Lectures 5: Class demo

Contents

Imports

```python
# import the libraries
import os
import sys
sys.path.append(os.path.join(os.path.abspath(".."), (".."), "code"))
from plotting_functions import *
from utils import *

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

from sklearn.compose import make_column_transformer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.preprocessing import StandardScaler, OneHotEncoder

from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC

%matplotlib inline

pd.set_option("display.max_colwidth", 200)
DATA_DIR = os.path.join(os.path.abspath(".."), (".."), "data/")
pd.set_option("display.max_colwidth", 200)
```

Incorporating text features in the Spotify dataset

Recall that we had dropped `song_title` feature when we worked with the Spotify dataset in Lab 1.

Let's try to include it in our pipeline and examine whether we get better results.

```
spotify_df = pd.read_csv(DATA_DIR + "spotify.csv", index_col=0)
X_spotify = spotify_df.drop(columns=["target"])
y_spotify = spotify_df["target"]
```

```
X_train, X_test, y_train, y_test = train_test_split(
    X_spotify, y_spotify, test_size=0.2, random_state=123
)
```

```
X_train.shape
```

```
(1613, 15)
```

```
X_train
```

	acousticness	danceability	duration_ms	energy	instrumentalness	key
1505	0.004770	0.585	214740	0.614	0.000155	10
813	0.114000	0.665	216728	0.513	0.303000	0
615	0.030200	0.798	216585	0.481	0.000000	7
319	0.106000	0.912	194040	0.317	0.000208	6
320	0.021100	0.697	236456	0.905	0.893000	6
...	...	...	...	...	...	...
2012	0.001060	0.584	274404	0.932	0.002690	1
1346	0.000021	0.535	203500	0.974	0.000149	10
1406	0.503000	0.410	256333	0.648	0.000000	7
1389	0.705000	0.894	222307	0.161	0.003300	4
1534	0.623000	0.470	394920	0.156	0.187000	2

1613 rows × 15 columns

```
X_train.columns
```

```
Index(['acousticness', 'danceability', 'duration_ms', 'energy',
       'instrumentalness', 'key', 'liveness', 'loudness', 'mode',
       'speechiness', 'tempo', 'time_signature', 'valence', 'song_title',
       'artist'],
      dtype='object')
```

Dummy model

```python
from sklearn.dummy import DummyClassifier

results = {}
dummy_model = DummyClassifier()
# mean_std_cross_val_scores is defined in ../code/utils.py
results['dummy'] = mean_std_cross_val_scores(dummy_model, X_train, y_train, re
pd.DataFrame(results)
```

	dummy
fit_time	0.000 (+/- 0.000)
score_time	0.000 (+/- 0.000)
test_score	0.508 (+/- 0.001)
train_score	0.508 (+/- 0.000)

Feature categorization

```python
X_train.columns
```

```
Index(['acousticness', 'danceability', 'duration_ms', 'energy',
       'instrumentalness', 'key', 'liveness', 'loudness', 'mode',
       'speechiness', 'tempo', 'time_signature', 'valence', 'song_title',
       'artist'],
      dtype='object')
```

```python
X_train["key"].value_counts()
```

```
key
1     200
7     169
0     166
9     152
2     145
11    143
5     141
6     127
10    122
8     110
4      88
3      50
Name: count, dtype: int64
```

```
X_train["time_signature"].value_counts()
```

```
time_signature
4.0    1514
3.0      76
5.0      22
1.0       1
Name: count, dtype: int64
```

```
X_train["mode"].value_counts()
```

```
mode
1    1002
0     611
Name: count, dtype: int64
```

Let's look at the distribution of values in the `song_title` column.

```
X_train["song_title"].value_counts()
```

```
song_title
Pyramids                                       2
Look At Wrist                                  2
Baby                                           2
The One                                        2
Best Friend                                    2
                                              ..
City Of Dreams - Radio Edit                    1
Face It                                        1
The Winner Is - from Little Miss Sunshine      1
History                                        1
Blue Ballad                                    1
Name: count, Length: 1579, dtype: int64
```

- Most of the song titles are unique, which makes sense.
- What would happen if we apply one-hot encoding to this feature?
- How about encoding this as a text feature?

```python
X_train["artist"].value_counts()
```

```
artist
Drake              14
Disclosure         12
Rick Ross          11
WALK THE MOON      10
Crystal Castles     8
                   ..
Classixx            1
Jordan Feliz        1
Travis Hayes        1
The Silvertones     1
Phil Woods          1
Name: count, Length: 1131, dtype: int64
```

```python
numeric_feats = ['acousticness', 'danceability', 'energy',
                 'instrumentalness', 'liveness', 'loudness',
                 'speechiness', 'tempo', 'valence']
categorical_feats = ['time_signature', 'key']
passthrough_feats = ['mode']
artist_cat_feat = ['artist']
text_feat = 'song_title' # Define the text feature
```

Important

Note that unlike other feature types we are defining `text_feature` as a string and not as a list.

