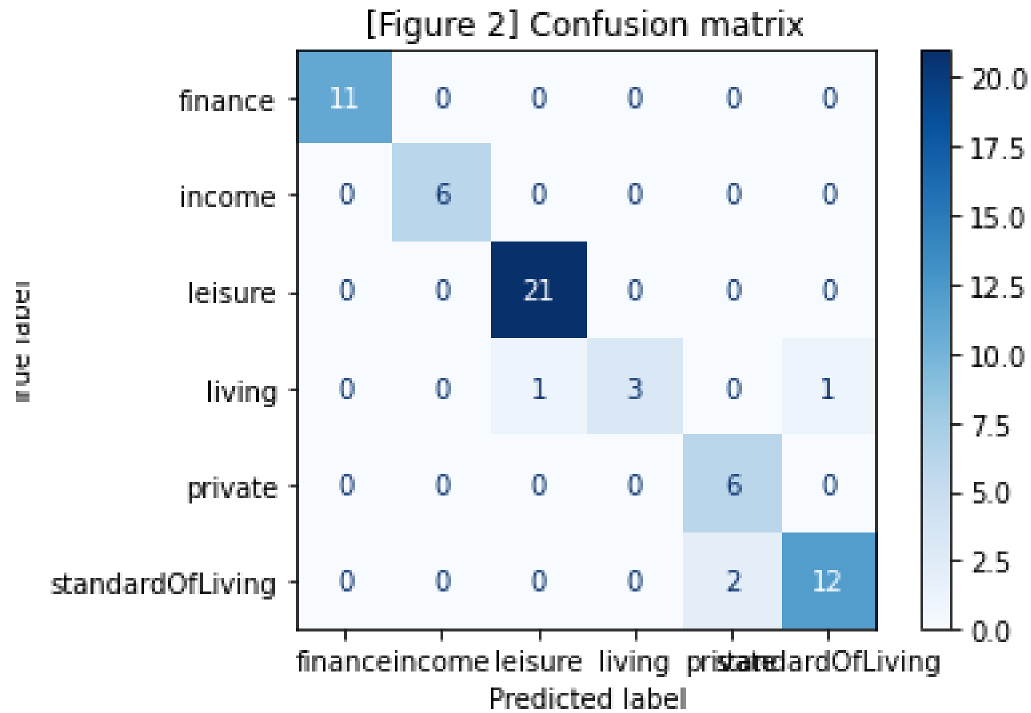
Initially I thought using a tfidf transformer would not increase our accuracy a lot because our features have fewer than 20 tokens that do not repeat often. But it actually decreases the accuracy a little bit.

A mean accuracy of ~0.88 and standard deviation of ~0.04 is acceptable however the big range of accuracies depending on the shuffled train/test split is a result of the very small dataset.

[8]:
```
# Final model

x_train, x_test, y_train, y_test = split_data(features, labels)
classifier = create_pipeline(with_tfidf=False)
classifier.fit(x_train, y_train)
```

[8]:
```
Pipeline(steps=[('vectorizer', CountVectorizer()), ('nb', MultinomialNB())])
```

[9]:
```
# Let's look at the confusion matrix for our model

plot = plot_confusion_matrix(classifier, x_test, y_test, cmap=plt.cm.Blues)
plot.ax_.set_title("[Figure 2] Confusion matrix")
plt.show()
```



[10]:
```python
# And print some statistics
print(classification_report(y_test, classifier.predict(x_test)))
```

```
                  precision    recall  f1-score   support

         finance       1.00      1.00      1.00        11
          income       1.00      1.00      1.00         6
         leisure       0.95      1.00      0.98        21
          living       1.00      0.60      0.75         5
         private       0.75      1.00      0.86         6
standardOfLiving       0.92      0.86      0.89        14

        accuracy                           0.94        63
       macro avg       0.94      0.91      0.91        63
    weighted avg       0.94      0.94      0.93        63
```