Sixth Practice ML

In this practice, we will learn how to train with **CV (Cross-Validation)** and how to choose features with **Feature Selection** algorithms.
We will use **sweetviz** (https://pypi.org/project/sweetviz/) to show the DataFrame report.
We will also use **tqdm** (https://tqdm.github.io/) to show a progress bar.

Downloads, Imports, and Definitions

We update packages that their Colab version is too old.

In [ ]:

```
# update plotly and pandas_profiling version
!pip install --upgrade plotly
!pip install sweetviz
```

```
Requirement already up-to-date: plotly in /usr/local/lib/python3.6/dist-pa
ckages (4.14.0)
Requirement already satisfied, skipping upgrade: six in /usr/local/lib/pyt
hon3.6/dist-packages (from plotly) (1.15.0)
Requirement already satisfied, skipping upgrade: retrying>=1.3.3 in /usr/l
ocal/lib/python3.6/dist-packages (from plotly) (1.3.3)
Requirement already satisfied: sweetviz in /usr/local/lib/python3.6/dist-p
ackages (2.0.2)
Requirement already satisfied: importlib-resources>=1.2.0 in /usr/local/li
b/python3.6/dist-packages (from sweetviz) (3.3.0)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.6/di
st-packages (from sweetviz) (1.4.1)
Requirement already satisfied: tqdm>=4.43.0 in /usr/local/lib/python3.6/di
st-packages (from sweetviz) (4.54.1)
Requirement already satisfied: pandas!=1.0.0,!=1.0.1,!=1.0.2,>=0.25.3 in /
usr/local/lib/python3.6/dist-packages (from sweetviz) (1.1.4)
Requirement already satisfied: jinja2>=2.11.1 in /usr/local/lib/python3.6/
dist-packages (from sweetviz) (2.11.2)
Requirement already satisfied: numpy>=1.16.0 in /usr/local/lib/python3.6/d
ist-packages (from sweetviz) (1.18.5)
Requirement already satisfied: matplotlib>=3.1.3 in /usr/local/lib/python
3.6/dist-packages (from sweetviz) (3.2.2)
Requirement already satisfied: zipp>=0.4; python_version < "3.8" in /usr/l
ocal/lib/python3.6/dist-packages (from importlib-resources>=1.2.0->sweetvi
z) (3.4.0)
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/py
thon3.6/dist-packages (from pandas!=1.0.0,!=1.0.1,!=1.0.2,>=0.25.3->sweetv
iz) (2.8.1)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/di
st-packages (from pandas!=1.0.0,!=1.0.1,!=1.0.2,>=0.25.3->sweetviz) (2018.
9)
Requirement already satisfied: MarkupSafe>=0.23 in /usr/local/lib/python3.
6/dist-packages (from jinja2>=2.11.1->sweetviz) (1.1.1)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in
/usr/local/lib/python3.6/dist-packages (from matplotlib>=3.1.3->sweetviz)
(2.4.7)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python
3.6/dist-packages (from matplotlib>=3.1.3->sweetviz) (1.3.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.6/di
st-packages (from matplotlib>=3.1.3->sweetviz) (0.10.0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.6/dist-p
ackages (from python-dateutil>=2.7.3->pandas!=1.0.0,!=1.0.1,!=1.0.2,>=0.2
5.3->sweetviz) (1.15.0)
```

We import our regular packages.

In [ ]:

```
# import numpy, matplotlib, etc.
import numpy as np
import pandas as pd
import seaborn as sns
import plotly.express as px
import matplotlib.pyplot as plt
import plotly.graph_objects as go

# sklearn imports
from sklearn import metrics
from sklearn import pipeline
from sklearn import linear_model
from sklearn import preprocessing
from sklearn import neural_network
from sklearn import model_selection
from sklearn.pipeline import Pipeline
from sklearn.pipeline import make_pipeline
from sklearn.linear_model import SGDRegressor
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import OrdinalEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.model_selection import train_test_split
```

Data Exploration

We use a dataset of used Ford cars.

Dataset Information

The types of the cars are:

SE

2020 Ford Fusion Hybrid SE FWD

SES

2020 Ford EcoSport SES 4WD

SEL

2020 Ford Edge SEL FWD

Attribute Information

1. **year**: the year of manufacturing (2000-2011)
2. **model**: the model of the car (SE, SES, SEL)
3. **price**: the price of the car (3800-21992)
4. **mileage**: the number of mileage that the car has done (4867-151479)
5. **color**: the color of the car ('Yellow', 'Gray', 'Silver', 'White', 'Blue', 'Black', 'Green', 'Red', 'Gold')
6. **transmission**: the transmission of the car ('AUTO', 'MANUAL')

Target Information

- **price**: we use the price as the target (regression problem)

Let's download the dataset from Github and explore it with Pandas tools.