Column transformer without `song_title` and `artist` features

```
preprocessor_no_text = make_column_transformer(
    (StandardScaler(), numeric_feats),
    ("passthrough", passthrough_feats),
    (OneHotEncoder(handle_unknown = "ignore"), categorical_feats),
)
```

Visualizing the transformed data

```
transformed_no_text = preprocessor_no_text.fit_transform(X_train)
transformed_no_text.shape
```

```
(1613, 26)
```

```
preprocessor_no_text
```

```
▸ ColumnTransformer
▸ standardscaler        ▸ passthrough      ▸ onehotencoder
  ▸ StandardScaler        ▸ passthrough      ▸ OneHotEncoder
```

```
ohe_feat_names = preprocessor_no_text.named_transformers_["onehotencoder"].get
ohe_feat_names
```

```
['time_signature_1.0',
 'time_signature_3.0',
 'time_signature_4.0',
 'time_signature_5.0',
 'key_0',
 'key_1',
 'key_2',
 'key_3',
 'key_4',
 'key_5',
 'key_6',
 'key_7',
 'key_8',
 'key_9',
 'key_10',
 'key_11']
```

```
feat_names = numeric_feats + passthrough_feats + ohe_feat_names
```

```
pd.DataFrame(transformed_no_text, columns=feat_names)
```

	acousticness	danceability	energy	instrumentalness	liveness	loud
0	-0.697633	-0.194548	-0.318116	-0.492359	-0.737898	0.39
1	-0.276291	0.295726	-0.795552	0.598355	-0.438792	-0.05
2	-0.599540	1.110806	-0.946819	-0.492917	-0.399607	-0.87
3	-0.307150	1.809445	-1.722063	-0.492168	-0.763368	-1.46
4	-0.634642	0.491835	1.057468	2.723273	-0.458384	-0.17
...	...	...	...	...	...	
1608	-0.711944	-0.200676	1.185100	-0.483229	-0.393077	0.9
1609	-0.715953	-0.500969	1.383637	-0.492380	0.482038	0.92
1610	1.224228	-1.267021	-0.157395	-0.492917	0.194687	0.68
1611	2.003419	1.699134	-2.459489	-0.481032	0.802042	-1.87
1612	1.687114	-0.899316	-2.483125	0.180574	-0.556344	-2.58

1613 rows × 26 columns

Building models

```
models = {
    "Decision Tree": DecisionTreeClassifier(),
    "KNN": KNeighborsClassifier(),
    "SVM": SVC()
}

for (name, model) in models.items():
    pipe_model = make_pipeline(preprocessor_no_text, model)
    results[name + " (no_text)"] = mean_std_cross_val_scores(pipe_model, X_tra
pd.DataFrame(results).T
```

	fit_time	score_time	test_score	train_score
dummy	0.000 (+/- 0.000)	0.000 (+/- 0.000)	0.508 (+/- 0.001)	0.508 (+/- 0.000)
Decision Tree (no_text)	0.011 (+/- 0.000)	0.001 (+/- 0.000)	0.693 (+/- 0.029)	1.000 (+/- 0.000)
KNN (no_text)	0.002 (+/- 0.000)	0.012 (+/- 0.022)	0.676 (+/- 0.028)	0.788 (+/- 0.009)
SVM (no_text)	0.024 (+/- 0.001)	0.011 (+/- 0.000)	0.737 (+/- 0.017)	0.806 (+/- 0.011)

Incorporating “song_title” feature

Let’s incorporate bag-of-words representation of “song_title” feature in our column transformer.

```
numeric_feats
```

```
['acousticness',
 'danceability',
 'energy',
 'instrumentalness',
 'liveness',
 'loudness',
 'speechiness',
 'tempo',
 'valence']
```

```python
text_feat
```

```
'song_title'
```

```python
preprocessor = make_column_transformer(
    (StandardScaler(), numeric_feats),
    ("passthrough", passthrough_feats),
    (OneHotEncoder(handle_unknown = "ignore"), categorical_feats),
    (CountVectorizer(stop_words="english"), text_feat)
)
```

```python
# Transform the data
transformed = preprocessor.fit_transform(X_train)
```

```python
preprocessor
```

```
▸ ColumnTransformer
▸ standardscaler    ▸ passthrough    ▸ onehotencoder    ▸ countvecto
▸ StandardScaler    ▸ passthrough    ▸ OneHotEncoder    ▸ CountVecto
```

```python
# Get the vocabulary
vocab = preprocessor.named_transformers_['countvectorizer'].get_feature_names_
```

```
column_names = numeric_feats + passthrough_feats + ohe_feat_names + vocab.toli
len(column_names)
```

```
1910
```

```
df = pd.DataFrame(transformed.toarray(), columns=column_names)
df
```

	acousticness	danceability	energy	instrumentalness	liveness	louc
0	-0.697633	-0.194548	-0.318116	-0.492359	-0.737898	0.3ç
1	-0.276291	0.295726	-0.795552	0.598355	-0.438792	-0.05
2	-0.599540	1.110806	-0.946819	-0.492917	-0.399607	-0.87
3	-0.307150	1.809445	-1.722063	-0.492168	-0.763368	-1.46
4	-0.634642	0.491835	1.057468	2.723273	-0.458384	-0.17
...	...	...	...	...	...	
1608	-0.711944	-0.200676	1.185100	-0.483229	-0.393077	0.9
1609	-0.715953	-0.500969	1.383637	-0.492380	0.482038	0.92
1610	1.224228	-1.267021	-0.157395	-0.492917	0.194687	0.68
1611	2.003419	1.699134	-2.459489	-0.481032	0.802042	-1.87
1612	1.687114	-0.899316	-2.483125	0.180574	-0.556344	-2.58

