Lecture 5: Class demo

Contents

Imports

```
# 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 ColumnTransformer, make_column_transformer
from sklearn.impute import SimpleImputer
from sklearn.model_selection import cross_val_score, cross_validate, train_tes
from sklearn.neighbors import KNeighborsClassifier
from sklearn.pipeline import Pipeline, make_pipeline
from sklearn.preprocessing import OneHotEncoder, OrdinalEncoder, StandardScale

%matplotlib inline

pd.set_option("display.max_colwidth", 200)

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

Data and splitting

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

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']
```

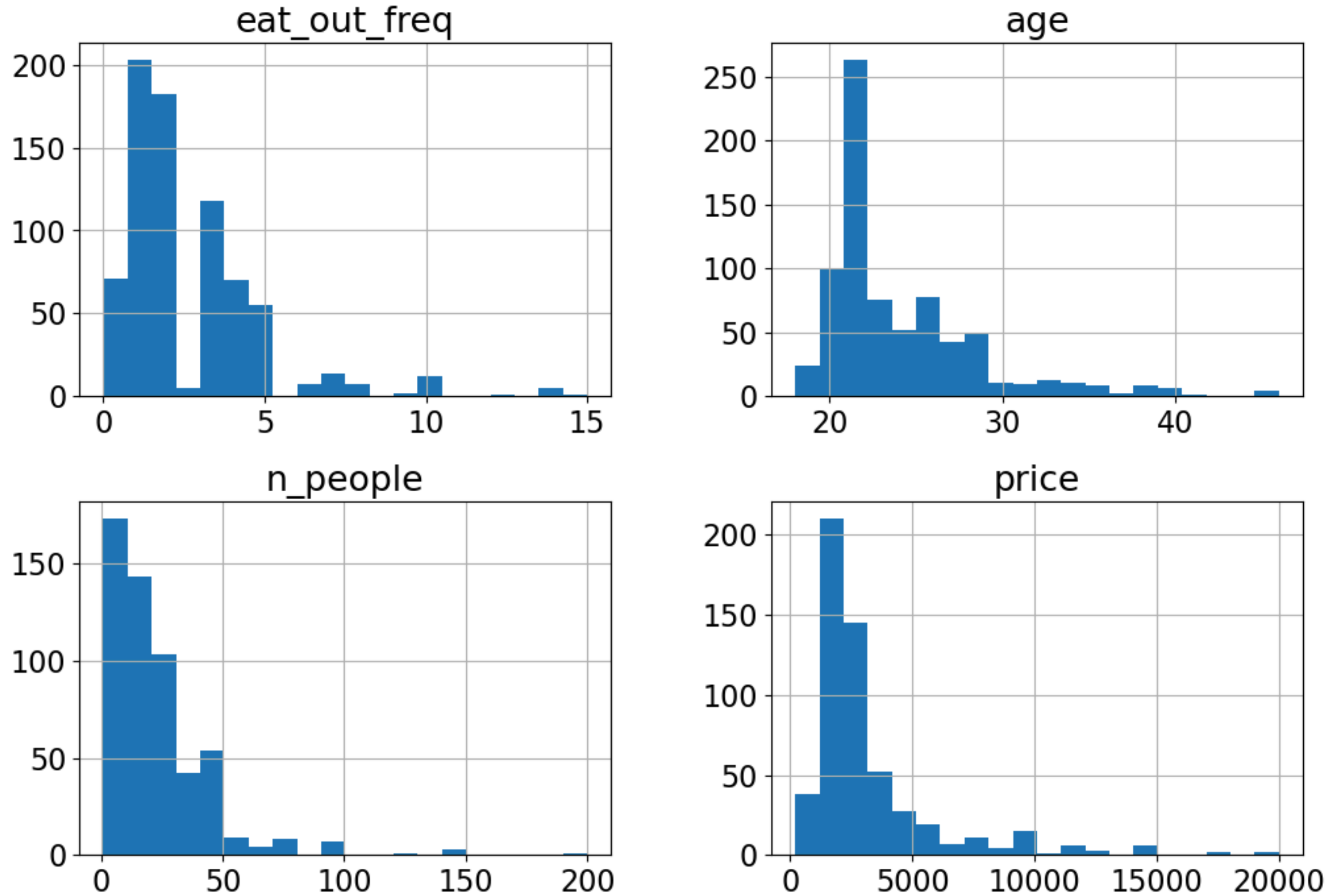
Below I’m perturbing this data just to demonstrate a few concepts. Don’t do it in real life.

```
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
```

