final_project

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1 Prediction of Fat Levels in Canadian Cheese

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2 Introduction

This **Jupyter Notebook** will be implementing *Machine Learning (ML)* models to predict the fat levels in *Canadian* cheeses.

2.1 Intended Outcome

We can utilize a rich understanding of the factors which yield high fat levels to reduce the risk of mass manufacturing an unsuccessful product.

We are already confident that the *Total Addressable Market (TAM)* is particularly concerned with fat level in cheeses (*as per a previous study on consumer tastes*). We would like to manufacture `lower fat` cheese products and this will act as our positive label.

2.2 What is Machine Learning?

Machine Learning is defined by *IBM* as *the use of statistical methods, algorithms that are trained to make classifications or predictions, and to uncover key insights in data mining projects. These insights subsequently drive decision making within applications and businesses, ideally impacting key growth metrics.*

2.3 Cheese Classification

We will be identifying different features within our dataset in order to classify our cheese products as either `lower fat` or `higher fat`.

2.3.1 Estimators

We will be training, and evaluating a set of *ML* models (i.e. estimators), which will be compared to a baseline model, in our case a *Dummy Classifier*.

This will involve :

Tactful preprocessing of our data with imputation, scaling, feature transformations

Training the classifier models with an appropriately split and balanced dataset.

Assessing the model with evaluation metrics.

Picking the estimator with the best validation score and finetuning the hyperparameters.

2.4 Dataset Description

This dataset provides an overview of the different types of Canadian cheeses. The original data was found on the *Government of Canada's Open Government Portal* but has unfortunately been taken down. What we have here is a wrangled and partially cleaned, modified version of the original dataset.

3 Exploratory Data Analysis

3.1 Import Packages

[1]:
```
import numpy as np
import pandas as pd

import altair as alt

import datetime as dt

from sklearn.model_selection import train_test_split, cross_validate

from sklearn.impute import SimpleImputer
from sklearn.feature_extraction.text import CountVectorizer

from sklearn.pipeline import make_pipeline
from sklearn.compose import make_column_transformer
from sklearn.preprocessing import (
    OneHotEncoder,
    StandardScaler,
)

from sklearn.dummy import DummyClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC

from sklearn.model_selection import GridSearchCV, RandomizedSearchCV

import sklearn.metrics
from sklearn.metrics import make_scorer, accuracy_score, precision_score,␣
 ↪recall_score, f1_score
from sklearn.metrics import ConfusionMatrixDisplay, confusion_matrix,␣
 ↪classification_report
```

```python
from sklearn import set_config

alt.data_transformers.disable_max_rows()

from cheese_functions import *
```

[2]:
```python
directory_df = pd.read_csv("data/canadianCheeseDirectory.csv")
display(directory_df.head())
```

```
   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]
```

[3]:
```
data_df = pd.read_csv("data/cheese_data.csv")
display(data_df.head())
```

```
   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
```

3.2 Split Training and Test Datasets

Let's start by separating our training and test datasets. We're going to be working with a *80%* training and *20%* test set split and set our `random_state` variable to *77*.

3.2.1 Golden Rule of Machine Learning

We don't want the test data to influence our model **in any way**. This must act as completely unseen data during the model training and validation process.

[4]:
```
train_df, test_df = train_test_split(data_df, test_size = 0.2, random_state =␣
↪77)
```

[5]:
```
X_train, y_train = train_df.drop(columns = ['FatLevel']), train_df['FatLevel']
X_test, y_test = test_df.drop(columns = ['FatLevel']), test_df['FatLevel']
```

3.3 Exploratory Data Analysis

3.3.1 Observe Outputs

Let's start by plotting a bar chart showing the quantity of each `FatLevel` in the training data.

[6]:
```
fig_number = 1

fat_prop = alt.Chart(
    train_df,
    title = alt.TitleParams(
        text = f'Figure {fig_number} : Fat Levels for Canadian Cheeses',
        subtitle = '''Data found on the Government of Canada's Open Government␣
↪Portal''',
        fontSize = 20, subtitleFontSize = 15,
        anchor = 'start'
    )
).transform_joinaggregate(
    total = 'count(*)'
).transform_calculate(
    pct = '1 / datum.total'
).mark_bar().encode(
    x = alt.X('count()', title = 'Quantity'),
    y = alt.Y('FatLevel:N', title = 'Fat Level'),
    tooltip = [alt.Tooltip('sum(pct):Q', format = '.2%', formatType = 'number',␣
↪title = '% of Total')],
    color = alt.Color(
        'FatLevel:N',
        scale = alt.Scale(
            domain = ['lower fat', 'higher fat'],
```

```
            range = ['teal', 'crimson']
        ),
        legend = alt.Legend(title = 'Fat Level')
    )
).properties(
    width = 500, height = 300,
).configure_axis(labelFontSize = 12, titleFontSize = 15)

display(fat_prop)

fig_number += 1
```

```
alt.Chart(…)
```

Imbalanced Data There's a high percentage of `lower fat` cheeses included in the training data, approximately *65.55%* of the dataset. We're going to need to balance the dataset so each of the `FatLevels` above are *50%*.

3.3.2 Data Sparsity

Let's get an understanding of the data sparsity (i.e. *NULL* values).