In [ ]:

```
# download usedcars.csv file from Github
!wget https://raw.githubusercontent.com/stedy/Machine-Learning-with-R-datasets/master/u
sedcars.csv
```

```
--2020-12-07 23:02:07--  https://raw.githubusercontent.com/stedy/Machine-L
earning-with-R-datasets/master/usedcars.csv
Resolving raw.githubusercontent.com (raw.githubusercontent.com)... 151.10
1.0.133, 151.101.64.133, 151.101.128.133, ...
Connecting to raw.githubusercontent.com (raw.githubusercontent.com)|151.10
1.0.133|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 4732 (4.6K) [text/plain]
Saving to: 'usedcars.csv.4'

usedcars.csv.4      100%[===================>]   4.62K  --.-KB/s    in 0s

2020-12-07 23:02:07 (42.9 MB/s) - 'usedcars.csv.4' saved [4732/4732]
```

In [ ]:

```
# Load the usedcars csv file
usedcars_df = pd.read_csv('usedcars.csv')
usedcars_df
```

Out[ ]:

	year	model	price	mileage	color	transmission
0	2011	SEL	21992	7413	Yellow	AUTO
1	2011	SEL	20995	10926	Gray	AUTO
2	2011	SEL	19995	7351	Silver	AUTO
3	2011	SEL	17809	11613	Gray	AUTO
4	2012	SE	17500	8367	White	AUTO
...	...	...	...	...	...	...
145	2006	SES	6200	95000	Silver	AUTO
146	2002	SE	5995	87003	Red	AUTO
147	2000	SE	5980	96841	Red	AUTO
148	2001	SE	4899	151479	Yellow	AUTO
149	2000	SE	3800	109259	Red	AUTO

150 rows × 6 columns

In [ ]:

```
# show usedcars_df info
usedcars_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 6 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   year          150 non-null    int64
 1   model         150 non-null    object
 2   price         150 non-null    int64
 3   mileage       150 non-null    int64
 4   color         150 non-null    object
 5   transmission  150 non-null    object
dtypes: int64(3), object(3)
memory usage: 7.2+ KB
```

In [ ]:

```
# show usedcars_df description
usedcars_df.describe()
```

Out[ ]:

	year	price	mileage
count	150.000000	150.000000	150.000000
mean	2008.726667	12961.933333	44260.646667
std	2.200966	3122.481735	26982.104322
min	2000.000000	3800.000000	4867.000000
25%	2008.000000	10995.000000	27200.250000
50%	2009.000000	13591.500000	36385.000000
75%	2010.000000	14904.500000	55124.500000
max	2012.000000	21992.000000	151479.000000

We can also use `sweetviz` to show a report on the data.
This report is lighter than `pandas_profiling` so it might work better on large datasets.

In [ ]:

```python
#  import sweetviz and show report on usedcars_df
import sweetviz as sw

usedcars_report = sw.analyze(usedcars_df)
usedcars_report.show_notebook(layout='vertical')
```

2.0.2

Get updates, docs & report issues here

Created & maintained by Francois Bertrand

Graphic design by Jean-Francois Hains

DataFra

31

Associations

DataFrame

1 year

VALUES:	150 (100%)	MAX	2,012.0	RANGE
MISSING:	---	95%	2,011.0	IQR
DISTINCT:	13 (9%)	Q3	2,010.0	STD
		MEDIAN	2,009.0	VAR
		AVG	2,008.7	
		Q1	2,008.0	KURT.
		5%	2,004.0	SKEW
		MIN	2,000.0	SUM

2 model

VALUES:	150 (100%)
MISSING:	---
DISTINCT:	3 (2%)

3 price

VALUES:	150 (100%)	MAX	21,992	RANGE
MISSING:	---	95%	16,995	IQR
DISTINCT:	117 (78%)	Q3	14,904	STD
		MEDIAN	13,592	VAR
		AVG	12,962	
		Q1	10,995	KURT.
		5%	6,987	SKEW
		MIN	3,800	SUM

4 mileage

VALUES:	150 (100%)	MAX	151k	RANGE
MISSING:	---	95%	97k	IQR
		Q3	55k	STD

We can also show a comparing report on two subsets of the data.
Let's compare the `AUTO` transmission and the `MANUAL` transmission.

In [ ]:

```
# show comparing report between AUTO and MANUAL
usedcars_model_report = sw.compare_intra(usedcars_df, condition_series=usedcars_df["tra
nsmission"]=='AUTO', names=usedcars_df["transmission"].unique())
usedcars_model_report.show_notebook(layout='vertical')
```

SweetVIZ
2.0.2
Get updates, docs & report issues here
Created & maintained by Francois Bertrand
Graphic design by Jean-Francois Hains

AU
34

Associations

AUTO

1 year

VALUES:	128 (100%)	22 (100%)
MISSING:	---	---
DISTINCT:	13 (10%)	5 (23%)

MAX	2,012.0	2,010.0	RANGE
95%	2,011.0	2,010.0	IQR
Q3	2,010.0	2,010.0	STD
MEDIAN	2,009.0	2,009.0	VAR
AVG	2,008.7	2,008.6	
Q1	2,008.0	2,008.0	KURT.
5%	2,004.0	2,007.0	SKEW
MIN	2,000.0	2,006.0	SUM

2 model

VALUES:	128 (100%)	22 (100%)
MISSING:	---	---
DISTINCT:	3 (2%)	3 (14%)