1613 rows × 1910 columns

Visualizing the vocabulary

```
vocab[0:10]
```

```
array(['000', '10', '100', '10cm', '11', '112', '12', '1208', '144', '18'],
      dtype=object)
```

```
vocab[500:510]
```

```
array(['duele', 'duet', 'duke', 'dustland', 'dutchie', 'dynamite',
       'earth', 'easy', 'eazy', 'echelon'], dtype=object)
```

```
vocab[1800:1810]
```

```
array(['wide', 'wifey', 'wild', 'wildcard', 'wildfire', 'wiley',
       'willing', 'win', 'wind', 'window'], dtype=object)
```

```
vocab[0::100]
```

```
array(['000', 'ap', 'blind', 'cha', 'dallask', 'duele', 'flashlight',
       'grace', 'icarus', 'lafa', 'making', 'neck', 'pharaohs', 'redeem',
       'seeb', 'soundtrack', 'talons', 'unanswered', 'wide'], dtype=object)
```

Let's find songs containing the word *earth* in them.

```
earth_index_vocab = np.where(vocab == "earth")[0][0]
earth_index_vocab
```

```
np.int64(506)
```

```
earth_index_in_df = len(numeric_feats) + len(passthrough_feats) + len(ohe_feat
earth_index_in_df
```

```
np.int64(532)
```

```
earth_songs = df[df.iloc[:, earth_index_in_df] == 1]
earth_songs.iloc[:, earth_index_in_df - 2 : earth_index_in_df + 2]
```

	dutchie	dynamite	earth	easy
380	0.0	0.0	1.0	0.0
639	0.0	0.0	1.0	0.0

```
earth_songs.index
```

```
Index([380, 639], dtype='int64')
```

```
X_train.iloc[earth_songs.index]["song_title"]
```

```
1851              Softest Place On Earth
1948    Earth Song - Remastered Version
Name: song_title, dtype: object
```

Model building

```
models = {
    "Decision Tree": DecisionTreeClassifier(),
    "KNN": KNeighborsClassifier(),
    "SVM": SVC()
}

for (name, model) in models.items():
    pipe_model = make_pipeline(preprocessor, model)
    results[name + " (text)"] = mean_std_cross_val_scores(pipe_model, X_train,
pd.DataFrame(results).T
```

	fit_time	score_time	test_score	train_score
dummy	0.000 (+/- 0.000)	0.000 (+/- 0.000)	0.508 (+/- 0.001)	0.508 (+/- 0.000)
Decision Tree (no_text)	0.011 (+/- 0.000)	0.001 (+/- 0.000)	0.693 (+/- 0.029)	1.000 (+/- 0.000)
KNN (no_text)	0.002 (+/- 0.000)	0.012 (+/- 0.022)	0.676 (+/- 0.028)	0.788 (+/- 0.009)
SVM (no_text)	0.024 (+/- 0.001)	0.011 (+/- 0.000)	0.737 (+/- 0.017)	0.806 (+/- 0.011)
Decision Tree (text)	0.024 (+/- 0.001)	0.003 (+/- 0.000)	0.705 (+/- 0.025)	1.000 (+/- 0.000)
KNN (text)	0.007 (+/- 0.000)	0.013 (+/- 0.002)	0.682 (+/- 0.028)	0.786 (+/- 0.010)
SVM (text)	0.054 (+/- 0.002)	0.012 (+/- 0.000)	0.733 (+/- 0.027)	0.866 (+/- 0.004)

- Not a big difference in the results.
- Seems like there is more overfitting when we included the `song_title` feature.
- The training score of SVC is much higher when we include all features. Hyperparameter optimization of `C` and `gamma` may help.

- What about the `artist` column?
- Does it make sense to apply BOW encoding to it?
- Let’s look at the distribution of values in the `artist` column.

```python
X_train['artist'].value_counts()
```

```
artist
Drake              14
Disclosure         12
Rick Ross          11
WALK THE MOON      10
Crystal Castles     8
                   ..
Classixx            1
Jordan Feliz        1
Travis Hayes        1
The Silvertones     1
Phil Woods          1
Name: count, Length: 1131, dtype: int64
```

```
most_frequent = X_train["artist"].value_counts().iloc[:15]
most_frequent
```

```
artist
Drake               14
Disclosure          12
Rick Ross           11
WALK THE MOON       10
Crystal Castles      8
Big Time Rush        8
FIDLAR               8
Fall Out Boy         8
Demi Lovato          7
Kanye West           7
Kina Grannis         7
Backstreet Boys      7
Beach House          6
Young Thug           6
*NSYNC               6
Name: count, dtype: int64
```

```
preprocessor_artist = make_column_transformer(
    (StandardScaler(), numeric_feats),
    ("passthrough", passthrough_feats),
    (OneHotEncoder(handle_unknown = "ignore"), categorical_feats),
    (OneHotEncoder(dtype=int, handle_unknown="ignore", categories=[most_freque
    (CountVectorizer(max_features = 100, stop_words="english"), text_feat)
)
```

```
models = {
    "Decision Tree": DecisionTreeClassifier(),
    "KNN": KNeighborsClassifier(),
    "SVM": SVC()
}

for (name, model) in models.items():
    pipe_model = make_pipeline(preprocessor_artist, model)
    results[name + " (all)"] = mean_std_cross_val_scores(pipe_model, X_train,
pd.DataFrame(results).T
```

