

DanielFuYawYang_ML_Final

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1 Exploratory data analysis of the Cheese datasets

Title : Final project Machine Learning

Author: Daniel Fu Yaw Yang

[]:

2 Introduction

2.1 Question of interests

In this analysis, I will be analysing the cheese datasets.

I am interested in trying to get the highest precision of the fat level for the cheeses provided

- canadian_cheese.csv – This file contains information on cheese only from canada
- cheese.csv – This file includes information on cheese that we are more interested in :- moisture % and fat level

Let us start by importing methods and the tables to do some basic visualizations

```
[7]: import pandas as pd
import altair as alt

import sklearn
from sklearn.model_selection import train_test_split, cross_validate
from sklearn.tree import DecisionTreeClassifier
from sklearn.dummy import DummyClassifier
from sklearn.tree import DecisionTreeClassifier

from sklearn.pipeline import Pipeline, make_pipeline
from sklearn.compose import make_column_transformer
from sklearn.impute import SimpleImputer

from sklearn.preprocessing import (FunctionTransformer, Normalizer,
    ↳OneHotEncoder, StandardScaler, normalize, scale)
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC, SVR
from sklearn.linear_model import LogisticRegression
```

```

from sklearn.metrics import accuracy_score, precision_score, recall_score, \
    f1_score
from sklearn.model_selection import RandomizedSearchCV

from sklearn import metrics
from sklearn.metrics import plot_confusion_matrix, classification_report

```

```

[11]: # import all the required files

#canada_cheese_url = 'https://github.com/UBC-MDS/intro-ml-students/blob/main/
    ↪release/final_project/data/canadianCheeseDirectory.csv'
canadian_cheese_df = pd.read_csv("intro-ml-students/release/final_project/data/
    ↪canadianCheeseDirectory.csv")
#pd.read_csv(canada_cheese_url)

#cheese_url='https://github.com/UBC-MDS/intro-ml-students/blob/main/release/
    ↪final_project/data/cheese_data.csv'
cheese_df = pd.read_csv("intro-ml-students/release/final_project/data/
    ↪cheese_data.csv")
#pd.read_csv(cheese_url)

```

```

[12]: canadian_cheese_df.head()

```

```

[12]:
   CheeseId  CheeseNameEn \
0        228             NaN
1        242             NaN
2        301  Provolone Sette Fette (Tre-Stelle)
3        303             NaN
4        319             NaN

           CheeseNameFr  ManufacturerNameEn \
0      Sieur de Duplessis (Le)             NaN
1      Tomme Le Champ Doré             NaN
2  Provolone Sette Fette (Tre-Stelle)  Tre Stelle (Arla Foods)
3              Geai Bleu (Le)             NaN
4              Gamin (Le)             NaN

           ManufacturerNameFr  ManufacturerProvCode  ManufacturingTypeEn \
0  Fromages la faim de loup             NB      Farmstead
1  Fromages la faim de loup             NB      Farmstead
2              NaN             ON      Industrial
3  Fromages la faim de loup             NB      Farmstead
4  Fromages la faim de loup             NB      Farmstead

           ManufacturingTypeFr  WebSiteEn \
0      Fermière             NaN
1      Fermière             NaN

```

```

2      Industrielle  http://www.trestelle.ca/english/
3      Fermière      NaN
4      Fermière      NaN

      WebSiteFr ... Organic  CategoryTypeEn \
0      NaN ... 0 Firm Cheese
1      NaN ... 0 Semi-soft Cheese
2  http://www.trestelle.ca/francais/ ... 0 Firm Cheese
3      NaN ... 0 Veined Cheeses
4      NaN ... 1 Semi-soft Cheese

      CategoryTypeFr MilkTypeEn MilkTypeFr MilkTreatmentTypeEn \
0      Pâte ferme      Ewe      Brebis      Raw Milk
1      Pâte demi-ferme      Cow      Vache      Raw Milk
2      Pâte ferme      Cow      Vache      Pasteurized
3      Pâte persillée      Cow      Vache      Raw Milk
4      Pâte demi-ferme      Cow      Vache      Raw Milk

      MilkTreatmentTypeFr RindTypeEn RindTypeFr LastUpdateDate
0      Lait cru      Washed Rind      Croûte lavée      2016-02-03
1      Lait cru      Washed Rind      Croûte lavée      2016-02-03
2      Pasteurisé      NaN      NaN      2016-02-03
3      Lait cru      NaN      NaN      2016-02-03
4      Lait cru      Washed Rind      Croûte lavée      2016-02-03