3 price

VALUES:	128 (100%)	22 (100%)
MISSING:	---	---
DISTINCT:	102 (80%)	20 (91%)

MAX	21,992	15,988	RANGE
95%	16,998	14,979	IQR
Q3	14,992	13,994	STD
MEDIAN	13,714	12,638	VAR
AVG	13,093	12,200	
Q1	11,370	10,786	KURT.
5%	6,980	8,023	SKEW
MIN	3,800	7,995	SUM

4 mileage

VALUES:	128 (100%)	22 (100%)
MISSING:	---	---

MAX	151k	85k	RANGE
95%	100k	81k	IQR
Q3	56k	54k	STD

Cross-Validation

We can use CV (Cross-Validation) instead of breaking the data to train-validation splits.
When we use CV, we have better predictions of the test results.
It is similar to splitting the data, but we make sure that our split won't affect our result (we try a few possible splits).
We can use 2 CV:

1. **KFold**
2. **LPO** (Leave P out)

We will use **KFold** when we want speed.
We will use **LPO** when we want to be more precise and better predict the test score.
Let's start with Scikit-learn [KFold (https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.KFold.html#sklearn.model_selection.KFold)](https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.KFold.html#sklearn.model_selection.KFold).
Let's split the data into `k=5` folds.

In [ ]:

```
# divide the data to features and target
t = usedcars_df['price'].copy()
X = usedcars_df.drop(['price'], axis=1)
print('t')
display(t)
print()
print('X')
display(X)
```

```
t

0      21992
1      20995
2      19995
3      17809
4      17500
       ...
145     6200
146     5995
147     5980
148     4899
149     3800
Name: price, Length: 150, dtype: int64

X
```

	year	model	mileage	color	transmission
0	2011	SEL	7413	Yellow	AUTO
1	2011	SEL	10926	Gray	AUTO
2	2011	SEL	7351	Silver	AUTO
3	2011	SEL	11613	Gray	AUTO
4	2012	SE	8367	White	AUTO
...	...	...	...	...	...
145	2006	SES	95000	Silver	AUTO
146	2002	SE	87003	Red	AUTO
147	2000	SE	96841	Red	AUTO
148	2001	SE	151479	Yellow	AUTO
149	2000	SE	109259	Red	AUTO

150 rows × 5 columns

In [ ]:

```
# print the folds of the data
from sklearn.model_selection import KFold

kf = KFold(n_splits=2, shuffle=True, random_state=1)
for i, (train_ids, val_ids) in enumerate(kf.split(X)):
    print('Split', i)
    print("Train:", train_ids)
    display(X.loc[train_ids])
    display(t.loc[train_ids])
    print("Val:", val_ids)
    display(X.loc[val_ids])
    display(t.loc[val_ids])
    print()
```

```
Split 0
Train: [  0   1   3   7   8   9  10  13  15  20  21  22  23  24  25  26  2
7  30
  32  34  37  38  41  43  47  49  50  52  57  60  61  63  64  67  68  70
  71  72  74  76  79  80  81  82  83  86  87  88  89  93  96  97 100 101
 105 106 109 111 115 116 121 124 129 130 133 134 136 137 140 142 143 145
 147 148 149]
```

	year	model	mileage	color	transmission
0	2011	SEL	7413	Yellow	AUTO
1	2011	SEL	10926	Gray	AUTO
3	2011	SEL	11613	Gray	AUTO
7	2010	SEL	21026	Silver	AUTO
8	2011	SES	32655	Silver	AUTO
...	...	...	...	...	...
143	2004	SES	101130	Gray	AUTO
145	2006	SES	95000	Silver	AUTO
147	2000	SE	96841	Red	AUTO
148	2001	SE	151479	Yellow	AUTO
149	2000	SE	109259	Red	AUTO

75 rows × 5 columns

```
0      21992
1      20995
3      17809
7      16995
8      16995
       ...
143     6980
145     6200
147     5980
148     4899
149     3800
Name: price, Length: 75, dtype: int64
```

```
Val: [  2   4   5   6  11  12  14  16  17  18  19  28  29  31  33  35  36
39
  40  42  44  45  46  48  51  53  54  55  56  58  59  62  65  66  69  73
  75  77  78  84  85  90  91  92  94  95  98  99 102 103 104 107 108 110
 112 113 114 117 118 119 120 122 123 125 126 127 128 131 132 135 138 139
 141 144 146]
```

	year	model	mileage	color	transmission
2	2011	SEL	7351	Silver	AUTO
4	2012	SE	8367	White	AUTO
5	2010	SEL	25125	Silver	AUTO
6	2011	SEL	27393	Blue	AUTO
11	2011	SES	9199	Silver	AUTO
...	...	...	...	...	...
138	2003	SES	96000	White	AUTO
139	2005	SES	59013	Red	AUTO
141	2007	SE	86862	White	AUTO
144	2004	SES	119720	Black	AUTO
146	2002	SE	87003	Red	AUTO