Exploratory data analysis

```
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.

Modeling

Dummy Classifier

```
from sklearn.dummy import DummyClassifier

dummy = DummyClassifier()
scores = cross_validate(dummy, X_train, y_train, return_train_score=True)
pd.DataFrame(scores)
```

	fit_time	score_time	test_score	train_score
0	0.000606	0.000324	0.516556	0.514950
1	0.000354	0.000256	0.516556	0.514950
2	0.000334	0.000252	0.516556	0.514950
3	0.000323	0.000254	0.513333	0.515755
4	0.000341	0.000243	0.513333	0.515755

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

Let's try KNN on this data

Do you think KNN would work directly on `X_train` and `y_train`?

```
# Preprocessing and pipeline
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier()
# knn.fit(X_train, y_train)
```

- We need to preprocess the data before feeding it into machine learning models. What are the different types of features in the data?
- What transformations are necessary before training a machine learning model?
- Can we categorize features based on the type of transformations they require?

```
X_train[4:11]
```

	north_america	eat_out_freq	age	n_people	price	food_type	n
62	Yes	2.0	24	20.0	3000.0	Indian	
694	No	0.0	20	NaN	NaN	NaN	
890	No	5.0	21	50.0	3500.0	Canadian/American	
677	Yes	3.0	20	30.0	2000.0	Mexican	
161	No	0.0	27	NaN	NaN	NaN	
571	Yes	3.0	22	NaN	NaN	NaN	
11	Yes	2.0	21	30.0	3000.0	Chinese	

```
numeric_feats = ['age', 'n_people', 'price'] # Continuous and quantitative fea
categorical_feats = ['food_type', 'north_america'] # 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.columns
```

```
Index(['north_america', 'eat_out_freq', 'age', 'n_people', 'price',
       'food_type', 'noise_level', 'good_server', 'comments',
       'restaurant_name'],
      dtype='object')
```

```
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
```

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

```
north_america
Yes                      415
No                       330
Don't want to share        8
Name: count, dtype: int64
```

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

```
good_server
Yes    396
No     148
Name: count, dtype: int64
```

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

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

Let's begin with numeric features. What if we just use numeric features to train a KNN model? Would it work?

```
X_train_num = X_train[numeric_feats]
X_test_num = X_test[numeric_feats]
# knn.fit(X_train_num, y_train)
```

We need to deal with NaN values.

sklearn's `SimpleImputer`

```
# Impute numeric features using SimpleImputer
from sklearn.impute import SimpleImputer

imputer = SimpleImputer(strategy='median')

# fit the imputer
imputer.fit(X_train_num)

# Transform training data
X_train_num_imp = imputer.transform(X_train_num)

# Transform test data
X_test_num_imp = imputer.transform(X_test_num)
```

```
knn.fit(X_train_num_imp, y_train)
```

```
▾ KNeighborsClassifier
KNeighborsClassifier()
```

No more errors. It worked! Let's try cross validation.

```
knn.score(X_train_num_imp, y_train)
```

```
0.6706507304116865
```

```
knn.score(X_test_num_imp, y_test)
```

```
0.49206349206349204
```

We have slightly improved results in comparison to the dummy model.

Discussion questions

- What's the difference between sklearn estimators and transformers?
- Can you think of a better way to impute missing values?

Do we need to scale the data?

```
X_train[numeric_feats]
```

	age	n_people	price
80	21	30.0	2200.0
934	21	30.0	3000.0
911	20	40.0	2500.0
459	21	NaN	NaN
62	24	20.0	3000.0
...	...	...	...
106	27	10.0	1500.0
333	24	12.0	800.0
393	20	5.0	1500.0
376	20	NaN	NaN
525	20	50.0	3000.0

753 rows × 3 columns