[7]:
```
display(train_df.describe())
```

```
          CheeseId  MoisturePercent     Organic
count   833.000000       823.000000  833.000000
mean   1557.866747        46.955043    0.094838
std     451.129129         9.557279    0.293167
min     228.000000        12.000000    0.000000
25%    1288.000000        40.000000    0.000000
50%    1535.000000        46.000000    0.000000
75%    1902.000000        52.000000    0.000000
max    2390.000000        88.000000    1.000000
```

[8]:
```
display(train_df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 833 entries, 110 to 727
Data columns (total 13 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   CheeseId               833 non-null    int64
 1   ManufacturerProvCode   833 non-null    object
 2   ManufacturingTypeEn    833 non-null    object
 3   MoisturePercent        823 non-null    float64
 4   FlavourEn              649 non-null    object
 5   CharacteristicsEn      514 non-null    object
 6   Organic                833 non-null    int64
```

```
 7   CategoryTypeEn        814 non-null    object
 8   MilkTypeEn            832 non-null    object
 9   MilkTreatmentTypeEn   779 non-null    object
 10  RindTypeEn            583 non-null    object
 11  CheeseName            833 non-null    object
 12  FatLevel              833 non-null    object
dtypes: float64(1), int64(2), object(10)
memory usage: 91.1+ KB
```

```
None
```

It seems that the `FlavourEn`, `CharacteristicsEn`, `RindTypeEn` have a high amount of *NULL* values. Let's visualize the distribution in the dataset.

3.3.3 Observe Data Sparsity

[9]:
```
heatmap_df =  X_train.isna().reset_index()
heatmap_df.rename(columns = {'index' : 'Index'}, inplace = True)
heatmap_df = heatmap_df.melt(
    id_vars = 'Index',
    value_vars = [col for col in heatmap_df.columns.to_list() if col !=␣
 ↪'Index'],
    var_name = 'Columns',
    value_name = 'IsNull'
)
```

[10]:
```
sparsity_plot = alt.Chart(
        heatmap_df,
        title = alt.TitleParams(f'Figure {fig_number} : Cheese Dataset - Data␣
 ↪Availability', fontSize = 27.5)
).mark_rect().encode(
    x = alt.X(
        'Index:Q', title = '', axis = None
    ),
    y = alt.Y('Columns:N', title = 'Features'),
    tooltip = [alt.Tooltip('Index:Q', title = 'Index')],
    color = alt.Color(
        'IsNull:O',
        scale = alt.Scale(
            domain = [False, True],
            range = ['#000000', '#FFFFFF']
        ),
        legend = alt.Legend(title = 'Null Data')
    ),
).properties(
    height = 500, width = 600,
).configure_axis(labelFontSize = 15, titleFontSize = 20)
```

```
display(sparsity_plot)

fig_number += 1
```

```
alt.Chart(...)
```

3.3.4 Drop Columns From Dataset

From the visualization above, lets exclude `CharacteristicsEn`, `FlavourEn` due to the high level of data sparsity. Let's remove `RindTypeEn` as well. From displaying `train_df.info()` it seems as if the data sparsity is higher than it appears from Figure 2.

We should also drop the `CheeseIds` from our training dataset since these won't be useful for statistical modeling.

[11]:
```
X_train.drop(
    columns = ['CheeseId', 'CharacteristicsEn', 'FlavourEn', 'RindTypeEn'],
    inplace = True
)
```

3.3.5 Observe Feature Types

Let's distinguish the feature types in our dataset.

[12]:
```
describe_df = X_train.describe(include = 'all').T
display(describe_df)
```

```
                      count unique          top freq       mean       std  \
ManufacturerProvCode    833     10           QC  637        NaN       NaN
ManufacturingTypeEn     833      3   Industrial  371        NaN       NaN
MoisturePercent       823.0    NaN          NaN  NaN  46.955043  9.557279
Organic               833.0    NaN          NaN  NaN   0.094838  0.293167
CategoryTypeEn          814      6  Firm Cheese  276        NaN       NaN
MilkTypeEn              832      8          Cow  591        NaN       NaN
MilkTreatmentTypeEn     779      3  Pasteurized  640        NaN       NaN
CheeseName              833    830      Cheddar    2        NaN       NaN

                       min   25%   50%   75%   max
ManufacturerProvCode   NaN   NaN   NaN   NaN   NaN
ManufacturingTypeEn    NaN   NaN   NaN   NaN   NaN
MoisturePercent       12.0  40.0  46.0  52.0  88.0
Organic                0.0   0.0   0.0   0.0   1.0
CategoryTypeEn         NaN   NaN   NaN   NaN   NaN
MilkTypeEn             NaN   NaN   NaN   NaN   NaN
MilkTreatmentTypeEn    NaN   NaN   NaN   NaN   NaN
CheeseName             NaN   NaN   NaN   NaN   NaN
```

[13]:
```
objects_df = X_train.describe(include = 'object').T
display(objects_df)
```

	count	unique	top	freq
ManufacturerProvCode	833	10	QC	637
ManufacturingTypeEn	833	3	Industrial	371
CategoryTypeEn	814	6	Firm Cheese	276
MilkTypeEn	832	8	Cow	591
MilkTreatmentTypeEn	779	3	Pasteurized	640
CheeseName	833	830	Cheddar	2

[14]:
```
numeric_df = X_train.describe(include = ['int64', 'float64']).T
display(numeric_df)
```

	count	mean	std	min	25%	50%	75%	max
MoisturePercent	823.0	46.955043	9.557279	12.0	40.0	46.0	52.0	88.0
Organic	833.0	0.094838	0.293167	0.0	0.0	0.0	0.0	1.0

Numeric Feature The `MoisturePercent` column is a numeric feature.