75 rows × 5 columns

```
2      19995
4      17500
5      17495
6      17000
11     16992
       ...
138     7900
139     7488
141     6995
144     6950
146     5995
Name: price, Length: 75, dtype: int64
```

```
Split 1
Train: [  2   4   5   6  11  12  14  16  17  18  19  28  29  31  33  35  3
6  39
  40  42  44  45  46  48  51  53  54  55  56  58  59  62  65  66  69  73
  75  77  78  84  85  90  91  92  94  95  98  99 102 103 104 107 108 110
 112 113 114 117 118 119 120 122 123 125 126 127 128 131 132 135 138 139
 141 144 146]
```

	year	model	mileage	color	transmission
2	2011	SEL	7351	Silver	AUTO
4	2012	SE	8367	White	AUTO
5	2010	SEL	25125	Silver	AUTO
6	2011	SEL	27393	Blue	AUTO
11	2011	SES	9199	Silver	AUTO
...	...	...	...	...	...
138	2003	SES	96000	White	AUTO
139	2005	SES	59013	Red	AUTO
141	2007	SE	86862	White	AUTO
144	2004	SES	119720	Black	AUTO
146	2002	SE	87003	Red	AUTO

75 rows × 5 columns

```
2      19995
4      17500
5      17495
6      17000
11     16992
       ...
138     7900
139     7488
141     6995
144     6950
146     5995
Name: price, Length: 75, dtype: int64
```

```
Val: [  0   1   3   7   8   9  10  13  15  20  21  22  23  24  25  26  27
30
  32  34  37  38  41  43  47  49  50  52  57  60  61  63  64  67  68  70
  71  72  74  76  79  80  81  82  83  86  87  88  89  93  96  97 100 101
 105 106 109 111 115 116 121 124 129 130 133 134 136 137 140 142 143 145
 147 148 149]
```

	year	model	mileage	color	transmission
0	2011	SEL	7413	Yellow	AUTO
1	2011	SEL	10926	Gray	AUTO
3	2011	SEL	11613	Gray	AUTO
7	2010	SEL	21026	Silver	AUTO
8	2011	SES	32655	Silver	AUTO
...	...	...	...	...	...
143	2004	SES	101130	Gray	AUTO
145	2006	SES	95000	Silver	AUTO
147	2000	SE	96841	Red	AUTO
148	2001	SE	151479	Yellow	AUTO
149	2000	SE	109259	Red	AUTO

75 rows × 5 columns

```
0      21992
1      20995
3      17809
7      16995
8      16995
       ...
143     6980
145     6200
147     5980
148     4899
149     3800
Name: price, Length: 75, dtype: int64
```

We can also use Scikit-learn LeavePOut (https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.LeavePOut.html).
We can use LPO as LOO (Leave One Out) when specifying `p=1` . Let's leave `p=3` out. Lets use tqdm (https://tqdm.github.io/) to show progress bar.

In [ ]:

```
# find generator length
from tqdm.auto import tqdm

def find_generator_len(generator, use_pbar=True):
    i = 0

    if use_pbar:
        pbar = tqdm(desc='Calculating Length', ncols=1000, bar_format='{desc}{bar:10}{r_bar}')

    for a in generator:
        i += 1

        if use_pbar:
            pbar.update()

    if use_pbar:
        pbar.close()

    return i
```

In [ ]:

```
# calculate the groups of the data
from sklearn.model_selection import LeavePOut

lpo = LeavePOut(2)
for train_ids, val_ids in tqdm(lpo.split(X), desc='Computing P Models', total=find_generator_len(lpo.split(X))):
    pass
```

Let's create a method that gets: data and model and returns R2 score and MSE loss

In [ ]:

```
# calculate score and loss from cv (KFold or LPO) and display graphs
def get_cv_score_and_loss(X, t, model, k=None, p=None, show_score_loss_graphs=False, us
e_pbar=True):
    scores_losses_df = pd.DataFrame(columns=['fold_id', 'split', 'score', 'loss'])

    if k is not None:
        cv = KFold(n_splits=k, shuffle=True, random_state=1)
    elif p is not None:
        cv = LeavePOut(p)
    else:
        raise ValueError('you need to specify k or p in order for the cv to work')

    if use_pbar:
        pbar = tqdm(desc='Computing Models', total=find_generator_len(cv.split(X)))

    for i, (train_ids, val_ids) in enumerate(cv.split(X)):
        X_train = X.loc[train_ids]
        t_train = t.loc[train_ids]
        X_val = X.loc[val_ids]
        t_val = t.loc[val_ids]

        model.fit(X_train, t_train)

        y_train = model.predict(X_train)
        y_val = model.predict(X_val)
        scores_losses_df.loc[len(scores_losses_df)] = [i, 'train', model.score(X_train,
t_train), mean_squared_error(t_train, y_train)]
        scores_losses_df.loc[len(scores_losses_df)] = [i, 'val', model.score(X_val, t_v
al), mean_squared_error(t_val, y_val)]

        if use_pbar:
            pbar.update()

    if use_pbar:
        pbar.close()

    val_scores_losses_df = scores_losses_df[scores_losses_df['split']=='val']
    train_scores_losses_df = scores_losses_df[scores_losses_df['split']=='train']

    mean_val_score = val_scores_losses_df['score'].mean()
    mean_val_loss = val_scores_losses_df['loss'].mean()
    mean_train_score = train_scores_losses_df['score'].mean()
    mean_train_loss = train_scores_losses_df['loss'].mean()

    if show_score_loss_graphs:
        fig = px.line(scores_losses_df, x='fold_id', y='score', color='split', title=f
'Mean Val Score: {mean_val_score:.2f}, Mean Train Score: {mean_train_score:.2f}')
        fig.show()
        fig = px.line(scores_losses_df, x='fold_id', y='loss', color='split', title=f'M
ean Val Loss: {mean_val_loss:.2f}, Mean Train Loss: {mean_train_loss:.2f}')
        fig.show()

    return mean_val_score, mean_val_loss, mean_train_score, mean_train_loss
```