	fit_time	score_time	test_score	train_score
dummy	0.000 (+/- 0.000)	0.000 (+/- 0.000)	0.508 (+/- 0.001)	0.508 (+/- 0.000)
Decision Tree (no_text)	0.011 (+/- 0.000)	0.001 (+/- 0.000)	0.693 (+/- 0.029)	1.000 (+/- 0.000)
KNN (no_text)	0.002 (+/- 0.000)	0.012 (+/- 0.022)	0.676 (+/- 0.028)	0.788 (+/- 0.009)
SVM (no_text)	0.024 (+/- 0.001)	0.011 (+/- 0.000)	0.737 (+/- 0.017)	0.806 (+/- 0.011)
Decision Tree (text)	0.024 (+/- 0.001)	0.003 (+/- 0.000)	0.705 (+/- 0.025)	1.000 (+/- 0.000)
KNN (text)	0.007 (+/- 0.000)	0.013 (+/- 0.002)	0.682 (+/- 0.028)	0.786 (+/- 0.010)
SVM (text)	0.054 (+/- 0.002)	0.012 (+/- 0.000)	0.733 (+/- 0.027)	0.866 (+/- 0.004)
Decision Tree (all)	0.019 (+/- 0.000)	0.003 (+/- 0.000)	0.683 (+/- 0.019)	1.000 (+/- 0.000)
KNN (all)	0.008 (+/- 0.000)	0.013 (+/- 0.000)	0.681 (+/- 0.032)	0.792 (+/- 0.008)
SVM (all)	0.041 (+/- 0.000)	0.010 (+/- 0.000)	0.741 (+/- 0.027)	0.833 (+/- 0.006)

Tiny bit improvement in the mean CV scores but we are still overfitting.

(Optional) Incorporating text features in the restaurant survey dataset

Do you recall the restaurants survey you completed at the start of the course?

Let's use that data for this demo. You'll find a wrangled version in the course repository.

```
df = pd.read_csv(DATA_DIR + 'cleaned_restaurant_data.csv')
```

```
df
```

	north_america	eat_out_freq	age	n_people	price	food_type	noi
0	Yes	3.0	29	10.0	120.0	Italian	
1	Yes	2.0	23	3.0	20.0	Canadian/American	
2	Yes	2.0	21	20.0	15.0	Chinese	
3	No	2.0	24	14.0	18.0	Other	
4	Yes	5.0	23	30.0	20.0	Chinese	
...	...	...	...	...	...	...	
959	No	10.0	22	NaN	NaN	NaN	
960	Yes	1.0	20	NaN	NaN	NaN	
961	No	1.0	22	40.0	50.0	Chinese	
962	Yes	3.0	21	NaN	NaN	NaN	
963	Yes	3.0	27	20.0	22.0	Other	

964 rows × 11 columns

```
df.describe()
```

	eat_out_freq	age	n_people	price
count	964.000000	964.000000	6.960000e+02	696.000000
mean	2.585187	23.975104	1.439254e+04	1472.179152
std	2.246486	4.556716	3.790481e+05	37903.575636
min	0.000000	10.000000	-2.000000e+00	0.000000
25%	1.000000	21.000000	1.000000e+01	18.000000
50%	2.000000	22.000000	2.000000e+01	25.000000
75%	3.000000	26.000000	3.000000e+01	40.000000
max	15.000000	46.000000	1.000000e+07	1000000.000000

Are there any unusual values in this data that you notice? Let's get rid of these outliers.

```
upperbound_price = 200
lowerbound_people = 1
df = df[~(df['price'] > 200)]
restaurant_df = df[~(df['n_people'] < lowerbound_people)]
restaurant_df.shape
```

```
(942, 11)
```

```
restaurant_df.describe()
```

	eat_out_freq	age	n_people	price
count	942.000000	942.000000	674.000000	674.000000
mean	2.598057	23.992569	24.973294	34.023279
std	2.257787	4.582570	22.016660	29.018622
min	0.000000	10.000000	1.000000	0.000000
25%	1.000000	21.000000	10.000000	18.000000
50%	2.000000	22.000000	20.000000	25.000000
75%	3.000000	26.000000	30.000000	40.000000
max	15.000000	46.000000	200.000000	200.000000

Data splitting

We aim to predict whether a restaurant is liked or disliked.

```
# Separate `X` and `y`.

X = restaurant_df.drop(columns=['target'])
y = restaurant_df['target']
```

Below I'm perturbing this data just to demonstrate a few concepts. Don't do it in real life.