```
# Scale the imputed data

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(X_train_num_imp)
X_train_num_imp_scaled = scaler.transform(X_train_num_imp)
X_test_num_imp_scaled = scaler.transform(X_test_num_imp)
```

Alternative methods for scaling

- MinMaxScaler: Transform each feature to a desired range
- RobustScaler: Scale features using median and quantiles. Robust to outliers.
- Normalizer: Works on rows rather than columns. Normalize examples individually to unit norm.
- MaxAbsScaler: A scaler that scales each feature by its maximum absolute value.
    - What would happen when you apply `StandardScaler` to sparse data?
- You can also apply custom scaling on columns using `FunctionTransformer`. For example, when a column follows the power law distribution (a handful of your values have many data points whereas most other values have few data points) log scaling is helpful.

- For now, let's focus on `StandardScaler`. Let's carry out cross-validation

```
cross_val_score(knn, X_train_num_imp_scaled, y_train)
```

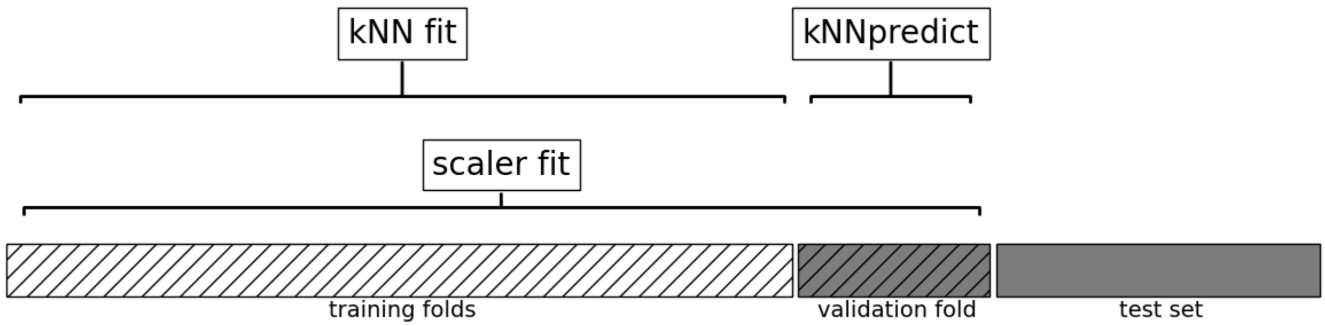
```
array([0.55629139, 0.49006623, 0.56953642, 0.54      , 0.53333333])
```

In this case, we don't see a big difference with `StandardScaler`. But usually, scaling is a good idea.

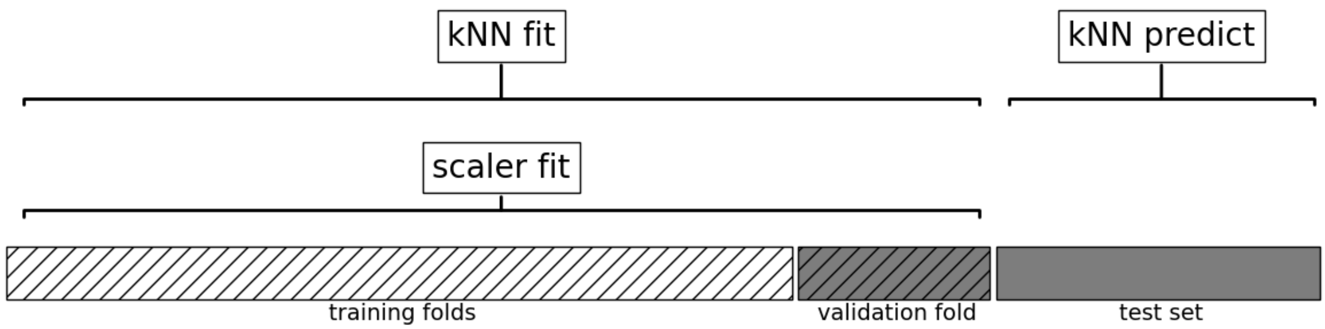
- This worked but are we doing anything wrong here?
- What's the problem with calling `cross_val_score` with preprocessed data?