In [ ]:

```
# determine categorical and numerical features
numerical_cols = X.select_dtypes(include=['int64', 'float64']).columns
categorical_cols = X.select_dtypes(include=['object', 'bool']).columns
all_cols = np.array(X.columns)

print('Numerical Cols:', numerical_cols)
print('Categorical Cols:', categorical_cols)
print('All Cols:', all_cols)
```

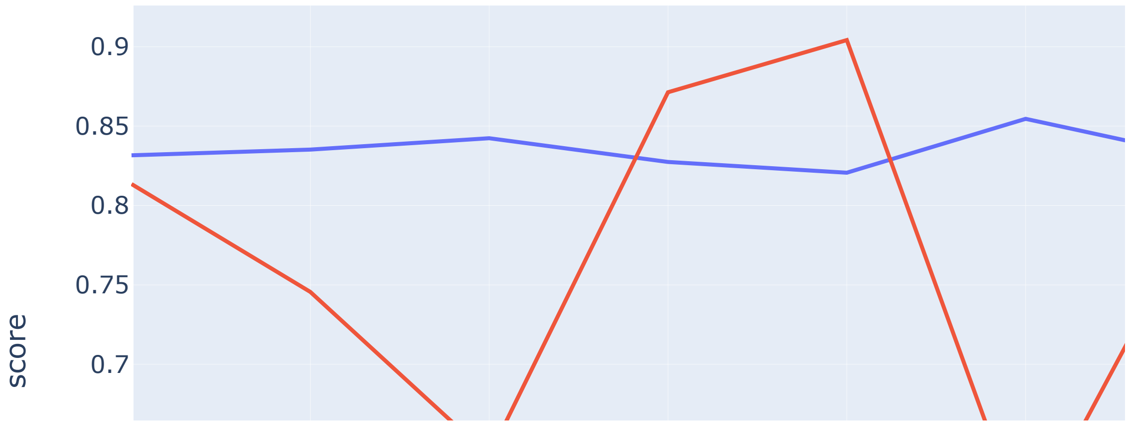
```
Numerical Cols: Index(['year', 'mileage'], dtype='object')
Categorical Cols: Index(['model', 'color', 'transmission'], dtype='objec
t')
All Cols: ['year' 'model' 'mileage' 'color' 'transmission']
```

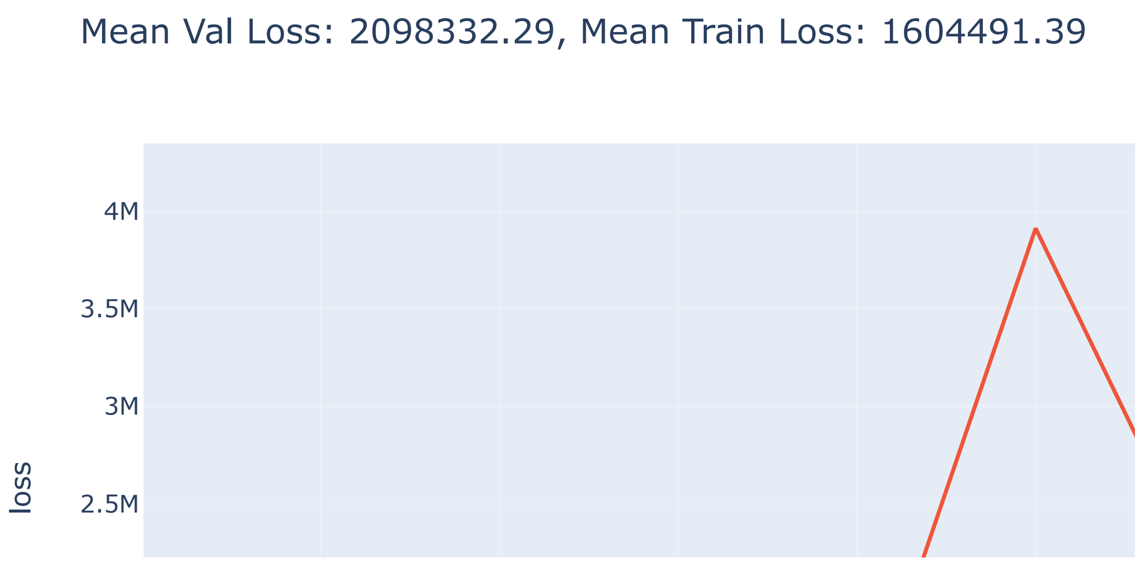
In [ ]:

```
# use column transformer to insert different transformers for each column
from sklearn.compose import ColumnTransformer

ct = ColumnTransformer([
    ("encoding", OneHotEncoder(sparse=False, handle_unknown='ignore'), categorical_cols
),
    ("standard", StandardScaler(), numerical_cols)])
model_pipe = make_pipeline(ct, SGDRegressor(random_state=1))
val_score, val_loss, train_score, train_loss = get_cv_score_and_loss(X, t, model_pipe,
k=10, show_score_loss_graphs=True)
print(f'mean cv val score: {val_score:.2f}\nmean cv val loss {val_loss:.2f}')
print(f'mean cv val score: {train_score:.2f}\nmean cv val loss {train_loss:.2f}')
```