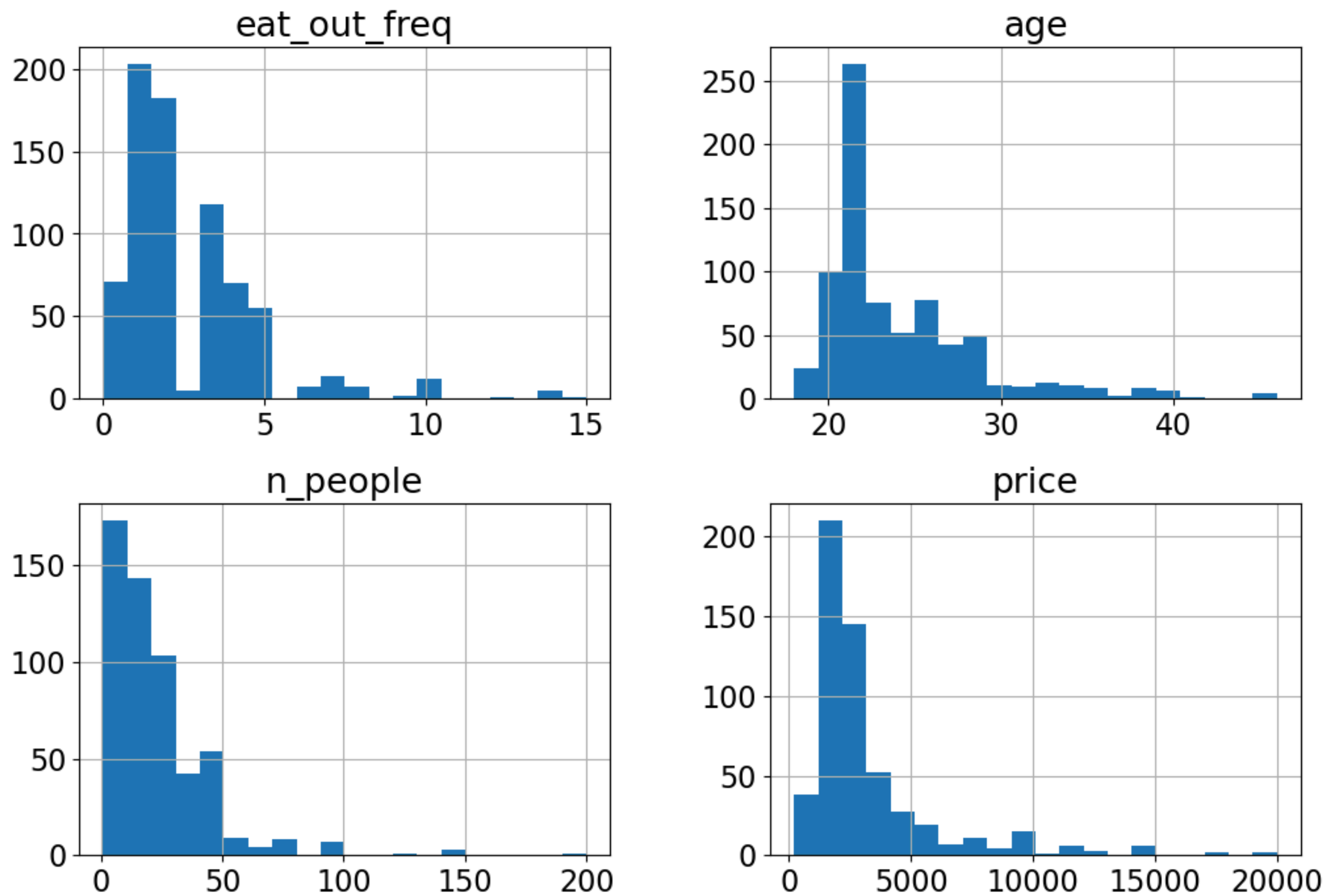
```
X.at[459, 'food_type'] = 'Quebecois'
X['price'] = X['price'] * 100
```

```
# Split the data

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando
```

EDA

```
X_train.hist(bins=20, figsize=(12, 8));
```



Do you see anything interesting in these plots?

```
X_train['food_type'].value_counts()
```

```
food_type
Other                 189
Canadian/American     131
Chinese               102
Indian                 36
Italian                32
Thai                   20
Fusion                 18
Mexican                17
fusion                  3
Quebecois               1
Name: count, dtype: int64
```

Error in data collection? Probably “Fusion” and “fusion” categories should be combined?

```
X_train['food_type'] = X_train['food_type'].replace("fusion", "Fusion")
X_test['food_type'] = X_test['food_type'].replace("fusion", "Fusion")
```

```
X_train['food_type'].value_counts()
```

```
food_type
Other                189
Canadian/American    131
Chinese              102
Indian                36
Italian               32
Fusion                21
Thai                  20
Mexican               17
Quebecois              1
Name: count, dtype: int64
```

Again, usually we should spend lots of time in EDA, but let's stop here so that we have time to learn about transformers and pipelines.

Dummy Classifier

```
from sklearn.dummy import DummyClassifier

results_df = {}
dummy = DummyClassifier()
results_df['dummy'] = mean_std_cross_val_scores(dummy, X_train, y_train, retur
pd.DataFrame(results_df)
```

	dummy
fit_time	0.000 (+/- 0.000)
score_time	0.000 (+/- 0.000)
test_score	0.515 (+/- 0.002)
train_score	0.515 (+/- 0.000)

We have a relatively balanced distribution of both ‘like’ and ‘dislike’ classes.

Preprocessing

How can we horizontally stack

- preprocessed numeric features,
- preprocessed binary features,
- preprocessed ordinal features, and
- preprocessed categorical features?