[15]:
```
numeric_feats = [feat for feat in numeric_df.index if len(X_train[feat].
 ↪unique()) != 2]
display(numeric_feats)
```

```
['MoisturePercent']
```

[16]:
```
fig_number = describe_features(
    effective_df = X_train,
    features = numeric_feats,
    fig_number = fig_number
)
```

```
The distinct values in the MoisturePercent column are :
[52.0, 40.0, 48.0, 55.0, 60.0, 39.0, 50.0, 56.0, 57.0, 46.0, 42.0, 58.0, 37.0,
44.0, 59.0, 88.0, 41.0, 43.0, 33.0, 35.0, 38.0, 27.0, nan, 36.0, 45.0, 61.0,
31.0, 80.0, 68.0, 62.0, 51.0, 64.0, 76.0, 34.0, 74.0, 47.0, 49.0, 29.0, 54.0,
40.3, 32.0, 22.0, 70.0, 86.0, 65.0, 75.0, 26.0, 78.0, 20.0, 23.0, 72.0, 63.0,
49.4, 12.0, 25.0, 53.0, 30.0, 17.0, 47.9, 42.8, 42.6, 83.0, 69.0, 51.7, 21.0]
```

```
alt.Chart(…)
```

Binary Feature The `Organic` column is a binary feature.

[17]:
```
binary_feats = [feat for feat in describe_df.index if len(X_train[feat].
 ↪unique()) == 2]
display(binary_feats)
```

```
['Organic']
```

[18]:
```
fig_number = describe_features(
    effective_df = X_train,
    features = binary_feats,
```

```
    fig_number = fig_number
)
```

```
The distinct values in the Organic column are :
[0, 1]
```

```
alt.Chart(...)
```

Categorical Features The `ManufacturerProvCode`, `ManufacturingTypeEn`, `CategoryTypeEn`, `MilkTypeEn`, `MilkTreatmentTypeEn` columns are categorical features.

[19]:

```
categorical_feats = objects_df[
    (objects_df['unique'] < 0.1 * objects_df['count']) &
    (objects_df['freq'] != 2)
].index.to_list()

display(categorical_feats)
```

```
['ManufacturerProvCode',
 'ManufacturingTypeEn',
 'CategoryTypeEn',
 'MilkTypeEn',
 'MilkTreatmentTypeEn']
```

[20]:

```
fig_number = describe_features(
    effective_df = X_train, features = categorical_feats,
    fig_number = fig_number, sort_by = 'x'
)
```

```
The distinct values in the ManufacturerProvCode column are :
['ON', 'QC', 'BC', 'AB', 'NB', 'NS', 'PE', 'MB', 'NL', 'SK']
```

```
alt.Chart(...)
```

```
The distinct values in the ManufacturingTypeEn column are :
['Industrial', 'Artisan', 'Farmstead']
```

```
alt.Chart(...)
```

```
The distinct values in the CategoryTypeEn column are :
['Semi-soft Cheese', 'Firm Cheese', 'Soft Cheese', 'Fresh Cheese', nan, 'Hard
Cheese', 'Veined Cheeses']
```

```
alt.Chart(...)
```

```
The distinct values in the MilkTypeEn column are :
['Cow', 'Goat', 'Ewe', 'Ewe and Cow', 'Cow and Goat', 'Cow, Goat and Ewe', 'Ewe
and Goat', 'Buffalo Cow', nan]
```

```
alt.Chart(...)
```

```
The distinct values in the MilkTreatmentTypeEn column are :
['Pasteurized', 'Raw Milk', 'Thermised', nan]
```

```
alt.Chart(…)
```

Free-Text Feature The `CheeseName` column is a free text feature in our dataset. This is going to be fun to tackle. Let's start by printing the values to see what we have to deal with.

[21]:
```
text_feats = objects_df[
        (objects_df['unique'] > 0.1 * objects_df['count']) &
        (objects_df['freq'] == 2)
    ].index.to_list()
display(text_feats)
```

```
['CheeseName']
```

[22]:
```
for feat in text_feats :
    print(f'''A few of the distinct values in the {feat} column are :␣
 ↪\n{list(X_train[feat].unique()[:10])}\n''')
```

```
A few of the distinct values in the CheeseName column are :
['Vaquinha  (Portuguese)', 'Gorgonzola (Castello)', 'Tête à Papineau', 'Petit
Rubis (Le)', 'Petites Soeurs (Les)', 'Cheddar 2 ans (Fromagerie Perron)', 'Brie
Normandie double crème', 'Médard (Le)', 'Champfleury (Vaudreuil)', "St.John's
Cow (Portuguese)"]
```

3.4 Preprocessing The Data

3.4.1 Transformation Pipelines

We're going to transform the feature types with respective transformation pipelines.