Mean Val Score: 0.75, Mean Train Score: 0.83






```
mean cv val score: 0.75
mean cv val loss 2098332.29
mean cv val score: 0.83
mean cv val loss 1604491.39
```

We can use our function to show CV vs. train graphs.
Let's create this graph for polynomial numerical features.

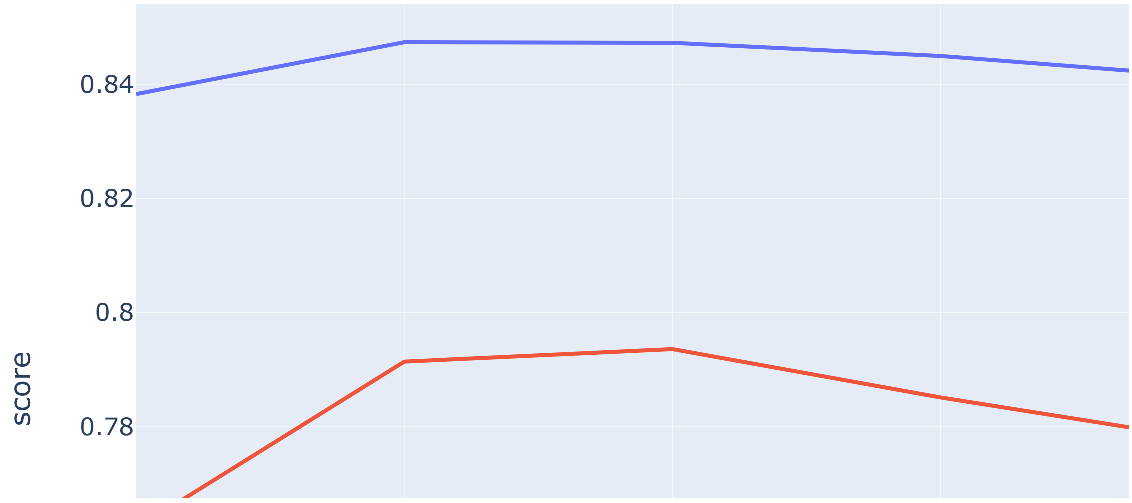
In [ ]:

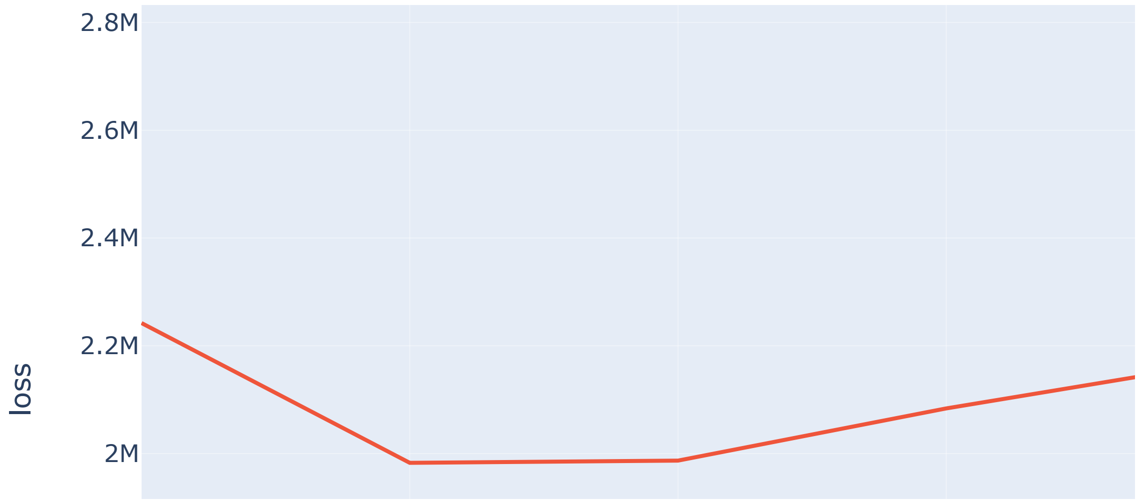
```
# show graph of score and loss by plynomial degree of numerical features
def show_degree_graphs_cv_train(X, t, model, k=None, p=None, max_degree=10):
    numerical_cols = X.select_dtypes(include=['int64', 'float64']).columns
    categorical_cols = X.select_dtypes(include=['object', 'bool']).columns

    val_train_score_loss_df = pd.DataFrame(columns=['degree', 'split', 'score', 'loss'
])
    for i in tqdm(range(1, max_degree), desc='Poly Degree'):
        ct_enc_std_poly = ColumnTransformer([
            ("encoding", OneHotEncoder(sparse=False, handle_unknown='ignore'), categori
cal_cols),
            ("standard_poly", make_pipeline(PolynomialFeatures(degree=i), StandardScale
r()), numerical_cols)])
        model_pipe = make_pipeline(ct_enc_std_poly, model)
        val_score, val_loss, train_score, train_loss = get_cv_score_and_loss(X, t, mode
l_pipe, transformer=ct, k=k, p=p, show_score_loss_graphs=False, use_pbar=False)
        val_train_score_loss_df.loc[len(val_train_score_loss_df)] = [i, 'train', train_
score, train_loss]
        val_train_score_loss_df.loc[len(val_train_score_loss_df)] = [i, 'cv', val_score
, val_loss]

    fig = px.line(val_train_score_loss_df, x='degree', y='score', color='split')
    fig.show()
    fig = px.line(val_train_score_loss_df, x='degree', y='loss', color='split')
    fig.show()

show_degree_graphs_cv_train(X, t, SGDRegressor(random_state=1), k=5 ,max_degree=8)
```