Let’s define a column transformer.

```
numeric_feats = ['age', 'n_people', 'price'] # Continuous and quantitative fea
categorical_feats = ['north_america', 'food_type'] # Discrete and qualitative
binary_feats = ['good_server'] # Categorical features with only two possible v
ordinal_feats = ['noise_level'] # Some natural ordering in the categories
noise_cats = ['no music', 'low', 'medium', 'high', 'crazy loud']
drop_feats = ['comments', 'restaurant_name', 'eat_out_freq'] # Dropping text f
```

```
X_train['noise_level'].value_counts()
```

```
noise_level
medium        232
low           186
high           75
no music       37
crazy loud     18
Name: count, dtype: int64
```

```
noise_levels = ["no music", "low", "medium", "high", "crazy loud"]
```

```
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import OrdinalEncoder

from sklearn.compose import make_column_transformer

numeric_transformer = make_pipeline(SimpleImputer(strategy="median"),
                                    StandardScaler())
binary_transformer = make_pipeline(SimpleImputer(strategy="most_frequent"),
                                   OneHotEncoder(drop="if_binary"))
ordinal_transformer = make_pipeline(SimpleImputer(strategy="most_frequent"),
                                    OrdinalEncoder(categories=[noise_levels]))
categorical_transformer = make_pipeline(SimpleImputer(strategy="most_frequent"
                                    OneHotEncoder(sparse_output=False, handle_

preprocessor = make_column_transformer(
    (numeric_transformer, numeric_feats),
    (binary_transformer, binary_feats),
    (ordinal_transformer, ordinal_feats),
    (categorical_transformer, categorical_feats),
    ("drop", drop_feats)
)
```

How does the transformed data look like?

```
transformed = preprocessor.fit_transform(X_train)
transformed.shape
```

```
(753, 17)
```

```
preprocessor
```

ColumnTransformer

pipeline-1	pipeline-2	pipeline-3
SimpleImputer	SimpleImputer	SimpleImputer
StandardScaler	OneHotEncoder	OrdinalEncoder

```python
# Getting feature names from a column transformer
ohe_feat_names = preprocessor.named_transformers_['pipeline-4']['onehotencoder
ohe_feat_names
```

```
["north_america_Don't want to share",
 'north_america_No',
 'north_america_Yes',
 'food_type_Canadian/American',
 'food_type_Chinese',
 'food_type_Fusion',
 'food_type_Indian',
 'food_type_Italian',
 'food_type_Mexican',
 'food_type_Other',
 'food_type_Quebecois',
 'food_type_Thai']
```

```python
numeric_feats
```

```
['age', 'n_people', 'price']
```

```python
feat_names = numeric_feats + binary_feats + ordinal_feats + ohe_feat_names
```

```python
transformed
```

```
array([[-0.66941678,  0.31029469, -0.36840629, ...,  0.        ,
         0.        ,  0.        ],
       [-0.66941678,  0.31029469, -0.05422496, ...,  0.        ,
         0.        ,  0.        ],
       [-0.89515383,  0.82336432, -0.25058829, ...,  0.        ,
         0.        ,  0.        ],
       ...,
       [-0.89515383, -0.97237936, -0.64331495, ...,  0.        ,
         0.        ,  0.        ],
       [-0.89515383, -0.20277493, -0.25058829, ...,  1.        ,
         0.        ,  0.        ],
       [-0.89515383,  1.33643394, -0.05422496, ...,  0.        ,
         0.        ,  0.        ]])
```

```python
pd.DataFrame(transformed, columns = feat_names)
```

	age	n_people	price	good_server	noise_level	north_america_want to
0	-0.669417	0.310295	-0.368406	0.0	3.0	
1	-0.669417	0.310295	-0.054225	1.0	1.0	
2	-0.895154	0.823364	-0.250588	1.0	2.0	
3	-0.669417	-0.202775	-0.250588	1.0	2.0	
4	0.007794	-0.202775	-0.054225	1.0	3.0	
...	...	...	...	...	...	
748	0.685006	-0.715845	-0.643315	1.0	2.0	
749	0.007794	-0.613231	-0.918224	1.0	2.0	
750	-0.895154	-0.972379	-0.643315	0.0	1.0	
751	-0.895154	-0.202775	-0.250588	1.0	2.0	
752	-0.895154	1.336434	-0.054225	1.0	3.0	

753 rows × 17 columns

We have new columns for the categorical features. Let's create a pipeline with the preprocessor and SVC.

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
models = {
    "Decision Tree": DecisionTreeClassifier(),
    "KNN": KNeighborsClassifier(),
    "SVM": SVC()
}

for (name, model) in models.items():
    pipe_num_model = make_pipeline(SimpleImputer(strategy="median"), StandardS
    results_df[name +' (numeric-only)'] = mean_std_cross_val_scores(pipe_num_m
pd.DataFrame(results_df).T
```

	fit_time	score_time	test_score	train_score
dummy	0.000 (+/- 0.000)	0.000 (+/- 0.000)	0.515 (+/- 0.002)	0.515 (+/- 0.000)
Decision Tree (numeric-only)	0.003 (+/- 0.002)	0.001 (+/- 0.000)	0.501 (+/- 0.033)	0.833 (+/- 0.010)
KNN (numeric-only)	0.002 (+/- 0.000)	0.004 (+/- 0.000)	0.525 (+/- 0.034)	0.674 (+/- 0.015)
SVM (numeric-only)	0.006 (+/- 0.000)	0.003 (+/- 0.000)	0.587 (+/- 0.033)	0.623 (+/- 0.006)