3.4.2 Binary Transformer

To begin, we perform imputation on the binary feature with the `most_frequent` value to replace missing values. Then we use `OneHotEncoder()` to numerically encode each binary value (i.e. *True*, *False*). Note that we only need to keep a single binary column and can drop the other.

[23]:
```
binary_transformer = make_pipeline(
    SimpleImputer(strategy = 'most_frequent'),
    OneHotEncoder(dtype = int, handle_unknown = 'error', drop = 'if_binary')
)
```

3.4.3 Numeric Transformer

We perform imputation on numeric features with the `median` value to replace missing values. Then we will standardize the numeric features to set sample mean to *0* and standard deviation to *1*.

[24]:
```
numeric_transformer = make_pipeline(
    SimpleImputer(strategy = 'median'),
    StandardScaler()
)
```

3.4.4 Categorical Transformer

We perform imputation on categorical features with the `most_frequent` value to replace missing values. Then we use `OneHotEncoder()` to numerically encode each categorical value.

[25]:
```
categorical_transformer = make_pipeline(
    SimpleImputer(strategy = 'most_frequent', fill_value = 'missing'),
    OneHotEncoder(dtype = int, handle_unknown = 'ignore')
)
```

3.4.5 Free-Text Transformer

We apply the `CountVectorizer()` tool on the free-text feature with the `most_frequent` value and convert the text messages to a matrix of word counts. Each text message is assigned a row and each column represents a word in the dataset vocabulary. The values in the matrix represents the frequency of occurance of the word.

[26]:
```
text_transformer = make_pipeline(
    CountVectorizer(binary = True)
)
```

3.4.6 Column Transformer

We map the feature types to the transformer pipelines made above and drop the remainder of the dataset columns.

[27]:
```
preprocessor = make_column_transformer(
    # Preprocessing Pipelines
    (binary_transformer, binary_feats),
    (numeric_transformer, numeric_feats),
    (categorical_transformer, categorical_feats),
    (text_transformer, text_feats[0]),
    remainder = 'drop'
)
```

4 ML Models

We will be implementing our preprocessor pipelines with multiple classifiers and viewing the results of each model.

We will be training our dataset with the following Classification ML models.

- *Logistic Regression* Classification

- *Decision Tree* Classifier
- *Random Forest* Classifier
- *K Nearest Neighbors (k-NN)* Classifier
- *Support Vector Machines (SVM)* Classifier

This set of classifiers includes

- Interpretable Modelling (i.e. *Logistic Regression*)
- Rule-Based Algorithms with If-Else Statements (i.e. *Decision Tree*, *Random Forest*)
- Similarity Based Models (i.e. *k-NN*, *SVM*)

[28]:
```
models = {
    'Logistic Regression' : {
        'pipeline' : make_pipeline(
            preprocessor, LogisticRegression(random_state = 77, class_weight =␣
↪'balanced')
        )
    },
    'Decision Tree' : {
            'pipeline' : make_pipeline(
                preprocessor, DecisionTreeClassifier(random_state = 77,␣
↪class_weight = 'balanced')
            )
        },
    'Random Forest' :
        {
            'pipeline' : make_pipeline(
                preprocessor, RandomForestClassifier(random_state = 77,␣
↪class_weight = 'balanced')
            )
        },
    'kNN' :
        {
            'pipeline' : make_pipeline(
                preprocessor, KNeighborsClassifier()
            )
        },
    'RBF SVC' :
        {
            'pipeline' : make_pipeline(
                preprocessor, SVC(random_state = 77, class_weight = 'balanced')
            )
        }
}
```

4.1 Baseline Model

We will be comparing our classifier models to a *DummyClassifier* estimator using *strategy* = *'most_frequent'*.

[29]:
```
dummy_pipe = make_pipeline(
    preprocessor,
    DummyClassifier(random_state = 77, strategy = 'most_frequent')
)
```

4.2 Evaluation Metrics

We will be comparing our model performance based on the following metrics :

- Accuracy
  - "Percentage of Predictions Which Are True"
- Precision
  - "Percentage of Positive Predictions Which Are True"
- F1 Score
  - Combined Score of : "Percentage of Positive Predictions Which Are True" "Percentage of All Positive Examples Which Are Positive Predictions"

4.2.1 Exclusion of Recall

We have excluded Recall from the Evaluation Metrics due to our interest in making the most out of the investment decisions we take as an organization.

In other words, we want to determine if a particular combination of features will yield a successful cheese product. The combinations we miss are unfortunate, but we want to prioritize the reduction (elimination?) of *False Negative* predictions.