0.84
0.82
0.8
0.78
score



We can see that the CV here is performing worse than the train.
It is closer to the real test results.
The best CV score on this set is when we specify `degree=3` .

Feature Selection

We want to choose the best features for our use case.
We have learned 3 methods of Feature Selection:

1. **Forward Feature Selection**
2. **Backward Feature Selection**
3. **Hybrid Feature Selection**

In **Forward Feature Selection** we start from zero features and add features until we reach the number of maximum features or until we reach the best score.
In **Backward Feature Selection** we start from the full feature set and remove features until we reach the number of minimum features or until we reach the best score.
In **Hybrid Feature Selection**, we start from zero features and add/remove features until we reach the best score.

We will use Scikit-learn [RFE (https://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.RFE.html#sklearn.feature_selection.RFE)](https://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.RFE.html#sklearn.feature_selection.RFE) that is based on the **Backward Feature Selection**.
We will specify the target number of features to find and the selector will stop when it will reach this number of features.

Let's find the best `n_features_to_select=3` features on our dataset.

In [ ]:

```
# choose the best 3 features of this dataset with SGDRegressor
from sklearn.feature_selection import RFE

numerical_cols = X.select_dtypes(include=['int64', 'float64']).columns
categorical_cols = X.select_dtypes(include=['object', 'bool']).columns
all_cols = categorical_cols.tolist() + numerical_cols.tolist()
ct_enc_std = ColumnTransformer([
            ("encoding", OrdinalEncoder(), categorical_cols),
            ("standard", StandardScaler(), numerical_cols)])
X_encoded = pd.DataFrame(ct_enc_std.fit_transform(X, t), columns=all_cols)

selector = RFE(SGDRegressor(random_state=1), n_features_to_select=3).fit(X_encoded, t)
X_encoded.loc[:, selector.support_]
```

Out[ ]:

	model	year	mileage
0	1.0	1.036340	-1.370208
1	1.0	1.036340	-1.239574
2	1.0	1.036340	-1.372513
3	1.0	1.036340	-1.214028
4	0.0	1.492208	-1.334733
...	...	...	...
145	2.0	-1.243000	1.886781
146	0.0	-3.066473	1.589407
147	0.0	-3.978209	1.955240
148	0.0	-3.522341	3.986996
149	0.0	-3.978209	2.417013

150 rows × 3 columns

We can see that the best 3 features are `model` , `year` , and `mileage` .

We can also use Scikit-learn [RFECV (https://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.RFECV.html)](https://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.RFECV.html) to use CV and choose the best number of features on this dataset.
The default CV is 5-fold cross-validation.
We will enter the Scikit-learn [RepeatedKFold (https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.RepeatedKFold.html)](https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.RepeatedKFold.html) to repeat each KFold a few times with different splits.