```
for (name, model) in models.items():
    pipe_model = make_pipeline(preprocessor, model)
    results_df[name + '(non-text feats)'] = mean_std_cross_val_scores(pipe_mod
pd.DataFrame(results_df).T
```

	fit_time	score_time	test_score	train_score
dummy	0.000 (+/- 0.000)	0.000 (+/- 0.000)	0.515 (+/- 0.002)	0.515 (+/- 0.000)
Decision Tree (numeric-only)	0.003 (+/- 0.002)	0.001 (+/- 0.000)	0.501 (+/- 0.033)	0.833 (+/- 0.010)
KNN (numeric-only)	0.002 (+/- 0.000)	0.004 (+/- 0.000)	0.525 (+/- 0.034)	0.674 (+/- 0.015)
SVM (numeric-only)	0.006 (+/- 0.000)	0.003 (+/- 0.000)	0.587 (+/- 0.033)	0.623 (+/- 0.006)
Decision Tree(non-text feats)	0.007 (+/- 0.000)	0.003 (+/- 0.000)	0.606 (+/- 0.041)	0.889 (+/- 0.008)
KNN(non-text feats)	0.006 (+/- 0.000)	0.003 (+/- 0.000)	0.600 (+/- 0.024)	0.736 (+/- 0.007)
SVM(non-text feats)	0.010 (+/- 0.000)	0.005 (+/- 0.000)	0.687 (+/- 0.011)	0.733 (+/- 0.008)

We are getting better results when we include numeric, categorical, binary, ordinal features.

Incorporating text features

We haven't incorporated the comments feature into our pipeline yet, even though it holds significant value in indicating whether the restaurant was liked or not.

```
X_train
```

	north_america	eat_out_freq	age	n_people	price	food_type	n
80	No	2.0	21	30.0	2200.0	Chinese	
934	Yes	4.0	21	30.0	3000.0	Canadian/American	
911	No	4.0	20	40.0	2500.0	Canadian/American	
459	Yes	5.0	21	NaN	NaN	Quebecois	
62	Yes	2.0	24	20.0	3000.0	Indian	
...	...	...	...	...	...	...	
106	No	3.0	27	10.0	1500.0	Chinese	
333	No	1.0	24	12.0	800.0	Other	
393	Yes	4.0	20	5.0	1500.0	Canadian/American	
376	Yes	5.0	20	NaN	NaN	NaN	
525	Don't want to share	4.0	20	50.0	3000.0	Chinese	

753 rows × 10 columns

Let's create bag-of-words representation of the `comments` feature. But first we need to impute the rows where there are no comments. There is a small complication if we want to put `SimpleImputer` and `CountVectorizer` in a pipeline.

- `SimpleImputer` takes a 2D array as input and produced 2D array as output.
- `CountVectorizer` takes a 1D array as input.

To deal with this, we will use sklearn's `FunctionTransformer` to convert the 2D output of `SimpleImputer` into a 1D array which can be passed to `CountVectorizer` as input.

```
from sklearn.preprocessing import FunctionTransformer
from sklearn.feature_extraction.text import CountVectorizer

reshape_for_countvectorizer = FunctionTransformer(lambda X: X.squeeze(), valid
text_transformer = make_pipeline(SimpleImputer(strategy="constant", fill_value
                                 reshape_for_countvectorizer,
                                 CountVectorizer(stop_words="english"))
text_pipe = make_pipeline(text_transformer, SVC())
cross_val_score(text_pipe, X_train[['comments']], y_train).mean()
```

```
np.float64(0.6493951434878588)
```

Pretty good scores just with text features! Let's examine the transformed data.

```
transformed = text_transformer.fit_transform(X_train[['comments']], y_train)
```

```
transformed
```

```
<Compressed Sparse Row sparse matrix of dtype 'int64'
	with 1841 stored elements and shape (753, 548)>
```

It's a sparse matrix. Let's explore the the vocabulary.

```
vocab = text_transformer.named_steps["countvectorizer"].get_feature_names_out(
vocab[:10]
```

```
array(['18', '30', '40mins', '65', 'actually', 'addition', 'affordable',
       'alcohol', 'ale', 'allergic'], dtype=object)
```

```
vocab[0:10]
```

```
array(['18', '30', '40mins', '65', 'actually', 'addition', 'affordable',
       'alcohol', 'ale', 'allergic'], dtype=object)
```

```
vocab[200:210]
```

```
array(['fusion', 'games', 'gave', 'general', 'genuinely', 'getting',
       'ginger', 'girlfriends', 'gluten', 'going'], dtype=object)
```

```
vocab[500:600]
```

```
array(['undressed', 'unfresh', 'uni', 'unique', 'unreasonable', 'upset',
       'usual', 'uwu', 'value', 'vancouver', 'variety', 'vds', 've',
       'vegan', 'vibe', 'vibes', 'vietnamese', 'view', 'visit', 'wait',
       'waited', 'waiter', 'waiters', 'waiting', 'waitress', 'walking',
       'want', 'warm', 'washrooms', 'wasn', 'water', 'watery', 'way',
       'weekend', 'went', 'wet', 'wife', 'wind', 'window', 'wine',
       'wings', 'winter', 'work', 'worst', 'wrong', 'yelling', 'yield',
       'yummy'], dtype=object)
```