```

[5 rows x 30 columns]

```
[13]: cheese_df.head()
```

```

[13]: CheeseId ManufacturerProvCode ManufacturingTypeEn MoisturePercent \
0      228      NB      Farmstead      47.0
1      242      NB      Farmstead      47.9
2      301      ON      Industrial      54.0
3      303      NB      Farmstead      47.0
4      319      NB      Farmstead      49.4

      FlavourEn \
0      Sharp, lactic
1      Sharp, lactic, lightly caramelized
2      Mild, tangy, and fruity
3      Sharp with fruity notes and a hint of wild honey
4      Softer taste

      CharacteristicsEn Organic \
0      Uncooked      0
1      Uncooked      0
2      Pressed and cooked cheese, pasta filata, inter...      0

```

3				NaN	0
4				NaN	1

	CategoryTypeEn	MilkTypeEn	MilkTreatmentTypeEn	RindTypeEn	\
0	Firm Cheese	Ewe	Raw Milk	Washed Rind	
1	Semi-soft Cheese	Cow	Raw Milk	Washed Rind	
2	Firm Cheese	Cow	Pasteurized	NaN	
3	Veined Cheeses	Cow	Raw Milk	NaN	
4	Semi-soft Cheese	Cow	Raw Milk	Washed Rind	

	CheeseName	FatLevel
0	Sieur de Duplessis (Le)	lower fat
1	Tomme Le Champ Doré	lower fat
2	Provolone Sette Fette (Tre-Stelle)	lower fat
3	Geai Bleu (Le)	lower fat
4	Gamin (Le)	lower fat

There are some features here that we will be dropping as they won't be helping us with our prediction; - CheeseId, - ManufacturerProvCode, - ManufacturingTypeEn, - CharacteristicsEn, - RindTypeEn, - CheeseName

```
[15]: cheese_train_df=train_df = cheese_df.
      →drop(columns=['CheeseId','ManufacturerProvCode',
      →'ManufacturingTypeEn','CharacteristicsEn','RindTypeEn','CheeseName'])

cheese_train_df
```

```
[15]: MoisturePercent                                FlavourEn \
0          47.0                                Sharp, lactic
1          47.9          Sharp, lactic, lightly caramelized
2          54.0          Mild, tangy, and fruity
3          47.0  Sharp with fruity notes and a hint of wild honey
4          49.4          Softer taste
...          ...
1037        37.0  Dill, Caraway, Chili Pepper, Cumin, Sage, Chiv...
1038        46.0          Mild and Deep Flavor
1039        40.0  Grassy tang and restrained saltiness that refl...
1040        34.0  Sweet and tangy flavours combine with hoppy no...
1041        31.5  Available in different flavor: original, herb ...
```


	Organic	CategoryTypeEn	MilkTypeEn	MilkTreatmentTypeEn	FatLevel
0	0	Firm Cheese	Ewe	Raw Milk	lower fat
1	0	Semi-soft Cheese	Cow	Raw Milk	lower fat
2	0	Firm Cheese	Cow	Pasteurized	lower fat
3	0	Veined Cheeses	Cow	Raw Milk	lower fat
4	1	Semi-soft Cheese	Cow	Raw Milk	lower fat
...

1037	1	Hard Cheese	Cow	Pasteurized	higher fat
1038	0	Fresh Cheese	Cow	Pasteurized	lower fat
1039	0	Veined Cheeses	Ewe	Thermised	higher fat
1040	0	Semi-soft Cheese	Ewe	Thermised	higher fat
1041	0	Fresh Cheese	Cow	Pasteurized	higher fat

[1042 rows x 7 columns]

Now we can import the data and split it to train and test data frames.

The dataframe will be split into train and test data and into a ratio 8:2 for the respective data and named `X_train`, `y_train`, `X_test` and `y_test` using a `random_state` of 123.

```
[16]: train_df, test_df = train_test_split(cheese_train_df, test_size=0.2,
    ↪random_state=123)
```

Now we are going to use `info()` to check if there are null values.. We will also see the percentage of lower fat and higher fat in the dataset provided

```
[17]: train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 833 entries, 482 to 1041
Data columns (total 7 columns):
#   Column                Non-Null Count  Dtype
---  -
0   MoisturePercent        821 non-null    float64
1   FlavourEn              637 non-null    object
2   Organic                833 non-null    int64
3   CategoryTypeEn         813 non-null    object
4   MilkTypeEn             832 non-null    object
5   MilkTreatmentTypeEn    781 non-null    object
6   FatLevel               833 non-null    object
dtypes: float64(1), int64(1), object(5)
memory usage: 52.1+ KB
```

from this data it looks like `MoisturePercent` and `Organic` column will help with our prediction as our feature for our target- `Fatlevel` as they have the least non-null entries and we arent really interested in milk type

But before that there are null values in our dataframe and we will try to “fix” it later after we find which feature will help us best

```
[19]: Moisture_to_fat = alt.Chart(train_df).mark_bar().encode(
    alt.X('FatLevel:N', title="Fat Level"),
    alt.Y('MoisturePercent:Q', title="Moisture Percent")
).properties(title='Percentage of Moisture to Fat level')
Moisture_to_fat
```

```
[19]: alt.Chart(...)
```

According to this bar graph, higher fat level has a lower moisture percentage.