[30]:
```
scoring_dict = {
    'accuracy' : make_scorer(accuracy_score),
    'precision' : make_scorer(precision_score, pos_label = 'lower fat'),
    'f1' : make_scorer(f1_score, pos_label = 'lower fat'),
}
```

[31]:
```
dummy_df = pd.DataFrame(
    cross_validate(
        estimator = dummy_pipe, cv = 10,
        X = X_train, y = y_train,
        scoring = scoring_dict,
        return_train_score = True
    )
).mean().apply(
    lambda x : round(x, 4)
).rename('Dummy Classifier').to_frame().T.reset_index().rename(
    columns = {'index' : 'model'}
)
```

```
display(dummy_df)
```

```
              model  fit_time  score_time  test_accuracy  train_accuracy  \
0  Dummy Classifier    0.0284      0.0144         0.6555          0.6555

   test_precision  train_precision  test_f1  train_f1
0          0.6555           0.6555   0.7919    0.7919
```

[32]:
```
scores_df = pd.DataFrame()

for model_name, model in models.items():

    model['scores'] = pd.DataFrame(
        cross_validate(
            estimator = model['pipeline'], cv = 10,
            X = X_train, y = y_train,
            return_train_score = True,
            scoring = scoring_dict
        )
    ).mean().apply(
        lambda x : round(x, 4)
    ).rename(
        model_name
    ).to_frame().T.reset_index().rename(
        columns = {'index' : 'model'}
    )

    scores_df = pd.concat([scores_df, model['scores']], axis = 0)
```

[33]:
```
# We Need to Concatenate the Classifier Scores to the Baseline Model Score.
scores_df = pd.concat([dummy_df, scores_df], axis = 0)
scores_df = scores_df.rename(
    columns = {
        col : col.replace('test', 'validation').replace('time', 'time (s)') 
 ↪for col in scores_df.columns.to_list()
    }
)
display(scores_df)
```

```
                 model  fit_time (s)  score_time (s)  validation_accuracy  \
0     Dummy Classifier        0.0284          0.0144               0.6555
0  Logistic Regression        0.0602          0.0141               0.8067
0        Decision Tree        0.0371          0.0141               0.8139
0        Random Forest        0.3108          0.0283               0.8366
0                  kNN        0.0290          0.0209               0.7934
0              RBF SVC        0.0680          0.0179               0.8294
```

```
   train_accuracy  validation_precision  train_precision  validation_f1  \
0          0.6555                0.6555           0.6555         0.7919
0          0.9198                0.8685           0.9615         0.8490
0          1.0000                0.8684           1.0000         0.8552
0          1.0000                0.8360           1.0000         0.8826
0          0.8609                0.8203           0.8679         0.8473
0          0.9160                0.8809           0.9559         0.8677

   train_f1
0    0.7919
0    0.9373
0    1.0000
0    1.0000
0    0.8975
0    0.9344
```

[34]:
```
fig_number = get_scores_chart(
    scores_df = scores_df,
    scoring = 'fit_time',
    fig_number = fig_number
)
```

```
                 model    score_type   score
0     Dummy Classifier  fit_time (s)  0.0284
1  Logistic Regression  fit_time (s)  0.0602
2        Decision Tree  fit_time (s)  0.0371
3        Random Forest  fit_time (s)  0.3108
4                  kNN  fit_time (s)  0.0290
```

```
alt.Chart(…)
```

We can see from the figure that the *Random Forest* had a much greater fitting time than the other classifiers, whereas the *k-NN* classifier model had the least fitting time. It's worthwhile to note that all of the classifiers had a relatively similar fitting time, aside from the *Random Forest* model.

[35]:
```
fig_number = get_scores_chart(
    scores_df = scores_df,
    scoring = 'precision',
    fig_number = fig_number
)
```

```
                  model       score_type   score
6      Dummy Classifier  train_precision  0.6555
7   Logistic Regression  train_precision  0.9615
8         Decision Tree  train_precision  1.0000
9         Random Forest  train_precision  1.0000
10                  kNN  train_precision  0.8679
```

```
alt.Chart(…)
```

We can see in this figure that the best *precision* validation score is from the *RBF SVC* model. We notice that the *Dummy Classifier* model had the lowest *precision* validation score. So far, the *RBF SVC* seems like a promising contender for hyperparameter optimization.

[36]:
```
fig_number = get_scores_chart(
    scores_df = scores_df,
    scoring = 'f1',
    fig_number = fig_number
)
```

```
                  model score_type   score
6      Dummy Classifier   train_f1  0.7919
7   Logistic Regression   train_f1  0.9373
8         Decision Tree   train_f1  1.0000
9         Random Forest   train_f1  1.0000
10                  kNN   train_f1  0.8975
```

```
alt.Chart(…)
```

We can see in this figure that the highest *F1* validation score is from the *Random Forest* model. The second highest *F1* validation score is from the *RBF SVC* model. The *Dummy Classifier* baseline model once again had the lowest *F1* validation score.

Given the high fitting time of the *Random Forest* model and our emphasis on *precision*, we will be selecting the *RBF SVC* model for hyperparameter optimization.

4.3 RBF SVC Model

4.3.1 Hyperparameter Optimization

Let's optimize the `C` and `gamma` hyperparameters in our model. We will find the best hyperparameters with `GridSearchCV`. We're going to iterate through and exhaust the hyperparameter possibilities since we only have `5^2 = 25` combinations.

We would like to be confident with our cheese product `fat level` predictions to a thorough extent. This will require only slightly more computing resources, which we can run in parallel with `n_jobs = -1`.