In [ ]:

```
# find best subset of features on this dataset
from sklearn.feature_selection import RFECV
from sklearn.model_selection import RepeatedKFold

numerical_cols = X.select_dtypes(include=['int64', 'float64']).columns
categorical_cols = X.select_dtypes(include=['object', 'bool']).columns
all_cols = list(categorical_cols) + list(numerical_cols)
ct_enc_std = ColumnTransformer([
            ("encoding", OrdinalEncoder(), categorical_cols),
            ("standard", StandardScaler(), numerical_cols)])
X_encoded = pd.DataFrame(ct_enc_std.fit_transform(X, t), columns=all_cols)

selector = RFECV(SGDRegressor(random_state=1), cv=RepeatedKFold(n_splits=5, n_repeats=1
0, random_state=1)).fit(X_encoded, t)
display(X_encoded.loc[:, selector.support_])

fig = go.Figure()
results = selector.cv_results_['mean_test_score'] # Getting the mean cv score for each
 set of features
fig.add_trace(go.Scatter(x=[i for i in range(1, len(results) + 1)], y=results))
fig.update_xaxes(title_text="Number of features selected")
fig.update_yaxes(title_text="Cross validation score (nb of correct classifications)")
fig.show()
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/base.py:446: UserWarning:

X does not have valid feature names, but RFECV was fitted with feature nam
es
```

	model	color	year	mileage
0	1.0	8.0	1.036340	-1.370208
1	1.0	3.0	1.036340	-1.239574
2	1.0	6.0	1.036340	-1.372513
3	1.0	3.0	1.036340	-1.214028
4	0.0	7.0	1.492208	-1.334733
...	...	...	...	...
145	2.0	6.0	-1.243000	1.886781
146	0.0	5.0	-3.066473	1.589407
147	0.0	5.0	-3.978209	1.955240
148	0.0	8.0	-3.522341	3.986996
149	0.0	5.0	-3.978209	2.417013

150 rows × 4 columns

Note: In some codes that use RFECV you might see the `selector.grid_scores_` attribute in use. Take into account that this is a deprecated attribute, and might lead to some errors in your code if you use the some of latest versions of sklearn.

In [ ]:

```
# find best subset of features on this dataset
from sklearn.feature_selection import RFECV
from sklearn.model_selection import RepeatedKFold

numerical_cols = X.select_dtypes(include=['int64', 'float64']).columns
categorical_cols = X.select_dtypes(include=['object', 'bool']).columns
all_cols = categorical_cols.tolist() + numerical_cols.tolist()
ct_enc_std = ColumnTransformer([
            ("encoding", OrdinalEncoder(), categorical_cols),
            ("standard", StandardScaler(), numerical_cols)])
X_encoded = pd.DataFrame(ct_enc_std.fit_transform(X, t), columns=all_cols)

selector = RFECV(SGDRegressor(random_state=1), cv=RepeatedKFold(n_splits=5, n_repeats=1
0, random_state=1)).fit(X_encoded, t)
display(X_encoded.loc[:, selector.support_])

fig = go.Figure()
fig.add_trace(go.Scatter(x=[i for i in range(1, len(selector.grid_scores_) + 1)], y=sel
ector.grid_scores_)) # <--- Here grid_scores_ is in use
# It works beacuse this code is a year old, if you'll run this cell the graph will be b
roken

fig.update_xaxes(title_text="Number of features selected")
fig.update_yaxes(title_text="Cross validation score (nb of correct classifications)")
fig.show()
```

	model	color	year	mileage
0	1.0	8.0	1.036340	-1.370208
1	1.0	3.0	1.036340	-1.239574
2	1.0	6.0	1.036340	-1.372513
3	1.0	3.0	1.036340	-1.214028
4	0.0	7.0	1.492208	-1.334733
...	...	...	...	...
145	2.0	6.0	-1.243000	1.886781
146	0.0	5.0	-3.066473	1.589407
147	0.0	5.0	-3.978209	1.955240
148	0.0	8.0	-3.522341	3.986996
149	0.0	5.0	-3.978209	2.417013

150 rows × 4 columns

The best subset of features is `model` , `color` , `year` , and `mileage` .
We can also use the already fitted best model with the `selector.estimator_` attribute.

More Information

Explanation on how to use KFold and LPO (Leave P Out):
Cross-validation: evaluating estimator performance (https://scikit-learn.org/stable/modules/cross_validation.html)

An answer on how to choose k in KFold:
Choice of K in K-fold cross-validation (https://stats.stackexchange.com/questions/27730/choice-of-k-in-k-fold-cross-validation)

An answer to the differences between KFold and LOO (Leave One Out):
10-fold Cross-validation vs leave-one-out cross-validation (https://stats.stackexchange.com/questions/154830/10-fold-cross-validation-vs-leave-one-out-cross-validation)

An answer on how to change tqdm bar size:
How to change tqdm's bar size (https://stackoverflow.com/questions/54362541/how-to-change-tqdms-bar-size)

An advanced example of Scikit-learn transformers:
Can You Consistently Keep Track of Column Labels Using Sklearn's Transformer API? (https://stackoverflow.com/a/57534118)

A Guide on how to use all CV algorithms of Sckikit-learn:
Cross-validation: evaluating estimator performance (https://scikit-learn.org/stable/modules/cross_validation.html)

Scikit-learn removed Bootstrap from the CV options:
What should I use instead of Bootstrap? (https://stackoverflow.com/questions/28030291/what-should-i-use-instead-of-bootstrap)

A function transformer in Scikit-learn:
sklearn.preprocessing.FunctionTransformer (https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.FunctionTransformer.html)

Documentation on Scikit-learn Feature Selection:
Feature selection (https://scikit-learn.org/stable/modules/feature_selection.html)