```
plot_improper_processing("kNN")
```

Cross validation



Test set prediction



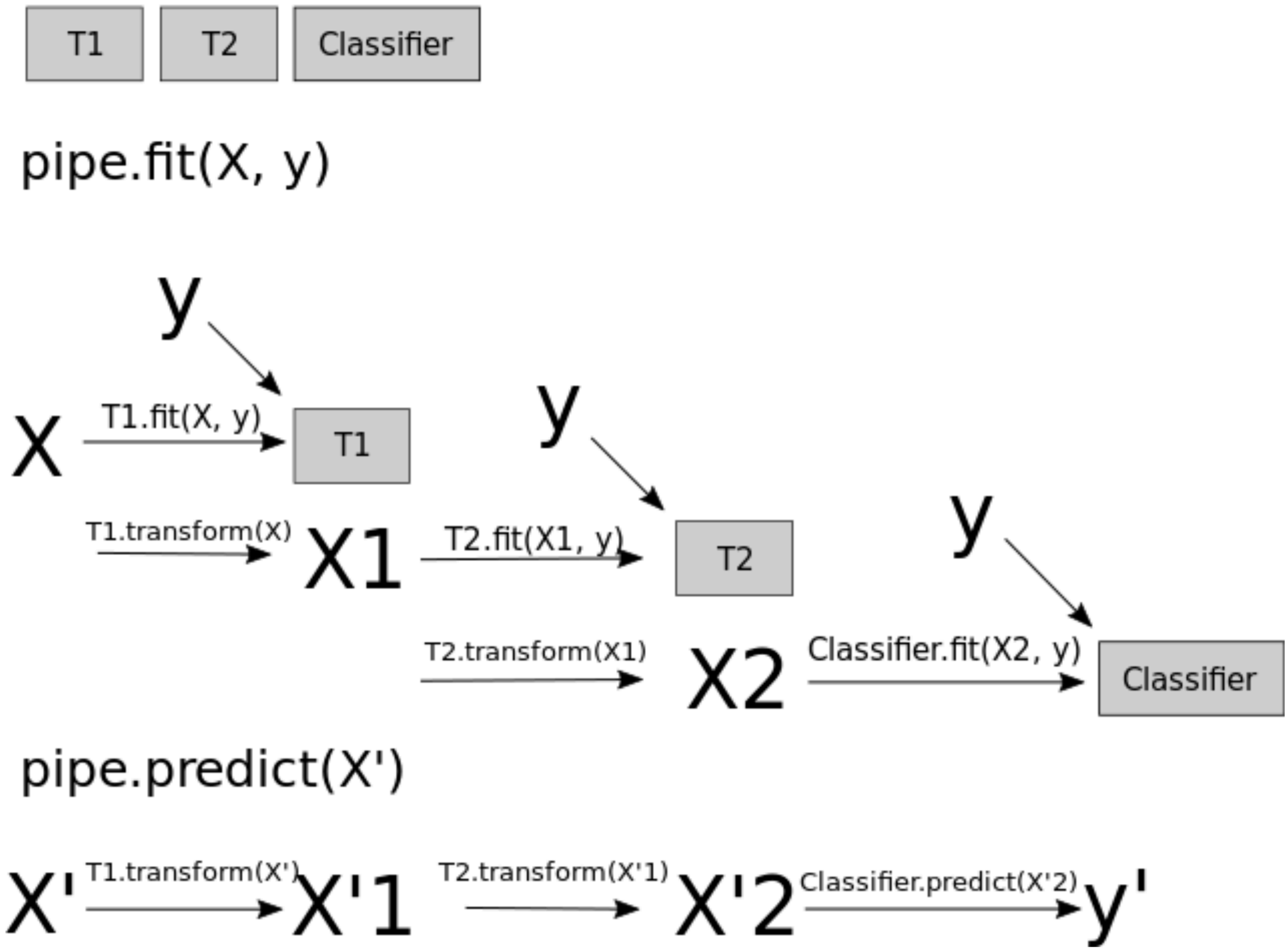
How would you do it properly? Enter sklearn pipelines!!