[37]:
```
# Handle Case Where Dataset Doesn't Contain Positive Predictions

import warnings
warnings.filterwarnings('ignore')
```

[38]:
```
param_grid = {
    "svc__C" : [0.001, 0.01, 0.1, 1, 10, 100, 1000],
    "svc__gamma" : [0.001, 0.01, 0.1, 1, 10, 100, 1000]
}

svc_search = GridSearchCV(
    estimator = models['RBF SVC']['pipeline'],
    param_grid = param_grid,
```

```
    cv = 10, scoring = scoring_dict['precision'],
    return_train_score = True, n_jobs = -1
)

svc_search.fit(X_train, y_train)
display(svc_search)
```

```
GridSearchCV(cv=10,
             estimator=Pipeline(steps=[('columntransformer',
                                                              ␣
↪ColumnTransformer(transformers=[('pipeline-1',
                                                                       ␣
↪Pipeline(steps=[('simpleimputer',
                                                                               ␣
↪          SimpleImputer(strategy='most_frequent')),
                                                                               ␣
↪         ('onehotencoder',
                                                                               ␣
↪          OneHotEncoder(drop='if_binary',
                                                                               ␣
↪                        dtype=<class 'int'>))]),
                                                                       ␣
↪['Organic']),
                                                                      ␣
↪('pipeline-2',
                                                                       ␣
↪Pipeline(steps=[('simpleimputer',
                                                                               ␣
↪          SimpleImputer(strategy='median'))…
                                                                        ␣
↪'MilkTreatmentTypeEn']),
                                                                      ␣
↪('pipeline-4',
                                                                       ␣
↪Pipeline(steps=[('countvectorizer',
                                                                               ␣
↪          CountVectorizer(binary=True))]),
                                                                       ␣
↪'CheeseName')])),
                                       ('svc',
                                        SVC(class_weight='balanced',
                                            random_state=77))]),
             n_jobs=-1,
             param_grid={'svc__C': [0.001, 0.01, 0.1, 1, 10, 100, 1000],
                         'svc__gamma': [0.001, 0.01, 0.1, 1, 10, 100, 1000]},
             return_train_score=True,
```

```
                   scoring=make_scorer(precision_score, pos_label=lower fat))
```

[39]:
```python
svc_df = pd.DataFrame(svc_search.cv_results_)

display(svc_df.head())
```

```
   mean_fit_time  std_fit_time  mean_score_time  std_score_time param_svc__C  \
0       0.086829      0.010177         0.018014        0.000244        0.001
1       0.083619      0.000372         0.017963        0.000357        0.001
2       0.084247      0.000902         0.018049        0.000283        0.001
3       0.083626      0.000217         0.018079        0.000135        0.001
4       0.083931      0.000695         0.018464        0.000981        0.001

  param_svc__gamma                                  params  split0_test_score  \
0            0.001  {'svc__C': 0.001, 'svc__gamma': 0.001}                0.0
1             0.01   {'svc__C': 0.001, 'svc__gamma': 0.01}                0.0
2              0.1    {'svc__C': 0.001, 'svc__gamma': 0.1}                0.0
3                1      {'svc__C': 0.001, 'svc__gamma': 1}                0.0
4               10     {'svc__C': 0.001, 'svc__gamma': 10}                0.0

   split1_test_score  split2_test_score  …  split2_train_score  \
0                0.0                0.0  …                 0.0
1                0.0                0.0  …                 0.0
2                0.0                0.0  …                 0.0
3                0.0                0.0  …                 0.0
4                0.0                0.0  …                 0.0

   split3_train_score  split4_train_score  split5_train_score  \
0            0.654667            0.654667            0.654667
1            0.654667            0.654667            0.654667
2            0.654667            0.654667            0.654667
3            0.654667            0.654667            0.654667
4            0.654667            0.654667            0.654667

   split6_train_score  split7_train_score  split8_train_score  \
0               0.656               0.656               0.656
1               0.656               0.656               0.656
2               0.656               0.656               0.656
3               0.656               0.656               0.656
4               0.656               0.656               0.656

   split9_train_score  mean_train_score  std_train_score
0               0.656            0.4588         0.300356
1               0.656            0.4588         0.300356
2               0.656            0.4588         0.300356
3               0.656            0.4588         0.300356
4               0.656            0.4588         0.300356
```

```
[5 rows x 32 columns]
```

Best Model

```
[40]: best_model = svc_search.best_estimator_

best_svc = svc_search.best_params_
print(f'The best value of C is {best_svc["svc__C"]} and the best value of gamma␣
 ↪is {best_svc["svc__gamma"]}.')

best_svc_score = round(svc_search.best_score_, 2)
print(f'The best validation precision is {best_svc_score}.')
```

```
The best value of C is 0.1 and the best value of gamma is 0.01.
The best validation precision is 0.88.
```