Now lets look at if Organic has any correlation:

```
[25]: Organic_to_fat= alt.Chart(train_df).mark_bar().encode(
      alt.X('FatLevel:N', title="Fat Level"),
      alt.Y("Organic:N", title="Organic or not")
    ).properties(width= 300,height = 300, title="Organic to Fat level")
Organic_to_fat
```

```
[25]: alt.Chart(...)
```

Now we can compare these two features using the plotted graph and it seems that the Moisture percentage will be the most helpful to help us with our prediction I am going to use the column FatLevel column as my target y and everything else that is left as feature X

```
[40]: X_train, y_train = train_df.drop(columns=['FatLevel']), train_df['FatLevel']
X_test, y_test = test_df.drop(columns=['FatLevel']), test_df['FatLevel']
```

```
[72]: train_df['FatLevel'].replace(['lower fat', 'higher fat'], [0,1], inplace=True)
test_df['FatLevel'].replace(['lower fat', 'higher fat'], [0,1], inplace=True)

train_df
```

/opt/conda/lib/python3.8/site-packages/pandas/core/series.py:4509:

SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
    return super().replace(
```

```
[72]:
```

	MoisturePercent	FlavourEn \
482	48.0	Sharp, hazelnutty
896	45.0	NaN
421	50.0	Mild
929	40.0	NaN
737	65.0	Acidulous
...
638	44.0	Mild
113	52.0	NaN
96	74.0	Milky, smooth and creamy
106	40.0	Sharp flavour
1041	31.5	Available in different flavor: original, herb ...

Organic	CategoryTypeEn	MilkTypeEn	MilkTreatmentTypeEn	FatLevel
---------	----------------	------------	---------------------	----------

482	0	Semi-soft Cheese	Cow	Pasteurized	0
896	0	Veined Cheeses	Cow	Pasteurized	1
421	0	Soft Cheese	Cow	Pasteurized	0
929	0	Semi-soft Cheese	Cow	Pasteurized	1
737	0	Fresh Cheese	Cow	Pasteurized	0
...
638	0	Soft Cheese	Cow	Raw Milk	0
113	0	Soft Cheese	Cow	Pasteurized	0
96	0	Fresh Cheese	Cow	Pasteurized	0
106	0	Semi-soft Cheese	Cow	Pasteurized	1
1041	0	Fresh Cheese	Cow	Pasteurized	1

[833 rows x 7 columns]

Let's make a baseline model using DummyClassifier. Build a DummyClassifier named dummy using strategy='most_frequent'. Perform crossvalidation on the training portion and return the training score

```
[74]: dummy = DummyClassifier(strategy='most_frequent')
dummy_score = pd.DataFrame(cross_validate(
    dummy, X_train, y_train, return_train_score=True))
print(dummy_score.mean())
```

```
fit_time      0.001137
score_time    0.000366
test_score    0.657860
train_score   0.657863
dtype: float64
```

Next is defining the different types of features present in the data that will be used in the modeling process. The feature types are:

- **numeric_features:** These are the numerical features in the data, such as MoisturePercent and Organic.
- **categorical_features:** These are the categorical features in the data, such as CategoryTypeEn, MilkTypeEn, and MilkTreatmentTypeEn.
- **binary_features:** These are the features that have only two possible values, such as Organic. It's worth noting that Organic is already included in numeric_features, but this is not an issue since it is a binary feature.
- **text_features:** These are the features that contain text data, such as FlavourEn.