```
# Create a pipeline
pipe_knn = make_pipeline(
    SimpleImputer(strategy="median"),
    StandardScaler(),
    KNeighborsClassifier()
)
```

```
cross_val_score(pipe_knn, X_train_num, y_train).mean()
```

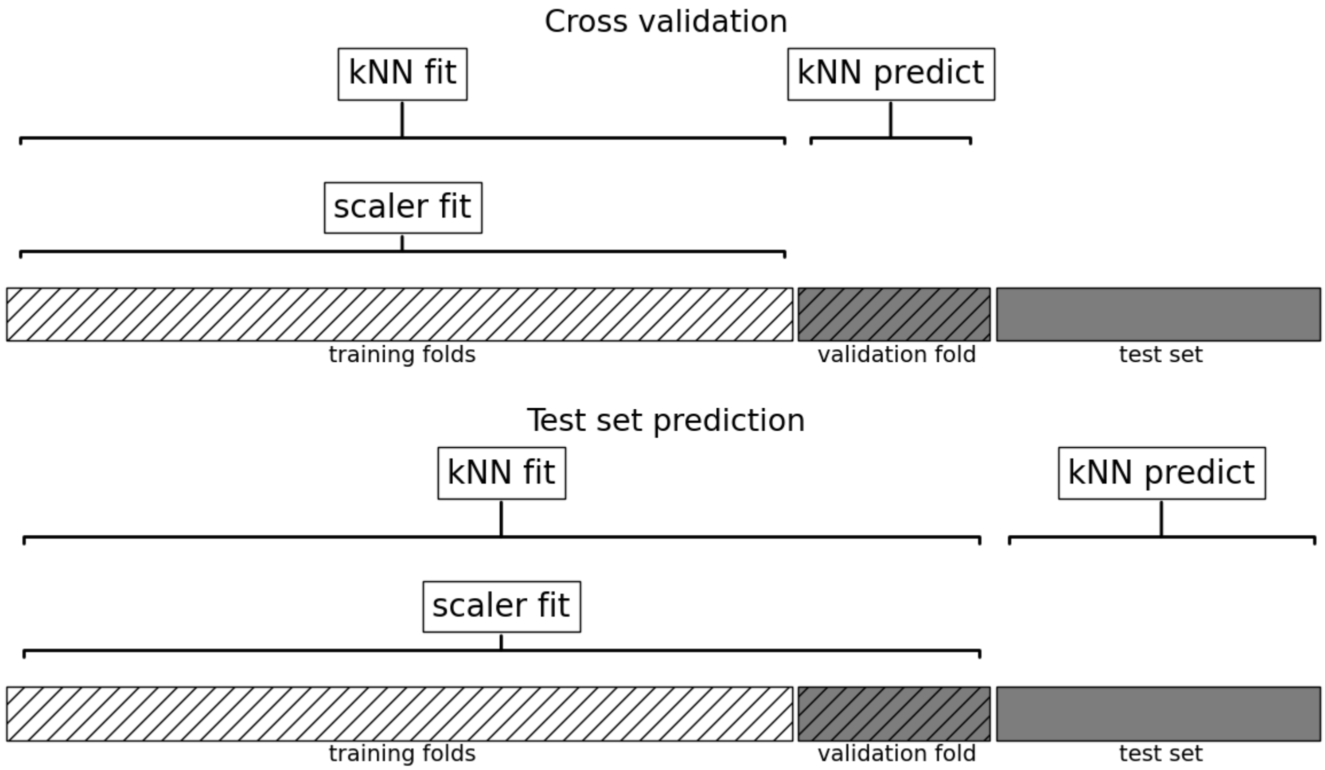
```
np.float64(0.5245916114790287)
```

- What is happening under the hood?
- Why is this a better approach?



[Source]()

```
plot_proper_processing("kNN")
```



Categorical features

Let's assess the scores using categorical features.

```
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
```

```
X_train[categorical_feats]
```

	food_type	north_america
80	Chinese	No
934	Canadian/American	Yes
911	Canadian/American	No
459	Quebecois	Yes
62	Indian	Yes
...	...	...
106	Chinese	No
333	Other	No
393	Canadian/American	Yes
376	NaN	Yes
525	Chinese	Don't want to share

753 rows × 2 columns

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

```
north_america
Yes                    415
No                     330
Don't want to share      8
Name: count, dtype: int64
```

```
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
```

```
X_train_cat = X_train[categorical_feats]
X_test_cat = X_test[categorical_feats]
```

```
# One-hot encoding of categorical features
from sklearn.preprocessing import OneHotEncoder
# Create class object
ohe = OneHotEncoder(sparse_output=False)

# fit OneHotEncoder
ohe.fit(X_train_cat, y_train)

X_train_cat_ohe  = ohe.transform(X_train_cat)# transform the train set
X_test_cat_ohe  =  ohe.transform(X_test_cat)# transform the test set
```

```
X_train_cat_ohe
```

```
array([[0., 1., 0., ..., 0., 1., 0.],
       [1., 0., 0., ..., 0., 0., 1.],
       [1., 0., 0., ..., 0., 1., 0.],
       ...,
       [1., 0., 0., ..., 0., 0., 1.],
       [0., 0., 0., ..., 0., 0., 1.],
       [0., 1., 0., ..., 1., 0., 0.]])
```

- It's a sparse matrix.
- Why? What would happen if we pass `sparse_output=False`? Why we might want to do that?