```
vocab[0::20]
```

```
array(['18', 'ask', 'better', 'cash', 'closing', 'country', 'dessert',
       'drunk', 'expecting', 'figuring', 'fusion', 'having', 'impeccable',
       'knowledgeable', 'love', 'nice', 'pain', 'played', 'quality',
       'removed', 'sauces', 'sitting', 'spoke', 'tacky', 'time',
       'undressed', 'waited', 'wings'], dtype=object)
```

Do we get better scores if we combine all features? Let's define a column transformer which carries out

- imputation and scaling on numeric features
- imputation and one-hot encoding with `drop="if_binary"` on binary features

- imputation and one-hot encoding with `handle_unknown="ignore"` on categorical features
- imputation, reshaping, and bag-of-words transformation on the text feature

```
from sklearn.feature_extraction.text import CountVectorizer
text_feat = ['comments']

preprocessor_all = make_column_transformer(
    (numeric_transformer, numeric_feats),
    (binary_transformer, binary_feats),
    (ordinal_transformer, ordinal_feats),
    (categorical_transformer, categorical_feats),
    (text_transformer, text_feat),
    ("drop", drop_feats)
)
```

```
preprocessor_all.fit_transform(X_train)
```

```
<Compressed Sparse Row sparse matrix of dtype 'float64'
	with 6927 stored elements and shape (753, 565)>
```

```
for (name, model) in models.items():
    pipe_model = make_pipeline(text_transformer, model)
    results_df[name + '(text)'] = mean_std_cross_val_scores(pipe_model, X_trai
pd.DataFrame(results_df).T
```

	fit_time	score_time	test_score	train_score
dummy	0.000 (+/- 0.000)	0.000 (+/- 0.000)	0.515 (+/- 0.002)	0.515 (+/- 0.000)
Decision Tree (numeric-only)	0.003 (+/- 0.002)	0.001 (+/- 0.000)	0.501 (+/- 0.033)	0.833 (+/- 0.010)
KNN (numeric-only)	0.002 (+/- 0.000)	0.004 (+/- 0.000)	0.525 (+/- 0.034)	0.674 (+/- 0.015)
SVM (numeric-only)	0.006 (+/- 0.000)	0.003 (+/- 0.000)	0.587 (+/- 0.033)	0.623 (+/- 0.006)
Decision Tree(non-text feats)	0.007 (+/- 0.000)	0.003 (+/- 0.000)	0.606 (+/- 0.041)	0.889 (+/- 0.008)
KNN(non-text feats)	0.006 (+/- 0.000)	0.003 (+/- 0.000)	0.600 (+/- 0.024)	0.736 (+/- 0.007)
SVM(non-text feats)	0.010 (+/- 0.000)	0.005 (+/- 0.000)	0.687 (+/- 0.011)	0.733 (+/- 0.008)
Decision Tree(text)	0.005 (+/- 0.000)	0.001 (+/- 0.000)	0.629 (+/- 0.031)	0.735 (+/- 0.004)
KNN(text)	0.003 (+/- 0.000)	0.004 (+/- 0.000)	0.572 (+/- 0.023)	0.646 (+/- 0.026)
SVM(text)	0.008 (+/- 0.000)	0.002 (+/- 0.000)	0.649 (+/- 0.022)	0.728 (+/- 0.005)

```
for (name, model) in models.items():
    pipe_model = make_pipeline(preprocessor_all, model)
    results_df[name + '(all)'] = mean_std_cross_val_scores(pipe_model, X_train
pd.DataFrame(results_df).T
```

	fit_time	score_time	test_score	train_score
dummy	0.000 (+/- 0.000)	0.000 (+/- 0.000)	0.515 (+/- 0.002)	0.515 (+/- 0.000)
Decision Tree (numeric-only)	0.003 (+/- 0.002)	0.001 (+/- 0.000)	0.501 (+/- 0.033)	0.833 (+/- 0.010)
KNN (numeric-only)	0.002 (+/- 0.000)	0.004 (+/- 0.000)	0.525 (+/- 0.034)	0.674 (+/- 0.015)
SVM (numeric-only)	0.006 (+/- 0.000)	0.003 (+/- 0.000)	0.587 (+/- 0.033)	0.623 (+/- 0.006)
Decision Tree(non-text feats)	0.007 (+/- 0.000)	0.003 (+/- 0.000)	0.606 (+/- 0.041)	0.889 (+/- 0.008)
KNN(non-text feats)	0.006 (+/- 0.000)	0.003 (+/- 0.000)	0.600 (+/- 0.024)	0.736 (+/- 0.007)
SVM(non-text feats)	0.010 (+/- 0.000)	0.005 (+/- 0.000)	0.687 (+/- 0.011)	0.733 (+/- 0.008)
Decision Tree(text)	0.005 (+/- 0.000)	0.001 (+/- 0.000)	0.629 (+/- 0.031)	0.735 (+/- 0.004)
KNN(text)	0.003 (+/- 0.000)	0.004 (+/- 0.000)	0.572 (+/- 0.023)	0.646 (+/- 0.026)
SVM(text)	0.008 (+/- 0.000)	0.002 (+/- 0.000)	0.649 (+/- 0.022)	0.728 (+/- 0.005)
Decision Tree(all)	0.012 (+/- 0.001)	0.004 (+/- 0.000)	0.620 (+/- 0.021)	0.893 (+/- 0.006)
KNN(all)	0.008 (+/- 0.000)	0.005 (+/- 0.000)	0.631 (+/- 0.020)	0.755 (+/- 0.015)
SVM(all)	0.018 (+/- 0.000)	0.006 (+/- 0.000)	0.699 (+/- 0.017)	0.786 (+/- 0.008)

Some improvement when we combine all features!