```
[75]: numeric_features = ['MoisturePercent' , 'Organic']
categorical_features = ['CategoryTypeEn' , 'MilkTypeEn' , 'MilkTreatmentTypeEn']
binary_features = ['Organic']
text_features = ['FlavourEn']
```

```
[76]: numeric_transformer = make_pipeline(SimpleImputer(strategy = 'median'),
                                         StandardScaler())
categorical_transformer = make_pipeline(SimpleImputer(strategy = 'most_frequent',
                                                    fill_value = 'missing'),
                                         OneHotEncoder(handle_unknown = 'ignore'))

binary_transformer = make_pipeline(SimpleImputer(strategy = 'most_frequent',
                                                    fill_value = 'missing'),
                                   OneHotEncoder(drop = 'if_binary'))
text_transformer = make_pipeline(SimpleImputer(strategy = 'most_frequent',
                                                    fill_value = 'missing'),
                                 CountVectorizer())
```

```
[ ]:
```

```
[61]: preprocessor = make_column_transformer(
        (numeric_transformer, numeric_features),
        (categorical_transformer, categorical_features),
        (binary_transformer, binary_features))
```

Next we calculate f1, precision, and recall to compare the accuracy for each scoring metric

I am going to test the performance of four different models on a dataset

```
[83]: scoring = ['f1', 'precision', 'recall', 'accuracy']

score_dict = {}
models = {
    "Logistic Regression": LogisticRegression(class_weight='balanced'),
    "Decision tree": DecisionTreeClassifier(class_weight='balanced'),
    "RBF SVM": SVC(class_weight='balanced'),
    "kNN": KNeighborsClassifier(weights='distance')
}

for model in models.items():
    pipe = Pipeline(steps=[("preprocessor", preprocessor),
                           (model)])

    scores = pd.DataFrame(cross_validate(
        pipe, X_train, y_train, scoring=scoring, return_train_score=True,
        cv=10))

    score_dict[model] = {'mean_train_f1': scores['train_f1'].mean().round(4),
                        'mean_test_f1': scores['test_f1'].mean().round(4),
                        'mean_train_precision': scores['train_precision'].
                        mean().round(4),
```



```

        'mean_test_precision': scores['test_precision'].
        ↪mean().round(4),
        'mean_train_recall': scores['train_recall'].mean().
        ↪round(4),
        'mean_test_recall': scores['test_recall'].mean().
        ↪round(4),
        'mean_train_accuracy': scores["train_accuracy"].
        ↪mean().round(4),
        'mean_test_accuracy': scores["test_accuracy"].mean().
        ↪round(4)}
score_df = pd.DataFrame(score_dict).T
score_df

```

```

[83]: mean_train_f1 \
Logistic Regression LogisticRegression(class_weight='balanced')
0.6860
Decision tree      DecisionTreeClassifier(class_weight='balanced')
0.8673
RBF SVM           SVC(class_weight='balanced')
0.7363
kNN               KNeighborsClassifier(weights='distance')
0.8560

mean_test_f1 \
Logistic Regression LogisticRegression(class_weight='balanced')
0.6774
Decision tree      DecisionTreeClassifier(class_weight='balanced')
0.7379
RBF SVM           SVC(class_weight='balanced')
0.6946
kNN               KNeighborsClassifier(weights='distance')
0.7325

mean_train_precision \
Logistic Regression LogisticRegression(class_weight='balanced')
0.6178
Decision tree      DecisionTreeClassifier(class_weight='balanced')
0.8178
RBF SVM           SVC(class_weight='balanced')
0.6404
kNN               KNeighborsClassifier(weights='distance')
0.8752

mean_test_precision \
Logistic Regression LogisticRegression(class_weight='balanced')
0.6125
Decision tree      DecisionTreeClassifier(class_weight='balanced')

```

```

0.7035
RBF SVM SVC(class_weight='balanced')
0.6035
kNN KNeighborsClassifier(weights='distance')
0.7519

mean_train_recall \
Logistic Regression LogisticRegression(class_weight='balanced')
0.7711
Decision tree DecisionTreeClassifier(class_weight='balanced')
0.9236
RBF SVM SVC(class_weight='balanced')
0.8666
kNN KNeighborsClassifier(weights='distance')
0.8402

mean_test_recall \
Logistic Regression LogisticRegression(class_weight='balanced')
0.7608
Decision tree DecisionTreeClassifier(class_weight='balanced')
0.7829
RBF SVM SVC(class_weight='balanced')
0.8213
kNN KNeighborsClassifier(weights='distance')
0.7188

mean_train_accuracy \
Logistic Regression LogisticRegression(class_weight='balanced')
0.7584
Decision tree DecisionTreeClassifier(class_weight='balanced')
0.9033
RBF SVM SVC(class_weight='balanced')
0.7878
kNN KNeighborsClassifier(weights='distance')
0.9034

mean_test_accuracy
Logistic Regression LogisticRegression(class_weight='balanced')
0.7514
Decision tree DecisionTreeClassifier(class_weight='balanced')
0.8104
RBF SVM SVC(class_weight='balanced')
0.7526
kNN KNeighborsClassifier(weights='distance')
0.8199

```

We can see that Fatlevel is an imbalanced distribution and it looks like the KNN model has the

highest accuracy and precision amongst the scoring metrics so we will be using it to hypertune. I am RandomizedSearchCV will be used since we have a smaller dataset now.