```
# Get the OHE feature names

ohe_feats = ohe.get_feature_names_out().tolist()
ohe_feats
```

```
['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',
 'food_type_nan',
 "north_america_Don't want to share",
 'north_america_No',
 'north_america_Yes']
```

```
pd.DataFrame(X_train_cat_ohe, columns = ohe_feats)
```

	food_type_Canadian/American	food_type_Chinese	food_type_Fusion	food_
0	0.0	1.0	0.0	
1	1.0	0.0	0.0	
2	1.0	0.0	0.0	
3	0.0	0.0	0.0	
4	0.0	0.0	0.0	
...	...	...	...	
748	0.0	1.0	0.0	
749	0.0	0.0	0.0	
750	1.0	0.0	0.0	
751	0.0	0.0	0.0	
752	0.0	1.0	0.0	

753 rows × 13 columns

```
cross_val_score(knn, X_train_cat_ohe, y_train)
```

```
array([0.54304636, 0.52980132, 0.55629139, 0.54666667, 0.55333333])
```

- What's wrong here?
- How can we fix this?

Let's do this properly with a pipeline.

```
# Code to create a pipeline for OHE and KNN
pipe_ohe_knn = make_pipeline(
    OneHotEncoder(sparse_output=False, handle_unknown="ignore"),
    KNeighborsClassifier()
)
```

```
cross_val_score(pipe_ohe_knn, X_train_cat, y_train)
```

```
array([0.54304636, 0.52980132, 0.55629139, 0.54666667, 0.55333333])
```

Ordinal features

Let's examine the scores using ordinal features.

```
noise_ordering = ['no music', 'low', 'medium', 'high', 'crazy loud']
```

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

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

```
X_train['noise_level'].isnull().any()
```

```
np.True_
```

There are missing values. So we need an imputer.

```
from sklearn.preprocessing import OrdinalEncoder
noise_ordering = ['no music', 'low', 'medium', 'high', 'crazy loud']

pipe_ordinal_knn = make_pipeline(
    SimpleImputer(strategy="most_frequent"),
    OrdinalEncoder(categories=[noise_ordering]),
    KNeighborsClassifier()
)
```

```
cross_val_score(pipe_ordinal_knn, X_train[['noise_level']], y_train)
```

```
array([0.54966887, 0.56953642, 0.57615894, 0.48666667, 0.56666667])
```

Right now we are working with numeric and categorical features separately. But ideally when we create a model, we need to use all these features together.

Enter column transformer!

How can we horizontally stack

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

Let's define a column transformer.

```
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_ordering]
categorical_transformer = make_pipeline(SimpleImputer(strategy="most_frequent"
                                        OneHotEncoder(sparse_output=False,
                                                      handle_unknown="ignore"))

# Define the column transformer
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?

```
categorical_feats
```

```
['food_type', 'north_america']
```

```
X_train.shape
```

```
(753, 10)
```

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

```
(753, 17)
```

```
preprocessor
```

ColumnTransformer

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

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

```
['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',
 "north_america_Don't want to share",
 'north_america_No',
 'north_america_Yes']
```

```
numeric_feats
```

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

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

```
transformed
```

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

You can also get feature names of the transformed data directly from the column transformer object.

```
feat_names = preprocessor.get_feature_names_out()
```

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

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

	pipeline-1__age	pipeline-1__n_people	pipeline-1__price	pipeline-2__good_server_Yes	pipeline-3__noise_level
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

```
from sklearn.svm import SVC

svc_all_pipe = make_pipeline(preprocessor, SVC()) # create a pipeline with col
cross_val_score(svc_all_pipe, X_train, y_train).mean()
```

```
np.float64(0.686569536423841)
```

We are getting better results!