4.3.2 Score Distribution

Let's look at the score distributions for the different hyperparameter combinations.

```
[41]: svc_plot_df = pd.melt(
    frame = svc_df,
    id_vars = ['param_svc__gamma', 'param_svc__C'],
    var_name = 'score_type', value_name = 'precision',
    value_vars = ['mean_train_score', 'mean_test_score']
)

display(svc_plot_df)
```

```
   param_svc__gamma param_svc__C        score_type  precision
0             0.001        0.001  mean_train_score   0.458800
1              0.01        0.001  mean_train_score   0.458800
2               0.1        0.001  mean_train_score   0.458800
3                 1        0.001  mean_train_score   0.458800
4                10        0.001  mean_train_score   0.458800
..              …            …               …          …
93              0.1         1000   mean_test_score   0.852853
94                1         1000   mean_test_score   0.717279
95               10         1000   mean_test_score   0.657860
96              100         1000   mean_test_score   0.657052
97             1000         1000   mean_test_score   0.657052

[98 rows x 4 columns]
```

```
[42]: # Create Altair Chart.
svc_plot = alt.Chart(
    svc_plot_df[(svc_plot_df['score_type'] == 'mean_test_score')],
    title = alt.TitleParams(
        text = f'Figure {fig_number} : RBF SVC Model Precision Scores',
```

```
        subtitle = ['Hyperparameter Tuning for C and gamma'],
        anchor = 'start', fontSize = 25, subtitleFontSize = 20
    )
).mark_circle().encode(
    x = alt.X('param_svc__gamma:O', title = 'gamma'),
    y = alt.Y('param_svc__C:O', title = 'C'),
    color = alt.Color(
        'precision:Q', title = 'Precision',
        scale = alt.Scale(
            scheme = 'viridis', reverse = True,
            domain = [
                svc_plot_df[
                    svc_plot_df['score_type'] == 'mean_test_score'
                ]['precision'].min(),
                svc_plot_df[
                    svc_plot_df['score_type'] == 'mean_test_score'
                ]['precision'].max()
            ]
        )
    ),
    size = alt.Size(
        'precision:Q', title = 'Precision',
        scale = alt.Scale(
            domain = [
                svc_plot_df[
                    svc_plot_df['score_type'] == 'mean_test_score'
                ]['precision'].min(),
                svc_plot_df[
                    svc_plot_df['score_type'] == 'mean_test_score'
                ]['precision'].max()
            ]
        )
    ),
    tooltip = [alt.Tooltip('precision:Q', title = 'Precision')]
).properties(
    width = 800, height = 500,
).configure_axis(
    labelFontSize = 15, titleFontSize = 17.5
).configure_title(
    fontSize = 25
)

fig_number += 1

display(svc_plot)
```

```
alt.Chart(…)
```

4.4 Test Data

Let's start by looking at the evaluation metrics for the best *RBF SVC* classifier.

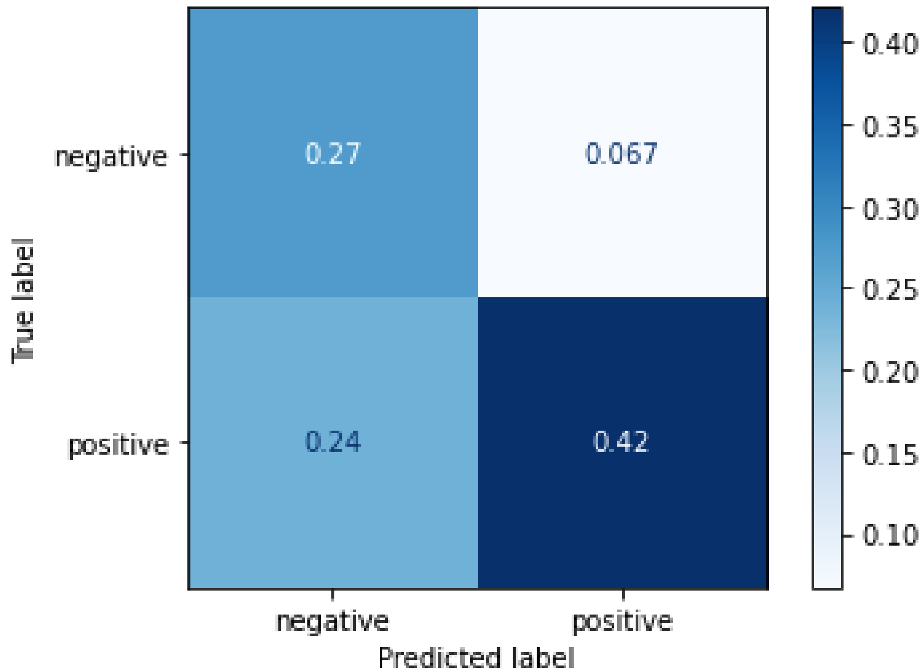
[43]:
```
## We need to drop the columns not used in the Machine Learning pipeline.

X_test.drop(
    columns = ['CheeseId', 'CharacteristicsEn', 'FlavourEn', 'RindTypeEn'],
    inplace = True
)
```

[44]:
```
svm_fatlevels_report = classification_report(
    y_true = y_test,
    y_pred = svc_search.predict(X_test),
    target_names = ['Lower Fat' if x == 'lower fat' else 'Higher Fat' for x in␣
↪svc_search.classes_]
)

print(svm_fatlevels_report)
```

```
              precision    recall  f1-score   support

  Higher Fat       0.53      0.80      0.64        71
   Lower Fat       0.86      0.64      0.73       138

    accuracy                           0.69       209
   macro avg       0.70      0.72      0.69       209
weighted avg       0.75      0.69      0.70       209
```

[45]:
```
svm_fatlevels_cm = ConfusionMatrixDisplay(
    confusion_matrix = confusion_matrix(
        y_true = y_test, y_pred = best_model.predict(X_test),
        normalize = 'all'
    ),
    display_labels = ['negative', 'positive']
)

svm_fatlevels_cm.plot(cmap = 'Blues')
```