```
[84]: pipe = Pipeline(steps=[('preprocessor', preprocessor),
                             ('kNN', KNeighborsClassifier(weights='distance'))])
param_grid = {
    "kNN__n_neighbors": range(1, 10),
    "kNN__algorithm": ['auto', 'brute']
}

random_search = RandomizedSearchCV(pipe, param_grid, cv=10, verbose=1,
    ↪n_jobs=-1,
                                n_iter=10, random_state=123,
    ↪return_train_score=True, scoring='accuracy')
random_search.fit(X_train, y_train)
best_params = random_search.best_params_
best_model = random_search.best_estimator_
best_score = random_search.best_score_
print(best_params)
print(best_score)
```

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits
{'kNN__n_neighbors': 7, 'kNN__algorithm': 'brute'}
0.8235513482501435
```

With a total of 100 fits using 10 folds we are able to obtain the best model, number of n_neighbors and precision score

With the optimized settings we can go ahead and score the test data

```
[67]: pred_y = best_model.predict(X_test)
precision_score(y_test, pred_y)
```

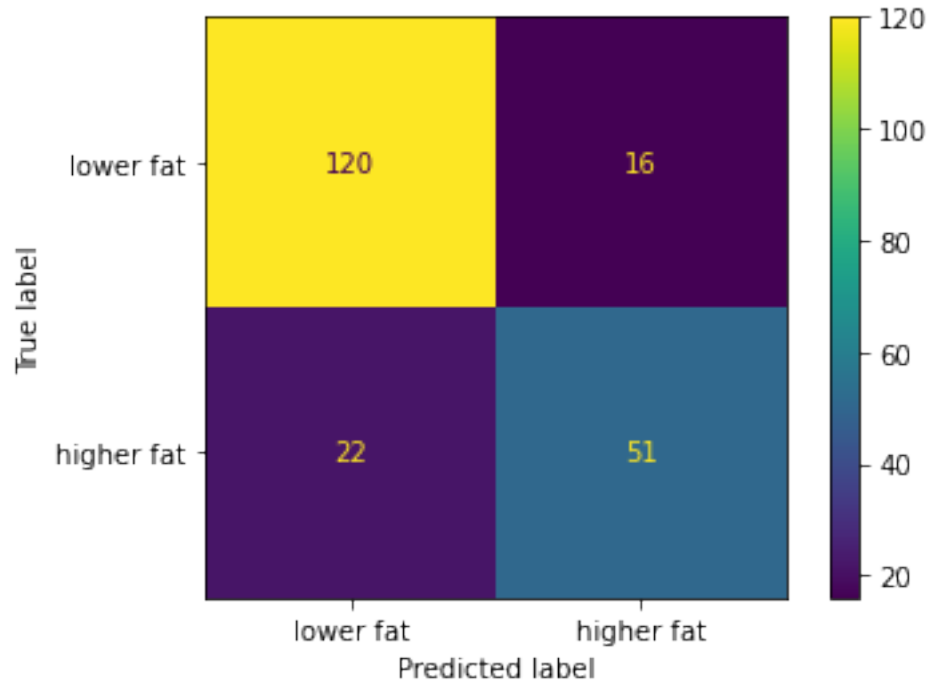
```
[67]: 0.7611940298507462
```

Now im gonna plot the confusion matrix along with the classification report

```
[70]: best_model.fit(X_train, y_train)

plot_confusion_matrix(best_model, X_test, y_test, display_labels=['lower fat',
    ↪'higher fat'])
```

```
[70]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7f828a664e20>
```



```
[71]: print(classification_report(y_test, pred_y,
    target_names=['lower fat', 'higher fat']))
```

	precision	recall	f1-score	support
lower fat	0.85	0.88	0.86	136
higher fat	0.76	0.70	0.73	73
accuracy			0.82	209
macro avg	0.80	0.79	0.80	209
weighted avg	0.82	0.82	0.82	209

3 Discussion

In this work, I analyzed the Cheese dataset and tried to compute which feature can produce the best score to predict the target FatLevel. Before answering this question, I did some exploratory data analysis to see which feature would correlate with the target best.

The KNNClassifier has the highest accuracy and precision.

The test precision score for this model came down to 0.8235513482501435 with 'n_neighbors' set to 7 and 'algorithm' to 'brute' as the optimized settings

4 References:

4.0.1 Introduction to Machine Learning, UBC

4.0.2 Cheese data - https://github.com/UBC-MDS/intro-ml-students/tree/main/release/final_project/data