[45]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7f4c233fea60>
```



We have highly reduced our *False Positive* predictions to *6.7%* with the *RBF SVC* model. This yields a *precision* score of *86%*.

Note that the *False Negatives* are much higher at *24%* of our predictions. This yields a lower *F1* score of *73%*

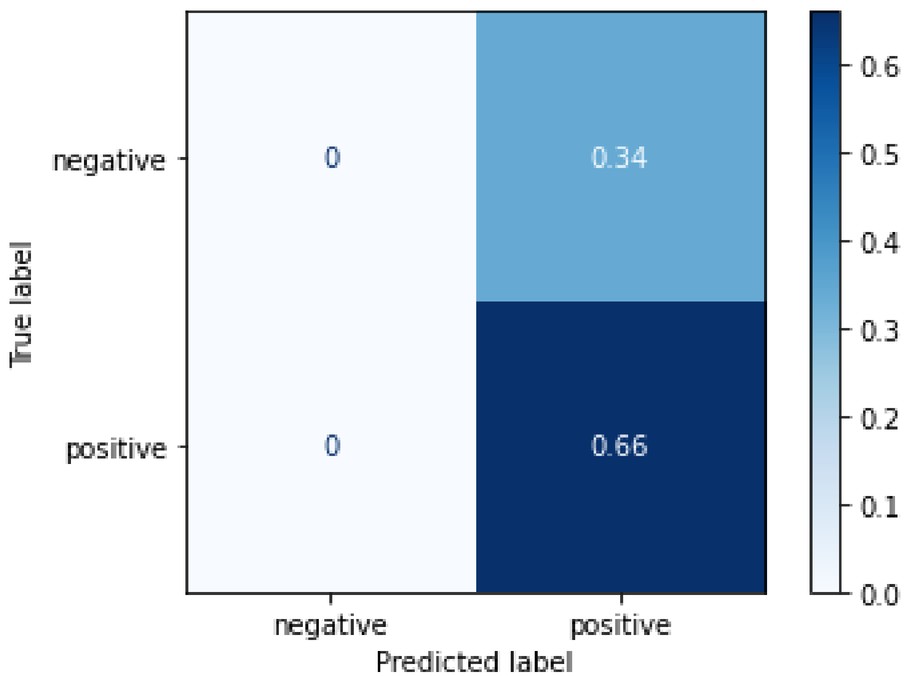
[46]:
```
baseline_fatlevels_report = classification_report(
    y_true = y_test,
    y_pred = dummy_pipe.fit(X_train, y_train).predict(X_test),
)

print(baseline_fatlevels_report)
```

```
              precision    recall  f1-score   support

  higher fat       0.00      0.00      0.00        71
   lower fat       0.66      1.00      0.80       138

    accuracy                           0.66       209
   macro avg       0.33      0.50      0.40       209
weighted avg       0.44      0.66      0.53       209
```

[47]:
```
baseline_fatlevels_cm = ConfusionMatrixDisplay(
    confusion_matrix = confusion_matrix(
```

```
        y_true = y_test, y_pred = dummy_pipe.fit(X_train, y_train).
 ↪predict(X_test),
        normalize = 'all'
    ),
    display_labels = ['negative', 'positive']
)

baseline_fatlevels_cm.plot(cmap = 'Blues')
```

[47]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f4c20b47ee0>



The *Dummy Classifier* baseline model was unable to make negative predictions. This is rather peculiar and yields a lower *precision* score of *66%*. Interestingly, the perfect *recall* score yields a higher *F1* score of *80%*.

5 Discussion

From this investigation, we were able to observe features which contribute to different fat levels in *Canadian* cheeses and use this in training a Machine Learning classifier to predict whether a cheese will be `lower fat` or `higher fat`.

5.1 Further Improvements

In order to improve the model performance, something which can be explored is the inclusion of the `CharacteristicsEn` and `FlavourEn` columns. These can be transformed with `CountVectorizer()` and we can see how the data sparsity in these columns affects the training and validation scores.

In addition to this, we can look at the `RindTypeEn` column and investigate the feature type and value distributions. There was some peculiar data sparsity here, which was apparent from displaying `train_df.info()`, however filtering the dataframe for *NULL* values didn't register the same data. Exploring this feature may be highly valuable for improving model performance across evaluation metrics.

5.2 Concluding Remarks

We were able to train a *RBF SVC* classifier which performed with *86%* precision. This will aid us in our larger goal of reducing the risk of mass manufacturing unsuccessful cheese products. Since we are predicting a low percentage of *False Negatives* at *6.7%*, we are able to be more confident with the bets that we make. It will be highly beneficial to deploy this model in evaluating test cheese products. If we provide this as a tool to manufacturing experts with extensive domain knowledge, we'll be able to develop a streamlined cheese production practice.

5.3 References

These resources provide the data, theory and code segments for the *ML* exploration in this notebook.

Government of Canada's Open Government Portal (provided by UBC, ExL) IBM - What is Machine Learning? * Introduction to Machine Learning * Assignment 5 * Assignment 6 * Assignment 7 * Assignment 8